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MODELLING ENDOGENOUS COMPLEXITIES IN RURAL ELECTRIFICATION:

ON THE LOCAL DYNAMICS OF GROWTH AND THE PLANNING OF OFF-GRID SYSTEMS

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To my wife and to all the persons who have taught, who are sharing, and who will still educate me to the values of love, justice, equality, and sustainability

Abstract

According to the Agenda 2030 launched by the United Nations in 2015, to ensure access to affordable, reliable, sustainable, and modern energy for all is now recognised as a fundamental goal to reach by 2030. Focusing on electrification, to ensure universal access to electricity, it is estimated that 2.6 billion people will have to be electrified by 2030, highlighting the need and the urgency to develop sustainable and appropriate approaches to electricity planning. According to this, this thesis deals with methods, approaches, and models for formulating and designing sustainable long-term electrification plans for rural off-grid areas of the world. In particular, the scientific literature highlights the lack of appropriate modelling frameworks for assessing, projecting, and integrating the electricity demand within the rural energy planning endeavour. It also reveals a weak understanding of the dynamic and multifaceted complexities that involve electricity access and socio-economic development.

To fill these gaps, this thesis sets a novel starting point for the research work on energy demand models and their integration in electrification planning procedures, by setting the following three specific objectives: *(1) To investigate and discuss the challenge of electricity demand assessment and modelling for rural electrification.* This objective is pursued through the development and analysis of specific case-studies, an extensive synthesis and capitalisation of the related scientific literature, and the characterisation of the main modelling fundamentals of this research field. The relevance of electricity demand in rural electricity planning is introduced, by discussing and demonstrating that unreliable forecasts and projections of short- and long-term electricity demand can negatively impact the techno-economic sizing of off-grid power systems. This implies a raising awareness on the criticality of electricity load assessment in rural electrification planning and advocates more research on this topic. The current methodologies adopted for projecting long-term energy demand along the planning horizon are then evaluated, finding that most of the rural energy planning literature neglects the aspect of long-term evaluation of electricity demand. It is also found that modelling long-term projections of energy demand needs to consider the multifaceted aspects related to it, which have both a technical and a socio-economic nature. This leads to the development of the main important causal loop diagrams that characterise the technical and socio-economic dimensions of the electricity-development nexus, proving that the evolution of rural electricity demand can be explained by endogenous dynamics. This result advocates the promotion of modelling techniques able to frame, understand, discuss, and quantitatively formulate the behaviour of complex systems, such as System Dynamics.

The second specific objective is *(2) To assess and model the fundamental dynamics, variables, and exogenous policies that characterise the electricity-development nexus and determine the evolution of electricity demand.* The chosen method to achieve this objective is system dynamics. All the steps are based on a real case-study as reference, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA Onlus. The *conceptualisation* of the model leads to the analysis of the dynamic problem to solve and the purpose to achieve, the model boundary and key variables, and their behaviour. The *formulation* phase results in the development of a novel simulation model which simulates the impact of electricity access and use on the socio-economic development experienced in Ikondo, and the related feedback on the community's electricity consumption. This result provides the first important goal in the research and modelling work committed to develop more general, flexible, and customizable energy demand models. The *calibration* of the model and the analysis of the uncertainties through the Markov-chain Monte-Carlo (MCMC) contributes to build confidence in the model structure by verifying its ability to replicate the observed historical behaviour of the system, and by uncovering model flaws and hidden dynamics. The calibration also confirms the appropriateness of system dynamics in modelling the complexities behind the

evolution of rural electricity demand, and it provides new modelling insights on some presumed dynamics and their impact on the electricity-development nexus. The *testing* of the model leads to a novel assessment of the most relevant dynamics and it provides a novel discussion on model results when its inputs take on different values, until the extreme ones, and as if the model were tested for different contexts than Ikondo. Policy testing is also performed for exploring model behaviour when subjected to different polices and exogenous decision-making processes. It provides a list of complementary activities to couple with electrification programmes for enhancing their positive impact on rural communities. These results can support the definition of useful guidelines and best practices for rural electrification, and they advocate an updating of the traditional monitoring and evaluation frameworks commonly used for assessing energy access projects.

The last objective is *(3) To integrate demand, load, and energy optimisation models in a more comprehensive electricity planning procedure*. This is pursued by developing a computational soft-link between the system dynamics model, a stochastic load profiles generator, and a heuristic energy optimisation tool. The result is a more comprehensive modelling framework for investigating electrification processes – if compared with the traditional approaches and hypotheses commonly adopted to assess and integrate electricity demand in rural electricity planning –, and it provides an important contribution towards the employment of the robust multi-year energy optimisation as the referring standard for off-grid electricity planning.

Keywords: rural electrification; electricity-development nexus; system dynamics; energy demand models; stochastic load assessment; energy modelling; energy optimisation.

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List of abbreviations

ABM	Agent Based Modelling
BRICS	Brazil, Russia, India, China and South Africa
DG	Distributed Generation
DP	Dynamic Programming
EO	Enumerative Optimisation
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
HH	Household
IEA	International Energy Agency
IGA	Income Generating Activity
IRES	Integrated Renewable Energy System
LP	Linear Programming
MCDM	Multi-Criteria Decision Making
MOP	Multi-Objective Programming
NASA	National Aeronautics and Space Administration
NGO	Non-Governmental Organization
NLP	Non- Linear Programming
NREL	National Renewable Energy Laboratory
OECD	Organisation for Economic Co-operation and Development
OSeMOSYS	Open Source Energy Modeling System
RES	Reference Energy System
SD	System Dynamics
SDG	Sustainable Development Goal
SME	Small-Medium Enterprises

Chapter 1

Introduction and Motivation

[…] disons plutôt que nous ne réformerons peut-être pas le monde, mais au moins nous-mêmes, qui sommes après tout une petite partie du monde; que chacun de nous possède plus de pouvoir sur le monde qu'il ne s'imagine ne posséder.
(Marguerite Yourcenar 1980)

We need megawatts not megawords
(Zambian government official 2010)

Energy is at the heart of the sustainable development agenda to 2030
(Fatih Birol, 2018)

This chapter introduces the topic of the research in the field of "access to electricity for sustainable development". It discusses the aim and motivation of the research, as well as the thesis outline and the contributions.

1.1. Background

When the world's governments met in June 2012 at a meeting known as the Rio+20 Summit, the main challenge was how to foster and support sustainable development. In the key conclusion of the Summit, the world's governments called for a new set of goals to guide the world during the next fifteen-year period from 2015 to 2030. With Rio+20, the UN started a process called Post-2015 Development Agenda, began in May 2013 and ended in August 2015 with a final document adopted at the UN Sustainable Development Summit in September 2015 in New York City. The document, called "Transforming our world: the 2030 Agenda for Sustainable Development", set the official launch of the 17 Sustainable Development Goals (SDGs). With the "Goal 7 - Ensure access to affordable, reliable, sustainable and modern energy for all", the Agenda 2030 recognises the evident and universally accepted nexus between energy and sustainable development in all its dimensions – economic, social and environmental. By 2030, the goal aims at ensuring access to electricity and clean fuels and cooking technology to all the global population. Indeed, about 1 billion people still live without electricity – with half of them living in sub-Saharan Africa –, and more than 3 billion people are still relying on biomass and unclean fuels for cooking in developing countries.

In line with this global goal of the Agenda, this thesis deals with strategies and practices for *sustainable* access to *electricity* in developing countries, and it focuses on *multidisciplinary* methods, approaches and models for formulating and designing appropriate, reliable and robust long-term electrification plans for *rural off-grid areas* of the world. Three main observations are worth to be done as preconditions to the motivations of this research:

- *"…sustainable access…"*: providing energy *per se* is not a sufficient condition for fostering sustainable development. On the contrary, inappropriate implementations of electrification projects could lead to a negative or null impact, or even impede the roadmap to sustainable development (Bhattacharyya 2012a; Ahlborg and Hammar 2014; Terrapon-Pfaff et al. 2014; Ikejemba et al. 2017b, 2017a). Deriving insights for planning sustainable power systems in developing countries is therefore a very current, being discussed, and compelling topic.
- *"…electricity…"*: the dynamics of demand growth and planning analysed in this thesis refer to electricity as energy carrier. Further works would consider the extension of the method and the results to capture the multi-carrier concept of "energy access", which includes the use of different energy forms to satisfy a variety of needs (e.g. cooking, heating, lighting, small-scale businesses) (Ramakumar 1996).
- *"…multidisciplinary…"*: in the relatively new research field on energy access, many issues are still unsolved, and the investigation of potential solutions is currently involving multidisciplinary and exploratory research approaches. In this framework, this thesis tries to set a starting point for the research work on energy demand models for rural settings, and it is meant to contribute to the same effort of other researchers focused on this issue.
- "*…rural off-grid areas…"*: The International Energy Agency (IEA) confirms that around 84%[1] of the population without electricity access lives in rural areas. In such areas, off-grid systems are forecast to deliver electricity to 70% of people (IEA 2016), due to financial (e.g. very high cost) and technical constraints (e.g. distances and morphological issues) to grid extension. According to (Mandelli et al. 2016a), in this thesis, the term "off-grid" refers to such systems that operate detached from the national grid. A particular focus is given on off-grid microgrids (i.e. conversion unit(s) coupled with a distribution grid).

1.2. Aim and Motivation of the research

To achieve the SDG7 and provide electricity for all by the 2030, the World Bank estimates that 2.6 billion people should be electrified in developing countries (IEA and World Bank 2015). Rural electrification is expected to largely contribute to the achievement of electricity access goals, since

[1]IEA – Energy Access Database. Retrieved from: https://www.iea.org/energyaccess/database/. Accessed: September 2018.

people still living without electricity will live predominantly in rural areas (IEA 2011; International Energy Agency 2016). In this framework, the need to develop sustainable and appropriate approaches to electricity planning clearly emerges. Moreover, with progresses in expanding access to electricity, the IEA estimates a rapid growth of energy demand in the next 25 years, especially in sub-Saharan Africa – based on its New Policies Scenario (IEA 2014). In the non-OECD regions, it is indeed expected that the total energy demand exceeds the OECD regions' one by 89% in 2040 (U.S. Energy Information Administration 2016), especially in Southeast Asia, China and India. A large contribution to the regional and national growth of electricity demand in developing countries is given by the expected evolution of electricity demand in rural off-grid areas.

In this framework, the general objective of my research is to contribute to formulating and designing sustainable long-term rural electrification plans for off-grid areas of the world. This goal is pursued by tackling the following three main issues through the following specific objectives:

Problem 1. In rural energy planning, the assessment of long-term electricity demand is one of the most critical and complicated steps. Indeed, wrong projections of electricity demand could negatively impact the local socio-economic development and cause an inappropriate sizing of local energy solutions, leading to supply shortages or cost recovery failure, as argued by Riva et al. (Riva et al. 2018b), Cabral et al. (Cabraal et al. 1996a, 1996b), Kivaisi (Kivaisi 2000). From the literature, it emerges a lack of understanding and research on this issue, which entails a little attention and consideration of the long-term evolution of electricity demand within rural electrification-based studies and models. One of the reasons is due the fact that the socio-economic complexities behind the evolution of the electricity demand in rural areas are far from being completely analysed, discussed and characterised.

Objective 1 *To investigate and discuss the challenge of electricity demand assessment and modelling for rural electrification.* This will set the starting point for solving the Problem 1, and answering to the following research questions: How does electricity demand impact on the planning solution of off-grid systems? How does the current literature on rural electrification tackle the analysis and evaluation of electricity demand? Which are the complexities behind the evolution of rural electricity demand? From a modelling point of view, which can be the potential way forward for assessing the evolution of rural electricity demand?

Problem 2. A second reason which prevents a proper understanding and assessment of the long-term dynamics that determine the evolution of electricity demand in rural areas is the lack of appropriate quantitative models for characterising and formulating the energy-development nexus. Indeed, "the dynamics of growth and electrification are complex, involving many underlying [socio-economic] forces" (Khandker et al., 2013, pg. 666). The presence of these complexities suggests that simple black-box regression models or predefined sets of relations of cause and effect are not appropriate to model the energy-development nexus and the dynamics behind the evolutions of electricity demand. Rather, models for projecting and forecasting energy demand should involve detailed multidisciplinary analysis, which takes a wide range of factor into account (Sterman 1988). Thus, being able to provide an appropriate modelling framework for formulating the dynamics behind such nexus between electricity and development can lead to more reliable electricity demand projections and reliable planning strategies for rural electrification.

Objective 2 *To assess and model the fundamental dynamics, variables, and exogenous policies that characterise the electricity-development nexus and determine the evolution of electricity demand.* This will contribute to solving the Problem 2, and answering to the following research questions: How to formulate the dynamics behind electricity-development nexus and generate reasonable long-term projections of electricity demand in rural areas? Why do not we see the same outcome in terms of electricity evolution patterns and rural development every time we bring electricity?

Problem 3. As for the long-term electricity demand, also the estimation of the short-term dynamics of electricity load and the integration to sizing methods are extremely important for planning rural electricity networks; and, according to the literature, they are complex modelling challenges. Hartvigsson et al. (Hartvigsson and Ahlgren 2018) compared load profiles for different types of customers connected to a mini-grid in rural Tanzania, and they found that interview-based load profiles can fail to provide an accurate overall estimate. Nevertheless, Mandelli et al. (Mandelli et al. 2016d) remarked that when dealing with off-grid rural electrification, daily load profiles are generally derived without proper models or methods. Moreover, despite the existence of a number of methodologies and energy optimisation models for the long-term planning of the energy supply (e.g. Homer, EnergyPLAN, OSeMOSYS, MESSAGE, MARKAL, TIMES, LEAP, DER-CAM, OnSSET), the integration of both short- and long-term variabilities in the optimisation is almost never explored and included for rural electricity planning purposes.

Objective 3. *To integrate demand, load, and energy optimisation models in a more comprehensive electricity planning procedure.* This will contribute to solving the Problem 3, and answering to the following research question: Does the inclusion of short- and long-term electricity demand lead to a more appropriate power capacity planning of mini-grids and tariff definition mechanisms?

1.3. Thesis outline and contributions

1.3.1. "All learning depends on feedback"

In the system dynamics field, *learning* is also considered a feedback loop (Sterman 1994), and it often requires more than one person. Indeed, notable contribution to the development of this thesis has been provided by the research work of the colleague Elias Hartvigsson (Hartvigsson 2015, 2016, 2018, Hartvigsson et al. 2015, 2018a), who set the basis for the use of the system dynamic theory in the field of rural electrification. He focused on the analysis of the endogenous dynamics that affect the viability of mini-grids through the modelling of feedbacks between electricity availability and the operators' ability to increase generation capacity, and between the growth in electricity usage and electricity availability. He used system dynamics especially as an approach for *understanding and improving* the system under analysis from the perspective of the *energy utility*. Part of this thesis stands on his main findings and adds the following foci as for the use of system dynamics:

1. as an approach for *characterising* the electricity demand-development nexus and its multifaceted dynamics;
2. for *projecting* long-term electricity demand scenarios;
3. from the perspective of the *energy planner*.

This thesis is therefore meant to contribute to the same effort of other researchers focusing on energy demand models and rural electrification, with the final goal of investigating the socio-economic complexities of the rural electricity-development nexus, providing a more reliable approach for modelling long-term projections of rural electricity demand, and planning more reliable off-grid power systems.

1.3.2. Outline

This thesis is organised in a specific structure which follows a methodological outline divided in two parts (Fig. 1).

- *Part I.* The first part aims at pursuing the Objective 1 of the thesis, which brings different elements of originality: the development and analysis of specific case-studies, an extensive synthesis and capitalisation of the related scientific literature, and the characterisation of the main modelling fundamentals of this research field. The relevance of electricity demand in rural electricity planning is first introduced (Chapter 2), followed by a novel clarification, analysis, and categorisation of the published energy planning studies in rural areas in order to track the similarities, weaknesses and strengths, as well as the current methodologies adopted for projecting long-term energy demand along the planning horizon (Chapter 3). This highlights that modelling long-term projections of energy demand needs to consider the multifaceted aspects related to it, leading to the development of causal loop diagrams for analysing the complex nexus between electricity demand and rural development (Chapter 4). A final comparison between the system dynamics and the agent-based modelling approaches is carried out for building upon the quantitative modelling of the endogenous complexities behind the electricity demand-development in rural areas (Chapter 5).

– *Part II.* The second part aims at pursuing the Objective 2 and Objective 3 of the thesis, by describing the modelling effort and results achieved. System dynamics is the first method employed for the conceptualisation (Chapter 6), formulation (Chapter 7), calibration (Chapter 8), and testing (Chapter 9) of a novel simulation model which investigates the complex dynamics of the electricity-development nexus observed in a real case-study in a rural community in Tanzania. A novel computational soft-link is then developed (Chapter 10) for integrating the simulation model with a load profile generator and an energy optimisation model, in order to provide a more comprehensive modelling framework for developing more robust energy optimisation processes.

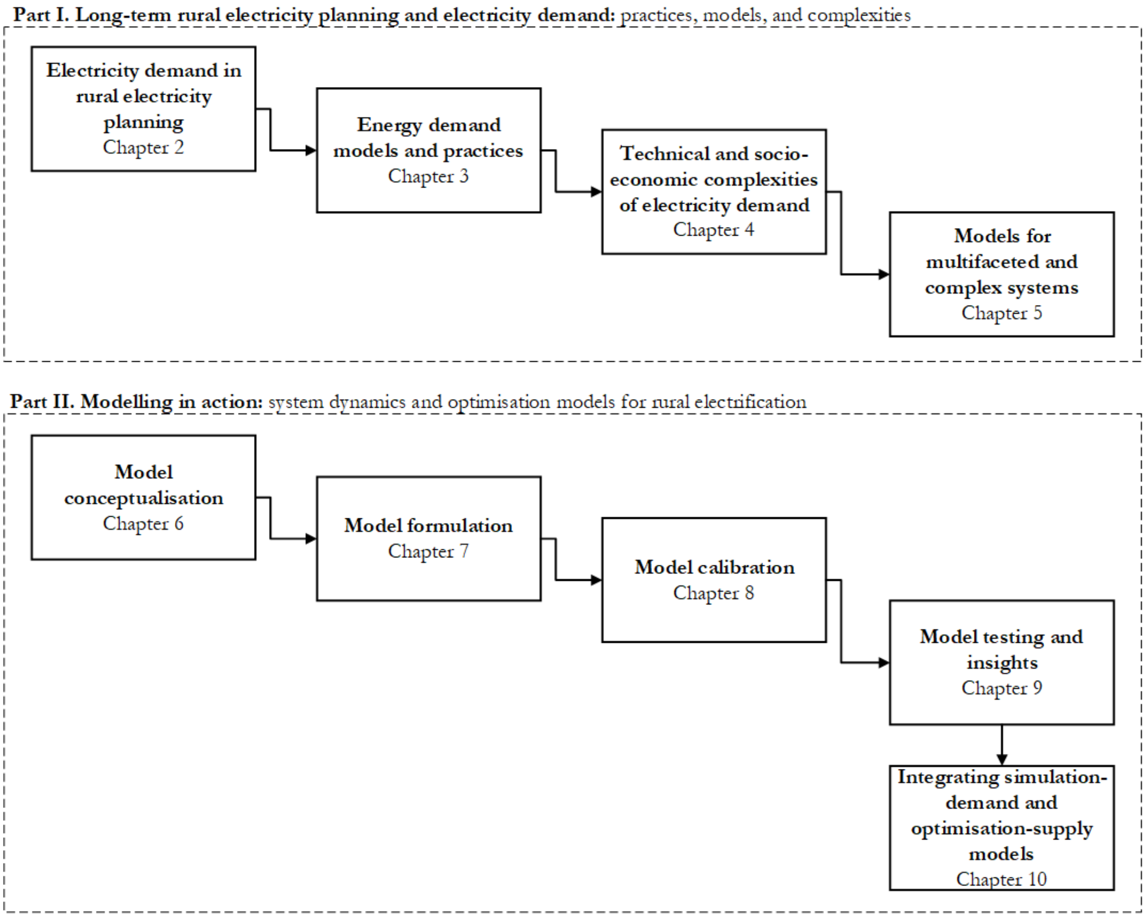

Fig. 1. Methodological outline and summary of thesis contribution.

The contents of each chapter are detailed below:

Chapter 2. This chapter introduces the relevance of electricity demand in rural electricity planning. In particular, both the short- and long-term dimensions of electricity demand are discussed, demonstrating how unreliable forecasts and projections can impact on the techno-economic sizing of off-grid microgrid power systems. Two case studies are introduced for supporting the discussion. The first *CASE 1* reports and discusses an on-field analysis carried out in rural Tanzania to assess the electricity needs and to estimate reliable load curves for assessing the profitability of an eventual rural electrification project considered by the NGO CEFA Onlus. The second *CASE 2* investigates the combined effect of short- and long-term electricity demand on the electricity planning solution of a rural community in rural India. The chapter is the first contribution to achieving Objective 1, by analysing how different methods and evaluations of electricity demand can differently impact on the electricity planning solution. This chapter is based on the following publications:

Riva F., Berti L., Mandelli S., et al., On-field assessment of reliable electricity access scenarios through a bottom-up approach: The case of Ninga SHPP, Tanzania, in: 2017 *6th Int. Conf. Clean Electr. Power*, Santa Margherita Ligure, Italy, 2017: pp. 340–346. doi:10.1109/ICCEP.2017.8004837.

Riva F, Gardumi F, Tognollo A, Colombo E. (2019) Soft-linking energy demand and optimisation models for local long-term electricity planning: An application to rural India. *Energy,* 166, 32-46. doi: 10.1016/j.energy.2018.10.067.

Chapter 3. The chapter contributes to Objective 1, by investigating the main demand models used in the rural energy planning literature. It proposes a first clarification, analysis, and categorisation of the published energy planning studies. Indeed, several studies were carried out on long-term rural energy planning since around the '80s, but the different foci, terminology and methodologies make it difficult to track the similarities, weaknesses, and strengths, especially regarding the methodology adopted for projecting long-term energy demand along the planning horizon. As a novelty, the analysis of both the "demand" and the "supply" aspects of the rural energy planning studies is combined, stressing the need to consider the two parts of the planning as linked and interdependent. For this purpose, it is followed an approach that classifies the studies firstly in accordance with specific subcategories suggested by the literature (viz. spatial coverage, planning horizon, energy carrier, decision criteria mathematical models and energy uses), and secondly in accordance with the methodology they employ to forecast the evolution of the energy demand. The final section of the chapter highlights that modelling long-term projections of energy demand in these areas is a complex issue, involving both technical and socio-economic dimensions. This chapter is based on the following publication:

Riva, F., Tognollo, A., Gardumi, F., Colombo, E. (2018). Long-term energy planning and demand forecast in remote areas of developing countries: Classification of case studies and insights from a modelling perspective. *Energy Strategy Reviews,* 20, 71-89. doi: 10.1016/j.esr.2018.02.006.

Chapter 4. In order to investigate further the complexities behind the evolution of rural electricity demand, this chapter undertakes a comprehensive and extensive analysis of the peer-reviewed literature on electricity access and its impact on rural socio-economic development, and vice versa. It contributes to Objective 1 by investigating the socio-economic and technical complexities which involve the nexus between electricity demand and development, as well as by setting a basis for the modelling of electricity demand in rural areas and, hence, the planning of off-grid mini-grids. The analysis is carried out by developing graphical causal loop diagrams that allow to capture, visualise, and discuss the complexity and feedback loops characterising the following multiple dimensions of the electricity-development nexus: *income generating activities*, *market production and revenues*, *household economy*, *local health and population*, *education*, and *habits and social networks*. This chapter is based on the following publication:

Riva, F., Ahlborg, H., Hartvigsson, E., Pachauri, S., & Colombo, E. (2018). Electricity access and rural development: Review of complex socio-economic dynamics and causal diagrams for more appropriate energy modelling. *Energy for Sustainable Development*, 43, 203-223. doi: 10.1016/j.esd.2018.02.003.

Chapter 5. This chapter sets the basis for building upon the modelling of the endogenous complexities behind the electricity-development nexus from a quantitative point of view, which is the last result for pursuing Objective 1. To this aim, the interconnections of multiple factors, the high uncertainty level, strong non-linear phenomena, and the presence of time delays and feedbacks suggest System Dynamics (SD) as a potential appropriate systems-modelling approach. On the other hand, the agent-based complexities behind diffusion mechanisms, energy consumers' behaviour, social interactions, spatial constraints, and decision-making processes suggest Agent-based Modelling (ABM) as a further modelling tool. In order to compare the two methods and guide the final choice towards the most appropriate approach, an ad-hoc case-study is developed. This chapter is based on the following conference paper:

Riva F, Colombo E, Piccardi C. Modelling social networks in innovation diffusion processes: the case of electricity access in rural areas. Proc. *35th Int. Conf. Syst. Dyn. Soc.*, Cambridge, USA: System Dynamics Society; 2017.

Chapter 6. This is the first chapter of the part II of the thesis. In accordance with the issues emerged in the analysis on the electricity-development nexus and the specific objectives of the thesis, the dynamic problem to solve and the purpose of the SD model are defined. A real case-study is introduced as reference for achieving these purposes and for going further in the conceptualisation and the next stages of the modelling process, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA Onlus. It sets the basis for achieving Objective 2, since it allows to identify the model boundary and key variables, describe their behaviour and the related reference modes, and represent the feedback loops of the system.

Chapter 7. This chapter reports the *formulation* of the simulation model: its mathematical specification of its structure and decision rules – i.e. the conversion of the feedback diagrams to algebraic, differential, and integral equations. The simulation framework is based on Vensim DSS ® software. Its formulation follows an iterative process based on the questionnaires implemented in the field, the information shared with the local experts, and the analysis and re-redefinition of the structure by the modeller. The final structure of the model is defined by the main dynamics highlighted in the conceptualisation process, and it counts 11 main sub-models: *IGAs formation and Income*, *Market demand, Market production and revenues, Agricultural revenues, Population, Time savings, Education, IGAs electricity connections, HHs electricity connections, Household appliances diffusion,* and *Electrical Energy consumption*. The model simulates the impact of electricity access and use on the socio-economic development experienced in Ikondo, and the related feedback on the community's electricity consumption. The contents of this chapter are included in the proceedings of the 36th International Conference of the System Dynamics Society:

Riva F, Investigating and modelling endogenous socio-economic dynamics in long-term electricity demand forecasts for rural contexts of developing countries. *36th Int. Conf. Syst. Dyn. Soc.*, Reykjavík, Iceland: System Dynamics Society; 2018.

Chapter 8. This chapter reports the *calibration* of the simulation model, in order to (i) verify the ability of the model to replicate the observed historical behaviour of the system, (ii) uncover model flaws and hidden dynamics, and (iii) identify a reasonable set of parameters' values most consistent with relevant the knowledge of the system. The calibration is performed by relying on historical data on the electricity consumption in the Ikondo village, and on local interviews to define the search space for all the calibrating parameters. The Powell algorithm is used to run the optimisation. The Markov-chain Monte-Carlo (MCMC) is then used to explore the appropriateness of the calibration of the model, and to assess potential good proxies of the confidence bounds of the calibrated parameters. The contents of this chapter are included in the proceedings of the 36th International Conference of the System Dynamics Society:

Riva F, Investigating and modelling endogenous socio-economic dynamics in long-term electricity demand forecasts for rural contexts of developing countries. *36th Int. Conf. Syst. Dyn. Soc.*, Reykjavík, Iceland: System Dynamics Society; 2018.

Chapter 9. This chapter reports the main insights from model testing and use, by assessing the main fundamental dynamics, variables, and exogenous policies that characterise the model, as stated in the Objective 2. After the discussion of some aspects related to the concept of model validation in the SD theory, *direct structure tests* are performed to check the coherence between the mode structure with the existing empirical and theoretical knowledge about the actual structure of the analysed system. *Structure-oriented behaviour tests* are then implemented for assessing the most relevant dynamics, and for discussing the results of the model when its inputs take on different values, until the extreme ones and as if the model were tested for different contexts than Ikondo. *Policy testing* are performed for exploring model behaviour when subjected to different polices and exogenous decision-making processes, in order to perform a kind of *what-if* analysis on the model outcome, derive some useful insights on the polices implemented by CEFA, and propose potential improvements. Further tests are implemented for evaluating the importance and the impact of electricity access on some socio-economic dynamics, and the reverse feedback. Finally, the *sensitivity analysis* is performed to test the robustness of the conclusions that can be derived from the main model output on varying the assumptions over a plausible range of uncertainty.

Chapter 10. This chapter addresses the Objective 3. It reports and discusses the modelling effort in soft-linking demand, load, and energy optimisation models for more appropriate electrification planning procedures. To derive stochastic long-term load profiles, the *LoadProGen* tool model is modified and improved in order to simulate and aggregate a number of daily profiles in line with the duration of the desired scenario and the projections obtained with the SD model. The integration with the *Poli.NRG* energy model is implemented in order to optimise the size of the energy supply technologies through a heuristic procedure under a number of constraints and inputs (e.g. the long-term electric load profiles, the availability of renewable resources, and the fraction of admissible unmet load). A Hydro-batteries is considered, in order to investigate what would have been a potential optimal capacity to install for supplying the projected electricity demand of Ikondo from 2005 to the end of 2017. The same optimisation is implemented by considering a PV-batteries system for the planning of the first 3 years of the horizon, given the flexible nature of solar systems and the low variability in the electricity demand in the first years. In order to highlight the benefits and challenges of the soft-linked procedure, the results are compared with the traditional approaches and hypothesis commonly adopted in the literature to assess and introduce electricity demand in rural electricity planning processes.

Chapter 11. This chapter provides a summary of the thesis contributions, implications, strengths and weaknesses of the work, and it discusses the potential future works and research activities.

1.3.3. Other contributions

In the framework of this thesis, other publications not mentioned above had an influence on the contributions and the research path followed during the doctoral activities of the Author. They allowed to build confidences on models, theories, and approaches adopted in this work, as well as to explore and increase the knowledge about the issue of access to energy in developing countries and the related multidisciplinary and multifaceted complexities.

On Journal

Barbieri J, Parigi F, Riva F, Colombo E. Laboratory Testing of the Innovative Low-Cost Mewar Angithi Insert for Improving Energy Efficiency of Cooking Tasks on Three-Stone Fires in Critical Contexts. *Energies;* 11(12), 3463: doi: 10.3390/en11123463.

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Riva F, Lombardi F, Pavarini C, Colombo E. Fuzzy interval propagation of uncertainties in experimental analysis for improved and traditional three – Stone fire cookstoves. *Sustain Energy Technol Assessments* 2016; 18: 59-68. doi:10.1016/j.seta.2016.09.007.

Conference contributions

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Part I

Long-term rural electricity planning and electricity demand: practices, models, and complexities

This part addresses the Objective 1 of the thesis. It includes a wide analysis of the issue of electricity demand in rural electrification, the synthesis and the capitalisation of the related scientific literature, the characterisation of the main modelling fundamentals of this research field, and the proposal of useful guidelines for other researchers.

Chapter 2

Relevance of electricity demand in rural electricity planning

No one wishes to have electricity for itself, but people want it for what it can do
(Bastakoti 2006)

This chapter introduces the relevance of electricity demand in rural electricity planning. In particular, both the short- and long-term dimensions of electricity demand are discussed, demonstrating how unreliable forecasts and projections can impact on the techno-economic sizing of off-grid microgrid power systems. Two case studies are introduced for supporting the discussion. The first *CASE 1* reports and discusses an on-field analysis carried out in rural Tanzania to assess the electricity needs and to estimate reliable load curves for assessing the profitability of an eventual rural electrification project considered by the NGO CEFA Onlus. The second *CASE 2* investigates the combined effect of short- and long-term electricity demand on the electricity planning solution of a rural community in rural India. The chapter is the first contribution to achieving Objective 1, by analysing how different methods and evaluations of electricity demand can differently impact on the electricity planning solution. This chapter is based on the following publications:

Riva F., Berti L., Mandelli S., et al., On-field assessment of reliable electricity access scenarios through a bottom-up approach: The case of Ninga SHPP, Tanzania, in: 2017 *6th Int. Conf. Clean Electr. Power*, Santa Margherita Ligure, Italy, 2017: pp. 340–346. doi:10.1109/ICCEP.2017.8004837.

Riva F, Gardumi F, Tognollo A, Colombo E. (2019) Soft-linking energy demand and optimisation models for local long-term electricity planning: An application to rural India. *Energy,* 166, 32-46. doi: 10.1016/j.energy.2018.10.067.

2.1. Foreword

Different Authors define *energy planning* in several ways, emphasizing multiple important aspects. In general, the literature refers to energy planning as the process aimed at developing long-term policies for supporting the development, implementation, and management of local, national, regional or even global energy systems. Prasad et al. (Prasad et al. 2014) quote some authors underling that any energy planning needs to foster sustainable development. They considered energy planning as *"a roadmap for meeting the energy needs of a nation [which] is accomplished by considering multiple factors such as technology, economy, environment, and the society that impact the national energy issues"* ((Prasad et al. 2014) p. 686). Hiremath et al. (Hiremath et al. 2007) write that the *"energy planning endeavour involves finding a set of sources and technologies in order to meet the energy demand in an optimal manner"* (p. 729). Deshmukh (Deshmukh 2011) suggests that energy planning aims above all at developing an optimal plan for the allocation of energy resources, by considering future energy requirements according to several technical, economic, social and environmental criteria. Yusta and Rojas-Zarpa (Rojas-Zerpa and Yusta 2014) state that *"energy planning implies finding a set of sources and conversion equipment that optimally satisfy the energy demand of all activities"* (p. 67). In view of the above discussion and being aware of both the policy- and design-oriented concept of energy planning, this thesis refers to **energy planning as that process aimed at (i) selecting (viz. identifying, sizing and designing) conversion technologies (ii) by performing an optimisation based on appropriate criteria (viz. either strictly mathematical programming or multi-criterial analyses if dealing with less quantitative objectives) (iii) for matching a certain demand with the available energy resources.** This definition emphasizes the importance of objective criteria in order to confer a more scientific meaning and nature to the concepts of "optimal plan /optimally" that emerged from the literature. This definition is also in line with the final goal of this thesis, which mainly focuses on the development of appropriate models for supporting the design phase of rural off-grid energy systems. In the framework of this thesis, since the energy carrier considered is electricity, the term *electricity planning* is used.

2.2. *Short-term* electricity load and techno-economic sizing

The assessment of electricity load demand is one of the key-elements when planning distributed electricity systems. In a short-term perspective, electricity use is expressed as a "load profile", which contains two important information necessary to size and design off grid systems:

- *Energy needed [kWh]*. It is the area below the electricity profile, and it defines the quantity of electricity consumed in the 24 hours.
- *Peak power [kW]*. It is the maximum instantaneous electric power demand, which can occur in the 24-hours.

The knowledge of these two information allows to properly size the power capacity of a power system, as well as the back-up and storage capacity, particularly where economic resources are scarce, as Kusakana discusses (K. Kusakana 2012). In rural off-grid systems, due to the high unpredictability of people behaviours and the lack of historical data, the estimation of electricity load is a very complex modelling challenge (Blodgett et al. 2017; Hartvigsson and Ahlgren 2018). In the literature, models of a different kind are employed for computing the expected daily load profiles, as reviewed by Hong and Fan (Hong and Fan 2016). Nevertheless, as remarked by Mandelli et al. (Mandelli et al. 2016d), when dealing with off-grid *rural* electrification, daily load profiles are generally derived without proper modelling or methods: electric loads are estimated adapted from profiles that came from the literature and/or similar contexts, as done by Nfah et al. (Nfah and Ngundam 2009), Phrakonkham et al. (Phrakonkham et al. 2012a), Semaoui et al. (Semaoui et al. 2013), Sen and Bhattacharyya (Sen and Bhattacharyya 2014a), and Sigarchian et al. (Sigarchian et al. 2015) for rural contexts in Africa and Asia; or by introducing assumptions on the functioning periods of electric appliances or load factors, as done by Al-Karaghouli and Kazmerski (Al-Karaghouli and Kazmerski 2010), Bekele et al. (Bekele and Tadesse 2012a), and Gupta et al. (Gupta et al. 2011a). Often, these approaches can represent the only viable options in case of complete lack of quantitative data. In case of data availability, parameterized models can be used, but their application is very limited to specific contexts with almost standardized habits and uses of energy, as Orosz et al. (Orosz et al. 2018) demonstrate for rural health centres in sub-Saharan Africa. In this framework, Mandelli et al. (Mandelli et al. 2016d), with the contribution of the Author of this thesis (Mandelli et al. 2017), introduced a novel mathematical bottom-up stochastic procedure, which they formalised in the software *LoadProGen* (Load Profile Generator) implemented in MATLAB® [2]. So far, applications of these methods seem limited to the development of short-term load profiles – within one year at most.

The next sub-section reports a case-study, which aims at highlighting the importance of short-term electricity in rural electricity planning. It specifically reports the results of an on-field analysis carried out in rural Tanzania to assess the electric needs and estimate reliable load curves for an eventual rural electrification projects considered by CEFA NGO.

[2]The software and its updates can be downloaded free-of-charge from the *Energy4Growing* website.

2.3. *CASE 1: "The case of Ninga SHPP"*

In 2016 the Italian NGO called CEFA carried out a feasibility study for implementing a small hydro power plant situated in the region of Njombe, Tanzania. This new important project is called "Ninga-SHPP" and consists of a 6 MW Small Hydro Power Plant (SHPP) that should provide access to electricity to 13 rural villages and will produce an excess of electricity that can be sold to the national electric grid operator TANESCO. In this context, an appropriate forecast of the eventual electricity demand, once the villages will be provided with access to electricity, is mandatory to correctly estimate the sustainability of the project (Ahlborg and Sjöstedt 2015) and the possible cash flows derivable from selling the electricity surplus to TANESCO.

2.3.1. CEFA's Ninga-SHHP: feasibility analysis

This feasibility study was finalized in March 2015. The proposed 6 MW capacity would exploit the water of South Ruaha River, and it will supply an area of 10,000 km² situated in Njombe Region, approximately 55 km north-east far from Njombe township, through an electric line (33kV) 82 km long. The plant will be a run-of-river and subject to variable seasonal river flows. The main technical features of the proposed power plant are shown in (Table 1).

Table 1. Technical features of the Ninga-SHPP power plant.

Intake location	UTM 725.465 E; 9.001.143 N 1397.50 m asl
Powerhouse location	UTM 725.167 E; 9.001.159 N 1322.24 m asl
Penstock length	177.5 m
Gross head	76 m
Electrical power	6.0 MW
Expected annual energy output	26,410,000 kWh

Since the project considers that the exceeding energy produced by the SHPP could be sold to the TANESCO, any eventual surplus of energy produced during the more "favourable" months will represent a source of economic revenues. This is the reason why an accurate load demand evaluation of the 13 villages is required to calculate the excess of saleable energy produced by the plant and to estimate correctly the economic attractiveness of the project.

2.3.2. Load profile forecasting

Un-electrified rural areas are characterized by high uncertainty and low quality of data. The software LoadProGen developed by Mandelli et al. (Mandelli et al. 2016d) was used given the possibility to rely on simple input data that can be easily collected by means of local surveys or assumed by practical experience on similar context conditions. To derive input data for running LoadProGen, since the 13 villages are not electrified, data were collected from Nyombo and Kidegembye villages, which are located around 15 km north of Ninga (Fig. 2). The two villages were electrified by TANESCO through grid extension in 2014.

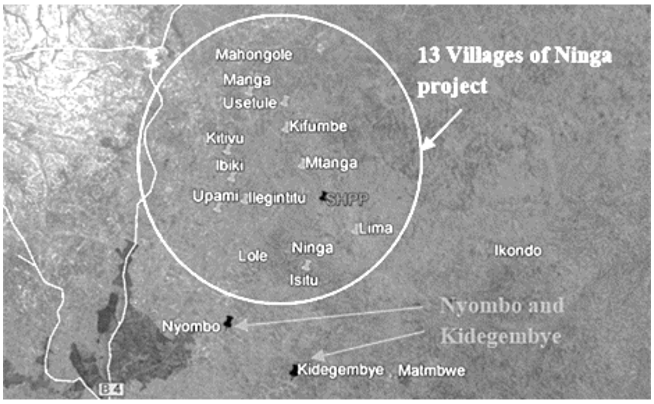


Fig. 2. Google Earth view of the 13 villages of the study area [from (Riva et al. 2017)].

CEFA's team confirms that those two electrified villages are characterized by very similar features to the 13 non-electrified villages on Ninga project: similar number of household members (on average

4/5 members per family), similar structure of the villages (2-3 main roads where most of productive activities are located), same type of productive usages, similar economic conditions (viz. average income) of households, and similar size of the villages (i.e. on average around 400 households per village and 2,000 inhabitants).

Based on these assumptions, data about electric appliances and habits adopted by people in the 2 electrified villages (Nyombo and Kydegembye) were collected and used in LoadProGen to estimate the load curve profile of the 13 non-electrified villages. The population was divided into three "categories" which are Households (HHs), Public Services (PBs) and Productive Usages (PUs). The HHs were divided in 33 user classes that correspond to the number of HHs interviewed in the electrified villages of Nyombo and Kydegembye. Therefore, each HH user class (HH_1, HH_2, HH_3, HH_4…etc.) represents 1/33 of the total population of the 13 villages. The PSs were divided into 4 User Classes: Schools, Offices, Dispensaries, Churches. The PUs were divided in 7 User Classes: Milling machines, Carpentries, Shops, Haircutters, Guest Houses, Garages, Pubs. When people interviewed were unable to describe the minimum continuous functioning time of appliance once it turns on, values were hypothesized based on literature research (Blennow and Bergman 2004).

2.3.3. Results and discussion

Due to very high number of data analysed by LoadProGen and the extensive computational time of the software, two Excel-based input data files were created, and two separated load curves were obtained: the first for the 33 user classes of HHs, supposing 1 family per user class, and the second accounting for all the users of the 11 user classes of PSs & PUs. Supposing then to electrify 30%, 50% and 70% of the 5607 families, the simulated HHs curve is multiplied accordingly to the number of families of the corresponding scenario, and then added to the PSs & PUs curve. For each LoadProGen simulation, *n* stochastic load curves with the same input data were created, based on following conditions:

$$\begin{cases} \dfrac{\overline{y}(k)_n - \overline{y}(k)_{n+1}}{\overline{y}(k)_n} \leq \delta \text{ for } k \geq 95\% \\ \dfrac{\overline{std}\left[y(k)_n\right] - \overline{std}\left[y(k)_{n+1}\right]}{\overline{std}\left[y(k)_n\right]} \leq \delta \text{ for } k \geq 95\% \end{cases} \tag{1}$$

Where *k* refers to the profile time steps (viz. the minutes), $\bar{y}(k)_n$ is the average load value of n generated profiles at the time step k, and $\overline{std}[y(k)_n]$ is the average standard deviation of the load value of n generated profiles at the time step k. Given an acceptable value of tolerance δ=0.25%, *n* is identified when the two conditions have been verified for at least the 95% of the time steps. For the three scenarios, *n* result equal to 254, 208 and 208 for respectively the Scenario 30%, 50% and 70%.

Scenario 30%, 50% and 70%

For the three scenarios, 30%, 50% and 70% of HHs are supposed to respectively have access to electricity once the Ninga-SHPP project will be completed: 1,526 HHs for Scenario_30%, 2,803 HHs for Scenario_50% and 4,065 HHs for Scenario_70%. The total mean cumulative curves simulated with LoadProGen for the three scenarios are reported in Fig. 3.

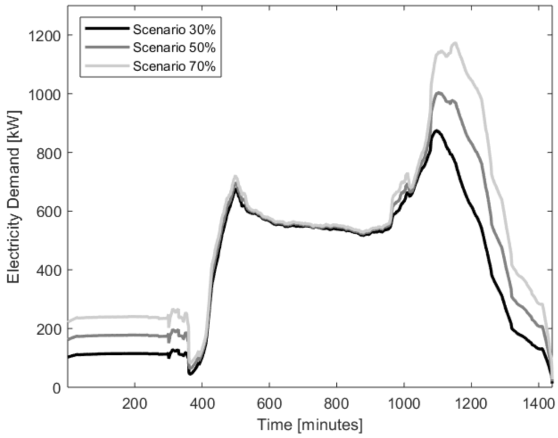


Fig. 3. Mean load curves for the three different Scenarios [from (Riva et al. 2017)].

In the Scenario_30%, the daily energy demand of the villages is equal to 9.7 MWh, while the load peak value is equal to 0.87 MW. In the Scenario_70%, the daily energy demand is equal to 12.5 MWh and load peak value is equal to 1.17 MW. In the middle of the day, the load curve of the different scenarios roughly overlaps because energy contribution to the load curve in daytime is mainly due to Productive Usages, that are the same in all the three scenarios. In all the scenarios, it can be observed that the peak value of the load curve is at sunset between 19:00 and 20:00, when people come back home from work and they turn on lights, radios, and televisions.

In order to highlight the "stochasticity" accounted by LoadProGen, the Scenario_50% is represented in Fig. 4 with the relative uncertainty bands that respectively represent the lowest and highest values of electricity demand which can occur in each of the 1440 minutes (duration of a day in minutes) among the 208 simulated curves.

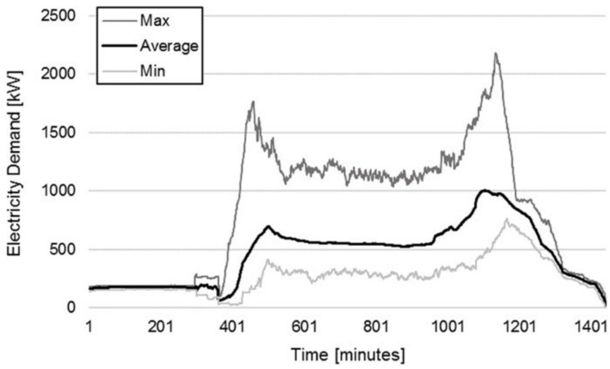


Fig. 4. Load curve of the thirteen villages: Scenario_50% [from (Riva et al. 2017)].

As shown in the graph, uncertainty bands are very broad, especially due the application of LoadProGen in contexts with a very high number of users: 2803 HHs, 96 PSs and 351 PUs for Scenario_50%.

Comparison between preliminary and LoadProGen-based load profiles

In this sub-section, the results obtained with LoadProGen are compared with the electricity demand assessment carried out during the feasibility study by relying on a traditional deterministic approach (Fig. 5).

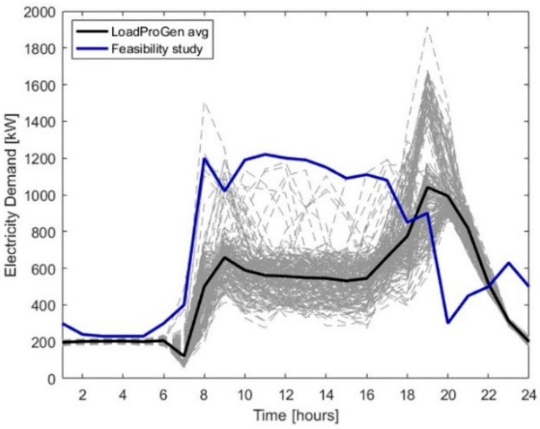


Fig. 5. Comparison between feasibility and LoadProGen-based load curve [from (Riva et al. 2017)].

By looking at the mean values of the profiles, the daily energy demand (viz. the area under the load curve) evaluated by the company is 17.5 MWh, higher than the 12 MWh estimated by LoadProGen. This has a direct impact on the monthly and yearly excess of energy that can be sold to TANESCO in the two cases. Results in Table 2 confirms that the saleable surplus of energy evaluated with LoadProGen is around 10% higher than that derived by the company's results, and this makes the profitability of the project more attractive, since the "surplus" of energy produced is here saleable to TANESCO and does not represent a loss, but a potential source of profit.

Table 2. Monthly and yearly energy produced and excess of energy [MWh] for the two conducted studies[3].

		LoadProGen		Traditional approach	
	Energy Produced [MWh]	**Energy demand [MWh]**	**Energy Surplus [MWh]**	**Energy demand [MWh]**	**Energy Surplus [MWh]**
Ann.	27'230	4'387	*22'842*	6'391	*20'838*

Furthermore, the "shape" of the two load curves is significantly different: the peak load value is during central hours of the day with the traditional approach (between 10:00 and 13:00), while the profile generated with LoadProGen is at sunset (between 18:00 and 19:00). The reason is due to the simplified hypotheses made during the prefeasibility study, as indicated in the "Ninga SHPP Business Plan 2015". It emerged that the feasibility study overestimated the electricity consumption of machinery used by PUs of the villages. Indeed, the functioning hours of some machinery – "Mills" (power peak 15,000W) and "Carpenter, welding, battery charging" (2,000W), that are some of the most consuming appliances used during the day – were considered equal to their functioning windows. As a matter of fact, the effective functioning time of working machines is much lower than respective functioning windows during day time (e.g. functioning time of "Mill" is equal to 180 minutes while the width of functioning windows is equal to 10h – from 08:00 to 18:00). Consequently, this caused an overestimation of the energy contribution of PUs to the total load curve and a shifting of the peak value.

2.3.4. Conclusion

The case confirms the importance of considering short-term uncertainties in planning rural electricity systems. Indeed, by relying on the stochastic LoadProGen tool implemented to the Ninga hydroelectric power system, this analysis suggests that such more reliable estimates might have a non-negligible impact on the evaluation of the eventual profitability of the project. Moreover, such minute- and hourly-based estimations might reveal as extremely important also when designing off-grid microgrids powered by higher intermittent and uncertain renewable resources – like solar and wind – , in order to find the most appropriate and cheapest configuration of power plants able to satisfy a certain electricity demand.

[3] The energy produced taken from the feasibility study report provided by CEFA.

2.4. *Long-term* electricity demand in rural contexts

In a long-term perspective, electricity use is expressed as a "demand". Based on its New Policies Scenario (IEA 2014), the International Energy Agency (IEA) estimates a rapid growth of the energy demand in sub-Saharan Africa and in India in the next 25 years (IEA 2015) (Fig. 6 and Fig. 7). In the non-OECD regions, the total energy demand is expected to exceed the OECD regions' one by 89% in 2040 (U.S. Energy Information Administration 2016), especially in Southeast Asia, China and India. In developing countries, energy access-oriented policies and actions may contribute to the growth of the global energy demand (Fig. 8). Indeed, for achieving the total access to electricity goal, the World Bank estimates that 2.6 billion people should be electrified by 2030 in developing countries (IEA and World Bank 2015).

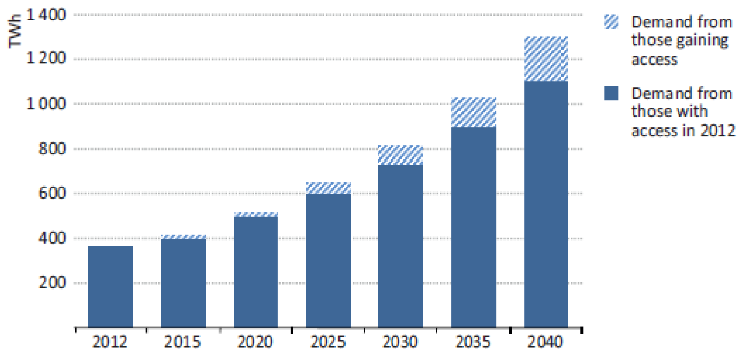


Fig. 6. Expected future electricity demand in sub-Saharan Africa [from (International Energy Agency 2015)].

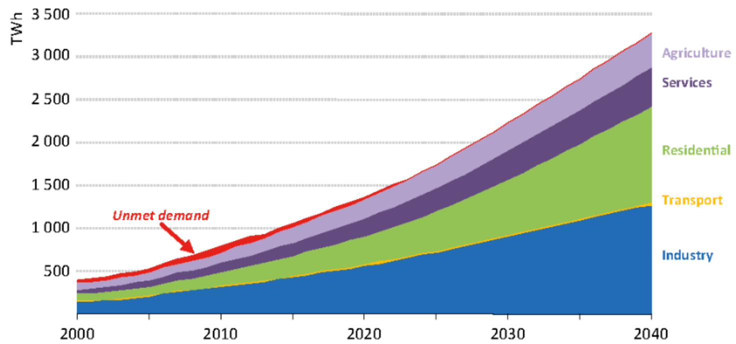


Fig. 7. Electricity demand by sector in India according to the IEA2015 New Policies Scenario [from (IEA 2015)].

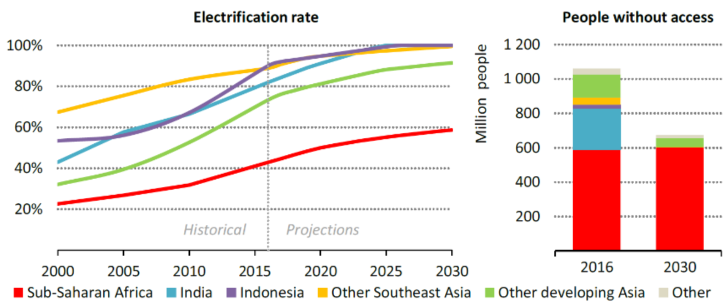


Fig. 8. Electrification rate and population without access to electricity according to the IEA2017 New Policies Scenario [from (International Energy Agency 2017)].

2.4.1. Rural demand evolution outlook

As confirmed by the grey and scientific literature, a large contribution to the regional and national growth of electricity demand in developing countries is given by the expected evolution of electricity demand in rural areas. Mustonen (Mustonen 2010) used LEAP model to investigate possible developments and growth paths for electricity demand from 2006 to 2030 for a rural village in Lao People's Democratic Republic. Daioglou (Daioglou et al. 2012) and Ruijven (van Ruijven et al. 2011) modelled and investigated the growth of household electricity demand in rural India, China, South East Asia, South Africa and Brazil. Nerini (Fuso Nerini et al. 2015) identified 4 scenarios of energy demand growth in the village of Suro Craic in Timor Leste, based on the ESMAP/World Bank multi-Tier framework for measuring energy access. Nfah et al. (Nfah et al. 2007) reported annual data of electricity demand for a Cameroonian household, indicating a clear positive trend of electricity consumption over a period of 8 years. In their bottom-up model, Debnath et al. (Debnath et al. 2015) suggested that electricity demand in rural households in Bangladesh will rise significantly by 2050. Xiaohua et al. (Wang et al. 2006) indicated that the rural households in the Shouyang County in China have experienced a growth of electricity use especially due to increased ownership levels of electrical appliances. Zomers suggested that in the case of developing countries, rural electricity demand can increase "at more than just a few per cent per annum ((Zomers 2003), pg. 71)". Gustavsson (Gustavsson 2007b) presented data from a case-study of a photovoltaic-Energy Service Company (PV–ESCO) project company in Lundazi, rural Zambia, indicating that the clients of the system have purchased and used a growing number of appliances over time. Muñoz et al. (Muñoz et al. 2007) reported monthly data of electricity consumption in two different Moroccan villages, showing a positive trend of electricity load from 2002 to 2006. Morante and Zilles (Morante and Zilles 2001) and Reinders et al. (Reinders et al. 1999) reported that in the village of Sukatani, in the Province of West Java, Indonesia, households have experienced was a large increment of electricity consumption between 1992 and 1997, from 4.65 to 7.65 kWh/month. Habtetsion and Tsighe (Habtetsion and Tsighe 2002) investigated the electrification rate of 13 rural villages in Eritrea, finding that an annual growth of connections of 17%, and an annual consumption growth rate of 54%. They suggested that the reason can be attributable to the availability of electricity, which supported people's engagement in new businesses that in turn required further electricity. Dinkelman (Dinkelman 2011) indicated that in the electrified areas of South Africa, the percentage of households who cooked with electricity and used electrical lighting have more than tripled between 1996 and 2001, respectively. Terrapon-Pfaff et al. (Terrapon-Pfaff et al. 2014) reviewed the sustainability of small-scale renewable energy projects in developing countries, indicating that in 57% of the cases, the electricity demand increased over time based on new devices used by people and new connections requested. Alazraki and Haselip (Alazraki and Haselip 2007) reported the experience of PERMER electrification project in the rural province Jujuy and Tucumán, where people expressed their desire to double the capacity of their standalone PV system in order to use more electrical appliances. Khandker et al. (Khandker et al. 2013) reported data of electrical appliances ownership between 2002 and 2005 in rural Vietnam, and it emerged a growth in ownership as people kept consuming electricity from the grid. Den Heeten et al. (Den Heeten et al. 2017) mapped the current domestic electricity needs in rural Cambodia, and they estimated a significant growth in the electricity consumption and power request for the future.

2.4.2. Long-term electricity demand and capacity planning

Besides confirming positive evolution patterns of electricity demand in rural areas, the literature confirms also to pay attention to the long-term electricity demand when designing power systems: wrong predictions could lead to an inappropriate sizing of energy solutions (Wolfram et al. 2012), shortages or cost recovery failure for local utility due to unsustainable tariffs (Hartvigsson et al. 2015), and then negatively impact local prosperity. Cabral et al. (Cabraal et al. 1996a, 1996b), Kivaisi (Kivaisi 2000), Moksnes et al. (Moksnes et al. 2017), Neves et al. (Neves et al. 2014), and Riva et al. (Riva et al. 2018b, 2018a) stressed the need to pay attention to electricity load evolution when planning electrification programmes, since the marginal costs of electricity services vary among supply alternatives (*i.e.* small photovoltaic (PV) systems when the load is low, grid-extension when it is high). In their scenarios for electricity planning in Senegal, Sanoh (Sanoh et al. 2012) verified that electrification strategies and capital costs are very sensitive to the expected demand levels. Brivio et al. (Brivio et al. 2017) demonstrated that in Photovoltaic-batteries based microgrid systems, the optimal size of the components is sensitive to the load evolution pattern, especially the capacity of the battery system. Fuso Nerini (Fuso Nerini et al. 2015) demonstrated how the cost of the energy system for reaching different tiers of electricity access (*i.e.* different levels of energy demand to satisfy) in the village of Suro Craic in the years 2010-2030 may vary from few hundreds to 8000 US$. Hartvigsson et al. (Hartvigsson et al. 2015) showed how the power supply capacity of energy systems for rural areas should be considered accurately based on the long-term projections of electricity demand, since a demand larger than the installed capacity can generate lack of power availability that may affect the willingness of people to stay connected and the utility revenues. Rhonda LeNaí Jordan (Jordan 2013) investigated how the long-term endogenous electricity demand dynamics can significantly impact on the capacity planning of electricity systems in Tanzania. Mulugetta et al. (Mulugetta et al. 2000) reported the experience of PV-based electrification in a village in Zimbabwe, indicating that the main problems have started to occur as soon as people realised that standalone PV have not allowed them to use as much electricity as they wanted. Jacobson (Jacobson 2007) suggested the rural electrification in Kenya must consider the implementation of large systems, in order to satisfy the present and future households electricity needs, otherwise people have to constrain their energy choices due to the limited capacity of the implemented power systems. In their comprehensive review, Baldwin et al. (Baldwin et al. 2015) indicated that after the implementation of power systems, rural consumers tend to increase their electricity use by purchasing and using more electrical appliances, and capacity constraints and limitations could become a serious issue over time. Gustavsson (Gustavsson 2007b) reported the experience of rural electrification through solar home systems in Zambia, suggesting that the design of the systems must consider the consumers' possibility to acquire additional appliances, which in turn can exceed the capacity of the systems and then accelerate the deterioration of the batteries due to long periods of low state of charge. Agoramoorthy and Hsu (Agoramoorthy and Hsu 2009) and Brass et al. (Brass et al. 2012) confirmed that the undersize of power systems due the underestimation of long-term electricity demand evolution is a frequent problem in rural distributed generation projects. Ulsrud et al. (Ulsrud et al. 2011) reported that the reliability of the power supply of the remote villages in the Sunderban Islands, India, have been negatively affected by the under-sizing of the power systems due to the unplanned growth of electricity use. Komatsu et al. (Komatsu et al. 2013) surveyed three districts located in the inner regions of Bangladesh, reporting that in most of the cases the inadequate load assessment caused to the implementation of undersized systems, leading to a continuous use of kerosene rather than electricity by people. The importance of projecting the future load demand was stressed also by Kandpal and Kobayakawa (Kobayakawa and Kandpal 2014), and (Inversin 2000).

From the literatures, it emerges that model and predict reliable long-term evolution patterns of electricity demand for rural areas is one of the main challenges in the rural electrification field. Tackling this challenge would allow to set more reliable investments plans, which is also pivotal to increase the involvement of the private sector (viz. utilities, social enterprises or cooperative) in rural electrification. The next sub-section reports a case-study, where long-term demand scenarios are tested in an optimisation model for energy system planning. The goal is to put more emphasis on the techno-economic implications of short- and long-term load variability on rural electricity planning and set a first-step towards more reliable rural electricity projection models.

2.5. *CASE 2. "The case of Katgaon community"*

This study reports a case of electricity planning of a rural Indian community where both the short- and long-term aspects of electricity demand are introduced, tested, and discussed.

2.5.1. Local context description: Katgaon community

Katgaon is a small village of Osmanabad district, in the State of Maharashtra. It has a population of 7'800 individuals. The village is connected to the national electricity grid, but the supply is characterised by high level of unreliability, due to the infrastructural weakness: scheduled blackouts occur, and the total daily supply of electricity is guaranteed for about 16 hours per day for households and 8 hours per day for agriculture activities. Even within these "guaranteed" time windows, the electricity supply is weakened by unscheduled blackouts that can last for several hours and by voltage fluctuations. In this work, the focus is on a small community of twelve households who rely on agriculture-based activities and are willing to be provided with a more reliable electricity supply system. Data about the household monthly income and size were gathered though local surveys carried out in 2014 by the researchers working for the Sanjeevani Project[4] (Table 3).

Table 3. Household size and income data gathered during local assessment

N° Family	1	2	3	4	5	6	7	8	9	10	11	12
Household Size [people]	7	5	5	4	5	6	15	7	5	5	6	6
Monthly household income [USD 2000]	134	69	111	245	134	156	735	557	356	111	56	445

2.5.2. *B-UP* long-term demand scenario

The first tested scenario, namely *Bottom-up* (B-UP), is an adaptation and application of van Ruijven's model (van Ruijven et al. 2011) for projecting the household electricity needs to the case study of Katgaon village. Specifically, the main correlations and data are derived from van Ruijven's paper (van Ruijven et al. 2011), local surveys data and assumptions. Then, a MATLAB ® code is developed, which projects the ownership of the electrical appliances of each household of our case study along a 20 years scenario, from 2014 to 2034, and then used to build the related yearly load profiles. The different parts of the model are described in detail in the following sub-sections.

Exogenous input parameters

Based on local surveys and the information concerning the income of the considered 12 families, they are clustered in quintiles, and associated with an average value of *household expenditures* per capita per year at time 0 ($HHEx_0$). The expenditures from the income values for each household are derived according the ratio between the value of Household Final Consumption Expenditure and Gross National Income for India in 2014, derived from World Bank data[5]. The values for *house floor space* ($HHFS$) for each quintile is assumed based on van Ruijven's projections (van Ruijven et al. 2011). The values are reported in Table 4.

Table 4. Household expenditures per capita per year (HHEx$_0$) and house floor space (HHFS) for each quintile input data for each quintile.

	Q1	Q2	Q3	Q4	Q5
N° household	2, 11	3, 5, 6, 10	1	7	4, 8, 9, 12
HHEx$_0$ [$/capita/yr]	174.8	275.5	368.8	489.9	773.2
HHFS [m^2]	40	45	50	60	70

The collected information about the electrical appliances the households currently own and their profile of use are employed to allocate future appliances among the households and to create the future load curve profiles, as further discussed in the next sub-sections.

[4] https://isf.polimi.it/sanjevani-project/

[5] The World Bank data. Available at: http://data.worldbank.org/country/india. [Accessed 2016].

Total appliances ownership

Given the input data on the $HHEx_0$ per quintile, the model projects those values along the 20-years scenario (Fig. 9) – based on correlations derived from (van Ruijven et al. 2011). The values of *floor space* $HHFS$ are assumed to not vary along the 20-years scenario: people do not vary significantly the layout of their houses and the number of components per household is estimated to be the same.

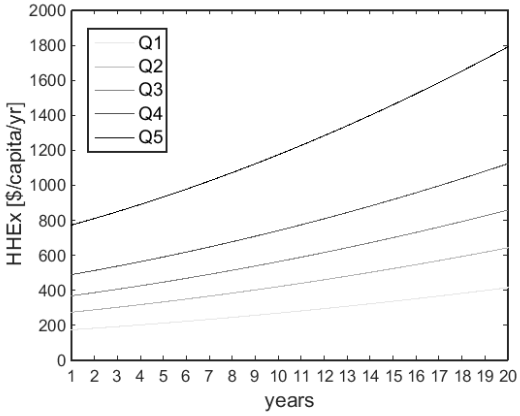
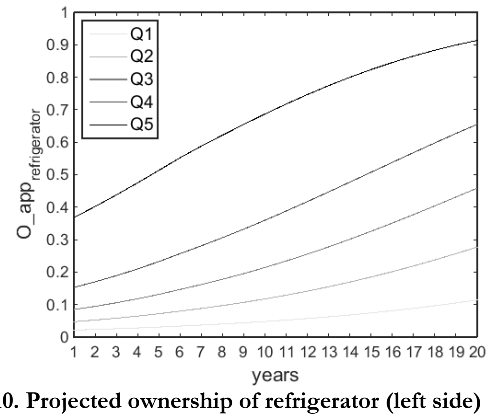


Fig. 9. Household Expenditures Projection (HHEx) for each quintile along the 20-years scenario [from (Riva et al. 2019)].

Once the values of $HHEx$ are projected along the 20-years scenario, the van Ruijven et al.'s correlations and S.K. Singh's model (Singh 2008) are employed to predict year-by-year the diffusion and the ownership of electrical appliances among each households quintile. The choice of the type of appliances is based on local surveys and on the end-use functions and clusters considered by van Ruijven et al. (van Ruijven et al. 2011). In this case-study, 11 appliances are considered: Fan, Air Cooler, Air Conditioner, Refrigerator, Washing Machine, Radio, Television (TV), Personal Computer (PC), Electric Iron, Mobile phone and Electric bulbs. The dynamics of the first nine appliances ownership are simulated by following the mathematical description of V. Letschert and M. McNeil (Letschert and Mcneil 2007) through a Gompertz-curve:

$$O\_app_j = \alpha_j \cdot EXP\left\{-\beta_j \cdot EXP\left(\frac{-\gamma_j}{1000}\right) \cdot HHEx\right\} \tag{2}$$

where O_app_j is the percentage of households per quintile which own appliance j; $HHEx$ are the household expenditures per capita per quintile; α_j is the upper asymptote of the curve evaluated by van Ruijven et al. (van Ruijven et al. 2011), which depends on the type of appliance *j*, historical Indian ownership values, and the $HHFS$ (in case of fan); β_j and γ_j are shape-parameters, estimated by non-linear regression using historical data for each appliance *j* (Letschert and Mcneil 2007; van Ruijven et al. 2011). Fig. 10 reports the trend of O_app for refrigerators and fans among the households' quintiles; values greater than 1 mean that each household is forecast to own more than one device.



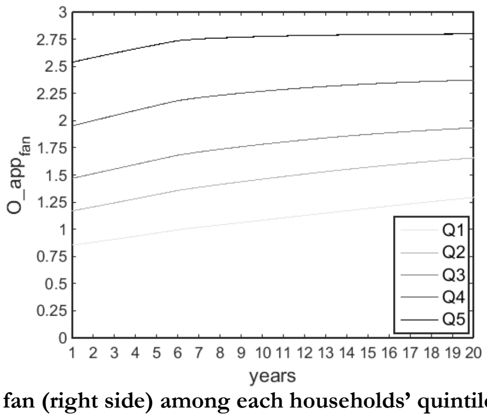


Fig. 10. Projected ownership of refrigerator (left side) and fan (right side) among each households' quintile [from (Riva et al. 2019)].

Singh's Gompertz-curve is employed to simulate the ownership of mobile phones among the entire population at year t (Singh 2008):

$$O\_app_{\text{mobile phone}} = \frac{1}{100} \cdot \alpha_{\text{mobile phone}} \cdot EXP\left\{-\beta_{\text{mobile phone}} \cdot EXP\left(t-1995\right) \cdot HHEx\right\} \qquad (3)$$

where $\alpha_{\text{mobile phone}}$, $\beta_{mobile\ phone}$ and $\gamma_{mobile\ phone}$ equal respectively 120, 0.1639 and 16.4, estimated by non-linear regression by Singh (Singh 2008).

Household appliances ownership

Once the total appliances ownership among the entire population year-by-year is determined, the following step of our approach consists in allocating the projected diffusion of appliances among the 12 households; N_app_j indicates the amount of device j that a household will own throughout the 20-years based scenario. For the first nine appliances, devices are randomly allocated among the households of each quintile based on the values of O_app_j. The allocation of mobile phones is performed among the entire population, without differences between the quintiles, since the direct experience of the Author in developing countries suggests that mobile phones are often considered a basic commodity even in developing countries and it does not depend strongly on the income. Finally, the diffusion of electric bulbs ($j = 11$) for lighting is introduced for the 12 households considering that after the electrification, at year $t = 1$, the first electrical appliance that people are willing to purchase is a device for lighting the house, as currently occurs in rural contexts of developing countries (Prasad and Dieden 2007). Fig. 11 reports some of the projected appliances of a household of the fifth quintile (Q5) along the 20-years scenario:

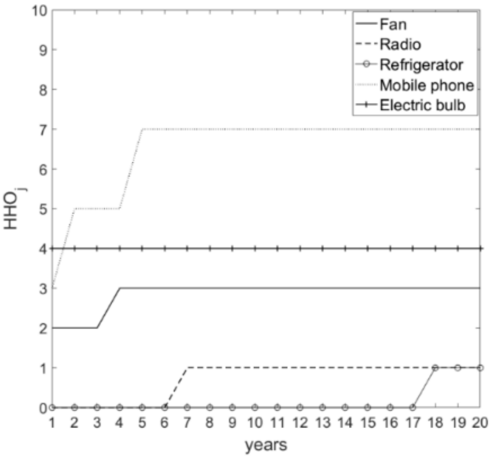


Fig. 11. Ownership of fan, radio, refrigerator, mobile phone and electric bulbs for a household of the 5th quintile [from (Riva et al. 2019)].

Short-term load profiles

The knowledge of the household appliances ownership along the 20-years scenario allowed to derive the total yearly load curves (*yLC*) for the entire community. The software LoadProGen, version 1.0, developed by Mandelli et al. (Mandelli et al. 2016d) was used. With *LoadProGen*, *p=250* possible daily load curves for each year of our scenario were generated. Since the aim of the study was to test the effect of short- and long-term variability of electricity demand within long-term electricity planning, the 3 most significative cases of load curves were identified and used as input for the next stage of the electricity planning procedure: (i) the flattest one (MIN case), (ii) the mean among all the 250 hourly profiles (MEAN case), and (iii) the most fluctuating one (MAX case). Fig. 12 reports the MIN, MEAN, and MAX daily hourly load curves for the 1st (left-side) and the 20th (right-side) year. Considering the MEAN curve at the 1st and the 20th year of the scenario, there is sensible a growth of the energy use between the 1st and the 20th year especially, around the peak power.

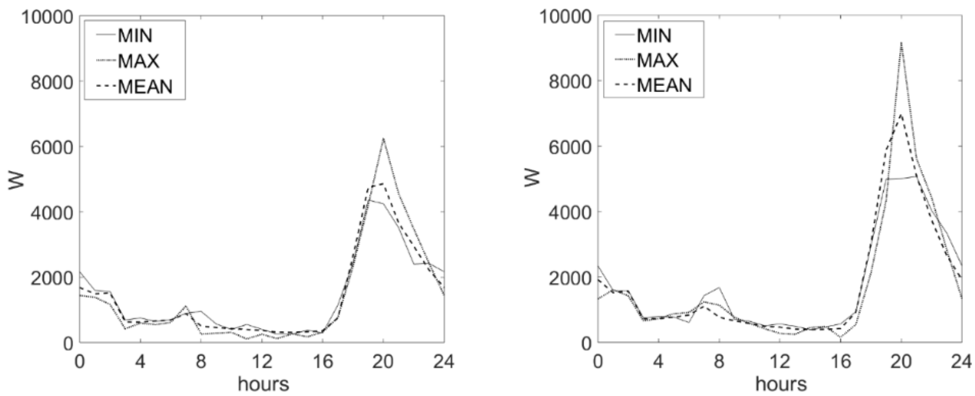


Fig. 12. MIN, MAX, MEAN hourly load curves generated for the 1st (left) and the 20th (right) year of the scenario [from (Riva et al. 2019)].

2.5.3. *CST* and *HT* long-term demand scenarios

In order to test the impact of different long-term electricity demand projections on the electricity planning results, two further scenarios were assumed of electricity demand in addition to the long-term bottom-up (*B*-UP) scenario created in the previous sub-sections: the *constant* (CST) and *historical trend* (HT) scenarios.

- *Constant (CST) scenario.* This scenario did not take into account any evolution of electricity demand along the planning horizon. For all the 20 years of the simulation, the MIN, MAX and MEAN electricity load curves derived previously for the 1st year of the B-UP scenario were used.
- *Historical trend (HT) scenario.* This scenario is derived by evaluating the historical trend of electricity power consumption per capita obtained from World Bank data on India from 1971 to 2013 (The World Bank Group). The historical data are interpolated in order to extrapolate the trend through MATLAB © use of *polyfit* and *polyval* functions. An average value of 4.5% electricity demand growth per year was obtained. The demand projected along the planning horizon was then calculated starting from the MIN, MAX and MEAN load profiles derived previously for the 1st year of the *B-UP* scenario and multiplying each hourly value of the profiles for +4.5% from year to year.

In conclusion, 9 scenarios of electricity demand were obtained: 3 potential daily load curves for 3 different scenarios of growth (Table 5).

Table 5. Scenarios of electricity demand projections.

		Long-term evolution		
		Bottom-up scenario	*Constant scenario*	*Historical trend*
Daily variability	*MIN*	B-UP_MIN	CST_MIN	HT_MIN
	MEAN	B-UP_MEAN	CST_MEAN	HT_MEAN
	MAX	B-UP_MAX	CST_MAX	HT_MAX

Fig. 13 reports the MEAN load curves for the 20th year for the three scenarios, confirming that the load demand is sensitive to the approach adopted to build the scenario.

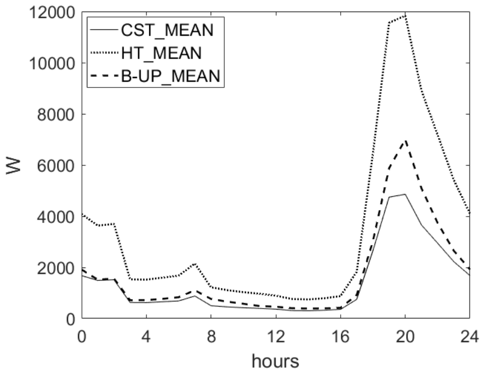


Fig. 13. Daily load curves for the B-UP_MEAN, CST_MEAN, HT_MEAN scenarios of the 20th year [from (Riva et al. 2019)].

2.5.4. Optimisation model for energy system planning

To test the effect of short- and long-term demand on the planning solution, the least cost long-term energy supply mix for the Katgaon community was identified for each of the scenarios of electricity demand summarised above. For this step, the Open Source Energy Modeling System (OSeMOSYS) (Howells et al. 2011) was employed, a linear optimisation modelling framework for long-run energy planning. OSeMOSYS is selected as it is a well-documented, open source and free modelling framework. Among the existing formulations of OSeMOSYS, the one in GNU MathProg was used. OSeMOSYS computes for each year of the planning horizon the electricity supply mix (in terms of capacity and generation) which allows the demand to be met at the lowest cost, under constraints dictated by the techno-economic characteristics of the supply technologies and the availability of resources. For this application, the possible Reference Energy System (RES) for Katgaon was developed: the RES is a schematic and aggregated representation of the energy supply chain of the system under study, from the primary resources to the end uses. In the RES of Katgaon (Fig. 14), three different power generation technologies are considered: diesel generator (DG), wind micro turbine (MW) and solar photovoltaic panel (SPV). All of these three are fed by primary resources and generate electricity as output. The DUMMY represents a fictitious tank fuel for supplying DG with gasoline. This chosen RES represents one of all the potential configurations for Katgaon.

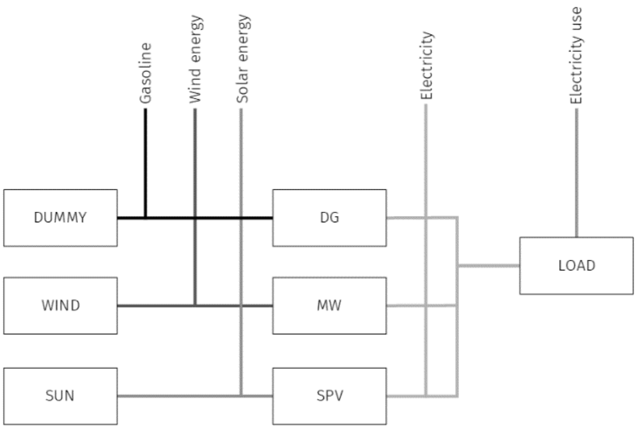


Fig. 14. The RES for Katgaon community [from (Riva et al. 2019)].

The 9 scenarios of electricity demand were introduced in input to OSeMOSYS. In OSeMOSYS, the electricity demand input is set through two parameters: the *specified annual demand*, which is the projected total annual electricity consumption, and the *specified demand profile*, which specifies the fraction of specified annual demand to be satisfied in each time-step, namely "time-slice". In our simulations, 24x12 time-slices were considered, that is, 24 hourly time-slices of a typical day for each of the 12 months in one year. Every day of the year was assumed to have the same load curve described by 24-h time-slices in each of the 9 scenarios. However, the monthly discretization was introduced in order to consider the high variability of renewable resources across the year. For renewable technologies, the capacity factors of solar and wind resources were computed for each time-slice[6], by using the NREL's and NASA databases.

2.5.5. Results and discussion

The results were obtained by using the *OSeMOSYS_2015_08_27* version of OSeMOSYS[7]. The results of the 9 scenarios were compared by focusing on the *net present cost (NPC)* and the *total capacity installed* every year along the planning horizon.

Fig. 15. Total capacity installed along the planning horizon for the 9 scenarios, divided by source [from (Riva et al. 2019)].

The results in Fig. 15 show that DG is the technology installed with the largest capacity. Indeed, in the absence of batteries, DG satisfy the electricity load during the peak hours and the time windows characterised by very low or null solar capacity factor (i.e. cloudy days and night). MW technology is never selected due to very low wind speeds (see the Supplemental Information): these are lower than the cut-in velocity of the selected power turbine (2.7 m/s) during most of the months, making it unprofitable to invest in such technology. Fig. 15 confirms also that both the daily- and the long-term variation of the electricity load impact the choice of the optimal electricity supply mix. The total capacity installed by 2034 when the lowest daily variability index is assumed (MIN) and the one when the highest daily variability index is assumed (MAX) differ by 33%, 60% and 32% for the CST, B-UP and HT scenarios, respectively. This is even clearer by analysing the results displayed in Fig. 16 concerning the new optimal yearly capacity to install every year. The MAX scenarios, which are the ones with the highest daily variability indexes, consider the installation of much more DG capacity, for covering the peaks and guaranteeing more flexibility in power production. In turn, the MIN scenarios are characterised by a higher proportional installation of renewable SPV capacity. This fact highlights

[6] The capacity factor represents the ratio between the useful energy generated and the potential energy output at the maximum capacity of a technology in each time-slice

[7] OSeMOSYS - Open Source Energy Modelling System: http://www.osemosys.org/

the importance of assessing the short-term variability of the load in renewable electricity planning. Moreover, according to Vishnupriya and Manoharan (Vishnupriyan and Manoharan 2017), and Chauhan and Saini (Chauhan and Saini 2016), these results confirm that appropriate load control and management measures can effectively contribute to better distributing the daily load in rural micro-grids, and therefore increase the renewable fraction of micro-grid generation.

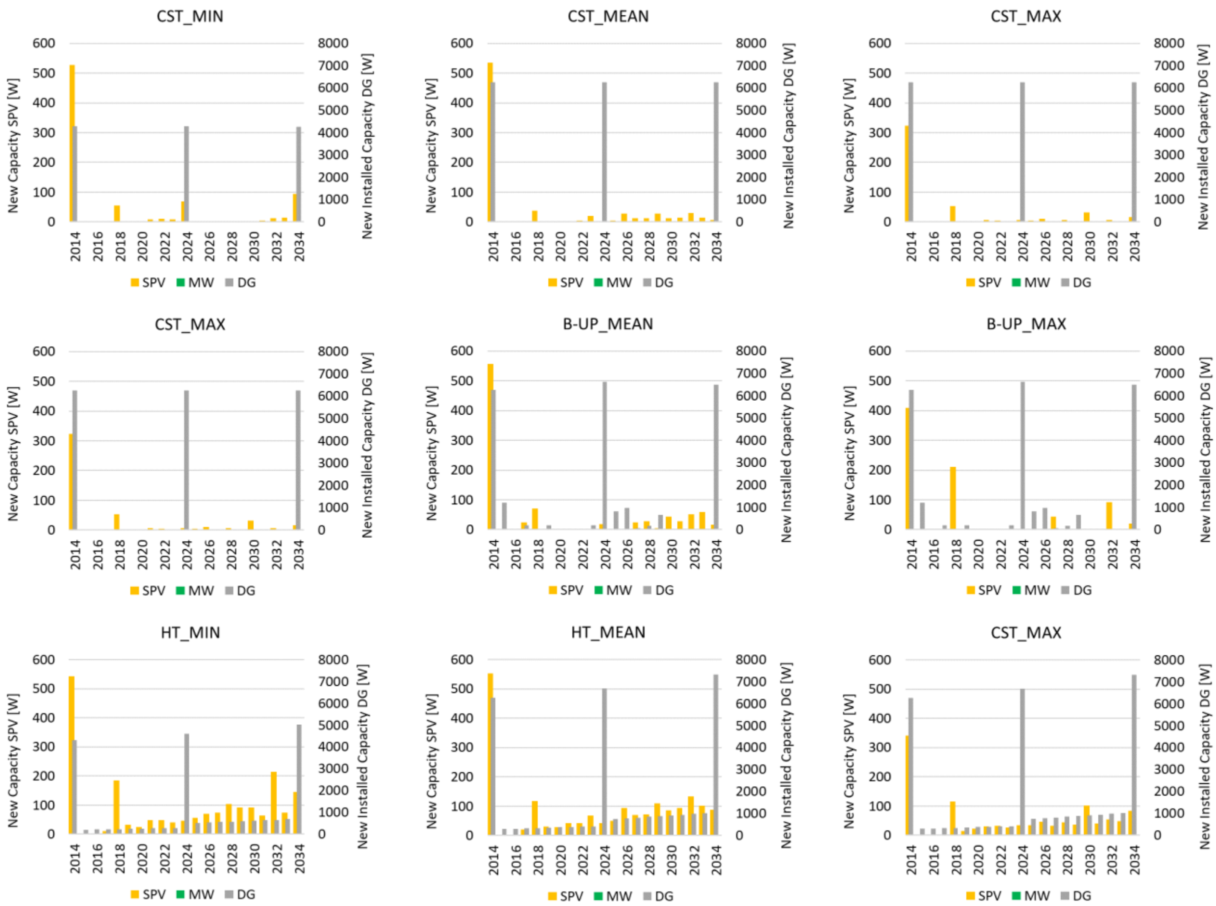


Fig. 16. New yearly capacity installed along the planning horizon for the 9 scenarios, divided by source [from (Riva et al. 2019)].

This difference increases even more by considering the long-term variability of the electricity load: in the MEAN cases, the B-UP and HT total capacities installed by 2034 are 41% and 144% higher than the CST scenario, respectively (Fig. 17). Also Brivio et al. (Brivio et al. 2017), who analysed the design and sizing process of a PV-batteries micro-grid in Uganda, find that different scenarios of load growth impact considerably on the capacity of power system, but to a lesser extent – viz. 25% of load growth along 20 years, as in our B-UP scenario compared to the CST, caused an expected increase of about 9% and 23% for the size of the PV and batteries capacities, respectively.

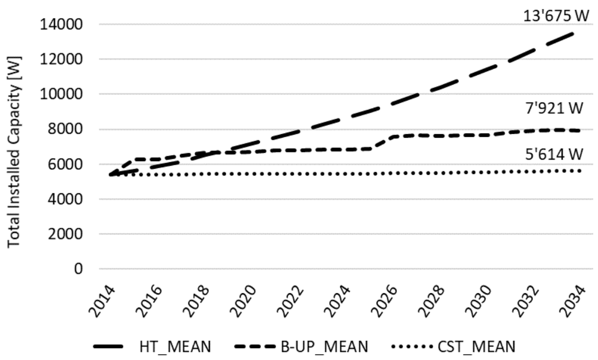


Fig. 17. Comparison of the total capacity installed along the planning horizon for the MEAN scenarios [from (Riva et al. 2019)].

Such results have direct economic implications, as reported in Fig. 18. The cost difference between the solutions optimised with the lowest daily variability index (MIN) and the highest daily variability index (MAX) are respectively 7%, 8% and 6% for the CST, B-UP and HT scenarios. The long-term evolution of the electricity demand impacts considerably on the costs: considering the MEAN cases, the NPCs of the B-UP and HT optimal solutions are respectively 17% and 50% more expensive than the CST scenario. These results confirm that long-term variations of electricity demand have a considerably higher impact on the costs of the systems than the daily variations of the load profiles.

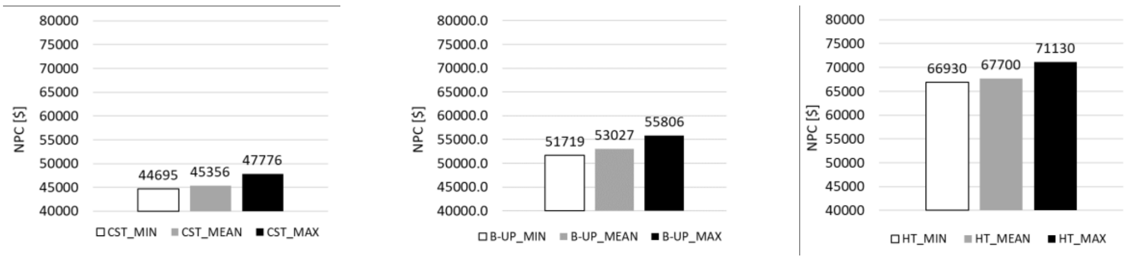


Fig. 18. Net Present Cost (NPC) of the final solution optimised by OSeMOSYS for the 9 scenarios [from (Riva et al. 2019)].

2.5.6. Conclusion

The results confirm that daily- and long- term variations of electricity load impact the optimal electricity supply mix considerably. These results have a significant impact also on the costs. This finding confirms that wrong projections of the long-term evolution of the electricity demand have direct implications on the costs of energy systems, the process of tariff definition, the profitability of investments promoting the diffusion of off-grid microgrids in developing contexts, and the local socio-economic sustainability of an energy project. Moreover, considering the *B-UP* case, the introduction of socio-economic indicators to make long-term projections allowed to set a first step in the identification and modelling of the determinants at the basis of the electricity demand. This reduced the level of "arbitrariness" in the selection of the scenario. On the contrary, the *CST* and *HT* were totally arbitrary. At the same, this contribution highlighted the need to investigate further the determinants of long-term electricity demand, since the projections used in this case-study depend on exogenous econometric relations, whose application for local specific contexts is questionable. Moreover, the resolution of the short-term daily load and the long-term demand growth were limited to 1 hour and 1 year, respectively. This was due to the effective manageability of a limited number of time-slices in OSeMOSYS.

Chapter 3

Review of energy planning case studies and demand models

The dynamics of growth and electrification are complex, involving many underlying forces
(Khandker et al. 2013)

Trend extrapolation seems naive to many observers, who point out – quite correctly – that energy demand forecasts are often the result of extensive studies involving detailed, multidisciplinary analysis and sophisticated models.

(Sterman 1988, 2000)

The chapter contributes to Objective 1, by investigating the main demand models used in the rural energy planning literature. It proposes a first clarification, analysis, and categorisation of the published energy planning studies. Indeed, several studies were carried out on long-term rural energy planning since around the '80s, but the different foci, terminology and methodologies make it difficult to track the similarities, weaknesses, and strengths, especially regarding the methodology adopted for projecting long-term energy demand along the planning horizon. As a novelty, the analysis of both the "demand" and the "supply" aspects of the rural energy planning studies is combined, stressing the need to consider the two parts of the planning as linked and interdependent. For this purpose, it is followed an approach that classifies the studies firstly in accordance with specific subcategories suggested by the literature (viz. spatial coverage, planning horizon, energy carrier, decision criteria mathematical models and energy uses), and secondly in accordance with the methodology they employ to forecast the evolution of the energy demand. The final section of the chapter highlights that modelling long-term projections of energy demand in these areas is a complex issue, involving both technical and socio-economic dimensions. This chapter is based on the following publication:

Riva, F., Tognollo, A., Gardumi, F., Colombo, E. (2018). Long-term energy planning and demand forecast in remote areas of developing countries: Classification of case studies and insights from a modelling perspective. *Energy Strategy Reviews,* 20, 71-89. doi: 10.1016/j.esr.2018.02.006.

3.1. Review of long-term energy planning studies

3.1.1. Foreword

Although this thesis focuses on rural electrification, electricity is not the only energy carrier considered in the review. This rationale behind this decision is based on two considerations:

i. Some of the case studies consider both electricity and the other carriers in the planning;
ii. Considering only electricity planning case studies would have limit the analysis of the demand models, since some techniques are both applicable to the demand of electricity and the demand of other energy carriers.

3.1.2. Rationale and methodology of the review

In order to comprehensively investigate energy planning methods and applications (*i.e.* including input data processing, such as the load profile, and the final results), only real-life case studies or potential applications for real contexts are analysed, excluding papers that present only the theoretical methodologies. For example, Bernal-Agustin et al. (Bernal-Agustín and Dufo-López 2009) propose a multi-objective evolutionary algorithm and a genetic algorithm to find the most appropriate hybrid energy system to minimise the costs and the unmet demand. They relied on a reference daily load profile for implementing the optimisation. However, they did not provide any details about the daily demand or potential applications, therefore their study was not classified. Gupta et al. (Gupta et al. 2011a, 2011b, 2011c) analyse a hybrid energy system in order to determine its cost optimal operation. In the first (Gupta et al. 2011a) and second part (Gupta et al. 2011b) of the work they develop the mathematical model for the optimisation and the necessary algorithm to control the dispatch of battery storage systems. Only the third part (Gupta et al. 2011c) was classified because it described the application and simulation of the energy system for a real case study.

At a spatial level, only local rural energy planning for developing countries (and BRICS) was considered, whereby works referring to other contexts or to global and national scales were not included in the review. For example, Clark et al. (Clark and Isherwood 2004) and Wies et al. (Wies et al. 2005) focus on a remote power system for a village in Alaska, so their studies were included. The same applied for Bala (Bala 1997), who propose a bottom-up approach to minimise CO2 emissions for Bangladesh, but at national level.

On the contrary, no restriction was put on the type of off-main grid system that the case studies proposed: standalone systems, microgrids and distributed hybrid microgrids were considered, according to the classification given by Mandelli et al. (Mandelli et al. 2016a).

The papers were selected starting from a web research on *Science Direct editorial platform* and *Scopus database,* and from references mainly taken from (Bhattacharyya 2012b; Rojas-Zerpa and Yusta 2014; Mandelli et al. 2016a). At the end, 126 papers were studied and 84 were selected for the analysis and classification. Even if no range of publication date was fixed, Fig. 19 shows how, among the papers selected in this study, the greatest number of publications is concentrated between 2004 and 2015.

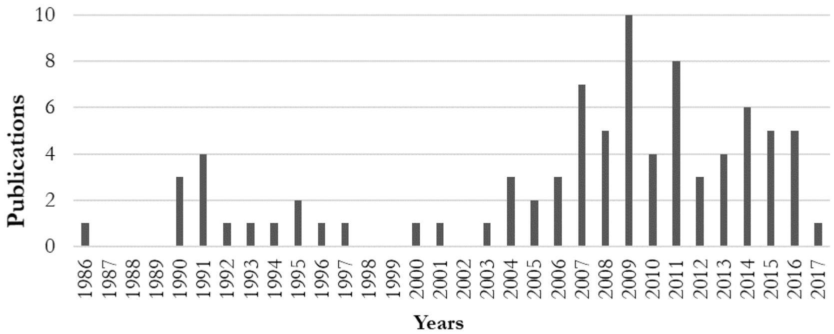


Fig. 19. Publication on local energy planning over the years [from (Riva et al. 2018b)].

3.1.3. Classification and analysis of long-term energy planning case-studies

The classification of the case-studies was inspired by other reviews on energy modelling and planning. Prasad et al. (Prasad et al. 2014) present the risks, uncertainties and errors involved in energy planning, as well as a review of models for energy planning (*econometric models*, *optimisation models*, *simulation models* and the related computer-assisted tools), highlighting that energy plans must foster sustainable development, and should be tackled with appropriate tools and correctly validated. Focusing only on decentralised energy planning, also Hiremath et al. (Hiremath et al. 2007) limit their analysis to the classification and description of the models that can be used for carrying out an appropriate planning process: *optimisation models*, *decentralised energy models*, *energy supply/demand driven models*, *energy and environmental planning models*, *resource energy planning models* and *models based on neural networks*. Deshmuk (Deshmukh 2011) discuss how to develop an Integrated Renewable Energy System (IRES) to find the optimal energy resource allocation in energy planning processes and suggests an alternative classification based on *methodology adopted (bottom-up* vs. *top-down*), *spatial coverage*, *sectoral coverage* and *temporal coverage*. He also concluded that "the application of models for matching the projected energy demand with a mix of energy sources at decentralized level is limited" ((Hiremath et al. 2007) pg. 749), highlighting the need to increase the research on this topic and the attention on the aspect of future energy demand. Focusing on developing countries, Nicole van Beeck (Beeck and van van Beeck 1999) propose nine criteria to classify models for energy planning: *purposes of energy models*, *model structure*, *analytical approach (bottom-up* vs. *top-down*), *underling methodology*, *mathematical approach*, *geographical coverage*, *sectoral coverage*, *time horizon*, *data requirements*. Van Beeck conclude that an appropriate planning model should at least include sub-models for energy demand, energy supply, and impacts. Yusta et al. (Rojas-Zerpa and Yusta 2015) investigate the most utilised multi-criteria decision methods for electrification planning in rural areas and they reviewed approximately 120 publications related to energy planning (Rojas-Zerpa and Yusta 2014), focusing mainly on 50 cases studies of decentralised power supply plans. They classify them according to *referring country*, *mathematical model*, *methodology application*, *adopted criteria*, *implemented technologies* and *target population*.

It emerges that most of the current review studies apply their classifications especially to the *models* used in the energy planning and the majority of them limits the analysis to electricity systems. Nevertheless, energy planning is a wider process, which includes multiple considerations, decisions and energy carriers and it is not limited to the choice of the most appropriate mathematical model to employ. An appropriate classification should rather be applied to the rural energy planning process as a whole, in order to provide a comprehensive overview on the approaches used in the literature so far and highlight the similarities, weaknesses and strengths. Based on the above-mentioned works, an extended and more comprehensive classification was introduced with the following categories: (i) spatial coverage, (ii) planning horizon, (iii) energy carrier, (iv) energy uses, (v) decision criteria mathematical models, and (vi) demand models. Categories (i), (ii) and (iv) were selected from Deshmuk (Deshmukh 2011) and Nicole van Beeck (Beeck and van van Beeck 1999). Category (v) is based on Yusta et al. (Rojas-Zerpa and Yusta 2014), while category (iii) was introduced to understand the level of attention paid by the existing energy planning literature to the different energy carriers commonly employed in rural settlements. Category (vi) refers to models and methodologies employed to project energy demand along the planning horizon, and it is treated in a separate and dedicated section, given the relevance in the framework of this thesis.

Spatial coverage: local and regional coverage

The studies were categorised based on the extension of the geographical domain they consider: *local coverage* considered a village, a community, and a group of small villages (Joshi et al. 1991; Malik et al. 1994; Kanase-Patil et al. 2010) or set of remote houses (Gupta et al. 2011c; Semaoui et al. 2013) located in the same region of the same nation; *regional coverage* included remote islands or institutional divisions according to linguistic boundaries or morphological constraints.

Authors identify and specify the spatial coverage of their work in different ways. Local studies appear to be the most precise studies, sometimes indicating even the geographic coordinates (Borhanazad et al. 2014) and the number of people living in the target area (Himri et al. 2008). For example, Salehin et al. (Salehin et al. 2016) combine a HOMER-based techno-economic optimisation with a RETScreen-based energy scenario analysis for assessing a PV-Diesel and a Wind-Diesel power system in a small locality of 1000 people in Kutubdia Island, Bangladesh. Gupta et al. (Gupta et al. 2007) study a hybrid energy system for the Juanpur block in India, specifying even the extension of the location and the number of households. On the contrary, as the spatial coverage increases, the case studies tend to be less precise, such as Silva et al. (Silva and Nakata 2009), who focus on the applicability of multi-objective methods to assess the introduction of renewable technologies for general "Non-interconnected Zones" in Colombia.

From this first categorisation, about 79% of the cases analysed are *local* energy planning, suggesting a lack of *regional* studies. Moreover, in some cases the spatial coverage of the study was vaguely defined. This might prevent the extension of the approach and the findings to other similar cases of energy planning in analogous contexts. Finally, it emerges that modelling frameworks for local planning (e.g. HOMER ®) allow to analyse and take into account detailed technical aspects of the planned energy systems; on the other hand, regional planning mainly concerns the selection of the optimal energy supply strategy, such as the identification of the energy mix and the solution of the off-/on-grid dilemma.

Planning horizon: short, medium and long term

The second category referred to the time scale considered for implementing the energy planning. Four subcategories were identified: *short-term* (from one month to one year), *medium-term* (from one to ten years), *long-term* (beyond fifteen years) and *not-specified* term. The distribution of the works between these subcategories is reported in Fig. 20.

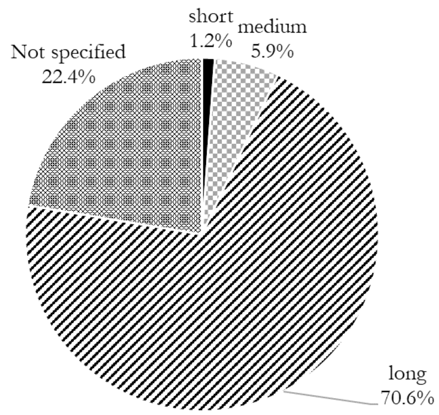


Fig. 20. Classification of case studies: Planning Horizon [from (Riva et al. 2018b)].

Authors usually introduce the planning horizon in two different ways: some specify explicitly the lifespan of the project or lifetime of the energy system; others do not point out the planning period but report the lifetime of the components such as PV, diesel gen-set or wind turbine used to calculate the net present value or the discounted costs of the system. For example, Haddadi et al. (Saheb-Koussa et al. 2009) specify three different lifetimes for the systems implemented, equal to 10, 15 and 20 years. Similarly, Sen et al. (Sen and Bhattacharyya 2014b) indicate a project's lifetime of 25 years. On the contrary, Silva et al. (Silva and Nakata 2009) do not point out the lifetime of the entire project but make the lifetime of the technologies explicit, in order to calculate the net present cost of the renewable energy system. Daud et al. (Daud and Ismail 2012) state clearly that the life cycle period of the system is assumed to be the maximum lifetime of the main components of the system. In cases where the project lifetime was not indicated, the maximum lifetime between all the system components defined the planning horizon used to classify the study, e.g. Arun et al. (Arun et al. 2009).

Papers that do not specify any information for deriving the planning horizon were accounted for in the "not-specified" category. For example, Kanase-Patil et al. (Kanase-Patil et al. 2011) applied the Integrated Renewable Energy Optimization Model (IREOM) for the electrification of dense forest areas in India in order to minimise the cost of energy generation over an amortisation period of *n* years. Again, Gupta et al. (Gupta et al. 2007) vaguely note that the unit costs are calculated on the basis of the lifetime of the plants, without indicating a precise value.

This analysis highlighted that about 70% of the studies refer to long-term energy planning, while almost one-quarter does not specify enough information to derive the planning horizon. Only one paper performs a short-term regional analysis, considering a planning horizon of 1 year (Devadas 2001). This lack of information about the time horizon undermines the robustness of the planning results, since it prevents their replicability, as well as any uncertainty analysis on the evolution of the techno-economic parameters (e.g. energy demand, costs, efficiency). The classification of the case studies based on their planning horizon further provided useful insights about the details achievable by each energy model: short-term energy models allow the analyst to consider more precisely short time steps (seconds or minutes), specific operation constraints of the analysed energy systems and their response in case of unexpected conditions and phenomena (e.g. fluctuations, changes in weather conditions, variabilities of renewable resources). Long-term models usually rely on longer time resolutions (hours, days, weeks). This could prevent the analysis of short-term dynamics but allows the introduction of long-term variables (*e.g.* future energy demand along the planning horizon, useful life-time of the technologies, discount rates) that are pivotal to a more comprehensive energy planning (*viz.* more complete economic analyses, more reliable choice of off-grid systems' components and size).

Energy carrier: electricity and thermal energy and oil products

In general, the term "energy carrier" refers to the energy form of the energy inputs required within the various sectors of a society to perform the related functions. In this work, this category classifies the case studies based on the energy form of the energy produced by the power systems subject to the planning. Three types of energy carrier are identified: electricity, thermal energy and oil products.

Electricity results as the most considered energy carrier in the case studies (Fig. 21), especially within those focusing on rural electricity planning and employing HOMER ® software for the optimal sizing of the off-grid distributed system (Kamel and Dahl 2005; Agalgaonkar et al. 2006; Akella et al. 2007; Himri et al. 2008; Nayar et al. 2008; Nfah et al. 2008; Nfah and Ngundam 2009; Setiawan et al. 2009; Alzola et al. 2009; Kanase-Patil et al. 2010; Lau et al. 2010; Nandi and Ghosh 2010; Al-Karaghouli and Kazmerski 2010; Bekele and Palm 2010; Demiroren and Yilmaz 2010; Türkay and Telli 2011; Bekele and Tadesse 2012b; Sen and Bhattacharyya 2014a; Kolhe et al. 2015; Ramchandran et al. 2016; Salehin et al. 2016; Amutha and Rajini 2016; Fulzele and Daigavane 2016; Haghighat Mamaghani et al. 2016).

The thermal energy carrier is the second most considered in the case studies, especially for the residential sector. This sub-category includes the case studies that carry out a planning of the optimal energy systems that produce thermal energy for space heating and cooking – often based on non-commercial energy (e.g. biomass and agricultural residues for cooking) – highlighting the urgency to address the issue of access to modern energy for cooking in rural areas of developing countries. For example, Malik and Satsangi (Malik and Satsangi 1997) apply a mixed integer/linear programming model for planning the most cost-effective energy system for cooking in the rural areas in Wardha District, India. Joshi et al. (Joshi et al. 1991) investigate the most appropriate energy system – based on fuel wood, agriculture residues and animal dung – for producing thermal energy for cooking and for space heating in three villages of different zones of rural Nepal.

Oil products are considered by only 4% of the case studies; for example, Srinivasan and Balachandra (Srinivasan and Balachandra 1993) consider diesel as a potential non-renewable energy carrier for satisfying the energy demand in the transport and agricultural sector of Bangalore North taluk in India.

Many case studies implemented energy planning by considering more than one energy carrier. For example, Devadas (Devadas 2001) present a linear programming-based model to optimally allocate energy resources and related conversion technologies to different end-uses such as household consumption, agriculture and transport, considering electricity for irrigation and lighting, liquefied petroleum gas for cooking, and kerosene for the lamps of lower income consumers. When dealing with households' energy needs, different case studies considered both electricity for end-use appliances and thermal energy for cooking (Srinivasan and Balachandra 1993; Howells et al. 2005; Hiremath et al. 2010a; Fuso Nerini et al. 2015).

In accordance with Pachauri et al. (Pachauri et al. 2013), this review indicates that rural energy planning studies mainly concern electricity planning, revealing that little quantitative analysis focuses on the other energy carriers. More comprehensive approaches would be needed to tackle all the challenges concerning sustainable rural energy planning, including the study of options to supply energy for cooking. This carrier is highly prioritised in the Sustainable Energy for All (SE4All) global Agenda (United Nation and World Bank 2017), as one of the pillars for achieving the SDG7 (United Nations 2015).

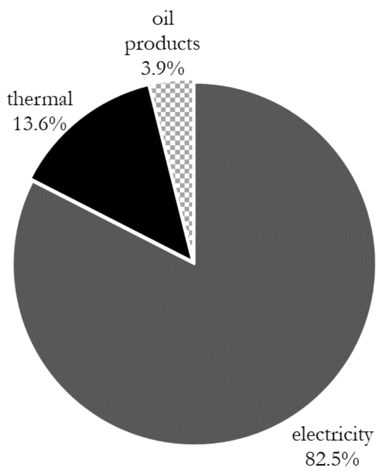


Fig. 21. Classification of case studies: Energy Carrier [from (Riva et al. 2018b)].

Decision criteria mathematical models

In accordance with Yusta and Rojas-Zerpa (Rojas-Zerpa and Yusta 2014), the mathematical models lying behind the planning procedure were classified into seven sub-categories (classes of models): *Linear Programming* (LP), *Multi-Criteria Decision Making* (MCDM), *Multi-Objective Programming* (MOP), *Non- Linear Programming* (NLP), *Dynamic Programming* (DP), *Enumerative Optimisation* (EO) and *other*.

LP is used to analytically optimise a linear objective function subject to a set of linear constraints. Compared to the other models, it is a computationally fast and easy-to-solve method. Nevertheless, in a few cases it requires significant simplifications, for real physical phenomena to be represented by linear relationships. In the analysed case studies, it is especially employed to minimise the cost of matching supply and demand (Balachandra and Chandru 2003; Akella et al. 2007; Zhang et al. 2013), both in the local and regional planning studies. The category further includes models using Mixed Integer Linear Programming (MILP). There are several modelling languages: LINGO is a modelling software developed by Lindo Systems Inc. and it is used by Kanase-Patil et al. (Kanase-Patil et al. 2010) to calculate the cost of energy for an off- grid system in India. Fuso Nerini et al. (Fuso Nerini et al. 2015) use OSeMOSYS (Howells et al. 2011) to carry out the energy planning of Suro Craic village in Timor Leste.

MCDM solves problems involving more than one criterion of evaluation such as cost or price, efficiency and emissions and social aspects. For example, Semaoui et al. (Semaoui et al. 2013) rely on the (i) reliability and (ii) economic criterion for the optimisation for the optimal sizing of a stand-alone photovoltaic system in Algeria. Cherni et al. (Cherni et al. 2007) consider physical, human, social, natural and financial assets in their multi-criteria decision-support system (named SURE) used to calculate the most appropriate set of energy alternatives for supplying power to a rural Colombian community. The most common MCDM-based techniques include Analytic Hierarchic Process (AHP), Compromise Programming (CP), Goal Programming (GP), and Elimination and Choice Expressing Reality (ELECTRE). MCDM is a more comprehensive method to use since it provides a more in-depth, accurate and robust decision-making support (Trotter et al. 2017) to solve actual problems, especially for local case studies, where the local dimension of energy use and supply is largely affected by multidimensional techno-economic and social aspects. Nevertheless, the procedures that are commonly employed to weight the criteria suffer a high level of subjectivity.

MOP is a method for solving optimisation problems with more than one objective function. For example, Hiremath et al. (Hiremath et al. 2010a) set seven objective functions in their optimisation problem: minimisation of cost, maximisation of system efficiency, minimisation of use of petroleum products, maximisation of use of locally available resources, maximisation of job creation, minimisation of COx, NOx, and SOx emissions and maximisation of reliability. The Authors demonstrate that MOP-based models allow to represent more realistic problems, especially when they are characterised by a large number of alternatives. Nevertheless, MOP suffers from high computational costs since the number of optimisation-runs increases exponentially with the number of objectives.

NLP includes analytical optimisation problems whose variables and constraints are linked by non-linear relations, as usually occurs in most of the real-world problems. For example, Ashok (Ashok 2007) use a Quasi-Newton algorithm to determine the optimal number of renewable energy units for a typical rural community in India. The META-Net economic modelling tool adopted by Nakata and Kanagawa (Kanagawa and Nakata 2008) to analyse energy options in rural India is based on a NLP and partial equilibrium tool. Segurado et al. (Segurado et al. 2011) rely on H2RES software to plan the future power generation for S. Vincent Island in Cape Verde; the model is based on a single-objective optimisation, i.e. the minimisation of the Levelised Cost of Energy (LCOE), subject to nonlinear relations and constraints. Although NLP allows to model real physical phenomena through more precise and realistic non-linear relationships, the convergence of the model is usually highly dependent on the initial guess used to initiate the optimisation. Indeed, the examples above confirm that one of the main drawbacks of the NLP-based methods is the high level of complexity of the algorithms, that usually requires ad-hoc software.

DP is a technique for solving complex problems by splitting them into a sequence of smaller sub-problems, resolving and storing them in a data structure. Thus, DP does not identify a single optimisation algorithm: a variety of optimisation techniques can be employed to solve particular aspects of the main problem, as done by Nahman and Spirić (Nahman and Spirić 1997) and Bowe and Dapkus (Bowe et al. 1990). It is applicable to problems that require a sequence of interrelated decisions to be made, but it is a method that requires a very high level of expertise before being appropriately employed.

More recently, EO stands out as a methodology of practical interest and straightforward application. This approach calculates numerically the optimal solutions based on one or more objectives. Differently from LP and NLP that consider an objective function (linear or non-linear) to be maximised or minimised analytically (*viz.* through a mathematical analysis), EO is based on a numerical and heuristic optimisation that usually follows these steps: (i) the definition of a problem space (which is finite, discrete and includes all the potential solutions), (ii) the numerical evaluation at every, or almost every, discrete point in the space of the value of the function to be optimised, (iii) the enumeration of all the candidate solutions that respect the imposed constraints, and then (iv) the identification of the candidate solution(s) with the minimum or maximum value(s) of the function to be optimised. It is especially used for local applications with electricity as the main analysed carrier, and usually the objective is to minimise the cost function of electricity supply, by modifying the size of the supply technologies under a number of constraints (e.g. the availability of renewable resources, an imposed electricity load); in this case, the EO process starts with the definition of a searching space of all the potential technological solutions (in terms of size, components, *etc.*), it calculates the value of the investment cost function for all the discrete solutions that satisfy a certain energy demand, and then it identifies the final solution (viz. the final configuration of energy pant) with the lowest investment cost. A clear example of EO-based cost minimisation of off-grid microgrids is represented by Mandelli et al. (Mandelli et al. 2016c) and Brivio et al. (Brivio et al. 2017), who developed a novel methodology for sizing PV-batteries power systems, which embraces uncertainty on load profiles. They applied it to electricity planning in a peri-urban area of Uganda. HOMER ® software falls within the EO category: given the user-specified constraints and lower and upper limits on the size of the system, the tool simulates every possible system configuration within the search space. The HOMER Pro's Optimizer ™ facilitates this operation, selecting the solution that satisfies the lowest total net present cost (Lambert et al. 2006). For example, Kolhe et al. (Kolhe et al. 2015) apply HOMER ® for optimally sizing an off-grid distributed system for electrifying a rural community in Sri Lanka.

Case studies that do not fit any of the above-mentioned classes or do not provide enough information are identified as "Others". For example, Phrakonkham et al. (Phrakonkham et al. 2012b) minimise the annualised cost of energy for a remote village in Northern Laos with a genetic algorithm implemented in MATLAB ®. Rana et al. (Rana et al. 1998) use an intuitive sizing method: they calculate and identify the system with the lowest total life cycle cost of six combinations of three possible technology alternatives (*i.e.* standalone PV, biogas system, gasifier system) to optimally match the energy supply and demand. Segurado et al. (Segurado et al. 2011) rely on H_2RES software to maximise the penetration of renewable energy sources in the electricity system of S. Vicente Island in Cape Verde and they describe it simply as a "simulation tool".

Fig. 22 illustrates the distribution of the reviewed works across the described decision criteria methods.

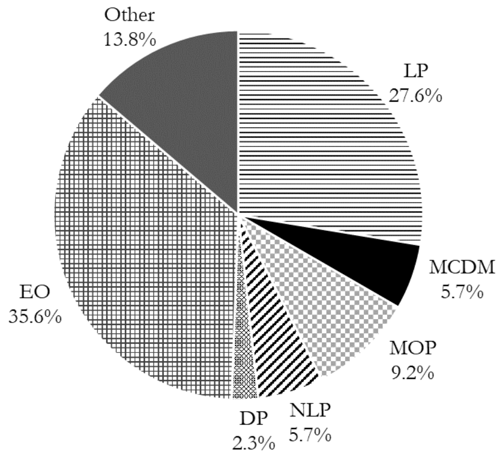


Fig. 22. Classification of case studies: Decision criteria mathematical models [from (Riva et al. 2018b)].

EO results to be the most used mathematical method. It is adopted in 35.6% of the case studies, especially those that rely on HOMER ®. LP follows, used in 27.6% of the case studies. LP is based on analytical optimisation, requiring less computational time and effort than EO methods. On the other hand, EO is not constrained by the need to set only linear equations, sometime overly simplistic (Sinha and Chandel 2015); it therefore results in a better representation of the actual dynamics and phenomena that characterise the operation of energy systems (e.g. some charge-discharge dynamics inside the batteries).

This part of the review results suggests that the literature has been mainly limited to mono-objective optimisation models so far. Considering the multifaceted issue of sustainable rural energy planning (Trotter et al. 2017) – which includes important socio-economic and environmental aspects, such as technology appropriateness, indoor air pollution, local know-how and capabilities –, MCDM and MOP models may provide more comprehensive frameworks for rural energy planning. Interesting options can consider the soft-linking with behavioural approaches, in order to take into account complex social aspects. As a pioneer example in this field, Moresino et al. (Fragnière et al. 2016) couple OSeMOSYS with a share of choice in order to take into account the consumers' real behaviour. In their case study, they focus on the consumer's preferences regarding the purchase and use of electric bulbs.

Energy service: residential, community, agricultural, industrial, commercial and not-specified

The considered energy users and the end-use of energy were: *residential*, *community*, *agricultural, industrial and commercial* and *not-specified*. In accordance with IEA's definition (OECD/IEA 2017), such categories are the most comprehensive ones of all energy uses. The energy consumption for the residential sector includes demand for lighting, cooking, air conditioning, food preservation, and powering domestic appliances such as radios, televisions, fans, etc. The community use of energy refers to schools, medical centres, radio stations, small shops, churches, and restaurants. An example is represented by Ferrer-Martì et al. (Domenech et al. 2014), who design an electrification plan for a community in Peru, considering households and five institutions as direct beneficiaries, namely the church, the school, the health-centre, restaurants and shops. The agricultural sector includes energy for farming activities: pumping water, ploughing, supplying tractors and other agricultural uses. The industrial sector considers rural industries and income generating activities, such as grain mills, coal kilns, small vans for products transportations, etc. The energy demand for the commercial sector refers to energy used for all the activities that need roads, telecommunication infrastructure, water and irrigation networks, bank and credits facilities; transportation (unless otherwise specified) is included as well, with the hypothesis that few people use cars or mini-vans as private use in rural contexts.

Very few case studies specify the sector covered by the planning (Akella et al. 2007; Amutha and Rajini 2016; Mandelli et al. 2016c, 2016b), but they provide a description of the type of technology and appliance to supply (Bujorianu 2012; Fuso Nerini et al. 2015) or the end-uses of energy (Iniyan et al. 1998; Howells et al. 2005) – such as lighting, cooking, pumping, heating, cooling and transportation. Fig. 23 illustrates how case studies are distributed among the five demand sectors.

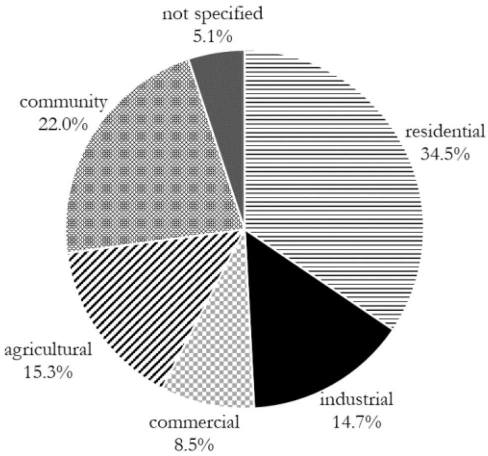


Fig. 23. Classification of case studies into the five Demand Sectors [from (Riva et al. 2018b)].

It emerges that rural energy planning deals more with residential demand, in accordance with Bhattacharyya (Bhattacharyya 2012b), who stated that "the demand in rural areas arises mainly from the use of domestic appliances" (p. 678). However, the literature concerning the nexus between energy and rural development shows the need to increase the focus on the industrial use of energy, elsewhere called *productive use of energy*. Specifically, it indicates that access to energy, when it is supported by complementary activities – e.g. educational activities, capacity building and awareness campaigns –, can be a pivotal driver in developing new business (Bowonder et al. 1985; Ravindranath and Chanakya 1986; Kumar Bose et al. 1991; Meadows et al. 2003; Cabraal et al. 2005; Bastakoti 2006; Mapako and Prasad 2007; Gibson and Olivia 2010), with a consequent increase in the industrial energy demand. It emerges that load demand models that are able to differentiate commercial from residential demand and to consider the potential growth of business activities and their future energy load would contribute substantially to defining a more comprehensive and reliable energy planning model for rural areas. This consideration supports the objectives of this thesis. Moreover, this interconnection between access to energy, the development of new business and the consequent positive feedback on future commercial energy load suggests that energy load simulation should be an endogenous feature in rural energy planning models. According to that, Jordan (Jordan 2013) and Hartvigsson et al. (Hartvigsson et al. 2018b) demonstrate that it is important to consider electricity demand endogenously in electric power systems planning.

3.2. Overview of energy demand models for rural energy planning

3.2.1. Traditional modelling frameworks

The scientific literature has addressed the classification of models for forecasting energy demand. Suganthi et al. (Suganthi and Samuel 2012) present a comprehensive review of the various energy demand models, as well as applications for both developing and developed countries. They find that econometric models are the most used, especially to link energy demand with Gross National Products, energy price, gross output and population indicators. They propose new models, such as genetic algorithms, fuzzy logic, and particle-swarm optimisation, as emerging techniques able to link energy, economy and environment for planning the future energy demand in a sustainable manner. Nevertheless, they do not report any example of application of these methods for local contexts and rural areas of developing countries. Focusing only on developing countries, Bhattacharyya and Timilsina (Bhattacharyya and Timilsina 2009, 2010) propose a literature review of existing energy demand forecasting methods and highlight the methodological diversities among them. Their purpose is to investigate whether the existing energy demand models are appropriate for capturing the specific features of developing countries. They find that mainly two approaches are used: econometric (or top-down) and end-use (bottom-up) accounting. The latter is able to produce more realistic projections as compared to the former, since it relies on detailed engineering representation of energy systems, it is based on the identification of the services and end-uses for which demand is forecast (Bhattacharyya and Timilsina 2010) (e.g. the appliance, the nominal power of the machines, the operation time) and it allows a representation of complex aspects such as innovation diffusion, income shifts and behavioural changes. It suffers, however, from data deficiencies (Bhattacharyya and Timilsina 2010), since these are very specific and contextual. On the contrary, econometric accounting is usually based on macroeconomic and aggregate data that are easily available, especially at national or regional level. Table 6 presents an abstract of the main features, strengths and weaknesses of these two most diffuse approaches discussed by Bhattacharyya and Timilsina and Swan et al. (Swan and Ugursal 2009).

Table 6. Characteristics of bottom-up and top-down models.

	Bottom-up	Top-down
Strength	- detailed sectorial representation of energy demand - realistic projections - local demand representation - modelling of energy services and uses - possible representation of complex aspects such as innovation diffusion, income shifts, and behavioural changes	- identification of the relationship between economic variable and aggregate demand - reliance on aggregate data easy to obtain - reliability on historical trends able to drive the model
Weakness	- huge data deficiency especially for developing countries - not able to capture price-based policy and price signals	- inability to capture technological diversity and technical progress

In the next section, the models and approaches for long-term projections of the energy demand employed in the case studies classified in sub-section 3.1.3 are assessed, in the attempt to derive insights and guidelines for supporting the development of appropriate demand models for rural energy planning in developing countries.

3.2.2. Categorisation and adoption of demand models used in rural energy planning

The case studies were classified based on the mathematical forecasting approach adopted; five categories of long-term energy demand projecting approaches are identified: *fixed demand*, *arbitrary trends*, *extrapolation*, *system dynamics (SD)* and *input/output* (*I/O*).

Fixed demand

The *fixed demand* category was introduced for those energy planning case studies that consider a fixed value of energy demand – i.e. no evolution of energy consumption – along the planning horizon. Case studies that do not specify how they project the demand along the planning horizon were also considered within the 'fixed demand' category. For example, Zhang et al. (Zhang et al. 2013) consider a fixed electricity demand throughout the whole lifetime of the system (15 years) and generate random weekly load profiles based on typical values of load for rural villages of Southeast Asia. Similarly, in a MOP-based planning of three micro-grids in rural Iran, Borhanazad (Borhanazad et al. 2014) consider a constant "hourly load profile for a typical rural area" ((Borhanazad et al. 2014) p. 300) derived by local assessments, without considering any evolution along the planning period. Almost all the case studies that employ HOMER ® software to design electricity micro-grids belong to this category (Kamel and Dahl 2005; Agalgaonkar et al. 2006; Akella et al. 2007; Himri et al. 2008; Nayar et al. 2008; Nfah et al. 2008; Nfah and Ngundam 2009; Setiawan et al. 2009; Alzola et al. 2009; Kanase-Patil et al. 2010; Lau et al. 2010; Nandi and Ghosh 2010; Al-Karaghouli and Kazmerski 2010; Bekele and Palm 2010; Demiroren and Yilmaz 2010; Türkay and Telli 2011; Bekele and Tadesse 2012b; Sen and Bhattacharyya 2014a; Kolhe et al. 2015; Ramchandran et al. 2016; Salehin et al. 2016; Amutha and Rajini 2016; Fulzele and Daigavane 2016; Haghighat Mamaghani et al. 2016), since the software considers a fixed demand curve along the planning horizon and the only variability lies at a daily and seasonal level.

Arbitrary trends

The *arbitrary trends* method is characterised by the assumption that the energy demand would evolve at a constant pace during each year of the planning; the trend is often taken from observation of national plans and "goals" of energy access or of growth trends. For example, for a case study focusing on India, Nakata and Kanagawa (Kanagawa and Nakata 2008) assume the total energy demand increases linearly during the planning horizon according to the expected annual growth of population in the country, which they find to be 1.4% from CIA data in 2015. Such arbitrary trends are frequently combined with multiple scenarios of energy demand, in order to include a set of descriptive pathways that indicate how future events may occur. For example, Fuso Nerini et al. (Fuso Nerini et al. 2015) set arbitrary trends of energy demand growth in the rural village of Suro Craic depending on the different *Tiers* of electricity access defined by the World Bank (S.G. Banerjee et al. 2013). Similarly, Domenech et al. (Domenech et al. 2014) investigate the current energy demand of a community of Alto, Peru, with local surveys. They derive arbitrary trends of demand growth from considerations on the "development of small productive activities and/or enjoyment of some domestic comforts" ((Domenech et al. 2014) p. 280). Ferrer-Martì et al. (Ferrer-Martí et al. 2011) propose a "low-demand" scenario characterised by constant demand for energy for households, the school and a health centre and a "high-demand" scenario to consider a wider fulfilment of the basic needs and possible production uses. On the one hand, these case studies confirm that relying on multiple scenarios based on arbitrary trends is particularly suitable in contexts characterised by high uncertainty; on the other, it emerges that arbitrary scenarios do not provide a unique clear estimation of how the demand could evolve in the future and their use in planning processes requires the employment of stochastic and/or robust mathematical optimisation models, such as the EO-based model used by Brivio et al. (Brivio et al. 2017).

System Dynamics (SD)

System Dynamics (*SD*) models are used to capture the nonlinear behaviour of complex systems over time, by relying on the use of causal and feedback relationships. SD models are characterised by stocks, which are the state variables of the dynamic system, and their inflows and outflows (rates), which increase or decrease the value in the stock. Among the analysed case studies, Hartvigsson et al. (Hartvigsson et al. 2018b) develop a SD model coupled with DER-CAM energy optimisation tool to simulate long-term projections of electricity demand in rural Tanzania and test two capacity expansion strategies on rural mini-grid operator's long-term economic performance. Their goal is to analyse the feedback between electricity availability and the operator's ability to increase generation capacity, and between the growth in electricity usage and electricity availability. The study confirms the advantage of using SD for modelling complex interactions between different socio-economic aspects in rural energy systems. Also Zhen (Zhen 1992) apply a SD approach to model the complexities of rural energy demand and develop a model to project the development of the energy supply and demand for a rural village in the North China.

Extrapolation

The *Extrapolation* technique corresponds to the method used by Malik et al. (Malik et al. 1994; Malik and Satsangi 1997) in '90s to perform the rural energy planning for Wardha district, India, from 1985 to 2000. The authors provided very few details about the model they employed; they just mentioned few sources through which they gathered data about demographic, agricultural and livestock characteristics (called "items") of some villages of the district in 1981 and estimates for 2000. Based on these scattered data, they built a *beta*-probabilistic distribution for each item, through which they then extrapolated an expected value of each item for the entire district. This technique was not found in other cases studies, probably due to the problem of data scarcity, which prevents the use of this method for rural energy planning.

Input-output (I/O)

Input-output models (I/O) have long been used for macro-economic and top-down analysis, with scarce application to rural energy planning, probably because they cannot be employed for modelling informal activities and non-monetary transactions, due to the lack of reliable data. An example of use is given by Subhash et al. (Subhash and Satsangi 1990), who carried out the energy planning for an Indian village cluster by developing an I/O model. The model adopts inter-sectorial relations for projecting sector scenarios of the economy in the long-term.

3.3. Observations from the literature and the way-forward

Fig. 24 summarises the distribution of the reviewed studies across the different demand projection approaches. It clearly emerges that three quarters of the case studies do not consider the variation of demand over the planning horizon, weakening the reliability and robustness of the design phase of the planning, especially for long-term approaches. Indeed, the lack of data availability is the most critical issue that prevents the totality of the case studies from using econometric techniques to forecast and project energy demand. For this reason, the largest part relies on the use of a fixed demand along the planning horizon, which is a huge and unrealistic simplification. This is the case of about all the reviewed case studies that employ the EO-based HOMER ® software or its improvements to carry out the electricity planning. Among the case studies with a long-term planning horizon, our study reveals that only 25% of them apply at least one of the remaining techniques for projecting energy demand. Among these, the most used approach assumes a fixed growth every year (*arbitrary trend*) justified by previous studies, historical trends or specific assumptions, that may fail in capturing the complexities behind the evolution of energy demand in rural contexts. Therefore, they are often combined with a *scenarios*-based approach, as done by (Subhash and Satsangi 1990; Hiremath et al. 2010b; Ferrer-Martí et al. 2011; Fuso Nerini et al. 2015; Brivio et al. 2017; Mandelli et al. 2017), which is very useful to deal with uncertainties in the demand; nevertheless, the use of *scenarios*-based approaches must be compatible – at reasonable computational effort and time – with the decision criteria mathematical models employed for the energy planning.

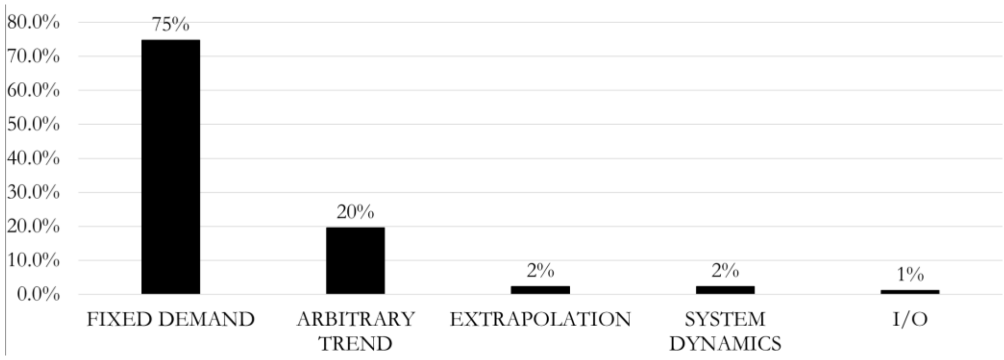


Fig. 24. Percentage of energy demand forecasting approaches adopted in the case studies [from (Riva et al. 2018b)].

In order to overcome the limitations of the current literature on energy demand models for developing countries, Urban et al. (Urban et al. 2007) list the main characteristics of the energy system of developing countries that should be captured by energy models: the supply shortages, the transition from traditional to commercial fuels, the role of income distribution, the urban/rural split, the underdeveloped markets and informal activities, structural changes in the economy and subsidies. Moreover, especially in rural areas, energy access planning should firstly consider the structural change in the socio-economic dynamics caused by the introduction of new energy technologies, such as the leapfrogging of economies (*e.g.* new income generating activities and opportunities) (Bhattacharyya and Timilsina 2009, 2010). As Khandker et al. (Khandker et al. 2013) state, "the dynamics of growth and electrification are complex, involving many underlying forces" (p. 666) and feedback mechanisms: rural electrification is expected to positively impact new economic and educational opportunities, which in turn might make electricity and appliances more affordable, increasing the local electricity demand. Secondly, an appropriate model for demand projection in rural areas must account for the demand for end-use functions and appliances (Daioglou et al. 2012), in order to understand the user-value of electricity use (Hirmer and Cruickshank 2014), analyse the drivers behind their diffusion, the operation and change in use and finally build reliable load profiles. This in turn depends on acceptability, deeply-rooted consumer behaviours, social networks-based diffusion mechanisms, affordability, elasticity of the demand, people's disposable income and willingness to pay and the inertia of the stock of available appliances. This is why Swan at al. (Swan and Ugursal 2009) state that bottom-up end-use approaches are more suitable for contexts where there is a rapid technological development as in developing countries. In this context, Table 7 summarises and proposes the need to move towards mathematical approaches and instruments able to capture both the technical and the socio-economic-related dimensions of energy demand evolution.

Table 7. Socio-economic- and energy-related dimensions of energy demand evolution in rural contexts.

Economic dimension

- Considering the informal activities/economies that may bias available aggregate data on income (Urban et al. 2007)
- Considering income distribution and inequity among users, who may behave differently among different socio-economic classes (Urban et al. 2007), since energy transition is highly dependent on the financial resources of people and their capability to mobilise these (Ahlborg 2015)
- Modelling the new income generating activities and possibilities driven by more reliable access to energy (Bhattacharyya and Timilsina 2009, 2010), considering that where the majority of people live below or close to the economic poverty line, the potential for beneficial dynamics between electricity access and local business and industrial development is very limited (Ahlborg and Hammar 2014)

Social dimension

- Modelling the urban and rural demand separately, since people have different needs and constraints (Urban et al. 2007; van Ruijven et al. 2011)
- Considering also non-monetary factors that may influence the users, such as past experience, social norms, and trust-based information and perceptions of quality, satisfaction and social network (Chakravorty et al. 2014; Hartvigsson et al. 2015; Aklin et al. 2016; Rai and Henry 2016)

Energy dimension

- Modelling the demand for end-use appliances following a bottom-up approach (Daioglou et al. 2012)
- Considering the "user choice" of fuels and transition from traditional to modern energies, and vice-versa (Urban et al. 2007), especially for energy for cooking (Cameron et al. 2016)

All these aspects confirm that rural energy demand is deeply linked with the socio-economic development that electricity use can bring in a local context. Therefore, being able to understand and model aspects and dynamics behind such nexus between electricity and development can lead to more robust energy planning and solutions in rural areas. However, while the relationship between electricity use and development is known from a macroscopic and macroeconomic point of view, the local dimensions of the electricity-development nexus in rural contexts are not completely captured and characterized. Indeed, according to Matinga and Annegarn, when referring to local rural contexts, "simple deterministic relations between electricity access and development outcomes do not reflect reality" ((Matinga and Annegarn 2013) pg. 301). Also Ahlborg (Ahlborg 2015) confirms the presence of multiple interfaces and feedbacks that shape outcomes in electrification processes. The literature also suggests that the nexus between electricity use and rural socio-economic development has dynamic components, meaning that the nexus is characterized by complex feedbacks that can reinforce or balance impacts over time (Ulsrud et al. 2011). Khandker's (Khandker et al. 2013) study of Vietnam's rural electrification program exemplifies how a "virtuous circle of development" emerged as significant investments in other rural infrastructure services were undertaken (viz. water supply, roads, health and education) and rural electrification contributed to greater educational attainment, more business opportunities, and higher income, which in turn improved the affordability of electricity and appliances, leading to an increase of total electricity load and more investments in rural electrification. Khandker, as well as others (Kanagawa and Nakata 2008), suggests that electrification, if supported by enabling complementary actions, can lead to positive feedbacks on future electricity demand in a rural context.

For all these reasons, a first step towards the development of a more appropriate rural electricity demand model, an in-depth understanding and conceptualisation of the electricity-development nexus is advised, which is the aim of the next Chapter.

Chapter 4

Electricity demand and socio-economic complexities

We will make electricity so cheap that only the rich will burn candles
(Thomas Edison 1879)

If I had a rich man in front of me, I would ask for electricity at home. I'm tired to go to bed and wake up based on the sun-light
(Anonymous Namibian breeder)

Current subsidies to fossil fuel from governments are worth around half the funding needed to bridge the global energy access gap, to double renewable energy and energy efficiency rates by 2030
(International Institute for Sustainable Development 2017)

In order to investigate further the complexities behind the evolution of rural electricity demand, this chapter undertakes a comprehensive and extensive analysis of the peer-reviewed literature on electricity access and its impact on rural socio-economic development, and vice versa. It contributes to Objective 1 by investigating the socio-economic and technical complexities which involve the nexus between electricity demand and development, as well as by setting a basis for the modelling of electricity demand in rural areas and, hence, the planning of off-grid mini-grids. The analysis is carried out by developing graphical causal loop diagrams that allow to capture, visualise, and discuss the complexity and feedback loops characterising the following multiple dimensions of the electricity-development nexus: *income generating activities*, *market production and revenues*, *household economy*, *local health and population*, *education*, and *habits and social networks*. This chapter is based on the following publication:

Riva, F., Ahlborg, H., Hartvigsson, E., Pachauri, S., & Colombo, E. (2018). Electricity access and rural development: Review of complex socio-economic dynamics and causal diagrams for more appropriate energy modelling. *Energy for Sustainable Development*, 43, 203-223. doi: 10.1016/j.esd.2018.02.003.

4.1. Electricity access and rural development

4.1.1. State-of-the art

Reviews studies of the socio-economic impacts of rural electrification in developing economies started emerging in the 1980s. Within the context of the International Labour Office's World Employment Programme's research, Fluitman published a working paper in 1983, where he reviewed the available literature on rural electrification, its effects on rural industrialisation, and its impact on such socio-economic objectives as employment and income generation. The paper concluded that the socio-economic benefits of providing people with access to electricity in rural areas seemed to be overestimated. Also, he saw a need for "more judicious planning, formulation and evaluation of rural electrification programmes (pg. v)" for maximising the positive impacts of electrification-oriented investments. In more recent years, other review papers on this topic have been published both in the grey and scientific literature. Among the grey literature, many country- or region- specific reports and evaluations papers are from donor organizations (World Bank 2002; Khandker et al. 2009a, 2009b, 2012; UNDP Asia-Pacific 2012). The first chapter in the joint GIZ-ESMAP study "Productive Use of Energy" (PRODUSE) is a review of the impact of electricity access on economic development (Attigah and Mayer-Tasch 2013). Their main conclusion is that, despite a growing body of literature that indicates positive impacts of electricity on local productivity, the magnitude of such impacts is highly country- and context-specific. The Independent Evaluation Group (IEG) (Independent Evaluation Group (IEG) 2008) of the World Bank Group published a document, which reviews the methodological advances made in measuring the socio-economic benefits of rural electrification on local communities in low-income countries. They conclude that electrification can have positive impacts on local communities, in terms of growth of local income generating activities, time-savings, educational and health improvements, but such results lack a quantitative scientific evidence basis.

In the scientific literature, reviews examine the cumulative evidence base as well as the methodological basis for measuring impacts. The survey by Ozturk (Ozturk 2010) focuses on the causal relationship between electricity consumption and economic growth at country-level, by investigating papers that employ econometric approaches to find relations between national Gross Domestic Product (GDP) and electricity consumption indicators. Cook (Cook 2011) reviews the literature on the role and relation of electricity infrastructure in rural areas on economic growth and social development. Brass et al. (Brass et al. 2012) offer a comprehensive review on the main outcomes – viz. short- and long-term economic, educational and health implications – of distributed generation (DG) projects and programmes in developing countries. Terrapon-Pfaff et al. (Terrapon-Pfaff et al. 2014) evaluate the impact and the sustainability of 23 small-scale renewable energy projects in developing countries, suggesting that the majority of the projects had positive effects on sustainable development.

The existing grey and scientific literature focus mainly on how rural electrification and electricity use affect local socio-economic development, while the reverse feedbacks are not systematically explored. The aim of this chapter is therefore to build-on the findings of the previous reviews, by adding an analysis of the consequent feedbacks of socio-economic developments on electricity demand. Indeed, the electricity-development nexus is characterized by complex dynamic interactions, feedbacks, and behaviours. The understanding of such complex interactions requires therefore a more comprehensive investigation, which aims at analysing the "electricity-development nexus" as a system and not as a set of possible unidirectional correlations between multiple dimensions – i.e. electricity use and access on one side, and socio-economic indicators on the other.

4.1.2. Rationale and methodology of the analysis

78 peer-reviewed articles are reviewed using Science Direct editorial platform and Scopus databases – Fig. 25 reports the main sources, highlighting the multidisciplinarity of the topic. Only case-studies (and reviews of them) that report and discuss in-depth qualitative and quantitative findings about the nexus between electricity consumption and socio-economic development at a local level are considered. In accordance with Brass et al. (Brass et al. 2012), grey papers and reports produced by intergovernmental organizations, NGOs, donors, and government agencies are excluded, since their

active role in electrification projects and programmes might have biased the reporting of results and potential failures. The only exception is represented by Meadows et al.'s review (Meadows et al. 2003), which covers an unusually wide range of case studies of rural electrification and reports quantitative data. Studies that only cite anecdotal evidence from other sources, as well as papers that limit their focus to feasibility studies, cost-benefit analyses, and prospective studies are excluded. In terms of technologies, the local electricity-development nexus is evaluated by considering the implementation phases (viz. material supply, construction, start-up) as a given.

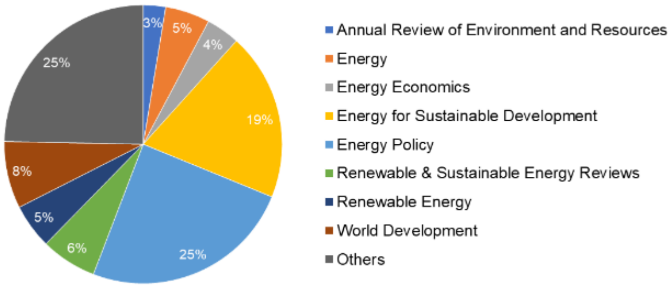


Fig. 25. Journals in which the reviewed papers were published [from (Riva et al. 2018a)].

The main findings are discussed and synthetized by representing the complex socio-economic dynamics through causal loop diagrams that highlight the reinforcing and balancing relations between the main variables characterising the nexus. Causal loop diagrams are conceptual models to represent complex systems, and therefore they include variables that are *meaningful* to people (Luna-Reyes and Andersen 2003). The variables in each diagram represent the different key-aspects of the electricity-development nexus mentioned in the literature. The arrows indicate the causal relationships; the positive "+" signs on the arrows indicate that the effect is positively related to the cause: an increase in the variable at the tail of the arrow causes the variable at the arrowhead to rise above what it would otherwise have been, in the absence of an increase in the cause. On the contrary, the negative "–" polarity of the arrows means that if the cause increases then the effect decreases.

From the literature, only two main dimensions of the nexus emerged clearly, and they are analysed separately: (1) the *economic dimension* and (2) the *social dimension*. For these two dimensions, sub-nexuses are identified, each one analysed with a separate causal-loop. Causal loop diagrams are usually developed through group modelling, or through the employment of already known systems archetypes (e.g. the *Limits to Growth* archetype), or through sub-concepts found in the literature. In this analysis, the causal-loop diagrams for each sub-nexus are derived from the review on the electricity-development nexus, following these iterative steps:

a. *Listing* the principal variables mentioned in the literature related to the given sub-nexus (e.g. Free-time, Productivity, Income, Business, Electricity Use, Small-Medium Enterprise, Time for working, Energy demand);
b. *Grouping* words with the same or similar meaning in one variable with the same name (e.g. Business, Small-Medium Enterprise = Income Generating Activity);
c. *Linking* the variables through arrows with positive or negative polarity by extrapolating them from direct quotations from the articles (e.g. "Access to electricity can impact SMEs by enabling the use of electric tools and equipment, thus increasing productivity per worker [(Kirubi et al. 2009), pg. 1212]" gives: *Electrical appliance availability* ("Access to electricity") $\xrightarrow{+}$ *Electricity demand* ("electric tools and equipment") $\xrightarrow{+}$ *Productivity* ("productivity per worker"). This is an iterative process, since each quotation can suggest a new link or a new intermediate variable to add until convergence to a final diagram that is coherent with all the information provided by the literature.

4.2. Economic dimension

The nexus between electricity demand and local economic development develops over time. In the following, three main sub-nexuses through which economic development might impact on the structure of a local rural economy and future electricity demand are discussed: (i) the nature and amount of *income generating activities*, (ii) *production and revenues*, and (iii) changes to the *household economy*.

4.2.1. Income generating activities

The term income generating activities (IGAs) refers to all business activities and small-medium enterprises (SMEs) that provide a person with a regular or irregular cash-flow by selling goods and services, regardless of the type of the business, the size or the location. The potentially positive dynamics between electricity use and creation and spread of IGAs are reported and explained at different analytical levels within the scientific literature. In this sub-section, the analysis of these dynamics is organised into three different levels. First, it is reported on literature that indicates a positive linear impact of electricity use on the creation of IGAs, but without explaining it. Second, studies that report some causal reasons behind such potential impact are discussed, and third, the literature that cover nexus dynamics including feedbacks between creation of new IGAs and electricity consumption is discussed. As expressed by Rao, "the causal effect of electricity supply on NFE [non-farm enterprises] income is complex, and both direct and indirect" ((Rao 2013) p. 535). Last, in this sub-section, the mechanisms that hinder a positive dynamic and the suggestions made by scholars on how to enhance the development of rural IGAs are discussed.

The majority of papers simply state that access to electricity brings about an increase in local IGAs, especially the electricity-reliant ones. This portion of the literature lacks description of the complexity of the nexus, as summarized in Table 8.

Table 8. Examples of impact of electricity use on IGAs' growth.

Reference	**Mentioned impact of electricity use on new IGAs**
Ravindranath et al. (Ravindranath and Chanakya 1986)	Access to electricity supported the creation of electric flour mills in Malanganj and B.N.Pura Indian villages
R. Kumar Bose et al. (Kumar Bose et al. 1991)	Access to electricity led to a 20% increase in business activities in three villages in Eastern Uttar Pradesh
B. Bowonder et al. (Bowonder et al. 1985)	Access to electricity led to the creation of repair and serving shops and village entertainment enterprises such as movie tents and community televisions (TVs) in eight rural communities in India
Cabraal et al. (Cabraal et al. 2005)	25% of households with electricity operated a home business in Philippines, compared to about 15% of households without electricity
Gibson and Olivia (Gibson and Olivia 2010)	Households connected to electricity increased their participation in non-farming enterprises by 13.3% in rural Indonesia, with the percentage of enterprises operated by rural households 43% higher after access to electricity
Mapako and Prasad (Mapako and Prasad 2007)	Results of the surveys on 73 small enterprises in the south west of Zimbabwe are reported with all the types and number of activities that were created after electrification; the total number of employees in these areas is reported to have been increased by 270%.
Bastakoti (Bastakoti 2006)	The Nepalese areas served by the Andhikhola Hydroelectric and Rural Electrification Centre (AHREC) experienced the creation of 54% more rural industries after electrification, allowing 600 more employees to have an income.
Prasad and Dieden (Prasad and Dieden 2007)	Data from South African national surveys suggest that somewhere between 40% and 53% of the increase in small, medium and micro-enterprises uptake is attributable to the grid roll-out.
Peters et al. (Peters et al. 2011)	The creation of electricity-reliant firms in regions with access in Rural Benin has been "a clearly positive effect of electrification" ((Peters et al. 2011) p. 781).
Jacobson (Jacobson 2007)	48% of the households interviewed in rural Kenya reported that the use of solar electricity supported some work- or income-related activities.
Adkins et al. (Adkins et al. 2010)	98.1% of adopters of solar lanterns in Malawi reported that the use of solar electricity supported some work- or income-related activities.
Kooijman-van Dijk and Clancy (Kooijman-van Dijk and Clancy 2010)	25% of households with electricity operated a home business in Philippines, compared to about 15% of households without electricity

At a second analytical level, some papers analyse the benefits of electrification on employment generation (related to construction, service provision and electricity use) in more detail by discussing the causal relations between access to electricity and the operation of rural economies. First, employment opportunities arise from the creation of new electrical infrastructures needed to satisfy local electricity demand and with the spread of new appliances and devices. In the causal diagram representing the dynamics between electricity demand and IGAs (Fig. 26), this positive relation is represented by the link between *Electricity demand → Off-grid system related organizations → IGAs*. Studies such as those by Kumar et al. (Kumar et al. 2009) and Somashekhar (Somashekhar et al. 2000) report the creation of organizations in charge of manufacture, installation, operation and maintenance of new power generation infrastructures in India. Biswas et al. (Biswas et al. 2001) suggest that the operation, maintenance and administration activities of renewable energy technologies can bring positive impacts on the rural employment rate in Bangladesh. Second, an effect of rural electrification is the freeing up of time thanks to the use of electric appliances and services (instead of manual labour), especially for women who can use more time for home production (Grogan and Sadanand 2013; Khandker et al. 2013) and market activities (Dinkelman 2011). The time savings allow for the establishment and extension of IGAs as mentioned in (Bastakoti 2006; Mulder and Tembe 2008; Kumar et al. 2009; Gurung et al. 2011; Sovacool et al. 2013). This dynamics is represented through the positive *Electricity demand → Free-time → IGAs* links. Finally, Dinkelman (Dinkelman 2011) indicates that South African electrification affected rural labour markets also by facilitating new activities for men and women, who started producing market services and goods at home through the adoption of new electrical appliances (*e.g.*, food preparation, services requiring electric appliances) – positive *Electrical machines and devices → IGAs* link.

At a third level of analysis, some literature delves into more depth and investigates the propensity to establish new activities, invest in and extend IGAs, and the related feedbacks on electricity demand. As already highlighted, the possibility to use electrical devices makes new activities possible and for people to invest in: telephone booths, shops that produce and sell yoghurt, fresh drinks (Kirubi et al. 2009; Sovacool et al. 2013), ice-cream (Bastakoti 2006), office support services – e.g. faxing, word processing, photocopying, printing shops, computer centres (Lenz et al. 2017) –, energy stores, laundry services, hair dressers, photo studios (Bastakoti 2006; Shackleton et al. 2009; Peters et al. 2011), saw mills, welders (Peters et al. 2011), village entertainment enterprises such as movie tents and community TVs (Bowonder et al. 1985; Bastakoti 2006), cold stores (Bastakoti 2006; Matinga and Annegarn 2013) – the positive *Electrical appliances availability → Propensity to invest → IGAs* link. Related to this, the diffusion and use of new electrical appliances and machines both require and allow the establishment of new small business activities that can offer regular maintenance and charging services (*Electricity demand → Local maintenance services*), as reported for rural Eritrea (Habtetsion and Tsighe 2002), Mali (Sovacool et al. 2013) (Moharil and Kulkarni 2009) (Meadows et al. 2003), and India (Bowonder et al. 1985). The presence and availability of local maintenance, in turn, encourages people to invest in electrical machines for starting new income generating activities, because of the easy access to repair services (Cook 2011) – positive *IGAs → Local maintenance services → Propensity to invest → Electrical machines and devices → IGAs* reinforcing loop. Thus, causal relationships are identified between the generation of new IGAs, development of maintenance services, people's willingness to make investments in electric devices and machines and further growth in electricity load – *IGAs → Local maintenance services → Propensity to invest → Electrical machines and devices → Electricity demand.*

What the literature also highlights is how the decision to set up a new business activity is highly dependent on the financial resources of people and their capability to mobilize these (Meadows et al. 2003; Ahlborg 2015) – this is the reason why income increases from businesses or employment favour especially rich and middle income households (Jacobson 2007; Cook 2011; Kooijman-van Dijk 2012; Khandker et al. 2013; Matinga and Annegarn 2013) and increase economic inequality. Investment barriers often hinder poorer households from starting small businesses (*IGAs → Income inequality → Access to financial capital*). As a consequence, income is a pivotal driver of the decision to invest in new IGAs and new electrical devices to support businesses (Obeng and Evers 2010). Therefore, increasing the income earning opportunities and revenues, or reducing costs – for a larger part of the population – related to electricity use has a direct positive feedback on potential new investments in productive electricity demand (Ahlborg and Sjöstedt 2015) – the positive *IGAs → Average Income → Access to financial capital → Propensity to invest → Electrical machines and devices* feedback on *Electricity demand.*

Importantly, a significant portion of the literature is sceptical of the positive effects of electrification on the establishment and expansion of new IGAs (Stojanovski et al. 2017). The main reason provided by these studies is the high poverty and inequality level, which usually characterizes these contexts. As stated by Ahlborg and Hammar (Ahlborg and Hammar 2014), as long as a majority of people live below or close to the economic poverty line, the potential for beneficial dynamics between electricity access and local business and industrial development is very limited. Alazraki and Haselip (Alazraki and Haselip 2007) report that only 3% of people interviewed in rural provinces of Jujuy and Tucumán, Argentina, stated that access to electricity through PV-powered SHS allowed them to start a new business. Kooijman-van Dijk and Clancy state that employment opportunities as a consequence of access to electricity in Bolivian, Tanzanian and Vietnamese villages consist mainly of flexible and "unpaid involvement of family members" ((Kooijman-van Dijk and Clancy 2010) p. 18). Lenz et al. (Lenz et al. 2017) indicate that the majority of rural Rwandan households they interviewed were still farmers after electrification, with no significant changes in IGAs before and after electrification. One of the most recurrently identified obstacles to the expansion of rural business is the lack of a dynamic local market (Neelsen and Peters 2011; Kooijman-van Dijk 2012; Baldwin et al. 2015), leading to the "crowding out effect" of the existing firms, i.e. the creation of new IGAs that is followed by stagnation or economic losses among already existing IGAs (Kooijman-van Dijk and Clancy 2010; Peters et al. 2011), or a reduction of wages due to an abundance of labour supply over labour demand (Dinkelman 2011). This effect was represented through the positive link *IGAs → crowding out* which negatively affect the *Average Income* variable. In some contexts, the lack of credit for investment in new electrical equipment and grid connection represents a barrier to the set-up of new activities (Bhattacharyya 2006; Grimm et al. 2013). For example, some entrepreneurs in rural Benin could not electrify their manufacturing processes because of the high cost for changing to more modern electricity-driven technologies (Peters et al. 2011); and more than three quarters of entrepreneurs interviewed in two rural communities near Lake Victoria in Uganda said that grid connection has too high a break-even point on the return on investment (Neelsen and Peters 2011). Peters et al. (Peters et al. 2009) suggest that when there is a single-person business, electric machinery may have an hourly cost higher than human labour. This confirms that the lack of *Access to financial capital* discourages people in setting up or modernizing their business, i.e. it reduces people's *Propensity to invest* and consequently the diffusion of new *Electrical machines and devices*. The decision to start a new activity and the consequent expansion of IGAs is also sometimes limited by the low quality of electricity supply (the negative *Power unreliability → Propensity to invest* link). Gibson and Olivia (Gibson and Olivia 2010) report that households in Indonesian villages, which never suffer blackouts, have an average of 1.3 more non-farm enterprises than in villages with frequent black-outs.

In order to overcome such barriers, several papers propose some complementary activities and actions to enhance the positive impact of electrification on the development of new IGAs, especially where no business "stemmed from electrification itself" ((Matinga and Annegarn 2013) p. 299). This is especially important in order to support women entrepreneurs who in many countries find it harder than men to mobilise financial capital (Ellis et al. 2007). These exogenous activities are represented through dashed red arrows in the diagram of Fig. 26. Facilitating access to credit and finance is the most common recommendation (Biswas et al. 2001; Bastakoti 2006; Adkins et al. 2010; Kooijman-van Dijk and Clancy 2010; Gurung et al. 2011; Peters et al. 2011; Brass et al. 2012; Baldwin et al. 2015), since it allows people to set-up new IGAs, and facilitates a regular cash-flow, which in turn helps build financial capital (Bastakoti 2006) (*micro-credits → Access to financial capital*). Several studies (Bastakoti 2006; Cook 2011; Kooijman-van Dijk 2012; Sovacool et al. 2013; Baldwin et al. 2015) encourage stimulating the development of local markets and demand to decrease the crowding out effect (*market stimulation → Market demand → crowding out*) and increase people's willingness to invest in new business opportunities (*market stimulation → Market demand → Propensity to invest*), and disseminating new technical skills through educational activities, business and manufacturing training for supporting the start of new IGAs (*capacity building → IGAs*). Providing access to accessible roads (*infrastructures → Market demand*) is also mentioned as a complementary activity (Kirubi et al. 2009; Gibson and Olivia 2010; Kooijman-van Dijk and Clancy 2010).

Fig. 26 represents the dynamics described above, highlighting the positive and negative feedbacks among variables, as well as indicating the complementary activities and conditions that positively enhance the dynamics. The diagram indicates that the propensity to invest is a key-aspect affecting the growth of future electricity demand and the creation of new IGAs. Further, the diagram shows that people's propensity to invest is positively affected by their financial capacity, the availability of electric machines and a local reliable maintenance service, and the growth of local market demand for goods and services. In particular, in case of investments in an electricity-reliant business, the "propensity to invest" variable signifies both the start of new electricity consumer-IGAs, as well as increased demand from existing electricity consumer-IGAs that expand their business by investing in more appliances and machinery.

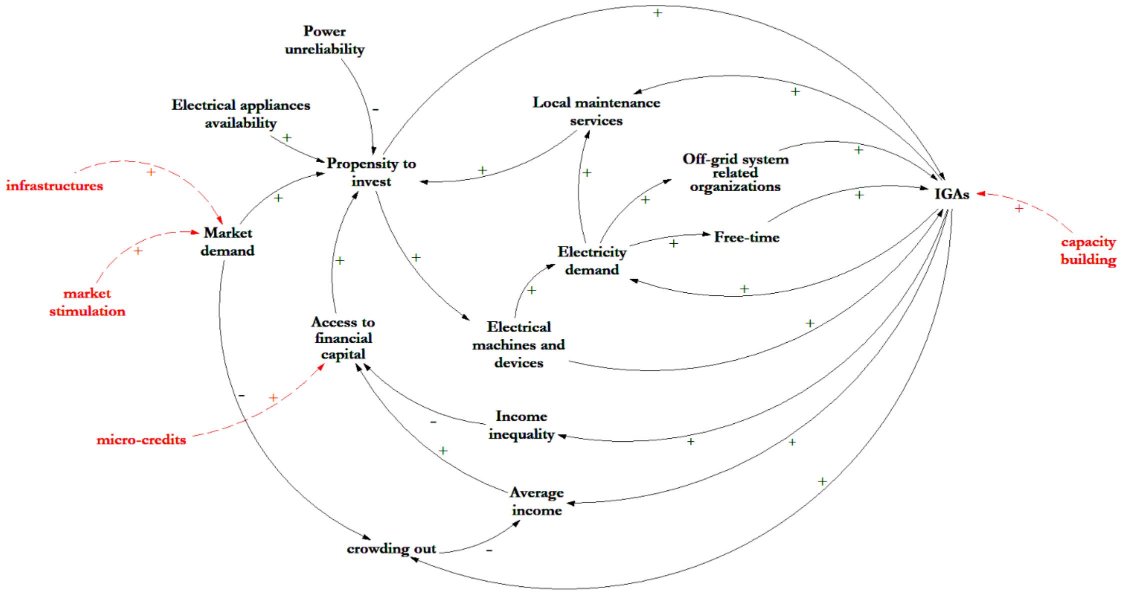


Fig. 26. Causal loop diagram representing the dynamics between electricity demand and IGAs [from (Riva et al. 2018a)].

4.2.2. Market production and revenues

The second sub-nexus between access to electricity and economic impacts is through local market production by IGAs and local revenues. The potentially positive dynamics of electricity demand and market production are discussed through different levels of analysis. First, it is reported on literature that indicates a positive potential impact of electricity demand on the productivity in local markets. Next, studies that analyse the impact of electricity use on the local markets are discussed – *viz.* the effect of electricity demand on market *demand* and *supply*. In the case of literature reporting low or no impacts, some complementary activities from the literature that might enhance the benefits of electricity on the operation of local markets are highlighted. Finally, the feedbacks identified in the literature between local market production and electricity demand are also reviewed.

The first level of literature analysis suggests that electricity use increases local production and people's productivity, especially in new electricity-reliant businesses, as exemplified in Table 9.

Table 9. Examples of impact of electricity use on market production and revenues.

Reference	**Mentioned impact of electricity use on market production and revenues**
Ranganathan and Ramanayya (Ranganathan and Ramanayya 1998)	An extra kWh of electricity generated an incremental surplus of agricultural production for Indian farmers
Meadows and Kate (Meadows et al. 2003)	In India, energy-intensive enterprises that obtained access to modern energy achieved enhanced income levels of 30-40% more than enterprises that did not gain access.
Peters et al. (Peters et al. 2011)	In villages located in Northern Benin, the profits of connected firms were considerably higher, *viz.* 73.8% higher (statistically significant at the 5% level), than those of non-connected firms, and this is especially true for electricity-reliant firms.
Kooijman-van Dijk (Kooijman-van Dijk 2012)	It is found a positive relation between 'electricity use for enterprise products and services' and income from enterprises in the Indian Himalayas, although electricity is not considered the definitive solution to poverty reduction.
Gustavsson (Gustavsson and Ellegård 2004; Gustavsson 2007a)	In Zambia, lighting in the evening could improve teachers' income, enabling them to earn some extra income by teaching in the evening.
Cabraal et al. (Cabraal et al. 2005)	Households managing small cottage industries in rural India were able to increase their daily income using electric lighting to extend their productive hours after nightfall.

The studies that focus on the dynamics behind the possible increase in enterprises' productivity and revenues suggest that access to electricity and use may positively or negatively impact local markets by affecting local *supply* and *demand* of goods and services.

Market demand

Focusing on local market demand, the number of consumers for a given business may increase thanks to the increased use of communication devices and advertisements (Jacobson 2007) (*Electricity demand → Communication devices → Market demand*). Communication devices – e.g. TVs, radio and phones – may also introduce changes in aspirations and expenditures of rural households (Matinga and Annegarn 2013) for goods and services, diversifying purchases and leading people to shop locally rather than elsewhere (Shackleton et al. 2009). Neelsen and Peters (Neelsen and Peters 2011) report that electric lighting and the consequent increase in perceived security attracted potential customers also during the evenings in rural Uganda. Kirubi et al. (Kirubi et al. 2009) and Kooijman-van Dijk (Kooijman-van Dijk 2012) suggest that electric appliances allow for improvements in products' quality (*Electricity demand → Product quality → Market demand*) and production and/or selling of new products (*Electricity demand → Product innovation → Market demand*) which can attract more consumers or increase the demand per-capita, with positive impacts on local production and the consequent revenues (*Market demand → Goods/services sold → Net revenues*). In this context, Peters et al. highlight the risk that "to the extent that local consumer's purchasing power is diverted to the new electricity-reliant manufacturers, existing non-reliant manufacturers are likely to suffer a drain on business" ((Peters et al. 2011) pg. 778), increasing inequality. Multiple studies report that such increases in the demand for products and services in turn causes an increase in price, due to market equilibrium rules (Meadows et al. 2003; Cabraal et al. 2005; Sovacool et al. 2013). However, this conventional equilibrating market mechanism does not always appear to apply in developing economies – as Banum and Sabot (Barnum and Sabot 1977) report for Tanzanian rural markets – which raises questions about the actual impact of improvements in products' quality on the price of goods.

Market supply

On the production-side, there are four mechanisms whereby electricity use can have a positive impact: (i) enhancing communication, (ii) enhancing work productivity, (iii) enabling longer work days, and (iv) decreasing energy-related costs. First, communication devices help improve the efficiency of business activities and the related market revenues (*Electricity demand → Communication devices → Production efficiency → Net revenues* in Fig. 27). Cabraal et al. (Cabraal et al. 2005) report that the use of telephones in rural Thailand enabled farmers to regularly check prices in Bangkok and significantly increase their profits, while the use of the internet by Indian farmers allowed them to obtain current information on market prices and good farming practices, and consequently order appropriate agricultural inputs. Jacobson (Jacobson 2007) suggests that Kenyan owners of business activities benefited from receiving regular business information via television and radio, while the use of cell phones helped retail shops and other service-oriented businesses to place orders, make business deals, be in contact with their clients, and finally increase sales. This positive outcome of electricity use for productive purposes has been highlighted also by Khandker et al. (Khandker et al. 2013) for Vietnam.

Second, the use of electric machinery and appliances can help increase productivity, i.e. the number of products and services that an enterprise can supply in a given time period, which in turn increases the supply of goods to the local market. However, if the demand stays equal, it generates a drop in the price of goods, which can be offset by an increase in the volume of sales made (depending on the type of product/service), in turn increasing revenues (*Electricity demand → Productivity → Market supply → Goods / services sold → Net revenues*). Kirubi et al. (Kirubi et al. 2009) report that the small-medium enterprises in a community-based electric micro-grid in rural Kenya experienced a significant increase in revenues in the order of 20–80%. Kooijman-van Dijk (Kooijman-van Dijk and Clancy 2010; Kooijman-van Dijk 2012) indicates that, when the market-demand is high, tailors that used electric sewing machines were able to increase the productivity by two to three times more than the average, while grain millers reported processing larger volumes of grains per day. The increase in demand for higher-quality products and services supplied by the use of electric machinery may enable sellers to fetch higher prices and increase revenues (Meadows et al. 2003; Kooijman-van Dijk 2012; Sovacool et al. 2013). On the other hand, an increase in productivity brought about by access to modern machines may decrease the need for human resources, causing a decrease in the employment rate and individual revenues (the negative *Productivity → Human labour → Average income* feedback): Meadows et al. (Meadows et al. 2003) report that in rural Indonesia, the introduction of a wind power pump reduced human labour input by a factor of 10, from 1040 to 100 hours.

Third, access to electricity may improve sales and businesses by extending operating hours thanks to lighting (Alazraki and Haselip 2007; Mishra and Behera 2016) (*Electricity demand → Evening work time → Market supply*). Meadows et al. (Meadows et al. 2003) state that the introduction of battery-operated lamps in rural Bangladesh allowed tailors to work for four more hours and thereby increase their revenue by 30%, while rice milling activities were performed during 7 to 9 p.m. in Hosahalli village (India). Agoramoorthy and Hsu (Agoramoorthy and Hsu 2009) report on the experience of some households in India, who suggest that lanterns provide opportunities to expand business and allow more time to work at night when compared to fuel-based lighting sources. Jacobson (Jacobson 2007) suggest that lighting in the evening can benefit and positively impact teachers' income in rural schools in Kenya, enabling them to grade papers, plan evening lessons at home and earn some extra money. Similar increases in productive hours during evenings are reported by Komatsu et al. (Komatsu et al. 2011), who report that households in the rural districts of Comilla, Kishoreganj, and Manikganj in Bangladesh extended their working hours by about two or more hours in the evening, while 56% of connected firms surveyed by Peters et al. (Peters et al. 2009) in Copargo (Benin) declared working longer thanks to lighting that extended their daily operating hours. The same effect of night-lighting was reported by Chakrabarti (Chakrabarti and Chakrabarti 2002) and Baldwin et al. (Baldwin et al. 2015), who indicated that, in Sagar Dweep island in West Bengal (India), shopkeepers and workers engaged in handicrafts extended their working hours in the evening. The increase of daily working hours is especially common for commercial activities located in residential areas, where the demand is higher (Neelsen and Peters 2011), shops and barbers (Meadows et al. 2003; Kooijman-van Dijk and Clancy 2010), and restaurants, whose increasing in operating hours has a direct impact on revenues (Kooijman-van Dijk 2012).

Several papers are also sceptical about the positive effects of electrification on the extension of operating hours. For example, Adkins et al. (Adkins et al. 2010) state that less than 10% of solar lantern users experienced expanded business opportunities by working more at night. In rural Indian Himalayas, only half of entrepreneurs with access to light worked regularly in the evening (Kooijman-van Dijk 2012), because of structural barriers, such as distance from main roads or time limitations of workers. In some cases, evening light is considered merely a means of guaranteeing more flexibility at work (Kooijman-van Dijk and Clancy 2010; Kooijman-van Dijk 2012). Moreover, for producing enterprises, increasing working hours does not result in new consumers, but simply increases production volumes (Kooijman-van Dijk 2012). Sometimes, an increase in productivity as a result of more efficient machines may even reduce working hours (Kooijman-van Dijk and Clancy 2010) (the negative *Productivity → Evening work time* feedback). These findings suggest that two determining factors for increasing night operation may be the availability and reliability of electricity during night hours (Kooijman-van Dijk and Clancy 2010; Obeng and Evers 2010) (the negative *Power unreliability → Evening work time* feedback) and market demand (*Market demand → Evening work time*).

Fourth, there is evidence that the use of electricity for productive purposes may increase profit margins by reducing the cost associated with other energy resources (Habtetsion and Tsighe 2002) (*Electricity demand → Traditional sources of energy → Energy cost → production efficiency → Net revenues*). Matinga and Annegarn (Matinga and Annegarn 2013) report that some shopkeepers experienced a marginal reduction of operational costs associated to refrigeration, since they found gas more expensive than electricity. Electricity may be cheaper than diesel for running machinery, as evidenced in Mawengi (Tanzania), where electric milling machines significantly reduced the cost of milling the staple maize in comparison to the previous use of diesel-powered machinery (Ahlborg 2015). In Vietnam, milling 1 ton of rice with diesel costs at least four times more than by using electricity (*viz.* US$ 2.6 against US$ 0.6) (Kooijman-van Dijk and Clancy 2010). In the Syangja District in the western region of Nepal, an electric mill could reduce costs by 30-50% with respect to diesel-powered ones (Bastakoti 2003). Sometimes, savings are attributable to a shift from grid power supply to stand-alone or microgrids (Kumar et al. 2009). However, fuel-shifting may sometimes cause higher expenditures for the producer (*Power unreliability* increases *Energy cost*).

As a matter of fact, energy-cost savings are extremely dependent on the quality of electricity supply, since unreliable access to electricity – i.e. frequent black-outs, high voltage fluctuations and frequency instability – may negatively impact productivity and cause huge economic losses (Kooijman-van Dijk 2012) and very low satisfaction with electricity supply (Aklin et al. 2016), as well as the need to pay for back-up energy options like diesel. In rural Indonesia, power supply unreliability reduced the number of activities operated by each household (Gibson and Olivia 2010). Zomers (Zomers 2003) and Meadows et al. (Meadows et al. 2003) report unreliable energy service as one of the main problems that entrepreneurs in rural areas encounter. Unreliable or expensive electricity can, hence, increase the cost of production leading to an increase in price and consequent decrease of market demand and sales. Such drawbacks related to service quality and cost may deter entrepreneurs from gaining access, as in the case of rural Uganda (Neelsen and Peters 2011).

In light of the discussion above, factors and feedbacks that explain how electricity use can either positively boost, or have a little impact on, economic production at the local level can be identified. In order to enhance electricity-related productivity, the literature indicates the need for complementary activities and certain preconditions. First of all, reliable electricity supply is a key factor for enhancing the productivity of small-scale operators and rural enterprises (Meadows et al. 2003; Wolde-Rufael 2005), highlighting the importance of appropriate operation and management activities (*appropriate O&M of power system* can reduce *Power unreliability* and in turn decrease the negative effect of unreliability on *Productivity*). Second, access to favourable credit terms can support the decision of local entrepreneurs to adopt new electrical devices, and therefore increase their production (Bastakoti 2003; Peters et al. 2009; Kooijman-van Dijk and Clancy 2010) (*micro-credits → Electricity demand*). A sustainable increase in production requires an accompanying increase in market demand (Peters et al. 2009), also in the evenings (Kooijman-van Dijk 2012). To facilitate such a development, other infrastructures such as roads and telecommunications need improvements, as these can reduce transactions costs and make rural IGAs "competitive in out-sourcing of business services and products destined for the lucrative urban markets"((Kirubi et al. 2009) p. 1219) (*infrastructures → Market demand → Goods/services sold*). For example, Lenz et al. (Lenz et al. 2017) report that in rural Rwanda, only rural communities located next to a main road and frequented by casual customers from outside experienced a net increase in income through sales of improved services and goods. In this context, capacity building plays an important role in supporting entrepreneurs' social skills and networks to access new markets (*capacity building → Production efficiency*), and technical skills to innovate and sell products (*capacity building → Product innovation*) (Bastakoti 2006; Kooijman-van Dijk 2012).

Given the social, economic and geographical conditions of poor rural areas, the major impact of electricity use on local economies occurs when there is an increase in the net revenues or people's incomes. Improved access to financial capital may result in a positive feedback on local electricity demand, enhancing positive dynamics at a firm-level, where net revenues can be invested in more electrical machinery (*Net-revenues → Average income → Access to financial capital → Electricity demand*) or in extending operating hours and business opportunities (*Net-revenues → Market supply*). A positive feedback can develop also at household-level if more income allows people to increase their expenditures, boosting the market demand for (new) goods and services, which in turn provides households with further opportunities to reduce costs and make money (Kooijman-van Dijk and Clancy 2010) (the reinforcing loop described by *Average income → Market demand → Goods/services sold → Net revenues → Average income*). The financial status of families is a pivotal parameter to consider for modelling their willingness to increase electricity load, especially in terms of appliance ownership. For example, Aklin et al. (Aklin et al. 2015) suggest a positive relation between income and electricity access by deriving econometrically the relation between household's wealth, electrification status (*viz.* if an household has access to electricity or not) and hours of electricity used per day (for Indian households living in slums, urban and rural areas). The nexus between household economy and electricity demand are more thoroughly addressed in the next dedicated sub-section of the paper.

Fig. 27 presents the causal loop diagram for electricity demand and market production and revenues. It visualizes the dynamics above, highlighting the positive and negative feedback among variables, as well as indicating the complementary activities and conditions that may enhance the dynamics (the dashed red lines). The main feedback on growth in electricity demand is an increase of people's income and access to financial capital.

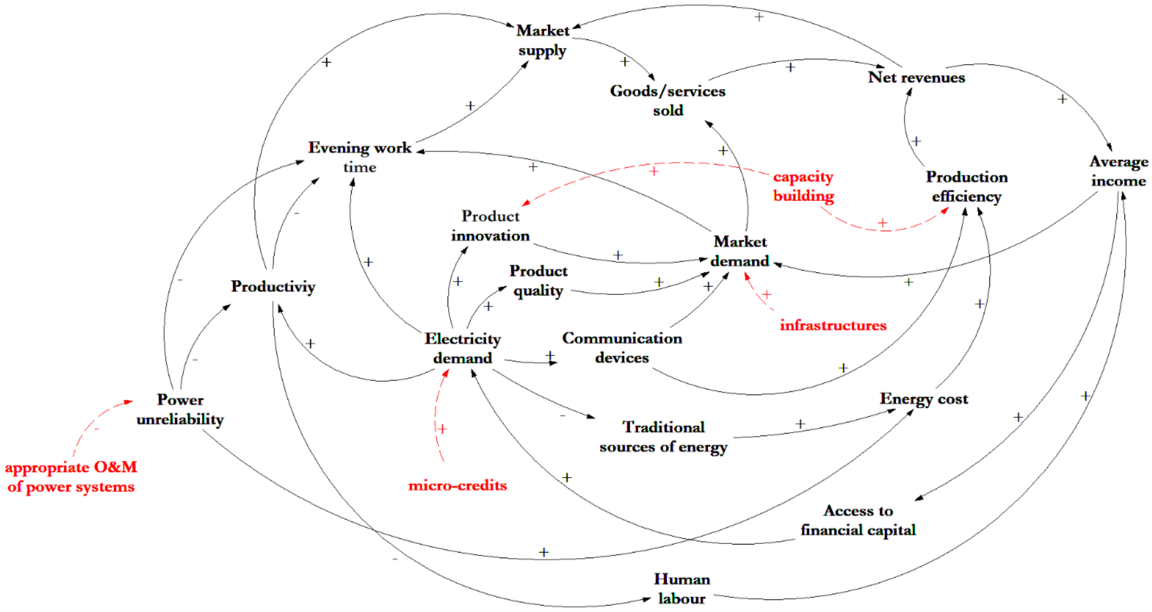


Fig. 27. Causal loop diagram representing the dynamics between electricity demand and local market production [from (Riva et al. 2018a)].

4.2.3. Household economy

In the previous sections, a positive loop was identified between increasing electricity demand, an increase in net IGAs and their sales of goods and services, which in turn can increase market revenues. Since the feedback of net revenues on electricity use involves domestic access to financial capital, this sub-section focuses specifically on the nexus between electricity use and households' economy, which involve different dynamics than that related to business activities alone.

Table 10. Examples of impact of electricity use on household economy.

Reference	**Mentioned impact of electricity use household economy**
Shackleton et al. (Shackleton et al. 2009)	Entrepreneurs who invested in small "productive use containers" powered by solar panels benefited from extra monthly sources of income in South Africa.
Sovacool et al. (Sovacool et al. 2013)	It is described the effect of the distribution of "multifunctional platforms", *i.e.* "small 8-12 horsepower diesel engines mounted on a chassis, to which various components can be attached" (pg. 117), in rural Mali. There, families experienced about 13.6% extra income per year (*viz.* about $68 in additional revenue per year per family, considering that the average household lives on $1.37 per day).
Gibson and Olivia (Gibson and Olivia 2010)	Income shares of non-farm enterprises (NFEs) are higher for rural Indonesian households that are connected to the public electricity network, *viz.* about 3.7% against 2.2%; it is indicated that the quality of power supply has a direct effect on income from productive activities, since the share of rural income from non-farm enterprises is estimated to be 27% higher for households in villages that never suffer blackouts (*Power unreliability* → *Average income*).
Balisacan et al. (Balisacan et al. 2003)	Households' income benefits are mainly experienced by richer families (*Income from IGAs activities* → *Income inequality*): a 10% improvement in access to electricity raised income among the poor by only 2%.
Rao (Rao 2013)	Through a multivariate regression, it is estimated that at the village level, access to at least 16 h of electricity per day might be responsible for 18% higher income for connected Indian NFE than non-connected ones. The study further finds that the expected income for an electrified household is 43% higher based on a propensity score matching model.
Bensch et al. (Bensch et al. 2011)	It is found a positive difference in income between connected and non-connected households in Rwandese electrified villages. It is also confirmed a difference in income also between connected households in electrified villages and households in non-electrified villages that they identity as "likely to connect to an electricity grid". Nevertheless, the robustness and significance of the results disappear when regional differences are accounted for, suggesting caution regarding the finding of a positive effect of electricity on income.
Khandker et al. (Khandker et al. 2013)	In 42 Vietnamese communes, household electrification is responsible for a growth of 21% and 29% in total and non-farm income, respectively. They found also a substantial spill-over benefit to non-connected households (*Electricity demand* → *Spill-over effect* feedback that reduces *Income inequality*).

As a direct effect of the dynamics identified in the previous sections, the increase in market production and employment given by electricity use can boost households' financial capacity by a positive change in financial inflow (Ranganathan and Ramanayya 1998; Cabraal et al. 2005) (*Electricity demand → Net revenues → Income from IGAs activities* in Fig. 28). Table 10 reports some examples from the literature, which suggests that access to electricity benefits the household economy, since electricity-reliant IGAs are more productive than their unconnected counterparts, in the range of 30% to 78% more, depending on the context. However, few studies provide statistically reliable estimates with appropriate intervals of confidence and clear definitions of the baseline used, reducing the reliability of data for modelling purposes.

Electricity use impacts also on households' *financial outflows*, *viz.* expenditures. As discussed in the previous sub-section, this is mainly due to improvements in products' quality and the availability of new products and services, following the modernization of production and other technologies (*Electricity demand → Product quality → Average market expenditures* and *Electricity demand → Product innovation → Average market expenditures*). It attracts more consumers and increase the per capita demand for some products and services (*Average market expenditures → Market demand*). Second, since households' expenditures depend on people's access to financial capital, the potential increase in family income has a direct effect on boosting the demand for goods and services (*Average income → Access to financial capital → Average market expenditures → Market demand*). Indeed, as Kooijman-van Dijk and Clancy (Kooijman-van Dijk and Clancy 2010) state, there must be a willingness to pay for the expected "new" goods and services produced by new IGAs. Khandker et al. (Khandker et al. 2012) indicate that electrification in India increased household per capita food expenditure by 14%, non-food expenditure by 30%, and total expenditure by more than 18%. Zhang and Samad (Samad and Zhang 2016) report lower results, suggesting that gaining access to the grid in India is associated with an 8.4% increase in households' per capita food expenditure, a 14.9% increase in per capita non-food expenditure, and a 12% increase in per capita total expenditure. Again, these positive results are also dependent on the reliability of access to electricity and the quality of power supply (*Power unreliability* decreases *Market demand*). Zhang and Samad indicate that every one-hour increase in power outages may decrease food expenditures by 0.2% on average, which in turn, potentially, reduce farmers' incomes. What these results indicate is that increase in household's access to financial capital can feed back on electricity demand, *i.e.* the increase in families' expenditures can in turn stimulate the modernization and electrification of market production and the use of electric lighting for evening work (*Access to financial capital → Average market expenditures → Market demand → Market supply → Electricity demand*).

Electricity use causes changes in people's expenditures for domestic energy supply. Considering lighting alone, the literature confirms that households experience a reduction in expenditures for energy use, especially for purchasing kerosene (Ulsrud et al. 2015; Grimm et al. 2017) (*Electricity demand* has a negative feedback on *Traditional sources of energy* that cause a reduction on *Energy cost expenditures*). Edwin et al. (Adkins et al. 2010) report that in rural Malawi, after the introduction of LED lanterns, lighting expenditures – all sources excluding the cost of the device – had fallen from $1.06 per week to $0.15 per week after lantern purchase. Similarly, Agoramoorthy and Hsu (Agoramoorthy and Hsu 2009) indicate that after the spread of solar lanterns in Indian Dahod District, each household saved on average $91.55 (±63.06, n=100) in energy costs per year, a huge saving if compared to households' yearly income ranging from $150 to $250. Wijayatunga and Attalage (Wijayatunga and Attalage 2005) report that when the cost for grid expansion is borne by the government, households in Sri Lanka are estimated to pay only $1 per month on average, which represents a relatively high cost saving if compared to the about $5.4 of avoided cost for kerosene usage and battery-charging. Lenz et al. (Lenz et al. 2017) report that households electrified by grid-extension in 42 rural communities in Rwanda experienced a reduction of one-third in their energy expenditures. A reduction of energy expenditures therefore means an increase in people's access to financial capital that can be allocated for more market or food expenditures (*Energy expenditures → Access to financial capital → Average market expenditures*), contributing to a positive feedback on local market production and electricity consumption.

However, the picture changes when the cost of power production technologies and non-lighting appliances are considered, with households experiencing sometimes an increase in energy expenditures after electrification (Davis 1998; Bensch et al. 2011)(Martinot et al. 2002) (*Electricity demand →Energy cost expenditures*). Wijayatunga and Attalage (Wijayatunga and Attalage 2005) report that for households that received a subsidy of about $100 for a solar home system (SHS) in Sri-Lanka, the monthly repayment of the system stood at $8.4 for a period of 5 years, that is, $3 higher than the cost of avoided kerosene usage and battery-charging – *i.e.* a little over 15% of their income was spent on the SHS repayment, whereas the expenditure on kerosene and battery-charging before SHS installation was only around 10% of their income. Komatsu et al. (Komatsu et al. 2011) indicate that households with a SHS spent more in total on energy supply than before, because of the monthly payments for the system, though the reduced costs of kerosene and rechargeable batteries account for 20–30% of the monthly payments. Moreover, kerosene saved by some households can represent a source of income if sold to non-electrified neighbours (Roy 2000). Wamukonya and Davis (Wamukonya and Davis 2001) state that Namibian households experienced a marked increase in energy expenditure after electrification. Indeed, whilst a shift from the use of candles and paraffin to electric lighting may decrease direct energy costs, the adoption and use of other appliances like irons, refrigerators, TVs, *etc.*, can substantially increase the final energy bill. If the increase of energy expenditures is not supported by a proportional increase of income, it can cause a decrease in market expenditures and in turn a decrease in market supply and electricity use.

Income, therefore, plays an important role in defining the capacity of people to increase their electricity use and their willingness to pay for electricity (Kobayakawa and Kandpal 2014; Alam and Bhattacharyya 2017) (*Average income → Access to financial capital → Electricity demand*), especially in its two main constituents:

– **The installed load.** The literature suggests that the willingness of people to be connected, and to buy and own electrical household appliances, depends on their income. In their rural electrification model, Hartvigsson et al. (Hartvigsson et al. 2018b) define the potential number of electrical connections as a function of different socio-economic parameters, including the average income of people. Lenz et al. (Lenz et al. 2017) state that the wealthier or more modern a household is, the more inclined it will be to get a connection. In their Residential Energy Model Global (REGM), Ruijven et al. (van Ruijven et al. 2011) and Daioglou et al. (Daioglou et al. 2012) represent the ownership of household electric appliances, through a logistic (or S-shaped) curve, as a function of household's expenditures (considered in their work as a proxy of income). Louw et al. (Louw et al. 2008) suggest that the use of electricity by low-income South-African households is a cost-based decision based on income, especially regarding the ownership of electrical appliances, which depends on prices of devices and people's affordability. The importance of appliances' costs in relation to people affordability is also pointed out by Prasad (Davidson et al. 2006).

– **The kWh of electricity consumed.** The quantity of electricity consumed is another aspect that might be influenced by people's income. Louw et al. (Louw et al. 2008) conclude that for South African households the demand for electricity shows elasticities[8] ranging from between 0.24 and 0.53, depending on the model. Pachauri and Filippini (Filippini and Pachauri 2004) used disaggregate survey data for about 30,000 Indian households, and conclude that electricity is income inelastic in the winter, monsoon and summer seasons. They estimate that elasticity ranges between 0.60–0.64 across the three seasons. Tiwari (Tiwari 2000) derive similar results by analysing the income elasticity to electricity demand for the city of Bombay, estimating values ranging from 0.28 to 0.40 based on income group. Moharil and Kulkarni (Moharil and Kulkarni 2009) suggest that despite the higher cost of electricity, people living on Sagardeep Island in West Bengal demanded more power for entertainment, comfort and developing job opportunities irrespective of their income level, suggesting very low levels of demand elasticity. Alkon et al. (Alkon et al. 2016) use nationally representative household data from India, 1987–2010, and suggest that household income is not a primary determinant for willingness to pay for high-quality modern energy. Hence, the literature seems to suggest that electricity is income inelastic (*i.e.* the quantity of electricity demanded increase less than proportional to an increase in income), since it is often considered a

[8] "Elasticity is a measure of a variable's sensitivity to a change in another variable. In business and economics, elasticity refers to the degree to which individuals, consumers or producers change their demand or the amount supplied in response to price or income changes. It is predominantly used to assess the change in consumer demand as a result of a change in a good or service's price" (Source: (Investopedia, LLC 2014)).

basic need. However, the relatively high positive values estimated (between 0.24 and 0.64, depending on the context) suggest that an eventual increase in the economic status of people would lead to a rise in electricity consumption of households, although less than proportionally.

To enhance a positive feedback of household economy on electricity demand, the literature suggests some complementary activities to increase households' willingness to buy and use electricity. Among the recommendations, scholars suggest that electrification projects must be accompanied by sustainable "cost of connection" policies, such as international "smart" subsidies or cost-sharing mechanisms (Sovacool et al. 2013) for covering initial investments (Zomers 2003; Baldwin et al. 2015) (*cost of connection polices* → *Access to financial capital*). The importance of appropriate tariffs built into sustainable payment plans – like the pre-paid mechanism (Moharil and Kulkarni 2009) that allow people to pay up front, sometimes via their mobile phones, which reduces travel costs (Gustavsson 2004) – is also highlighted in the literature. Such plans can favour the poor (Bhattacharyya 2006, 2013). In this context, energy needs of rural communities should be considered top of the agenda of national energy policy making processes (Habtetsion and Tsighe 2002), *e.g.* through a proper regulation on energy pricing, taxes, laws and product standards on energy (Biswas et al. 2001). Further, the literature advise actors to create awareness among beneficiaries (*awareness activities* → *Electricity demand*), by first, creating demand for the "service" provided by energy technologies, rather than for the technology itself (Mulugetta et al. 2000), and second, involving the local community and consumers, especially women (Sovacool et al. 2013), in managing and operating energy systems (Sebitosi and Pillay 2005; Adkins et al. 2010; Sovacool et al. 2013; Terrapon-Pfaff et al. 2014). Complementary activities, thus, involve: (a) customer educational programmes (Sovacool et al. 2013); (b) the introduction and integration of some energy end-use services (e.g. lighting, pumping) into daily routines and practices (Somashekhar et al. 2000); (c) the implementation of demonstration initiatives designed to create knowledge regarding electricity use (Wamukonya and Davis 2001) and to boost demand for energy technologies (Baldwin et al. 2015), and; (d) the support for the widespread ownership of mobile telephones and accessibility of TVs sets (Matinga and Annegarn 2013) (represented through the positive *socio-economic grants* → *Access to financial capital* → *Electricity demand* feedback). Lastly, improving capacity building and access to information (know-how) on mechanical and technical matters at the household level – e.g. the basic understanding of the capacity of the system (Gustavsson and Ellegård 2004) – (*capacity building* → *Electricity demand*) as well as organizing reliable and competent customer service (Alazraki and Haselip 2007) and ensuring an appropriate O&M of the system (*appropriate O&M of power systems* → *Power unreliability*) are considered important drivers for growth of electricity demand.

Fig. 28 describes these relations between electricity demand and households' access to finance, expressed through its two main determinants, *viz.* income and expenditures.

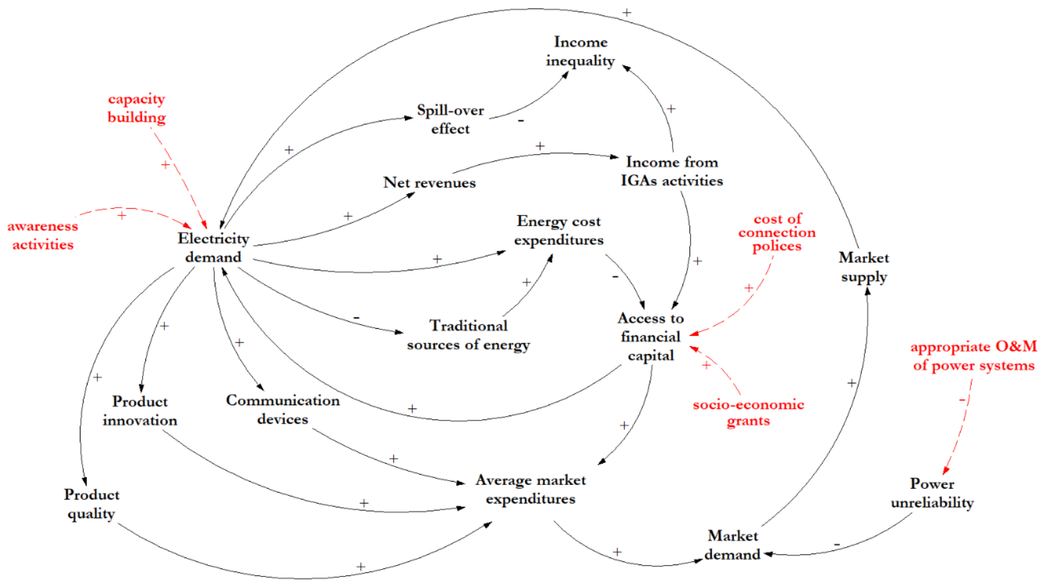


Fig. 28. Causal loop diagram representing the dynamics between electricity demand and household's economic availability [from (Riva et al. 2018a)].

4.3. Social dimension

In this section, the complex causalities between electricity demand and social dimensions of local development are discussed on three main aspects: (i) the dynamics of *local population* and *health*, (ii) *education*, and (iii) *habits, living standards and social networks*.

4.3.1. Local health and population

The literature suggests that increasing electricity access and use is beneficial to people's health (Wolde-Rufael 2005; Mulder and Tembe 2008; Sovacool et al. 2013) and can impact on local population dynamics. These dynamics are discussed by investigating the health dimension at the household, work and hospital level, and also by analysing the impact of electricity on local population growth and related feedbacks.

At a *household* level, access to electricity is reported to be an important driver for improved health of household members. For example, Wamukonya and Davis (Wamukonya and Davis 2001) indicate that respectively 49% and 35% of surveyed grid-electrified and solar-electrified rural Namibian households reported an improvement in health since getting electricity. The diffusion of electrical appliances can contribute to improving people's health status through:

- the use of electric refrigerators, which bring benefits by preserving food and drinks from external contamination and sustaining the qualities of food longer (Kirubi et al. 2009) (*Electricity demand → Food-preservation devices → People's health* in Fig. 29;
- electric lighting that can reduce household air pollution and associated lung disease and eye problems, as well as and burns and poisonings caused by the use of kerosene (Alazraki and Haselip 2007; Gurung et al. 2011; Brass et al. 2012; Aklin et al. 2015; Grimm et al. 2017) (*Electricity demand → Traditional sources of energy → People's health*);
- access to clean and safe groundwater, which can help reduce health diseases (e.g. typhoid, diarrhoea, parasitic infections (World Health Organization 2003)) associated with contaminated sources of water (*e.g.* surface water) (Somashekhar et al. 2000; Cabraal et al. 2005; Bastakoti 2006; Sovacool et al. 2013) (*Electricity demand → Water pumping devices → People's health*).

Secondly, as a consequence of more income and free time following electricity use, people are reported to care more for their health (Sovacool et al. 2013) (*Electricity demand → Free-time → People's health*). Indirectly linked to electricity, complementary activities that support the realization of sanitary facilities reduce the risk of infective and bacterial disease (Gurung et al. 2011) (*sanitary facilities → People's health*).

At *work* level, Bastakoti (Bastakoti 2006) reports that electrification of energy intensive IGAs led to a cleaner and more healthy operating environment in rural Nepalese villages, especially by reducing the health effects caused by the operation of diesel generators, including polluting fumes and irritation caused by grease and fuel on the body (*Electricity demand → Work security → People's health*). Similarly, Kooijman-van Dijk and Clancy (Kooijman-van Dijk and Clancy 2010) indicate that the use of electric machines are characterized by lower noise levels, dust and smoke and contributed to guaranteeing a healthier and less stressful working environment in rural Bolivia, Tanzania and Vietnam.

At *hospital* level – *viz.* local dispensaries, health centres and hospitals – access to electricity is reported to considerably improve the quality and quantity of medical services offered to local people (*Electricity demand → Health centres electric devices → Medical services → Quality of medical service*). Firstly, refrigeration facilities allow for storing medications, vaccines and blood (Habtetsion and Tsighe 2002; Cabraal et al. 2005; Brass et al. 2012; Aglina et al. 2016; Lenz et al. 2017), and modern machines are used in a variety of medical examinations and treatments, such as laboratory examinations, X-ray analyses (Bastakoti 2006) and surgical machines (Brass et al. 2012). Moreover, when on-grid or off-grid electricity-access replaces or reduce the use of diesel, kerosene and LPG for running appliances and machineries, hospitals might experience high energy cost savings (Lenz et al. 2017). In this context, the literature specifies that the diffusion and installation of new electric equipment is highly dependent on the possibility of local health centres to afford them (Peters et al. 2009) (*Hospital financial liquidity → Electricity demand*) and the reliability of power supply (Brass et al. 2012) (*Power unreliability → Electricity demand*), suggesting the importance of giving *financial support* to local hospitals and guaranteeing an *appropriate O&M of power systems*. Secondly, electric lighting can highly contribute to improving medical services by extending operating hours at night (Gustavsson 2007b; Moharil and Kulkarni 2009; Aglina et al. 2016) and increasing security during surgeries and childbirths (Cabraal et al. 2005) (*Electric demand → Health centres electric devices → Safety → Quality of medical service*). Thirdly, improved communication increases the possibility for health centres to provide people with more information about health-care, prevention of diseases, and to retrieve clients information (Cabraal et al. 2005; Aglina et al. 2016) (*Electricity demand → Health centres electric devices → Health-care related knowledge → People's health*), as well as attract more qualified and trained staff (Cabraal et al. 2005; Lenz et al. 2017).

The improvements of people's health status and medical services can result in a positive feedback on electricity use. An improved health status reduces the need to frequently spend time being sick and money for health service, therefore it preserves households' financial capacity and allows for free-time to dedicate to other activities (*People's health → Free-time* and *People's health → Health-care related expenditures*), but at the same time it reduces the *People turnout at local health centres*. On the other hand, the potential improvement of local medical services can positively impact on households' access to financial capital and time as well, as in rural Nepal (Bastakoti 2006) where people experienced lower cost and need to travel to cities nearby for health care (*Quality of medical service → People turnout at local health centres* that reduces *Long travels for medical treatment* and then increase *Free-time;* and *Quality of medical service → People turnout at local health centres* that reduces *Long travels for medical treatment* and *Health-care related expenditures*). This in turn can benefit local hospitals that experience a higher patient turnover and larger financial inflows (that can be invested in new machines and installed electric load) (*People turnout at local health centres → Hospital revenues → Hospital financial liquidity → Electricity demand*). As explained in sub-sections 4.2.1 and 4.2.3, an increase in people's access to financial capital given by reduced costs for health care can have a positive feedback on electricity demand (a reduction in *Health-care related expenditures* supports the positive *Access to financial capital → Electricity demand* feedback), while more time being healthy can increase the time spent on economically productive activities, sometimes the creation of new IGAs, and subsequently an increase in electricity demand (*People's health → Free-time → Electricity demand*).

The literature suggests that improvements in local health-care can have a direct positive impact on some dynamics that influence levels of population growth. Cabraal et al. (Cabraal et al. 2005) refer to a study carried out in rural Bangladesh in 2003, which reports an infant mortality rate of 4.27% in electrified households, compared to 5.38% and 5.78% in non-electrified households in electrified villages and non-electrified villages respectively. Brass et al. (Brass et al. 2012) suggest that improved medical centres can reduce maternal mortality rates (*Safety → Mortality rate → Local population*). Apart from having a positive impact on the health of mothers and children, electricity can positively impact on population growth locally by changing the in- and out-migration to areas (*Rural-to-urban migration rate → Local population*): Neelsen and Peters (Neelsen and Peters 2011) point out that electrification contributed to the expansion of a southern Ugandan village, which in turn boosted market demand and profits for local IGAs (*Local population → Market demand*). Similarly, others (Kanagawa and Nakata 2008; Gurung et al. 2011) report a business in-migration of people who moved in to electrified villages – in Nepal and India respectively – in order to achieve higher levels of income, while Jacobson (Jacobson 2007) suggests a long-term reduction in rural-to-urban migration when rural electrification is followed by local economic growth and positive effects on education. Dinkelman (Dinkelman 2011) suggests that rural electrification in South Africa impacted rural labour markets by reducing the outflow of individuals from rural areas. On the other hand, improvements in socio-economic conditions attributable to electrification might reduce household size, as Ranganathan and Ramanayya report for electrified households in rural Uttar Pradesh (Ranganathan and Ramanayya 1998), by reducing the fertility-rate (*Electricity demand → Access to financial capital → Fertility rate → Local population*).

As a direct feedback on electricity consumption, an increase in local population is followed by an increase in the number of electricity connections and total electricity demand (*Local population → Electricity connections → Electricity demand*). Secondly, it can cause a potential increase in local market demand with a positive impact on creation of IGAs and business productivity, which in turn generate a growth in electricity demand (see sub-section 4.2.2) (*Local population → Market demand → Access to financial capital → Electricity demand*).

Fig. 29 shows these nexus causalities between electricity demand and local health and population.

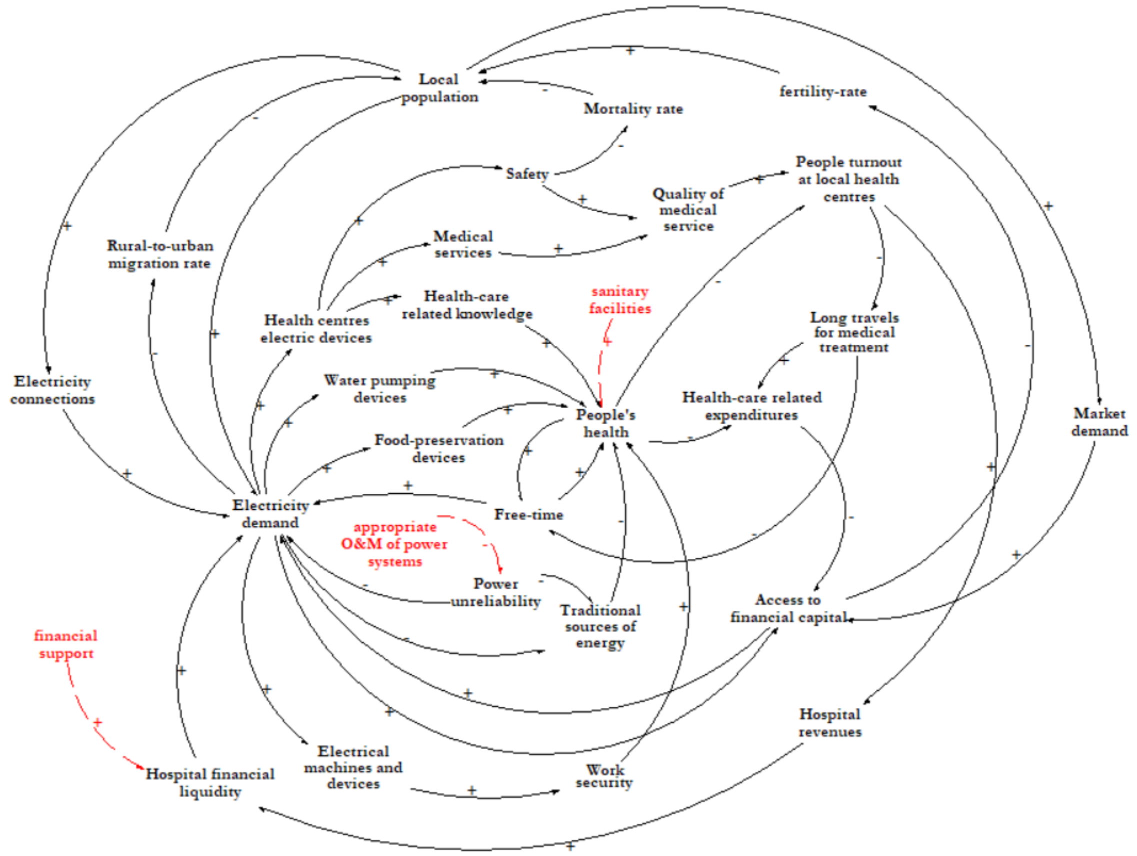


Fig. 29. Causal loop diagram representing the dynamics between electricity demand and local health and population [from (Riva et al. 2018a)].

4.3.2. Education

The impact of access to electricity on education is a widely-discussed topic in the literature. From a general point of view, the use of electricity seems to be associated with improved educational standards of people (Alam et al. 1998), also in poor countries (Wolde-Rufael 2005), as reported in Table 11.

At *school*, the use of electric lighting might benefit students by extending study hours (Aglina et al. 2016) (*Electricity demand* → *Study time at school* in Fig. 30) and by allowing evening (Gustavsson 2007a) or early morning classes (Alazraki and Haselip 2007) (*Electricity demand* → *Evening and morning classes*). Peters et al. (Peters et al. 2009) find that in rural Benin, electric lighting and the provision of evening classes allow students to work on family business and do housework during the day, contributing to the household economy (*Evening and morning classes* → *Daily-time for work* → *Average income*). Electricity availability allows the use of new devices like computers (Bastakoti 2006; Alazraki and Haselip 2007), audio-tapes (Bastakoti 2006), TVs and radios (Alazraki and Haselip 2007; Brass et al. 2012) for educational purposes, and fans for creating a more comfortable environment for all students, finally enhancing the teaching and learning quality (Alazraki and Haselip 2007), as well as the recruitment and hiring of teachers (Aglina et al. 2016) (*Electricity demand* → *Quality of education* and *Electricity demand* → *Teacher attraction* → *Quality of education*). In this context, the availability of funds for schools is pivotal for improving equipment and installed load, as confirmed by Bastakoti (Bastakoti 2006), who reported the diffusion of modern devices especially in private schools. In this regard, electricity might support schools in generating new income to allocate to educational improvements. In Zimbabwe, a rural school started a milling service and generated new income (Mapako and Prasad 2007) – it generates the reinforcing *Electricity demand* → *school IGAs* → *school financial availability* → *Electricity demand* loop. To summarize, these effects contribute to increasing children and adults' *school enrolment*, attendance of classes and grades achievements (Dinkelman 2011; Gurung et al. 2011; Sovacool et al. 2013), i.e. *Education attainments*.

Table 11. Examples of impact of electricity use on education.

Reference	Mentioned impact of electricity use on education
Nakata and Kanagawa (Kanagawa and Nakata 2008)	In rural areas of Assam, India, data indicate that a 1-point increase in the percentage of households electrified result in 0.17-point improvement in the percentage of literate people older than 6 years. Also, it is suggested that domestic electricity consumption per capita has a positive correlation with educational attainment, indicating that those households with very low initial levels of electricity consumption can achieve high educational benefits from increasing their consumption of electricity. Further, the literacy rate of Assam state is estimated to rise from 63.3% to 74.4% if all the rural areas were to be electrified, other factors being equal.
Aglina et al. (Aglina et al. 2016)	An increase in electricity access is correlated with an improved literacy rate in the Economic Community of West African States (ECOWAS), though countries with low national electrification rates, such as Cote d' Ivoire and Mali, have better literacy rates than Ghana that scores higher in both urban and rural electrification rate, indicating the influence of other factors.
Ranganathan and Ramanayya (Ranganathan and Ramanayya 1998)	The increase in literacy rate that occurred in Uttar Pradesh and Madhya Pradesh during the period 1991-1997 is, respectively, nearly half and two-thirds attributable to electrification.
Grogan and Sadanand (Grogan and Sadanand 2013)	Rural Nicaraguan men and women are more than twice as likely to have completed primary education if they live in households with access to electricity.
Sovacool et al. (Sovacool et al. 2013)	The communities that embraced the Multifunctional Platform (MFP) energy program[9] in Mali revealed lower drop-out rates, higher test scores, and higher proportions of girls entering school. A possible reason might be the time freed-up by electricity use (see sub-Section 4.2.1) (Mulder and Tembe 2008), which contributes to decreased irregular attendance (Aglina et al. 2016) and improved marks at school (Gustavsson 2007a).
Dinkelman (Dinkelman 2011)	Electrified rural areas in South Africa have higher fractions of adults with a high school-degree, compared to non-electrified communities
Gurung et al. (Gurung et al. 2011)	Increase in informal education among women in the electrified Tangting village, Nepal
Khandker et al. (Khandker et al. 2013)	An econometric model applied to 42 Vietnamese communes indicates that household electricity connection is correlated with a 9% higher school-enrolment rates for girls and 6.3% for boys.

Since electricity use has been found to enhance socio-economic status of rural households, there is also an indirect effect of electrification on school enrolment. Smits and Huisman's work (Huisman and Smits 2009) demonstrate, through a multilevel logistic regression analysis applied to 30 developing countries, that an increase in the level of household's wealth, parents' occupation (especially the father), and education has a positive impact on primary school enrolment of children (*Electricity demand → Average income → Education attainments*). Similarly, Al-Zboun and Neacşu (Al-zboun and Neacşu 2015) interviewed more than 2000 principals and directors of public schools in Jordan, and found that a lack of opportunities, low economic level of households, low quality of educational infrastructures, and low cultural level of parents were pivotal factors affecting the non-enrolment of children in primary schools. This suggests that complementary activities to support community awareness of educational benefits might enhance enrolment (*educational benefits awareness campaigns → School enrolment*). A result that contradicts these findings, is from Lenz et al. (Lenz et al. 2017) who indicate, based on both econometric models and qualitative interviews with teachers, that the probability of rural Rwandan households sending their children to school does not increase as an effect of grid-electrification.

At *home*, many studies mention the increase in evening study hours as the main benefit of electricity on education (Baldwin 1987; Somashekhar et al. 2000; Wamukonya and Davis 2001; Wijayatunga and Attalage 2005; Alazraki and Haselip 2007; Moharil and Kulkarni 2009; Kumar et al. 2009; Gurung et al. 2011; Aklin et al. 2015; Baldwin et al. 2015; Aglina et al. 2016; Mishra and Behera 2016; Grimm et al. 2017; Lenz et al. 2017) (*Evening study time → Education attainments*). Since electricity allows replacing or decreasing fuels use (e.g. kerosene, paraffin, candles) and the related environmental and economic

[9] "a government managed, multilaterally sponsored energy program that distributed a small diesel engine attached to a variety of end-use equipment" ((Sovacool et al. 2013) pg. 115).

drawbacks (Cabraal et al. 2005), Gustavsson and Ellegård (Gustavsson and Ellegård 2004) report that children study at night in 89% of households with a solar home system, compared to 42% of non-electrified households, where children complain about smearing eyes, lack of candles or paraffin and too weak light (*Electricity demand → Electrical lighting* decreases *Traditional sources of energy's drawbacks* and then increases *Evening study time*. Gurung et al. (Gurung et al. 2011) indicate an increase of reading hours for students after electrification of Tangting village, Nepal, due to a reduction in the use of hazardous traditional lamps. Komatsu et al. (Komatsu et al. 2011) report that the introduction of SHS in Comilla, Kishoreganj, and Manikganj districts in rural Bangladesh allowed children to study in a better environment and to extend their study-time from 8–9 pm until 10–11 pm. Similarly positive results for solar PV based lighting were seen in Ludanzi, Zambia (Gustavsson 2007b) and Gujarat State, India (Agoramoorthy and Hsu 2009).

A part of the literature reports limited or very little positive impact of electricity use on educational attainment. Jacobson (Jacobson 2007) indicates that despite nearly 80% of rural Kenyan households surveyed by the author having school age children, solar lighting was used for studying in only 47% of these homes. Gustavsson (Gustavsson 2007a) reports no evidence of actual improvements of school children's marks as a consequence of access to solar services in the surveyed Eastern Province of Zambia (Gustavsson 2007a). Bastakoti (Bastakoti 2006) and Komatsu (Komatsu et al. 2011) find that in rural western Nepal and Bangladesh respectively, children reported an overindulgence in watching TV that limited their willingness to complete their homework in time (*Electricity demand → Entertainment devices → Evening study time*). In this context, the availability and quality of power supply are two crucial factors (*Power unreliability → Evening study time*). In analysing the social changes in Kenya achieved with solar electrification, Jacobson (Jacobson 2007) suggests that children in households with a larger PV system are much more likely to have access to electric light for studying than children in households with smaller systems. Gustavsson and Ellegård (Gustavsson and Ellegård 2004) also report that children complained about black-outs and restrictions in the use of the power as crucial limiting factors for evening study.

Improving educational attainment can generate positive feedbacks on electricity demand in the long term. Louw et al. (Louw et al. 2008) suggest that education is one of the factors that drives households' fuel choices, as well as the "subsequent energy portfolio used" (p. 2813). Urpelainen and Yoon (Urpelainen and Yoon 2015) conducted a survey among 760 respondents in rural Uttar Pradesh, India, and found that high levels of education increased the willingness to pay for a SHS. Aklin et al. (Aklin et al. 2015) derive econometrically the relation between household's educational level (*viz.* average years of education) and both electrification status (*viz.* if a household has access to electricity or not) and daily hours of electricity for Indian households living in slums, urban and rural areas. They find that more educated households have more need for electric assets and may be more willing to pay for a connection (*Education attainments → Connection rate → Electricity demand*). Similarly, Bensch et al. (Bensch et al. 2011) estimate a probit-regression model to determine that the variable "years of education of household head" is positively correlated at 1% significance level with connection status in Rwanda. On the contrary, Kandpal and Kobayakawa (Kobayakawa and Kandpal 2014) find that in Kaylapara village, Sagar Island of West Bengal (India), the mean class completed by the family head does not show significant difference between households with and without connection to the micro-grid. Rao and Ummel (Rao and Ummel 2017) evaluate the marginal change in the probability to own a refrigerator, a washing machine and a TV in India, South Africa and Brazil in relation to head-of-household's years of schooling, suggesting that more educated households are more willing to adopt new technologies (*Education attainments → Willingness to adopt → Electricity to adopt*). Cabraal et al. (Cabraal et al. 2005) report empirical evidence from rural India and Peru, where the combined provision of electricity and education has been found to generate a greater effect on households' income than each variable taken separately. As a matter of fact, Kirubi et al. (Kirubi et al. 2009) report the experience of Mpeketoni Polytechnic educational institution in Kenya, which after connection to the grid became an important source of technical know-how and skills for youths who then found employment in local IGAs, generating a time-delayed feedback between *Educational attainment* and *Average income* (marked with two dashes in Fig. 30). Khandker et al. (Khandker et al. 2013) suggest that higher educational benefits achieved by rural Vietnamese children as an effect of electrification might have resulted in higher and more productive employment levels. In his econometric study, Rao (Rao 2013) found that the years of education of household' head is a positive determinant of income for Indian NFEs. Since households' income and financial availability have been found to be pivotal drivers of electricity use, all these studies confirm that improving peoples' educational attainments can positively impact future electricity consumption (*Education attainments → Average income → Electricity demand*).

Fig. 30 reports the diagram of nexus causalities between electricity demand and educational attainment. The mark on the causal link, which connects *educational attainment* and *average income*, indicates a time-delay in the occurrence of the represented feedback as evident from the literature. It is also highlighted the importance of combining electrification activities with awareness campaigns regarding the benefits of education, programmes of financial support to local schools (*financial support → school financial availability*), and correct O&M of the power systems (*appropriate O&M of power system → Power unreliability*).

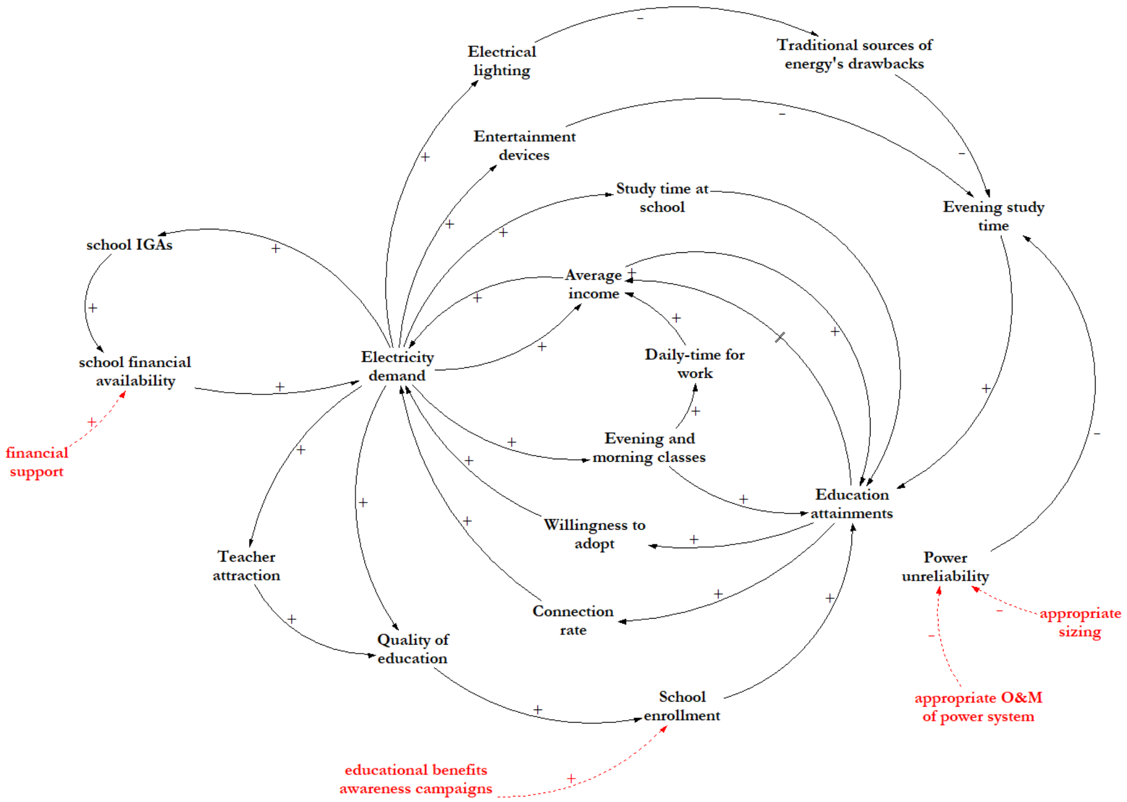


Fig. 30. Causal loop diagram representing the dynamics between electricity demand and education [from (Riva et al. 2018a)].

4.3.3. Habits and social networks

In terms of changes in people's daily habits and activity scheduling, the availability of electrical lighting can contribute to extending the length of people's active day (*Electricity demand → Electrical lighting → Daily-time extension* in Fig. 31). Matinga and Annegarn (Matinga and Annegarn 2013) report that the provision of access to electricity in Tsilitwa village, South Africa, allowed household members to wake up earlier, about half-hour before sun-rise, and go to bed about 2-3 hours later. Similarly, Roy (Roy 2000) indicates that the lighting hours in households provided with solar lanterns in a rural Indian village went up from 2 hours to 4 on average (and up to 6 hours in some cases). Lenz et al. (Lenz et al. 2017) state that in rural Rwanda, "the availability of electricity in the communities clearly had a significant effect on the daily routine of all household members" (p. 99), since it extended the day by 50 minutes on average. On the contrary, Grimm et al. (Grimm et al. 2017) did not find statistically significant changes in the time spent on daily and evening domestic labour between electrified and non-electrified rural households in Rwanda. In addition to this daily time extension, the literature reports that access to electricity can facilitate household activities by decreasing the burden of work and time. Kumar (Kumar et al. 2009) reports that in 5 centres in Sagar Dweep Island in India, 38% of households stated a benefit from time savings for cooking (*Electricity demand → Efficiency (completion rate) of housework → Daily burden of housework*), while 17% indicated having more time for household work at night (*Evening housework → Daily burden of housework*). More time available for women's household work at night has been reported also by others (Agoramoorthy and Hsu 2009; Moharil and Kulkarni 2009). Obviously, the diffusion of TVs and entertainment devices might reduce time dedicated to housework (*Electricity demand → Entertainment devices → Evening housework*). Bastakoti (Bastakoti 2006) indicates that the use of electric water pumps in rural Nepal allowed people to reduce time for collecting water from 7-8 hours per day initially to 1/2 hour per family, increasing available time for farming and leisure activities. Also Grogan and Sadanand (Grogan and Sadanand 2013) report a decrease in time for fetching water (and firewood) in Nicaragua. Komatsu et al. (Komatsu et al. 2011) report that households owning a SHS in rural Bangladesh spend less time for recharging car batteries at recharge stations, experiencing less burdens (*viz.* heavy weights to carry), and more free time (saving at least 40 minutes for the round trip on average plus the recharging time for batteries).

According to Grogan and Sadanand (Grogan and Sadanand 2013) in Nicaragua, "electrification, particularly for poor people, may be more about the extension of the working day than about labour-saving appliances" (p. 253). In this context, time freed-up by electricity can be devoted to productive activities and it has been found to have a positive effect on people's propensity to start a new IGA, with a consequent feedback on electricity demand (sub-section 4.2.1 and 4.2.2) (*Daily burden of housework → Free-time → Average income → Electricity demand*). Grogan and Sadanand (Grogan and Sadanand 2013) suggest that the daily time spent by rural Nicaraguan women living in electrified households in salaried work can be three times as much as the time spent by women living in unelectrified households. Similarly, they report that men living in households with access to electricity decreased by half their time spent in family agriculture and doubled the time spent in non-agricultural activities. On the contrary, Lenz et al. (Lenz et al. 2017) do not observe a change in income generation patterns as an effect of free-time in electrified Rwandan households. More available free-time seems to increase time dedicated to reading and cultural activities (Gustavsson 2004; Bastakoti 2006; Gurung et al. 2011), which may potentially benefit people's educational attainments and all the consequent feedbacks that has on electricity use (*Free-time → Education attainments → Electricity demand*). However, Sovacool et al. (Sovacool et al. 2013) highlight that people are sometimes unable to capitalize on the free time created, suggesting the need to implement parallel educational activities and capacity building (*educational awareness activities → Education attainments* and *capacity building → Average income*).

The evolution of electricity demand can impact the social structure and network of electrified communities (Baldwin et al. 2015). In Tsilitwa village, South Africa, Matinga and Annegam report that differences in household electrical appliances intensified the feelings of exclusion and inequality, highlighting that "electrical appliances displayed in houses of the better-off represent a world from which they [poorest families] felt excluded" ((Matinga and Annegarn 2013), pg. 295), pushing people into changes in aspirations and spending (*Electricity demand → People aspirations → Average market expenditures*). However, this reinforcing feedback is sometimes hindered by the local social habits, traditions, gender relations and culture that can negatively influence people's aspirations and investment decisions, such as people in Zanzibar having food preferences for traditionally prepared food over use of electric cookstoves, or male control over money and technology, limiting women's abilities to purchase household equipment (Winther 2008). Rahman and Ahmad (Rahman and Ahmad 2013) observe that the diffusion of SHS in rural Bangladesh brought mostly recreational and leisure benefits. Bastakoti (Bastakoti 2006) indicates that the possession of a television is considered a luxury and status symbol in rural South Africa. On the other hand, the same author suggests that families without cable frequently go to their richer neighbours' homes to watch TV, increasing households' meetings and time together (*Electricity demand → Entertainment devices → Social connectivity*). Komatsu (Komatsu et al. 2011) and Lenz et al. (Lenz et al. 2017) report the same dynamics also for rural Bangladeshi and Rwandan households respectively. Similarly, Gustavsson and Ellegård (Gustavsson and Ellegård 2004) report that children living in villages located in the district of Nyimba, Zambia, gathered together in one of the houses with a SHS to study. Lighting and the related perceived improved security, as well as evening market operation, seem to increase outdoor and/or indoor evening meetings and chats, and connectivity among people (Gustavsson 2004; Alazraki and Haselip 2007; Shackleton et al. 2009; Kooijman-van Dijk and Clancy 2010; Matinga and Annegarn 2013) (*Electricity demand → Electrical lighting → Social connectivity*). Even within the same household, Wijayatunga et al. (Wijayatunga and Attalage 2005) report that 68% of surveyed households in Badulla district, Sri

Lanka, claimed to benefit from having more time together through activities such as watching television while having dinner.

Electrification allowed enhanced access to information (Kooijman-van Dijk and Clancy 2010), communication and connectivity even outside local communities (Baldwin et al. 2015) (*Electricity demand → Communication devices*). Jacobson (Jacobson 2007) report that rural electrification in Kenya facilitated rural–urban communication through the diffusion of television, radio, and cellular telephone charging, increasing rural–urban connectivity, especially for the rural elite and middle class. Similarly, Rwandan households interviewed by Lenz et al. (Lenz et al. 2017) indicated that mobile phones are especially used for calling people who live outside the province. Gustavsson (Gustavsson 2007a) suggests that children and adults in rural Zambia experienced more access to news and events taking place outside the rural community through radio and TV broadcasts.

In accordance to the theory of innovation diffusion (Bass 1969; Peres et al. 2010), enhancing connectivity and social networks increase the process of word of mouth, acceptability of new products, and related probability to become an adopter, enhancing the diffusion of electrical products and its feedback on the evolution of electricity demand (*Social connectivity → Word of mouth (social connectivity) → Electricity demand*). In this context, local government officials or heads of the villages can play the role of "influentials" (Van den Bulte and Joshi 2007; Goldenberg et al. 2009; Urmee and Anisuzzaman 2016) in bringing electricity to their communities and enhancing the diffusion of electrical devices (Kooijman-van Dijk and Clancy 2010). Since the use of television and radio might facilitate the ability of business advertisers to reach a wider audience (Jacobson 2007) and increase local demand for goods and services, local shops and retailers can experience higher trades and revenues, with related feedbacks on electricity use, as discussed in sub-section 4.2.1 and 4.2.2 (*Communication devices → Advertisement → Market demand → Electricity demand*).

Fig. 31 reports the diagram of nexus causalities between electricity demand, habits and social networks.

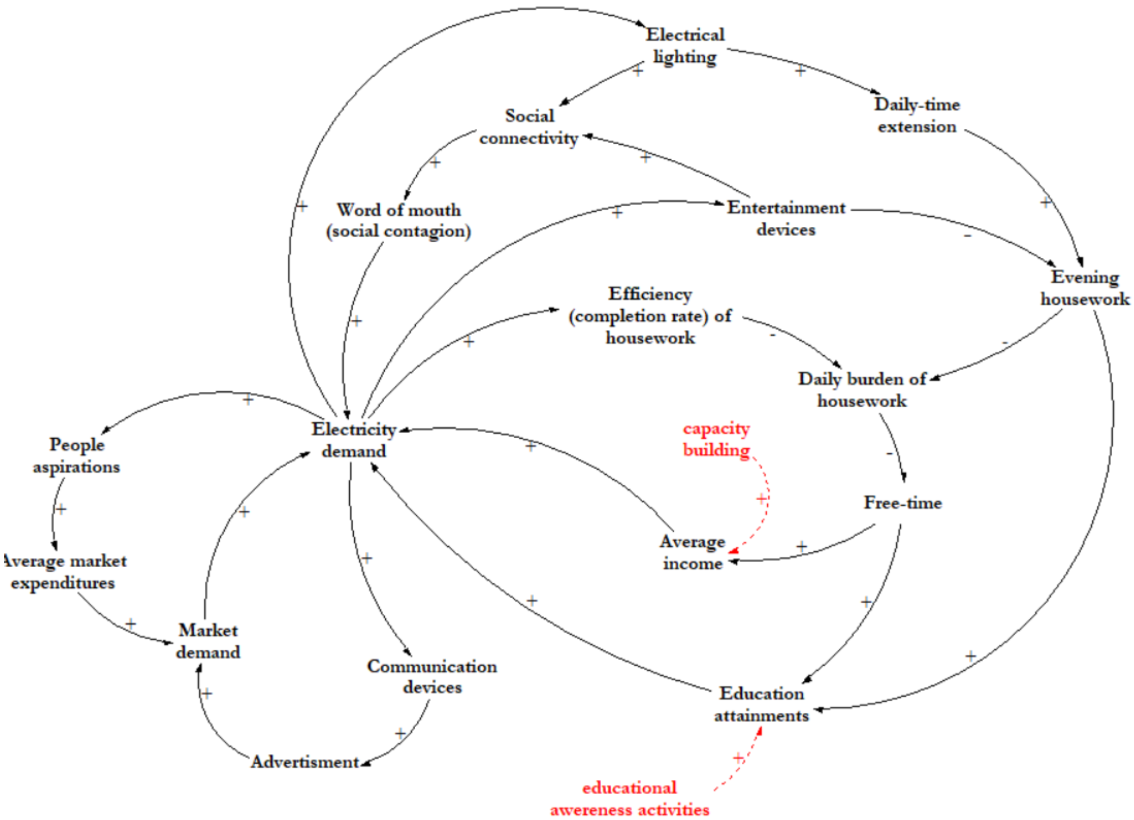


Fig. 31. Causal loop diagram representing the dynamics between electricity demand, habits, and social networks [from (Riva et al. 2018a)].

Chapter 5

Modelling insights for dealing with complexities

Give me a place to stand on, and I will move the Earth
(δῶς μοι πᾶ στῶ καὶ τὰν γᾶν κινάσω)
(Archimedes of Syracuse c. 287 – c. 212 BC)

All models are wrong
(George Box 1976)

This chapter sets the basis for building upon the modelling of the endogenous complexities behind the electricity-development nexus from a quantitative point of view, which is the last result for pursuing Objective 1. To this aim, the interconnections of multiple factors, the high uncertainty level, strong non-linear phenomena, and the presence of time delays and feedbacks suggest System Dynamics (SD) as a potential appropriate systems-modelling approach. On the other hand, the agent-based complexities behind diffusion mechanisms, energy consumers' behaviour, social interactions, spatial constraints, and decision-making processes suggest Agent-based Modelling (ABM) as a further modelling tool. In order to compare the two methods and guide the final choice towards the most appropriate approach, an ad-hoc case-study is developed. This chapter is based on the following conference paper:

Riva F, Colombo E, Piccardi C. Modelling social networks in innovation diffusion processes: the case of electricity access in rural areas. Proc. *35th Int. Conf. Syst. Dyn. Soc.*, Cambridge, USA: System Dynamics Society; 2017.

5.1. Modelling endogenous complexities

5.1.1. From qualitative conceptualisation…

The previous analysis on the electricity-development nexus confirms that it is a complex system. As such, the behaviour/outcome of the nexus cannot be intuitively understood (Forrester 1971). In order to improve understanding of complex systems, a number of computer aided modelling methods have been developed over the last decades, e.g. agent-based modelling and system dynamics. With the usage of these tools and methods, complex problems can be analysed and tested in computer environments in order to improve understanding of the studied systems.

Through the use of causal diagrams, the analysis presented a conceptualization of factors and processes found in the energy-development nexus (see Fig. 26 to Fig. 31). Causal diagrams are similar to the causal loop diagrams used in system dynamics (SD) modelling methods. SD is a systems-modelling approach first developed by Prof. J.W. Forrester, Massachusetts Institute of Technology (MIT), in 1950s and formalised in his famous book entitled *Industrial Dynamics* (Forrester 1961). It is used for understanding, describing, tackling and modelling well-defined endogenous problems concerning existing systems that are suitable to be formulated as interaction between elements through causal relationships. In SD, causal loop diagrams are commonly used for formulating a problem through a dynamic hypothesis, for communicating a model (Morecroft 1982), and for making qualitative analysis of complex systems (Wolstenholme and Coyle 1984). Even though conceptual models are often used as intermediate steps towards simulation models (Robinson 2008), important insights can be drawn from qualitatively analysing conceptual models (Wolstenholme and Coyle 1984). A few of the factors in the energy-development nexus were identified to be exogenous, but the main part of the diagram depicts the relationship of the factors through closed causal loops. The causal loop diagrams show how factors identified in the energy-development nexus literature are interconnected, thereby improving our understanding of the energy-development nexus. This results in two main insights:

i. As factors are largely interconnected, it is not suitable to use reductionist methods to analyse the energy-development nexus: e.g. the relationship cannot be sufficiently studied using only a limited set of factors without having knowledge of the full contextual setting. Instead a *systems-thinking approach* that includes the full complexity is needed and advised.
ii. Many of the identified factors are connected through feedback loops. In order to identify the system's behaviour and to capture the dynamics in the energy-development nexus, a *simulation approach* that takes feedbacks into account is needed.

5.1.2. …to quantitative simulation models

The initial procedure in developing many models consists of a process of identifying factors and processes that are important for the considered problem, as done in the analysis of the nexus. A process of formulation of a *simulation model* follows. This part consists of formulating factors into variables and formulating the explicit mathematical relationships between variables. In terms of modelling complex systems, the identification of factors and processes is a substantial part of the modelling work load. Even though there are several tools (Luna-Reyes and Andersen 2003) available to help modellers and scientists to identify and assign variables and parameters in models, the process of quantification is inherently problematic when dealing with social science problems. Indeed, Bhattacharyya and Timilsina (Bhattacharyya and Timilsina 2010) criticised most global energy models that forecast future residential energy demand based on relatively simple relationships between energy consumption and income or GDP per capita, since they neglect such specific socio-economic dynamics of developing countries and use aggregate macro-data. In line with the findings of Chapter 3, sub-section 3.3, the use of bottom-up models for assessing and projecting energy demand seems the most suitable option for identifying the socio-economic- and energy-related dimensions of energy demand evolution in rural contexts. Ruijven et al. (van Ruijven et al. 2011) and Daioglou et al. (Daioglou et al. 2012) integrate some of the typical features of energy systems in developing countries mentioned by Urban et al. (Urban et al. 2007) in their bottom-up Residential Energy Model Global (REMG) applied to India, China, South East Asia, South Africa and Brazil. The model adopts deterministic correlations derived from econometric studies and regression analysis on national data to project the energy use of households. Despite being an interesting approach, the use of such approaches for local applications might however be prevented and not generalised due to the lack of local long-term quantitative data, as frequently happens in rural areas. Moreover, it adopts exogenous correlations for some socio-economic variables, which contradicts the endogenous nature of such dynamics, as emerged from the analysis of the electricity-development nexus. System dynamics represents an appropriate candidate approach for modelling a problem characterised my many feedbacks and endogenous dynamics. In this regards, Hartvigsson et al. (Hartvigsson et al. 2015; Hartvigsson 2016) highlight how SD can be a valuable methodological approach to capture the long-term dynamics behind the evolution of energy demand in developing contexts, since the latter are affected by high uncertainty, strong non-linear phenomena, complex diffusion mechanisms, time-adjustments of technology perceptions, time delays, and feedbacks.

Despite the advantage of using SD for modelling complex dynamics, these models can present some limitations when modelling the social interactions that ensue within social networks and impact on consumers' energy behaviours, since SD-based modelling assumes individuals to be always well-mixed and in many cases the interactions between compartments to occur randomly (Lamberson 2017). Rai and Henry (Rai and Henry 2016) indicate, therefore, that agent-based modelling (ABM) can represent a powerful tool for representing the complexities behind the energy consumers' behaviour, such as social interactions and spatial constraints. Indeed, ABMs can be used for representing systems as collections of individual or collective entities (namely "agents"), whose decision-making processes, actions and interactions are simulated in order to assess the effects on the system over time.

ABMs and SD seem promising approaches for formulating simulation models able to make long-term projections of rural electricity demand. In order to guide the final choice, the next sub-section reports a case-study, which aims at comparing the two approaches employed for simulating a simple problem: the diffusion of electricity connections in fictious rural village, which is an important variable of the electricity demand.

5.2. CASE 3. "Modelling the Forest or Modelling the Trees"

The aim of this case-study is to compare the ABM and SD approaches for modelling the process of diffusion of electricity connections in fictious rural village, which is an important at the basis of the electricity demand. In particular, 3 different cases of innovation diffusion models are modelled with a SD-approach and compared with the same cases modelled through a discrete ABM-approach. For the sake of brevity clarity, just one case is reported here, that is the most significant and meaningful from a modelling point of view. The others are reported in the *Appendix A*. The ABM-approach is implemented by rejecting the classical SD-assumption that individuals reveal the same behaviours with respect to their social contacts – modelling a homogeneous "*forest*" – and by introducing the modelling of social networks in the process – modelling each single "*tree*" of the forest. The title of this case-study is inspired from the work of Schieritz and Milling *Modeling the Forest or Modeling the Trees A Comparison of System Dynamics and Agent-Based Simulation* (Schieritz and Milling 2003).

5.2.1. SD and ABM approaches for innovation diffusion

In rural un-electrified contexts, the growth of electricity connections can be interpreted as the diffusion of an innovation. Since the 1960s, a body of literature, *e.g.* the marketing-oriented one, has been focusing the research on modelling innovation diffusion (Mahajan and Bass 2011), especially in recent years since the spread of innovations of new products and services has become increasingly multifaceted and complex (Peres et al. 2010). In this context, the research has put effort in exploring the implication that different diffusion hypotheses may have in targeting new product prospects and developing marketing strategies to attract potential new adopters and consumers. The result has been the development of analytical models for describing and forecasting the diffusion of innovation in a social system.

In 1969, Frank Bass set up the framework whereon many diffusion models have been based in the following years. In his well-known work (Bass 1969), Bass modelled the spread of innovations in a social system through the representation of two main dynamics:

- The time-invariant tendency to adopt through external influences (p) – *e.g.* advertising and other communications independent from the social network.
- The social contagion (q) that results from interactions among the agents of the social system – *viz.* adopters and potential adopters of an innovation.

With his model, by assuming that potential adopters become aware of the innovation also through time-invariant external inputs – *viz.* p –, "Bass solved the start-up problem ((Sterman 2000), pg. 332" typical of previous classical logistic growth models (*e.g.* Verhulst model (Verhulst 1838), Richards model (Richards 1959)), that were unable to explain the genesis of the initial adopters of an innovation. From a mathematical point of view, the Bass model describes the diffusion process as follows:

$$\frac{dF(t)}{dt} = [p + q \cdot F(t)][1 - F(t)] \tag{4}$$

where $F(t)$ is the proportion (*viz.* the fraction of the adopters compared to the total population) of ultimate adopters that have already adopted at time t. The analytical solution of this differential equation leads to the following expression:

$$F(t) = \frac{1 - e^{-(p+q)\cdot t}}{1 + \left(\frac{q}{p}\right) \cdot e^{-(p+q)\cdot t}} \tag{5}$$

Multiplying $F(t)$ times N, *i.e.* the total population of ultimate adopters, gives the total number of adopters $A(t)$ at time t.

As it emerges from the above mathematical representation, the main assumptionat the basis of the Bass model is that the social network where the spread of an innovation takes place is assumed to be fully connected and homogenous. Indeed, the parameter q can be interpreted as the product of a "contact rate" c – *i.e.* the number of people that a person come into contact with in a fixed time step – and an "adoption fraction" i – *i.e.* the probability that a person becomes adopter after a contact with an already-adopter. The diffusion process based on this "fully connected and homogenous" hypothesis is suitable to be formulated and simulated with the classical stock and flow diagrams of system dynamics (SD), as confirmed by a number of studies and books coming from SD-based literature: Sterman (Sterman 2000) represents the time-invariant tendency to adopt and the social contagion of the Bass model as two positive feedbacks, respectively interpreted as the effect of advertising and the mechanism of word of mouth. The same Author models random variations in the adoption mechanism by introducing some adoption noise in the model described in (Rahmandad and Sterman 2012). Milling (Milling 1986) adopt the Bass model from a SD perspective to describe the innovation diffusion process of a generic class of products, introducing relevant managerial variables like (i) market development and technological substitution, (ii) capital investment, production volume and cost, and (iii) product price and operating result. Mooy et al. (Mooy et al. 2004) combine the classical Bass model with the SIR model of epidemic spreading discussed in (Sterman 2000), and model the conscious choice to become a non-consumer by relying on the sociological theory of *memetics*. More recently, Park et al. (Park et al. 2011) develop a forecasting model for Hydrogen Fuel Cell Vehicles based on the Bass diffusion model and they simulated it using SD. De Santa-Eulalia et al. (Santa-Eulalia et al. 2011) rely on a SD perspective to combine the Bass model with a Discrete Choice Model and Conjoint Analysis, determining the relative purchase probability based on products' utilities and describing products as a finite set of perfectly substitutable attributes. Chen and Chen (Chen and Chen 2007) study product diffusion mechanisms from a SD perspective due to the enormous complexity of micro level factors; in addition to the classical Bass coefficients of innovation and imitation p and q, their model incorporated the "price" decision variable, the effect of advertising policies and product brand. Based on the general framework of innovation diffusion for monopolistic markets described by Milling (Milling 1996), Maier (Maier 1998) uses SD to extend traditional innovation models in order to incorporate competition effects among firms and to map the process of substitution among successive product generations. Kumar et al. (Kumar et al. 2015) introduce a preliminary integrated diffusion model to show the complexity of the mobile diffusion phenomenon, which often does not reflect the S-shape trend typical of Bass innovation diffusion: they suggest to model adoption as one of five phase changes of the diffusion process (*viz.* persuasion, adoption, implementation, confirmation, abandonment). Ulli-Beer (Ulli-Beer et al. 2010) overcome the inability of Bass model to capture acceptance and rejection dynamics by proposing a generic model structure for the simulation of acceptance-rejection behaviour.

As reported above, many Authors focused their research on proposing improvements and solutions to the main limitations of Bass and SD-based models. They suggest how SD-based models may reveal some limitations in modelling the complexity of consumer energy behaviours, referring mainly to a lack of representation of social interactions that ensue within social networks. Indeed, networks play an important role in shaping individuals' access to information and perceptions of energy technologies – their costs and possible benefits –, and their willingness to adopt new patterns of behaviour (Henry and Vollan 2014; Rai and Henry 2016). As suggested by Rahmandad and Sterman (Rahmandad and Sterman 2008), network topology and individual heterogeneity affect the diffusion dynamics (of epidemics, products, *etc.*), generating some behaviours that deterministic SD models, contrary to ABMs, cannot reproduce. Moreover, when the homogeneity and perfect mixing assumptions of the classical SD models are not respected, the gap between the SD model and the mean behaviour of the stochastic agent-based models is statistically significant. To encourage the research on this topic, they finally suggest examining further dimensions of heterogeneity and other networks, as well as varying the percentage and distribution of initially infectious people, i.e. initially adopters.

Trying to pursue the same final modelling goal and to contribute to the same effort of other researchers, this work investigates and discusses the hypothesis of "perfect-mixing" of adopters and non-adopters within innovation diffusion mechanisms, and it introduces an extra complexity in innovation diffusion models, i.e. the modelling of social networks. A speculative approach is used by relying on an ideal case of innovation diffusion in a rural community and designing some experiments.

Network-based diffusion scenarios are developed through discrete agent-based modelling (ABM) approaches – modelling the "*trees*" –, and results are then compared to classical continuous diffusion models simulated through a system dynamics (SD) approach – modelling the "*forest*".

5.2.2. Network models

For modelling social networks in diffusion processes, representing an ideal rural community is represented through 3 types of networks: (i) Random, (ii) Barabási & Albert, and (iii) Social.

Random (RND) networks

A random graph can be generated by starting from a set of N isolated vertices and then adding links between them at random – *i.e.* with uniform probability p, where $0 < p < 1$ – as introduced by Erdös and Rényi in 1959 (Erdös and Rényi 1959). In RND networks, the probability that any given node has exactly k links, *i.e.* the node has degree k, is given by the following binomial expression:

$$\binom{N-1}{k} p^{k} (1-p)^{N-1-k} \tag{6}$$

For large N and small p, this binomial expression can be approximated by a Poisson distribution (Jackson 2008). Then the degree distribution has the following expression:

$$p(k) = \frac{e^{-k_{avg}} \cdot k_{avg}^{k}}{k!} \tag{7}$$

where $k_{avg}=(N\text{-}1)\cdot p$ is the average degree. Since they are based on a completely random wiring, RND networks are often used as "null models" to describe the absence of any structure or pattern. This is in contrast with most real-world observed networks, where *e.g.* the social, biological, or technological pressure shapes structures which are far from being purely random.

Barabási-Albert (BA) networks

Whilst in RND graphs nodes pick their partner nodes to link to uniformly at random, in a large number of different social networks, especially related to technological, biological, or social interdependencies, new nodes "pick nodes in proportion to the current degrees of the existing nodes ((Jackson 2008), pg. 168)". Such process of network construction has been introduced by Barabási and Albert (Barabási and Albert 1999), based on the principle of "preferential attachment": starting from a small number N_0 of arbitrarily connected nodes, a new node j with m links is added at each step $j = N_0 + 1, N_0 + 2, \ldots, N$. Each one of the m links is connected from j to an existing node i with probability proportional to the current degree k_i of node i. The final structure of such network, hereafter named BA, is characterized by some "older" nodes typically with a very high degree and the rest of the nodes with a small-medium number of connections, leading, for large N, to a power law degree distribution of the network of the form:

$$p(k) \approx k^{-q} \tag{8}$$

In real-world networks, q turns out to range between 2 and 3 as experimentally observed by some authors (Barrat et al. 2008; Newman 2010; Barabási 2016), while q=3 in the case of BA networks.

Social (SC) networks

The two above described network models (RND and BA networks) lack many of the features typical of social networks, *i.e.* networks of acquaintances among individuals, which are characterized by some peculiarities (Newman et al. 2002; Newman and Park 2003; Boguñá et al. 2004): broad degree distribution, high clustering (*i.e.* when individuals tend to create tightly knit groups with a relatively high density of connections), small average distance, and assortative degree distribution (*i.e.* highly connected nodes are more frequently connected with other highly connected nodes).

Toivonen et al. (Toivonen et al. 2006) proposed a model to generate artificial graphs able to capture such peculiarities of "social networks". Based on their model, a network forms starting from a (small) number N_0 of nodes (as in BA networks) and it grows through a mechanism encouraging the creation of triangles and, as a consequence, of high clustering:

- a new node j is added to the network at each step of the procedure $j = N_0 + 1, N_0 + 2, \ldots, N$;
- firstly, the node j is connected to m_r nodes randomly selected, where $m_r \geq 1$ is a random integer number extracted at each step from a given distribution. After this step, node j is connected to the nodes $i = 1, 2, \ldots, m_r$;
- secondly, m_s neighbour nodes of each node i are randomly selected and connected to j as well, where $m_s \geq 0$ is a random integer number. This step encourages the formation of connected groups and thus yields large clustering.

Following this algorithm, if N is large, the final network shows an average degree $k_{avg} = 2 \cdot m_{r,avg} \cdot (m_{s,avg} + 1)$, while the probability that any given node has k links is given by the following power-law distribution:

$$p(k) = \alpha \cdot (k + \beta)^{-2/m_{s,avg} - 3} \tag{9}$$

5.2.3. Modelling diffusion scenarios

The diffusion mechanism here refers to the diffusion of electrical connections in a rural community of $N = 1000$ people, which has hypothetically received potential access to electricity at time $t = 0$. The simulation horizon has been set equal to $T = 240$ months, that is 20 years, which roughly corresponds to the lifetime of a typical off-grid microgrid system composed by photovoltaic panels and batteries. The simulated diffusion model includes an element of originality, which made it different and more meaningful than the classical Bass model: the effect of splitting the entire population among two different classes of potential adopters: the *influentials* and the *imitators*. As stated by Goldenberg et al. (Goldenberg et al. 2009), "in social systems, growth processes are believed to be strongly influenced by people who have a large number of ties to other people. […] such people are called influentials, opinion leaders, mavens, or hubs (pg. 1)", who may have the potential to accelerate or block the adoption of a product. From a modelling point of view, Van den Bulte and Joshi (Van den Bulte and Joshi 2007) describe influentials as people who are more disposed to new developments (*i.e.* affected by external influences as advertising), who in turn affect both other influentials and the imitators. On the other hand, imitators have a time-invariant tendency to adopt through external influence p equal to 0 and the social contagion parameter q depends on the agents they come in contact with. Moreover, the adoption process of imitators does not affect the choice of influentials. The mathematics of this type of diffusion mechanism is the following:

$$\text{influentials:} \quad \frac{dF_1(t)}{dt} = \left[p_1 + q_1 \cdot F_1(t)\right]\left[1 - F_1(t)\right] \tag{10}$$

$$\text{imitators:} \quad \frac{dF_2(t)}{dt} = \left\{p_2 + q_2 \cdot \left[w \cdot F_1(t) + (1-w) \cdot F_2(t)\right]\right\}\left[1 - F_2(t)\right] \tag{11}$$

with the subscripts 1 and 2 referring respectively to influentials and imitators; w denotes the relative importance that imitators attach to influentials' versus other imitators' behaviour ($0 \leq w \leq 1$). When w is equal to θ – with θ the proportion of influentials in the total population (N) –, the influentials' and imitators' behaviour have the same effect (*i.e.* weight) on the other imitators' choice. When $w > \theta$, imitators care much about the decision to adopt taken by influentials, while $w < \theta$ means that imitators are more affected by the decision undertaken by their "counterparts". In our simulations, the proportion of influentials is non-deterministically selected among the N agents, but they are selected with higher probability among people (*i.e.* rural households) with the highest degree. A stochastic process is introduced by supposing that each node $s = 1, \ldots, N$ of the network is classified as influential with probability p_s equal to:

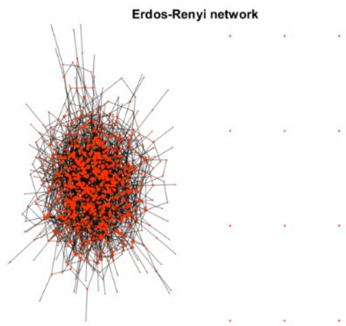
$$p_s = \vartheta \cdot \frac{k_s}{k_{avg}} \tag{12}$$

Obviously, in the correspondent SD model, where the homogeneity and perfect mixing hypothesis stands, such modelling choice simply consists in defining two different stocks of adopters: one with $(1 - \theta)N$ imitators and the other with θN influentials.

In the simulated case, $\theta = 0.15$, and 6 scenarios are simulated: for k_{avg} equals to 4 and 8, w varies equal to one-fifth of θ, θ, and five times θ – *viz.* respectively $w = 0.03$, $w = 0.15$, $w = 0.75$. The adoption fraction is set $i = 0.02$ for imitators and $i = 0.1$ for influentials, and the time-invariant tendency to adopt $p = 0.01$ for influentials and 0 for the imitators. Such diffusion process was tested for all the three types of network (*viz. RND*, *BA*, *SC*) described before, while the hypothesis at the basis of each simulated mechanism was also modelled in the equivalent SD model. Each one of the 6 scenarios accounts for 20 simulations per type of network, for a total of 61 simulations per scenario: 20 for RND, 20 for BA, 20 for SC and 1 for the deterministic Bass model simulated through a SD-based approach. In this way, our simulations statistically embrace the stochasticity due to the process of networks creation and discrete diffusion.

5.2.4. Software environment

The simulations were implemented in the MATLAB-Simulink © computing environment. For SD simulations, the stock-and-flows model was created by using Simulink, while specific MATLAB scripts for the agent-based diffusion models and for generating the networks were developed. The scripts for network formation were firstly ran in order to generate pools of graphs to use with the agent-based diffusion models. For each type of network – RND, BA and SC – 2 pools of graphs for k_{avg} equal to 4 and 8 were generated, for a total of 3x2 pools of networks. Each pool contains 20 graphs, like the number of simulations per each scenario of the three cases. Examples of RND, BA and SC graphs created in MATLAB are represented in Fig. 32. C_{avg} is the computed mean clustering coefficient (Newman 2010), which quantifies the density of triangles in the graph, representative of tightly connected subnetworks. It is worth to note that RND graph presented some isolated nodes due to the random process adopted to generate it, while C_{avg} of the SC network is by far the highest one, as expected.

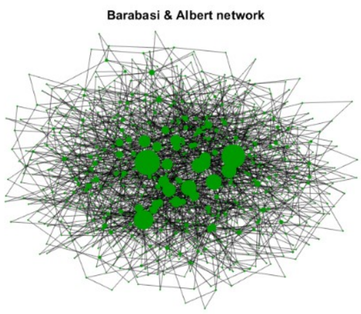


k_{max}=11

k_{min}=0

$k_{avg,eff}$=4.000

C_{avg}=0.003



k_{max}=63

k_{min}=2

$k_{avg,eff}$=3.994

C_{avg}=0.0153

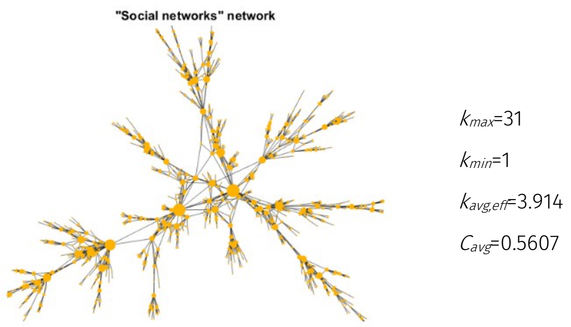


Fig. 32. Plots of RND, BA and SC graphs for k_{avg}=4 and N=1000.

Fig. 33 report the sketch of the SD models employed for the simulated case.

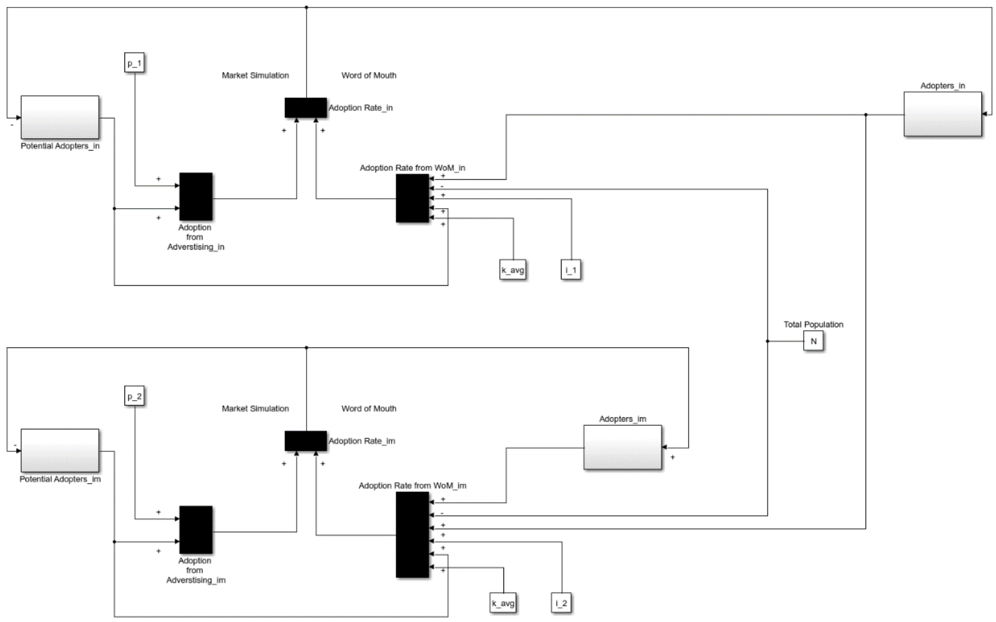


Fig. 33. Stock and flows diagram developed in Simulink © for Case 3.

5.2.5. Results and discussion

In this section, the results of the simulations performed in the three cases are reported. For each simulation of each scenario, the "electricity adoption curves" representing the total number of adopters of electrical connections *A(t)* at time *t* are plotted. The blue curves represent the SD model, while red, green and yellow curves represent respectively the result of the diffusion process on RND, BA and SC networks. For the AMB simulations with the three types of network, the dashed lines represent the 20 simulations per scenario, and the bold line highlights the average of the simulations. The results are then discussed by comparing the stochastic agent-based adoption curves with the related SD model: for each scenario of the three cases, the *min* and *max* time interval needed by the agent-based stochastic curves to reach 50% and 95% of diffusion are compared, together with the values obtained with the SD model. The time history of the fraction of the population adopting over time *t* is also reported, to highlight some particular patterns due to the subdivision of the population among *influential* and *imitator* households.

Results for k_{avg} = 4 and w = 0.03, 0.15, 0.75 are plotted in Fig. 34, left column, while results for k_{avg} = 8 are on the right column.

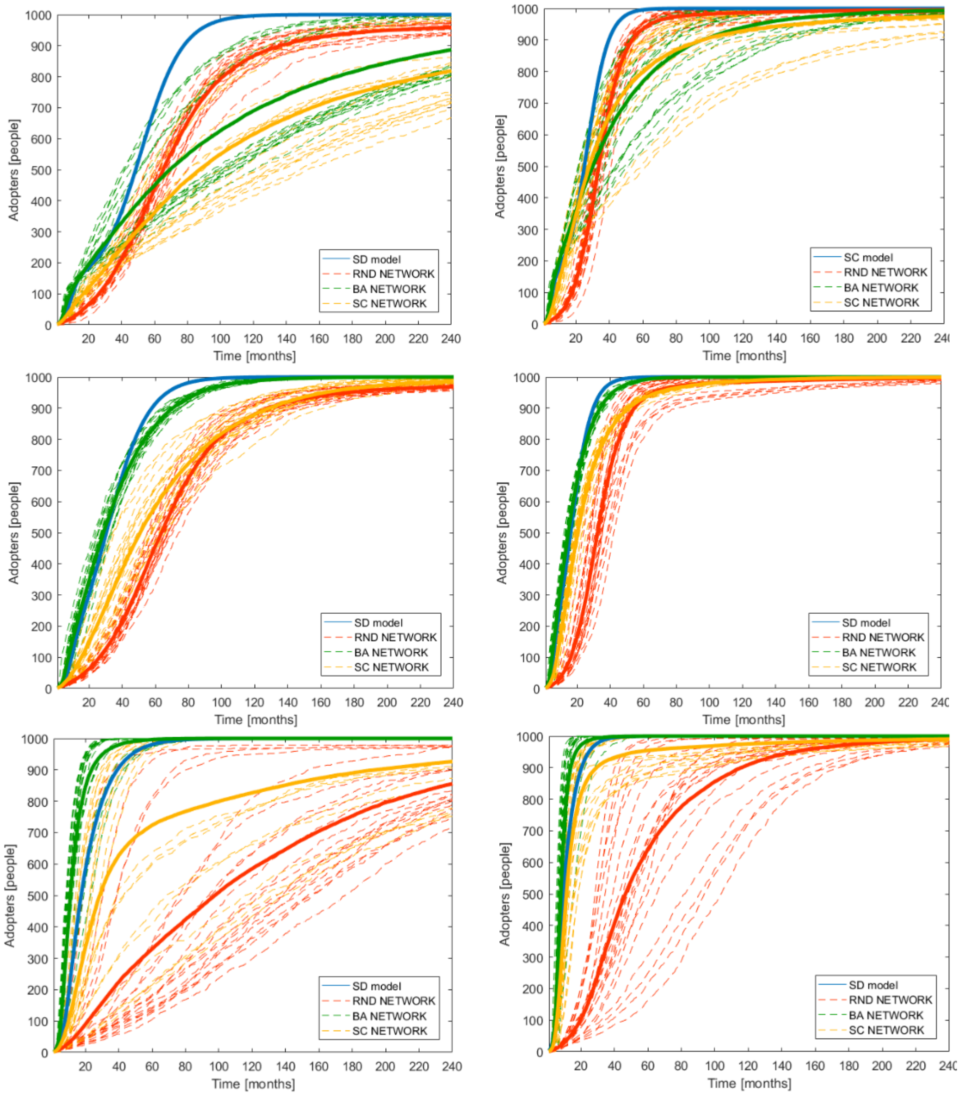


Fig. 34. Diffusion curves for *Case 3*: results for k_{avg}=4 (left) and 8 (right). From top to bottom, w=0.03, 0.15, 0.75.

The figure confirms that the ABM of the Van den Bulte-Joshi process shows high variability and stochastic uncertainty. Indeed, the model highly depends on the stochastic process adopted for "assigning" the role of *influential* among the N agents in a given network. For w = 0.03, the BA process reveals the highest variability; indeed, a very low w means a low relative importance that imitators attach to influentials' versus other imitators' behaviour. Therefore, whereby there are many nodes with very high degrees and the stochastic process assigns the role of *influential* to the nodes with the maximum degrees, such nodes have low influence on the neighbours marked as imitators, despite their high contacts. On the contrary, whereby the stochastic process assigns the role of *influential* also to lowly-connected nodes and the preferential attachment mechanism generates less highly-connected nodes, some imitators result to be highly connected, speeding-up the diffusion process. This consideration is valid also for SC networks, even if with less intensity, since the highest degrees of the networks are lower than the BA ones.

When w = 0.15 (*i.e.* $w = \theta_s$ the proportion of influential on the whole population), the relative importance that imitators attach to influentials' versus other imitators' behaviour is always the same. Therefore, the path of the diffusion process is similar to a classical diffusion model, with RND and SC processes showing a more stretched behaviour.

When w = 0.75, the RND and the SC (only when k_{avg} = 4) processes show an extremely high variability. For RND processes, this is because the stochastic process of *influential* role distribution may assign the role of *influential* to some isolated nodes or to nodes with very low degrees. When this situation occurs, imitators may be mainly, or even only, connected to their "counterparts", whose behaviour has a low influence on them, and the diffusion process get considerably lower. The same may occur for SC processes, because when $k_{avg} = 4$ the role of *influential* may be assigned to lowly-connected nodes.

The next Fig. 35 represents the fraction of the population adopting over time t for the 4 diffusion processes when k_{avg} is equals to 4, to highlight some particular patterns due to the subdivision of the population among influential and imitator households.

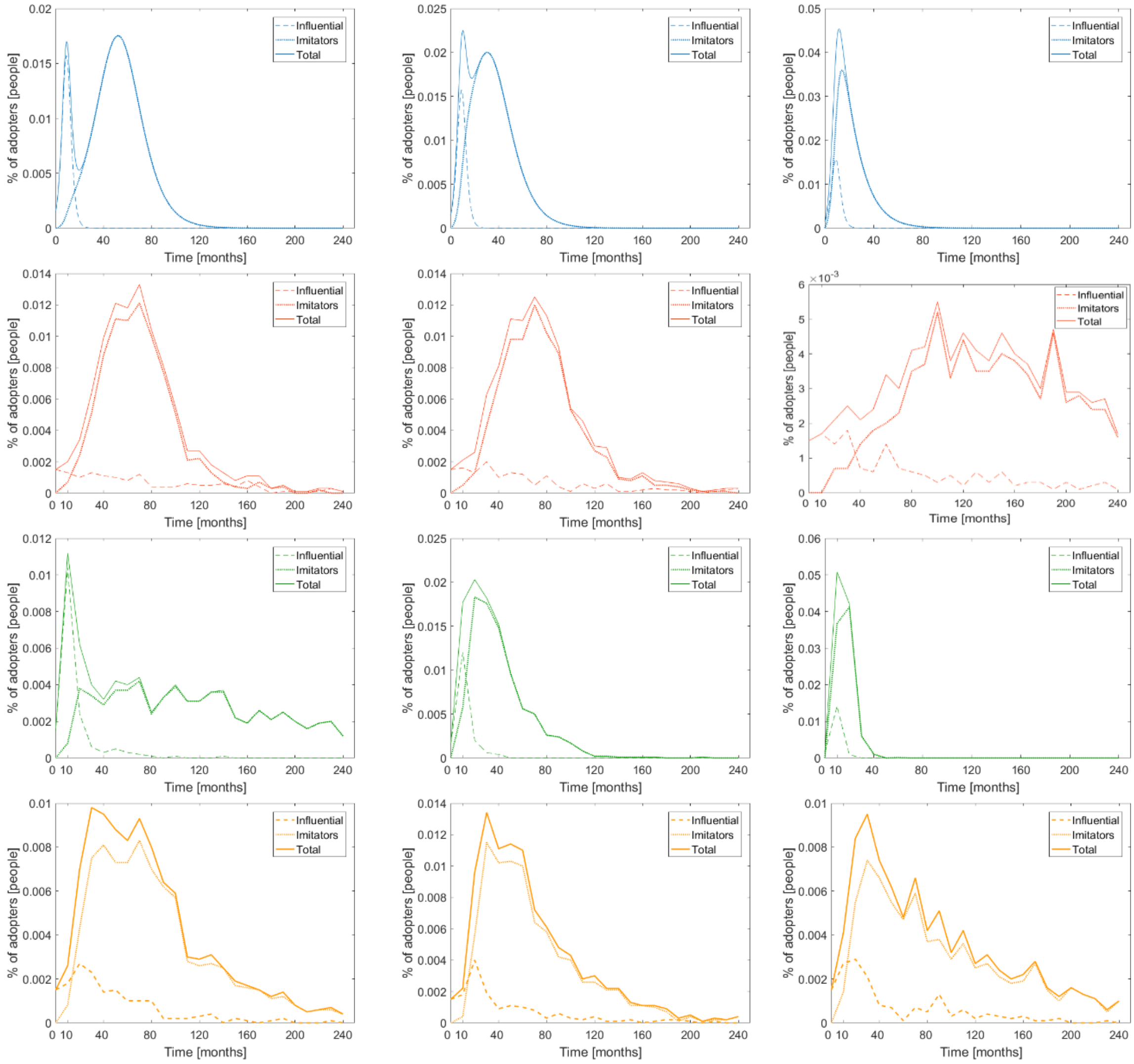


Fig. 35. Adoption fraction over time *t* when k_{avg}=4. From top to bottom: SD model, ABM on RND, BA, SC networks, and *w*=0.03 (left), *w*=0.15 (centre), *w*=0.75 (right).

The trend of the curves for the Bass model confirms the particular "double-waves" pattern generated by Van den Bulte and Joshi in (Van den Bulte and Joshi 2007). They reflect the "intermediate plateaux" visible in the diffusion curves of Fig. 34. This pattern is due to a different adoption rate which characterizes the influentials and the imitators. For w = 0.75, the imitators are so much influenced by influentials' behaviour that also their diffusion rate ramps up quickly. In agent-based models, the generation of "double-waves" pattern is not evident due to the stochasticity of the processes, which have been simulated in discrete time, while the SD model is in continuous time. The rate of adoption of the agent-based models reflects what shown in Fig. 34 and discussed above.

The comparisons between the min and max time interval needed by the agent-based stochastic curves to reach 50% and 95% of diffusion, and the values of the SD model are reported in Table 12 – the values in brackets represent the difference with respect to the Bass model.

Table 12. Results.

	50%		95%	
Scenario k_{avg}=4, w=0.03	*min*	*max*	*min*	*max*
RND	56 (+6)	81 (+31)	147 (+59)	239 (+151)
BA	42 (-8)	121 (+71)	128 (+40)	*Not reached*
SC	56 (+6)	81 (+31)	156 (+68)	*Not reached*
SD	*50*		*88*	
Scenario k_{avg}=4, w=0.15	*min*	*max*	*min*	*max*
RND	56 (+25)	75 (+44)	139 (+71)	211 (+143)
BA	24 (-7)	35 (+4)	83 (+15)	94 (+26)
SC	35 (+4)	67 (+36)	131 (+63)	203 (+135)
SD	*31*		*68*	
Scenario k_{avg}=4, w=0.75	*min*	*max*	*min*	*max*
RND	19 (+1)	177 (+159)	54 (+5)	*Not reached*
BA	9 (-9)	26 (+6)	21 (-28)	54 (+5)
SC	15 (-3)	140 (+122)	36 (-13)	*Not reached*
SD	*18*		*49*	
Scenario k_{avg}=8, w=0.03	*min*	*max*	*min*	*max*
RND	31 (+5)	42 (+16)	53 (+8)	117 (+72)
BA	22 (-4)	52 (+26)	64 (+19)	187 (+142)
SC	23 (-3)	63 (+37)	73 (+28)	*Not reached*
SD	*26*		*45*	
Scenario k_{avg}=8, w=0.15	*min*	*max*	*min*	*max*
RND	25 (+8)	43 (+26)	48 (+13)	143 (+108)
BA	13 (-4)	19 (+2)	39 (+4)	46 (+11)
SC	19 (+2)	27 (+10)	62 (+27)	87 (+52)
SD	*17*		*35*	
Scenario k_{avg}=8, w=0.75	*min*	*max*	*min*	*max*
RND	29 (+18)	105 (+94)	47 (+21)	209 (+183)
BA	6 (-5)	16 (+5)	11 (-15)	35 (+9)
SC	9 (-2)	19 (+8)	20 (-6)	163 (+137)
SD	*11*		*26*	

The results reflect the trend visible from the diffusion curves described above. When w = 0.03, the variability is very high for all the three agent-based processes, especially for k_{avg} = 4 and the BA curves. The time interval between the min and the max curves is wider than 2 years when approaching 50% of the adoption for RND and SC process at k_{avg} = 4, while it reaches 6.5 years for BA process. When approaching 95% of adoption, the interval increases a lot for all the processes, from 7 to 9 years. Apart from the minimum value of BA, the curves are all stretched to the right with respect to the SD model, and some processes do not even reach 95% of adoption. For k_{avg} = 8, the interval between the min and the max values for the agent-based process is from 1 to 3 years when approaching 50% of adoption, while it increases till about 5 and 10 years when approaching 95% for respectively the RND and BA, while the max SC process never reach it.

The scenario with w = 0.15 is the least variable one. Apart from the minimum value of BA, the curves are all stretched to the right with respect to the SD model, especially for the RND and SC models that approach 95% of adoption respectively about 12 and 11 years later than the Bass model for k_{avg} = 4, and about 9 and 4 years later for k_{avg} = 8.

When w = 0.75, the RND process is always stretched to the right with respect to the Bass model – curves approach 95% of adoption from 5 to 192 months later both with k_{avg} = 4 and k_{avg} = 8 – and presents the highest variability. When k_{avg} = 4, the time interval between the min and the max curves is wider than 13 and 15 years when approaching respectively 50% and 95% of the adoption. When k_{avg} = 8, such time interval is wider than 6 and 13 years when approaching respectively 50% and 95% of the adoption. The SC model presents a high variability as well, especially for k_{avg} = 4: the time interval between the min and the max curves is wider than 8 when approaching 50% of adoption and infinite when approaching 95%. When k_{avg} = 8, such time interval becomes considerable – *i.e.* almost 12 years – only when approaching 95% of the adoption.

In many simulations, the agent-based processes do not reach 100% of adoption for k_{avg} = 4, and the relative portion of population is numerically relevant in the cases resumed in Table 13. While RND networks present some isolated nodes that prevent complete adoption, the lacking adoption by some agents in case of BA and SC network processes is due to the too short simulation horizon.

Table 13. Percentage of adoption at t=241 months for RND, BA and SC processes at k_{avg}=4

	max adoption		
	w=0.03	*w=0.15*	*w=0.75*
RND	93.2-98.0	95.7-97.9	71.6-97.8
BA	79.0-99.9	-	-
SC	91.3-99.5	97.2-99.6	75.2-100

In case of k_{avg} = 8, the maximum adoption fraction is less than 100% in 16 simulation of SC model, and the final adopters range from 909 to 1000.

5.3. Choosing system dynamics

The literature debate between SD and ABMs and the previous case study led to this fundamental consideration: considering the composition of the social structure and behaviour of each-single agent through ABMs can lead to significantly different results. On the other hand, the case-study pointed-out that the results obtained with ABMs are affected also by large variability. Despite being an interesting result from a "speculative" and stochastic point of view, the practicality of having tens, hundreds, or even thousands of significantly different scenarios is questionable or even useless if the final aim is to build more reliable electricity demand scenarios and energy plans. Model calibration can be a solution, but it would encounter three complications:

- availability of a huge amount of data for the calibration of the socio-economic network, and the parameters characterising each single agent;
- knowledge of specific social-science competences for the definition of the social structure of rural communities;
- questionable applicability and possibility to extend the results to different contexts.

Moreover, these considerations refer only to the simulations of the innovation diffusion process analysed in case-study, which is just one of the multiple dynamics and multifaced complexities observed in the electricity-development nexus. E.g. the increase in population would require the ability to investigate and model the dynamics of growth of social networks, with the introduction of further parameters, logics, and hypothesis difficult to assess with few data. The lack of access to enough reliable data when working in rural areas in developing countries adds further difficulties to the agent-based modelling process.

Given these potential drawbacks of using ABM, the multiplicity of cause-effect relations and feedbacks, and time-delays characterising the nexus between electricity demand and socio-economic development, the modelling framework based on SD seems a more appropriate approach. In addition to this, SD theory offers a modelling process which contributes to a more holistic understanding of a system and its relevant causalities. Also the literature in the field of energy and development supports the suitability of SD for modelling complex issues. Alam (Alam 1997) develops a SD-model for representing and simulating an integrated rural energy system for rural Bangladesh, suggesting that "System-dynamic methodology appears to be the most appropriate technique for handling complex systems (pg. 593)", due to the presence of many feedback loops in farming energy systems. Musango et al. (Musango et al. 2011) and Brent et al. (Brent et al. 2011) state that SD has the potential for assessing the sustainability of renewable energy technology in developing countries by accounting the economic, social, environmental and other factors that might influence the process of energy technology development. Hartvigsson et al. suggest that SD allows to make a holistic analysis of energy systems in rural contexts "where the introduction of new technological and social arrangements creates new interfaces between technology, people and their societal and natural surroundings ((Hartvigsson et al. 2015), pg. 2)".

Moreover, the use of SD allows to significantly reduce the amount of quantitative data needed for building a model. Of course, as for ABMs, also SD-based modelling requires long-term time series both in model development and validation. On the other hand, the validation process of SD models offers a more structured and codified procedure which gives much emphasis also to qualitative information. Especially in rural areas, high-quality qualitative data can often be obtained through case studies and structured interviews. As rural residents often have a plethora of practical knowledge and 'know-how', even though they lack precision, they can be good sources for retrieving estimates on reference modes and historical trends.

5.4. System dynamics and rural electrification

Application of system dynamics in the energy sector counts hundreds of scientific publications. A research on *Scopus* limited to "Energy" as subjected area and "System Dynamics" as keyword counted 362 papers from 1985 to 2018, whose 350 from 2000 to 2018. According to the Energy *Special Interest*

Group (SIG) of the System Dynamics Society[10], developments and applications of system dynamics in the field of energy are related to: Energy systems technology development modelling, Technology assessment, Energy impact on sustainable development, Energy economics, Investment analysis, Energy market modelling, Energy regulations and policies, Environmental impact assessment and strategic environmental assessment, Renewable energy technology and economics, Energy-environmental policy design and assessment, Institutional questions related to Energy, Sustainable Development and Environment Protection.

Although these studies mainly focus on developed countries, applications of SD for analysing the electricity sector in developing countries are mainly represented by the research works of Isaac Dyner on the electricity market and penetration of renewable energy technologies in Colombia (e.g. (Dyner et al. 1995; Bunn and Dyner 1996; Castaneda et al. 2017; Redondo et al. 2018; Zapata et al. 2018)) and Hassan Qudrat-Ullah on electricity policies in Pakistan (e.g. (Huang and Chen 2005; Qudrat-Ullah 2005; Qudrat-Ullah and Seong 2010)). Electricity production and use in developing countries are also analysed in the *Threshold 21* and *iSDG* models, two simulation tools based on SD developed by the Millennium Institute[11] to support comprehensive, integrated long-term national development planning, and to investigate the interconnections between the 17 SDGs. Applications of SD in the field of rural electrification is very limited. Steel (Steel 2008) develops a SD model to simulate the decision-making process of electricity consumers in rural Kenya, while choosing between grid and off-grid power options at national level. She identifies that low electrical reliability generates a vicious loop, which causes losses of economic resources and reduces the reliability even more. Jordan (Jordan 2013) uses SD to compute the electricity demand in a long-term power capacity expansion model for Tanzania, demonstrating that electricity demand should be treated as an endogenous factor in energy planning processes, rather than exogenous. Zhang and Cao (Zhang and Cao 2012) analyses the future energy supply mix for a rural Chinese region by using SD to simulate the nexus between rural economic development, social development (*viz.* growth in population) and energy consumption. Notable contributions have been done by Hartvigsson in investigating the main dynamics affecting the success of failure of micro-grid projects in rural Tanzania (Hartvigsson 2015, 2016, 2018, Hartvigsson et al. 2015, 2018a). He focused on the analysis of the endogenous dynamics that affect the viability of mini-grids through the modelling of feedbacks between electricity availability and the operators' ability to increase generation capacity, and between the growth in electricity usage and electricity availability. He used system dynamics especially as an approach for *understanding and improving* the system under analysis from the perspective of the *energy utility*. Part of this thesis stands on his main findings and adds the following foci as for the use of system dynamics:

1. as an approach for *characterising* the electricity demand-development nexus and its multifaceted dynamics;
2. for *projecting* long-term electricity demand scenarios;
3. from the perspective of the *energy planner*.

This thesis is therefore meant to contribute to the same effort of other researchers focusing on energy demand models and rural electrification, with the final goal of investigating the socio-economic complexities of the rural electricity-development nexus, providing a more reliable approach for modelling long-term projections of rural electricity demand, and planning more reliable off-grid power systems.

[10] https://www.systemdynamics.org/energy

[11] https://www.millennium-institute.org/integrated-planning

Part II

Modelling in action: system dynamics and optimisation models for rural electrification

This part addresses the Objective 2 and Objective 3 of the thesis. It describes the main steps of the system-dynamics modelling process (i.e. conceptualisation, formulation, calibration, testing and validation), as well as the use and integration of the model with an optimisation-based approach for off-grid micro-grid systems.

Chapter 6

Model Conceptualisation and introduction to the *Ikondo* case

A map is not the territory
(Alfred Korzybski 1931)

Develop a model to solve a particular problem, not to model the system
(Sterman 2000)

This is the first chapter of the part II of the thesis. In accordance with the issues emerged in the analysis on the electricity-development nexus and the specific objectives of the thesis, the dynamic problem to solve and the purpose of the SD model are defined. A real case-study is introduced as reference for achieving these purposes and for going further in the conceptualisation and the next stages of the modelling process, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA Onlus. It sets the basis for achieving Objective 2, since it allows to identify the model boundary and key variables, describe their behaviour and the related reference modes, and represent the feedback loops of the system.

6.1. Problem statement

Defining the appropriate problem to solve through a model is the first pivotal step of the modelling process. This allows to include only the relevant dynamics and factors, and finally contribute to improving the knowledge of the system and the system itself. Different problems do emerge when electrifying rural communities (viz. the *system*), as defined in the "Problem 2" of the thesis:

1. **electricity demand evolves following unexpected paths**: How to formulate the dynamics behind electricity-development nexus and generate reasonable long-term projections of electricity demand in rural areas?
2. **electricity access does not always bring rural development**: Why do not we see the same outcome in terms of electricity evolution patterns and rural development every time we bring electricity?

These issues are obviously linked and subjected to many complexities:

- low understanding of the socio-economic structure of local rural communities (*structural uncertainty*);
- multifaced and multidimensional factors characterise the system (*structural uncertainty*);
- unknown impact and relevance of such factors on the electricity consumption, and vice versa (*parameter uncertainty*).

In turn, and in-line with the "Objective 2" of the thesis (sub-section 1.2), the statement of the problems allows to define the two-fold specific purpose of the model:

> *"(i) to assess the fundamental dynamics, variables, and exogenous policies that characterise the electricity-development nexus and (ii) generate long-term projections of electricity use to support rural electrification".*

In this work, the attempt to achieve this purpose is pursued by developing and testing a simulation model based on a real case study, and soft-linking it with a model for generating electricity load profile and sizing an off-grid microgrid.

6.2. The Ikondo case-study

6.2.1. Analysis of the context

CEFA Onlus was founded in 1972 by a group of agricultural cooperatives based in Bologna, Italy. It promotes initiatives of development, cooperation and international volunteer service. CEFA supports projects in rural regions of the Mediterranean, East Africa and Latin America to establish sustainable and durable development processes in local communities. In Tanzania, it promotes interventions in the fields of water supply, agriculture, agro-processing and rural electrification since '80s. In this period, the NGO has realised three mini hydro-electric power plants in the rural areas of Iringa and Njombe regions, which currently serve around 10 villages connected to the mini-grids. The main characteristics of the three projects are listed in Table 14.

The village of Ikondo is the target context of this thesis. According to the latest 2016-data gathered by CEFA, Ikondo has a population of around 4000 people, divided in approximately 820 households (HHs). The village is characterised by an agriculture-based livelihood, with around 100-120 Income Generating Activities (IGAs) started after the electrification of the community in 2005. The power plant is managed by a local utility, namely Matembwe Village Company (MVC), founded by CEFA and now independent. It is in charge of managing and operating the plant and the line, defining the tariff, maintaining the relations with the national utility TANESCO and the Tanzanian Rural Electrification Agency (REA). CEFA founded also a local micro-credit utility, namely SACCOS, which is also in charge of recording and collecting the monthly electricity bills in the village.

Table 14. Hydroelectric plants implemented by CEFA in Tanzania [adapted from (Riva et al. 2017)].

Matembwe

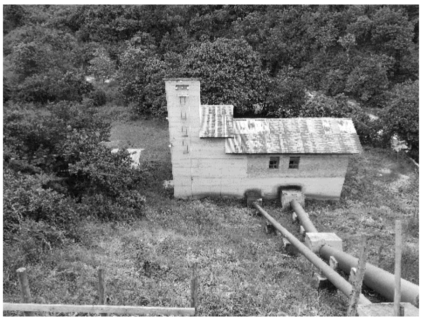
The first power plant was realised in the village of Matembwe, in the District of Njombe, in 1984. The hydropower plant has a nominal power of 120 kW and supplies electricity to 2 villages serving about 700 connections through a 19 km of medium voltage (MV) distribution network, and it is connected to TANESCO.

Bomalang'ombe

The second power plant is in the village of Bomalang'ombe, in the District of Kilolo. The hydropower plant has a nominal power of 250 kW and supplies electricity to 3 villages serving about 400 connections through a 17.3 km of MV distribution network. The plant is not connected to TANESCO. The availability of electric power determined a rapid development of the village of Bomalang'ombe, that in these years has seen its population grow from 5,000 to more than 12,500 inhabitants.

Ikondo

The third power plant was realized in the village of Ikondo, in the District of Njombe. The hydropower plant was built in 2005 with a nominal power of 83 kW in order to supply electricity to the village of Ikondo, through 8 km of MV distribution network. Ikondo is a run-of-river plant, which uses the water provided by the river Kyepa. The project intended to trigger the development to the village of Ikondo, a very isolated settlement in the District of Njombe. In 2016, CEFA completed the upgrade of the power facility with an additional 350 kW turbine – achieving an overall generation capacity of 433 kW – and the realization of 47 km of MV distribution network that reached other 4 villages in the immediate surroundings, the Matembwe micro-grid and the national grid.



6.2.2. Data collection campaign

Data collection on the field was carried out in three time-slot by the author of this work, other colleagues at Politecnico, and the current Project Energy manager of CEFA. Table 15 reports the main information regarding the data collection campaigns.

Table 15. Main information concerning the on-field interviews.

Period	**Target**	**Villages**	**Aim**
June 2016	***33*** Electrified HHs and ***18*** IGAs in electrified areas	Electrified villages of Nyombo and Kidegembye	- Defining ranges of income, expenditures; - Gathering information about the electricity use (*n° and type of appliances, operation time, time windows, power*).
September 2017	***38*** Electrified HHs and ***25*** IGAs in electrified areas	Electrified villages of Ikondo and Ukalawa	- Defining ranges of income, expenditures; - Defining hours of working, farming, and for housework; - Defining ranges of connection cost; - Gathering information about the electricity use (*n° and type of appliances, operation time, time windows, power*).
January 2018	- ***6*** experts: (1) the Country Director of CEFA in Tanzania; (2) The Manager Director of MVC; (3) the Manager Director of SACCOS; (4) (Ex)Manager Director of MVC; (5) MVC accountant; (6) The Manager director of the Bomalang'ombe Village Company (BVC) and head of the electricians in Ikondo; - ***3*** IGAs: (1) one grocery; (2) one garage; (3) one carpentry; - ***2*** farmers: (1) a land owner; (2) a poor farmer; - ***2*** women: (1) MVC accountant; (2) House keeper for CEFA and clothes seller; - ***2*** teachers: (1) Head of Matembwe primary school; (2) Head of Kanikelele's primary school; - ***1*** physician at Matembwe dispensary.	Electrified villages of Ikondo and Matembwe	- Understanding the history of development of Matembwe-Ikondo; - Conceptualising (i.e. identifying the main variables and dynamics) the electricity-development nexus for Ikondo; - Discussing the structure of the model - Gathering quantitative data about the variables and parameters formulated in the model (see model calibration in Chapter 8); - Collecting the data of monthly electricity consumption for Ikondo consumers from 2005 to 2017 included.

- The interviews were based on questionnaires composed by both open and multiple-choice questions;
- The interviews to the Country Director of CEFA, The Manager Director of MVC, and The Manager director of the BVC were in Italian;
- The interviews to the other experts, the teachers, and the physician were in English;
- The interviews to the local people, HHs, and IGAs were in English and translated in Swahili by a local Tanzanian interpreter.

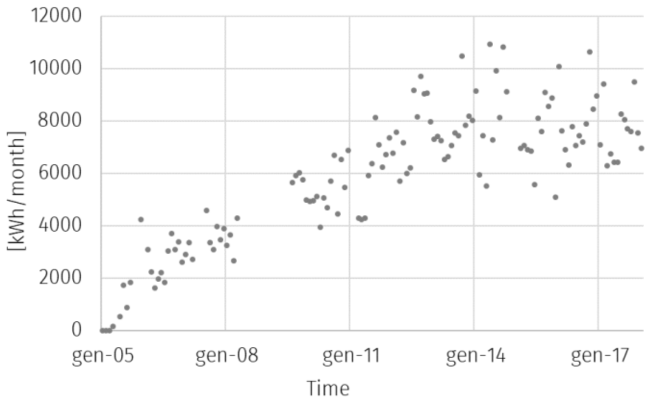
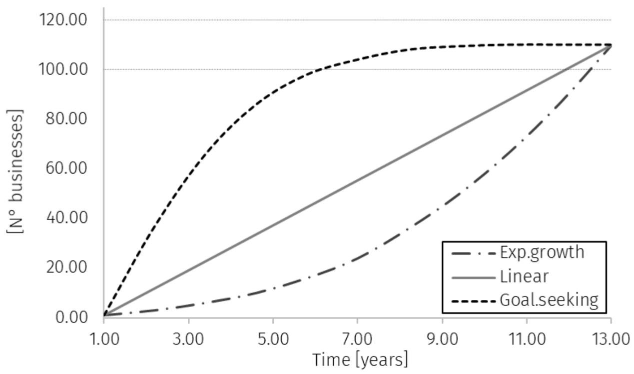
6.3. Boundary selection and dynamic hypothesis

Defining the appropriate variables of a model entails the inclusion of the fundamental endogenous dynamics and the exclusion of the negligible ones. Since model conceptualisation does not involve simulation, this endeavour will be completed with the formulation and testing of the model – the modelling process is iterative –, but at this stage it allows to simplify the structure and enhance the knowledge of the analysed system.

6.3.1. Reference modes

Chapter 3 confirms the importance of relying on a "long-term thinking" when dealing with rural electrification. The electricity-development nexus is affected by delays of years or even decades. Given the availability of data from the implementation of the Ikondo back in 2005, the time-horizon is set to 13 years. In this time horizon, data and surveys help to define potential reference modes of the system, viz. set of graphs and other descriptive data showing the development of the problem over time ((Sterman 2000)).

Table 16. Reference modes and insights.

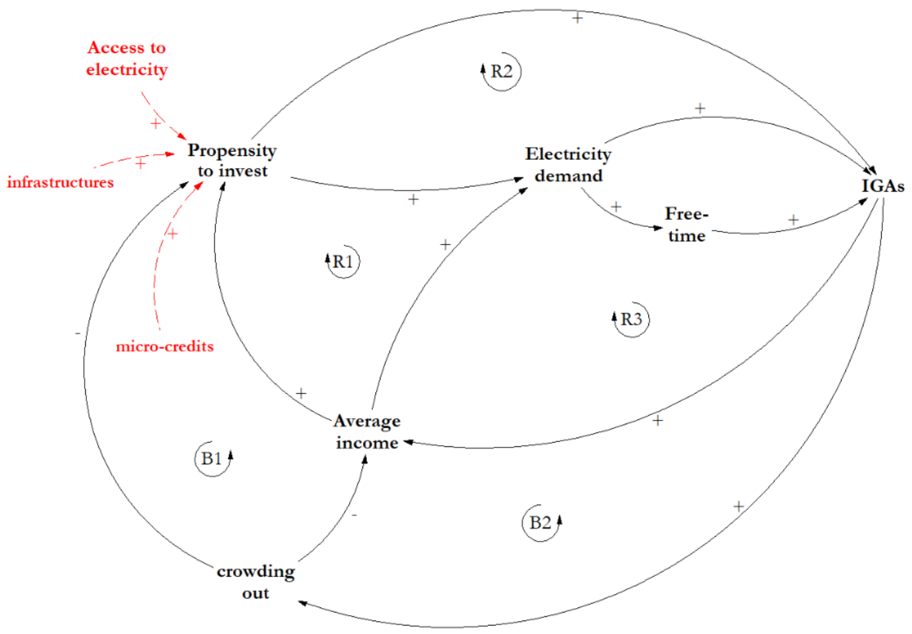
	Monthly data of the total electricity consumption of the Ikondo community. Electricity consumptions grew from 2005 to 2017. Moreover, the growth did not occur at a constant rate along all the horizon, and it shows a high level of short-term variability, confirming the presence of non-linear dynamics.
	Reference modes of the growth of business activities with electrification. The local experts stated that Ikondo had at most 2 business in 2005, while it now counts around 100/120 at the 13th year. According to this, one expert suggested an *Exponential growth* rate, while data related to the electrical connections of the local business suggest a *Goal seeking* behaviour.
"*respect to the initial situation, the average income of the village is more than tripled* (the manager director of the MVC)"	This indicates an expected substantial growth of income from the beginning of 2005 to the present days.
"*People work more in the evening, while farmers can continue their work during the night* (the manager director of the MVC / BVC / SACCOS /local workers / local farmers)"	This suggests an expected growth in the time spent for doing business and farming activities during the night hours.
"*Before electricity, 50% of students usually passed the exams at the end of the primary school, now 67%* (Dean of Kanikelele's primary school)	This indicates an expected increase in the educational attainments for the community after electrification.

6.3.2. Mapping key variables and dynamics

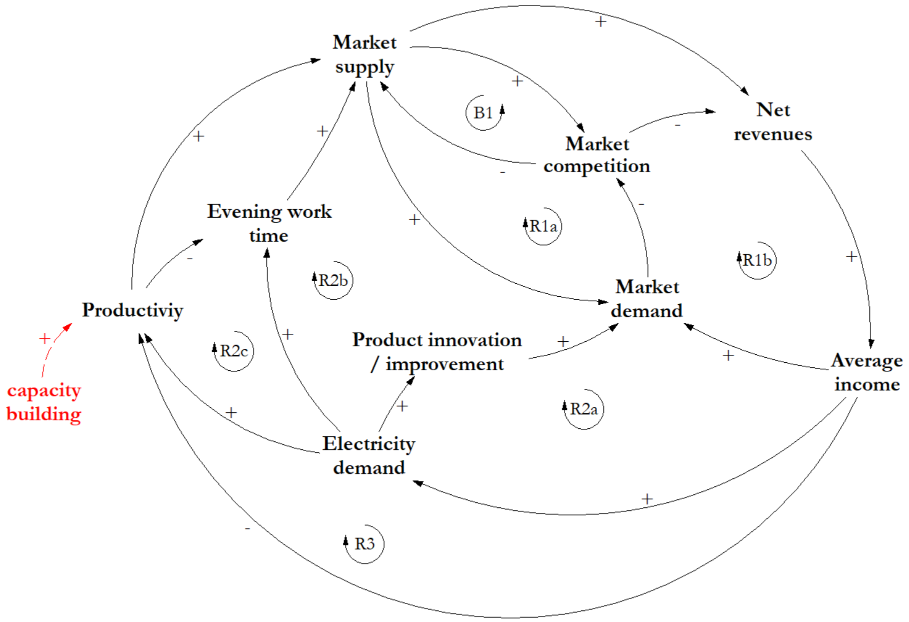
The identification of the key variables and dynamics for the Ikondo village are based on the causal loop diagrams drawn in Chapter 4 for the electricity-development nexus, and modified according to the local surveys. One dimension of the nexus is not conceptualised, that is the *Health and population* dimension. As a matter of fact, despite the clear positive impact of electricity on health, it did not emerge any significant feedback on electricity demand from the on-field interviews. Moreover, the complete absence of quantitative information prevented the attempt to include this dimension in the model structure. As a consequence, the population dynamics are considered and formulated as exogenous.

Table 17 reports the "modified" causal loop diagrams for Ikondo, and the related explanation.

Table 17. Causal loop-diagrams of the main variables and dynamics of the system.

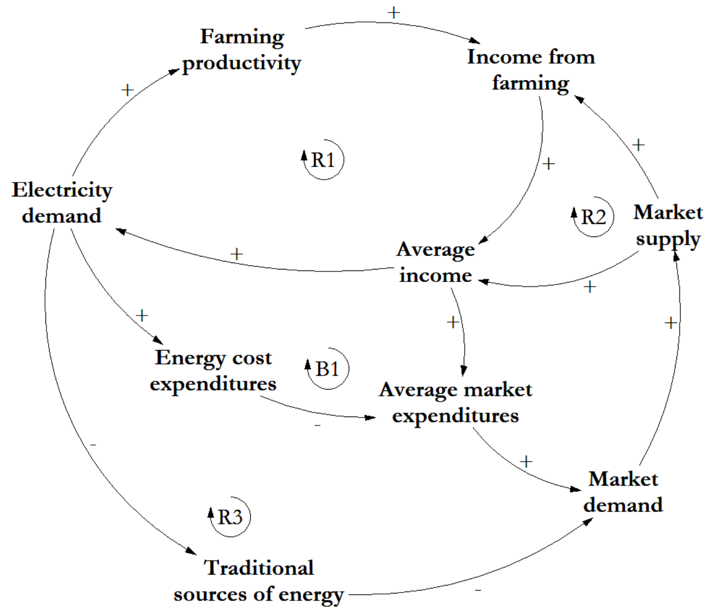


- *R1*: *Propensity to invest* → *Electrical demand* → *IGAs* → *Average income* → *Propensity to invest*. Given the possibility to exploit electricity (*Access to electricity*), good roads (*infrastructures*) and access to affordable loans (*micro-credits*), people can invest in electrical machineries and appliances, set-up a business, increase their income and be more willing to invest again.
- *R1*: *Propensity to invest* → *IGAs* → *Average income* → *Propensity to invest*. Similar as R1 but concerning all the IGAs that do not require electricity but that were generated as a result of the increase in community welfare.
- *R3: Electricity demand* → *Free-time* → *IGAs* → *Average income* → *Electricity demand*. Electricity use at home and at work allows to free-up time to use for setting up new business, increasing income that can reinvest again in more appliances at home or at work.
- *B1: IGAs* → *crowding out* → *Propensity to invest* → *IGAs*. The growth in the number of businesses increases also the competition and the saturation of the market for a certain product or service, reducing the propensity to invest in such activity.
- *B2: IGAs* → *crowding out* → *Average income* → *Electricity demand* → *IGAs*. The crowding out and the competition balance the sales and market turnover, decreasing the revenues per person, and balancing the use and conception of electricity at home and for productive purposes.

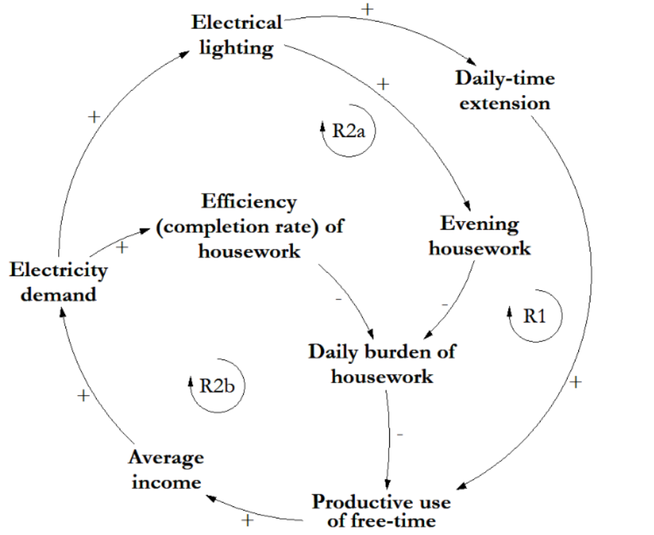


- *R1a*: *Market supply* → *Market demand* → *Market competition* → *Market supply*. The increase of market supply per effect of electricity (previous loop) has a three important feedbacks on market demand: (1) people can find locally most of the goods and services that they were used to buy outside before electrification, decreasing the costs and therefore increasing their purchasing power; (2) the external demand for goods and services increases, especially from the villages in the immediate surroundings and by trading; (3) the market supply of some businesses satisfies the demand for raw materials and services for some other IGAs. The increase of market demand reduces the market competition, which in turn encourages more production.
- *R1b: Market supply* → *Net revenues* → *Average income* → *Market demand* → *Market competition* → *Market supply*. The increase of market supply increases the revenues, and so the average income that can be spent for more demand of goods and services, increasing the market supply.
- *B1: Market supply* → *Market competition* → *Market supply*. This is the fundamental balancing loop, which controls the market equilibrium between supply and demand.
- *R2a: Electricity demand* → *Product innovation /improvement* → *Market demand* → *Market competition* → *Net revenues* → *Average income* → *Electricity demand*. The use of electricity causes an increase of market demand as a result of product innovation and quality improvement, increasing the sales, the revenues, and the income that can be reinvested in more electricity consumption at work or at home.
- *R2b: Electricity demand* → *Evening work time* → *Market supply* → *Net revenues* → *Average income* → *Electricity demand*. The use of electricity for evening lighting allowed local IGAs to work more and increase their sales, the revenues, and the income that can be reinvested in more electricity consumption at work or at home.
- *R2c: Electricity demand* → *Productivity* → *Market supply* → *Net revenues* → *Average income* → *Electricity demand*. The electrification of local production as a result of electricity use (e.g. electrical milling machines, carpentries, garages) increases the productivity, the sales, the revenues, and the income that can be reinvested in more electricity consumption at work or at home.
- *R3: Average income* → *Productivity* → *Market supply* → *Net revenues* → *Average income*. The increase in income is partially reinvested in the local business, increasing the productivity, the sales, the revenues, and the income that can be reinvested again in the activity.

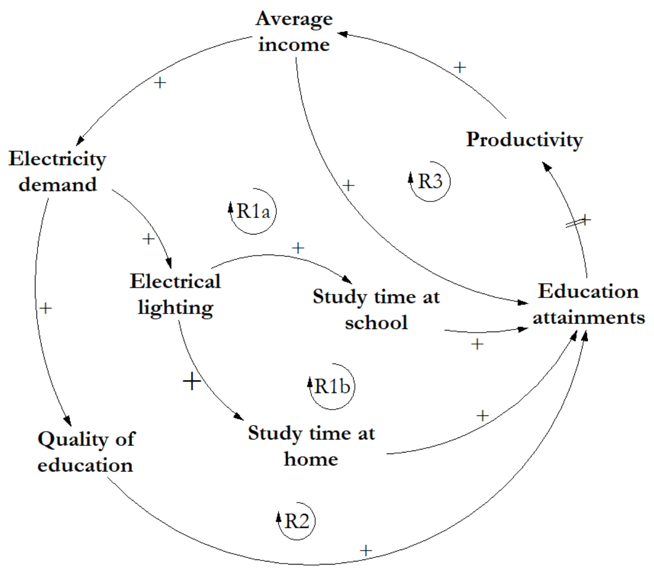
In all the reinforcing loops *R2*, capacity building emerged to be an important factor for improving local productivity.



- *R1: Electricity demand → Farming productivity → Income from farming → Average income → Electricity demand.* Electrical lighting allows people to continue farming activities in the night (e.g. shelling), increasing their production to sell and the income that can be reinvested again in the activity.
- *R2: Market supply → Income from farming → Average income → Average market expenditures → Market demand → Market supply.* The increase of market supply as a result of electrification (see the loops before) generates a positive spill-over effect also for farmers because the development of local market of good and services attracts more external consumers who purchase also local food products. This increases the average income, the expenditures, the market demand, and then supply.
- *R3: Electricity demand → Traditional sources of energy → Market demand → Market supply → Average income → Electricity demand.* The use of electricity reduces the need to purchase and consume the expensive kerosene. This increases the households' purchasing power, the demand for other goods and services in the local market, the local supply, and then the income that can be reinvested in more electricity consumption at work or at home.
- *B1: Electricity demand → Energy cost expenditures → Average market expenditures → → Market demand → Market supply → Average income → Electricity demand.* This balancing loop prevents the unlimited growth of electricity use. Increasing the electricity demand (*viz.* connections and consumption), the expenditures for electricity increase, decreasing the households' purchasing power, the demand for other goods and services in the local market, the local supply, and then the income that can be reinvested in more electricity consumption at work or at home.



- *R1: Electricity demand → Electrical lighting → Daily-time extension → Productive use of free-time → Average income → Electricity demand.* Electrical lighting allows people to extend the day, continue farming activities and working in the night, and potentially increase the income that can be reinvested in more electricity consumption at work or at home.
- *R2a: Electricity demand → Electrical lighting → Evening housework → Daily burden of housework → Productive use of free-time → Average income → Electricity demand.* Electrical lighting allows local women to postpone some housework during the evening, and then exploiting more daily time for continuing farming and working, which in turn allows to potentially increase the income that can be reinvested in more electricity consumption at work or at home.
- *R2b: Electricity demand → Efficiency (completion rate) of housework → Daily burden of housework → Productive use of free-time → Average income → Electricity demand.* Electricity at home can facilitate and speed-up some daily housework (e.g. the electric rice cooker decreases time for cooking), allowing local women to exploit more daily time for continuing farming and working, which in turn allows to potentially increase the income that can be reinvested in more electricity consumption at work or at home.



- *R1a / R1b: Electricity demand → Electrical lighting → Study time at school / Study time at home → Education attainments → Productivity → Average income → Electricity demand.* With electricity at schools / at home, evening studying time allows the pupils to continue studying after the sunset, increasing their educational attainment. This contributes to enhance people's skills and know-how in the long-term – the delay is marked with the two dashes on the causal link –, which is an important driver for increasing productivity, and then income that can be reinvested in more electricity consumption at work, at home, or at school as well.
- *R2: Electricity demand → Quality of education → Education attainments → Productivity → Average income → Electricity demand.* Electricity at schools allows to install and use a local pump, preventing the students to lose a lot of time for gathering the water in other wells in the villages, increasing their educational attainment.
- *R3: Average income → Education attainments → Productivity → Average income.* Local experts confirmed that the percentage of income spent for education is a significant fraction of the total amount. According to the literature (Huisman and Smits 2009), the income level can be considered a stimulus for increasing the local educational level of children, which has a long-term feedback on their future income.

Chapter 7

Formulation of the simulation model

Specification of the mathematical structure and decision rules

A point of view, or a model, is realistic to the extent that it can be adequately interpreted, understood, and accepted by other points of view
(Churchman 1973)

Constructing models, hence, is a process in which expert consensus regarding the feedback structure is essential to the credibility of any given model
(Scholl 2001)

This chapter reports the *formulation* of the simulation model: its mathematical specification of its structure and decision rules – i.e. the conversion of the feedback diagrams to algebraic, differential, and integral equations. The simulation framework is based on Vensim DSS ® software. Its formulation follows an iterative process based on the questionnaires implemented in the field, the information shared with the local experts, and the analysis and re-redefinition of the structure by the modeller. The final structure of the model is defined by the main dynamics highlighted in the conceptualisation process, and it counts 11 main sub-models: *IGAs formation and Income*, *Market demand, Market production and revenues, Agricultural revenues, Population, Time savings, Education, IGAs electricity connections, HHs electricity connections, Household appliances diffusion,* and *Electrical Energy consumption*. The model simulates the impact of electricity access and use on the socio-economic development experienced in Ikondo, and the related feedback on the community's electricity consumption. The contents of this chapter are included in the proceedings of the 36th International Conference of the System Dynamics Society:

Riva F, Investigating and modelling endogenous socio-economic dynamics in long-term electricity demand forecasts for rural contexts of developing countries. *36th Int. Conf. Syst. Dyn. Soc.*, Reykjavík, Iceland: System Dynamics Society; 2018.

7.1. Modelling framework

According to (Sterman 2000), the formulation of a simulation model considers the specification of its structure and decision rules – viz. the conversion of the feedback diagrams to algebraic, differential, and integral equations –, as well as the estimation of the parameters' value and the initial conditions.

In this study, the simulation framework is based on Vensim DSS ® software developed by Ventana Systems. For each discrete time-step *dt*, the software solves all the equations that describe the dynamic behaviour of the modelled system. Thus, the time bounds, and the integration method represent fundamental settings.

Table 18. Time bounds, and integration method set in Vensim DSS ®.

Time unit (t_u)	*Week*
Time step (Δt)	*0.25*
Initial time (Week)	*1*
Final time (Week)	*679.25*
Integration method	*Euler:*
	$Y_{t+dt} = \int_{t}^{t+dt} x \cdot dt = Y_t + x_t \cdot \Delta t$

The initial and final time correspond to the January 2005, and the last month of available data at the end of December 2017.

7.2. Structure formulation

The structure of the model is based on dynamics described in the previous chapter through the conceptualised causal loop diagrams. Its formulation followed an iterative process based on the questionnaires implemented in the field and the information shared with the local experts of CEFA. The formulation of the final structure of the model is based on 11 main modelling blocks (or sub-models): *IGAs formation and Income*, *Market demand, Market production and revenues, Agricultural revenues, Population, Time savings, Education, IGAs electricity connections, HHs electricity connections, Household appliances diffusion,* and *Electrical Energy consumption*.

The model is composed by around 80 levels (*viz.* integral equations), 260 auxiliary variables (viz. algebraic and differential equations), 140 parameters, and 8 look-up tables. For formulating individuals' behaviour, to deal with the classical SD-hypothesis of perfect mixing and homogeneity within the levels, the agents of the model are represented as households divided in two classes: low income households (LI HHs) (i.e. who rely only on agricultural-based activities) and high-income households (HI HHs) (i.e. who rely both on agricultural-based activities and work in an IGA). This assumption, discussed and reasoned with local CEFA's experts, does not consider a very small fraction of the population, viz. the very poor people who live on alms, and very rich traders or large-land owners.

The model simulates the impact of electricity access and use on the socio-economic development experienced in Ikondo's community. It then evaluates the feedback on the community's electricity consumption by generating long-term evolutions of the electricity load of the entire community along the simulated time horizon. The next sub-sections are devoted to the definition of the main equations formulated for the most relevant 7 modelling blocks out of the total 11 ones. The remaining sub-models are reported in *Appendix B*. The time-dependent auxiliary variables are explained for each equation; unless otherwise specified, time-independent variables are all calibration parameters.

7.2.1. IGAs formation and Income

The dynamics of IGAs formation is composed by a cascade (or aging chain) of two 1st-order delays (Fig. 36). One delay occurs during the setting-up of the IGAs – e.g. material procurement and authorization –, and the second is due to the time delay required for dismissing a fraction of such activities that go bankruptcy.

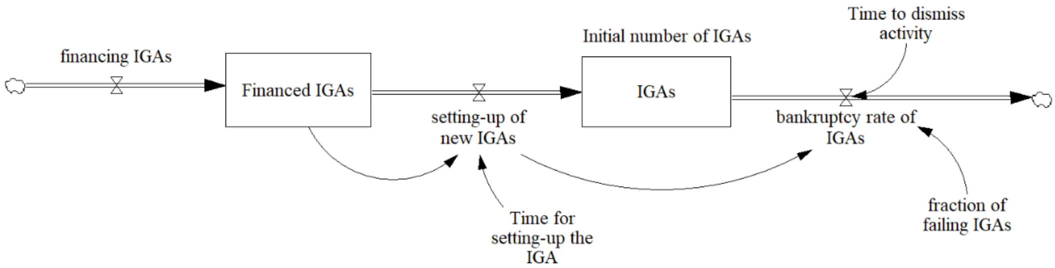


Fig. 36. Cascade of two 1st-order delays representing the IGAs formation process.

$$\begin{cases} IGAs(t) = \int_t \left(setting\text{-}up\ of\ new\ IGAs(t) - bankruptcy\ rate\ of\ IGAs(t) \right) \cdot dt \\ setting\text{-}up\ of\ new\ IGAs(t) = \dfrac{Financed\ IGAs(t)}{Time\ for\ setting\text{-}up\ the\ IGA} \\ Financed\ IGAs(t) = \int_t \left(financing\ IGAs(t) - setting\text{-}up\ of\ new\ IGAs(t) \right) \cdot dt \end{cases} \tag{13}$$

The *setting-up of new IGAs* contains also a positive inflow of 2 IGAs, respectively a tailor shop and a carpentry, implemented by CEFA in January 2017 (information based on data on IGAs electricity connections). Local surveys suggested that the dynamics of financing IGAs takes place through two different mechanisms (Eq. (14)):

(1) *by emulation*: people ask for a loan without a proper market analysis, but just emulating their peers who open a business;

(2) *by market inspection*: people do a proper market analysis before opening a new activity. The analysis concerns the investigation of the *type* and *number* of activities potentially needed in the local market.

$$\begin{cases} financing\ IGAs(t) = IGAs\ by\ emulation(t) + IGAs\ by\ market\ inspection(t) \\ IGAs\ by\ emulation(t) = setting\text{-}up\ of\ new\ IGAs(t) \cdot fraction\ of\ IGAs\ started\ by\ imitation \\ IGAs\ by\ market\ inspection(t) = Perceived\ needed\ new\ IGAs(t) \cdot Fraction\ of\ feasible\ IGAs(t) \end{cases} \tag{14}$$

The variable *Perceived needed new IGAs(t)* depends on the operation of the local market and the level of local demand unsatisfied by the local supply (sub-section 7.2.3), while the variable *Fraction of feasible new IGAs* represents the fraction of potential IGAs to be financed based on people's lag in perceiving electricity benefits – electricity access was provided in February 2005, one month after the initial time set in the simulation –, their available time for dedicating themselves to a new business – modelled as a logistic function –, and their financial means (Eq. (15)).

$$\begin{cases} Fraction\ of\ feasible\ IGAs(t) = Fraction\ of\ affordable\ IGAs(t) \cdot Time\text{-}based\ propensity(t) \cdot Electricity\ availability\ effect(t) \\ Time\text{-}based\ propensity(t) = \dfrac{1}{1 + e^{-\left[k\text{-}time \cdot \left(T\text{-}sigmoid - Total\ weekly\ available\ time\right)\right]}} \\ Electricity\ availability\ effect(t) = \int_t \dfrac{Electricity\ availability(t)}{Time\ to\ perceive\ electricity\ benefits} dt \\ Electricity\ availability(t) = \begin{cases} 0 & if \quad t < 1\ month \\ fr\ of\ potentially\ affordable\ IGAs\ connections & if \quad t \geq 1\ month \end{cases} \end{cases} \tag{15}$$

Where the *fr of potentially affordable IGAs connections* is a calibration parameter that reflects the fact that some IGAs could be unable to pay the electrical connection, due to two main reasons: (1) distance from the electrical junction boxes, and (2) unaffordability. These IGAs could potentially benefit form electricity through spill-over effects caused by a more buoyant market situation. Indeed, as stated by a local expert, "some IGAs are not connected, but locate themselves close to the connected ones, hoping to attract more clients and exploiting some diffuse light". *T-sigmoid* and *k-time* are calibration parameters of the logistic function. The variable *Fraction of affordable IGAs* represents the fraction of IGAs that people can afford based on two financing mechanisms: (i) access to micro-credit, and (ii) self-financing. In Ikondo, micro-credit is managed by the same electricity utility (i.e. SACCOS), and supported by CEFA. The financing through micro-credit is the product between the fraction of people who ask for a loan and the amount of income they are willing to spend to pay the debt back, divided by the investment, the interest (i.e. 2% according to SACCOS), and the payback period. The remaining people who self-finance their activity are supposed to pay all the investment at once.

People's income is directly affected by the cost for opening a business. For the HI and LI class, the income variable represents the households' financial availability within each time unit Δt (viz. 1 week). It increases or decreases based on the changes in the financial inflows that people experience every week, and it follows the dynamics of a 1st-order negative feedback with explicit goal (Sterman 2000) (Fig. 37).

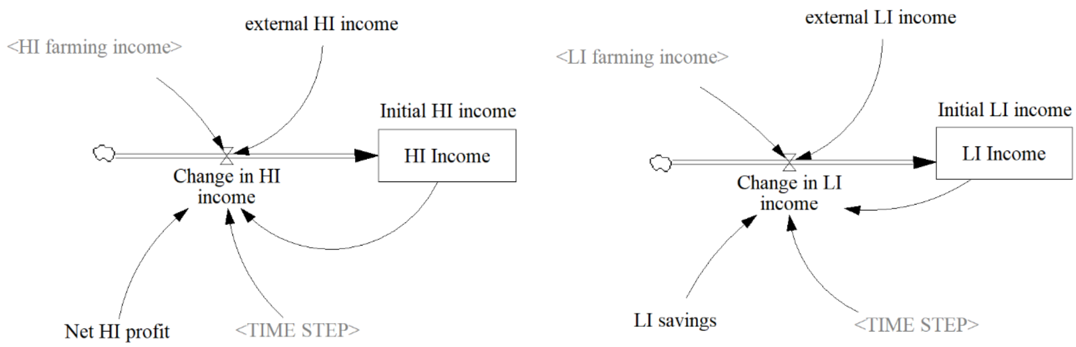


Fig. 37. Stock-and-flow diagrams for HI Income and LI Income variables.

For both the household categories, income depends on people's revenues from their agricultural revenues and from relatives' remittances. HI HHs have also a net income inflow given by the profit from their business activity (*Gross HI profit*, sub-section 7.2.3) minus their debt that they incurred with the micro-credit utility. LI HHs do not have a business but tend to save part of their financial availability needed to self-finance the investments for opening an IGA (Eq. (16)).

$$\begin{cases} \int_t \dfrac{dHI\ Income(t)}{Change\ in\ HI\ Income(t)} = \int_t dt \\ Change\ in\ HI\ Income(t) = \dfrac{\left(external\ HI\ income(t) + Net\ HI\ revenues(t) + HI\ farming\ income\ (t)\right) - HI\ Income(t)}{\Delta t} \\ \int_t \dfrac{dLI\ Income(t)}{Change\ in\ LI\ Income(t)} = \int_t dt \\ Change\ in\ LI\ Income(t) = \dfrac{\left(external\ LI\ income(t) + LI\ farming\ income(t) - LI\ savings\right) - LI\ Income(t)}{\Delta t} \end{cases} \tag{16}$$

7.2.2. Market demand

Local demand for goods and services is the main driver for the operation of a rural market (Riva et al. 2018a). Demand is based on the households' expenditures within each time unit Δt. In accordance with local surveys, the household expenditures on a weekly basis are equal, in absolute value, to the *Income(t)* variable. This hypothesis stands on these two considerations:

1. People living in rural and poor areas do not have the propensity to save money (confirmed also by the local experts);
2. Potential savings are already accounted in the *Net HI profit* and *LI savings* variables of Eq. (16).

Households' expenditures in the local market represent a fraction of the total weekly expenditures. The *Fraction of market expenditures* is therefore the difference between 100% and the fraction of income spent for the following main local assets: food, healthcare, education, and electricity. Expenditures for healthcare and education are exogenous constant inputs, while food and electricity expenditures are endogenous and time-dependant variables. The review of the electricity-development nexus highlights that electricity use in local shops may introduce changes in rural households' expenditures for goods and services, due to improvements in products' quality and innovation, which increases the demand per-capita. This dynamics is formulated for both LI and HI households as a decrease in the fraction of expenditures for food, in favour of an increase in the percentage of income spent for local goods, and services modelled as a 1st-order negative feedback with explicit goal (Eq.(17)).

$$\begin{cases} \int_t \dfrac{dElectricity\ effect\ on\ expenditures(t)}{max\ increase\ of\ week\ expenditures - Electricity\ effect\ on\ expenditures(t)} = \int_t increase\ of\ market\ expenditures(t) \cdot dt \\ increase\ of\ market\ expenditures(t) = fr\ increase\ of\ market\ expeditures \cdot Trend\ in\ connected\ IGAs(t) \\ Fr\ income\ for\ food(t) = initial\ fr\ income\ for\ food - \int_t \dfrac{Electricity\ effect\ on\ expenditures(t)}{Time\ to\ adapt\ market\ expenditures} \cdot dt \end{cases} \tag{17}$$

The *Fr income for food* cannot decrease below a certain minimum such that the total expenditures for food within each time unit Δt is not lower than the initial expenditures for food at time $t=1$ – i.e. the fraction of income spent for food decreases as long as households increase their income without decreasing the absolute value of expenditures for food. The *Trend in connected IGAs* represents the fractional rate of IGAs that get connected to the micro-grid (sub-section 7.2.4).

The household expenditures in the local market multiplied by the number of households and divided by the average price of goods give the total household demand, of which just a percentage can be potentially satisfied locally due to lack of resources (e.g. specific building material) (Eq. (18)).

$$\begin{cases} HI\ demand(t) = \dfrac{Fr\ of\ market\ expenditures\ HI(t) \cdot HI\ Income(t)}{Average\ price\ of\ goods(t)} \\ LI\ demand(t) = \dfrac{Fr\ of\ market\ expenditures\ LI(t) \cdot LI\ Income(t)}{Average\ price\ of\ goods(t)} \\ Total\ potential\ HHs\ demand(t) = HI\ demand(t) \cdot HI\ households(t) + LI\ demand(t) \cdot LI\ households(t) \\ HHs\ demand(t) = fraction\ of\ feasible\ HHs\ market\ supply \cdot Total\ market\ demand(t) \end{cases} \tag{18}$$

The *Average price of goods* is a time-dependent variable because it highly depends on the level of local supply of goods and services (Fig. 38, Eq. (19)). Local interviews confirmed that the availability of local products as a consequence of the opening of new IGAs allows people to spend less money and time for travelling towards other markets outside Ikondo.

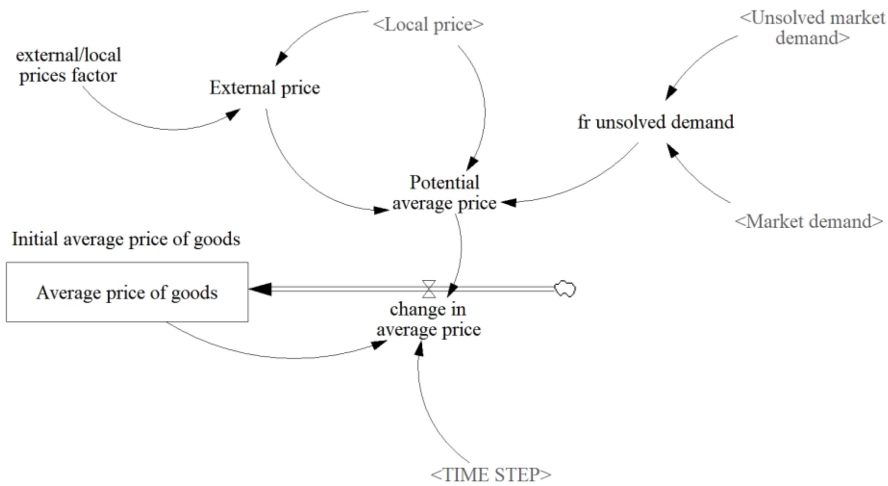


Fig. 38. Stock-and-flow diagram for the *Average price of goods* variable.

$$\begin{cases} \int_t \dfrac{dAverage\ price\ of\ goods(t)}{change\ in\ average\ price(t)} = \int_t dt \\ change\ in\ average\ price(t) = \dfrac{Potential\ average\ price(t) - Average\ price\ of\ goods(t)}{\Delta t} \\ Potential\ average\ price(t) = fr\ unsolved\ demand(t) \cdot External\ price + \left(1 - fr\ unsolved\ demand(t)\right) \cdot Local\ price \\ fr\ unsolved\ demand(t) = \dfrac{Unsolved\ market\ demand(t)}{Total\ market\ demand(t)} \\ External\ price = Local\ price \cdot external/\ local\ prices\ factor \end{cases} \tag{19}$$

The *fr unsolved demand* variable represents the fraction of the total market demand that cannot be satisfied locally (sub-section 7.2.3). The local market does not supply just the households demand, but also three other classes of customers:

1. The *local electricity utility MVC*: according to its charter, MVC has to reinvest almost 50% of its revenues within the local community. The model captures this practice as a market demand of the utility for local supply and goods (*Utility demand*).
2. The *IGAs*: some IGAs supply themselves with raw materials from other local business – *viz.* the market costs of some activities represent revenues for others. This dynamics is constrained by the lack of some specific raw materials, and modelled as 1st-order negative feedback with the calibration parameter *max fr of internal IGAs supply* set as upper limit (Eq.(20)).

$$\begin{cases} IGAs\ demand(t) = \dfrac{Market\ costs(t)}{Specific\ supply\ cost(t)} \cdot fr\ of\ internal\ IGAs\ supply(t) \\ \int_t \dfrac{d(fr\ of\ internal\ IGAs\ supply(t))}{max\ fr\ of\ internal\ IGAs\ supply - fr\ of\ internal\ IGAs\ supply(t)} = \int_t change\ in\ internal\ IGAs\ supply(t) \cdot dt \\ change\ in\ internal\ IGAs\ supply = \dfrac{setting\text{-}up\ of\ new\ IGAs(t)}{IGAs(t)} \cdot fr\ increase\ in\ internal\ IGAs\ supply \end{cases} \tag{20}$$

   The *Market costs* and the *Specific supply cost* variables represent the sum of all the costs and the average specific cost of the local IGAs at time *t*, respectively. These variables are time dependent because the size of the market changes with time and because the specific cost of goods and services changes with the electrification of the village.

3. The *external costumers*: local surveys suggest that the electrification of the village and the consequent expansion of the local market have been pivotal drivers for the attraction of external costumers living in the villages nearby Ikondo. This dynamics is modelled as a 1st-order positive feedback (Eq.(21)).

$$\begin{cases} \int_t \dfrac{d(External\ market\ expenditures(t))}{External\ market\ expenditures(t)} = \int_t change\ in\ external\ demand(t) \cdot dt \\ change\ in\ external\ demand(t) = fr\ \ change\ in\ external\ market\ demand \cdot\ perceived\ \ trend\ of\ market\ supply(t) \\ External\ market\ demand(t) = External\ market\ expenditures(t) \cdot Local\ \ price(t) \end{cases} \tag{21}$$

   The *perceived trend of market supply* is the smoothed trend of the variable representing the market supply at time *t* perceived by people (sub-section 7.2.3).

The *Total market demand* of the village is the sum of the households' demand (*HHs demand*), the demand of the utility (*Utility demand*), the demand of the local IGAs (*IGAs demand*), and the demand of external costumers (*External demand*).

7.2.3. Market supply

The dynamics behind the supply of goods and services in the local market are driven by the number of local IGAs (already described in sub-section 7.2.1), the productivity of each single business, and the time of operation. In the field of economics, the representation of the production of goods and services relies on the so-called "production function", which relates the physical output Q of a production process to quantities of inputs $X_1, X_2, \ldots, X_n$.

$$Q = f(X_1, X_2, \ldots \tag{22}$$

Different forms of production function exist, from the classical linear function – with application to low income rural areas (Schmitz 1965) –, to more complicated models. The Cobb-Douglas is a particular functional form of the production function, widely used to represent the technological relationship between two or more inputs and the total output that can be produced by those inputs. It takes the name from the work of Charles Cobb and Paul Douglas almost one century ago (Charles W. Cobb and Paul H. Douglas 1928). In its generalised form, the Cobb-Douglass function is proportional to the product of *n* terms representing the inputs of the production, each one to the power of their output elasticities (Eq. (23)).

$$Q = A\prod_{i=1}^{n} X_i^{\lambda_i} \tag{23}$$

where λ_i is the output elasticity of input X_i, which measures the responsiveness of the output Q to a change in X_i. A is the total factor productivity, which measures the portion of output Q not explained by the input quantities X_i. An application of Cobb-Douglas low-income contexts is proposed by McArthur and Sachs (McArthur and Sachs 2013), who adopt it to represent the agricultural-based production of rural African economies as a function of physical capital, labour, and land area as production inputs.

In this study, a formulation based on Cobb-Douglas is used to express the market production of local IGAs as the product between the working time and the productivity of each IGA. The latter is expressed in terms of units of goods produced by each IGA in the unit of time (hours), based on the following production time-varying inputs:

- *HI Income*, as a proxy of the physical capital.
- *Primary education level.*

The total factor productivity A_{market} is not constant as well, but it is a function of the electrification rate of the business activities and the effect of capacity building activities, as stated by CEFA's experts. According to local surveys, changes in productivities do not immediately follow changes in the production inputs, but after a time lag due to people's hesitation to new investments and the physical time to adapt their business to increase in the available capital and new knowledges. Eq. (24) below reports the mathematical formulation of the market production.

$$\begin{cases} HI\ capital\ effect(t) = \left(\dfrac{HI\ Income(t)}{Initial\ HI\ Income}\right)^{\varepsilon\text{-}IGAs\ income} \\ I\ education\ effect(t) = \left(\dfrac{I\ educational\ level(t)}{Initial\ educational\ level}\right)^{\gamma\text{-}edu} \\ A_{market}(t) = Reference\ factor\ productivity \cdot \left(1 + electrification\ effect(t) + \vartheta\text{-}capacity\ building\ elasticity\right) \\ electrification\ effect(t) = fraction\ of\ EE\text{-}reliant\ IGAs(t) \cdot \beta\text{-}el \\ Potential\ productivity(t) = A_{market}(t) \cdot HI\ capital\ effect(t) \cdot I\ education\ effect(t) \\ \displaystyle\int_t \frac{Actual\ productivity(t)}{Potential\ productivity(t) - Actual\ productivity(t)} = \frac{1}{Time\ to\ adapt\ productivity} \cdot \int_t dt \\ Actual\ production\ per\ IGA(t) = Actual\ productivity(t) \cdot Actual\ operating\ hours(t) \end{cases} \tag{24}$$

The *fraction of EE-reliant IGAs* variable represents the percentage of IGAs that are highly dependent on electricity use (sub-section 7.2.4), while the variables related to the educational level are proxies of the educational attainment of primary education in the village, which benefited from access to electricity (see *Appendix B*). The expression of *Actual production per IGA* for each time *t* is indeed comparable to a Cobb-Douglas formulation (Eq. (25)) with increasing returns of scale (i.e. the sum of the exponents is greater than one), which means that the output increases by more than proportional respect to changes in its inputs.

$$\textit{Actual production per IGA} \propto \textit{Actual operating hours}^{1} \cdot \left(\textit{HI Income}\right)^{\varepsilon\text{-}\textit{IGAs income}} \cdot \left(\textit{I educational level}\right)^{\gamma\text{-}\textit{edu}} \qquad (25)$$

The product between the *Actual production per IGA* and the total number of *IGAs* gives the value of *Total market supply* at each time *t*, while its backward discrete derivate (represented with the *nabla* symbol ∇) represents the trend of the market supply at time *t* perceived by people used in the previous sub-section for defining the *External demand* (Eq. (26). The backward discrete derivate is evaluated along the time unit t_u=*1 week*, and not along the time-step *Δt*, in order to make the model more robust to potential integration errors, but at the expense of the accuracy of the derivate.

$$\begin{cases} \textit{Total market supply(t)} = \textit{Actual production per IGA(t)} \cdot \textit{IGAs} \\ \textit{preceived trend of market supply(t)} = \dfrac{\nabla_{t_u}\left(\textit{Perceived total market supply(t)}\right)}{t_u} \\ \nabla_{t_u}\left(\textit{Perceived total market supply(t)}\right) = \textit{Perceived total market supply(t)} - \textit{Perceived total market supply}(t - t_u) \\ \displaystyle\int_t \left(\frac{d(\textit{Perceived total market supply(t)})}{\textit{Total market supply(t)} - \textit{Perceived total market supply(t)}} \right) = \frac{1}{\textit{Time to perceive market dynamics}} \int_t dt \end{cases} \qquad (26)$$

The variable *Actual operating hours* represents the working time of each IGA, which is based on the market demand, the households' available time, and the extension of evening working time made available by electricity use for lighting. This variable is modelled as a 2nd-order information delay due to:

1. The time needed to form expectations about potential changes in market dynamics. When the market supply is not balanced by market demand, local businesses adapt their production accordingly. This dynamics requires a certain amount of time to be perceived by people working in local activities.
2. The time needed to change operating hours. As soon local businesses perceive a potential change in the working time, they need time to implement it. Direct observation in the field suggests that their response to potential changes in the working time varies depending on weather it is a potential increase or a necessary reduction in their operating hours. Indeed, people are more willing to increase their working time, and reluctant to reduce it.

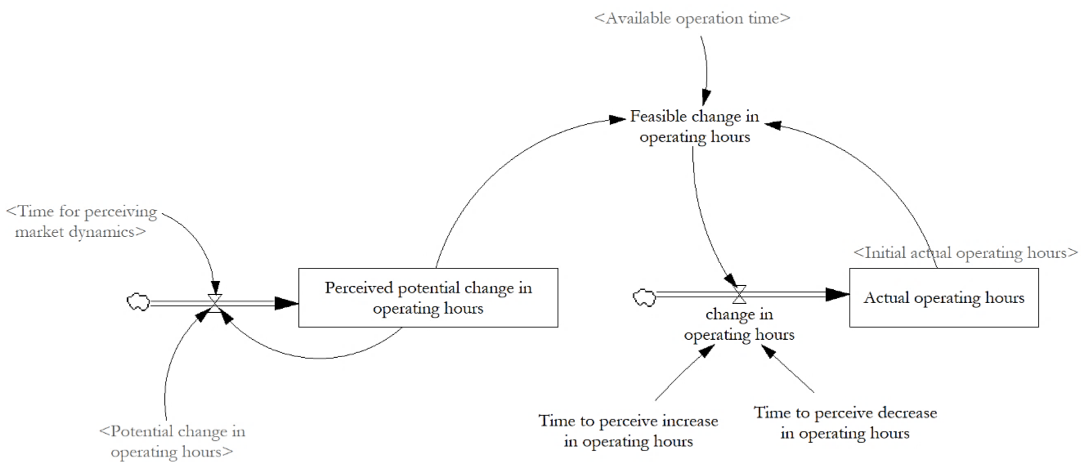


Fig. 39. Stock-and-flow diagram for the *Actual operating hours*.

$$
\begin{cases}
\int_t \left(\dfrac{d(\text{Perceived potential change in operating hours(t)})}{\text{change in perceiving op. time(t)}} \right) = \int_t dt \\
\text{change in perceiving op. time(t)} = \dfrac{\text{Potential change in operating hours(t)} - \text{Perceived potential change in operating hours(t)}}{\text{Time to perceive market dynamics}} \\
\int_t \left(\dfrac{d(\text{Actual operating hours(t)})}{\text{change in operation time(t)}} \right) = \int_t dt \\
\text{change in operation time(t)} = \dfrac{\text{Feasible change in operating hours}}{\begin{cases} \text{Time to perceive increase in operating hours} & \text{if Feasible change in operating hours} > 0 \\ \text{Time to perceive decrease in operating hours} & \text{if Feasible change in operating hours} < 0 \end{cases}} \\
\text{Feasible change in operating hours(t)} = \begin{cases} F1 & \text{if Perceived potential change in operating hours(t)} > 0 \\ F2 & \text{otherwise} \end{cases} \\
F1 = MIN\left(\text{Perceived potential change in operating hour(t), Available operation time(t)} - \text{Actual operating hours(t)}\right) \\
F2 = MAX\left(\text{Perceived potential change in operating hours(t),} - \text{Actual operating hours(t)}\right)
\end{cases}
\tag{27}
$$

The variable *Available operation time* represents the maximum number of hours that people can spend for working (see *Appendix B*). The *Potential change in operating hours* is related to the weekly balancing between local supply and demand. If they differ, the *Unbalanced market demand* generates a potential change in the IGAs production (Eq. (28)).

$$
\begin{cases}
\text{Unbalanced market demand(t)} = \text{Total market demand(t)} - \text{Total market supply(t)} \\
\text{Potential change in IGAs production(t)} = \dfrac{\text{Unbalanced market demand(t)}}{\text{IGAs(t)}} \\
\text{Potential change in operating hours(t)} = \dfrac{\text{Potential change in IGAs production(t)}}{\text{Actual productivity(t)}}
\end{cases}
\tag{28}
$$

When the value of the *Unbalanced market demand* is positive, it represents an unsolved market demand (Eq. (29)), which represents the main driver for creating new expectation about the creation of new IGAs.

$$
\begin{cases}
\text{Unsolved market demand(t)} = MAX\left(\text{Unbalanced market demand(t)}, 0\right) \\
\text{Theoretical needed new IGAs(t)} = \dfrac{\text{Unsolved market demand(t)}}{\text{Actual production per IGA(t)}} \\
\int_t \dfrac{d(\text{Perceived needed new IGAs(t)})}{\text{Theoretical needed new IGAs(t)} - \text{Perceived needed new IGAs(t)}} = \dfrac{1}{\text{Time to perceive market dynamics}} \int_t dt
\end{cases}
\tag{29}
$$

The limiting factor between the market supply and demand gives the quantity of goods and services sold in the local market, the total market revenues, and the households' net profit.

$$
\begin{cases}
\textit{Selling rate(t)} = MIN\left(\textit{Total market supply(t)} - \textit{Total market demand(t)}\right) \\
\textit{Market revenues(t)} = \textit{Selling rate(t)} \cdot \textit{Local price(t)} \\
\textit{Market costs(t)} = \textit{Total market supply(t)} \cdot \textit{Specific supply cost(t)} \\
\textit{Market profits(t)} = \textit{Market revenues(t)} - \textit{Market costs(t)} \\
\textit{Gross HI profit(t)} = \dfrac{\textit{Market profits(t)}}{\textit{HI households(t)}}
\end{cases}
\tag{30}
$$

The *Specific supply cost* variable represents the mixed average production cost faced by all the IGAs. Direct observation in the field suggests that the local costs changed after electrification, especially for electricity-reliant (EE-reliant) IGAs, that can now save money by using electricity (e.g. electricity-driven milling machines instead of diesel-based mills). The variable is the weighted average between (i) an ideal mean cost supposing no electricity use, and (ii) the ideal mean cost of the EE-reliant IGAs. The mean cost of the EE-reliant IGAs is expressed as the production cost without electricity use multiplied by a decreasing factor which considers the effect of electricity use on production costs.

$$
\begin{cases}
\textit{Specific supply cost(t)} = \textit{supply cost without EE(t)} + \textit{supply cost with EE(t)} \\
\textit{supply cost without EE(t)} = \textit{production cost without EE} \cdot \left(1 - \textit{fraction of EE-reliant IGAs(t)}\right) \\
\textit{supply cost with EE(t)} = \textit{production cost with EE} \cdot \textit{fraction of EE-reliant IGAs(t)} \\
\textit{production cost with EE} = \textit{production cost without EE} \cdot \textit{Fractional decrease in cost given by EE}
\end{cases}
\tag{31}
$$

The *Local price* is the product between the *Specific supply cost* and a constant calibration parameter, namely *price to cost factor*, which represents the mark-up ratio. This is of course a simplification, useful to set price is a quick and easy way (Sterman 2000). Nevertheless, in developing local markets, the dynamics of behind the equilibrium, or market-clearing, price (viz. when supply exceeds demand, prices fall) does not always work, as Barnum and Sabot (Barnum and Sabot 1977) found out for urban Tanzania.

7.2.4. IGAs electricity connections

According to the *CASE 3. "Modelling the Forest or Modelling the Trees"*, the diffusion of electrical connections can be potentially explained as an innovation diffusion. Indeed, as suggested by Sterman, "The spread of rumours and new ideas, the adoption of new technologies, and the growth of new products can all be viewed as epidemics spreading by positive feedback as those who have adopted the innovation "infect" those who have not ((Sterman 2000), pg. 323)". Local surveys indicated two important supporting factors of the diffusion of electrical connections for both IGAs and HHs:

1. The *peer*- and the *awareness*-effect, which are the same drivers considered in the Bass formulation (Bass 1969; Sterman 2000);
2. The *financial availability*, which is a constraint for people who cannot afford electrical connections.

In particular, the affordability of the electrical connection represents (i) a barrier for users living too far from the nearest electrical junction box, or (ii) e time-delay for getting the connection. Given these considerations, the formulation of the IGAs connections dynamics reflects a "corrected" Bass model in order to consider the income effect (Eq. (32)).

$$\begin{cases} \textit{Unconnected IGAs(t)} = \textit{IGAs(t)} - \left(\textit{Connected IGAs(t)} + \textit{IGAs to be connected(t)}\right) \\ \textit{Potential IGAs to be connected(t)} = \textit{Unconnected IGAs(t)} \cdot \textit{fraction of potentially affordable IGAs connections} \\ \textit{IGAs decision to connect rate(t)} = \textit{IGAs awareness(t)} + \textit{IGAs social contagion(t)} \\ \textit{IGAs awareness(t)} = \textit{Potential IGAs to be connected(t)} \cdot \textit{awareness effect IGAs} \\ \textit{IGAs social contagion(t)} = \textit{Potential IGAs to be connected(t)} \cdot \textit{social contagion IGAs} \cdot \dfrac{\textit{IGAs to be connected(t)+Connected IGAs(t)}}{\textit{IGAs}} \\ \displaystyle\int_t \frac{d(\textit{IGAs to be connected(t)})}{\textit{IGAs decision to connect rate(t)} - \textit{IGAs connection rate(t)} - \textit{bankruptcy of IGAs to be connected(t)}} = \int_t dt \\ \textit{bankruptcy of IGAs to be connected(t)} = \textit{bankruptcy rate of IGAs(t)} \cdot \textit{fr of IGAs to be connected(t)} \\ \textit{IGAs connection rate(t)} = \textit{IGAs to be connected(t)} \cdot \textit{affordable connections by IGAs(t)} \\ \displaystyle\int_t \frac{d(\textit{Connected IGAs(t)})}{\textit{IGAs connection rate(t)} - \textit{bankruptcy of connected IGAs(t)}} = \int_t dt \\ \textit{bankruptcy connected IGAs(t)} = \textit{bankruptcy rate of IGAs(t)} \cdot \textit{fr of connected IGAs(t)} \end{cases} \tag{32}$$

The variable *affordable connections by IGAs(t)* is a time-dependent variable, and represents the average percentage of connections that each IGA can afford at time *t*. It is expressed as a fraction of the *HI Income* that all the households composing an IGA are willing to invest in the connection (Eq. (33)).

$$\textit{affordable connections by IGAs(t)} = \left(\frac{\textit{HI Income(t)} \big/ \textit{IGAs per HH}}{\textit{IGA connection cost(t)}} \right) \cdot \textit{Willingness to pay for connection for IGAs} \tag{33}$$

The *IGA connection cost(t)* is a time-dependent variable due to the changes in the tariff scheme implemented by CEFA over the years. Indeed, both data and interviews with the experts confirmed that before 2006-2007, the cost of connection was much lower and based on a fixed-price mechanism. After that period, the tariff was increased and customised for each household based on the proximity to the nearest electrical junction box (Eq. (34)).

$$\textit{IGA connection cost(t)} = \begin{cases} \textit{IGA connection cost in period I} & \textit{if} \quad \textit{TIME} < \textit{Duration of period I for IGAs} \\ \textit{GA connection cost in period II} & \textit{elsewhere} \end{cases} \tag{34}$$

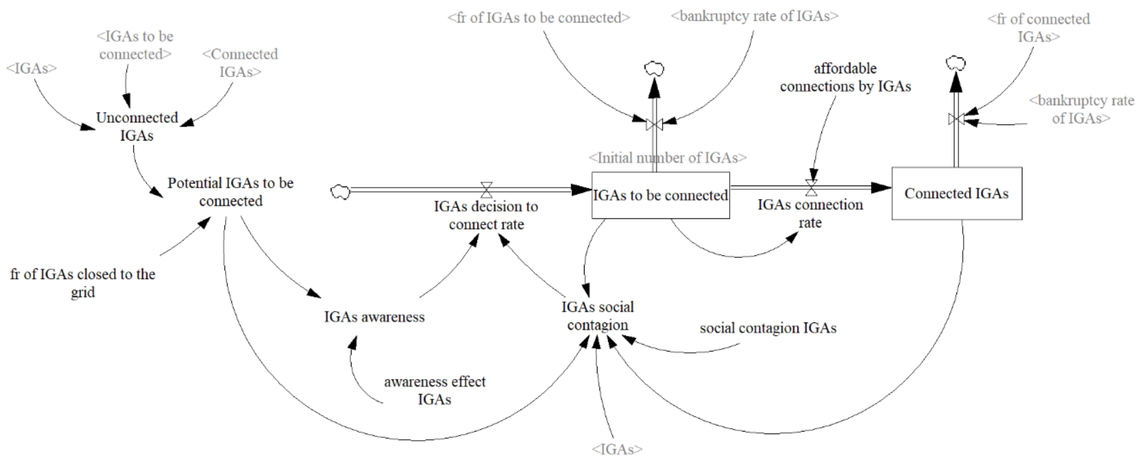


Fig. 40. Stock-and-flow diagram for the IGAs connections process.

Notably, the *Initial number of IGAs* are "innovators" of the diffusion process, viz. already determined to be connected and set as initial value in the *IGAs to be connected* stock. The product between the *Connected IGAs* variable and the calibration parameter *fraction of EE-reliant IGAs respect to connected IGAs* provides the number of *Connected EE-reliant IGAs* and *Connected not EE-reliant IGAs*, to identify the large energy-consuming IGAs (e.g. milling machines, carpentries, garages) from the others, respectively. Another hypothesis is that the connection rate does not account for the time needed for physically extending and installing the connection, since it is negligible if compared to the time delay due to affordability reasons.

7.2.5. HHs electricity connections

The formulation of the electricity connections diffusion for households is based on a two-level chain, one for each HHs class. Each level contains the same equations formulated for IGAs connections. Two are the main differences:

i. The proximity of the HHs to the grid is not a fixed parameter, but it is a time-dependent variable. Indeed, contrary to the IGAs, which were almost all set-up after electrification, the village planning of the houses dates back to years before electrification. Although local surveys suggest that some families decided to move and rebuild their house close to the mini-grid, many households are still waiting for the extension of the network to their neighbourhoods. This is formulated as a 1st-order negative feedback with explicit goal (viz. the *Total access to electricity = 1*), and the discrete *Trend in HH connections* multiplied by the effect of internal migration is as a proxy of the network expansion.

$$\begin{cases} \displaystyle\int_t \frac{d(\mathit{fr\ of\ HHs\ close\ to\ the\ grid(t)})}{\mathit{network\ expansion(t)}} = \int_t dt \\ \mathit{network\ expansion(t)} = \left(\mathit{Total\ access\ to\ electricty} - \mathit{fr\ of\ HHs\ close\ to\ the\ grid(t)}\right) \cdot \mathit{household\ approach(t)} \\ \mathit{household\ approach(t)} = \mathit{Trend\ in\ HH\ connections(t)} \cdot \mathit{internal\ migration\ effect} \\ \mathit{Trend\ in\ HH\ connections(t)} = \dfrac{\nabla_{t_u}\left(\mathit{Total\ connected\ HHs(t)}\right) / t_u}{\mathit{Total\ households(t)}} \\ \mathit{Total\ connected\ HHs(t)} = \mathit{Connected\ HI\ HHs(t)} + \mathit{Connected\ LI\ HHs(t)} \end{cases} \tag{35}$$

ii. The "innovators", viz. the households already determined to be connected, are just a fraction of the initial HHs, not all the initial population.

As for the formulation of the IGAs connections, the affordable connections by HI and LI HHs are fractions of the *HI Income* and *LI Income* that the *HI* and *LI HHs to be connected* are willing to invest in the connection.

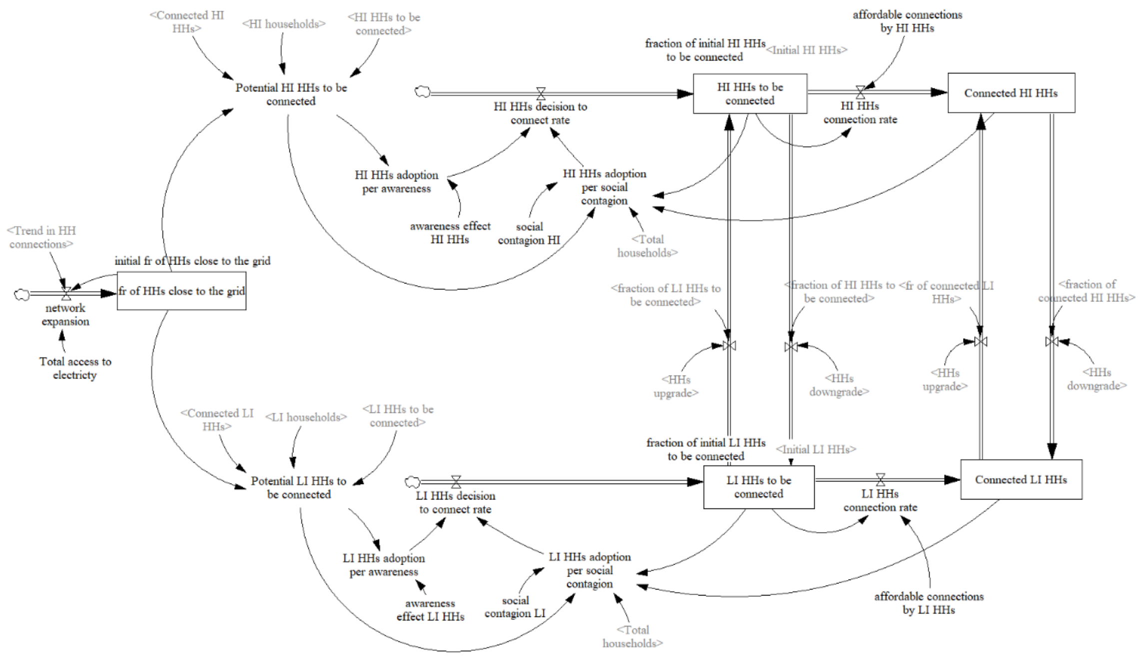


Fig. 41. Two-level chain of the HHs connections.

7.2.6. Household appliances diffusion

The local surveys and the literature confirm that the financial availability is the key factor for the decision to buy new electrical appliances, followed by people's willingness to imitate their peers. E.g., in their Residential Energy Model Global (REGM) applied to India, China, South East Asia, South Africa and Brazil, Ruijven et al. (van Ruijven et al. 2012) and Daioglou et al. (Daioglou et al. 2012) represent the diffusion and ownership of household electric appliances through a logistic (or S-shaped) curve, as a function of household's expenditures (considered in their work as a proxy of income). Also, Louw et al. (Louw et al. 2008) suggest that the use of electricity by low-income South-African households is a cost-based decision based on income, especially regarding the ownership of electrical appliances, which depends on prices of devices and people's affordability.

With this precondition, the sub-model concerning the diffusion of electrical appliances among households is based on Hartvigsson et al. (Hartvigsson et al. 2018a), who represent the diffusion of an electrical appliance i in a Tanzanian rural village as the product between the average income and a parameter, namely "diffusion rate", which represent the expected ownership of appliance i per unit of income. In accordance with this, the diffusion of each appliance is formulated as a 1st-order delay with a saturation limit, which represents the maximum number of appliance i that each family can realistically own (Eq. (36)). Fig. 42 represents an example for the diffusion of lights for HI households.

$$\begin{cases} \int_t \dfrac{d(\mathit{Appliance}_i(t))}{\mathit{appliance}_i\ \mathit{purchasing\ rate}(t)} = \int_t dt \\ \mathit{purchasing\ rate}_i(t) = \begin{cases} \dfrac{\mathit{Potential\ appliance}_i - \mathit{Appliance}_i(t)}{\mathit{Time\ to\ purchase\ appliances}} & \mathit{if}\quad \mathit{Potential\ appliance}_i < \mathit{saturation}_i \\ 0 & \mathit{elsewhere} \end{cases} \\ \mathit{Potential\ appliance}_i = \mathit{Income}(t) \cdot \mathit{diffusion\ rate}_i \end{cases} \tag{36}$$

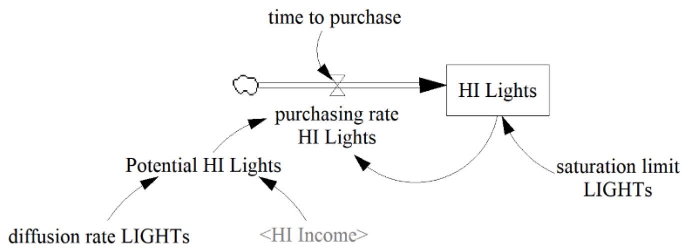


Fig. 42. Stock-and-flow diagrams for the diffusion process of HI Lights.

The classes of appliances modelled in this work are based on two surveys to 67 households with access to electricity carried out in 4 electrified villages in the Ikondo-Matembwe area in May 2016 (Nyombo and Kidegembye) and September 2017 (Ikondo and Ukalawa). The main 6 classes of appliances owned by at least 3% of the survey households are resumed in Table 19 below.

Table 19. Main classes of electrical appliances owned by the interviewed people in Ikondo-Matembwe area.

Electrical appliance class	*Ownership*
Lights (indoor and/or outdoor)	100%
Phone chargers	84%
Stereos	67%
TVs	48%
Irons	24%
Decoders	4%

7.2.7. Electrical energy consumption

This sub-model contains the formulation of the energy demand of the entire Ikondo community. The total electricity consumption of the entire community is given by the sum of the electricity demand of households and IGAs.

$$\mathit{Total\ electricity\ demand}(t) = \mathit{Total\ HHs\ electricity\ demand}(t) + \mathit{Total\ IGAs\ electricity\ demand}(t) \tag{37}$$

Household electricity demand

For HHs, the *Total HHs electricity demand* in each *dt* (Eq. (38)) is the summation of the electricity consumption of the two income groups (viz. HI and LI HHs), which is in turn defined as the summation of the product between the number of connected users within each income group (*Connected HH$_j$*), the number appliances owned for each class (*Appliance$_j$*), their nominal power (*Electric Power$_i$*), their functioning time within each *dt* (*Functioning time for appliance$_i$*), and the power plant reliability (*El Reliability*).

$$\begin{cases} \textit{Total HHs electricity demand(t)} = \sum_{j=1}^{2} \textit{Connected HHs}_j\textit{(t)} \cdot \textit{HHs electricity consumption(t)} \\ \textit{HHs el. load(t)} = \sum_{i=1}^{6} \textit{Appliance}_i\textit{(t)} \cdot \textit{Electric Power}_i \cdot \textit{Functioning time for appliance}_i\textit{(t)} \cdot \textit{El Reliability} \end{cases} \tag{38}$$

With *Connected HH$_j$* and *Appliance$_j$* defined in sub-sections 7.2.5 and 7.2.6, respectively; *Electric Power$_i$* for all the 6 classes of appliances is a calibration parameter, and the *El Reliability* is a parameter that considers the unmet load due to unexpected outages. The *Functioning time for appliance$_i$* a time-dependent variable, which depends on the elasticity of household electricity demand. Indeed, the electricity-development nexus and the model conceptualisation suggest that the electricity load in the *dt* is an aspect that might be influenced by people's income and electricity cost. People adjust their electricity consumption by limiting the functioning time (i.e. the time of use) of their appliances, especially the most energy consuming ones. The formulation of this dynamics follows a 1st-oder delay applied to both connected HI and LI HHs, since the hypothesis is that people can potentially adjust their electricity consumptions once received the bill every month (for the sake of clarity, Eq. (39) is formulated for households in general, but the same equations both apply for HI and LI HHs).

$$\begin{cases} \textit{fr change in time to use electricity(t)} = \textit{Electricity-Income elasticity} \cdot \textit{change in fr income for el. use(t)} \\ \textit{change in fr income for el. use(t)} = \dfrac{\textit{Fr income for el. use(t)} - \textit{Fr income for el. use(t} - \textit{time to adapt electricity use)}}{\textit{Fr income for el. use(t)}} \\ \textit{Fr income for el. use(t)} = \dfrac{\textit{HHs electricity bill(t)}}{\textit{Income(t)}} \\ \int_t \dfrac{d(\textit{Functioning time for appliance(t)})}{\textit{Functioning time for appliance(t)} \cdot \textit{fr change in time to use electricity(t)}} = \dfrac{1}{\textit{time to adapt electricity use}} \cdot \int_t dt \end{cases} \tag{39}$$

Where the *time to adapt electricity use* parameter represents a lag of at least 4.25 weeks (i.e. 1 month), and the *Electricity-Income elasticity* is a calibration parameter representing households' load sensitivity to changes in the electricity cost respect their income. *HHs electricity bill* is the variable representing the cost of electricity in the unit of time t_u for the connected HHs. It is calculated as the monthly fixed electricity fee (converted to a weekly basis in accordance with the t_u) plus the product between the electricity consumption of each household in the time unit t_u (*HHs el. load*) and the variable electricity fee. The two components of the fee are derived from MVC's data and introduced as look-up tables, apart from the missing values from 2005 to 2010 set as calibration parameters (Fig. 43).

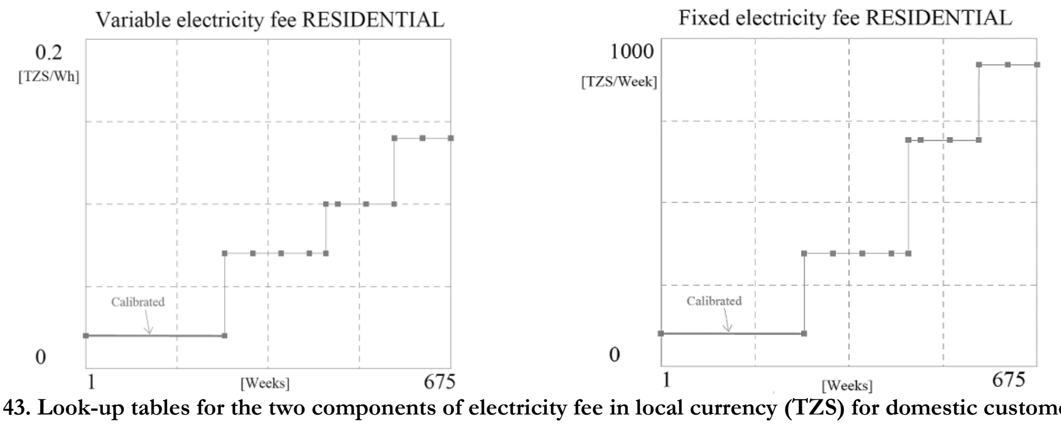


Fig. 43. Look-up tables for the two components of electricity fee in local currency (TZS) for domestic customers.

Productive electricity demand

For IGAs, the *Total IGAs electricity demand* in each *dt* is the summation of the electricity consumption of the two types of IGAs (viz. EE-reliant IGAs and the others), which is in turn defined as the product between the number of users of each type of IGAs (*Connected IGAs$_j$*), the related electric energy consumption in the t_u (*IGAs electricity demand$_j$*), and the power plant reliability (*El Reliability*).

$$Total\ IGAs\ electricity\ demand(t) = \sum_{j=1}^{2} Connected\ IGAs_j(t) \cdot IGAs\ electricity\ demand_j(t) \cdot El\ Reliability \quad (40)$$

With *Connected IGAs$_j$* defined in sub-section 7.2.4. *IGAs electricity demand$_j$* is a time-dependent variable, which depends on the elasticity of productive electricity demand. Indeed, electricity consumption represents a significant share of the total production costs especially for EE-reliant IGAs. Local IGAs adjust their electricity consumption based on changes in the electricity tariff. The formulation of this dynamics follows a 1st-oder delay applied to both *EE-* and *notEE-connected IGAs*, with the same hypothesis that local business can potentially adjust their electricity consumptions every month (for the sake of clarity, Eq. (41) is formulated for "IGAs" in general, but the same equations both apply for EE- and notEE-connected IGAs). The *Variable el. fee for IGAs* is derived from MVC's data and introduced as look-up table.

$$\begin{cases} fr\ change\ in\ IGA\ el.\ demand(t) = \dfrac{fr\ change\ in\ IGAs\ electricity\ fee\ (t) \cdot Electricity\text{-}Fee\ elasticity\ for\ IGAs}{time\ to\ adapt\ electricity\ use} \\ fr\ change\ in\ IGAs\ el.\ fee(t) = \dfrac{Variable\ el.\ fee\ for\ IGAs(t) - Variable\ el.\ fee\ for\ IGAs(t - time\ to\ adapt\ electricity\ use)}{Variable\ el.fee\ for\ IGAs(t)} \\ \int_t \dfrac{d(Time\ of\ productive\ electricity\ use(t))}{change\ in\ electricity\ use\ for\ IGAs(t)} = \int_t dt \\ IGAs\ el.\ load(t) = El.Power\ IGA \cdot Time\ of\ productive\ electricity\ use(t) \end{cases} \quad (41)$$

The parameter *El.Power IGA* is different between the two types of IGAs and they are calibration parameters. Also the variable *change in electricity use for IGAs(t)* is different between *notEE-reliant IGAs* and *EE-reliant IGAs*. For *notEE-reliant IGAs*, it is modelled as a co-flow of the working hours (viz. the *Actual Operating hours* of Eq. (27)), with the hypothesis that the utilisation of electricity in these IGAs increases proportional to the working hours but decreases proportional to the change in the electricity fee (Eq. (42)). For *EE-reliant IGAs*, the utilisation time of electricity is much lower than the working hours – they are characterised by very low coincidence factors (Hartvigsson and Ahlgren 2018) –, and it changes based only on variations in the electricity fees (Eq. (43)).

$$\begin{cases} change\ in\ el.use\ for\ not\ EE\text{-}reliant\ IGAs(t) = fr\ of\ operating\ time\ with\ electricity \cdot change\ of\ el.\ utilisation(t) \\ change\ of\ el.\ utilisation(t) = \left(change\ in\ operation\ time(t) + fr\ change\ in\ IGA\ el.\ demand(t)\right) \end{cases} \quad (42)$$

$$change\ in\ el.use\ for\ EE\text{-}reliant\ IGAs(t) = fr\ change\ in\ EE\text{-}reliant\ IGA\ el.\ demand(t) \quad (43)$$

The calibration parameter *fr of operating time with electricity* indicates the fraction of the working hours during which electricity is used. The sum between the fixed electricity fee for productive use and the product between the *IGAs el. load* and the variable electricity fee gives the *IGAs electricity bill* for the two types of IGAs. As for the HHs electricity fees, the two components of the tariff are derived from MVC's data and introduced as look-up tables, apart from the missing values from 2005 to 2010 that are introduced as calibration parameters.

Local utility revenues

The sum of the expenditures for electricity consumption and the new connections for both households and business activities (Eq. (44)) gives the total *El. utility revenues*, which was introduced in sub-section 7.2.2 for defining the market demand.

$$
\begin{cases}
\textit{HI HHs el. use expenditures(t)} = \textit{HI HHs electricity bill(t)} \cdot \textit{Connected HI HHs(t)} \\
\textit{LI HHs el. use expenditures(t)} = \textit{LI HHs electricity bill(t)} \cdot \textit{Connected LI HHs(t)} \\
\textit{HHs connections expenditures(t)} = \textit{HH connection cost(t)} \cdot \left(\textit{LI HHs connection rate(t)} + \textit{HI HHs connection rate(t)} \right) \\
\\
\textit{EE-reliant IGAs el. use expenditures(t)} = \textit{EE-reliant IGAs electricity bill(t)} \cdot \textit{Connected EE-reliant IGAs(t)} \\
\textit{notEE-reliant IGAs el. use expenditures(t)} = \textit{notEE-reliant IGAs electricity bill(t)} \cdot \textit{Connected notEE-reliant IGAs(t)} \\
\textit{IGAs connections expenditures(t)} = \textit{IGAs connection cost(t)} \cdot \textit{IGAs connection rate(t)}
\end{cases}
\tag{44}
$$

Chapter 8

Model Calibration

Assessing behaviour reproduction and uncovering hidden flaws and dynamics

Sherlock Holmes: "It is a capital mistake to theorize before one has data"
(Arthur Conan Doyle 1887)

In God we trust. All others must bring data
(Edwards Deming 1900s)

As for the future, your task is not to foresee, but to enable it
(Pour ce qui est de l'avenir, il ne s'agit pas de le prévoir, mais de le rendre possible)
(Antoine de Saint-Exupèry 1948)

This chapter reports the *calibration* of the simulation model, in order to (i) verify the ability of the model to replicate the observed historical behaviour of the system, (ii) uncover model flaws and hidden dynamics, and (iii) identify a reasonable set of parameters' values most consistent with relevant the knowledge of the system. The calibration is performed by relying on historical data on the electricity consumption in the Ikondo village, and on local interviews to define the search space for all the calibrating parameters. The Powell algorithm is used to run the optimisation. The Markov-chain Monte-Carlo (MCMC) is then used to explore the appropriateness of the calibration of the model, and to assess potential good proxies of the confidence bounds of the calibrated parameters. The contents of this chapter are included in the proceedings of the 36th International Conference of the System Dynamics Society:

Riva F, Investigating and modelling endogenous socio-economic dynamics in long-term electricity demand forecasts for rural contexts of developing countries. *36th Int. Conf. Syst. Dyn. Soc.*, Reykjavík, Iceland: System Dynamics Society; 2018.

8.1. Calibration settings

Model calibration is a fundamental step of the formulation of a SD-model. According to Sterman (Sterman 2000), model calibration should not be used to assess the validity or confirming the model, but for building confidence in it. Accordingly, it is here employed for assessing the structure and the uncertainty of the model, since it aims at:

(i) verifying the ability of the model to replicate the observed historical behaviour of the system;
(ii) uncovering model flaws and hidden dynamics;
(iii) identifying a reasonable set of parameters' values most consistent with relevant the knowledge of the system, that could be employed for further applications of the model.

The model calibration needs appropriate and reliable data. According to Jay W. Forrester (Forrester 1980), three types of data are necessary to develop the structure in models: *numerical* (e.g. time series), *written* (e.g. operating procedures, archival materials), and *mental data* (e.g. people's impressions, their perception of the system). In this study, numerical data are used for comparing model behaviour, while mental and written data are employed to set the search-space of the optimisation.

8.1.1. Historical time-series

The lack of reliable and available data is one of the most critical challenges for tracking the progress and supporting the research and new investments in rural electrification. In this context, CEFA has been implementing a data recording system of electricity use information from the beginning of 2005, when the Ikondo plant started producing electricity. For accounting purposes, 2 main types of time-series data have been tracking:

(1) Number of metered electricity connections;
(2) Monthly electricity consumptions of all the connected users.

Each data point contains the information (viz. "data items") resumed in Table 20. The villages of Isoliwaya, Kanikelele, Nyave, and Ukalawa were electrified through the extension of the transmission line implemented in 2016, and they are not considered in this work since they are outside the boundary of the system. Similarly, also CEFA's facilitates and cooperatives are excluded due to data scarcity, a different accounting mechanism of electricity use, and because their operations do not cope with the dynamics of market supply described in sub-section 7.2.3. Schools, churches, administrative offices are excluded as well since they are outside the boundaries of the analysis.

Table 20. Data items for CEFA's time-series data

Consumer type	Households IGAs (Public services)
Villages	Ikondo (Isoliwaya) (Kanikelele) (Nyave) (Ukalawa)

Raw data were processed to fix some issues observed in the main database – Table 21 reports the main problems and the implemented solutions. The final panel database contains 524 data points. Fig. 44 and Fig. 45 report the time-series data of monthly electricity consumptions and the number of metered electricity connections for both the HHs and the IGAs. The solid black lines, whose values vary from 0 to 100% (the holes in the lines indicate 0% of data availability), represent the percentage of data available each month after the data processing.

Table 21. Data processing rules of CEFA's database.

Issue	Condition		Solution
Missing data points	*> 1 consecutive missing datum*	→	*REMOVAL* of the datum
	= 1 isolated missing datum	→	*MEAN VALUE* between the first (two) preceding and the first (two) consecutive value(s)
Aggregated records	*data referring to 2 different months are recorded all in 1 month*	→	The aggregated records *SPLITTED IN HALF* in two monthly values
Monthly outlier	*the value of electricity demand for a month differs more than 75% from the first preceding and the first consecutive available value*	→	*REMOVAL* of that monthly datum

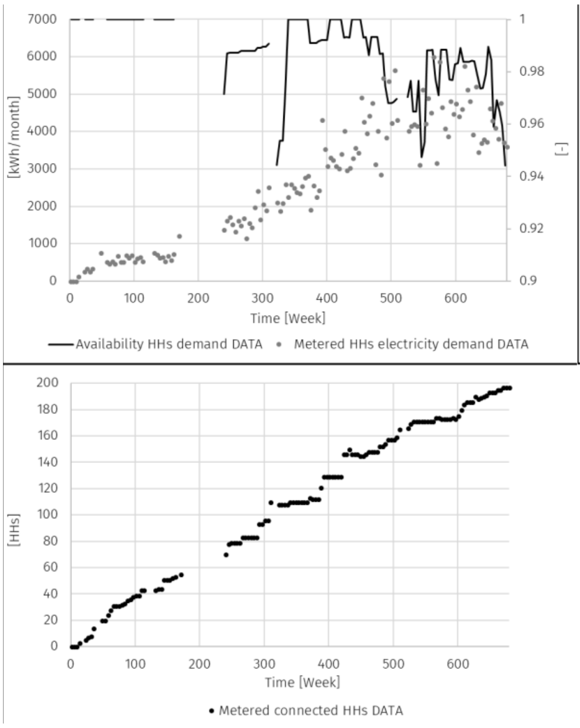


Fig. 44. Data on monthly electricity demand for HHs [*129 data points*] (top) and on the number of HHs connected to the mini-grid [1*31 data points*] (bottom).

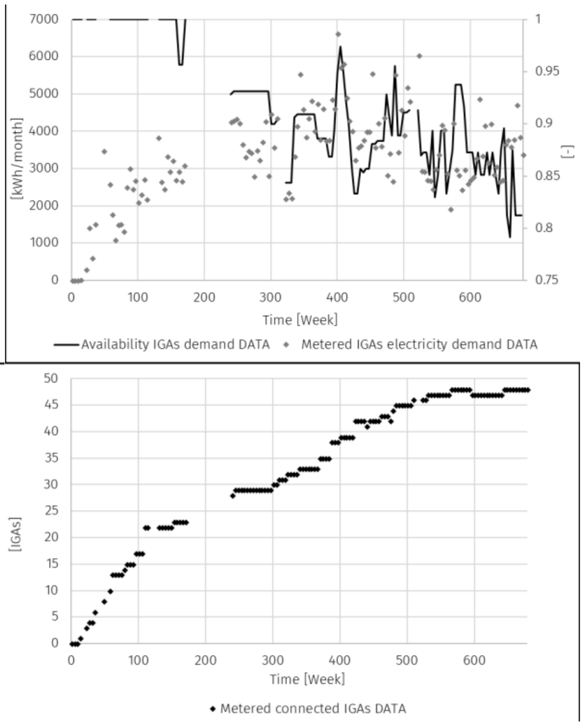


Fig. 45. Data on monthly electricity demand for IGAs [*131 data points*] (top) and on the number of IGAs connected to the mini-grid [133 data points] (bottom).

8.1.2. Optimisation Controls

Model calibration is a mathematical optimisation, which finds the combination of the parameters, which minimises the difference between model output and historical data. Two are the main controls to set in order to perform an appropriate optimisation: the *Optimiser* and the *Search-space*.

Optimiser

The settings of the optimiser define the mathematical procedure to employ in Vensim DSS ® in order to search the optimal solution. The Powell's algorithm is used, based on a numerical procedure proposed by Michael J. D. Powell (Powell 1964). It consists in an iterative algorithm, which starts from an initial point (i.e. an initial set of values for all the parameters to optimise) through a set of initial search-vectors, and proceeds towards bi-directional minimisations along each vector and their linear combinations until final convergence.

Search-space

The definition of the search-space for the optimisation guarantees that the final solution is found within feasible values of each parameter to calibrate. The model counts 139 constant parameters, 123 of which are calibrated through the definition of an appropriate search-space based on the literature, local interview, modeller's choice. For each calibrated parameter, Table A 6 in the *Appendix C* reports the search-space and the related source and reference. The acronyms *LB* and *UB* stand for "Lower Bound" and "Upper Bound", respectively.

8.1.3. Payoff Definition

In the calibration process of a dynamic model, the payoff is a number that summarizes the goodness of a simulation respect to the available data. Let us consider the optimisation of a model through the calibration on one variable respect to the corresponding single time-series: for each iteration *k* performed by the optimiser, the model is simulated with such set of calibration parameters' values corresponding to that iteration *k*. During each simulation *k*, the difference between the historical datum and the simulated value of the corresponding model variable is computed for each time *t*, along with any possible likelihood term *a*, then squared and divided by the scale parameter *weight*. The opposite of the sum of all such differences computed along the entire horizon *T* gives the payoff of the simulation *k* (Eq. (45)). The final iteration performed by the optimiser is the one with the minimum value of the payoff that determines the end of the calibration.

$$payoff_k = -\sum_{t=1,\ dt}^{T}\left[\frac{\left(model\ vaue(t) - datum(t)\right)^2}{weight} - a\right] \tag{45}$$

The scale parameter *weight* is a fundamental element to choose if the optimisation of a model is performed on mores variables and corresponding time-series that have different orders of magnitude. E.g., performing an optimisation on a variable which varies between 0-1 and on another one which varies between 0-10000 means that a small change in the 0-10000 variable will far outweigh the 0-1 variable. So, a weight of the order of 10000 will bring the 0-10000 variable into the same range as the 0-1 one. The scale parameter allows therefore to define the following formulation of the payoff in case of calibration on multiple variables $v=1,\dots,V$ and corresponding time-series (Eq. (46)):

$$payoff_k = -\sum_{t=1,\ dt}^{T}\sum_{v=1}^{V}\left[\frac{\left(model\ vaue_v(t) - datum_v(t)\right)^2}{weight_v} - a_v\right] \tag{46}$$

The *weight* and the likelihood term *a* can be express arbitrarily and in different ways. In this study, they are formulated in the way described in Eq. (47), which makes it possible to estimate the weight as a calibration parameter.

$$\begin{cases} weight_v = \dfrac{StdDev_v^{\ 2}}{2} \\ a_v = \ln\left(StdDev_v\right) \end{cases} \tag{47}$$

Where the *StdDev* is standard deviation of the measurement error for the variable *v*, which is estimated by the model itself during the optimisation process.

In accordance with the 4 historical time-series data introduced in sub-section 8.1.1, 4 model variables are employed for calculating the minimum payoff, as reported in Table 22.

Table 22. Data and variables used for the definition of the calibration payoff.

Data used	compared to **Model variable**
Metered IGAs electricity demand DATA (Fig. 45-top)	Since the availability of IGAs electricity demand data is not always 100%, data are compared to the time-dependent variable *Partial IGAs electricity demand* obtained by the product between the *Total IGAs electricity demand* variable (sub-section 7.2.7, Eq.(40)) with the time-series *Availability IGAs demand DATA* (as clearly visible in Fig. 45-top) containing the values of data availability for electricity demand of local businesses.

Metered connected IGAs DATA (Fig. 45-bottom)	Local surveys pointed out the presence of shared meters for business. The *Metered connected IGAs DATA* time-series is therefore compared to the time-dependent variable *Metered IGAs* obtained by multiplying the variable *Total connected IGAs* (sub-section 10.2.9, Eq. (32)) with the calibration parameter *fraction of sharing meter*.
Metered HHs electricity demand DATA (Fig. 44-top)	Since the availability of HHs electricity demand data is not always 100%, the data are compared to the time-dependent variable *Partial HHs electricity demand* obtained by the product between the *Total HHs electricity demand* variable (sub-section 7.2.7, Eq.(38)) with the time-series *Availability HHs demand DATA* (as clearly visible in Fig. 44-top) containing the values of data availability for electricity demand of local households.
Metered connected HHs DATA (Fig. 44-bottom)	Local surveys did not point out the presence of shared meters for residential connections. Data are compared to the *Total connected HHs* (sub-section 10.2.9, Eq. (35)) variable.

8.2. Results and discussion

Fig. 46 reports the calibrated output of the *Total electricity demand* variable, which represents the total monthly consumption of electricity by the Ikondo community. From the result, different interesting considerations about the model behaviour and dynamics can be reported.

1. First, the initial months show the trend typical of a S-shape diffusion curve, but with a short *early-stage* of adoption. This suggests that electricity access is not perceived as an actual innovation by people, but something that they already know, desire, and are willing to pay for. This conclusion is supported also by the relatively high calibrated values of *awareness effect* parameters, as discussed in Table 26.
2. Second, the change in the trend after the first 20/25 months caused by the change of the tariff scheme of the electrical connections has a significant impact on the electricity consumption. This indicates the importance of connection cost on the diffusion of the connections.
3. Third, also the electricity tariff emerges to be a definitively significant determinant of the electricity demand, as clearly visible with step-changes in the figure. In accordance with (Hartvigsson 2018), this confirms the importance of affordability when planning rural electrification strategies.

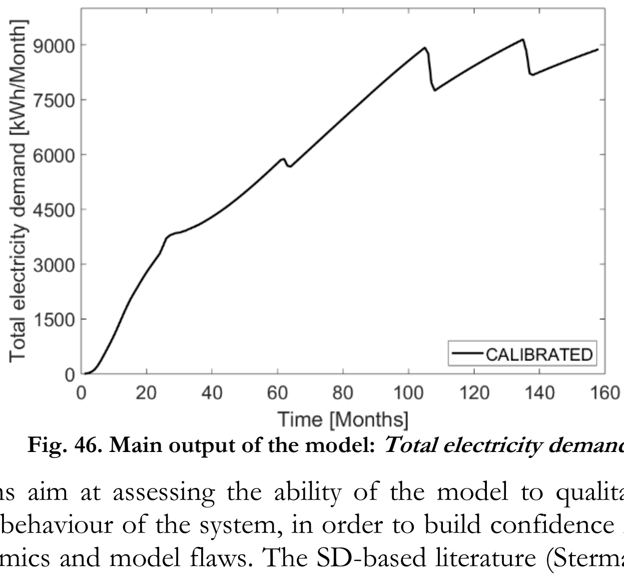


Fig. 46. Main output of the model: *Total electricity demand.*

The next sub-sections aim at assessing the ability of the model to qualitatively and quantitatively reproduce the actual behaviour of the system, in order to build confidence in the model results, and uncover hidden dynamics and model flaws. The SD-based literature (Sterman 1984, 2000; Bala et al. 2017) proposes various statistical measures for assessing the correspondence between model and data of the calibration. In this work, two approaches were followed:

i. *Descriptive statistics* to assess the point-by-point fit;
ii. *Experts and data assessment*, by comparing the end-time values of some simulated variables with the experts' opinion and data.

8.2.1. Behaviour consistency with data

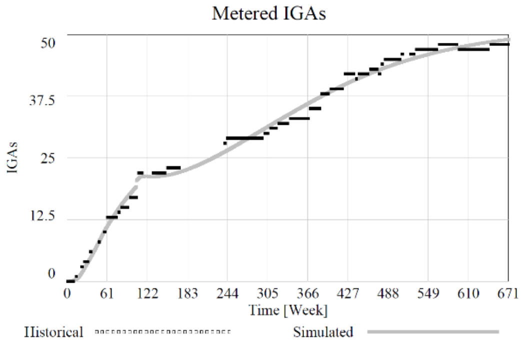
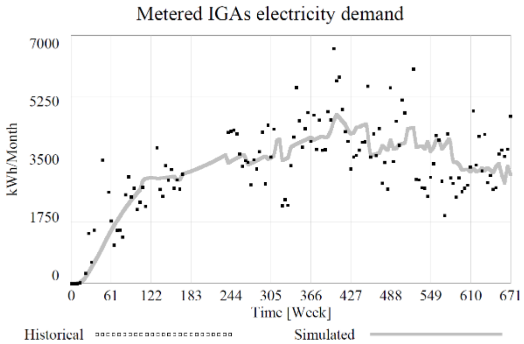
Many common metrics exist for measuring the error between a data series on *n* observations and the model output over the relevant time horizon. Table 23 reports the ones employed in this study.

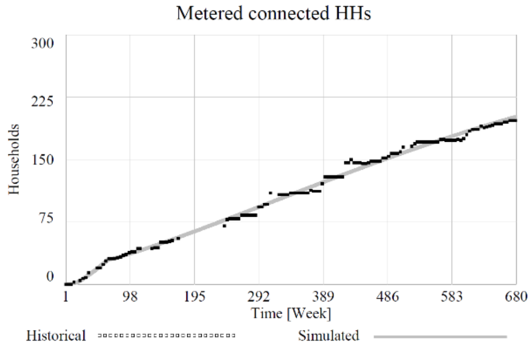
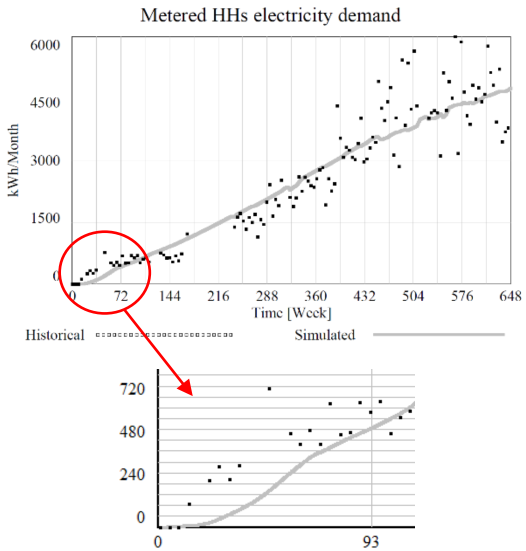
Table 23. Metrics used for assessing the fit between model output and data

Metrics	Formulation and meaning
Coefficient of determination R^2	$R^2 = \left[\frac{1}{n} \cdot \sum_{i=1}^{n} \left(\frac{\left(X_{d,i} - \bar{X}_d\right)}{s_d} \cdot \frac{\left(X_{m,i} - \bar{X}_m\right)}{s_m} \right) \right]^2$ This measure represents the ability of a regression to explain the variability of data. – 0% indicates that the model explains none of the variability of the response data around its mean; – 100% indicates that the model explains all the variability of the response data around its mean. This parameter cannot be used to predict the error, since it does not assess the causality between dependent and independent variables and the goodness of fit.
Mean Absolute Percent Error *MAPE*	$MAPE = \frac{1}{n} \cdot \sum_{i=1}^{n} \frac{\left\| X_{m,i} - X_{d,i} \right\|}{X_{d,i}}$ This measure is a proxy of the accuracy of a forecast. It presents some drawbacks due to the fact that its interpretation is undefined for values closed to 0 (Kim and Kim 2016), it gives more penalty on positive errors than on negative errors (Hyndman and Koehler 2006), and assumes that percentages of variable *X* make sense.
Theil's Inequality U^M, U^S, U^C	The Theil statistics is an elegant decomposition of the Mean Square Error (MSE), which is an absolute measure of the average of the squares of the errors: $MSE = \frac{1}{n} \cdot \sum_{i=1}^{n} \left(X_{m,i} - X_{d,i} \right)^2$ As for the variance, the MSE has the disadvantage of put more penalty to large errors much than small ones and, being an absolute value, it does not provide an immediate perception of the error. The *Theil's Inequality* provides an easily interpreted breakdown of the MSE by dividing it in 3 main components: $U^M = \frac{\left(\bar{X}_m^2 - \bar{X}_d^2\right)}{MSE}$ It is a measure of the *bias* that occurs when the model output and the data series have different mean. $U^S = \frac{\left(s_m^{\ 2} - s_d^{\ 2}\right)}{MSE}$ It is a measure of the *unequal variation* that occurs when the model output and the data series have different trends. $U^C = \frac{2 \cdot \left(1 - \sqrt{R^2}\right) \cdot s_m \cdot s_d}{MSE}$ It is a measure of the *unequal covariation* that occurs when the model output and the data series are imperfectly correlated, viz. they differ point by point

The previous statistics were calculated for the 4 variables used for defining the payoff and discussed in Table 22, indicating a good statistical fit between model and data, increasing the confidence in the model output.

Table 24. Statistics applied to calibration results

Graphical fit	Statistics	Comment
 	R^2 = 0.99	The model explains almost all the variability of the response data around its mean.
	MAPE = 4.4%	The model presents a high level of accuracy, since the variability of data around the mean of the model output is very low.
	U^M = 0.00	*NO bias* The model output and the data series have the same mean.
	U^S = 0.00	*NO unequal variation* The model output and the data series have the same trend.
	U^C = 1	*ONLY unequal covariation* The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. In particular, the model is not able to reproduce the "step-trend" of data that in this case is probably due to the process of IGAs formation that is not continuous in time. It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.
 	R^2 = 0.61	The model explains more than half of the variability of the response data around its mean.
	MAPE = 21.2%	The model presents a quite low level of accuracy, since the variability of data around the mean of the model output is not negligible. This means that the model is not able to capture the variability of data. This issue can be solved by (i) introducing and calibrating a random error term, or (2) by formulating the dynamics that can explain such variability. Potential reasons of this variability can be: – *Intra-season variabilities,* due to the dependency of people financial availability with the harvesting period; – *Daily load variability*, due to the unpredictability of people's habits and use of electricity within the 24 hours. This high level of variability is not a systematic error, since the purpose is not to study such variabilities in the long-term forecast, and because intra-days uncertainties are specifically modelled through a stochastic load profile generator in Chapter 10.
	U^M = 0.01	*NO bias* The model output and the data series have the same mean.
	U^S = 0.04	*NO unequal variation* The model output and the data series have quite the same trend.
	$U^C = 0.95 \cong 1 - U^S$	*ONLY unequal covariation* The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.

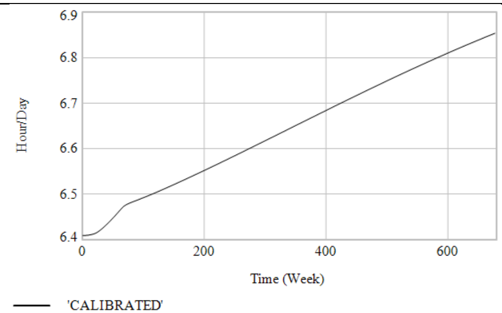
	$R^2 = 0.99$	The model explains almost all the variability of the response data around its mean.
	MAPE = 3.6%	The model presents a high level of accuracy, since the variability of data around the mean of the model output is very low.
	$U^M = 0.00$	*NO bias* The model output and the data series have the same mean.
	$U^S = 0.00$	*NO unequal variation* The model output and the data series have the same trend.
	$U^C = 1.00$	*ONLY unequal covariation* The error term is exclusively attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. In this case, the "step-trend" in the data is probably due to the fact that the physical process of grid extension – viz. the constructions of further junction boxes in unelectrified areas of the village – is obviously not continuous in time. Once a junction box is built, the houses in its surroundings can start asking for a connection (if they can afford it). The other households that live farther have to wait that a new junction box is built, and this probably creates a wait with no further connections (viz. the flat side of the steps). It is an UNSYSTEMATIC error since the purpose is not to study cycles and short-term trends in the data.
	$R^2 = 0.88$	The model explains much of the variability of the response data around its mean.
	MAPE = 20.3%	The model presents a quite low level of accuracy, since the variability of data around the mean of the model output is not negligible. This means that the model is not able to capture the variability of data. The potential reasons and solutions are the same mentioned for electricity demand of IGAs. Moreover, the model underestimates the household demand in the first weeks of the simulations. Although this does affect the total electricity demand of the community (the IGAs demand is much higher) and the purpose of the model, the causes of this deviation respects to data are worth to be investigated. The problem is probably intrinsic to the perfect-mixing hypothesis of system dynamics, which cannot capture the presence of some actors (e.g. very rich people) who behave differently from the average. Although these actors represent a very small fraction of the population, at the beginning of the simulation their different behaviour could be predominant since they are reasonably the first people to be connected and to consume electricity. In accordance with the *CASE 3* presented in Chapter 5, ABM would have probably captured this dynamics. On the other hand, this consideration is valid just for the first simulation time period, and the hypothesis of perfect-mixing remains reasonable over the entire simulation horizon.
	$U^M = 0.00$	*NO bias* The model output and the data series have the same mean.
	$U^S = 0.09$	*NO unequal variation* The model output has almost 10% different trend.
	$U^C = 0.90 \cong 1 - U^S$	*ONLY unequal covariation* The error term is attributable to an error term with zero mean, which makes the model output and the data series to differ point by point. It is an UNSYSTEMATIC error since the purpose is not to study cycles in the data.

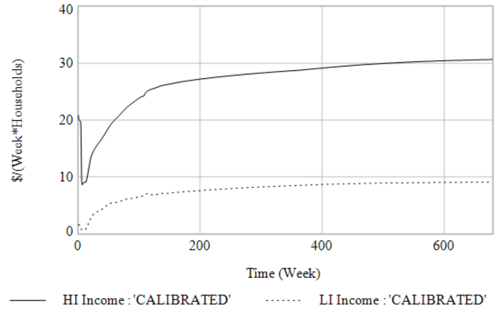
8.2.2. Behaviour consistency with the experts' knowledge

The second approach for assessing the ability of the model in reproducing the data considered the comparison of the output values of some variables against the knowledge of the experts and the data gathered during the surveys carried out on September 2017 in Ikondo. Table 25 reports the variables analysed and the potential range of values indicated by the experts at the end of the simulation time, and at the week corresponding to September 2017 in the simulation. The same table reports also the values of the variables simulated by the model, some graphical representations, and the related discussion.

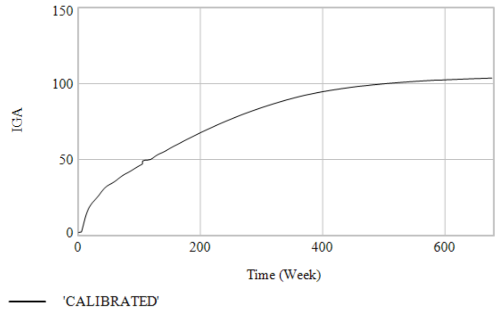
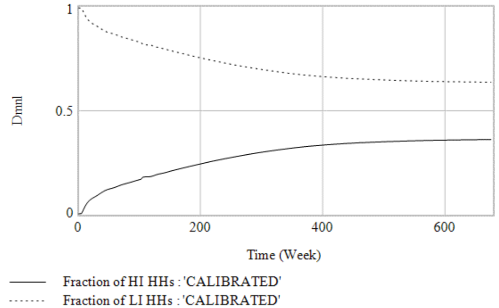
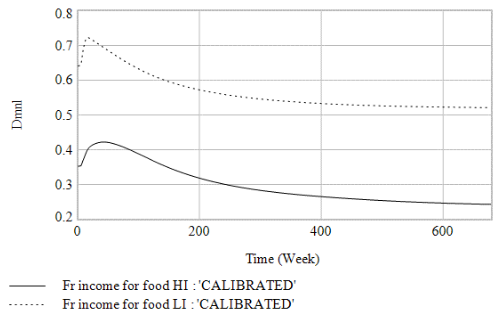
Table 25. Comparison between model's output, local data and experts' assessment.

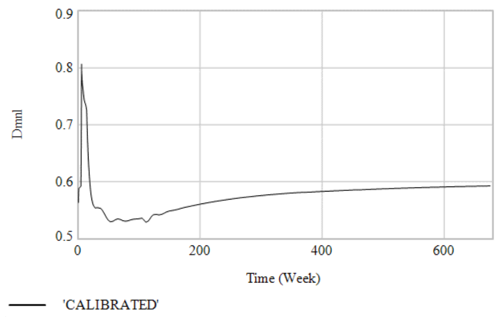
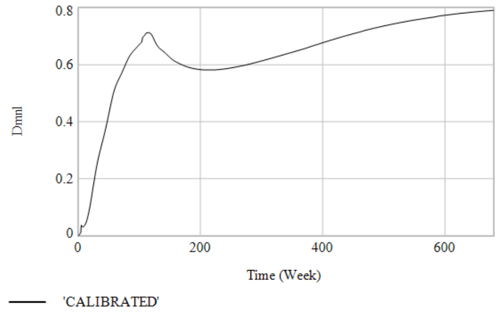
	t=665.75		*t=679.25*		
Variable	***Range from data***	**Simulated**	***Range from experts' opinion***	**Simulated**	***Graphical representation and discussion***
Total daily farming hours for LI HHs *[Hours/day]*	*[3 - 8]*	6.85			The daily time available for farming reflects the trend of the number of HHs connected to the grid (Table 24). As soon as HHs get connected, they start exploiting more time for continuing their farming activities in the evening.
HI Income *[\$/Week/HHs]*	*[3.1-133.8]*[12]	30.66			After electrification, both HI and LI farmers experience a drop in their weekly income. This is due to the initial high level of unsatisfied market demand, which creates a backlog of perceived needed new IGAs. To set-up all such initially desired IGAs, the initial level of debt that people take out with the micro-credit utility, or the savings needed to set-up the business, is high. Once reduced the backlog, income starts increasing.
LI Income *[\$/Week/HHs]*	*[0.9 - 15.4]*	9.08			

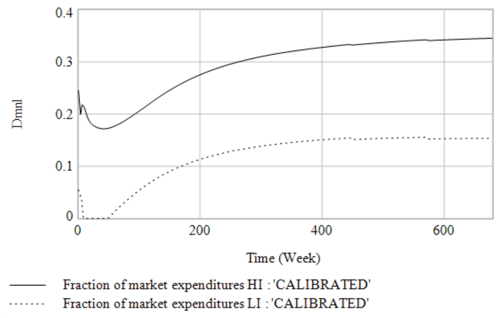
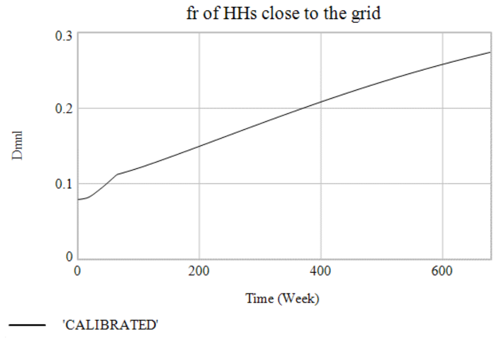
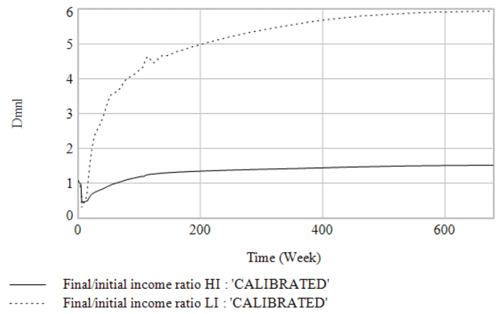




[12]According to S. Pachauri in (Filippini and Pachauri 2004), data of households' expenditure is considered more representative of the economic activity of people than households' income: income data are hard to obtain for developing countries, since poor households do not pay income tax, many subsistence activities are not monetised and during surveys people often hide part of their income. Moreover, this is in line with the modelling hypothesis such that on a weekly basis, households' expenditures are equal to their income inflow.

IGAs *[IGAs]*	*[40 - 120]*	104		The trend of the variable clearly shows an initial rapid growth of IGAs, due to the initial high level of unsatisfied market demand, and therefore a backlog of needed IGAs. Once reduced the backlog, the process of IGAs formation follows a smoother path. The step visible around time 100 *weeks* is due to an exogenous input of 2 IGAs from CEFA.
Fraction of HI HHs *[-]*	*[0.28 - 0.42]*	0.36		The fraction of HI HHs follows the same trend of the IGAs variable, while the fraction of LI HHs is its 1's complement.
Fraction of LI HHs *[-]*	*[0.52 - 0.78]*	0.64		
IGA income ratio HI HHs *[-]*	*[0.40 - 0.95]*	0.73		
farming income ratio HI HHs *[-]*	*[0.05-0.50]*	0.24		
farming income ratio LI HHs *[-]*	*[0.75 - 1]*	1.00		
Fr income for food HI *[-]*	*[0.05 - 0.30]*	0.24		At the beginning of the simulation horizon, HHs experience a drop in their income to take out the debt with the micro-credit and save money to invest in IGAs. In this time-frame, in order to keep the demand for food at the same initial level, HHs increase their fraction of income for food expenditures at the expense of lower market expenditures. It then starts decreasing due to the gradual increase of HHs' expenditures for new and/or improved goods and services at the expense of lower relative food expenditures.
Fr income for food LI *[-]*	*[0 - 0.7]*	0.52		

Fraction of external/internal *[-]* farming revenues	*[0.5 - 0.9]*	0.59		This variable represents the ratio between the farming turnover from the external and internal customers. As clearly visible, the external demand of agricultural products represents more than half of the total demand. At the beginning of the simulation horizon, HHs experience a drop in their expenditures to take out the debt with the micro-credit and save money to invest in IGAs. In this time-frame, the external demand for food product is therefore largely predominant. It then decreases below the initial level, due to an increase of the HHs' income and expenditures for food per effect of the increasing socio-economic development triggered by electricity. It then starts increasing again due to the gradual increase of HHs' expenditures for more goods and services at the expense of lower relative food expenditures.
fr of connected IGAs *[-]*	*[0.67-0.80]*	0.79		This variable shows an interesting behaviour. It initially increases rapidly due to the affordable cost of the connection – viz. IGAs get connected almost at the same time they set-up. With the change of the connection tariff, the process of IGAs connection become slower than the process of IGAs creation, causing the negative trend displayed in the figure. As soon as the number of IGAs reaches the plateau, the backlog of IGAs to connect starts reducing, inverting the sign of the derivative.

Fraction of market expenditures HI *[-]*	*[0.05 - 0.60]*	0.35		At the beginning of the simulation horizon, HHs experience a drop in their market expenditures to take out the debt with the micro-credit and save money to invest in IGAs. In this period, in order to keep the demand for food at least at the same initial level, the demand for market products and services decreases. For LI HHs, it even goes to zero for some months. It then starts increasing again due to the gradual increase of the socio-economic development triggered by electricity, and to the improvement and innovation of market products.
Fraction of market expenditures LI *[-]*	*[0.1 - 0.6]*	0.15		
fr of HHs close to the grid *[-]*	*~ 50%*	**27%**		This variable reflects the trend of the number of HHs connected to the grid (Table 30). As soon as HHs get connected, the micro-grid expands accordingly. This is the only variable, which takes on a value significantly different from the expert opinion at the end of the simulation horizon.
Final/initial income ratio HI *[-]*	*> 3*	1.52		This figure reflects well the "economic boom" (as said by the experts) experienced in Ikondo-Matembwe after electrification. After an initial drop in their weekly income due to the payback of the dept, both farmers and business man increased their financial availability. This benefited especially the farmers due to an increase of the food trading. In fractional terms, HHs with an IGAs experienced a relative lower increase of the income, but the percentage of people moving from the LI to the HI condition increased from almost 0% to 36%.
Final/initial income ratio LI *[-]*		5.95		

The last comparison concerns the income from farming activities. According to the experts, in terms of farming revenues, LI HHs earns more from this activity than HI HHs. The simulations reported in Fig. 47 confirm this assessment.

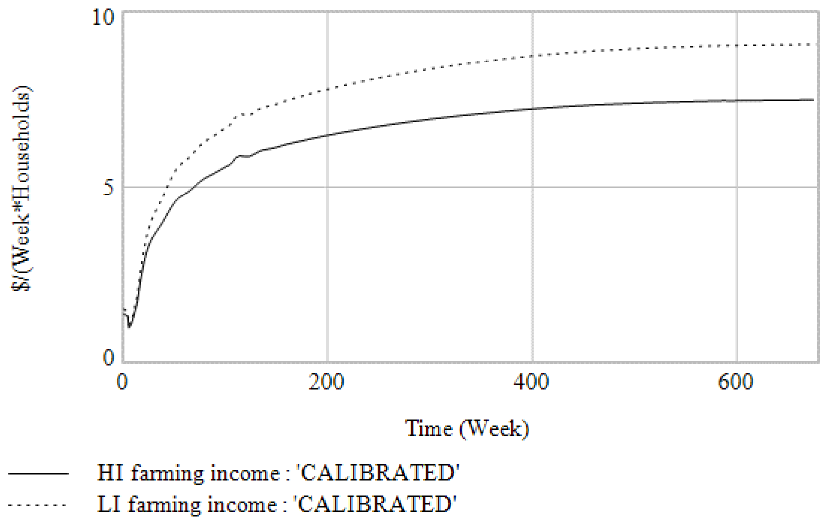


Fig. 47. Simulations for farming income variable for HI and LI HHs.

The comparison of Table 25 confirms that the model output is in line with the experts' judgment. Indeed, just one simulated variable does not reflect the value suggested by the one expert, namely the variable representing the fraction of HHs close to the grid who could potentially afford the electrical connection. This could be due to two main reasons:

1. A bias in the expert judgment, since it is the comment of only one person, namely the head of the electricians and manager director of BVC;
2. There are hidden dynamics not captured by the model and not emerged from the local surveys, other than the distance from the grid, which prevents a fraction of the population from obtaining the electrical connection.

Since the final objective of the model is not to understand the barriers to household connections, this inconsistency between experts' opinion and model output does not weak significantly the confidence in the model.

8.2.3. Surprising and interesting parameter values

In this sub-section, some of the optimised values of the parameters are reported and discussed in Table 26. All the calibrated values are reported in Table A 7 in the *Appendix D*. The calibrated values are the results of an iterative optimisation process. Indeed, the deterministic Powell algorithm does not prevent the possibility to find local minima, which are numerically sound, but not coherent with the reality, although this issue has been partially prevented for some parameters by the definition of precise search-space. Again, this set of values does not pretend to represent exactly the actual value of the parameters, since other combinations of value would fit in a similar way. Rather, they represent the starting point for analysing the uncertainty of the model (see the next sub-section 8.3), assessing the ability of the model in describing an observed historical behaviour, uncovering hidden dynamics and model flaws, determining the prevalent and weak dynamics, and finally obtaining a set of values that could be used as a reliable starting point for the application of the model to further case studies.

Table 26. Reporting and discussion of the values of the calibrating parameters.

N°	Parameter	Search-space	Calibrating value	Relevant comments
1)	awareness effect HI HHs *[1/Week]*	[0.000029 - 1]	0.976000	These relatively high values reflect the fact that electricity access is not perceived as an innovation by people.
2)	awareness effect IGAs *[1/Week]*	[0.000029 - 1]	1	
3)	awareness effect LI HHs *[1/Week]*	[0.000029 - 1]	0.021341	
4)	BETA – el *[-]*	[0 - 1]	0.897	Electricity has a relevant impact on local market productivity, especially due to the electrification of EE-reliant IGAs (e.g. Mills).
14)	EffectOfHomeElectricity *[-]*	[0 - 0.1]	0.0003	As suggested by the teachers in Ikondo primary school, electricity at home is not as much relevant as electricity at school for improving the pupils' educational attainment.
25)	Electricity-Income elasticity HHs *[-]*	[-1 - 0]	-0.09	This low value confirms what stated by the experts regarding this parameter: electricity is very cheap for households, and they do not change significantly their consumption patterns based on changes in the electricity price.
39)	fr increase of market expenditures *[-]*	>0	0.90	The fractional increase in the market expenditures is almost proportional to the increase in IGAs connection
45)	fraction of external source of LI income *[-]*	[0 - 0.05]	0.00	LI people are also the ones with no social networks outside the village.
49)	fraction of initial HI HHs to be connected *[-]*	[0 - 1]	0.83	The initial HI HHs are the ones already willing to be connected.
53)	GAMMA – edu *[-]*	[0 - 0.1]	0.002	It confirms that market productivity is inelastic respect to primary education attainments – viz. changes in the primary educational levels do not impact significantly on the market productivity.
56)	housework reduction given by electricity *[Hour/Day]*	[0 - 1.3]	0.1	Electricity does not significantly impact on the burden of housework; indeed, the local women who confirmed a reduction in the housework confirmed that it was due to the electrical rice cooker, a technology that very few people can afford.
78)	internal migration effect *[-]*	≥ 1	1.004	This value indicates that the practice of moving the house close to the electrified area is not common, despite one expert mentioned it.
84)	Max time for night housework *[Hour/Day]*	[0 - 4]	0.6	Households do not dedicate much time for night housework.
85)	Max time for night working *[Hour/Day]*	[0 - 4]	3	It confirms that night time for working is largely exploited by IGAs connected to electricity.
87)	maximum fraction of income for debt repayment *[-]*	[0 - 1]	1	This value suggests that when people plan to ask for a loan, they consider all their income for payback the loan. This is also suggested by the manager of the micro-credit, who indicated that when people obtained the loan, they want to pay it back as soon as possible.
102)	THETA - capacity building elasticity *[-]*	[0 - 1]	0.03	The effect of capacity building is not so high as expected.
110)	Time to perceive decrease in operating hours *[Week]*	≥1	241015	This shows that people are hesitant in reducing time spent at work, seeking to use all the time available for trying to sell their goods and services.
111)	Time to perceive electricity benefits *[Week]*	≥1	1	People are already aware of the benefits of electricity, as expected.
112)	Time to perceive increase in operating hours *[Week]*	≥1	2.7	Contrary to parameter 110), if available, people are very willing to use all their time available for working and trying to sell their goods and services.

8.3. Markov Chain Monte Carlo (MCMC) for payoff sensitivity

According to Rahmandad et al. (Rahmandad et al. 2015), Markov-chain Monte-Carlo (MCMC) is an approach to explore the appropriateness of the calibration of a model, and to assess potential good proxies of the confidence bounds of calibrated parameters. It was here employed since it allows to characterize a payoff distribution without making any assumption on its mathematical properties (van Ravenzwaaij et al. 2018). MCMC is a sequential process based on the Metropolis-Hastings criterion (Hastings 1970). Given the initial set of values $\overline{\theta^0}$ of the parameters (e.g. the calibrated values found before), the Markov Chain first starts with the Monte-Carlo practice for sampling a new proposal set of parameter values $\overline{\theta}'$ from a generic proposal symmetric distribution. According to the Bayes theorem valid for a generic set of parameters $\overline{\theta}$ (Eq. (48)), the MCMC accepts/rejects each new proposal set of parameter values $\overline{\theta}'$ by evaluating its $p(\overline{\theta}'|D)$ (*i.e.* the posterior distribution given the dataset *D*) by just relying on its prior distribution $p(\overline{\theta}')$ (*i.e.* the uniformly distributed priors in the search space of each parameter set before during the calibration) and its likelihood function $p(D|\overline{\theta}')$ specified by the specified payoff model (Eq.(46) is exactly the formulation of a log likelihood).

$$p(\boldsymbol{\theta} \mid D) \propto p(D \mid \boldsymbol{\theta}) \cdot p(\boldsymbol{\theta}) \tag{48}$$

Autocorrelation of the residuals can bias the results of the MCMC and the confidence bounds on the parameters. Indeed, autocorrelation could make the payoff function (Eq.(46)) the incorrect log likelihood, since it assumes independence of the residuals. Fig. 48 reports the residuals evaluated on the 4 payoff functions employed in the calibration, and the related Durbin-Watson test used for assessing the autocorrelation (Durbin and Watson 1950, 1951).

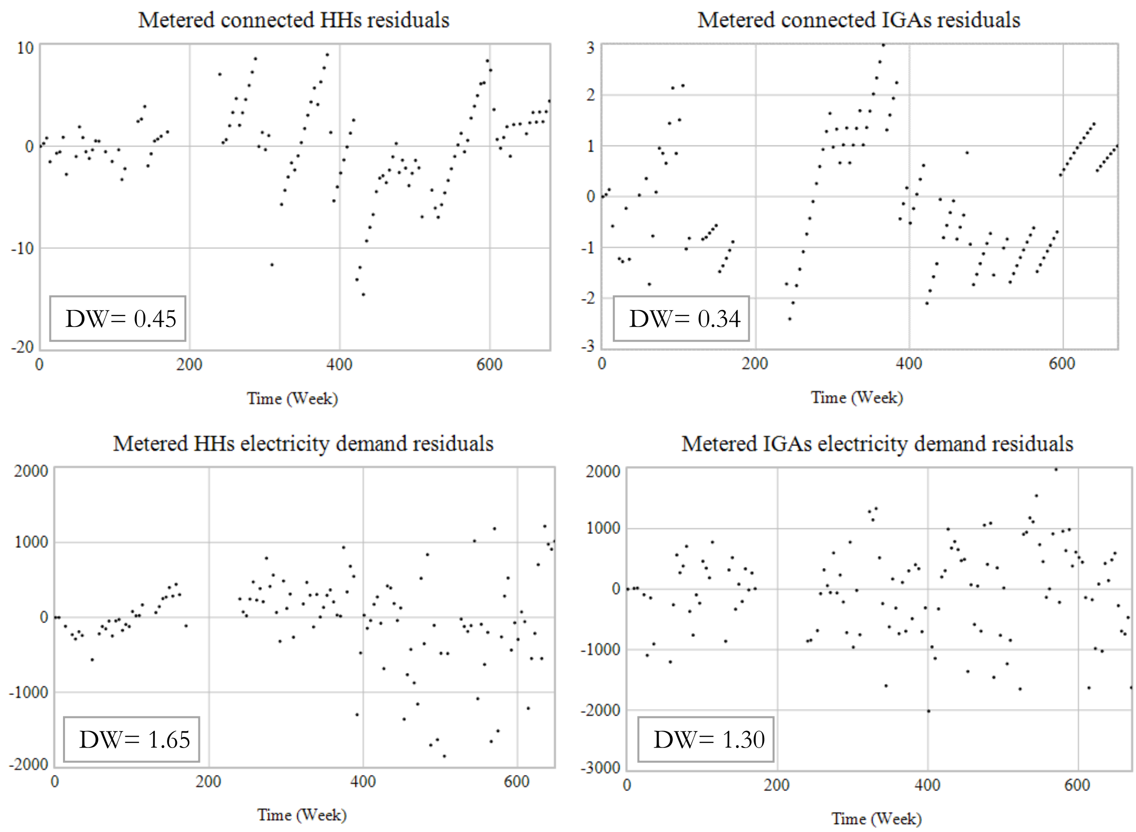


Fig. 48. Residuals and Durbin-Watson test for the variables used for defining the payoff.

According to (Field 2013), as a very conservative rule of thumb, values less than 1 or greater than 3 of the DW test definitely confirm that the residuals are affected by autocorrelation. This information, together with the plot of the residuals, was considered sufficient for considering just the residuals of *Metered connected IGAs* and *Metered connected HHs* as clearly autocorrelated. It is worth nothing that also the graph of the residuals of the *Metered HHs electricity demand* suggests an initial sign of autocorrelation, due to the inability of the model to estimate properly the household demand in the first weeks of the simulations (as seen in Table 24 in the statistics applied to calibration results). Given these results, the payoff sensitivity is here carried out by relying just on the payoff evaluated on the *Metered IGAs electricity demand* and *Metered HHs electricity demand* variables, whose calibration is not affected by significant levels of autocorrelation. This modelling decision avoids implementing the MCMC on the potentially biased likelihood surfaces specified by the payoff function of the *Metered connected IGAs* and *Metered connected HHs*, since the related residuals are clearly affected by autocorrelations. Moreover, this choice does not prevent the definition of the confidence bounds on all the calibrating parameters, since also the parameters more related to *Metered connected IGAs* and *Metered connected HHs* have a direct or indirect impact on the *Metered IGAs electricity demand* and *Metered HHs electricity demand*. On the contrary, this choice should give more large confidence bounds and more preventive estimations of them.

For the sake of transparency and replicability, the main MCMC settings implemented in Vensim DSS ® are listed in Table 27.

Table 27. MCMC options set in Vensim DSS ®.

Setting	Value	Explanation
:MC*LIMIT*	20000	The maximum number of iterations to perform
:MC*BURNIN*	500	The number of iterations, which identifies the *burn-in* or *convergence* period, to allow the chain to converge towards the "right" values of the parameters. Since the MCMC is implemented after the Powell calibration, the *burn-in* is set very short since it is potentially superfluous
:MC*NCHAINS*	2	Number of Markov Chains to run per parameter
:MC*INITMETHOD*	Hybrid	It represents a hybrid strategy for initializing each chain, through which a random direction is chosen. Then, the move in such direction is scaled iteratively by half or doubled until the largest possible move with a reasonable chance of acceptance (at least 5%) is found.

The MCMC process returns the list of all the accepted points (i.e. the accepted set of $\bar{\theta} = \{\theta_1, \theta_2, \ldots, \theta_{123}\}$ values of the parameters). The confidence bounds of each parameter were evaluated at 90% of confidence by considering the 0.05 and 0.95 percentiles of the list of all the accepted points $\bar{\theta} = \{\theta_1, \theta_2, \ldots, \theta_{123}\}$. Complete results are reported in *Appendix E*.

Chapter 9

Testing and exploring the model

Je pense, donc Je suis / Cogito, ergo sum
(Descartes 1637)

Truth – which is much too complicated to allow anything but approximations
(von Neumann 1947)

No matter how powerful computers become, modelers will always face tradeoffs between the size and complexity of a model and the ability to understand its behavior, carry out sensitivity analysis, and test policies
(Rahmandad and Sterman 2008)

This chapter reports the main insights from model testing and use, by assessing the main fundamental dynamics, variables, and exogenous policies that characterise the model, as stated in the Objective 2. After the discussion of some aspects related to the concept of model validation in the SD theory, *direct structure tests* are performed to check the coherence between the mode structure with the existing empirical and theoretical knowledge about the actual structure of the analysed system. *Structure-oriented behaviour tests* are then implemented for assessing the most relevant dynamics, and for discussing the results of the model when its inputs take on different values, until the extreme ones and as if the model were tested for different contexts than Ikondo. *Policy testing* are performed for exploring model behaviour when subjected to different polices and exogenous decision-making processes, in order to perform a kind of *what-if* analysis on the model outcome, derive some useful insights on the polices implemented by CEFA, and propose potential improvements. Further tests are implemented for evaluating the importance and the impact of electricity access on some socio-economic dynamics, and the reverse feedback. Finally, the *sensitivity analysis* is performed to test the robustness of the conclusions that can be derived from the main model output on varying the assumptions over a plausible range of uncertainty.

9.1. Formal aspects of testing and validation

9.1.1. All models are wrong

"A model is a simplification, an abstraction, a selection, because our models are inevitably incomplete, incorrect – wrong (Sterman 2002 pg. 525)." These are the words used by John Sterman in his very famous Jay Wright Forrester Prize Lecture in 2002 for discussing the complexity of model testing within the systems science. In the past, this consideration that models are obvious simplifications of the real world allowed the social science community to overcome the classical *logical positivism* theory of knowledge, which asserted that a statement is cognitively meaningful only if it is verifiable through empirical observation (Barlas and Carpenter 1990). System thinking theory supports the opposite thesis: testing a model just for "proving" that it is "right" – e.g. by focusing just on the statistical fitting of historical data – limits the utility and credibility of a model. Indeed, *"[…] because all models are wrong, we reject the notion that models can be validated in the dictionary definition sense of 'establishing truthfulness', instead focusing on creating models that are useful, on the process of testing, on the ongoing comparison of the model against all data of all types, and on the continual iteration between experiments with the virtual world of the model and experiments in the real world (Sterman 2002 pg. 521, 525)".*

Of course, this concept must not be misunderstood. Being aware that verification and validation are formally impossible must not lead to discount the role of statistical parameter estimation, or to consider qualitative insights more important than numerical reliability, or to neglect to assess model behaviour against historical data. On the contrary, muddled model formulations, and erroneous and biased conclusions must be prevented by rigorously defining constructs, performing appropriate measurements, and relying on robust statistical and stochastic tools. Using again Sterman's words, *"[…] **ignoring numerical data or failing to use statistical tools when appropriate is sloppy and lazy.** In my experience, many who avoid the proper use of numerical data do so not because they believe it is the best way to help people learn or solve important problems but because they don't want to take the time or don't have the skills to do it. **No excuse.**"*

9.1.2. The nature of "validity"

Since SD belongs to the class of causal models, its paradigms are naturally interdisciplinary. Model equations are indeed often derived by "conversation with people" (Meadows 1980; Barlas and Carpenter 1990), and using just empirical – in the classical sense – and data-driven approaches to model validation cannot be enough to build confidence in a model. This is the reason why the SD-theory puts emphasis on the role of soft-variables and extends the concept of "empirical" validation information beyond the mere numerical statistics. Using Forrester's definition, validation is therefore the *"process of establishing confidence in the soundness and usefulness of a model (*(Forrester and Senge 1980) *pg. 210)"*, and not a process of "acceptance/rejection" based on the output behaviour. This process can be carried out through formal tests – by comparing a model to the empirical reality – and it requires proper documentation and chances of replicability. Moreover, the SD-theory highlights the "relative" nature of validation: confidence in the usefulness of a model can be established only in relation with its specific purpose(s).

9.1.3. Tests for improving confidence in a model

The SD-based literature offers a wide variety of tests aimed at building confidence in a model (Forrester and Senge 1980; Hellman 1982; Sterman 1984, 2000; Barlas 1996; Qudrat-Ullah and Seong 2010; Bala et al. 2017). This thesis relies on the outline proposed by Barlas (Barlas 1996). According to Barlas, the final goal of SD models – being "white-box (or "theory-like") models – is not just to reproduce or predict a given dynamic behaviour, but also to explain the endogenous and exogenous reasons that generate such behaviour. This is the reason why assessing the validity of a SD model must start with tests for evaluating the appropriateness of the its internal structure, and not just the output behaviour. Thus, the logical order of validation proposed by Barlas is the following:

- *Direct structure tests*: they involve direct comparisons with the existing empirical (viz. directly obtained) and theoretical (viz. generalized from the literature) knowledge about the actual structure of the analysed system. These tests do not involve simulation.
- *Structure-oriented behaviour tests*: they involve simulation, in order to generate certain behaviours and compare them with observed behaviour of the real system. These tests are performed by exploring model behaviour and output according to different situations and contexts respect to the Ikondo case study.
- *Behaviour pattern tests*: they aim at measuring the accuracy of a model in reproducing the behaviour patterns of the real system. This test was performed in sub-section 8.2 after the calibration.

Each one of the three stages of model validation includes different type of tests, thoroughly described by Sterman (Sterman 2000). Barlas' outline is a guideline for establishing confidence in a model though recursive model revisions, and not just a single sequential process. This excludes the type of binary reject/not reject decision at the end of model testing, as typically done in purely correlational black-box models, which rely mainly on the statistical significance testing for assessing the validity of a model. Moreover, not all the tests are necessary for building confidence in a model.

In the present study, the testing and validation phase was approached following its feedback and recursive nature. Just for the sake of clarity and transparency, it is here reported as a sequence of the main tests carried out during the model building process.

9.2. Direct structure tests

In this study, 4 different *direct structure* tests are performed to build confidence in the structure of the model (Table 28).

Table 28. *Direct structure* tests performed.

Test	Purpose *(from (Sterman 2000))*	How it is performed
1. Boundary Adequacy	To guarantee that the boundaries of the model include the fundamental endogenous concepts and key-variables.	– *Theoretically*: the literature review and the causal diagrams of Chapter 6 report a broad view of all the endogenous dynamics of the nexus between electricity demand and development. – *Empirically*: the interviews in Ikondo-Matembwe to the experts and the local people allowed to simplify and modify the causal loops for the Ikondo energy context and find the most important endogenous dynamics (e.g. exclusion of heath dimension, simplification of the education dimension).
2. Structure Assessment	To confirm that: (1) the model structure is consistent with relevant descriptive knowledge of the system; (2) the level of aggregation is appropriate; (3) the model conforms to basic physical laws such as conservation laws; (4) the decision rules capture the behaviour of the actors in the system.	Since the information needed for comparing the structure of a model with the real system is very qualitative, the tests for structure confirmation cannot rely simply on sets of numerical data. (1) *Theoretically:* by formulating consolidated dynamics that might occur also in rural contexts (e.g. innovation diffusion process for electricity connection based on awareness and social contagion effects). *Empirically*: by confirming and modifying such dynamics during the interviews in Ikondo-Matembwe to the experts (e.g. the inclusion of the financial aspect and willingness to pay in the diffusion process).

		(2) *Theoretically*: CASE 3 confirmed that aggregating agents causes a huge simplification in diffusion process. On the other hand, lack of specific competences, information and data on social structures would have undermined the significance and interpretation of the results. *Empirically*: Local surveys suggest the appropriateness of the main levels of aggregation, e.g. the subdivision of HI/LI population, and notEE/EE-reliant IGAs ("*I could work without electricity*" said the owner of a phone-kiosk, while "*Electricity is everything*" stated the owner of a local carpentry). The outliers (as extraordinarily rich businessmen or beggars) represent a very small fraction of the population. (3) Unphysical and unexpected model flaws are carefully checked by model inspection. In particular, MIN/MAX functions are introduced where variables, especially levels, have upper/lower limits. (4) *Theoretically*: studying decision rules that might occur also in rural contexts (e.g. market supply-demand dynamics that drives the creation of new IGAs). *Empirically*: confirming and modifying such rules during the interviews in Ikondo-Matembwe to the experts (e.g. the inclusion of IGAs that start just by imitation).
3. Dimensional Consistency	To check that the right- and left-hand sides of each equation are dimensionally consistent, without the use of ad-hoc dummy parameters with no physical meaning.	Inspection of every equations, by relying also to the *Units check* tool of Vensim DSS ®.
4. Parameter Assessment	To guarantee that constant parameters are consistent with the knowledge of the system, both *conceptually* (i.e. they have real world counterparts) and *numerically* (i.e. with enough accuracy).	The calibration process, together with the definition of the search-space, and the MCMC method are used to assess parameter values, check their values with the knowledge of the local context, and estimate their accuracy.

9.3. Integration error

This test aims at assessing the sensitivity of the model to the choice of the time step Δt or numerical integration error. A robust model should not be sensitive to change to them.

9.3.1. Time-step Δt

For testing the appropriateness of the time step, the "cutting-in-half" test was conducted. It consists in selecting a first-tentative time step Δt_1, simulating the model with a Δt_2 obtained by cutting the time-step in half and the checking if the results change substantially. If not, Δt_1 is appropriate; otherwise, the iteration continues with Δt_2. According to the rule of thumb suggested by Sterman (Sterman 2000), the time step of first tentative was taken equal to one-fourth (viz. 0.25) the size of the smallest time constant of the model (viz. 1 week). To check if the results are sensitive to changes in the time-step, the values of the 4 main variables used for defining the payoff were analysed at the final time of the simulations. In particular, the iterative "cutting-in-half" procedure was conducted until the fulfilment of the condition on the Δt-error term ξ expressed in Eq. (49) in Table 29. The first iteration confirmed the appropriateness of the time-step Δt equal to 0.25 (Table 29).

Table 29. Δt-error term for the main 4 output variables of the model.

	Variable	ξ
$$\xi = \frac{x_{t=FINAL,\,dt} - x_{t=FINAL,\,dt/2}}{x_{t=FINAL,\,dt}} \le 5\% \qquad (49)$$	*Metered IGAs*	2.6%
	Partial IGAs electricity demand	1.2%
	Total connected HHs	0.9%
	Partial HHs electricity demand	3.1%

9.3.2. Integration error

For testing the appropriateness of the integration method, it was checked that varying the method did not cause substantially changes in the simulation results if compared to the Euler method.

The method compared to Euler is the classical Runge-Kutta, generally referred to a "RK4", with fixed and automatically adjust increments. Differently from the Euler integration, which assumes that the derivates (i.e. rate) are constant through the finite time-step Δt, the RK4 method allows to compute a more accurate integration. The numerical approximation of the integral at time $t+dt$ is determined by the value of the level at time t plus a weighted average of four increments, where each increment is the product of the time-step Δt, a weight coefficient w_i, and an intermediate evaluation k_i of the derivate ("rate") (Eq. (50)).

$$Y_{t+dt} = \int_{t}^{t+dt} x \cdot dt = Y_t + \Delta t \cdot \left(\sum_{i=1}^{4} w_i \cdot k_i \right) \qquad (50)$$

The weight of RK4 with fixed increment is given a priori by the so-called *Butcher tableau* (Butcher 1963). In case of automatically adjust increment, the latter is evaluated and computed during each integration step based on the integration error[13].

As done previously, the values of the 4 main variables used for defining the payoff were analysed at the final time of the simulations, checking the error term respect to the Euler method. Table 30 confirms that the model is not highly sensitive to changes of the integration method, with variations within acceptable margins of error of around 5%.

Table 30. *dt*-error term for the main 4 output variables of the model.

Variable	ξ	
	RK4-Auto	**RK4-fixed**
Metered IGAs	5.2%	5.3%
Partial IGAs electricity demand	4.2%	4.1%
Total connected HHs	1.9%	1.9%
Partial HHs electricity demand	3.6%	3.6%

9.4. Behaviours and policies testing: exploring the model for different contexts

9.4.1. Behaviour sensitivity: assessing fundamental dynamics

The behaviour sensitivity test is useful for determining those parameters to which the model is highly sensitive (Barlas 1996). It contributes to build confidence in the model by checking that also the real

[13]More details available on the RK method employed in Vensim are available in the software help (https://www.vensim.com/documentation/index.html?rungekutta.htm).

system would exhibit similar high sensitivity to the corresponding parameters. The test was conducted empirically, by evaluating how sensitive was the Powell optimisation payoff respect to the univariate variation of each parameter. In particular, for each parameter at time, it was calculated the variation necessary to cause a change of 20%, 15%, 10% and 5% in the payoff. The numbers of parameters causing those changes in the payoff through variations lower than the 20%, 15%, 10%, and 5% thresholds are tracked in Fig. 49.

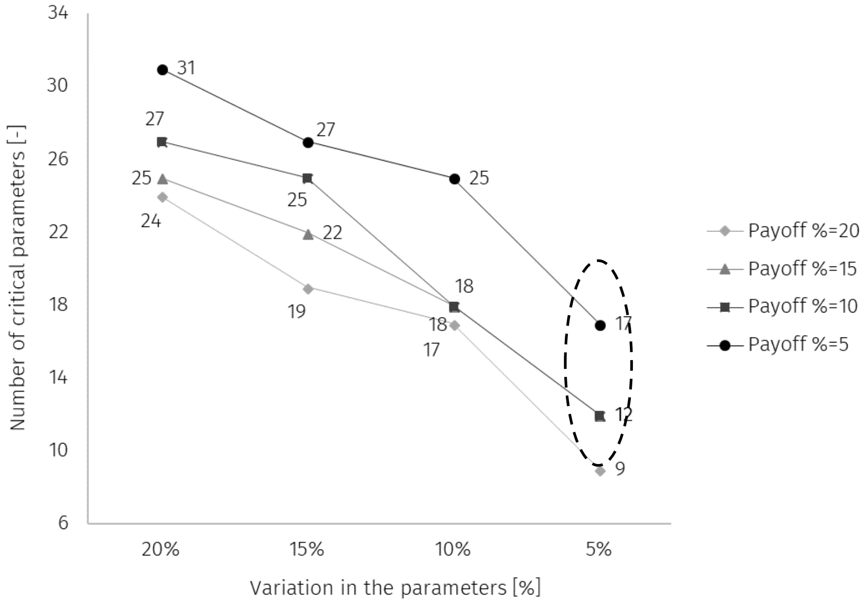


Fig. 49. Number of critical parameters on varying the changes tested on the payoff.

As expected, the number of critical parameters gradually decreases by moving towards higher payoff changes, viz. the higher is the desired payoff change, the lower is the number of parameters that, one at a time, generate such payoff change. Also, given a certain payoff change, the number of critical parameters decreases by reducing the variation threshold, viz. the lower is the variation of the parameters, the lower will be their impact on the payoff change.

The most critical parameters are the ones on the right-side of the figure in the dashed circle, viz. the parameters that cause a change of 20%, 15%, 10%, and 5% on the payoff by varying less than 5%. For checking that the real system would exhibit similar high sensitivity to the corresponding parameters, the analysis was performed on the two extremes, viz. the 17 and 9 parameters that cause a change of 5% and 20% on the payoff, respectively.

The 9 critical parameters that cause a change of 20% in the payoff with a variation of less than 5% are definitely the most critical in the whole model. Table 31 discusses the weight of the same parameters in the real world, confirming their importance.

Table 31. Parameters that cause a change of 20% in the payoff with a variation of less than 5% in their values.

Parameter	Variation[14]	Discussion
Initial number of IGAs	-4.0% / +4.4%	This parameter is a proxy of the initial economic level of the village. For Ikondo, it corresponded to 1-2 IGAs. Local experts associate the electrification of Ikondo-Matembwe to the "economic boom" of the two communities. This expression directly implies that different initial wealth conditions would have led to different socio-economic dynamics and evolution patterns of electricity use.

[14] Where just one value is reported is because the opposite value reached the boundaries of the search space.

Initial external market demand fr change in external food expenditures fr change in external market demand	-3.3% / + 3.1% - 4.9% / + 4.2% - 1.8% / + 1.6%	These 3 parameters indicate the quality and entity of the commercial trading in Ikondo for both food, and non-food goods and services. Both the literature (Lanjouw and Lanjouw 2001; Haggblade et al. 2010) and local surveys suggest the critical importance of trading in rural economies. Interviews to the experts suggest that before electrification «there was nothing in Ikondo, just poor subsistence farmers», while now there is a significant trading that positively affects LI and HI HHs. The Food and Agriculture Organization (FAO) (Tracey-White 2003), in the chapter "Identifying the need for rural markets", confirms the benefits for local communities in having formal operating markets for enhancing potential trades both inside and outside the villages. Indeed, it mentions the poor quality of roads and low level of attraction of external consumers as potential threats of local markets.
Initial available operation time	-3.8% / +4.2%	This parameter is a proxy of the initial productivity level of the village. For Ikondo, it corresponded to few hours of working during the daylight hours. The main benefit that local owners of the IGAs associate to the electrification of Ikondo-Matembwe is the extension of the working time. This directly implies a that different initial working time would have led to different socio-economic dynamics and electricity use evolution patterns. This is evident by observing not-electrified village of Kitole, closed to Ikondo. Compared to the initial condition of Ikondo, in the village there are more IGAs, but most of them have at least a solar panel, and they all mention "extended working hours" as the first main benefit of electricity.
Initial fr income for food expenditures LI	-5.0% / +4.8%	Farming activities represent the main source of income for the majority of people. Changes in people's expenditures for agricultural products have indeed two important feedbacks on the dynamics behind the electricity use: – variations on the income of LI HHs, which represent the majority of the total HHs, and therefore on their possibility and willingness to connect to electricity and consume it; – variations on the income spent in the local market from both LI and HI HHs, with consequent changes in the HI revenues, and therefore on HI HHs' possibility to connect to electricity and consume it.
Reference factor productivity	- 3.6% / + 4.0%	Productivity and the concept of "marginal product" are fundamental aspects in micro-economics. The concept is directly related to the dynamics of demand/supply of the market, which is valid also for rural areas (Ayenew et al. 2016). Increasing or decreasing the productivity of IGAs would cause a change in the local market competition, and therefore on the number of IGAs. Indeed, the component of the payoff that is most sensible to variation of this parameter is the number of connected IGAs (*Metered connected IGAs*).

fraction of feasible HHs market supply	- 4.7% / + 4.1%	This parameter takes into account a fundamental dynamics cited by all the experts interviewed: the more market demand is locally satisfied, the less are the household expenditures, and the greater would be the consumer purchasing power of people. Electrification in Ikondo led to the creation of new business, allowing people to locally purchase goods and services, without the need to spend more time and money for going outside Ikondo. The importance of this dynamics is highlighted also by Shackleton et al. (Shackleton et al. 2009) in a remote rural area of South Africa.
Initial Population	- 2.4% / 2.3%	Population has a direct and indirect impact on the electricity use, and therefore on the calibration payoff: – *Direct*: the more people there are, the higher will be the number of HH connections and the total electrical consumption, and vice versa; – *Indirect*: the initial population determines the initial fraction of unsatisfied market demand, that is the variable at the basis of the IGAs formation mechanism (sub-section 7.2.1). Therefore, the higher the population will be, the higher would be the market supply, and the potentially connected IGAs, and vice versa.

In addition to these 9 parameters, Table 32 lists the other 9 parameters that cause a change of 5% in the payoff with a variation of less than 5%.

Table 32. Parameters that cause a change of 5% in the payoff with a variation of less than 5% in their value.

Parameter	Variation[15]	Discussion
fr income for education expenditures HI	-2.4% / +2.6%	The manager director of the electric utility MVC clearly stated that households, especially the HI ones, take much care of the education of their children, and they spend a large fraction of their income for it. Since they are HI HHs, a change of this fraction would directly cause a sensible change in the market expenditures, and therefore on the dynamics affecting the local economy.
Initial fr income for food expenditures HI	-3.8% / +4.0%	*as for* Initial fr income for food expenditures LI
Initial external agricultural expenditures	-3.7% / +3.6%	As discussed for the market of goods and services, this parameter indicates the quality and entity of the commercial trading in Ikondo for agricultural products. Both the literature (Delgado 1995; Tracey-White 2003; K. Gadhok 2016a, 2016b), and local surveys highlight the critical importance of agricultural trading in rural economies.
price to cost factor	-2.5% / +2.6%	Price and production costs are fundamental aspects in micro-economics. They are directly related with the dynamics of demand/supply of the market, and they are valid also for rural areas (Ayenew et al. 2016). Increasing or decreasing the price of local goods and services would cause a change in the total local market revenues, and therefore on the affordability of HI HHs, and their demand on the local market.

[15] Where just one value is reported is because the opposite value reached the boundaries of the search space.

fr change in internal IGAs supply	-3.6% / +3.5%	The supply-chain for local IGAs is a critical issue. The owner of a carpentry stated that he buys most of the raw material outside because of lower prices, and due to economies of scale. These parameters represent a proxy of the diversification of the local market, which is an important factor for rural market development (Alobo Loison 2015).
max fr of internal IGAs supply	-2.5% / +2.3%	
internal migration effect	+ 4.1%	This parameter impacts directly on the number of connected HHs, which is also a variable with a high weight on the payoff.
fr of potentially affordable IGAs connections	-3.6% / +3.6%	This parameter impacts directly on the number of connected IGAs, which is also the variable with the highest weight on the payoff. Moreover, it indirectly impacts on the IGAs productivity and the working hours, and therefore on the local economy structure.

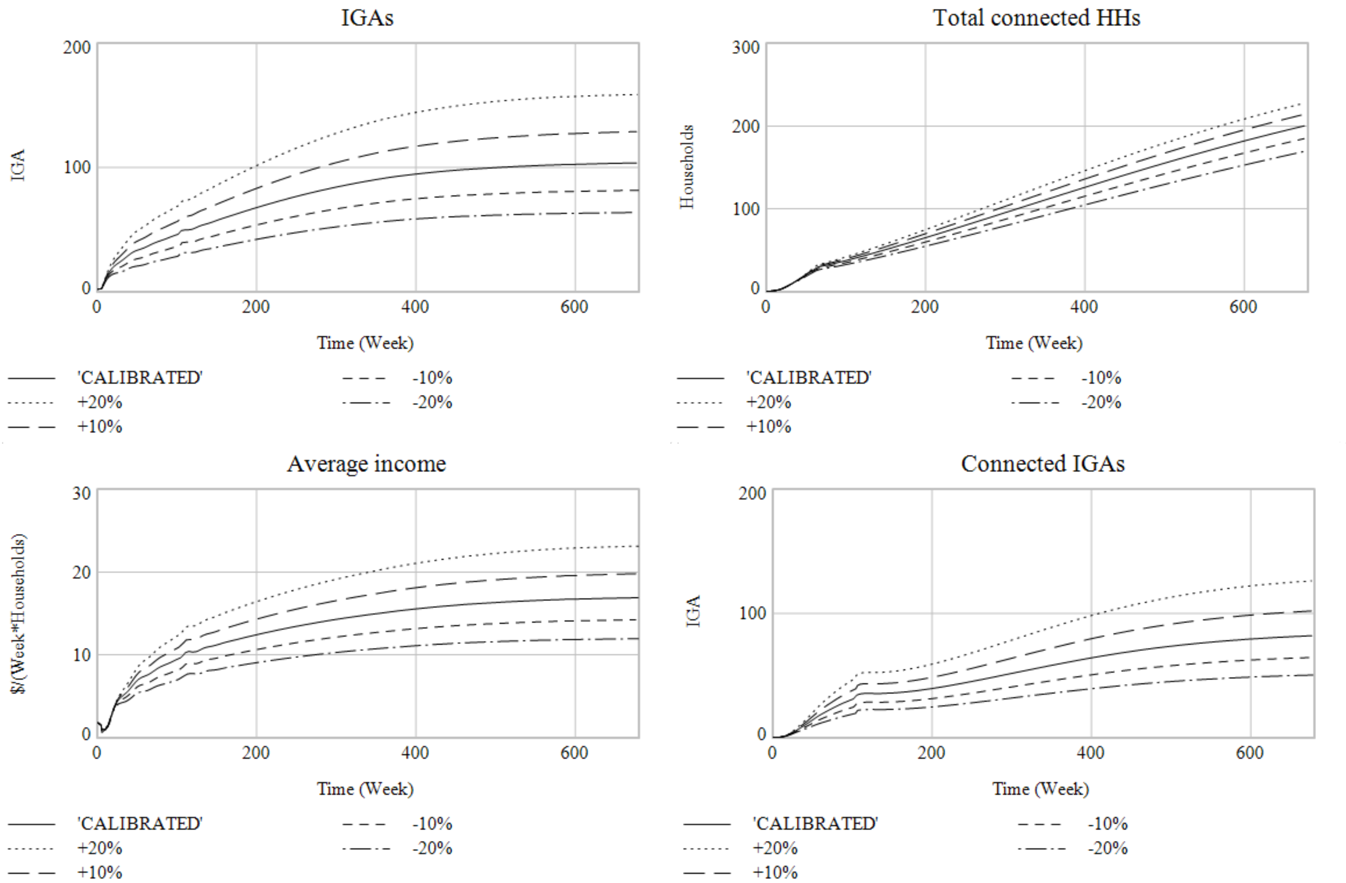
9.4.2. Exploring model output for different and extreme conditions

This test aims at discussing the results of the model when its inputs take on different values, until the extreme ones. This test was performed on its 17 more sensible parameters, evaluating the response of the model by varying such parameters *ceteris paribus* within a feasible physical interval. It was verified that the model response is in line with the expectations[16]. When the lower/upper bounds could not be physically defined, the model was stressed to the lowest/highest possible value, until the occurrence of dynamics not considered in the model boundaries (e.g. no more only-agricultural reliant LI HHs). For most of the sensible parameters, the model behaviour is discussed also by displaying some of the most meaningful outputs of the model by varying the related sensible parameter by -20%, -10%, +10%, +20% respect to the calibrated value, as if the model were tested for different contexts than Ikondo. The figures represent a kind of graphical representations of the *RESPONSEs*-bullets discussed for each extreme value of the parameters (see Table 33).

[16]Where not otherwise specified, the consideration of the model's response is respect to the calibrated simulation.

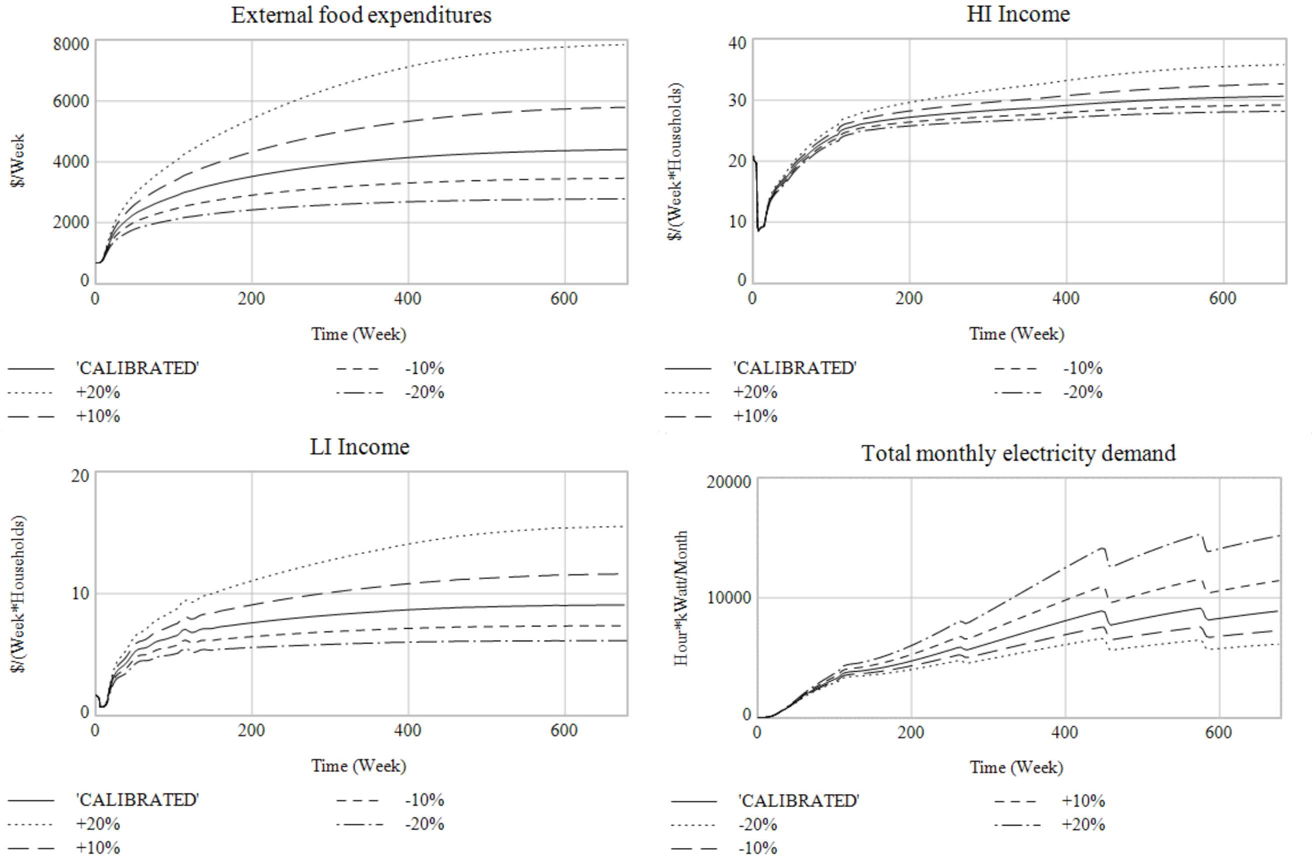
Table 33. Tests on the most sensible parameters.

Parameter	***Extreme conditions and graphical exploration of model output for different contexts***	
Initial external market demand / fr change in external market demand / Initial external agricultural expenditures	*MIN:* 0 *MEANING:* simulation of a closed economy *RESPONSE:* low economic progress; average income of the village remains very low; very low connections and electricity use.	*MAX: tested* *MEANING:* simulation of a market with high trading level. *RESPONSE:* very high economic progress; higher number of IGAs; average income of the village increases for both the HI HHs LI HHs; higher number of connections and electricity demand.



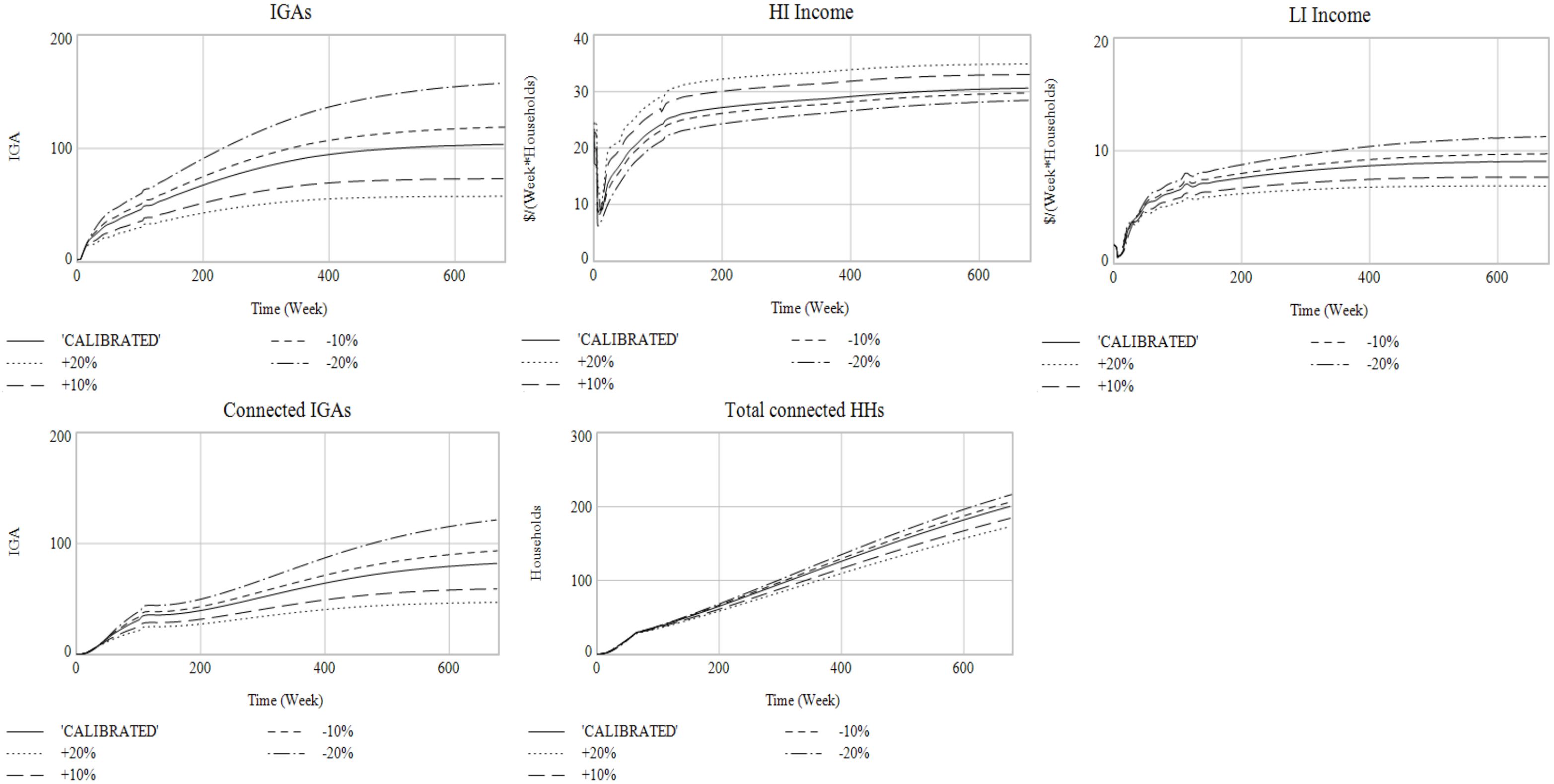
These results confirm that the closer a local economy is, the lower would be the impact of electrification. This indicates the importance of supporting electrification with complementary activities for improving the accessibility of isolated villages (e.g. improvement of roads and communications).

fr change in external food expenditures	*MIN:* 0 *MEANING:* simulation of a closed agricultural economy *RESPONSE:* slower economic progress, income of the LI HHs remains very low; income of HI HHs increases very little; number of IGAs is 50% lower; HHs and IGAs connections reduced by 50%, with >50% reduction of electricity demand.	*MAX: tested* *MEANING:* simulation of a market with high trading level. *RESPONSE:* very high economic progress, higher number of IGAs, average income of the village increases for both the LI HHs and the HI HHs. Higher number of connections and electricity demand.



These results confirm that changes in the agricultural livelihood and dynamics largely impact on the electrification output. This suggests that agricultural activities play an important role also after electrification and the creation of new business. For example, CEFA experts stated that in the village of Bomalang'ombe, close to Ikondo, many farmers abandoned agricultural activities after the creation of new IGAs, limiting the overall benefits of electrification on the local community, creating disparities and too much dependence on electricity quality and reliability. Moreover, this indicates that implementing awareness campaigns intended to improve farming productivity for attracting external consumers is definitively a win-win strategy.

Reference factor productivity	*MIN: tested* *MEANING:* simulation of a market with very high competition. Local IGAs are able to satisfy a very little fraction of the market demand. *RESPONSE:* very high number of IGAs formation; little decrease in the HI income, due to market competition; little increase of LI income, since there are more rich people that spend more in food; sensible increase in the connected IGAs and IGAs electricity demand. Very little change in the number of connected HHs and residential electricity demand.	*MAX: tested* *MEANING:* simulation of a market with no competition. The existing IGAs are able to satisfy alone the market demand. *RESPONSE:* no formation of new IGAs; HI income of the very few IGAs is very high, due to the absence of market competition; little decrease of LI income, since the new households caused by the increase in the population are all farmers, enforcing the vicious circle of poverty; large reduction of electricity connections and demand.



These results suggest that in contexts characterised by an already high level and quality of labour, electricity use benefits less people and businesses, increasing inequality. To avoid this, these results suggest that providing access to electricity in such contexts should be supported by complementary activities aimed at innovating the local production, increasing the market competition on new goods and services. Moreover, this result points out a potential limit of the supply-demand model due to the perfect mixing hypothesis of SD. In this formulation, there is no diversification between businesses, since all of them satisfy the market demand equally and operate under "perfect competition" rules. A further disaggregation based on people's ranking of priorities – e.g. essential goods vs luxury goods – can be a solution for achieving more realistic results, but the larger is the disaggregation, the more appropriate would be the transition towards ABMs.

fraction of feasible HHs market supply

MIN: tested

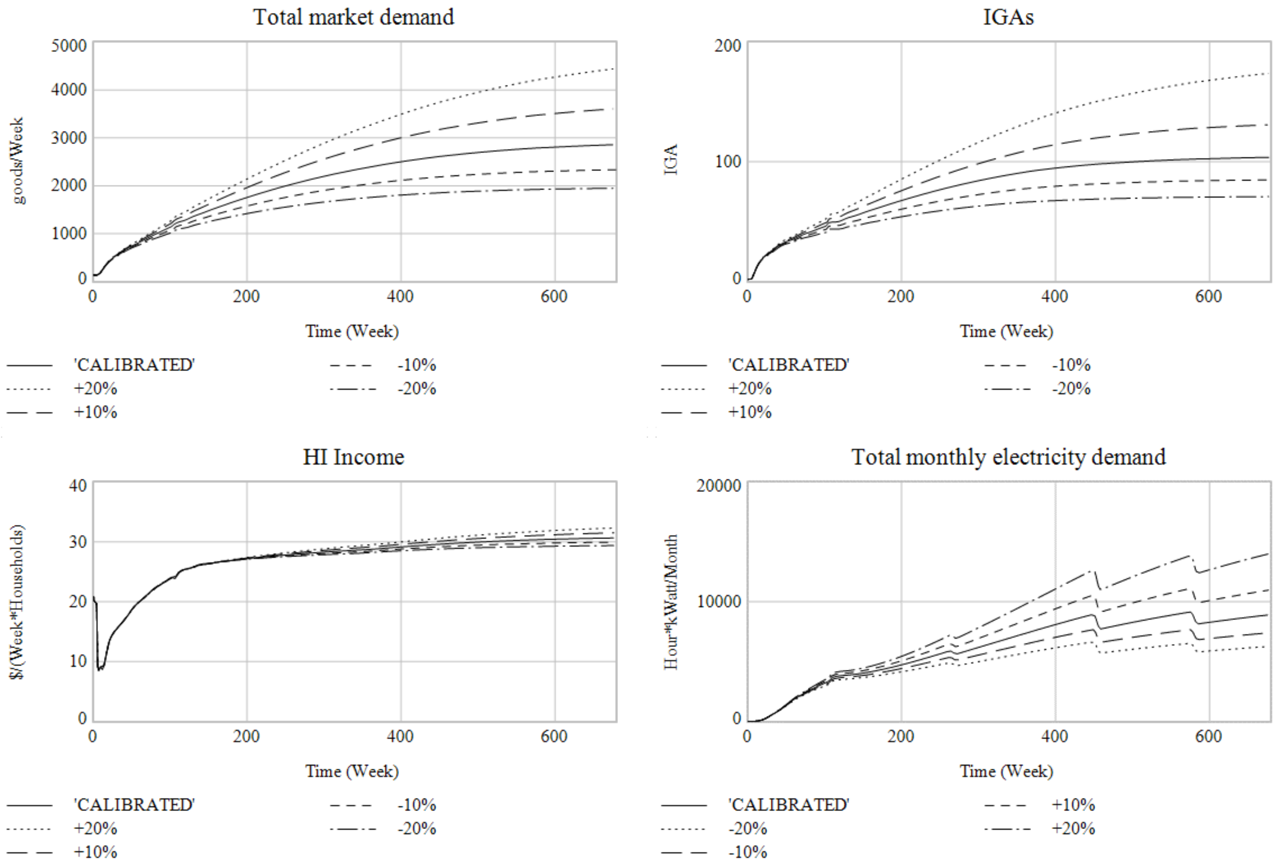
MEANING: simulation of a market able to satisfy 0% of the local HHs demand.

RESPONSE: very low number of IGAs formation, which satisfies just the supply-chain of other IGAs and the external demand. HI income remains unchanged respect to the initial condition; little increase of LI income respect to initial condition, since there are more IGAs (and therefore HI HHs) respect to the initial condition; lower IGAs and HHs connections and demand.

MAX: 1

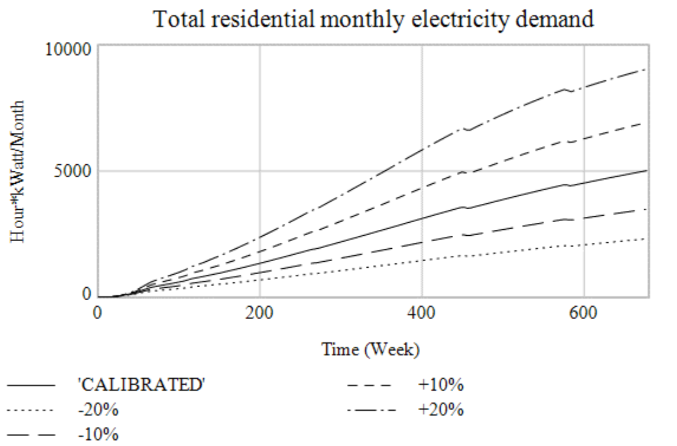
MEANING: simulation of a market able to satisfy 100% of the local HHs demand.

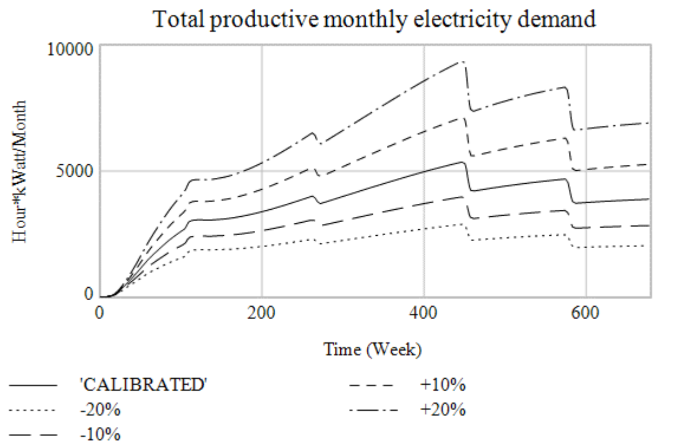
RESPONSE: higher number of IGAs formation; little increase in the HI income, due to a higher market demand but also a higher market competition; increase of LI income, since there are more rich people that spend more in food; increase in the connected IGAs and IGAs electricity demand. Lower proportional increase in the number of connected HHs and residential electricity demand.



These results highlight that a local context which could potentially have the resources for satisfying all the local market demand is very suitable for introducing access to electricity. On the contrary, a very isolated village with no resources would not develop just with access to electrification, but it needs complementary activities for obtaining enough productivity inputs and resources.

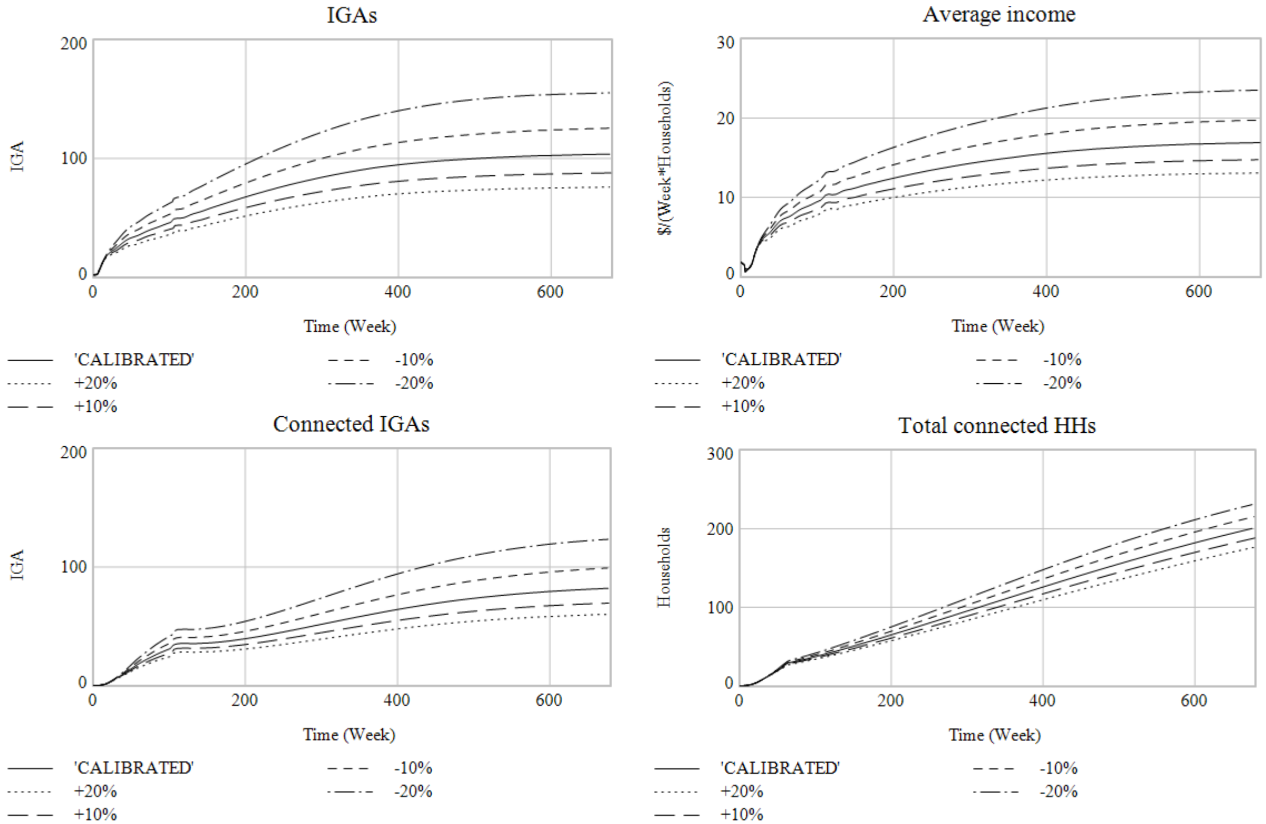
<table>
<tr><td>Initial Population</td><td>MIN: 1/3 of the calibrated value
MEANING: simulation of a smaller community.
RESPONSE: very low number of IGAs formation, cause by the backlog effect of the initial “perceived” needed new IGAs. This backlog causes the set-up of too many IGAs, which create a too high delayed market competition and then a delayed decrease in HI Income. In turn, this causes a delayed decrease in the LI Income. Much lower IGAs and HHs connections and demand.</td><td>MAX: equal to the carrying capacity
MEANING: simulation of a larger community.
RESPONSE: higher number of IGAs formation due to initial higher unsatisfied market demand; little increase in the HI income and LI income, due to a higher internal and external market demand; increase in the connected IGAs and IGAs electricity demand. Lower proportional increase in the number of connected HHs and residential electricity demand.</td></tr>
<tr><td></td><td colspan="2">





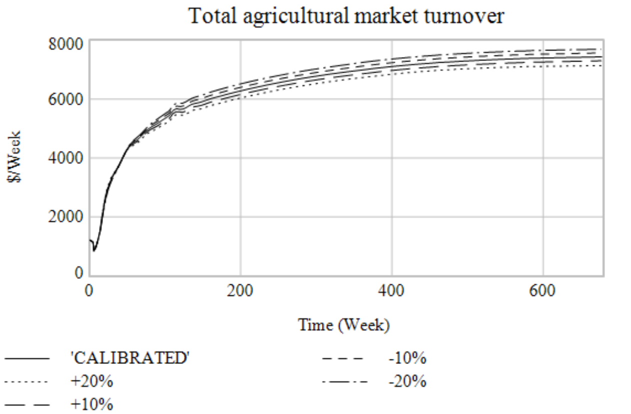
These results suggest that, ceteris paribus, more populated villages can gain more from access to electricity. This could have an important policy implication: in unelectrified areas, electrification programmes should start from the biggest communities.</td></tr>
<tr><td>fr income for education expenditures HI</td><td>MIN: tested
MEANING: less expenditures for education and more for market
RESPONSE: higher number of IGAs formation; increase in the HI income, due to higher market demand (HI HHs spends more for market goods and services); increase of LI income, since there are more rich people that spend more in food; increase in the connected IGAs and IGAs electricity demand. Lower proportional increase in the number of connected HHs and residential electricity demand.</td><td>MIN: → 1
MEANING: HI HHs spend almost all their income in education.
RESPONSE: very low number of IGAs formation, which satisfy just the supply-chain of other IGAs, the external demand, and the LI demand; little increase in HI income respect to the initial condition; little increase of LI income respect to initial condition, since there are more IGAs (and therefore HI HHs) respect to the initial condition; lower IGAs and HHs connections and demand.</td></tr>
</table>

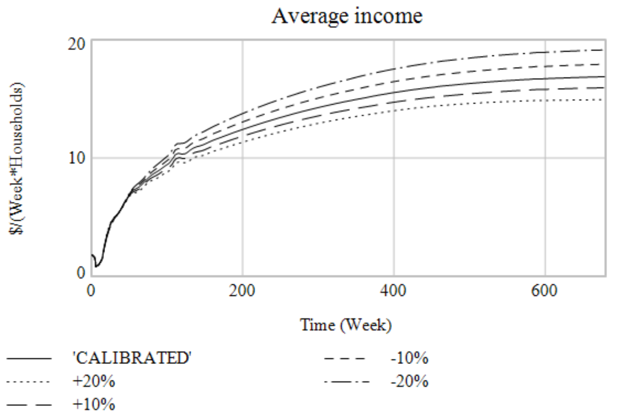
Initial number of IGAs	*MAX: tested (~1)* *MEANING:* simulation of almost absence of initial IGAs *RESPONSE:* higher number of IGAs formation due to initial higher unsatisfied market demand; increase in both HI income and LI income, due to a higher internal and external market demand; increase in both connected IGAs /HHs and IGAs/HHs electricity demand.	*MIN: tested* *MEANING:* simulation of initial IGAs able to satisfy the local demand. *RESPONSE:* very low IGAs formation due to population increase. HI and LI average incomes remain almost constant. Lower number of connected IGAs /HHs and lower IGAs/HHs electricity demand.

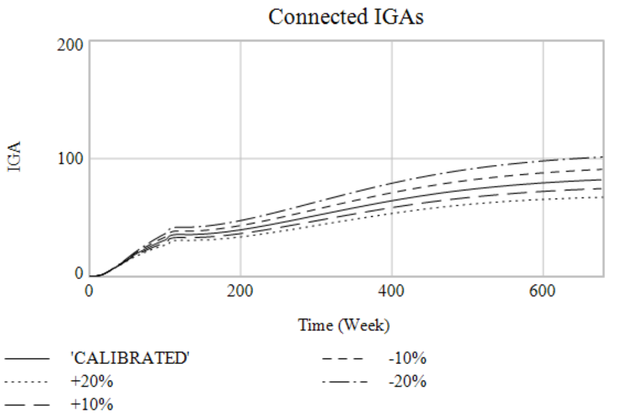


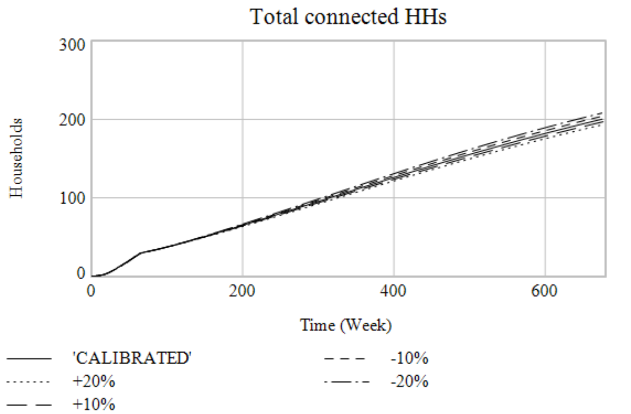
These results suggest that contexts characterised by an already high number of IGAs, ceteris paribus, experience less proportional benefits from electrification, especially because the trend of market development is smoother, attracting less external market demand. The results explain also the so-called "economic boom" of Ikondo-Matembwe villages, were people were all subsistence farmers before electrification. Moreover, as for *Reference market productivity,* this result points out a potential limit of the supply-demand model due to the perfect mixing hypothesis of SD. In this formulation, there is no diversification between businesses, since all of them satisfy the market demand equally and operate under "perfect competition" rules. A further disaggregation based on people's ranking of priorities – e.g. essential goods vs luxury goods.

Initial fr income for food expenditures HI	*MIN: tested* *MEANING:* less HI expenditures for food and more for market. *RESPONSE:* higher number of IGAs formation; increase in the HI income, due to higher market demand (HI HHs spends more for market goods and services); increase of LI income: although the fraction of HI expenditures for food is lower, since the HI income is higher and there are more HI HHs, the HI expenditures for food are higher in the absolute term, albeit slightly; increase in the connected IGAs and IGAs electricity demand. Lower proportional increase in the number of connected HHs and residential electricity demand.	*MAX:* → 1 *MEANING:* HI HHs spend almost all their income in food *RESPONSE:* very low number of IGAs formation, which satisfy just the supply-chain of other IGAs, the external demand, and the LI demand; HI income reaches the almost the same level of the calibrated simulation, since the lower demand is balanced by a lower number of IGAs; LI income reaches the almost the same level of the calibrated simulation since more fraction of HI income spent for food, but with lower HI Income; much lower IGAs connections and demand; lower HHs demand, and little decrease in HH connections.



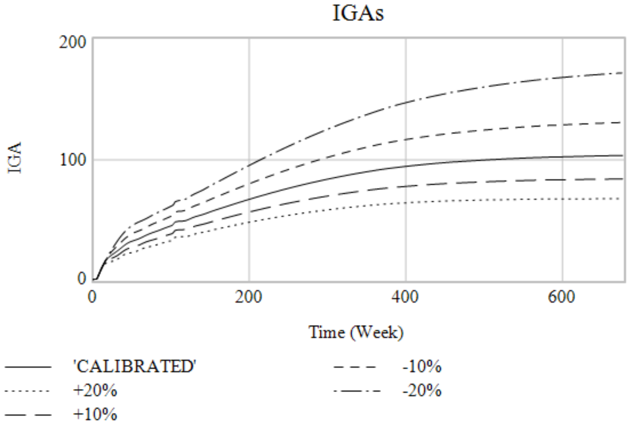


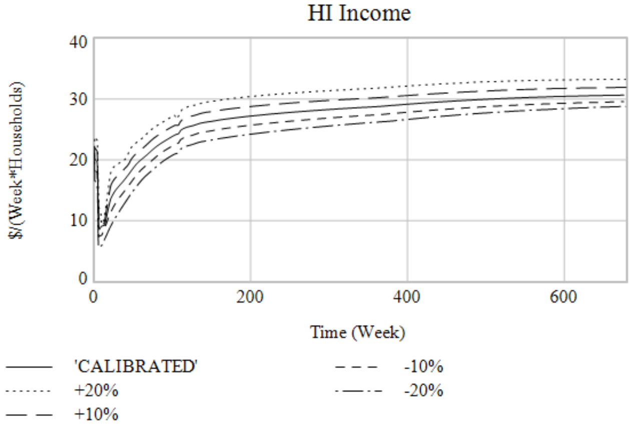


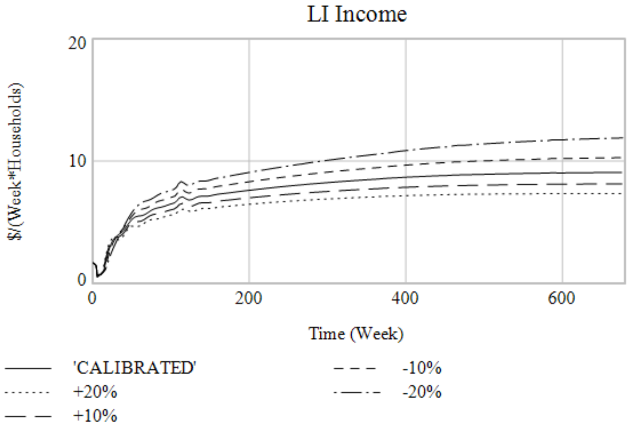


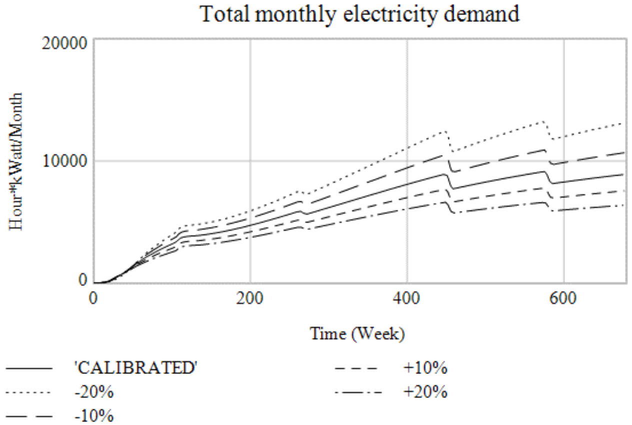
These results indicate that in contexts where people live just on subsistence farming, electricity use alone cannot boost sustainable development. In such contexts, electrification programmes should therefore be supported by activities and awareness campaign aimed at diversifying people's basket of goods and services.

Initial available operation time	*MIN: tested* *MEANING:* initial low time spent for working *RESPONSE:* higher number of IGAs formation (due to lower production per IGA); little decrease in the HI income, due to market competition; little increase of LI income, since there are more rich people that spend more in food; sensible increase in the connected IGAs and IGAs electricity demand. Little change in the number of connected HHs and residential electricity demand.	*MAX: 168 (viz. 24x7)* *MEANING:* HI HHs spend all their time for working *RESPONSE:* formation of very few IGAs (i.e. 6); HI income of the very few IGAs is very high, due to the absence of market competition; LI income remains equal to its initial value, since the new households caused by the increase in the population are all farmers, enforcing the vicious circle of poverty; large reduction of electricity connections and demand.



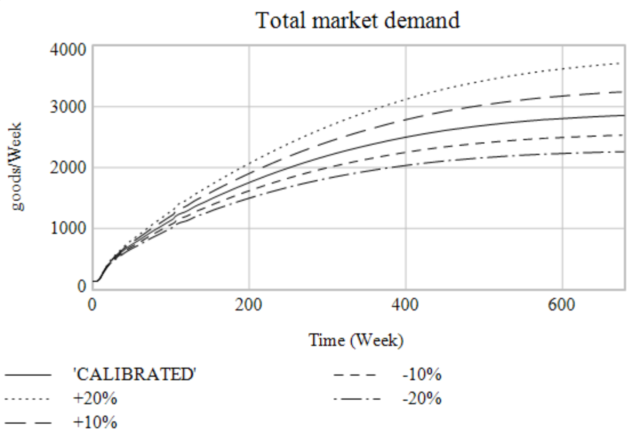


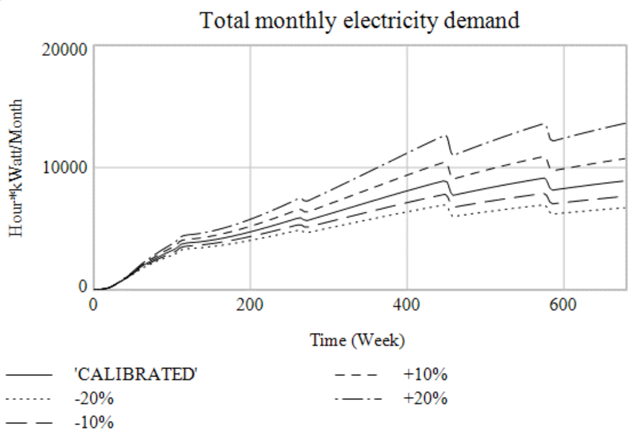




This test provides useful insights concerning contexts characterised by very high inequality and disparity between different socio-economic classes. Where the entire demand is satisfied by very few market suppliers, electricity use has a very low impact on local development. Therefore, electrification programmes must first try to reduce inequality by socio-economic complementary initiative. A further disaggregation of IGAs based on people's ranking of priorities – e.g. essential goods vs luxury goods – and removing the "perfect competition" market rules would probably reduce the impact of this parameter on the payoff.

<table>
<tr><td>Initial fr income for food expenditures LI</td><td>MIN: tested
MEANING: less LI expenditures for food and more for market.
RESPONSE: higher number of IGAs formation; increase in the HI income, due to higher market demand (HI HHs spends more for market goods and services); increase of LI income: although the fraction of LI expenditures for food is lower, since the LI and HI income is higher and there are more HI HHs, the total expenditures for food are higher in the absolute term; increase in the connected IGAs and IGAs electricity demand. Lower proportional increase in the number of connected HHs and residential electricity demand.</td><td>MAX: → 1
MEANING: LI HHs spend almost all their income in food
RESPONSE: low number of IGAs formation, which satisfy just the supply-chain of other IGAs, the external demand, and the HI demand; HI income reaches almost the same level of the calibrated simulation, since the lower demand is balanced by a lower number of IGAs; LI income reaches the same level of the calibrated simulation and more quickly since more money are spent for food; much lower IGAs connections and demand; little increase of HHs connections and electricity demand, since LI income increases more rapidly.</td></tr>
<tr><td>price to cost factor</td><td>MIN: =1
MEANING: no mark-up for IGAs
RESPONSE: low number of IGAs formation, which are set-up just for covering the local market demand; LI income is lower because there are fewer rich people and with lower income; HI income is lower than LI income, since the only source of income for HI HHs is now agriculture, but with a lower productivity respect to LI HHs; lower IGAs and HHs connections and demand.</td><td>MAX: → ∞
MEANING: very large mark-up for IGAs
RESPONSE: decrease in market demand due to unaffordable prices of goods and services (just HI and external demand); lower number of IGAs (i.e. 6); HI income tends to an extremely high level; LI income grows a lot since the food expenditures of the HI HHs are extremely high; connections and demand of IGAs decrease; connections and demand of HHs increase enormously.</td></tr>
<tr><td>fr change in internal IGAs supply / max fr of internal IGAs supply</td><td>MIN: 0
MEANING: the supply chain of IGAs is all outside the village
RESPONSE: lower IGAs formation; lower growth of HI and LI Income; lower connections and electricity use</td><td>MAX: tested
MEANING: the supply chain of IGAs is all local
RESPONSE: very high economic progress; higher number of IGAs; average income of the village increases for both the HI HHs and LI HHs; higher number of connections and electricity demand.</td></tr>
<tr><td></td><td colspan="2">





This output confirms that the diversification of local IGAs is an important determinant of local development. In contexts characterised by very low skills, electricity does not create expected benefits. Electricity use should therefore not just support an increase of the quantity of local business, but also the type and the quality. This suggests that electrification must be supported by effort devoted to increase people's skills in delivering new services and products.</td></tr>
</table>

fr of potentially affordable IGAs connections	*MIN:* 0 *MEANING:* unelectrified IGAs *RESPONSE:* no formation of new IGAs; almost null HI and LI income increase; null IGAs connections and demand; much lower HHs connections and demand, since the fraction of richer HI HHs is almost null.	*MAX: 1* *MEANING:* all the IGAs can potentially afford the connections; *RESPONSE:* more IGAs can work during the evening, increasing their productivity. This generates an increase in the competition, decreasing the IGAs formation by little. HI income increases because there are less IGAs for the same market demand. LI income decreases by little, due to less rich people spending on food.
internal migration effect	*MIN:* 1 *MEANING:* no immigration effects *RESPONSE:* no sensible changes respect to the calibrated model.	*MAX:* $\rightarrow \infty$ *MEANING:* all the HHs can potentially afford the connections; *RESPONSE:* all the households get connected in the simulation horizon. Since there are more people who must pay for electricity, the total demand for market goods and services is reduced, with a decrease in the total IGAs. Moreover, HHs increase their time available during evening more quickly; this causes a more rapid creation of IGAs and therefore a more rapid reduction of the gap between unsolved market demand and market supply. This causes a reduction in the backlog of IGAs to set-up and therefore a reduction in the total IGAs, again. This suggests that a slow rate of residential access to electricity is more sustainable, since it allows people to diversify their basket of goods and services.

9.4.3. Policy testing

These tests aim at exploring model behaviour when subjected to different polices and exogenous decision-making processes. The final goal is to perform a kind of *what-if* analysis and derive some useful insights on the polices implemented by CEFA and potential improvements. In some cases, performing such tests required some changes in the model structure, which are described in detail in the next paragraphs.

Micro-credit

The effect of micro-credit is here assessed by exploring the following two scenarios:

i. absence of micro-credit;
ii. total access to microcredit (all people used micro-credit to set-up a business).

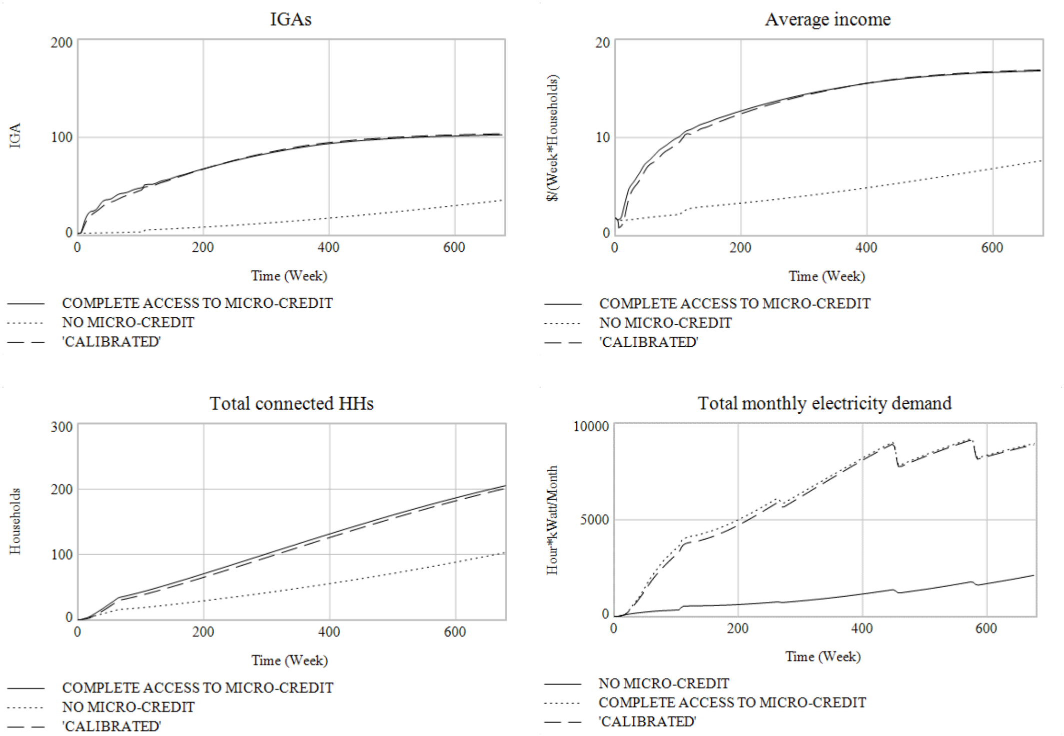


Fig. 50. Effect of micro-credit on some of the main outputs.

These results indicate that access to micro-credit had a significant impact on the socio-economic development of the local community and the consumption of electricity. In case of no access to micro-credit, the number of businesses, the average income of the village, and the number of people that get access to electricity is reduced by half, since people have fewer financial resources to use. All these effects cause a significant lower total electricity demand. On the other hand, these outputs suggest also that a partial access to micro-credit, as in the calibrated case-study, does not lead to significantly different results respect to the case of complete access to micro-credit. Rather, looking at the first two figures on the top-side of Fig. 50, it seems that the case of complete access to micro-credit leads to an initial phase of oscillations in the number of IGAs. This can be explained by considering that with more access to micro-credit, more people can afford the setting-up of a new business, speeding-up the process of financing, and causing a continuous overshooting and undershooting dynamics that slowly gets damper and then stabilises (Fig. 51). This dynamics – the SD-based literature explains it through the famous *Beer Distribution Game* (Sterman 2000) – is caused by the fact that the decision of setting-up a new IGA is based just on the actual existing number of IGAs and the perceived needed ones, neglecting the work-in-progress IGAs in the supply chain (i.e. IGAs to be financed, and IGAs already financed to be set-up). In addition to this, by increasing the access to micro-credit, the time-delay between the corrective action (viz. financing new IGAs) in response to the perceived gap between the desired and actual number of IGAs is reduced, leading to more evident and frequent oscillations.

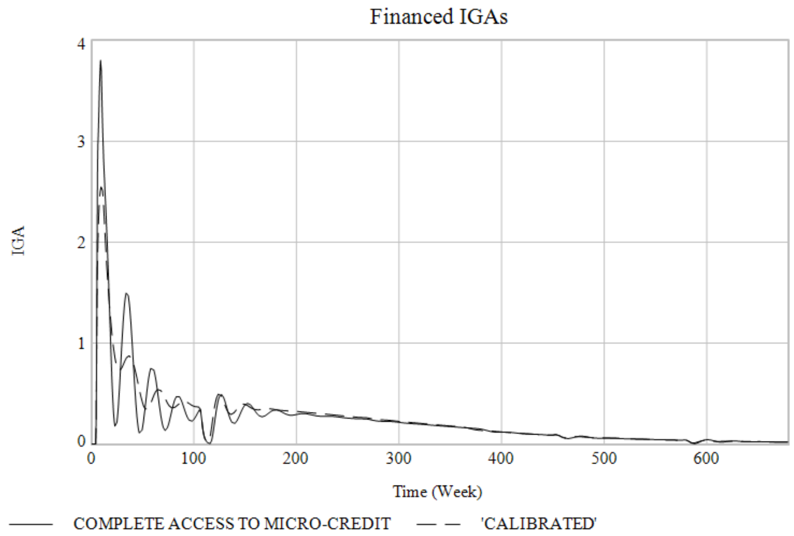


Fig. 51. Clear overshooting and undershooting dynamics of the *Financed IGAs* variable.

Cost of electricity and social responsibility

Almost all the interviewed people in Ikondo-Matembwe indicated the electricity cost set by the local utility MVC to be very affordable. The effect of the electricity price is here assessed by exploring the following two scenarios:

i. increasing the variable electricity cost by 5 after 1 year, by keeping constant the fraction of revenues that the MVC reinvests within the local community (viz. *with social responsibility* case);
ii. increasing the variable electricity cost by 5 after 1 year, by setting the fraction of revenues that the MVC reinvests within the local community equal to 0 (viz. *without social responsibility* case).

The outputs in Fig. 52 confirm that increasing the electricity cost, obviously, decreases the financial availability of HHs for goods and services, especially the LI HHs. In case of social responsibility from the utility, this does not impact on the socio-economic development of the village, while it causes a decrease in the total community electricity demand, especially for the EE-reliant IGAs. Indeed, according to the model output, the electricity expenditures with the current electricity tariff implemented by the MVC represent around 10% of their profit. Instead, HHs are used to pay a lot for traditional sources of energy (e.g. kerosene, candles, paraffine), and their electricity demand elasticity is indeed very low. Moreover, the expenditures for electricity with the current electricity tariffs implemented by the MVC represent around 1-2% of their total income, that is a very small fraction. In the case of absence of social responsibility, increasing the electricity cost impacts also on the number of IGAs and the average income, due to a decrease in the HHs market demand. These results suggest that increasing the cost of electricity does not alter the socio-economic structure of local communities if a reinvestment of the utility revenues within the local community is guaranteed. This is an interesting result, especially useful when exogenous or endogenous events require an increase of the electricity tariff. On the other hand, any increment is followed by a significant decrease of electricity use, which must be considered in the planning phase of the electricity system, in order to avoid shocks in the tariff values, especially for the EE-reliant businesses.

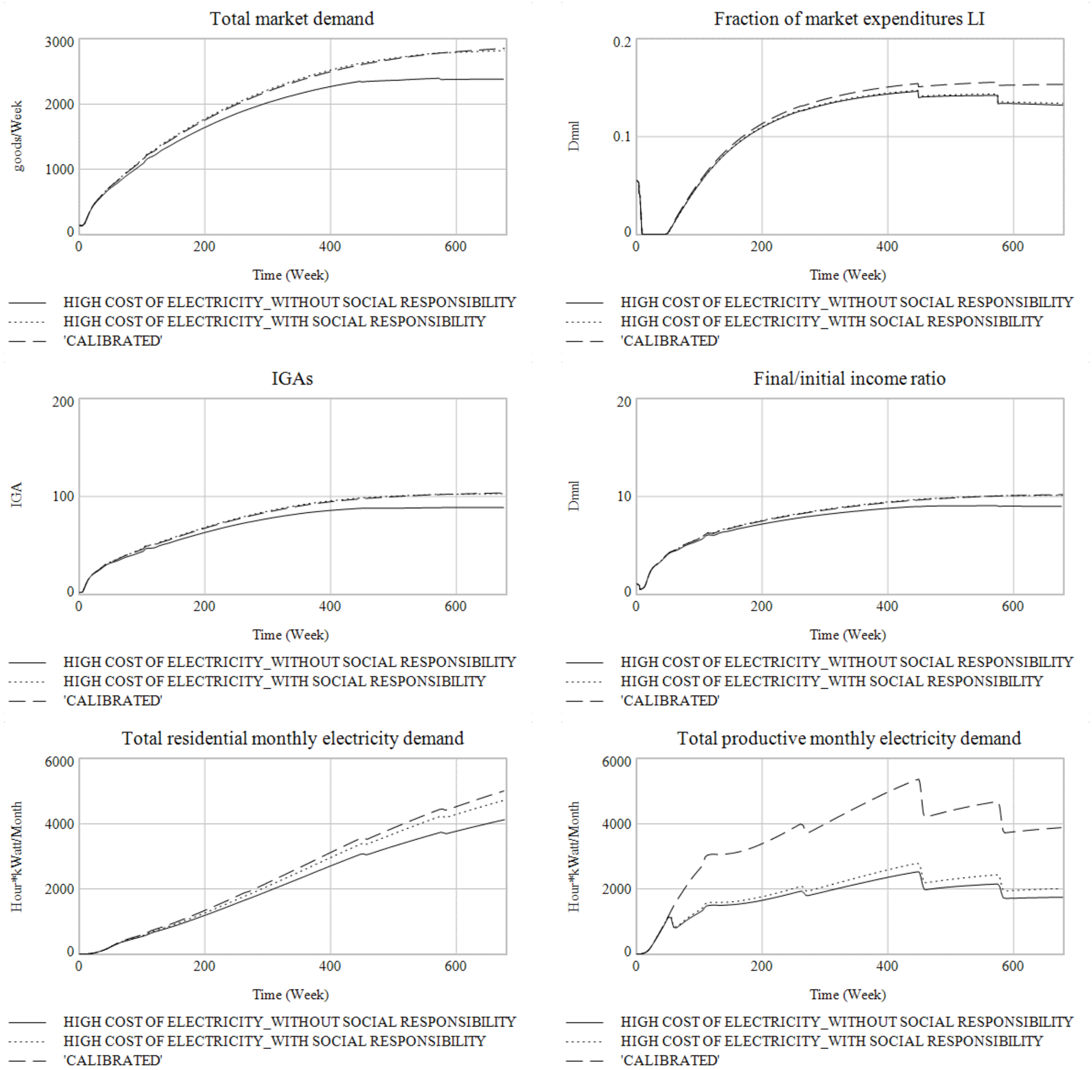


Fig. 52. Effect of electricity cost on some of the main outputs.

Electricity reliability

Electricity reliability is one of the most important factors to consider for implementing sustainable electricity plans in rural communities, as emerged by the literature on the electricity-development nexus (Chapter 5), and stated by Hartvigsson et al. (Hartvigsson et al. 2015, 2018a; Hartvigsson 2018).

In the case of Ikondo, the local surveys and data confirmed the high quality of the electricity service delivered to people. For this reason, the reliability parameter was introduced in the model as an exogenous measure of "unavailability" of the service, which has a feedback just on the actual time of electricity use (Eq. (38)). In order to consider the impact of electricity reliability on people willingness to have access to and consume electricity, the model has been modified by adding a new variable, namely "customer's response" to electricity quality, which multiplies the following variables:

i. *Potential IGAs to be connected* and *Potential HHs to be connected*, since people are less willing to be connected for a weak electricity service;
ii. *Total HHs electricity demand* and *Total IGAs electricity demand*, since people are less willing to consume and pay for an unreliable electricity supply;
iii. *Electricity availability effect*, which represents the propensity of people in investing in a new IGA given the availability of electricity.
iv. *increase of market expenditures*, which represents the grade of innovation and improvements of market goods and services thanks to electrification.

According to Hartvigsson et al. (Hartvigsson et al. 2018a), the variable can be expressed by a logistic function, which depends on the reliability of electricity:

$$customer's\ response = \frac{1}{1+e^{-k_{cr}\cdot(El.Reliability - El.Reliability_0)}} \qquad (51)$$

The parameter k_{cr} influences the steepness of the logistic function (Fig. 53, left-side) – viz. the higher it is, the more unexpected would be the response of the customer around a certain crucial value of reliability). The parameter *El. Reliability*$_0$ is the crucial value of the sigmoid's midpoint – viz. where the variable *customer's response* is reduced to 50% of its maximum (Fig. 53, right-side).

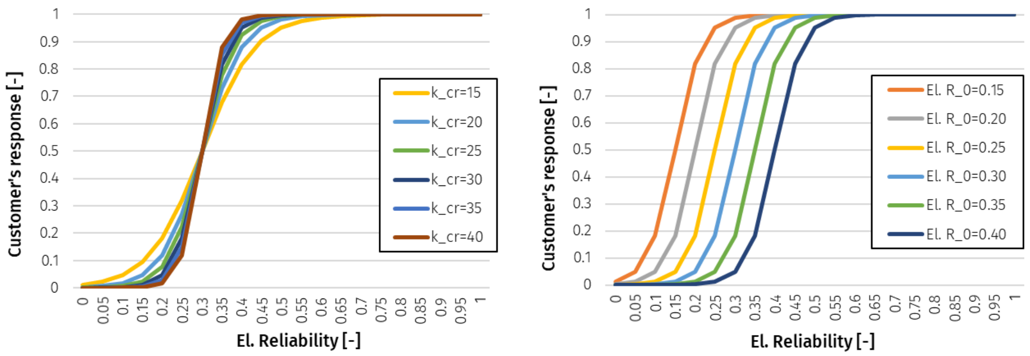


Fig. 53. Logistic function of *customer's response* variable by varying k_{cr} and keeping *El. Reliability*$_0$ *= 0.3* (left-side), and by varying *El. Reliability*$_0$ and keeping k_{cr} *= 30.*

To test the effect of customer's response to changes in the power reliability, the model behaviour is explored by decreasing the El. Reliability by 0.01%, 0.05%, and 0.1% per time step. The parameters k_{cr} and *El. Reliability*$_0$ are set equal to 25 and 31 in accordance with the mean values taken from (Hartvigsson et al. 2018a).

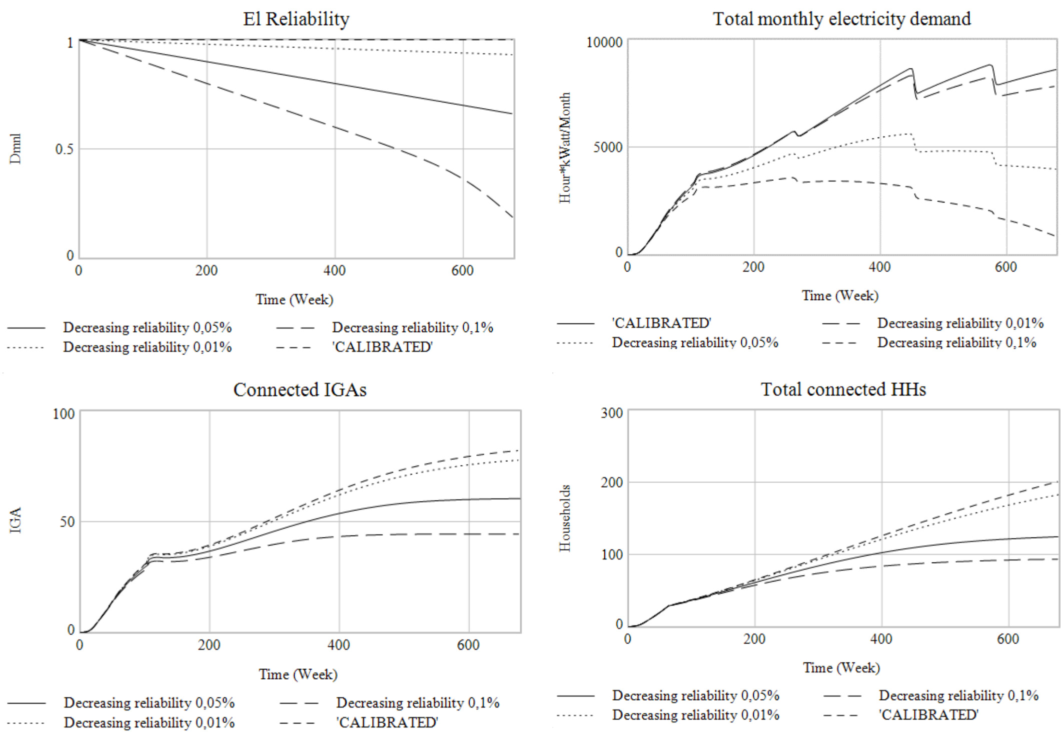


Fig. 54. Effect of electricity reliability on some of the main outputs.

As expected, decreasing the quality of the electricity service, electricity connections and use are lower respect to the calibrated case. In some cases, the consumption even starts decreasing after a certain point (Fig. 54). The assumption here is that people do not disconnect, even for low levels of reliability, since the fixed component of the tariff to pay every month is very low; otherwise, the impact would be even worse, causing a high rate of disconnections, as demonstrated also by Hartvigsson et al. (Hartvigsson et al. 2018a). This result confirms the need to introduce the concept of reliability and/or consumer satisfaction in the traditional "binary" metrics – viz. *access* or *not access* to electricity – usually employed for tracking the global progress in providing universal electricity access. Indeed, using just the initial number of connections as an indicator for electrification programs can cause low reliability and unaffordable electricity prices, due to the underestimation of the affordability- and reliability-related complexities.

9.4.4. Testing further socio-economic dynamics

These tests aim at evaluating the importance and the impact of electricity access on some socio-economic dynamics, and the reverse feedback. This contributes to assess further dynamics of the electricity -development nexus and to initiate the process of model simplification.

Electricity-education

Based on the calibrated results and in accordance with (Kanagawa and Nakata 2008), Fig. 55 confirms that electricity allows to achieve non-negligible improvements in the educational attainment of local children in primary school, especially as a result of lighting at school – the step of Fig. 55 as indicated by surveys at Kanikelele's school.

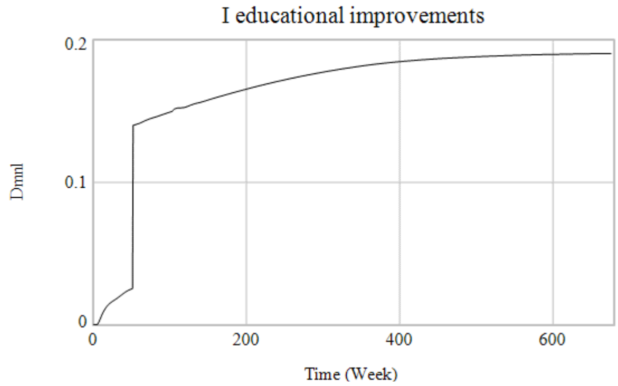


Fig. 55. Educational improvements in Ikondo.

On the contrary, formal education seems to have a negligible impact on electricity use: the total electricity consumption at the final time is just 4.4% lower. This result confirms what emerged from the interviews to the locals, who often mentioned the primary education as the least important factor for both opening a business and improving the productivity.

Electricity-use of time

As emerged from the survey, almost all the interviewed people mentioned the time available during the evening hours as an important effect of electricity use. The simulations (Fig. 56) indicate that the evening hours are employed especially for productive purposes, rather than farming. Moreover, the trend of the *operation time* curve starts decreasing at a certain point. This is caused by the change in the electricity connection tariff in 2006, which created a fractional decrease in the IGAs connection rate, without affecting the rate of IGAs formation. The trend keeps increasing again as the number of IGAs starts reaching the plateau.

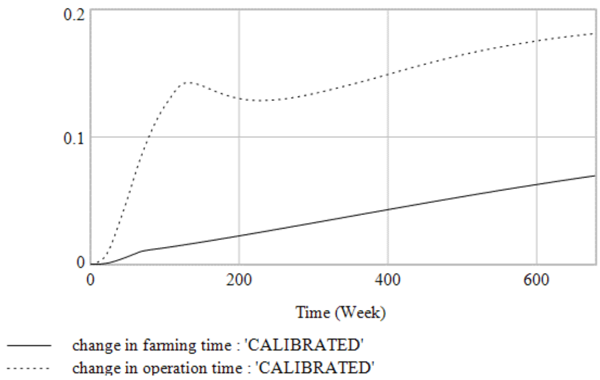


Fig. 56. Effect of electricity use on time available for working and farming [% of change].

The feedback on the economic dynamics and the electricity demand is displayed in Fig. 57. Removing the feedback of the time-variable has a non-negligible impact on the number of IGAs and HI Income.

In particular, the number of IGAs increases, since the local market demand cannot be satisfied in the evening and more IGAs are needed for increasing the daily production. This is in line with the literature which does not report an increase of businesses as a result of night lighting. On the contrary, the decrease in the HI Income is in line with the local surveys, that suggested an increase in the sales and revenues as a result of the evening working. Fig. 57 confirms also that from an aggregated point of view, the feedback of time freed-up by electricity use on the community demand is negligible (i.e. demand 3% higher at the end of the time horizon). On the other hand, focusing just on the IGAs demand, the disaggregated feedback generates an increase of 11% in the electricity use, since there are more IGAs.

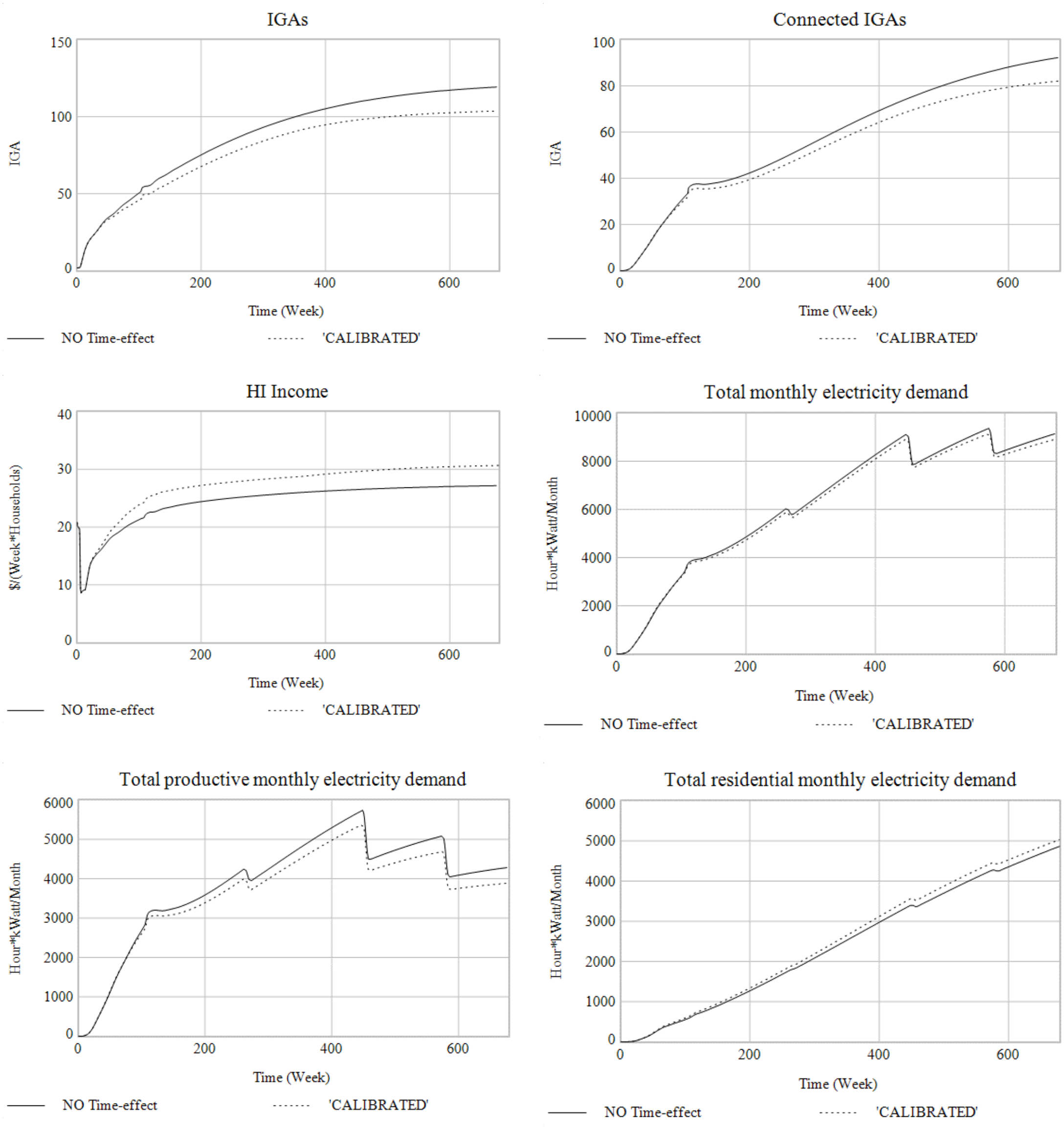


Fig. 57. Feedback of time on some of the main outputs.

Electricity-market improvements

This test aims at assessing the effect of electricity use on the local market demand for new local products with higher quality, and the feedback on electricity use. The same behaviour is generated by investigating the effect of price reduction due to market expansion because of electrification. The results show that neglecting these dynamics would significantly bias the estimation of the final community electricity demand. This confirms again an important lesson to consider when measuring the impact of electrification actions: the level of isolation of a village and the proximity to other electrified areas are fundamental conditions to take into account. In villages well connected with other electrified areas, the relative impact of electrification would be considerably lower, since such villages are benefited from a spill-over of the surrounding areas. This is evident also from the surveys in the unelectrified village of Kitole, close to Matembwe and Ikondo, who is characterised by a higher welfare level respect to Ikondo before electrification.

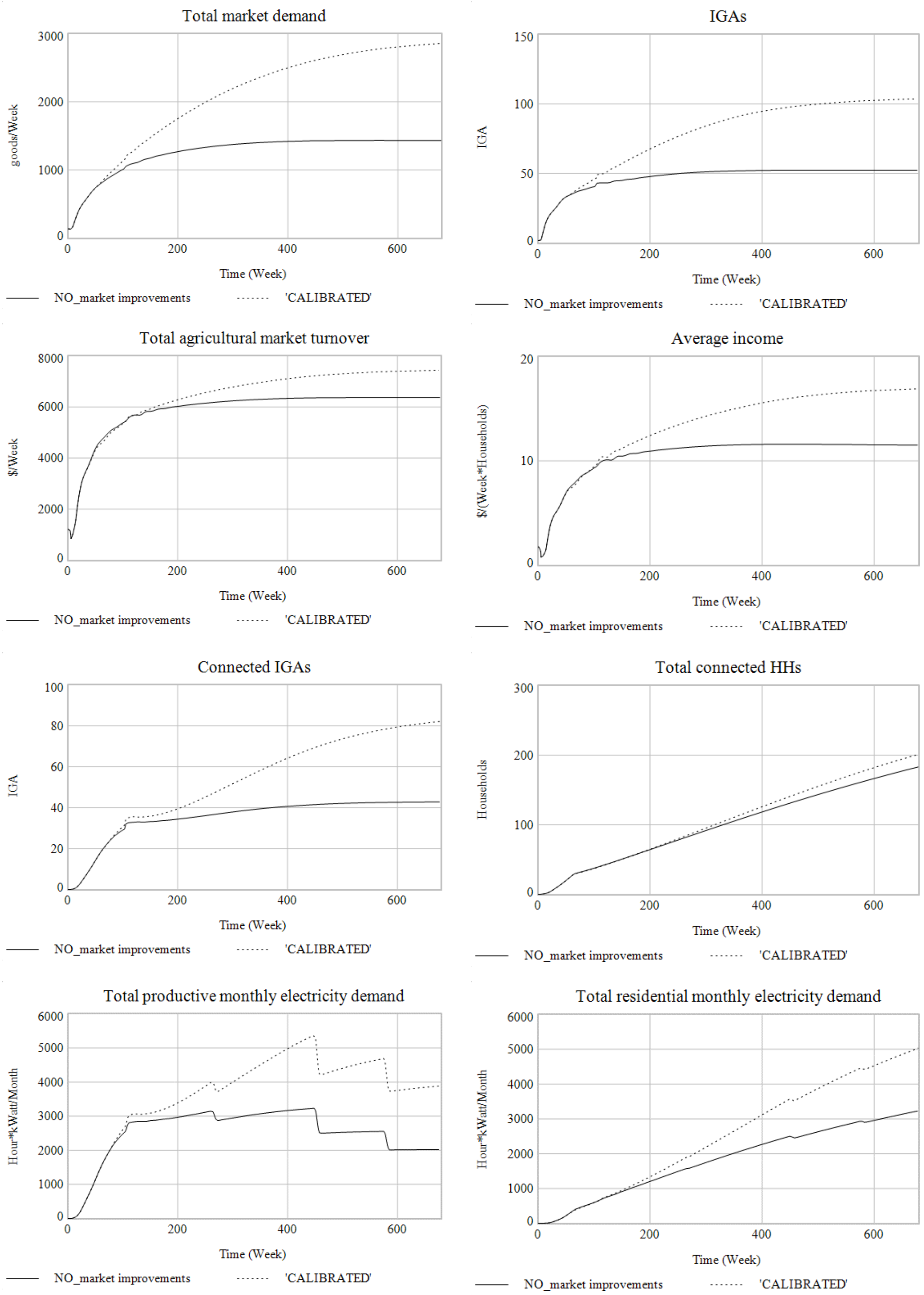


Fig. 58. Feedback of market improvements on some of the main outputs.

9.5. Sensitivity Analysis

This test aims at assessing the robustness of the conclusions that can be derived from the main model output on varying the assumptions over a plausible range of uncertainty. In this work, the presence of potential sensitivity to parametric assumptions was assessed by simulating the model with multiple numerical values of its parameters.

Two decision rules for sensitivity analysis had to be addressed, namely:

- ***Number of parameters to test.*** The analysis was performed by varying the 17 most sensible parameters found in sub-section 9.3. For the sake of comparison, the sensitivity analysis was performed also by testing all the parameters in a second step.
- ***Sensitivity range.*** The uncertainty bounds evaluated in sub-section 8.3 were employed. In order to avoid being overconfident in the uncertainty bounds, according to Sterman (Sterman 2000), the range used for the sensitivity was at least twice as wide as the statistical uncertainty bounds.
- ***Number of simulations.*** Performing a comprehensive sensitivity analysis by testing all the combinations of possible values within the sensitivity ranges is not feasible. E.g., considering to sample 100 values for each single parameter and test all the combinations between the 17 most sensible ones, the number of simulations to test would be 100^{17}. Moreover, since some parameters are totally independent in the real world, testing all the combinations could lead to unrealistic values. The same consideration applies in case of testing all the combinations between just the minimum and maximum values of the chosen parameters. An alternative could be performing a *univariate* sensitivity by testing 100 samples for each parameter per time, and then sum-up the effect. Also in this case, this would not be an appropriate choice for testing the sensitivity in SD models that are significantly nonlinear in most of the cases. Therefore, it was decided to perform 20'000 near-random *multivariate* simulations through a *Latin hypercube* method, in order to explore the combined effect of varying the parameters at the same time.
- ***Sampling method.*** The 20'000 simulations were performed by using a near-random sampling based on the *Latin hypercube* method, in order to be sure to sample the entire sensitivity range of each parameters. It is an approach introduced in 1979 by McKay et al. (McKay et al. 1979). Simply, given the 20'000 samples to perform, the method divides the cumulative density function of each parameter's distribution – it is uniform in the case of this study – in 20'000 equal intervals; for each one of the 17 parameters, given *a* and *b* the extremes of the uniform distribution, the sample $s=1,\ldots,20'000$ is selected from the interval $\left[\frac{(s-1)\cdot a}{20'000}, \frac{s\cdot b}{20'000}\right]$. Then, all the samples made on the chosen parameters are randomly combined in a 17-dimensional pairs. This method is a refinement of the complete random Monte-Carlo simulation, since it should guarantee that the sampling from each parameter's distribution covers the actual entire variability.

Fig. 59 reports the results obtained by performing the sensitivity analysis on the *Total community electricity demand obtained*, which represent the electricity demand of the entire community, viz. IGAs plus HHs. The sensitivity was performed both on the 17 most sensible parameters and compared with the same analysis performed on all the calibration parameters. The plotted values are limited to a confidence bound equal to 90% represented by the red areas in the graph, meaning that 5% of the simulations are cut-off from the top and the bottom of the areas. The other coloured areas represent the 80% (in orange) and 60% (in yellow) confidence bounds. The comparison between the two results (Table 34) confirms that testing also the combinations between all the other less sensible parameters is not particularly useful, since the results do not significantly differ.

The results clearly show that the model is highly sensitive to the uncertain parameters in the long-run. On the other hand, this variability is reflected also by data, which are very scattered. On the contrary, the uncertainty bars are tight in the short-run, and they are not able to capture the variability of the data. Given the general objective of the model, viz. projecting long-term electricity demand to support local electricity plans, these results can suggest a potential practical use of the model for designing sustainable power systems in further applications. As reproduced in Fig. 60, the model could be used for making projections of electricity demand for the initial 3-4 years, and then supporting the design of the initial size of an off-grid microgrid able to satisfy the worse/highest (i.e. the upper red) demand curve. This would overestimate the actual mean demand, but it also would ensure to cover potential peaks and power fluctuations and, in the meantime, gather data for assessing the trend of the demand curve.

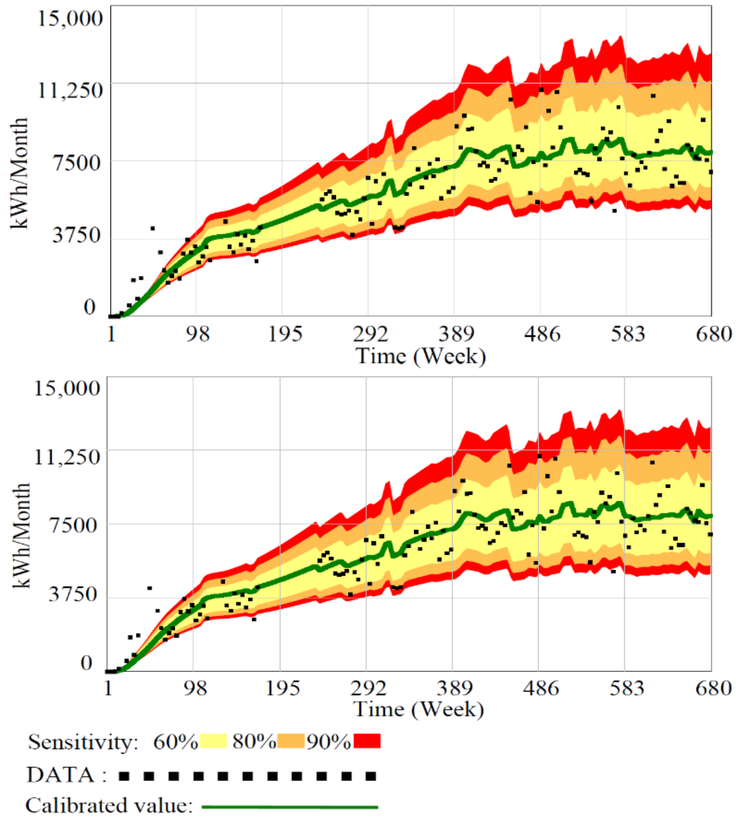


Fig. 59. Sensitivity results tested on the *Total community electricity demand* obtained by varying the 17 most sensible parameters (top-side), and all the parameters (bottom-side).

Table 34. Deviations between the two sensitivity analyses evaluated on the confidence bounds at the final time of the simulations (percentages referred to the analysis performed on the 17 parameters).

90%-sup	*90%-inf*	*80%-sup*	*80%-inf*	*60%-sup*	*60%-inf*
+2.2%	*+4.6%*	*+2.1%*	*+3.8%*	*+2.2%*	*+3.7%*

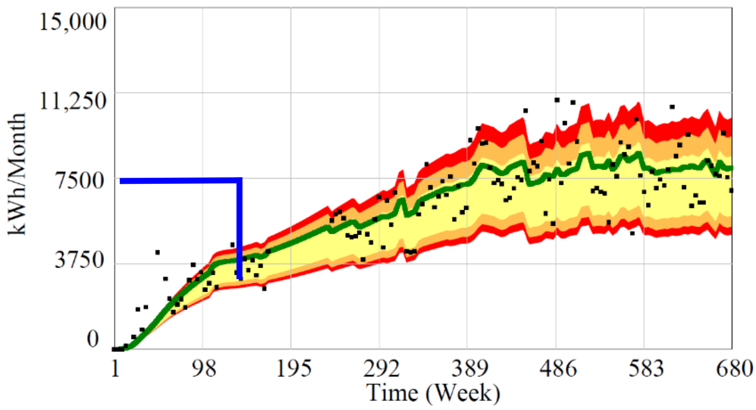


Fig. 60. Sensitivity *cont'd.*

Chapter 10

Soft-linking demand and optimisation models

If your hate could be turned into electricity, it would light up the whole world.
(Nikola Tesla)

We need to bring sustainable energy to every corner of the globe
(Ban Ki-moon 2011)

This chapter addresses the Objective 3. It reports and discusses the modelling effort in soft-linking demand, load, and energy optimisation models for more appropriate electrification planning procedures. To derive stochastic long-term load profiles, the *LoadProGen* tool model is modified and improved in order to simulate and aggregate a number of daily profiles in line with the duration of the desired scenario and the projections obtained with the SD model. The integration with the *Poli.NRG* energy model is implemented in order to optimise the size of the energy supply technologies through a heuristic procedure under a number of constraints and inputs (e.g. the long-term electric load profiles, the availability of renewable resources, and the fraction of admissible unmet load). A Hydro-batteries is considered, in order to investigate what would have been a potential optimal capacity to install for supplying the projected electricity demand of Ikondo from 2005 to the end of 2017. The same optimisation is implemented by considering a PV-batteries system for the planning of the first 3 years of the horizon, given the flexible nature of solar systems and the low variability in the electricity demand in the first years. In order to highlight the benefits and challenges of the soft-linked procedure, the results are compared with the traditional approaches and hypothesis commonly adopted in the literature to assess and introduce electricity demand in rural electricity planning processes.

10.1. Generation of stochastic long-term load profiles

Sub-section 2.1 and 2.5 confirmed that both short- and long-term variabilities have a significant impact on the planning of off-grid systems. Based on the sensitivity analysis performed in the previous Chapter, 5 representative projections and the related simulation parameters were selected (Fig. 61), namely:

- the *CALIBRATED* projections;
- the following 4 percentiles: *70%, 80%, 90%, 95%.*

For these 5 scenarios, long-term load profiles were generated by developing a soft-link with a stochastic load profile generator.

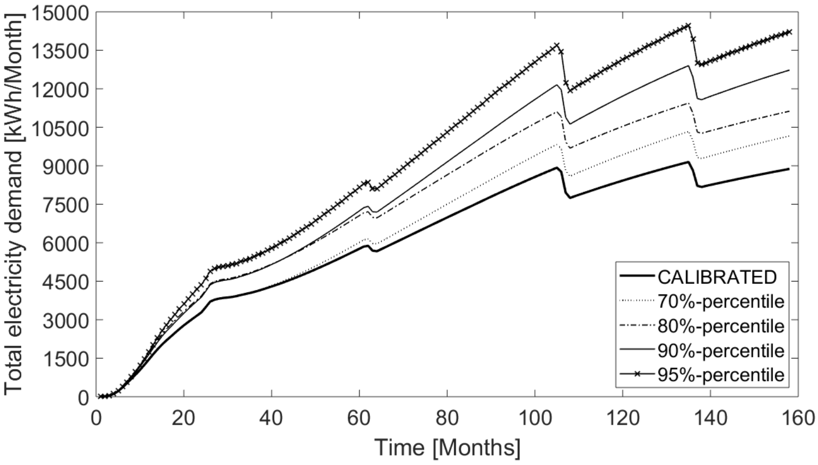


Fig. 61. SD simulations used for generating long-term load profiles.

10.1.1. *Lifetime*-load profiles generator

In line with *CASE 1* and *CASE 2,* the software *LoadProGen* developed by Mandelli et al. (Mandelli et al. 2016d) and implemented in MATLAB® represents an appropriate tool for estimating load profiles characterised by a high level of uncertainty. The software has the following features (Mandelli et al. 2016e):

- input data (see Table 35) can be easily collected by means of local surveys or assumed by practical experience on similar context conditions;
- the load profile formulation is based on a bottom-up approach, since it relies on the real features of each electric appliance within a specific type of user class;
- it defines the behaviour of the appliances and the power peak value correlating the number of users with their declared usages of each appliance;
- the procedure is based on a stochastic process; it takes into consideration uncertainties by formulating different realistic profiles according to the given the input data.

Table 35. Input data required by LoadProGen (from (Mandelli et al. 2016e)).

j	type of electrical appliances (e.g. light, mobile charger, radio, TV)
uc	specific user class (e.g. household, school, stand shop, clinics)
n_{uc}	number of users within class *uc*
$N\_app_{j,uc}$	number of appliances *j* within class *uc*
$P_{j,uc}$	nominal power rate [W] of appliance j within class *uc*
$h_{j,uc}$	overall time each appliance *j* within class *uc* is on during a day [min]: functioning time
$w_{F,j,uc}$	period(s) during the day when each appliance *j* within class *uc* can be on: functioning windows
$d_{j,uc}$	functioning cycle [min], i.e. minimum continuous functioning time once appliance *j,uc* is on
$Rh_{j,uc}$	% random variation of functioning time appliance *j,uc*
$Rw_{j,uc}$	% random variation of functioning window appliance *j,uc*

The software adopts a stochastic approach, computing a different daily load profile each time it runs. It starts computing the total daily electric need within each user class *uc*, the possible theoretical maximum power peak, and the time when the peak may occur. Based on an empirical correlation existing between the amount of users within each user class (n_{uc}), the load factor ($f_{L,uc}$) and the coincidence factor ($f_{C,uc}$), the software computes the reference value of the power peak for the considered user class. The reference value of the power peak for each user class is employed to compute the class's daily load profiles: firstly, the software defines the functioning of each appliance *i* by randomly sampling the switching on times within the relative functioning windows $w_{F,j,uc}$; secondly, it aggregates the functioning of the single appliances to compute the daily load profile and the resulting power peak for the considered user class; thirdly, the software implements an iterative process, which makes the resulting power peak converge towards the reference power peak, assuming a tolerance defined by the designer. *LoadProGen* repeats the previous steps for each user class in order to compute the total daily load profile. Each run of the software generates one daily load profile, constituted by a series of *x* values, each one representing the load (W) over a time-step that can be 1 second, 1 minute, 15 minutes, or 1 hour.

In its original version, *LoadProGen* allows the user to perform an arbitrary number of daily load profiles. In the framework of this thesis, the software was modified in order to simulate long-term scenarios of electricity loads: in its new modified version, the tool generates a number of daily profiles in line with the duration of the desired scenario, and it automatically aggregates them. The aggregation was formulated in the original code by adding an external routine, which runs *LoadProGen* as many times as the number of the *N* days (viz. the planning horizon) of the desired scenario and according to a *calendar*-file, which associates each day of the scenario to a specific input data file. One input data file can represent one single day – in this way the number of input data files is equal to the number of days of the scenario – or a "cluster" of k_i days (e.g. a season) – in this way the number of input files is equal to the number of such "clusters" of the scenario. This new version of the software is called *Lifetime-LoadProGen* (Fig. 62).

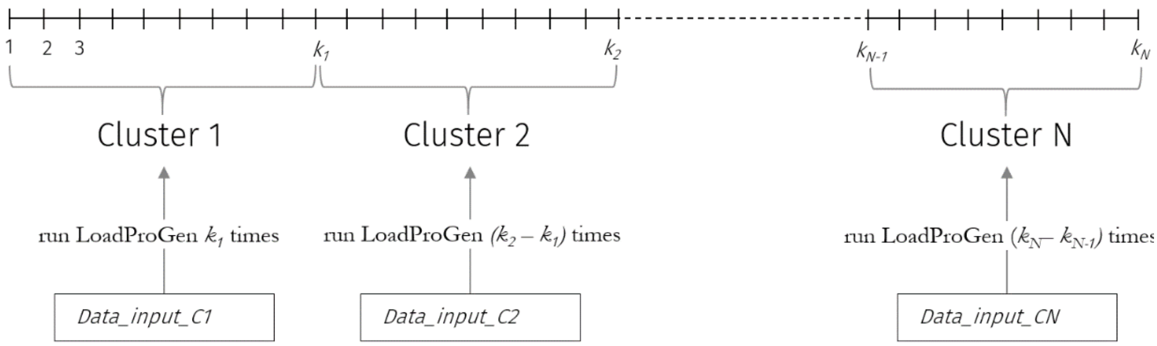


Fig. 62. Operation of *Lifetime-LoadProGen*.

10.1.2. Soft-linking SD and load models

The SD model was soft-linked with the *Lifetime-LoadProGen* tool by using the values of 38 output variables from the SD model, and converting them in the correct variables to use in the input data files for the software. The computer modelling environment used was MATLAB ®. The variables were grouped in Fig. 63, and soft-linked with the corresponding variables to use in the software.

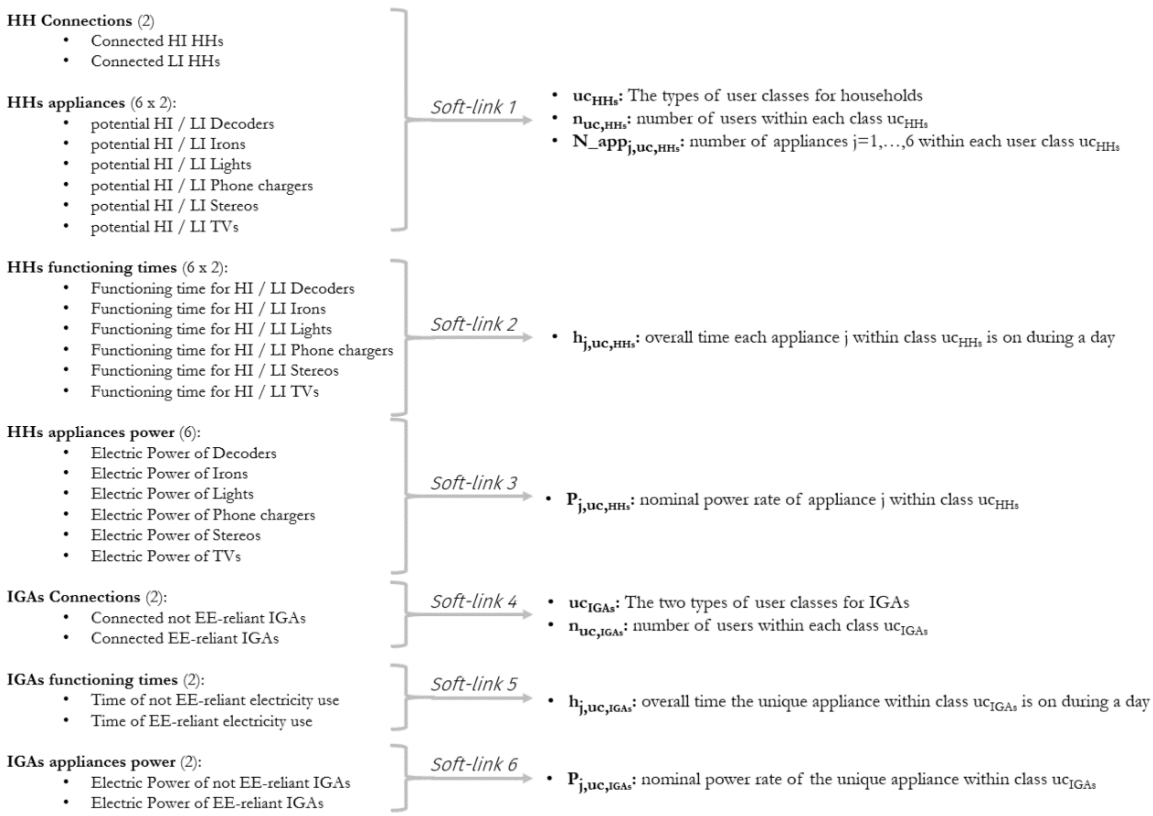


Fig. 63. Outline of the soft-link between SD and load models.

The first soft-link was used to determine the number of potential user classes between households, based on the type and number of appliances. For each appliance, the SD model provides simulated time-series of the ownership level for the two income groups (Fig. 64). The soft-link evaluates the total integer number of appliances to allocate for each time-step by multiplying these diffusion curves times the curves of HI and LI HHs connections – previously rounded to the nearest integer for each time-step. The soft-link then assigns the appliances among the connected households according to a random distribution, obtaining the $N_{app_{j,uc,HHs}}$ variables. All the combinations obtained with such random allocation provide the types and number of the HHs user classes uc_{HHS}, and the number of users in each one ($n_{uc,HHs}$).

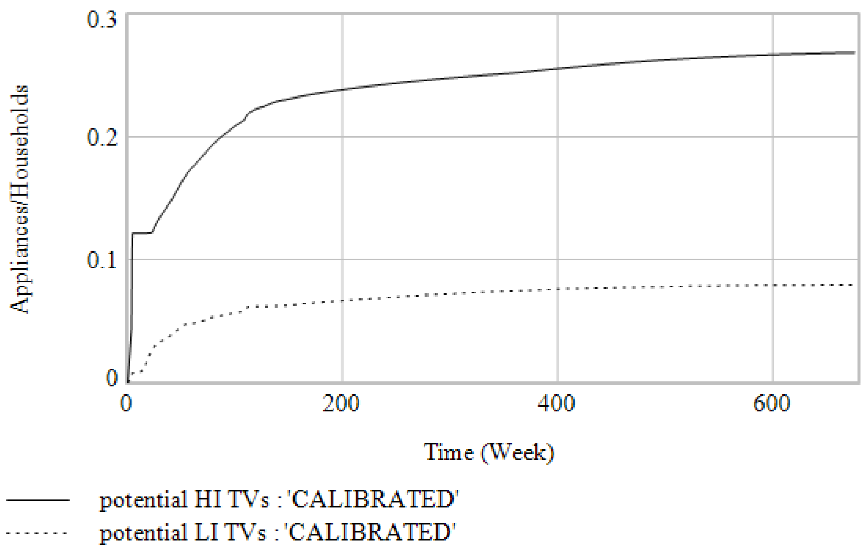


Fig. 64. Diffusion curve for the appliance TV.

The other variables related to the operation time of the appliances were soft-linked with the software just by converting the units of measurement:

- *Functioning time for HI / LI [appliance]* converted from [hour/week] in $h_{j,uc,HHs}$ [minutes/day];
- *Time for not EE- / EE- reliant IGAs* converted from [hour/week] in $h_{j,uc,IGAs}$ [minutes/day].

The *Connected not-EE-reliant IGAs* and *Connected EE-reliant IGAs* time-series are rounded to the nearest integer for each time-step, giving the number of IGAs ($n_{uc,IGAs}$) for the 2 IGAs user classes (uc_{IGAs}).

Since the calibrated model confirms that the working days are lower than 7, i.e. 6.43, this information was included in the soft-link by defining both week and weekend days in the calendar file. During the weekend days, the working time is shorter, i.e. (7 – 6.43)·100 = 57% shorter.

10.1.3. Results

The soft-link was applied on the 5 selected scenarios reported above in Fig. 61. In order to be consistent with the SD model, the long-term load profiles were simulated along the same 13-years horizon. Each year of the horizon was divided in 4 time-clusters (or seasons) of around 91 days each, for a total of 13x4 clusters. Each cluster was defined by 1 input file, obtained by applying the soft-link to the values of the above-mentioned 38 SD output variables in correspondence to the day in the middle of the time cluster. E.g. the 1st of March is the representative day for all the days from the 1st of January to the 30th of April. The time-step of all the 13x365 daily load profiles was 15-minutes. In order to compare the results with the traditional approach commonly adopt in the literature for planning the capacity of off-grid microgrids, a further long-term load scenario was developed with the same hypotheses considered in *CASE 1* for the prefeasibility study of Ninga SHPP commissioned by CEFA: the estimated number of connections promptly realizable is around 50% of the households, and 100% for the businesses (viz. 2 in 2005), with assumptions on the load factors of the electric appliances.

Load profiles of 5 representative days and the one obtained with the traditional approach are displayed in Fig. 65. The 5 profiles clearly reflect the positive trend of growth of the electricity demand. The difference between year X and XIII does not emerge anymore, since the demand in those years assumes almost the same level (see next Fig. 67). Moreover, the following considerations can be derived:

1. The consumptions of IGAs, especially the EE-reliant ones, clearly determine the peak and reach the higher levels;
2. The household consumption determines the area of the base level of the demand, as visible in the morning and evening hours. It increases with the years, due to the growth in the residential connections.
3. With time comes clearer load shapes: a first peak in the morning, due to both starting household and IGAs activities; a little decrease during the day, since farmers are mainly busy in the land, and the only load is consumed by the IGAs; the highest peak in the evening, due to both the evening household activities at home and the IGAs operations.
4. Two pitfalls emerge in the use of the traditional approach: regarding the short-term variability of the load, the approach overestimates the effective functioning time (*i.e.* load factor) of the working machines (e.g. Mills); regarding the long-term, the hypothesis that 50% of the population gets immediately connected overestimates considerably the base load.

Fig. 66 reports the comparison of two load profiles of a representative week and weekend day. As expected, the weekend days are characterised by lower electricity consumptions, due to less IGAs production.

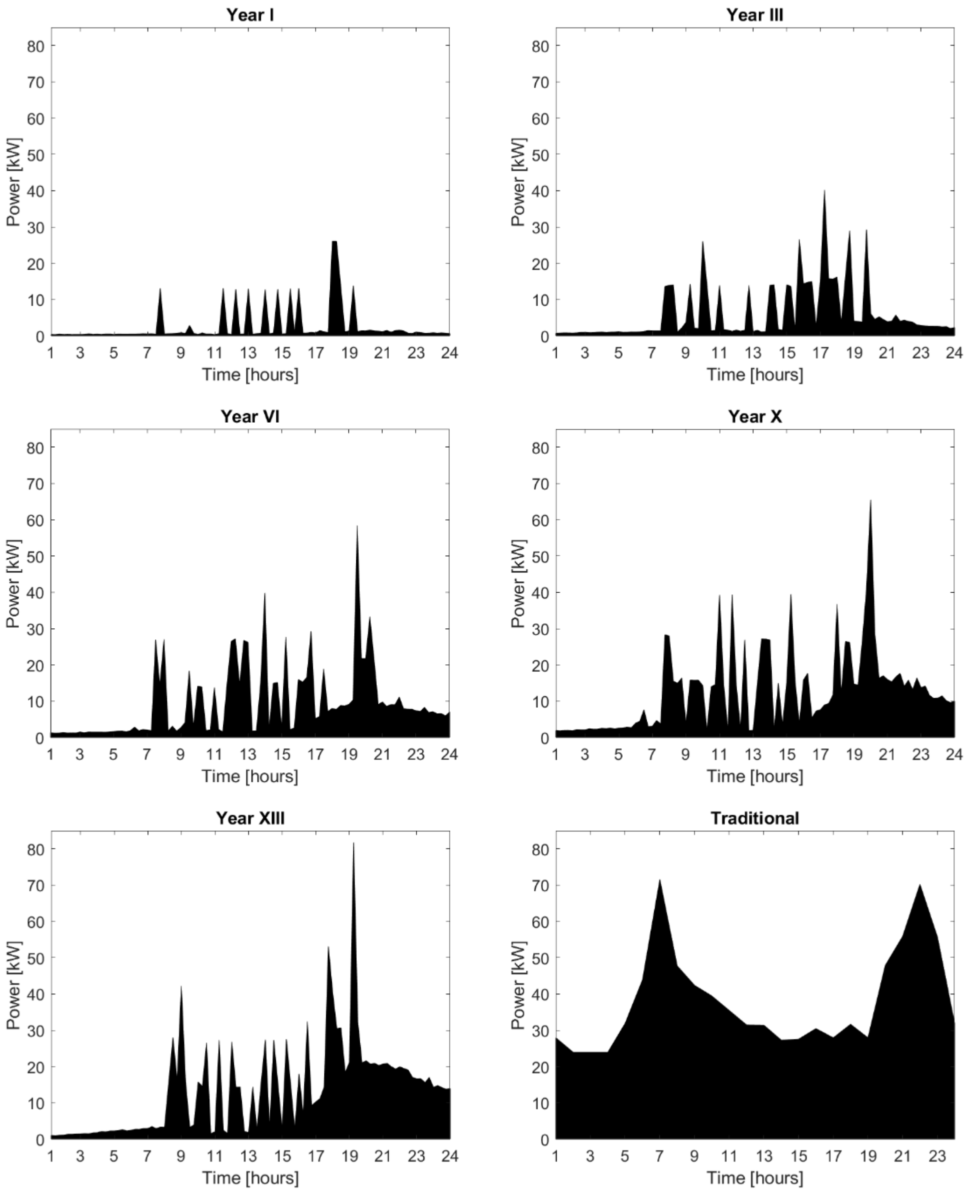


Fig. 65. Load profiles for 6 random days at the 4th moth, and year 1, 3, 6, 10, 13 of the planning horizon.

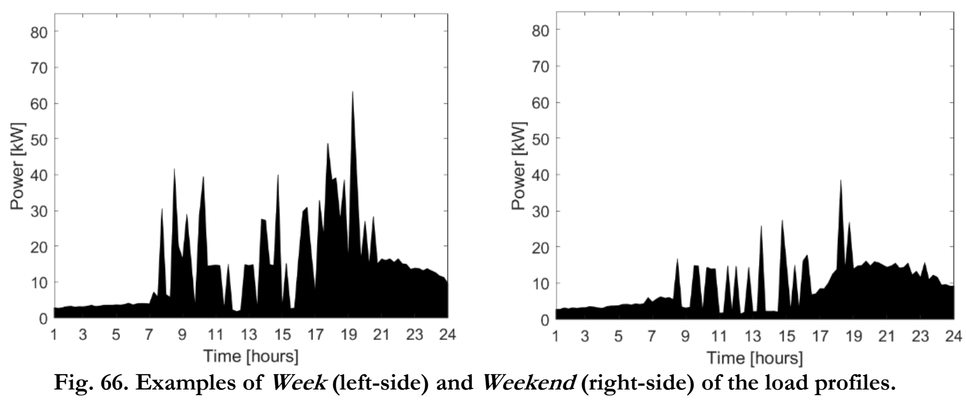


Fig. 66. Examples of *Week* (left-side) and *Weekend* (right-side) of the load profiles.

Since data regarding the actual load profiles are not available, the validation of the shape of the curve is not possible. In particular, the most critical parameters are the ones regarding the installed power and the operation time of the *EE-reliant* and *notEE-reliant* IGAs. These parameters come from the calibration done on the SD model by using the available data on the monthly energy consumed by IGAs. Still, the calibrated values of installed power and operation time represent just one of the potential combinations of values that can fit with the available monthly energy data. On the other hand, the lack of data would prevent any other way for estimating of the right combination of power and operation time. If data will be available in the future, a possible way for drawing more accurate load profile would be using *Lifetime-LoadProGen* for calibrating the right combination of power and operation time of IGAs, as follows:

i. In the SD model, specifying and calibrating a more general parameter representing the energy consumed by the two types of IGAs;
ii. Running *Lifetime-LoadProGen* with multiple combination of installed power and operation time coherent with the calibrated value of energy found at the step before;
iii. Using the available data of load profiles for evaluating the best combination that minimizes the error between data and load simulations.

1. The only possible test done for assessing the reliability of the results of *Lifetime-LoadProGen* was on the monthly values of energy simulated with the software. All the simulated profiles were therefore used *a-posteriori* to calculate the total electricity curves demand for the 5 scenarios, and then compared with the demand curves obtained with SD (Fig. 67).

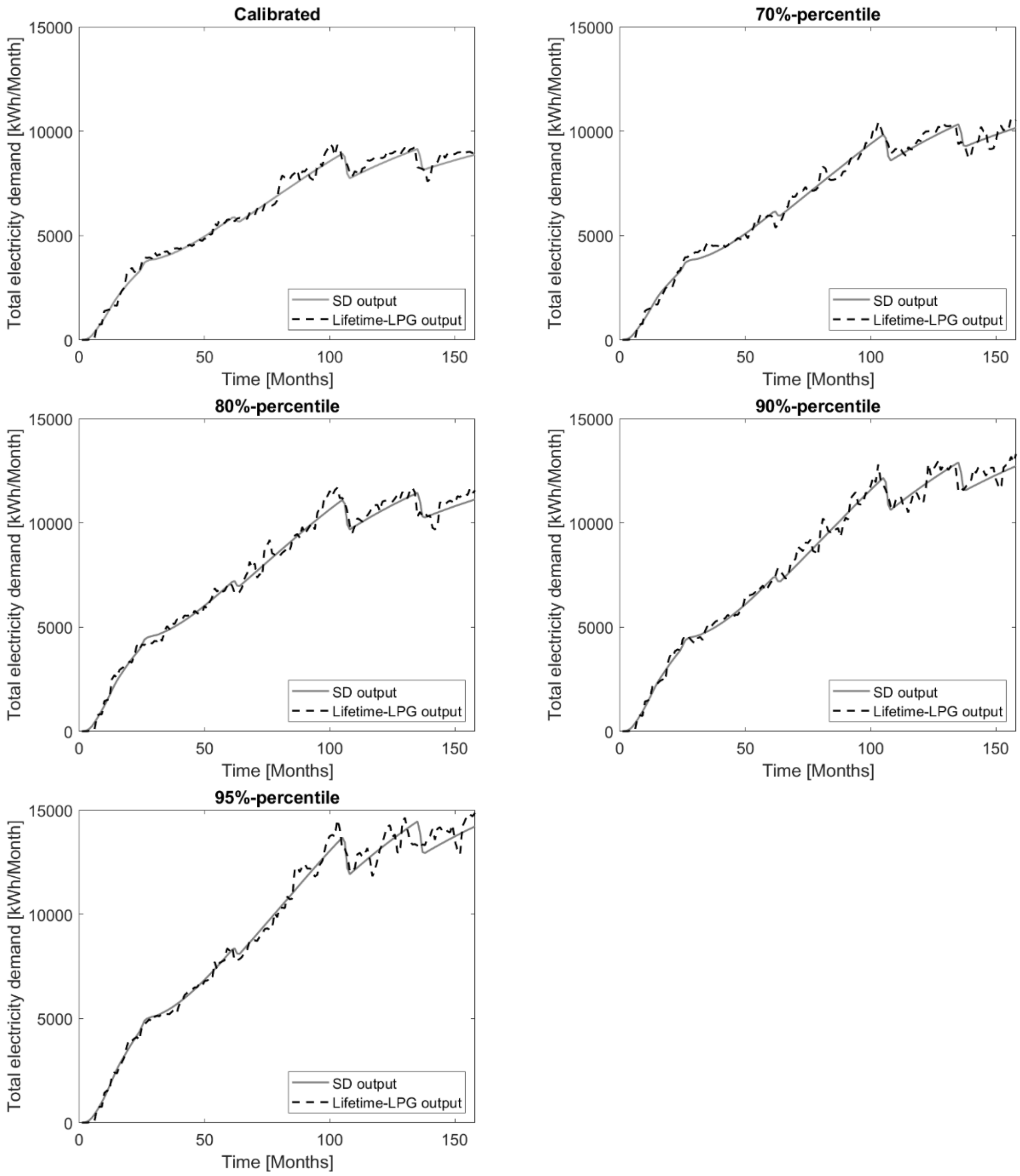


Fig. 67. Long-term load profiles for the selected scenarios, and comparison with the SD output.

The results confirm the ability of the *Lifetime-LoadProGen* to replicate the SD model behaviour. Moreover, two interesting considerations are worth to be done:

1. The *Lifetime-LoadProGen* curves are subjected to more variability, as a result of the stochasticity nature of the software, which generates different daily curves at each run, and due to the randomness adopted to set the different user classes generated with the first soft-link. The latter overcomes the perfect-mixing hypothesis adopted in the SD model to represent just two HHs classes: the HI and LI.
2. Despite being more variable, the curves generated with the load model are still not able to capture all the variability of the actual data, suggesting the need to move towards ABM approaches for achieving more precise curves.

10.2. Optimisation model for energy system planning

10.2.1. The Poli.NRG tool

The review of the energy planning case studies in Chapter 3 highlighted the availability of a number of different mathematical approaches, and related tools, for planning off-grid systems. In this work, *Poli.NRG* software was employed given the possibility to add arbitrary long-term profiles in the optimisation process. The tool was developed in MATLAB® by the Electrical Power System Group of Politecnico di Milano, and referenced in (Mandelli et al. 2016c, 2017; Brivio et al. 2017). The tool is based on a numerical and heuristic optimisation, and the objective is to minimise the cost function (viz. the Net Present Cost (NPC)) by modifying the size of the supply technologies under a number of constraints (e.g. the availability of renewable resources, an imposed electricity load). In its original form, the software was released for planning photovoltaic (PV) systems with solar panels and batteries. In the framework of this thesis, the software was modified and adapted also for considering hydro power sources in order to investigate what would have been a potential optimal off-grid capacity to install for supply the projected electricity demand of Ikondo from 2005 to the end of 2017. The acronym "NRG" in the name of the software stands for Network Robust Design. The term "Robust" refers to the capability of the software to consider these two constraints of the design process:

1. *Variability of the yearly electric load.* The software allows the user to give in input multiple probably electric load curves for a same year.
2. *Growth of the energy demand.* The software can consider different arbitrary scenarios of growth of energy demand over time.

Components modelling

The main equations that define the PV system, the battery bank and the inverter are reported (Brivio et al. 2017). The energy generated by the PV-system in each time step is:

$$E_{PV}(k) = \left\{ PV_{size} \cdot f_{PV} \cdot \frac{\bar{G}_T(k)}{\bar{G}_{T,STC}} \cdot \eta_{BOS} \right. \tag{52}$$

The term PV_{size} represents the installed power of the PV capacity [kW]; f_{PV} is the derating factor; η_{BOS} is the balance of system efficiency; $\bar{G}_T(k)$ is the solar radiation incident on the PV array in the current time step [kW/m²], while $\bar{G}_{T,STC}$ is the incident radiation at standard test conditions [1 kW/m²].

In the case of hydro generation, the energy generated by the Hydro-system in each time step is:

$$E_{hyd}(k) = \begin{cases} Hyd_{size} \cdot CF_{hyd}(k) \cdot \eta_{hyd} & if\ CF_{hyd} < 1 \\ Hyd_{size} \cdot \eta_{hyd} & if\ CF_{hyd} \geq 1 \end{cases} \tag{53}$$

The term Hyd_{size} represents the installed power of the hydro turbine [kW]; η_{hyd} the hydro turbine efficiency; $CF_{hyd}(k)$ is the capacity factor of the system in relation to the availability of the hydro resource, specifically:

$$CF_{hyd} = \frac{h_{net}(k) \cdot \dot{Q}_{river}(k)}{\left(h_{net} \cdot \dot{Q}_{river}\right)_{Hyd_{size}}} \tag{54}$$

Where h_{net} is the effective available head [m] at time-step k, and $\dot{Q}_{river}$ is the available and exploitable flow rate [m^3/s] at time-step k, while $(h_{net} \cdot \dot{Q}_{river})_{Hyd_{size}}$ is the minimum combination of flow rate and available head needed to produce a power output at least equal to Hyd_{size}.

The battery bank is modelled as an ideal storage system, which includes information on the minimum State of Charge (*SOCmin*), the power-to-energy ratio $(P/E)_{Battery}$ to consider the maximum power output of the battery bank as regards the rated capacity, and the charge-discharge efficiency. The lifetime of the battery bank is computed by considering the expected average cycles to failure in accordance with the imposed depth of discharge reached.

Finally, since the system architecture is based on an AC-bus, the inverter for the PV is defined according to the maxim capacity of the PV system, and considering the inverter efficiency.

Dispatching strategies

All the energy produced by the hydro is exploited by the load, otherwise stored.

Optimization

For each time step k (i.e. 15-minutes) of the load and the CF_{hyd}, the optimizer computes the balance between the energy $E_{hyd}(k)/E_{PV}(k)$ produced by the turbine/PV panels and the load demand $LC(k)$. The difference (divided by the inverter efficiency in case of PV) is the amount of energy that flows through the battery bank. On the contrary, a discharge from the battery to the load occurs if the difference between the energy produced and the load demand is negative. The energy which flows through and from the battery determines the state of charge of the storage, which is updated at each time-step k, and which is subjected to the *SOCmin* and the $(P/E)_{Battery}$ constraints. The ratio between the energy that is supplied to the load and the actual load demand at each k gives the Loss of Load Probability (LLP), which represents the fraction of unmet load in each time-step.

The optimisation process follows an imperialistic competitive algorithm, which starts with the definition of a searching space of all the potential technological solutions – i.e. the ranges of hydro/PV power and battery capacity to be investigated – and continues with an iterative process that progressively explores the searching space and calculates the value of the Net Present Cost (NPC) (Eq. (55)) and Levelized Cost Of Electricity (LCOE) (Eq. (56)) for all the discrete solutions that satisfy a certain long-term energy demand and the constraint set by the user on the LLP, i.e. the maximum acceptable LLP. Finally, the algorithm stops once the final solution (viz. the final configuration of energy pant) with the lowest NPC is found. In case of multiple lifetime load profiles, the optimizer repeats the same process for all of them, and then identifies an area of solutions by computing the weighted average of all the obtained optimum points.

$$NPC = \sum_{y=1}^{LT} \frac{Inv(y) + O\&M(y)}{(1+r)^y} \tag{55}$$

$$LCOE = \frac{r \cdot (1+r)^{LT}}{(1+r)^{LT} - 1} \cdot \frac{NPC}{(1-LLP) \cdot \sum_{k=1}^{LT} LC(k)} \tag{56}$$

where $y=1,\ldots, LT$ represents each year of the plant lifetime LT, $Inv(y)$ is the yearly investment and replacement costs of the components of the system, $O\&M(y)$ represents the operation and maintenance yearly costs, and $(1 + r)^y$ is the discount factor.

10.2.2. Power system configuration

The configuration scheme of the Hydro-batteries system is displayed in Fig. 68, while the details of the technological components considered in the simulation set-up are resumed in Table 36.

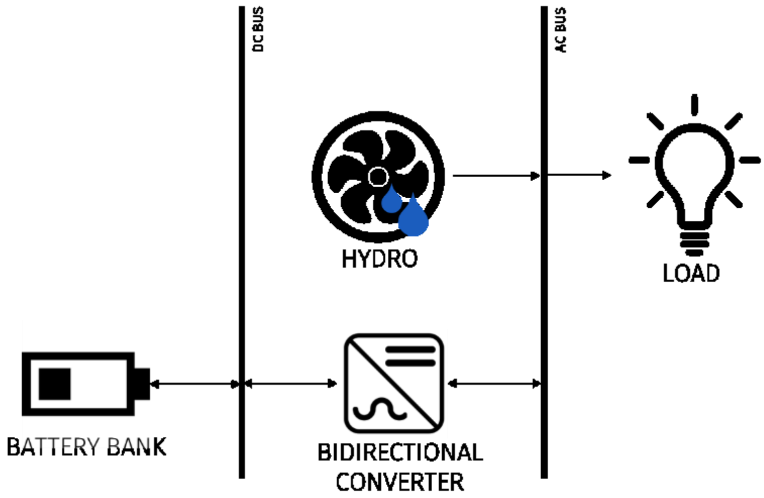


Fig. 68. Configuration scheme of the energy system.

Table 36. Economic and technological details of the system components (from (Kenfack et al. 2009; Hafez and Bhattacharya 2012; Brivio et al. 2017; IRENA 2017)).

	Capital cost	*Other information*
Hydro turbine	3600 [$/kW]	η_{hyd} = 75%
Battery bank	290 [$/kWh][17]	Lead-Acid 6V – 1156 Ah - Ratio power/energy = 0.50 [kW/kWh] - Minimum SOC = 40% - Max years before replacement = 8 [years] - Charge and discharge efficiency, including the inverter efficiency = 85% and 90% - Max cycles before replacement = 1500

The same optimisation was implemented for a PV-batteries system for the planning of the first 3 years of the horizon, given the flexible nature of solar systems, rather than hydro, and the low variability in the electricity demand in the first years (Technical details in Fig. 70, Table 37).

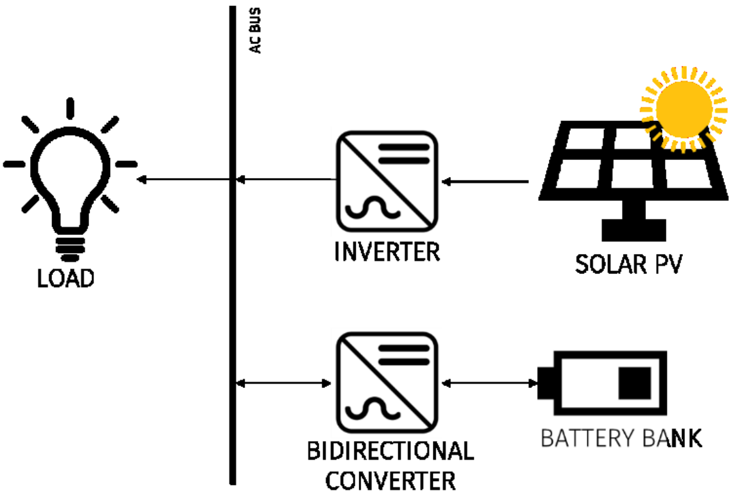


Fig. 69. Configuration scheme of the energy system.

[17] Including the bidirectional converter.

Table 37. Economic and technological details of the system components (from (IRENA 2016, 2017; Brivio et al. 2017)).

	Capital cost	*Other information*
PV system	1800 [$/kW]	η_{BOS} = 85% f_{PV} = 2 %/yr
Inverter	1000 [$/kW]	η_{inv} = 90%
Battery bank	290 [$/kWh][17]	Lead-Acid 6V – 1156 Ah - Ratio power/energy = 0.50 [kW/kWh] - Minimum SOC = 40% - Max years before replacement = 8 [years] - Charge and discharge efficiency, including the inverter efficiency = 85% and 90% - Max cycles before replacement = 1500

10.2.3. Resource assessment and other simulation set-up

Data on the hydroelectric resource were obtained by CEFA reports. The data on the daily flow rate of the Kiepa river were derived from the analysis of direct observation from 1993 to 2015 and resumed in Fig. 70.

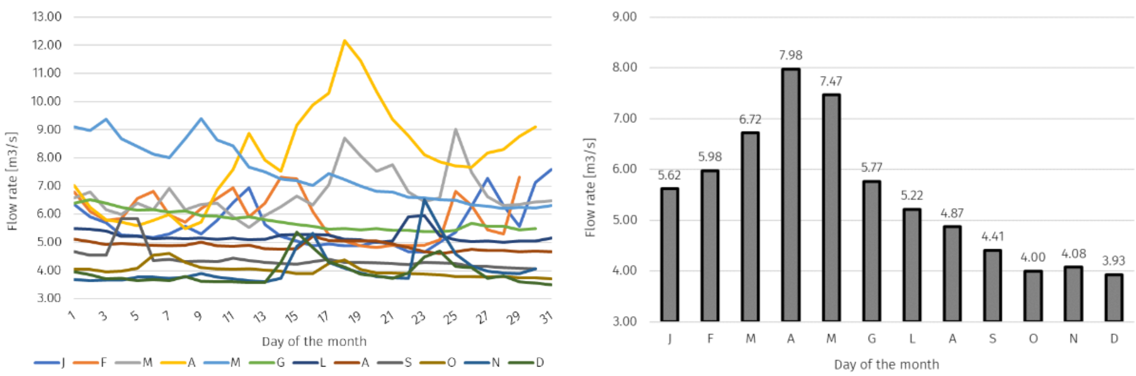


Fig. 70. Daily flow rate (left-column) and average daily flow rate at monthly basis (right-column) of Kiepa river obtained by analysis on direct measurement from 1993 to 2015.

For calculating the capacity factor, the minimum available hydroelectric power that can be potentially produced by exploiting all the available hydraulic head h_{net} of 18 m during the year is calculated with Eq.(57).

$$P_{min\ available} = \eta_{hyd} \cdot h_{net} \cdot \rho_{water} \cdot g \cdot \dot{Q}_{river}\big|_{MIN} \qquad (57)$$

where $\eta_{hyd} = 0.75$, ρ_{water} is the density of water [1000 kg/m³], g is the acceleration due to gravity [9.81 m/s²] and $\dot{Q}_{river}\big|_{MIN}$ is the lowest flow rate during the year. The value of the minimum available hydroelectric power for the Kiepa river results to be around 460 kW, largely higher than the most optimistic long-term projection of the load curve (viz. the 95-percentile) (Fig. 71). Therefore, the Capacity Factor was set equal to 1 along all the simulation horizon.

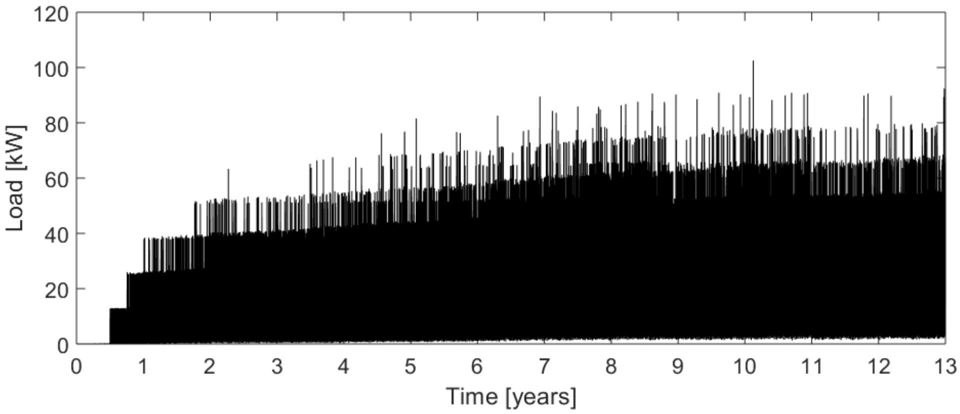


Fig. 71. Projected long-term electricity load for Ikondo.

For the solar resource, data on global irradiation on tilted surface were collected from the Renewables.Ninja database[18], an open web platform for simulating the hourly power output from PV panels located anywhere in the world, based on (Pfenninger and Staffell 2016; Staffell and Pfenninger 2016). Daily examples of the solar capacity factor for all the 12 months of the year are represented in Fig. 72. The tilt of the panel was set equal to 16°, according to (Idowu et al. 2013) and tested on Renewables.Ninja database.

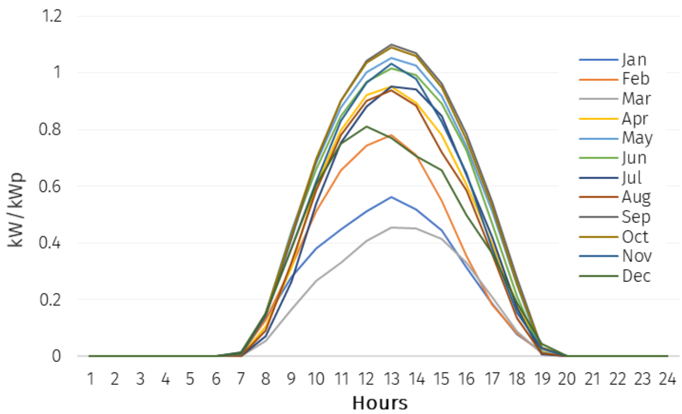


Fig. 72. Solar profiles for 12 days of the year.

The remaining techno-economic parameters set in the software are resumed in Table 38.

Table 38. Further inputs of *Poli.NRG.*

	Value	***Unit***
Economics		
O&M cost for the overall plant	100	€/kW$_{hyd}$
Installation cost as % of investment cost of Hydro / PV capacity+Battery bank+Inverter	20	%
Project lifetime (LT)	30[19]	year
Rate of interest	16	%
Reliability		
Loss of Load Probability (LLP)	2[20]	%

10.2.4. Results and Discussion

For the hydro case, Poli.NRG was used with the 5 projections of long-term electricity load profiles derived in the previous sub-section, plus the profile computed with the traditional approach. For the

[18] https://www.renewables.ninja/

[19] The project lifetime is set equal to 30 years. The value is necessary for the calculation of the NPC and the depreciation. It does not affect the optimisation horizon, which is equal to the size of the long-term load profile, viz. 13 years.

[20] Set equal to 1 minus the calibrated value of the *El.Reliability* of the SD model.

solar case, just the 3 initial years of the same load profiles were used. The results are compared by focusing on the investment cost NPC [$], the installed power of the hydro turbine Hyd_{size} [kW], the battery size *BESS* [kWh], and the cost of electricity LCOE [$/kWh]. The differences in percentage are calculated respect to the "CALIBRATED" scenario.

HYDRO PLANT (13 years)	**PV PLANT (3 years)**

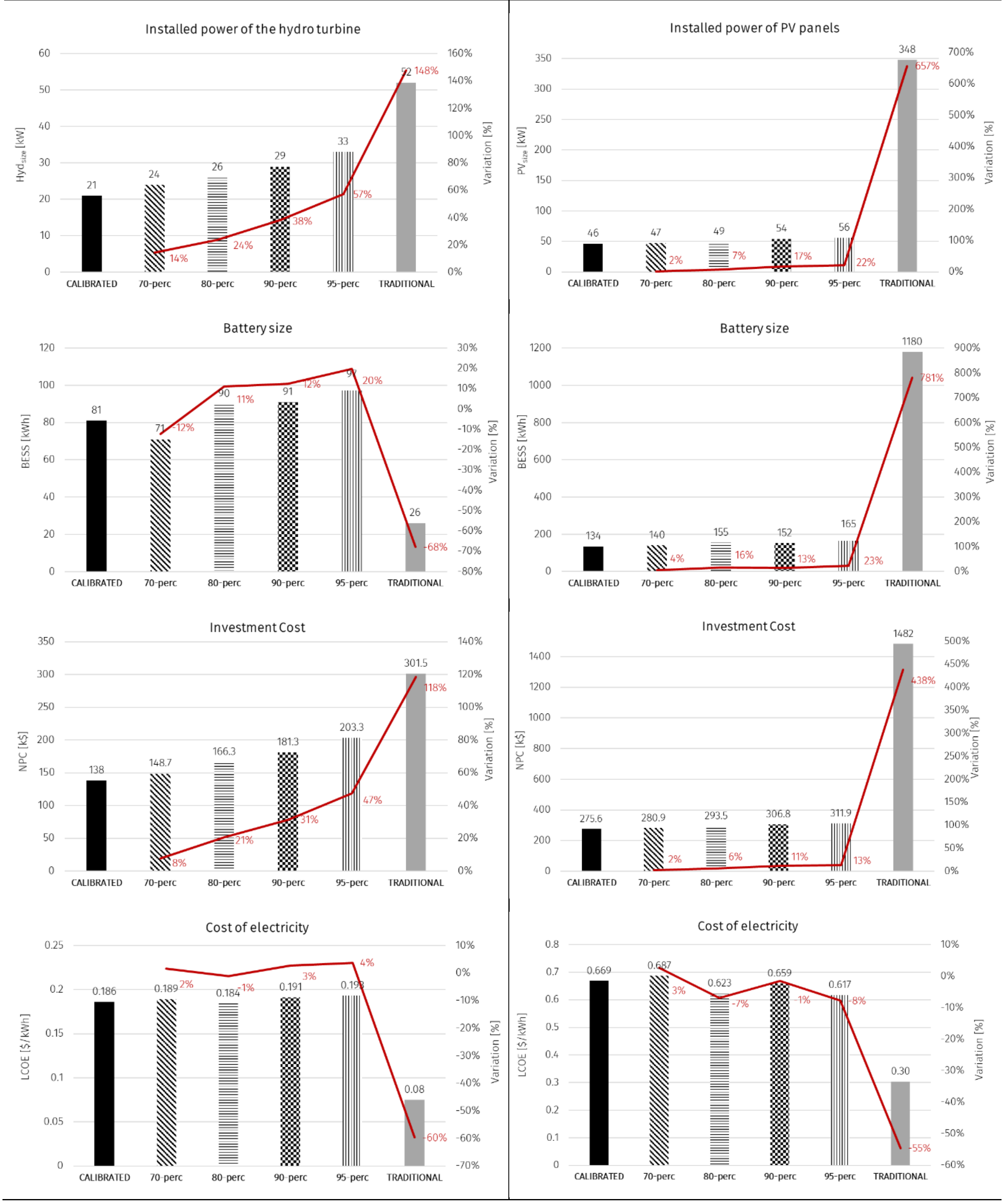


Fig. 73. Main results for the hydro (left-side) and the PV (right-side) case.

Fig. 73 confirms that the long-term variation of the electricity load impacts considerably the size of the optimal hydro solution. The total hydro and battery capacities installed in the most preventive scenario (*i.e.* 95-percentile of the load) differ by 57% and 20% respect to the calibrated scenario. Such results have direct economic implications, as clearly visible in the figure representing the NPC. In the case of PV, instead, the results confirm that the differences between the 5 scenarios is not highly significant, reflecting the low variability of the data and the SD model in the first 3-4 years of the simulation horizon.

For both the optimisations, the results change more significantly respect to the output obtained with the traditional case. Especially in the 3-years optimisation of the PV systems, the sizing process based on the traditional case leads to completely different results, due to a huge oversizing. This has practical implications especially on the LCOE: the cost obtained with the traditional approach is considerably lower than the others, since the energy consumed is higher and there is no stochasticity in the load and no fluctuating power peaks. This has practical implications on the business model, since tariffs based on lower expectations of LCOE than the actual ones could reveal as unsustainable, jeopardizing the return on the investment, and therefore the quality of maintenance and the long-term success of the project (as also found by Hartvigsson et al. (Hartvigsson et al. 2015, 2018a)). This result points out an important consideration and a potential use of the SD model: based on the policy testing performed on it, increasing the cost of electricity would cause a decrease in the total electricity demand, especially by local IGAs; the combination of the SD output and the result of the optimisation would allow to define an appropriate tariff scheme and payment strategy, in order to guarantee an affordable service to people and a margin of profit for the utility. E.g., in this case of Ikondo, the tariffs set by the local utility are lower than the LCOE found in the two hydro and PV cases, since the investment cost was covered through national or international grants, and the tariff set based on the cost of operation and maintenance. This allowed to achieve higher levels of willingness to pay by people. Particularly in the case of PV, the LCOE values are particularly higher due to the fact that the solar irradiation is not particularly economic convenient to exploit in that part of Tanzania.

In the end, the results allow to point out two important conclusions and policy implications on the practicality and use of the SD simulations:

- *entire horizon-long (long-term)*: despite the results being much more reliable respect to the traditional approach for assessing long-term load profiles, planning the system capacity with simulations along the entire planning horizon (as in the hydro case) is riskier, given the higher variability of the SD model output in the long-term that is reflected also in the results of the optimisation. On the other hand, in case of high financial availability (e.g. grants) able to cover the initial investment, the optimisation based on the 95-percentile is the most robust design scenario. This points out that the "long-term" use of the SD model integrated with the load and energy models is more useful for policy testing and for a preliminary planning of the future investments, as well as for investigating the long-term dynamics of the electricity-development nexus.
- *first years-long (short-term):* the sizing process based on initial 3-4 years (as in the PV case) of the simulated energy demand is more robust to variations and uncertainty of the SD model; therefore, sizing the plant based on the 95-percentile projections allows to cover almost all the load variability without increasing considerably the investment cost respect to the calibrated case. This strategy can be useful in case of low financial availability and no external grants, which requires a precise tariff definition for guaranteeing an acceptable return on the investment. Nevertheless, also in this case the long-term simulations along all the planning horizon can be useful to assess estimations of how the demand can evolve, test polices, and start planning the further investments. This is of course more suitable in case of more modular power technologies, as PV and Wind, rather than hydro. This points out that the "short-term" use of the integrated model is especially useful for the energy optimisation process.

Finally, these final considerations set a starting point for further modelling work focused on robust and stochastic optimisation, in order to overcome the limitations of the scenarios-based approach adopted here in the two electricity planning processes.

Chapter 11

Conclusions and future work

The scientist is not a person who gives the right answers, he is one who asks the right questions
(Claude Lévi-Strauss, 1964)

The electric light did not come from the continuous improvement of candles
(Oren Harari)

This chapter provides a summary of the thesis contributions, implications, strengths and weaknesses of the work, and it discusses the potential future works and research activities.

11.1. Relevance and contributions

Around the world, around 1 billion people do not have sustainable access to electricity. This is considered a limiting factor to the socio-economic development of rural communities in developing countries. During the last decades, international donors, organizations, NGOs, universities, energy planners, practitioners, and private companies have been investing a lot of resources in programmes and projects that aim at improving rural people's socio-economic conditions through access to energy. Despite these investments, the scientific literature reports only fragmentary and sometimes controversial results regarding the impacts of energy programmes, and most of the times the causes are attributable to the inappropriate planning of the off-grid power system capacities. In this context, wrong projections and assessments of the long-term electricity demand contribute to the over- and under-sizing of electricity systems and related infrastructures, especially in off-grid areas. This is caused by a limited knowledge and modelling of the long-term impact of electricity access on local socio-economic development and the consequent feedback on electricity demand. Moreover, the scientific investigation of this topic is rarely coupled with the research on off-grid rural electricity planning, leading to an insufficient attention to "long-term aspects" in the traditional practices, models and methods for rural electrification. In this framework, the lack of models and approaches for investigating and understanding the determinants of rural electricity demand, making long-term reliable projections, and integrating the insights within planning methodologies represent an informational and research gap that the present thesis tried to fill.

The main findings of this thesis are presented in terms of discussions relating to the three objectives and associated research questions (**Q**) presented in sub-section *1.2: Aim and Motivation of the research.*

Objective 1: To investigate and discuss the challenge of electricity demand assessment and modelling for rural electrification.

Q 1.1: *How does electricity demand impact on the planning solution of off-grid systems?*

In "Chapter 2 - Relevance of electricity demand in rural electricity planning", the relevance of electricity demand in rural electricity planning was highlighted and clearly stated by reporting literature examples and case-studies. In order to put more emphasis on the importance of short- and long-term electricity evaluation within the planning endeavour, two original case studies were carried out. The first case confirmed that the appropriate assessment and modelling of short-term determinants of electricity demand can lead to considerably different results in terms of both load profile and energy consumption respect to the traditional approaches to electricity load forecasting. The second case tested the inclusion of socio-economic aspects in modelling long-term electricity demand and it demonstrated that the output of energy planning process is highly dependent on the long-term aspects of electricity demand. With these two case studies, it was therefore found and demonstrated that *short- and long-term assessments are both essential and critical aspects to carry out when designing rural mini-grid.* Within the scientific community committed in addressing electricity access-related challenges, this finding will contribute to raise awareness on the criticality of electricity load assessment in rural electrification planning. These results advocate therefore more research effort for the investigation of appropriate rural electricity demand models.

Q 1.2: *How does the current literature on rural electrification tackle the analysis and evaluation of electricity demand?*

In "Chapter 3 - Review of energy planning case studies and demand models", a comprehensive literature review on long-term rural energy planning was provided. 85 studies were classified in accordance with their type (planning horizon, energy carrier, decision criteria mathematical models, and energy uses) and with the methodology they employ to forecast the evolution of the energy demand, if any. A first synthesis of strengths and weaknesses, and fields of applicability of the approaches used so far were provided, as well as the main modelling insights that can be derived from their applications in order to improve current practices in rural energy planning. This implied *the establishment of a set of potential new literature gaps in the field of rural energy modelling and* *electrification that open new research opportunities (e.g. multi-objectives optimisation techniques, strengthening the research on thermal energy access, assessment of production uses of energy)*. From the review, another fundamental finding that emerged is that *most of the rural energy planning literature neglects the aspect of long-term evaluation of electricity demand*. Indeed, few studies assume a dynamic demand over the years and most of them forecast its evolution through arbitrary trends and scenarios. For the first time in this research field, this critical drawback and shortcoming of the current practices for rural electrification is stated and highlighted. These findings imply also that current software and models for optimising rural power systems should now align their infrastructures, algorithms, and new releases to include the long-term characterisation of electricity demand.

The chapter provided also an original discussion on the main potential multifaceted aspects and dimensions that affect the evolutions of electricity demand in rural contexts, highlighting the link between the rural electricity demand and the socio-economic development that electricity use can bring in a local context. This led to another important finding: *electricity demand evolution and rural socio-economic development are somehow linked*, which represented the basis for the further in-depth analysis of the electricity-development nexus.

Q 1.3: *Which are the complexities behind the evolution of rural electricity demand?*

"Chapter 4 - Electricity demand and socio-economic complexities" allowed to answer to this research question by offering an important contribution in the rural electrification field: a comprehensive analysis, through causal loop diagrams, of all the dynamic complexities related to the impact of electricity access and consumption on rural socio-economic development, and vice versa. The results confirmed that the energy-development nexus is complex to an extent that it can be usefully described as a 'complex system', where all the following dimensions are endogenously interconnected between each other and with electricity demand: income generating activities, market production and revenues, household's economy, local health and population, education, and habits and social networks. This confirmed that *the evolution of rural electricity demand can be explained by endogenous dynamics*. From a qualitative point of view, the analysis gave insights also about the reasons why electricity access does not always bring development. This has an important research implication in the field of rural energy modelling, since it finally confirms the need to overcome traditional top-down and/or regression-based models for analysing the nexus between electricity use and rural development. It also emphasized the important role of some complementary activities and infrastructural preconditions to couple with access to energy programmes in order to achieve long-term rural development. E.g. good roads and telecommunication systems, capacity building activities, financial support for school equipment.

Q 1.4: *From a modelling point of view, which can be the potential way forward for assessing the evolution of rural electricity demand?*

"Chapter 5 - Modelling insights for dealing with complexities" set an important step for building upon the quantitative modelling of the endogenous complexities behind the electricity development nexus. Two simulation approaches for modelling complex systems were investigated, namely system dynamics (SD) and agent-based modelling (ABM), in an ad-hoc speculative case study regarding the diffusion of electricity connections in a fictious rural setting. As first original contribution, ABM and SD were compared by simulating a more complex and realistic diffusion process than the classical Bass model, viz. the splitting of the population between "influential" and "imitators". The obtained results indicated that *modelling social interactions is advisable in order to improve the accuracy of electricity demand projections and the design of mini-grids*, since different structures of social networks can lead to unexpected scenarios of electricity demand growth. Such understanding may be pivotal for local electricity utilities, which manage off-grid systems in very remote contexts characterised by deeply-rooted social structures and beliefs, especially when they make their investment plans, and define the electricity tariffs for guaranteeing a positive return on the investment. In terms of research implications, this chapter would contribute also to the same effort of other researchers to propose improvements and solutions to the hypothesis of "perfect-mixing" and homogeneity assumed by SD within stocks and flows.

The obtained results suggest also that *ABMs are not suitable for comprehensively characterizing the electricity-development nexus,* given the scarce availability of data, the required knowledge of specific social-science competences for the definition of the social structures, and questionable applicability to different contexts. This led to the selection of SD due to the high uncertainty, strong non-linear phenomena, time-adjustments of technology perceptions, time delays, and feedbacks characterising the issue of rural electricity demand, as well as the possibility to derive modelling insights by relying on less data.

Objective 2: To assess and model the fundamental dynamics, variables, and exogenous policies that characterise the electricity-development nexus and determine the evolution of electricity demand.

Q 2.1: *How to formulate the dynamics behind electricity-development nexus and generate reasonable long-term projections of electricity demand in rural* areas?

System dynamics was used to build a simulation model in order to answer to this research question. In "Chapter 6 – Model Conceptualisation and introduction to the Ikondo case", the first step of the SD-based modelling process is reported. It consisted in the conceptualisation of the model, which considered the problem(s) and purpose(s) definition, the identification of the model boundary and key variables, and the graphical representation the feedback loops of the system. This phase was carried out based on a real case-study used as reference and for going further in the next stages of the modelling process, i.e. a hydroelectric-based electrification programme implemented in the rural community of Ikondo, Tanzania, in 2005 by the Italian NGO named CEFA. Considered a "successful case of rural electrification" by locals, practitioners, and academics, an important element of originality and contribution of this chapter was the improved characterisation of the electricity-development nexus and the main determinants of the electricity demand based on a real case. In "Chapter 7 – Formulation of the simulation model", the mathematical structure and the decision rules of the model were specified. Three elements of originality can be recognised. First, the formulation of quantitative and bottom-up white-box (i.e. causal-descriptive) relations that characterise the electricity-development nexus through 11 sub-models. Second, the formulation of a model able to simulate long-term projections of rural electricity consumptions. Third, despite its formulation is based on a specific case-study (which is a limitation), the model reflects, represents, and assesses many of the dynamics typical of rural areas of developing countries, setting a novel modelling reference for further investigations on this research topic. These 3 elements together allow to enhance the research on the rural energy demand and the energy-development nexus, providing the first step in the research and modelling work committed to develop more general, flexible, and customizable energy demand models. In "Chapter 8 – Model calibration", the model behaviour was compared to the available data, by relying on appropriate statistical measures that confirmed the ability of the model to replicate the observed historical behaviour of the system. Also, the calibration contributed to highlight the presence of further determinants of the rural electricity demand that did not emerge from the analysis of electricity-development nexus but worth to be further investigated: intra-season variabilities, due to the dependency of people financial availability on the harvesting period, and daily load variability, due to the unpredictability of people's habits and use of electricity within the 24 hours. Then, the calibration process confirmed the appropriateness of system dynamics in modelling the complexities behind the evolution of rural electricity demand. Still, it also revealed the need to investigate further modelling techniques to improve and/or overcome the SD hypothesis of perfect-mixing which caused a mismatch between data and model output in the first time-steps of the simulations. Finally, as last element of originality, the calibration and the use of Monte Carlo Markov Chain allowed to derive quantitatively modelling insights on some presumed dynamics and their impact on the electricity-development nexus. E.g. the relatively high values of *awareness effect* in the diffusion process of electrical connections revealed that electricity access is not perceived as an innovation by people. These three chapters together led to the following important finding: *the modelling process based on system dynamics offers a comprehensive modelling framework for quantitatively assessing, simulating, and exploring the dynamics behind the evolution of rural electricity demand.*

Q 2.2: *Why do not we see the same outcome in terms of electricity evolution patterns and rural development every time we bring electricity?*

In "Chapter 9 – Testing and exploring the model", the model is tested and explored in order to derive insights about its structure and to increase the knowledge of the electricity-development nexus and the dynamics behind the evolution of rural electricity demand. As a novelty, the most critical and fundamental dynamics and parameters were assessed: it was found that *the dynamics and initial conditions related to market operation, farming trading, population, and households' economy are the most fundamental determinants of the electricity-development nexus*. E.g. varying the level of trade of the agricultural products can affect considerably the total electricity demand, indicating that changes in the local agricultural livelihood and dynamics largely impact on the electrification output, and that agricultural activities play an important role in the creation of new business also after electrification. This implies that future electrification programmes can stand on these results for identifying the most critical aspects to deal with in order to guarantee the long-term sustainability of energy access projects (e.g. to implement awareness campaign for the productive use of electricity for agricultural purposes). Moreover, the interrelation between further socio-economic dynamics and electricity demand was tested. E.g. formal education seemed to be highly affected by electricity availability, but it has a negligible feedback on electricity use, while the effect of electricity use on market improvements, and the related feedback, resulted to be highly interdependent dynamics. This can have two implications: (1) from the research point of view, the process of model simplification can start from these findings for identifying the negligible dynamics; (2) potential use of the model for the definition of appropriate indicators and thresholds for updating the traditional monitoring and evaluation frameworks commonly used for assessing energy access projects.

The role of exogenous policies was also tested, finding that *access to micro-credit, ensuring affordable electricity tariff and higher power reliability are critical and essential actions to guarantee for enhancing and maximising the socio-economic impact of electricity use on rural communities*. This allowed to set good practices, minimal prerequisites, and complementary activities that should be included in every electrification project, with potential implications on the current frameworks adopted by international organisations and donors for defining and financing energy access programmes.

Objective 3: To integrate demand, load, and energy optimisation models in a more comprehensive electricity planning procedure.

Q 3.1: *Does the inclusion of short- and long-term electricity demand lead to a more appropriate power capacity planning of mini-grids and tariff definition mechanisms?*

"Chapter 10 – Soft-linking demand and optimisation models" reports the modelling effort to integrate SD with a stochastic load and an energy optimisation model for supporting the planning of off-grid power systems. In the first part, the integration with the load model allowed to introduce short-term uncertainties in long-term demand dynamics. It is found that *introducing short-term variabilities into long-term electricity demand projections allows to define power peaks and base consumptions more accurately*. E.g. the consumptions of businesses, especially the most reliant on electricity, clearly determine the peak and reach the higher levels. This remarks that neglecting the electrical consumption of potential new business when planning mini-grid capacities – that is often a current practice in rural electrification – leads to inaccurate and unreliable load profiles estimations; in turn, this can determine an erroneous sizing of the battery system. These findings offer an important contribution towards the employment of the multi-year energy optimisation as a standard for off-grid electricity planning.

The integration of the SD and the load models into a heuristic optimisation energy model provided a new modelling framework for assessing optimal energy planning strategies: the "long-term" use of the integrated model can be more useful for long-term policy testing and for preliminary planning processes of future investments, as well as for investigating the long-term dynamics of the electricity-development nexus. The "short-term" (viz. by means of a step-by-step progressive optimisation) use can be instead more useful for the energy sizing process. These conclusions are strictly related to the type of optimisation employed in this thesis (viz. a heuristic optimisation). This led to the following finding and implication: *Stochastic or Robust multi-year optimisation methods are needed to appropriately size off-grid mini-grids in the long-run.*

11.2. Strengths and weakness

In the relatively new research field on energy access, many issues are still unsolved, and the investigation of potential solutions is currently involving multidisciplinary and exploratory research approaches. In this framework, this thesis tries to set a starting point for the research work on energy demand models for rural settings, and it is meant to contribute to the same effort of other researchers focused on this issue. It needed the investigation and study of different disciplines, and the analysis and applications of the related principles and methods to tackle the multifaceted complexities of rural electrification. This is of course one of the most important strengths of the work, since electricity access-related issues are too often approached through limiting monodisciplinary methods and techniques.

A general strength of the approach followed to pursue the first objective can be recognised in the comprehensive and critical review of the literature, which allowed to identify the research gaps to fill, the problems to tackle, and potential methods to use. Whilst the literature review was particularly useful for conceptualising the electricity-development nexus and obtaining comprehensive causal loop diagrams, this practice hides also a potential weakness: (i) the neglecting of some other important dynamics that other methods (e.g. group modelling) would have identified, and (ii) the lack of spatial specifications and insights (e.g. the electricity-development nexus in rural Africa is characterised by different dynamics respect to the South-American one).

As for the second objective, the main strengths are related to the adoption of system dynamics as modelling approach by accurately following the main steps of the modelling process, from the conceptualisation to the testing and validation phase. At the same time, the main weakness is related to the use of a specific case-study for building the model. Of course, this confirmed some of the dynamics identified in the review of the electricity-development nexus, but at the same time it lacks immediate applicability to different contexts. On the other hand, the testing phase allowed to quantitatively assess the fundamental dynamics that characterise the evolution of electricity demand, paving the way for simplifying and generalising the model. Another potential weakness is related to the system dynamics hypothesis of perfect mixing within the stocks representing the population, the income generating activities, and their attributes. This hypothesis allowed of course a simple and meaningful representation of all the dynamics identified in the review of the electricity-development nexus, but at the same time it was responsible of some inaccurate correspondences between data and model outputs. The calibration with available time-series of data is another strength, which confirmed the ability of the model to replicate the observed historical behaviour of the system and uncover model flaws and hidden dynamics. It allowed also to identify a reasonable set of parameters' values most consistent with the relevant the knowledge of the system, but further time-series should have been needed for inferring more significant considerations on the calibrated values of the parameters. This highlights the urgency of increasing efforts and resources devoted to collect, store, and share open data for enhancing the research on rural electrification.

Finally, the integration of the long-term electricity demand simulation model, the load profile generator, and the heuristic energy optimisation model offers a new comprehensive modelling framework for carrying out reliable rural electrification plans. At the same time, the use of different proprietary software, which can hardly be hard-linked, is a current weakness.

11.3. Future works

The discussion above leaves some open questions and room for some further improvements in the future, which are here discussed. First, besides the SD model seems fitting the data with good statistical accuracy, it is not able to capture the short-term variability of the data, suggesting the presence of hidden dynamics, intrinsic random variabilities dependent to human behaviour. This suggests the possibility to explore the integration with ABMs and methods to deal with data uncertainties and variability (e.g. Kalman filtering). Second, the behaviour sensitivity highlights that just 17 parameters appear as critical. Future steps of the research would consider the simplification of the model in order to focus just on the fundamental dynamics and make it simpler and more immediate to use, as well as more flexible for its use in different contexts. This should also overcome the dependency of the structure to the initial conditions, and open research activities intended to extend the model to different larger scales. Third, the optimisation is still based on a scenario- and mono-objective-oriented approach, while different approaches based on multi-objectives stochastic and robust optimisation could potentially provide more useful, more comprehensive, and clearer policy indications. Last but not least, the extension of the model to the thermal energy carrier is advised, since another main challenge of energy access in developing countries is the planning of sustainable energy for cooking and thermal needs.

Appendices

Appendix A – SD and ABM *cont'd*

This appendix reports other two comparison cases between SD and ABM. The diffusion mechanism here refers always to the diffusion of electrical connections in a rural community of N = 1000 people, which has received potential access to electricity at time t = 0. The simulation horizon has been set equal to T = 240 months, that is 20 years, which roughly corresponds to the lifetime of a typical off-grid microgrid composed by photovoltaic panels and batteries.

Case 1

In the first case, the classical Bass model from a SD perspective and the equivalent agent-based discrete models with the RND, BA and SC networks were simulated. 5 scenarios were created by varying the average degree (k_{avg}) of the network (*i.e.* the "contact rate" c for the Bass model) – 4, 6, 8, 10 and 12. The time-invariant tendency to adopt p was set equal to 0.002 and the social contagion term q was represented as the product between the average degree of the network k_{avg} and a specific term, namely "adoption fraction" i introduced by Sterman (Sterman 2000), equals to 0.02. In the ABM case, the diffusion mechanism is simulated by updating the states of each node s who, at each time step t, has a certain probability to become an adopter based on the state of the neighbours:

$$prob_s(t) = p + i \cdot n_{A,s}(t) \tag{58}$$

with $n_{A,s}(t)$ the number of neighbours of node s that are adopters at time t. In ABM mechanisms, the fraction of the adopters compared to the total population $F(t)$ is given by the sum of all the agents (*viz.* nodes) who are marked as adopters at time t. Initially none of the nodes is adopter, thus $F(t)$=0.

Results for k_{avg} equals to 4, 8 and 12 are plotted in Fig A. 1.

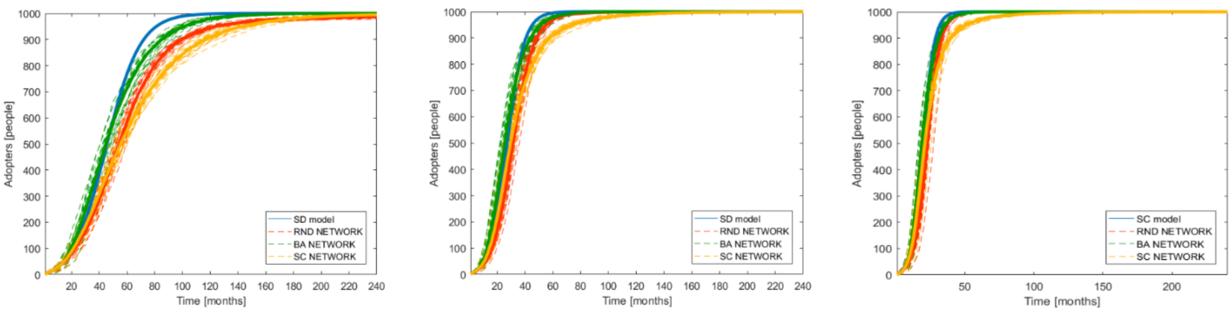


Fig A. 1. Diffusion curves for *Case* 1: results for k_{avg}=4, 8 and 12.

From the figures, it clearly emerges that a decrease in k_{avg} of the network (*viz.* the "contact rate" c) stretches out the diffusion curves, since people have less contacts and share less information. All the curves show the same trend, that is the S-curve typical of the classical continuous diffusion models. The comparisons between the min and max time interval needed by the agent-based stochastic curves to reach 50% and 95% of diffusion, and the values of the SD model are reported in Table A 1 – the values in the brackets represent the difference with respect to the SD model.

Table A 1. Results of *Case 1.*

	50 %		95%	
Scenario k_{avg}=4	*min*	*max*	*min*	*max*
RND	51 (+4)	60 (+13)	117 (+35)	132 (+50)
BA	41 (-5)	51 (4)	95 (+13)	111 (+29)
SC	49 (+2)	61 (+14)	129 (+47)	159 (+77)
SD	*47*		*82*	
Scenario k_{avg}=6	*min*	*max*	*min*	*max*
RND	36 (+1)	46 (+11)	70 (+11)	81 (+22)
BA	29 (-6)	38 (3)	63 (+4)	74 (+15)
SC	36 (+1)	42 (+7)	91 (+32)	107 (+48)
SD	*35*		*59*	
Scenario k_{avg}=8	*min*	*max*	*min*	*max*
RND	29 (+1)	37 (+9)	51 (+5)	60 (+14)
BA	23 (-5)	32 (+4)	48 (+2)	59 (+13)
SC	25 (-3)	34 (+6)	68 (+22)	86 (+40)
SD	*28*		*46*	
Scenario k_{avg}=10	*min*	*max*	*min*	*max*
RND	24 (0)	32 (+8)	41 (+3)	48 (+10)
BA	20 (-4)	27 (+3)	41 (+3)	48 (+10)
SC	20 (-4)	31 (+7)	54 (+16)	67 (+29)
SD	*24*		*38*	
Scenario k_{avg}=12	*min*	*max*	*min*	*max*
RND	22 (+1)	28 (+7)	36 (+3)	41 (+8)
BA	17 (-4)	23 (+2)	34 (+1)	39 (+6)
SC	19 (-2)	27 (+6)	46 (+13)	57 (+24)
SD	*21*		*33*	

The results reflect the trend visible from the plots of Fig A. 1. The agent-based curves are almost all "shifted" on the right, *i.e.* the diffusion process takes longer to complete, apart from the initial stage of the BA and SC process, that reach the 50% of adoption from 2 to 6 months before the SD model. Once approaching to the end of the process, all the agent-based min and max curves reach 95% of adoption respectively from 1 to 47 months, and from 6 to 77 months later. In particular, the SC processes tend to the 100%-plateau later than the other process.

Case 2

In the second case, based on the experience of the author in the access to energy-related research, some hypotheses that may fit with the contexts under study were introduced: in rural areas, the effect of advertising is supposed to be minimal, especially where people lack electricity and consequently TV, radios, mobile phones, *etc.* As a consequence, p was set equal to 0.0. To allow the diffusion mechanism to start and spread, and to solve the start-up problem, it was considered to "seed" some initial adopters (*i.e.* a portion A_0 of the N agents) at time $t = 0$. Such initial adopters were not randomly selected among the N agents, but they were selected starting from people (*i.e.* households) in the rural community with the highest degree. The hypothesis here is that to enhance the diffusion of electricity use in rural electrification programmes, a best practice is providing the most connected users with initial electrical appliances for free, hoping to trigger a positive dynamic of word of mouth in the whole community. Obviously, in the SD model, where the homogeneity and perfect mixing hypothesis stands, such modelling choice simply consists in "filling" the stock of adopters with an initial portion A_0 of N. 6 scenarios were developed: for k_{avg} equals to 4 and 8, the initial portion of adopters A_0 was set equals to 1, 5 and 10% of N. As per the previous case, adoption fraction i is equal to 0.02.

Results for k_{avg} equals to 4 and A_0 = 1%, 5%, 10% of N are plotted in Fig A. 2.

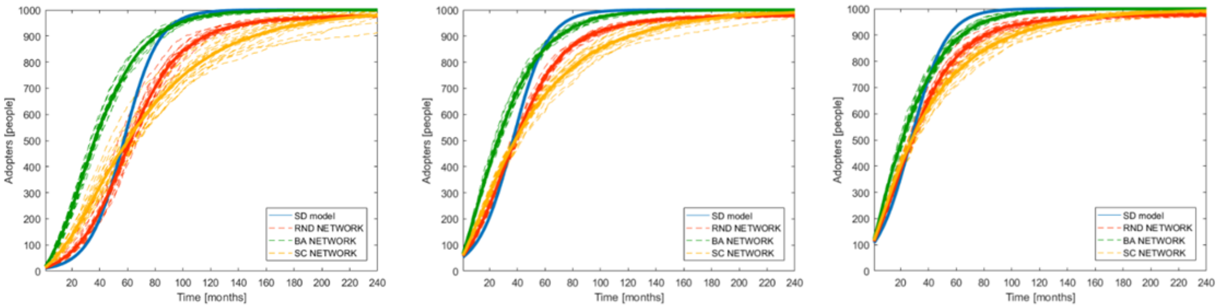


Fig A. 2. Diffusion curves for Case 2: results for kavg=4 and A0 = 1%, 5%, 10%.

From the figures, it emerges that, obviously, an increase of A_0 tends to compress the curves to the left, since more initial adopters contribute to the diffusion process from the beginning at time 0. The second result, as expected, is that the ABM processes nose up in the first months, while they slowly approach the plateau at the end. The initial rapid increase is because the "seeded" nodes are those with the highest degrees: they therefore facilitate the initial process of diffusion, attracting more neighbours through the mechanism of word of mouth. While approaching to the saturation, the lacking potential adopters are the ones with the lowest degrees, who are the hardest agents to attract.

The comparisons between the min and max time interval needed by the agent-based stochastic curves to reach 50% and 95% of diffusion, and the values of the SD model are reported in Table A 2 – the values in the brackets represent the difference with respect to the Bass model.

Table A 2. Results of *Case 2.*

	50%		95%	
Scenario k_{avg}=4, A_0=1	*min*	*max*	*min*	*max*
RND	54 (-4)	68 (+10)	136 (+41)	161 (+66)
BA	34 (-24)	40 (-18)	92 (-3)	105 (+10)
SC	48 (-10)	69 (+11)	146 (+51)	241 (+146)
SD	*58*		*95*	
Scenario k_{avg}=4, A_0=5	*min*	*max*	*min*	*max*
RND	36 (-2)	42 (+4)	113 (+38)	140 (+65)
BA	24 (-14)	29 (-9)	82 (+7)	96 (+21)
SC	37 (-1)	45 (+7)	133 (+58)	211 (+136)
SD	*38*		*75*	
Scenario k_{avg}=4, A_0=10	*min*	*max*	*min*	*max*
RND	26 (-2)	31 (+3)	98 (+33)	129 (+64)
BA	20 (-8)	24 (-4)	74 (+9)	86 (+21)
SC	26 (-2)	33 (+5)	123 (+58)	168 (+103)
SD	*28*		*65*	
Scenario k_{avg}=8, A_0=1	*min*	*max*	*min*	*max*
RND	28 (-2)	32 (+2)	51 (+3)	58 (+10)
BA	17 (-13)	20 (-10)	42 (-6)	47 (-1)
SC	22 (-8)	26 (-4)	63 (+15)	76 (+28)
SD	*30*		*48*	
Scenario k_{avg}=8, A_0=5	*min*	*max*	*min*	*max*
RND	17 (-2)	20 (+1)	41 (+3)	47 (+9)
BA	13 (-6)	15 (-4)	38 (0)	46 (+8)
SC	15 (-4)	18 (-1)	56 (+18)	76 (+38)
SD	*19*		*38*	
Scenario k_{avg}=8, A_0=10	*min*	*max*	*min*	*max*
RND	13 (-2)	15 (0)	37 (+4)	42 (+9)
BA	11 (-4)	13 (-2)	35 (+2)	43 (+10)
SC	13 (-2)	16 (+1)	54 (+21)	70 (+37)
SD	*15*		*33*	

The results reflect the trend visible from the diffusion curves described above. In the first months, the process on BA network reaches 50% of adoption always from 24 to 2 months before the SD model, depending on A_0. Few stochastic SC and RND simulation processes reach 50% of adoption before –

from 10 to 1 months before –, since 50% is reached few months later *on average*, from 1 to 11 months at most. Once approaching to the end of the process, BA simulations approach the saturation before the Bass model only in the case with k_{avg}=8, A_0=1%. RND and SC min and max curves reach 95% of adoption later respectively from 9 to 66 months, and from 28 to 146 months later. In particular, the process on SC network tends to the 100%-plateau later than the other processes, sometimes more than 10 years later.

In many simulations, the agent-based processes do not reach 100% of adoption, and the relative portion of population is numerically relevant for some RND and SC simulations with k_{avg}=4, as resumed in Table A 3. The adoption is sometimes uncompleted in RND processes because the networks present some isolated nodes, from 11 to 26, that can never become adopters as long as the term p is set equal to 0. On the contrary, since the process of SC network formation does not allow the presence of isolated nodes, the lacking adoption by some agents is due to the too short simulation horizon. With the aim to develop a sustainable energy business plan, this information would be pivotal for a local utility that must be able to project how many people would connect to the grid in the useful life of an off-grid electricity plant.

Table A 3. Percentage of maximum adoption at t=241 months for SC and RND processes at k_{avg}=4.

	max adoption		
	A_0=1%	A_0=5%	A_0=10%
RND	97.1-98.3	97.2-98.5	97.0-98.5
SC	91.3-99.5	97.1-99.5	98.4-99.9

Appendix B – Formulation of further sub-models

Agricultural revenues

Ikondo, as many sub-Saharan African villages, has an economy based on agriculture. Almost the totality of the households has their own land for self-consumption or even subsistence, local trade, or even wholesales outside the village. The total market potential of agricultural products – viz. the agricultural market turnover – is modelled as the sum of all the local expenditures for food for both HI and LI HHs, excluding the self-consumption – interviewed people tent to consider the farming costs (e.g. fertilizers, seeds, instruments) in their expenditures for food –, and the external demand. The external demand increased after electrification through a 1st-order positive feedback: electricity triggered the development of local market of good and services, attracting more external consumers who started purchasing also local food products (Eq. (59)).

$$\begin{cases} \textit{Food expenditures(t)} = \textit{Income(t)} \cdot \textit{Fr income for food(t)} \cdot (1 - \textit{fr of food expenditures referred to farming costs}) \\ \int_t \dfrac{d(\textit{External food expenditures(t)})}{\textit{External food expenditures(t)}} = \int_t \textit{change in external food expenditures}(t) \cdot dt \\ \textit{change in food expenditures(t)} = \textit{fr change in external food expenditures} \cdot \textit{weekly trend of market supply(t)} \end{cases} \tag{59}$$

The *fr of food expenditures referred to farming costs* is a calibration parameter, which considers the fact that local people, when interviewed, were used to include their farming costs and reinvestments in the "food expenditures" item. This formulation is based on the hypothesis that the reinvestments in farming activities entails an income outflow for specialised material (etc. fertilisers, machines, seeds) bought outside the village. The sum between the *Food expenditures* of all the HI and LI HHs and the *External food expenditures* gives the *Total agricultural market turnover*. A variable which represents the inequality in farming productivity between HI and LI HHs is introduced in order to allocate the agricultural market potential to each class of households – viz. the more productive a farmer is, the larger will be his share of *Total agricultural market turnover*. According to local surveys and the literature, the farm productivity emerged to depend on 3 main input factors:

1. *Financial resources*. The locals manifested a high propensity to invest their savings in the farming activity. The more they can earn, the more they reinvest in their land;
2. *Education*. An increased knowledge and improved educational level, supported by access to school, practical information through access to electricity and media, and capacity building, helped in increasing people's farming productivity, as confirmed by (Alene and Manyong 2007) and (Pudasaini 1983) in Nigeria and Nepal, respectively;
3. *Time*. Available time, especially night time at home lighted by electricity, is used by households for shelling, cleaning, and preparing their products. LI HHs, in particular, showed this behaviour, while HI HHs use their free-time for managing their IGA.

As for the productivity of the local market, the model relies on a Cobb-Douglas formulation for modelling the farming productivity (Fig A. 3). The latter is time-dependent, since local farming households need time to adapt their faming habits, creating a 1st-order delay between any change in the above-mentioned factors and the related impact on their productivity. The Eq. (60) below shows the mathematical formulation of the farming productivity for HI HHs.

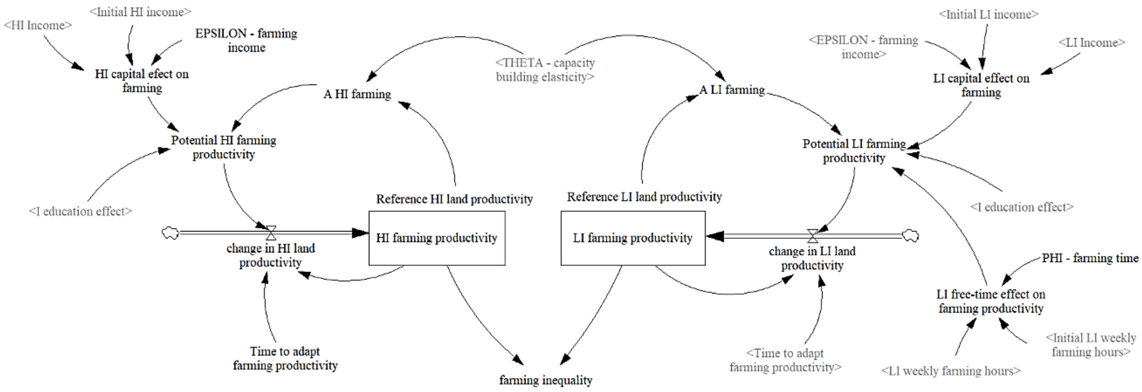


Fig A. 3. Stock-and-flow diagrams for the *HI* and *LI farming productivity*.

$$\begin{cases} \int_t \dfrac{d(HI\ farming\ productivity(t))}{change\ HI\ farming\ productivity(t)} = \int_t dt \\ change\ HI\ farming\ productivity(t) = \dfrac{Potential\ HI\ farming\ productivity(t) - HI\ farming\ productivity(t)}{Time\ to\ adapt\ farming\ productivity} \\ Potential\ HI\ farming\ productivity(t) = A_{HI\ farming}(t) \cdot HI\ capital\ effect\ on\ farming(t) \cdot I\ education\ effect(t) \\ A_{HI\ farming}(t) = Reference\ HI\ farming\ productivity \cdot (1 + \vartheta\text{-}capacity\ building\ elasticity) \\ HI\ capital\ effect\ on\ farming(t) = \left(\dfrac{HI\ Income(t)}{Initial\ HI\ Income} \right)^{\varepsilon\text{-}farming\ income} \end{cases} \quad (60)$$

With *Reference HI farming productivity* a calibration parameter representing a proxy of the initial farming productivity. For LI HHs, the formulation of the *LI farming productivity* is exactly the same, apart from an additional term, namely *LI free-time effect on farming productivity*, in the *Potential LI farming productivity*, which represents the increase in free-time used for farming activities as production input in the Cobb-Douglas formulation (Eq. (61)).

$$\begin{cases} LI\ free\text{-}time\ effect\ on\ farming\ productivity(t) = \left(\dfrac{Available\ farming\ time(t)}{Initial\ available\ farming\ time} \right)^{\varphi\text{-}farming\ time} \end{cases} \quad (61)$$

The *farming inequality* is then the ratio between the *LI farming productivity* and the sum between *LI farming productivity* and *HI farming productivity*. A value equal to 0.5 of the inequality means identical productivity between LI and HI HHs. The allocation of the *Total agricultural market turnover* weighted on the inequality variable and on the number of the HI and LI households gives the share of income from farming activities for HI and LI HHs (Eq. (62)).

$$\begin{cases} farming\ inequality(t) = \dfrac{LI\ farming\ productivity(t)}{HI\ farming\ productivity(t) + LI\ farming\ productivity(t)} \\ HI\ farming\ income = \dfrac{\left(1 - farming\ inequality(t)\right) \cdot Total\ agricultural\ market\ turnover(t)}{LI\ households(t) \cdot farming\ inequality(t) + HI\ households \cdot \left(1 - farming\ inequality(t)\right)} \\ LI\ farming\ income = \dfrac{farming\ inequality(t) \cdot Total\ agricultural\ market\ turnover(t)}{LI\ households(t) \cdot farming\ inequality(t) + HI\ households \cdot \left(1 - farming\ inequality(t)\right)} \end{cases} \quad (62)$$

Population

System dynamics offers two main different approaches for modelling population dynamics:

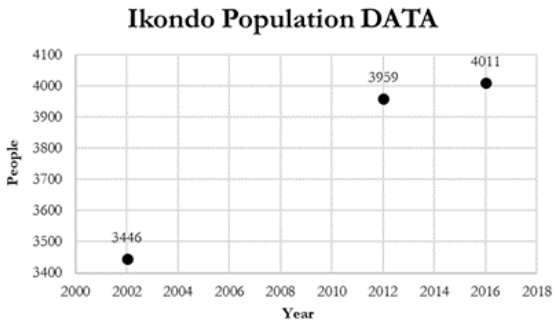
A. *"Lump-sum" model.* Population is formulated just through one stock, representing all the individuals, and flows indicating the demographic processes of reproduction, migration and mortality.

B. *Disaggregated model.* Population has a n^{th}-order material delay formulation, viz. a cohort-flow-based structure or "aging chain", where each cohort represents the dynamics of one age or size or sex class – e.g. (Sutrisno and Handel 2012).

The choice of the more appropriate approach depends of course of the objective of the model, the level of structural detail that is worth to be investigating and the data availability. In this work, the lack of disaggregate data prevented the use of a cohort-based model, in favour of a more effective and meaningful "lump-sum" model. Local interviews with the experts confirmed that Ikondo experienced a significant population growth after electrification, especially due to external migration. The very few aggregate data found in the grey literature and provided by CEFA confirm the positive population trend emerged during the qualitative interviews, although it is not quantitively possible to attribute such increase of the population to electrification.

Table A 4. Ikondo Population DATA.

Year	Population	Reference
2002	3446	(Tanzania National Bureau of Statistics 2011)
2012	3959	(Tanzania National Bureau of Statistics et al. 2013)
2016	4011	2016 CEFA's survey



The trend of data seems growing with a greater derivative between 2002 and 2012, then slowly increasing between 2012 and 2016. This is the typical trend of such systems initially dominated by positive feedback (viz. the more people there are, the higher net birth rate will be), which eventually approaches the equilibrium given by the carrying capacity of its environment (e.g. food/space/resource constrains) (Sterman 2000). The resulted behaviour of systems driven by such dynamics is called *S-shaped* growth, and the *logistic* model is one of the most common model used to represent it (Eq.(63)).

$$\begin{cases} \int_t \dfrac{d(Population(t))}{change\ in\ population(t)} = \int_t dt \\ change\ in\ population(t) = \left(1 - \dfrac{Population(t)}{Population\ Carrying\ capacity}\right) \cdot Population(t) \cdot maximum\ fr\ population\ growth \end{cases} \tag{63}$$

Where the variable *change in population* is a net value, which considers the difference between the birth rate, death rate, inflow and outflow migration. The *maximum fr population growth* is a calibration parameter and represents the fractional growth rate when the population is very small. Fig A. 4 confirms the appropriateness of the *logistic* formulation for modelling Ikondo's population. It reports the results of a single simulation of the *Population* sub-model with manually-calibrated values of *maximum fr population growth*, *Population Carrying capacity*, and *Initial population* at 2005 equal to 0.004 [1/Week], 4052 [People], and 3670 [People], respectively.

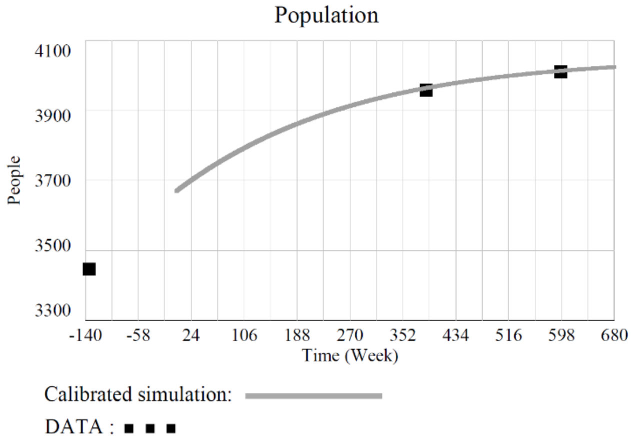


Fig A. 4. Simulation of the *Population* sub-model with aggregate data taken from Table A 4. X-axis=0 is the first week of 2005, viz. the Initial Time of the simulation model.

The dynamics of the population determines the dynamics of household growth. Since the type of household (LI or HI) is an "attribute" of the population stock, a coflows-based structure is used to model the households' dynamics. Coflows represent a useful modelling tool in the SD theory, which allows to model the attributes of a particular item (population in this case) that flow through a stock-and-flow system (Fig A. 5).

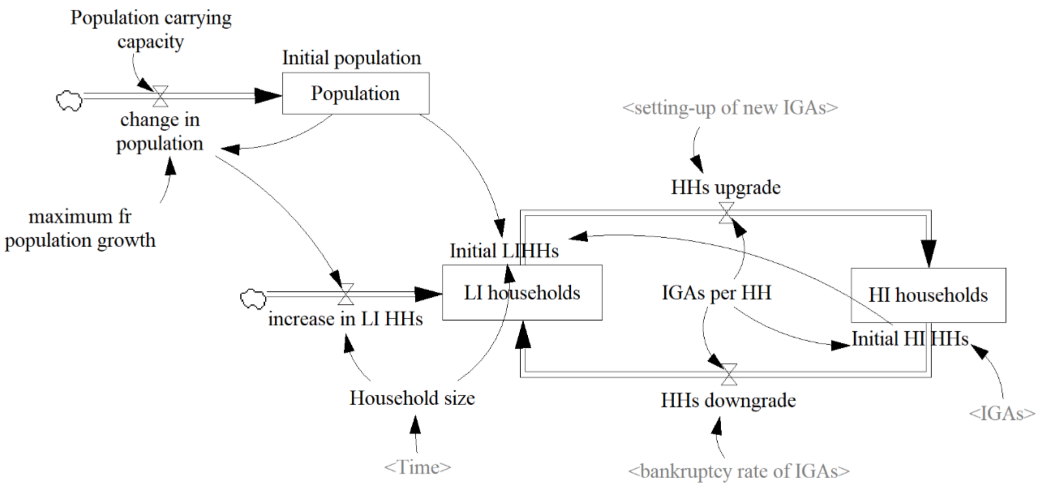


Fig A. 5. Population → Households coflow.

$$\begin{cases} LI\ \ households(t) = Initial\ \ LI\ HHs + \int_t \left(HHs\ downgrade(t) + increase\ in\ LI\ HHs(t) - HHs\ upgrade(t) \right) \cdot dt \\ Initial\ \ LI\ HHs = \dfrac{Initial\ \ Population}{Household\ \ size(t_0)} - Initial\ \ HI\ HHs \\ HHs\ downgrade(t) = \dfrac{bankruptcy\ rate\ of\ IGAs(t)}{IGAs\ per\ HH} \\ increase\ \ in\ LI\ HHs(t) = \dfrac{change\ in\ total\ population(t)}{Household\ size(t)} \\ HHs\ upgrade(t) = \dfrac{setting\text{-}up\ of\ new\ IGAs(t)}{IGAs\ per\ HH} \\ HI\ \ households(t) = Initial\ \ HI\ HHs + \int_t \left(HHs\ upgrade(t) - HHs\ downgrade(t) \right) \cdot dt \\ Initial\ \ LI\ HHs = \dfrac{IGAs(t_0)}{IGAs\ per\ HH} \end{cases} \tag{64}$$

The *Household size* variable is a time-dependent look-up table, which linearly interpolates values from the grey literature reported in Table A 5.

Table A 5. Ikondo Household size DATA.

Year	Household size	Reference
2002	*4.6*	Value set equal to the 2012 value. Since the value of household size did not change for the Njombe [According to (Tanzania National Bureau of Statistics 2011) and (Mkupete 2010)]
2012	4.6	(Tanzania National Bureau of Statistics et al. 2013)
2016	4.9	2016 CEFA's survey

Time savings

According to the literature review on the electricity-development nexus, the conceptualisation of the model, and the local surveys, electricity had a significant impact on people's available time and habits. In turn, available time had a feedback on both working and farming time. In particular, two factors increased households' available operation time:

- *Lighting* the business place, which allows HI households to continue their income generating activities during the evening dark hours;
- *Lighting* at home, which allows both LI and HI women to delay their housework in the evening and dedicate more daily hours for farming and conducting the IGA. Moreover, electrical lighting and electrical appliances allow also to decrease time for housework (e.g. electrical rice-cooker was found to reduce cooking time). For LI HHs, lighting at home allows them to continue some farming activities in the evening.

Summing-up these effects, the A*vailable operation time* and the *Available farming time* for both HI and LI HHs are obtained. The Eq. (65)-(66) below show the mathematical formulation of the housework time freed-up by electricity and the total available farming time for LI HHs, respectively. The dynamics of *Available farming time* follows the dynamics of a 1st-order negative feedback, since people, especially in rural contexts, have not always the perception of free-time as a resource, causing a delay, represented through the *Time to perceive potentially free time for farming* variable, in perceiving the available time for farming.

$$\begin{cases} \textit{Weekly free-time} = \left(\textit{Night time for LI housework(t)} + \textit{Saved LI housework time(t)}\right) \cdot \textit{working days in a week} \\ \textit{Night time for LI housework(t)} = \int_t \textit{time-shift of LI housework(t)} \cdot dt \\ \textit{time-shift of LI housework(t)} = \textit{Max time for night housework} \cdot \textit{Trend in LI connections(t)} \\ \textit{Saved LI housework time(t)} = \int_t \textit{decrease in LI housework time(t)} \cdot dt \\ \textit{decrease in LI housework time(t)} = \textit{Trend in LI connections(t)} \cdot \textit{housework time reduction given by electricity} \\ \textit{Trend in LI connections(t)} = \dfrac{\nabla_{t_u}\left(\textit{fr of connected LI HHs(t)}\right)}{t_u} \end{cases} \tag{65}$$

The *Max time for night housework* is a limit given by the people's sleeping time (usually at 23:00-24:00 on average), while the *housework time reduction given by electricity* represents the daily housework hours saved by the use of electricity appliances and light. The *fr of connected LI HHs* is the fraction of LI households connected to electricity respect all the LI households (see the sub-section before)

$$\begin{cases} \int_t \frac{Available\ farming\ time(t)}{Potential\ \ available\ farming\ time(t) - Available\ farming\ time(t)} = \frac{1}{Time\ to\ perceive\ more\ time\ for\ farming} \int_t dt \\ Potential\ \ available\ farming\ time(t) = Initial\ available\ farming\ time + Weekly\ LI\ free\text{-}time(t) + Available\ night\ farming\ time(t) \\ Available\ night\ farming\ time(t) = Max\ time\ for\ night\ farming \cdot fr\ of\ connected\ LI\ HHs(t) \end{cases} \quad (66)$$

Where the *Max time for night farming* is a limit given by the people's sleeping time.

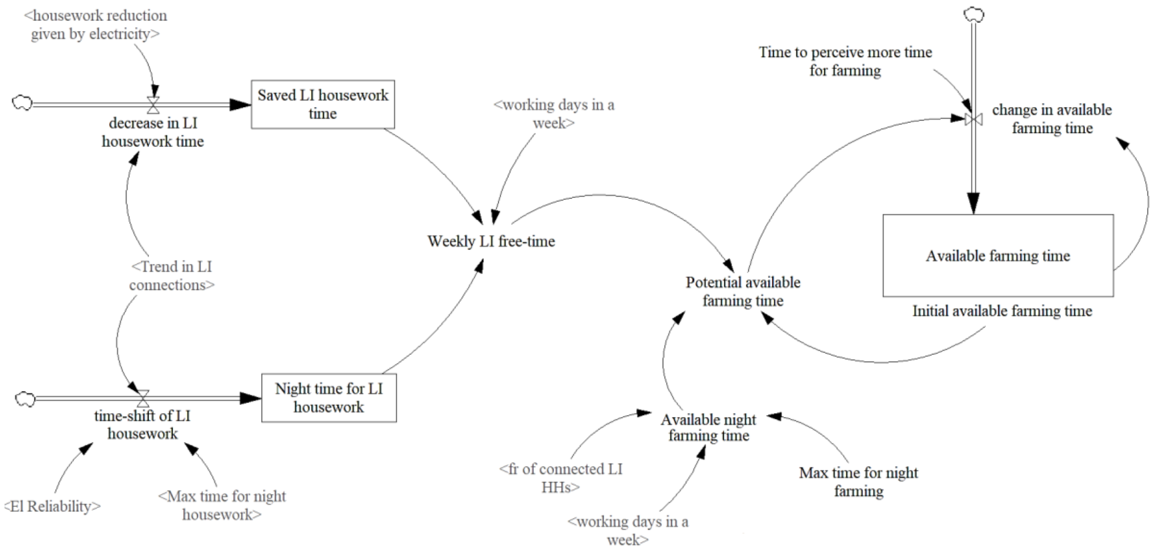


Fig A. 6. Stock-and-flow diagram for the *Available farming time*.

The same dynamics and formulation stand also for the *Available operation time*. The only difference is that the *Available night operation* time is not calculated based on the *fraction of connected LI HHs*, but on the fraction of the connected IGAs that are available and willing to work on the night (Eq. (67)).

$$\begin{cases} Available\ night\ operation\ time(t) = Max\ time\ for\ night\ working \cdot fr\ of\ connected\text{-}IGAs\ working\ at\ night(t) \cdot El\ Reliability(t) \\ fr\ of\ connected\text{-}IGAs\ working\ at\ night(t) = fr\ of\ connected\ IGAs(t) \cdot Night\text{-}working\ feasibility \end{cases} \quad (67)$$

Where the *Night-working feasibility* is a calibration parameter showing the fraction of IGAs willing and potentially available to work in the evening.

Education

In accordance with the electricity-development nexus, access to electricity impacted also on the educational level in Ikondo area. Based on the causal loop diagrams drawn in the conceptualisation phase, the dynamics behind electricity use and education is represented through two main variables used as proxy of the local educational attainment: the *Net intake in primary* school and the *Primary completion.* Huisman and Smits (Huisman and Smits 2009) rely on a multilevel *logistic* regression model to describe the main independent variables explain the primary enrolment rate in 30 developing countries. In their study, they find that the odds of being enrolled in primary school is between 27% to 42% higher for 8-11 years old children with a father employed in a "upper-non-farm" activity than children with fathers relying on farming activities. Based on this information, the trend of HI HHs – formulated through a discrete backward difference along the time-unit $t_u = 1\ week$ – is used as a proxy of the improvement in the employment status of local households, in order to formulate the increase in *Net intake in primary* variable (Eq. (68)).

$$\begin{cases} Net\ \ intake\ primary(t) = Initial\ intake\ primary + \int_t change\ in\ net\ intake\ primary(t) \cdot dt \\ change\ in\ net\ intake\ primary(t) = EffectOfFatherOccupationOnPrimaryEnrollment \cdot \dfrac{\nabla_{t_u}\left(Fraction\ of\ HI\ HHs\right)}{t_u} \\ Fraction\ \ of\ HI\ HHs = \dfrac{HI\ \ Households}{Population} \end{cases} \tag{68}$$

For the *Primary completion*, the interviews at the Kanikelele's school confirmed that electricity at school and at home contributed to increase the completion rate already a year after gaining access to (Eq.(69)). In particular, they attributed an increase of 34% to electricity at school, which is modelled through a STEP function (viz. a discontinuity at *t=1 year*).

$$\begin{cases} \int_t \dfrac{d\left(Primary\ completion(t)\right)}{change\ \ in\ completion(t)} = \int_t dt \\ change\ \ in\ completion(t) = change\ in\ completion\ due\ to\ el.\ at\ school(t) + change\ in\ completion\ due\ to\ el.\ at\ home(t) \\ change\ in\ completion\ due\ to\ el.\ at\ school(t) = Electricity\ at\ school \cdot EffectOfSchoolElectricity \cdot Primary\ completion\ rate(t) \\ Electricity\ \ at\ school = \begin{cases} 1 \ \ if\ \ TIME = 1\ year \\ 0 \ \ elsewhere \end{cases} \\ change\ in\ completion\ due\ to\ el.\ at\ home(t) = EffectOfHomeElectricity \cdot Trend\ in\ HH\ connections(t) \\ Trend\ in\ HH\ connections(t) = \dfrac{\nabla_{t_u}\left(Total\ \ connected\ HHs\right)}{t_u} \end{cases} \tag{69}$$

Where the *EffectOfSchoolElectricity* and *EffectOfHomeElectricity* are calibration parameters. For both the integrals in Eq.(68) and Eq.(69), the integrated variables cannot grow to infinity, but they are limited to 100%, obviously.

Appendix C – Search space for calibrating parameters

Table A 6 Search-space definition.

N°	Parameter		Search-space	Reason/Source
1)	awareness effect HI HHs	[1/Week]	[0.000029 - 1]	*LB*: minimum value found in (Sterman 2000; Massiani and Gohs 2015) and Van den Bulte's comprehensive review on Bass model utilisation in the innovation diffusion-based literature (Van Den Bulte 2002). Values converted in [1/Week] unit of measurement. *UB*: 1 is the maximum feasible value in a diffusion process, meaning complete awareness of the innovation product (*i.e.* the connection to electricity). Setting the *UB* to 1 is suggested by local interview carried out in 2016 and 2017 in the non-electrified villages of Ninga, Lole, Mahongole, and Kitole, where almost all the people expressed their willingness and wish to have electricity in the villages.
2)	awareness effect IGAs	[1/Week]	[0.000029 - 1]	As 1)
3)	awareness effect LI HHs	[1/Week]	[0.000029 - 1]	As 1)
4)	BETA - el	[-]	[0 - 1]	*LB*: minimum feasible value for the effect of electrification of local IGAs on the total factor productivity of the local market. *UB*: the increase in the electrification rate of local IGAs and the increase in the total factor productivity of the local market are linearly proportional.
5)	diffusion rate DECODERs	[Appliances/$/Week]	[0.0028 - 0.0084]	Bounds calculated based on the surveys carried out in 2016 and 2017 to electrified households in the villages of Nyombo, Kidegembye, Ukalawa, Ikondo. Given the appliance type *i*, the total surveyed households *N* who own n_i devices of type *i*, and *WeekExp* the weekly expenditures of the surveyed households, the average diffusion rate is calculated as follow: $$diffusion\ rate_i = \frac{\frac{1}{N}\sum_{k=1}^{N} n_i}{\frac{1}{N}\sum_{k=1}^{N} WeekExp_k} \quad (70)$$ Values are checked to have the same order of magnitude of the values of diffusion rate obtained by (Hartvigsson et al. 2018a) for a Tanzanian

				village in the Njombe area. The *LB/UB* are calculated from the value obtained with the equation (70) changed by ±50%, respectively. The week expenditures reported by the surveyed people have been used as a proxy for their income, as suggested by the literature (Alene and Manyong 2007; van Ruijven et al. 2011).
6)	diffusion rate IRONs	[Appliances/$/Week]	[0.0080 - 0.0308]	As 5)
7)	diffusion rate LIGHTs	[Appliances/$/Week]	[0.2171 - 0.6960]	As 5)
8)	diffusion rate PHONE CHARGERs	[Appliances/$/Week]	[0.0605 - 0.2245]	As 5)
9)	diffusion rate STEREOs	[Appliances/$/Week]	[0.0237 - 0.0814]	As 5)
10)	diffusion rate TVs	[Appliances/$/Week]	[0.0118 - 0.0730]	As 5)
11)	Duration of phase I for HHs	[Week]	[61.5 – 66.0]	*LB/UB* from CEFA's database on the number of IGAs connected to the mini-grid. They represent the two months over the discontinuity visible in the data of Fig. 44-bottom.
12)	Duration of phase I for IGAs	[Week]	[105.25 – 109.50]	*LB/UB* from CEFA's database on the number of IGAs connected to the mini-grid. They represent the two months over the discontinuity visible in the data of Fig. 45-bottom.
13)	EffectOfFatherOccupationOnPrimaryEnrollment	[-]	[0.27 - 0.42]	*LB/UB* from (Huisman and Smits 2009) who find that the odds of being enrolled in primary school is between 27% to 42% higher for 8-11 years old children with a father employed in a "upper-non-farm" activity than children with fathers relying on farming activities.
14)	EffectOfHomeElectricity	[-]	[0 - 0.1]	*LB*: minimum feasible value meaning no effect of domestic lighting on pupils' school performance. *UB:* set by the modeller.
15)	EffectOfSchoolElectricity	[-]	[0.272 - 0.408]	The interviews at the Kanikelele's school in 2018 attributed an increase of 34% to electric lighting at school. *LB/UB* are calculated from 34% changed by ±20%, respectively.
16)	El Reliability	[-]	[0.9583 - 0.9995]	Interviews to the manager directors of the local utility MVC confirmed that the duration of grid blackouts varied from even 60 minutes every day before the grid extension implemented in 2016 to 5 minutes every week after 2016.

				$\begin{cases} LB = 1 - \dfrac{60\left[{}^{min}/_{day}\right]}{60\left[{}^{min}/_{hour}\right]\cdot 24\left[{}^{hour}/_{day}\right]} = 0.95830 \\ LB = 1 - \dfrac{5\left[{}^{min}/_{week}\right]}{60\left[{}^{min}/_{hour}\right]\cdot 24\left[{}^{hour}/_{day}\right]\cdot 7\left[{}^{day}/_{dweek}\right]} = 0.9995 \end{cases}$ (71)
17)	Electrical power of Decoders	[Watt/Appliances]	>4	*LB*: Set by the modeller.
18)	Electrical power of Iron	[Watt/Appliances]	[960 - 1440]	Value of 1.2 kW set by the modeller plus ±20%.
19)	Electrical power of Lights	[Watt/Appliances]	>5	Set by the modeller, considering a LED bulb of 5W as minimum.
20)	Electrical power of Phone charger	[Watt/Appliances]	[2.856 – 4.284]	Set by the modeller, considering a typical charger of 5.1V/0.7A=3.57W ±20%.
21)	Electrical power of Stereos	[Watt/Appliances]	>8	As 17)
22)	Electrical power of TVs	[Watt/Appliances]	>64	As 17)
23)	Electricity-Fee elasticity for EE-reliant IGAs	[-]	[-1 - 0]	*LB*: minimum feasible value for the elasticity of IGAs electricity use respect to changes in the fee. *UB*: maximum feasible value for the elasticity of IGAs electricity use respect to changes in the fee.
24)	Electricity-Fee elasticity for notEE-reliant IGAs	[-]	[-1 - 0]	As 23)
25)	Electricity-Income elasticity HHs	[-]	[-1 - 0]	*LB*: minimum feasible value for the elasticity of HHs electricity use respect to changes in the electricity cost and income. *UB*: maximum feasible value for the elasticity of HHs electricity use respect to changes in the electricity cost and income.
26)	EPSILON - farming income	[-]	[0 - 1]	*LB*: changes in farming income does not impact on the farming productivity. *UB*: changes in the farming income cause a proportional change in the farming productivity.
27)	EPSILON - IGAs income	[-]	[0 - 1]	*LB*: changes in HI income does not impact on the market productivity. *UB*: changes in the HI income cause a proportional change in the market productivity.
28)	external/local prices factor	[-]	[1 - 3]	*LB*: minimum value meaning local prices are equal to the costs that households experience for buying the same goods out of Ikondo. *UB:* set by the modeller.

29)	Fixed electricity fee in TZS before 2010	[TZS/(Week*Households)]	[0 - 345.2]	*LB*: minimum feasible value meaning no fixed components in the tariffs for households. *UB:* value of fixed component of the residential electricity fee in 2010.
30)	fr change in external food expenditures	[-]	[0 - 1]	*LB*: minimum feasible value. *UB*: maximum feasible value.
31)	fr change in external market demand	[-]	[0 - 1]	As 30)
32)	fr change in internal IGAs supply	[-]	[0 - 1]	As 30)
33)	fr decrease in cost given by EE	[-]	[0 - 1]	As 30)
34)	fr food expenditures referred to farming investments	[-]	[0 - 0.5]	*LB*: minimum feasible value. *UB*: in the *Household Budget Survey 2007 – Tanzania Mainland*, the "food not-purchased" (considered as a proxy of the farming income reinvest in the activity) is almost 50% of the total income spent for food items.
35)	fr income for education expenditures HI	[-]	[0.01 - 0.4]	*LB/UB* set based on local interviews to the experts.
36)	fr income for education expenditures LI	[-]	[0.01 – value in 35)]	As 35)
37)	fr income for medical expenditures HI	[-]	[0.018 - 0.2]	As 35)
38)	fr income for medical expenditures LI	[-]	[0.018 - 0.2]	As 35)
39)	fr increase of market expenditures	[-]	>0	*LB*: minimum feasible value.
40)	fr of operating time with electricity	[-]	[0-1]	As 30)
41)	fr of people using microcredit	[-]	[0.32 - 0.48]	The local interview to the manager director of the micro-credit utility SACCOS suggests that 40% of people use micro-credit loans for finance a new business. The *LB/UB* are set equal to this value plus ±20%.
42)	fr of potentially affordable IGAs connections	[-]	>0	As 39)
43)	fraction of EE-reliant IGAs respect to connected IGAs	[-]	[0.08 - 0.18]	Set by the modeller considering the historical data of IGAs connections in Ikondo.
44)	fraction of external source of HI income	[-]	[0 - 0.05]	*LB*: minimum feasible value. *UB:* set by the modeller since local surveys suggest that this fraction is "very low".
45)	fraction of external source of LI income	[-]	[0 - 0.05]	As 44)
46)	fraction of failing IGAs	[-]	[0.24 - 0.36]	Local interviews to the experts suggest that 30% of starting business closed the activities after few months or years. The *LB/UB* are set equal to this value plus ±20%.
47)	fraction of feasible HHs market supply	[-]	[0.6 - 0.9]	Local interviews to the experts suggest that 75% of goods and services can be found locally. The *LB/UB* are set equal to this value plus ±20%.
48)	fraction of IGAs that want to start by imitation	[-]	[0.4 - 0.6]	Local interviews to the experts suggest that 50% of starting businesses are by imitation, without a proper market analysis. The *LB/UB* are set equal to this value plus ±20%.

49)	fraction of initial HI HHs to be connected	[-]	[0 - 1]	As 30)
50)	fraction of initial LI HHs to be connected	[-]	[0 - 1]	As 30)
51)	fraction of revenues used by the utility for O&M	[-]	[0.4 - 0.6]	The local interview to the manager director of the local utility MVC confirms that the MVC reinvests 50% of its revenues in local productive and social activities. The LB/UB are set equal to this value plus ±20%.
52)	fraction of sharing meter	[-]	[0.48 – 0.72]	Local interviews to the experts suggest that there are about 80 business connected, some of them sharing the same meter. Since data confirmed that there were 48 metered business until the end of December 2017 (one month before the survey), the average fraction of people sharing the connection is $\frac{48}{80}$=0.6. The LB/UB are set equal to this value plus ±20%.
53)	GAMMA - edu	[-]	[0 - 0.1]	*LB*: minimum feasible value for the effect of change in education level on the market productivity. *UB*: set by the modeller since not all the local experts mention the school education as a market productivity input.
54)	HH connection cost in phase I	[$/Households]	[53.7 - 67.1]	LB/UB based on the min/max values of electricity connections obtained before the Duration of phase I for HHs (N° 11) indicated in the surveys carried out in 2017 in the electrified households in the villages of Ikondo
55)	HH connection cost in phase II	[$/Households]	[114 - 357.8]	LB/UB based on the min/max values of electricity connections obtained after the Duration of phase I for HHs (N° 11) indicated in the surveys carried out in 2017 to electrified households in the villages of Ikondo and Ukalawa.
56)	housework reduction given by electricity	[Hour/Day]	[0 - 1.3]	*LB*: minimum feasible value indicating no electricity effect on housework. *UB*: value suggested during the interview to a local woman.
57)	IGA connection cost in phase I	[$/IGA]	[53.7 - 67.1]	As 54)
58)	IGA connection cost in phase II	[$/IGA]	[114 - 357.8]	As 55)
59)	IGAs per HH	[IGA/Households]	[0 - 1]	*LB*: minimum feasible value. *UB:* set by the modeller.[21]
60)	Initial available operation time	[Hour/Week]	[1 - 84]	*LB*: minimum feasible value. *UB*: maximum value obtained by multiplying 12 potential working hours of sunlight times 7 working days per week.

[21]The appropriateness of the bounds set by the modeller are checked a-posteriori by controlling that the calibrated value of the parameter does not corresponds exactly with the bound itself.

61)	Initial daily farming hours for LI HHs	[Hour/Day]	[4.8 - 7.2]	Local surveys in the villages of Ikondo and Ukalawa suggest that 6 hours per day is the daily farming time for agricultural activities for farmers without access to electricity (here used a proxy for the situation in Ikondo before access to electricity). The *LB/UB* are set equal to this value plus ±20%.
62)	Initial EE-IGAs coincidence factor	[-]	[0.0176 – 0.1246]	*LB/UB*: minimum and maximum values of the coincidence factors derived from (Hartvigsson and Ahlgren 2018), who metered the daily electricity loads Mills and Workshops from a Tanzanian Village.
63)	Initial external agricultural expenditures	[$/(Week*Households)]	>0	As 39)
64)	Initial external market demand	[goods/(Week*Households)]	>0	As 39)
65)	Initial fr income for food expenditures HI	[-]	[0 - 1]	As 30)
66)	Initial fr income for food expenditures LI	[-]	[0 - 1]	As 30)
67)	Initial fr of HHs close to the grid	[-]	[0 - 1]	As 30)
68)	Initial fr of internal IGAs supply	[-]	[0 - 1]	As 30)
69)	Initial net intake primary	[-]	[0.5948- 0.8922]	Data from the World Bank[22] indicates a net intake rate in primary school of 74.35% in 2004 (year before the implementation of Ikondo power plant). The *LB/UB* are set equal to this value plus ±20%.
70)	Initial number of IGAs	[IGA]	[0 - 2]	*LB*: minimum value indicated by local interviews to the experts. *UB*: maximum value indicated by local interviews to the experts.
71)	Initial Population	[People]	>3446	*LB*: population of Ikondo in 2002 (Tanzania National Bureau of Statistics 2011).
72)	Initial time to use Decoders	[Hour/Week]	[14 - 42]	*LB*: minimum value obtained with the surveys carried out in 2016 and 2017 to the electrified households in the villages of Nyombo, Kidegembye, Ukalawa, Ikondo. *UB*: maximum value obtained with the surveys carried out in 2016 and 2017 to the electrified households in the villages of Nyombo, Kidegembye, Ukalawa, Ikondo.
73)	Initial time to use Irons	[Hour/Week]	[0.25 - 2]	As 72)
74)	Initial time to use lights	[Hour/Week]	[7 - 91]	As 72)
75)	Initial time to use Phone chargers	[Hour/Week]	[3 - 49]	As 72)
76)	Initial time to use Stereos	[Hour/Week]	[7 - 91]	As 72)
77)	Initial time to use TVs	[Hour/Week]	[7 - 42]	As 72)
78)	internal migration effect	[-]	≥ 1	Electrification had a null (=1) and positive (>1) effect on the internal migration

[22]https://data.worldbank.org/indicator/SE.PRM.NINT.ZS?locations=TZ.

79)	Investment for a new IGA	[$/IGA]	>0	As 39)
80)	k-time	[-]	[0 - 1]	As 30)
81)	max fr of internal IGAs supply	[-]	[0 - 1]	As 30)
82)	max increase of week expenditures	[-]	>0	As 39)
83)	Max time for night farming	[Hour/Day]	[0 - 4]	*LB*: minimum feasible value. *UB:* local surveys suggest that night activities can potentially last from the sunset (6 pm – 7 pm) until 10-11 pm.
84)	Max time for night housework	[Hour/Day]	[0 - 4]	*LB*: minimum feasible value *UB:* local surveys suggest that night activities can potentially last from the sunset (6 pm – 7 pm) until 10-11 pm..
85)	Max time for night working	[Hour/Day]	[0 - 4]	As 83)
86)	maximum fr population growth	[1/Week]	>0.000209	*LB*: it is the growth rate experienced in Ikondo if calculated linearly between 2002 and 2016 data reported in Fig A. 4
87)	maximum fraction of income for debt repayment	[-]	[0 - 1]	As 30)
88)	Night-working feasibility	[-]	[0.4 - 0.6]	The interviews to the experts suggest that about 50% of the connected local businesses stay open in the evening using electrical lighting. The *LB/UB* are set equal to this value plus ±20%.
89)	Payback	[Week]	[4.25 - 52]	The interview to the manager director of the micro-credit SACCOS suggest that loans are usually payback in few months and within 1 year. *LB*: one month (viz. $\frac{365/7}{12}$=4.25 weeks) *UB*: one year (viz. $\frac{365}{7}$=52 weeks)
90)	PHI - farming time	[-]	[0 - 1]	*LB*: more available time for farming does not change farming productivity. *UB*: changes in the HI income cause a proportional change in the market productivity.
91)	Population carrying capacity	[People]	>4011	*LB*: datum of Ikondo's population in 2016
92)	Power EE-IGA	[Watt/IGA]	[36-329]	*LB/UB*: minimum and maximum values from 2016 surveys to the IGAs in the villages of Nyombo and Kidegenbye, excluding Mills, Carpentries, and Garages.
93)	Power notEE-IGA	[Watt/IGA]	[2530-26113]	*LB/UB*: minimum and maximum values from 2016 surveys to Mills, Carpentries, Garages, and big shops in the electrified villages of Nyombo and Kidegenbye.
94)	price to cost factor	[-]	[1 - 4]	*LB*: minimum feasible value meaning unitary mark-up (viz. prices equal to the costs).

				UB: set by the modeller.[23]
95)	production cost without EE	[$/goods]	>0	As 39)
96)	Reference factor productivity	[goods/(IGA*Hour)]	>0	As 39)
97)	Reference HI land productivity	[-]	>0	As 39)
98)	Reference LI land productivity	[-]	>0	As 39)
99)	social contagion HI	[1/Week]	[0.0029 - 0.0365]	*LB/UB*: minimum and maximum values found in Van den Bulte's comprehensive review on Bass model utilisation in the innovation diffusion-based literature (Van Den Bulte 2002). Values converted in [1/Week] unit of measurement.
100)	social contagion IGAs	[1/Week]	[0.0029 - 0.0365]	As 99)
101)	social contagion LI	[1/Week]	[0.0029 - 0.0365]	As 99)
102)	THETA - capacity building elasticity	[-]	[0 - 1]	*LB*: minimum feasible value for the effect of informal education (viz. capacity building) on the market and farming productivities *UB*: the increase in the informal education activities and the increase in the market and farming productivities are linearly proportional.
103)	Time for setting-up the IGA	[Week]	[1 - 26]	The interviews to the experts suggest that people take from "few weeks up to 6 months for starting a business". *LB*: one week *UB*: 6 months (viz. $\frac{365/7}{12} \cdot 6 = 26$ weeks)
104)	Time to adapt electricity use	[Week]	>4.25	*LB*: people can adjust their electricity consumption to changes in their income and electricity fee based on the frequency they receive the bill, that is 1 month (viz. $\frac{365/7}{12} = 4.25$ weeks) in the case of Ikondo.
105)	Time to adapt farming productivity	[Week]	≥1	As 39)
106)	Time to adapt market expenditures	[Week]	≥1	As 39)
107)	Time to adapt productivity	[Week]	≥1	As 39)
108)	Time to dismiss activity	[Week]	≥1	As 39)
109)	Time to get the loan	[Week]	[0 - 2]	The interview to the manager director of the micro-credit SACCOS confirms after the request, if the loan request is eligible, they receive the loan in maximum 2 weeks.
110)	Time to perceive decrease in operating hours	[Week]	≥1	As 39)
111)	Time to perceive electricity benefits	[Week]	≥1	As 39)

[23]The appropriateness of the bounds set by the modeller are checked a-posteriori by controlling that the calibrated value of the parameter does not corresponds exactly with the bound itself.

112)	Time to perceive increase in operating hours	[Week]	≥1	As 39)
113)	Time to perceive market dynamics	[Week]	≥1	As 39)
114)	Time to perceive more time for farming	[Week]	≥1	As 39)
115)	Time to perceive more time for working	[Week]	≥1	As 39)
116)	Time to purchase appliances	[Week]	≥1	As 39)
117)	T-sigmoid	[Hour/Week]	≥1	As 39)
118)	Variable electricity fee PRODUCTIVE in TZS before 2010	[TZS/(Watt*Hour)]	[0 - 0.12]	*LB*: minimum feasible value meaning free-of-charge electricity use for households. *UB:* value of variable component of residential electricity fee in 2010.
119)	Variable electricity fee RESIDENTIAL in TZS before 2010	[TZS/(Watt*Hour)]	[0 - 0.07]	*LB*: minimum feasible value meaning no fixed components in the tariffs for IGAs. *UB:* value of variable component of productive electricity fee in 2010.
120)	Willingness to pay for connection for IGAs	[-]	[0 - 1]	As 30)
121)	Willingness to pay HI	[-]	[0.048 – 0.072]	Van Gevelt et al. (van Gevelt et al. 2016) find that the willingness-to-pay for grid connection in a Rwanda village is 6% for high income households. The *LB/UB* are set equal to this value plus ±20%.
122)	Willingness to pay LI	[-]	[0.128 – 0.192]	Van Gevelt et al. (van Gevelt et al. 2016) find that the willingness-to-pay for grid connection in a Rwanda village is 16% for low income households. The *LB/UB* are set equal to this value plus ±20%.
123)	working days in a week	[Day/Week]	[6 - 7]	Local surveys to CEFA's people confirmed that people work at least 6 full days per week, while Sunday working can be limited by religious functions and leisure.

17 other constant parameters are introduced in model. Their values are not calibrated since they represent physical limits and/or values, and actual values derived from the local contexts (Table A 7).

Table A 7. Other not-calibrated parameters.

N°	**Parameter**		**Search-space**	**Reason/Source**
1)	Initial HI income	[$/(Households*Week)]	21.45	Calibrated manually, since it depends on the equilibrium of demand and supply of goods/services and agricultural markets. It is set equal to the value of HI Income variable at $t=1+\Delta t$.
2)	Initial LI income	[$/(Households*Week)]	1.635	Calibrated manually, since it depends on the equilibrium of demand and supply of goods/services and agricultural markets. It is set equal to the value of LI Income variable at $t=1+\Delta t$.
3)	max net intake rate primary school	[-]	1	Physical limit
4)	max primary school completion rate	[-]	1	As 3)

5)	Monthly fraction of interest	[-]	0.02	Interest applied to the loans granted by SACCOS, as confirmed by the manager director of the micro-credit utility.
6)	Number of CEFA's IGAs	[IGA]	2	From CEFA's database on electricity consumption: one carpentry and one tailor shop connected on January 2007.
7)	saturation limit DECODERs	[Appliances/Households]	1	The saturation limit is the maximum potential occurrence of a specific appliance. For each type of appliance, it is set as the actual maximum occurrence observed during the surveys carried out in 2016 and 2017 to the electrified households in the villages of Nyombo, Kidegembye, Ukalawa, Ikondo.
8)	saturation limit IRONs	[Appliances/Households]	2	As 7)
9)	saturation limit LIGHTs	[Appliances/Households]	15	As 7)
10)	saturation limit PHONE CHARGERs	[Appliances/Households]	6	As 7)
11)	saturation limit STEREOs	[Appliances/Households]	3	As 7)
12)	saturation limit TVs	[Appliances/Households]	3	As 7)
13)	Total access to electricity	[-]	1	As 7)
14)	TZS to US$	[$/TZS]	0.000447	The TZS/US$ currency exchange on January 2018[24].
15)	Watt to kWatt	[kWatt/Watt]	0.001	Conversion
16)	week	[Week]	1	Parameter indicating a $\Delta t=1$ *week*
17)	weeks in a month	[Week]	4.25	Rounded off actual value

[24]Currency exchange rates at https://www.xe.com.

Appendix D – Calibrated parameters' values

Table A 8. Reporting and discussion of the values of the calibrating parameters.

N°	Parameter	Search-space	Calibrating value	Relevant comments
1)	awareness effect HI HHs	[0.000029 - 1]	0.976000	These relatively high values reflect the fact that electricity access is not perceived as an innovation by people.
2)	awareness effect IGAs	[0.000029 - 1]	1	
3)	awareness effect LI HHs	[0.000029 - 1]	0.021341	
4)	BETA - el	[0 - 1]	0.897	Electricity has a relevant impact on local market productivity, especially due to the electrification of EE-reliant IGAs (e.g. Mills).
5)	diffusion rate DECODERs	[0.0028 - 0.0084]	0.0084.	
6)	diffusion rate IRONs	[0.0080 - 0.0308]	0.019898.	
7)	diffusion rate LIGHTs	[0.2171 - 0.6960]	0.336978.	
8)	diffusion rate PHONE CHARGERs	[0.0605 - 0.2245]	0.126054.	
9)	diffusion rate STEREOs	[0.0237 - 0.0814]	0.0437.	
10)	diffusion rate TVs	[0.0118 - 0.0730]	0.0318.	
11)	Duration of phase I for HHs	[61.5 – 66.0]	63.7	
12)	Duration of phase I for IGAs	[105.25 – 109.50]	109.5	
13)	EffectOfFatherOccupationOnPrimaryEnrollment	[0.270 - 0.420]	0.271	
14)	EffectOfHomeElectricity	[0 - 0.1]	0.0003	As suggested by the teachers in Ikondo primary school, electricity at home is not as much relevant as electricity at school for improving the pupils' educational attainment.
15)	EffectOfSchoolElectricity	[0.272 - 0.408]	0.291	
16)	El Reliability	[0.9583 - 0.9995]	0.98	
17)	Electrical power of Decoders	>4	5.09765.	
18)	Electrical power of Iron	[960 - 1440]	1134.33.	
19)	Electrical power of Lights	>5	15	
20)	Electrical power of Phone charger	[2.856 – 4.284]	4.30194.	
21)	Electrical power of Stereos	>8	10.0005.	
22)	Electrical power of TVs	>64	80	
23)	Electricity-Fee elasticity for EE-reliant IGAs	[-1 - 0]	-0.83	The use of electricity for EE-IGAs is very sensitive to changes in the prices, since they are characterised by a massive use of energy.
24)	Electricity-Fee elasticity for notEE-reliant IGAs	[-1 - 0]	-0.69	Also for notEE-IGAs, the use of electricity is sensitive to changes in the prices. Indeed, since they do not totally depend on energy, saving money is always considered a priority.

25)	Electricity-Income elasticity HHs	[-1 - 0]	-0.09	This low value confirms what stated by the experts regarding this parameter: electricity is very cheap for households, and they do not change significantly their consumption patterns based on changes in the electricity price.
26)	EPSILON - farming income	[0 - 1]	0.07	
27)	EPSILON - IGAs income	[0 - 1]	0.05	
28)	external/local prices factor	[1 - 3]	2	
29)	Fixed electricity fee in TZS before 2010	[0 - 345.2]	214.0	
30)	fr change in external food expenditures	[0 - 1]	0.43	
31)	fr change in external market demand	[0 - 1]	0.47	
32)	fr change in internal IGAs supply	[0 - 1]	0.11	
33)	fr decrease in cost given by EE	[0 - 1]	0.45	
34)	fr food expenditures referred to farming investments	[0 - 0.5]	0.39	
35)	fr income for education expenditures HI	[0.01 - 0.4]	0.34	
36)	fr income for education expenditures LI	[0.01 – value in 35)]	0.17	
37)	fr income for medical expenditures HI	[0.018 - 0.2]	0.06	
38)	fr income for medical expenditures LI	[0.018 - 0.2]	0.14	
39)	fr increase of market expenditures	>0	0.90	The fractional increase in the market expenditures is almost proportional to the increase in IGAs connection
40)	fr of operating time with electricity	[0-1]	0.60	
41)	fr of people using microcredit	[0.32 - 0.48]	0.41	
42)	fr of potentially affordable IGAs connections	>0	0.82	
43)	fraction of EE-reliant IGAs respect to connected IGAs	[0.08 - 0.18]	0.13	
44)	fraction of external source of HI income	[0 - 0.05]	0.04	
45)	fraction of external source of LI income	[0 - 0.05]	0.00	LI people are also the ones with no connections outside the village.
46)	fraction of failing IGAs	[0.24 - 0.36]	0.31	
47)	fraction of feasible HHs market supply	[0.60 - 0.90]	0.85	
48)	fraction of IGAs that want to start by imitation	[0.40 - 0.60]	0.46	
49)	fraction of initial HI HHs to be connected	[0 - 1]	0.83	The initial HI HHs are the ones already willing to be connected.
50)	fraction of initial LI HHs to be connected	[0 - 1]	0.08	
51)	fraction of revenues used by the utility for O&M	[0.4 - 0.6]	0.53	
52)	fraction of sharing meter	[0.48 – 0.72]	0.60	
53)	GAMMA - edu	[0 - 0.1]	0.002	It confirms that market productivity is inelastic respect to primary education attainments – viz. changes in the primary educational levels do not impact significantly on the market productivity.
54)	HH connection cost in phase I	[53.7 - 67.1]	57.5	

55)	HH connection cost in phase II	[114 - 357.8]	194.1	
56)	housework reduction given by electricity	[0 - 1.3]	0.1	Electricity does not significantly impact on the burden of housework; indeed, the local women who confirmed a reduction in the housework admitted it was due to the electrical rice cooker, a technology that very few people can afford.
57)	IGA connection cost in phase I	[53.7 - 67.1]	54.1	
58)	IGA connection cost in phase II	[114 - 357.8]	324.0	The IGAs face very high connection costs.
59)	IGAs per HH	[0 - 1]	0.33	
60)	Initial available operation time	[1 - 84]	55	
61)	Initial daily farming hours for LI HHs	[4.8 - 7.2]	6.4	
62)	Initial EE-IGAs coincidence factor	[0.0176 – 0.1246]	0.0740	
63)	Initial external agricultural expenditures	>0	0.8577	
64)	Initial external market demand	>0	0.1547	
65)	Initial fr income for food expenditures HI	[0 - 1]	0.35	
66)	Initial fr income for food expenditures LI	[0 - 1]	0.64	
67)	Initial fr of HHs close to the grid	[0 - 1]	0.08	
68)	Initial fr of internal IGAs supply	[0 - 1]	0.0454	
69)	Initial net intake primary	[0.5948- 0.8922]	0.7674	
70)	Initial number of IGAs	[0 - 2]	1.83	
71)	Initial Population	>3446	3670	
72)	Initial time to use Decoders	[14 - 42]	25.16	
73)	Initial time to use Irons	[0.25 - 2]	0.57	
74)	Initial time to use lights	[7 - 91]	50.12	
75)	Initial time to use Phone chargers	[3 - 49]	3.98	
76)	Initial time to use Stereos	[7 - 91]	55.08	
77)	Initial time to use TVs	[7 - 42]	27.03	
78)	internal migration effect	≥ 1	1.004	This value indicates that the practice of moving the house close to the electrified area is not common, despite one expert mentioned it.
79)	Investment for a new IGA	>0	1483	
80)	k-time	[0 - 1]	0.703	
81)	max fr of internal IGAs supply	[0 - 1]	0.615	
82)	max increase of week expenditures	>0	0.143	
83)	Max time for night farming	[0 - 4]	1.4	
84)	Max time for night housework	[0 - 4]	0.6	Households do not dedicate much time for night housework.
85)	Max time for night working	[0 - 4]	3	It confirms that night time for working is largely exploited by IGAs with the connections

86)	maximum fr population growth	>0.000209	0.004	
87)	maximum fraction of income for debt repayment	[0 - 1]	1	This value suggests that when people plan to ask for a loan, they consider all their income for payback the loan. This is also suggested by the manager of the micro-credit, who indicated that when people obtained the loan, they want to pay it back as soon as possible.
88)	Night-working feasibility	[0.4 - 0.6]	0.56	
89)	Payback	[4.25 - 52]	48.9	
90)	PHI - farming time	[0 - 1]	0.1	
91)	Population carrying capacity	>4011	4052	
92)	Power EE-IGA	[2530-26113]	4598	
93)	Power notEE-IGA	[36-329]	65	
94)	price to cost factor	[1 - 4]	3.06	
95)	production cost without EE	>0	1.27	
96)	Reference factor productivity	>0	0.372	
97)	Reference HI land productivity	>0	0.63	
98)	Reference LI land productivity	>0	0.69	
99)	social contagion HI	[0.0029 - 0.0365]	0.0119	
100)	social contagion IGAs	[0.0029 - 0.0365]	0.0032	
101)	social contagion LI	[0.0029 - 0.0365]	0.0148	
102)	THETA - capacity building elasticity	[0 - 1]	0.03	The effect of capacity building is not so high as expected.
103)	Time for setting-up the IGA	[1 - 26]	1.15	
104)	Time to adapt electricity use	>4.25	6.13	
105)	Time to adapt farming productivity	≥1	10.8	
106)	Time to adapt market expenditures	≥1	98.3	
107)	Time to adapt productivity	≥1	60.2	
108)	Time to dismiss activity	≥1	1.2	
109)	Time to get the loan	[0 - 2]	0.8	
110)	Time to perceive decrease in operating hours	≥1	241015	This show that people is very hesitant in reducing time spent at work, seeking to use all the time available for trying to sell their goods and services.
111)	Time to perceive electricity benefits	≥1	1	People are already aware of the benefits of electricity, as expected.
112)	Time to perceive increase in operating hours	≥1	2.7	On the contrary, if available, people are very willing to use all their time available for working and trying to sell their goods and services.
113)	Time to perceive market dynamics	≥1	9.7	
114)	Time to perceive more time for farming	≥1	5.5	
115)	Time to perceive more time for working	≥1	21.6	

116)	Time to purchase appliances	≥1	1	
117)	T-sigmoid	≥1	19.1	
118)	Variable electricity fee PRODUCTIVE in TZS before 2010	[0 - 0.12]	0.10	
119)	Variable electricity fee RESIDENTIAL in TZS before 2010	[0 - 0.07]	0.07	
120)	Willingness to pay for connection for IGAs	[0 - 1]	0.022	
121)	Willingness to pay HI	[0.048 – 0.072]	0.055	
122)	Willingness to pay LI	[0.128 – 0.192]	0.130	
123)	working days in a week	[6 - 7]	6.43	

Appendix E – Parameters' confidence bounds

Table 39. Parameters' confidence bounds assessed through MCMC.

N°	Parameter	Confidence bounds	
1)	BETA - el	0.888	0.911
2)	GAMMA - edu	0.000	0.003
3)	awareness effect IGAs	0.996	1.000
4)	awareness effect LI HHs	0.016	0.032
5)	awareness effect HI HHs	0.957	0.982
6)	fraction of initial HI HHs to be connected	0.817	0.839
7)	fraction of initial LI HHs to be connected	0.057	0.087
8)	Time to perceive electricity benefits	1.000	1.008
9)	social contagion HI	0.011	0.012
10)	social contagion IGAs	0.003	0.004
11)	social contagion LI	0.014	0.015
12)	production cost without EE	1.260	1.286
13)	Time to perceive market dynamics	9.623	9.789
14)	THETA - capacity building elasticity	0.017	0.039
15)	Time to adapt productivity	59.660	61.027
16)	Time to adapt market expenditures	97.326	99.070
17)	Time to dismiss activity	1.199	1.222
18)	maximum fraction of income for debt repayment	0.994	1.000
19)	Max time for night farming	1.348	1.424
20)	Time to perceive increase in operating hours	2.632	2.701
21)	Time to perceive decrease in operating hours	238753.980	243402.630
22)	Time to perceive more time for working	21.413	21.859
23)	fraction of external source of HI income	0.040	0.041
24)	fraction of external source of LI income	0.001	0.002
25)	fr decrease in cost given by EE	0.433	0.463
26)	fraction of revenues used by the utility for O&M	0.531	0.536
27)	Initial number of IGAs	1.814	1.855
28)	Payback	48.146	49.240
29)	fr food expenditures referred to farming investments	0.391	0.401
30)	fr income for education expenditures HI	0.341	0.348
31)	fr income for education expenditures LI	0.164	0.172
32)	fr income for medical expenditures HI	0.056	0.060
33)	fr income for medical expenditures LI	0.135	0.139
34)	IGA connection cost in phase II	321.488	325.480
35)	IGA connection cost in phase I	53.902	54.209
36)	HH connection cost in phase I	57.330	57.666
37)	HH connection cost in phase II	190.250	196.594
38)	Initial fr income for food expenditures HI	0.341	0.363
39)	Initial fr income for food expenditures LI	0.629	0.651
40)	Initial external agricultural expenditures	0.848	0.868
41)	Initial external market demand	0.144	0.160
42)	Max time for night housework	0.518	0.593
43)	Initial available operation time	54.224	55.785
44)	Time for setting-up the IGA	1.019	1.351
45)	working days in a week	6.429	6.445
46)	external/local prices factor	1.977	2.015
47)	k-time	0.694	0.720
48)	T-sigmoid	18.979	19.344
49)	fraction of sharing meter	0.595	0.601
50)	fr change in external food expenditures	0.424	0.439
51)	fr change in external market demand	0.455	0.481
52)	housework reduction given by electricity	0.082	0.112
53)	Night-working feasibility	0.557	0.562
54)	Max time for night working	3.101	3.209
55)	Reference factor productivity	0.361	0.382
56)	Time to get the loan	0.746	0.788

57)	Time to perceive more time for farming	5.468	5.592
58)	Willingness to pay for connection for IGAs	0.019	0.032
59)	Willingness to pay HI	0.055	0.056
60)	Willingness to pay LI	0.129	0.131
61)	price to cost factor	3.036	3.119
62)	EPSILON - farming income	0.055	0.084
63)	EPSILON - IGAs income	0.040	0.058
64)	fraction of IGAs that want to start by imitation	0.462	0.466
65)	PHI - farming time	0.085	0.108
66)	Initial daily farming hours for LI HHs	6.390	6.432
67)	Duration of phase I for HHs	63.656	63.760
68)	Duration of phase I for IGAs	109.469	109.500
69)	IGAs per HH	0.316	0.333
70)	fr of people using Microcredit	0.409	0.412
71)	Investment for a new IGA	1470.303	1498.328
72)	fraction of failing IGAs	0.306	0.308
73)	Reference HI land productivity	0.621	0.638
74)	Reference LI land productivity	0.683	0.704
75)	Time to adapt farming productivity	10.751	10.940
76)	Initial fr of internal IGAs supply	0.035	0.055
77)	fr change in internal IGAs supply	0.100	0.124
78)	max fr of internal IGAs supply	0.607	0.627
79)	fraction of feasible HHs market supply	0.846	0.853
80)	Initial fr of HHs close to the grid	0.075	0.085
81)	internal migration effect	1.000	1.015
82)	fr of potentially affordable IGAs connections	0.805	0.827
83)	EffectOfSchoolElectricity	0.289	0.292
84)	EffectOfHomeElectricity	0.000	0.001
85)	Initial net intake primary	0.764	0.771
86)	EffectOfFatherOccupationOnPrimaryEnrollment	0.270	0.272
87)	max increase of week expenditures	0.130	0.157
88)	fr increase of market expenditures	0.883	0.904
89)	El Reliability	0.979	0.980
90)	Electricity-Fee elasticity for EE-reliant IGAs	-0.841	-0.816
91)	Initial EE-IGAs coincidence factor	0.073	0.075
92)	Power notEE-IGA	61.096	68.611
93)	Power EE-IGA	12130.983	12604.870
94)	fr of operating time with electricity	0.588	0.614
95)	Electricity-Fee elasticity for notEE-reliant IGAs	-0.708	-0.680
96)	fraction of EE-reliant IGAs respect to connected IGAs	0.130	0.132
97)	Electricity-Income elasticity HHs	-0.097	-0.081
98)	diffusion rate DECODERs	0.008	0.008
99)	diffusion rate IRONs	0.020	0.020
100)	diffusion rate LIGHTs	0.332	0.343
101)	diffusion rate PHONE CHARGERs	0.125	0.128
102)	diffusion rate STEREOs	0.043	0.045
103)	diffusion rate TVs	0.031	0.033
104)	Time to purchase appliances	1.000	1.005
105)	Time to adapt electricity use	6.042	6.193
106)	Initial time to use lights	48.902	50.887
107)	Initial time to use Decoders	24.902	25.646
108)	Initial time to use Irons	0.554	0.586
109)	Initial time to use Phone chargers	3.977	4.001
110)	Initial time to use Stereos	54.206	55.964
111)	Initial time to use TVs	26.609	27.316
112)	Electrical power of Decoders	5.037	5.132
113)	Electrical power of Iron	1126.495	1140.247
114)	Electrical power of Lights	14.825	15.102
115)	Electrical power of Phone charger	4.279	4.319
116)	Electrical power of Stereos	9.926	10.062
117)	Electrical power of TVs	79.170	81.329

118) Fixed electricity fee in TZS before 2010	210.501	217.681
119) Variable electricity fee RESIDENTIAL in TZS before 2010	0.069	0.070
120) Variable electricity fee PRODUCTIVE in TZS before 2010	0.103	0.106
121) Initial Population	3631.521	3711.061
122) Population carrying capacity	4015.843	4086.792
123) maximum fr population growth	0.000	0.016

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