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ENERGY DEMAND ANALYSIS WITHIN LONG-TERM RURAL ENERGY PLANNING: A CRITICAL REVIEW AND SIMULATION FOR A MORE APPROPRIATE MODELLING APPROACH

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Abbreviation Index

AC	Alternating Current
AEO	Annual energy Outlook
CF	Capacity Factor
DC	Direct Current
DCs	Developing Countries
DEP	Decentralized Energy Planning
DG	Distributed Generation
DP	Dynamic Programming
DSM	Demand Side Management
EO	Enumerative Optimisation
ESMAP	Energy Sector Management Assistance
EUR	Euro
GDP	Gross Domestic Product
ICS	Improved Cook Stoves
IEA	International Energy Agency
INR	Indian Rupiee
LDCs	Least Developed Countries
LEAP	Long-range energy alternatives Planning System
LP	Linear Programming
LPG	Liquefied Petroleum Gas
MCDM	Multi-Criteria Decision Making
MDGs	Millennium Development Goals
META	Model for Electricity Technology Assessments
MOP	Multi-Objective Programming

NLP	Non-Linear Programming
NOCT	Nominal Operating Cell Temperature
NREL	National Renewable Energy Laboratory
OECD	Organisation for Economic Co-operation and Development
RES	Reference Energy System
RET	Renewable Energy Technology
STC	Standard Test Conditions
WB	World Bank

Abstract

Energy planning is a fundamental tool for meeting the energy needs of a nation and it is accomplished by considering multiple factors such as resource availability, costs and efficiency technologies, environmental impact and energy demand. Energy demand modelling is an essential component in order to achieve an appropriate and robust energy planning. This thesis deals firstly with the review of energy planning case studies highlighting the methodological diversities for the main dimensions that characterise different approaches in the framework of off-grid systems for rural areas in developing countries. Then the analysis focuses on techniques to forecast electricity demand for long-term energy planning with the aim to identify firstly the more used models and secondly the appropriate features and key requirements for a better evaluation of electricity demand in local areas. The study finds that end-use accounting approach should produce more realistic electricity demand projections within these contexts, while different methods may lead to different results both in terms of investment cost and installed capacity. Based on the achievements obtained by the critical review of energy demand models, a bottom-up approach is designed for a case study in an Indian village. The model has been conceived with collaboration of UNESCO Chair in energy for Sustainable Development research group - Department of Energy. Three scenarios are developed to compare different approaches of demand evolution over years, namely a *bottom-up*, *constant* and *time-based interpolation* forecasting techniques. The three scenarios computed are entered in a long-term energy system optimization model, namely OSeMOSYS. The simulation performed with the different demand approaches aimed to investigate quantitative how the various demand profile impact over years on the energy planning of a case study selected for India. Data of costs, efficiencies and availability of resources are entered to simulate the reference energy system selected. Results prove that various forecasting electricity demand impact differently both in term of total discounted cost and capacity installed.

keywords: energy planning, electricity demand, bottom-up approach, residential sector, rural areas, linear optimisation model, India

Sommario

La pianificazione energetica è uno strumento importante per valutare il sistema energetico migliore al fine di soddisfare la domanda di energia di una determinata regione; la realizzazione di tale sistema coinvolge molteplici fattori tra cui le risorse disponibili in loco, costi e prestazioni delle tecnologie coinvolte nella progettazione, impatto ambientale e la domanda energetica da soddisfare. La modellazione della domanda energetica è un elemento essenziale per ottenere una pianificazione energetica adeguata e robusta. Questa tesi si propone di investigare quali sono i modelli di previsione di domanda elettrica per una pianificazione energetica di contesti rurali e di identificare i requisiti necessari per un approccio più appropriato ai contesti rurali per i paesi in via di sviluppo.

È stata eseguita un'ampia revisione di letteratura riguardante i casi studio di pianificazione energetica per il dimensionamento di sistemi off-grid per aree rurali. La revisione si pone l'obiettivo di comprendere come venga considerata effettivamente la domanda energetica in questi contesti; da essa emerge come l'evoluzione del consumo energetico per una pianificazione di lungo periodo venga considerato in modo semplicistico (trend di crescita arbitrari) o del tutto trascurato.

In seguito, sono stati identificati i requisiti principali per la modellazione di un approccio bottom-up per la previsione a lungo termine della domanda elettrica del settore residenziale codificato in Matlab e integrato ad un modello esistente per la generazione di profili di carico elettrico giornaliero in un villaggio in India. Altri due scenari di crescita della domanda sono stati sviluppati per il villaggio analizzato come termine di confronto, selezionati alla luce della precedente revisione.

I tre scenari di domanda sono stati in seguito inseriti come input in OSeMOSYS, un modello di ottimizzazione lineare per la pianificazione a lungo termine di sistemi energetici. I risultati ottenuti mostrano come vari approcci di previsione della domanda elettrica impattano diversamente sia in termini di costo finale sia maggiormente in termini di capacità installata.

parole chiave: pianificazione energetica, domanda elettrica, approcci bottom-up, settore domestico, aree rurali, ottimizzazione lineare, India

Introduction

This thesis deals with access to energy in rural areas of developing countries; more specifically, it aims at analysing a specific issue related to the approaches undertaken for energy planning, namely the estimation and projection of energy consumptions over a long-term horizon. The International Energy Agency foresees for the year 2040 that the energy demand will increase of 70% with an average annual growth rate of 2%; estimating that non-OECD countries will lead the growth in global demand as they are experiencing rapid economic and population growth. The social and economic development of a community is highly dependent on its energy sector. An appropriate energy planning contributes to a better quality of life and to socio-economic development of a country. For these reasons energy allocation is gaining importance at the local level. Energy demand modelling is an essential component for energy planning and for formulating energy strategies that intend to be reliable besides the very first year. The growing importance of developing countries in the world energy scene, highlighted the problem that the same approach used in developed countries for the study of energy consumption cannot be applied in rural areas. This can yield to define incoherent scenario leading to results that are far from the actual demand. The present work is therefore aimed at analysing and investigating the issue of energy demand forecasting within long-term rural energy planning, by (i) reviewing and identifying the main approaches used to forecast demand for rural environments and highlighting the most appropriate features for better forecasting approach, (ii) implementing a more appropriate simulation model, and (iii) investigating how different energy demand scenarios may impact the results of an energy planning for a real case study.

Chapter 1 is dedicated to an overview of the issue regarding the access to energy in developing countries. It deals with the general definition of energy planning focusing on the specific characteristics of rural areas and the role of energy demand in these environments.

Chapter 2 presents the literature review of energy planning case studies in rural and remote areas of developing countries, providing the outlook of the energy demand forecasting approaches adopted. The analysis goes on with an evaluation of the most important features and requirements for developing an appropriate energy demand model, with a specific focus on electricity demand in the residential sector.

Chapter 3 is dedicated to the implementation of a new Matlab model for forecasting the growth of households' electric consumption. The model is implemented and described through a direct application to a case study of energy planning in rural India. Two other energy demand growth scenarios are also explained based on the review carried out in Chapter 2.

Chapter 4 describes the development of an OSeMOSYS-based long-term energy planning for the case study considered. The data input entered in the model consist of: the reference energy system, the three different demand trends of consumption and technical, economic and meteorological parameters needed for the implementation of the planning. The post-processing analysis compares the results obtained through the model simulation including a sensitivity analysis on the discount-rate parameter for each of the three simulations.

Chapter 5 in conclusion underlines further eventual improvements both for the bottom-up demand model and the energy planning model, describing some potential critical issues and prompting suggestions for future works.

1 Energy planning in Developing Countries

Energy is a crucial factor for human development and life quality. As the United Nations Development Programme states: "*Energy affects all aspects of development – social, economic and environmental – including livelihoods, access to water, agricultural productivity, health, population levels, education, and gender-related issues*" [1].

In many developing countries (DCs), the majority of people live in rural areas and practice a subsistence economy. Since many regions are afflicted by numerous wars, villages lack of infrastructures and facilities with high rate of mortality and illiteracy, especially in women. The lack of electricity has many different negative consequences on local communities who live in these contexts: difficulties in water supply, dependence on unclean biomass based cooking facilities, poor sanitation, no time for income activities, unsafely streets. Many benefits from electrification are expected at different levels: village or community centres to supply energy for public services, local enterprises and farms in the surroundings of the village and all single households. Benefits of access at the household level lead to have positive impact on indoor air quality, education and hygiene, reduction in firewood consumption and reduced time use for household task.

The issue that is common across all three levels of access is the reliability of electricity supply. It is necessary for health centre, local industries but also for vital domestic activities to have a sufficient quality of power supply.

Projects of electrification depends on the characteristics of the region such as income level, GDP per capita, availability of resources in the geographical area tacking into account. A global approach to increase rural electrification rates can be misleading thus an energy planning must be developed considering all the aspects of the specific region. Figure 1.1.1 shows the percentage of population with access to electricity (blue bars), the gross domestic product divided by midyear population in current U.S. dollars (red bars). Data refer to least developed countries (LDCs)[1] and highlight the non-correlation between a high GDP and a high access to energy.

[1] The least developed countries (LDCs) are defined as low-income developing countries suffering from severe structural impediments to sustainable development. In *World Bank – Data* webpage data characterised this group are found.

Thence every rural planning must be followed local criteria instead of a global approach.

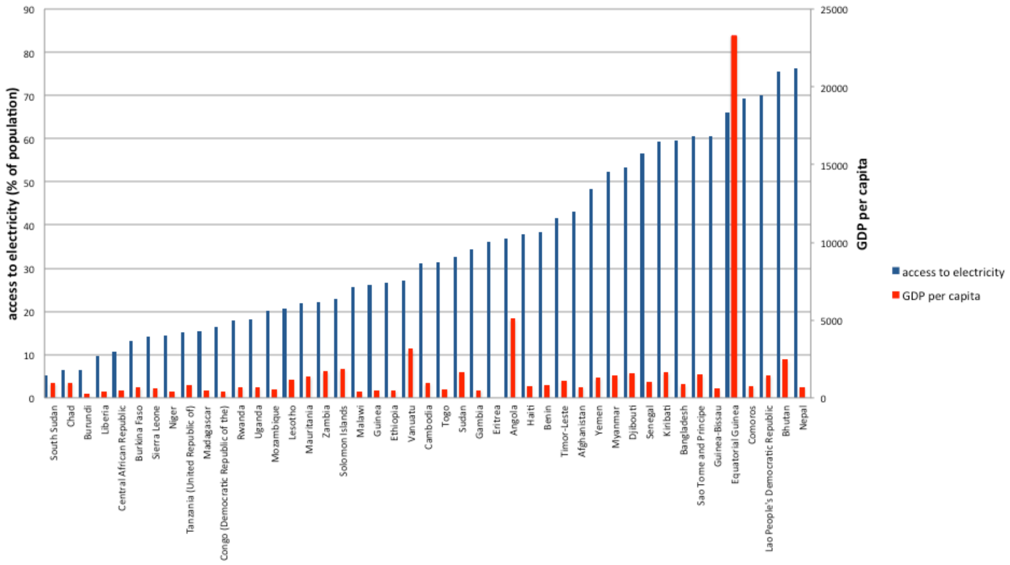

Figure 1.1.1 - Comparison between the percentages of access to electricity with GDP per capita (current US$) for LDCs in 2012 by World Bank

Another factor that features the success of electrification programmes in rural areas is developed sustainable long-term plans. This is due to the fact that capital costs are covered by long-term concessional loans, long-term governmental engagement and projects that allow local utilities to acquire sufficient autonomy to avoid national and international political interference.

The last parameter that strongly influences the outcome of a reasonable energy planning is the demand for electricity over the planning years. In some countries investments in infrastructures and energy utilities are low compared to the potential demand for energy and depending on the forecast request criteria of planning are different between regions. This issue will be developed in detail in this thesis.

1.1 Access to electricity in rural contexts

1.3 billion people or 18% of the world population, lack access to electricity in 2011, of which approximately 95% live in rural areas of South Asia and Sub-Saharan Africa[2]. Despite there is no consensus about the definition of *rural areas*, which actually varies from country to country according to national statistical offices, there are typical and quite clear features that are shared. In DCs, rural areas are sparsely populated, geographically isolated and of difficult accessibility. The electricity market in poor areas is characterized by low access rate and low load factors. Connection to the national centralized grid is generally limited to those towns and villages along major roads and neighbouring areas. When it is available, reliability and accessibility problems can arise, since electricity may cost as much as 10 times more than in urban areas. For the large rural population that is distant from power grids, mini-grid or off-grid systems provide the most viable means of access to electricity.

1.1.1 Present background

The International Energy Agency (IEA) [3] estimates that in the New Policies Scenario, 315 million people in rural areas gain access to electricity, with around 80 million of these being through off-grid systems and around 140 million people through mini-grids.

The World Bank – Global Electrification database (WB) [4] estimates that nearly 1.09 billion people, 15.4% of the world population, did not have access to electricity in 2012. 88% of the 15.4% of population that lacks electricity live in rural areas and, since 2000, the two-thirds of people gaining access to electricity live in urban areas so the population without electricity has become more concentrated in rural areas. The challenge of supplying electricity in rural areas in a reliable and accessible ways remains one of the major worldwide objectives of the present century.

As a consequence the research focusing on local energy planning is a primary necessity in order to decrease the number of people who live without modern energy services. The aim is to provide the most basic human utilities such as cooking, light, heating and water extraction.

1.2 Introduction to local energy planning

A number of existing studies surveyed the methodologies, models and techniques to develop energy systems for small low-energy villages. Yusta et al. [5] examine the mathematical methods developed for electrification planning in rural environments with decentralised energy sources. Iniyan et al. [6] analyse and review the various emerging issues related to the energy modelling. The result of the paper is that the energy demand of developing countries can be no longer satisfied by the traditional models used for developed countries. The main characteristics of energy systems adopted in developed countries are based on technologies that use traditional resources such as oil, gas and carbon designed for centralized grid and a high-income availability. It can be resulted in inequities, external debt and environmental degradation. Hiremath et al. [7] give an overview of different decentralized energy models used worldwide and show how different types of energy planning and optimization models, supply demand models, regional models, resources models and neural models have been carried and applied at decentralized level. Bhattacharyya [8] reviews alternative methodologies that are used for off-grid electrification projects to identify the features of each approach and presents their strengths and weakness.

1.2.1 Rural electrification planning

The review of rural energy planning is a concept of recent origin with limited application. Therefore, while models and approaches of energy planning at a centralized level are already reviewed and consolidated in literature, energy planning and electrification options for decentralized applications, as well as the number of available energy models, are developing growing fast. As a consequence, many techniques of planning are under experimentation also for answering the issue of energy access in developing countries. The need of a classification scheme to understand the differences and similarities between energy models is necessary in order to facilitate the selection of the proper energy models.

1.2.2 Definition of energy planning and planning terms

Before to analyse all the methodologies, techniques and approaches adopted in these contexts, it is mandatory to define in a clear way what is the general meaning of energy planning.

Different authors have defined energy planning in several ways, and emphasis is given to multiple important aspects. Prasad et al. [9] quote some authors underling that any energy planning needs to foster sustainable development. Hiremath et al. [7] write that energy planning endeavour involves finding a set of sources and technologies in order to meet the energy demand in an optimal manner. Deshmukh [10] suggests that the main objective of energy planning activity is to develop an optimal plan for energy resource allocation, with the consideration of future energy requirement according to several criteria: minimum cost, environmental emissions, maximum employment generation, social acceptance, system efficiency etc.

In view of above discussion, it is clear that any energy planning has to match a certain demand with certain energy resources through conversion technologies in an optimal manner. Technologies and type of resources depend on the contexts on which the planning is elaborated. The criteria that should be followed depend on the ultimate goal of the planning, based usually on the needs of the context, the institutions that commission the development of the plans. For example, in poor contexts where the economic activities are barely sufficient to survive the day, the minimum cost of the energy system is the objective of the planning model. In villages where there is availability of expenditures for productive activities the main objective can be the efficiency of electric system.

Once an inclusive and comprehensive definition of energy planning is achieved, it is important to understand how the literature classifies energy planning studies.

An example of classification is given by Nicole van Beeck [11] that makes a distinction between general purpose for energy modelling (forecasting, exploring, backcasting) and more specific purpose such as demand/supply analysis, impact analysis or appraisal. Bhattacharyya [8] reviews alternative methodologies that are used for off-grid electrification projects, so he categorises the studies that gains access to electricity looking only at the methodological options such as optimisations tools, Multi Criteria Decision-Making (MCDM) tools, system-based participatory tools etc. Prasad et al. [9] present a literature review analysing the different facets of energy planning. The authors describe in detail the decision-making techniques as a crucial topic to understand how energy systems confront the energy supply and demand. A second classification is based on energy planning models; the authors differentiated models on the methodology to deal with the planning. Prasad et al. identify econometric models which apply statistical methods based on economic data, optimisation models using one or more objective functions and simulation models that simulate a system with a less complex model using scenario analysis to include in the process all the uncertainties assumed during the simplification. A last classification is based on the inquiry methods of energy planning; this dimension of energy planning is used to develop an expert survey (inquiry method) for determining the potential of energy technologies. Deshmukh [10] deals with the analysis of optimal energy resource allocation in the energy planning process focusing on the Indian country. To introduce the optimal resource allocation applied for the village of Jhunjhunu in India, the author introduces a classification of energy planning models on the basis of four classes: methodology adopted, spatial coverage, sectorial coverage and temporal coverage. The review developed focuses on the renewable energy allocation methods at both national and local level of energy planning, then he presents a review of which kinds of models are available according to the four classes cited before. The author also proposes a review of renewable energy decision-making methods identifying only two categories suitable for local level energy planning.

Yusta et al. [5] examine the mathematical methods utilised for electrification planning in rural environments with decentralised energy sources. The methodologies the authors identify in the reviewed works are: Linear Programming (LP), Multi-Criteria Decision Making (MCDM), Multi-Objective Programming (MOP), Non-Linear Programming (NLP), Dynamic Programming (DP), Enumerative Optimisation (EO) and other (Life cycle cost analysis). The choice the author is dictated by the objective of the paper: underling the shift of the one objective paradigm towards the new paradigm of more than one evaluation criterion.

What it is important to understand from the previous reviews is that there are various categories under which energy planning approaches can be classified, through a different numbers of sub categories that depends on the level of precision the author wants. Choosing a type of classification or another depends also on what is the objective of the review, as previously described. Moreover, a critical issue when classifying energy models is that there are many ways of characterizing different models, while there are only few models -if any- that fit into one distinct category. Based on the above discussion, Chapter 2 will try to set a unique classification of energy planning.

1.3 The role of electricity demand in energy planning

The growth of energy demand, in particularly the electricity demand, defined as the total gross electricity generated without the accounting of the own use of the power generation and the transmission and distribution losses, has been always a factor of interest in many sectors and for several reasons both in developed and developing countries. According to IEA-World Energy Outlook 2015-Chapter 8 [12] the electricity demand increases by more than 70% over 2013-2040 in New Policies Scenario[2], with non-OECD countries responsible for 7 out of every 8 additional units of global electricity demand.

[2] According to the International Energy Agency definition the New Policies Scenario takes account of broad policy commitments and plans that have been announced by countries, including national

Electricity keeps on growing from 2000 in all regions in each of the IEA scenarios, and remains the fastest growing forms of energy in final use.

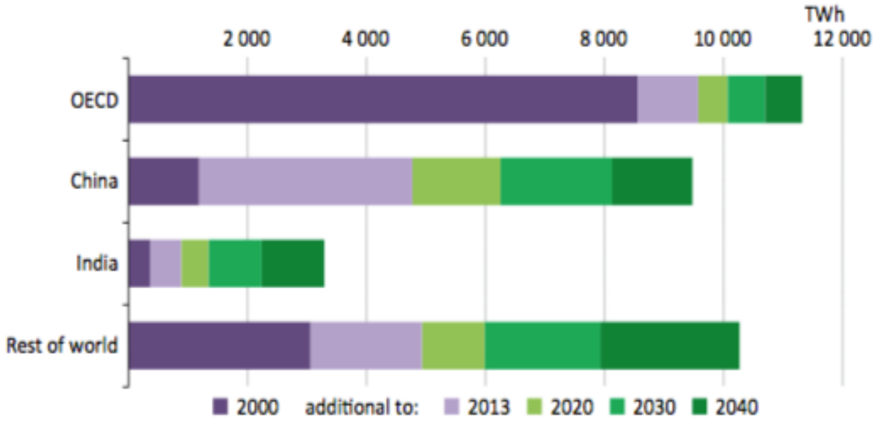

Figure 1.3.1 - Electricity demand by region in the New Policies Scenario

The main increase of consumption is due to non-OECD countries with an average annual growth rate of 2.9% for the New Policies Scenario. Among them, Southeast Asia, China and India have the highest annual growth rate with a value of 3.8%, 2.6% and 4.9% respectively, as it is illustrated in Figure 1.3.1.

Many authors, because of the great impact on energy planning, have investigated how energy demand may grow in developing countries.

Nfah et al. [13] have been modelled a solar/diesel/battery hybrid power system for the electrification of a typical rural households and school in remote areas of the far north province of Cameroon. In the paper is shown the evolution of annual energy demand profile for one household of three people selected as the typical household in the village, for the period 1996-2004, shown in Figure 1.3.2. This remarks energy consumption and use intensely evolve also at a village level.

pledges to reduce greenhouse-gas emissions and plans to phase out fossil-energy subsidies, even if the measures to implement these commitments have yet to be identified or announced.

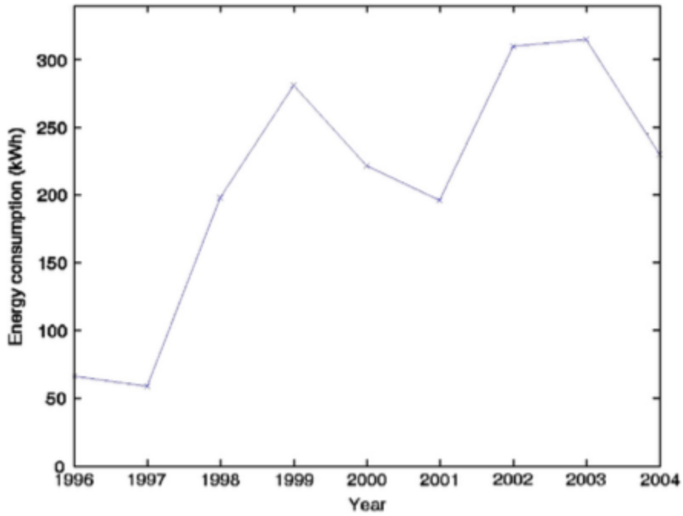

Figure 1.3.2 - Annual energy consumption of a typical rural household, [13]

Daioglou et al. [14] develop a model for the projection of household energy use in DCs. Through a bottom-up simulation model they describe the demand for several end-use functions. The model used has been developed for the Indian residential sector and her adapted for analysis of other nations. On the base of available historical data from census and surveys of each country, *World Development Indicators* of the *World Bank,* International Energy Agency and independent databases, three scenarios are used to describe possible future trends developed by Global Energy Assessment. The results for the projections of end-use functions for rural population shows an increase in all regions, as it is illustrated in Figure 1.3.3.

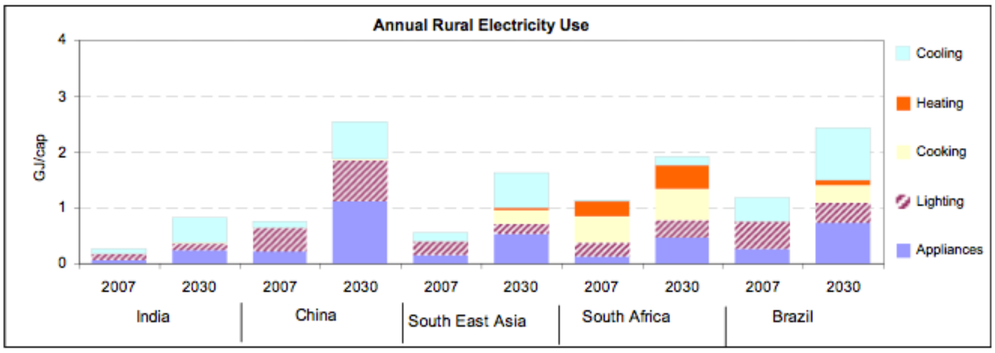

Figure 1.3.3 - Annual electricity use per capita (GJ/per capita), [14]

A global model for rural electrification is described by van Ruijven at al. [15]. The model is used to assess trends in electrification over the next decades, and the investment costs needed. The model is used to calculate four different scenarios that vary according to a low and high demand and the capital costs of the components associated with increasing on grid-based electrification.

Cabraal et al. [16] compare the benefits in term of investment costs between a solar home systems with a grid-based power supply. The authors show that there are critical points to pay attention to decide whether which of the two supplying electricity options are least-cost. As it can be seen in Figure 1.3.4 and Figure 1.3.5, the choice depends on: daily energy consumption of a household, total number of households served, number of households served per unit service area (in km^2), load growth.

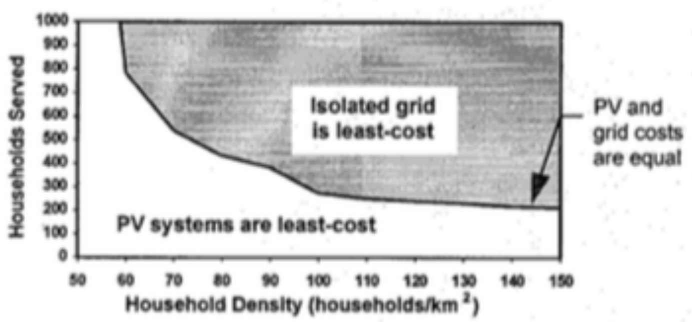

Figure 1.3.4 - Break-even threshold for grid-based and solar home system fro an isolated village, [16]

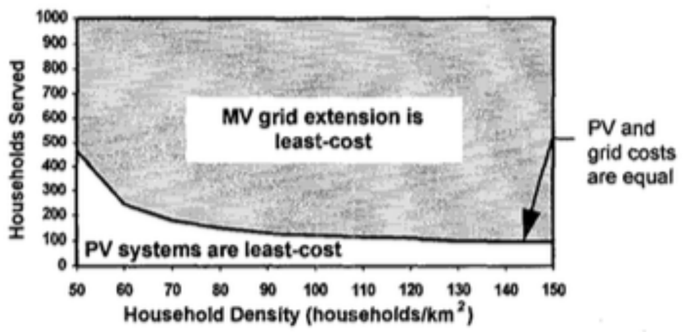

Figure 1.3.5 - Break-even threshold for grid-based and solar home system for a village located 5 km from MV line, [16]

These variables change over the years so it is mandatory to investigate how they change and which is the best method to analyse it.

The need of forecasting energy demand comes from two reasons: the first one is the necessity, for a medium or long term, to obtain the amount of electric energy requests, in order to allow the technologies installed to follow the potential increase of demand for a rural village. The second necessity to predict is particularly peculiar for contexts where data are available in a sporadic way or through past literature or surveys. For many countries both at regional and local level, last available data are registered years before the project year, hence the author has to estimate the consumption until the current year in which she/he is developing the study. For example Srinivasan et al. [17] consider the energy consumption in an Indian region in 1987-88 and projects the demand for energy in 1995-96 for optimum allocation.

Hartvigsson et al. [18] investigate how a correctly dimension of the capacity of a minigrid for rural electrification, affects the cost-recovery for a long period horizon through a system dynamic model. To analyse the utility's ability to reach cost-recovery, data on the amount of electricity sold is needed and so the value of the electric consumption of each consumer and how many consumers the utility has. Thus it is necessary to describe the electric growth through the 20 years planning period. A Cobb-Douglas production function is used driven by available capital, labour and demand which in turn is influenced by income. With the casual loop diagram, developed through the system dynamic model the economic growth is link with the numbers of users and the electricity usage. It is studied also the impact of three different initial generation scenarios on the electricity usage and number of customers. The authors show as the different scenarios affect the consumption along the years; lower the consumption is minor the income for the utility is and this leads to less money spend on maintenance of the technical system.

Hartvigsson [19] presents also a work that compares the economic impact on a minigrid utility between two different load modelling approaches: a system dynamic model previously mentioned and a bottom-up load model developed in Matlab. He states that the income and the expenditure of an electric utility are affected by power utilization rate so it is important to consider improved load model details.

Focusing on a rural local case of energy planning Nerini et al. [20] estimate the cost of energy access for a small village in Timor Leste. The optimization model used to calculate the costs of providing electricity needs the energy demand for the studied period, from 2010 to 2030. A multi-tier approach, to gain energy access proposed by the World Bank, was explored. The approach divides energy access in six different levels; the appliances own by the village are associated to seven categories of energy demand such as lighting demand, communication technologies demand etc. and for each tier is assigned the typical appliance used in order to fit the WB multi-tier approach. Taking into account the typical electricity usage for the considered appliance and the power required in each tier, the yearly projected demand has been calculated. By 2025 all households were assumed to reach the target of the respective tier according to the Timorese government, and then the electricity demand is assumed to increase only with a constant average value of the population, equal to 1.5% per year. In Figure 1.3.6 it is shown the resulting pathways for reaching the target tier of access to energy, in unit of energy and highlighting the consumption for the six categories of energy demand, over the period of planning.

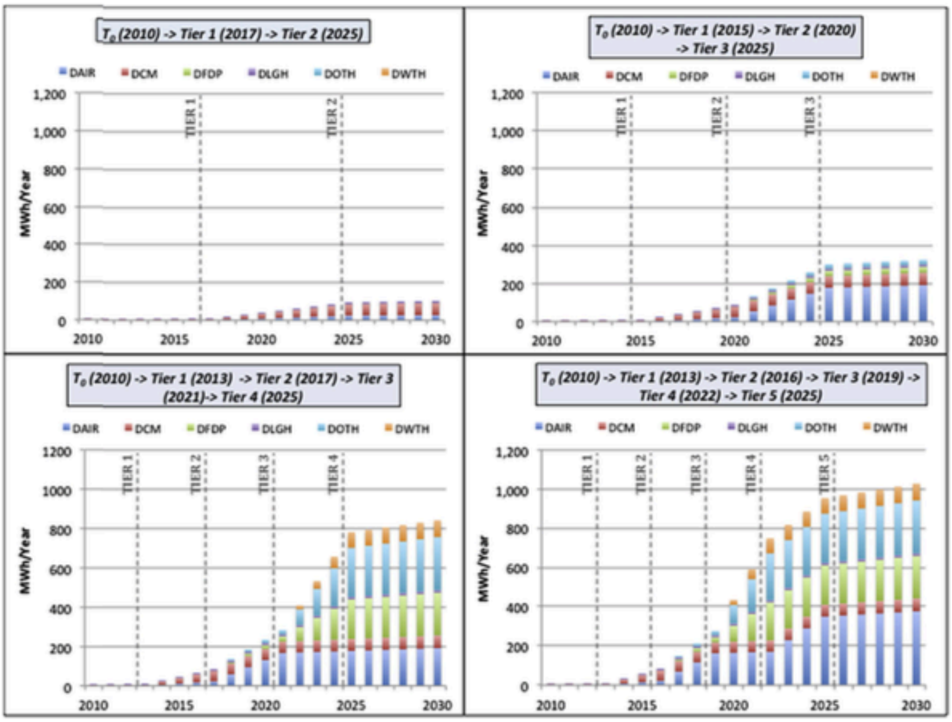

Figure 1.3.6 - Projected electricity consumption for the Suro Craic village, for achieving the different tiers of consumption[3] until 2030, [20]

Mustonen [21] uses the Long-range Energy Alternatives Planning System (LEAP) model to study possible development paths for energy demand from 2006 to 2030 for a rural village in Lao People's Democratic Republic. Three scenarios were constructed to investigate the trajectory of electricity demand: residential demand (RES) characterised by a slow growth based only on household electrification and

[3] In each box of the figure the six categories of energy demand analysed by the author are indicated: DAIR stands for space thermal comfort demand, DCM for communication technologies demand, DFDP for food processing demand, DLGH for lighting, DOTH for other demands and DWTH for water heating demand.

two stores that generate income where electricity demand rises slowly from 3 MWh up to 16 MWh). An income generating activities (INC) scenario with several income generating activities that create daytime demand in the power system (with a growth from 9 MWh up to 72 MWh). Finally a public services (PBL) scenario based on the introduction of public sector services (lighting for village offices and school) supported through various parallel development projects (with a electricity demand rises from 9 MWh up to 76 MWh). With these different paths of growth not only the value of MWh required is different, but the realization of the MDGs occurs with different strategies thorough the scenarios. For example, education is reached through the improvement of lighting for RES, increasing expenditure on education for INC and night classes and school with streets lighting for security for PBL.

Understanding clearly how the energy consumption evolves over the years is crucial for a reliable planning and energy system sizing. Predicting the electricity demand in an untruthful way could plague the social and economic development, supply shortages, under-recovery of costs through energy prices of the energy companies of the region under study.

1.4 Remarks

Considering how the power consumption is analysed for the planning has a deep impact on the results.

The papers described in the previous section, highlight how difficult can be to forecast energy consumption in contexts characterised by high and fast growth and where the availability and quality of data information is difficult to obtain.

Another factor that influences the results is the selection of the drivers to follow to predict the increasing demand that leads to different investment costs, energy system design to meet the demand and the type of power supply, if grid or off-grid based electrification etc.

The auxiliary of a scenario approach is often used for developing countries. These scenarios follow the regional policies, or the OECD Environmental Outlook as in [15], or multi-tier categorization proposed by the World Bank as in [20]. But at the moment of designing components and technologies to supply electricity a question arises: which is the best scenario? Therefore, which are the size and the resources necessary to meet the demand?

Carbraal et al. [22] state that in order to select the appropriate rural energy supply technologies for economic and financial evaluation, the load characteristic such as level of service specified, village characterized, must be defined.

In order to understand how this question is answered or which are the best approaches to study the forecast of electric consumption, particularly for medium and long planning horizon, it emerges the need to review how this issue has been previously tackled by real examples of energy planning studies. Therefore, in the next chapters, a review of energy planning case studies will be present, focusing mainly on how they consider the forecast of energy demand in their study.

As previously indicated in section 1.2.2, in literature it is possible to find review on classification about energy planning. Yusta et al. [5] review the most utilised mathematical methods for electrification planning in rural areas with distributed generation, so the paper shows only one aspect of a typical case study. The same target of classifying is followed by Hiremath et al. [7] who present the ways in which energy models can be classified: optimization models, decentralized energy models, energy supply/demand driven models, energy and environmental planning models, resource energy planning models and models based on neural networks. Nicole van Beeck [11] presents a project that aims at developing a decision support method with which the selection of appropriate energy systems can be simplified in those region experiencing rapid growth as local villages in developing countries. This work includes nine ways of classifying energy model, but it does not list real case studies as my review proposes to do.

After it has been defined what is energy planning and what are the different modalities to categorise energy models, a significant number of case studies of energy planning have been selected and successively reviewed according to a specify classification in order to capture all the aspects that characterised them. The aim of selecting the classes for the classification is to highlight all the principal characteristics of the case study analysed. Not only the methodological approach or the mathematical model applied but also the features that describe the case in all its dimensions. Considering the classification of Deshmukh [10] and Yusta [5] the following categories are identified: spatial, planning horizon, methodology, energy vector, demand sector, decision criteria analysis and data inputs. In the next chapter the classes will be described in detail together with the assumptions made.

In the end, the thesis will aim to contrite to investigate how energy demand is evolving in local DCs context and probe how energy demand projections impact on long-term energy plans and the design process of energy systems.

2 Literature review within the energy planning case studies framework

The research methodology to select the papers of the following review consists of some main criteria. First of all, each article has to abide the definition of energy planning previously provided. For example Díaz et al. [23] develop a comparative analysis between three different off-grid technologies for the rural electrification of a group of families in Argentina. According to the quoted definition of planning the field performance described by the authors is not an optimization but an operation review of three types of autonomous diesel/renewable generators. Another paper [24] analyses the energy supply and use of a rural village in Mali and the dynamics of seasonal variation in energy demand for a year. The study does not use any mathematical model to optimize the matching between supply and demand.

Secondly, the aim of this review is to analyse only real-life case studies or potential applications for a real context, excluding papers which present only the theoretical methodologies such as Xiaohua et al. [25]. For example Bernal-Agustin et al. [26] apply the multi-objective evolutionary algorithm and a genetic algorithm to find the best combinations of a hybrid energy system in order to minimize the costs and the unmet demand. A reference daily load profile has been considered in to implement the optimization. No application or details are used to describe the demand. Other cases analysed during the review, developed an off-grid system with a theoretical demand for a hypothetic village. The reason why I excluded not implemented real case studies or potential applications is basically that my research aims to investigate the energy planning in all its aspects, included the processing of input data, such as the demand, and the results. This is wanted to give added value to scientific review already published and, above all, it will be necessary for the next section when the research of a suitable and appropriate model for analysing one of these aspects (the projection of energy demand) will be developed for a real case study.

Another constrains looks at what I nominated the spatial coverage. Only rural energy systems in DCs are consider because of what is the objective of this thesis. South Africa and India were also considered due to the particular attention of local academia to rural areas and rural electrification issues. Whereby global and national papers are not included in the review. For example, Clark et al. [27] focus upon a remote power system for local communities but for a village in Alaska and with a hypothetical request of electricity, so it does not fit for two of the review's constraints. Bala in [28] computes a bottom-up approach to minimize CO_2 emissions for Bangladesh, but at national level.

The case studies reviewed proposed all decentralized energy systems, both stand-alone and micro-grid systems, when they deal only with electrification. The main difference between micro-grid and hybrid micro-grid is that the former has one conversion unit and they relay on one single source. Grid-based power is the least-cost option for large concentrations of household or industrial loads. It offers economies of scale, due to large fixed-cost investment in distribution lines and generation facilities. But is not the most attractive option at regional and village-size level [15]. The selection of off-grid case studies was not a prerogative, but it comes out during the analysis. This is due to the purpose of classifying only rural areas, where people are scattered and live far from urban centre and, local and regional energy planning. This outcome was expected from the scientific literature that widely addresses the analysis of off-grid systems for rural electrification in developing countries. The factors that sustain a strategy based on small-scale generation systems are clearly listed in Mandelli et al. review [29]. The authors identify five dimensions in which small-scale generation systems could be more attractive the centralised solution. Environmental factors for the growing issue of green house gases emissions and morphological obstruction to new transmission lines, economic obstacles due to increasing conventional fuel costs and transmission and distribution ones. This leads also to political attentions to the dependence from fossil fuels and to reduce costs of the supply chain in centralised systems. Social factors, for the increasing interest in "green technologies" and autonomy communities. The last dimension is technological evolution of storage systems and small power technologies. Zeyringer et al. [30], present an example of grid extension electrification in Kenya, comparing it with stand-alone PV system. They find that, under current circumstances the implementation of stand-alone PV systems is the more cost-effective solution in area with low population density. Because of high transmission and distribution costs the WEO-2013 [2] quotes that 30% of rural areas in the world are electrified with grid extension, and the remaining areas are connected either with mini-grids (65% of this share) or small, stand-alone off-grid solutions (the remaining 35%). Hence the quite obvious result of having almost 100% of of-grid systems case studies in the review.

No constraints were set to the choice of scientific journals. Papers were selected starting from a web research on *Science Direct editorial platform* and *Scopus database,* according to few main key words relevant to the aim and the objectives of the review. Energy planning, rural electrification, access to energy in DCs are some of the key words digit. A second method of research was to consider existent review of this matter, pick up all the articles listed and check if the argument studied fitted with the scope of the review, such as [8], [29], [5].

No range of publication date was fixed, but as a matter of facts, regarding the papers included in this work, the number of publications increase in the 5 years following the 2005. Figure 1.4.1 shows the trend over the years of the publications considered in this thesis.

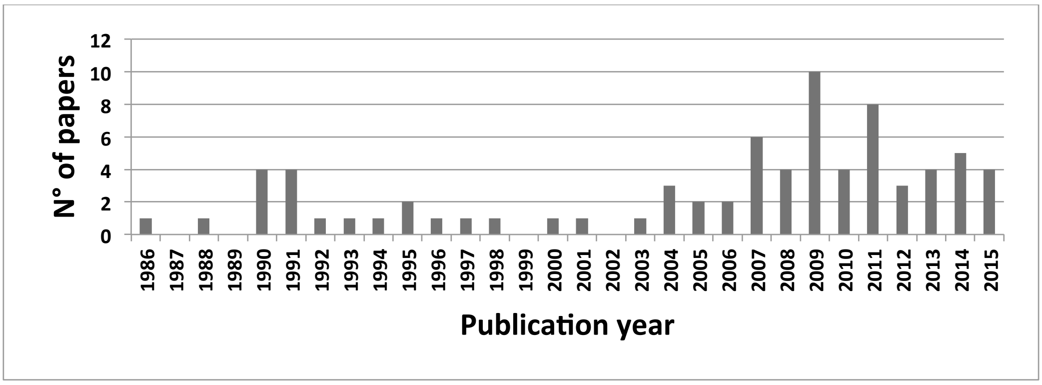

Figure 1.4.1 - Trend of publications over the years

Taking into consideration all these constraints, 114 papers have been analysed and 77 selected for the following classification.

2.1 Description of energy planning categories

In this context the review has been organized in six main categories: spatial coverage, planning horizon, methodology paradigm, energy vector, demand sector and decision criteria analysis. The rationale of this classification is based on two energy planning reviews and the purpose to analyse how the selected papers consider the forecast of energy demand within the energy planning scenario. The problem of how consumption is considered will be the topic of the next section.

Spatial coverage, methodology adopted, demand sector and planning horizon are the categories selected by *chapter 29 - Energy Resource Allocation in Energy Planning* of *Handbook of renewable energy technology* by Zobaa and Bansal [10]. Here the author analyses the instruments necessary to find optimal energy resource allocation in the energy planning process. Before starting with the simulation of a Goal Programming model for the Indian district of Jhunjhunu, the chapter introduces a classification of energy planning methods: planning by models, planning by analogy and planning by inquiry. The energy planning by the models methodology is divided in the optimization and econometric models and the four categories of classification are introduced and discussed with the aim to identify the approach for micro-level energy planning in developing countries.

Another analysis of rural electrification methodologies is carried out by Yusta et al. [5]. The paper discusses the most commonly used methodologies in the planning of rural electrification via decentralised energy sources. The class of decision criteria analysis of the present review is based on that work.

The complete review with the selected papers is reported in *Appendix 1*; it includes all the belonging categories of the case studies.

2.1.1 Spatial coverage

The energy planning model can be classified in terms of its spatial coverage. The coverage can be for local and regional regions. The division is based on the extension of geographical area: a local case study considers a village or a community or a group of small villages located in the same region of the same nation. A regional coverage can be an island or a big city or an institutional division according to linguistic boundaries or morphological constraints. As already stated, national and global coverage are not considered in the review because the model's characteristics, the methodology used and the topic of the planning do not match with aim of the classification. For example Edmonds et al. [31] present a model that has been used to develop a long-term global base case for CO_2 emissions. For low income economies in developing countries energy system may not support local development so environmental attention is not mandatory. Parshall et al. [32] develop a national electricity planning model to guide grid expansion in countries with low pre-existing electricity coverage. Global and national models describe the world economy or situation and the topic of the planning is to reduce energy waste using a top-down approach or try to increase efficiency of a pre-existing power system.

Local coverage includes small areas with few villages [33] or a set of houses [34]. It has been found that authors identify the spatial coverage in different ways. Himri et al. [35] present a study for a remote village in Algeria, specifying the number of consumers living in the area. Musgrove [36] develops a dynamic programming model to find the optimal operating strategy for satisfying an electrical load of 1 kW obtained from a previous survey. The same methods are applied for describing the regional coverage. Gupta et al. [37] study a hybrid energy system for the Juanpur block in India. The authors specify the location and the numbers of households and population. Silva et al. [38] focus on the applicability of multi-objective methods (see next paragraph 2.1.5) to assess the introduction of renewable technologies for the *Non-interconnected Zones (NIZ)* in Colombia.

No particularly assumptions are necessary for this classification. 60 of the 77 cases analysed are local planning and 16 are regional.

2.1.2 Planning horizon

Models can also be classified on the basis of time scale considered for plan implementation. Under this class five subcategories are chosen to represent the case studies: very-short term (hours, days, weeks), short term (months, one year), medium term (from one to ten years), long term (beyond fifteen years) and not specified term. The distribution of the percentage is reported in Figure 2.1.1.

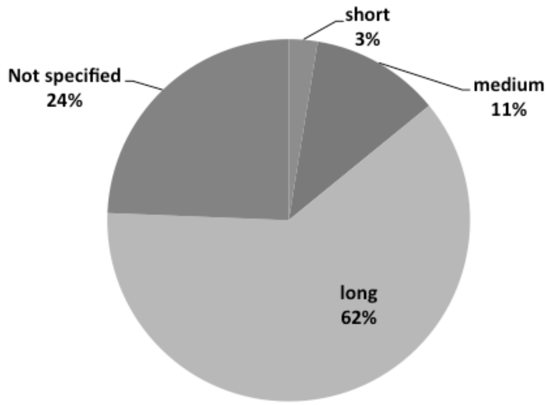

Figure 2.1.1 - Planning horizon distribution

Defining the right category of a case study for the planning horizon requires some assumptions in order to respect the real meaning of this class. Papers present three ways to define temporal coverage: some authors use to explicitly specify the lifespan of the project as or the energy system lifetime, others studies do not point out the planning period but report the lifetime of the components such as PV, diesel genset or wind turbine used to calculate the net present value or the discounted costs of the system. For example, Haddadi et al. [39] specify three different lifetimes for the systems implemented, equal to 10,15 and 20 years. Equally Sen et al. [40] indicate 25 years as the project's lifetime. Silva et al. [38], instead, do not point out the lifetime of the project but consider a life time for the technologies in order to calculate the net present cost of the renewable energy system. Daud et al. [41] state clearly that the life cycle period of the system is taken to be the maximum life time of the component. The second typology of planning horizon indication is based on the idea that for the calculation of the discounted or amortization costs the life of all technologies is needed. I assume, for all the case studies, that the maximum lifetime between all the system components, defined the planning horizon of the entire system. This case is especially adapted to describe case studies that use Homer[1] as mathematical model, where technical data information about the components are always listed, but also for other decision criteria analysis as in [42] where Arun et al. tabulate the photovoltaic array life as an economic parameter considered for system optimization.

For those papers, which do not write any of the two information, they are accounted in the not-specified category. For example, Kanase-Patil et al. in [43] apply the Integrated Renewable energy Optimization Model (IREOM) for the electrification of dense forest areas in India in order to minimize the cost of energy (COE) generation. Searching for the period during which the costs of the system are discounted, no value are found but the authors talk about only of an amortization period in years. Another example of not specified case study is in the Gupta et al. paper [37], in which the authors do not specify for how long the planning is developed, but generally noted that the unit costs are calculated on the basis of life of plants without a precise value.

2.1.3 Methodology paradigm

Depending on how energy planning impacts on economic issues, the planning methodology approach can be classified as bottom-up or top-down. For example, for a top-down approach the electricity supply can influence the prices, the labour and goods market of the households in the areas analysed. For bottom-up engineering approach, instead, energy planning does not condition the microeconomic variables. The bottom-up approach is used for energy sector in isolated contexts where its linkage with economic sector is not considered. The approach is driven by the end-use demand; macro-economic parameters such as energy prices or changes in GDP are exogenous parameters to the model. The challenge with bottom-up approaches is that they rely on characteristic information about appliances' consumption, difficult to source. Top-down models individualize

[1] The Homer Micropower Optimization Model is an optimization and sensitivity computer model developed by the U.S. National Renewable Energy Laboratory (NREL) to model a power energy system fluxes and life-cycle cost.

the technology to install to match supply and demand following the development of economic indicators. They are appropriate tools to endogenously derive the macro-economic indicators for a reference future, so it is useful in the cases of developed countries wherein technological efficiencies and rate of capital investment have already reached close to saturation levels.

The result obtained is pretty obvious: 92.2% of the papers adopt a bottom-up approach and the remains 7.8% use a top-down paradigm based on an econometric technique. For example Zeyringer et al. [30] compare a grid extension solution with stand-alone photovoltaic systems for optimization of electricity supply in Kenya. The authors use the Kenyan Integrated Household budget survey data, i.e. micro-economic data such as costs of technologies, considered the best representative data available to study the household electricity demand. Weisser [44] focuses on the integration of renewable technologies for small islands heavily dependent on fossil fuels, applying a comparative economic. Top-down models are most applied for aggregated load analysis because they accuracy decrease with the increase of incorporation of human behaviour data. The databases that report information about electric power consumption (kWh per capita), energy use, education, economy and growth are not complete and record only national data. Thus in a rural context, a bottom-up approach is the most suitable and accurate even if not easy to implement because of they require specific appliances usage data.

2.1.4 Energy vector

Depending on the need of energy, the availability of resources and the target of the policies for which the study could be developed, four types of energy vector has been defined: *electricity*, for example for lighting or water pumping, *thermal*, *oil products* and *non-commercial energy*. Devadas [45] discusses the central importance of energy inputs in development and presents a Linear Programming Model for optimum resource allocation in rural system. In order to allocate optimum resources to different subsystems such as household, agricultural, transport of the energy system, the author investigated all the types of activities in which the rural system is involved. So the energy vectors involved are: electricity for irrigation and lighting, liquefied petroleum gas for cooking, kerosene for the lamps of the poorer people and organic and inorganic fertilizers for farms activities. Weisser [44] argues that the economics of introducing Renewable Energy Technologies (RETs) on small island developing state, are potentially favourable over the application of fossil fuel technologies. Therefore, also the consumption of fuel is taking into account but to produce electricity, so the energy vector is only electricity. In a context where the energy planning considers mainly stand-alone and mini-grids systems as the most suitable options to bring energy, electricity is the main energy vector with a percentage of 75% of the total analysed.

The category of non-commercial energy is integrated in the classification in order to consider those case studies that focus on the use of crops and animal dungs for stoves or mud stoves, fuel wood for cooking. For example, Malik and Satsangi in [46] apply mixed integer/linear programming technique for rural areas in Wardha District in India. The evolution in time of the main crops in the district are surveyed and extrapolated to understand the need of irrigation, this is written down in the electricity category. Data about crop residue and dung are surveyed as energy devices for cooking. In [47] Joshi et al. elaborate information about fuel wood, agriculture residue and animal dung for cooking and for space heating. The first primary energy requirement is placed in non-commercial energy, while the second one in thermal energy vector. To clarify the difference between thermal and non-commercial energy used for the cooking sector, heat that comes from bio-gasifier technologies i.e. solid biomass as fuel in a gasifier applied for cooking is allocated in thermal class, such as in [43]. In Figure 2.1.2 it is illustrated the belonging to different energy vector of case studied reviewed.

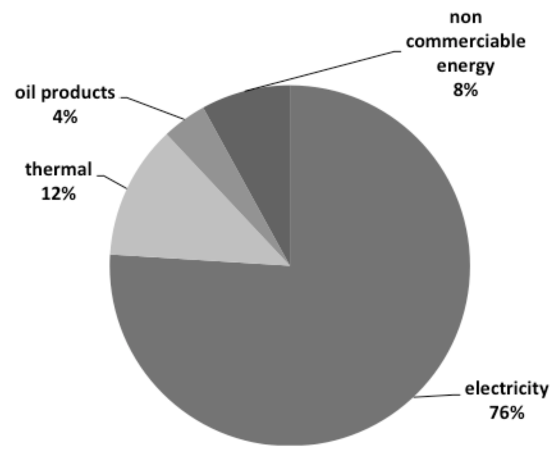

Figure 2.1.2 - Energy vector distribution

As it is shown in the pie chart, electricity sector results to be the most analysed by researches in developing an energy planning for rural areas. Heat or thermal energy vector is typically used for process applications in industry, for space and water heating and cooking in the building sector [2]. This consideration takes into account the whole world, but the case studies reviewed analyse only small areas in developing countries. The demand sector analysis points out that industrial sector accounts for 14 %, and not all the sector is fed by thermal energy but electricity is equally necessary for small industries. This results in a low percentage of thermal sector. Moreover, thermal energy used for building sector is consumed in Europe for more than 40% according to WEO-2013, mainly in the form of bioenergy for space heating. In a rural context modern and efficient technologies producing thermal energy, such as (non-traditional) bioenergy, geothermal and solar thermal have no application. Instead, most of the contribution of renewables to heat production comes from biomass used in traditional ways for cooking. The cooking energy service is included in the residential sector in the present review, but for systems that supply energy for households it is found that few cases consider the cooking service. Iniyan et al. [48] do not explicitly indicate the demand sector, but end-uses services among which the cooking end-use. Hiremath et al. [49] optimise a decentralized bioenergy system to produce biogas for cooking end-use and biomass for power generation. Nerini et al. [20] for example, elaborate the evolution of energy for cooking aside from the provision of electricity. The cooking demand is considered in a different group from for example communication, space thermal and food processing demand, with particular attention to the cooking options reference energy system and peculiar assumption for the projections.

2.1.5 Decision criteria mathematical models

With this category it is examined the mathematical models and, if indicated the algorithms used to optimize the system designed to supply energy in the rural environments.

Decision criteria analysis has been classified into seven 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 optimize an objective function given a sets of constraints on the variables, for example minimizing the cost of matching supply and demand, [50] or maximizing the income of households in a rural village. The category includes models using Mixed Integer Linear Programming (MILP) algorithm, and codes developed in Matlab and C++ software, used to solve linear set of equations. There are several modelling languages: LINGO a modelling software developed by *Lindo Systems Inc.* used by Kanase-Patil et al. [33] to calculate the cost of energy for an off-grid system in India. GNU MathProg, a subset of the AMPL (A Mathematical

Programming Language) used by Nerini et al. [20] to solve the linear equations of the model applied.

MCDM solves problems involving more than one criteria of evaluation such as cost or price and efficiency. It includes Analytic Hierarchic Process (AHP), Compromise Programming (CP), Goal Programming (GP), Compromise Programming (CP) and Elimination and Choice Expressing Reality (ELECTRE). AHP decomposes all the decision problems in sub-problems and the hierarchy is built. Every sub-problem is compared to each other using data but also judgments. AHP converts these evaluations to numerical values. GP can be thought of as an extension or generalisation of linear programming to manage multiple measures. For every measure is given a goal to be achieved. Thanks to a function (a vector or a weighted sum) the unwanted deviations from the target values are minimised. CP is similar to goal programming in that it uses the concept of minimum distance. In distance-based techniques the concept of non-dominance is used to select the best solution or choice of alternative. The unique solution is found when no other feasible solution exists, that will cause an improvement in a value of the objective or criterion functions without making a value of any other objective function worse.

MOP is a method of solving problems where there are large numbers of variables that are considered and classic optimization techniques may consume excessive computational time or be unable to take into account all the characteristics associated with the posed problem. Case studies that use the concept of Pareto optimality are included in this category. Hiremath et al. [49] use a goal-programming method in order to analyse the DEP through bottom-up approach, seven objectives functions are considered: minimization of cost, maximization of system efficiency, minimization of use of petroleum products, maximization of use of locally available resources, maximization of employment generation, minimization of CO_x, NO_x and SO_x emissions and maximization of reliability of renewable energy systems.

Non Linear Programming includes optimisation problem which objective function or non-linear and/or the feasible region is determined by non-linear constraints. Ashok [51] uses a Quasi-Newton algorithm(a mathematical method to solve non-linear equation) to solve optimization problem to determine the optimal number of renewable energy units for a typical rural community in India.

Dynamic Programming is a technique to map out algorithms, it is based on the split of a complex problem into a sequence of smaller sub-problems; its essential characteristic is the application of the optimal substructure to find the optimal solution of the main problem. Once each sub-problem is optimised the solution is stored instead of re-computing it. Thus, DP does not identify a single optimization algorithm, but a variety of optimization techniques can be employed to solve particular aspects of the main problem. It is an optimization procedure applicable to problems that require a sequence of interrelated decisions to be made. Musgrove [36] uses a dynamic programming model called RAPSODY to find the optimal operating strategy at minimum cost. It takes into consideration capital, operating and maintenance and fuel costs of the system composed by wind turbine, photovoltaic array, battery storage and the auxiliary diesel generator. The dynamic programming solves the problem through the optimization of different steps, and if the problem is composed of complex systems which interact one with the other, the system-dynamics methodology can be used to compute the energy system as Alam et al. do in [52] to optimise inflammable outputs for biogas production and edible outputs to improve the quality of life.

More recently, EO and its implementation as Software Homer stand out as a methodology of practical interest and straightforward application. Combinatorial optimization model is also included in this category. This approach considers the optimization based on one objective, differently from what MCDM does with the development of a solution that finds the best compromise, but it calculates numerically the optimal solution. Enumerative optimisation uses numerical analysis algorithms for optimisation problems. Depending on the form of the objective function and the constraints, optimisation can be linear or enumerative. As for the linear programming models, the use of enumerative techniques are characterised by an objective function such as the minimum cost, variables such as the size of a technologies and some constraints such as availability of resources. Türkay et al. [53] apply Homer to find the Net Present Value for a stand-alone system composed of solar photovoltaic, wind turbines and fuel cells to supply electricity for a university.

Some papers are characterised by two criteria decision, for example [54] and [33], due to the validation and comparison between two results. The case studies that do not fit with anyone of the classes are identified as "Others". For example [55] optimizes the annualized least cost of energy for a remote village in Northern Laos with genetic algorithm implemented in Matlab. Rana et al. in [56] use an intuitive sizing method. They calculate the least total life cycle cost of the system designed with the combination of six possible technology alternatives (stand alone PV, biogas system, gasifier system) to best match the demand. Several cases were theoretically developed and for every of them the life cycle cost were calculated.

In Figure 2.1.3 the percentage of decision criteria methods distribution is illustrated.

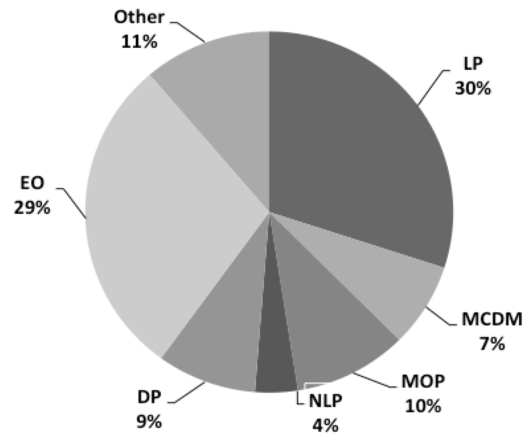

Figure 2.1.3 - Decision criteria mathematical methods distribution

2.1.6 Demand sector

Based on demand sector, case studies can be classified as *residential*, *community*, *industrial*, *commercial* and *agricultural*. The energy consumption for residential sector includes: the demand for lighting, cooking and various appliances present at home such as radios, televisions, fans etc. At community level, energy is required for: schools, medical centres, radio stations, small shops, churches, and restaurants. Ferrer-Martì et al. [57] design the electrification system for a community in Perù; the beneficiaries of the project are households and four institutions, namely church, school, health-center, restaurants, shops. For agricultural demand: energy for water pumps, ploughs, tractors with agricultural implements. Industrial sector includes: rural industries, grain mills, coal kilns, small vans for products transportations etc. For commercial sector it is considered all the activities that need roads, telecommunication uses, water and irrigation networks, bank and credits facilities; it is also included transportations in general (unless otherwise specified) because in rural contexts few people use cars or mini-vans as private use.

Sometimes the paper does not list the sector covered by the planning but it describes the technologies that are involved [58], or indicates electricity as the energy demand in the area studied, [59]. In this case, if any others remarks are pointed out, all the categories have been ticked. Some other articles list end-uses such as lighting, cooking, pumping, heating, cooling and transportation: in this case all the demand sectors that could use these facilities are ticked [48].

Figure 2.1.4 shows the percentage of which sector the demand is analysed.

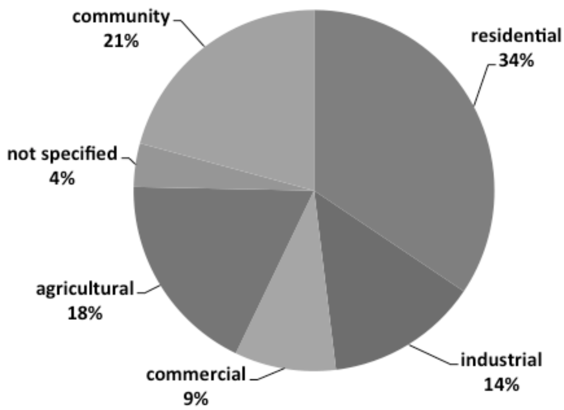

Figure 2.1.4- Demand sector distribution

It is evident that energy planning deals more with residential demand. This is reasonable because of at local level for villages where the main issues is getting through the day, a domestic need of energy for cooking or water and lighting is the primary importance.

The following analysis try to fill the gap between a systematic review of current energy forecasting methods and their application for a case study in order to understand the pertinence of various approaches for DCs. The next section focuses on how the previously analysed medium and long-term planning case studies consider and predict the input of energy demand with a special emphasis on domestic sector for local rural areas in DCs.

2.2 Energy demand analysis

Through the classification of the rural case studies, the attention is also focused to the hypothesis, assumptions and methodologies use to forecast energy demand.

As Kivaisi says in [60], the most important part of a planning is the evaluation of the electric energy demand as accurately as possible.

In the framework of energy planning for rural electrification, distributed generation (DG) literature, the study areas include papers that review energy models such as Nicole van Beeck [11] that present none ways to classify energy models, Hiremath et al. [7] focus on the various types of energy models, the previously mentioned Yusta [5] looks at the mathematical models. Other works are based on the classification on off-grid systems in DCs as Mandelli et al. [29], analysis of models, inquiry method, decision criteria, possible risks and errors in energy planning to face the issue of an efficient method for the development of a nation as Prasad et al. in [9]. Devadas [61] presents a paper to identify the important parameters that control the economy in the rural system at household level. Other studies focus on the social, economic and environmental benefits of integrating renewable system in the energy system as Elhadidy et al. in [62], or Nakata et al. [63] who look at the advantages of providing electricity and heat in rural Japan with a renewable system. Díaz et al. [64] compare the field performance of diesel, hydro-diesel and photovoltaic-diesel for communities in Argentina. A lack of the energy demand analysis of local rural energy planning arises in scientific literature. The importance of electricity demand in energy planning is pointed out at paragraph 1.3 of this thesis. Thus it is interesting, within this framework, to handle with the topic of energy consumption treatment in order to understand the issue and the possible solution to obtain a consistent energy planning in all its dimensions.

The sizing of any energy system needs the power requirement of the analysed area. Therefore the aim of this section is to understand how energy demand projections are considered within energy planning studies previously reviewed. To do this a brief investigation about published reviews of energy demand models in the scientific literature is consider. For example Bhattacharyya et al. [65] publish a comparative study of energy demand models that reviews existing energy demand forecasting methodologies, in order to investigate whether the existing energy demand models are appropriate for capturing the specific features of developing countries. Suganthi et al. [66] present a detail list of the various energy demand models, used not only for DCs but also econometric models typically applied for developed countries. Swan et al. [67] focus on the residential sector to present an update review of approaches to model energy consumption reported in literature.

The following analysis will show how demand is accounted in energy planning case study previously reviewed, through a classification of energy demand approaches based on some published review about this argument.

2.2.1 Demand forecasting approaches

The choice of demand forecasting classes is due to the considerations noted during the reading of each case study. Few papers explicitly state the model use to predict demand over years; for those cases that do not apply a specific method already categorised in literature, an attempt to group them into classes that describe the function or mathematical technique was carried out.

It has been individualized eight classes for the demand forecast category: *constant*, *assumed function*, *extrapolation*, *system dynamic*, *time-series*, *regression*, *scenarios* and *I/O*.

Regression models in which the function of forecast is characterised by a dependent variable that is a linear combination of some parameters or coefficients and an independent variable. The regression data can be linear or the parameters can be estimated by a least squares technique as in [48] together with a scenario approach.

Input-output models (I/O) have long been used for economic analysis and hardly captured he rural-urban divide. They exclude informal activities and non-monetary transactions, for this reason this approach is resulted to be used only one time in [68].

The *scenario* approach has been widely used in climate change and energy efficiency policy making for example from the International energy Agency. Scenarios refer to a set of descriptive and possible pathways that indicate how the future may unfold. It is a particularly suitable method in a developing world. Scenarios are not new to energy analysis and result always to be an integral part of other demand forecasting approach: Ferrer-Martì et al. [69] couple a low-demand scenario with constant value of demand for household, a school and a health centre, and a high-demand scenario in which is defined a double consumption to consider a wider fulfilment of the basic needs and possible production uses. Domenech et al. [57] use two scenarios, in the first energy and power demands cover basic lighting and communications consumption, and for the second is assumed a 50% more demand in relation with the first scenario. So in this case the issue of changing consumption is solved with scenario, constant and assumed function approaches.

Time-series models use time series trend analysis for extrapolating the future energy requirement; it depends only on time variable. Time-series forecasting used historical or previously data to predict future values, instead the regression analysis, which is used to study how the current values of one independent time series can affect another current or future time series. Different techniques have been developed to predict electricity demand: a simple first-order autoregressive time-series model, logistic curves, Markov model [58] and other models for technology diffusion as Gompertz for projecting energy demand. The results from these sophisticated methods seem to depend on model specification and the strategies for data analysis. For limited sample sizes, these methods are unlikely to produce appropriate results, therefore simple ordinary least square, in linear regression model, can lead to super-consistent results.

Malik et al. [46] , [70] approximate the data by a probability distribution function starting from historical surveys. This kind of approach to predict the future demand is not accounted in the Suganthi review, and it is named by the author as "extrapolation" technique.

In rural electrification *system dynamic* approach has been used with a lesser extension. There are more cases of system dynamic application in rural energy planning than in representation of trend in time for electricity consumption. This methodology was initially developed for managerial decision-making but later has been successfully applied to other areas including electricity sector. System dynamic is characterized by an iterative process making use of casual and feedback relationship. The model is computed with the main box, called stock, where fluxes of main variables, called flows, increase or decrease the value in the stock, the possibility of adding auxiliary variables that influence directly or indirectly the variable in the stock is used to enhance and detail the model. Recent studies using this kind of approach are Hartvigsson et al. [18] attempt to study how initial investments on capacity generation affect cost-recovery, electricity usage and user diffusion in rural areas. System dynamic is also applied to model electricity demand for the forecast of 21 years in Malaysia, by Akhwanzada in [71].

A *constant* class is introduced to identify those plans that consider energy demand constant along the planning period. Even if the time coverage is up 10 years some authors assume no evolution of energy consumption. Zhang et al. [72] adopt a typical daily load profile, obtained from literature, during all the system lifetime of 15 years. Cherni et al. [73] study a model to supply energy for a sustainable development of a community in Colombia. In this paper is not considered a proper demand forecast but the energy system is designed in order to support a potential growth of the community and its electric consumption.

The *assumed function* is the first primitive step to study how consumption can change over years. This method is characterized by the assumption that the growth takes place with a constant percentage for every year, often it is estimated from historical data series for the village as in [20]. Assumed function is combined frequently with the development of scenarios in which the value of growth changes.

2.2.2 Results and discussion

In Figure 2.2.1 is shown the percentage of the different demand forecasting approach for every case study analysed.

The issue of the analysis is clearly evident: more than half of articles do not consider the variation of demand in time. The energy planning focuses only on the system variables such as capital costs, efficiency, emissions etc., but energy demand management is required for proper allocation of the available energy resource and so to design a consistent energy system.

A deeper consideration of how many medium and long term planning do not predict the consumption highlights most the carelessness of the problem. The review reveals that only 18.75% of energy planning studies that belong to long-term planning horizon category apply forecast techniques for the energy demand. The total percentage of medium and long planning horizon planning that does not keep constant energy consumption is 28%.

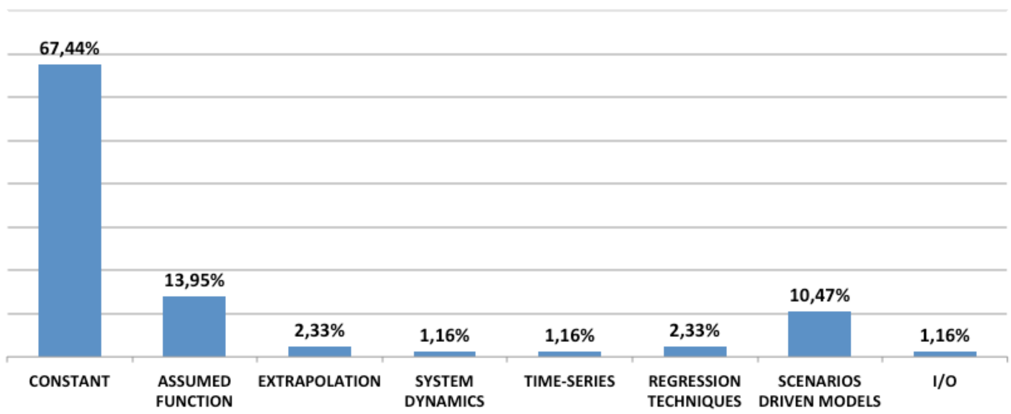

Figure 2.2.1 - Demand forecast distribution

The other two approaches more used are assumed a fixed growth every year (*assumed function*) justified by previous studies or historical trends together with the support of a *scenario approach*.

31% of papers that do not consider the evolution of consumption in time use Homer model for energy planning. This underlines one of the weaknesses of such enumerative model. In Homer the daily average demand in kWh/d is entered and the number of years on which the program calculates the discounted costs is selected. The same value is kept constant for all over the years.

In the next section the analysis focuses on the residential demand sector of supply, introducing a suitable model in order to present the features that a correct approach has to follow.

2.3 Energy demand features for a rural village: towards a better modelling approach

Considering what has been highlighted up to this point, few studies examine the matter of which is the best option to forecast the request of energy for rural areas in DCs.

As pointed out before, the demand sector to which energy planning case studies address the project of an off-grid system is the residential one, with a percentage of 34% of reviewed papers. Moreover, looking only at local spatial coverage, so less extensive areas with smaller population and households, 67% deals with residential sector. According to IEA in 2013 the share of electricity consumption for the residential sector in the world was 38.6%. As it is shown in the map below (Figure 2.3.1), the share of residential in total final consumption for the year 2013, is concentrated in developing areas of the world.

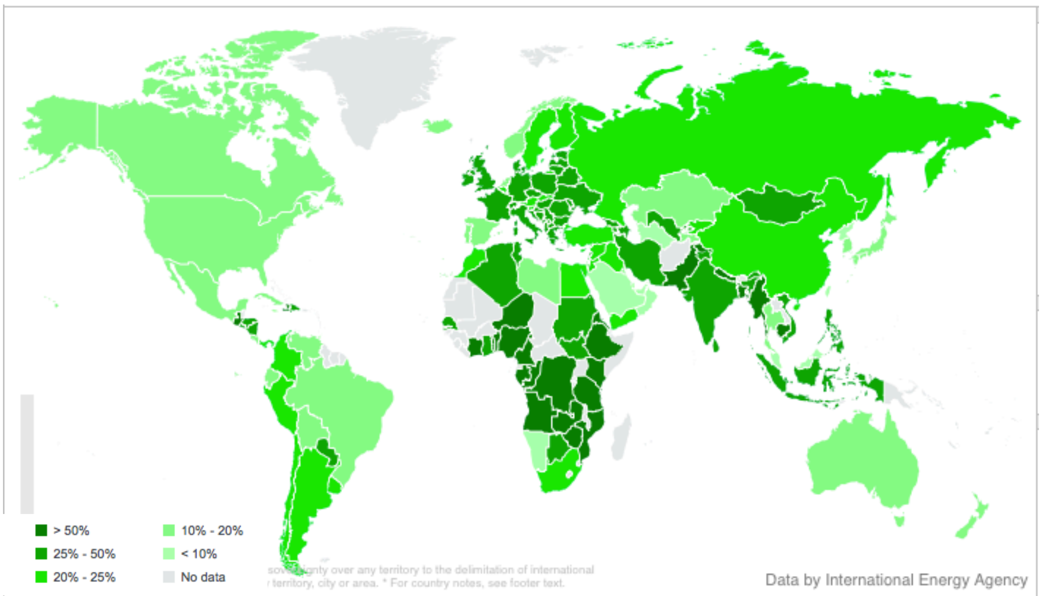

Figure 2.3.1 - Percentage of residential total final consumption in 2013. Data from IEA database

Bhattacharyya in [8] reviews alternative methodologies to electrify with off-grid systems in order to identify features of each methodology and highlight their strengths and weaknesses. As the author reports, the demand in rural areas is due mainly to the use of domestic appliances, so the residential sector proves to be the main critical request of energy.

For these reasons, from this point on, all the considerations and features analysed will focus on the domestic sector and on the electric sector. Thus will be considered the consumption of a household in terms of end-use electricity appliances, water heating, space heating inside the dwelling and lighting over years. Regarding the energy sector, the choice of considering only electricity is due to high percentage of papers reviewed that use electricity as energy source to feed loads, as it has been shown in Figure 2.1.2. Moreover, the electric demand is tricky to predict because of the considerable impact it has on the system sizing. Regarding the social and economic development electricity has a significant role to face the issue of access to energy in these contexts, especially considering the increasing importance that off-grid small-scale electricity generation is achieving in rural areas [29]. Moreover, cooking service is often studied separately from the other residential needs. Nerini et al. [20] develop a special focus to the techno-economical analysis of alternatives for cooking. Open wood fires and improved wood stoves are fed with traditional fuel, and their use over the years is limited by the sustainable wood availability in the area surrounding the village. The multi-tier approach, adopted in the paper, introduces BLEN cooking that uses biogas, LPG, electricity or natural gas in the last two tiers. This distinguished analysis is due not only to the large cooking tradition in rural families but also to the different evolution that can follow this sector both for the consumption and the type of fuel due to technology innovations. Iniyan et al. [48] consider the cooking end-use divided from lighting, pumping heating and other usages that have as input electricity or biomass.

The limitation of discarding both the public utilities such as schools, health centres, street lighting, water pumps and the productive sector such as small local industries, agricultural activities lead to a considerable suppression of electric demand. This thesis is a first attempt to compute the forecast of electricity demand for long-term planning. The aim is not to find the definitive model that includes all the variables that describe the electric and heat consumption for rural areas, but to understand, after a literature review, the main features that a demand model has to be characterised and to give a first general approach for future works. Therefore, next steps will be to include the community, industrial, agricultural and others sectors that the author will judge to influence the consumption and energy services such as cooking.

2.3.1 Through a more appropriate approach to energy demand analysis

In scientific literature there are several reviews about the methodologies for analysing energy demand and supply, which examine broadly the existent models and highlight their strengths and weaknesses. Bhattacharyya et al. [74] critically review econometric and end-use studies both at aggregated and sectorial level in order to determine the specific features for modelling energy demand of DCs. Suganthi et al. [66] review all the energy models applied for demand forecasting and they classify them under twelve broad headings. Prasad et al. [9] consider all energy models both for demand and energy supply with a wide categorization according to their characteristics. Swan at al. [67] focus on the review of top-down and bottom-up models for the forecast of residential demand.

Before listing the features that lead to the most appropriate approach it is useful to describe which are the problems of energy modelling in DCs. Adapting demand model used for developed countries for a rural area causes the omission of a large informal sector. In DCs occur a slow technology diffusion, the population rely on traditional energies, the rising of an upper income level does not mean always a transition to modern energies and the speed at which this happened is naturally different between DCs and developed economies. The developing areas are characterised by few and unreliable documented data, as GDP or income value, and the disaggregation of earnings make inadequate to represent the residential demand with a common representative consumer.

Considering the existent approaches, it is clear that two main blocks are identified: top-down or econometric and bottom-up or engineering end-use approach.

Since the characteristics of the two groups have been described in detail by the above-mentioned reviews, in the following lines it is presented an abstract of the main features, with the fundamental strengths and weaknesses, Table 2.3.1. The purpose of the next table is to give the opportunity to the reader to maintain the logical thread of the subject, providing all the information to understand it.

	END-USE	ECONOMETRIC
STRENGTH	• detailed sectorial representation • more realistic projections than with econometric techniques	• identified the relationship between economic variable and aggregate demand

	• consideration of the consumption of an individual consumer or of a restrict group of people	• the need only of aggregate data easy to obtain • reliability on historical trends able to drive the model
WEAKNESS	• huge data deficiency especially for DCs • not able to capture price-based policy and price signals	• do not catch the technological diversity and • technical progress

Table 2.3.1 - Characteristics of end-use models and econometric models

The question that arises is: which are the features that have to be abided by the demand models? Two aspects have to be taken into consideration: a good description of domestic requirements and a reasonable method to forecast the electric demand for long-term planning scenarios. First of all it is necessary to consider the structural change of the target area, and the possibility of leapfrogging of economies. Secondly, a good model for rural areas must account the demand for end-use appliances that depends on, as well as the costs, acceptability (according a deeper consideration of the behaviours), the inertia of appliances stocks that limits flexibility in the short-run due to the availability of the items in the village.

Looking at the existent approaches used to predict demand, some characteristics are found not to be helpful in the rural context. For example, models that look only at the price as main driver of demand are found to be inadequate in DCs, [74]. Price is found not to play a significant role to the variation of consumption, where income drives the demand. A literature review on empirical studies of the residential electricity demand leads Ziramba [75] to assert that the residential electricity demand is price-inelastic, i.e. electric consumption is poorly responsive to price changes. However, the price and demand dependency is a controversial topic. For some contexts it has been studies how an increase of price can lead to a change in the custom of some appliances. Therefore the issue should be investigated with a more in-depth analysis.

Instead a factor that fairly responsive to change in demand is the increase of population. Bhattacharyya at al. [74], focusing on end-use studies for residential energy demand, state that data of growth population is taken as an increase of residential activities. He also states that it is necessary to separate the demand of rural areas to the urban one, because of the differences in income level variations and so the changing demands for the two areas. Indeed a first level of disaggregation is to split urban and rural areas cause to the substantial disparities between the two areas, as stated by Filippini et al. [76].

The matching between the weaknesses and the adequate characteristics needed for a residential demand model lead to an end-use approach. Furthermore, based on what it is just pointed out, the proper guidelines for a consistent residential demand model for DCs are: population variable as a proper indicator to drive the growth of demand, a proper economic indicator (*i.e.* household expenditures), the consideration of the ownership of electric appliances and dwelling area, and the related absorption of energy. It is also important not to consider a single common consumer but introduce a disaggregate level of consumption by expenditures or income class.

Swan at al. [67] state that bottom-up approach techniques are more suitable for context where there is a rapid technological development as in DCs.

The bottom-up approach has been used to forecast demand by several authors: Boonekamp [77] applies a bottom-up model for the simulation of the future energy use of household in the period 1990-1995. The model incorporated demographic and lifestyle impacts to forecast the energy use of households split into space heating, hot water, washing/drying, cooking, cooling, lighting and other appliances. Michalik et al. [78] build up a bottom-up approach taking into account characteristics of appliances and customers' life styles. The peculiarity is the way in which they apply one the typical feature for this context: the disaggregation of consumers. The authors divide into four main categories the surveyed households characterised by employment and children as factors determining a customer's life style. Then each of the four families, as they called, is broken into six groups reflecting the possession of the major energy-consuming devices. Mustonen [21] develops a LEAP -scenario analysis of a village energy consumption in Lao People's Democratic Republic. LEAP, the Long-range Energy Alternatives Planning System, is a widely used software tool for energy policy analysis and climate change mitigation assessment developed at the Stockholm Environment Institute. It is a scenario-based modelling tool that can be used to track energy consumption, production and resource extraction in all sectors of an economy. In this paper the methodology of the model on the demand side follows an end-use driven analysis for long-range scenarios. Keeping the population per household constant, residential energy consumption in the model is driven by the number of households.

A bottom-up simulation model for household energy use has been developed by Daioglou et al. [14] . This model called REMG, global residential energy model, has been selected by previous considerations as the unique model that matches the features for the target location of this thesis.

2.3.2 Remarks

Through the analysis of scientific literature and of energy planning case studies, focusing how models consider the forecast of electric consumption, it has been identified that bottom-up approaches are the best methods to project demand over the planning period.

A model that fits the characteristics features of the residential sector in a rural area for a developing country is finally selected to represent the target of this work.

Van Ruijven et al. [79], as previously mentioned, developed a bottom-up simulation model for projecting households energy use in India, and Daioglou et al. [14] extended it to five developing world regions: India, China, South East Asia, South Africa and Brazil. They named it global residential energy model (REMG). It captures some of the specific dynamics of developing countries as it is said in the previous sections: underdeveloped markets and informal activities (street vendors, waste pickers, black market, home-based workers), the transition from traditional to modern fuels, urban/rural difference that needs a disaggregating model equations which considers different income levels.

Concluding this first part, it is interesting to note that papers using a simple and intuitive end-use or bottom-up accounting method are common in practice in order to evaluate the demand data input for an energy planning, and complex econometric methods for forecasting demand, which are commonly published in academic literature, are rarely practiced for a real case study.

In the second half of the thesis three different scenarios will be entered as demand input in order to evaluate the impact on the final planning solution. Firstly a bottom-up model will be implemented, based on REMG van Ruijven model, together with other two comparative approaches. A "constant" scenario to account for a lower consumption in respect to the bottom-up approach, and a "time-dependent interpolation" scenario with a higher evolution of electric demand over time respect to the bottom-up scenario. These scenarios will be adapted for the Indian village of Katgaon selected according to some reasons described in Chapter 3. Once the electric consumption is computed it will be entered in an energy planning model to understand how forecast demand conditions the final result of the energy system dimension and cost.

3 Modelling projections for residential energy use

The aim of this chapter is to present three different scenarios which describe the forecast of electricity demand for a long period planning. The electric consumption is evaluated for the domestic sector in a small village located in the State of Maharashtra in India. The choice of this area is due to the availability of detailed data and information about the needs, customs and traditions necessary to develop a reasonable forecast for the village. Local data was obtained by a careful assessment of the local situation through questionnaires and surveys carried on within the *Sanjeevani Project* implemented by *Ingegneria Senza Frontiere - Milano*. The location of the village met the requirements for the objective of the case study: a rural village in a developing country.

The first scenario is described in Section 3.2. It models the demand through the equations of the REMG [79] model. It should represent the most appropriate approach for a local rural area obtained by the review analysed in Chapter 2. In Section 3.3 the other scenarios of forecast are described, then the comparison of the three approaches is summarized in order to understand the different trends over the years. The second method, called the II Scenario, is built up on the basis of the most used approach to account the electric consumption in the local energy planning literature. To compare these two options with a third one an assumed-function approach is chosen that forecast the demand with a method less elaborate than the REMG model but that considers the demand change over the years, based on the World Bank historical data.

This chapter is necessary in order to obtain the demand inputs, that will be entered in the energy planning model draw up with OSeMOSYS software, which will allow some consideration on how a rough processing of the future trend of consumption leads to an inaccurate planning and thus, to a wrong sizing of the energy system.

3.1 Case study: Katgaon village

Thanks to the information collected in the context of the *"Sanjeevani Project"* of *Ingegneria Senza Frontiere - Milano*, in the next lines is illustrated a brief description of the main characteristics of the local context.

3.1.1 General information

Katgaon is a small village of the district of Osmanabad in the State of Maharashtra. Katgaon has a population of 7800 individuals, of which 60% males and 40% females. Most of the households live on agriculture (about 70% of workers are farmers), but the poor conditions of farmers in this region cause a high rate of migration toward the big cities of Maharashtra. The total area of the village, including lots and uncultivated lands, is about 5126 hectares. The community sector is characterised by a hospital, an animal health treatment centre, a telephone office, 5 nursery schools, a primary school, a secondary school, a bank, a post office and the local government office. There are approximately 100 shops, mainly small restaurants, mini markets and grinding mills. The village is connected to the national electric grid; there are two different grids, one for the village and one for the land.

The village is connected to the national electric grid but the supply is not continuous, as the Electricity Regulator determines scheduled blackouts to balance out the infrastructural weakness of the grid and to reduce energy consumption. For the domestic supply there are 16 hours of electricity per day and for agriculture there are 8 hours of electricity per day. Furthermore few unscheduled blackouts are present during the day but they last for several hours; a low voltage of the grid is another issue due to the excessive length of the grid, the under sizing of transformers and a shortage power supply for the users connected. For these reasons, the necessity to renew the current electric supply system arises.

3.1.2 Household characteristics and energy uses

The collection of demographic and economic data of the households had faced a difficulty due to the farmers' restraints in giving the exact answers to the interviewers. A small community of twelve families had been selected for the survey, thanks to a local association that selected the group of families to be interviewed. These households will be the target group of a pilot scheme to supply electricity through off-grid systems.

The average household size, of the target families surveyed, is 7 members with an equal presence of male and female. A household unit is considered to be composed of wife, husband, children and any other relatives or dependants residing within the household and eating from the same kitchen on a daily basis. All the household members, except children, spend all the day in the field, from the morning till the evening, and carry out domestic activities early in the morning or late in the evening.

The principal energy services utilized by households residing in rural areas in DCs can be categorized into lighting, power for mobile phone recharging, other media and information technologies such as radio and television, cooking and heating.

For the developed model only electricity usage is considered, cooking and water heating are ruled out because the peculiar treatment for electricity and the comfortable climatic conditions that make unnecessary a domestic space heating.

In this work 11 appliances are considered, based on local surveys and the most recurrent devices used in residential India, as emerged by Ruijven [79]:

- Fan
- Air Cooler
- Air Conditioner
- Refrigerator
- Washing Machine
- Radio
- Television (TV)
- Personal computer (PC)
- Electric Iron
- Mobile phone
- Electric bulbs

3.2 A bottom up approach for local projection of energy demand

This scenario adapts and applies the REMG model, developed by van Ruijven et al. [79], for projecting the household electricity needs to the local case study of Katgaon village. Specifically, the main correlations are derived from van Ruijven model that are computed in a MATLAB code which projects the ownership of the electrical appliances of each Indian household considered for the period of the present planning project, from 2014 to 2034. Then the code is coupled with the model developed by Mandelli et al. in [80] for generating daily electricity load profiles.

A diagram of the model is shown in Figure 3.2.1.

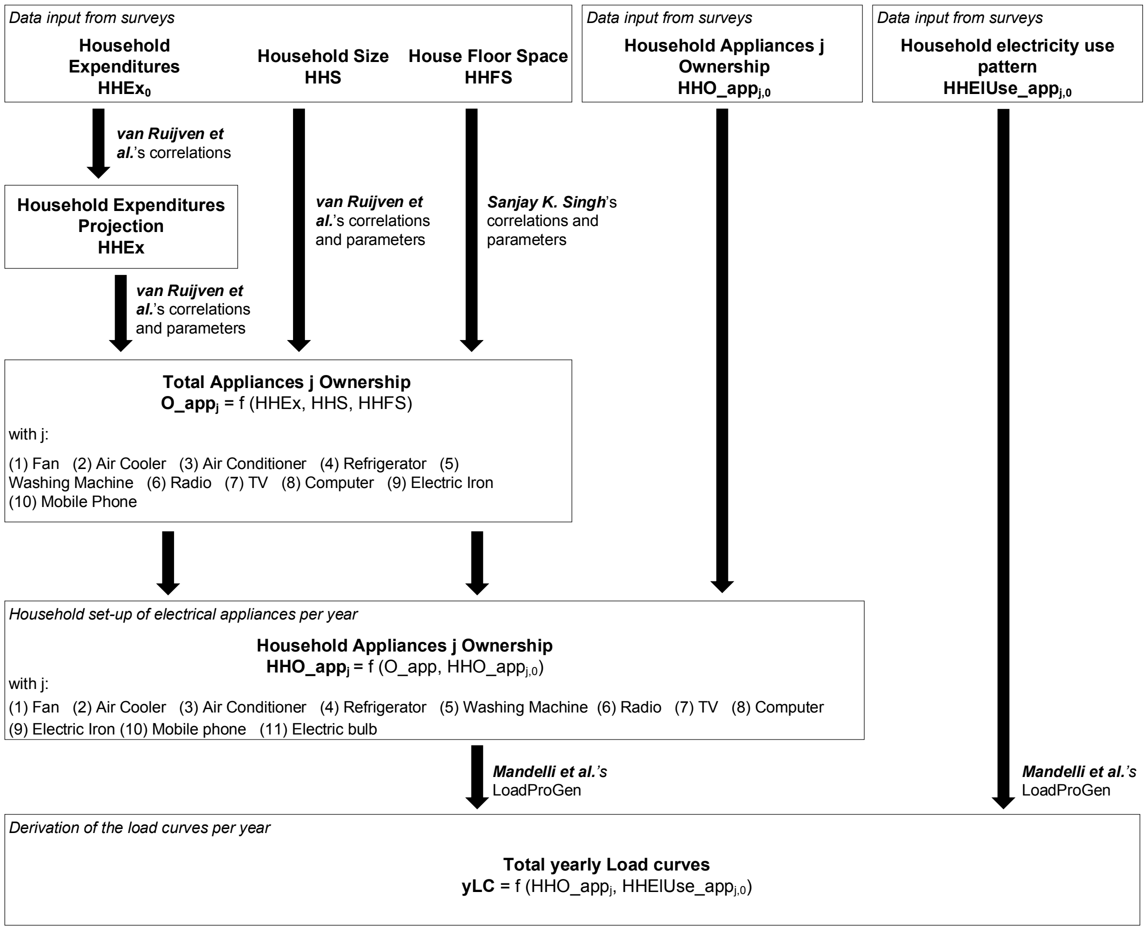

Figure 3.2.1 - Outline of the residential energy use model

The implementation of the following code is an achievement of UNESCO Chair in energy for Sustainable Development research group at Politecnico di Milano – Department of Energy.

3.2.1 Model formulation

The 12 considered households are clustered in quintiles and for every group an average value of *household expenditures* per capita per year at time 0 ($HHEx_0$) is associated. Through the local surveys, data regarding the *house floor space* (*HHFS*), and *household size* (*HHS*) are collected and estimated for each household of the five quintiles. *HHS* represents the number of components per household. The 12 families are then allocated in the proper quintile as it is shown in Table 3.2.1.

	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

Table 3.2.1 - Households belonging to the five quintiles according to the expenditures per capita per year ($HHEx_0$) and house floor space (HHFS)

The future projections of household expenditure along the 20-years planning horizon are based on correlations and considerations of Ruijven [79]. In general, household size decreases with increasing income level but since it impacts only on the projections of the use of mobile phones, in the first stage of this approach the *HHS* is assumed to be constant along the planning scenario. The same hypothesis is done for the value of *HHFS*; people do not vary the layout of their houses.

The next step is to predict year-by-year the diffusion of the total number owns by the families and to calculate the distribution of el. appliances among each households quintile. It has been employed the correlations used by Ruijven and the model defined by S.K. Singh [81]. The type of appliances listed above, is based on local surveys and by the end-use functions and clusters considered by van Ruijven et al. For fans, air coolers, air conditioners, refrigerators, washing machine, radios, TV, PC and electric bulbs the total number of each aplliances own by the population every years is simulated with the mathematical description of V. Letschert and M. McNeil [82] through a Gompertz-curve:

$$O\_app_j = \alpha_j \cdot EXP\left\{ -\beta_j \cdot EXP\left(\frac{-\gamma_j}{1000} \right) \cdot HHEx \right\} \tag{1}$$

with O_app_j the percentage of households per quintile who own appliance j; $HHEx$ are the household expenditures per capita per quintile; the parameter α_j is the upper asymptote of the curve which depends on the type of appliances j, historical Indian ownership values, and the $HHFS$ (in case of fan); parameters β_j and γ_j are shape-parameters which are estimated by non-linear regression using historical data for each appliance j

To simulate the ownership of mobile phones among the entire population at year t S.K. Singh's Gompertz-curve is employed [81]:

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

with $\alpha_{\text{mobile phone}}$, $\beta_{\text{mobile phone}}$ and $\gamma_{\text{mobile phone}}$ equal respectively to 120, 0.1639 and 16.4, which are estimated by non-linear regression using historical data [79], [83].

After that, as shown in Figure 3.2.1, the model allocates the forecasted diffusion of appliances among the 12 households (HHO_app_j) is evaluated. Information about the electrical appliances they actually own ($HHO\_app_{j,0}$) and their profile of use have been collected on field. With N_app_j it is indicated the amount of device j that a household will own throughout the 20-years based scenario. For the group of nine appliances previously mentioned, devices are randomly allocated among the households of each quintiles based on the values of O_app_j. The allocation implemented in MATLAB is always randomly assigned but it follows some logic conditions:

a. it starts at years t once the forecasted percentage O_app_j, of households who own appliance j at year t becomes higher than the real percentage of people who own j at the beginning of the scenario (*viz.* the percentage of people who own j during the surveys);
b. the MATLAB function allocates the appliance j to a household randomly selected in among those with the least quantity of j in considered quintile;
c. households who already own an air cooler (j=2) at year t are not considered for the allocation of air conditioners (j=3), and vice versa.

These constraints do not transform the random-logic used in a particular and defined approach for the forecast, but they are introduced to avoid big and not-justified inequalities within the quintiles and overestimation of the consumption due to a double accounting of the appliance's ownership.

Since mobile phone is considered a basic commodity even in DCs it is allocates without differences between the quintiles. Mobile phones are randomly allocated among the components of all the 12 households each year, based on the forecasted yearly value of $O\_app_{mobile\ phone}$. The allocation of mobile phones within each household is subjected to the following constraint:

$$N\_app_{\text{mobile phones}} \leq \alpha_{\text{mobile phone}} \cdot \frac{HHS}{100}$$

with $\alpha_{\text{mobile phone}}$ the saturation level of function , which represents the maximum number of mobile phones per 100 inhabitants owned by Indians in the future [81]; *HHS* is the number of people for households.

Finally, the diffusion of electric bulbs (*j*=11) for lighting is not calculated with equation (1), but it is based on the following hypothesis:

i. households who already own electric bulbs at the beginning ($t = 0$) are not expected to own more lighting devices in the years. This hypothesis is based on the fact we did not estimate a significant increase of the *household floor space* ($HHFS$) during the 20-years scenario;
ii. after the electrification, at year $t = 1$, the first commodity that people is willing to purchase is a device for lighting the house;
iii. the minimum number of electric bulbs that are allocated at year $t = 0$ among the households is defined for each quintile as follows:
    a) the household who owns the lowest and not-null number of lighting devices set the minimum level of ownership of bulbs for the quintile;
    b) if every household in the quintile does not own any lighting device, we allocated 1 electric bulb per household – based on local surveys, this is the most typical situation of the poorest families.

Figure 3.2.2 represents some of the forecasted amount of appliances for a household of the fifth quintile (Q5) towards the 20-years scenario:

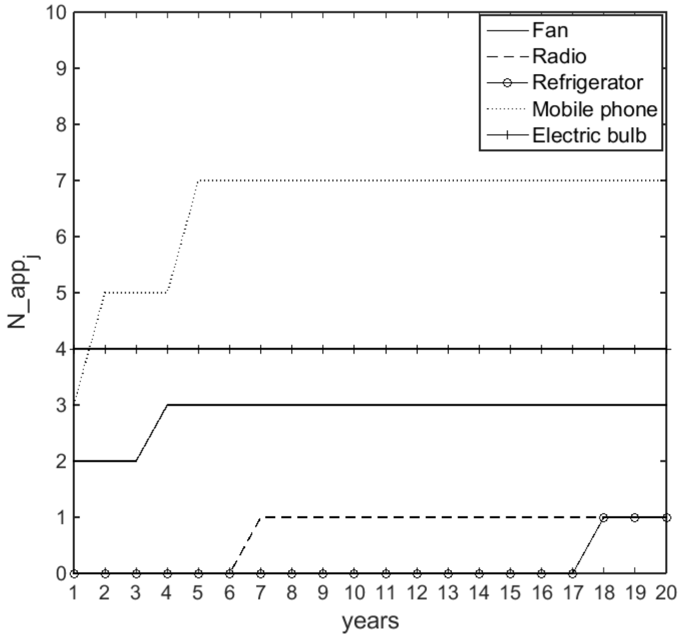

Figure 3.2.2 - Ownership of fan, radio, refrigerator, mobile phone and electric bulbs for a household of the fifth quintile over the years

3.2.2 Load curves

As shown in Figure 3.2.1 the next step is to derive the daily load curve for every year of the planning period, which is a function of the just achieved HHO_app_j and the surveyed value of electricity use for each appliance for the 12 families. Load demand profile is a required and essential input when modelling off-grid power systems with renewable, not fully predictable energy sources and storage components in the context of rural electrification. Demand must be met with local resources and an assessment that comes from a process that considers livelihood need and thus energy needs. Usually analyses of low-income villages are limited to aggregate daily consumption of energy; as it has been demonstrated in Chapter 2, the majority of demand analysis as an input for the energy planning, do not disaggregate energy-consuming activities according to the time of day-the so-called "load curve" or energy demand "profile".

In the review developed, case studies that take into consideration the evaluation of a daily, monthly or hourly load profiles for off-grid systems can lack of reasonable justification of consumption data. [83], [43] estimate electric loads without a clear motivation or explanations of their origins, [13], [34], [40], [55] adapt the load from profiles that come from similar contexts and [84], [85], [86], [37] introduce some assumption on the functioning periods or load factors.

Mandelli et al. [80] through a brief literature overview of user's electric consumptions modelling, highlight the problems regarding specific approaches for daily load profile for rural consumers and develop a mathematical procedure based on microscopic data such as electrical devices, energy use pattern for different users' classes to formulate load profiles. The bottom-up approach is formalized in the software *LoadProGen* (Load Profile Generator) implemented in MATLAB. For a detail description of the input data requires, operational elements and algorithm implemented it is referred the readers to the article [80]. In the next lines a summary of input data required and results obtained are presented.

In order to run *LoadProGen* properly, information from local surveys and the results of the household appliances ownership derived in the previous sub-section 3.2.1are following listed:

- 12 user class, corresponding to the 12 households
- N_app_i is the number of appliances i owned by each user class along the planning horizon, derived sub-section 3.2.1
- nominal power rate P_{ij} of appliance i within class j is derived from Murthy et al. [87]
- the overall time each appliance i within class j is on during a day (h_{ij}) is derived from local surveys and Murthy et al. [87]; any variation of the h_{ij} value along the 20-years scenario is supposed
- based on the local information regarding the appliances usage, the functioning windows ($w_{F,ij}$) and the minimum continuous functioning time once appliance ij is on (d_{ij}) are estimated
- the random variation of functioning time appliance ij (Rh_{ij}) and the random variation of functioning window appliance ij (Rw_{ij}) is equal to 5% to take into account the uncertainties related to h_{ij} and w_{ij}.

LoadProGen is run in order to generate p possible daily load curves for each year of our scenario. 250 load curves are generated for every year. Since local surveys did not point out any variations in the daily pattern of appliances usage, each day is supposed to be characterized by the same daily load curve for the year. Figure 3.2.3 and Figure 3.2.4 report respectively the results for one of the 250 generated daily load curves for the first and the twentieth year of our scenario.

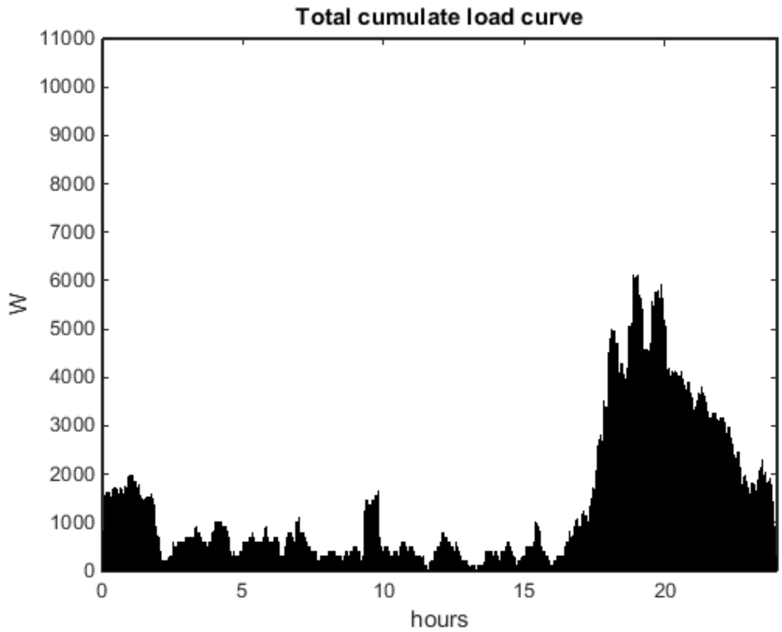

Figure 3.2.3 - Results of one of the 250 daily curves generated for the 1st year of the scenario

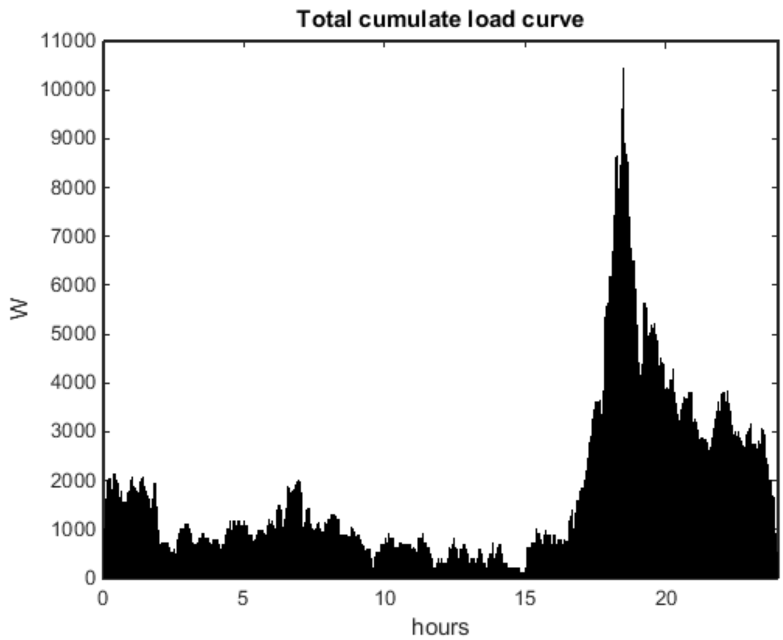

Figure 3.2.4 - One of the 250 daily load curves generated for the 20th year of the scenario

3.2.3 Results

Results are discussed in two segments: the first one analyses the outcomes of the model implemented to forecast the ownership of appliances among families, the second one discusses the trend of electricity use over the years, obtained from load curves.

A constant value for electric bulbs is mainly due to consider the value of *house floor space* (*HHFS*) constant along the years. With the increasing number of families, expenditures households do not buy lighting but fans for refreshing or radio and mobile phones for communication. Over the years the commodity that mainly increases, for the fifth quintile, is the mobile phone. The hypothesis to maintain the constant value of *HHS* does not prevent the growth of these appliances. In Figure 3.2.5 is shown the change over years of the 11 appliances owned by the 12 families in the village.

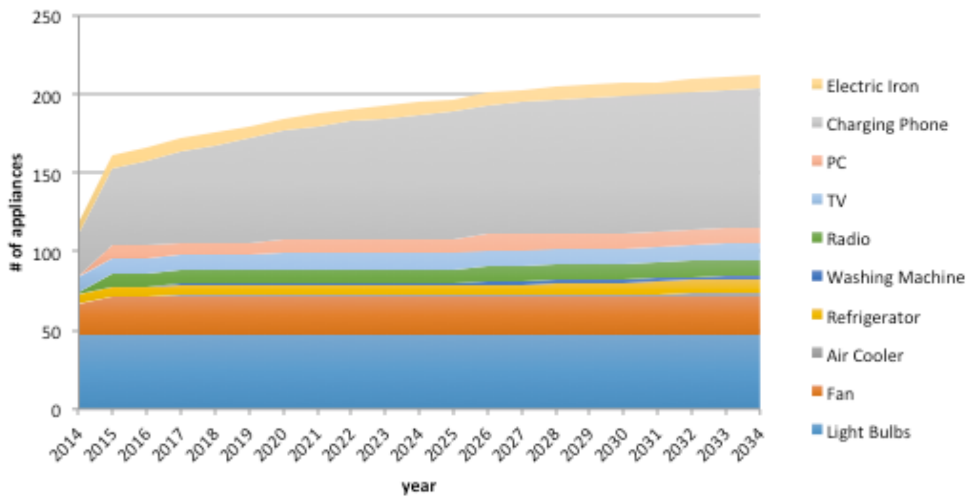

Figure 3.2.5 - Number of appliances belonging to the 12 households for each year of the energy planning

As shown in Figure 3.2.3 and Figure 3.2.4 the model evaluates 250 daily load curves with a time-step of one hour, equal for every day of the year; 250*20 curves are hence calculated. The objective for the next Chapter is to generate a robust energy plan for Katgaon village for the next 20-years, using a value of kWh/y for every year. So it is needed a single value of electric consumption per day: this is done calculating an average value for every hour of the representative day of the year. Figure 3.2.6 and Figure 3.2.7 show the trend of the mean of the 250 daily load curves in Watts, obtained by *LoadProGen* for the year 2014 and 2034 respectively.

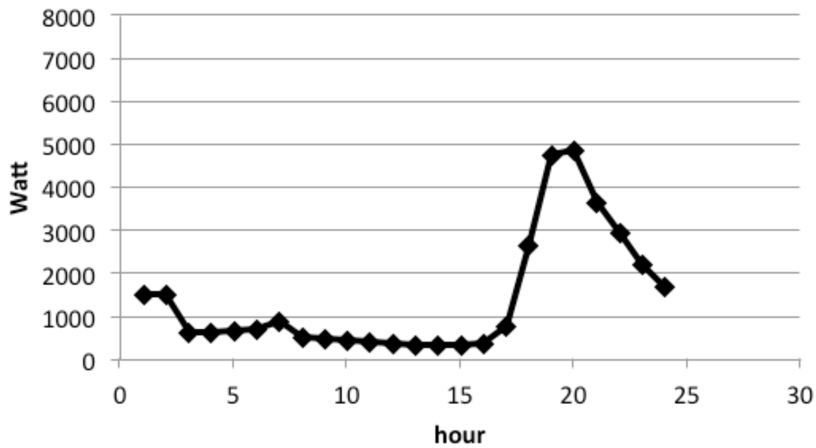

Figure 3.2.6 - Mean daily load curve for the 1st year for Katgaon village

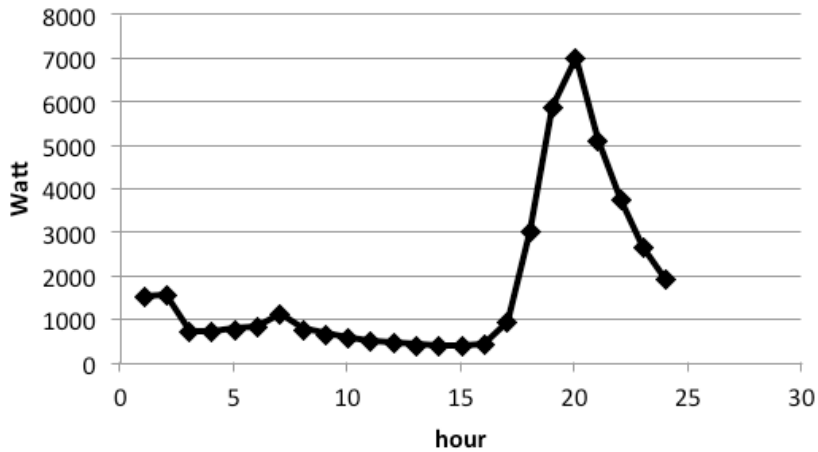

Figure 3.2.7 - Mean daily load curve for the 20th year for Katgaon village

An interesting comparison is shown in Figure 3.2.8. It is represented the daily power output for the reference day of the first, third and last year of the planning for the selected families in Katgaon. It can be seen that the ratio of consumption between the first and last year is characterised by a high difference in the evening. This increase has to be accounted during the evaluation of the peak demand and especially for the sizing of energy system. The ratio between daily consumption in 2034 and 2016 is lower than the one between 2034 and 2014, but the sizing has to be able to supply the worst peak demand from the beginning of the energy planning. Thus it is important to forecast the energy demand for the entire lifetime of the project.

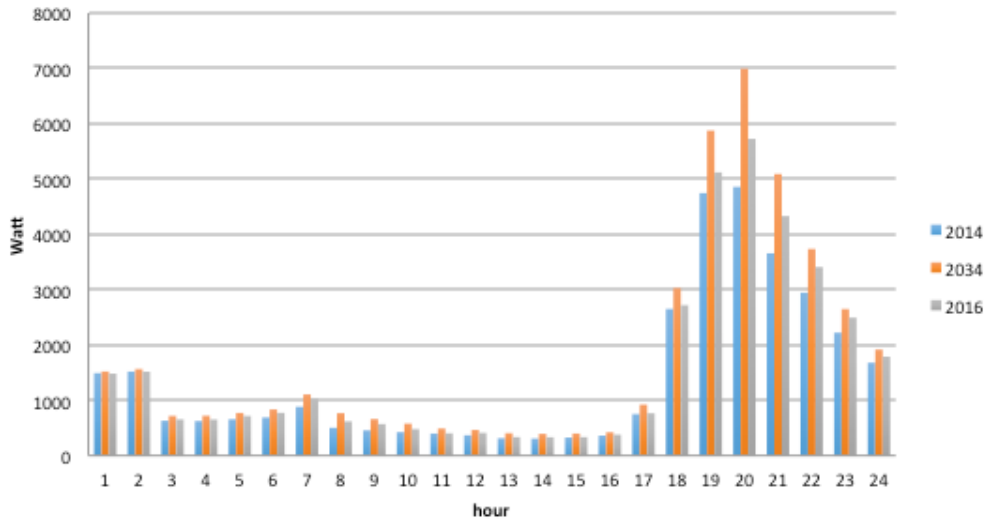

Figure 3.2.8 - Daily electric consumption [W] of the 12 households in Katgaon for 1st, 3rd and 21st year of the energy planning

The final result used as input for the energy planning model is shown in Figure 3.2.9. It represents the residential electricity consumption (kWh/y) for each year of the energy planning for Katgaon. It has been calculated by multiplying the output value of mean daily consumption and the number of days in a year since for each year it has been assumed the same consumption without difference in season or between week days and week end, as previously explained.

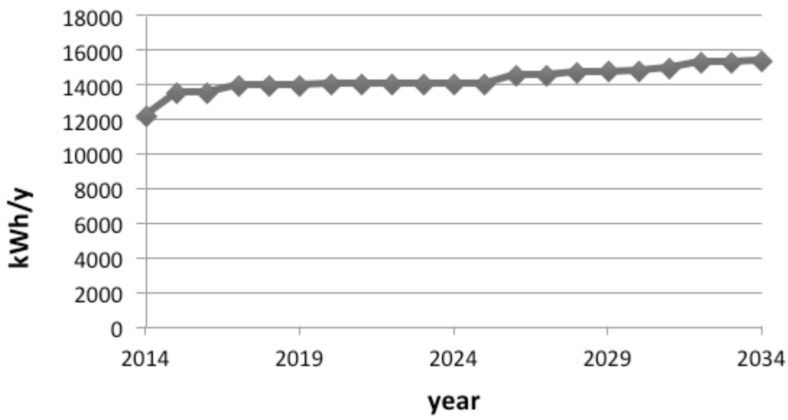

Figure 3.2.9 - Final electricity demand for the whole village of Katgaon (kWh/y) for each year of planning

3.2.4 Strength and weakness

Bottom-up approaches are the most suitable in the rural contexts. Other authors have published studies about the application of this method to analyse electric consumption and to forecast demand in their planning. The strengths of the REMG model with the *LoadProGen* software can be found comparing it with the features of end-use approaches used by the case studies of the present review.

Howells et al. [88] include load curves for modelling electric appliances. The authors use the conditional demand analysis (CDA) method to face the problem of different demand profile from different electric appliances supplying the same energy service. For example, if demand for the cooking services is growing it could be happened that the electrical load profile of the electric stove remains constant, and especially it could be happened that load profile of a microwave is different from the one of electric stove, even if they belong to the same cooking service. Moreover, survey of energy services can lead to a load curve that is different from the load curve that is actually experienced when the local area is later electrified. CDA can result a method that “drives” consumption to a default trend. Once this result is obtained, the amount of energy used per hour, by appliance of the same energy services, differs according to the efficiency of the appliance being used. The logic used in Howell’s work does not divided appliances by energy services but it values the quantity of energy on the number of commodities a household possesses. Moreover, Howells et al., once built the daily load curve with a resolution of six 4-h time-slices, forecast them with the support of five scenarios that are different according to the level of electrification but it is assumed a growth of 2% per year for all energy services. The advantage of the model here developed is that it does not use a policy of “control” of the demand, but with a random function (just making sure of the non-divergence of a specific appliance for a household) distributes the commodities through the population.

Shen [89] sizes a solar array and battery system at minimum cost, based on the energy efficiency model for a typical house in remote areas in Malaysia. The users’ electric consumptions relay on a daily load profiles that remains the same over the year. For the given time-step of an hour, an average constant power load defines the daily profile. 7 loads are considered together with the total usage in a day (h) and the respective power. Only one type of family is taken into consideration without any other level of disaggregation and no information is specified about the modality of distribution of the time usage in a day.

Looking at bottom-up models for residential demand, Debnath et al. [90] combine four scenario of four variables: population, GDP electrification index and public energy conservation index and access to grid electricity. With the combination of these variables, 256 different pathways are produced then grouped in a highest, lowest and optimal energy demand pathways for rural households in Bangladesh. The electricity demand is calculated as a function of access to grid electricity, number of rural household, public energy conservation factor, GDP electrification index that represents the "causality between energy and GDP", operation hours of an appliances, number of appliance and rated power consumption of an appliance. The first inconsistency that can be noted is the presence of a factor typically used for developed country: GDP. In the model implemented in my work, no macro-economic variables are used to forecast the growth of consumption; the value of expenditure of the villagers in Katgaon describes the energy demand for DCs in a more adequately manner [74]. The value of household size in 2050 in Bangladesh is assumed to be the same of the household size of Malaysia in 2010 because Malaysia is a Muslim country with similar sociocultural aspects of Bangladesh; thus it is used an analogy assumption.

The weaknesses of the model are essentially due to hypothesis consider and the overlooked factors. In general, the decrease of household size occurs with a higher income level [79]. From the trend of UN-Habit [91] rural population in India is estimated to change with a rate of +0.4% from 2000 to 2030 and the total number of households increases with an annual rate of change of +2.28%, +1.85% and +1.14% respectively in the years 2000-2010, 2010-2020 and 2020-2030. Thus it can be stated the number of households must be considered growing with smaller percentages over years. This can influence the consumption for a rural village and future works should be considered this value in the model.

Among the variables not considered that could influence the electric demand are: the possible connection of a national grid and the cooking energy service that can be characterized by electric stoves for high-income level families in future years The first lack is not a problem in the immediate future if off-grid systems are not expected to be connected to the main grid; as IEA states about 60% of the additional electricity generation requested to provide universal access to energy, is expected to be generated through off-grid systems [92]. About electricity absorbed by cooking sector, if progresses are expected in the rate of electrification, only minor changes are foreseen in terms of access to modern fuels for cooking; still 2.5 billion people are expected to rely on unclean biomass based cooking facilities in 2030 [2]. Moreover, possible solutions may consist in promoting a shift towards

LPG or most likely in ICS fed with biomass. Therefore the final result is not expected to vary a lot, since electric cook stoves are not expected to be largely adopted in the future as a cooking device.

Other factors can be entered in the model such as the cost of energy, preference for the end-use service, price of the appliances, availability of appliances [74], but the percentage of error for the estimation of future consumption increases with the unreliability of data.

3.3 Different scenarios of demand growth

In the next sub-sections, I will present the two more used approaches to evaluate the demand as a result of the analysis carried out in Chapter 2. The characteristics of the three scenarios are presented in the Table 3.3.1.

Scenario	Source data for the 1st year	Method of forecasting
1st	Local surveys	Bottom-up
2nd	Local surveys	Constant
3rd	Local surveys	Time-series extrapolation

Table 3.3.1 - Method of forecasting and source of data for the first year of energy planning by scenario

As it will be demonstrated in Chapter 4, different methods of considering change in electric requirement lead to different results in, for example, the sizing of the system.

3.3.1 Scenario II: Constant demand

Looking at the analysis carried out in Chapter 2 it is evident that less than half case studies consider the change in demand for a long period planning. For example Arun et al. [42] develop an optimum photovoltaic-battery system for the city of Ajaccio for a 20 years planning horizon with a constant load of 42 W prevailing over the entire day. Jana et al. [93] find the best allocation patter for domestic lighting for Narayangarh Block in India for 20 years life-span; daily energy consumption for domestic lighting is expressed by a single value for the four fuel sources without taking into consideration the variation in time.

The common and simplistic approach to consider the electric consumption unchanged in time is here used to highlight the certain error that an energy planning study can get in the final sizing of the energy system. The value used in this second scenario is the kWh/y at the first year obtained with the model described in sub-section 3.2: 12210 kWh/y in 2014, which remain the same till 2034, with the same daily load curve.

3.3.2 Scenario III: Time-based interpolation for demand forecasting

The third and last scenario chosen consists of a polynomial interpolation created through the known data of electric power consumption (kWh per capita) by the World Bank Data for the Indian country. The resulting polynomial curve is then extended beyond the end of the known data in order to obtain electric consumption for the village of Katgaon from 2014 to 2034. This approach is selected because the forecast is based on a constant percentage of growth, as described after in this sub-section. Assumed function method consists, as explained in sub-section 2.2.1, in a constant value of growth inferred by historical trend, sustainability or policy decisions. For example, Weisser [44] estimates a constant growth of 8% based on past trajectories of electricity peak demand and annual consumption. Energy consumption is driven by the rate of birth that is a control measure prescribed by a specific policy mode, in Alam et al. [52].

Once data from 1971 to 2013 were interpolated with the MATLAB function *polyfit* of degree n=3, values of consumption were extrapolated through the MATLAB function *polyval* that returns the values of a polynomial of degree *n* evaluated at variable *x*, time in years in this case – this is the reason of the term *time*-based interpolation. The input argument p is a vector of length n+1 whose elements are the coefficients in descending powers of the polynomial evaluated with *polyfit*. In Figure 3.3.1 is shown the kWh/per capita consumption according to WB data (in blue) and the resulting kWh/per capita interpolated (in orange).

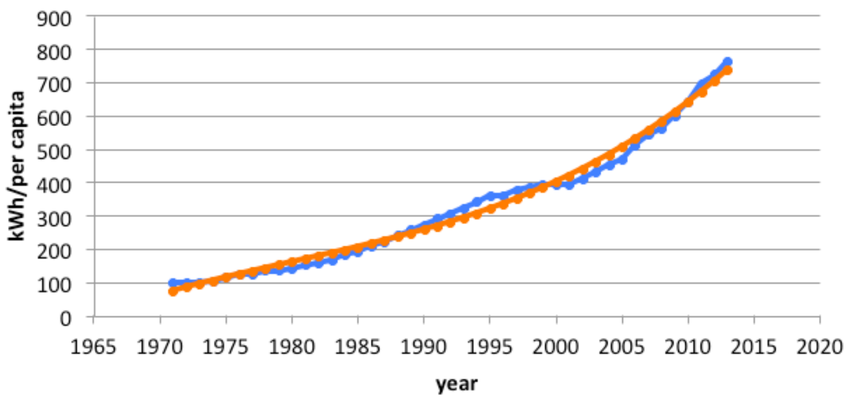

Figure 3.3.1 - Electric consumption in kWh/per capita from WB data (blue) and MATLAB extrapolation in kWh/per capita (orange) from 1971 to 2013 in India

Once the interpolation has been computed, energy consumption per capita data by WB database is evaluated for the 21 years of planning, hence from 2014 to 2034. The rate of increase is then calculated to obtain an average value of +4.5% for each year. Successively this percentage is applied to the daily electric consumption estimated for the year 2014 by data surveyed for the daily consumption of the I Scenario, as formulated in the following equation.

$$DailyDemand_{2015,III\_Scenario} = DailyDemand_{2014,I\_Scenario} * (1 + {}^{4.5}/_{100})$$

In Figure 3.3.2 it is drawn the trend obtained over time for the III Scenario.

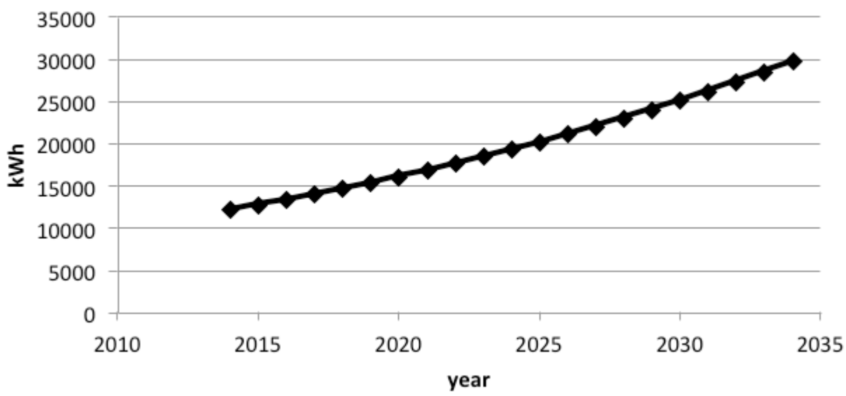

Figure 3.3.2 – Electric consumption in kWh/per capita for the planning horizon of Katgaon

The same load curve obtained by *LoadProGen* for I Scenario at year 2014 results to be equal for the same year for III Scenario. For the year 2015, the resulting load curve for III Scenario has the same trend over the 24 hours of the day of the I Scenario, but modifying by the constant percentage obtained with the previous described interpolation, Figure 3.3.3.

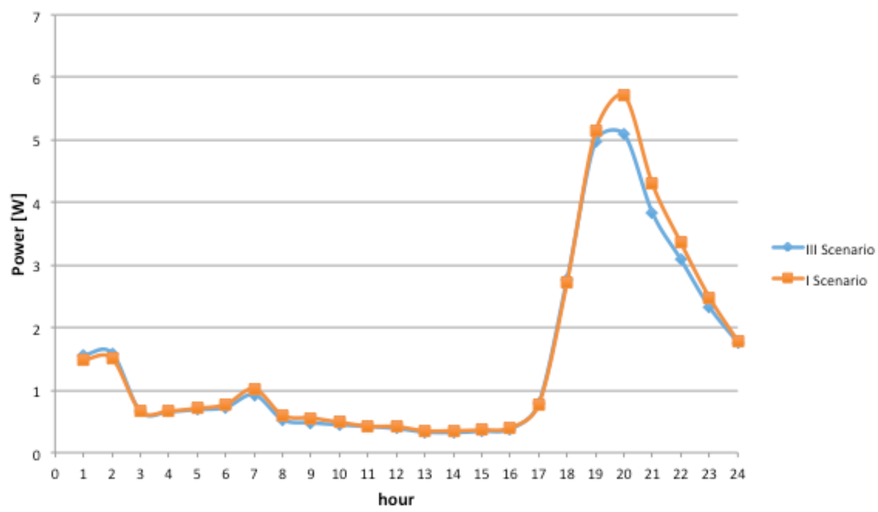

Figure 3.3.3 - Daily load profile per each hour of the day for the tear 2015 for the I and III Scenario

As it can be seen for the year 2015 the interpolation in time results in a low increase of consumption for III Scenario in respect to I Scenario. This result will be not the same for the future years.

3.3.3 Comparison of the three scenarios

In Figure 3.3.4 it is represented the percentage of the difference in accounting the demand growth by means of the model developed in sub-section 3.3.1, I scenario, and a constant demand of 33452.12 Wh/day for the entire village, II scenario. The deviation is the ratio between the difference of the Wh/day of I scenario and the constant consumption of the II scenario, with the value of II scenario for every year. Thus the consumption for the 2015 for I scenario is higher than the one of the II of 10.58%, and so on.

Year	Deviation of I respect to II	Deviation of III respect to II
2014	0.00%	0.00%
2015	10.58%	4.79%
2016	10.69%	9.80%
2017	14.46%	15.02%
2018	14.45%	20.47%
2019	14.61%	26.16%
2020	14.95%	32.08%
2021	15.07%	38.25%
2022	15.13%	44.68%
2023	15.21%	51.36%
2024	15.23%	58.30%
2025	15.27%	65.51%
2026	19.27%	73.00%
2027	19.34%	80.77%
2028	20.78%	88.83%
2029	20.80%	97.18%
2030	20.88%	105.84%
2031	22.34%	114.80%
2032	24.96%	124.07%
2033	25.55%	133.67%
2034	25.62%	143.59%

Figure 3.3.4 – Deviation of daily electric consumption for Katgaon village over the planning horizon, between the I and II Scenario (second column) and III and II Scenario (third column)

The same evaluation is done between III and II Scenario. The deviation is always calculated as the ratio between the differences of the two scenarios consumption and the value of the II scenario, year-by-year.

The next Chapter will show how the application of these three different scenarios of energy demand will impact on the energy planning of Katgaon community.

4 Effect of forecast demand through local planning model

The previous chapter provided the input of electricity demand of three different approaches, describing their methodology of implementation and highlighting the critical issues that arise comparing them. In particular, considering demand forecasting methods analysed in sub-section 2.2 and the suitable features for rural areas in DCs achieved by literature in 2.3, three scenarios are developed. The present chapter will address the impact of the three approaches on the energy planning of Katgaon village presented in the sub-section 3.1. The study will be supported by a linear optimisation model of energy planning, which will be used to perform the energy system selected on different demand input along the planning horizon. Model results will be subsequently discussed to underline economic and sizing differences between the bottom-up, constant and assumed function approach.

4.1 The Open Source Energy Modeling System-OSeMOSYS

For the analysis, an energy model was created using the Open Source Energy Modeling System (OSeMOSYS). OSeMOSYS is a linear optimization model with a medium- to long-term time horizon. It is build on an open source programming language called GNU MathProg and solver (GLPK, GNU Linear Programming Kit). Other different programming language can be employed to resolve the algebraic formulation of the code.

OSeMOSYS has been chosen, instead of other optimisation tools such as Homer, for the possibility to enter data, predicted over years. In OSeMOSYS parameters, such as demand, costs and efficiencies have to be calculated along the planning horizon of the case study. The model elaborates the capacity needed to meet the variable demand each year according energy balances equations, and then estimates the total discounted costs at the first year of planning. Differently, Homer requires as demand input value the annual average daily load, and combines capital, maintenance and fuel costs to find the total net present cost for the energy system. The same hourly load profiles synthesized by Homer are maintained constant for the project lifetime. Moreover, OSeMOSYS allows accessing the code making the addition of new up-date functionality easy to implement. For example, it allows the definition of new technologies and fuels and a technology can be defined to consume and produce any combination of fuels. Furthermore, at the end of the code summary results are printed in a selected comma separated values file, with the possibility to add the printing of required variables for a potential post-processing.

In addition OSeMOSYS does not require a license fee, in fact it does not use proprietary software or commercial programming languages and solvers. This is particularly useful in DCs where research funds are few and human capacity employed in energy research and energy modelling is limited.

4.1.1 Introduction to OSeMOSYS structure

A conceptual description of the model elements is discussed in this section. In order to have a general idea of the main features it will be explain broadly how OSeMOSYS is structured, underling the key factors to understand the variables of the case study analysed.

The aim of this chapter is not to deepen the algebraic formulation and the model's implementation; it is used as a tool to obtain the size of the energy system at minimum cost for three demand scenarios. Thus a reiterative description of the seven functional component "blocks" in which the model is disaggregated is shown in Table 4.1.1, based on Howells et al. [94].

Block	Description of the block
1) Objective	It minimizes the net present value cost (NPV) of an energy system for a given demand and a discount rate.
2) Costs	Costs include operating, capital, eventually emission production penalties and salvage value for each technology in each year and for each region modelled. - operating costs is the sum of **FixedCost**[r,t,y] and **VariableCost**[r,t,m,y] - the **CapitalCost**[r,t,y] includes the value of the investment for new capacity installed
3) Storage	**CapitalCostStorage**[s,y,r] is the investment costs of storage additions, defined per unit of storage capacity

4) Capacity Adequacy

Each technology has to meet the energy use or production requirements at a time-slice level and at an annual level. Capacity Adequacy ensures that there is adequate capacity for each technology.

- Capacity Adequacy "A" accounts for the total capacity available as a sum of the accumulated new capacity and residual capacity of the same technology left over the model period. The total rate of activity is then determined for each technology, mode of operation and time-slice. The total rate of activity must be smaller than the total capacity available de-rated by the **CapacityFactor**[r,t,l,y]
- Capacity Adequacy "B" states that the annual production (or use) activity for each technologies for each time-slice should be less the total capacity available de-rated by **CapacityFactor**[r,t,l,y] and the **AvailabilityFactor**[r,t,y]

5) Energy Balance

Energy Balance makes sure that the production, use and demand for fuel and energy services are feasible at each time-slice and annually.

- Energy balance "A" considers the rate of fuel production and use (obtained by multiplying the rate of activity to **OutputActivityRatio**[r,t,f,m,y] and **InputActivityRatio**[r,t,f,m,y] respectively) for each mode of operation. Then the total production is estimated by multiplying the rate of fuel production for the length of the time-slice. Finally the total production of each fuel should be larger than or equal to its demand an use
- Energy balance "B" considers the balance between the annual production and annual use for each fuel considering also the accumulated annual demand

6) Constraints

For each technology, year and region modelled constraints are given for:

- total capacity
- new capacity investment
- annual activity
- model period activity
- a reserve margin allowed by the total capacity for each technology
- a reserve margin needed by the demand
- the production of renewable technologies
- the production of a particular fuel of a renewable technology

7) Emissions	Emissions account for the pollutants emit for each mode of operation of a technology

Table 4.1.1 - Description of the seven functional component blocks of the code

As it can be seen in Table 4.1.1, OSeMOSYS defines the parameters (highlighted in bold) that have to be entered by the analyst following the indexes inside the squared brackets. They are listed in Table 4.1.2 and represent the sets defined at the beginning of data file. Equations of the code are formulated for all combinations of all (or a selection of) the sets outlined below.

Indexes	Description
e	Emissions to be accounted for
t	Type of technology modelled. It is included any element of the energy system which generates a fuel (e.g. a wind turbine, diesel generator), converts one energy form into another (e.g. battery, fuel cell) or consumes fuel (e.g. LPG stoves, air conditioner)
f	Energy carriers (fuels) required in the model produced by a technology. Also demands for energy services are defined as fuels in OSeMOSYS (e.g. lighting, water heating needs)
y	Time coverage of the model
r	Country, region or village modelled
m	The number of mode of operation that a technology can have. Modes of operation are usually defined if a technology can use various input or output fuels. The "capacity" remains constant simply because the same piece of machinery produces both outputs.
l	"l" indicates the type of time-slice using to divide in time step the entire year
s	The storage set contains the storage facilities
ls	Type of Season. Fro example Summer, Winter and Intermediate
ld	It indicates in how many part is divided a week, named DayType. For example if ld=2 the week can divided in 1=week days and 2= week ends
lh	"lh" is called DailytimeBracket and indicates the number of brackets that the days is divided in, e.g. by hours or mornings, afternoons and evenings.

Table 4.1.2 - Brief explanation of all indexes used in the algebraic formulation, [95]

In sub-section 4.2 will be described the indexes used for the present case study.

The temporal resolution in OSeMOSYS is defined by consecutive years modelled, which are themselves split up into so called "time-slice". They have no inherent chronology: in [20] Nerini et al. divide the day in six groups of four hours and the year in three season. This results in a total of 18 (6 x 3) time-slices. One time-slice could represent all the first quarter (from 2:00 AM to 6:00 AM) of the winter days, another one the second quarter (from 6:00 AM to 10:00 AM) of the summer days.

Chronological information is required when modelling storage: the last three indexes in Table 4.1.2 are required only if storage will be used in the model and they need to be defined as numerical, consecutive values.

OSeMOSYS consists of a model file and a data file defined in text files. Using the Command Prompt the solver is called together with the model file, containing the equations and data file where input numbers are set.

4.1.2 The Reference Energy System under study

Given the functional 'blocks' described Table 4.1.1, a question arises: What sets of technologies should be used to feed electric loads? Which are the energy carriers that link technologies? So what should the 'reference energy system' (RES) look like? Energy carriers include energy vectors such as electricity, gasoline, coal, uranium or renewable source such as irradiation or wind. But also energy services as lighting, heating or transport. Technology can use and/or produce an energy carrier.

A RES is a simplified network representation of the fuels, technologies and transformations necessary for supplying energy to various forms of end-use activities. It physically described the energy flows in a system from resources to end-use both for industrialised countries at national level and DCs at regional level, as it is stated in [96]. An example of RES for DCs is implemented by Howells et al. in [88]. The paper reports the energy planning for a low-income rural village in Africa; six energy services were considered such as cooking with open fire, stove cooking, LPG ring, wood fire, wood stoves, electric stove and others as end-uses. This RES for the non-electrified community is characterised by biomass, import LPG, solar etc. energy supplies. Nerini et al. [20] elaborate a complex RES due to a complete consideration of the energy demand for the village of Suro Craic in Timor Leste, shown in Figure 4.1.1.

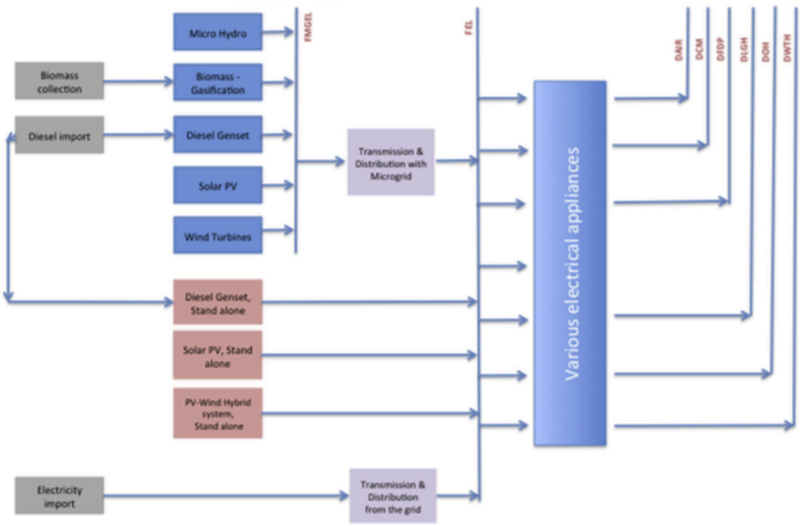

Figure 4.1.1 - The electrical reference energy system for the model of Suro Craic village, [20]

Nerini et al. research investigates the costs of reaching different levels of energy access for the provision of electricity to the rural population with three possible electrification options: stand alone solutions for single households, mini-grid technologies and connection to the national grid and import of electricity.

In Figure 4.1.2 the RES for Katgaon village is sketched: to the left are boxed the reservoir from which derive the input for the four technologies selected. Wind and solar energy are the renewable sources that feed wind turbines and photovoltaic panels. The dummy box is set as a technology in the data file, it is not a real part of the model. It is used as a fictitious tank from which the diesel generator can feed itself. Special attention needs to be done for the battery technology. The presence of a storage options is gaining importance thus renewable technologies are expanding especially in DCs, where gasoline transport is economically expensive due to a lack of distribution logistics and good roads. Moreover, electricity produced by carbon power station lacks of reliability due to low transmission efficiency and frequent outages. Katgaon village recorded several scheduled blackouts: for the domestic supply there are 16 hours of electricity per day. Prasad et al. [97] develop a new method of optimization of the size of a PV-wind system with battery backup for the site Popuhar in India. Shen [89] optimize the size of a solar photovoltaic system combined with batteries for a case study in Malaysia. The methodology to model storage is straightforward. Manuel Welsch in [98] describes in a detailed way how storage is modelled in OSeMOSYS. The implementation of storage characteristics accounts for several deficiencies. For battery storage system it is not accounted the loss of the efficiency with the increase of the number of charge and discharge cycles. In this case study the storage option is considered as a virtual battery: when the battery (BY), sets as a technology, charges itself and the electricity fills up the storage (BYS). Instead, when the battery is required to supply electricity the storage discharges to the charge the load. The ability of technology to switch between these two processes is determined by the number of ModesOfOperation. It is indexed by the letter "m". Modes of operation are usually defined if a technology can use various input or output fuels. In this case the type of fuel is always electricity but with m=1 BY works as a load and with m=2 as a technology that produces energy. The link between BY and BYS is identified by two parameters: **TechnologyToStorage**[r,t,s,m] links BY to BYS for charging the storage by assigning a value of 1. The storage is given in the columns and technology in the rows for each mode of operation. The example of how it is set for Katgaon model is shown below.

param	TechnologyToStorage	default	0:=
[R1,*,*,1] :	BYS	:=	
BY	1	;	

With the parameter **TechnologyFromStorage**[r,t,s,m] BY is linked to BYS facility for discharging the storage by assigning a value of 1.

param	TechnologyFRomStorage	default	0:=
[R1,*,*,2]:	BYS	:=	
BY	1	;	

To generate electricity, four different power options are available as it is illustrated in Table 4.1.3: diesel generator (DG), wind micro turbine (MW), solar photovoltaic panel (SPV) and battery storage (BY). These represent the technologies set in the data file. The only energy service considered is outlined in the right part of the figure as 'LOAD'. It represents the absorption of electric energy by domestic sector in Katgaon as evaluated in Chapter 3.

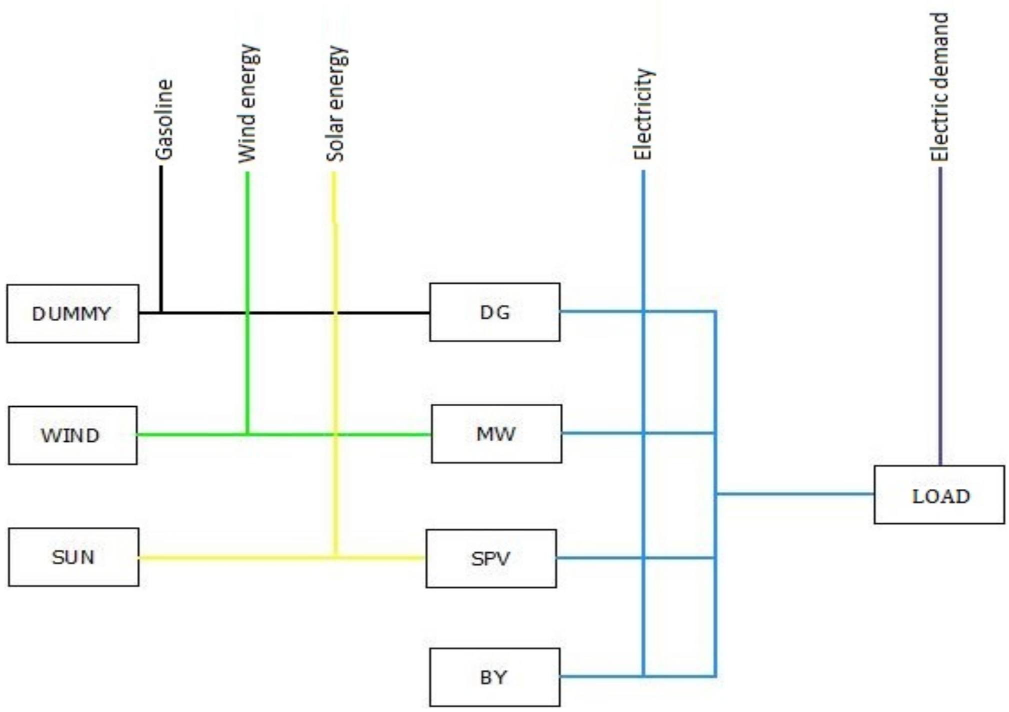

Figure 4.1.2 - The electrical reference energy system for the model

Electricity supply technologies	Fuel used
Diesel generator	Gasoline
PV generator	Solar
Micro wind turbine	Wind
Electricity storage technology	
Battery	Electricity

Table 4.1.3 - Energy supply technologies

The selected RES does not cover all the applicable solutions for the village, for example stand alone solutions or the comparison with the connection to the Indian grid and possible import of electricity. But it is used for the analysis and comparison of the cost estimation of supplying energy for the three Scenario described in Chapter 3, with a standard set of selected technologies.

The succeeding versions of OSeMOSYS, developed from the original code, can be found on the www.osemosys.org website. In the following sub-sections it is described the process of evaluation of the input parameters for the data file computed by the code version *OSeMOSYS_2013_05_10* available on the OSeMOSYS website [99].

4.2 Data input description

In this sub-section the values of parameters are described in the way they are estimated for the first year and how they are forecasted along the planning period of the model. Even if the focus of this thesis is not on a real implementation of the designed energy system for Katgaon, but rather on estimating the cost and the size of the capacity difference in setting different forecast demand, all input data have been chosen to be as representative as possible for the case study under consideration. This occurs through several internationally recognized data sets free available on the Internet and scientific literature dealing with economic evaluation of technologies for small villages in DCs. Information on single data source can be made available under request to the author.

4.2.1 Demand data input

The evaluation of the energy requirement for the village along years has been fully described in Chapter 3. Three different scenarios are set up according the parameters require in OSeMOSYS. Demands for energy carriers, such as electricity, is modelled as a *specified annual demand*, which has a specific demand profile during the year that must be satisfied instantly. The unit used for this model is kWh/y due to small requirements for the village. The parameter in which is included the demand is called **SpecifiedAnnualDemand**[r,f,y], it contains the total specified demand for the year. The parameter is entered as a matrix that can be specified for each fuel/energy service demand.

param	SpecifiedAnnualDemand	default	0:=		
[R1,*,*]:	2014	2015	2016	2017	2018
F1	12210.02	13502.19294	13515.6	13975.56	13003.77

The distribution by time-slice is included in the **SpecifiedDemandProfile**[r,f,l,y] parameter. It indicates the annual fraction of energy service or fuel demand that is required in each time slice. For each year these should sum up to one.

param	SpecifiedDemand Profile	default	0:=	
[R1,F1,*,*]	2014	2015	2016	2017
G0001	0.003785449	0.003405093	0.003395628	0.003292719
G0002	0.003854829	0.003454055	0.003476788	0.003393956
G0003	0.001598245	0.001528111	0.001500154	0.001518916
G0004	0.001585771	0.001526927	0.001495876	0.00153072

With R1 is specified the region of Katgaon with the first scenario input and F1 indicates the fuel electricity. In the matrix before unveiled values are presented for the earlier five years and with values only of the first scenario as an example.

A brief clarification about the meaning of time-slice is now outlined to avoid misunderstandings. For this study, it has been developed a load curves, with hourly resolution. Thus, it has been adopted 24-h time-slices for every day; every day of a month is always the same (*viz.* the electricity demand from 00:00 to 01:00 in January is the same for all the 31 days of the month). This results in 12 x 24 time-slices. According to this partition, the identification used for time-slices of the whole year is represented by the nomenclature *G0001*. It corresponds to the first hour of a day, thus from 00:00 to 01:00 of January. Therefore *G0002* is the second hour, from 01:00 to 02:00 of January. Time-slices are necessary in order to define the temporal resolution in OSeMOSYS. Each of them combines a fraction of the year with specific load characteristics. For example, the value for the first time-slice of the first year of planning, as reported above for the electric demand, is calculated as follow:

$$SpecifiedDemandProfile_{G0001\_2014} = \frac{MeanDailyLoadPower_{G0001\_2014} * 31}{SpecifiedAnnual\ Demand_{2014}}$$

where $MeanDailyLoadPower_{G0001\_2014}$ indicates the W for the first hour of the reference day of January for 2014.

4.2.2 Capacity factor of renewable technologies

Among the parameters that have to be entered in the data file, capacity factor needs a particular attention as it limits technology outputs by time-slice, and together with the availability factor, defines how much capacity is produced and is available to supply the electric load.

The **CapacityFactor**[r,t,l,y] is defined for each region, technology, time-slice and year. It converts annual capacity to the capacity available for each time-slice, i.e., the actual energy output vs. the potential energy output at the maximum capacity of a technology. Renewable technologies need the definition of a capacity factor for each time-slice because wind and solar irradiation (kWh/m^2) are available with variations in different times of the year. According to what has just been defined, capacity factor (CF) is formulated as follow:

$$CF_{time\_slice} = \frac{E_{REAL}|_{time\_slice}}{E_{MAX}}$$

where E_{REAL} is the actual energy produced by the technology, and E_{MAX} the maximum energy obtained if the technology would absorb all the source that can accept.

4.2.2.1 Solar PV

Data for the evaluation of the PV capacity factor are taken from [100]. The value of hourly total incident radiation on a tilted surface is calculated using the HDKR model that takes into account the actual value of the solar resource (the global solar radiation incident on a horizontal surface), the orientation of the PV array, the location on Earth's surface, the time of year and the time of the day, using the following formula [101] :

$$\bar{H}_T = (\bar{H}_b + \bar{H}_d A)\bar{R}_b + \bar{H}_{\rho_g}\left(\frac{1-cos\beta}{2}\right) + \bar{H}_d\left\{(1-A)\left(\frac{1+cos\beta}{2}\right)\left[1+sin^3\left(\frac{\beta}{2}\right)\right]\right\}$$

where $\bar{H}_T$ is the monthly total incident radiation on a tilted surface, $\bar{H}_b$ is the monthly mean daily beam radiation on horizontal surface, $\bar{H}_d$ is the monthly mean daily diffuse radiation, A is anisotropy index, which is the function of transmittance of the atmosphere for beam radiation, $\bar{R}_b$ is the ratio mean daily beam radiation on the tilted surface to that on a horizontal surface, $\bar{H}_{\rho_g}$ is the monthly mean daily radiation due to ground reflectance and β is the slope of PV array. It was used a slope value of 26° and an azimuth value of 0°. These values are taken from [100], based on the solar panels installed on the local hospital roof by Indian government. For the ground reflectance, it is set up a value of 25%, which is the standard value used for agricultural land. No tracking systems are installed for maintenance and economic reasons.

The output of the formula is the kW/m^2 for every hour of a year. In order to adapt the output to the time-slices of the model, the average incident solar radiation is calculated for the 24 hours of the reference day for every month of the year:

$$I_{ave_T\_ij} = \frac{1}{n}\sum_{k=1}^{n} h_{i,k}$$

with *i* is indicated the first hour of the day *k*, for all the *n* days of the month *j*. For example, if *i*=1, *j*=1 the incident solar radiation is calculated as the sum of the hours from 01:00 am to 02:00 am for each of the 31 days of January. Figure 4.2.1 shows the $I_{ave_{T\_ij}}$ in kW/m^2 with j=1 and i=1,…,24 .

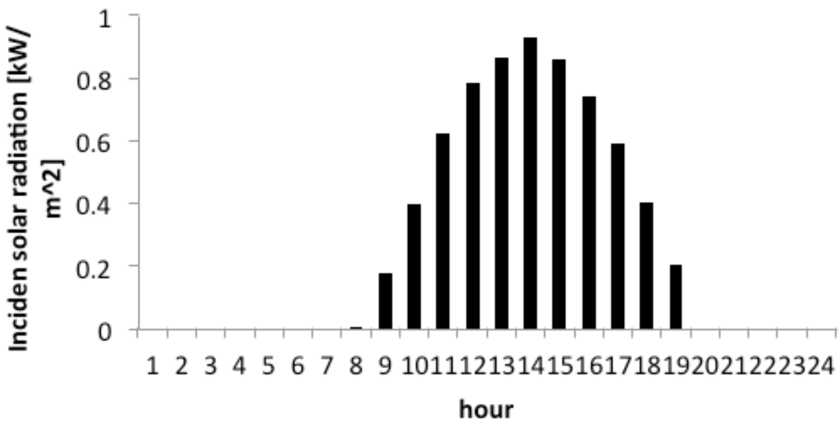

Figure 4.2.1 - The average incident solar irradiance [kW/m^2] for a typical day in January

Once energy source data are calculated the valuation of CF for the solar panels is developed. Based on the sizing equation below, it has been estimated the CF value for every hour of the year. The output is considered constant over the planning horizon of the energy planning as it is assumed that the solar irradiation is characterised by the same trend for future years and the same solar PV module is installed in the village.

The PV capacity factor is expressed through the following equation:

$$CF_{solar\_ij} = \frac{I_{ave_{T\_ij}}}{I_S}\left\{1 + \left[\left(\frac{\gamma}{100}\right)\left(\left(T_{ave_{cell\_ij}} + 273.15\right) - T_{amb_{STC}}\right)\right]\right\}\eta_{BOS}$$

where I_{ave_T} indicates the solar irradiance above defined, I_S is the irradiance at Standard Conditions, γ is the temperature coefficient of power, $T_{amb_{STC}}$ is the ambient temperature at Standard Conditions, η_{BOS} refers to the components and equipment that move DC energy produced by solar panels through the conversion system which in turn produces AC electricity and $T_{ave_{cell\_ij}}$ the average cell temperature for hour i and month j. The ambient temperature was given for every hour of the year, so the same formulation for $I_{ave_{T\_ij}}$ is used to obtain the average temperature for each time-slice. Once these values are evaluated $T_{ave_{cell\_ij}}$ is calculated as:

$$T_{ave_{cell\_ij}} = T_{amb\_ij} + \left[\left(\frac{I_{ave_{T_{ij}}}}{I_{NOCT}} \right) (NOCT - T_{NOCT}) \right]$$

The CF equation accounts for all the effects that decrease the potential energy output at the maximum capacity to the actual energy output for each time-slice. With η_{BOS} it is considered losses due to electricity transformation from DC to AC, with γ it is considered the fact that the power output of a PV array decreases with increasing panel temperature. In reality, the output of a PV array depends strongly and nonlinearly on the voltage to which it is exposed. The maximum power point (the voltage at which the power output is maximized) depends on the solar radiation and on the temperature. If the PV array is connected directly to a DC load or a battery bank, it will often be exposed to a voltage different from the maximum power point, and performance will suffer. A maximum power point tracker (MPPT) is a solid-state device placed between the PV array and the rest of the DC components of the system that decouples the array voltage from that of the rest of the system, and ensures that the array voltage is always equal to the maximum power point. By ignoring the effect of the voltage to which the PV array is exposed, it is effectively assumed that a maximum power point tracker is present in the system.

Table 4.2.1 lists all the technical data characterised the panel. The selection of this particular PV module is based on a web research of Indian companies that provide solar energy solutions and make available the data sheet of their products.

Standard irradiance I_S[kW/m^2]	1
Temperature coefficient of power γ [%/°C]	-0.415
Ambient temperature at STC $T_{amb_{STC}}$[K]	298.15
Balance-of-System η_{BOS}	0.85
Solar irradiance at NOCT condition I_{NOCT} [kW/m^2]	0.8
$NOCT$ [K]	318.15
Ambient temperature at NOCT conditions T_{NOCT}[K]	293.15
Lifetime	20

Table 4.2.1 - Input values for the solar panels capacity factor

Standard Test Conditions (STC) to conduct uniform comparisons of photovoltaic modules by different manufactures are defined as 1000 W/m^2 irradiance, 25° C cell temperature, Air Mass 1.5. The conditions under which temperature reaches the

Nominal Operating Cell Temperature (NOCT) of 45°C are 800 W/m^2 irradiance on cell surface and air temperature of 20°C.

4.2.2.2 Micro Wind turbine

The steps to obtain the CF of the wind turbine are described below. The procedure starts, as for the solar CF, from the evaluation of the wind speed [m/s] average for each time-slice and corrected with the wind profile power law, which assumes that the wind speed is exponentially proportional with height. For the village of Katgaon, hourly wind resource data were available from [100], based on the longitude and the latitude of the village location. Otherwise hourly data can be generated with 12 monthly average wind speeds and 4 additional statistical parameters: the Weibull shape factor, the autocorrelation factor, the diurnal pattern strength, and the hour of peak wind speed. The annual wind speed for the location is measured with anemometer height at 50 m. The exponential law is set to calculate the variation of wind speed with height and with the surface roughness length typical for crops:

$$u = u_1 \left(\frac{z}{z_1}\right)^{\alpha}$$

where u [m/s] is the wind speed at height z [m], and u_1 is the known wind speed at the reference height z_1 equal to 50 m. The exponent α is an empirically derived coefficient that varies depends upon the stability of the atmosphere. According to information gives by Homer, once the location is entered, power law exponent is set equal to 0.14. The height at which the micro turbine is installed is assumed to be at 12 m. Once the correct wind speed is calculated for the site of Katgaon, the average wind for each time-slice is computed according to the same relationship used for the $I_{ave_T\_ij}$ for every hour i and every month j. In Figure 4.2.2 it is shown the average wind speed after the exponential correction for every hour of each month of the year. As for the solar source, the wind speed is assumed constant over the years.

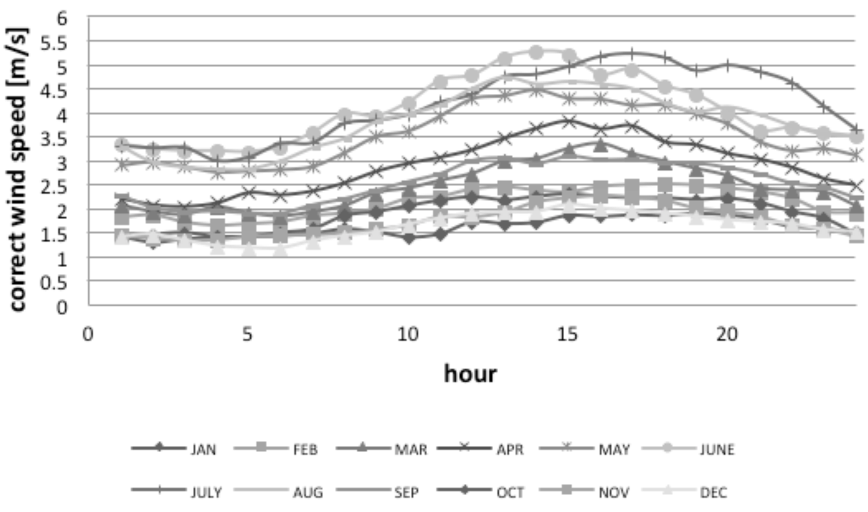

Figure 4.2.2 - Average wind speed [m/s] for each time-slice corrected with wind profile power law

The selection of the wind turbine is based on data of wind speed and a web research in order to find the technology that can produce energy at such low speeds and on the availability of company to provide technical data necessary to develop the capacity factor. These features were fit by a 650 W turbine produced by *'Unitron Systems'* company established in India in 1987. *Unitron* turbine power curve, technical and economic information were kindly provided by the technical consultant Mr Ravindranath, Figure 4.2.3.

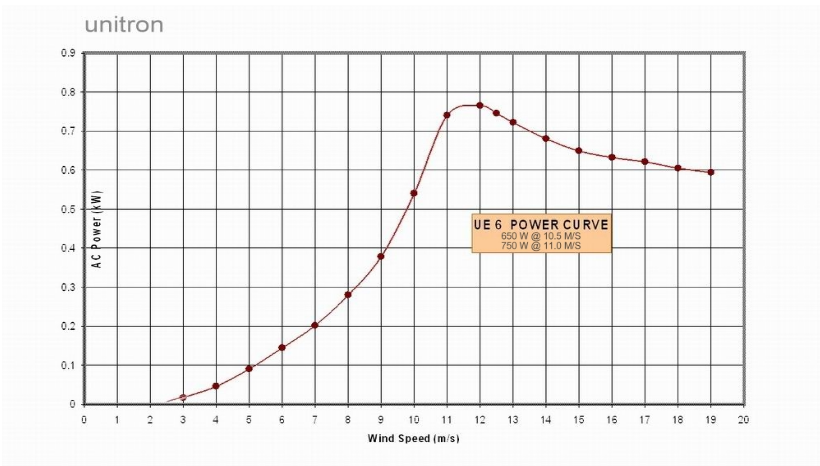

Figure 4.2.3 - Power curve provided by *'Unitron Systems'* Company

Because the power curve was provided without the mathematical function that expresses the relationship between the AC power [kW] at a given wind speed, a polynomial interpolation of the first increasing part of the power curve is developed to find the function of the wind speed with the AC power, Figure 4.2.4.

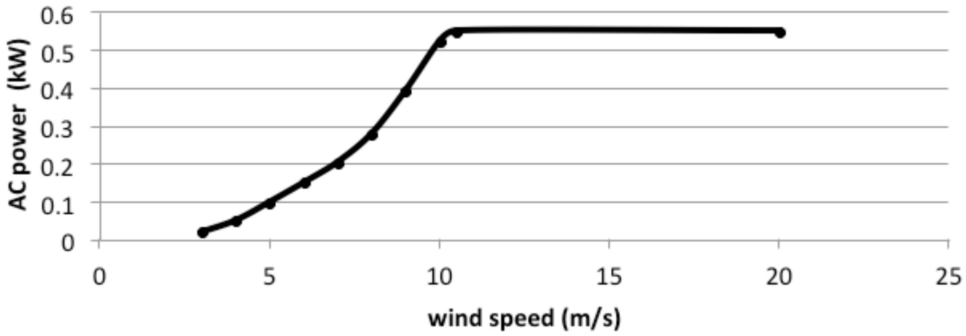

Figure 4.2.4 - Power curve of Unitron UE - 6 / 650 W

Being the rated wind of 10 m/s and the maximum wind speed of about 5.26 m/s, as it can look at Figure 4.2.2, the power curve is characterised by a constant AC power for values with a wind speed greater than 10 m/s.

Once the requested data are set, wind capacity factor is assessed for each time-slice.

$$CF_{wind\_ij} = \frac{1/2\, \rho A w^3_{corr\_ij} C_{p,BETZ} * \eta_{idr}}{1/2\, \rho A w^3_{RATED} C_{p,BETZ} * \eta_{idr}}$$

ρ is air density assumed constant with the altitude, A is the swept area, w_{corr_ij} is the wind speed corrected with the height, $C_{p,BETZ}$ is the Betz's efficiency and η_{idr} is the hydraulic efficiency.

Thus:

$$CF_{wind\_ij} = \frac{{w_{corr\_ij}}^3}{{w_{RATED}}^3}$$

Through the availability of power data, the final capacity factor equation for the wind turbine is calculated as:

$$CF_{wind\_ij} = \frac{P_{w\_corr\_ij}}{P_{RATED}}$$

where the numerator indicates the AC power produced at w_{corr_ij} for each hour *i* in the month *j*, and P_{RATED} is the power at w_{RATED}. Technical data are specified in Table 4.2.2.

Air density ρ [kg/m^3]	1.225
Diameter d [m]	2.2
Swept Area [m^2]	3.7
Betz's coefficient $C_{p,BETZ}$	0.59
Hydraulic efficiency η_{idr}	0.94
Rated wind w_{RATED} [m/s]	10
Rated power [W] P_{RATED}	650
Cut-in wind w_{cut-in} [m/s]	2.7
Number of blades	3
Lifetime	20

Table 4.2.2 - Technical data of Unitron UE - 6 / 650 W wind turbine for Katgaon village

CF_{wind_ij} is set to 0 when $w_{corr\_ij} < w_{cut-in}$, this is due because micro wind turbine does not start in this conditions.

4.2.3 Costs of system components

In OSeMOSYS, costs are incurred when the technology is active as the product of its activity and a given variable cost, when it has non-zero capacity as the product of its capacity and a given fixed costs and when it is invested in as the product of new investment and a given capital cost. For the technologies listed in Table 4.1.3, a deep analysis of the real costs and the future value of the components are discussed in this sub-section. In Table 4.2.3 a concise description of the cost parameters is presented.

CapitalCost[r,t,y] It is given as a function of the technology as well as the year in which the technology is invested. As not all technologies incur in a capacity cost, this is left as zero by default. The unit used in this model is $/W

FixedCost[r,t,y] It represents the fixed costs per unit of capacity for a given technology *t*. The unit used is $/W

VarriableCost[r,t,m,y] It is the cost per unit of activity, for a given mode of operation *m*. It is set to zero by default. The unit used is $/kWh

Table 4.2.3 - Brief glossary of cost terms

Capital and fixed cost trends of photovoltaic technology are assumed to follow the Annual Energy Outlook (AEO) 2015 [102] forecasts and the National Renewable Energy Laboratory (NREL) - Annual Technology Baseline 2015 [103] respectively. Information have been obtained from the website http://en.openei.org/wiki/Main_Page, a dataset about energy information on several topics sourced from industry and government agencies. Capital cost is composed of the PV module cost and the BOS cost. The BOS includes cost of structural installation, racks, site preparation, inverter, labour costs for installation etc., [104]. For the wind turbine technology the capital cost has been provided by *'Unitron Systems'* company: the selling price of the 650 W turbine with controller and switch gear will be about 72000 Indian Rupiee i.e. 955.44 EUR (with an exchange rates at 17th March 2016 of 1 INR = 0.0132712 EUR). A 12 m pipe tower costs 38000 Indian Rupiee 504.26 EUR. With an exchange rate of 1 INR=0.015 $, the final capital cost is valued for 2.5455 $/W in 2016. Through the same datasets of the PV component, capital cost is forecasted along the planning horizon, based on [103] as for the fixed costs. Variable costs for the RETs are accounted to be paltry, hence, for those technologies not incurring a variable cost, it is set to zero by default.

For the battery technology the capital and fixed costs are set, including the investment, replacement and O&M cots. For technical and economic values Sen et al. [40] information have been adapted for Katgaon village. The projections of costs for the planning horizon are evaluated through NREL – Renewable electricity Futures Study [105].

For diesel generator the capital cost is based on data from *National Electrical Industry* [106] an Indian company that manufactures electric motors and makes available data sheet of its products on the website. After few data processing to obtain the $/W capital cost through information provided from Model for Electricity Technology Assessments (META tool) by the Energy Sector Management Assistance Program (ESMAP) of the WB [107], capital, fixed and variable costs are set and successively projected along years. As variable costs have been accounted O&M and fuel costs.

Information on single data source can be made available under request to the author.

4.3 Simulation results and discussion

This section reports the results obtained by running the three energy planning scenarios corresponding to the three different inputs of electricity demand. Relevance is given on the *cost difference* of supplying electricity under the different scenarios and the *total capacity installed* every year. Total discounted costs for the planning period is expected to increase from the I to the II Scenario, which considers the electricity demand as constant along the planning horizon.

The RES illustrated in Figure 4.1.2 includes the battery component connected to renewable technologies in order to use the non-conventional fuels even when resources are not available, for example during the night when PV panels are not working, but they had previously charged the storage system. Batteries system has further advantages for an off-grid system; Bhattacharyya et al. [40] integrate batteries also to maintain a constant voltage during peak loads or a shortfall from the grid in generation capacity. Usually the system of batteries is charged when there is an excess power generation and discharged whenever there is a lack in power with respect to the electric demand. In this case OSeMOSYS evaluates the economic advantage to install battery capacity instead of supplying power with diesel generator or directly from the renewable technologies. In the simulations, although the data file has been filled in with all the storage information, the battery system has not be simulated due to bugs inside the original OSeMOSYS-code, within the block implementing the storage equations. The possibility to implement a more scrutinized analysis about this issue will be consider in *Future Works* together with a first outline of the approaches to face with RES sketched in Figure 4.1.2.

4.3.1 Cost comparison

In this sub-section a general overlook of the total discounted cost is presented. In OSeMOSYS the objective function is to minimize cost over the years of the energy planning. The following equation represents how data parameters are accounted to generate the final cost.

$$DiscountedCapitalInvestment_{r,t,y} = \frac{CapitalCost_{r,t,y} * NewCapacity_{r,t,y}}{(1+d)^n}$$

It is composed by three components: the first component takes into account the capital cost for region *r*, for each technology *t* at year *y,* multiplied by the new capacity installed for region *r*, for each technology *t* at year *y* due to an increasing demand and/or the replacement of the component at the end of the final life-time. The discount factor $1/(1+d)^n$ is composed by the discount rate *r* to the power of the year of calculation *n*, for example *n*=1 for the first year of the planning.

The second component includes variable and fixed costs, called operating costs:

$$DiscountedOperatingCost_{r,t,y}=\frac{FixedOperatingCost_{r,t,y}+VarOperatingCost_{r,t,y}}{(1+d)^{n+0.5}}$$

The third term included in the evaluation of total discounted cost is the salvage value i.e. the estimated resale value of a system component at the end of its useful life.

A sensitivity analysis is done on the discount rate. The parameter is used to calculate the discount factor for the start of each year. Thus it is used when discounting new capacity investments, operating costs and the salvage value for each technology, as previously shown. In its general definition the discount rate is an interest rate used to convert a future income stream to its present value [108]. For example, it could be the interest charged by a central bank on loans to a local company or to a private investor. When solving for the future value of money, the choice of discount rate can change the evaluation of the Net Present Value. In the present analysis two different values of the discount rate parameter are set in the data file for Katgaon. The lower has been chosen according to what Nerini et al. [20] consider to be the most suitable for the village of Suro Craic in Timor Leste, a DCs in Southeast Asia. A Social Discount Rate (SDR) of 3% is chosen in order to promote sustainability. According to Roumboutsos et al. [109] a such smaller discount rates intends to follow the notion of sustainability of a project in the evaluation of a public investment. To highlight the different outcomes taking a larger value for the parameter, a percentage of 36% is set to compare the total final cost. Generally, lower discount rate such as 3% or 5%, usually adopted to annualise capital investments, does not represent the actual situation, especially in rural areas. Households living in these contexts are characterised by low and volatile income, leading to private money-lenders instead of bank consumers loans. According to Gupta et al. [110] and Ruijven et al. [79] a representative discount rate of 36%, due to the rate of interest of local money-lenders. Additionally savings for these families are very low, so capital availability is limited and investment costs are depreciated soon. Final costs are shown in Table 4.3.1

Discount Rate	I Scenario [$]	II Scenario [$]	III Scenario [$]
3%	69,279.4	58,706.9	92,241.0
36%	15,770.4	14,197.6	16,292.2

Table 4.3.1 - Total discounted cost by discount rate and electricity demand Scenario

A first result is that total discounted cost increases with the electric consumption for both the discount rate applied. To understand the reason why the final cost is lower for a discount rate of 36%, and why the cost of the three scenarios are different, the capacity installed for the six cases should be evaluated (Table 4.3.2).

I Scenario	Total Capacity [W]		
Discount Rate	PV	Wind	DG
3%	1105.73955	0	18015.51
36%	0	0	18015.52
II Scenario	**Total Capacity [W]**		
Discount Rate	PV	Wind	DG
3%	631.3683	0	14570.25
36%	0	0	14570.25
III Scenario	**Total Capacity [W]**		
Discount Rate	PV	Wind	DG
3%	2215.2959	0	24375.24
36%	0	0	24375.24

Table 4.3.2 - Total installed capacity [W] by technology, for each scenario and for the two discount rates

For each scenario, at a discount rate of 36%, the model installs only the capacity of DG. This is due to the high capital cost of RETs respect to DG (about an order of magnitude more), at the beginning of the planning. Total discounted cost turns out to be lower if capital and operating costs are spread out along the planning period or if costs are high at the end of the energy planning. In this work projections of costs are assumed to decrease over time due to engineering and manufacturing scale-up of more efficient technologies, competition between existing business, market expansion, entry of new competitors in the industrial sector etc. Thus, high operating costs over years of DG do not impact on the discounting back of net costs. The high capital cost of RETs, at the very staring year of the planning, impact higher than the capital cost of DG. For a discount rate of 3%, high costs at the last of the planning period impact more on the total discounted cots than of a discount rate of 36%. Thus, higher fixed and variable costs, including fuel costs, of DG produce an increase of the impact on the final cost, hence OSeMOSYS assesses cheaper the installation of PV panel instead to feed DG with gasoline, whenever irradiation is available.

Table 4.3.3 summarizes the percentage differences in terms both of capacity installed and cost of the systems for the Scenario I and III respect to Scenario II (the case of constant demand electricity along the planning horizon) – for a discount rate of respectively 3% and 36%. In the table it is reported also the percentage difference in terms of daily energy consumption at year 2034 respect to Scenario II. The table confirms how an increase of electricity demand always impacts on a substantial growth of capacity installed along the planning. The level of increase of costs is lower than the percentage of increase of capacity installed, especially when the discount rate is high, as discussed above. Therefore a scenario that predicts higher consumptions affects more the capacity installed that total discounted cost, especially with high discount rates.

	I vs II	III vs II
Deviation in daily el. consumption at 2034 [%]	25.62	143.59
Discount Rate	**% of increase of cots**	**% of increase of cots**
3%	18.01	57.12
36%	11.08	14.75
	% of increase of capacity	**% of increase of capacity**
3%	25.78	75.31
36%	23.65	67.29

Table 4.3.3 - Comparison between the II and the II and III scenario of forecast demand, both for total discounted cost and total capacity

This is further illustrated in Figure 4.3.1. In the main axes is plotted the total discounted cost (red), in the secondary axes total installed capacity is drawn (blue), for the three scenarios with a discount rate of 3%. Over time, the variation of costs between the three scenarios is smaller than the variation of installed capacity between the same scenarios. This graphically reports what previously said about the deeper impact on Watts installed than on cost of the system with an increasing electric consumption.

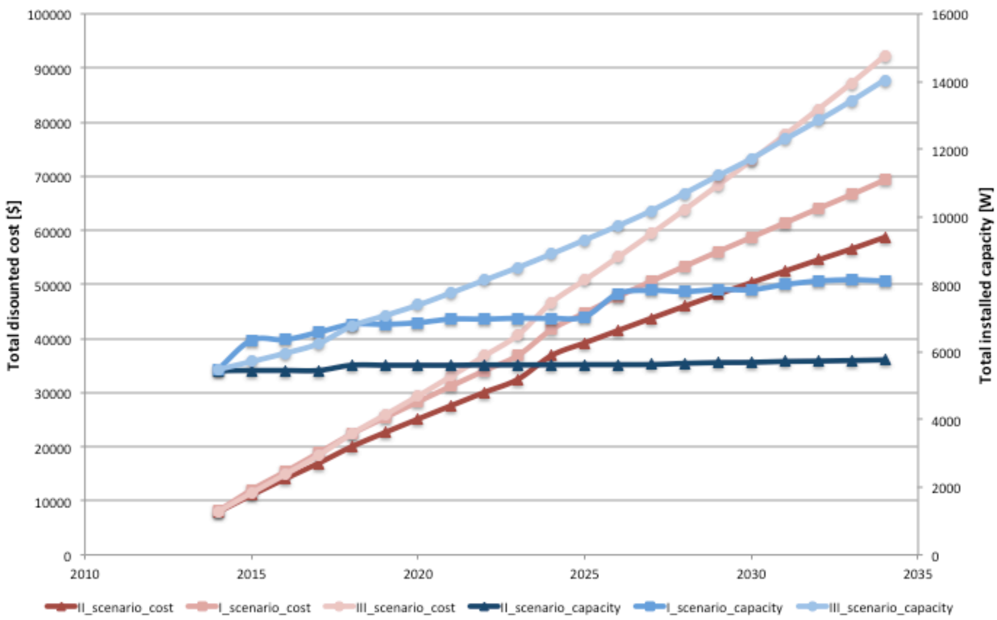

Figure 4.3.1 - Total Discounted Cost (red) and Total Annual Capacity (blue) for the three demand scenarios with discount rate at 3%

A last clarification is discussed looking at Table 4.3.2. For each scenario, the total capacity installed for the diesel generator is the same between the two different discount rates. This is because the DG is always sized in order to supply electricity during the peak hours that is when the SPV does not receive irradiation. The hours between 19:00 and 20:00 are in fact characterised by peak load during the day, as shown in Figure 3.2.8.

4.3.2 System architecture comparison

A further analysis has been developed in order to understand how the renewable technologies impact on the structure of the system. Thus, the previous configuration characterised by a hybrid-system that integrates photovoltaic panels, wind turbines with diesel generator is compared with a system characterised by a single diesel generator, which is assumed to supply all the electric demand for the 12 households in the village. Total discounted costs for the system composed only by the DG are shown in Table 4.3.4.

Discount Rate	I Scenario [$]	II Scenario [$]	III Scenario [$]
3%	71,797.7	60,946.1	95,934.6
36%	15,770.4	14,197.6	16,292.2

Table 4.3.4 - Total Discounted Costs for the three scenarios with a diesel generator supply system

Compared with the results summarized in Table 4.3.1, this demonstrates that integration with renewable technologies leads to monetary savings in term of final cost. With a discount rate of 3% the final investment increases with the growth of electric consumption. For the second scenario a hybrid system costs 3.8% less compared to an energy system supplied only by DG. In monetary terms this is equivalent to 2240 $, which is about the 62% of the annual income for a household in Katgaon. Moreover, the introduction of emissions penalties in the total discounted cost will raise the costs of supplying demand only with conventional fuels. For a discount rate of 36% costs do not change, in comparison with Table 4.3.1, because a DG solution system is always estimated to be the minimum cost option.

A final consideration is done about the I Scenario, with the energy demand scenario obtained with the model described in Chapter 3. For the hybrid energy system, with a discount rate of 3%, diesel generator is found to be the component mainly installed over years with an average of 1000 Watt per year for the PV technology, which corresponds with 5 solar panels of 240 Watt, and zero wind turbines, as it is illustrated in Figure 4.3.2.

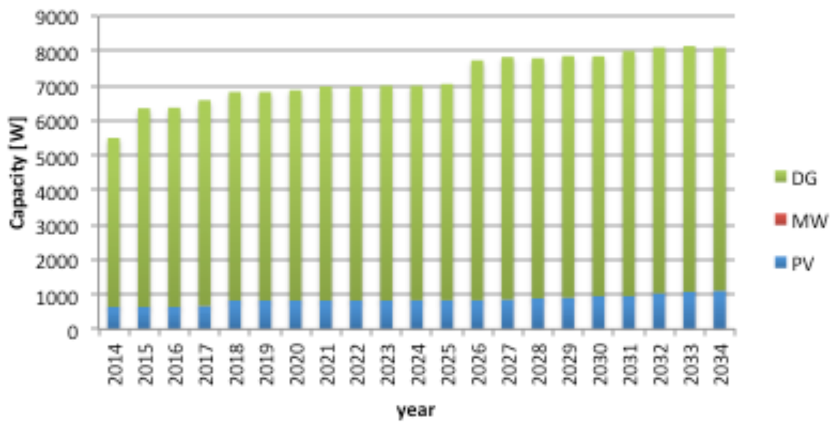

Figure 4.3.2 - Total Annual Capacity [W] installed for the supplying of electricity demand of the first scenario

This values are mainly due to the capital, fixed and variable costs of the components. At year 2014, capital costs are equal to: 0.58 $/W for DG, 3.12 $/W for MW and 2.5 $/W according to the literature sources described in sub-section 4.2.3. Moreover, the wind resource has been measured to raise a maximum value of 5.25 m/s with the high correction, for a mini-turbine characterised by a cut-in speed of2.7 m/s. In *Future Works* will be presented the possibility to introduce the battery system in order to better understand which advantages could occur in term of costs. The last annotation is that the accounting of an emission penalties can lead to a lower DG installed capacity.

4.3.3 Final discussion

The importance of the estimation of future consumption was demonstrated in this chapter. By using a case study approach, it was possible to estimate cost differences that a local enterprises, private investments or local institutions might faces in supplying increasing electric consumption at the first year of investment. For the evaluated case study, changing in costs and capacity installed for the same village according to different forecast demand approach states that attention has to be paid to demand input for a long-term planning period.

Some limitations arise within OSeMOSYS evaluations. The model implemented considers a proportional increase of capacity with the growth of electric consumption. The addition of electric power capacity, in particular for a hybrid micro-grid as the one considered in this thesis, has not to be taken for granted. Hybrid micro-grids embrace several conversion units, which supply electricity to single of several consumers, from single families to community services or small local activities. The need of an extra kilowatt does not simply imply the installation of one more kilowatt of capacity, but could entail further analysis depending on various factors. This is due to limited elasticity of the capacity for the micro-grid. The sizing has to include not only the unit of technology but also cables dimension, transformers, charger controllers and converters. For every unit of new capacity required, it has to be accounted for components that convert electric power from DC to AC called inverter, and/or from AC to DC called rectifier. The count of these components affects the total capacity that has to be installed, through the corresponding efficiency and the total discounted cost due to their capital, replacement and O&M fixed costs. Moreover, the correct integration of inverters inside the energy system has to estimate how many units of, for example, PV panels can be connected to a single converter according to the specific characteristic of it. This could be done with a further implementation in the model code: mixed integer programming may be applied for certain function, like the optimisation of PV solar systems capacity expansions. The parameter **CapacityofOneTechnologyUnit [r,t,y]** allows to define the minimum size of one capacity addition, but a mixed integer linear programming is needed to solve the code, which increase a lot the computational effort. These considerations lead back to the attention of the importance, during the design phase, to size the energy system on its maximum capacity based on the maximum consumption. Thus, for a long-run period planning, the relevance of a correct evaluation of energy demand over time is confirmed once again.

5 Future works

This thesis has introduced a first step application of a bottom-up approach for the forecast of electric consumption in a rural area. There are several additional implementations both for I Scenario model and OSeMOSYS application for analysis and comparison of different approaches to predict energy demand in the case study evaluated. In this section, some of them are discussed.

Bottom-up model for forecasting energy demand: the review of energy planning papers, with a focus on models to predict energy demand, has led to know the main features necessary to implement a proper model for a rural area in DCs. In the design code process, some assumptions are taken on in order to facilitate the coding of the model. To estimate the function of total appliances ownership for the twelve families selected for the study, two variables are considered constant along years: *household size (HHS)* and *household floor space (HHFS),* as stated in sub-section 3.2.1. To improve the function, the two parameters can be allowed to change along the years. In particularly, the *HHS* has found to increase slowly with the growth of income. The general trend of *household floor space* per capita increases with higher income levels, with a decreasing growth rate and lower floor space levels with higher density population, as studied by Ruijven et al. [79].

The energy vector analysed is the electricity one for the residential demand sector. This selection is justified at paragraph 2.3. A further consideration can be to include in the model the thermal vector, in order to examine also the cooking energy service and space heating. Moreover, inside the village health centres, schools, small local activities and agricultural demand for mills, water pumps and tractors can influence the total energy consumption for the location.

Ruijven et al. [15] assert that the potential for mini-grid and off-grid technologies varies widely depending on demand density, that is closely related to population density. So a variable to increase the precision of the code can be the density of the population, considering also the geographical extension of the rural area under study.

OSeMOSYS mini-grid system sizing: this thesis considers a RES characterised by two renewable technologies, a diesel generator feeds by conventional fuel and battery storage. In general storage (i.e. batteries) is always implemented when systems rely on renewables sources. As stated at the beginning of Chapter 1, during the simulation the parameters that emulate batteries have been blocked because code equations are not supported for the integration of renewable technologies with storage. With the hypothesis to connect the storage to the mini-grid and charge it with the surplus electricity produced by SPV and MW, and discharge it, for example, during the evening and/or for low wind speed, it is expected that the maximum power installed for the diesel generator will decrease in respect to the results illustrated in Table 4.3.2. Moreover, a sensitivity analysis on fuel costs and on capital cost of battery technology can show the variation over time of power installed and unity of technologies needed to supply the demand, based on the different evolution of fuel costs and the application of different battery type, such as lead-acid or the more efficient Li-Ion cells. At the beginning of the data file generation for the energy system studied in this thesis, the parameters for integration of battery storage with renewable technologies were entered. A *Surette 6CS25P* lead-acid battery had been selected referring to a paper written by Sen et al. [111]. This is due to the availability of costs information and the application of the mentioned technology for the Indian context by the authors. A critical issue that arises during the input values in the data file is that capital and fixed costs have to be entered in dollar per unit of capacity. But, as described in [105], total cost of a storage application must account for both a power component (kW of discharge capacity) and an energy component (kWh of discharge capacity, depending on hours of discharge at rated output). The rated output depends on current discharge, if it increases the rated capacity decreases, i.e. the battery supplies less energy to the mini-grid. This leads to a variation of energy component costs with useful capacity and, hence, to the charge/discharge rate. Lead-acid technologies, especially for DCs application (where low-cost technologies with low-efficiency performance are proposed), are characterised by a no specific limit to the discharge/charge current value, even if performances vary with it. Two parameters are present in OSeMOSYS to describe these features, called **StorageMaxChargeRate**[r,s] and **StorageMaxDischargeRate**[r,s] (where *r* represents the region and *s* the storage, as shown in Table 4.1.2), in unit of power, but they do not depend on the charge/discharge current. Hence, they had been estimated very high for the mini-grid. A solution can be entered the two values as variable inside the code instead of parameters in the data file. Moreover, a problem arises with another storage parameter, called **MinStorageCharge**[r,s,y] that represents the limit below which the storage facility cannot be empties i.e. the technical parameter identified as *minimum state of charge* in technical sheet. The issue is due to a zero capacity installed with a default value of 0.2 that means the battery can be discharged at maximum value of 80% of the storage level. Thus, the data file is ready to be computed once the bug of the code will be worked out.

Conclusions

The aim of this thesis was to analyse the issue of energy demand forecasting within long-term rural energy planning, highlighting how different energy demand scenarios may impact the results of energy planning.

The issue to investigate energy demand models arose from the continuous increase of energy demand in rural areas and the need to find sustainable and appropriate solutions to decrease the number of people who live without modern energy services and, hence, the necessity of providing proper tools for a suitable energy planning.

Therefore, the first part of the present work focused on an extensive review of energy planning case studies through a classification that aimed firstly at emphasizing the general aspects of the energy planning project and, secondly identifying the most appropriate demand forecasting approaches adopted in the literature. The scientific literature has extensively addressed the classification of energy demand models applied to forecast demand without, to the authors knowledge, considering the interaction with the sizing of the energy system.

The analysis of methodologies to forecast energy demand revealed the critical issue of the energy demand dimension within energy planning. The review showed that 67% of case studies do not consider a variation over time of energy consumption, applying a *constant* projection of the demand over the project lifetime. Moreover, only about 19% of energy planning studies, belonging to long-term planning horizon category, applies forecast techniques to account energy demand.

After, the thesis focused on the analysis of the features and drivers that best characterised the trend of residential electricity demand in the specific context of rural areas. The selection of this peculiar demand sector was due to the high adsorption of electricity by households living in the rural areas and the residential sector being the main critical request of energy. It was covered only electricity since 76% of the selected papers reviewed use electricity as main energy source to charge loads. The analysis had led to a more appropriate approach for energy demand evaluation: bottom-up methods were found to be the suitable techniques to study the projection of electric demand for a long-term energy planning. Basic characteristics most frequently recommended for the implementation a correct bottom-up forecasting approach are: disaggregation level of consumption by expenditures or income of the rural population, the consideration of the ownership of electric appliances per household and the related absorption of energy, population variable inclusion to drive the growth of demand, the relation of household floor space parameter with income and integration of the informal sector in predicting the electric consumption of local activities. The so-called REMG model, elaborated by Bas J. van Ruijven et al. in *"Model projections for household energy use in India",* was re-adapted, through the collaboration with the UNESCO Chair in Energy for Sustainable Development research group at Politecnico di Milano – Department of Energy, for the development of a bottom-up model of energy demand forecast. This model was applied for a case study in India with a planning horizon of 21 years. In order to compare the engineering approach implemented with the more used methods obtained from the literature review, it was considered expedient to join two more forecasting approaches based on data surveyed from the Indian village. Thus, a constant demand scenario, defined as II Scenario, and a time-based interpolation scenario (from World Bank macro data), identified as III Scenario was flanked with the here developed bottom-up approach, identified as I Scenario. At the 21st year and last year of the project, I Scenario presents the 25.62% more electricity consumption than II Scenario, and III Scenario the 143.59% more than with II Scenario.

With the aim of drawing definitive conclusions about the different impact that various forecasting approaches have on the final objective function of the optimisation of the energy system, a linear optimisation energy planning model was implemented in OSeMOSYS. Trends of electric demand estimated with the three Scenarios were entered in the model as input parameters. Cost analysis was carried out for the technologies of the reference energy system selected, accounting for capital, fixed and variable costs over the planning period. To consider the real power output or renewable technologies, the formulation of capacity factors was elaborated. A glitch compelled the author to the simplification of the reference energy system applied for the simulation. This issue concerns the battery: the model's code was not able to correctly evaluate the output of annual capacity. A sensitivity analysis on the discount rate was considered in order to assess how the total discounted cost of the energy system changes for a low value of 3% and a higher value of 36%. The results of the simulation proved that a greater consumption of energy has a different impact both on investment costs and installed capacity. In particular, with a discount rate of 3%, I and III Scenario require 18% and 57% more capital investments, respectively, than II Scenario. In terms of installed capacity, the difference for I and III Scenario compared with II Scenario was found to be higher, in proportion, than the difference in term of costs. I Scenario installs 26% more capacity than the II one, and III Scenario needs 75% more than the I Scenario. With a discount rate of 36%, the differences between I, II and III result were lower both in terms of total discounted cost and capacity. This is due to the fact that the RETs capacity is not considered by the planning scenarios, because of the higher impact of renewable technologies on the final cost: solar PV and wind turbines capital costs are more expensive than diesel generator. Thus the model, in order to minimize costs, sets the energy system only with the diesel generator technology.

Appendix

This section presents the complete review of the 77 papers classified according to the six categories described in Chapter 2. It is indicated the *reference* of the article, the acronym of *Decision Criteria Mathematical Models*, *Spatial Coverage* (local and regional), *Planning Horizon* (short, medium, long and *not specified*), *Methodology* (bottom-up and top-down), *Energy Vector* (electricity, thermal, oil production, chemical and not commercial energy) and *Demand Sector* (residential, industrial, commercial, agricultural, community and *not specified*).

reference	Dec. cri.	Spatial		Planning horizon				Methodology		Energy vector					Demand sector					
		local	regional	short	medium	long	n.s.	bottom-up	top-down	el.	th.	oil pr.	ch.	no comm.	res.	ind.	comm.	agric.	com.	n.s.
[112]	MOP	X				X		X		X				X	X					
[59]	DP	X			X			X		X					X	X	X	X	X	
[46]	LP		X			X		X		X		X		X	X	X		X		
[113]	LP, DP	X				X		X		X	X			X	X					
[49]	MOP	X				X		X		X	X				X		X	X		
[114]	MCDM		X			X		X		X					X	X				
[50]	LP		X	X	X			X		X					X	X	X	X		
[88]	LP	X				X		X		X					X					
[93]	MOP		X			X		X		X					X					
[115]	EO	X				X		X		X								X	X	
[116]	EO		X			X		X		X					X	X				
[20]	LP	X				X		X		X					X					
[117]	LP		X	X				X		X	X	X		X	X	X	X	X		
[33]	LP, EO	X				X		X		X					X	X		X	X	
[44]	MCDM	X				X			X	X					X	X		X		
[118]	DP	X					X	X		X					X			X		
[30]	LP	X				X			X	X					X					
[111]	EO	X				X				X					X	X	X	X	X	
[68]	LP	X				X		X		X					X	X	X	X		
[119]	LP	X			X			X		X				X	X	X	X	X		
[120]	EO	X				X		X		X					X	X	X	X		
[57]	MCDM	X					X	X		X					X			X	X	

reference	Dec. cri.	Spatial		Planning horizon				Methodology		Energy vector					Demand sector					
		local	regional	short	medium	long	n.s.	bottom-up	top-down	el.	th.	oil pr.	ch.	no comm.	res.	ind.	comm.	agric.	com.	n.s.
[60]	Other	X				X		X		X					X				X	
[121]	LP	X					X	X		X					X					
[58]	DP		X		X				X	X	X				X	X	X	X	X	
[42]	EO		X			X		X		X										X
[122]	DP		X			X		X		X										X
[39]	MCDM		X		X	X		X		X					X					
[13]	Other	X					X	X		X					X				X	
[41]	Other	X				X		X		X	X									
[72]	LP	X				X		X		X					X					
[121]	Other	X					X	X		X					X	X	X		X	
[34]	MCDM	X				X		X		X					X					
[125]	MOP	X					X	X		X					X				X	
[41]	Other	X				X		X		X					X				X	
[89]	Other	X					X	X		X					X					
[55]	Other	X				X		X		X										X
[126]	MOP	X				X		X		X					X					
[127]	NLP	X				X		X		X										X
[51]	NLP	X				X		X		X					X					
[97]	EO	X				X		X		X										X
[37]	LP		X				X	X		X					X	X	X	X		
[73]	MCDM	X				X		X		X					X			X	X	
[38]	MOP		X			X		X		X					X					

reference	Dec. cri.	Spatial		Planning horizon				Methodology		Energy vector					Demand sector					
		local	regional	short	medium	long	n.s.	bottom-up	top-down	el.	th.	oil pr.	ch.	no comm.	res.	ind.	comm.	agric.	com.	n.s.
[69]	LP	X					X	X		X					X				X	
[128]	MOP		X				X	X		X										
[123]	LP	X					X			X					X	X		X		
[129]	MOP	X				X				X	X				X				X	
[130]	LP	X					X	X		X						X		X		
[36]	DP	X				X		X		X										X
[48]	LP				X			X		X					X	X	X	X		
[17]	LP	X			X			X		X	X	X			X			X		
[69]	LP	X		X				X		X					X				X	
[35]	EO	X				X		X		X										X
[54]	EO		X			X		X		X					X	X	X	X		
[52]	DP	X			X			X			X			X	X					
[56]	Other	X				X		X		X	X			X	X	X		X		
[131]	LP	X					X		X	X					X				X	
[132]	LP	X					X		X	X								X		
[133]	LP	X					X		X	X					X					
[53]	EO		X			X		X		X									X	
[134]	EO	X				X		X		X					X					
[135]	EO	X				X		X		X									X	
[136]	EO	X				X		X		X									X	
[137]	EO	X				X		X		X								X	X	
[138]	EO	X				X		X		X								X	X	

reference	Dec. cri.	Spatial		Planning horizon				Methodology		Energy vector					Demand sector					
		local	regional	short	medium	long	n.s.	bottom-up	top-down	el.	th.	oil pr.	ch.	no comm.	res.	ind.	comm.	agric.	com.	n.s.
[139]	EO	X				X		X		X								X	X	
[85]	EO	X				X		X		X								X	X	
[140]	EO	X				X		X		X									X	
[86]	EO	X				X		X		X								X	X	
[43]	EO	X				ammort. of years		X		X	X				X	X		X	X	
[141]	EO	X				lifetime of years		X		X									X	
[83]	Other		X			X		X		X					X					
[142]	EO	X				lifetime of yars		X		X									X	
[143]	NLP	X				X		X		X	X				X				X	
[47]	LP	X			X			X		X	X	X		X	X					

References

[1] UNDP, "Sustainable Energy." .

[2] International Energy Agency, *World Energy Outlook 2013*. 2013.

[3] International Energy Agency, "Africa Energy Outlook," pp. 1–233, 2014.

[4] "GB @ data.worldbank.org." [Online]. Available: http://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS.

[5] J. C. Rojas-Zerpa and J. M. Yusta, "Application of multicriteria decision methods for electric supply planning in rural and remote areas," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 557–571, 2015.

[6] S. Jebaraj and S. Iniyan, "A review of energy models," *Renew. Sustain. Energy Rev.*, vol. 10, no. 4, pp. 281–311, 2006.

[7] R. B. Hiremath, S. Shikha, and N. H. Ravindranath, "Decentralized energy planning; modeling and application-a review," *Renew. Sustain. Energy Rev.*, vol. 11, no. 5, pp. 729–752, 2007.

[8] S. C. Bhattacharyya, "Review of alternative methodologies for analysing off-grid electricity supply," *Renew. Sustain. Energy Rev.*, vol. 16, no. 1, pp. 677–694, 2012.

[9] R. D. Prasad, R. C. Bansal, and A. Raturi, "Multi-faceted energy planning: A review," *Renew. Sustain. Energy Rev.*, vol. 38, pp. 686–699, 2014.

[10] S. Deshmukh, "Energy Resource Allocation in."

[11] N. Van Beeck, "Classification of Energy Models," no. May, 1999.

[12] M. W. Thring, *World Energy Outlook*, vol. 23, no. 4. 2014.

[13] E. M. Nfah, J. M. Ngundam, and R. Tchinda, "Modelling of solar/diesel/battery hybrid power systems for far-north Cameroon," *Renew. Energy*, vol. 32, no. 5, pp. 832–844, 2007.

[14] V. Daioglou, B. J. van Ruijven, and D. P. van Vuuren, "Model projections for household energy use in developing countries," *Energy*, vol. 37, no. 1, pp. 601–615, 2012.

[15] B. J. van Ruijven, J. Schers, and D. P. van Vuuren, "Model-based scenarios for rural electrification in developing countries," *Energy*, vol. 38, no. 1, pp. 386–397, 2012.

[16] A. Cabraal, M. Cosgrove-Davies, and L. Schaeffer, "Best practices for photovoltaic household electrification programs," *Conf. Rec. Twenty Fifth*

IEEE Photovolt. Spec. Conf. 1996, pp. 1357–1362, 1996.

[17] R. Srinivasan and P. Balachandra, "Micro-level energy planning in India-a case study of Bangalore North Taluk," vol. 17, no. January 1993, pp. 621–632, 1995.

[18] E. Hartvigsson, E. Ahlgren, J. Ehnberg, and S. Molander, "Rural Electrification Through Minigrids in Developing Countries: Initial Generation Capacity Effect on Cost-Recovery," in *33rd International Conference of the System Dynamics Society*, 2015, pp. 1–12.

[19] E. Hartvigsson, "Using system dynamics for long term bottom-up electric load modeling in rural electrification," in *The 34th International Conference of the System Dynamics Society*, 2016.

[20] F. Fuso Nerini, R. Dargaville, M. Howells, and M. Bazilian, "Estimating the cost of energy access: The case of the village of Suro Craic in Timor Leste," *Energy*, vol. 79, no. C, pp. 385–397, 2015.

[21] S. M. Mustonen, "Rural energy survey and scenario analysis of village energy consumption: A case study in Lao People's Democratic Republic," *Energy Policy*, vol. 38, no. 2, pp. 1040–1048, 2010.

[22] A. Cabraal, M. Cosgrove-davies, and L. Schaeffer, *AVYSt 1996 Best Practices for Photovoltaic Household Electrification Programs Lessons from Experiences in Selected Countries*, no. 324. 1996.

[23] P. D??az, C. A. Arias, R. Pe??a, and D. Sandoval, "FAR from the grid: A rural electrification field study," *Renew. Energy*, vol. 35, no. 12, pp. 2829–2834, 2010.

[24] N. G. Johnson and K. M. Bryden, "Energy supply and use in a rural West African village," *Energy*, vol. 43, no. 1, pp. 283–292, 2012.

[25] W. Xiaohua and F. Zhenmin, "Sustainable development of rural energy and its appraising system in China," *Renew. Sustain. Energy Rev.*, vol. 6, no. 4, pp. 395–404, 2002.

[26] J. L. Bernal-Agustín and R. Dufo-López, "Multi-objective design and control of hybrid systems minimizing costs and unmet load," *Electr. Power Syst. Res.*, vol. 79, no. 1, pp. 170–180, 2009.

[27] W. Clark and W. Isherwood, "Distributed generation: Remote power systems with advanced storage technologies," *Energy Policy*, vol. 32, no. 14, pp. 1573–1589, 2004.

[28] B. K. Bala, "Computer modelling of the rural energy system and for CO2 emissions for Banlgladesh," vol. 22, no. 10, pp. 999–1003, 1997.

[29] S. Mandelli, J. Barbieri, R. Mereu, and E. Colombo, "Off-grid systems for rural electrification in developing countries: Definitions, classification and a comprehensive literature review," *Renew. Sustain. Energy Rev.*, vol. 58, pp. 1621–1646, 2016.

[30] M. Zeyringer, S. Pachauri, E. Schmid, J. Schmidt, E. Worrell, and U. B. Morawetz, "Analyzing grid extension and stand-alone photovoltaic systems for the cost-effective electrification of Kenya," *Energy Sustain. Dev.*, vol. 25, pp. 75–86, 2015.

[31] O. Eidge, A. Universities, and C. Avenue, "A long-term global energy-economic model of carbon dioxide release from fossi . fuel use," pp. 74–88, 1983.

[32] L. Parshall, D. Pillai, S. Mohan, A. Sanoh, and V. Modi, "National electricity planning in settings with low pre-existing grid coverage: Development of a spatial model and case study of Kenya," *Energy Policy*, vol. 37, no. 6, pp. 2395–2410, 2009.

[33] A. B. Kanase-Patil, R. P. Saini, and M. P. Sharma, "Integrated renewable energy systems for off grid rural electrification of remote area," *Renew. Energy*, vol. 35, no. 6, pp. 1342–1349, 2010.

[34] S. Semaoui, A. Hadj Arab, S. Bacha, and B. Azoui, "Optimal sizing of a stand-alone photovoltaic system with energy management in isolated areas," *Energy Procedia*, vol. 36, pp. 358–368, 2013.

[35] Y. Himri, A. Boudghene Stambouli, B. Draoui, and S. Himri, "Techno-economical study of hybrid power system for a remote village in Algeria," *Energy*, vol. 33, no. 7, pp. 1128–1136, 2008.

[36] A. R. De L. Musgrove, "the Optimization of Hybrid Energy Conversion Systems Using the Dynamic Programming Model-," *Int. J. energy Res.*, vol. 1, no. November 1986, 1988.

[37] a. Gupta, R. P. Saini, and M. P. Sharma, "Design of an Optimal Hybrid Energy System Model for Remote Rural Area Power Generation," *2007 Int. Conf. Electr. Eng.*, 2007.

[38] D. Silva and T. Nakata, "Multi-objective assessment of rural electrification in remote areas with poverty considerations," *Energy Policy*, vol. 37, no. 8, pp. 3096–3108, 2009.

[39] D. Saheb-Koussa, M. Haddadi, and M. Belhamel, "Economic and technical study of a hybrid system (wind-photovoltaic-diesel) for rural electrification in Algeria," *Appl. Energy*, vol. 86, no. 7–8, pp. 1024–1030, 2009.

[40] R. Sen and S. C. Bhattacharyya, "Off-grid electricity generation with

renewable energy technologies inIndia: An application of HOMER," *Renew. Energy*, vol. 62, pp. 388–398, 2014.

[41] A. K. Daud and M. S. Ismail, "Design of isolated hybrid systems minimizing costs and pollutant emissions," *Renew. Energy*, vol. 44, pp. 215–224, 2012.

[42] P. Arun, R. Banerjee, and S. Bandyopadhyay, "Optimum sizing of photovoltaic battery systems incorporating uncertainty through design space approach," *Sol. Energy*, vol. 83, no. 7, pp. 1013–1025, 2009.

[43] A. B. Kanase-Patil, R. P. Saini, and M. P. Sharma, "Sizing of integrated renewable energy system based on load profiles and reliability index for the state of Uttarakhand in India," *Renew. Energy*, vol. 36, no. 11, pp. 2809–2821, 2011.

[44] D. W. Ã, "Costing electricity supply scenarios : A case study of promoting renewable energy technologies on Rodriguez , Mauritius," vol. 29, pp. 1319–1347, 2004.

[45] V. Devadas, "Planning for rural energy system : part III," vol. 5, pp. 271–297, 2001.

[46] S. B. Malik and P. S. Satsangi, "Data Extrapolation Techniques Systems Planning," vol. 38, no. 14, pp. 1459–1474, 1997.

[47] B. Joshi, T. Bhatti, and N. Bansal, "Decentralized energy planning model for optimum resource allocation with a case study of the domestic sector of rurals in Nepal," *Int. J. …*, vol. 15, no. September 1990, pp. 71–78, 1991.

[48] S. Iniyan, L. Suganthi, and J. T.R., "Renewable energy planning for India in 21st century," vol. 14, no. 1991, pp. 453–457, 1998.

[49] R. B. Hiremath, B. Kumar, P. Balachandra, and N. H. Ravindranath, "Bottom-up approach for decentralised energy planning: Case study of Tumkur district in India," *Energy Policy*, vol. 38, no. 2, pp. 862–874, 2010.

[50] P. Balachandra and V. Chandru, "Supply demand matching in resource constrained electricity systems," *Energy Convers. Manag.*, vol. 44, no. 3, pp. 411–437, 2003.

[51] S. Ashok, "Optimised model for community-based hybrid energy system," *Renew. Energy*, vol. 32, no. 7, pp. 1155–1164, 2007.

[52] M. S. Alam, A. M. Z. Huq, and B. K. Bala, "An integrated rural energy model for a village in Bangladesh," vol. 46, no. 1, pp. 59–76, 2014.

[53] A. Demiroren and U. Yilmaz, "Analysis of change in electric energy cost with using renewable energy sources in G??kceada, Turkey: An island example," *Renew. Sustain. Energy Rev.*, vol. 14, no. 1, pp. 323–333, 2010.

[54] A. K. Akella, M. P. Sharma, and R. P. Saini, “Optimum utilization of renewable energy sources in a remote area,” *Renew. Sustain. Energy Rev.*, vol. 11, no. 5, pp. 894–908, 2007.

[55] S. Phrakonkham, G. Remy, D. Diallo, and C. Marchand, “Pico vs Micro hydro based optimized sizing of a centralized AC coupled hybrid source for villages in Laos,” *Energy Procedia*, vol. 14, no. 0, pp. 1087–1092, 2012.

[56] S. Rana, R. Chandra, S. P. Singh, and M. S. Sodha, “Optimal mix of renewable energy resources to meet the electrical energy demand in villages of Madhya Pradesh,” *Energy Convers. Manag.*, vol. 39, no. 3–4, pp. 203–216, 1998.

[57] B. Domenech, L. Ferrer-Martí, P. Lillo, R. Pastor, and J. Chiroque, “A community electrification project: Combination of microgrids and household systems fed by wind, PV or micro-hydro energies according to micro-scale resource evaluation and social constraints,” *Energy Sustain. Dev.*, vol. 23, pp. 275–285, 2014.

[58] T. R. Bowe, W. D. Dapkus, and J. B. Patton, “Markov Models,” vol. I, no. 7, pp. 661–676, 1990.

[59] J. Nahman and J. Spiric, “Optimal planning of rural networks,” *Electr. Power Energy Syst.*, vol. 19, no. 8, pp. 549–556, 1997.

[60] R. T. Kivaisi, “Installation and use of a 3 kW p PV plant at Umbuji village in Zanzibar,” *Renew. Energy*, vol. 19, pp. 457–472, 2000.

[61] V. Devadas, “Planning for rural energy system: part I,” *Renew. Sustain. Energy Rev.*, pp. 203–226, 2001.

[62] M. A. Elhadidy and S. M. Shaahid, “Role of hybrid (wind + diesel) power systems in meeting commercial loads,” *Renew. Energy*, vol. 29, no. 1, pp. 109–118, 2004.

[63] T. Nakata, K. Kubo, and A. Lamont, “Design for renewable energy systems with application to rural areas in Japan,” *Energy Policy*, vol. 33, no. 2, pp. 209–219, 2005.

[64] P. Díaz, C. A. Arias, R. Peña, and D. Sandoval, “FAR from the grid: A rural electrification field study,” *Renew. Energy*, vol. 35, no. 12, pp. 2829–2834, 2010.

[65] S. Bhattacharyya and G. R. Timilsina, “Energy Demand Models for Policy Formulation A Comparative Study of Energy Demand Models,” no. March, 2009.

[66] L. Suganthi and A. A. Samuel, “Energy models for demand forecasting - A

review," *Renew. Sustain. Energy Rev.*, vol. 16, no. 2, pp. 1223–1240, 2012.

[67] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renew. Sustain. Energy Rev.*, vol. 13, no. 8, pp. 1819–1835, 2009.

[68] C. Subhash and P. S. Satsangi, "An integrated planning and implementation-strategy for rural energy systems," *Energy*, vol. 15, no. 10, pp. 913–920, 1990.

[69] L. Ferrer-Martí, R. Pastor, G. M. Capó, and E. Velo, "Optimizing microwind rural electrification projects. A case study in Peru," *J. Glob. Optim.*, vol. 50, no. 1, pp. 127–143, 2011.

[70] S. B. Malik, "INTEGRATED MULTI-LEVEL ENERGY SYSTEMS PLANNING MODELS FOR RURAL INDIA," 1994.

[71] S. Akhwanzada and R. bin M. Tahar, "Long-term Electricity Forecasting: A System Dynamics Approach," *Iceeb*, vol. 33, no. Iceeb, pp. 5–6, 2012.

[72] X. Zhang, S.-C. Tan, G. Li, J. Li, and Z. Feng, "Components sizing of hybrid energy systems via the optimization of power dispatch simulations," *Energy*, vol. 52, no. August 2015, pp. 165–172, 2013.

[73] J. A. Cherni, I. Dyner, F. Henao, P. Jaramillo, R. Smith, and R. O. Font, "Energy supply for sustainable rural livelihoods. A multi-criteria decision-support system," *Energy Policy*, vol. 35, no. 3, pp. 1493–1504, 2007.

[74] S. C. Bhattacharyya and G. R. Timilsina, "Modelling energy demand of developing countries: Are the specific features adequately captured?," *Ene2009_Bhattacharyya_Modelling energy demand Dev. countries, are speci?c fea tures adequately captured.pdf Policy*, vol. 38, no. 4, pp. 1979–1990, 2010.

[75] E. Ziramba, "The demand for residential electricity in South Africa," *Energy Policy*, vol. 36, no. 9, pp. 3460–3466, 2008.

[76] M. Filippini and S. Pachauri, "Elasticities of electricity demand in urban Indian households," *Energy Policy*, vol. 32, no. 3, pp. 429–436, 2004.

[77] P. Boonekamp, "Monitoring the energy use of households using a simulation model," *Energy Policy*, vol. 25, no. 7–9, pp. 781–787, 1997.

[78] G. Michalik, "Structural modelling of energy demand in the residential sector: 1. Development of structural models," *Energy*, vol. 22, no. 10, pp. 937–947, 1997.

[79] B. J. van Ruijven, D. P. van Vuuren, B. J. M. de Vries, M. Isaac, J. P. van der Sluijs, P. L. Lucas, and P. Balachandra, "Model projections for household energy use in India," *Energy Policy*, vol. 39, no. 12, pp. 7747–7761, 2011.

[80] S. Mandelli, M. Merlo, and E. Colombo, "Novel procedure to formulate load profiles for off-grid rural areas," *Energy Sustain. Dev.*, vol. 31, pp. 130–142, 2016.

[81] S. K. Singh, "The diffusion of mobile phones in India," *Telecomm. Policy*, vol. 32, no. 9–10, pp. 642–651, 2008.

[82] L. VE and McNeil MA, "Coping with residential electricity demand in India's future - How much can efficiency achieve?," pp. 1027–37, 2007.

[83] B. K. Bala and S. A. Siddique, "Optimal design of a PV-diesel hybrid system for electrification of an isolated island-Sandwip in Bangladesh using genetic algorithm," *Energy Sustain. Dev.*, vol. 13, no. 3, pp. 137–142, 2009.

[84] P. Balachandra and V. Chandru, "Modelling electricity demand with representative load curves," *Energy*, vol. 24, no. 3, pp. 219–230, 1999.

[85] A. Al-Karaghouli and L. L. Kazmerski, "Optimization and life-cycle cost of health clinic PV system for a rural area in southern Iraq using HOMER software," *Sol. Energy*, vol. 84, no. 4, pp. 710–714, 2010.

[86] G. Bekele and G. Tadesse, "Feasibility study of small Hydro/PV/Wind hybrid system for off-grid rural electrification in Ethiopia," *Appl. Energy*, vol. 97, pp. 5–15, 2012.

[87] K. V. N. Murthy, G. D. Sumithra, and A. K. N. Reddy, "End-uses of electricity in households of Karnataka state, India," *Energy Sustain. Dev.*, vol. 5, no. 3, pp. 81–94, 2001.

[88] M. I. Howells, T. Alfstad, D. G. Victor, G. Goldstein, and U. Remme, "A model of household energy services in a low-income rural African village," *Energy Policy*, vol. 33, no. 14, pp. 1833–1851, 2005.

[89] W. X. Shen, "Optimally sizing of solar array and battery in a standalone photovoltaic system in Malaysia," *Renew. Energy*, vol. 34, no. 1, pp. 348–352, 2009.

[90] K. B. Debnath, M. Mourshed, and S. P. K. Chew, "Modelling and Forecasting Energy Demand in Rural Households of Bangladesh," *Energy Procedia*, vol. 75, pp. 2731–2737, 2015.

[91] U. N. H. S. Programme, "Financing Urban Shelter - Global Report on Human Settlements," 2005.

[92] H. Khatib, "IEA World Energy Outlook 2011-A comment," *Energy Policy*, vol. 48, pp. 737–743, 2012.

[93] C. Jana and R. N. Chattopadhyay, "Block level energy planning for domestic lighting-a multi-objective fuzzy linear programming approach," *Energy*, vol.

29, no. 11, pp. 1819–1829, 2004.

[94] M. Howells, H. Rogner, N. Strachan, C. Heaps, H. Huntington, S. Kypreos, A. Hughes, S. Silveira, J. DeCarolis, M. Bazillian, and A. Roehrl, "OSeMOSYS: The Open Source Energy Modeling System. An introduction to its ethos, structure and development.," *Energy Policy*, vol. 39, no. 10, pp. 5850–5870, 2011.

[95] M. Laranja, E. Uyarra, and K. Flanagan, "Working Paper Series," 2007.

[96] M. Beller, A. Doernberg, A. Hermelee, and K. C. Hoffmant, "IMPACTS OF NEW ENERGY TECHNOLOGIES AS MEASURED AGAINST REFERENCE ENERGY SYSTEMS," 1979.

[97] A. R. Prasad and E. Natarajan, "Optimization of integrated photovoltaic-wind power generation systems with battery storage," *Energy*, vol. 31, no. 12, pp. 1607–1618, 2006.

[98] M. Welsch, M. Howells, M. Bazilian, J. F. DeCarolis, S. Hermann, and H. H. Rogner, "Modelling elements of Smart Grids - Enhancing the OSeMOSYS (Open Source Energy Modelling System) code," *Energy*, vol. 46, no. 1, pp. 337–350, 2012.

[99] "osemosys-dowload @ users.osemosys.org." [Online]. Available: http://users.osemosys.org/osemosys-dowload.html.

[100] C. Moroni and F. Antonio, "Energy access & the nexus with water and food. design of a pilot project for irrigation in a rural Indian village," Politecnico di Milano, 2015.

[101] P. Version, "International Journal of Scientific and Research Publications MAY 2012 Edition," vol. 2, no. 5, 2012.

[102] E. M. Module and T. Optimism, "Cost and Performance Characteristics of New Generating Technologies , Annual Energy Outlook 2016," no. June, pp. 1–4, 2016.

[103] N. Blair, K. Cory, M. HAnd, L. Parkhill, B. Speer, T. Stehly, D. Feldman, E. Lantz, C. Augustine, C. (NREL) Turchi, and P. (NREL) O'Connor, "Annual Technology Baseline," United States, 2015.

[104] Irena, "Renewable Power Generation Costs in 2012 : An Overview," no. January, p. 92, 2012.

[105] National Renewable Energy Laboratory (NREL), "Renewable Electricity Futures Study," *U.S. Dep. Energy*, vol. 1, p. 280, 2012.

[106] "aboutus @ www.indiadiesel.com." [Online]. Available: http://www.indiadiesel.com/aboutus.htm.

[107] "META @ esmap.org."

[108] "Oecd.Org. OECD Glossary of Statistical Terms." [Online]. Available: https://stats.oecd.org/glossary/detail.asp?ID=77.

[109] A. B. Roumboutsos, "Sustainability, social discount rates and the selection of project procurement method," *Int. Adv. Econ. Res.*, vol. 16, no. 2, pp. 165–174, 2010.

[110] S. Gupta and N. H. Ravindranath, "Financial analysis of cooking energy options for India," *Energy Convers. Manag.*, vol. 38, no. 18, pp. 1869–1876, 1997.

[111] R. Sen and S. C. Bhattacharyya, "Off-grid electricity generation with renewable energy technologies inIndia: An application of HOMER," *Renew. Energy*, vol. 62, pp. 388–398, 2014.

[112] R. Ramanathan and L. S. Ganesh, "Energy Resource Allocation Incorporating Qualitative and Quantitative Criteria: an Integrated Model Using Goal Programming and AHP," 1995.

[113] F. Zhen, "A Study of Energy Supply and Demand System on Village Level." China.

[114] A. Papadopoulos and A. Karagiannidis, "Application of the multi-criteria analysis method Electre III for the optimisation of decentralised energy systems," *Omega*, vol. 36, no. 5, pp. 766–776, 2008.

[115] B. E. Turkay and A. Y. Telli, "Economic analysis of standalone and grid connected hybrid energy systems," *Renew. Energy*, vol. 36, no. 7, pp. 1931–1943, 2011.

[116] G. N. Prodromidis and F. A. Coutelieris, "A comparative feasibility study of stand-alone and grid connected RES-based systems in several Greek Islands," *Renew. Energy*, vol. 36, no. 7, pp. 1957–1963, 2011.

[117] V. Devadas, "Planning for rural energy system : part II," vol. 5, pp. 271–297, 2001.

[118] T. K. Das, D. Chakraborty, and S. Seth, "Energy consumption and prospects for renewable energy technologies in an Indian village," *Energy*, vol. 15, no. 5, pp. 445–449, 1990.

[119] S. B. Malik, P. S. Satsangi, S. C. Tripathy, and R. Balasubramanian, "Mathematical model for energy planning of rural India," *Int. J. Energy Res.*, vol. 18, no. 4, pp. 469–482, 1994.

[120] M. L. Kolhe, K. M. I. U. Ranaweera, and A. G. B. S. Gunawardana, "Techno-economic sizing of off-grid hybrid renewable energy system for

rural electrification in Sri Lanka," *Sustain. Energy Technol. Assessments*, vol. 11, pp. 53–64, 2015.

[121] K. Kusakana, H. J. Vermaak, and B. P. Numbi, "Optimal sizing of a hybrid renewable energy plant using linear programming," 2012.

[122] I. Tegani, A. Aboubou, M. Becherif, M. Y. Ayad, O. Kraa, M. Bahri, and O. Akhrif, "Optimal sizing study of hybrid wind/PV/diesel power generation unit using genetic algorithm," *Int. Conf. Power Eng. Energy Electr. Drives*, vol. 85, no. 1, pp. 134–140, 2013.

[123] R. P. Saini, M. P. Sharma, and A. Gupta, "Modelling of Hybrid Energy System for Off Grid electrification of Clusters of Villages." .

[124] A. Gupta, R. P. Saini, and M. P. Sharma, "Modelling of hybrid energy system-Part III: Case study with simulation results," *Renew. Energy*, vol. 36, no. 2, pp. 474–481, 2011.

[125] B. O. Bilal, V. Sambou, C. M. F. Kébé, P. A. Ndiaye, and M. Ndongo, "Methodology to size an optimal stand-alone PV/wind/diesel/battery system minimizing the levelized cost of energy and the CO 2 emissions," *Energy Procedia*, vol. 14, pp. 1636–1647, 2012.

[126] H. Borhanazad, S. Mekhilef, V. Gounder Ganapathy, M. Modiri-Delshad, and A. Mirtaheri, "Optimization of micro-grid system using MOPSO," *Renew. Energy*, vol. 71, pp. 295–306, 2014.

[127] P. Paliwal, N. P. Patidar, and R. K. Nema, "Determination of reliability constrained optimal resource mix for an autonomous hybrid power system using Particle Swarm Optimization," *Renew. Energy*, vol. 63, pp. 194–204, 2014.

[128] S. S. Deshmukh and M. K. Deshmukh, "A new approach to micro-level energy planning-A case of northern parts of Rajasthan, India," *Renew. Sustain. Energy Rev.*, vol. 13, no. 3, pp. 634–642, 2009.

[129] X. Pelet, D. Favrat, and G. Leyland, "Multiobjective optimisation of integrated energy systems for remote communities considering economics and CO2 emissions," *Int. J. Therm. Sci.*, vol. 44, no. 12, pp. 1180–1189, 2005.

[130] R. Ramakumar, K. Ashenayi, and P. S. Shetty, "A linear programming approach to the design of integrated renewable energy systems for developing countries," no. 4, pp. 18–24, 1986.

[131] C. S. Sinha and T. C. Kandpal, "Optimal Mix of Technologies for Rural India - the Lighting Sector," *Int. J. Energy Res.*, vol. 15, no. January, pp. 331–346, 1991.

[132] C. S. Sinha and T. C. Kandpal, "Optimal Mix of Technologies for Rural India - the Irrigation Sector," *Int. J. Energy Res.*, vol. 15, no. January, pp. 331–346, 1991.

[133] C. S. Sinha and T. C. Kandpal, "Optimal Mix of Technologies in Rural India : cooking," vol. 15, no. September 1990, pp. 85–100, 1991.

[134] K. Y. Lau, M. F. M. Yousof, S. N. M. Arshad, M. Anwari, and A. H. M. Yatim, "Performance analysis of hybrid photovoltaic/diesel energy system under Malaysian conditions," *Energy*, vol. 35, no. 8, pp. 3245–3255, 2010.

[135] A. A. Setiawan, Y. Zhao, and C. V. Nayar, "Design, economic analysis and environmental considerations of mini-grid hybrid power system with reverse osmosis desalination plant for remote areas," *Renew. Energy*, vol. 34, no. 2, pp. 374–383, 2009.

[136] S. K. Nandi and H. R. Ghosh, "Prospect of wind-PV-battery hybrid power system as an alternative to grid extension in Bangladesh," *Energy*, vol. 35, no. 7, pp. 3040–3047, 2010.

[137] S. Kamel and C. Dahl, "The economics of hybrid power systems for sustainable desert agriculture in Egypt," *Energy*, vol. 30, no. 8 SPEC. ISS., pp. 1271–1281, 2005.

[138] E. M. Nfah, J. M. Ngundam, M. Vandenbergh, and J. Schmid, "Simulation of off-grid generation options for remote villages in Cameroon," *Renew. Energy*, vol. 33, no. 5, pp. 1064–1072, 2008.

[139] G. Bekele and B. Palm, "Feasibility study for a standalone solar-wind-based hybrid energy system for application in Ethiopia," *Appl. Energy*, vol. 87, no. 2, pp. 487–495, 2010.

[140] E. M. Nfah and J. M. Ngundam, "Feasibility of pico-hydro and photovoltaic hybrid power systems for remote villages in Cameroon," *Renew. Energy*, vol. 34, no. 6, pp. 1445–1450, 2009.

[141] J. A. Alzola, I. Vechiu, H. Camblong, M. Santos, M. Sall, and G. Sow, "Microgrids project, Part 2: Design of an electrification kit with high content of renewable energy sources in Senegal," *Renew. Energy*, vol. 34, no. 10, pp. 2151–2159, 2009.

[142] C. Nayar, M. Tang, and W. Suponthana, "Wind/PV/diesel micro grid system implemented in remote islands in the republic of maldives," *2008 IEEE Int. Conf. Sustain. Energy Technol. ICSET 2008*, pp. 1076–1080, 2008.

[143] M. S. Orosz and A. V Mueller, "Dynamic Simulation of Performance and Cost of Hybrid Pv-CSP-LPG Generator Micro Grids with Applications to Remote Communities in Developing Countries," pp. 1–9, 2015.