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Beyond optimal cost in energy models: overview of methodologies and application to the Italian energy system as a case-study.

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Abstract

Energy system optimization models (ESOMs) have helped policy makers over the years outlining the most cost-effective strategies for the deployment of energy technologies. However, research in the last years has shown how the least cost strategy often neglects other important issues, such as land usage or the mismatch in energy balance between regions. For this reason, policy makers are showing an increased interest in finding alternative strategies, as long as the increase in total cost is limited with respect to the cost-optimized strategy. This thesis, hence, provides an overview of all existing methods to generate near optimal solutions in ESOMs, and implements one of these methodologies into a supply-side ESOM, named Hypatia, applying the methodology to a case study inspired by the decarbonization of the Italian electricity sector by 2050. The near optimal solutions obtained, which refer to alternative decarbonization strategies, present different electricity mixes at equal electricity produced throughout the planning period. Highest land usage reduction is obtained when solar photovoltaic is preferred in the electricity mix. Conversely, the capacity factor is maximized for the whole sector in 2050 when hydroelectric, biofuels and waste power plants are prevalent in the mix. Lastly, the alternative strategy with the lowest total carbon dioxide emissions entails the largest deployment of new wind on-shore capacity, among all scenarios found. Overall, results present insightful energy strategies, which can be tailored to policy makers's needs worldwide.

Keywords: near optimal solutions, energy system optimization models, land usage, structural uncertainty, method to generate alternatives

Abstract in lingua italiana

I modelli di ottimizzazione dei sistemi energetici (in inglese ESOM) hanno aiutato politici e legislatori nel corso degli anni a delineare le strategie più economiche per l'implementazione di nuove tecnologie energetiche a lungo termine. Tuttavia, la ricerca degli ultimi anni ha dimostrato come la strategia dal minimo costo spesso trascuri altre questioni importanti, come l'uso del suolo o il disallineamento del bilancio energetico tra le regioni. Pertanto, i responsabili politici stanno mostrando un crescente interesse nel trovare strategie alternative, purché l'aumento del costo totale rispetto alla strategia più economica sia limitato. Questa tesi fornisce, dunque, una panoramica di tutti i metodi esistenti per generare soluzioni quasi ottimali negli ESOMs, e l'implementazione di una o più di queste metodologie in un ESOM incentrato sul lato generazione dell'energia, chiamato Hypatia, applicando la metodologia a un caso di studio ispirato dalla decarbonizzazione del settore elettrico italiano entro il 2050. Tutte le strategie alternative generate presentano un diverso mix energetico, a parità di energia elettrica prodotta lungo tutto il periodo di pianificazione. Gli scenari mostrano una prevalenza di solare fotovoltaico nel mix di generazione con la più alta riduzione dell'uso del suolo. Al contrario, la massimizzazione del fattore di capacità dell'intero settore elettrico al 2050 si ottiene con una prevalenza nel mix energetico di centrali idroelettriche e centrali alimentate da biocarburanti e rifiuti. Infine, tra tutti gli scenari individuati, la strategia alternativa con le più basse emissioni totali di anidride carbonica comprende il più grande dispiegamento di nuova capacità eolica on-shore. Nel complesso, i risultati mostrano delle strategie energetiche a diverso carattere nozionistico, che possono quindi essere adattate alle esigenze dei responsabili politici di tutto il mondo.

Parole chiave: soluzioni vicino all'ottimo, modelli di ottimizzazione dei sistemi energetici, utilizzo del suolo, incertezze strutturali, metodi per la generazione di alternative

Contents

Introduction

Countries all over the world have pledged to fight climate change by setting targets for the reduction of green house gases emissions. These targets will help mitigate the effects of the increase in global mean temperature caused by anthropogenic activities, as stated by international cooperation treaties such as the Paris Agreement [24]. In order to pursue these climate goals, policy makers all over the World need to lay down detailed and specific energy technology strategies. To do so, the most common tools utilized are Energy Systems Optimization Models (ESOMs), which are models that usually find a single optimal solution by minimizing the total system cost and respecting certain physical constraints, in the pursue of predetermined targets such as decarbonization by a specific year [17]. Indeed, it is in the interest of policy makers, as well as tax-payers, to reach climate goals in the most advantageous economical way for all.

At the same time, research in energy modeling during the last years has focused on finding alternative solutions, different from the least-cost one [4]. This is because traditional single-optimal solution ESOMs do not take into consideration certain social issues which are almost impossible to transcribe into variables in a mathematical model, because of their intrinsic nature. These issues may vary from public acceptance of a specific technology, to the overcrowding of one technology in a specific region with respect to the actual energy consumed by the population of this region, just to make two examples. These problems affect policy makers decisions, and therefore, their relevance when planning an energy strategy, should not be underestimated. That is why policy makers have stated that they are willing to pay more, to a certain extent, in order to cope with these issues. How much they are willing to exceed in total cost is a matter which will be discussed later in this thesis work. But this is not the only reason why, in recent years, the focus of energy modeling has shifted to the exploration of alternative solutions different to the lest-cost optimal one. Real world energy transition has shown that traditional ESOMs are quite unlikely to predict the actual solution of the future [22]. This is because these models, as per their definition, should not be considered crystal balls able to see into the future, but they should be seen as tools that lay out the main guidelines in order to reach specific energy policy targets. Therefore, it becomes paramount to research an extensive number of other possible feasible solution, that could very well represent the actual "real world" energy transition.

The current framework of methodologies to tackle uncertainties in ESOMs may differ depending on the what is the main challenge that researchers want to face in their models. First of all, it is important to understand what the uncertainties are and what is their role when looking for alternative solutions.
Uncertainties in energy optimization models can be of two kinds [26]:

- Parametric uncertainties: they are given by the aleatory nature of some economic or social parameters, like for example fuels and technologies costs, discount rates, learning rate curves, and so on.
- Structural uncertainties: they are given by the model inadequacy to represent real life conditions.

The first kind of uncertainties are easier to tackle with respect to the second one. In fact, having to deal with an input parameter whose value may change in the future and therefore affect the overall results of the optimization, requires a sensitivity analysis on that parameter. This consists of selecting a range of plausible values, rerun the model for each value and assess the impact on the results. However, nowadays it is more common to see innovative methodologies to perform sensitivity analyses which involve probabilistic distributions of the uncertain parameters (Monte Carlo simulation analysis), stochastic programming or robust optimization [26]. These methods (together with other methods not mentioned here, but still valid for parametric uncertainties) allow to analyze different deterministic or distributed solutions, different with respect to the single optimal solution case, in a direct and concise cause-relation way between input and output.

The second kind of uncertainties are, on the other hand, significantly trickier. Indeed, models often do not consider issues that are not mathematically represented in their equations, and therefore, cannot be studied with sensitivity analyses on some input parameters. These problems can hence be linked to the structural uncertainties of ESOMs, and they therefore need different methodologies from the previous one to be analyzed and to find possible pathways to cope with them. While usually research studies on structural uncertainties have focused only on increasing the accuracy to depict real world of ESOMs by making them more and more complex and structured, in recent years a new methodology has been introduced to face these uncertainties without altering heavily the structure of the model.

This methodology, introduced first in energy modeling by DeCarolis, is called "Modeling to generate alternatives" (MGA) [4]. It is commonly utilized for linear optimization and single objective problems, but as it will be seen later in this thesis, it has many possible applications, and the ways in which it can be utilized are various and valid for the exploration of alternative solutions in energy modeling. However, the general principle at the base for the implementation of this method consists of these three different steps:

- First, the optimal single solution is found with the minimization of the total cost of the system as the objective function.
- Second, the total cost becomes a new constraint of the model in the search of alternative solutions. These new solutions will indeed have a total system cost which can be higher than the previous one, but not exceed it by a certain value set arbitrarily by introducing a cost slack.
- Third, with this new constraint, a new objective function needs to be defined. Its definition is of pivotal importance when looking for near-optimal solutions and, as it will be seen later, it is the key aspect on which research works on MGA have been focusing in the last years.

Hence, using the MGA methodology answers policy makers demands to explore alternative solutions, which are more expensive in monetary cost, but solve possible problematic issues which may arise in the future. The way in which it creates a set of near-optimal solutions is adequate when exploring different pathways Countries want to embrace in the climate change challenge. On the other hand, however, simply implementing this method is not enough when studying single specific study cases, since there are different options when choosing possible new constraints, the new objective functions, new parameters attributed to the variables of the function and so on.
This is why it is of paramount importance to study, analyze and compare different MGA applications of recent research works in this field, and then implement the most appropriate one for a specific case study to see how it affects the results. That is exactly what this thesis intends to do, starting from one specific research work, which is Lombardi et al. (near-optimal solutions for the decarbonization of the energy sector of Italy in 2050), and then proceeding to study different existing ways to generate near-optimal solutions, compare them and implement one for the original case study.
The approach which will be therefore followed in this thesis consists first of an advance literature review of the current framework in the field of near-optimal solutions in energy modelling. This section is fundamental in order to find the most suitable methodology for the generation of alternative energy mix solutions in the Italian net-zero 2050 case.

Then, the following section concerns the implementation of the methodology found in the literature review section, with a focus on the results and comments about their interpretation. Lastly, a final section compares the results found with Lombardi et al., with the solutions for the specific case study, and with other MGA implementations.

1 | Literature review

In this chapter, the process followed in order to conduct the needed literature review is described in careful detail.
As stated in the introduction, this literature review is a fundamental aspect of this thesis, as it helps to understand the current framework of methods used to generate alternative solutions. In particular, the main focus of the review is centered on those methods that cope with structural uncertainties, rather than parametric uncertainties. As before mentioned, these latter uncertainties are not really related to the problem discussed at the beginning of the introduction and the range of methods to deal with them is already quite vast and explored.
In particular, the goal is to find methods like the "Modeling to generate alternatives" one, which allow to generate and explore possible near-optimal solutions, without increasing the complexity of the model. In order to later implement these methods, they need to meet specific requirements which are compatible with the study case of this thesis. These requirements translate into specific key words and research filters, which will help to detect the most suitable research works.

1.1. Methodology

Literature reviews can be carried out in different ways and with the help of a vast range of available commercial tools. In this thesis, the "Systematic literature review" is chosen as the most appropriate one for the purpose of this work, because of its scientific rigorous approach in finding relevant scientific articles. This approach defines a specific search string and systematically analyzes all the corresponding literature. In case of an excessively high number of articles found, the review selects a subset of the literature to focus through one or more selection criterion. In this way, all relevant research available on a specific topic is reviewed.
The tool utilized for the review is *Scopus - Advanced literature research*, which allows to find articles by entering specific query strings. These query strings are a combination of commands regarding the possible words that appear in the title, in the abstract or in the

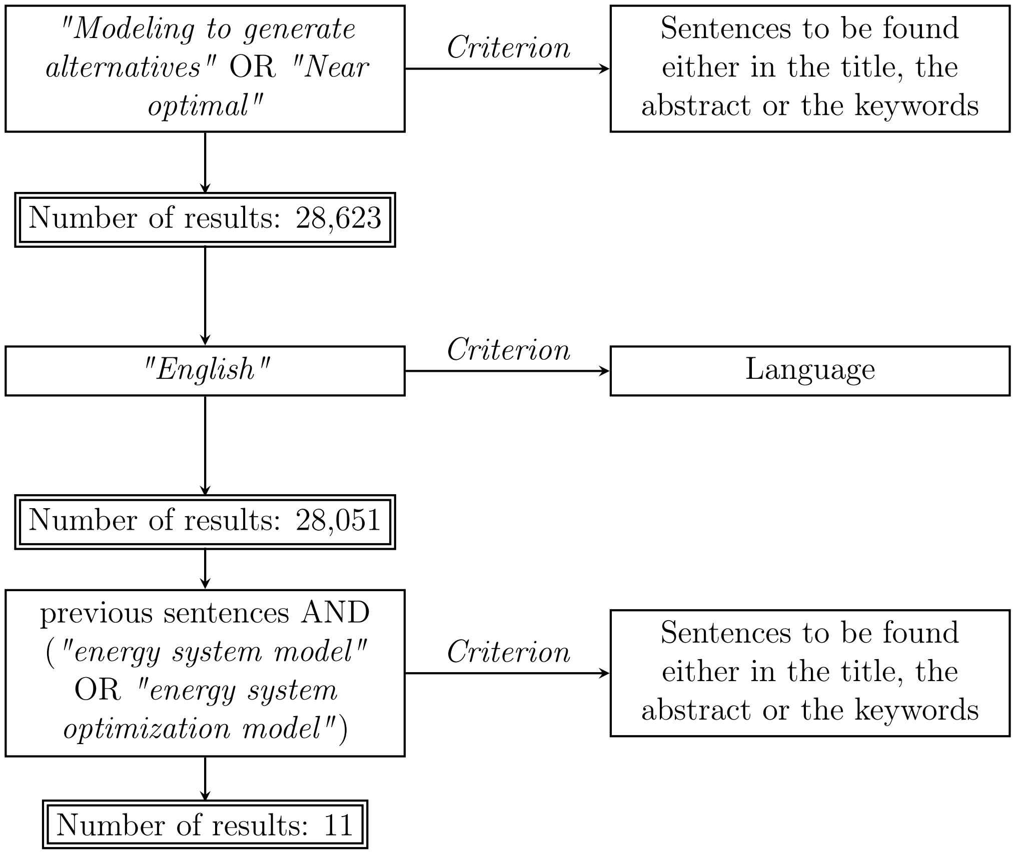


Figure 1.1: Schematic representation of the Advanced Literature research

keyword section of the papers. Moreover, commands include filters on the language of the article, on the date of publication, on possible restricted access and many other criteria. For the purpose of this thesis work, the query strings used in Scopus were selected to be relevant only for the words or sentences present in either the title, the abstract or the keywords, and for the language of the research works, which needs to be in the English language in order to make this thesis accessible for international readers. No particular relevance was given to the date of publication, since the energy modeling research field (and in particular methods to tackle uncertainties) is relatively young. All other criteria were deemed unnecessary for the finding of the most suitable research works.
After having conducted several advanced literature researches on uncertainty analyses applied to energy systems modeling, the results appeared to be unconnected to the research question of this thesis, since their focus was mainly on parametric uncertainties. However, thanks to a shift of the focus more directly on the generation of near-optimal solutions and different MGA applications, a final advanced literature research [appendix] was selected as the one to find the most adequate results.

As it can be seen from the Figure 1.1, the words researched in either the title, the abstract or the keyword with the Scopus command *TIT-ABS-KEY()*, consist of two short sentences:

- *"Modeling to generate alternatives"*, as it looks for the most common methodology to cope with structural uncertainties, developed by DeCarolis and used also in the reference research work at the center of this thesis (Lombardi et al.).
- *"Near optimal"*, as it looks in general for ways to generate or explore near-optimal solutions.

By using the search string above, the research included all articles, written in English, which included the phrases "modeling to generate alternatives" or "near-optimal" either in their abstract, title, or keywords. The literature search is further constrained so that the articles found are relevant to energy system optimization models, i.e., they include this term either in their abstract, title or keywords.

1.2. Results

The final results of the advanced literature research are 11 research papers. In this section, they are carefully scrutinized, while a discussion about which research work to implement for the study case of the decarbonization of Italy in 2050 will follow in the next section.

The following research papers were found:

1. *"Policy Decision Support for Renewables Deployment through Spatially Explicit Practically Optimal Alternatives", 2020, Lombardi, F., Pickering, B., Colombo, E., Pfenninger, S.*

   As stated in the introduction, this paper is used as the benchmark to explore and compare different alternative near-optimal solutions.
   In this work, the authors first find the least-cost optimal solution for the Italy 2050 decarbonization of the energy sector case study. Then, they add a new constraint which is the relaxation of the total system cost, and thanks to a new objective function, they are able to find near-optimal solutions. This new objective function is the minimization of decision variables such as the new installed capacity of renewable technology, where each variable is multiplied by a weight, which depends on the theoretical maximum capacity that could be installed of a specif technology in a certain region. Indeed, one of the issues with the single optimal solution, relevant to Italian policy makers, is the overcrowding of one technology in a specific region,

which might seem unfair for the local population not only because of the environmental impact this technology might cause, but also because the energy produced in that area would be much greater than the one needed for local consumption. This is also connected to another issue which might be the one to put great stress on certain transmission lines, while leaving others underutilized. Thanks to this MGA approach implemented in this paper, many solutions are found which can help to partially solve the before mentioned issues.

2. *"Balancing GHG mitigation and land-use conflicts: Alternative Northern European energy system scenarios", 2022, Chen, Y.-K., Kirkerud, J.G., Bolkesjø, T.F.*

   While the work from Lombardi et al. focuses on a quantitative approach to find near-optimal solutions, this paper centers its attention on a qualitative way to implement the MGA and find near-optimal solutions. The specific case study is about the deployment of large scale renewables in Northern European countries, and in particular how to find alternative solutions, different from the optimum, which cope with the problem of renewable technologies land use. The methodology implemented for the generation of near-optimal solutions is the same as before, with the exception of the new objective function. In this case, the authors opt for two desirable scenarios, with the creation of two new variables which qualitatively represent land occupation. With their optimization, the authors rely that the two near-optimum solutions found are guaranteed to be the best ones to cope with this particular issue.

3. *"Modeling all alternative solutions for highly renewable energy systems", 2021, Pedersen, T.T., Victoria, M., Rasmussen, M.G., Andresen, G.B.*

   This research work implements an alternative method to find near-optimal solutions, which is called *"Mapping All Alternatives" (MAA)*. The specific case study is an application of this method on an European electricity system model, and its implementation consists of creating a space of all near-optimal solutions, starting from the single least-cost optimum one. MAA does that by defining first a tetrahedron which is the border of near-optimum solutions, thanks to a constraint on the total cost of the system. Then it populates the area of this tetrahedron (space of near-optimum solutions) thanks to the definition of multiple simplex (which in two dimensions correspond to triangles). This allows to create a vast number of alternative solutions, which could be explored by policy makers in order to solve specific issues related to the single optimum one, all inside a space delimited by the constraint of the cost relaxation.

4. *"Exploring flexibility of near-optimal solutions to highly renewable energy systems",*

2021, Pedersen, T.T., Victoria, M., Rasmussen, M.G., Andresen, G.B.

This paper is complementary to the previous one (as it was written and pubblished by the same authors) and is, indeed, a more detailed analysis of the results of the MAA method application to an European electricity system model.

5. *"Finding a Portfolio of Near-Optimal Aggregated Solutions to Capacity Expansion Energy System Models", 2020, Buchholz, S., Gamst, M., Pisinger, D.*

   This article centers the focus on the generation of maximally different solutions, in capacity expansion problems (CEP). It does this by finding first the optimal investment strategy for this kind of problem, then, like in the MGA approach, it sets a new constraint on the total cost of the new installed capacity. The interesting peculiarity is the new objective function, which consists of finding the most different investment strategy inside the cost constraint. It does that by maximizing the absolute value of the difference between the newest strategy and the previous ones. In this iterative approach, it creates a portfolio of investment strategy solutions, different from the optimal one, which could be explored by policy makers.

6. *"Exploring the impact space of different technologies using a portfolio constraint based approach for multi-objective optimization of integrated urban energy systems", 2019, Jing, R., Kuriyan, K., Kong, Q., Zhang, Z., Shah, N., Li, N., Zhao, Y.*

   This research work combines the MGA method to a multi-objective optimization problem, which consists of finding the optimal technology portfolio for integrated urban energy systems. The case study to which it applies is the optimal deployment of these energy systems in urban China. The methodology implemented starts with the generation of a baseline optimal solution, and then it creates a space of alternative solution by processing iteratively each technology present in the baseline portfolio. This process comprehends two steps: the first one is to exclude completely that technology and the second one is that the technology module is called gradually with an acceptance parameter inside the portfolio. Then, thanks to the application of the Direct Least Squares Fitting of Ellipses algorithm via Matlab[], the best fitting ellipse containing all the alternative solutions generated following the described methodology is created.

7. *"Integrated renewable energy systems for Germany-A model-based exploration of the decision space", 2019, Nacken, L., Krebs, F., Fischer, T., Hoffmanna, C.*

   In this paper, the authors study the implementation of the MGA method on the case study of the German energy system. The methodology implemented is very similar to the one seen in Lombardi et al. research work, with the exception of the assignation of weights in the new objective function. In this case, the minimization of the decision variables, is characterized by a product of the Cartesian set (-1,1) with the variables. This means that if the variables are for example 2, the new near optimal solutions will be four and they will be found by multiplying the variables respectively by (1,1), (-1,1), (1,-1), and (-1,-1). In this specific case study, the variables are 8, meaning that this method is going to find 2^8 near optimal solutions, for each slack of the total system cost relaxation.

8. *"A review of approaches to uncertainty assessment in energy system optimization models", 2018, Yue, X., Pye, S., DeCarolis, J., Li, F.G.N., Rogan, F., Gallachóir, B.Ó.*

   This article is a review of the current framework of methods used to cope with uncertainties in ESOMs. The methods mentioned include the MGA one for structural uncertainties, while for parametric uncertainties, it describes the *Monte Carlo analysis*, *Stochastic programming* and *Robust optimization*.

9. *"Ensuring diversity of national energy scenarios: Bottom-up energy system model with Modeling to Generate Alternatives", 2017, Berntsen, P.B., Trutnevyte, E.*

   In this research work, the MGA method is implemented for the study of near optimal solutions in the case study of the energy transition of the Swiss electricity supply system. The peculiarity in this case, is to not add any cost constraint in the research of alternative solutions. Indeed, it simply creates two new objective functions which are the minimization and the maximization of the same function. This function is the sum of all the decision variables, which are mainly the new installed energy capacity of specific technologies, each multiplied by its own weight. This weight is sampled randomly within a uniform distributed set (-1,1). With each sample, it is possible to find two alternative solutions, therefore, the authors of this work repeat this procedure 20 times, in order to have the possibility at the end to explore 40 different alternative solutions.

10. *"Does cost optimization approximate the real-world energy transition?", 2016, Trutnevyte, E.*

    This article tries to answer the question which ponders how good energy optimization models actually simulate the real World energy transition. The author uses as a case study the energy transition of the United Kingdom between 1990 and 2014, and it compares the real one with a single least-cost optimal solution of an ESOM and near-optimal solutions generated with the MGA method. The way near-optimal solutions are generated in the model is similar to the same methodology approached by Lombardi et al., with the exception of the weights used in the new objective function. In this case, the weights are values which are generated randomly in the range between 0 and 1.

11. *"Modelling to generate alternatives with an energy system optimization model", 2016, DeCarolis, J.F., Babaee, S., Li, B., Kanungo, S.*

    This research work, written and pubblished by many authors including DeCarolis, who can be safely described as the "father" of the MGA method to find near optimal solutions, is the application of this method on an energy system optimization model, while analyzing the specific case study of the electricity sector of the United States of America. It is at the center of all the previous works presented, which implement MGA in their research studies, including the main reference of this thesis by Lombardi et al.

1.3. Discussion

1.3.1. Analysis of the results

After having seen a brief description of each systematic literature research result, it is now possible to discuss whether the research works found are either suitable or useful for this thesis purposes. Indeed, the desired objective is to implement one or more of the aforementioned methods to generate alternative near optimal solutions to the case study of Italy's decarbonization of the electricity sector by 2050. In this way, it would be possible to analyze and compare the results to the ones found by Lombardi et al. [10].
Firstly, a consideration can be made about the nature of some of the papers found. The research work conducted by Yue et al. [26] contains a general description of the current methodologies used to tackle uncertainties in ESOMs and for this reason, even if it might be useful for a general knowledge on the subject of energy modeling, it does not provide actual methods to implement the generation of near optimal solutions. Instead, the paper published by DeCarolis et al. [5], being already important for the work done by Lombardi et al., which is the reference work for this thesis, is not going to be further analyzed.
Certain methodologies found in the review are deemed as not suitable for linear programming single objective cost-optimization problems. For example, the method described by Jing et al. [9] is designed for mixed integer linear programming multi-objective problems and therefore, not suitable for the ESOM used for the case study of this thesis. Moreover,

its objective is to find the optimal portfolio of technologies in integrated urban energy systems, which may differ from the cost-optimal energy system desired in this thesis. Buchholz et al. [1] was also deemed as not suitable for this thesis, since it is developed for capacity expansion problems with the research of the optimal investment strategy.

Pedersen et al. [15] [16] introduces a new alternative and promising way to find near optimal solutions. Indeed, the possibility to define the limits of a space of solutions under a cost-constraint and then populate that space allows to find a significant number of alternatives easy to explore and analyze. In addition, this methodology also implicitly guarantees the robustness of the solutions found, which is one of the main critiques of the MGA method developed by DeCarolis. Moreover, another interesting aspect of this work is the use of the Gini coefficient for the analysis of regional energy self-sufficiency. The Gini coefficient is a parameter commonly used in economics to measure financial inequality among the population of a region or a country. Pedersen et al. adapt this coefficient to the energy field to measure the energy produced in a certain region compared to the one actually consumed by its population. In this way, the Gini coefficient is a representation of how far a region is from energy self-sufficiency, which as stated in the introduction, could be a severe issue for the local population, and therefore relevant to policy makers. However, because of the complex algorithms used to define and populate the near optimal space, this method requires heavy computational tools which cannot be adopted in this thesis. Even though, on the other hand, the idea to use the Gini coefficient to measure energy self-sufficiency is suitable for the aim of this thesis. Indeed, in order to tackle the aforementioned issue of regional energy disparities between production and demand, the Gini coefficient will be taken up in the following chapters.

Chen et al. [2] focuses instead on a qualitative approach to generate near optimal solutions. In this way, the number of solutions found significantly decreases, thus, policy alternatives would also decrease. In addition, this methodology searches fewer solutions, given a clear purpose at the start of the research, which translates into a higher efficiency in finding the best possible solution for a specific issue.
One critique which could arise after reviewing this method, is that rather than a way to generate alternative near optimal solutions, this approach is more resembling of a multi-objective approach. Indeed, instead of finding alternative solutions by assigning weights to the decision variables of a new objective function (like in the work of Lombardi et al.), it creates two new variables, whose minimization serves as the specific objective in the new objective functions. However, this critique falls behind the fact that the methodology introduced in this paper follows the iterative procedure of the classic MGA method introduced by DeCarolis. Therefore, instead of optimizing simultaneously multiple objectives

like in usual multi-objective optimization problems, it generates first a least-cost optimal solution, and then it uses new objective functions by adding the constraint of a total cost relaxation with different values of slack.
Hence, implementing this method on the ESOM utilized for this thesis, for the specific case study of Italy's decarbonization, could be a valid approach in pursuing the aim of this work. Indeed, by using the method introduced by Chen et al., it would be possible to analyze and compare results with the ones by Lombardi et al., as well as to compare a qualitative and a quantitative approach when generating alternative near optimal solutions.

The remaining literature found present a methodology to finding near optimal solutions similar to the one presented by Lombardi et al. , with the exception of the method used to define weights in the new objective function. The noticeable difference lies in the fact that, while Lombardi et al. [10] use an arbitrary approach when defining the weights (based on the maximum theoretical capacity which could be installed of a specific technology in a specific location), the authors of these three articles use a randomized approach. Thus, solutions vary from the Cartesian product of the set (-1,1) proposed by Nacken et al. [13], to the random value generated in the range from 0 to 1 proposed by Trutnevyte [22], and then again to lastly the value sampled from a uniform distribution of the set (-1,1) proposed by Trutnevyte et al. [23].
This random approach in generating weights for the new objective function, could therefore bring new interesting insights when generating near optimal solution for the specific case study of the thesis. Indeed, assigning random values from a uniform distribution to the decision variables weights, would consequentially result in a uniform distribution of close to optimal solutions. A key aspect is that not only it would do that, but it would also do it while maintaining the same objective function and the same cost relaxation with respect to the least cost solution. Hence, a possible implementation of this method in the new objective function to be later defined, might bring new insights when trying to explore alternative solutions, different from the ones found by Lombardi et al,, and could consequentially aid in the pursue of the thesis purpose, as stated in the earlier chapters.

1.3.2. Conclusions

After reviewing the methodologies used for the generation of alternative near optimal solutions in ESOMs, the most suitable ones are chosen to be implemented in the following chapters of this thesis. They will be reformulated in order to adapt to the energy system optimization model and the specific case study present in the work conducted by Lombardi et al. [10]. The main difference from the methodology implemented in their

work will rely on the definition of the new objective function, after the least-cost optimal solution has been found and the new cost constraint has been added.
As seen in the previous section, the qualitative approach proposed by Chen et al. [2] is the most appropriate one so to assess how much they differ from the ones found by Lombardi et al.'s quantitative approach. The new qualitative objective functions to be introduced in the model and, in particular, their definition, are going to be at the center of the next chapter. In fact, they obviously will have to represent plausible solutions to the policy makers' issues presented in the introduction chapter, such as land occupation or energy self-sufficiency of a region (for this latter, it might be useful to implement new variables like the Gini coefficient seen in the work conducted by Pedersen et al. [15]).
Moreover, with new qualitative objective functions implemented in the model, an alternative way of assigning weights to the decision variables of the functions could be used. This would help find alternative near optimal solutions which might have not yet been explored by Lombardi et al. in their work. Again, as seen in the previous section, this new approach is going to be based on random generation from distributed sets, like in the methodologies proposed by Trutnevyte [22]. The specific methodology to be followed for the generation of the decision variables weights will also be at the center of the next chapter.

2 | Methodology

In this chapter, all the features that have been implemented in the model to reach the targets of this thesis are going to be discussed. They range from the mathematical formulation of the new objective functions and constraint, to the definition of the optimization mode, from the new utilities of the model, to the script needed to run the model in 'close to optimal' optimization mode, and so on.
First, it is of crucial importance to describe the energy system optimization model used. Indeed, before going into deeper detail on how to generate close to optimal solutions, it is a better practice to understand how the model normally works and what can be implemented in it for the aim of this work.

2.1. Hypatia

Hypatia is an energy system optimization model written and developed by SESAM [14], a research group at Politecnico di Milano. It is written in the objective-oriented Python programming language and it is possible to edit and run it through different available source code editors (e.g. Visual Studio Code 2, the one used in this thesis). Thanks to its technology-oriented structure, Hypatia allows to optimize even complex energy system frameworks, with a premium accuracy in time and space resolution. Moreover, Hypatia allows the user to choose between two different optimization modes, "Operation" and "Planning". In the first, the model optimizes for the operational analysis in one year, while in the second, Hypatia optimizes for continuous capacity deployment analysis over multiple years. For the aim of thesis, and therefore for the case study of Italy's decarbonization by 2050, only the "Planning" mode is of interest. However, all the new features that will be implemented for the generation of close to optimal solutions, can be adopted also for the "Operation" mode.
The model, as stated by the authors, is inspired by other popular energy system optimization models, such as Calliope, the one utilized by Lombardi et al. in their work to generate close to optimal solutions. However, while most of the other open-source ESOMs, included Calliope, use Pyomo to solve optimization problems, Hypatia relies on

CVXPY.
CVXPY is an innovative domain-specific language for convex optimization problems, which enables writing the optimization problem in a natural way following plain mathematical rules, contrary to the strict standard form required by solvers. Moreover, the use of CVXPY does not lessen the number of solvers that can be utilized for Hypatia, which indeed remains high, both for open-source and for commercial ones.

The structure of the model is divided in different "blocks". In the following list, a brief analysis of what each block does is carried out:

- *Backend*

  The Backend modules are the backbone of the whole model. Here all the input data is processed, the variables and constraints are defined and calculated, and lastly, in the "Build.py" module, the optimization problem is defined along with its objective functions. For this reason, most of the conceptual features which need to be implemented to generate close to optimal solutions, are going to be done in *Backend* modules.

- *Utilities*

  In the Utilities block, everything regarding auxiliary features of the model is stored. From the calculation of utility functions, which are then needed in the description of the problem, to the correct label of different categories of technologies and carriers.

- *Main*

  The "Main.py" module inside the Main block is where the model is defined as a class. This definition is needed so to initialize and run a model, since it helps to clearly visualize the different steps when running the optimization problem present in the Backend. In fact, thanks to the class input arguments and methods, the user is able to perform in a dedicated script all the steps needed, from the definition and initialization of the Model, to the writing of the optimization problem results. The precise steps will be seen more in detail later, when this dedicated script needed to run the model will be discussed.

- *Analysis*

  Lastly, the Analysis block is responsible for the analysis and postprocessing of the model results. A key aspect when working with energy system optimization models, since it fosters the communication with people and organizations interested in the final results of the model, such as policy makers or private companies.

As briefly previewed in the *Main* block, a fundamental feature of Hypatia is also a module (e.g., "Run.py") where to run the model. In this, the user can define and run the model built by executing the following dedicated steps:

1. First, initialize the model by directing it towards the path of desired input sets and by choosing whether to run it in operation or in planning mode.
2. Define the path where the input parameters are stored and allow the model to read them.
3. Run the model, while deciding also which solver needs to be used for the problem optimization, among the available ones.
4. Last, store the results of the run in a dedicated path, given that the optimization of the problem terminated successfully.

A proper "run.py" module is fundamental in order to properly define models and generate close to optimal results. Indeed, in the following sections we are going to see how, in this module, there is also the need to define and update new parameters of the model, which are pivotal to the generation of alternative solutions with different objective functions.

Undoubtedly, Hypatia comprehends numerous other features ranging from the definition of equations, variables, and classes, to the postprocessign of optimization results. Any additional detail regarding the structure of the model can be found in [14].
The new features implemented in Hypatia are discussed in the following sections. First, the objective functions are defined in Section 2.2, Next, the design of the new cost constraint is described in Section 2.3. Finally, the structure of the new module dedicated to the running of the model is presented in Section 2.4.

2.2. Objective functions

In this section, the new objective functions introduced in the model are discussed. Together with the cost constraint, the definition of a new objective function is an important step of the MGA method [5] to generate close to optimal solutions in energy system optimization models. Indeed, after having obtained the first optimal solution of the problem, which is traditionally the least-cost one, there is a change in the objective function, together with the definition of a new constraint.
Since the definition of the new objective functions to implement is more relevant to the aim of this thesis, they are discussed first.

Literature review results (section 1.2) show that most of the methods to generate alternative solutions exhibit two types of new objective functions:

- *Qualitative*

  The new objective function focuses on the research for a possible solution to a well identified issue, which is possibly different from the one identified by the first objective function. Instead of the quantity of close to optimal solutions, this kind of objective function focuses on the accuracy on its specific target, generating thus just one solution.
  Examples are the two objective functions proposed by Chen et al. [2], where the specific targets are respectively the minimization of occupied land and the minimization of impacted area by energy technologies.

- *Quantitative*

  The new objective function aims at finding alternative solutions close to the least cost one, possibly focusing on multiple issues simultaneously. In this case, the focus is shifted more on the number of alternative solutions in the neighbourhood of the optimal one. Then, by analyzing the results obtained, the overall accuracy of the solutions found may be increased.
  Typically, these functions are the minimization of the sum of some decision variables (usually the installed generation capacity of each technology), each multiplied by a coefficient, often called weight. The value of these weights can be given based on some criteria (e.g., the ideal maximum capacity in Lombardi et al. [10]), or they can be extracted randomly from a distributed sample of numbers (e.g. the uniform distribution between 0 and 1 in the work by Trutnevyte [22])

Qualitative objective functions are of interest for the aim of this thesis. In fact, two of Italy's biggest issues with traditional least cost solutions are the land occupation of renewable technology and energy balance mismatch among its macroregions [10]. These issues, therefore relevant to the decarbonization of the Italian electricity production sector, could be therefore tackled with targeted qualitative objective functions.

But qualitative functions have also undergone some criticisms because of their nature.
In the work by Chen et al. [2], it is maintained that the optimization problem related to qualitative objective functions is very similar to that of a multi-objective optimization one. Even though this might not necessarily be a negative aspect, it is a different optimization structure compared to near optimal solutions. Indeed, multi-objectives problems have a different structure and the way their optimization is done is conceptually different from single-objective. For this reason, it is incorrect placing on the same level qualitative

objective functions and multi-objectives optimization problems.
This difference in the structure is important, since close to optimal solutions always work with a specific cost constraint on the least cost one. Therefore, all solutions found are still in the neighbourhood of the optimal one in terms of total cost. In this way, the first optimal solution is still prioritized, as all the following close to optimal solutions are, because of their nature, influenced by it.
Contrary to the multi-objective optimization problems, where the solution could come with a cost significantly higher than the one it would have had with a least cost single optimization.

In general, having a higher number of solutions is better for several aspects.
First, single optimal solutions hardly capture the multifarious nature of the real world energy transition. Conversely, the higher the number of close to optimal solutions, the higher the likeliness of considering insightful aspects of the real world energy transition [22]. Indeed, qualitative objective functions try to solve as much as possible specific issues, but there might be other hidden close to optimal solutions which could potentially be similar and, in addition to that, be helpful for other issues.
Second, close to optimal solutions can support policy makers addressing specific issues. In fact, exploring alternative solutions through a qualitative objective function tailored to a specific policy issue allows to model and explore policy strategies addressing specific issues at a cost that is still close to the lowest. In contrast, having just one close to optimal solution may not advise policy makers on a range of possible strategies as crisply as multiple close to optimal solutions would do
Lastly, close to optimal alternatives help find solutions to problems which are hard to be mathematically transcribed into a model [4].

Given all these reasons, in this thesis a combined quantitative and qualitative approach was pursued while defining two new objective functions. The qualitative part is given by the definition of the functions, which will try to solve as much as possible specific issues. Then, after the first run of each function, each of the decision variables of the function is multiplied by a different weight. By running multiple times and giving every time a new value to the weights, a desired number of close to optimal solutions is obtained. In this way, the objective functions are guaranteed to be also quantitative.

The two new objective functions to be implemented in Hypatia regard two different topics:

- *Land usage*
- *Energy balance mismatch*

In the following subsections, a more careful description of what they concern, the reference for them and how they are implemented in the model will follow.
To every decision variable of the two functions, a weight, whose value is extracted randomly from a uniform distribution sample between 0 and 1, is multiplied allowing to reach a desired number of close to optimal solutions.

2.2.1. Land usage

The deployment of renewable technologies to generate electricity is fundamental to achieve decarbonization targets in the Paris Agreement [24]. However, renewable energy deployment has not been an easy task, among other reasons, due to land usage concerns [8].
Indeed, electricity production technologies all require a different amount of land in order to generate the same amount of energy. This factor, which can be called "Land Usage", has sparked a fiery debate over the years, involving not only policy makers but also local communities [21].

Land usage is important for three main reasons. First, from an economic perspective land is a strategic asset and using it for energy production could make it difficult or impossible carrying out other activities. Such activities can vary from the housing of people to agriculture or manufacturing industries.
Second, from a social perspective,land is connected with labour and employment. Thus, a higher land use may involve higher employment in the region, all others factors held true.
Third, from an environmental perspective a land occupation with power production technologies may negatively affect the landscape or scenery of an area.
However, this is not a priori true, in the sense that visual impact is also related to other features of a plant, like for example the presence of condensation towers or the physical attributes of a specific plant. Moreover, there are other types of environmental impact which could be of more importance to local population (e.g. air and water pollution, acoustic, and so on).

In general, renewable technologies, such as solar photovoltaic and wind, have a higher specific Land Usage than traditional fossil fuel power plants. This means that at equal installed capacity, the land used by renewable sources is significantly more, as it can be seen in a table of reference values A.1.
It is reasonable believing that land usage should be minimized, even though it comes with a greater cost.

Thus, the research of close to optimal solutions, with a qualitative objective function about the minimization of land usage, is pertinent to the target of this thesis. The one which is implemented in this work, comes from the work on close to optimal solutions by Chen et al. [2], with a readjustment to the model used, which in this case is Hypatia.

The mathematical description of the objective function is the following:

$$obj.func. = min(\sum_{i}^{years}\sum_{j}^{tech} x_{i,j} \cdot LU_{i,j}) \tag{2.1}$$

Where:

$$LU_{year,tech} = LU_{specific_{year,tech}} \cdot TotCapacity_{year,tech} \tag{2.2}$$

Land usage $[m^2]$ is a matrix given by the positional product of elements inside two matrices of the same size, which are respectively the specific land usage of each energy technology for every year $[\frac{m^2}{GW}]$ and the total installed capacity of each technology for every year $[GW]$.
Specific land usage is an input parameter of the model, where the values chosen for each technology remain constant over the years. The entity of these values can be seen in *Table A.1* in appendix A, together with the references of where they come from.

While in the objective function it is possible to observe the positional product of the elements of two matrices. Respectively, the just seen land usage matrix and a matrix of the weights needed for the quantitative part of the objective function (*Section 2.2*9. The value of these weights is assigned in the following way:

$$\begin{cases} x_{tech} = 1, & \text{if it is the first time running Land obj. func.} \quad (2.3a) \\ x_{tech} = rand(0,1), & \text{if it is NOT the first time running Land obj. func.} \quad (2.3b) \end{cases}$$

This means that a value of 1 is given for each technology during the first run of close to optimal solutions with this objective function. While for the other close to optimal solutions with the same function, the weight for each technology is extracted randomly from a uniform distribution sample between 0 and 1.
Notice how for both cases the different random value is given only to each technology. Indeed, this value is then kept constant over the years, in order to maintain the same weight for each technology during time. When the model is then run again for a new close to optimal solution, a new weight is assigned to each technology.

The product between the weights and land usage results in one final matrix, whose sum over the technologies and over the years is the global objective of the model that needs to be minimized (equation 2.1).

The implemented code, written in Python, used to define and use this equation into the model can be found in appendix B. However, it is suggested to first read how the running module (section 2.4.2) is structured and then proceed to have a look at all the new code lines implemented in Hypatia.

2.2.2. Energy balance mismatch

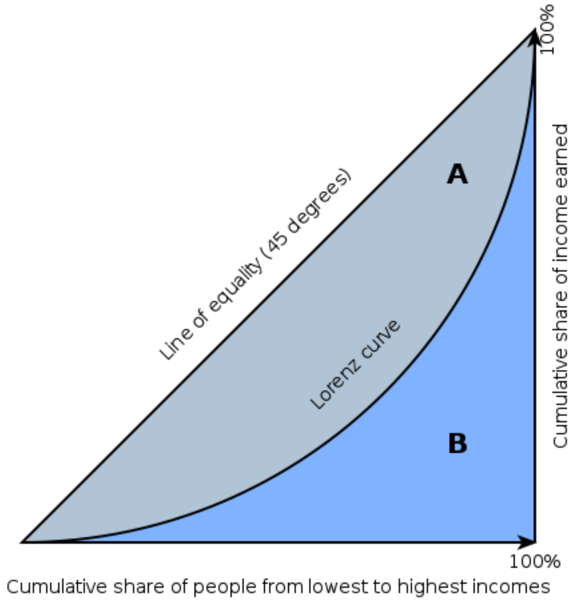
Another issue with the current energy transition, is the one linked to the mismatch of the energy balance. For this mismatch, it is intended the disparity between the energy demand and the energy production of a single region [15].
There are many reasons behind why this happens and why it is actually an emerging issue, with policy makers that are now more inclined to pay attention to it.

First, disparity between energy demand and production happens because one region does not have enough energy resources to meet its demand. Therefore, it is forced to import electricity from the production of another region. Consequently, this implies that the other region which exports electricity, has more energy resources than it needs to meet its demand.
Other sources of disparity between energy demand and supply include logistic issues, economic or regulatory convenience in producing in a certain region, or the scarcity of land.

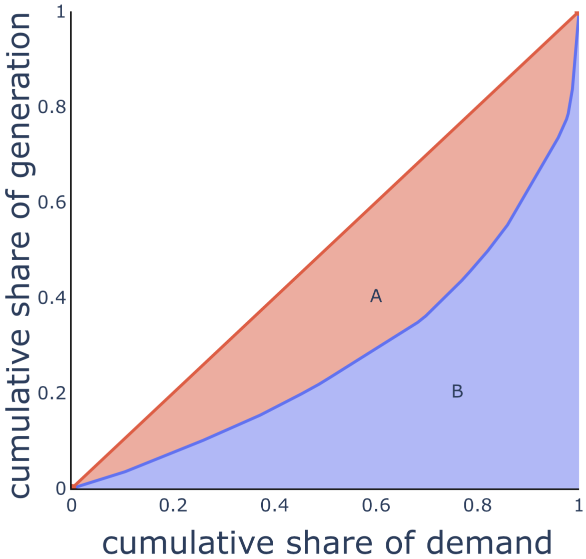
A mismatch in the energy balance is problematic for many reasons.
First, in regions where the Global horizontal irradiance (GHI) or the average wind speed are higher than anywhere else, a higher production of electricity from renewables can be expected. In these regions, the use of transmission lines to export it to other parts of the country is also expected.
However, renewable technologies for the generation of electricity, as seen in the previous subsection 2.2.1, bear the highest Land Usage factors. As a consequence, in such regions there might be an overcrowding of power generation technologies, which in turn comes with a significant occupancy of land, while other regions can just reap the benefits of such electricity production, without bearing the same burdens.
One example from this, which is also cited in Lombardi et al. [10], is the region of Sardinia in Italy. In least-cost traditional energy systems optimization models, Sardinia features a great deployment of wind energy, much higher than the regional electricity demand. Such a situation might be undesirable from a policymaking perspective.

Second, energy balance mismatch may cause the congestion of transmission lines. Indeed, the higher the electricity export from one region to the other, the higher the usage of transmission lines. This results in a prolonged stress of the infrastructure, together with the fact that in case of damages or maintenance, the energy reliability of the importing region could potentially be at risk.

In this thesis, an objective function regarding energy balance mismatch was implemented, to generate close to optimal solutions. However, to mathematically describe such a problem is not an easy task (one of the main principles behind close to optimal solutions). Therefore, taking inspiration from the reference in Pedersen et al. [15], an economics index, the Gini coefficient, was used and adapted to the energy domain.
The Gini coefficient is an index traditionally used to measure inequality between the incomes of cumulative shares of the population in a certain region or country. In Pedersen et al. [15], it is readjusted so that the inequality is a representation of the energy balance mismatch and it is shown between the cumulative share of energy demand and the cumulative share of energy production of regions in a country, or countries in an agglomerate of countries.
A graphical representation of the Gini coefficient is shown in figure 2.1 whereby the concept was framed for economic and energy-domain analysis. The equality line represents what would happen in the case of perfect equality (i.e., in the energy case, the cumulative share of demand matches perfectly the cumulative share of production). While the Lorentz curve depicts what happens in reality (i.e., in the energy case, the difference between the cumulative share of demand and production in some regions).



(a) Economics Gini [18]



(b) Energy Gini [15]

Figure 2.1: Visual representation of the Gini coefficient

The Gini coefficient is calculated in both cases as the ratio between the area delimited by the equality line and the Lorenz curve, and the overall area:

$$Gini = \frac{A}{A+B} \tag{2.4}$$

The Gini values range between 0 (perfect equality, Lorenz and equality curves are the same) and 1 (complete inequality, i.e. in the energy case there is one region/country generating all the energy).
Hence, the second objective function to be implemented in the model for this thesis, is set to minimize the overall Italian energy inequality, operationalized by means of the Gini coefficient. This Gini is a function which takes as input the total demands and the total productions of all N regions and returns the Gini value.

$$obj.func. = min(Gini([TotDem_{reg1}, .., TotDem_{regN}], [TotProd_{reg1}, .., TotProd_{regN}])) \tag{2.5}$$

Where the total demand is calculated as the sum over the years of the yearly typical-day demands of each region, which are input parameters of the model:

$$TotDem_{reg} = \sum_{i}^{years} Dem_{reg,i} \tag{2.6}$$

And the total production is calculated as the sum over the years and technologies of the product between the annual typical-day electricity productions of each region, and a random weight assigned to each technology:

$$TotProd_{reg} = \sum_{i}^{years} \sum_{j}^{tech} x_{i,j} \cdot AnnualProd_{reg,i,j} \tag{2.7}$$

The weights are, once again, a way to generate multiple close to optimal solutions with a qualitative objective function, and therefore make it also quantitative. The way in which its values are assigned is exactly the same as the one used for the land objective function (equations 2.3).

The code written in Python to implement this objective function in Hypatia, can be found in Appendix B. However, it is once again recommended checking the code after having read the section on the running module (section 2.4.2), at the end of this chapter.

Moreover, together with the objective function, in Appendix B is possible to find the code of the Gini function used in it to look for the global objective.
In this function, the aim is to compute the cumulative shares of the total demands and productions of the regions, based on given percentiles, and then calculate the areas de-

limited by the equality and Lorenz curves. The structure is as follows:

1. Take the vectors of regional total demands and productions as an input.
2. Define an array, whose length is given by the number of regions, of evenly spaced numbers over the (0,100) interval. This creates the percentiles needed to rearrange demand and production.
3. For every percentile, from 0 and to 100, calculate the cumulative share of both demand and production.
4. At this point, there are two arrays with the values of the cumulative shares of demand and production, from 0 to 100. The length of these arrays is the same as the one of percentiles, since every value of cumulative share is calculated based on all the percentiles.
5. The perfect equality area $(A + B)$ and the Lorenz area (B) are calculated with integrals of the values of cumulative shares.
6. The Gini coefficient is calculated as the difference between the perfect equality and Lorenz areas, therefore (A), over the perfect equality area. As per definition.
7. The function returns the value of the Gini coefficient just found.

This function is therefore called when looking for close to optimal solutions with a qualitative objective function on energy balance mismatch (equation 2.5). In particular, the value the function returns is minimized as the global objective, to obtain the solution that minimizes energy balance mismatch as much as possible.

This objective function only works in a model set with multiple regions, so to assess energy balance mismatch between regions or countries.

2.3. Cost constraint

After having seen the definition of the close to optimal objective functions, it is now possible to move to the other fundamental step of the MGA method [5]: the addition of a constraint on the total cost.
Indeed, in order to effectively be close to optimal solutions, the new objective functions are calculated under one extra constraint on the cost of the system. In particular, the total actualized cost of the energy system cannot exceed a specific value.
This value is given by the total cost of the least-cost traditional optimization solution, and by a parameter called "cost relaxation", so that the additional cost constraint can be

mathematically expressed like this:

$$TotCost_{close2optSolutions} \leq TotCost_{leastcostSolution} \cdot (1 + CR) \tag{2.8}$$

Therefore, the cost relaxation represents the percentage (expressed in decimals notation) of the total cost of the least-cost optimal solution, which cannot be exceeded while looking for close to optimal solutions. Such value corresponds to how much more policy makers are willing to pay extra for alternative solutions in ESOMs. According to Trutnevyte [22], a maximum acceptable value of cost relaxation for them is around 30%.

In Hypatia, every constraint has its own module located in the constraints directory inside the *Backend* block of the model. Therefore, this additional cost constraint has been implemented in the model through its own module called "Close2optimalCost.py". In the module, whose code is possible to see in Appendix B, the constraint is defined as a class which takes as an input the "Constraint" class. In this way, it initializes the constraint with the model data and variables, and it allows, through a dedicated method called "rules", to append the mathematical formulation of the additional cost constraint.

Every class of constraints is then added to a list of constraints, called "CONSTRAINTS", in a dedicated module. This allows to add all the constraints when building the model in the "Build.py" module.
To add the additional cost constraint, a new list, called "CLOSE2OPTCONSTRAINTS", is created in the same constraints list module. In this way, it will be possible to use this additional cost constraint only when looking for close to optimal solutions, which is indeed the only time when it is needed.
The operational way in which this is done, will be seen in the next section of this chapter. While, in appendix B, the new module of the constraints list can be found.

2.4. Running the model

In the previous section, it has been seen how Hypatia is structured and what the main core features are when building the desired model.
After having clarified these concepts, it is now possible to proceed to a detailed analysis of all the things needed to work with and run the built model.

2.4.1. Optimization mode

Hypatia already has the option to choose an optimization mode, regarding whether the model needs to be run in "Planning" or "Operation" mode.
However, an additional optimization mode needs to be implemented in the model for the aim of this thesis. This concerns the possibility to choose whether the user wants to run the model with just the single traditional least-cost solution or with both the single solution and the multiple close to optimal solutions.

In the model, this choice is translated into a feature present when defining the model in the running module. Indeed, this definition happens by calling the class Model, together with its input arguments.
These arguments are:

1. *Path*, where it is indicated where the sets of the model desired to build are stored.
2. *Mode*, where it is possible to choose between "planning" and "operation".
3. *Name*, where it is possible to give a name to the model (this input is optional).

Therefore, to generate close to optimal solutions, a new input argument is added to the class, called *Optimization*. This argument, just like *Mode*, lets the user decide between two different optimization modes:

- "Single", to generate just one traditional least-cost solution.
- "Close2opt", to generate multiple close to optimal solutions, together with the single least-cost one

This new feature is implemented in Hypatia in the script of the "Model" class, in the "Main.py" module. In particular, *Optimization* is defined with a dedicated class called with the same name and present in the "constants.py" module in *Utilities* block of the model.
This process is done, just like for *Mode*, to make the optimization mode be of either two specific kinds, which are the ones just mentioned. Indeed, every other string different from "Single" and "Close2opt", written for the optimization mode when defining the model in the run module, is considered an invalid input argument.

The specific code, written in Python implementing this feature, can be found in Appendix B.
This comprehends both the part in the "Main.py" module and the one in the "constants.py" module.

2.4.2. Run module

The run module is a dedicated script, which contains all the steps needed to define, run and store the results of the model built.
For these dedicated steps, as also seen in section 2.1, the methods present in the class "Model" are used.

Given the aim of this thesis, the run model cannot simply contain the steps to run just once. Instead, its structure should be a cycle that runs multiple times to get all the desired solutions. Note how for desired solutions, it is intended the single least-cost one, plus the close to optimal ones, obtained with the objective functions described in section 2.2.
Moreover, a feature must be implemented, that allows to decide the desired number of solutions to look for with each objective function. While doing this, it is worth remembering that the Gini objective function only works with a multiregion model.

Lastly, together with the number of solutions, the script must also have features to let the user decide the optimization mode, discussed in the previous subsection 2.4.1, and the value of cost relaxation, described in section 2.3.

Before getting into deeper detail on how everything works in the module, in figure 2.2, it is possible to observe a schematic representation of the cyclical structure inside the run module. This is the one implemented in Hypatia to generate close to optimal solutions.

As it can be observed, the first part of the module consists of defining some new parameters. These parameters are an important tool to generate close to optimal solutions, since they are a way to communicate, to the build module, the solution wished to obtain.

For example, the parameter "Sol_num" is the iterative component in the cycle, which allows to run several models consecutively. It is always initialized to 1 before the cycle begins, and it iteratively grows by one with every run, until it reaches the user-defined value of total number of solutions. Notice however, how this happens only if the optimization mode defined is "Close2opt", otherwise the cycle ends after the first run.

Moreover, the solution number, together with the parameter Last_Gini, is in charge of communicating with the build model, so that the desired objective function and constraints are chosen.
Indeed, even though the steps in the highlighted process box in figure 2.2 are standard for every run (as they are dictated by all the same methods in the "Model" class), the model built is actually different for every obtained solution.

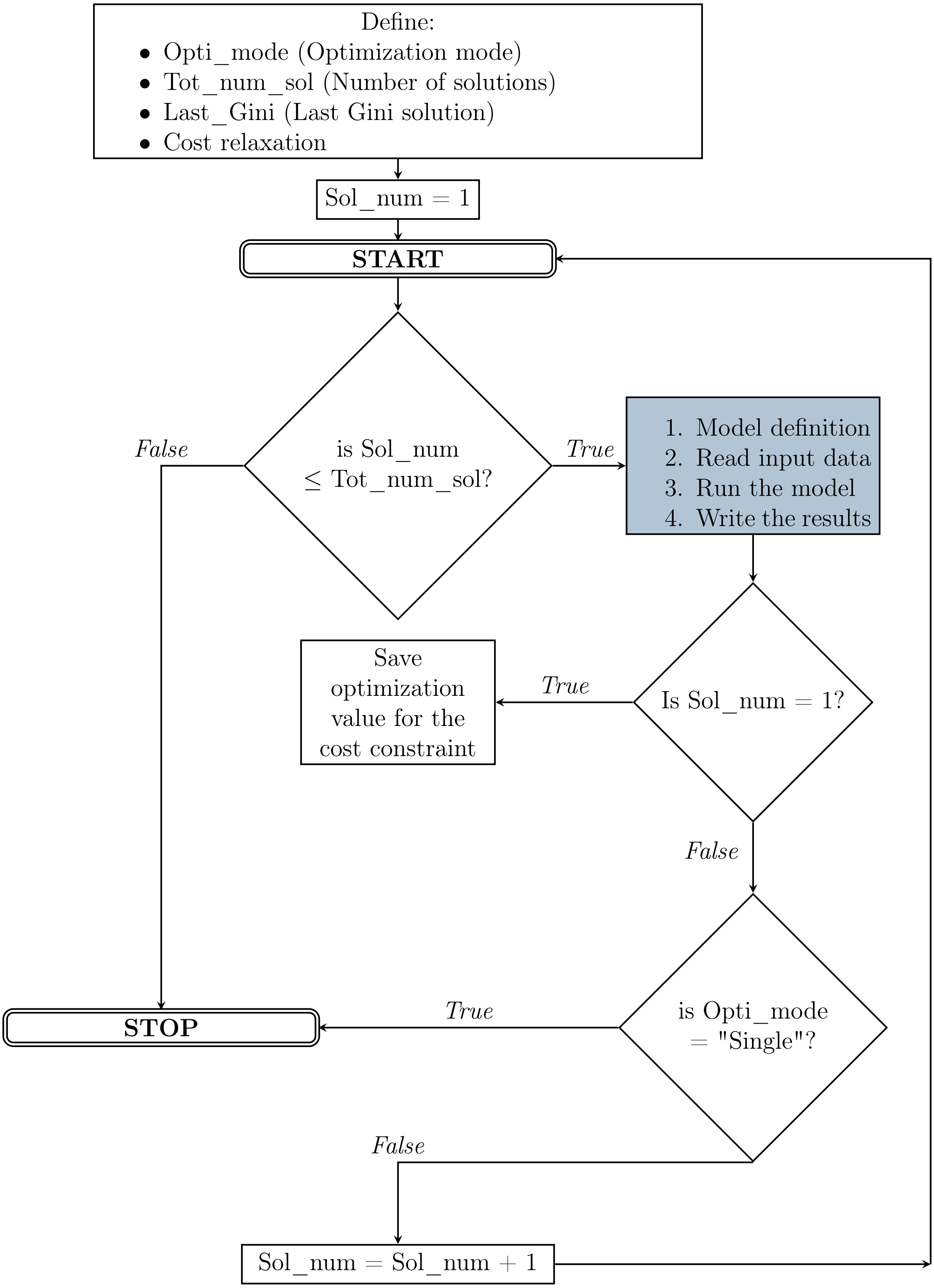


Figure 2.2: Schematic representation of the cycle in the running module

This is possible thanks to the calling of the methods in the "BuildModel" class present in the "Build.py" module. In fact, this calling depends on user-defined parameters, and in this particular case, on the optimization mode, the solution number, and the last Gini solution.
A representation of what happens in the build model for every solution number, when running in close to optimal optimization mode, can be observed in tables 2.1 and 2.2. Notice how the representation changes based on whether the model run is single or multi-region, since it has already been stated how the energy balance mismatch (Gini) objective function only works with multiple regions.

Multiregion objective functions

Solution Number	Objective function	Cost constraint
1	Traditional least-cost	No
2	Gini, no weights ($x_{tech} = 1$)	Yes
3 $\rightarrow$ Last_Gini	Gini, with weights ($x_{tech} = rand(0, 1)$)	Yes
Last_Gini + 1	Land, no weights ($x_{tech} = 1$)	Yes
Last_Gini + 2 $\rightarrow$ Tot_num_sol	Land, with weights ($x_{tech} = rand(0, 1)$)	Yes

Table 2.1: Objective function for every solution number - Multiregion

Single region objective functions

Solution Number	Objective function	Cost Constraint
1	Traditional least-cost	No
2	Land, no weights ($x_{tech} = 1$)	Yes
3 $\rightarrow$ Tot_num_sol	Land, with weights ($x_{tech} = rand(0, 1)$)	Yes

Table 2.2: Objective function for every solution number - Single region

As an example, the solutions obtained in a multiregion model, when the total number of solutions is 11 and the last Gini solution is 6, are:

- 1 least-cost traditional (solution number 1)

- 1 Gini with no weights (solution number 2)
- 4 Gini with weights (solution numbers 3 $\rightarrow$ 6)
- 1 Land with no weights (solution number 7) and 4 Land with weights (solution numbers 8 $\rightarrow$ 11)

Because of the definition of the MGA method to generate close to optimal solutions [5], every time the model is run in "close to optimal" mode, solution number 1 must always be of the traditional least-cost type.
In this way, the optimal value at the end of the first run, which is the least possible total cost of the system, is saved and used in the additional cost constraint (see section 2.3) for all the other runs of the cycle.

The whole script written in Python for this running module, called "Run.py", can be found in appendix B. For the cycle (figure 2.2), it was decided to implement a "while" cycle that keeps running with new solutions until the solution number is equal to total number of solutions.
In the script, it is possible to notice how the solution number, the cost relaxation and the last Gini solution, together with the optimal value of the first run, are actually saved in another module called "Utilities_close2opt.py" present in the *Utilities* block of Hypatia. The reason behind why this is done, is because all these parameters are called in other modules of the model (the build module for the solution number and the last Gini solution, and the cost constraint module for the optimal value of the first run and the cost relaxation).
If these parameters were to be imported directly from the run module, and since this latter at turn imports the whole Model, the terminal would raise circular import errors, bringing the whole model to not work.

Therefore, "Utilities_close2opt.py" works as an intermediate module where to store the correct and updated values of the aforementioned parameters.

In appendix B, the script of this module can be found. Notice however, how the values for every parameter are just to initialize them. Indeed, after the first run, everyone of them is updated to the correct value, and this value is then imported in the other modules, where needed.
The only value which is purposely set at 1, is the one for the solution number. In fact, in this way, the cycle in the run module always begins with the solution number equal to 1.

This concludes the chapter on the methodology behind the work of this thesis.
After having observed all the features implemented in Hypatia, the reasons why they were

done, and how the model works, it is now possible to proceed and observe the results for the specific case study of this thesis, applied to the model just described.

3 | Results and discussion

The methodology just seen in chapter 2 can be applied to any single objective energy system optimization model. With some cautious modifications, it could also be applied to other optimization models, not mandatorily related to the energy domain.

In this thesis, the aim is to obtain near optimal solutions with this methodology applied to a case study, which in this case is inspired by the decarbonization of Italy electricity generation sector by 2050. Being inspired by the Italian case does not exclude the alternative scenarios found from being relevant to policy makers all over the World.
Therefore, in this chapter, the analysis of the solutions to this specific problem is carried out, together with a thorough description of the reference energy system built and used in Hypatia.

3.1. Reference Energy System

The Reference Energy System (RES) is the framework of the energy system used in an energy system optimization model. The target, when building a RES, is to represent as much as possible the real energy system of the case study under analysis.
Indeed, the RES must try to comprehend all the existing energy technologies and take into consideration all parametric constraints, in the period of analysis.

As a consequence, a vast amount of data is required to describe complex energy systems, such as the electricity production one in Italy. The more detailed the representation of the real-world energy system, the more similar model results look to real-world phenomena. Nevertheless, in doing so data needs increase as well.

For this reason, in this thesis a simplified RES is built to analyze the near optimal solutions of the case study. The focus of this work is on generating multiple alternative solutions next to the least-cost one, rather than detailing all plants of the national energy system. Hence, a simplified version of the Italian electric power production sector is considered suitable enough for the aim of this thesis.

A schematic representation of the RES built for this thesis, to test the generation of near optimal solutions, can be seen in figure 3.1. In it, it is possible to observe:

- The generation technologies, in rectangular-shaped boxes
- Energy carriers, in rounded boxes and in bold
- Storage technologies, in diamond-shaped boxes
- Transmission and distribution technologies, in the trapezium-shaped box
- The final demand of electricity, in the double marked box

Boxes highlighted in blue represent technologies whose production variables are at the center of the optimization of the problem. On the other hand, energy carriers are seen as the inputs and outputs of these technologies, necessary to meet the final electricity demand.

Moreover, the transmission and distribution of electricity is present so to consider grid losses, through the efficiency of the electrical lines. The value of this efficiency, in the specific study case of this thesis, is 96%.

Another notable aspect of the RES structure is the oil refinery. This conversion technology has multiple inputs (crude oil, natural gas and electricity), which are needed to generate the oil products, then used in oil power technologies.

Before running the model, it has been seen in section 2.4 how Hypatia reads the defined input parameters needed to obtain meaningful results. These parameters were obtained by a report commissioned by the International Energy Agency (IEA) [11].
They range from the residual capacity of each generation and storage technology, to the technical and economic lifetime of technologies, from the capacity factor of resources, to the efficiencies of technologies, and so on.

However, there are some parameters which require a discussion, given the importance for the specific case study of this thesis.

The decarbonization of the power sector requires a policy, which contributes to the gradual abandon of traditional fossil fuels in favor of renewable technologies. This policy can be set in the model through input parameters.
In fact, the entity of some parameters, like for example the minimum or maximum capacity to be installed of a certain technology or the minimum share of renewable capacity installed, constitutes implicitly a policy.

For this work, it was decided to set the minimum values of renewable production and minimum renewable electric penetration for each year of the model run. In this way, a

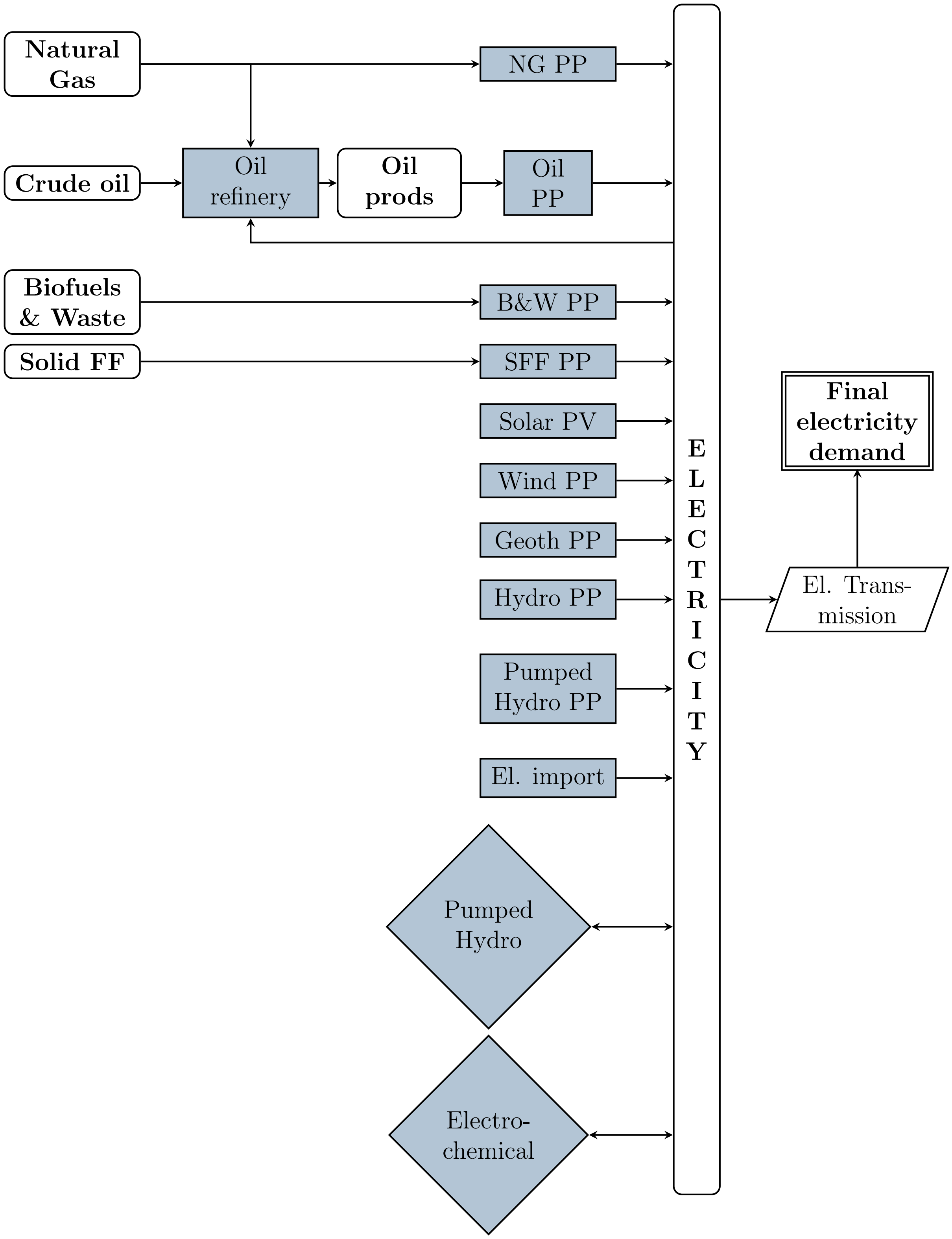


Figure 3.1: Schematic representation of the study case Reference Energy System

minimum deployment of renewable technologies is guaranteed, with a consequent decrease of emissions.
Undoubtedly, these values cannot be set arbitrarily, but they need to be realistic and actually follow the country intended policies on the paths to reach climate goals [24]. For this work, it was decided to use as a reference the Italian national integrated plan for energy and climate (PNIEC) [12].

From the PNIEC, the values for the minimum renewable production share, which are equal to the ones for the renewable electric penetration, are reported in table 3.1. It can be observed how these values increase until 2030, after which they are then assumed to remain constant until 2050.

Year	Min Res Production Share (%)
2020	0
2021	36.2
2022	38.2889
2023	40.3778
2024	42.4667
2025	44.5556
2026	46.6444
2027	48.7333
2028	50.8222
2029	52.9111
2030	55

Table 3.1: Minimum share of renewable power production [12]

In the PNIEC, there are also guidelines on the yearly values for the total minimum capacity installed of each renewable technology. However, these values were not used in the model, in order to possibly increase the diversity among close to optimal solutions.

Other parametric constraints comprehend a maximum total installed capacity for those generation technologies whose value is limited by a maximum resource availability. In Italy, some technologies are already almost using their full potential, such as hydroelectric and geothermal power plants [12].

Moreover, another constraint was set, on the basis of climate policies, by setting the maximum new capacity of solid fossil fuel and oil power plants to 0 [12].

Final electricity demand is also included in a constraint, as the demand nees to be met with production and storage.
The data used for the electricity demand in Italy from 2020 to 2050, was obtained from the European Union reference scenario 2020 (EU-REF2020) [3]. Considering the projection of electricity consumption shares for every sector, obtained through the PNIEC, it was then possible to compute the yearly electricity demand of Italy, from 2020 to 2050.

Lastly, another climate policy was implemented in the model, aimed at further reducing greenhouse gas emissions. In fact, together with the policy on the minimum share of renewable technologies, a carbon tax was implemented in the model through its input parameters.
The value of this carbon tax is in the range of 0 to 120 €$/ton_{CO_2}$, by taking as a reference current values in European countries [25].
In this specific case study, the model runs with a carbon tax value in this range, and then, in order to assess its impact, a sensitivity is carried out in section 3.2.10.

After having discussed the reference energy system and some important input parameters of the model, it is possible to proceed analyzing the results of the model, for the specific case study of this thesis.

3.2. Results analysis

The Hypatia model was run with the reference energy system of section 3.1 and with the code implementation described in chapter 2 to generate close to optimal solutions.
The run module, discussed in section 2.4, also requires some additional parameters when running with multiple near optimal solutions. In particular, the total number of solutions and the cost relaxation of the additional cost constraint are needed to be set by the user.

For this thesis, it was decided to generate near optimal solutions with three different values of cost relaxation. According to Trutnevyte [22], policy makers are not willing to exceed a 30% increase of total cost, from the least cost solution. Therefore, cost relaxations of 5%, 15% and 25% were devised.

For every value of cost relaxation, it was then decided to obtain a total number of solutions of 21. These 21 solutions comprehend the first least cost one, and then 20 near optimal solutions with the land objective function 2.2.1. Of these alternative solutions, the first one (i.e., solution number 2, see section 2.4.2) is going to be obtained with no weights on the decision variables, while all the other have random weights, as described in section 2.2.

This number was preferred to others so to obtain statistically relevant results, while still considering a limited computational power of the machine used to run the model.

In addition, it has also been discussed in section 3.1 how the policy used for the reduction of emissions is a combination of carbon tax and the PNIEC [12] guidelines.
For these results, it was decided to use a value of carbon tax of 80 $€/ton_{CO_2}$. The reason why this particular value was chosen can be referred to it being in the range of current European countries values $[0, 120]$ $€/ton_{CO_2}$ [25]. To assess the impact of this value, in section 3.2.10 a sensitivity analysis on carbon tax is carried out.

To summarize, table 3.2 shows all the conditions in which the model has been run to obtain the following near optimal solutions.

Model framework

Cost relaxation	5%, 15% and 25%
Total number of solutions	21 (for every CR value)
Objective function	Land
Policy	PNIEC and carbon tax (80 $€/ton_{CO_2}$)
RES	figure 3.1

Table 3.2: Conditions used to obtain near optimal solutions

3.2.1. Must-have technologies

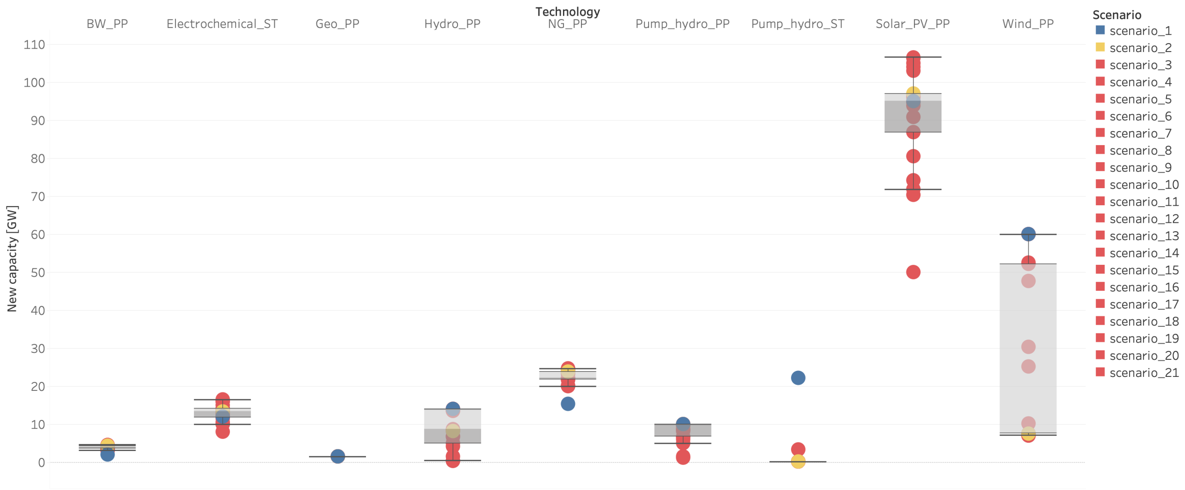
Model results provide insights on the deployment of technologies in the period of study, and the emissions and costs related to this deployment.

A first important insight on the near optimal strategies found can be given by an analysis on must-have technologies. These are the generation and storage technologies which, no matter the cost relaxation or the weights used in the objective function, are always present in the new deployment between 2020 and 2050.

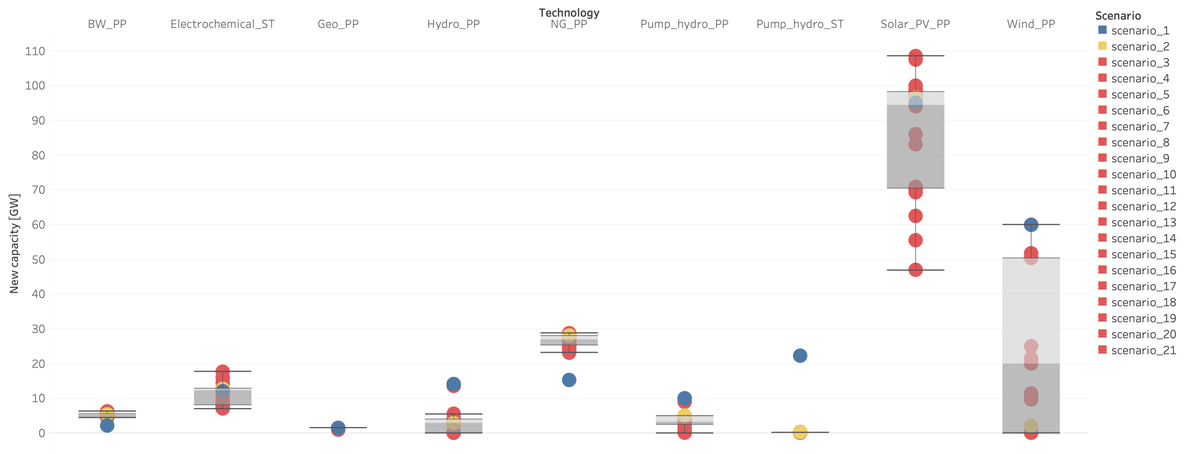
This kind of analysis, which is also present in the work by Lombardi et al. [10], is used to assist policy makers in choosing the best possible energy mix based on their specific needs.
Indeed, in this case study inspired by the Italian electricity sector, it is already possible to understand which technologies the policy maker could avoid deploying during the planning time, and which ones instead are present in every scenario.

By looking at the new capacity installed for every technology, in the period 2020-2050, it is possible to already understand what the must-have technologies in the near optimal solutions are.
An interesting way to do so is by representing, for every technology, the dispersion of values of new capacity installed in every solution. In figure 3.2, this is carried out, for every cost relaxation value, with a box plot that also represents the median value of new capacity installed and the percentiles of the dispersion. The colours of the different values represent the least cost solution (in blue), the near optimal solution found with the land objective function with no weights (in yellow) and near optimal ones with weights on the function (in red). Therefore, in yellow it is represented the qualitative solution on the minimization of land usage.

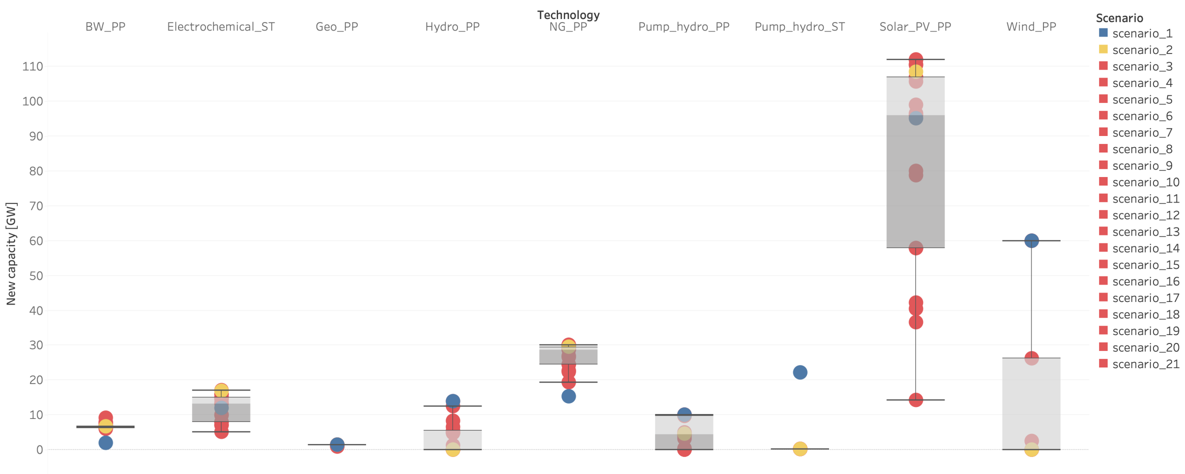
The values are represented for every cost relaxation, since this parameter could affect which technologies are must-have and which are not.
Indeed, the first thing that it is possible to observe is that, depending on the cost relaxation value, wind power plants are or are not must-have technologies for alternative scenarios found under a land minimization approach.
For a value of 15% and 25%, it is not a must-have technology, due to the value of new capacity installed being 0 in some near optimal scenarios. This means that, when the objective is the minimization of land usage, policy makers know that there are some alternative energy mixes in which no new capacity of wind is installed. This is true of course, only under the condition that they are willing to spend up to 15 and 25 percent more than in the least cost approach.
On the other hand, if the cost relaxation value is 5%, wind turbines become must-have technologies, given that the value of new capacity installed never reaches zero. However, remembering that wind on shore has a higher specific land usage value (table A.1) than other renewables such as solar, geothermal and biofuels & waste, wind new capacity in near optimal alternatives is always lower than in the least cost mix. For example, the difference in wind new installed capacity, between a cost minimization approach and a land minimization one (yellow solution), is around 50 GW.



(a) Cost relaxation = 5%



(b) Cost relaxation = 15%



(c) Cost relaxation = 25%

Figure 3.2: New capacity installed in the period 2020-2050

Solar photovoltaic is a must-have technology for all near optimal solutions, at every cost relaxation value. Moreover, in some alternatives the new capacity installed of this technology is even higher than in the least cost energy mix.
This is a relevant result, as there could be policy makers who need to minimize land of their territory and have a higher availability of solar energy rather than wind energy. Indeed, these results show that these resource availability conditions are favourable for them in the exploration of alternative strategies.

Another must-have technology is the production of electricity in natural gas power plants. Indeed, the new capacity installed of these plants is always positive among all solutions found.
In addition, it is possible to observe how the new capacity of gas power plants is always higher in alternative strategies. This can be explained by the fact that this technology has a specific land usage value which is lower than the ones of renewable technologies, by several orders of magnitude.
However, the difference in new installed capacity of this technology, between a land and a cost minimization approach, is limited to few GWs. The reasons can be identified:

- Near optimal solutions are obtained with a constraint on the total cost of the least cost solution. Given that natural gas power production is more expensive than renewables because of carbon tax and variable costs, the deployment of natural gas power production is limited.
- The model runs following guidelines of PNIEC on the reduction of emissions, and therefore, it must satisfy the policy-mandated minimum share of renewable technologies to be installed in the planning period.

While the installed capacity of power production technologies from renewable energy sources significantly increases, even if their specific land usage value is much higher than the one of natural gas power plants.

Hydroelectric power plants, both classic and pumped, are not must-have technologies when looking at near optimal solutions found with a land minimization approach. While in the least cost solution, both of these technologies are used up to their full potential (Italian values as the case study is inspired by this country), in near optimal solutions, their high specific land usage values make them a non essential technology.
This is an interesting aspect particularly for policy makers of those countries whose territory does not have much hydroelectric potential left, if not any.

A similar discussion can be made for geothermal power plants. This technology, given the

new capacity installed in the solutions found, cannot be considered a must-have technology.
This is, once again, an advantageous aspect for those countries which do not have the possibility to install much of this particular kind of plants.

Biofuels and waste power plants, on the other hand, are a must-have technology in the solutions found. Indeed, even if the new capacity installed of these plants is relatively low, the near optimal strategies always present a positive value for this technology, which is also always higher than in the cost minimization approach.
The reason behind this is that biofuels and waste plants have the lowest value of specific land usage among renewable technologies. Their role therefore is important in every energy mix, even though it is limited by an overall low efficiency and high costs.

As far as storage is considered, electrochemical storage is considered a must-have technology, on the opposite of pumped hydroelectric storage, which almost in every land minimization approach strategy does not see any new capacity installed.
The reason why the model prefers one with respect to the other, can be once again referred to specific land usage values, the ones at the center of the land minimization approach. The difference in order of magnitude among these two values makes also the quantitative approach of assigning weights less relevant, so that all near optimal solutions have a similar strategy regarding storage deployment.

Lastly, it can also be noted how the values for the new capacity installed of oil and solid fossil fuel power plants are not reported. This is done, as section 3.1 explains, because in the case study, after which these results are inspired, no new installed capacity of these two technologies is scheduled from 2020 to 2050.

3.2.2. Policy relevant solutions

The results obtained with the methodology of this thesis allow to explore many different energy strategies, which all produce the same amount of electricity in the same period and respect the same constraints and policies (table 3.2 in section 3.2).
Starting from the energy mix in the cost minimization approach (figure 3.3), it is therefore possible to observe all the alternative solutions found with a land minimization approach, for every cost relaxation value (figures C.1, C.2 and C.3 in appendix C).

The whole spectrum of possible decarbonization strategies suggested by the near optimal solutions can be seen in Appendix C. Here, a selection of policy-relevant examples will be reviewed and analyzed, providing insights on how they could meet the needs of policy makers around the world.

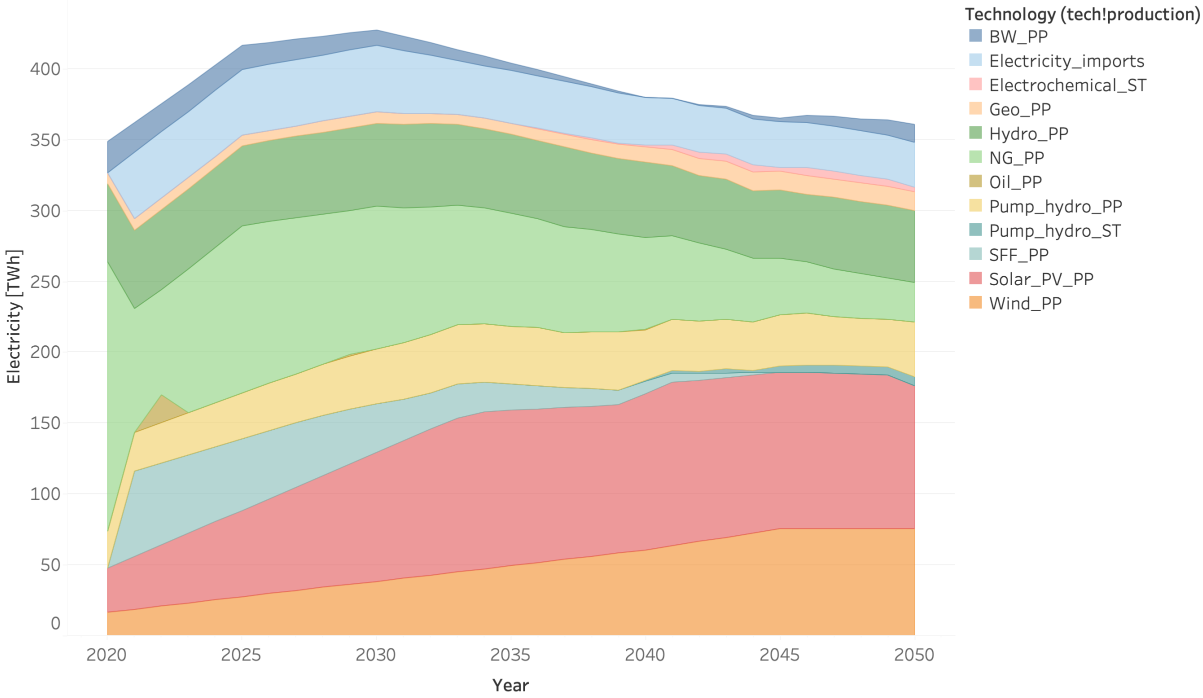


Figure 3.3: Energy mix in the least cost scenario

To do so, first it is important to understand how the land objective function operates and what the ways by which it is able to reach its target are. In fact, the function can follow different paths when it minimizes the occupation of land through the years.

As the objective function focuses on land usage values of technologies, the model optimizes by preferring technologies with lower land usage values. Moreover, the weights assigned to every technology enable an increase or decrease in their land usage, making them more or less preferable to the minimization target.
By doing so, land usage is reduced in every alternative strategy found, with respect to the one obtained under a cost minimization approach. Moreover, this reduction is also the maximum for scenarios number 2 at every cost relaxation value, given that they represent the land minimization approach without any weights on the function (equation 2.1).
This can be observed in figure 3.4, which represents how much land usage in alternative solutions decreases in percentage with respect to the cost minimization approach strategy. The darkest colors of the heat map represent the scenarios in which land usage reduction is the highest.

Scenario	Cost relaxation [%] 5	15	25
scenario_2	-33,78%	-45,60%	-50,70%
scenario_3	-24,97%	-43,75%	-48,82%
scenario_4	-24,37%	-43,66%	-50,33%
scenario_5	-33,69%	-43,61%	-49,77%
scenario_6	-32,29%	-39,95%	-42,80%
scenario_7	-31,87%	-41,75%	-39,38%
scenario_8	-31,38%	-44,31%	-42,80%
scenario_9	-33,74%	-37,60%	-48,59%
scenario_10	-32,65%	-45,27%	-43,26%
scenario_11	-29,03%	-45,55%	-40,24%
scenario_12	-33,54%	-43,51%	-49,67%
scenario_13	-33,47%	-38,55%	-49,92%
scenario_14	-28,68%	-43,66%	-50,69%
scenario_15	-29,12%	-44,22%	-50,57%
scenario_16	-29,07%	-37,55%	-50,31%
scenario_17	-28,78%	-38,80%	-50,36%
scenario_18	-32,16%	-41,82%	-49,57%
scenario_19	-32,16%	-43,95%	-42,80%
scenario_20	-32,67%	-39,35%	-32,21%
scenario_21	-32,28%	-44,03%	-47,90%

Land usage
-50,70% -24,37%

Figure 3.4: Overall land usage difference with respect to least cost

However, this is not the only way by which the land objective function minimizes land usage. Alternative solutions are found in the optimization by also maximizing the electricity production of every technology.

Being the objective function (equation 2.1), in fact, centered around the installed capacity of all generation and storage technologies, there is no correlation between the energy production and land usage. This is done rightly so, due to the fact that the actual size of a plant does not depend on the amount of electricity produced, but rather on its installed capacity.

For this reason, even if the production of electricity is virtually the same among all solutions found, the total overall capacity installed of technologies is lower in a land minimization approach. This can be observed, for example with a cost relaxation of 15%, in figure 3.5, where the total capacity installed in 2050 is represented in the different scenarios (the colors meaning is the same as in figure 3.2).

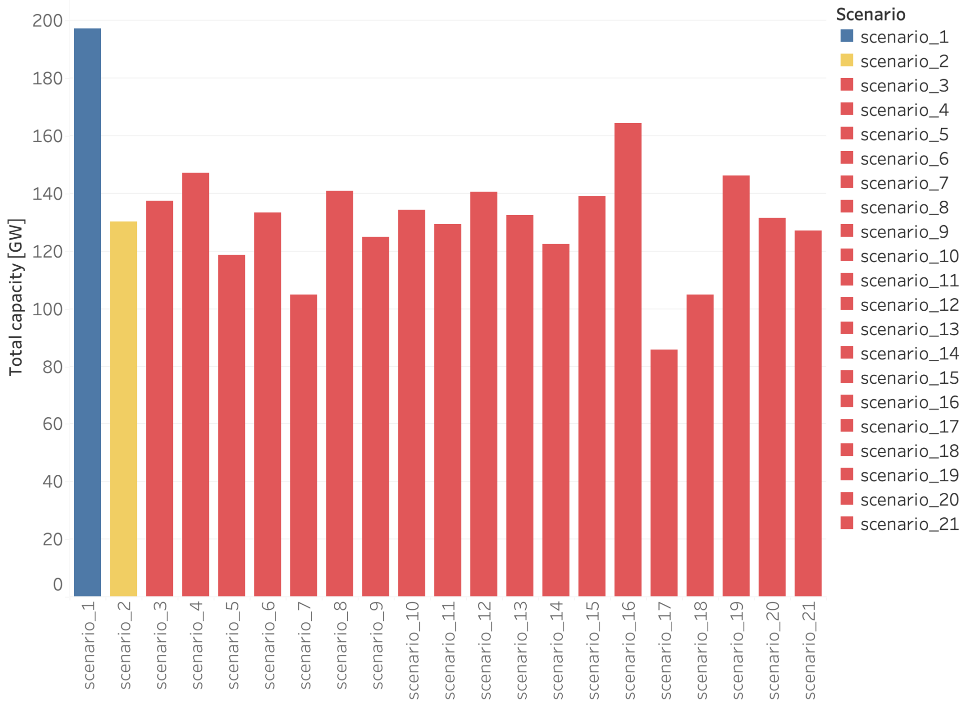


Figure 3.5: Total capacity installed in 2050, cost relaxation = 15%

Having a lower capacity installed, at the same electricity production, translates into a higher capacity factor, as it can be deducted by its yearly definition (equation 3.1).

$$CF = \frac{ElectricityProduction}{InstalledCapacity \cdot 8760h} \tag{3.1}$$

A higher capacity factor can conceptually mean several things. In general, it can be a representation of the increased availability of a technology, likely due to the positive results of research and development done for its application or due to a higher availability of energy resources [6].
In either case, it is something policy makers may be interested in, as it shows an overall better management of resources through the whole value chain of generation and storage technologies.

The alternative strategies found with a land minimization approach all have a higher capacity factor in 2050 with respect to the least cost scenario, as shown in figure 3.6.

Scenario	Cost relaxation [%] 5	15	25	Least cost
scenario_1				0,2085
scenario_2	0,3016	0,3162	0,2944	
scenario_3	0,2645	0,2995	0,3729	
scenario_4	0,2504	0,2794	0,2904	
scenario_5	0,3054	0,3472	0,3237	
scenario_6	0,3645	0,3087	0,3273	
scenario_7	0,2812	0,3919	0,3552	
scenario_8	0,2638	0,2923	0,3274	
scenario_9	0,3062	0,3299	0,3759	
scenario_10	0,3142	0,3061	0,5172	
scenario_11	0,2480	0,3185	0,5030	
scenario_12	0,2910	0,2930	0,2997	
scenario_13	0,2826	0,3111	0,3171	
scenario_14	0,3883	0,3364	0,2978	
scenario_15	0,2528	0,2958	0,3261	
scenario_16	0,2487	0,2505	0,2872	
scenario_17	0,2451	0,4791	0,2877	
scenario_18	0,3684	0,3929	0,2894	
scenario_19	0,2788	0,2813	0,3274	
scenario_20	0,3060	0,3127	0,4978	
scenario_21	0,3548	0,3235	0,2940	

CF 2050 [-]
0,2085 0,5172

Figure 3.6: Total capacity factor in 2050

From a policy maker perspective, this is an interesting result, as it gives the possibility to focus on two different targets.
Indeed, the same objective function, by minimizing land usage in two different and combined approaches, enables the user to explore alternatives. These alternatives can give useful insights with a higher stress on either the quantitative land usage reduction with respect to the cost minimization approach or the capacity factor of the whole electricity system at the end of the planning period, year 2050.
It is useful for the aim of this thesis and for a better visualization of this concept, to represent the total land usage reduction versus the capacity factors in 2050 for every solution, at every cost relaxation value. In figure 3.7, this is done by giving a different color to every cost relaxation value and to the least cost solution. Moreover, the shape of every scenario indicates whether the solution was found with a cost minimization approach (circle shape), or with a land minimization one (square shape for the ones with no weights

and cross shape for the others with weights).

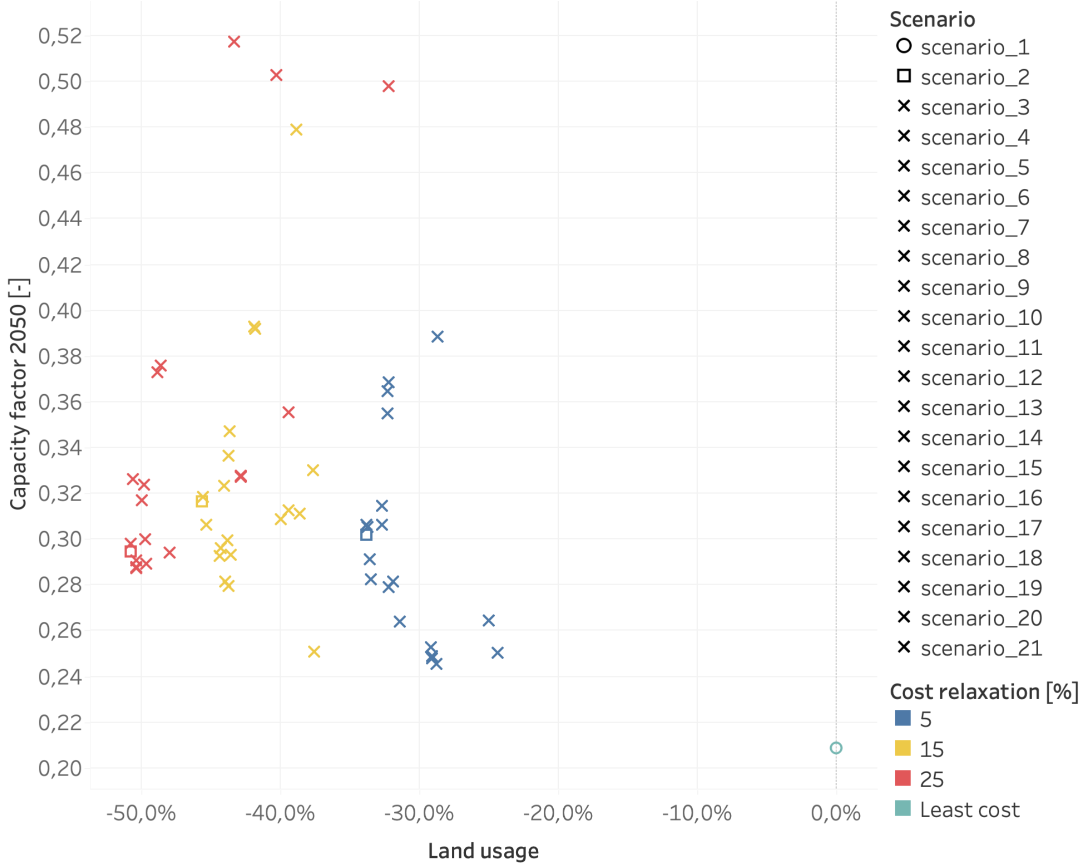


Figure 3.7: Overall land usage and capacity factor in 2050 for every solution obtained

Starting from figure 3.7, it is hence possible to identify strategies with three different priorities:

- The strategies with the highest land usage reduction.
- The strategies with the highest capacity factor in 2050.
- The different cost relaxation values, with which the previous strategies are obtained.

These three priorities are tailored around the needs of policy makers, which for example might be interested in obtaining the solution with the highest reduction of land used throughout the years, with the lowest cost relaxation value. Or another example could be a policy maker who is able to afford a higher cost relaxation value, but is rather interested in the highest capacity factor.

The different combinations of these plausible policy makers needs, enables the individuation of specific solutions among the ones found. These alternative strategies, together with their main characteristics, can be observed in the following subsections.

3.2.3. Highest land usage reduction, lowest cost relaxation

This strategy is particularly relevant for those policy makers who have urgent land occupation issues, but a limited budget to face this problem. Countries with similar characteristics are, for example, small-sized developing ones.

The strategy which would best fit their needs, according to the results found with a case study inspired by the Italian electric sector, is solution number 2, at cost relaxation value of 5% (figure 3.8). Indeed, solutions number 2, for every cost relaxation value, are the ones with the highest land usage reduction, since they are obtained with a qualitative land minimization approach (no weights on the function).

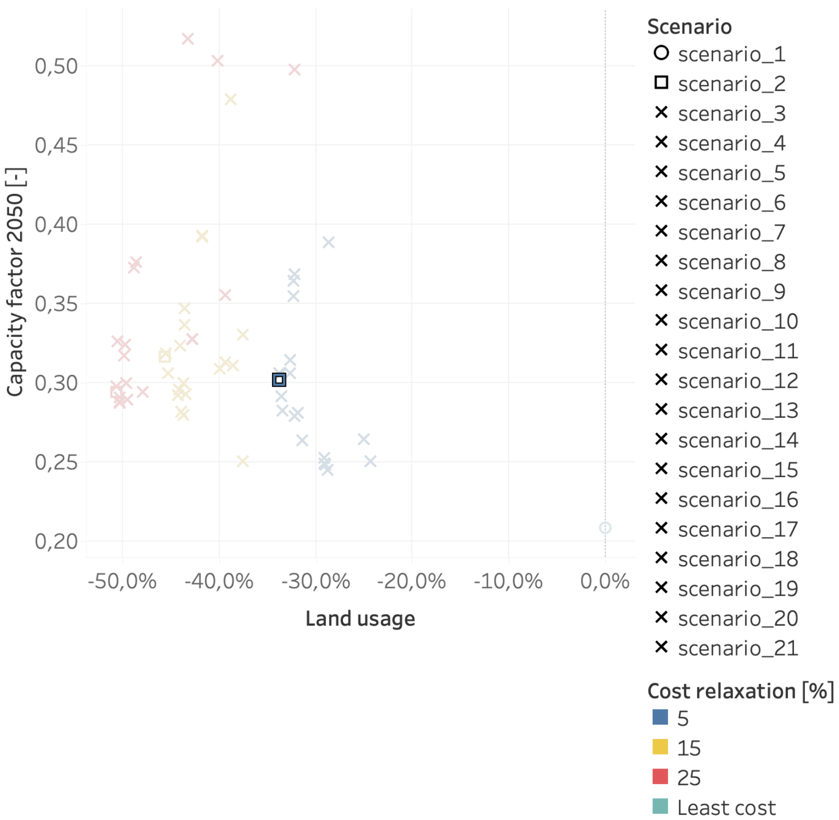


Figure 3.8: Scenario 2, cost relaxation = 5%

The energy mix of this strategy, which can be observed in figure 3.9, shows a significant presence of solar PV at the expense of wind power plants, due to their high land usage value. However, wind is still present in the mix in 2050.

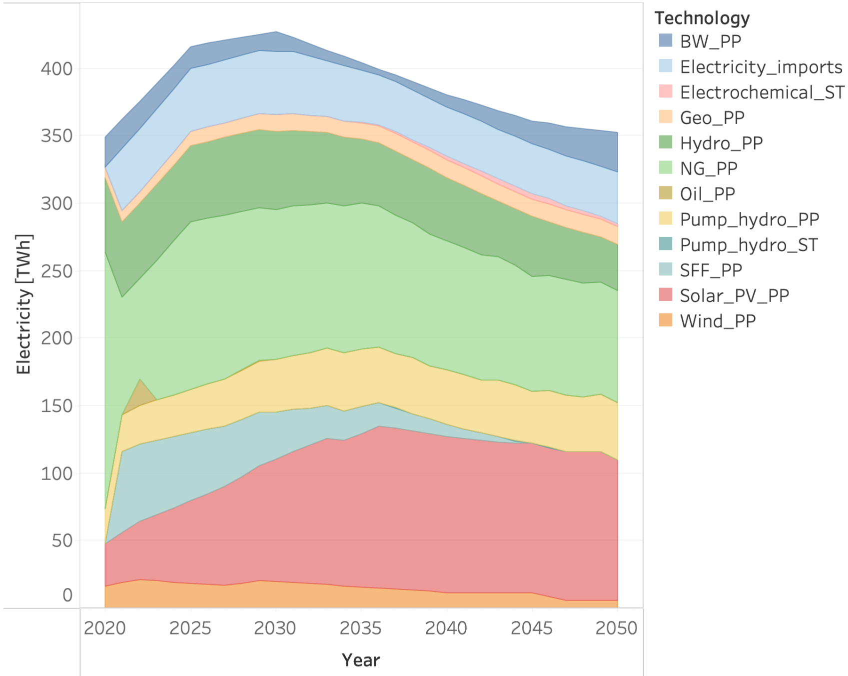


Figure 3.9: Electricity mix of scenario 2, cost relaxation = 5%

The main characteristics of this strategy are summarized in table 3.3. In general, it emerges how this solution can be suitable for those countries, whose priorities are the lowest land usage and lowest cost relaxation, and that in addition have rather a higher availability of solar energy (global horizontal irradiation) than wind energy (average wind speed), as the new total installed capacity of these technologies show in the table.
The capacity factor is not distant from the strategy in the cost minimization approach (0.2085), showing how policy makers in this case do not have a particular interest in improving technologies and the usage of resources.

Cost relaxation	5%
Land usage	-33.78%
Capacity factor in 2050	0.3016
Total cumulative CO2 emissions [MtonCO2]	8.655
Solar PV new capacity [GW]	97
Wind PP new capacity [GW]	7.6

Table 3.3: Main characteristics of lowest land usage, lowest cost relaxation strategy

3.2.4. Highest capacity factor, lowest cost relaxation

This scenario represents countries which have an interest in increasing the capacity factor, and therefore in a more efficient management of resources in the energy technologies value chain.
More precisely, this solution is relevant to those policy makers who wish to reduce the land usage by having a more reliable electric system, rather than by looking at technologies with higher specific land usage values. Therefore, they are also confident that the country has the skills and the know-how to keep the same electricity production at a lower installed capacity. However, policy makers in this particular situation wish to reach this target with a limited cost increase with respect to the cost minimization approach.

Among the results found in this thesis, the scenario is represented by solution 14, for a cost relaxation value of 5% (figure 3.10).

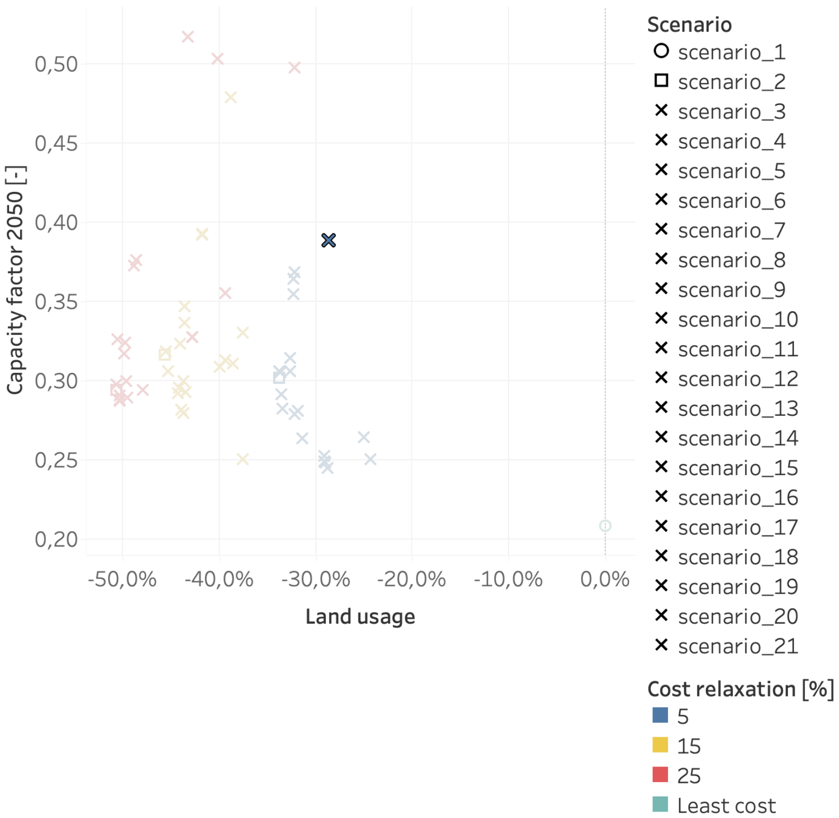


Figure 3.10: Scenario 14, cost relaxation = 5%

This strategy is the one, by definition, with the lowest total capacity installed in 2050. Its energy mix, represented by figure 3.11, shows how the production coming from solar PV is lower with respect to the previous case. Being, indeed, the capacity factor of solar the most limited by the availability of resources (solar energy), it is avoided in favor of other technologies.

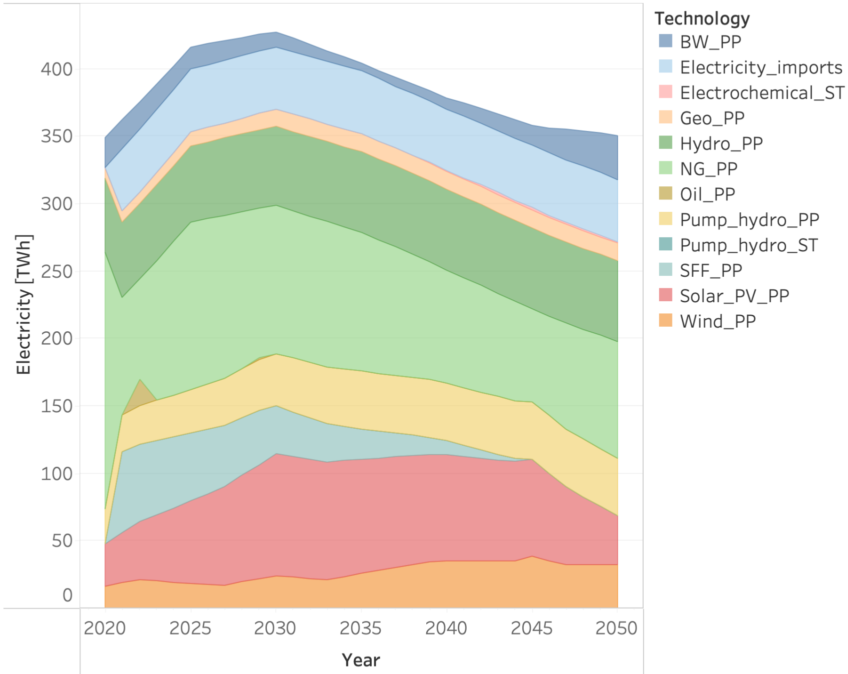


Figure 3.11: Electricity mix of scenario 14, cost relaxation = 5%

Therefore, policy makers who seek a reduction of land usage with the maximization of the capacity factor in 2050, at a low cost relaxation value, have an advantage if they do not intend to invest mostly on solar pv, but rather on other technologies.
The main characteristics of the scenario relevant to policy makers in this situation are reported in table 3.4.

The difference in 2050 capacity factor, with respect to the strategy of section 3.2.3, is almost 0.1, which is significant in terms of fewer capacity installed.
However, this comes with an increase of around 5 percentage points of land usage. Hence, the issues related to the overall occupation of land by energy technologies should be less stringent for policy makers in this scenario.

Cost relaxation	5%
Land usage	-28.68%
Capacity factor in 2050	0.3883
Total cumulative CO2 emissions [MtonCO2]	8.565
Solar PV new capacity [GW]	50
Wind PP new capacity [GW]	25.3

Table 3.4: Main characteristics of highest capacity factor, lowest cost relaxation strategy

3.2.5. Highest land usage reduction, intermediate cost relaxation

In this scenario, policy makers are interested in the maximum possible reduction of land usage, with a cost budget that is higher than in section 3.2.3.
For example, this is therefore suitable for developed countries with very limited available land for the deployment of energy technologies, and a financial budget that is also limited (however not as much as the one of developing countries).

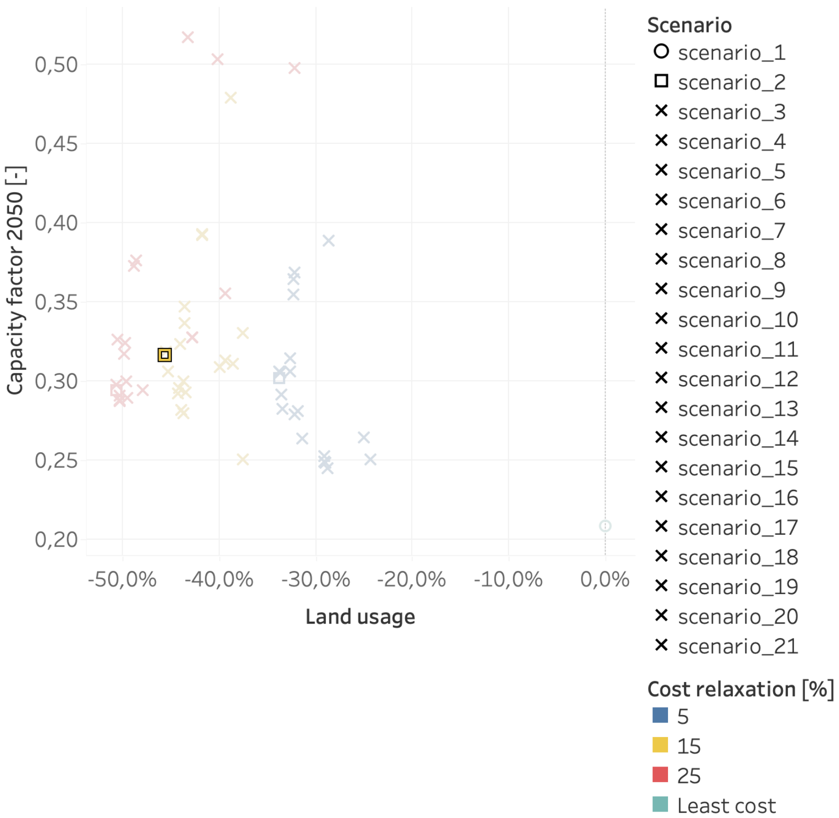


Figure 3.12: Scenario 2, cost relaxation = 15%

Among the solutions found, the strategy which fits best the policy makers needs in this case is scenario number 2, at a cost relaxation value of 15% (figure 3.12).

In this scenario, the production of technologies with the lowest specific land usage values (natural gas plants, solar PV, biofuels and waste plants) increase at the expense of the ones with higher values (hydroelectric and wind plants). This can be observed in the energy mix of figure 3.13, where the production of wind and hydroelectric is significantly reduced in 2050.

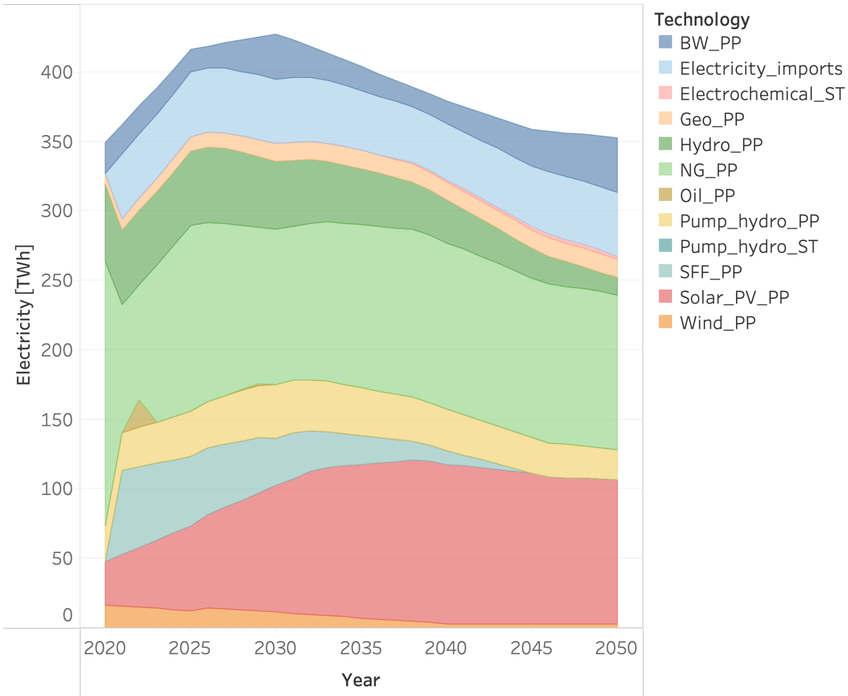


Figure 3.13: Electricity mix of scenario 2, cost relaxation = 15%

Countries who have a combination of particularly favorable conditions for the deployment of solar photovoltaic and particularly disadvantageous ones for the deployment of wind power plants, should hence pursue this strategy for the lowest land usage possible.
In particular, the land usage difference with respect to the least cost approach is around 45%, which is also around 12 percentage points more than in the cost relaxation case of 5% (table 3.3). Thus, the higher the willingness to exceed the cost of the least cost approach, the higher the reduction of land usage.

Cost relaxation	15%
Land usage	-45.60%
Capacity factor in 2050	0.3162
Total cumulative CO2 emissions [MtonCO2]	9.33
Solar PV new capacity [GW]	96.6
Wind PP new capacity [GW]	2

Table 3.5: Main characteristics of lowest land usage, intermediate cost relaxation strategy

3.2.6. Highest capacity factor, intermediate cost relaxation

In this case, countries with a similar financial situation of the previous section, intend to minimize land usage by increasing the capacity factor as much as possible. Indeed, even if this maximization comes with a higher land usage than in the previous case, their focus is more on the optimization and management of resources regarding the energy sector, which translates into a higher capacity factor.

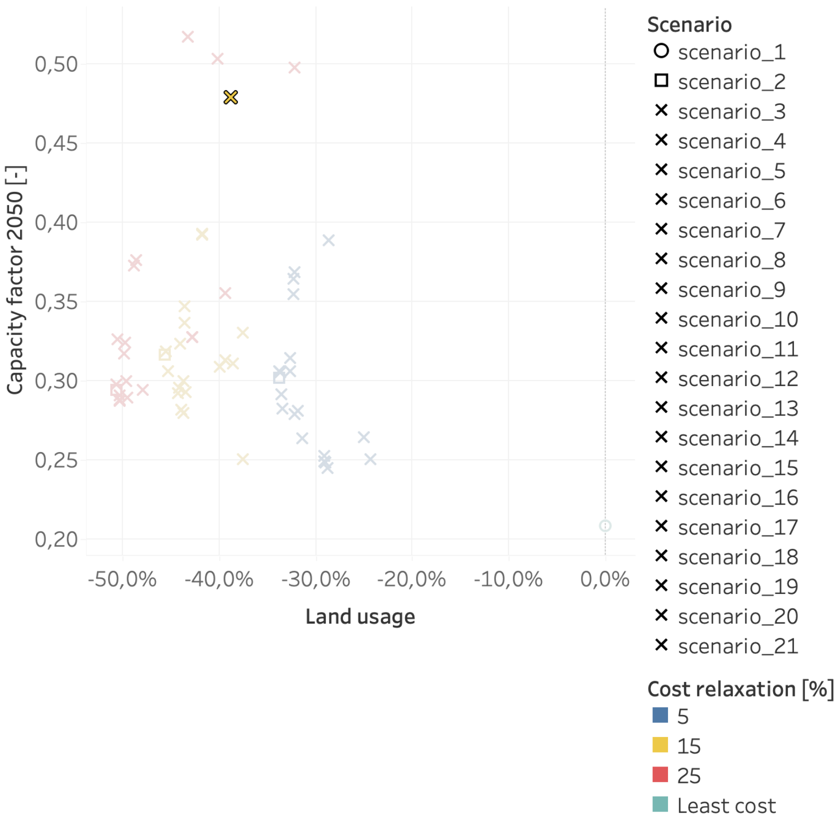


Figure 3.14: Scenario 17, cost relaxation = 15%

Policy makers of countries with these ambitions, should therefore have high level technical and managerial skills, when it comes to the energy technologies sector.
The most suitable strategy, for policy makers with these needs, is best represented by solution number 17 at a cost relaxation value of 15% (figure 3.14).

The energy mix in this scenario (figure 3.15) minimizes as much as possible the production of solar PV (which however is still present as it is considered a must-have technology), due to its low capacity factor.
Wind power production is also strongly limited, reaching a phase out in 2040. This happens due to a combination of difficulties in increasing its capacity factor and a high specific land usage value.
Pumped and classic hydroelectric power plants are instead the real "winners" in this strategy, as their production significantly increase with respect to the previous scenario (section 3.2.5). The reason behind this is related to the technologies improvement in capacity factor, leading to a decrease of installed capacity and a higher electricity production.

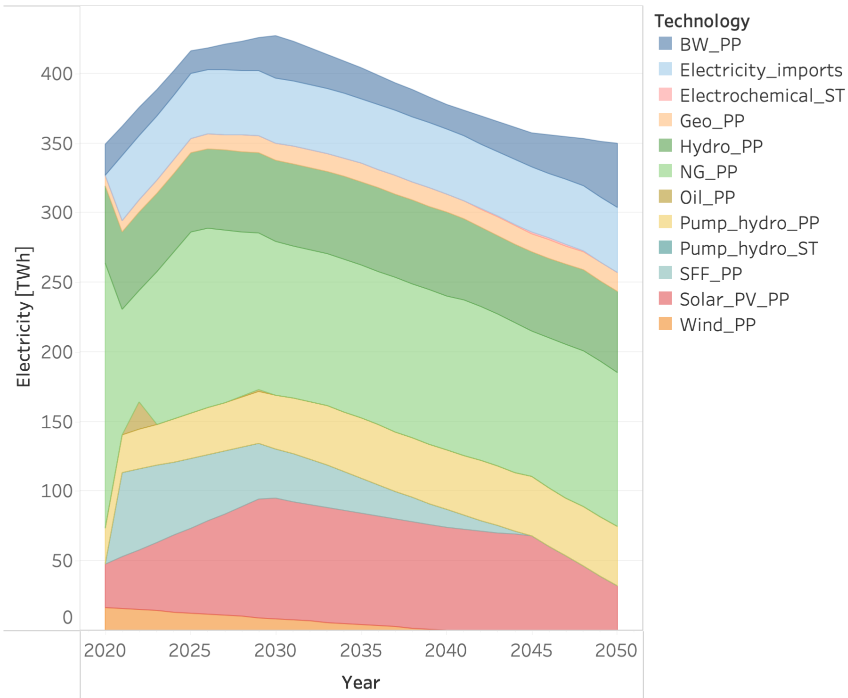


Figure 3.15: Electricity mix of scenario 17, cost relaxation = 15%

This strategy therefore has a strong impact on the increase of capacity factor, as no new capacity of wind is installed.
This is a particularly relevant result, as there could be countries who intend to work on land usage reduction, without installing any new wind turbines. The reasons why they

don't want to use this technology could be numerous and related, for example, to their visual impact or to low availability of wind energy.
However, this can be done if the country has a high potential for hydroelectric power plants, and is willing to use around 7 percentage points more of land than in the previous scenario (section 3.2.5).
Seven percentage points could really make a difference for some countries, but it still has to be considered how the overall reduction of land usage with respect to the cost minimization approach is of 38.8%, as it can be observed from table 3.6.

Cost relaxation	15%
Land usage	-38.8%
Capacity factor in 2050	0.4791
Total cumulative CO2 emissions [MtonCO2]	9.277
Solar PV new capacity [GW]	46.9
Wind PP new capacity [GW]	0

Table 3.6: Main characteristics of highest capacity factor, intermediate cost relaxation strategy

3.2.7. Highest land usage reduction, highest cost relaxation

In this scenario, the focus is shifted on the research of the strategy with the lowest possible land usage, for countries with favourable economic conditions, as the cost relaxation value is the highest.
Hence, given the correlation between cost relaxation and land usage (the higher the first one, the lower the second one), this scenario is best suited for policy makers who are looking for the maximum reduction of land occupied by energy technologies, among all the solutions found in this thesis.
Countries with similar needs are, for example, developed ones with the most urgent issues related to the usage of land.

The desired strategy is represented by the qualitative land minimization approach at the highest cost relaxation value, which, in this thesis results, is scenario number 2 at 15% cost relaxation (figure 3.12).

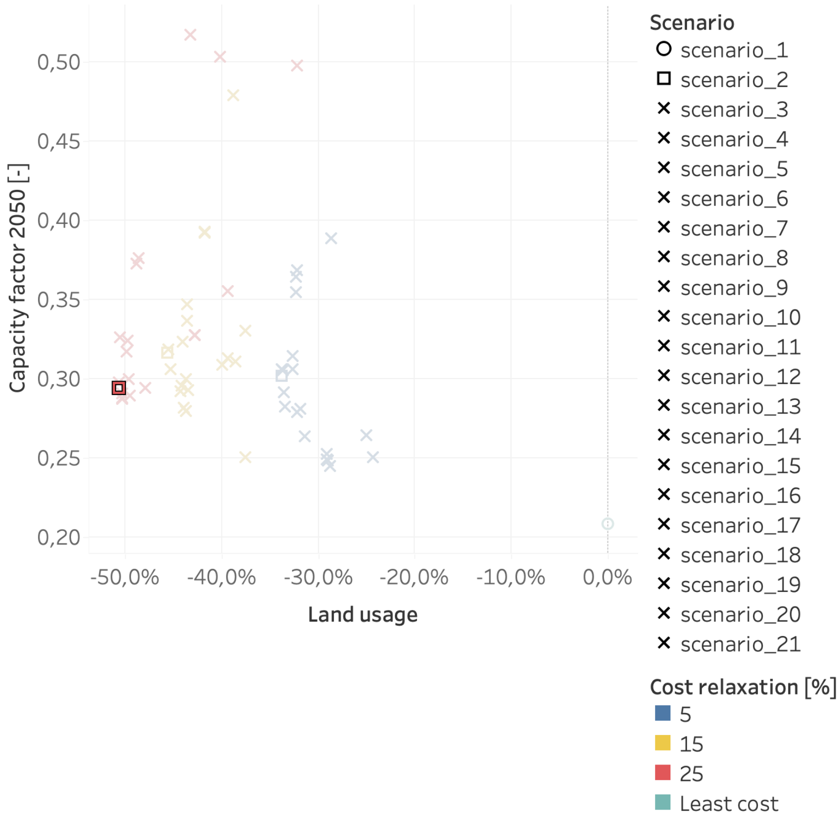


Figure 3.16: Scenario 2, cost relaxation = 25%

In this strategy, which bases the optimization mostly on specific land usage values, solar photovoltaic has an increase in electricity production (figure 3.17) with respect to all the other strategies seen before, including the least cost one (figure 3.3).
In this particular case, this comes at the expense of wind turbines, whose production slowly phases out in 2040 (no new capacity of this technology is installed), and classic hydroelectric power plants, whose production phases out in 2050. It can also be observed that the phase out does not happen for pumped hydroelectric power plants, as they have a higher capacity factor. However, their production is also limited.

In general, countries with the biggest ambitions in reducing land usage, can adopt this strategy, which consists of a strong deployment of solar panels. This technology, indeed, benefits also from its ability to be deployed in a decentralized approach, which is not possible for other technologies.
This deployment, however, is suitable for countries with high availability of solar energy, like for example Italy, which is the inspiration of the case study of this thesis.

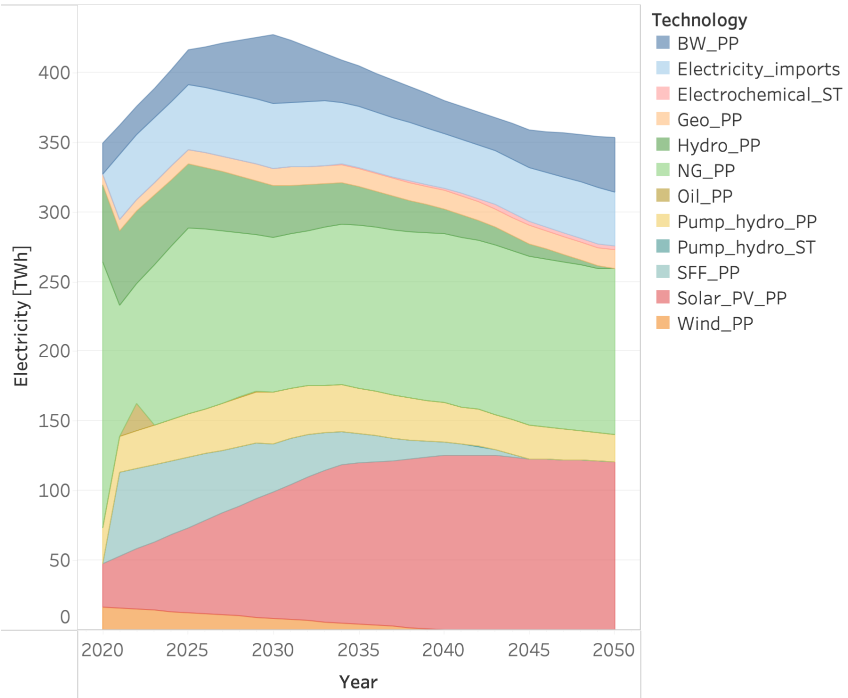


Figure 3.17: Electricity mix of scenario 2, cost relaxation = 25%

In this scenario, it is possible to save throughout the planning period around half of the land used in the cost minimization approach (table 3.7).
An interesting and relevant results for policy makers with very stringent issues of this kind, who, however, should also have the conditions to install a new capacity of around 108 GW of solar photovoltaic.

Cost relaxation	25%
Land usage	-50.7%
Capacity factor in 2050	0.2944
Total cumulative CO2 emissions [MtonCO2]	9.418
Solar PV new capacity [GW]	108.4
Wind PP new capacity [GW]	0

Table 3.7: Main characteristics of lowest land usage, highest cost relaxation strategy

3.2.8. Highest capacity factor, highest cost relaxation

Lastly, there may be some policy makers who wish to reduce land usage by maximizing the capacity factor of the whole electric system. Moreover, they intend to do so with the highest possible cost increase with respect to the cost minimization approach.

They have this particular target since they not only have the skills required to enhance the production per capacity of energy technologies, but they also have the budget to apply these skills.

The best suited strategy for this case is then solution number 10 at a cost relaxation value of 25% (figure 3.18), which appears to be also the strategy with the highest capacity factor in 2050 among all the ones found in this thesis.

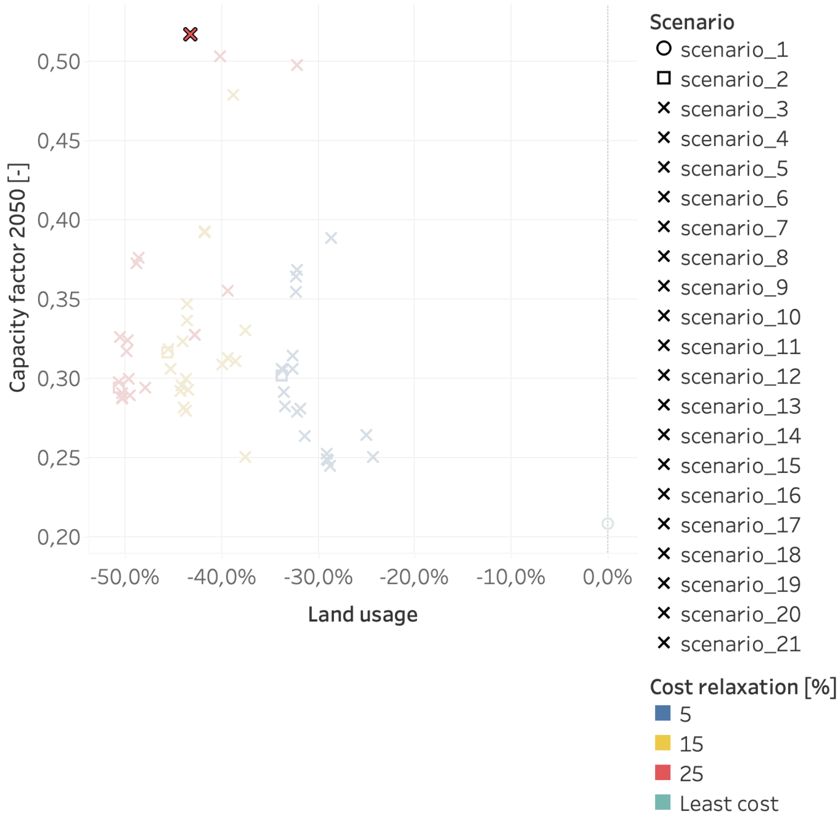


Figure 3.18: Scenario 10, cost relaxation = 25%

As it can be observed from the energy mix of this strategy in figure 3.19, solar and wind electricity production strongly decreases in this scenario. This happens because of their limited availability to their respective energy resources, and a cost constraint that allows to depend less on these technologies.

Instead, the production mix depends more on other technologies, such as for example biofuels and waste power plants. This technology has a significant increase in electricity production, particularly during the last years of the planning period. This is relevant to those policy makers who have high availability of biofuels and waste, as energy resource, or intend to invest more in this technology.

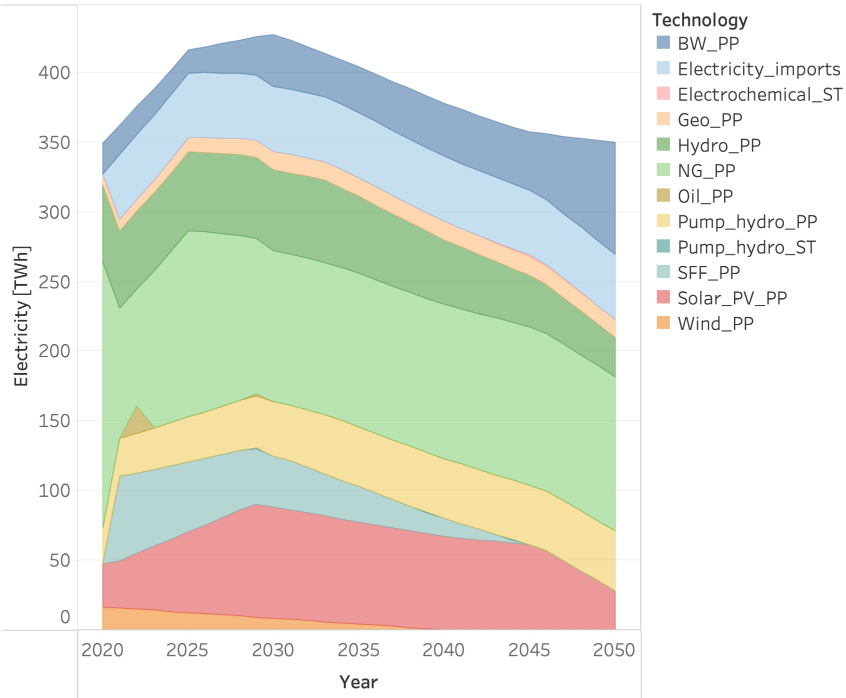


Figure 3.19: Electricity mix of scenario 10, cost relaxation = 25%

Moreover, enhancing the production coming from biofuels and waste is also an index of the country pledge to depend on a more circular economy, another fundamental target of the Paris agreement [24].

As it can be observed in table 3.8, the strong increase in 2050 capacity factor of this strategy with respect to the cost minimization approach one (from 0.2085 to 0.5172) is also accompanied by a decrease of land usage by around 43%.
Even if it is not as much as the highest reduction of land usage scenario (section 3.2.7), it is still a relevant value, considering policy makers needs.
Moreover, it can also be noted that, between this scenario and the previous one, there is a difference of new solar PV capacity installed of around 65 GW. This is a fundamental result of the alternative solutions found in this thesis, as it enables policy makers to pursue very different strategies and reach similar targets, on the basis of their specific needs.

Cost relaxation	25%
Land usage	-43.26%
Capacity factor in 2050	0.5172
Total cumulative CO2 emissions [MtonCO2]	9.347
Solar PV new capacity [GW]	42.2
Wind PP new capacity [GW]	0

Table 3.8: Main characteristics of highest capacity factor, highest cost relaxation strategy

3.2.9. Lowest emissions

It has been discussed in the previous sections how policy makers may seek different objectives when exploring alternative solutions, under a land minimization approach. However, these objectives were all concerning different aspects of the reduction of land usage, while policy makers could be also interested in an alternative strategy with a target external to the optimization problem.

One example, which is at the center of this section, is that there might be countries interested in the alternative strategy which comes with the lowest total CO2 emissions. Therefore, while still pursuing a strategy that reduces the land used, policy makers are able to choose the one with the least impact in terms of greenhouse gases emissions. This could be very well the case for those nations who have issues related to land use, but at the same time have committed to very stringent climate targets [24], that cannot be neglected.

The CO2 emissions over the years of all the alternative strategies found in this thesis, under the land minimization approach, are represented in figure 3.20. In it, every colour represents a different cost relaxation value, together with the colour of the solution found under the least cost approach.

First, it can be observed that the least cost solution fails to reach decarbonization target by 2050. This could have been seen also earlier from the profile of the energy mix (figure 3.3), where there is still production of electricity from natural gas power plants in 2050.

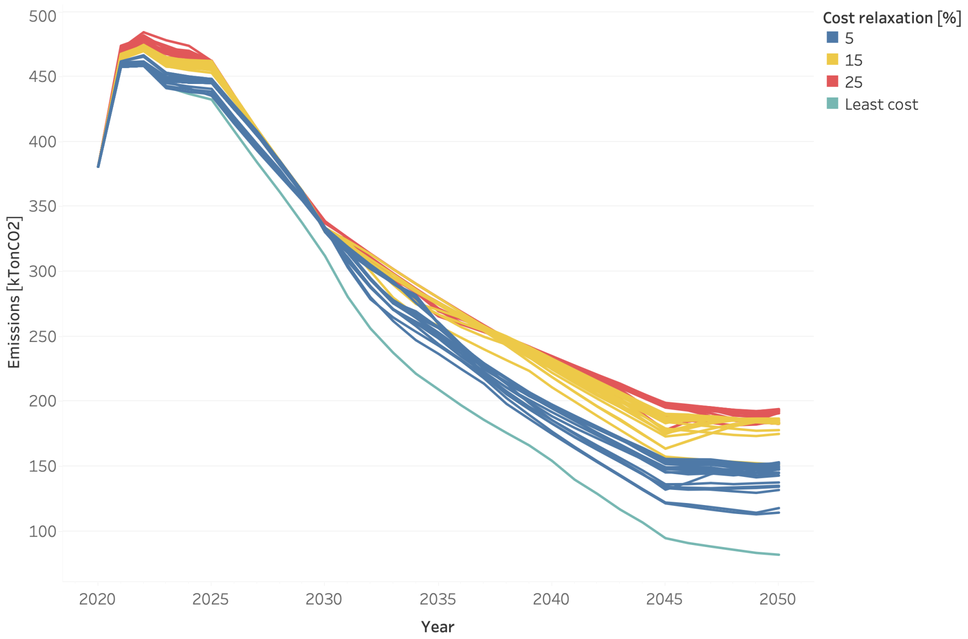


Figure 3.20: CO2 emissions over the years for every scenario

Not reaching this target is not a matter of the methodology used in the model, but rather a matter of the policies implemented. Policies used to obtain these results are simply not strict enough to get rid of natural gas dependency in the electricity sector. Moreover, it is best to remember that a simplified reference energy system has been adopted, which does not take into consideration other innovative technologies, such as for example carbon capture and storage. Regardless, this theme is beyond the objectives of this thesis, which are to find and analyze alternative strategies based on policy makers needs.

As far as these alternative strategies are concerned, in figure 3.20 is possible to observe how they all have higher emissions with respect to the strategy found under cost minimization. This can be explained by the higher deployment and electricity production of natural gas power plants. Indeed, the significantly low specific land usage value of this technology, coupled with the possibility to increase its capacity factor, increases its overall use in every alternative strategy found. This was explained also in section 3.2.1, as natural gas power plants are considered must-have technologies for every cost relaxation value.

However, the emissions differ among every alternative scenario, as the electricity mix changes every time. This can be observed in figure 3.21, where the total emissions of CO2 of every strategy, summed over the years, are represented in a heat map.

Scenario	Cost relaxation [%] 5	15	25	Least cost
scenario_1				7,510
scenario_2	8,655	9,330	9,418	
scenario_3	8,151	9,282	9,314	
scenario_4	8,118	9,223	9,410	
scenario_5	8,661	9,284	9,395	
scenario_6	8,655	9,231	9,282	
scenario_7	8,555	9,186	9,357	
scenario_8	8,496	9,304	9,282	
scenario_9	8,655	9,149	9,308	
scenario_10	8,602	9,313	9,347	
scenario_11	8,405	9,309	9,373	
scenario_12	8,644	9,268	9,403	
scenario_13	8,638	9,133	9,399	
scenario_14	8,565	9,284	9,410	
scenario_15	8,385	9,203	9,378	
scenario_16	8,418	8,865	9,392	
scenario_17	8,399	9,277	9,406	
scenario_18	8,651	9,212	9,390	
scenario_19	8,631	9,235	9,282	
scenario_20	8,594	9,219	9,384	
scenario_21	8,644	9,213	9,296	

CO2 emi [MtonCO2]

7,510 9,418

Figure 3.21: Total CO2 emissions of every scenario

The darker the colour of the map in figure 3.21 , the higher the total CO2 emissions. As it was just mentioned earlier in the section, the alternative strategies found under the land minimization approach all have higher values of total emissions than in the least cost approach. However, what is far more relevant, as it is useful for policy makers needs, is that it is possible to identify the alternative solution with the lowest value of total CO2 emitted during the planning period.

This particular strategy, which hence reduces land usage while minimizing the increase of CO2 emissions with respect to the least cost one, is represented by scenario number 4, at a cost relaxation value of 5%.

In the energy mix of this strategy, represented in figure 3.22, is possible to observe a decreased production of electricity from natural gas power plants, with respect to all the other alternative strategies seen before.

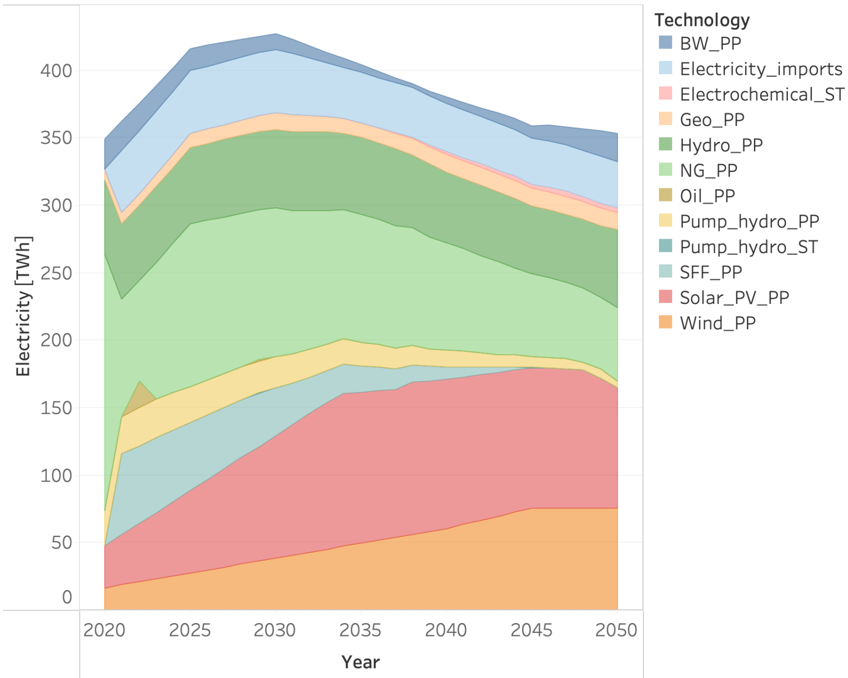


Figure 3.22: Electricity mix of scenario 4, cost relaxation = 5%

This is possible thanks to an increased production of all the other technologies and, particularly for this scenario, the one coming from solar photovoltaic and wind power plants. In this strategy, different from the ones seen before, a good combination of both technologies is present during the whole planning period, similar to the case of the solution found under the cost minimization approach (figure 3.3).

As it can be observed in table 3.9, this scenario allows to save around a quarter of land, with respect to the least cost one. While it is true that this reduction in land usage is the lowest among the alternative strategies found, it is still a significant amount and relevant to policy makers.

This strategy is therefore suitable for those nations that wish to obtain a reduction in land usage, while not increasing too much natural gas production and, as a consequence, CO2 emissions.
It is possible, even with the lowest value of cost relaxation, at the condition that the country also has high resources availability, as far as solar and wind energy are concerned.

Cost relaxation	5%
Land usage	-24.37%
Capacity factor in 2050	0.2504
Total cumulative CO2 emissions [MtonCO2]	8.118
Solar PV new capacity [GW]	86.9
Wind PP new capacity [GW]	60

Table 3.9: Main characteristics of lowest emissions strategy

3.2.10. Sensitivity analysis

The analysis of the results just seen were obtained with the conditions of table 3.2, with a fixed value of carbon tax. However, the carbon tax is a feature of Hypatia, whose implementation is not explicitly related to the objective of this thesis.
Assessing its impact on the generation of near optimal solutions is therefore due, in order to increase the validity of the results just seen.

The approach used in this thesis to assess this impact is a sensitivity analysis, which consists of running the model every time with a different value of carbon tax. The values are extracted from a range of reasonable ones, which for this particular case corresponds to the range of actual current carbon taxes in European countries: [0,120] €$/ton_{CO_2}$ [25]. In particular, it was decided to run the model starting from a carbon tax value of 0 €$/ton_{CO_2}$, and then proceed to 120 €$/ton_{CO_2}$ with a step of 20 €$/ton_{CO_2}$.

Therefore, the conditions through which the solutions of this sensitivity analysis have been obtained, can be summarized in table 3.10.

Model framework

Cost relaxation	15%
Total number of solutions	11 (for every carbon tax value)
Objective function	Land
Policy	PNIEC & carbon tax [0,20,40,60,80,100,120] €$/t_{CO_2}$
RES	figure 3.1

Table 3.10: Conditions used to obtain near optimal solutions

The total number of solutions was decided on a computational effort basis, while the value for cost relaxation was set at 15% as it is the median value among the ones used for the results of the previous sections.

As far as total emissions and cost are concerned, the impact of carbon tax on least cost solutions is represented in figure 3.23. The colours in the figure indicate the different carbon tax values, while the shapes represent whether the strategy observed was obtained under a cost minimization approach (circle shape) or under a land minimization one (square shape for the qualitative solution, cross shapes for all the others).
Being a carbon tax, by definition, a policy for the reduction of emissions, it is possible to observe how the total emissions decrease as the value of carbon tax increases.
In addition, as also expected, a higher price on the amount of CO2 emitted corresponds almost linearly to a higher total cost of the system.

What is however far more interesting and relevant to this thesis, is the impact of carbon tax on the generation of near optimal solutions.
In fact, the diversity among this alternative strategies at every carbon tax value, does not ensure the same correlation between total emissions and carbon tax, seen in the ones found under cost minimization.
On the contrary, in the range 20-80 $€/ton_{CO_2}$, it is possible to observe many near optimal solutions which could potentially cross and lead to having, for example, a solution at 40 $€/ton_{CO_2}$ emit more CO2 than one at 60 or 80 $€/ton_{CO_2}$.

Therefore, while for traditional least cost solutions we can state that a higher carbon tax leads to lower total emissions, the same cannot be stated for near optimal solutions. The diversity among near optimal solutions shows that an increase in the carbon tax does not always entail a reduction in overall emissions.

Hence, as far as emissions are concerned, in near optimal solutions the impact of carbon tax is less relevant than in traditional results. This results in the need of a more careful and detailed exploration of all the alternative scenarios, if the focus of policy makers is more on emissions or decarbonization pathways, rather than on the land minimization.

Regarding the financial aspect of results, a carbon tax does not have any impact on the total cost of near optimal solutions. The reason behind this is related more to the way these alternative results are generated rather than to the carbon policy.
Indeed, all near optimal solutions exploit as much as possible the cost constraint imposed for their generation (section 2.3), resulting in an equal total cost value for each carbon tax.

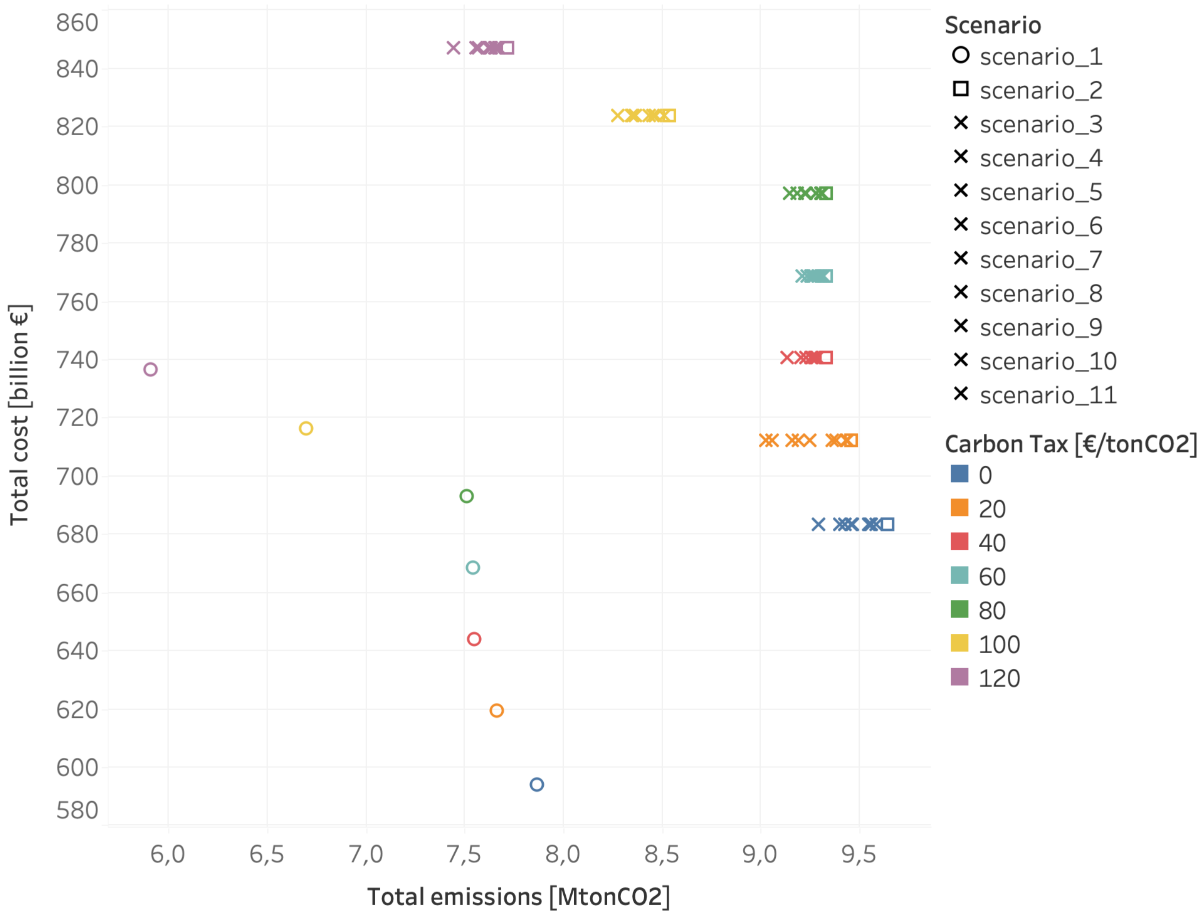


Figure 3.23: Total cost and CO2 emissions at different values of carbon tax

Another consideration should be made on the impact of carbon tax values on the diversity among near optimal solutions. Figure 3.23 already shows that the dispersion among alternative scenarios does not indicate a specific trend, when varying the price of carbon.

This non-existing trend can be better observed in figure 3.24, which represents the value of renewable capacity share in 2050 for every solution found, at different values of carbon tax.

The fact that there is likely no correlation is relevant, as it shows that one of the desired targets of the methodology implemented in this thesis, which is the diversity among the alternative scenarios generated, does not seem particularly affected by an external policy implemented in the model. On the contrary, the size of the dispersion of renewable capacity share values remains approximately the same for every carbon tax value.

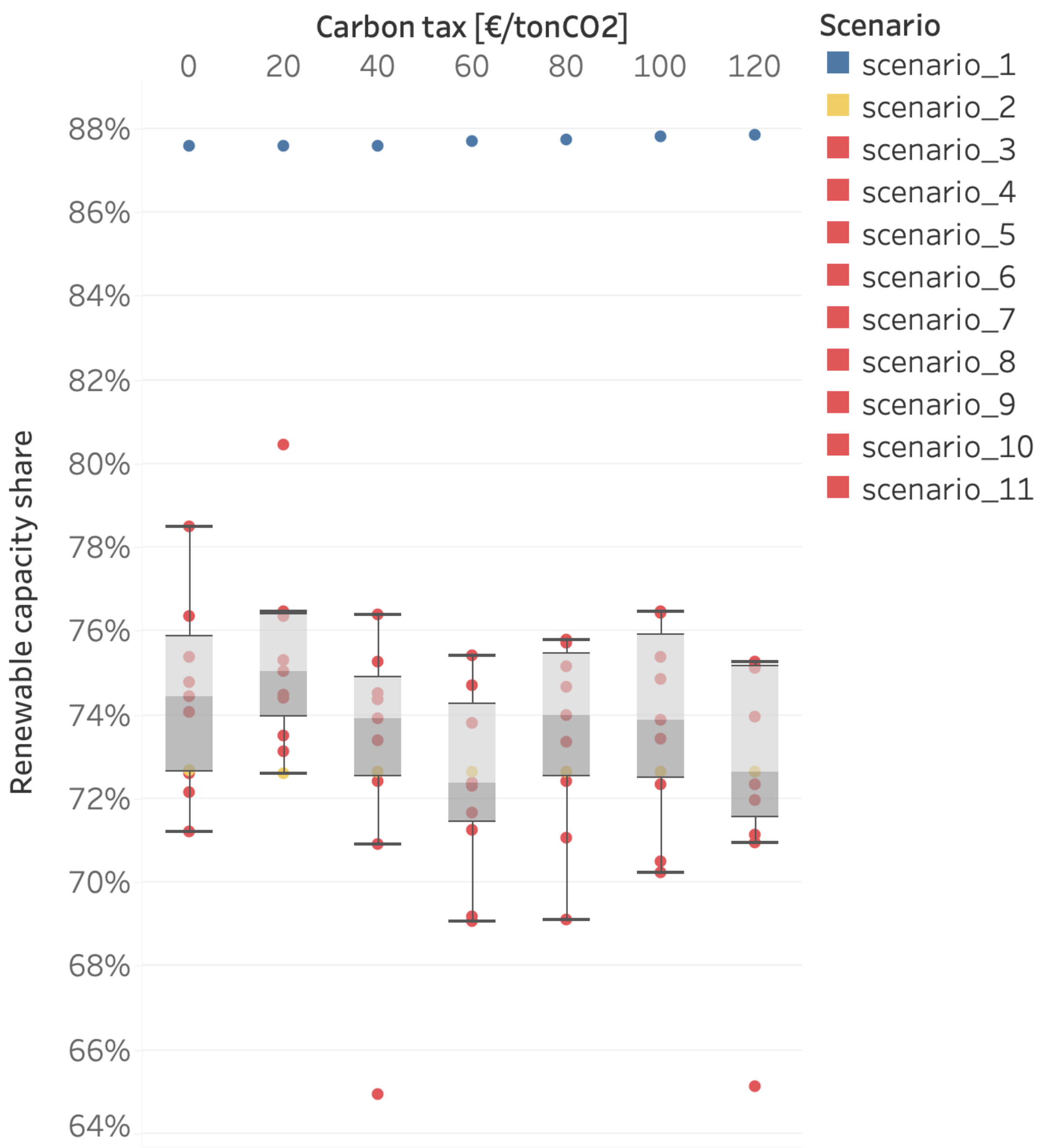


Figure 3.24: Share of renewable capacity installed in 2050

The median value of renewable capacity share of each distribution ranges between 72 and 75%, while the dispersion size is around plus or minus 4% (figure 3.24.
However, there are some outliers for the carbon tax values of 20,40 and 120 €$/ton_{CO_2}$, which are not present for other values. Indeed, these outliers represent respectively an alternative scenario in which the share of renewable capacity installed in 2050 is higher than 80%, and two alternative ones where the same share is about 65%.

These outliers may represent a small hint of a correlation between carbon tax values and the diversity of alternative scenarios found. However, with the results given by this sensitivity analysis, these outliers are not relevant enough to state that they show a specific trend, as they are likely more due to the weights used in the land objective function to generate them (equation 2.1).

Moreover, the values of this renewable capacity share do not differ significantly when varying carbon tax. The reason behind this is likely that the guidelines of PNIEC [12] on the minimum production of renewable technologies have a stronger effect on the results than the carbon tax policy.
Hence, the insights given to policy makers in the sections of this chapter are still valid and relevant, even when the country intends to follow different values of carbon tax as a policy to reduce CO_2 emissions.

This sensitivity analysis concludes the results discussion chapter. It is now therefore possible to proceed into delivering the final remarks of this thesis.

4 | Conclusions and future developments

In the chapters of this thesis, the different steps in the exploration of alternative solutions in energy system optimization models, beyond the cost optimal one, have been reported.

First, in chapter 1, an overview of all the existing methodologies to generate near optimal solutions in ESOMs is conducted. Through a systematic literature research method on Scopus, it was possible to perform multiple reviews, leading to a final one. The scientific works obtained with the last research are then discussed, so to analyze the most relevant ones for the targets of this thesis.
This discussion lastly leads to opt for the use of a combination of the most relevant works for the definition of the methodology to be implemented in this thesis, for the generation of near optimal solutions.

Then, in chapter 2, a thorough description of the methodology implemented in this thesis, together with a short description of the supply-side energy system optimization model used (Hypatia), is carried out.
This comprehends the definition of the two new objective functions to implement in the model for the generation of near optimal solutions, according to the model to generate alternatives (MGA) method developed by DeCarolis et al [5]. These new functions regard two different topics related to issues policy makers often face when deploying energy technologies. The first one is on the minimization of land usage by energy generation and storage technologies, while the second one is on the minimization of energy balance mismatch between regions or macroregions of the same country, through the use of the Gini coefficient.
Moreover, according again to the MGA method, the description of the new cost constraint to be implemented in the model is also reported in the methodology chapter.
Lastly, the new run module is also included in the same chapter as it shows the method in which the model is able to run multiple solutions, with different optimization targets, at the same time. The module, which is structured as a while-cycle, together with the

objective functions and the cost constraint can be observed in appendix B written in pseudocode (while in the model it is implemented written in the Python programming language).

Finally, in chapter 3, the results of the methodology implemented are analyzed and discussed, only after a brief description of the reference energy system used for the case study of the thesis.
The case study, inspired by a decarbonization of the electricity sector of Italy by 2050, is represented by a simplified reference energy system, where the generation and storage technologies meet a projected final demand of electricity, in the planning period 2020-2050.
The results obtained are then discussed on the basis of policy makers plausible different needs. Indeed, first it is performed an analysis on what technologies can be considered must-have in any alternative scenario. Then, based on the different aspects of the new optimization approach, which reflect real policy makers needs, some alternative strategies found are described and discussed. Lastly, a sensitivity analysis on the impact of carbon tax on the results of the model is carried out.

The results, obtained with a land minimization approach (therefore with the land objective function), show the importance of going beyond least cost solutions in energy system optimization models. Indeed, with the method used, it was possible to explore a number of different strategies, tailoring them on the needs of policy makers.

Various examples of country needs are identified and the near optimal energy system configurations best suiting such needs are obtained. As a first example, a country with an interest in reducing as much as possible land usage, should pursue strategies which comprehend a higher deployment of solar photovoltaic rather than the one of other technologies. Moreover, based on the increase of cost which policymakers are willing to pay to pursue these alternative strategies, wind generation technology may or may not be a must-have technology. As a second example, a country could be more interested in pursuing land usage reduction by maximizing the overall capacity factor of the total electricity sector, even if does not lead to the largest reduction of land used. In this scenario, the suggested strategy focuses on the increased electricity production of technologies not strongly limited by energy resources, such as hydrolectric power plants (both pumped and classic) and biofuels and waste power plants. An increased production of this last type of technology can also help a country in becoming more dependent on a circular type of economy, an important cornerstone to reach the targets of the Paris Agreements [24].

As a third example, countries might also be interested in the alternative strategy with the least possible amount of total CO2 emissions. Among the solutions found with the methodology of this thesis, the most suitable strategy for this need comprehends an energy mix which focuses strongly on the production of solar PV and wind power plants. Particularly for this latter technology, the new capacity to be installed of it is the highest among all alternative strategies found. Enforcing, thus, the importance of electricity production from wind energy in the efforts to reduce greenhouse gases emissions.

A sensitivity analysis was carried out on the value of the carbon tax, given the high uncertainty over this figure. Results show that this parameter has an impact on the emissions of the alternative scenarios found. Meaning, hence, that a careful exploration of the near optimal solutions found is required, if the policy makers targets are to obtain lower emissions with higher carbon tax values, as there might not always be a direct correlation.
While the total cost of alternative strategies is not affected by the value of carbon tax. This is due to the cost constraint imposed for the research of near optimal solutions, which forces the model in searching alternatives that exploit all the available cost budget.
Lastly, another important aspect evinced from the sensitivity analysis is how the diversity among solutions is not affected by the carbon tax value. Resulting, thus, in making stronger the insights given to policy makers about the different strategies.

The most evident limitation coming from the results of this thesis is how the near optimal solutions were obtained only with one of the two new objective functions implemented. Indeed, the alternative strategies which can be generated with an approach on the minimization of the energy balance mismatch between regions are not present in the thesis. Unfortunately, the reason behind these missing results is linked to a shortage of time in finding all the data and parameters required for the building of a multiregional reference energy system.
However, being this mainly a matter of time availability, a possible future development for this work is building a multiregional model inspired by the Italian electricity system, and use the energy balance mismatch objective function to generate near optimal solutions. The scenarios found can then be compared, not only with the one obtained with a cost minimization approach, but also with the results of this thesis (strategies found under land minimization approach).
This comparison could likely point out strategies which give more relevant insights to policy makers, particularly on the possibility to solve multiple issues related to energy technologies deployment at the same time.

Another theme of the thesis which can be analyzed further concerns the total cost of near optimal solutions. Indeed, results obtained in this work were all found on the border

of the cost constraint implemented. Meaning, hence, that all the alternative strategies exploit as much as possible the financial budget, given by the cost relaxation on the least cost strategy total cost.
This aspect is not conceptually negative, as there is no problem with obtaining strategies that use all the available financial resources. However, finding solutions which are not on the border of the cost constraint, but rather have a total cost in between the least cost one and the highest possible one, might increase the diversity in the energy mixes of the different strategies. As a consequence, the relevant insights for policy makers could also increase, making the exploration of different strategies more tailored on their specific needs.

Lastly, as also mentioned in section 3.2.9, the results of this thesis fail to reach decarbonization targets of the case study under analysis. This is not a target of this work, given that the case study serves more as an inspiration for the research of alternative energy strategies. However, it might be relevant, as far as insightful scenarios for policy makers are concerned, to reach a decarbonized electricity sector in 2050.
To achieve this target, more stringent climate policies are required in the running of the model. These policies can range from the highest minimum values of electricity production from renewable sources, to a stronger presence of fiscal policies on emissions and electricity production. Moreover, also a more detailed reference energy system, with the presence of innovative technologies for the reduction and capture of CO_2 emissions, would likely contribute to making the electricity sector carbon neutral in 2050.

There are numerous ways in which the methodology implemented in this thesis could be further tested. What instead remains the core key of this work is the importance of going beyond a cost minimization approach in energy system optimization models. Doing so guarantees indeed an exploration of alternative energy deployment strategies, which could possibly solve important issues that affect the everyday life of people. This is fundamental, as the energy transition most countries are currently undergoing right now must always be as just and fair as possible for every single individual.

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A | Appendix A

Specific Land Usage

Technology	Value	Reference	Unit of measure
Geothermal power plant	39255	[20]	$\frac{m^2}{MW}$
Solar PV	18000	[2]	$\frac{m^2}{MW}$
On-shore Wind	50505	[2]	$\frac{m^2}{MW}$
Hydroelectric power plant	141460	[7]	$\frac{m^2}{MW}$
Pumped Hydroelectric power plant	141460	[7]	$\frac{m^2}{MW}$
Geothermal heat plant	39255	[20]	$\frac{m^2}{MW}$
Pumped Hydroelectric storage	141460	[7]	$\frac{m^2}{MW}$
Electrochemical storage	6.25	[2]	$\frac{m^2}{MWh}$
Steam Methane Reforming	18.29	[2]	$\frac{m^2}{MW}$
Solid Fossil Fuels Power Plant	40	[2]	$\frac{m^2}{MW}$
Oil Power Plant	40	[2]	$\frac{m^2}{MW}$
Natural Gas Power Plant	30	[2]	$\frac{m^2}{MW}$
Oil refinery	323.49	[19]	$\frac{m^2}{MW}$
Natural Gas Combined Power Plant	22.5	[2]	$\frac{m^2}{MW}$
Biofuels and Waste Combined Heat Plant	1650	[2]	$\frac{m^2}{MW}$

Table A.1: Specific land usage values for every technology

B | Appendix B

Algorithm B.1 Cost constraint "Close2optimalCost.py"

```
from hypatia import Utilities_close2opt
from hypatia.backend.constraints.Constraint import Constraint

class Close2optimalCost(Constraint):
    def rules(self):
        rules = []
        rules.append(
        Utilities_close2opt.optimal_value · (1 +Utilities_close2opt.cost_relaxation) -
        cp.sum(self.variables.totalcost_allregions_act) ≥ 0
        )
        return rules
```

Algorithm B.2 Land objective function in "Build.py"

```
from hypatia import Utilities_close2opt
from hypatia.utility.constants import ModelMode

if self.model_data.settings.mode == ModelMode.Planning then
    if Utilities_close2opt.Solution_number = 2 then
        total_land_occupation = 0
        for self.model_data.settings.regions do
            for self.vars.land_usage[reg].keys do
                randomic_matrix = np.ones ((len (self.model_data.settings.years), len (self.model_data.settings.technologies[reg][key])))
                total_land_occupation += cp.sum (cp.sum (cp.multiply (randomic_matrix, self.vars.land_usage[reg][key]), axis = 0, keepdims = True), axis = 1, keepdims = True)
            end for
        end for
        self.global_objective = total_land_occupation
    else
        total_land_occupation = 0
        for self.model_data.settings.regions do
            for self.vars.land_usage[reg].keys do
                randomic_matrix = np.tile(np.random.random ((1,len (self.model_data.settings.technologies[reg][key]))), (len (self.model_data.settings.years),1))
                total_land_occupation += cp.sum (cp.sum (cp.multiply (randomic_matrix, self.vars.land_usage[reg][key]), axis = 0, keepdims = True), axis = 1, keepdims = True)
            end for
        end for
        self.global_objective = total_land_occupation
    end if
end if
```

Algorithm B.3 Energy balance mismatch objective function "Build.py"

```
from hypatia import Utilities_close2opt
from hypatia.utility.constants import ModelMode

if self.model_data.settings.mode == ModelMode.Planning then
    total_demand = { }
    total_production = { }
    for self.model_data.settings.regions do
        for self.vars.demand[reg].keys do
            total_demand[reg] = cp.sum(self.vars.demand[reg][key], keepdims = True)
        end for
    end for
    if Utilities_close2opt.Solution_number = 2 then
        for self.model_data.settings.regions do
            for self.vars.production_annual[reg].keys do
                randomic_matrix = np.ones ((len (self.model_data.settings.years), len (self.model_data.settings.technologies[reg][key])))
                total_production[reg] = cp.sum( cp.sum( cp.multiply(randomic_matrix, self.vars.production_annual[reg][key]), axis = 0, keepdims= True), axis = 1, keepdims= True)
            end for
        end for
    else
        for self.model_data.settings.regions do
            for self.vars.production_annual[reg].keys do
                randomic_matrix = np.tile(np.random.random ((1,len (self.model_data.settings.technologies[reg][key]))), (len (self.model_data.settings.years),1))
                total_production[reg] = cp.sum( cp.sum( cp.multiply(randomic_matrix, self.vars.production_annual[reg][key]), axis = 0, keepdims= True), axis = 1, keepdims= True)
            end for
        end for
        total_demand_array = np.array (list(total_demand.values()))
        total_production_array = np.array (list(total_production.values()))
        self.global_objective = Utilities_close2opt.Gini(total_demand_array, total_production_array)
    end if
end if
```

Algorithm B.4 Running module "Run.py"

```
from hypatia import Model
from hypatia import Utilities_close2opt

define (optimization_mode, number_of_solutions, last_GINI_solution, cost_relaxation)

assert last_GINI_solution ≤ number_of_solutions

solution_number = Utilities_close2opt.Solution_number

while solution_number ≤ number_of_solutions do
    model = Model(path = "sets path", mode = "Planning", optimization = optimization_mode)
    model.read_input_data("parameters path")
    optimal_value = model.run(solver="Solver name")
    model.to_csv(path = "results path" + "/results_" + str(solution_number), force_rewrite = True, postprocessing_module = "it2020")

    if solution_number = 1 then
        Utilities_close2opt.optimal_value = optimal_value
    end if

    if optimization_mode = "Single" then
        break
    else
        solution_number = solution_number + 1
        Utilities_close2opt.Solution_number = solution_number
        Utilities_close2opt.cost_relaxation = cost_relaxation
        Utilities_close2opt.Last_GINI _solution = Last_GINI _solution
    end if
end while
```

Algorithm B.5 Utility module (with Gini function) for near optimal solutions "Utilities_close2opt.py"

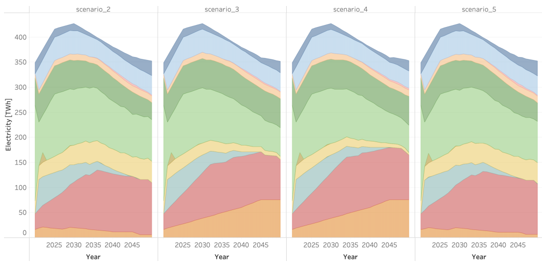
```
Solution_number = 1
optimal_value = 1
cost_relaxation = 0
Last_GINI_solution = 1

def Gini(demand,generation):
assert(len(demand) == len(generation))
bins = np.linspace(0., 100., len(demand))
total_demand = float(np.sum(demand))
total_generation = float(np.sum(generation))
for bins_values do
    demand_vals = demand[demand ≤ np.percentile(demand, bins_values)]
    demand_fraction = (np.sum(demand_vals) / total_demand) · 100.0
    yvals_demand.append(demand_fraction)
    generation_vals = generation[generation ≤ np.percentile(generation, bins_values)]

    generation_fraction = (np.sum(generation_vals) / total_generation) · 100.0
    yvals_generation.append(generation_fraction)
end for
perefect_equality_area = np.trapz(yvals_demand, x=yvals_demand)
lorenz_area = np.trapz(yvals_generation, x=yvals_demand)
gini_val = abs((perfect_equality_area - lorenz_area) / float(perfect_equality_area))
return gini_val
```

C | Appendix C

In this appendix, any additional figure is shown.



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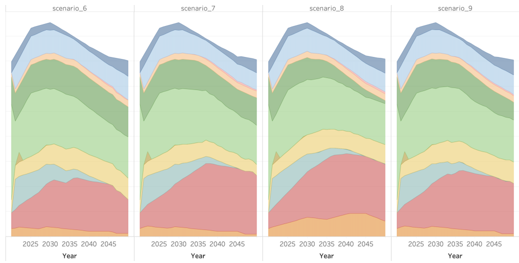
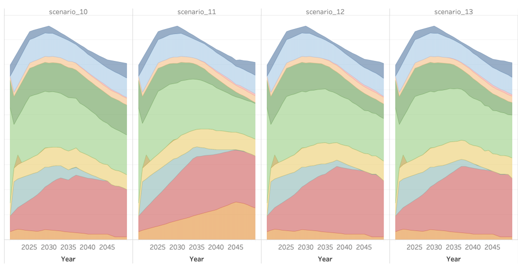
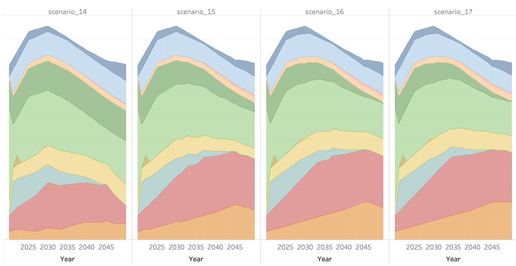


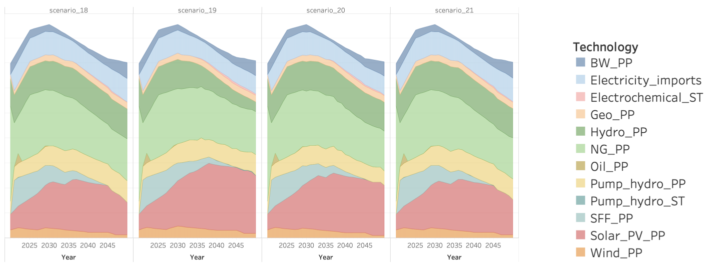
(b) Scenarios 6-9



(c) Scenarios 10-13

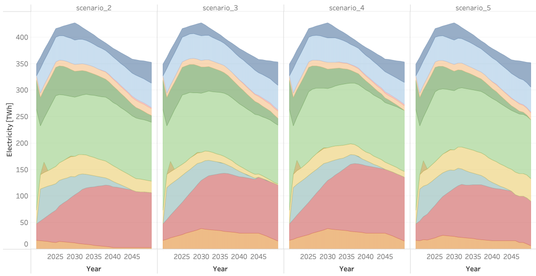


(d) Scenarios 14-17

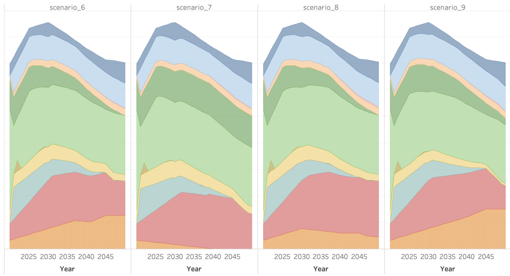


(e) Scenarios 18-21

Figure C.1: Energy mix of all the alternative strategies, cost relaxation = 5%



(a) Scenarios 2-5



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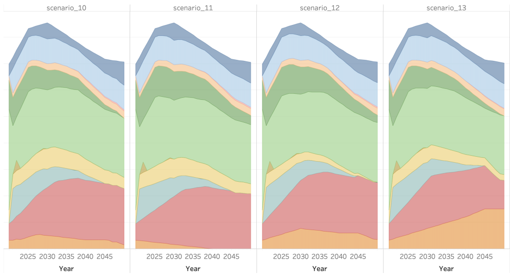

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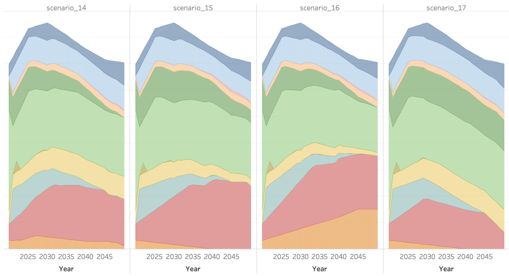

(d) Scenarios 14-17

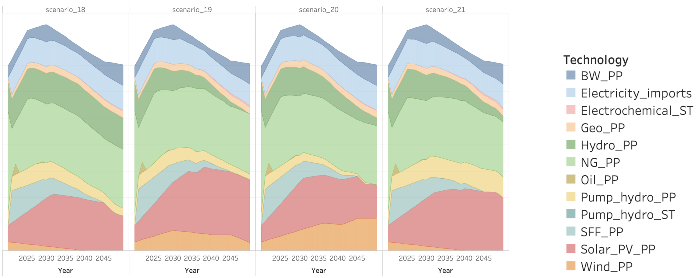

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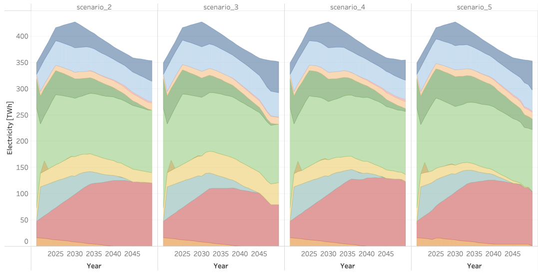
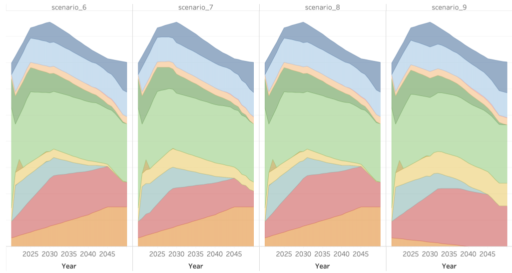
Figure C.2: Energy mix of all the alternative strategies, cost relaxation = 15%



(a) Scenarios 2-5



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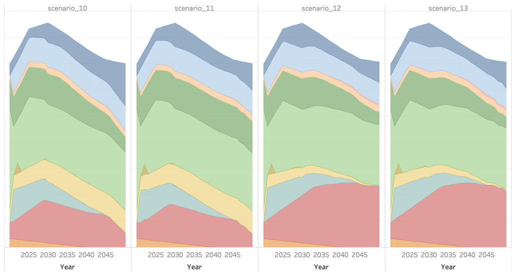

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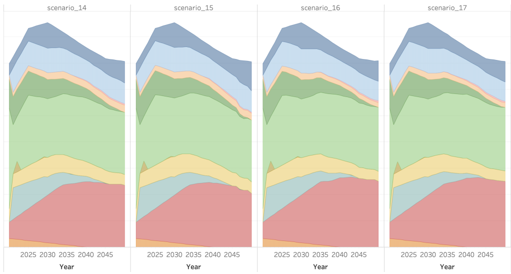

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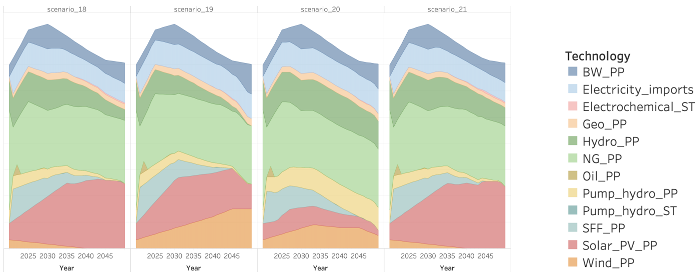

(e) Scenarios 18-21

Figure C.3: Energy mix of all the alternative strategies, cost relaxation = 25%

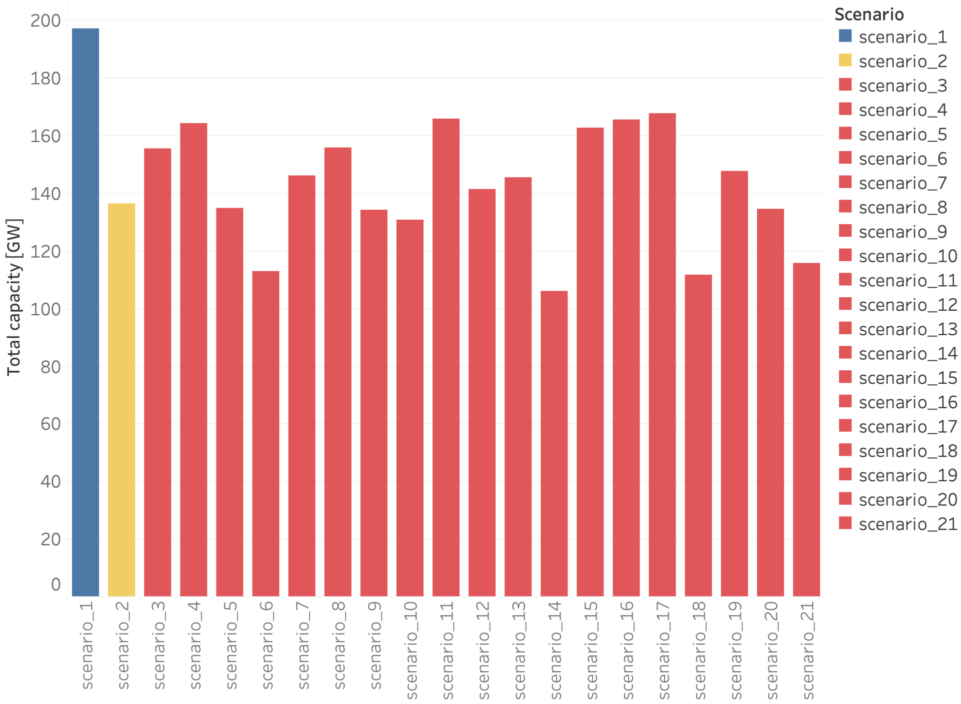

Figure C.4: Total capacity installed in 2050, cost relaxation = 5%

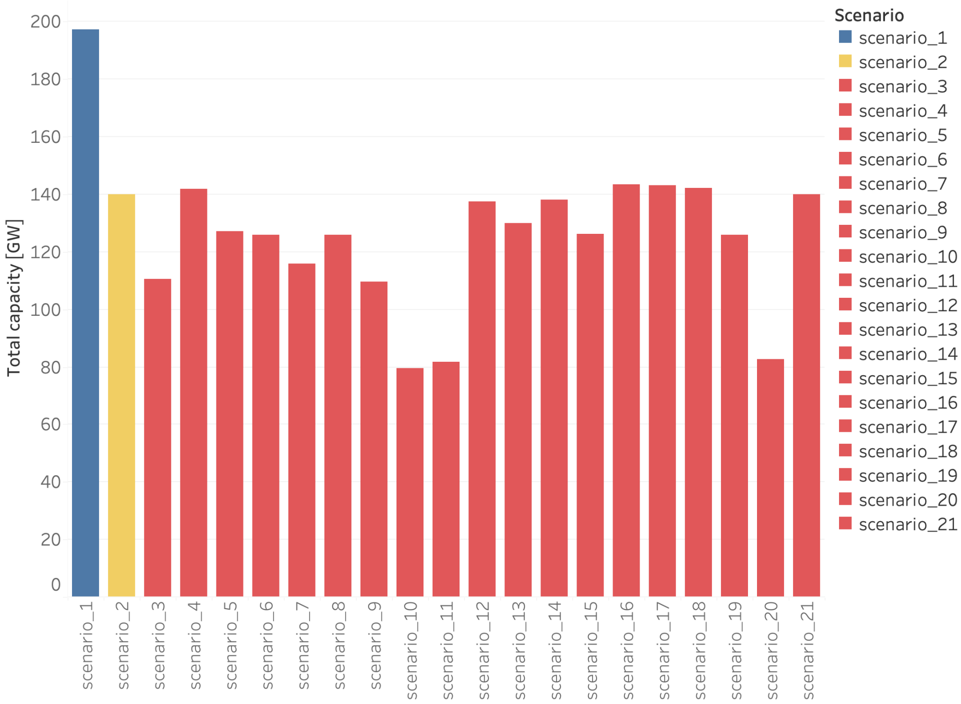

Figure C.5: Total capacity installed in 2050, cost relaxation = 25%

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List of Symbols

Variable	**Description**	**SI unit**
$\boldsymbol{LU}$	Land usage	m^2
$\boldsymbol{LU}_{specific}$	Specific land usage	$\frac{m^2}{GW}$
$\boldsymbol{x}$	Objective function weights	[-]
$\boldsymbol{TotCapacity}$	Total installed capacity	GW
$\boldsymbol{TotDem}$	Total energy demand	GWh
$\boldsymbol{TotProd}$	Total energy production	GWh
$\boldsymbol{AnnualProd}$	Annual energy production	GWh
$\boldsymbol{TotCost}$	Total cost	€
$\boldsymbol{CR}$	Cost relaxation	[-]
$\boldsymbol{CF}$	Capacity factor	[-]

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This thesis would have not been possible without the help of Dr Cruz Torres and Dr Pellecchia. Their help, patience and availability towards me throughout the whole work has been relentless and invaluable.