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Novel modeling approaches for analyzing the design of distributed multi-energy systems

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I wish to thank …

Abstract

This dissertation describes a set of methodological improvements in the analysis of distributed energy systems and their design, with a particular focus on systems involving more than one energy vector (multi-energy systems). The question of the planning of such systems is becoming extremely important and needing of novel approaches due to an energy fruition scenario which is going to greatly mutate due to several changes which can be mostly reconducted to the need of making the fruition of energy more sustainable and with a lesser environmental impact. Such paradigm changes are of diverse nature: coming from both technological trends, social changing paradigms and an always more impellent policy commitment towards reducing the carbon footprint of our society. As an example they can be attributed to the continuously increasing penetration of renewable non-controllable energy conversion sources, the delocalization of energy systems into a distributed paradigm, and the drastic changes of the modality of the fruition of some energy related commodities with the increasing presence of air conditioning and electric vehicles for example. Given the complex nature of such problems, and therefore the computationally demanding nature of the models needed to gain insights about their workings, a renovated focus is put on obtaining models which allow for the analyses to be undertaken in reasonable amounts of time in this novel energy systems context without compromising on the necessary level of detail into the modeling. In this thesis, we define two potential approaches in doing so, tackling two different challenges that emerged from the available literature.

We define a novel approach for the consideration of the temporal dimension in the planning of distributed energy systems. Specifically, the approach aims at properly considering the multi-decade timespan over which a decision concerning the potential adoption of energy systems has to be made. In this setting where some relevant parameters such as the capital costs for the investments in the technologies might change even significantly over such long periods. The approach is implemented within a framework having at its core an optimization problem, solved through mixed-integer programming and heuristic techniques. The validity is then tested on a realistic test case modeled by referring to an open dataset of energy related consumptions for a set of households located in the United States, where the goal of the methodology is finding the optimal year of adoption of an electricity

storage system (if any) considering its dropping costs over the multi-year planning horizon.

We define a methodology to consider various sources of uncertainty within simulations performed by means of an already well established model: being the EnergyPLAN model for smart multi-energy systems. This is achieved by defining a framework that models a set of uncertain inputs such as the availability of solar radiation, the uncertainty in the user demands for space heating and sanitary hot water, and finally the uncertain nature of the demands of an electric vehicle fleet. The test case over which the methodology is tested is the city of Osimo, situated in Italy, which can be assumed to be a small scale multi-energy system, and about which much data needed for the modeling is available through its municipal energy company. The goal of the analyses is to understand how two different flexibility assets: namely a large heat pump coupled with a thermal storage system, and a fleet of electric vehicles equipped with smart charging, can aid in welcoming high shares of non controllable renewable energy sources (photovoltaic panels). This to avoid the feeding of a large share of electricity generation surplus to the national distribution system (thus increasing auto consumption) and to understand the impact on carbon emissions to gain a potential policy related insight.

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List of Abbreviations

CHP – Combined Heat and Power

DHN – District Heating Network

EV – Electric Vehicle

HP – Heat Pump (electric)

MES – Multi Energy System

MILP – Mixed Integer Linear Programming

PV – Photovoltaic

RES – Renewable Energy Source

TES – Thermal Energy Storage

Chapter 1.

Introduction

While climate change has been for years only a topic discussed by scientists and policymakers, now the debate is on the mouths of a much bigger audience. The effects of climate change are more tangible than ever, with consequences that directly impact both our society and economies. And this is only one of the faces of the drawbacks of a model of development that needs to be re-thought following a more sustainable approach as highlighted by the United Nations with a set of goals laid down in the 2030 agenda for sustainable development [1]. Within the scope of this thesis, the 7th and 11th goals deserve a particular interest: being them respectively "*affordable and clean energy*" and "*sustainable cities and communities*". As a matter of fact already more than 50% of the world population already lives in urban areas and such quantity is projected to significantly increase in the near future [2]; to the point that the vast majority of the world's population will be living in cities, making them also the places where the most energy is consumed. At the same time numerous reports from research institutions and industries indicate that we are far from addressing the challenges brought by climate change in an effective way, since we appear to be very far from the targets set in the Paris agreements [3], [4]. In this sense many countries and organizations have already took action by enforcing and constantly updating policies aimed at a deep decarbonization of our society in many sectors: such as carbon taxes or impositions on the share of electricity coming from renewable energy sources [5].

For the magnitude and the urgency of the reasons described a rational usage of energy in urban contexts is gaining a renovated interest by the research community. Among energy related studies the field that deals with studying and understanding how the energy needs will shift in time, and therefore how to direct potential efforts in influencing such trends, is commonly referred to as "energy planning". The practice of energy planning is then aimed at understanding how the energy scenery will evolve and, depending on the type of stakeholder whose interests are represented by the planning practice (whether an energy company, a government or a local community), prepare for such future in the best way possible, given the intrinsic uncertainties that come with it. The research on the planning of energy systems has been historically undertaken with the assistance of a wide variety of computer models to represent the workings of such very complex systems from a wide variety of angles, in order to understand their inherent complexities and obtain actionable insights needed for policy or other types of decision making.

These models have been continuously improved through the years but a set of very actual paradigm changes are calling for new modelling techniques and model capabilities in order to provide insight on modern energy systems. Among such paradigm shifts lies the already mentioned continuously increasing presence of renewable energy sources. Several studies indicate that solar photovoltaic (PV) and wind electricity generation technologies capital costs are constantly dropping and are expected to tumble in the near future [6], [7], being already below grid parity in some countries regarding their levelized cost per kWh of electricity generated. Another potentially influential factor lies in the dropping costs of various storage technologies such as specifically battery technologies [8], which is again pushed by a fast technological development as battery powered vehicles appear again to be the very near future of private mobility [9]. The heavy presence of such vehicles will be itself a great paradigm shift, with a sector which is itself very influential in terms of energy requirements and emissions shifting its needs from fossil based fuels to electricity, posing together with the increased penetration of non controllable electricity generation sources significant challenges to existing electricity transmission and distribution infrastructures [10][11]. A last mention is needed regarding the already anticipated income of policies such as carbon taxes, that might alter the economical tradeoffs of existing technologies in a timespan which is of interest in energy planning practices.

The just described scenario can be synthetized as a dramatic change of the scenery in energy systems design, which calls for a word above all and that word is flexibility. Flexibility could be granted by means of a wide set of approaches (both technological and social/behavioral) but one that could integrate all of such is the distributed energy systems paradigm: both for electricity (which has historically been provided under a top down centralized scheme) and all the rest of energy related commodities (and not only) that might be needed by a modern society in the so called smart multi energy systems. As a matter of fact the correct “amount” of distributed generation is still under debate [12] it’s beyond doubt that energy has a local dimension and the needs of the challenge cannot be met following a one-fits-all approach [13].

1.1 Smart distributed multi energy systems

Firstly, a distinction needs to be made between the concept of distributed energy system and a multi energy system. The former refers to an energy system which generates part (or all of) the needed energy commodity close to the site of consumption [14]. As opposed to the predominant paradigm (at least in developed countries) of large producers using a complex transmission and distribution infrastructure (electricity being the main example) a distributed system allows to meet the needs of the local user by using a set of locally deployed energy conversion assets, cutting on distribution losses and enabling in tailoring such systems to the needs of the user.

A multi energy system (MES) is the expansion of this concept to multiple energy vectors: as defined in [15] a MES is a system in which "*electricity, heat, cooling, fuels, transport, and so on optimally interact with each other at various levels*". Following such definition a MES could be also a large scale system (e.g. a large district heating plant), but within the scope of thesis the focus will be put on small district scale MES. The benefits of a MES approach lie in the possibility of exploiting potential interactions between traditionally decoupled sectors, such as for example electricity, heating, cooling and transport in achieving better usages of primary energy resources and welcoming higher shares of non-controllable renewable energy sources [16], [17]. The concept of MES has been widely analyzed in the literature using a wide span of potential test cases, from groups of buildings to towns. To give some examples it has been widely shown how the coupling of local electricity, heating and cooling networks can help in better welcoming high shares of non-controllable energy sources and lowering emissions [18][19][20][21]. The same has been done for the role of storage [22][23][24] and the presence of a EVs fleet [25][26]. All of the studies confirm the mentioned flexibility potential of the integration of energy vectors, allowing for the reduction of CO2 emissions and a greater uptake of non controllable electricity generation sources.

For this reasons the research efforts are translating into actual demonstrational projects, aimed at furtherly assessing the validity of these approaches both in the planning [27] and in the operational/management phases of such projects [28]–[30]. A distributed MES thus allows to achieve of the benefits of both the two paradigms, cutting on transmissions losses and exploiting synergies between different energy related sectors in achieving solutions which are tailored to the local conditions of the setting under analysis. While the concept of MES can be thought of as a purely "technical" paradigm there is also a paradigm shift more on the social side with the establishment of local energy communities, whose paradigm is currently undergoing regulation within the EU. In this sense a community is defined as a "*legal entity controlled by natural persons, local authorities, including municipalities, or small enterprises and micro-enterprises, based on voluntary and open participation, whose primary objective is to provide environmental, economic or social community benefits rather than financial profits*" [31], [32]. In this context the institution of such entities could furtherly help towards addressing the local dimension of energy needs, given the same entity would be both the user of a given demand and the provider of the same commodity.

It is then clear how the distributed MES paradigm could be an asset in addressing some of the challenges related to energy systems, which ultimately lead to achieving a more sustainable society.

A last note addresses the size of a distributed/local energy system, which is not clearly defined in the available literature. A study reviewed the definitions of a distributed energy system [33], and a further and more recent review is provided in [12], with the conclusion that there is really not an agreed standard on what qualifies a distributed/local energy system in terms of size and availability of a greater infrastructure connection, as long as the production is physically located close to the consumer. For this reason within the scope of this thesis, the size of a distributed/local energy system is defined as ranging from the size of a cluster of buildings to a small town.

1.2 Analyzing distributed multi energy systems

As anticipated distributed MES are intrinsically very complex objects to analyze even if only their techno-economical workings are under analysis. This lead and it is still leading to the development of a very wide set of models which focus on different aspects of such systems. They could be aimed at analyzing systems from a planning instead of an operational perspective; the analysis of only a given subset of considered energy systems/user demanded commodities; the driver of the analysis, whether focusing on an economical instead of an environmental aspect and so on. In the literature there is a vast amount of models, using different modeling approaches for the analysis of different aspects of distributed energy systems [34]. While some of these models are only defined in terms of their mathematical definition, thus they have to be programmed within a proper environment, others have developed in software packages, some of which are commercial products and some others are available with a free license, up to completely open source models [35]. The mathematical approaches behind the models are very wide, using different degrees of both linear and discrete programming, and with a great importance of the algorithmic approach, given the inherent difficulties in tackling such demanding problems.

The models that are available as self-contained software packages can be classified using a wide set of criteria, spanning from: the level of discretization both in the temporal and spatial dimensions, the ease of use also with the presence of a graphical user interface, the type of license under which the model is available and so on [36]. A more comprehensive description of the distributed systems modeling scenery is beyond the scope of this thesis, so it's delegated to a very abundant literature [37], [38][36].

The scope of this thesis is to propose improved approaches in techno-economic analysis models for distributed MES, and in this sense a broad distinction can be made between optimization and simulation models. In the first the best possible choice of a given set of parameters is computed by pursuing the minimization or maximization of a given criteria (or a set of them) provided the existence of some constraints. In an energy systems scenario this could translate in two broad categories of problems: optimizing design or optimizing operations. An example of a problem falling in the first category could be finding the optimal set of technologies to meet multiple user demands over a representative timespan; while an example of the second could be finding the best management strategy for a given set of systems in a similar context, but removing the option of using non owned systems. Examples of energy systems optimization models are: OSeMOSYS [39], [40], H.O.M.E.R. [41], EnergyPRO [42] and Calliope [43]. Simulation models on the other hand just wish to replicate the way a physical system works, allowing for its behavior and evolution over time to be studied more in detail; in this case the insights regarding "best" solutions are drawn from a "what-if" scenarios approach. While some of the just mentioned optimization models are also able to just simulate energy systems, a model which is created exclusively for simulation purposes is the EnergyPLAN model [44].

Given the intrinsic complexity of MES in any model falling in any of the categories just described there is a trade-off to face regarding the level of represented detail and the computational complexity in solving the model. There are a number of approaches for dealing with such compromise and achieve a level of detail which is representative enough for the insights that are sought to be still valid, and in the meantime limit computational effort to a manageable size. Being the already mentioned challenges for novel energy systems models such compromise has to be re-thought in order to have models able to provide insights on modern energy systems.

1.2.1 What's missing

As highlighted in the previous paragraph many authors have reviewed and given a summary of the energy systems modeling scenery; among those a 2014 review study [45] highlights the needs to address some challenges in established paradigms in energy systems modeling in spite of the issues described earlier on in this chapter. By narrowing such challenges to the ones related to the simulation and optimization of energy systems two of them are raised and described.

Regarding optimization models is highlighted how the challenge is addressing the changing importance of the time and space dimensions which call for an increased resolution, while at the same time keeping a tractable model from a computational perspective. The time/space dimensions are in-fact needing a renovated interest given the anticipated challenges regarding the distributed dimension of energy (space) and the ever increasing presence of non controllable energy sources and parameters evolution over very large timespans which call for both an high temporal resolution in a long term scenario analysis paradigm [46], [47]. With simulation models one of the highlighted challenges regards the degree to which uncertainty is represented and accounted for while gaining insights from energy systems models, which can be distinguished in two broad types: an epistemic uncertainty which can be improved with an effort from the modeler in obtaining more or better data, and an aleatory uncertainty which can be addressed by using appropriate techniques such as stochastic programming or Monte Carlo based simulation approaches [48].

The importance of the uncertainty aspect, specifically in the design of distributed energy systems, is also described in a separate review study [49] which goes more into the detail of the various sources of the uncertainties, their potential impact while analyzing energy systems and the available approaches in doing so. It is highlighted how an improper consideration of uncertainty sources within the design of distributed MES could lead to suboptimal solution and/or misleading insights regarding the outcomes of such models. Uncertainty can be defined as "*any deviation from the unachievable ideal of completely deterministic knowledge of the relevant system*" [50], and the deterministic approach is actually the one that is mostly followed within the analysis of energy systems, making the outcomes of such models heavily dependent on the assumptions behind the deterministic parameters. An effort is then needed to characterize these sources of uncertainty in order to account for their impact, and the characterization strategy greatly depends on the characteristics of the phenomenon which is to be modeled. Such uncertainty sources could come from the availability of a non controllable resource (solar radiation, wind etc.), to an unsteady user demand, the cost of a particular technology and so on; and the technique used to characterize it could depend both on the characteristics of the phenomenon itself and the data which is available.

Given the huge amount of uncertainty sources within the analysis of distributed MES a proper consideration is then key in order to obtain valuable insights, especially within the challenges anticipated in the first part of the introduction.

1.3 Contributions to the state of the art and thesis outline

Given the context introduced so far in this chapter this thesis illustrates a set of contributions to improve the described state of the art in the practice of analyzing the planning of distributed multi energy systems, both when optimization and simulation duties are sought. The approaches directly tackle the challenges highlighted in the previous paragraph, addressing the needs for a proper representation of the complex temporal dimension when an optimal design choice is sought, and the impact of uncertainties while analyzing a given context. The contributions both involve programming approaches and the usage of freely available energy models, and the proposed methodologies are tested by means of analysis performed on realistic test cases, which are modeled with a mix of available data and further modeling efforts.

The first contribution is a methodology to analyze the optimal planning of distributed energy systems that considers how some of the simulation parameters might change in time over a planning horizon of multiple decades. This is achieved by defining an enhanced representation of the time horizon, using two different timescales over which to compute the operational and strategic decision making phases. The model is solved by means of a custom-made heuristic algorithm, allowing both the convergence to an optimal solution while keeping an acceptable computational tractability. The methodology is tested on a realistic test case modeled by means of freely available measured data, where the potential adoption of a technology is studied over a long-term planning horizon.

The second contribution is a framework that wishes to correctly assess the intrinsic variability of some simulation parameters within the simulation of local energy systems with high penetration of renewables, achieved by means of the EnergyPLAN model. Specifically the variability sources that are represented are the availability in time of the solar resource and the demands of a set of commodities from the users such as heating, electricity and electric mobility. A tailored approach is used for each of the uncertainty sources, using both data-driven and mechanistic approaches to represent uncertain realistic hourly distributions for the mentioned variables. The methodology is tested on a real test case representing a small town with an already heavy presence of non controllable renewable energy source, which configures itself as a MES. The goal of the analysis is understanding to which degree such high penetration (and potentially an increased one) can be used locally in order to increase the energy independency of the town; and also understand the main drivers towards reducing the carbon footprint in such high RES penetration contexts.

Chapter 2.

A methodological approach for the long term planning of distributed energy systems

2.1 Preface to chapter 2

In this chapter, we introduce a methodology to assess the impact of parameters that exhibit a significant change over long timespans (multiple decades) and that might affect the optimal design of distributed energy systems. As anticipated the scenery regarding on energy systems will be affected by potentially game changing aspects such as the significant drop on the costs of some key technologies. Thus a methodology is needed to consider such changes while determining the optimal design of a distributed energy systems: a context where the decisions that are made will be in place for several years (more than a decade). In this chapter we then propose a mathematical model of the optimal design of the energy systems needed to meet several energy related demands of a user, by also considering parameters that change over time. The work has been undertaken in two parts, with a first activity aimed at obtaining a model to compute such optimal design for a representative year with a reasonable computation time. Secondly, the model has been expanded to include the multiple year modeling in a way that could again grant a reasonable computational time. This has been achieved by defining two different timescales over which perform analyses related to the optimal design: a yearly timescale with hourly resolution over which the operational strategies of the used technologies is computed, and a secondly a multi-decade timescales with yearly resolution over which the decisions regarding potential investments is computed. Both of the parts have been realized by coding a mathematical model in the AMPL programming environment.
My role in the work described in this chapter regarded the development of the idea of dividing the optimization in two distinct phases (yearly and plurennial), and the

elaboration and characterization of the case studies used to validate the approach. The rest of the model has been developed conjunctly with Dr. Roberto Rosetti and Mr. Andrea Pizzuti, which also entirely took charge of the programming activities. All the activities have been supervised by prof. Gabriele Comodi and prof. Fabrizio Marinelli, which contributed with comments and editorial assistance.
From the activities described in this chapter we obtained two peer-reviewed publications: a conference paper presented at the ICORES 2019 conference held in Prague [51], and another conference paper presented at the ICAE 2019 conference held in Västerås [52].

2.2 Introduction and state of the art

To the best of the authors knowledge the only approach available in the literature that tries to consider the impact of parameters changing over a multiple years timespan is the one proposed in [53], which integrates a previously proposed optimization approach [54] by the same authors takes couples the EnergyPLAN simulation model with an external optimization shell using evolutionary algorithms. The goal of the model is to study transition pathways for a national/regional scale energy system. On the other hand quite a few studies that wish to analyze the optimal design of distributed energy systems have been proposed using a wide set of mathematical approaches. These vary from exact techniques such as MILP to evolutionary or other heuristics based techniques: while the former can guarantee to achieve a globally optimal solution [37] they are computationally much more demanding than the latter, especially in the context of energy systems design, where the size of the problem (in terms of variables to compute) in usually very large. For this reason within the present study an ad-hoc heuristic approach is used, with such type of approaches already followed in the literature by many authors [55], both to address the optimal energy systems design (in terms of components size) [56], [57] and the optimal network configuration [58], [59].

The approach described in this chapter is aimed at analyzing scenarios that represent local energy systems challenges, and wishes to do so by using a metaheuristic approach (improving the one proposed in [51]) for both the multi-year design phase and the operational phase, thus achieving an optimal solution for both.

The approach is validated with the application on a realistic scenario, that considers a residential user with an high penetration of non-controllable renewable electricity generation source (a PV system), where the decision under analysis is the potential purchase of an electricity storage (a battery system) considering different retributions for a feed-in tariff and the dropping price of the storage system in the years to come. The residential district is modeled by referring to a dataset which includes real consumption data for a set of households in the United States [60], measured with high temporal resolution for a whole year, from which the consumption data for electricity (excluding space cooling appliances), cooling and heating are obtained. Thus, all of the three commodities are considered in the analysis in order to also consider the potential role of cross-vector technologies.

2.3 Methodology

2.3.1 Case study modeling strategy

In order to model the district an energy hub we adopted an energy hub modeling strategy as in [61], an energy hub can be defined as an integrated unit within which the conversion, storage and usage of different energy vectors (but also any other type of commodity) takes place. Thus, the energy hub has to get resources from outside its boundaries (e.g. natural gas, grid electricity, solar radiation…) and manipulate it internally by means of specific technologies in order to meet the demands of a given user, such technologies can already be present within the hub's boundaries but they can also be purchased in order to do so by sustaining an appropriate cost. The operations of the energy hub are then usually simulated over a representative period of time, aimed at obtaining relevant insights regarding for example: costs sustained over the mentioned timespan, CO2 or other pollutants emissions, and potential investments in new technologies in order to lower the total costs.

The energy hub is then a general scheme that can be adapted to diverse settings, and this is used to model the case study that will be used to test the proposed methodology. As mentioned in the previous paragraph the test case is a residential district which needs three distinct energy vectors to properly function, thus the proposed energy hub is shown in Figure 1.

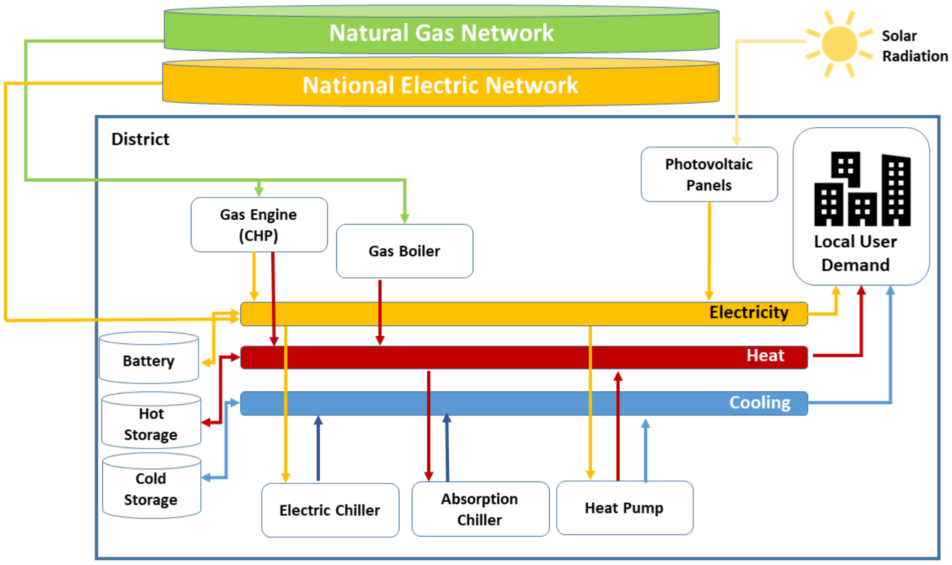


Figure 1 - Energy hub conceptualization

In the Figure different types of elements are visible. Firstly the three energy vectors in the form of buses from which the vectors can be both withdrawn and fed in: for electricity, space cooling and space heating. Interacting with such buses there are both the technologies in charge of converting/producing the energy vectors and the user that absorbs them to meet the demands. Finally there are three external sources for three different resources: natural gas and electricity to be purchased from the respective distribution infrastructures, and solar radiation to power the local PV system. It is also considered that the electricity can be fed back to the grid given a proper compensation (feed-in tariff) if such electricity is produced with the PV panels.

All of the elements in the energy hub have then to be quantified in order to represent the test case of the residential district, which means representing the demands, the solar energy availability and a set of realistic costs for the considered technologies and the purchasing of external resources from the national distribution infrastructures.

2.3.2 Proposed framework

In order to solve the multi decade optimization problem a strategy to tackle the time dimension of the problem has been implemented in a framework, which is shown in Figure 2. The goal of the whole framework is to compute the optimal design for the energy systems needed to meet the users demand over a planning horizon of multiple decades, by minimizing the total costs sustained in such timespan. Such costs relate both to operating the already existing assets (such as maintenance costs or acquisition of externally purchased commodities), and also to the investments needed to purchase new equipment.

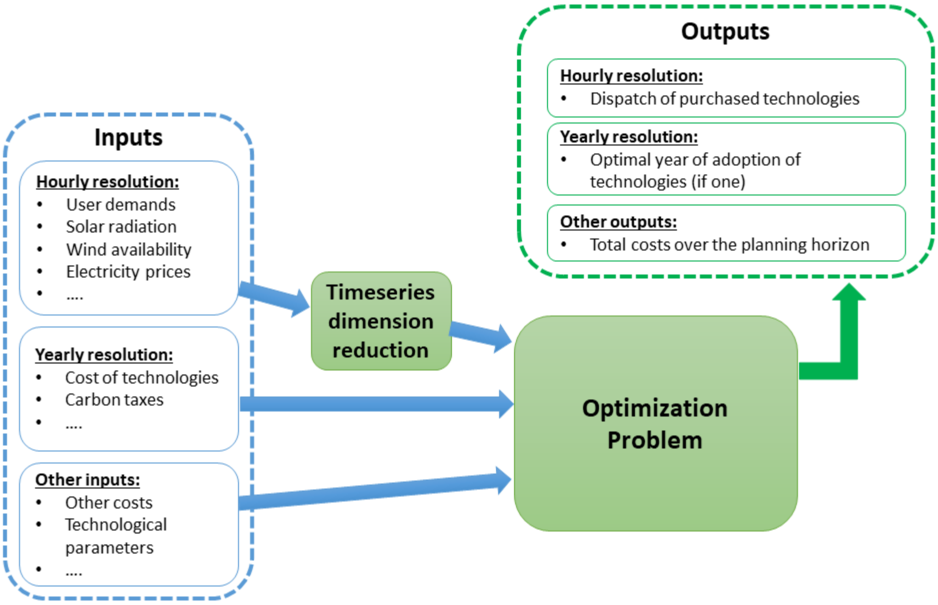


Figure 2 - Visualization of the proposed framework

The core of the approach, and therefore of the framework, is the modeling of the time horizon of interest (over which to choose potential new investments) which is achieved by defining two distinct time scales with different features, the approach is shown graphically in Figure 3, and the two timescales have the following characteristics:

- A multi-decade timescale with yearly resolution (in blue in Figure 3), over which to compute investment decisions that are then function of a specific year
- A yearly timescale with hourly resolution over which to compute decisions on how to manage the technologies available in meeting the users demands (in green in Figure 3), which are defined with the same hourly resolution.
  This timespan if furtherly reduced by selecting only an appropriate number of time-slices in order to reduce even more the computational effort.

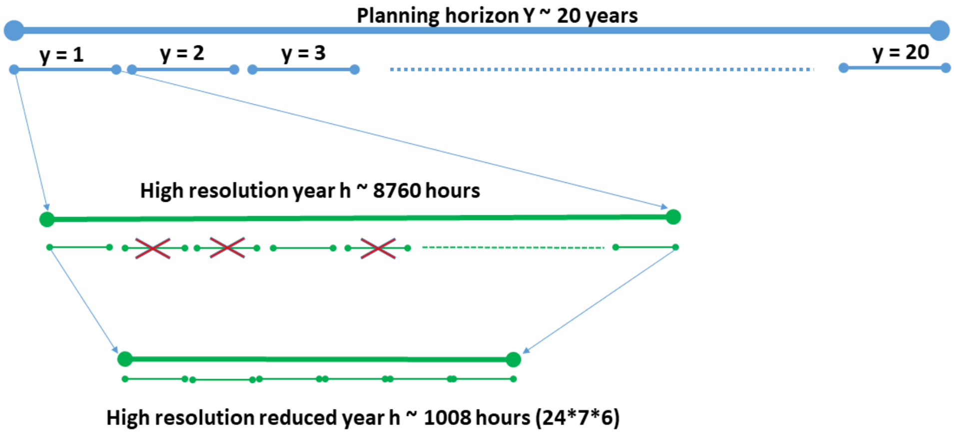


Figure 3 - Graphical representation of the two timescales

As shown in Figure 2 the inputs to the problem are then defined depending on the timescale they refer to. The user demands and the solar radiation availability are defined on an hourly basis for a representative year. Some other parameters may though be defined to vary over time on a longer time horizon, and this is the case of the cost of some of the technologies or for example the incurrence of new policies or regulations, such as for example the imposition of a carbon tax by the local regulation entity from a given year onwards. Finally, some parameters preserve the same value regardless of the passing time, and this is the case for example of the costs of technologies which are considered to be already mature.

As shown in Figure 2 an intermediate step is added before solving the actual optimization problem and this is aimed at reducing the timespan over which the computation of the operational phase is performed from a year to a subset of representative weeks, in order to reduce the computational burden of the whole analysys. This is achieved by means of a clustering procedure, similarly as in [62], to select weeks from the yearly timespan based on a set of features which are computed for each week of the available timeseries data, in this case a year.

Specifically the technique that is used is the k-means clustering algorithm [63], which implementation is taken from the SciKitLearn python package. The week is chosen as the smaller time slice to simulate in order to properly take into account the role of storage technologies within the district. A common storage technology application lies in storing electricity surplus from non controllable renewables during the day for a later usage during the night (home battery system coupled with PV), and for this the slicing of the timespan in representative days would actually work fine. But other type of applications actually take advantage of offsets on a weekly basis, as for example in industries which exhibit much lower energy demands during the weekends when they're closed. Even though within this work the framework is tested on a residential user scenario the time slices are kept to a week in order to make it more general.

The clustering procedure works as follows:

- The yearly timespan is sliced in weeks and to each week is assigned an identifier which is an integer value
- For each of the weeks a set of features is computed:
  i) Average weekly electricity demand in kWh
  ii) Average weekly heating demand in kWh
  iii) Average weekly cooling demand in kWh
  iv) Average weekly available solar radiation in kWh/m2
- A predefined set of clusters, meaning representative weeks, is computed by analyzing the similarities in the mentioned features. The number of clusters is arbitrarily set to 6, to hopefully represent two winter, two summer and two mid-season weeks.

Following such procedure the year intended to represent the realistic timespan over which to represent the district will be reduced from one year to 6 weeks, still maintaining an hourly resolution.

All of the mentioned parameters are then fed as inputs to an optimization problem, which as mentioned is split up in two distinct problems: a strategic one where the investment decisions are computed, and an operational one where the different systems available are scheduled in order to meet the demands of the users. The approach is shown graphically in Figure 3.

Both of the two problems use a MILP (Mixed Integer Linear Programming) modeling approach for both the variable representing investment decisions and the ones representing the dispatch strategy in the operational phase. The two timescales are modeled by defining two distinct sets over which such variables are defined:

- A set H to represent the year in hourly resolution, where the dimension of H following the dimensionality reduction is 1008 (24 hours * 7 days * 6 weeks)
- A set Y to represent the planning horizon with yearly resolution, where the dimension of *Y* is 32 (from 2018 to 2050

Following such definition the investments in a given technology are defined by a binary variable which is also function of the specific year, returning in that way also the optimal year of adoption of the given technology.

Other than the ones modeling the workings of the technologies an additional set of constraints is enforced in order to force a realistic technological lifetime (which is provided as a simulation parameter for each available system) over the usage of the systems. The planning horizon spans multiple decades, but many of the potential technologies actually have a much shorter technical lifetime. Thus, if an investment on a given technology is made by the algorithm that same technology will have to be re-purchased by sustaining again its cost once its technical lifetime has expired.

The modeling of the technologies workings follows a linear approach, with conversion efficiencies assumed to be constant regardless of the operating conditions in terms of load etc. As examples the equations representing the workings of a chiller and a PV panel are the following:

$$E_{PV}(sz,h,y) = \eta_{PV}(sz) * Irr(h)$$

$$C_{EC}(sz,h) = COP_{EC}(sz) * E_{EC}(sz,h)$$

Where $E_{PV}(sz,h,y)$ is the electricity produced by a PV system, which is function of the PV system efficiency through its model *sz*, and the instant solar radiation available which is expressed by *Irr* as a function of the hour *h*. And where $C_{EC}(sz,h)$ is the instant cooling power produced by the electric chiller of size *sz*, which is a function of the system itself through its COP value, and the instant electricity provided at the same time located with the hour h.

While the production of the PV system is rigidly connected to the amount of radiation available (provided as a simulation parameter), a fully schedulable component like the electric chiller is controlled by computing the variable E_{EC} of the electricity provided, which is bound to be between zero and the maximum cooling power that the chiller sz can provide given its technical specifications: this is expressed by means of the following equation:

$$0 \leq C_{EC}(sz, h) \leq C_{EC}^{max}(sz)$$

The objective quantity to minimize, meaning the total costs sustained over the whole planning horizon, is expressed by means of the sum of two quantities: the investment cots C_{inv} and the operational costs C_{op}. The expression of the operational costs is the following:

$$C_{OP} = \sum_{y}\sum_{h}(E_{grid}(h, y) * c_{grid}(h, y) + NG_{net}(h, y) * c_{NG}(h, y))$$

Where $E_{grid}(h,y)$ is the electricity purchased from the local distribution grid in kWh and $c_{grid}(h,y)$ is its cost in \$/kWh, which can also vary in time to represent complex pricing schemes or changes over long time horizons. In the same way $NG_{net}(h,y)$ is the quantity of natural gas withdrawn from the distribution network and c_{ng} its cost. For the investment costs, the equation is the following:

$$C_{inv} = \sum_{tech}\sum_{sz}\sum_{y}(C_{sys}(tech, sz, y) * X_{sys}(tech, sz, y))$$

Where $C_{sys}(tech,sz,y)$ indicates the cost of a generic system, which is a function of tech, indicating the type of technology (whether a chiller or a boiler), sz indicating its size (among the ones in consideration for the given technology tech) and y indicating the year, for the technologies that exhibit a change in costs over the planning horizon. The investment in the system is controlled by means of the binary variable X_{sys} that depends on the same set of conditions.

The objective of the optimization is then to minimize the total costs:

$$C_{tot} = C_{OP} + C_{inv}$$

The whole optimization problem is split up in two sub problems, solving respectively the strategic and the operational phases described by the two timescales, with both the two problems providing a distinct contribution to total costs, which is ultimately the quantity to be minimized by the algorithm.

Synthetically, the heuristic algorithm shown in Figure 4 acts as follows:

- By solving the problem *M* a first trial design is obtained following a criteria based on the total amount of demand per energy vector over the multi-decade timespan. Such design returns a set of technologies which are purchased to hopefully meet such demands, this by following a simple conversion equation modeling the workings of the technologies. Then, by consequence an approximation of the total costs (both investment and operational) sustained is also returned.
- The design obtained from the solution of problem *M* is then fed into the problem M_h where it's tested on the hourly resolution timespan of the slices obtained as indicated in the previous paragraph, thus linking the two phases. The solution obtained in this phase can then be both feasible and unfeasible, in the case the technologies configuration can't actually meet the demands on an hourly basis. In case the solution is unfeasible an unmet demand quantity is computed and used as a feedback for the next round of *M*.

The algorithms then proceeds in solving the two phases iteratively until a predefined stopping criterion is met, at that point the solution that achieved the lowest cost is chosen as optimal.

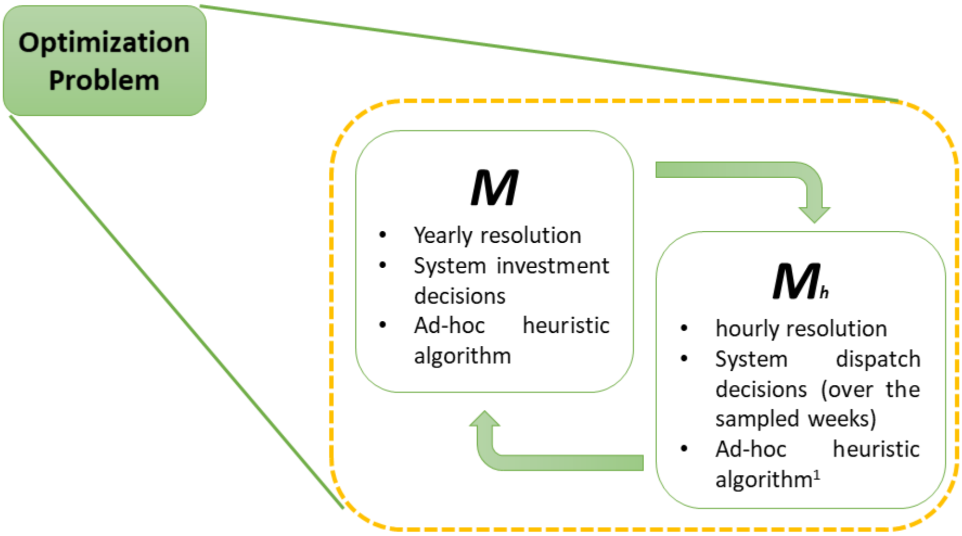


Figure 4 - Workflow of the optimization problem solving algorithm

2.3.4 Case study characterization

The test case, which is a realistic residential district, has been modeled by aggregating the demands of 150 households from the already mentioned open dataset [60], and obtaining the relative demands (for electricity, space cooling and space heating) and the available radiation for a whole year with hourly resolution, thus recreating a realistic simulated year for the whole district. The question that the proposed approach aims at solving is the convenience in purchasing a battery system for the district, thus a pivotal importance lies in the presence of a non schedulable energy production system. Given that the real district already shows a heavy presence of PV systems, its the capacity is left unaltered.

Once the energy demands are retrieved from the open dataset, those are then fed to the clustering procedure in order to sample 6 representative weeks. In the following Figures the energy demands for the three commodities (electricity, space heating and space cooling) are shown for three of the sampled weeks: a summer, a winter and a mid-season one. Figure 5 shows the electricity demand, Figure 6 the heating demand and Figure 7 the cooling demand in kW for a period of one week.

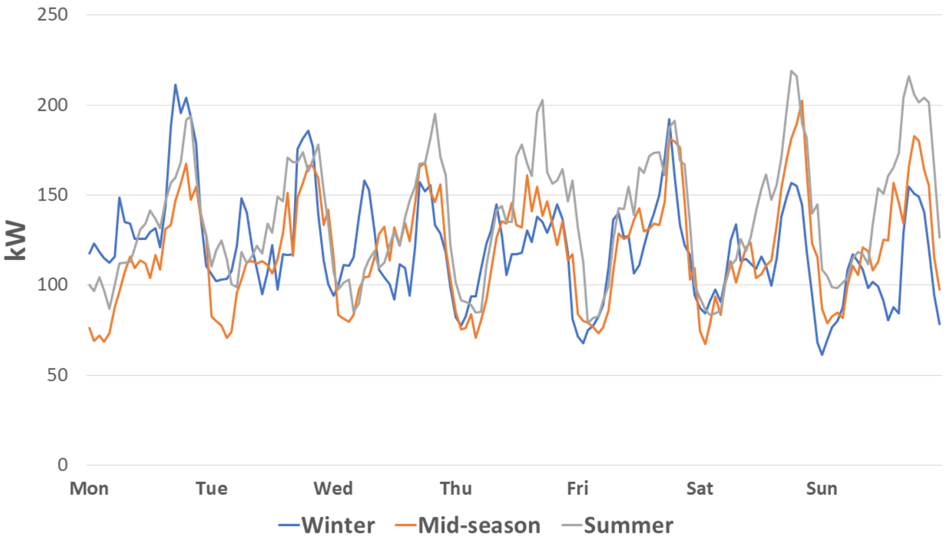


Figure 5 - Electricity demand of three sampled weeks

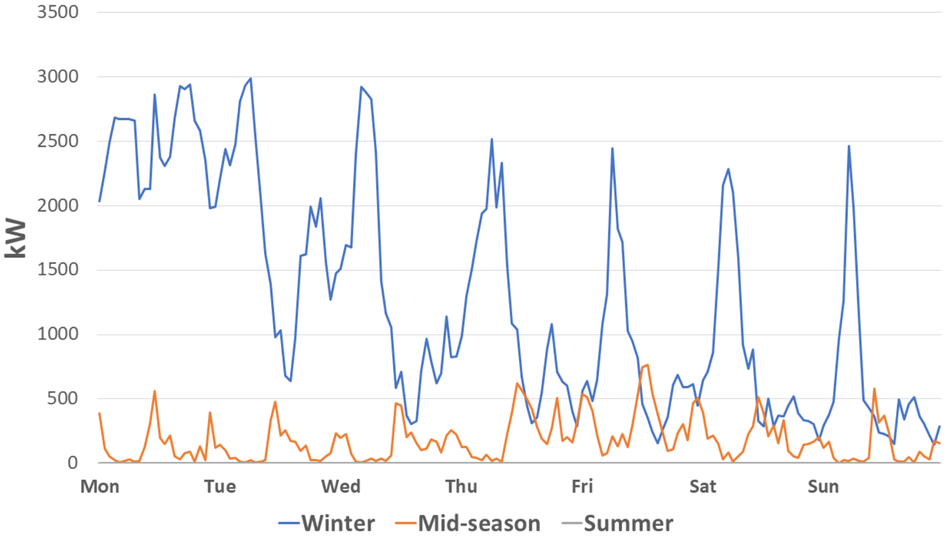


Figure 6 - Heating demand of three sampled weeks

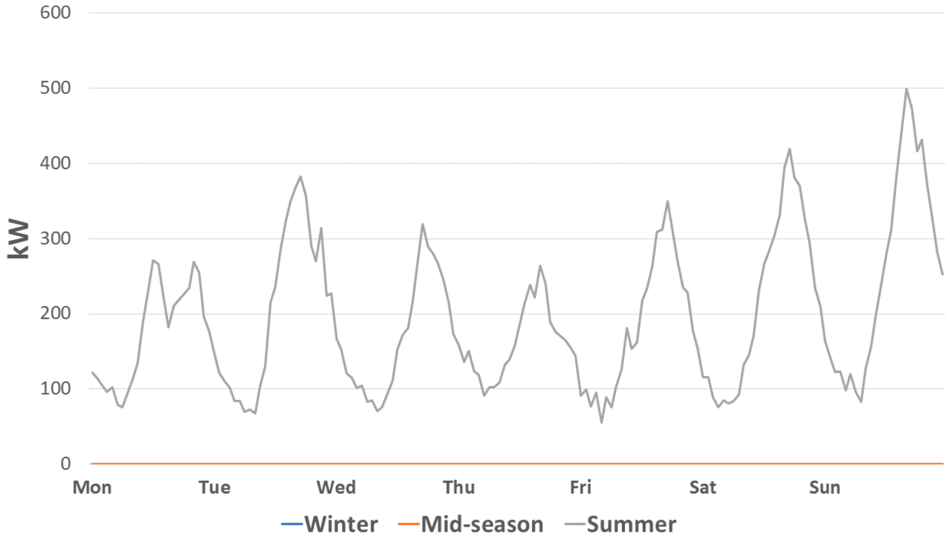


Figure 7 - Cooling demand of three sampled weeks

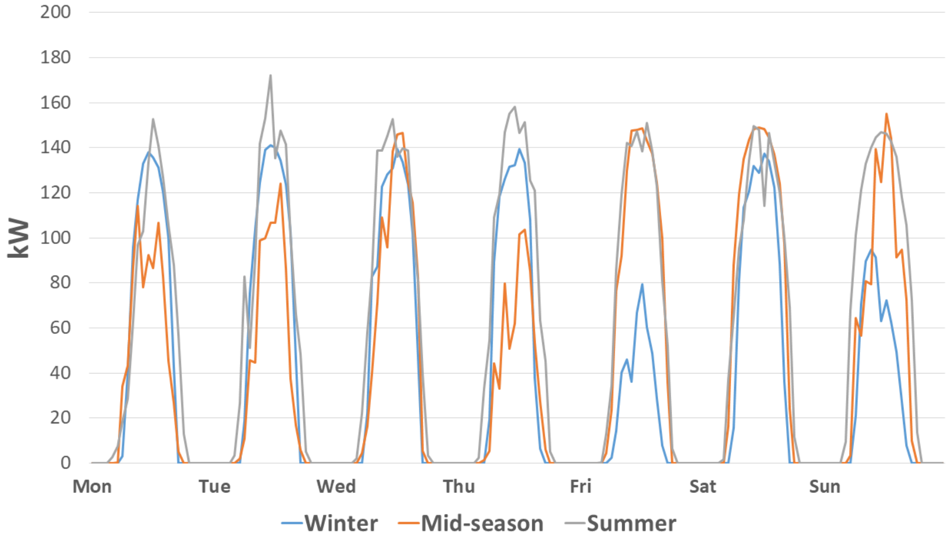


Figure 8 - PV system production of three sampled weeks

As explained the PV system size is given as an optimization parameter and amounts to around 250 kWp, the system will then produce electricity depending on the solar radiation that is available in the actual hourly timestep. The hourly radiation is also given as a simulation parameter according to the sampled weeks, for the same weeks as in the previous figures the electricity production from the PV system is shown in Figure 8.

Finally the costs for the systems involved need to be characterized. The systems which are considered in the analysis are the following:

- A PV system, which size is given as an input to begin with
- A natural gas boiler to meet the heating demand
- An electric split system to meet the cooling demand
- A battery system to use locally the surplus from the PV panels instead of feeding it to the grid

As explained the goal of the analysis is to evaluate a potential investment in batteries considering the cost which is dropping in time, such drop in costs has been determined following the estimations in [64] and it's shown in Figure 9 for the desired planning horizon. The rest of the technical parameters used in the simulations are shown in Table 1.

Lastly the ageing of the PV system is also simulated by considering a drop in performance (being its system efficiency) of 0.3% per year; this given the relative importance that the phenomenon could have in a long time horizon due to the direct relationship of the output of the PV system, which ultimately drives the need to adopt a battery system.

	Boiler	**Split System**	**PV**	**Battery**
Investment cost	60 $/kW	250 $/kW	500 $/kWp	Figure 9
Maintenance cost	2 $/kW/y	5 $/kW/y	10 $/kWp/y	2 $/kWh/y
Efficiency/COP	95%	3	18% (system)	95% (round trip)
Technical lifetime [years]	20	20	30	15

Table 1 - Technical and cost parameters

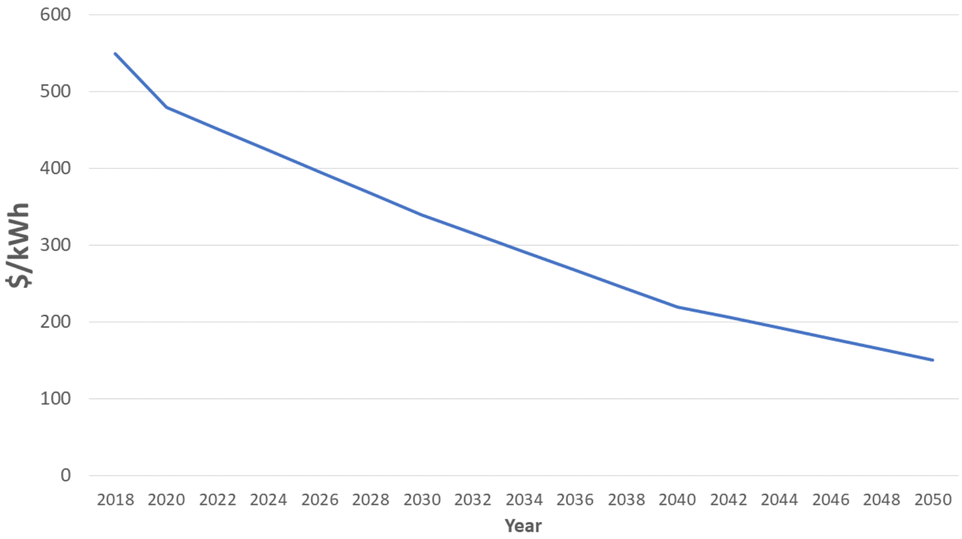


Figure 9 - Simulated drop in battery costs over the planning horizon

Also as anticipated the investment in the battery system is evaluated under different feed-in tariff compensation schemes, because it is expected that the investment in a battery system would make more sense with a smaller compensation from the local distributor for the electricity surplus. Thus while the purchase of electricity from the local grid is kept constant at 0.08 $/kWh the feed in tariff is set to drop from 0.04 $/kWh to 0.02 $/kWh with incremental steps of -0.0025 $/kWh.

2.4 Results

The obtained results entail the optimal design for the residential district over the planning horizon of 32 years. This includes as expected a boiler and a split system to meet respectively the demands of heating and cooling. However, focusing on the battery system this is not chosen by the algorithm in any of the scenarios. This means that even by considering the lowering costs a battery system adequate to absorb the surplus would still be more costly than feeding back such surplus into the main grid, even with a lowering feed-in tariff compensation. This is also to be ascribed to the performance losses of the PV system of the course of the planning horizon.

In order to test the correctness of the approach an additional test has been run by forcing the presence of a small battery storage system (50kWh of capacity with 25 kW of charging and discharging power) in the district. All of the results are shown in Table 2 indicating the total costs sustained over the planning horizon in order to meet the demands of the district. These are reported in two columns: the *C** column indicating the total costs without the purchase of a battery imposed, and the C^B where this happens.

FIT [$/kWh]	**C* [k$]**	**C^B[k$]**
0.02	5745.61	5785.39
0.025	5745.12	5785.19
0.03	5744.64	5785.00
0.035	5744.15	5784.80
0.04	5743.67	5784.60

Table 2 - Results of the experiments

A shown in Table 1 the solution that forces the presence of the battery is actually not very far in terms of life cycle costs from the one that just relies on feeding the electricity into the local grid, having on average a 0.7 % discrepancy between the two. This appears then to be very tightly related to the chosen test case, and it's reasonable to think that the battery would actually have been an appropriate investment with small changes to some of the input parameters, as for example the size of the PV system, or a different tariff scheme agreed with the local grid (also for purchasing). As an additional proof of the validity of the battery solutions C^B and more in general of the computations performed by the algorithm the dispatch strategy of one of the solutions for the battery cases is show in Figure 10.

Even given the relative simplicity of the test case and the assumptions made it is already possible to gain some insights from the results. Under the current circumstances the district would find itself feeding the electricity surplus to the local grid, which could ultimately lead to a lesser carbon footprint from a larger system perspective. Assuming that the choices on which technologies to adopt by the users would be probably driven by an economic criterion (as the one represented by the objective function of the problem) the policy insight to gain by a potential local utility really lies on whether the feeding of such electricity in the local grid is actually bearable.

However it has to be considered that decision could change easily for example in the case of adoption of electric vehicles by the users in the district.

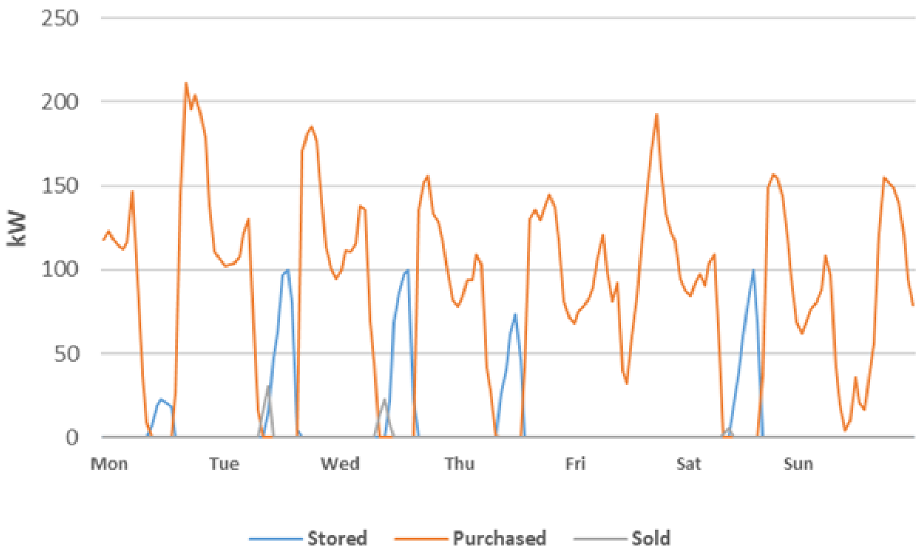


Figure 10 - Dispatch strategy of a battery case

All the simulations shown in Table 1 require a total of around 50 seconds to run on a moderately performant workstation (Intel Core i7 2.9 GHz with 16Gb RAM), which is actually a very short amount of time. The analysis could then be surely increased in terms of considered parameters and scenarios in order to have a more comprehensive approach to the decision making process.

2.5 Conclusions

In this chapter we presented a novel methodology for assessing the impact of parameters changing in time in the optimal design of distributed energy systems, where the time horizon of interest is the lifespan of a realistic urban district. Specifically the proposed approach wishes to correctly consider the changing capital costs while defining the optimal design of a system over a very long planning horizon of multiple decades.

This was achieved by defining a framework based on an optimization problem, which is solved with a novel ad-hoc heuristic algorithm that aims at minimizing the total costs sustained in meeting a set of energy demands of the local user. In doing so both the possibility of acquiring commodities (natural gas/electricity) from local distribution infrastructures and the purchase and deployment of new energy systems is considered.

The approach is tested on a realistic test case but by referring to an open dataset containing real measured consumption data from a set of households, with the decision under analysis being the potential purchase of an electric storage system (batteries) to handle the surplus of renewable generated electricity, considering also a projected drop in costs over the planning horizon. The investment is to be evaluated in a scenario where a feed-in tariff for the surplus electricity is in place, and the compensation for the tariff is set to decrease progressively. Furtherly the ageing of the PV system generating the electricity surplus is taken into account by imposing a fixed drop in performance per each year.

The results show that for the proposed test case a battery system is not an good investment, even if not so distant from the proposed solution of feeding the surplus electricity into the local grid in exchange for a feed-in tariff compensation. This can be ascribed to a set of factors; from the relative gap between the demands of the district and the size of the PV system which don’t allow for an adequate electricity surplus, to the drop in performance of the PV system itself.

Chapter 3.

A methodological approach to improve the results of simulations of high renewable penetration local energy systems

3.1 Preface to chapter 3

The work described in this chapter aims at proposing an innovative approach to the analysis of urban districts which show an high penetration of non programmable renewable energy sources, and other sources of uncertainty such as user demands of different nature. In particular the goal is to obtain insights regarding how to deal with such large amount of electricity surplus form renewable source by using different technological approaches. This by considering both already established technologies like an electric heat pump and a thermal energy storage, and also a potential fleet of EVs equipped with smart charging. The evaluation is achieved by means of a framework based on the simulation model EnergyPLAN, where a real local energy system is analyzed and three different sources of uncertainty are considered: the availability of the solar resource and the demands of the users in terms of heating and electric mobility. Specifically the energy system is the small town of Osimo in Italy, about which the local municipality company of Astea kindly provided accurate measured data for the year 2018. The focus is put on the multiple needs of the local energy system within a proper smart energy system paradigm and the evaluation is undertook by considering only technical simulations which balance energy fluxes of different kind over a one year period, without taking into account the economics implied in doing so.
In this work I entirely undertook the work concerned in designing the framework, the modeling activities, the coding and the necessary elaborations on the provided raw data. Professors Poul Alberg Østergaard and Gabriele Comodi contributed with comments and editorial assistance.

3.2 Introduction and state of the art

As anticipated in the introduction uncertainty will play a key role in the future's energy systems, and a proper characterization and consideration in energy models will then become compulsory [37]. An approach relying on a limited amount of time slices might in fact lead to under/over estimations of several features while analyzing energy systems. For this reasons the following framework is proposed to handle a great degree of inputs, representing many sources of variability in the input parameters (some with an arbitrary variations and others with a proper stochastic feature representation), and still returning useful results in a very short amount of time thanks to the fast simulation capabilities of the EnergyPLAN model, which is developed by the Department of Planning at Aalborg University, and it can be obtained as a free software package with a graphical user interface. Within the available literature the EnergyPLAN simulation model has already been coupled with externally developed code in order to enhance its capabilities, as in [54] where an optimization model for a national scale system is proposed.

As highlighted in [65] the EnergyPLAN model has been used mostly to analyze country/state level scenarios, and in a minor way local areas. By narrowing such studies to a municipality/town scale (the one of interest in this chapter) there are examples for different scenarios in Europe: in Denmark for the cities of Aalborg [66][67] and Frederikshavn [68][69], in Finland for the city of Loviisa [70], and finally in Italy for the cities of Corinaldo [71] and Altavilla Silentina [72]. In the mentioned studies a set of technological solutions is evaluated in the respective realistic scenarios with the aim of mitigating the environmental impact by means of different technological solutions: such as the increase of RES or the incentivation of CHP.

What's lacking is a focus on the potential beneficial impact of smart EVs in such high RES shares systems. This has been done already in some studies focusing on national/regional scale system: in [73] the integration of EVs on a national scale in Italy is investigated considering increasing shares of solar powered RES, but there is also a lot of interest regarding the integration of EVs in local energy systems, especially while in presence of significant RES penetration. Such as in [74] for a single building scale energy system, a large city in [75] or a neighborhood in [76], where the integration of EVs is evaluated in conjunction with the electrification of a DHN.

All of the described models use a perfect foresight approach to the input parameters, thus not considering the stochastic nature of some of the input parameters, and this is what the work described in this chapter aims at doing. The framework which is proposed aims at analyzing such systems by considering both the uncertainties entailed in the available yield from the solar systems and the ones regarding some of the user demands, in both cases by considering the time varying nature of the two quantities.

Specifically the proposed approach is tested on a realistic test case representing a small town, which can be described by means of real measured data provided by the local municipal energy company. A first investigation on the potential deployment of EVs in same town has been done in [77], where the payback of the investment in an urban charging infrastructure by the same company is evaluated and found to be short even without incentives.

The rest of the chapter is structured as follows: in 3.3 all of the proposed framework is described explaining in detail all of the available data and the modeling approaches used for each source of uncertainty, in 3.4 the results of a set of simulations are shown, where the goal is to investigate low carbon options for the local energy system, finally in 3.5 the conclusions to the chapter are drawn.

3.3 Methodology

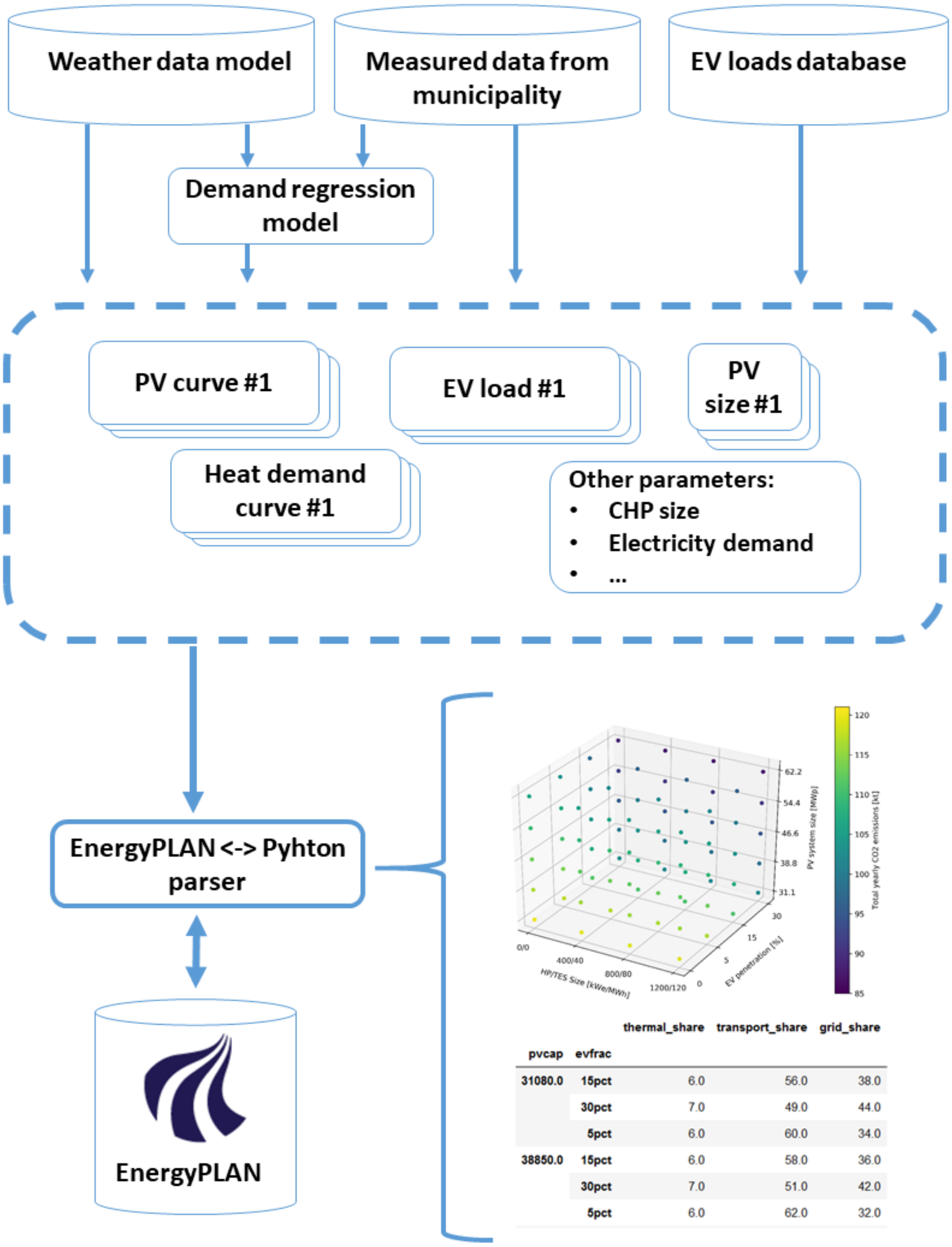
3.3.1 The framework at a glance

As for the work described in the previous chapter this one also proposed a complex framework, which is shown in Figure 11. While previously the modeling of the energy systems was implemented by a directly coded mathematical model, in this case it is delegated to the EnergyPLAN model. EnergyPLAN is capable of simulating the operation of very complex single-node (thus no spatial dimension representation) multi energy systems over the course of a year with an hourly temporal discretization. The simulations can be executed both by means of a graphical user interface or through a command line, and in both cases the input parameters are passed on to the model by means of plain text files.

For this reason the rest of the framework, which is entirely based on the python programming language, acts as a shell that elaborates a set of inputs, provides them to the EnergyPLAN model and retrieves the quantities of interest into tables once the model is launched externally .

The framework is constituted of a set of blocks, where each serves a specific function. While an extensive description of each block is done in the following paragraphs a brief description of each block/functional part is the following:

- A block that retrives solar radiation, temperature and other weather data with hourly resolution for the location of interest from an external web-based open model
- A set of data provided by the Osimo municipality's owned company Astea, regarding user demands, energy flows with the national transmission grid etc, measured for the full year of 2018 with hourly resolution.
- A block to build realistic EV load patterns with hourly resolution, based both on data retrievable from open datasets and a set of technical assumptions
- A demand regression block, intended to combine both the available consumption data and the simulated historical metereological data into a set of plausible yearly demand curves with hourly resolution, by using a regression model
- A block that combines all of the available data into a set of realistic yearly profiles to represent variability in the simulation conditions, and therefore into a set of simulations to run
- A python based EnergyPLAN parser, that feeds all of the plausible years to the simulation engine and simulates them automatically by means of scripting
- A block to retrieve the results of the simulations (which are formatted into tables) and extrapolate tables and plots, being the actual output of the framework



		thermal_share	transport_share	grid_share
pvcap	**evfrac**			
31080.0	**15pct**	6.0	56.0	38.0
	30pct	7.0	49.0	44.0
	5pct	6.0	60.0	34.0
38850.0	**15pct**	6.0	58.0	36.0
	30pct	7.0	51.0	42.0
	5pct	6.0	62.0	32.0

Figure 11 - Visualization of the EnergyPLAN based proposed framework

3.3.2 Model of the Osimo municipality in EnergyPLAN

Astea is the Osimo's municipality energy company, and it's in charge of managing a district heating network (DHN) , the two way power exchanges with the main transmission grid operated by Enel, and the inflow of natural gas. The DHN is powered by three different systems: a CHP system powered by a natural gas engine (1.2 MWe in size), three natural gas boilers and a small electric high temperature heat pump (34.5 kWe). On the electricity side within the local grid are present a set of distributed generation systems: the already mentioned CHP system, a small hydroelectric turbine, a set of PV systems operated directly by Astea (80.4 kWp in total) and a large amount of privately owned PV systems (estimated to around 31 MWp in size). A graphical representation of all of the systems is shown in Figure 12.

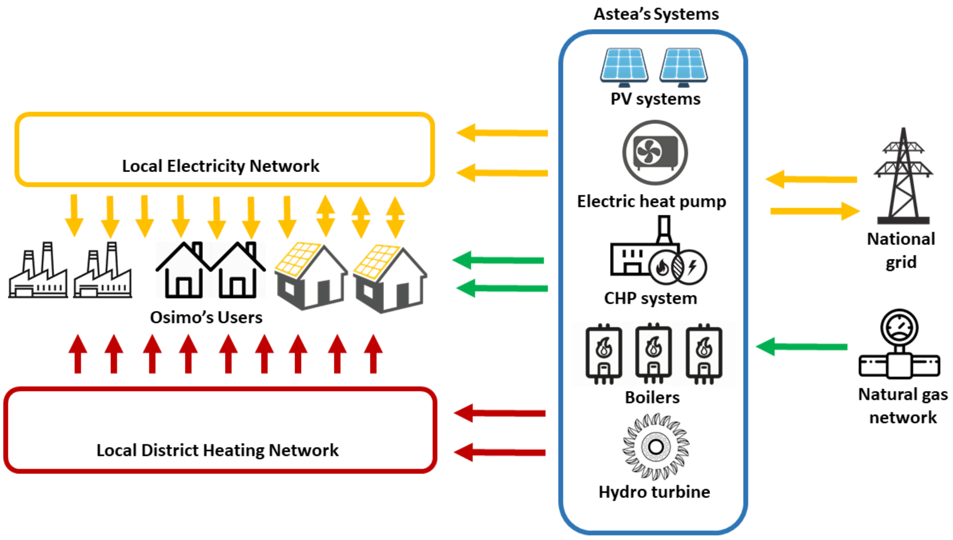


Figure 12 - Schematization of Osimo's distributed energy systems configuration

The data provided by Astea can then be listed as follows:

- A year of electricity production from the directly monitored PV systems for the year 2018, monitored with hourly resolution in terms of average capacity factor. As in Figure 13.

- A year of thermal energy fed into the local district heating network for the year 2018, measured in terms of waterflow and inlet/outlet temperatures with hourly resolution. As in Figure 14.
- Net electricity exchanges with the main national grid (both energy withdrawn and fed) for the year 2018, measured with hourly resolution. As in Figure 15.
- Capacity and average electric and thermal efficiencies for the CHP system (natural gas fired).
  1.2 MWe with 39.9% and 41.5% electric and thermal efficiencies respectively
- Capacity and average thermal efficiencies for the boiler systems (natural gas fired).
  13.5 MWt with 95% thermal efficiency.
- Capacity and average conversion efficiency (COP) for the electric heat pump.
  34.8 kWe with 4.6 average COP
- Size of the PV system owned by Astea and estimate on the total size of the privately owned systems.
  80.4 kWp and 31 MWp respectively

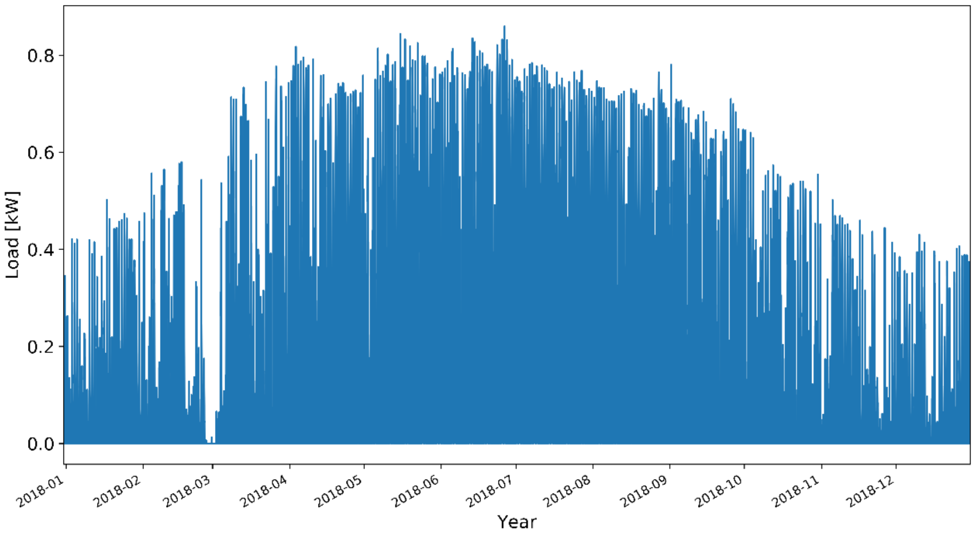


Figure 13 - Actual PV capacity factor in Osimo in 2018

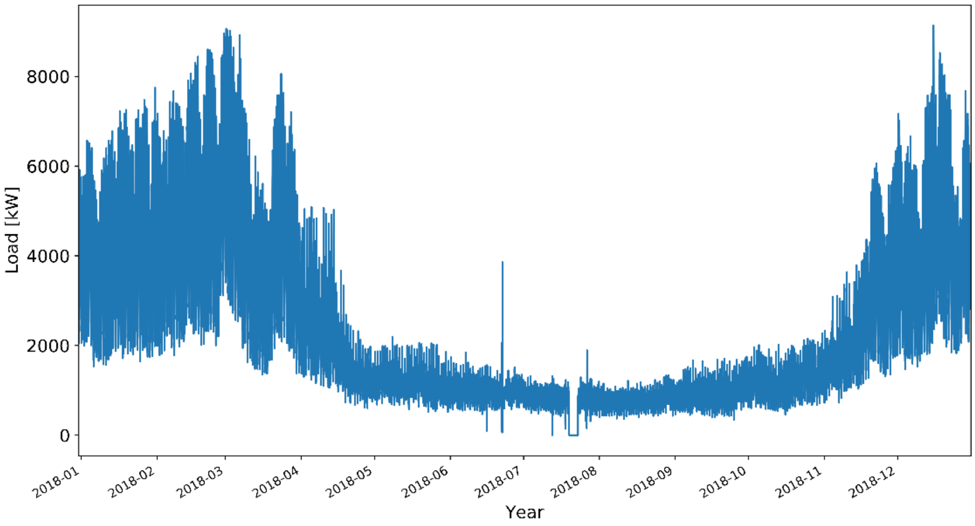


Figure 14 - Actual DHN in Osimo in 2018

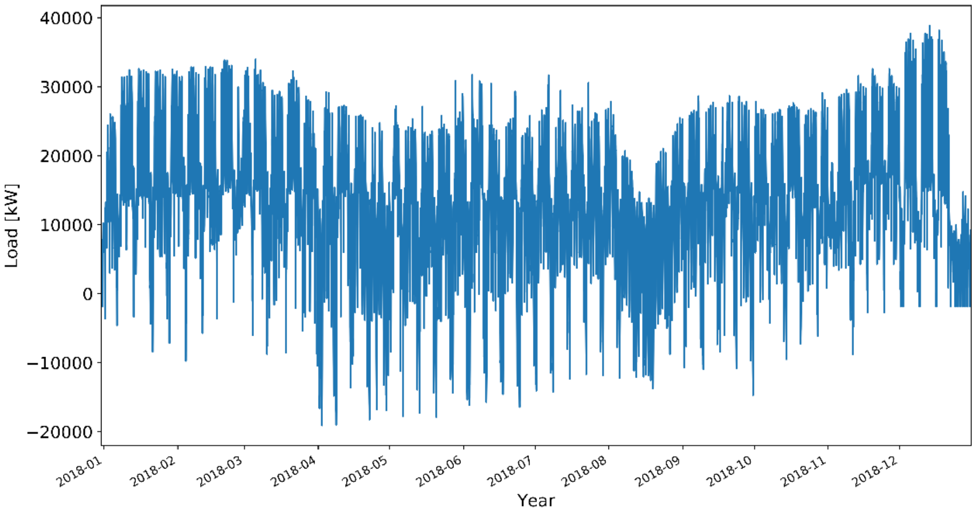


Figure 15 - Actual net load of Osimo in 2018 with respect to the national grid

Based on the provided data described in the previous paragraph a model of the city of Osimo has been built and implemented in EnergyPLAN. This considers all of the assets managed by the local utility Astea (thus not including the heating demand being met by means of individual heating solutions) and also the local transport sector in order to later properly consider the impacts of the gradual substitution of the local fleet of vehicles with battery electric vehicles.
Before actually analyzing the Osimo reference case a set of additional modeling efforts are needed.

Electricity demand

The electricity demand is not directly available and is then regressed based on the available net-load timeseries data provided by Astea. This is achieved with an energy balance equation computed for the whole yearly timeseries of 2018 on an hourly basis, the equation is the following:

$$D_{el}(h) = E_{chp}(h) + E_{hydro}(h) + E_{PV}^{Astea}(h) + E_{PV}^{pvt}(h) + E_{grid}^{+}(h) - E_{grid}^{-}(h)$$

Where $D_{ele}(h)$ is the hourly demand, $E_{CHP}(H)$ is the electricity produced by the CHP system, $E_{hydro}(h)$ the electricity produced by the hydroelectric turbine, the two $E_{PV}(h)$ terms the electricity produced by Astea's and private PV systsems respectively, and finally the two $E_{grid}(h)$ terms indicate the electricity which is purchased and sold to the national grid respectively (which are respectively the positive and negative part of the data shown in Figure 15). This is computed on an each hour basis as indicated by the index h, obtaining then a new yearly distribution shown in Figure 16. The total electricity demand amounts to around 164 GWh for the year 2018.

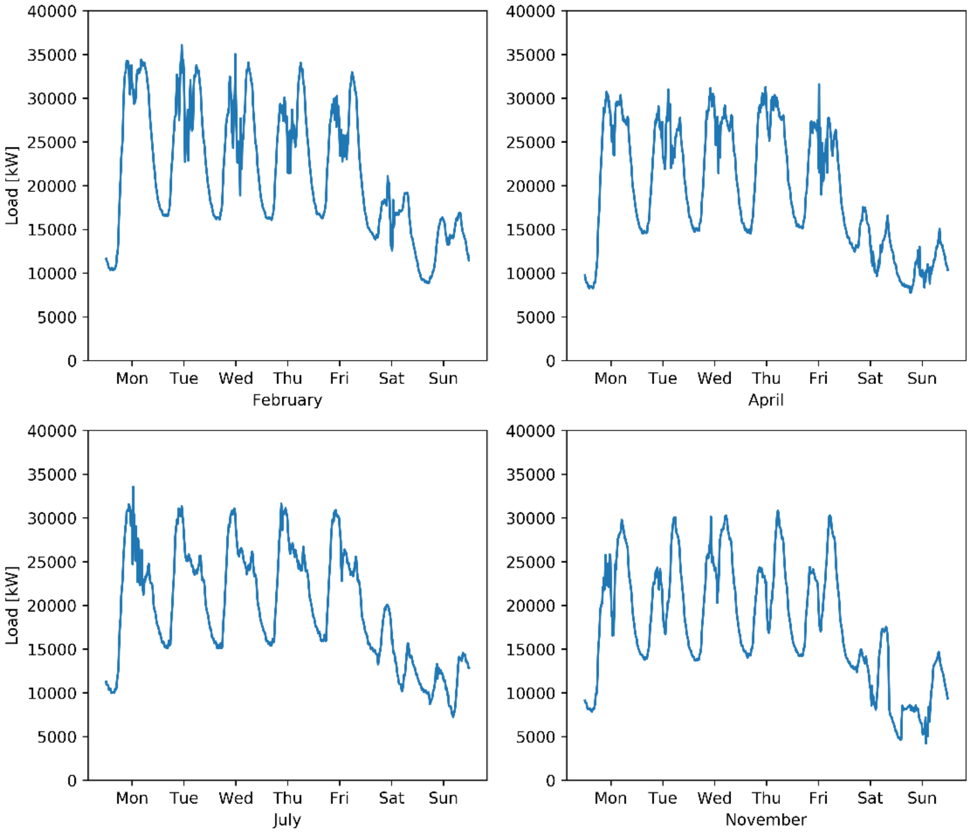


Figure 16 - Obtained electricity demand for four sampled weeks

<u>DHN demand</u>

The DHN demand is obtained directly from the data shown in Figure 14 by accounting also for the network losses. These are estimated directly by Astea by confronting the thermal power fed into the network to the one which is actually sold to the customers. The first quantity amounts to a total of 20,3 GWh for 2018 while the second only to 14,21 GWh, thus the network losses amount to approximately 30% and this is enough to model them in EnergyPLAN.

Transport Sector Model

EnergyPLAN allows transports to be modeled in different ways depending on the type of fuel: whether if they're propelled by fossil fuels or electricity. While the EVs demand model is described later on the model all of the other vehicles is obtained by referring to a public dataset provided by the Italian government [78] which lists all of the vehicles registered in Italy, region by region with a set of features. The dataset has been filtered in order to obtain all the entries regarding vehicles registered in Osimo, and the fuel for each type of car. The total amount of cars is of around 26500; the shares per each fuel type are also obtained to fit the modeling fields of EnergyPLAN, an approximation is done by omitting the types of fuel which cover a small share (less than 1% of the total) such as hybrid and battery vehicles.

To obtain the yearly energy demands for each type of fuel two parameters have been used: a fixed number of km of distance driven per day (assumed to be the same for each category of fuel) and a consumption per distance driven in kWh/km which characterizes every type of fuel [79]. The resulting parameters for the model are shown in Table 3.

	Number of cars	**Share on total park**	**Specific consumption [kWh/km]**	**Demand [GWh/year]**
Diesel	13746	~51%	0.8	154.88
Petrol	7467	~28%	0.8	85.03
Natural gas	3780	~15%	0.65	37.01
GPL	1625	~6%	0.65	14.8

Table 3 - EnergyPLAN parameters for the fossil fired transport sector

Available energy systems & other simulation settings

The energy systems managed by Astea have been all considered in the energyplan model, following the specifications mentioned before:

- A 13400 kJ/s natural gas boiler is added to Group 2 (which is used to simulate DHNs of medium sizes) with a 95% thermal conversion efficiency. The fuel is set to be natural gas.

- A 1200 kWe CHP system is added to Group 2 with 40% electric efficiency and 41,5% thermal efficiency. The fuel is set to be natural gas.
- A 31080 kWp PV system (Astea’s 80 + 31000 private) is added as a variable renewable electricity system, using the timeseries of the real measured capacity factor from 2018 as distribution profile
- A 110 kWp river hydro system is added as a variable renewable electricity again using the real measured data from 2018
- A 34,8 kWe heat pump with 4,6 COP is added as a heat only production system. (this system is new and has never been used in 2018)
- The access to the main electricity distribution grid is possible without limits in power at any given time.

Finally, the simulation is set to run in a technical simulation mode, using a contemporary heat and electricity demand balancing strategy. Also given the unlimited amount of electricity that can be exchanged with the main grid the management strategy for the heat pump is set to balance all electricity imports and exports instead of only the critical excess (CEEP in EnergyPLAN).

Other estimates on emissions

The only figure used to quantify the pollution generated from the local energy system is the total CO_2 emitted. Such total amount can be split up in three contributions: an amount needed to operate the stationary electricity/heat generation systems within the local energy system (CHP and boilers in this case), the amount ascribable to the transport sector and finally the amount generated in the national energy system by withdrawing electricity.
The CO_2 content of the fuels is left as default in EnergyPLAN, and this allows to obtain the first two contributions directly from a scenario run. The third contribution is computed externally by considering both the total amount of electricity which is withdrawn from the grid during the simulated year, and the amount which is fed as a surplus from the renewable PV systems. The CO_2 generated in the central system is then computed by means of the following equation:

$$CO_2^{grid} = \left(\sum_h E_{grid}^{+} - E_{grid}^{-} * \eta_{grid} \right) * c_{grid}$$

Where CO_2^{grid} is the total amount of CO_2 emitted using the national grid, the two E_{grid} terms are the same as described before and are summed over the whole year, considering the grid efficiency with η_{grid} for the part that is fed as a renewable surplus, finally c^{grid} is the specific emission in $kgCO_2/kWh$ for the Italian electricity generation park. The grid efficiency is estimated to 95%, while the specific emissions are estimated to 0.347 $kgCO_2/kWh$ of electricity [80].

Results

The Osimo base case (as it is now) is run in order to have a baseline over which to confront the results of the following experiments. The simulation returns a total amount of 126,12 kt of CO2 emitted during a year of operation, with the emission mostly due to the transport sector which accounts for 74,64 kt (59,2 % of the total), followed by the emissions in the national energy system with 41,82 kt (33,2% of the total) and finally the operation of the distributed energy systems with 6,63 kt (7,6 % of the total).

The heating demand is met by using mostly the boilers which take up nearly half of it (10,71 GWh provided out of 20,3), with the rest shared among the CHP (8,79 GWh) and the heat pump (0,79 GWh).

As expected the upper level national grid is used both to import electricity to meet the demand which the CHP and PV systems cannot cover, and also to absorb the PV surplus when not needed. The import averages 13,85 MW throughout the year with a total of 121,64 GWh withdrawn; the average export is of 0,37 MW with a total of 3,29 GWh exported. This is in line with the real measured data provided by Astea, which reports a total of 124,36 GWh withdrawn in 2018 and 4,02 GWh fed back to the grid.

This is also shown in Figure 18, where it can be seen how often electricity has to be returned to the grid due to a surplus in electricity production of the PV system, which accentuates in the summer and especially in the two weeks in august when most of the factories/public offices go on holiday.

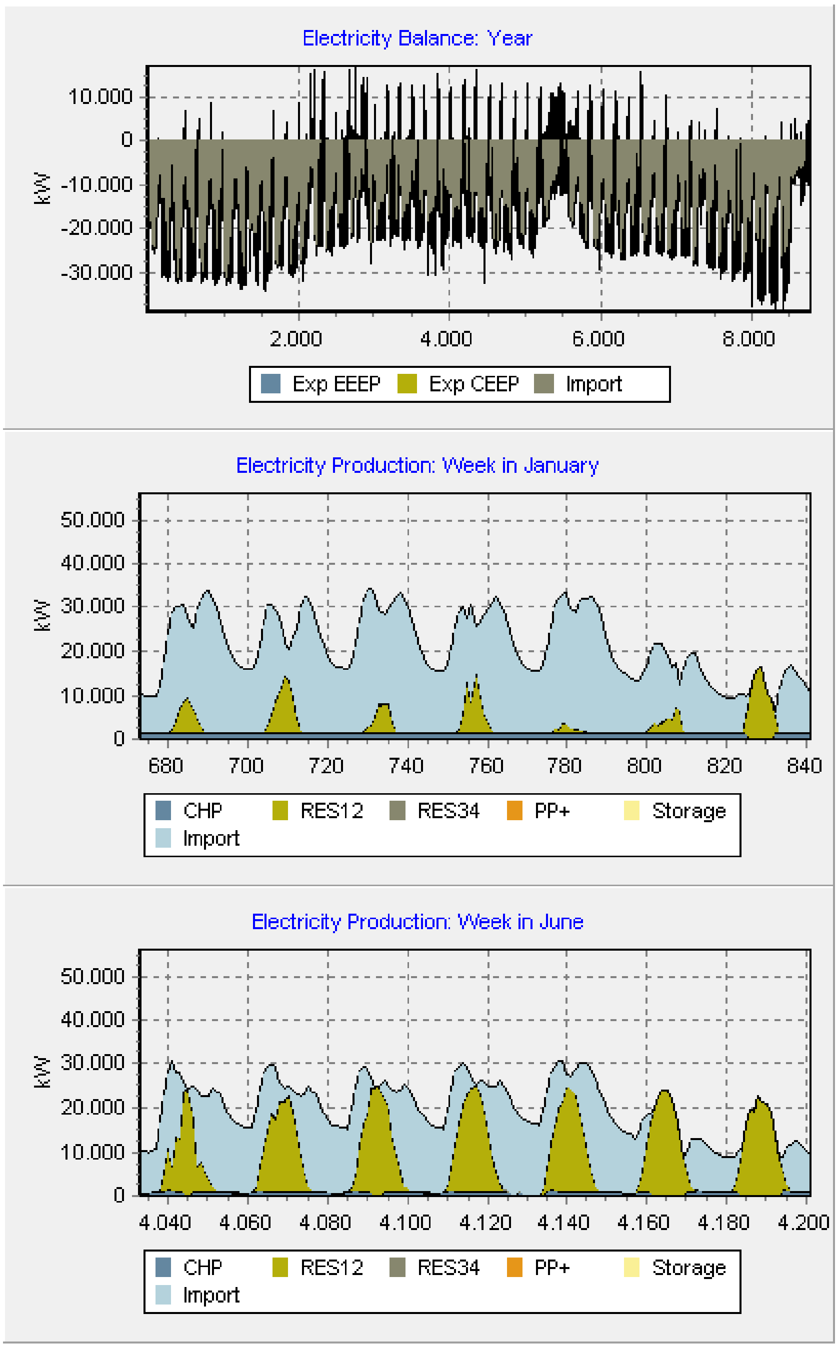


Figure 17 - Electricity exchanges with the national grid according to the EnergyPLAN simulation of the base case

3.3.3 The EV load model

Some of the analyses that will be undertaken aim at understanding the effects of a potential fleet of EVs within the local energy system. Such effects could be related to being an additional electric load, to a substitution of part of the conventional vehicle fleet and potentially in serving as a flexibility asset by means of a smart charging infrastructure.

EnergyPLAN models the presence of EVs both with a set of static parameters such as: the total yearly electricity demanded from the EVs fleet, the fraction of vehicles parked in peak hours etc. while modeling a smart charging equipped fleet. But also a timeseries curve with hourly resolution to represent how the total electricity load is distributed within the year on an hourly basis.

Then, a simple model is built to obtain realistic electricity load curves with hourly resolution for a given size of the EVs fleet in terms of total vehicles. Such amounts of vehicles have inevitably to be assumed given the very small fraction of EVs within the actual circulating fleet (less than 1% as said before) and this is done by referring to official estimations done by the Italian transmission grid manager Terna for the year 2030 [81]. There is a total of three scenarios to represent the uptake of EVs with different paces: a "slow progress" scenario with 5% market penetration of EVs, a "mid transition" scenario with 15% and a "green revolution" scenario with 30%. This given the current total amount of cars of 26500 vehicles returns respectively: 1300, 3900 and 7800 EVs. The same three levels of penetration will then be modeled with the model, by simulating the hourly electricity loads for the three different EVs fleet sizes.

The curves are obtained with a mixed approach, using both available measured data and a set of bottom-up assumptions. The part which is modeled by means of data concerns the charging habit of the users in terms of when the vehicles are actually plugged in for recharge during the day. This assumption is of particular importance, given that the main issue that a wide adoption of EV is causing, namely the "duck curve" [82] is actually due to the timing of the charging habits of the vehicles owners. The technical assumptions, which also contain a degree of randomness, regard some characteristics of the charging events themselves such as: the power requested by the charging stations, the distance driven by each car in a given day and finally the specific consumption in kWh/km. The whole approach is shown in graphically in Figure 18.

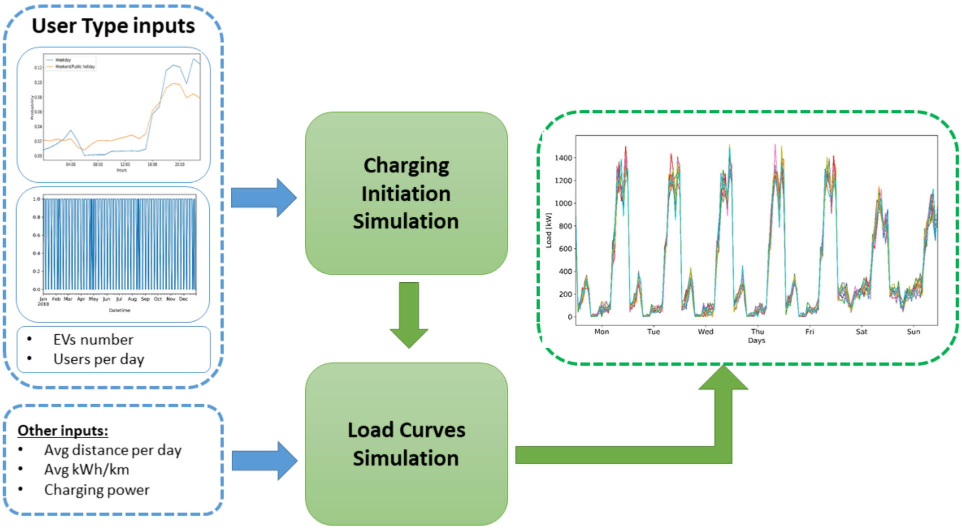


Figure 18 - Modeling approach for the generation of the EV loads

The behavior of the user in the charging process is obtained from the same dataset used in Chapter 2 [5], which also reports the power absorption for the charging stations in the households. The data is available with a 15 minutes resolution, and by analyzing the electricity absorption patterns it is possible to compute the hourly timestep when the charging event is initiated. This is done with a distinction in two behaviors (by appropriately filtering the data): a weekday usage profile and a weekend one, which is used also to represent any public holiday. The two profiles are shown in Figure 19 with an hourly resolution in terms of their probability density function. It can be seen that the patterns return a behavior similar to the one described in [82], with most of the charging events initiated in the late afternoon, when supposedly people come back from work, and even if less pronounced the pattern is replicated in the weekends/public holidays.

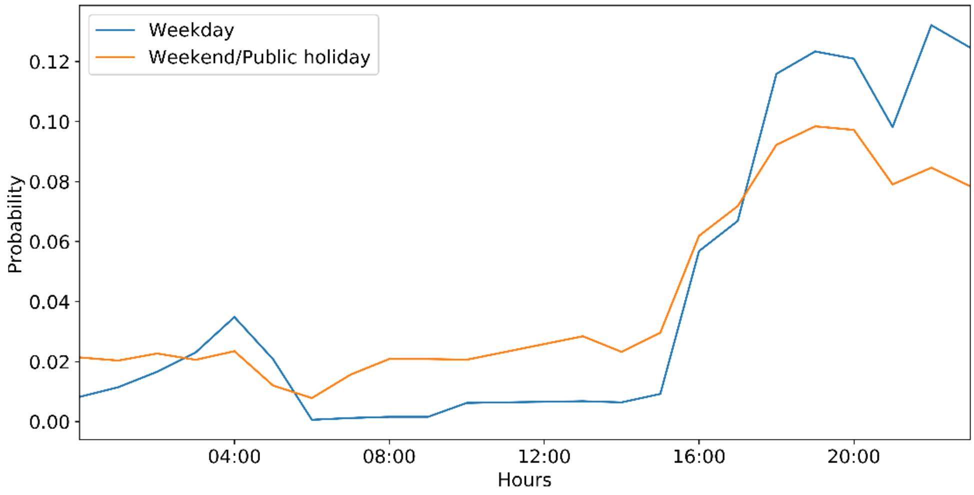


Figure 19 - Charging event probability density

Then for each charging event a unique value for the battery capacity that has been depleted during the day is randomly generated from the two distinct variables mentioned before. Both of the two are randomly generated from their respective distribution which is supposed to be uniform: between the values of 30 and 60 km regarding the distance driven daily, and between the values of 0.1 and 0.25 regarding the specific consumption in kWh/km over that distance. An additional degree of variability is introduced by supposing a fixed amount of cars from the fleet that don't drive within the specific day, and that is also generated randomly from an uniform distribution between 0 and 10%. Finally the last parameter is the power of the charging station which is set to 10 kW for all of the charging events for simplicity.

In order to generate the load curves a fleet of a fixed number of EVs is initiated (following the fleet sizes mentioned before) and their charging process is simulated throughout the whole year with hourly resolution. If for example a charge is initiated at 8 pm for a total 42 kWh to be recharged with a 10 kW charging station: the algorithm will add a 10 kWh load to the hour timestep between 8 pm and 9 pm and the three hours following to that, plus a 2 kWh load to the fifth hour. This procedure is repeated for all the charging events, for each hour, and for the whole year. As an example the weekly charging patterns obtained for five different weeks for an EV penetration of 5% (1300 vehicles) are shown in Figure 20.

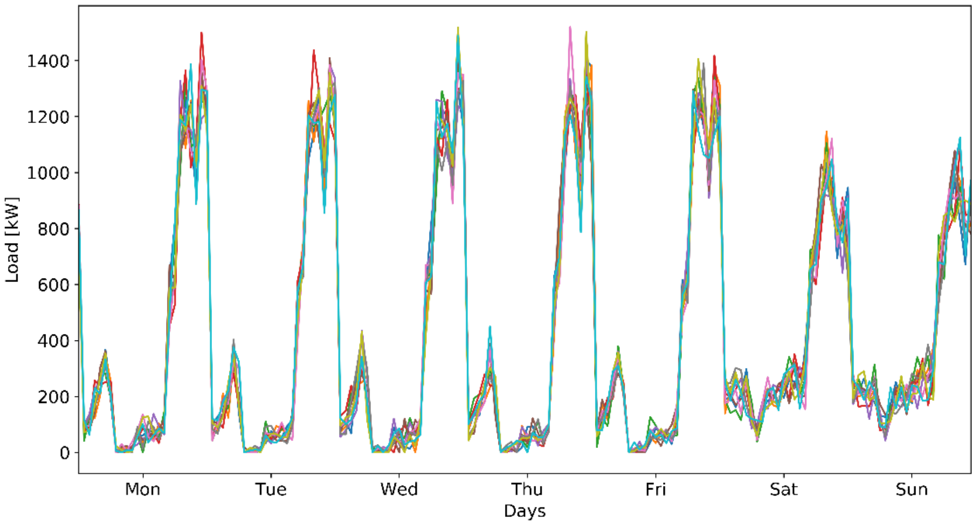


Figure 20 – Hourly charging pattern generated for five weeks for a 5% EV penetration

What described so far is simply to generate a realistic load pattern with hourly resolution for a fleet of EVs. EnergyPLAN accepts the electric mobility demand by means of two distinct set of parameters. Firstly the demand is defined by a normalized timeseries and a total yearly demand, which is basically an additional electricity demand with hourly resolution, and this is modeled as just described.

But in order to model the workings of fleet of EVs with smart capabilities an additional set of parameters is needed, and both a smart charging (meaning to possibility to partially dispatch the meeting of the EV demand) and a vehicle-to-grid (meaning the EVs acting as a virtual battery storage at disposal of the local grid) paradigms are possible. For the simulations in this chapter only the first capability, the smart charging, is considered for the EV fleet.

The parameters which are used to model the EV fleet with smart charging are assumed as in Table 4.

Parameter	**Value**
Capacity of grid connection	10 kW per car
Battery storage capacity	35 kWh per car
Maximum share of EVs driving during peak time	20%
Share of parked cars which are grid connected	80%
Grid to battery electric efficiency	90%

Table 4 - Technical parameters for the local EV fleet

3.3.4 The weather variability model

The data representing the heating demand and the solar yield is available as measured data from Astea only for the year 2018; for this reason a model that represents their inherent variability is also introduced, so to obtain a set of realistic timeseries data for plausible virtual years.

The approach is to use a set of modeling techniques based on data that can be retrieved from the openly available model of Renewable Ninja [83]–[85], which provides simulated weather data for any year ranging back to 2000 using two different reanalysis models [86], [87] , both based on satellite data. The mentioned website allows to both retrieve weather data and also to simulate the production of virtual renewable power plants (photovoltaic and wind) by specifying characteristics such as position, size of the system etc., obtaining in both cases curves that span a year with hourly resolution. Thus both the weather data and the production of a virtual PV plant of 1 kWp in size are obtained for the location of Osimo (Lat: 43,4861, Lon: 13,4824) for all of the yearly timespans available, ranging from 2000 to 2018.

The solar radiation uncertainty model

The uncertainty in the availability of solar radiation is simply represented by the 19 yearly profiles obtained from the Renewable Ninja portal for the virtual 1 kWp PV plant, straight from the available files the profiles are obtained. Figure 21 shows the variability in yield for all the curves retrieved from the model for four sample months. It can be seen that there is already a significant degree of variability entailed within the curves, for this reason there are no further modeling efforts on this aspect.

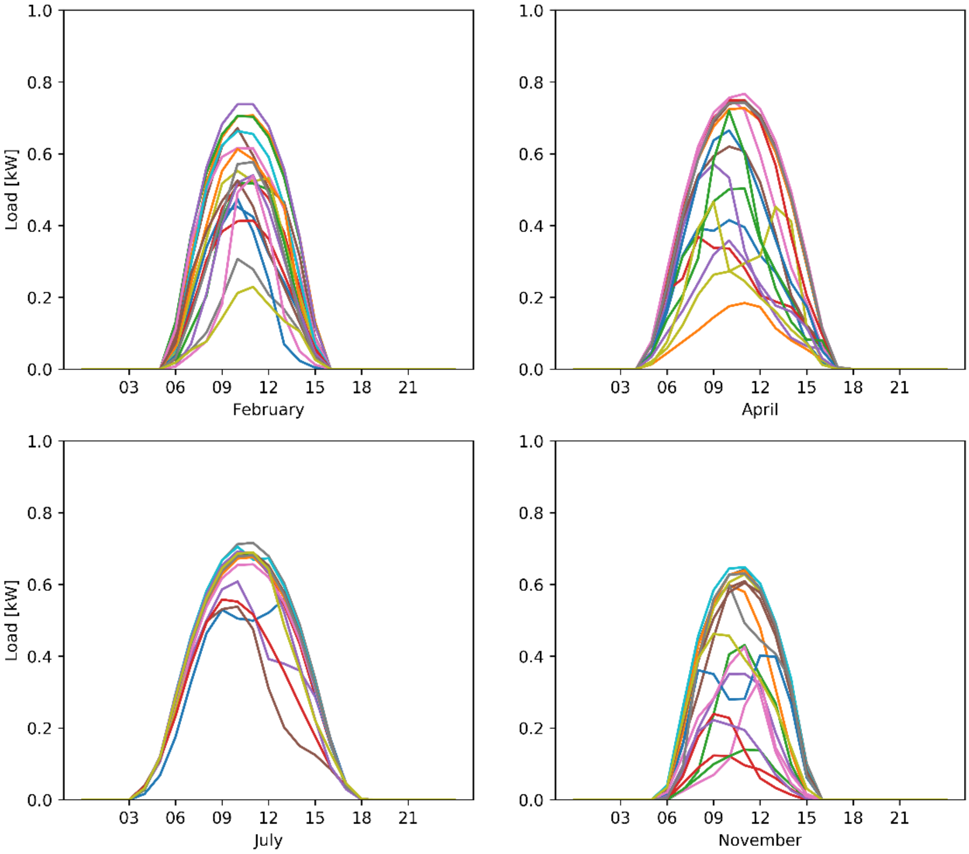


Figure 21 - Electricity yield distribution for a 1 kWp system in Osimo

The heating demand uncertainty model

The model of the uncertainty in the heating demand is itself based on a model that returns the heating demand from the virtual weather timeseries obtained from the Renewable Ninja model. This is obtained by training the prediction of the demand from a set of features which are defined on an hourly basis by means of a multivariate linear regression model, using the Scikit learn python package. The features are distinguished in weather related and usage pattern related.

Firstly the model is trained on the only year where both the demand and the weathe are available as measured data. The weather related features are obtained directly from the data provided by Astea, which provided hourly measurements for the greater part of 2018 for: air temperature in °C, relative humidity, air density in kg/m3 and wind speed in m/s. Of these only the first two are used to train the model given the unavailability of the others from the Renewable Ninja model. In order to provide an additional set of potential predictors to the model the moving average value has been computed for both the two predictors for a set of time windows ranging from 2 to 24 hours. In the next Figures the obtained hourly trends are shown for an example of two weeks period for winter, midseason and summer.

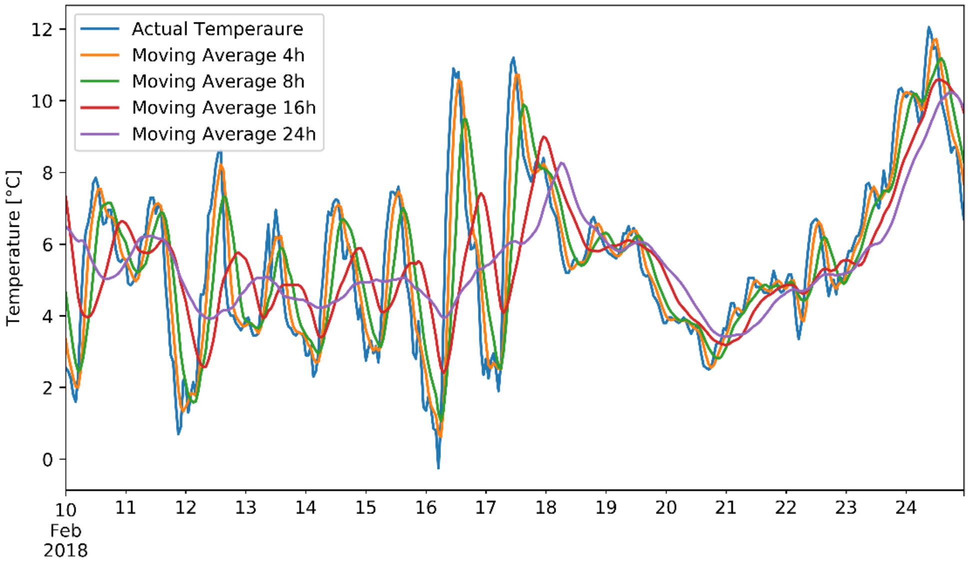


Figure 22 - Temperature actual measured value and moving averages for two winter weeks

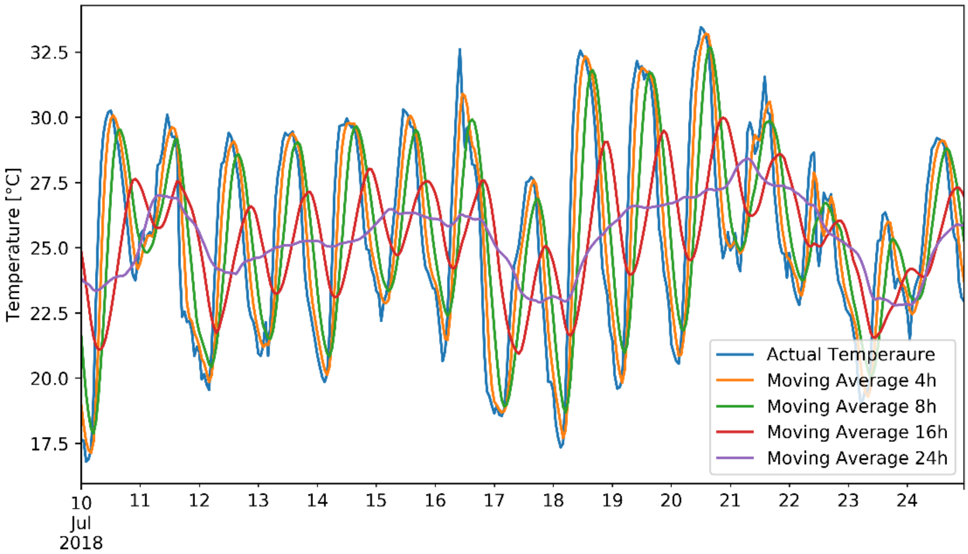


Figure 23 - Temperature actual measured value and moving averages for two winter weeks

A second set of features is aimed at modeling the behavior of the different types of users over the day and across a whole week. This is achieved by defining a binary value for each of these features for each hour. The first two aim at identifying the hourly timesteps belonging to working days over the year and the other the weekend/public holidays days, thus for each hour of a working day the first feature will be equal to 1, and equal to 0 for each weekend or public holiday day, and vice versa for the weekend/public holiday days. A second set of binary features wishes to represent two behavioral characteristic of the users, being the central hours of the day when most of the people is awake performing activities (such as being at work) and two peak time intervals in the morning and in the evening (as for example when people wake up and prepares for work, and when people come back from it). The daily pattern of the last two features is shown in Figure 24.

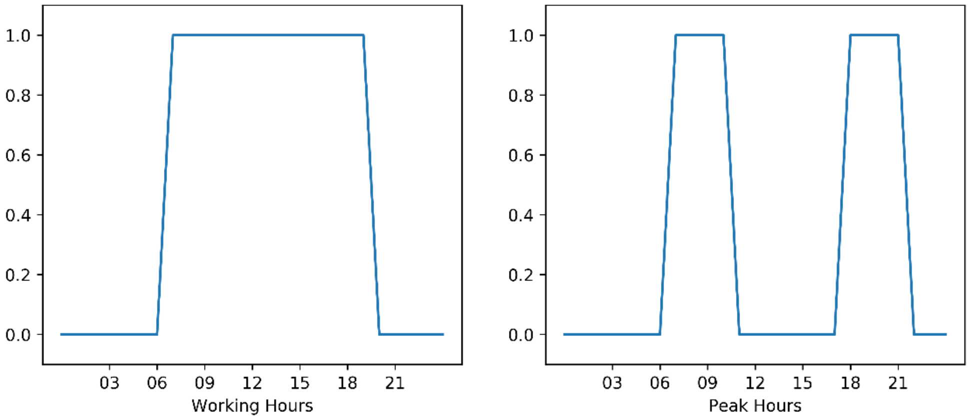


Figure 24 - Custom made binary features over one sample day

Once all of the features are defined for the whole year there is a further step, which is to split the demand and predictors timeseries in three subsets, to represent three distinct seasons being winter, summer and mid-season.

This is done in order to train three models with three distinct set of parameters, where each model represents a period in which the heating needs (and thus the demand of the DHN) are fundamentally different from the other. In the winter there is going to be a significant need of thermal energy for space heating purposes, less in the mid-season and finally none in the summer, where the heating is needed only to provide hot sanitary water.

The data is then split into training and test set for the three models using a 80% to 20% proportion, the performance of the three models on the test sets are shown in the following Figures 25 and 26, for the winter and summer weeks respectively.

From the Figrues it can be seen that the model still doesn't perform well in some of the days, but this level of accuracy can be considered more than enough given both the relative scarcity of data (one year of demand, and 9 months of weather data) and actual goal of the model: which is to represent the variability of the heating demand.

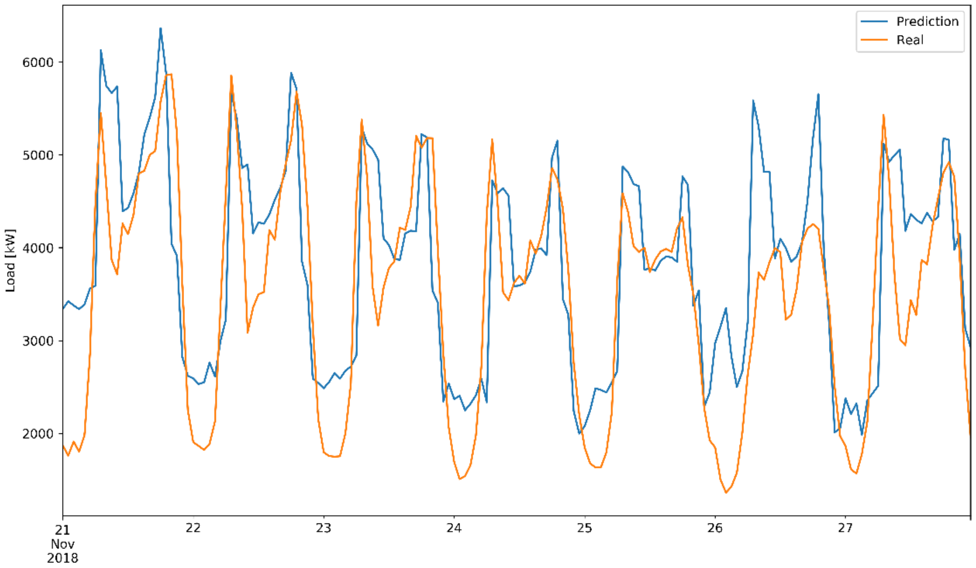


Figure 25 - Performance of the model on the test set on a winter week

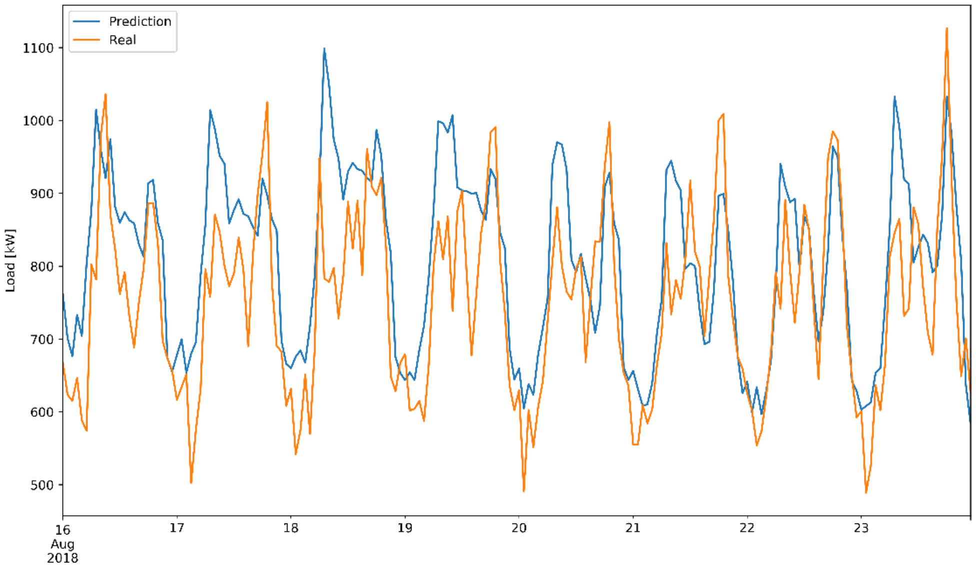


Figure 26 - Performance of the model on the test set on a summer week

Obtaining the virtual realistic timeseries

Once the model is trained this is used to obtain realistic timeseries of the heating demand from the available simulated weather data, which is of 20 yearly profiles as for the radiation. In the following Figure 27 the average temperatures from the obtained simulated data are shown for each month of the year for the same location of the city.

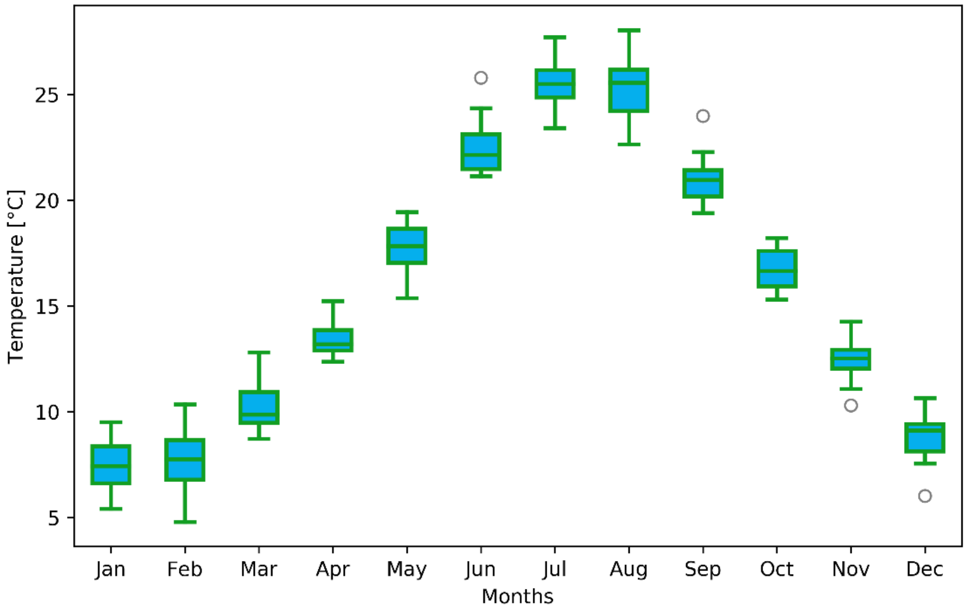


Figure 27 - Distribution of the temperatures in Osimo from 2000 to 2018 according to the Renewable Ninja model

The performance of the model in regressing the heating demands of the DHN are shown in the following Figures 28, 29 and 30 for a winter, summer and mid-season week respectively. This set of 20 curves is itself used to represent the inherent variability in the demand for the DHN.

Together with the 20 yield curves obtained for the PV system this returns a set of 20 plausible virtual years for the city of Osimo.

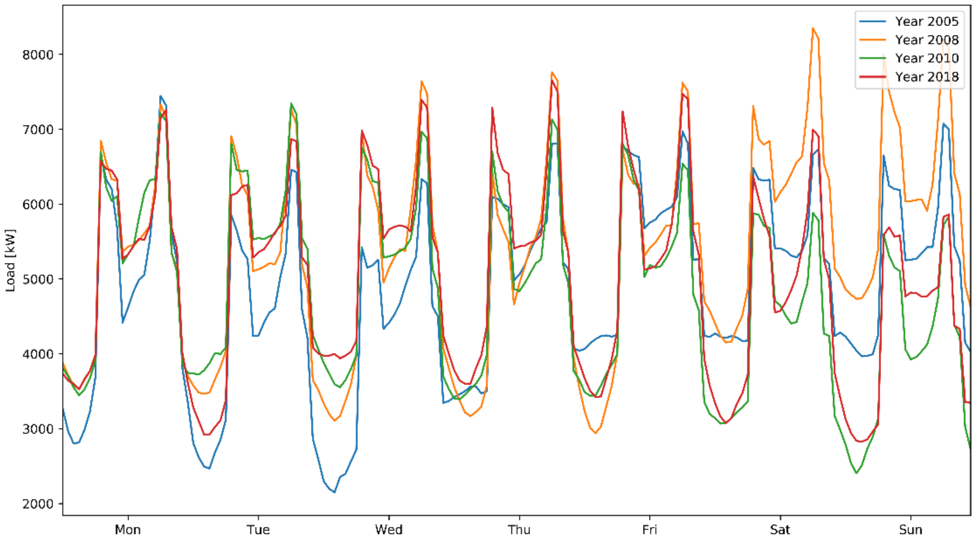


Figure 28 - Performance of the model on a winter week

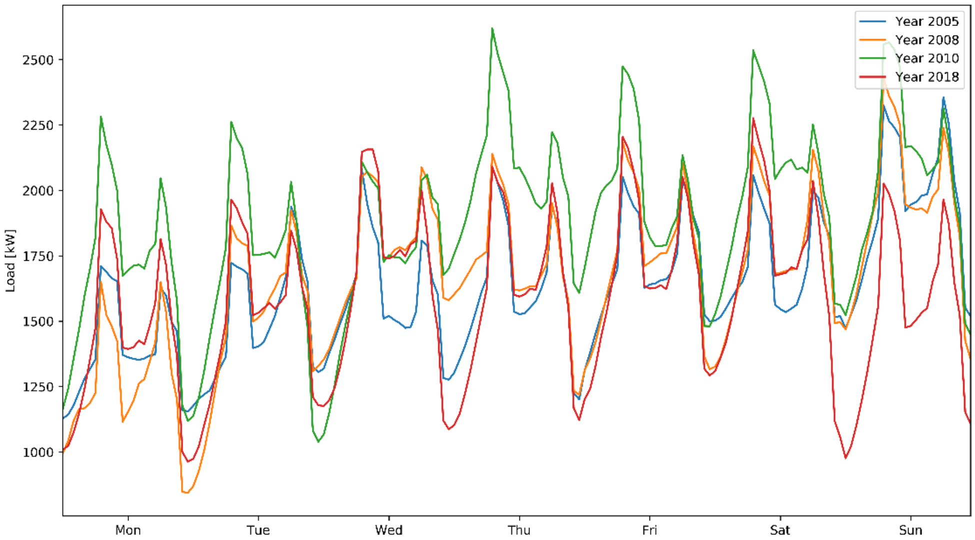


Figure 29 - Performance of the model on a mid-season week

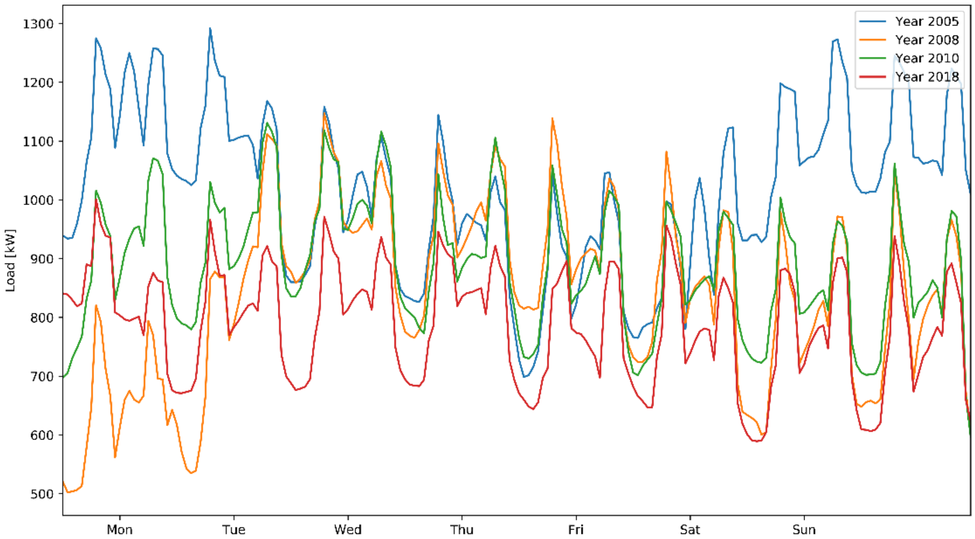


Figure 30 - Performance of the model on a summer week

3.3.5 Simulations design and variability representation

As shown in in the graphical representation of the framework in Figure 11 all of the uncertainty sources are mold in order to create a set of simulations. Some of the parameters will be kept constant while other will be let vary in order to create a set of virtual plausible scenarios, so that the obtained results will consider the inherent uncertainties.

As anticipated some of the simulation parameters will be changed arbitrarily in order to investigate their impacts on the energy system, while others will just vary in order to represent their inherent variability. All of the degrees of freedom of the proposed analyses are shown in the Table 5. In the Table a distinction is made between parameters that are changed in order to perform a sensibility analysis, and the ones that entail an uncertainty model.

The uncertainties sources are combined only considering the presence of different possible load patterns for the EVs fleet for every virtual year. From the modeling efforts described in the previous paragraph a set of 20 virtual meteorological years have been obtained, and for each of these a set of 3 (determined arbitrarily) different yearly charging patterns of the EVs demand is used. Thus a single set of simulations to study a particular technological asset (a flexible DHN or an increased EV penetration) will consist of 60 simulations.

	Sensibility analysis	**Modeled uncertainty**
PV System	5 sizes for the system	Modeled as in paragraph 3.3.4 (20 curves)
Building stock demands	None	Modeled as in paragraph 3.3.4 (20 curves)
EVs demand	3 EVs fleet sizes	Modeled as in paragraph 3.3.3 (3 curves per fleet size)
Conventional transports demands	4 demands according to the EVs fleet sizes	None
DHN Flexibility (HP and TES size)	4 sizes	None
Other conversion systems	None	None

Table 5 - Summary of the performed simulations

3.4 Results

In order to study the impacts of the two flexibility assets a set of experiments is performed.

Firstly, with Experiment #1, the city of Osimo is simulated as it is now (in terms of energy systems) with the only exception being the size of the PV capacity; this in order to isolate the effects of its presence with the inherent uncertainty, and in order to understand to what degree an integration of large shares of renewables is actually possible.

Secondly, with Experiments #2 and #3 the same increasing share of RES capacity is tested against two different flexibility providing technologies: being a more flexible DHN and a smart charging infrastructure for a potential fleet of EVs. In the first case the DHN is made more flexible by means of a large electric heat pump and a thermal storage system (which is currently absent), in the second the smart charging infrastructure allows the EVs electricity demand to be partially scheduled in order to make better use a of the available electricity surplus from the PV system.

Finally, with Experiment #4, both the two approaches are combined into the same scenarios in order to evaluate their coexistence in addressing the same issue.

All of the scenarios are evaluated considering different simulation outcomes, among which the ones which are given the most importance are the usage of the main national grid (both in terms of electricity imported and exported) in order to understand the degree of self-consumption of the RES generated electricity, and the total CO2 emissions across all sectors: heating, transport and national grid usage.

All of the results are reported as a set of boxplots showing the spread of the variable of interest, with each box representing a PV system size and, in the case of the increasing flexible DHN/EV penetration, also by differentiating this parameter.

3.4.1 Experiment #1 – Increased PV penetration in Osimo

As anticipated from the description of the Osimo test case the size of the current PV system (approximately 31 MWp) already implies the need to feed large amounts of electricity to the national system. In the tests, the size of the PV system is increased from the current 31.1 MWp by 25% at a time, up to 62.2 MWp, being double the current system size.

From the following Figures 31 and 32 it can be seen how, according to the model, an increasingly large PV system size acts both on the amounts of both imported and exported electricity. As expected while increasing the size of the PV system the export increases while the import decreases; but the export changes at an increased rate with respect to the import. By doubling the size of the PV system the median of the export simulations would increase by 23.7 yearly GWh, while the import would decrease by 18.7 GWh, thus indicating that the city’s energy systems would become always more reliant on the need to export to the main grid to cope with the increasing share of RES.

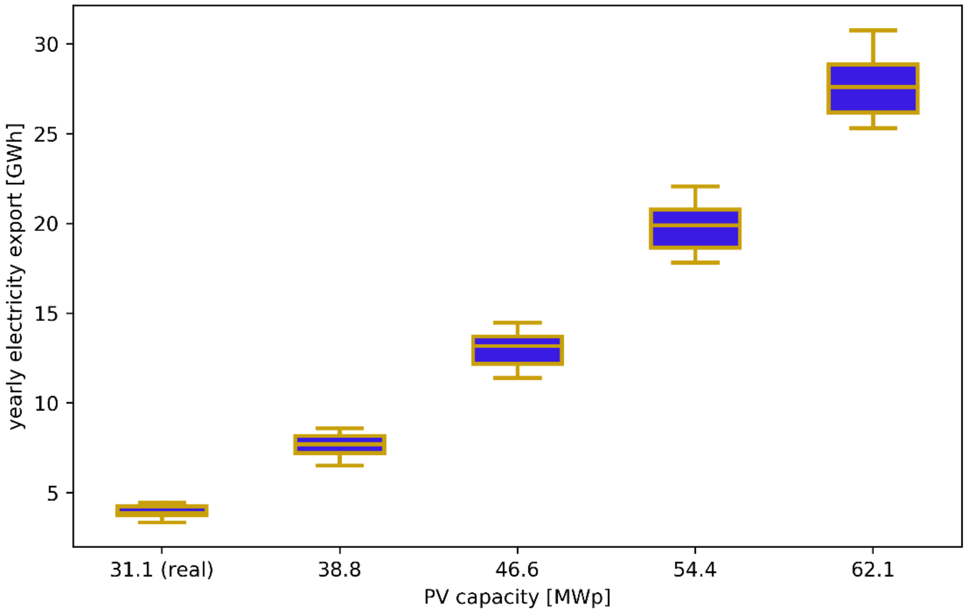


Figure 31 - Yearly electricity export in Experiment #1

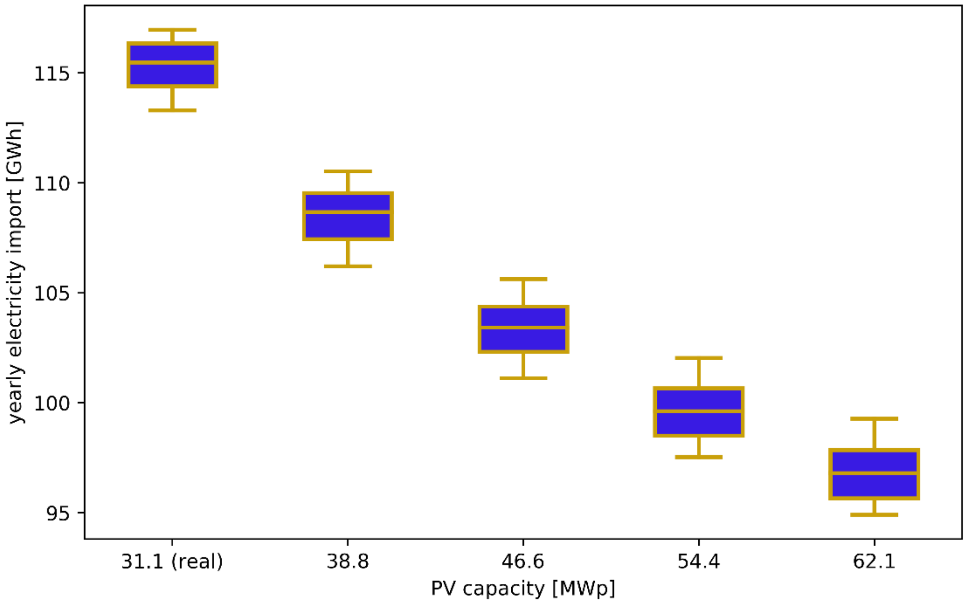


Figure 32 - Yearly electricity import in Experiment #1

This can be seen also by verifying the management strategy of the local CHP system by confronting the heat produced with the one produced by the local boiler. Even if from an absolute standpoint the reduction is limited (a difference in median of around 1.5 yearly GWh of heat, around 7.5% of the total demand), still the CHP system is curtailed in order to increase the local usage of the electricity produced by the RES, and by consequence the lack in heat production has to be taken up by the natural gas boilers, leading to an increase in emissions in the heating sector.

It has to be noted that this last effect is also due to the systems management strategy set to be used in the model, which aims at balancing both the heating and the electricity energy balances. A different strategy could aim at not impacting the usage of the local CHP system (by prioritizing the balancing of the heat vector), thus reducing the need to use the fossil fired boilers, but in that case the gap between the import and export of electricity from the main grid would probably be even more pronounced.

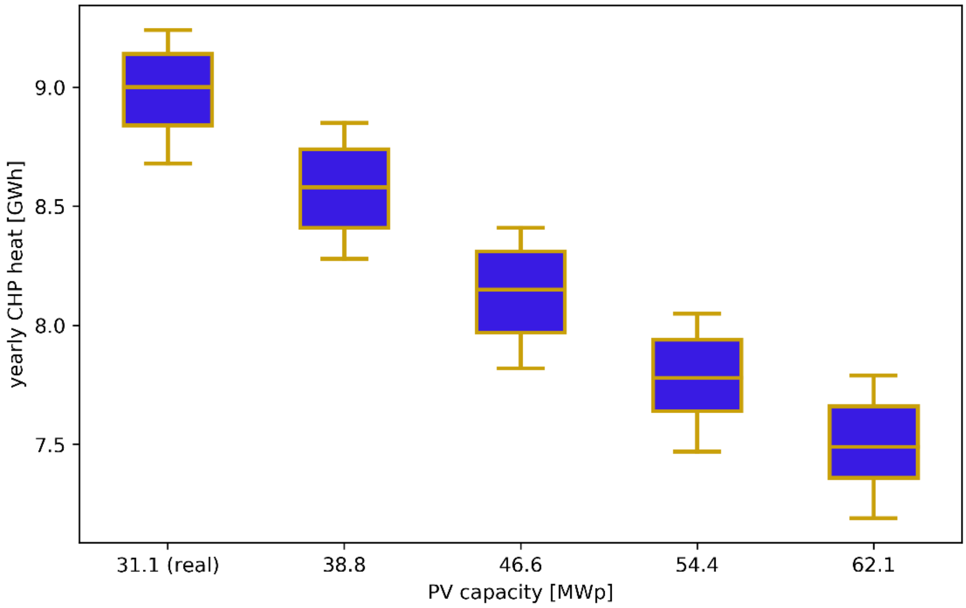


Figure 33 - Yearly CHP produced heat in Experiment #1

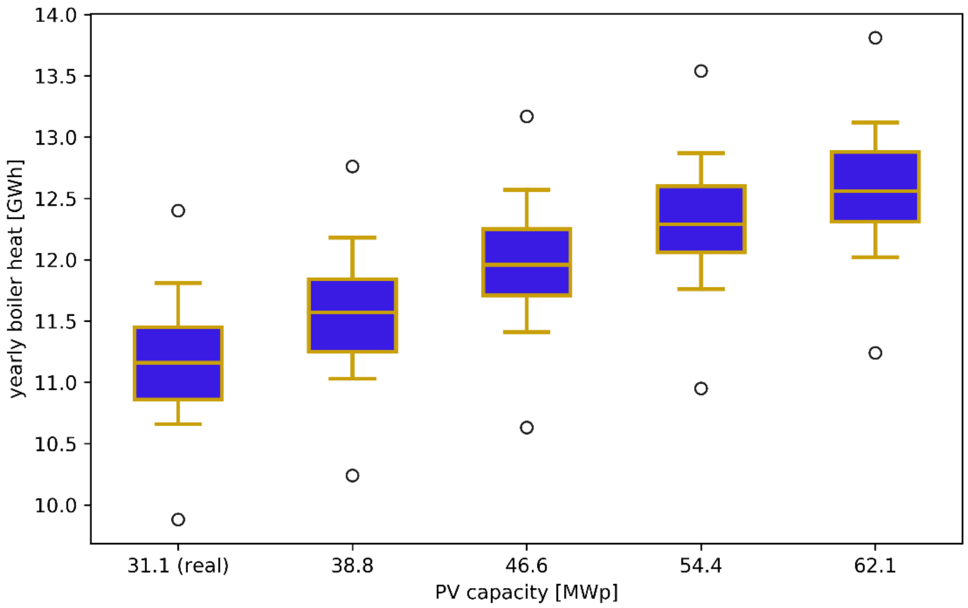


Figure 34 - Yearly boiler produced heat in Experiment #1

Finally, it can be seen in Figure 35 that, as expected, the increasing amount of the PV systems capacity within the district causes a decrease of the total CO_2 emissions generated over the simulated years, from a median of 120 kilo-tons to one of 105, achieving savings for around 15 kilo-tons. The emissions shown in the figure are the global ones, thus including the local heating and transport sector, plus the usage of the main national grid. Given that the effects on the heating sector are almost negligible this is almost entirely to be attributed to the changes in the national grid's usage, with the reduction of withdrawal and the increasing feeding of green electricity, with emissions caused by the usage of the national grid drop from 38.7 to 24.5 yearly kilo tons of CO2.

Being unchanged in the present experiment, the emissions of the transport sector keep being the highest fraction of the total emissions, with a share that surpasses 70% in the case with the highest PV penetration.

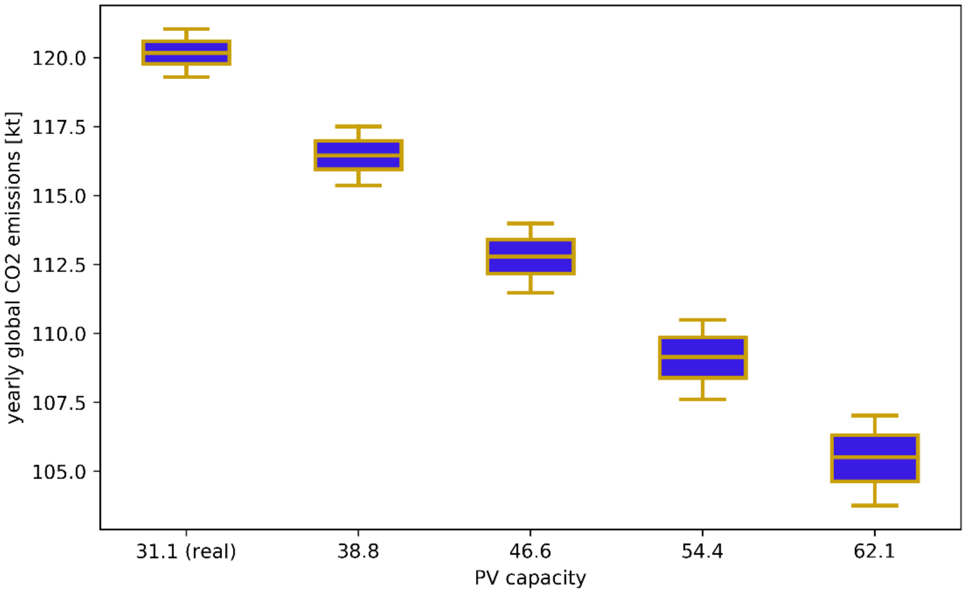


Figure 35 - Yearly CO2 emissions in Experiment #1

3.4.2 Experiment #2 – Osimo with an increasingly flexible DHN

In this experiment, the district heating network is rendered increasingly flexible by simultaneously increasing the size of both an electric high temperature heat pump and a thermal storage, in three discrete sizes. The heat pump is increased from the current 34.8 kWe to 400, 800 and 1200 kWe respectively in the three steps (maintaining the same 4.6 COP), while the TES is increased to 40,80 and 120 MWh of thermal energy storage capacity. Both the two systems are integrated within the same DHN according in the EnergyPLAN model. The range for both the two sizes are determined by considering the actual heating demand of the city as in Figure 14, the maximum sizes of both the HP and the TES in the proposed range allow to produce enough heating power to meet the demand of an average winter day and store the total of an average daily demand with the largest size in the set.

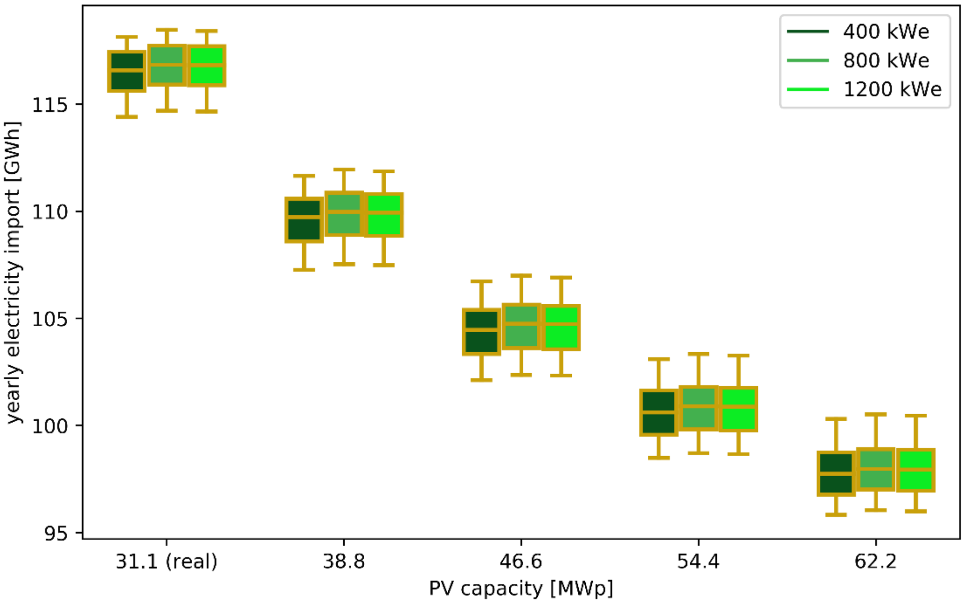


Figure 36 - Yearly electricity import in Experiment #2

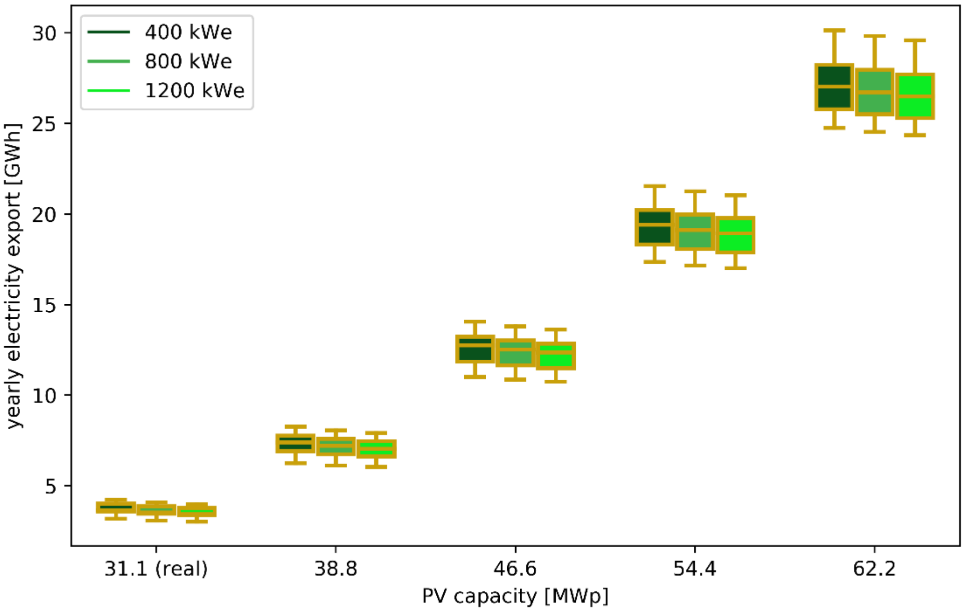


Figure 37 - Yearly electricity export in Experiment #2

In Figures 36 and 37, both the yearly electricity import and export are reported by distinguishing among the three degrees of flexibility of the DHN with three distinct boxplots. As expectable the trends in both the two quantities are the same as in the previous experiment, with a decreasing import and an increasing export, but also that the increasingly flexible DHN has nearly no effects in the two quantities.

There is a slight increase in imported and a slight decrease in exported electricity, but the main driver in the two quantities is still the increasingly large PV system capacity.

The most significant changes happen in the heating sector with, as one could expect, a significant drop in the heat produced by means of the natural gas boiler system in favor of the HP. On the other hand the heat produced by the CHP system still drops in approximately the same way as for Experiment #1 in order to furtherly use the renewable electricity. This is a trend that will be exhibited also in the following Experiments, as given the operational strategy followed by the algorithm the CHP has to necessarily be curtailed while increasing the size of the PV system, in order to make a larger use of the electricity generated.

But regarding the gas boiler and the electric HP a thing to notice is the different pace in such variations while increasing the degree of flexibility of the DHN, which is the same while switching from one flexibility level to the next. By increasing the flexibility from 400 kWe/40GWh to 800/80 the heat produced by the boiler drops by 2.15 GWh on average (across the PV system sizes) and the one from the heat pump increases by almost the same quantity. By applying the same flexibility increase from 800/80 to 1200/120 the decrease/increase in the heat produced by the two system is of around 0.55 yearly GWh (again across all the PV system sizes): suggesting that as one could expect there is an upper limit to the amount of heat that can be switched from fossil fired to electric.

This consideration could change by prolonging the timespan over which the TES has to be used, as for example by imposing a long term storage application, which is not yet considered but which could be an interesting further development of this analysis.

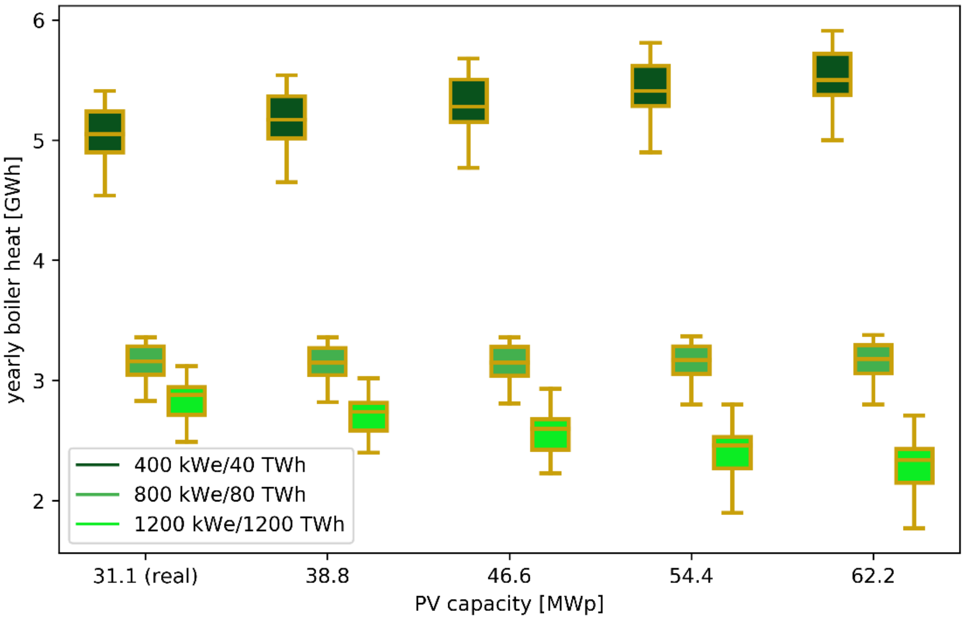


Figure 38 - Yearly boiler produced heat in Experiment #2

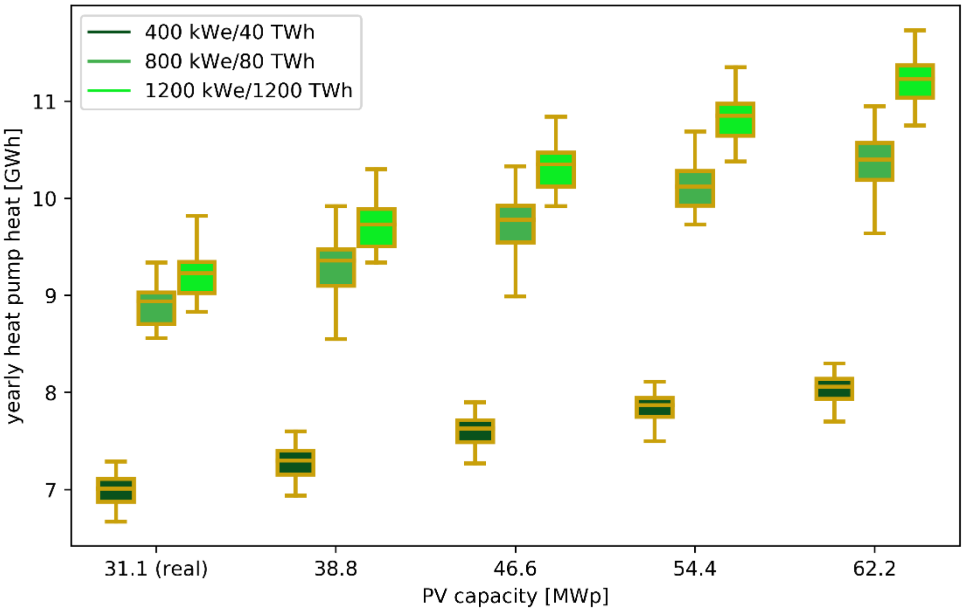


Figure 39 - Yearly heat pump produced heat in Experiment #2

Regarding the yearly global emissions, shown in Figure 40, the trend is similar to the one observed in Experiment #1. First of all it can be noticed that the influence of the flexibility of the DHN is almost negligible with respect to the emissions even while at its largest size. In Experiment #1 the yearly emissions in the case with the largest PV size had a median value of 105.5 yearly kilo-tons, while in this case they reach the lowest median value of 104.5 in the case with the most flexible DHN.

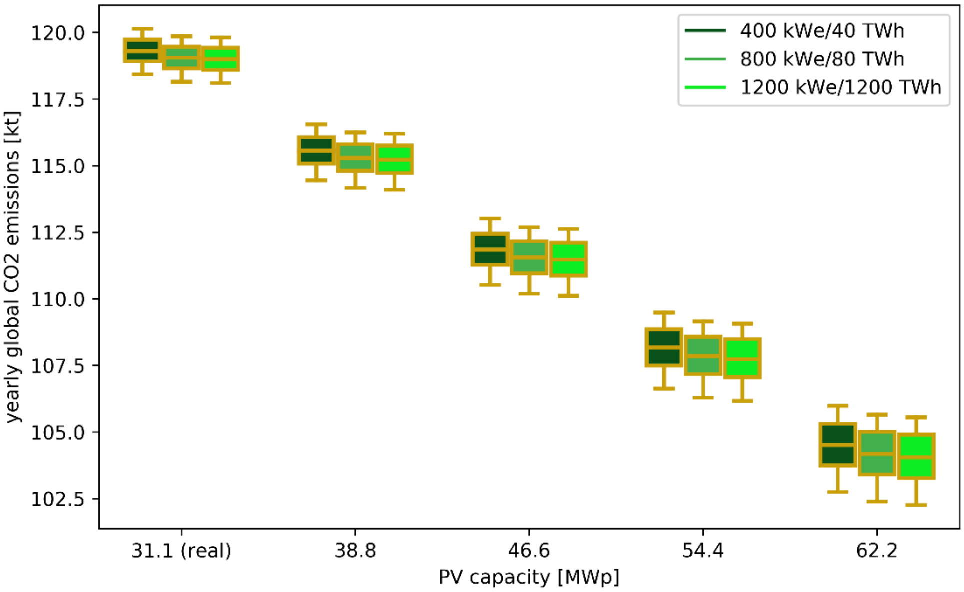


Figure 40 - Yearly CO2 emissions in Experiment #2

It has to be recalled that the DHN only serves a part of the heating needs of the city of Osimo, and the emissions of the privately owned heating sector are not reported in the Figure. Thus, even by greatly reducing the emissions of such sector there would still be a relatively low impact on the yearly global emissions even by deploying much larger HP or a TES system.

As a matter of fact by analyzing the impact of the HP and TES on the emissions caused by using distributed production systems (CHP and boilers), which are shown in Figure 41, it can be seen that there is actually a significant reduction effect. By analyzing the medians of the boxplots just by increasing the flexibility from the original of Experiment #1 to 400 kWe/40 TWh there are savings of 1.3 kilo-tons of CO_2, almost 20% of the original amount already with the lowest size of the PV system. With the DHN at its highest level of modeled flexibility, and with the largest size of the PV capacity, the savings raise to 2.6 kilo-tons, which is almost a 35% savings.

It can then be concluded that increasing the flexibility of the DHN is actually a great way of mitigating the emissions of the distributed energy system, but for the current test case the impact is just too small while making a comparison with the other sources of emissions.

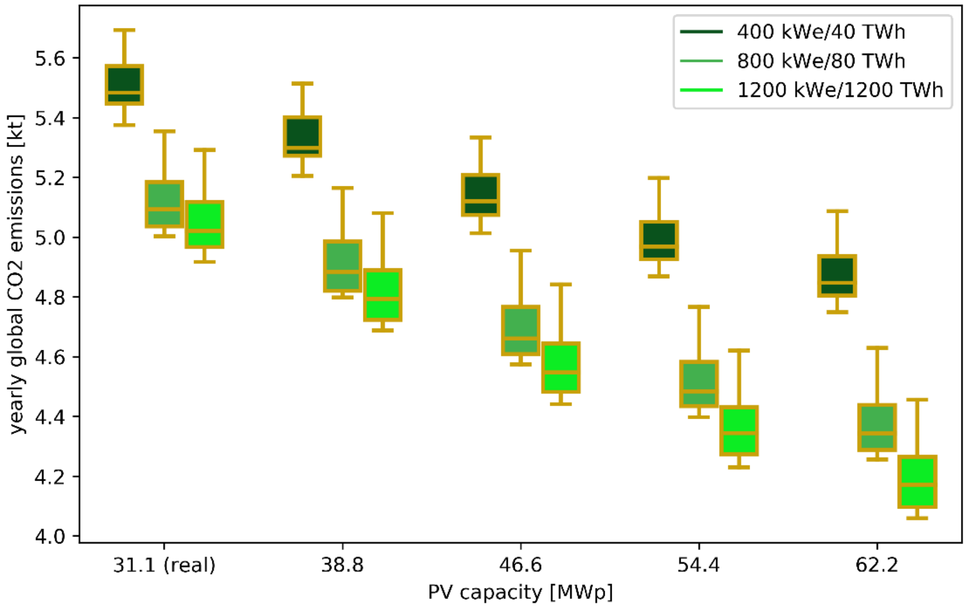


Figure 41 - Yearly CO2 emissions from the distributed generation systems Experiment #2

Such superior limit to this decarbonization approach could be of course overcome by enlarging the DHN to reach more customers, which as explained before is a technological option that is not analyzed within these analyses.

3.4.3 Experiment #3 – Osimo with increasing penetration of EVs with smart charge

In this experiment the goal is to investigate an increasing penetration of electric vehicles in the transport sector; the results are shown by means of the same three boxplots configuration as for the previous experiment to show the increasing EV penetration which is of 5%, 15% and 30%.

By looking at the plots for the electricity imported and exported it can be already seen how significant is the impact of the smart EV fleet in the grid usage pattern. As one could expect the increased presence of EVs both increases the electricity import and decreases the electricity export. In particular the drop in the need to export reaches almost zero at the current PV system size of 31 MWp even without the need for the highest EV penetration. Also, the last statement is true even by considering all the uncertainty sources which have been included in the model, as also the superior whisker of the boxplot lies approximately at zero.

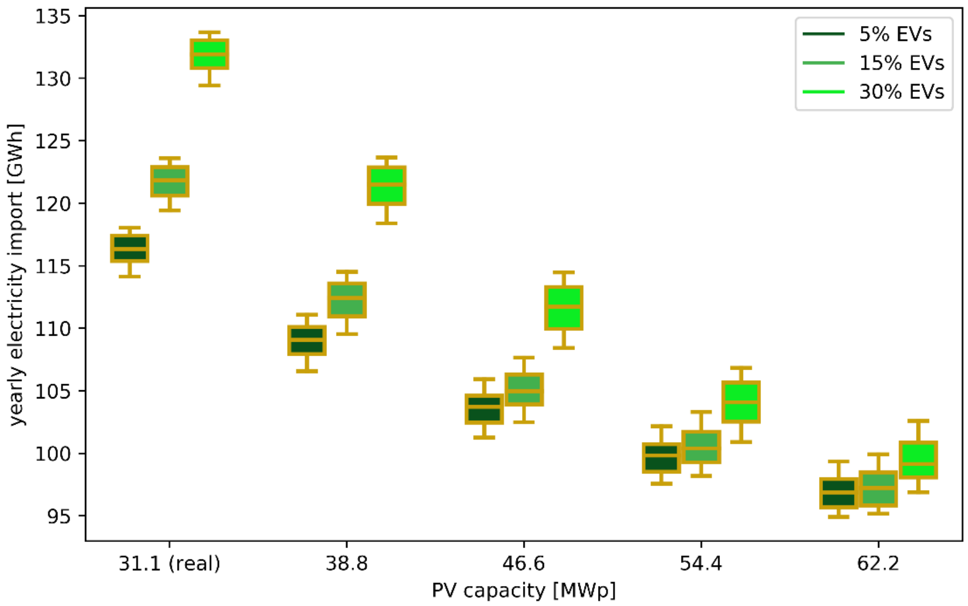


Figure 42 - Yearly electricity import in Experiment #3

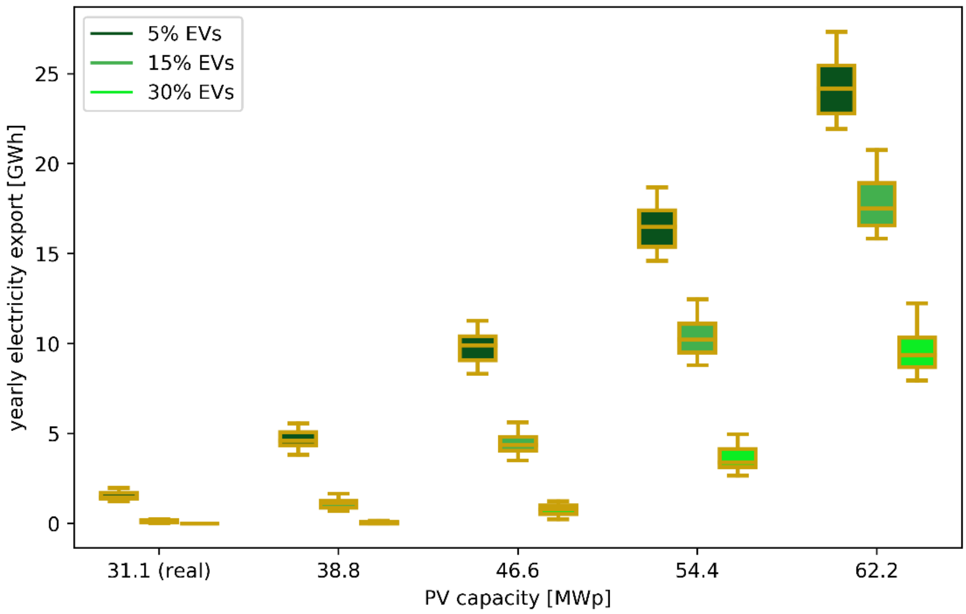


Figure 43 - Yearly electricity export in Experiment #3

On the matter of the global emissions, which are shown in Figure 43, it can be seen how significant is the decrease with the raising share of EVs in the transport sector, especially if compared with the flexible DHN. Such decrease is to be attributed to two distinct effects: the removal of a share of vehicles propelled by fossil fuel engines and the presence of the battery capacity of the EVs, which helps in increasing the local self-consumption of the PV electricity surplus.

The first contribution is fixed and only depends on the share of EVs, as explained before thus; the reduction of emissions due to just this effect is of 4.07, 12.13 and 24.27 yearly kilo-tons for a 5%, 15% and 30% EVs penetration respectively.

The second contribution can be obtained by removing the quantity to be attributed to the heating and transport sectors, in the following table both the emissions in terms of absolute CO2 emitted and in terms of share on the total amount are shown.

	31.1 MWp	**38.8 MWp**	**46.6 MWp**	**54.4 MWp**	**62.2 MWp**
5% EV	39.87	36.27	32.72	29.18	25.62
15% EV	42.22	38.59	35	31.45	27.89
30% EV	45.77	42.13	38.5	34.88	31.3

Table 6 - grid related yearly CO2 emissions [kt] in Experiment #3

	31.1 MWp	**38.8 MWp**	**46.6 MWp**	**54.4 MWp**	**62.2 MWp**
5% EV	34%	32%	30%	27%	25%
15% EV	38%	36%	34%	31%	29%
30% EV	44%	42%	40%	38%	36%

Table 7 - share of grid related CO2 emissions on total emissions in Experiment #3

The numbers show that while the presence of the schedulable EVs helps in increasing the self consumption of the electricity produced by means of RES, the emissions to be attributed to the usage of the national grid are actually increasing, both in absolute terms (Table 6) and by consequence as a share of the total emissions (Table 7). Thus the major effect in CO_2 emissions in mitigation coming from the heavy adoption of EVs is (in this case) to be attributed to removing a share of conventional vehicles from the streets.

While the presence of EVs equipped with smart charge does help in reducing the need to export electricity due to the availability of what is synthetically a large battery at the disposal of the local grid during the day, limiting the phenomenon of large surpluses during the day. However, this comes at the price of an increased usage of the national grid, making the local electric grid more of a passive consumer with respect to the national grid.

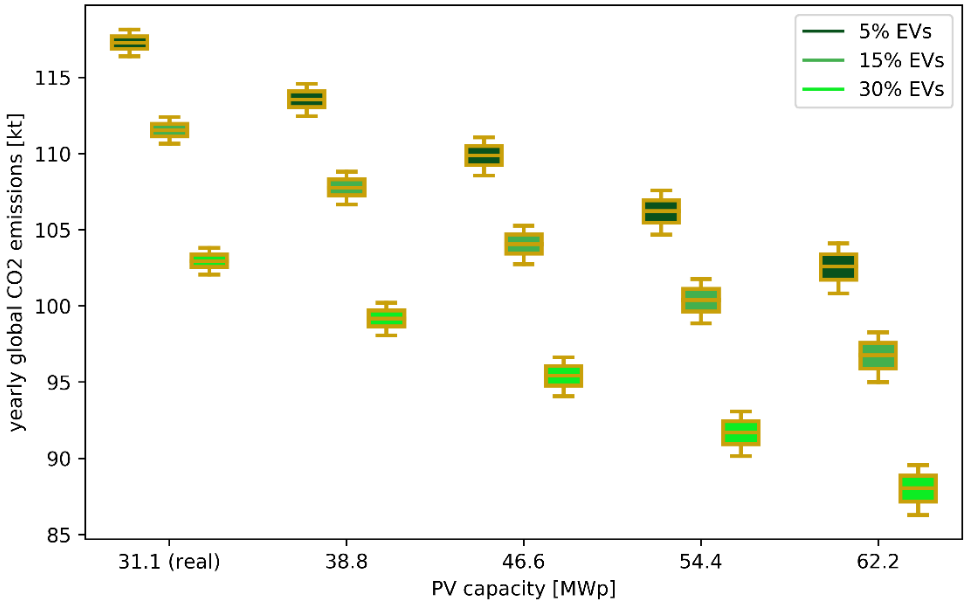


Figure 44 - Yearly CO2 emissions in Experiment #3

These results also highlight the fundamental importance of all the assumptions and modeling efforts made so far, highlighting once more the holistic nature of energy systems and their workings.

As anticipated in the introduction EVs are seen as a key asset in decarbonizing our society, and this appears to be true also according to these analyses, but the beneficial effect in the decarbonization process are mostly concentrated to a local dimension, with a large amount of EVs actually increasing the emissions in the traditional electricity production and distribution infrastructures. And this appears to be true also while in the presence of very high RES penetration and thus green electricity.

But the conclusions which are drawn so far are very dependent on the set of assumptions and estimations going into the model, highlighting once more the complex nature of energy systems analyses, and the holistic approach needed to gain significant and reliable insights. As a first example, the greatest share of the global emissions is to be attributed to the conventional transport, which has just been estimated by means of a representative car usage and specific consumption. A mis-estimation of such parameters could then lead to erroneous estimations of the beneficial impacts of EVs with decarbonization purposes.

A second example, related in this case to the modeling of the EV demand, lies in the assumptions regarding both the same parameters of daily usage but also in the hourly charge pattern, which is mostly concentrated in the later part of the day, when there is already no more solar electricity available. As explained the presence of EVs aids in self-consuming the electricity surplus from the PV system but it also increases the need to import electricity and this is due to the hourly mismatch between the demand and supply of electricity. An EV usage pattern more intense in the central hours of the day, or an increased smart charging capability with more cars parked and plugged in (assumptions in 3.3.3) could change even drastically the benefits of having an EV fleet.

3.4.4 Experiment #4 and results recap

A last set of scenarios wishes to study the simultaneous presence of both an EVs fleet and an increasingly flexible DHN, combining the two previous experiments. In this sense a set of new simulation is added to the ones just described, analyzing all of the combination of DHN flexibility with all the combinations of EVs penetration. The results are shown in the following four dimensional plots, where the quantity of interest is encoded by means of a color scale. The same results are shown more in detail in the contour plots of figures for the case of increased sizes of PV system, where each contour is a slice of the 4d plot at a fixed PV system size. In all the just mentioned plots the quantities reported are the medians of the boxplots shown so far. By analyzing the figures is clear that an increased PV penetration inevitably raises the amount of electricity which has to be fed to the national grid and thus cannot be auto consumed. This is true also if both the two flexibility approaches, namely a more flexible DHN and a smart charging equipped EV fleet, are used simultaneously. It's also confirmed what emerged in the description of the previous experiments, that the flexible EV fleet is much more effective in reducing the exports than the flexible DHN.

As shown by the color gradients in Figure 46 it then appears that the contribution of the flexible DHN in decreasing the electricity exports is almost negligible, but again this has to be attributed to its relatively small size in terms of energy demands. As already discussed in Paragraph 3.3.3.

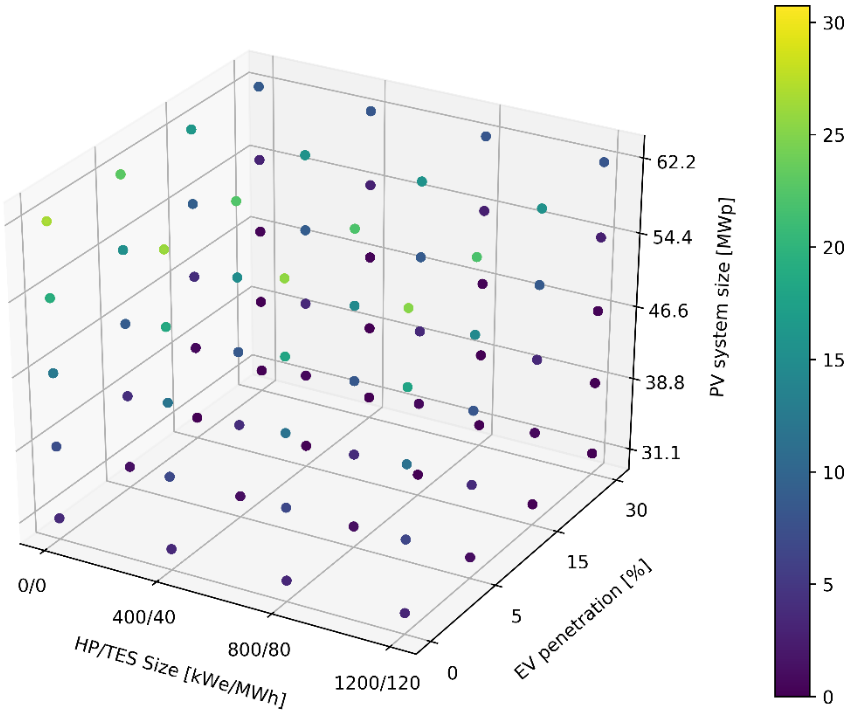


Figure 45 - Yearly electricity exports to the national grid across all the simulations

From the two plots regarding the yearly global emissions it’s confirmed again that the progressive penetration of EVs is the major driver in lowering the carbon footprint of the local energy system. With respect to the results of Experiment #3 the coexistence of both the two flexibility measures doesn’t really combine into a greater advantage in this sense.

The increase of the capacity of the PV system can itself lead to a much lower carbon footprint but, as seen in all of the Figures the best results are achieved only with high penetration of EVs. By itself the increase of PV alone can lead to reductions down to 105.5 yearly kilo-tons fo CO2, meaning a 16.3% reduction on the current amount, which is computed in paragraph 3.3.2. Actually around the same beneficial effects can be obtained just by increasing the share of EVs, that with a 30% penetration return a yearly 102.9 kilo-tons of CO2, a 18.4% reduction.

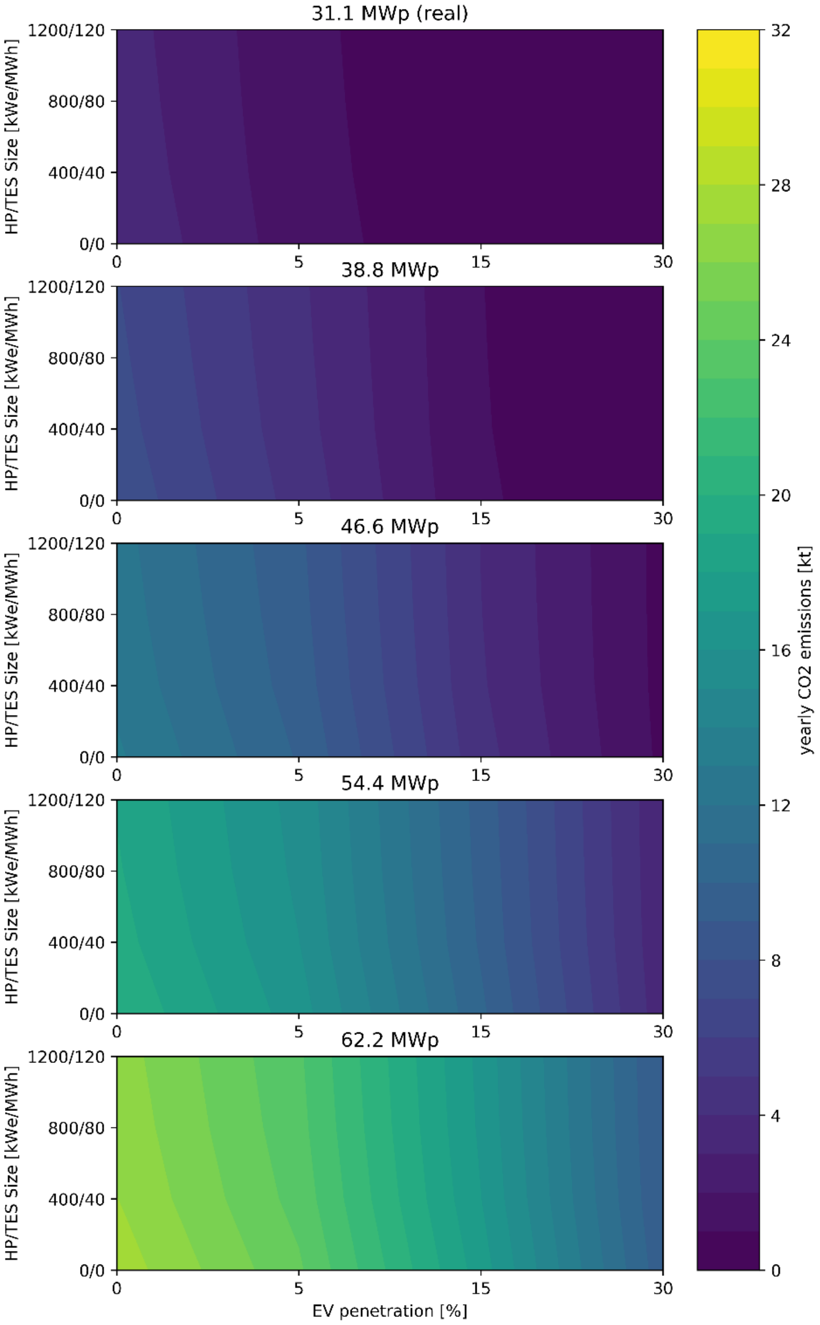


Figure 46 - Detail of yearly exports to the national grid across all the simulations

As anticipated an EV adoption of this magnitude in the short term (for example within 2030) consists in a very optimistic scenario, driven mostly from the consumer's behaviors and policies (such as incentives on the adoption of EVs) which are not really to be taken from the municipal energy company, whose goal might be to decrease its carbon footprint.

While these results suggest the importance that the EV fleet might have in helping welcome higher shares of non-controllable RES mostly from a technical/environmental point of view, the potential decision to be taken is still complex, especially in a context where other technologies might be of use towards the same goal. As for example the just mentioned expansion of the DHN with an increasingly electrified supply of thermal energy.

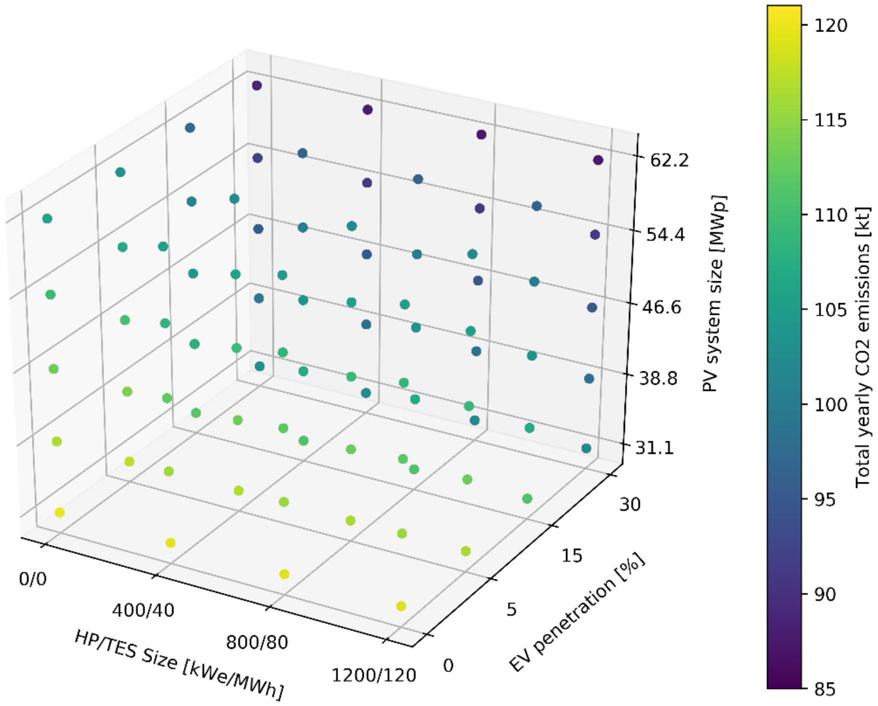


Figure 47 - Yearly CO2 emissions across all the experiments

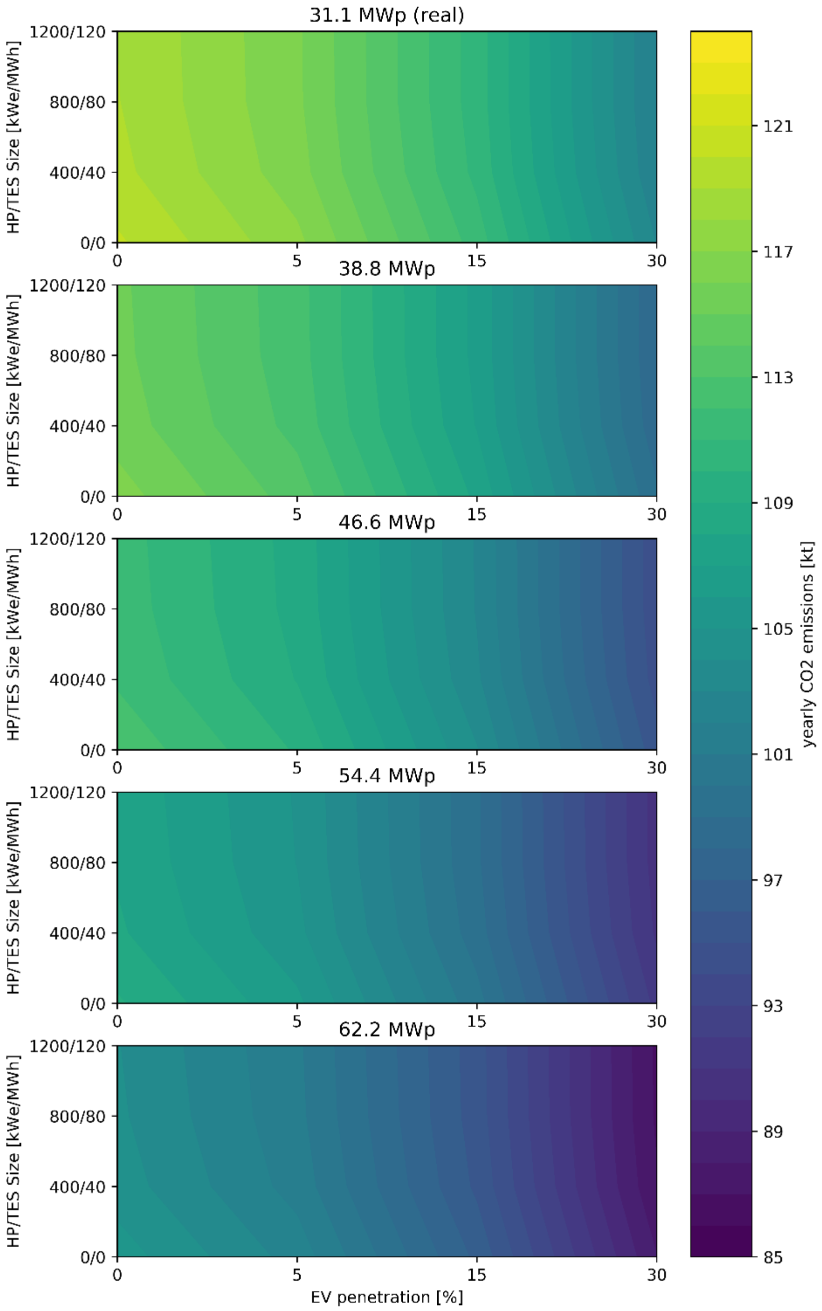


Figure 48 - Detail of yearly CO2 emissions across all the simulations

3.5 Conclusions

In this chapter we propose a framework aimed at enhancing an already well-established energy systems simulation model, with the goal of considering many of the intrinsic sources of uncertainty, and thus ultimately achieving better insights from the model. The goal is to understand how high penetration of non controllable RES can be better put to use in the interest of an increased self consumption of such production, or the decarbonization of the local energy system

In order to validate the framework a real case study is built with data provided by a municipal energy company meeting the needs of a small town in central Italy, the data models the energy demands of part of the city, plus the technical specifications of the DER assets within the local energy system.

Most of the uncertainty sources that were considered of interest and with a potential significant impact on the results of the simulation of the local energy system were characterized by building a dedicated model. Other aspects on the other hand were made vary with assumptions based on the available literature and from open databases. Among the needs of the local energy system a potentially significant one which has not been included in these analyses regards the privately own heating sector, which could itself be a relevant source of emissions, but also a potential new source of flexibility by means of an expansion of the DHN network in order to reach more customers. The proposed framework considers such uncertainties by launching a large set of simulations, in order to obtain a plausible range for the parameters of interest towards the goal of the analysis, which are the usage pattern of the main electricity grid and the yearly amount of emissions.

The simulations are then aimed at representing the operational aspect of the energy systems in terms of balances of energy with a fine time discretization. So the objective is to the meet the user demands at each timestep, without pursuing any type of economic goal in doing so.

The results indicate that both an increasingly flexible DHN and a significant penetration of EVs can help in both increasing the auto consumption of excesses of electricity produced by means of RES, and also help in mitigating the overall carbon footprint of the local energy system. The effect is however much more significant with the electrification of the transport sector, both in terms of carbon emissions mitigation and in terms of increased auto consumption capabilities. For the case of the emissions, the reduction is due to both a removal of much more polluting conventional vehicles, which offsets the additional electricity purchased from the national grid to charge the vehicles. Regarding the need to export electricity the EVs are again much more effective in reducing it, eliminating entirely the need to do so for the actual PV system capacity.

It has to be noticed though that the benefits of the flexible DHN are small in comparison due to the actual size of the network and the relative impact on emissions. And also that some of the parameters which have been estimated and not let vary in these analyses actually have a potentially significant impact on the results, and therefore the insights gained from them. Such parameters regard both the modeling of the conventional transport sector and the electric one.

Chapter 4.

Conclusions

4.1 Key findings

In this thesis a set of modelling approaches to tackle the gaps in the energy systems modelling literature were proposed. In particular the approaches were aimed at considering the complex impacts of the temporal dimension and of the uncertainties within the design and operation of multi energy distributed energy systems. As widely discussed in the introduction energy systems are intrinsically very complex; characterized by a dynamic nature over different timescales and a very large set of actors interacting with each other, each with its own mechanics and characteristics and a different impact on the outcome of the analysis performed, which as highlighted can point at answering to a very wide set of questions.

For these reasons energy systems related questions need to be faced with a holistic approach, and the same goes for the models used to perform the analyses that wish to answer such same questions. The models need to be tailor made for the question at hand, with an appropriate compromise between the detail of representation and the right approximations, all of which maintaining a tolerable computation tractability.

For these reasons the approaches proposed in this thesis aim at both goals, widening the capability of the current modelling approaches in providing insights which are more reliable, due to their being robust towards two challenges which are considered to be pivotal in the already available literature. In particular the proposed approaches are two; and wish to tackle the complexities inherent to the very long time dimension of energy related problems, and the impact of uncertainties while analysing systems with high penetration of non-controllable RES.

The first contribution, described in Chapter 2, wishes to consider the potential impact of parameters that might change over long timespans, such as for example within the technical lifetime analysed while studying the optimal planning of such system. Such parameters could consist for example in a particular technology changing in its capital costs due to technological development or economies of scale, or a demand of the users evolving through time. In particular the methodology is tested on a test case where the adoption of an electricity storage system is evaluated over a long time span in a scenario representing a residential user with a large penetration of non-controllable renewable electricity generation (PV), which shows a performance degradation through the years. This type of analysis is of particular interest given a well-established market trend indicating a plausibly significant drop in battery systems capital costs.

The results for the scenario indicate that even by considering such drop in costs a battery system would still not be a valid investment in a residential scenario without a significant increase in PV system capacity. Other than the conclusion regarding the economical aspect an insight is also gained from a policy perspective, indicating the need of incentivizing such technology.

The second contribution, described in Chapter 3, wishes to consider the impact of uncertainties in a much more complex analysis that wishes to investigate the best technological pathways for the decarbonisation of local multi energy systems of the size of a small town. The scenario is accurately modelled by considering different sectors of the multi energy system, being: a district heating network, a small CHP system, a large penetration of non-controllable RES (a PV system), a traditional transport sector fed by conventional fuels and a potential fleet of EVs. In particular the analysis wishes to uncover insights on which pathway can grant the most significant reduction in CO_2 emissions, whether a flexibilisation of the local DHN, or a smart charging infrastructure for the local EVs fleet. The innovative aspect in the proposed approach lies in the modelling, and thus consideration, of a set of uncertainties related to both the supply side of the local energy system (uncertainty in solar electricity availability) and the demand side (uncertainty in heating and electric mobility demands).

The results indicate that for the town test case under analysis a fleet of EVs in presence of a smart charging infrastructure is a much more effective way in dealing with high shares of non controllable RES with respect to a more flexible DHN. This leads to both a reduced carbon footprint and an increased auto consumption of the electricity surplus. So far the analysis lacks a consideration of the economics of both the two approaches, and also of other equally valid decarbonisation approaches. But this could already give some insights regarding a potential policy approach. While the investment in a smart charging infrastructure is a decision to be taken by the local municipality, a more centralized policy could be to incentivize such technological measure.

4.2 Future developments

The developments of the approaches described in this thesis could be very diverse and focus both on improving the approaches themselves in adding functionalities in order to have an even more holistic representation of the energy case studies that they wish to analyse, but also combine their strengths in a single model.

The framework proposed in Chapter 2 could be enhanced by considering a large set of technologies of which to evaluated the potential investment, or a set of other quantities of interest that mutate over long time horizons. As for example an increase in energy demands, or a mutation of the same in different patterns in order to represent a change is user behaviours, such as for example the progressive adoption of air conditioning or EVs. Or, to represent how the cost of provision of an external resource such as grid electricity or network natural gas, that itself is very susceptible to costs variations through the year, could impact the optimal degree of decentralization for the distributed energy system.

The framework proposed in Chapter 3 could be enhanced by extending the set of represented uncertainties to include in general more of the assumed parameters, but more importantly the ones that showed to be influential with respect to the analysis outcomes described in the results: such as for example the emissions of the fossil fired transport sector, or the pattern of EVs usage by the citizens. A further improvement would consist in adding also considerations of economic nature to the model, in order to obtain insights regarding how the different technological approaches compare in terms of costs.

On a bigger perspective the advantages of the two models could be combined in a single framework aiming at answering to optimal design problems by considering both a wide range of uncertainties in the present time, and how these combine over long time horizons with parameters showing a trend over such time. An optimization algorithm coupled with a very detailed modelling and representation of the energy systems of interest, which for example the EnergyPLAN model can grant, could be used to obtained better insights on potential policy and/or investment decisions. Such comprehensive framework could for example help in understanding how to design an incentive while pursuing a given objective: such as for example the mitigation of the carbon footprint of the energy system, the islanding capabilities etc.

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