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Exact and heuristic algorithms for the integrated planning of multi-energy systems

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Abstract

The aim of this thesis is to present exact and heuristic algorithms for the integrated planning of multi-energy systems. The idea is to disaggregate the energy system, starting first with its core the Central Energy System, and then to proceed towards the Decentral part. Therefore, a mathematical model for the generation expansion operations to optimize the performance of a Central Energy System (CES) system is first proposed. To ensure that the proposed generation operations are compatible with the network, some extensions (or updates) of the existing network are considered as well. All these decisions are evaluated both from an economic viewpoint, using the objective function of the problem, and from an environmental perspective, as specific constraints related to greenhouse gases (measured in CO2eq) emissions are imposed in the formulation.

Then, the thesis presents an algorithm for a bottom-up optimization model for solar organic Rankine cycle in the context of transactive energy trading. In this study, the impact that this technology can have on the peer-to-peer trading application in renewable based community microgrids is inspected. Here the consumer becomes a prosumer (functioning both as energy producer and consumer), and engages actively in virtual trading with other prosumers at the distribution system level. Moreover, there is an investigation of how different technological parameters of the solar Organic Rankine Cycle (ORC) may affect the final solution. Finally, I study the value of the solar ORC in the transactive energy trading context under different configurations and scenarios.

Finally, the thesis introduces a tactical optimization model for the maintenance operations' scheduling phase of a Combined Heat and Power (CHP) plant. Specifically, two types of cleaning operations are considered, i.e., online cleaning and offline cleaning. Furthermore, a piecewise linear representation of the electric efficiency variation curve is included, accurately describing the impact of load and inlet air temperature inside the compressor on the electric efficiency of the CHP plant. Given the challenge of solving the tactical management model, a heuristic algorithm is proposed. The heuristic works by solving the daily operational production scheduling problem, based on the final consumer's demand and on the electricity market price. The aggregate information from the operational problem is used to derive maintenance

decisions at a tactical level.

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Chapter 1

Introduction

The energy sector is constantly evolving, to face new challenges imposed by the climate change problem. Great measures have been implemented to aim at a sudden decarbonization of the energy system, especially in Europe. Technologies that exploit Renewable Energy Sources (RES) have quickly widespread, increasing the level of difficulty in managing the electricity grid. This has opened the discussion in the scientific community to understand what are the next steps to be made. In this sense, a new interest has increased in applying Operations Research (OR) techniques in the energy field. Both the OR community and the energy one have expanded their interest towards each other, to understand how these two disciplines could benefit from each other. Specifically, given the great investments that will be necessary in the energy sector in the future, see [1]-[2] for further details, having tools that could potentially prevent expenditure losses or optimize such investments seems to be essential.

The problems that can be tackled in the energy field are of various natures, from production plants' scheduling to transmission and distribution system management. They can be divided into three main categories depending on the time horizon they are considering. The so-called strategic problems, usually make decisions over a wide time range, typically several years. Instead, decisions made within the yearly time horizon are inspected by tactical problems. Finally, problems that consider short-period planning horizons are called operational problems.

Another consideration needs to be made on the type of power/energy being optimized. In fact, given the high penetration of Distributed Generations (DGs) in the network, Virtual Power Plant (VPP) as a new concept has come into view, with the intention of dealing with the increasing number of DGs in the system and handling effectively the competition in the electricity markets [3]. The idea is to manage networks of small energy-producing or storage devices, like solar panels and batteries, that are pooled together to serve the electricity grid. VPPs rely upon software systems to remotely and automatically dispatch and optimize generation or

demand-side or storage resources in a single, secure Web-connected system [4]. The advantage of VPPs is the possibility of using their energy to serve utilities during times of high demand or to store it for later use.
All these problems imply a level of difficulty that can generate memory requirement problems and computational time inefficiencies. Thus, the implementation of both exact and heuristic algorithms is necessary to find the perfect balance. Exact algorithms have been extensively studied and are considered adequate for moderately size instances, whereas heuristic algorithms are considered promising for very large instances [5]. This thesis will present both exact and heuristic solution strategies for different problems used in energy applications.

1.0.1 Multi-energy systems

All energy systems can be reduced to a black box, having a useful product as output, usually a final consumer's demand, and a supply of primary energy as input. The input/output interactions are typically described through conventional energy efficiencies, and without going into further details with the equipment's internal description [6]. Inside the black box, a series of thermodynamic variables and processes occur, to convert the inlet primary energy into a valuable output, as shown in Figure 1.1. The supply of primary energy can be various, depending on the type of technology considered, the most common are renewable energy sources or fossil fuels. The demand can be the combination of multiple energy types, such as electric energy and thermal energy. This is very common when the final consumer is a household or an industrial plant.

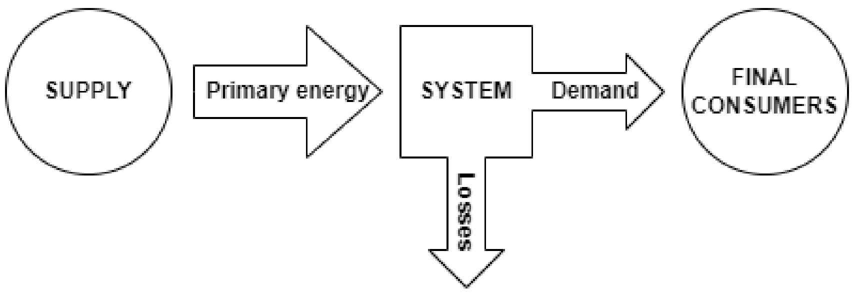

Figure 1.1: System scheme based on the black box concept

Following the same philosophy, this concept can be extended to a bigger picture considering a system where multiple energy production technologies are interconnected. In this case, splitting the black box will result in the combination of multiple subsystems, each of them identifiable with a different energy production technology, but all aiming to satisfy the demand of the final consumer. This concept is shown in Figure 1.2.

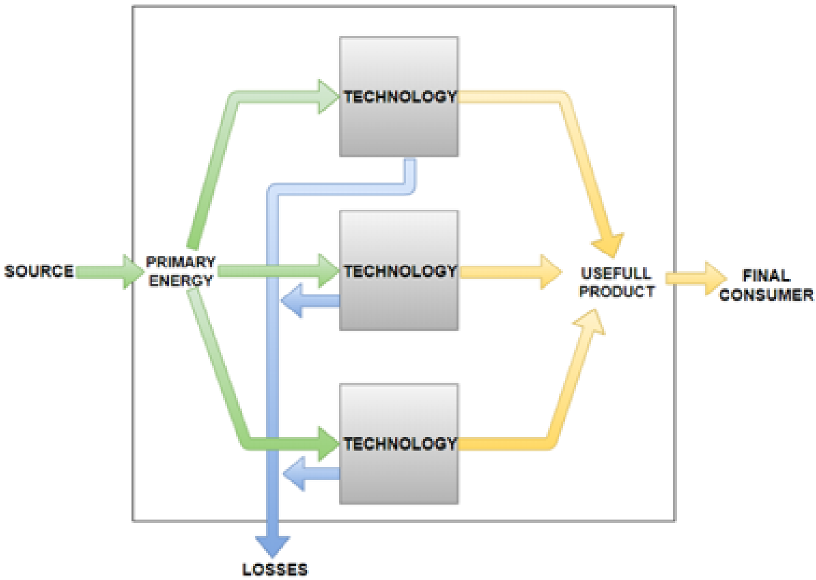

Figure 1.2: Multi-energy systems black box scheme

If we apply this basic concept to a wider realistic example, such as a nation, what we obtain is actually the national energy system. In fact, the energy system is basically a combination of several energy production plants that need to satisfy an abundance of demand scattered all over the country. In this wider scheme, all actors participating in the energy market such as producers, transmission system operators (TSOs), distribution system operators (DSOs) and consumers are considered. In traditional power systems, the transmission system operator TSO is responsible for the security of the grid [7]. The DSO functions are limited to operating the distribution network, make investments and perform network maintenance [8]. What comes out of this combination is an extremely complex structure, that needs to be constantly managed and optimized. The complexity of such structure has greatly increased lately, with the integration of different energy sectors like the electricity sector, the heating sector, and the natural gas sector. This concept is called *sector coupling*, which implies a progressive electrification of the heating sector and the mobility sector, and the widespread of technologies that combine the natural gas sector with the electricity one, such as Power to Gas (P2G) plants. The aim of sector coupling is increasing the cost efficiency of the total system and, concurrently, "contributing to achieving a clean, affordable, and secure energy system" [9].

The energy system can be viewed from a central or a decentral perspective, as shown in Figure 1.3. From a central perspective, a large-scale energy system (e.g. one country) requires to be planned as a whole. Central planning focuses on the large-scale generation, as well as the transmission grid. Renewable energy plants for self-consumption and most of the final consumers are located in distribution grids.

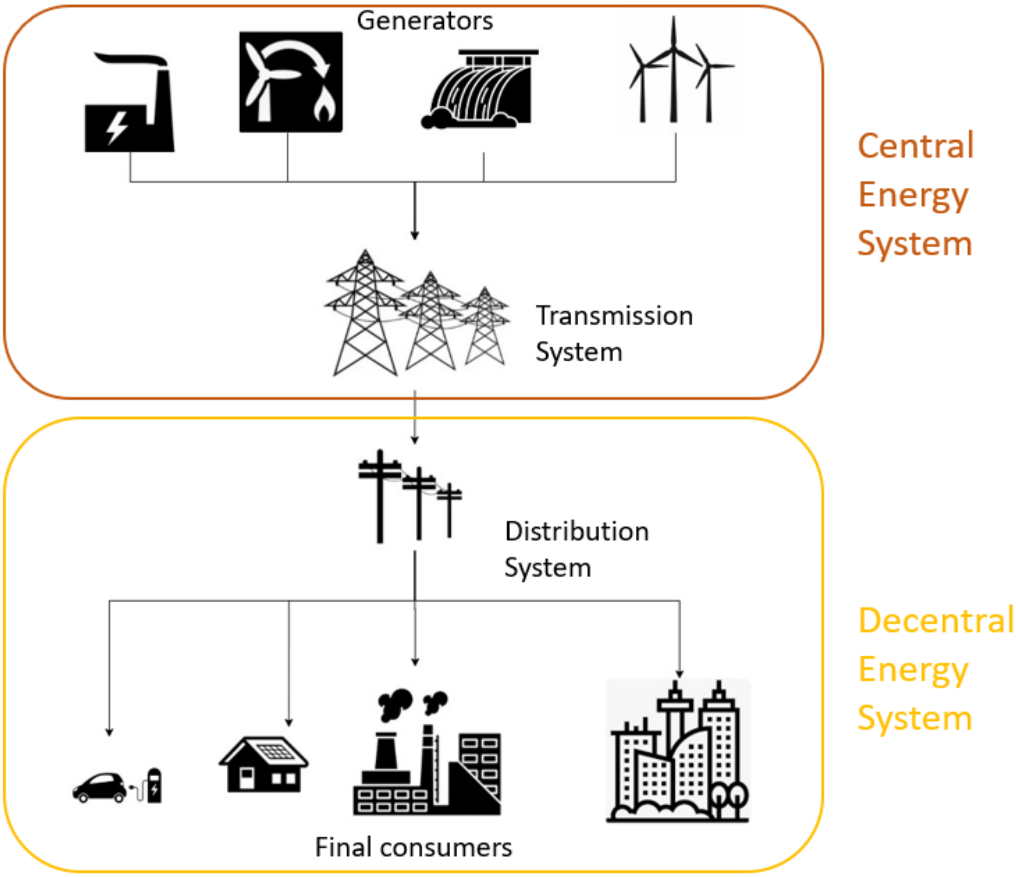

Figure 1.3: Caption

The Decentral Energy System (DES) is an inherent part of the Central Energy System (CES). However, due to the size and mathematical complexity of the resulting model, a detailed modeling of CES and DES within one planning model becomes computationally not effective. Therefore, the idea in this thesis is to first focus on problems related to the CES and then to problems related to the DES. This is consistent also with recent research directions to decentralize the management of the DES, for further details see Kok et al. [10].
Moreover, energy production plants feature numerous thermodynamic processes and variables that increase the level of difficulty for management tools. Thus, works that use operations research techniques on energy systems, frequently tend to treat energy production plants as black boxes, neglecting technical details. This choice is perfectly compliant with the need to find computationally effective algorithms, that are usually solved for long-term planning horizons, such as one year. At the same time, it may create inaccuracies in results, and a further gap from the realistic behavior of such plants. Thus, in this thesis the idea is to explore in detail different frameworks for the DES, to include more technical features in the algorithms.

1.0.2 Central Energy System (CES)

The CES represents the part of the energy system that is regulated by the TSO. This includes large-scale generation, like central power plants, power to gas plants, and wind power plants as well as the transmission grid.

The main optimization problem connected to the CES is the combination of an expansion planning problem and of a unit commitment problem. The expansion planning problem designs the future expansion of both the generation part and the transmission part, to be compliant with the expected GHG emissions stated by the EU, see Koltsaklis et al. [11] for further details. The unit commitment problem regulates the correct functioning of the grid, once it has been expanded, to fulfill the expected demand, see Montero et al. [12] for further details.

The CES is modeled using a graph. Every node in the graph is characterized by a generation capacity coming from different kinds of technologies that can be potentially expanded and a demand to be fulfilled. Every arc in the graph represents a transmission line between nodes. An example of such graph applied on Germany as test case is shown in Figure 1.4.

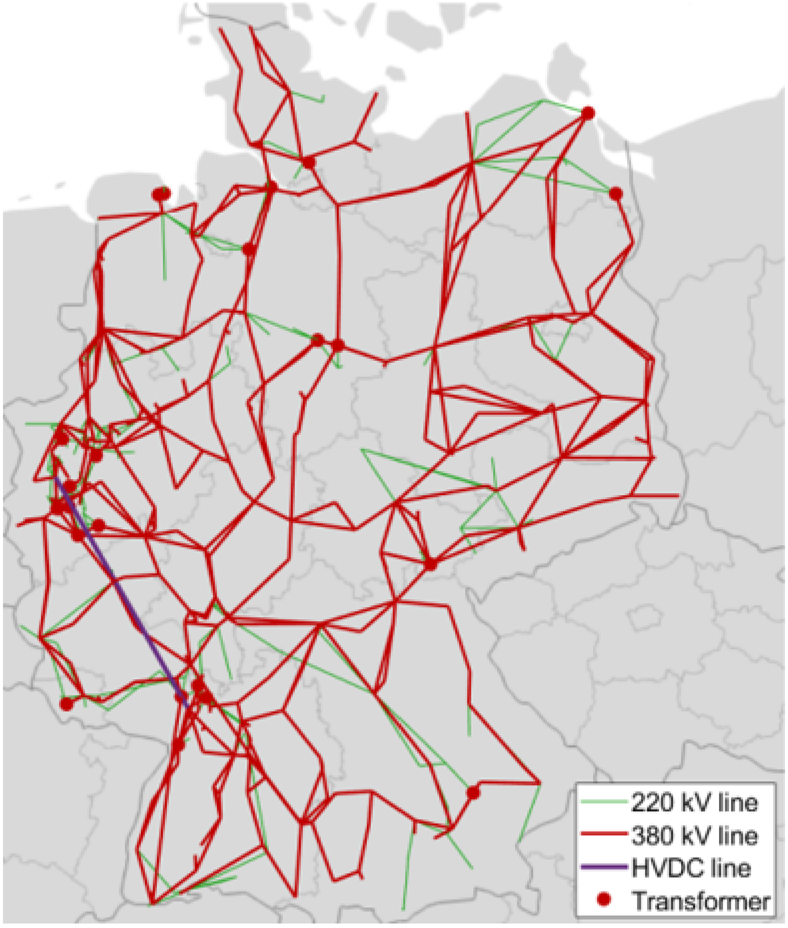

Figure 1.4: CES of Germany seen as a graph

A set of variables decides the investments needed to expand both the generation capacity of the nodes and the transmission capacity on the arcs. The hourly operation of the network is governed by Kirchhoff's circuit laws: the current law and the voltage law.

Due to long planning and construction times for new electric transmission lines, a TSO needs to plan grid infrastructure multiple years in advance. Thus, the planning horizon usually considered in the CES problem is at least a year.

In Chapter 2 a mathematical model for the generation expansion operations to optimize the performance of the CES is presented. Figure 1.5 shows an example of a potential expansion of the CES of Germany as a test case.

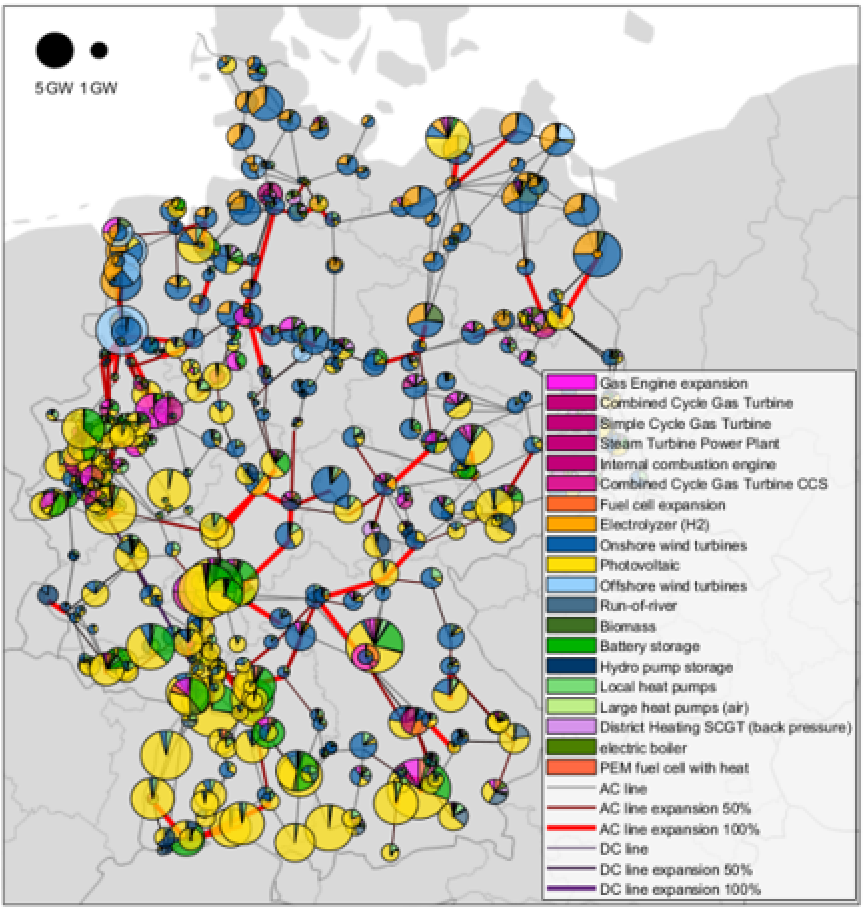

Figure 1.5: CES of Germany potential expansion

1.0.3 Decentral Energy System (DES)

The DES represents the part of the energy system that is regulated by the DSO. This includes utilities, distributed generation, like solar panels, combined heat and power plants, or small wind turbines, as well as the distribution grid.
The DES has historically always been managed centrally simultaneously with the CES. However, lately there has been a shift towards a decentralization of the management of this portion of the energy system, for further details see Kok et al. [10]. Following this idea the DES should be managed by local actors. This way, the consumers have the chance to actively engage to the energy market in a two-way communication between them and providers. This concept is called *transactive energy trading*, as shown in Figure 1.6

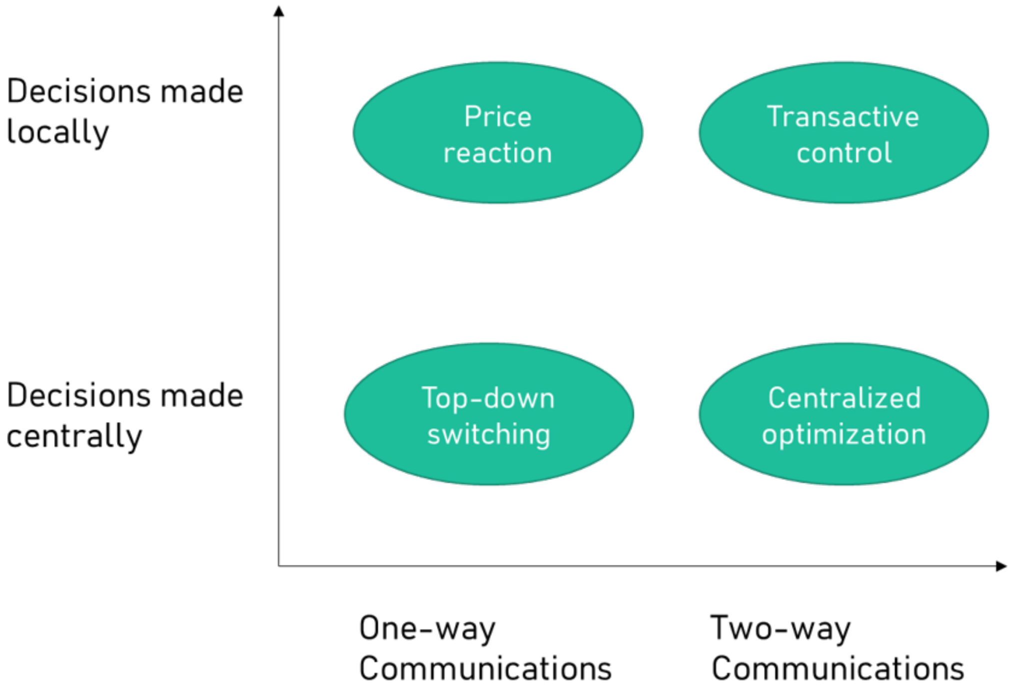

Figure 1.6: DES management classifications

The transactive energy trading concept opens the doors to new energy frameworks, like local energy markets, where neighboring consumers or producers engage actively in what is called Peer-to-peer (P2P) trading. New figures like prosumers, which are consumers that invested in their own energy production technology and are now also producers, increase their importance in the energy market. The need to find new frameworks for the DES comes actually with the widespread of RES, especially for self-consumption. Self-consumption stands for a scheme where a consumer decides to invest in an energy production technology to fulfill its own demand. It is basically a scheme where a prosumer consumes its own energy rather than just selling it on the market. A very common example in the RES field is solar panels, both for heating and electricity production, installed in households, see Luthander et al. [13] for further details. The prosumer can still decide to actively trade any surplus of energy production, or buy it when there is a lack of production.
Chapter 3 proposes an optimization algorithm for transaction energy trading, using a specific renewable technology called *solar organic Rankine cycle*. The algorithm is used to understand the effectiveness that a new RES technology like a solar organic Rankine cycle could have for self-consumption. Moreover, it optimizes operational decisions for a wider framework, that considers different prosumers actively engaging with each other in P2P trading.

Self-consumption can be extended also to systems with conventional energy pro-

duction technologies. For example, if the technology used can provide simultaneously multiple energy types, such as Combined Heat and Power (CHP) plants. This is a common solution for big industrial plants, that have a great energy consumption to satisfy. CHP plants use natural gas as fuel, to simultaneously produce heat and electricity. Therefore, they are considered conventional energy production plants. However, they are still incentivized by governments, due to their recovery of exhaust gases to produce thermal energy.
In Chapter 4 a tactical optimization model for the daily scheduling of a framework that considers an industrial plant as prosumer, and a CHP plant with two boilers as energy providers in a self-consumption scheme is explained. Moreover, the model contains a more technical level of detail for the single CHP plant.

1.0.4 Research contribution

This thesis presents exact and heuristic algorithms for the integrated planning of multi-energy systems. The idea is to disaggregate the energy system, starting first with its core the Central Energy System, and then to proceed towards the Decentral part. This is done with respect to a new trend in energy management to decentralize the control of such a system, specifically the distribution part. Moreover, this gives the opportunity to develop algorithms that feature technical details, predominantly regarding the production technologies involved, to achieve more realistic results.

Thesis structure

The remainder of this thesis is structured as follows:

- Chapter 2 presents a Linear Programming (LP) model for the generation expansion operations to optimize the performance of a Central Energy System (CES) system. The model includes extensions (or updates) of the existing network, to ensure the compatibility between the proposed generation operations and the transmission network.
  This work has been done in collaboration with my supervisor professor Michele Monaci, Paolo Paronuzzi from the University of Bologna, and Henrik Schwaeppe from RWTH Aachen University and it has eventually been published as part of the AIRO Springer Series book series with the title "An LP model for the Central Energy Systems".

- Chapter 3 shows a study of the impact that the Solar-ORC technology can have on the peer-to-peer trading application in renewable based community microgrids. We develop an optimization strategy based on two Mixed Integer Linear Programming (MILP) models.
  This work has been done in collaboration with Chiara Bordin from The Artic University of Norway and Sambeet Mishra from University of South-Eastern

Norway and is currently under revision of Energy journal with the title "A bottom-up optimization model for solar organic Rankine cycle in the context of transactive energy trading".

- Chapter 4 is dedicated to a tactical optimization model for the maintenance operations' scheduling phase of a Combined Heat and Power (CHP) plant. This work has been the result of a cooperation with Ola Jabali and Federico Malucelli from Politecnico di Milano.

- Chapter 5 contains an overall conclusion of this thesis, accompanied by some reflections on possible future developments and challenges.

List of Publications and Working Papers

- Cordieri, S.A., Monaci, M., Paronuzzi, P., Schwaeppe, H. (2023). *An LP Model for the Central Energy System.* In: Cosmi, M., Peirano, L., Raffaele, A., Samà, M. (eds) Operations Research and Data Science in Public Services. AIROYoung 2022. AIRO Springer Series, vol 11. Springer, Cham. https://doi.org/10.1007/978-3-031-34546-3_5

- Cordieri, S.A., Fumero, F., Jabali, O., Malucelli, F. (2022). *The Long-Haul Transportation Problem with Refueling Deviations and Time-Dependent Travel Time.* In: de Armas, J., Ramalhinho, H., Voß, S. (eds) Computational Logistics. ICCL 2022. Lecture Notes in Computer Science, vol 13557. Springer, Cham. https://doi.org/10.1007/978-3-031-16579-5_17. Not included in this thesis.

- Bordin, C., Cordieri, S.A., Mishra, S. (2023). *A bottom-up optimization model for solar organic Rankine cycle in the context of transactive energy trading*, submitted to Energy.

- S. A. Cordieri, O. Jabali, F. Malucelli, (2020), "A tactical maintenance optimization model for multiple interconnected energy production systems", Optimization Online, https://optimization-online.org/2020/05/7782/

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Chapter 2

An LP model for the Central Energy System

[1] In this chapter, I present a mathematical model for the generation expansion operations to optimize the performance of a Central Energy System (CES) system. To ensure that the proposed generation operations are compatible with the network, some extensions (or updates) of the existing network are considered as well. All these decisions are evaluated both from an economic viewpoint, using the objective function of the problem, and from an environmental perspective, as specific constraints related to GHG gases (measured in CO_2eq) emissions are imposed in the formulation.

2.1 Introduction

The energy sector has been a widely discussed topic during the last years. Given the recent worsening of climate conditions, worldwide governments, especially in European countries, had implemented new directives in order to limit the consequences of this problem. Nevertheless, the most recent energy crisis highlighted the strong dependency that energy systems still have on conventional energy sources and the consequences implied by this strategy also from a political point of view. Disruptive structural developments are still necessary to deliver on the European Union's COP21 commitments [1]. In this sense, a strategy adopted to achieve a decrease of Green House Gasses (GHG) emissions is the decarbonization of the energy sector, in spite of an increase of renewable energy sources. An efficient planning for future energy systems must also comprise the coupling of energy sectors as well as inter-dependencies of generation and transmission grid infrastructures [16]. The *energy coupling* concept consists in the integration of power and gas from a consumer perspective, thus leading to an electrification of the thermal and mobility sector.

[1] The results of this chapter appear in Cordieri et al. [15]

However, these strategies come with a significant change in the topology of energy generation that risks to compromise the stability of the transmission system. The system more and more often nears boundaries of safe operation, thus increasing the probability of undesired effects, e.g., loss of synchrony and voltage collapse [17]. Thus, adequate expansion and planning become essential.
In the context of integrated energy systems, the Central Energy System (CES) represents all the entities that are relevant in the decision making process currently regulated by the Transmission System Operator. The CES focuses on large-scale generation, like central power plants, power to gas plants and wind power plants as well as the transmission grid. All these entities are necessary to fulfill the final consumer's demand, on an hourly basis every day. The perfect planning of this system is a problem associated with significant challenges. Thus, providing CES planners with a decision support system able to compute efficient strategies to reach the aforementioned goals is fundamental. This study presents a Linear Programming (LP) model to define the generation expansion operations needed to improve the performance of the CES. The model includes extensions (or updates) of the existing network, to avoid inconsistencies between the proposed generation operations and the transmission network. All these decisions are evaluated both from an economic viewpoint, using the objective function of the problem, and from an environmental perspective, as specific constraints related to GHG gases (measured in CO_2 emissions) emissions are imposed in the formulation. The goal of the presented formulation is to model scenarios that represent an ideal future framework of the grid, towards which grid managers should strive. Given the size of the instances to be solved, the formulation introduces some modelling approximations, so that the resulting model can be solved with "reasonable" computing time and memory. The remainder of this chapter is organized as follows. Section 4.2 presents a literature review of the topics discussed in this paper, while Section 4.3 formally presents an LP model for the CES problem. Section 2.4 shows the numerical tests. Finally, Section 2.5 gives some conclusions and outlines possible research perspectives.

2.2 Literature review

The generation expansion planning and the transmission expansion planning problems have gained interest within the scientific community recently. These problems have been investigated from different perspectives, modelling different constraints and objective, and have been attacked with different solution methods [18]. Franken et al. [19] concentrated on the transmission expansion planning problem, explicitly adressing the Alternating Current (AC) systems and Phase Shifting Transformers (PSTs) as well as operational congestion management interventions. The authors proposed a multi-stage approach, based on Mixed Integer Linear Programming (MILP), aimed at determining the operating point of power flow controlling devices while minimising expansion costs. Hörsch et al. [20] introduced the Linear Optimal Power Flow (LOPF) algorithm, which uses a linearization of the AC load flow equations to optimize generator dispatch in a network subject to loading constraints of the network branches. The authors showed that this formulation is computationally more efficient than the angle formulation when solved by means of a commercial linear programming solver. Müller et al. [21] implemented an approach for evaluating multi-modal energy systems, showing the advantages of coupled addressing electricity, heat, fuel and mobility sectors. The modeling framework enables system planners to optimally plan future investments in a detailed transition pathway of the energy system of a country, considering politically defined climate goals. Additional transmission system expansion measures are identified by applying a heuristic method, which reinforces the transmission grid in order to make use of existing infrastructure. Schwaeppe et al. [22] proposed a mathematical model for the single-stage generation and transmission expansion planning, that is intended to provide a general framework for multi-energy planning. To reflect constraints in the transmission network a power transfer distribution factor (PTDF) approach is used. Other papers are more focused on the optimization of the generation part. Elsido et al. [23] introduced a MILP model and a two-stage optimization algorithm for determining the most profitable synthesis and design of Combined Heat and Power units within a district heating network with heat storage, while taking into account the optimal scheduling of the units over the year. Bischi et al. [24] developed a MILP model for optimizing the daily schedule of cogeneration systems and networks of heat and power plants. Given the significant computational time needed to solve the model on a weekly time horizon, the authors introduce a heuristic rolling-horizon algorithm, in which a sequence of weekly MILP submodels is solved, while considering production and consumption estimates based on demand profiles from historical data. Finally, some papers in the literature try to detect the correct integration of storage systems in the grid framework. Aghaebrahimi et al. [25] demonstrated that, despite high cost of energy storage systems, their presence in the grid framework may increase the total income from wind energy sales. Bordin et al. [26] addressed the coupling of renewable energy sources and storage systems, focusing on battery degradation costs, and proposed LP models for the optimal management of off-grid systems. Almost all the references in the literature focus on specific parts of the CES problem, or use modelling strategies that are different from those we adopt. To the best of our knowledge, the first attempt to give a comprehensive view of CES by using the LOPF strategy, was made by Schwaeppe et al. [27]. Our formulation extends the model proposed in [27] by including additional details related to the technologies used in the generation part, such as renewable plants and storage systems.

2.3 Methodology

In the following, a generic, single-stage expansion planning model for multi-energy systems is described. The formulation is intended to be described as pure linear program. The problem definition involves several technologies and consumers that are described by a set of nodes. These nodes are located in different areas, and are interlinked by a set of arcs representing the grid lines. The objective of the problem is to minimize a cost function that takes into account both the operational cost (including production costs and transmission costs), and costs for installing new facilities. In case the consumers' demands cannot be fully satisfied, a large penalty value is incurred in the objective function; similarly, costs for oversupply are taken into account. Finally, the formulation introduces a cap on the allowed CO_2 emissions, and evaluates a preliminary analysis of the expansion of the transmission network. In our formulation, we consider a set of candidate lines among the existing ones that can be further expanded up to a certain value, in terms of capacity. More precisely, the problem consists of a set $N = \{1, ..., n\}$ of electric nodes. Each node $j \in N$ has a subset $M(j)$ of available energy production technologies (both traditional ones and renewable ones). Specifically, $M(j) \subseteq I$, where $I = \{W, O, P, B, F\}$ is the set of technologies (W stands for wind turbines, O for offshore wind turbines, P for photovoltaic systems, B for batteries, and F for thermal power plants). A set $T = \{1, ..., \Theta\}$ of time slots is given. The transmission network topology is defined by a set $E = \{1, ..., m\}$ of edges, where each edge $e \in E$ is represented as $e = (u, w)$ where $(u, w) \in N$ and $u < w$. In addition to the electric power transmission grid, there is a thermal power system, that is characterized by a set $R = \{1, \ldots, r\}$ of thermal nodes. For each node $k \in R$, a set of available technologies $M_T(k) \subseteq J \cup L \cup Q$ is given, where $J = \{H, S\}$ is a set of purely thermal technologies (H stands for solar heating and S for thermal storage); $L = \{i = \big(k(i), j(i)\big) \colon k(i) \in R,\, j(i) \in N\}$ is a set of technologies converting electric energy from node $j \in N$ to heat for node $k \in R$ (e.g.heat pumps, rods, boilers), and $Q = \{i = \big(k(i), j(i)\big) \colon k(i) \in R,\, j(i) \in N\}$ is a set of technologies obtaining heat for node $k \in R$ while producing electric energy for node $j \in N$.

The behavior of each technology associated with a given node is described by a specific set of constraints and parameters. Installing a technology i at some node j is associated with an installation cost C^C_{ij} per unit of capacity and with the maximal capacity Y^{max}_{ij} that can be installed. For each battery $i = B$ and node $j \in N$ the unit production cost C^p_{Bj} to charge or discharge is given. For each power plant $i = F$ and node $j \in N$, the unit production cost C^p_{Fj} and an efficiency parameter η_{Fj} are given. The thermal storage in each node $k \in R$ is characterized by a unit production cost C^p_{Sk} to charge or discharge. For each thermal plant $i \in M_T(k)$ and node $k \in R$, the unit production cost is C^p_{ik}, whereas C^-_j and C^+_j denote the costs for power oversupply and deficit in node $j \in N$, respectively (note that $C^+_j >> C^-_j$). Finally,

for what concerns the network, we are given a set $E_{cand} \subseteq E$ of candidate lines for transmission corridor expansion. Each candidate line $g \in E_{cand}$ has an installation cost C^V_g to build the new line.
To model the problem, we introduce variables x_{ijt} representing the amount of power generated/withdrawn by technology i located at node $j \in N$ during time slot $t \in T$. In addition, variables y_{ij} represent the capacity that is installed for technology i at node $j \in N$. For each time slot $t \in T$ and each node $j \in N$, the curtailed power due to oversupply or congestion is given by variable s^-_{jt}, and the power deficit is defined by variable s^+_{jt}. Variable u_g represents the expanded fraction of candidate line along edge $g \in E_{cand}$. For each $t \in T$ and node $j \in N$ in which a battery is installed, we introduce a variable x^c_{Bjt} to denote the amount of energy that is used to charge the battery, and a variable x^d_{Bjt} for the amount of energy taken from the battery. For each node $k \in R$, the amount of thermal energy generated/withdrawn by technology i during time slot $t \in T$ is given by variable q_{ikt}, while variable $x_{ij(i)t}$ represents the amount of electric energy converted to heat from node j, through technology i in time slot $t \in T$. Variable q^c_{Skt} denotes the amount of energy used to charge the thermal storage located at node k during time slot t, and variable q^d_{Skt} is used for amount of energy that is taken from the thermal storage located at node k during time slot t.
Finally, there are some additional variables to detect the costs in the objective function. Variable c_{PROD} computes the total production cost, variable c_{INST} computes the total installation cost, variable c_{TRAN} computes the total transportation cost, variable c_{SLACK} computes the total opportunity cost for undersupply/oversupply and variable c^T_{et} computes the transmission cost for edge $e \in E$ during time slot $t \in T$.
All these figures are set to their value by constraints (2.1)-(2.4).

$$c_{PROD} = \sum_{t\in T}\left(\sum_{j\in N:B\in M(j)} C^p_{Bj}(x^d_{Bjt} - x^c_{Bjt}) + \sum_{j\in N:F\in M(j)} C^p_{Fj}\frac{x_{Fjt}}{\eta_{Fj}}\right)$$
$$+ \sum_{t\in T}\left(\sum_{k\in R:S\in J} C^p_{Sk}(q^d_{Skt} - q^c_{Skt}) + \sum_{k\in R}\sum_{i\in M_T(k):i\neq S} C^p_{ik}q_{ikt}\right) \tag{2.1}$$
$$c_{INST} = \sum_{j\in N}\sum_{i\in M(j)} C^C_{ij}y_{ij} + \sum_{k\in R}\sum_{i\in M_T(k)} C^C_{ik}y_{ik} + \sum_{g\in E_{cand}} C^V_g u_g \tag{2.2}$$
$$c_{TRAN} = \sum_{t\in T}\sum_{e\in E} c^T_{et} \tag{2.3}$$
$$c_{SLACK} = \sum_{t\in T}\sum_{j\in N}\left(C^+_j s^+_{jt} + C^-_j s^-_{jt}\right) \tag{2.4}$$

For time step $t \in T$ the electric demand D_{jt} to be supplied at node $j \in N$ is given. Constraints (2.5) compute the power injected in the grid (z_{jt}) in every node $j \in N$

during time slot $t \in T$, while constraints (2.6) impose the power balance on the grid.

$$z_{jt} = \sum_{i \in M(j)} x_{ijt} + D_{jt} + s^+_{jt} + s^-_{jt} \quad \forall j \in N, \forall t \in T \tag{2.5}$$

$$\sum_{j \in N} z_{jt} = 0 \quad \forall t \in T \tag{2.6}$$

Constraints (2.7)-(2.8) limit the slack variables of the problem, while constraints (2.9) limit the maximum capacity of renewable energy that can be installed in a node.

$$0 \leq s^+_{jt} \leq -D_{jt} \quad \forall j \in N, \forall t \in T \tag{2.7}$$

$$s^-_{jt} \leq 0 \quad \forall j \in N, \forall t \in T \tag{2.8}$$

$$y_{ij} \leq Y^{max}_{ij} \quad \forall j \in N \cup R, \forall i \in M(j) \cup M_T(k) \tag{2.9}$$

Parameter E_g represents the total emission related to installation of candidate lines in set E_{cand}. Moreover, any technology i installed at a node $j \in N \cup R$ is characterized by the equivalent CO_2 emission per unit of capacity installed (E^y_{ij}) and per unit of power generated/withdrawn (E^x_{ij}). These values are related to variable e_{ij} that represents the total emissions at node j due to technology i, while variable e_{ik} defines the total emissions at node k due to technology i. Constraints (2.10)-(2.11) define the emissions produced for every technology, while constraints (2.12) limit the total CO_2 emissions to a maximum value $EMISSION_{total}$.

$$e_{ij} = \sum_{t \in T} E^x_{ij} x_{ijt} + E^y_{ij} y_{ij} \; \forall j \in N, \forall i \in M(j) \tag{2.10}$$

$$e_{ik} = \sum_{t \in T} E^x_{ik} q_{ikt} + E^y_{ik} y_{ik} \forall k \in R, \forall i \in M_T(k) \tag{2.11}$$

$$\sum_{j \in N} \sum_{i \in M(j)} e_{ij} + \sum_{k \in R} \sum_{i \in M_T(k)} e_{ik} + \sum_{g \in E_{cand}} E_g u_g \leq EMISSION_{total} \tag{2.12}$$

Constraints (2.13) define the actual available energy for each technology i located at node j and producing renewable energy (i.e., for each $i \in \{W, O, P\}$), that exploits a renewable energy source according to the normalized feed-in $FEEDIN_{ijt}$ at time $t \in T$.

$$x_{ijt} = FEEDIN_{ijt} \, y_{ij} \; \forall t \in T, \forall j \in N, \forall i \in M(j) \cap \{W, O, P\} \tag{2.13}$$

Constraints (2.14)-(2.15) limit the charge and discharge values of batteries, respectively. Constraints (2.16) impose that the actual maximum storage capacity w^{max}_{Bj} of a battery located at a node j is a fraction of the maximum value CAP_{Bj}, while constraints (2.17) define the amount of energy injected/withdrawn in each battery at node j, according to efficiency parameters to charge or discharge η^c_{Bj} and η^d_{Bj}, respectively. Constraints (2.18) define the amount of energy h_{Bjt} to be stored in a battery located at a node j during time slot t, whereas constraints (2.19) impose this figure to be between a minimum value W^{min}_{Bj} and a maximum value, depending on the installed capacity. In our model, we assume the initial and final values for variables h_{Bjt} must coincide. Though we fixed these values to $\frac{y_{Bj}}{2}$, different values can be used to model different scenarios.

$$0 \leq x^d_{Bjt} \leq y_{Bj} \ \forall t \in T, \forall j \in N : B \in M(j) \tag{2.14}$$

$$-y_{Bj} \leq x^c_{Bjt} \leq 0 \ \forall t \in T, \forall j \in N : B \in M(j) \tag{2.15}$$

$$w^{max}_{Bj} = CAP_{Bj} y_{Bj} \ \forall j \in N : B \in M(j) \tag{2.16}$$

$$x_{Bjt} = x^d_{Bjt} + x^c_{Bjt} \ \forall t \in T, \forall j \in N : B \in M(j) \tag{2.17}$$

$$h_{Bjt} = h_{Bj,t-1} - \frac{x^d_{Bjt}}{\eta^d_{Bj}} - x^c_{Bjt}\eta^c_{Bj} \ \forall t \in T, \forall t \geq 1, \forall j \in N : B \in M(j) \tag{2.18}$$

$$W^{min}_{Bj} \leq h_{Bjt} \leq w^{max}_{Bj} \ \forall t \in T, \forall j \in N : B \in M(j) \tag{2.19}$$

$$h_{Bj0} = \frac{y_{Bj}}{2} \quad \forall j \in N : B \in M(j) \tag{2.20}$$

$$h_{Bj\Theta} = \frac{y_{Bj}}{2} \forall j \in N : B \in M(j) \tag{2.21}$$

Each edge $e \in E$ has a maximum capacity F_e in terms of flow, a unit transmission cost c^T_e and a constant line reactance (p.u.) X_e. Moreover, an incidence matrix is given, whose generic element K_{je}, for each edge $e \in E$ and node $j \in V$, takes value 1 if edge e starts on node j, -1 if edge e ends on node j, and 0 otherwise. C_{ec} represents a cycle matrix, that takes value 1 if edge $e \in E$ is element of cycle $c \in \{1, .., |E| - |N| + 1\}$, -1 if edge $e \in E$ is reversed element of cycle $c \in \{1, .., |E| - |N| + 1\}$, 0 otherwise. Variable f_{et} describes the power flow along edge $e \in E$ for each time slot $t \in T$. Constraints (2.22)-(2.23) represent the Kirchhoff laws that regulate the grid. Constraints (2.24)-(2.25) set a limit to the power flows, respect the limit of the grid lines. Constraints (2.26) define the transmission costs.

$$z_{jt} = \sum_{e \in E} K_{je} f_{et} \ \forall t \in T, \forall j \in N \tag{2.22}$$

$$\sum_{e \in E} C_{ec} X_e f_{et} = 0 \ \forall t \in T, \forall c \in \{1, .., E - N + 1\} \tag{2.23}$$

$$-F_e \leq f_{et} \leq F_e \ \forall e \in E - E_{cand}, \forall t \in T \tag{2.24}$$

$$-F_g - u_g R_g \leq f_{gt} \leq F_g + u_g R_g \ \forall g \in E_{cand}, \forall t \in T \tag{2.25}$$

$$-c^T_{et} \leq C^T_e f_{et} \leq c^T_{et} \ \forall e \in E, \forall t \in T \tag{2.26}$$

Constraints (2.27) ensure that the thermal demand H_{kt} of each node $k \in R$ is satisfied for each time step $t \in T$. Constraints (2.28) limit the amount of electric energy converted to thermal energy for technologies of group L, while constraints (2.29)-(2.30) compute the amount of thermal energy generated/withdrawn respectively of technologies of group L and of solar heating, where COP_{it} is the coefficient of performance for each conversion technology i and time slot tT, and $FEEDIN_{Hkt}$ is the normalized feed-in for node k producing thermal energy passively from external sources.

$$\sum_{i \in M_T(k)} q_{ikt} = H_{kt} \ \forall k \in R, \forall t \in T \tag{2.27}$$

$$-y_{ij(i)} \leq x_{ij(i)t} \leq 0 \ \forall i \in L, \ \forall j \in N, \ \forall t \in T \tag{2.28}$$

$$q_{ik(i)t} = -x_{ij(i)t} COP_{it} \ \forall i \in L, \forall j \in N, \forall k \in R, \ \forall t \in T \tag{2.29}$$

$$q_{Hkt} = -y_{Hk} FEEDIN_{Hkt} \ \forall k \in R : H \in M_T(k), \forall t \in T \tag{2.30}$$

The thermal storage in each node k is characterized by a minimal and maximal storage energy capacity, denoted by W_{Sk}^{min} and CAP_{Sk}, respectively. Efficiency parameters η_{Sk}^c, η_{Sk}^d and η_{Sk}^s are associated with charge, discharge, and for hourly standing, respectively, for storage at each node k. Constraints (2.31)-(2.33) limit the amount of energy used to charge/discharge the thermal storage, and the maximal energy capacity w_{Sk}^{max} for a thermal storage located at a node k. Constraints (2.34) define the amount of thermal energy generated/withdrawn for storage systems. Constraints (2.35) limit the energy stored in thermal storage systems h_{Skt} located at a node k during time slot t, to maximum and minimum values, while constraints (2.36)-(2.37) state the energy stored in thermal storage systems for the first time period to the given value W_{Sk0}, and for all the other time periods.

$$0 \leq q_{Skt}^d \leq y_{Sk} \ \forall t \in T, \forall k \in R : S \in M_T(k) \tag{2.31}$$

$$-y_{Sk} \leq q_{Skt}^c \leq 0 \ \forall t \in T, \forall k \in R : S \in M_T(k) \tag{2.32}$$

$$w_{Sk}^{max} = CAP_{Sk} y_{Sk} \ \forall k \in R : S \in M_T(k) \tag{2.33}$$

$$q_{Skt} = q_{Skt}^d + q_{Skt}^c \ \forall t \in T, \forall k \in R : S \in M_T(k) \tag{2.34}$$

$$W_{Sk}^{min} \leq h_{Skt} \leq w_{Sk}^{max} \ \forall t \in T, \forall k \in R : S \in M_T(k) \tag{2.35}$$

$$h_{Sk0} = W_{Sk0} \ \forall k \in R : S \in M_T(k) \tag{2.36}$$

$$h_{Skt} = h_{Sk,t-1} \eta_{Sk}^s - \frac{q_{Skt}^d}{\eta_{Sk}^d} - q_{Skt}^c \eta_{Sk}^c \ \forall t \in T, \forall k \in R : S \in M_T(k) \tag{2.37}$$

Moreover, for each power plant $i \in Q$ the backpressure coefficient BPC_i is given. Constraints (2.38) limit the amount of electric energy converted to thermal energy for technologies of group Q, while constraints (2.39) define this value.

$$0 \leq x_{ij(i)t} \leq y_{ij(i)} \ \forall i \in Q, \ \forall j \in N, \ \forall t \in T \tag{2.38}$$

$$q_{ik(i)t} BPC_i = x_{ij(i)t} \ \forall i \in Q, \ \forall j \in N, \ \forall k \in R, \forall t \in T \tag{2.39}$$

The following constraints (2.40)-(2.45) define the variables of the problem.

$$0 \leq x_{ijt} \leq y_{ij} \ \forall j \in N, \forall i \in M(j), \forall t \in T \tag{2.40}$$

$$z_{jt} \ \lesseqgtr \ 0 \ \forall j \in N, \forall t \in T \tag{2.41}$$

$$f_{et} \ \lesseqgtr \ 0 \ \forall e \in E, \forall t \in T \tag{2.42}$$

$$x_{Bjt} \ \lesseqgtr \ 0 \ \forall j \in N : B \in M(j), \forall t \in T \tag{2.43}$$

$$x_{Skt} \ \lesseqgtr \ 0 \ \forall k \in R : S \in M_T(k), \forall t \in T \tag{2.44}$$

$$0 \leq u_g \leq 1 \ \forall g \in E_{cand} \tag{2.45}$$

Finally, the objective function (2.46) minimizes the total costs calculated through constraints (2.1)-(2.4).

$$\min \quad c_{PROD} + c_{INST} + c_{TRAN} + c_{SLACK} \tag{2.46}$$

Table 2.1 summaries all the elements of the model.

Table 2.1: Sets, parameters and variables of the model

Sets	
$t \in T = \{1, ..., \Theta\}$	Set of time slots
$j \in N = \{1, ..., n\}$	Set of nodes
$I = \{W, O, P, B, F\}$	Set of technologies
$M(j) \subseteq I$	Subset of technologies available at node $j \in N$
$e \in E = \{1, ..., m\}$	Set of edges
$k \in R = \{1, ..., r\}$	Set of thermal nodes
$J = \{H, S\}$	Set of purely thermal technologies (H stands for solar heating, S for thermal storage)
$L = \{i = (k(i), j(i))\colon k(i) \in R,\, j(i) \in N\}$	Set of technologies converting electric energy from node $j \in N$ to heat for node $k \in R$
$Q = \{i = (k(i), j(i))\colon k(i) \in R,\, j(i) \in N\}$	Set of technologies obtaining heat for node $k \in R$ while producing electric energy for node $j \in N$
$M_T(k) \subseteq J \cup L \cup Q$	Subset of technologies available at node $k \in R$
$g \in E_{cand} \subseteq E$	Set of candidate lines for transmission corridor expansion
Parameters	
C^p_{Bj}	Unit production cost to charge or discharge of battery at node j
C^p_{Fj}	Unit production cost of power plant at node j
η_{Fj}	Efficiency of power plant at node j
C^C_{ij}	Installation cost per unit of capacity of technology i at node j
Y^{max}_{ij}	Maximum capacity of technology i that can be installed at node j
C^V_g	Installation cost to build new line g
C^p_{Sk}	Unit production cost to charge or discharge at node k
C^p_{ik}	Unit production cost of thermal plant i at node k
C^-_j and C^+_j	Costs for power oversupply and deficit at node j
D_{jt}	Electric demand to be supplied at node j for time step t
E_g	Total emission related to installation of candidate line g
E^y_{ij}	Equivalent CO_2 emission per unit of capacity installed of technology i at node j
E^x_{ij}	Equivalent CO_2 emission per unit of power generated/withdrawn by technology i at node j
$FEEDIN_{ijt}$	Normalized feed-in for each technology i at node j at time slot t
CAP_{Bj}	maximum storage capacity that can be installed at node j
W^{min}_{Bj}	Minimum electric storage at node j
η^c_{Bj} and η^d_{Bj}	Efficiency to charge or discharge for battery at node j
F_e	Maximum capacity in terms of flow for edge e
c^T_e	Unit transmission cost of edge e
X_e	Line reactance p.u. of edge e
K_{je}	Incidence matrix for edge e and node j
C_{ec}	Cycle matrix for edge e and cycle c
H_{kt}	Thermal demand for node k and time step t
COP_{it}	conversion performance for technology i and time slot t
$FEEDIN_{Hkt}$	Normalized feed-in from external sources for node k
W^{min}_{Sk}	Minimum thermal storage at node k
CAP_{Sk}	Maximum thermal storage at node k
η^c_{Sk}, η^d_{Sk} and η^s_{Sk}	Efficiency for charging, discharging, and for hourly standing of thermal storage at node k
W_{Sk0}	Initial value of thermal storage at node k
BPC_i	Backpressure coefficient for each power plant i
Variables	
x_{ijt}	Amount of power generated/withdrawn by technology i at node j during time slot t
y_{ij}	Capacity installed for technology i at node j
s^-_{jt} and s^+_{jt}	Slack variables of over/under supply for time slot t and node j
u_g	Expanded fraction of candidate line along edge g
x^c_{Bjt} and x^d_{Bjt}	Amount of energy used to charge/discharge the battery at node j during time slot t
y_{ik}	Capacity installed for technology i at termal node k
q_{ikt}	Thermal energy generated/withdrawn by technology i at node k during time slot t
$x_{ij(i)t}$	Electric energy converted to heat from node j, through technology i during time slot t
q^c_{Skt}	Energy used to charge the thermal storage at node k during time slot t
q^d_{Skt}	Energy taken from the thermal storage at node k during time slot t
c_{PROD}	Total production cost
c_{INST}	Total installation cost
c_{TRAN}	Total transportation cost
c_{SLACK}	Total opportunity cost for undersupply/oversupply
c^T_{et}	Transmission cost for edge e during time slot t
e_{ij}	Total emissions at node j due to technology i
e_{ik}	Total emissions at node k due to technology i
$EMISSION_{total}$	Total CO_2 emissions
w^{max}_{Bj}	Maximum storage capacity of a battery installed at node j
h_{Bjt}	Energy to be stored in a battery located at node j during time slot t
f_{et}	Power flow along edge e during time slot t
w^{max}_{Sk}	Maximum energy capacity for thermal storage at node k
h_{Skt}	Thermal storage systems at node k during time slot t

2.4 Numerical tests

We tested the model on two instances on three types of hardware architectures, using in all cases Gurobi as LP solver. Table 2.2 reports the main characteristics of the instances and of the hardware, as well as the results obtained in terms of computing time. Obviously, the time needed to compute an optimal solution depends on the instance and the machine used. While a solution for instance IEEE-118 was found by all the three machines, when considering the larger instance (UC1-575), a solution could be found only using a large amount of memory, as the one available on machine IAEW.

Instance IEEE-118 was used for preliminary tests, which confirmed the relevant role of renewable sources and storage systems: in particular, 49.75% and 29.1% of the maximum capacity was installed, respectively. Instance UCI-575, represents a more realistic case, associated with Germany in year 2050. The optimal solution has a total cost of operation and expansion equal to 38.26 billion Euros p.a. The more significant capacity expansion is experienced in wind power (205 GW) and photovoltaic power (402 GW), while storage systems and conventional power plants are expanded by 61 GW and 86 GW, respectively. We notice that 99.5% of the demand is fulfilled, with a contribution of 84% given by renewable sources. A large percentage of CO_2 emissions is produced by gas-fired power plants (66%), closely followed by grid expansion (23%).

Table 2.2

Instance	Electric nodes	Electric branches	Heat nodes	Storages	Time steps	Variables	Constraints
IEEE-118	118	165	296	106	8760	2.11e7	2.84e7
UCI-575	575	802	755	465	8760	6.87e7	9.35e7

	IEE-118	UC1-575	cpu	ram	os
LAPTOP (4 cores)	3:42h	Does not compute	Intel Core i7-7700HQ 2.80GHz	32 GB	Windows10
CLAIX2018 (16 cores)	2:10h	Does not compute	2x Intel Skylake	192 GB	Linux
IAEW (16 cores)	1:26h	11:25h	up to 2x56 threads	up to 1 TB	Linux

2.5 Conclusions and future developments

We proposed an LP model for the Central Energy System expansion planning, that minimizes both the operational cost and the installation cost. The model imposes limitations on the allowed CO_2 emissions, while satisfying the customers' demands. Moreover, the costs of oversupply or shortage are considered. To ensure that the proposed generation operations are compatible with the network, the problem takes

into consideration also a preliminary analysis of the expansion of the transmission network.
Moreover, we conducted some tests on two different instances, to detect the effectiveness of the methodology proposed, using Gurobi as a solver and three different types of machines. The results showed the high dependency of the memory required to find an optimal solution, on the number of time steps and number of cores used to solve the problem. In fact, while the smaller instance was successfully solved by all the machines, the larger one could be computed up to its optimum only by the machine with the larger memory available.
Finally, given the complexity of the problem and the size of the instances of real scenarios, a heuristic may be necessary to create more competitiveness from a computational point of view.
This is a preliminary work that requires additional research. From a modelling viewpoint, a further step in the direction of energy coupling consists in the integration of the gas network. From a computational perspective, the design and implementation of alternative solution methods, possibly based on the structure of the problem, could allow to solve larger instances and/or to reduce the computing time needed for obtaining an optimal (or near-optimal) solution.

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Chapter 3

A bottom-up optimization model for solar organic Rankine cycle in the context of transactive energy trading

[1] Solar Organic Rankine Cycles (ORC) based power production plants utilize solar irradiation for thermal power generation. Given the significant compatibility between the operating temperatures of solar irradiation based technologies and the temperature needs of the cycle, they can be a promising renewable technology. Moreover, their higher performance compared to steam Rankine cycles in small size applications, makes them interesting within the smart grid context and microgrid communities. In this study, we inspect the impact that this technology can have on the peer-to-peer trading application in renewable based community microgrids. Here the consumer becomes a prosumer (functioning both as energy producer and consumer), and engages actively in virtual trading with other prosumers at the distribution system level. Specifically, we concentrate on a microgrid where the solar ORC is combined with a storage system, to fulfill the final consumer's demand. In fact, the combination of these plants with storage systems is fundamental to increasing their predictability and competitiveness with conventional plants, but it is quite challenging from a management perspective. Thus, we develop a methodology based on operations research techniques to use this system at its optimal point. Moreover, we investigate how different technological parameters of the solar ORC may affect the final solution. Finally, we study the value of the solar ORC in the transactive energy trading context under different configurations and scenarios. The results highlight an overall gain in the implementation of a predictable and man-

[1] The results of this chapter appear in [28]

ageable system as the one we present in this paper for a P2P transactive energy trading context, on average 16% in terms of operational costs.

3.1 Introduction

The new millennium has started with several innovations driven by the fast evolution of technologies in the energy sector [6]. The worsening of climate conditions has created a challenge for worldwide governments. Despite the implementation of new directives to limit the consequences of climate change, the most recent energy crisis highlighted the strong dependency that energy systems still have on conventional energy sources. Disruptive structural developments are still necessary to deliver on the European Union's COP21 commitments [1], COP23 commitments [29] and UN sustainable goals [2]. In this sense, the scientific community is addressing these issues with widespread approaches, but the common trend is described by the words energy efficient and environmentally friendly. Electricity production from solar energy has been proven to be a viable option for green energy production [30]. Because of its abundance and availability, new solutions are continuously studied, to fully exploit its potential. Some studies are based on the idea to exploit the full knowledge and experience gained over the last century on conventional power generation technologies and cycles, but in a greener decarbonized framework. For what solar energy is concerned, a valid solution is represented by Organic Rankine Cycles (ORCs). These cycles apply the same principles of a traditional steam Rankine cycle, replacing water as working fluid with an organic fluid. Moreover, such cycles give the possibility to select the best working fluid and plant size depending on the available heat source. The possibility to select the best working fluid depending on the available heat source and the plant size results in multiple advantages: (i) more efficient turbomachinery, (ii) limited vacuum at condenser and (iii) higher performance compared to both steam Rankine cycles and gas cycles especially for heat sources lower than 400°C and power output lower than 20 MW [31]. Therefore, it seems perfectly suitable in a framework where a conventional heat source is substituted by a renewable one, i.e., solar energy. In fact, solar-driven technologies such as parabolic trough collectors can effectively produce heat at temperatures between 50 °C and 400 °C [32]. The framework consisting of an ORC driven by a solar heat source is referred to in the literature as Solar Organic Rankine Cycle (Solar-ORC).

Another research trend in the energy scientific community is smart grids. In such a system, vast numbers of devices, passively connected to the grid, will become actively involved in system-wide and local coordination tasks [10]. In this context transactive energy trading emerges as a valid contender, to optimally coordinate such a complex scheme. The focus in this concept is mainly on the distribution level and its actors. Here, smart homes, buildings, and industrial sites engage in automated market trade with others at the distribution system level and with a two-way negotiation based on prices and energy quantities [10]. In the future trend consumers become prosumers who can both produce and consume energy, but most importantly supply other consumers on a local level. This transactive energy trading among prosumers is called Peer-to-Peer (P2P) energy trading [33]. P2P is a decentralized form of transactive energy trading where prosumers are given the opportunity to engage without the need for an intermediary. This way, renewable energy integration is promoted either by investments in locally distributed energy resources made by prosumers or encouraging consumers to purchase green energy locally, if they are incapable of investing in renewable energy sources. Although at the early stage, the P2P electricity trading without the need for utilities is expected to increase as the awareness of the shared economy has grown and the microgrid has spread [34]. The main advantages of this system are: the power generation can be made meeting the requirements of the end users and the utilization of the resources can be optimized through the cooperative network between producers and consumers [35].

The objective of this study is to investigate:

- The compatibility between ORC and solar technology in very different locations weather-wise, Tromsø and Bologna.
- The potential that the Solar-ORC coupled with a storage system could have on a P2P transactive energy trading context. Given the applications of this technology for reduced plant sizes, see Tartiere et al. [31], it seems suited for the self-consumption requirements of a prosumer in such a trading context.

Moreover, we want to develop a tool that can optimize the management of the system we are considering. We do so, by means of operations research based techniques. First, we develop a MILP model for the operations scheduling of the Solar-ORC, called the S-ORC model. Then, we develop an MILP model for the P2P Transactive Energy Trading between multiple prosumers in a local energy market where some Solar-ORCs are present as power generations plants owned by some prosumers, called the TET model.

The remainder of this chapter is organized as follows. Section 4.2 presents a literature review of the topics discussed in this paper, while Section 3.2.1 shows the novelty and key contributions of this work. Section 3.3 explains the main technical notes, assumption, and definitions, specifically in Section3.3.1 we focus on the Solar-ORC, while in Section3.3.2 we focus on the transactive energy trading part. Section 3.4 formally presents the S-ORC model and the TET model, discussed respectively in

Section3.4.1 and 3.4.2. Section 3.5 shows the computational experiments, specifically Section 3.5.1 presents a sensitivity analysis on the S-ORC model, while Section 3.5.2 and Section 3.5.3 discuss the computational experiments respectively on the S-ORC model and on the TET model. Section 3.6 contains further discussions and reflections on the computational results, while Section 3.7 outlines possible research perspectives. Finally, Section 3.8 draws conclusions.

3.2 Literature review

In this section, we discuss the main contributions related to transactive energy trading with a solar organic Rankine cycle problem. This analysis is functional to contextualize the results that will be consequently presented.

This paper combines the study of several topics, which in the past have been usually analyzed separately. Therefore, it seemed more functional to group all the contributions depending on the main topic they focus on, as one can observe in Table 3.1. We classify the literature based on the main modeling features of the treated problems.

	Transactive energy trading	Peer-to-peer	Organic Rankine cycle	Solar-ORC	Energy storage	Simulation models	Prescriptive analytics
[31]			✓	✓			
[36]			✓	✓		✓	
[37]			✓	✓		✓	
[10]	✓						
[38]	✓	✓					
[34]	✓	✓					
[39]	✓	✓					
[40]			✓			✓	✓
[41]			✓			✓	✓
[30]			✓	✓	✓	✓	
[42]					✓		
[43]			✓	✓	✓	✓	
[44]					✓	✓	✓
[45]					✓	✓	✓
[46]	✓	✓				✓	✓
[47]			✓	✓	✓	✓	
[48]			✓	✓	✓	✓	
[49]	✓	✓				✓	✓
[50]	✓	✓				✓	✓
[51]	✓	✓				✓	✓
[52]			✓		✓	✓	
[53]					✓	✓	✓
[54]			✓		✓	✓	
Our paper	✓	✓	✓	✓	✓	✓	✓

Table 3.1: Classification based on objective from the literature

The discussion surrounding energy systems decentralization has drawn much attention among researchers to look into transactive energy trading, especially in a P2P framework. Kok et al. [10] give an insight on the main coordination mechanisms of the smart grid vision, and on the role of transactive energy trading in this context. Zia et al. [38] highlight potential reasons for avoiding the use of centralized microgrid transactive energy system, and discuss existing architectures for a decentralized transactive energy system. Park et al. [34] provide a comprehensive review of the design of peer-to-peer markets, as well as their challenges and opportunities, while Zhang et al. [39] discuss existing P2P projects. The scientific community's significant interest in P2P energy trading, has produced different strategies to tackle this problem. Esmat et al. [50] propose a platform for a decentralized P2P trading based on two key layers. A market layer features a short-term multi-staged multi-period market with a uniform pricing mechanism. Then a blockchain layer offers a high level of automation, security, and fast real-time settlements through smart contract implementation. Mishra et al. [46] develop a multi-agent approach, where a math-heuristic model is used in the context of decentralized power distribution system. In their work Wang et al. [49] present a method based on the double auction market. Here each prosumer firstly dispatches its flexible energy resources with the objective of minimum cost, then the coordination of energy resources among diversified prosumers can be achieved with the aid of P2P energy transactions. Finally, Khorasany et al. [51] implement a platform, where prosumers with excess energy and consumers communicate with each other to maximize their welfare. A double auction with an average mechanism is applied to determine the allocation and price of energy.

The role of Solar-ORCs has been widely discussed in the literature. Zhao et al. [40] provide a detailed literature review on each design procedure of ORCs using artificial intelligence algorithms. While a comprehensive view of the ORC market is given by Astolfi et al. [31], explaining the main ongoing applications and the role of Solar-ORCs. Pierobon et al. [41] show a multi-objective optimization with a genetic algorithm for the optimal design of ORCs. Other papers study specifically on Solar-ORCs, focusing on different aspects. Tchanche et al. Some works [36]- [37] investigate the impact of different organic working fluids on the plant's overall performance, while Chen et al. [48] introduce and evaluate using Aspen-HYSYS and MATLAB software, a Solar-ORC configuration where solar energy plays a key role in the production of energy and hydrogen fuel. Here the ORC is fed by a solar farm based on the parabolic trough solar collector (PTSC), and then a fraction of the electrical energy obtained is fed into an alkaline electrolyzer (AEL) to produce hydrogen fuel. Mehrpooy et al. [47] concentrate on the design optimization of the Solar-ORC, which is evaluated through a thermoeconomic performance. The optimal point was selected using TOPSIS decision making technique among the Pareto frontier of the genetic algorithm. Finally, Yu et al. [30] implement a simulation-based optimization model in Aspen HYSYS to optimize both the design and operation of a Solar-ORC.

One major challenge facing a solar driven energy source such as Solar-ORC, is the intermittency which makes it unreliable for steady energy supply. Through the energy storage concept, these renewable resources can be made to be reliable and steady energy sources [42]. The coupling of energy generation and storage has become a trend nowadays in the scientific community. Casati et al. [43] study the role of thermal energy storage for a Solar-ORC. Manfrida et al. [54] focus on a robust mathematical model of a Latent Heat Storage (LHS) system constituted by a storage tank containing Phase Change Material spheres. The model is simulated under dynamic (time-varying) solar radiation conditions with the software TRNSYS. Marefati et al.

[52] present the performance study of a Pumped-Hydro and Compressed-Air storage system, coupled with an organic Rankine cycle (ORC). Wang et al. [53] implement an LP optimization model for a combined heat and power (CHP) based DH system with RES and energy storage system (ESS). Finally some papers [45]-[44] propose optimization models that include battery degradation, and highlight its impact on having realistic performance of such systems.

While many works in the literature address some of the topics covered in this paper, the majority do it separately, featuring just some of them.
Therefore there exists a research gap in the form of:

- Technological representation of solar ORC in ways suitable for inclusion within mathematical optimization models for operational planning of energy systems.
- A practical understanding of the value of solar ORC in peer-to-peer interaction at the microgrid level.

To the best of our knowledge, the problem we introduce in this paper is the first to simultaneously feature a MILP model for transactive energy trading in a P2P context for a Solar-ORC coupled with a storage system.

3.2.1 Novelty and key contribution

The main contributions of this work can be divided into two categories: a methodological contribution and an analytical contribution.

From a methodology point of view, we propose a MILP model for Solar-ORCs coupled with a storage system that includes technological details. More specifically, the model considers detailed energy balances for the components of the cycle. It also contains thermodynamic properties of the fluid to see how different working fluids impact the performance of the plant. Moreover, battery degradation is also included, to optimize battery usage. Such a model is inserted in a wider optimization model for P2P transactive energy trading. Here several microgrids each of them representing a single prosumer, are able to exchange energy with each other. Both models can be used as stand alone models or can be easily included in large open source energy system models. Traditional energy systems models available in the literature, especially the largest ones, are usually technology agnostic, thus do not contain a detailed description of the technologies involved. In fact, technologies are usually treated as black boxes without considering technological features. This simplification may be functional for certain problems, and may be more competitive from a computational time point of view. However, including technological details can be the key to more realistic implementations and results. Moreover, having such details can open possibilities for new users, that specifically request such information.

The analytical contribution given by this paper is represented by an extensive sensitivity analysis. We first test different frameworks for the Solar-ORC with several working fluids and plant sizes. We implement this analysis to understand the general value of the Solar-ORC. Then we introduce the Solar-ORC in a P2P transactive energy trading framework to perform more analyses. The aim is to evaluate the value of such a system in this context and to better understand the benefit that this plant system could have on the community. We consider different scenarios, i.e. different energy communities. We create instances that represent domestic and, industrial users that can also be prosumers, thus satisfying their own demand. Finally, all the tests are repeated for different cities and different seasons of the year, to understand how the performance and value of the system may be affected.

3.3 Technical notes, assumptions, and definitions

In this section, we give an insight of which are the main technical aspects and assumptions concerning this work. Such insight is substantial for the reader to better understand the models that we propose later on. More specifically in section 3.3.1 the insight is referred to the Solar-Organic Rankine cycle, while in section 3.3.2 we focus on the transactive energy trading part.

3.3.1 Solar-Organic Rankine cycle

Solar-Organic Rankine cycles are characterized by using the sun as a source of thermal energy. In fact, a solar collector acts as an evaporator to heat the working fluid of the Rankine cycle. The use of solar irradiation for driving an ORC is a promising renewable energy-based technology due to the high compatibility between the operating temperatures of solar thermal collector technologies and the temperature needs of the cycle [55]. In fact, organic Rankine cycles usually operate at temperatures of up to 400 °C or 500 °C, which is perfectly compatible with thermal energy available from solar-based technologies.
The Solar-ORC scheme is depicted in Figure 3.1. The ORC sub-system consists of a pump, an evaporator, a turbine and a condenser. The organic working fluid is pumped from condensation pressure to evaporation pressure. After pumping, the organic working fluid is vaporized and superheated in the evaporator, using thermal energy supplied by solar panels. Next, the high temperature and high pressure vapor is expanded through the turbine to generate power. Finally, the working fluid is condensed in the condenser.

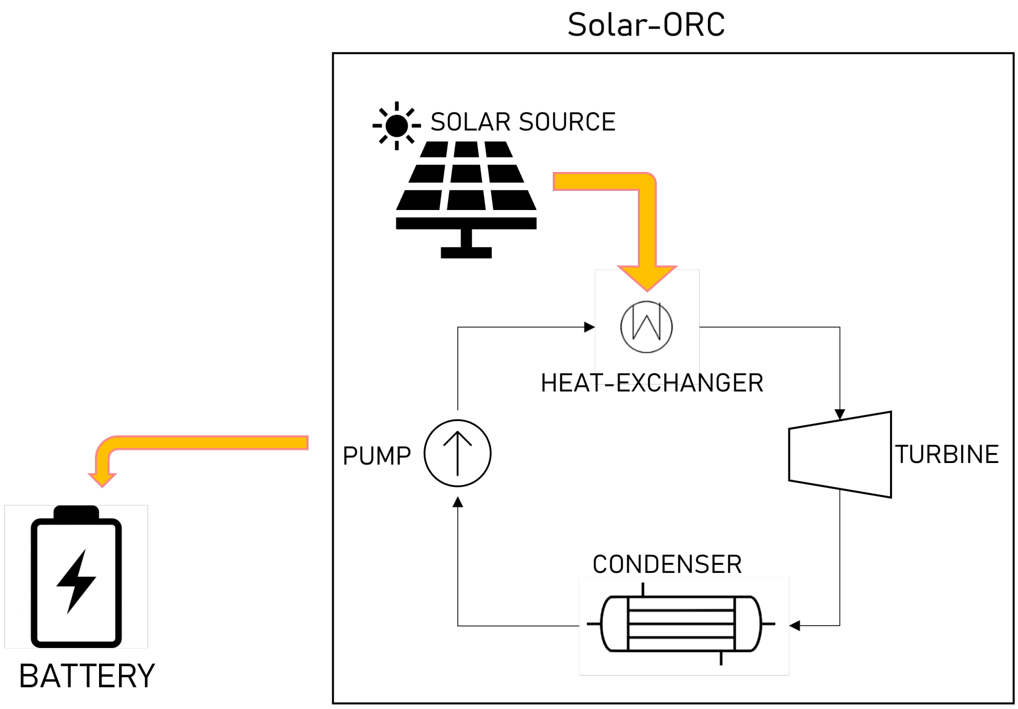

Figure 3.1: Scheme of the Solar-ORC

The scope of our research work is surrounding the economic operational optimization of the plant's scheduling. Thus, we include in our optimization process the components of the cycle, that are directly connected to the net power output of the plant, i.e., the pump, the turbine and the heat exchanger connected to the solar panels.

The regulation of the steam turbines is used at a constant velocity to adapt the power of the turbine. We assume to apply lamination as a regulation policy of the cycle. In this regulation the process is at constant enthalpy. By closing a valve, thus reducing the section area, at the entrance of the turbine the pressure of the steam is reduced, while the entropy rises. As the valve is closed, the constant enthalpy process occurs through the valve with an increase in entropy and a decrease in the availability of energy per unit of mass flow rate.

The thermodynamic properties of the working fluid are fundamental to determine the economics of an ORC. A bad choice could lead to a low efficient and expensive plant [36]. Thus, we include in our model a more detailed calculation of the mass flow rate of the working fluid, directly dependent on the type of organic fluid used. We choose to use density as the parameter representative of the thermo-

dynamic properties of the organic working fluid.
We present 9 different types of organic fluid, already well-known in the literature. These fluids are considered valid candidates. However, the methodology that we propose in Section 3.4 can be applied to any type of organic fluid.

Energy storage is an essential link in energy supply chain [42]. This is enhanced when it comes to most renewable energy resources, especially solar and wind. As a matter of fact, they occur intermittently, which makes them unreliable for a steady energy supply. If coupled with energy storage technologies, these renewable resources can increase their reliability.
Battery system technology is the most widespread energy storage device for power system application [56]. They seem to be a commonly applied solution lately to deal with renewable energy sources' instability. Nonetheless, the gain obtained in stabilizing the system may not be proportional to the increase in costs. In fact, the installation of batteries does not always automatically reduce the cost enough to pay for the installation [44]. Therefore, including an optimization of the storage system from a usage point of view, may be crucial to contain economic losses. In fact, the lifetime of a battery is highly influenced by the way it is operated, and by deterioration. Bad handling could result in more frequent substitutions of the battery, thus in higher costs.
The parameter that measures the life of a battery is called lifetime throughput. It defines the total dischargeable amount of energy in kWh, before it is no longer able to deliver energy, enough to satisfy the load requirements of the system. The residual number of cycles to failure is inversely proportional to the depth of discharge. Deeper discharge results in a lower number of related cycles to failure.
Another important parameter is the state-of-health of a battery. This is a percentage of the battery capacity available when fully charged relative to its rated capacity. The state-of-health accounts for battery aging. Manufactures guarantee that the capacity of the battery will not drop more than a certain percentage as long as the total energy drawn is kept within the lifetime throughput [45].
In our paper, we include both the lifetime throughput and the battery fade due to aging in our methodology. This way, the optimization process will avoid a non economically optimal use of the storage system.

3.3.2 Transactive energy trading

Transactive energy trading emerges as a valid option among smart grids handling tools. The concept of having local actors that handle the grid on a distribution level, opens the opportunity for consumers to be more active and involved. Considering that self-consumption has become greatly widespread, thanks also to incentives

given in the last decades by governments, the role of consumers has substantially changed. The so called prosumers are now important actors, that can no more be considered as passive entities. Especially, when the stability of the grid is involved, it becomes even more clear that new management options are necessary to deal with these deep changes in the grid's framework.
From the prosumers' point of view, especially those less experienced, having an automated market trade can be crucial. This way they can concentrate on the optimization of their own profit. In a self-consumption framework, the prosumers invest to fulfill their own consumption, usually using a renewable energy source. Thus, the profit comes mainly from handling his own demand. The possibility of selling overproduction to other prosumers, or buying when there's a lack of production, is a plus. In view of this concept, the goal of our work in the trading phase, is to only optimize the under/over supply of electricity among the micro-grids of our system. As we will discuss more in detail later on, this also will give us a great advantage from a computational point of view.

In this paper, we concentrate on short (hour)-medium (week) operational planning. We consider this to be more meaningful for the problem we are inspecting. Therefore, we concentrate on a weekly time range to lead computational experiments.

Figure 3.2 shows the scheme of the single microgrid that we want to optimize. The Solar-ORC is coupled with a battery, to fulfill the prosumer's demand. The grid is used to balance over/under supply by the Solar-ORC.

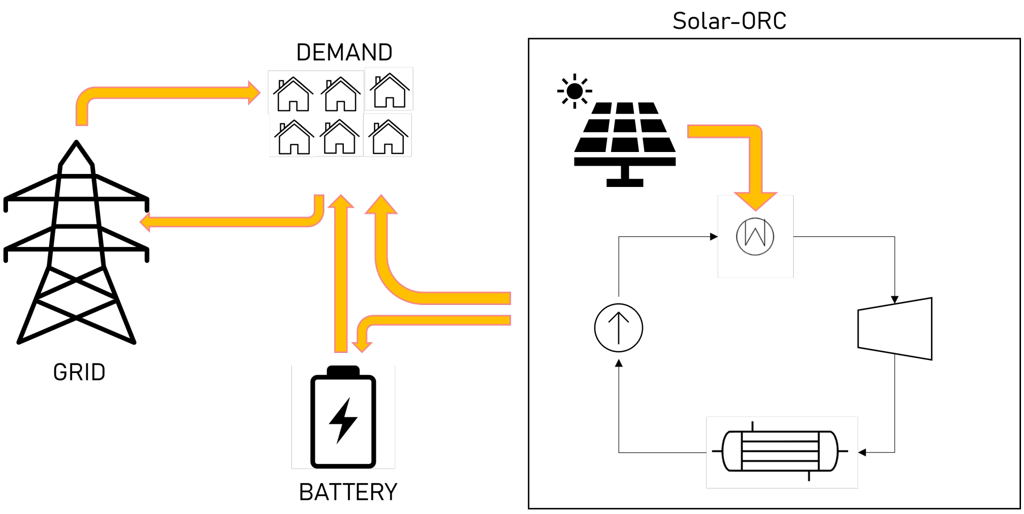

Figure 3.2: Scheme of the system considered

Figure 3.3 shows the total P2P transactive energy trading system that we want to optimize in our work. Here the microgrids that represent the single prosumers are able to interact with each other. The grid is used to balance the total over/under supply of the prosumers. The scheme is optimized considering virtual energy. In fact, the microgrids can be seen as VPPs.

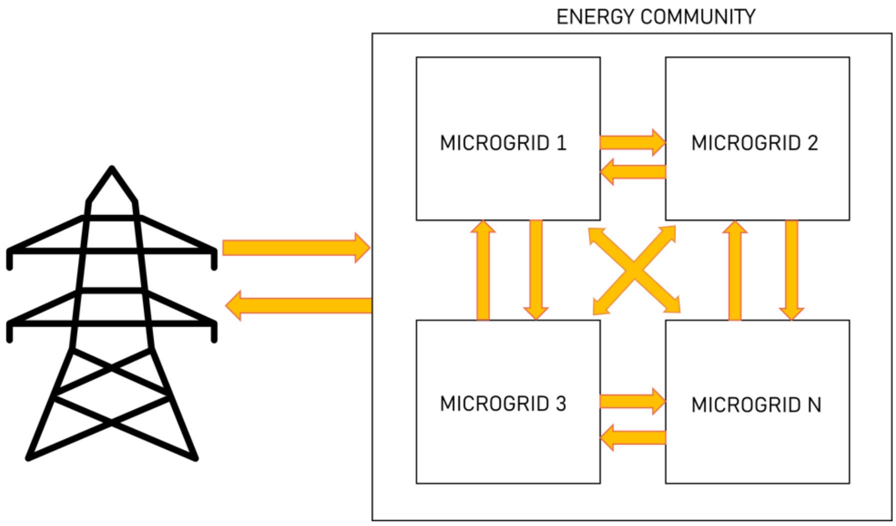

Figure 3.3: Scheme of the system used for the P2P trading

3.4 Methodology

In this section, we present the two MILP models that we used to optimize the problem previously presented. In section 3.4.1 we present an optimization model for the management of S-ORCs coupled with a storage system, called the S-ORC model. In section 3.4.2 we present an optimization model for Transactive Energy Trading, called the TET model, in a P2P context for a Solar-ORC coupled with a storage system. A list of acronyms is provided in table 3.2.

ORC	Organic Rankine Cycle
S-ORC	Solar-ORC
TET	Transactive Energy Trading
P2P	Peer-to-Peer
MILP	Mixed Integer Linear Programming

Table 3.2: List of acronyms

Table 4.1 summarises all the sets parameters and variables used in the S-ORC model and in the TET model.

Sets	
$t \in \{0, .., T\}$	Set of time intervals
$i \in N$	Set of microgrids
Parameters	
η_{th}	Efficiency of the heat exchanger
η_b	Charging/discharging efficiency of the storage system
η_I	Efficiency of the Solar-ORC
η_{solar}	Efficiency of the solar system
c_p	Cost of production
$c^t_{t,ij}$	Transmission cost from $i \in N$ to $j \in N$
c_b	Cost of charging/discharging
x_{min}	Minimum power boundary of the ORC
x_{max}	Maximum power boundary of the ORC
z_{min}	Minimum power boundary of the pump
z_{max}	Maximum power boundary of the pump
g_{min}	Minimum boundary of electricity that can be injected in the grid
g_{max}	Maximum boundary of electricity that can be injected in the grid
b_{min}	Minimum power boundary of the storage system
b_{max}	Maximum power boundary of the storage system
D^t	Demand of each $t \in \{0, .., T\}$
v	Velocity of the working fluid
A_{solar}	Area of the solar system
I^t_{solar}	Beam irradiation for every $t \in T$
f^{max}_{ij}	Maximum flux of electricity limit from prosumer $i \in I$ to prosumer $j \in J$
f^{min}_{ij}	Minimum flux of electricity limit from prosumer $i \in I$ to prosumer $j \in J$
ρ	Density of the working fluid
Δh_P	Enthalpy difference in the pump
Δh^t_T	Enthalpy difference in the turbine
B_{fade}	Battery fade in efficiency due to aging
$B_{throughput}$	Battery throughput
Variables	
g^t	Injection of electricity in $t \in \{0, .., T\}$
q^t_{in}	Thermal power coming from the heat exchanger for every $t \in \{0, .., T\}$
z^t	Power consumed by auxiliaries and pump in the ORC
b^t	Battery level for every $t \in \{0, .., T\}$
b^t_{in}	Power flow entering the battery for every $t \in \{0, .., T\}$
b^t_{out}	Power flow injected in the grid for every $t \in \{0, .., T\}$
b^t_{max}	Maximum capacity of the storage system
d^t	Storage system degradation
q^t_{solar}	Solar power injected in the heat exchanger for $t \in \{0, .., T\}$
x^t	Power produced by the Organic Rankine cycle for $t \in \{0, .., T\}$
m^t_{ORC}	Mass flow rate of the Organic Rankine Cycle for $t \in \{0, .., T\}$
A^t	Section area traversed by the mass flow rate for $t \in \{0, .., T\}$
f^t_{ij}	Flux of electricity sold from microgrid $i \in I$ to consumer $j \in J$
e^t_{in}	Electricity taken from the grid by the single microgrid every $t \in T$
e^t_{out}	Electricity sold to the grid by the single microgrid every $t \in T$
h^t_{in}	Electricity taken from the grid to balance the whole system every $t \in T$
h^t_{out}	Electricity sold to the grid to balance the whole system every $t \in T$

Table 3.3: Sets, parameters and variables used in the S-ORC model and in the TET model

3.4.1 S-ORC model

In the following, we present an optimization model for the management of S-ORCs coupled with a storage system, called S-ORC model.
The planning horizon is divided into $t \in T$ hourly intervals. Note that this can be adjusted to meet the needs of the application of the model. For each time interval, the final consumer's demand is given D^t. Several parameters are related to the thermodynamic characteristics of the system. The efficiency of the Solar-ORC is denoted by parameter η_I, while η_{th} is the efficiency of the heat exchanger. The maximum and minimum electric energy production limits of the Solar-ORC are x_{max} and x_{min}, whereas g_{max} and g_{min} limit the electricity available to be injected in the or needed by the system. In this sense, the grid is used in this model to balance the system in case of over/under production. Thus, the overproduction can be injected into the grid and vice versa underproduction can be withdrawn from the grid. The velocity v and density ρ of the working fluid are given, as the specific heating value $C_{P,ORC}$. The Solar-ORC is characterized by a temperature difference inside the pump ΔT_P and inside the turbine ΔT_T, whereas the efficiencies of the pump and the turbine are denoted as η_P and η_T.
The solar system is defined by the total area A_{solar} and the efficiency of the solar panel η_{solar}. For every time interval $t \in T$ the beam irradiation I^t_{solar} is given.
The storage system is defined by the charging/discharging efficiency η_b, and by a maximum and minimum limit the capacity, respectively b_{max} and b_{min}. We consider a battery as a storage system. To better evaluate the actual capacity of the battery, we introduce two parameters, the lifetime throughput of the battery $B_{throughput}$, and the battery fade B_{fade}. The lifetime throughput measures the life of a battery. It defines the total amount of energy in kWh that can be discharged before it cannot satisfy the load requirements of the system. Additionally, the battery fade is used to calculate the loss of capacity as the battery ages. The capacity of the battery will not drop more than a certain percentage, i.e. B_{fade} as long as the total energy drawn is kept within the lifetime throughput [45].
Every kWh of electricity produced by the Solar-ORC has a cost c_p while every kWh of electricity stored has a storage cost of c_b.

The objective of the model minimizes the total costs of production, given by the cost of production and the cost of storage. The electricity produced by the turbine of the Solar-ORC every time interval $t \in T$ is measured by variable x^t, while variables b^t_{in} and b^t_{out} measure the electricity respectively charged or discharged every $t \in T$.

$$\text{[S-ORC model] minimize} \sum_{t \in T} c_p x^t + c_b (b^t_{in} + b^t_{out}) \tag{3.1}$$

Constraints (3.2)-(3.4) define variable g^t, the electricity available to be used every

$t \in T$. Specifically, constraints (3.2) limit its capacity, while constraints (3.3)-(3.4) are energy balances on the system. Furthermore, variables e^t_{in} and e^t_{out} indicate the amount of electricity withdrawn or injected in the grid.

$$g_{min} \leq g^t \leq g_{max} \ \forall t \in T \tag{3.2}$$

$$g^t = x^t - z^t - \eta_b b^t_{in} + \frac{b^t_{out}}{\eta_b} \ \forall t \in T \tag{3.3}$$

$$g^t + e^t_{in} \geq D^t + e^t_{out} \ \forall t \in T \tag{3.4}$$

Constraints (3.5)-(3.7) describe the energy balances to define the actual electricity production of the Solar-ORC. More precisely constraints (3.5) connect the net energy produced, given by the subtraction of the energy produced by the turbine x^t and the one consumed by the pump z^t to the thermal energy coming from the heat exchanger for every $t \in T$. While constraints (3.6)-(3.7) measure the energy respectively produced by the turbine and consumed by the pump. Both these energies are regulated by the mass flow rate of the working fluid represented by variable m^t_{ORC}. The value of energy respectively produced by the turbine and consumed by the pump is limited by constraints (3.8)-(3.9).

$$x^t - z^t = \eta_I q^t_{in} \ \forall t \in T \tag{3.5}$$

$$x^t = m^t_{ORC} \Delta h_T \ \forall t \in T \tag{3.6}$$

$$z^t = m^t_{ORC} \Delta h_P \ \forall t \in T \tag{3.7}$$

$$x_{min} \leq x^t \leq x_{max} \ \forall t \in T \tag{3.8}$$

$$z_{min} \leq z^t \leq z_{max} \ \forall t \in T \tag{3.9}$$

$$\tag{3.10}$$

The mass flow rate of the working fluid for every $t \in T$ is calculated through constraints (3.11). Here variable A^t represents the actual section of the pipes, regulated every $t \in T$.

$$m^t_{ORC} = \rho A^t v, \ \forall t \in T \tag{3.11}$$

The solar system is managed through constraints (3.12)-(3.13). In fact, constraints (3.12) link the thermal energy provided by the solar panels to the thermal energy available at the heat exchanger of the Solar-ORC, whereas constraints (3.13) compute the thermal energy provided by the solar panels with respect to the beam radiation.

$$q^t_{in} \leq \eta_{th} q^t_{solar} \ \forall t \in T \tag{3.12}$$

$$q^t_{solar} = \eta_{solar} A_{solar} I^t_{solar} \ \forall t \in T \tag{3.13}$$

The battery management is provided by constraints (3.14)-(3.21). More specifically, constraints (3.14) measure the battery level b^t for each $t \in T$. At the beginning of the time horizon considered the energy stored in the battery and the energy withdrawn from it are both set to zero by constraints (3.15)-(3.16). The presence of variables y^t_{in} and y^t_{in} in constraints (3.17) guarantee that there is no simultaneous withdrawal and injection happening in the battery for every time step $t \in T$. In fact, y^t_{in} and y^t_{out} represent binary variables that take the value 1 if energy is respectively injected in or withdrawn from the battery in $t \in T$ and 0 otherwise.

$$b^t = b^{t-1} + \eta_b b^t_{in} - \frac{b^t_{out}}{\eta_b} \ \forall t \in T \tag{3.14}$$

$$b^0 = 0 \tag{3.15}$$

$$b^0_{out} = 0 \tag{3.16}$$

$$y^t_{in} = 1 - y^t_{out} \ \forall t \in \{0, .., T\} \tag{3.17}$$

$$b^t_{out} \leq b_{max} y^t_{out} \ \forall t \in \{0, .., T\} \tag{3.18}$$

$$b^t_{in} \leq b_{max} y^t_{in} \ \forall t \in \{0, .., T\} \tag{3.19}$$

The following set of constraints accounts for the degradation of the battery in time. Constraints (3.20) computes the degradation factor in each $t \in T$, which is then applied to the maximum capacity limit in constraints (3.21). Finally, constraints (3.22)-(3.23) limit the energy withdrawn/injected every $t \in T$.

$$\frac{B^{fade}}{B^{throughput}} |b^t - b^{t-1}| \leq d^t \ \forall t \in T \tag{3.20}$$

$$b^t_{max} \leq d^t b_{max} \ \forall t \in T \tag{3.21}$$

$$b_{min} \leq b^t_{in} \leq b^t_{max} \ \forall t \in T \tag{3.22}$$

$$b_{min} \leq b^t_{out} \leq b^t_{max} \ \forall t \in T \tag{3.23}$$

Finally, constraints (3.24)-(3.26) define the variables.

$$x^t, z^t, b^t, b^t_{in}, b^t_{out}, e^t_{in}, e^t_{out}, q^t_{in}, q^t_{solar}, m^t_{ORC} \ \geq 0 \ \forall t \in T \tag{3.24}$$

$$g^t \lesseqgtr 0 \ \forall t \in T \tag{3.25}$$

$$0 \leq y^t_{in}, y^t_{out} \leq 1 \ \forall t \in T \tag{3.26}$$

3.4.2 TET model

In the following, we present an optimization model for Transactive Energy Trading, called the TET model, in a P2P context for a Solar-ORC coupled with a storage system. The TET model is implemented after the S-ORC model to optimize the P2P trading among microgrids. In this sense, a set N of participants in the trading is defined. The participants are essentially consumers or prosumers that can participate as part of the demand, as part of the providers or both for every time step t in which the time range T is divided. The S-ORC model is solved in parallel for every participant, calculating the imbalances produced by over/underproduction of each system. These imbalances were handled in the S-ORC model by the grid, through variables e^t_{out} and e^t_{in}. The optimal values of these variables produced by the S-ORC model are then optimized by the TET model. In fact, they are used as parameters $e^t_{j,out}$ and $e^t_{j,in}$. More precisely $e^t_{j,in}$ is the energy needed by participant $j \in N$, while $e^t_{j,out}$ that can be traded by participant $j \in N$. The variables that represent the fluxes of energy that move among participants $j \in N$ every time step $t \in T$ are computed by variables f^t_{ij}. The grid is used once again to deal with imbalances. However, this time such imbalances concern the whole system and not the single participant. The pseudo-code of this process are shown in Algorithm 1.

```
Input: Set of participants N and set of time steps T;
for j ∈ N do
    Input: Parameters for the S-ORC model;
    Solve the S-ORC model;
    Output: e^t_{j,out} and e^t_{j,in}
end
Input: For every j ∈ N and t ∈ T e^t_{j,out} and e^t_{j,in};
Solve the TET model;
Output: Optimal solution for the TET model
```

Algorithm 1: Pseudo-code of the solving procedure

The methodology described is functional to the problem we are trying to solve. In fact, we want each single prosumer to first fulfill their own demand, and then to think about trading of residual capacity. Therefore, it seemed more practical to avoid a single optimization model that contained both the TET model and the S-ORC model.

The objective of the TET model (3.27) aims to minimize the overall costs of the trading system. Such costs are represented mainly by transmission costs given by parameter c^t_T for every kWh that goes from participant $i \in N$ to participant $j \in N$ every $t \in T$.

$$\text{[TET model] minimize} \sum_{t \in T} \sum_{i \in N} \sum_{j \in N} c^t_{T,ij} |f^t_{ij}| \tag{3.27}$$

Constraints (3.28)-(3.29) balance the energy sold to another participant or bought from another participant for every participant $i \in N$ and $j \in N$, every time step $t \in T$.

$$\sum_{j \in N} f^t_{ij} \geq e^t_{j,out} \ \forall t \in T, , \ \forall i \in N \tag{3.28}$$

$$\sum_{i \in N} f^t_{ij} \geq e^t_{j,in} \ \forall t \in T, , \ \forall j \in N \tag{3.29}$$

Constraints (3.30) balance the overall system with the grid, to control over/under production.

$$h_{in}^t + \sum_{i \in N} \sum_{j \in N} f_{ij}^t = h_{out}^t \; \forall t \in T \tag{3.30}$$

Constraints (3.31) limit the fluxes between all the participants $i, j \in N$ to a minimum and a maximum value, i.e f_{ij}^{min} and f_{ij}^{max}, every time step $t \in T$.

$$f_{ij}^{min} \leq f_{ij}^t \leq f_{ij}^{max} \; \forall t \in T, \; \forall i \in N, \forall j \in N \tag{3.31}$$

Finally constraints (3.32)-(3.33) define the variables.

$$f_{ij}^t \lesseqgtr 0 \; \forall i, j \in N \; \forall t \in T \tag{3.32}$$

$$h_{in}^t, h_{out}^t \geq 0 \; \forall t \in T \tag{3.33}$$

3.5 Computational experiments

In this section, we will present the results obtained by the computational experiments. The computational experiments have been done with four threads with 8 GB, on a computer having 4 cores and a processor Intel(R) Core(TM) i5-7200U @2.50 GHz. All the tests were performed using Gurobi 9.1.2 [57] as solver. The models were implemented using the JuMP package of Julia [58].

3.5.1 Sensitivity analysis on the S-ORC model

In this Section, we present the results obtained by performing a sensitivity analysis on the S-ORC model. This was done to inspect, how changing some specifics of the Solar-ORC would affect the system. The demand is represented by an industrial plant, that uses the Solar-ORC in a self-consumption setting. We solve every instance considering a time horizon of one week, with hourly intervals. All the instances presented, where solved within 0.06 seconds. First, we tested the model using 9 different types of working fluids for the Solar-ORC, to detect the effects that this might have on the mass flow rate. The working fluids have different specifics that are shown in Table 3.4.

Fluid	Molecular Weight [kg/mol]	T_{crit}[°C]	P_{crit}[MPa]	C_p [J/kg °C]	Density [kg/m$\hat{3}$]
Ethanol	0.046	240.8	6.148	2432	0.253100481
Methanol	0.032	240.2	8.104	2512	0.369822485
Cyclohexane	0.084	280.5	4.075	154.37	0.632911392
R134a	0.102	101	4.059	1268	0.8838
R141b	0.11695	204.2	4.249	895	0.195
RC318	0.2	115.2	2.778	898	0.028
R114	0.17	145.7	3.289	845	0.05
R113	0.187	214.1	3.439	867	0.215
R32	0.052	78.11	5.784	848	0.011

Table 3.4: Working fluids thermodynamic properties

Figure 3.4 shows the mass flow rate needed using different fluids for a 2 kW Solar-ORC, considering the same working conditions. As one can observe working fluids like Ethanol, Methanol, Cyclohexane and, R134a need a lower mass flow rate. Thus, from an economic perspective, these fluids can be interesting, especially for large capacity systems.

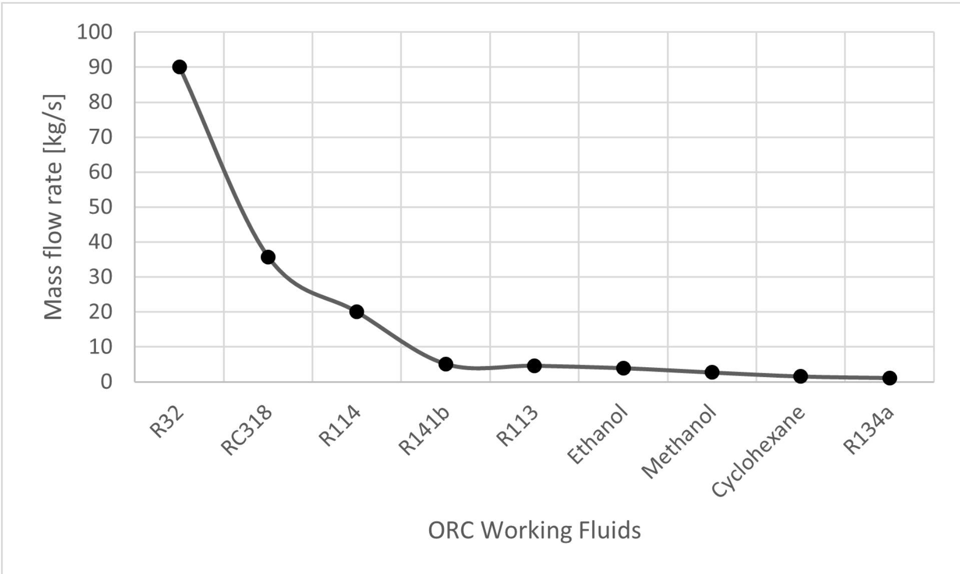

Figure 3.4: Mass flow rate for different type of working fluids

Subsequently, we analyzed the consequences on the system's performance by considering 9 different sizes of the ORC, shown in Table 3.5.

Size [kW]
0.5
1
1.5
2
2.5
3
3.5
4
4.5

Table 3.5: Organic Rankine Cycle sizes

Figure 3.5 shows the difference in objective function considering Ethanol as working fluid. As one can observe, the objective decreases by increasing the size of the plant, up to a certain threshold. The decrease in the objective is due to a decrease in the electricity provided by the grid, to satisfy the final consumer's demand. When the optimal size to satisfy such demand is reached, there is no economic benefit to increase the plant's size further. This is consistent with the self-consumption framework that we are considering.

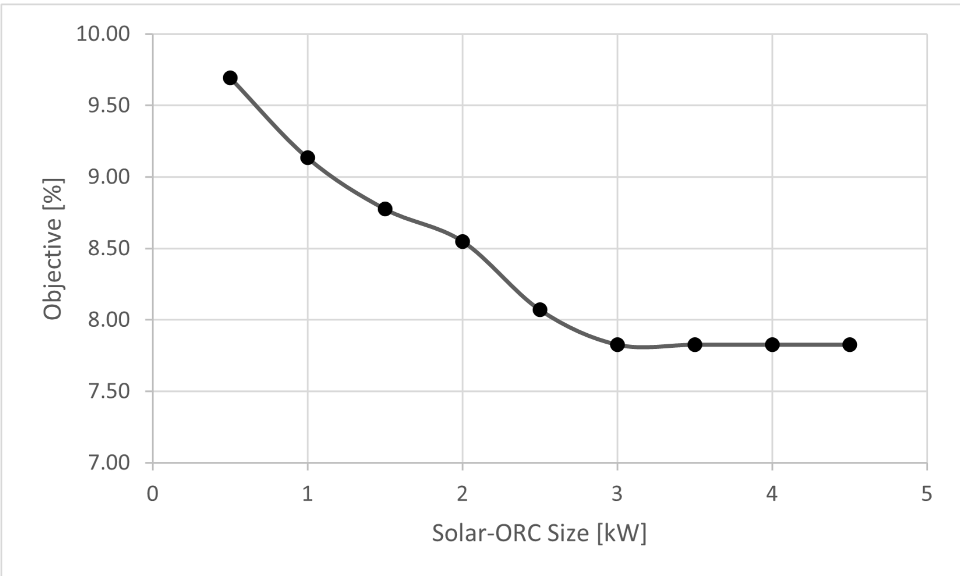

Figure 3.5: Objective difference with the size of Solar-ORC

Later we inspected the effect of weather conditions on the system. We detected four representative weeks in the months of April, July, October, and January. Moreover, we considered two locations for the system: the city of Bologna in Italy, and the

city of Tromsø in Norway. These cities represent two completely opposite scenarios, that could both potentially benefit from the system considered. In fact, Bologna (44.4949° N, 11.3426° E) is located in the northern part of Italy in Emilia-Romagna region. It has a typically humid temperate climate with cold, humid winters and hot, muggy summers. Precipitation is moderate, while the rains are fairly well distributed throughout the year, even if two maxima are noted in spring and autumn, and two relative minima in winter and summer. On the other hand, Tromsø (69.6492° N, 18.9553° E) is a city in Northern Norway located in the county of Troms and Finnmark. It is subject to a subarctic climate, with very cold winters and cool summers. Since we are north of the Polar Circle, the sun does not rise (polar night) from November 28th to January 14th, while it does not set (midnight sun) from May 19th to July 26th.
We present results for a 2 kW Solar-ORC using Ethanol as working fluid. We make the hypothesis of considering the same cost of electricity sold by the grid both in Bologna and Tromsø. This is done to highlight the real difference in terms of solar incidence between these two locations. This hypothesis stands for all the following tests unless specified.

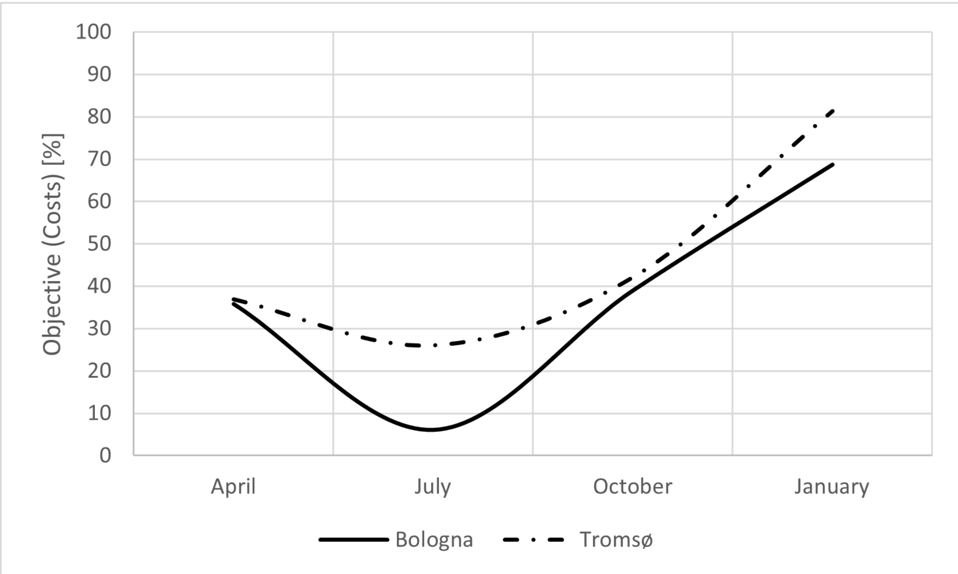

Figure 3.6: Comparison of objectives for two different locations for four significant weeks

As shown in figure 3.6 Bologna as a location gains a higher economic advantage than Tromsø, regardless of the season. However, this advantage is more significant during July and January. This is consistent with the weather conditions in Tromsø during winter, with almost no solar incidence. Moreover, regardless of the midnight sun phenomenon occurring in Tromsø during summer, the solar incidence in Bologna

is still higher due to its latitude.
We introduce also two more representative weeks in December and August, as shown in Figure 3.7. In fact, we want to inspect further possible minimum and maximum points. As one can observe, while the real minimum point is going to be between the last week of July and the first of August for both cities, the real maximum point is more evident in December for Tromsø than it is for Bologna where December and January are almost equivalent.

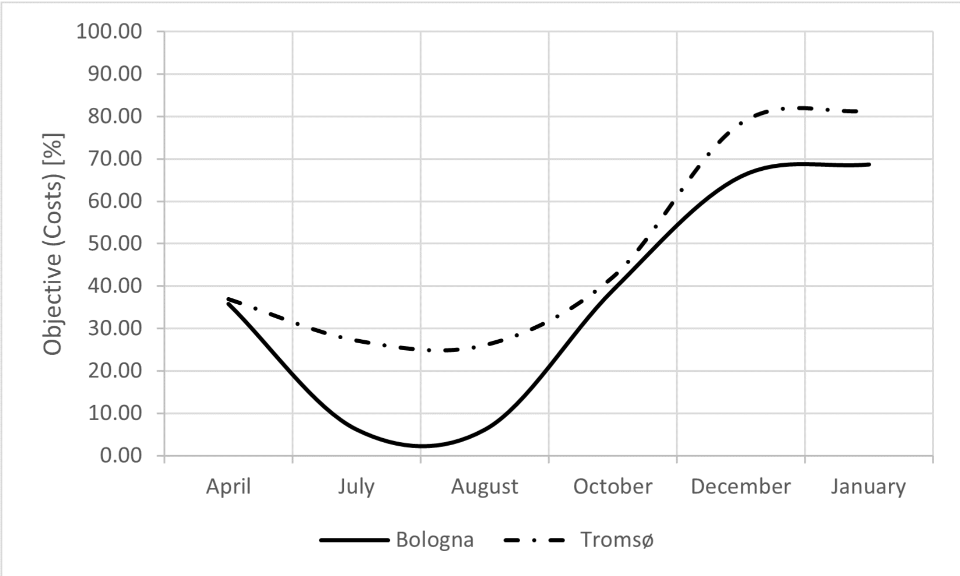

Figure 3.7: Comparison of objectives for two different locations for six significant weeks

3.5.2 Computational experiments on the S-ORC model

In this Section, we present results given by testing the S-ORC model. The results shown are referred to the city of Bologna. Figure 3.8 and figure 3.9 show the results given by the model in terms of Solar-ORC production, electricity withdrawn from the grid and battery usage.

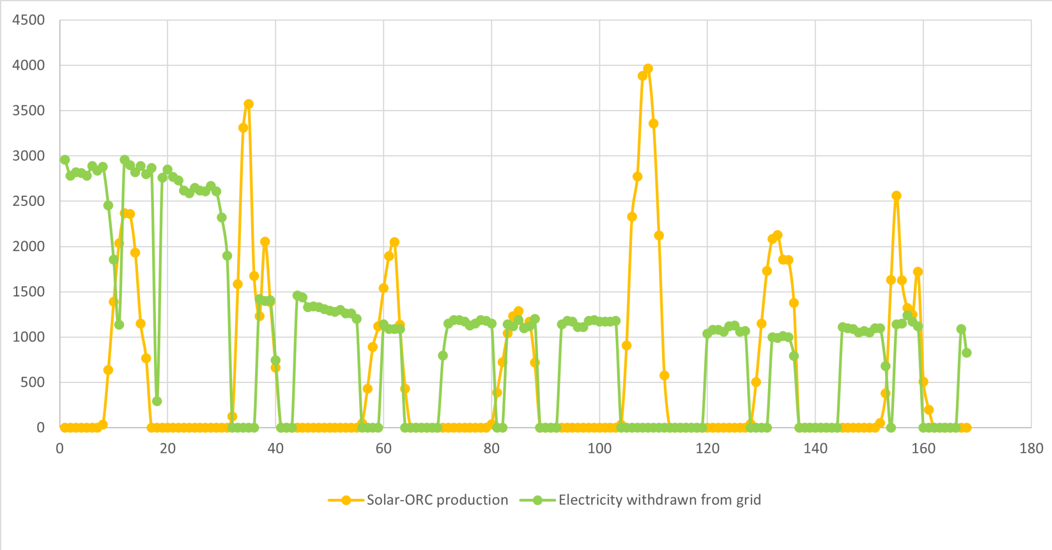

Figure 3.8: Solar-ORC production and electricity withdrawn from the grid for the city of Bologna

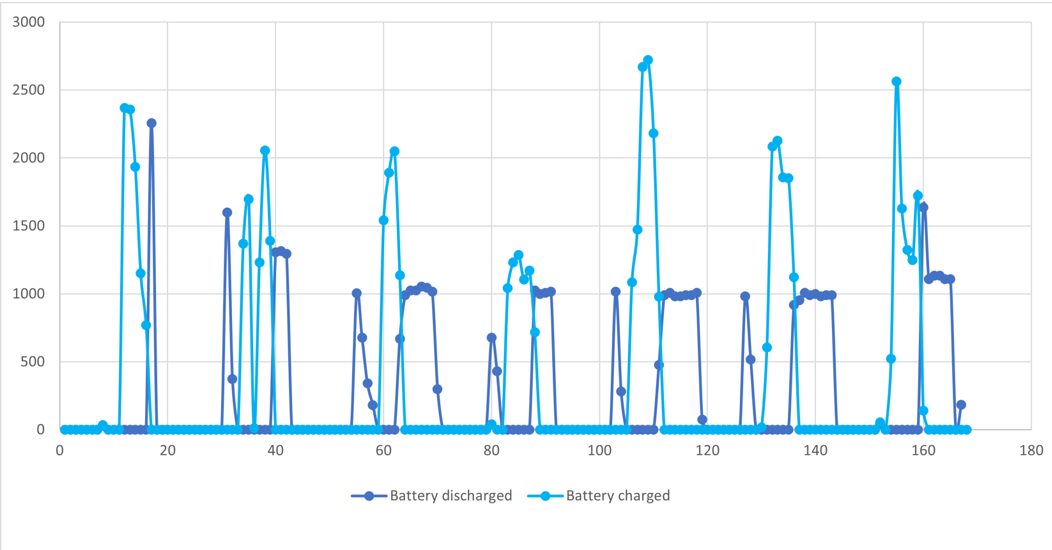

Figure 3.9: Battery charge and discharge for the city of Bologna

As one can observe in Figure 3.8 the grid is used by the S-ORC model to compensate for the lack of production by the Solar-ORC. Specifically, it is used most during the first time periods when there is no solar energy available and the battery is still not charged. This behavior is consistent with the realistic management of the plant. Moreover, as shown in Figure 3.9 usage of the battery is accordingly to its charging operations. In fact, the withdrawal from the battery starts consequently to charging operations, meaning there is actually available energy in the storage system.

3.5.3 Computational experiments on the TET model

A second step was to inspect the role that the Solar-ORC can potentially have when introduced in a peer-to-peer context. We tested the TET model with multiple instances. Each instance represents a different energy community. At first, we consider an instance that is described in Figure 3.10. Here, the components of the system are partly consumers and partly prosumers. The prosumers are supplied energy by a Solar-ORC in a self-consumption framework, thus the Solar-ORC should first satisfy their demand and then the other consumers' demand. We introduce different types of demand, i.e. industries (that work 24/7) and households.

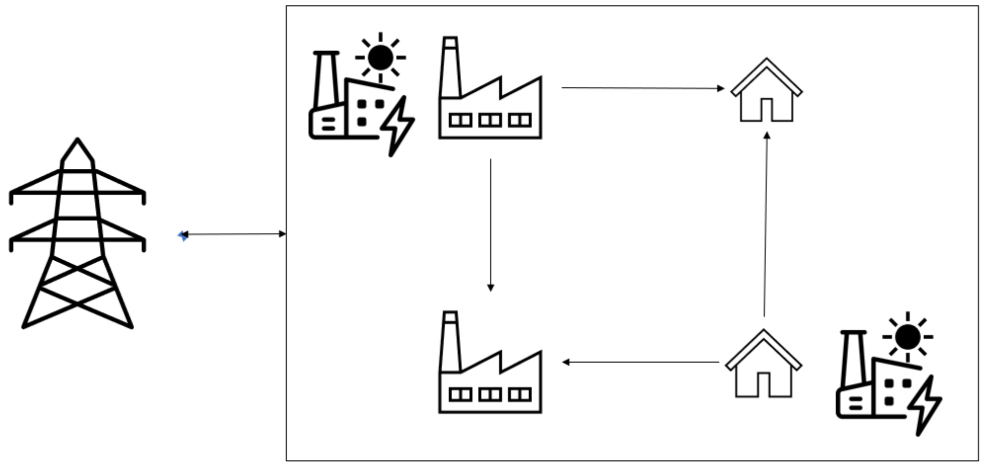

Figure 3.10: Sytem with different types of consumers, some of them being prosumers supplied by a Solar-ORC

Then, we consider an instance where all the consumers become prosumers, each of them being supplied by a different Solar-ORC. The system of the instance is represented in Figure 3.11.

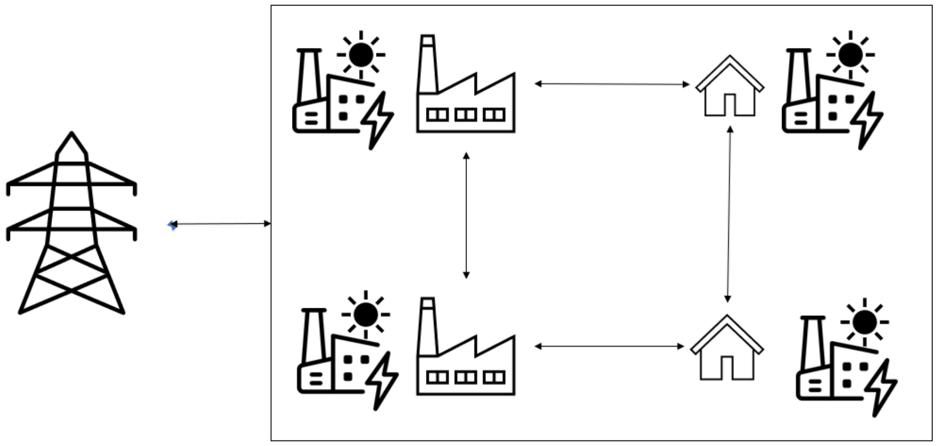

Figure 3.11: Sytem where all consumers are prosumers supplied by a the Solar-ORC

The results of such instances are shown in Figure 3.12.

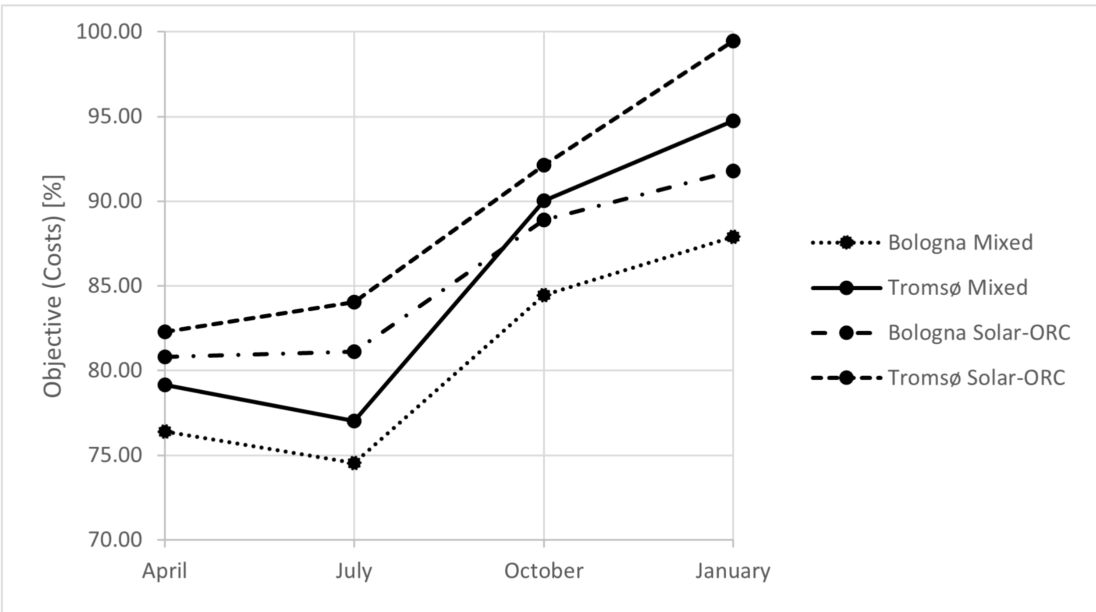

Figure 3.12: Results from the TET model tested on different instances

The introduction of Solar-ORC in a P2P trading context results in a economic gain of averagely 4%, compared to having a single Solar-ORC. The tests show a higher gain in terms of total operational costs for the Bologna location, on average 4.5%. This is coherent with the results obtained by the S-ORC model, as shown previously. The results obtained in Bologna by the S-ORC model are still better in terms of operational costs than the ones obtained in Tromsø by the TET model. This is justified by the latitude of Bologna and its greater solar irradiation. Moreover, the gain increased during the summer and spring seasons, in both locations. This is also consistent with the higher solar activity of such periods, as previously discussed.

3.6 Discussions

In this section, we discuss further the results presented in section 3.5. The results show that both the S-ORC model and the TET model produce realistic solutions. The use of Solar-ORC resulted in an improvement of 12% on average (10% for Tromsø and 14% for Bologna) in terms of operational costs, compared to not using such technology. Moreover, when introduced in a P2P trading context the improvement is even greater, around 16% on average (19% for Bologna and 14.7% for Tromsø). These solutions change reasonably with the weather conditions both in terms of latitude and season. In fact, given the same cost of electricity, Bologna tends to have greater economic gain compared to Tromsø. The difference in varies between 1% and 20%, with a medium value of 11.72%. This is consistent with the difference in solar incidence that these two locations have, because of their latitude. Furthermore, this difference is enhanced during the winter season, especially in December and January, where the difference in terms of costs is around 20%. As a matter of fact, during these months Tromsø is subject to the "Polar Night" phenomenon, with almost 24 hours of darkness. On the contrary, during springtime, the difference in the objective is almost none, around 1%, consistently with the weather in Bologna being often cloudy.

Concentrating just on the Tromsø instance, one can observe that the results change when taking into account local electricity prices. In fact, the objective values are drastically decreased due to lower local electricity prices, especially during summer when they are extremely low. Given that the electricity prices in Norway are significantly lower than in Italy, especially during summer, it might seem not much convenient to invest in a renewable energy source such as Solar-ORC. However, recently new studies, i.e. Nguyen et. al [59], have concentrated on solar power systems in this area, showing how Tromsø may profit from them. According to Eikeland et. al [60], the energy production of these systems could be coupled with Cruise ships' energy consumption. Cruise ships have a great demand, that needs to be fulfilled even when they are located in a harbor. If the energy supply from the harbor is not sufficient, the ships need to run their own motors to operate, thus producing a great environmental impact. Furthermore, Eikeland et. al [60] state that the highest number of visiting Cruise ships (C.S) is during the tourist season in June, July and August. This period coincides with the "Midnight Night" phenomenon in Tromsø, with almost 24 hours of solar power availability.

Another way to increase the exploitability of this technology in artic areas like Tromsø, could be the coupling with seasonal storage. Considering the before mentioned peculiar climate of this area, long-term storage seems even more appropriate. This way, the great solar energy availability in summer would be exploited also during winter. Thus, the economic advantage would be evenly distributed throughout the year.

A more detailed focus needs to be made on the computational time. Both the S-ORC model and the TET model are able to solve all the instances within a few seconds. This seems reasonable with the time range of optimization considering that never goes above one week. In this paper, we concentrate on this time range, since it is more meaningful for the short-medium operational planning time range that we are inspecting. Moreover, the TET model solves first multiple S-ORC models in parallel (one for each micro-grid) and then optimizes the trading within the S-ORC models. Thus, the computational time is given by the addition of the longest computational time among the parallel S-ORC models and the trading part computational time. This solution is less time costly than considering a single general optimization of the system and is more consistent with the self-consumption framework we are considering. In fact, in a self-consumption framework, the final user's goal is first to fulfill its demand through its own power production plant and then to adjust over/undersupply. In view of this concept, the goal of our model in the trading phase is to only optimize the under/oversupply of electricity among the micro-grids of our system.
Being computationally tractable, these modeling approaches can be of great value for a wide variety of energy and power systems tools. Indeed, they can be introduced in larger energy and power systems models, if the user wishes to investigate solar ORC in a broader context. Open source tools such as PyPSA, [61], highRES [62], GenX from MIT [63], Sienna from NRL [64], could benefit from such a technology-oriented approach to be included, for instance, as a module for more specialized studies.

3.7 Limitations of the work and future research

The results shown in section 3.5 highlight an overall gain in the implementation of a predictable and manageable system as the one we present in this paper for a P2P transactive energy trading context. However, in this paper, an investment costs analysis is not included. Having investment costs would give for sure a more complete view of the real gain of such systems. However, the scope of this paper was to produce an optimization model for the operational management of the system. The main

assumption is that all the technologies involved are already installed. In fact, our purpose was not to discuss strategies connected to the investment phase. Therefore, a suggestion for future directions related to this work could be to concentrate on the integration of investment decisions.
The role of seasonal storage could also be a future direction to investigate. It would be interesting to see how the presence of seasonal storage could impact the efficiency of the system and the economic gain.
Finally, further analysis could be made focusing on the impact of the real cost of electricity for the Tromsø instance. As we mentioned in section 3.6, in this study we concentrate on the meteorological impact on the system, using the same cost of electricity for Bologna and Tromsø. Thus, future works could inspect the role of electricity costs.

3.8 Conclusions

In this chapter, we investigate the potential that a power generation technology like a Solar-ORC could have in being introduced in a P2P transactive energy trading context.
In sight of this, we implemented a tool based on operation research techniques, able to optimize the scheduling of both the Solar-ORC and the trading process. First, we developed a MILP model for the operations scheduling of the Solar-ORC, the S-ORC model. Then, we developed an MILP model for the P2P transactive energy trading between multiple prosumers in a local energy market where some Solar-ORCs are present as power generations plants owned by some prosumers, the TET model.
We tested our models with four threads with 8 GB, on a computer having 4 cores and a processor Intel(R) Core(TM) i5-7200U 2.50 GHz. All the tests were performed using Gurobi 9.1.2 [57] as the solver. The models were implemented using the JuMP package Julia [58]. The model would be made available in the GitHub platform under the name "OPTI-ORC" (https://github.com/sambeets/OPTI-ORC).

First, we performed a sensitivity analysis on the S-ORC model, to inspect, how changing some specifics of the Solar-ORC would affect the system. We inspected the effects on the system given by different types of working fluids, different sizes of the Solar-ORC and different weather conditions. We solved every instance for hourly intervals within a time horizon of one week. Each instance presented were solved within 0.06 seconds.
From an economic perspective, fluids like Ethanol, Methanol, Cyclohexane and R134a are potentially more valuable, especially for large capacity systems. In fact, they need a lower flow rate compared to others, given the same weather conditions

and size of the plant.
On the contrary, when considering the same working fluid and weather conditions, the objective decreases by increasing the size of the plant, up to a certain threshold. In fact, when the optimal size to satisfy the demand of the prosumer is reached, there is no economic benefit to increasing the plant's size further. This is consistent with the self-consumption framework that we are considering.
We then inspected the effect of weather conditions on the system. We detected six representative weeks in the months of April, July, August, October, December, and January. Moreover, we considered two locations for the system: the city of Bologna in Italy, and the city of Tromsø in Norway, with the same plant size and working fluid. The absolute gain of keeping the base cost of electricity the same in the two locations resulted in more profit in Bologna. However, the relative gain to be realized may vary given the cost of electricity in Northern Norway is cheaper. Nevertheless, the scope of this paper is limited to absolute gains because of the focus on weather conditions in the system.

Regardless of the season, Bologna as a location gains a higher economic advantage than Tromsø, with two significant differences between July and August, and December.

The proposed S-ORC model closely resembles the real-world production process in the power plant.

The grid is used by the S-ORC model to compensate for the lack of production by the Solar-ORC, while the usage of the battery is accordingly to its charging operations.

Later we tested the TET model with multiple instances. Each instance represents a different energy community. The TET model was able to solve all the instances within a few seconds, giving reasonable results for all the prosumers involved. Coherently to the S-ORC model, the tests show a higher gain in terms of costs for the Bologna location, around 4.5% in terms of operational costs.

In conclusion, the results highlight an overall gain in the implementation of a predictable and manageable system as the one we present in this work for a P2P transactive energy trading context, on average 16% in terms of operational costs. Since the aim of this study was to produce an optimization model for the operational management of the system, an investment costs analysis is not included. Future directions related to this work would be to concentrate on the integration of investment decisions. Moreover, the introduction of long-term storage systems in artic areas like Tromsø, could be another suggestion for future studies.

Chapter 4

A tactical maintenance optimization model for multiple interconnected energy production systems

[1]

In this chapter fundamental issues related to the management of multiple interconnected energy systems are investigated. We develop a tactical optimization model for the maintenance operations' scheduling phase of a Combined Heat and Power (CHP) plant. Specifically, we consider two types of cleaning operations, i.e., online cleaning and offline cleaning. Furthermore, we include a piecewise linear representation of the electric efficiency variation curve, accurately describing the impact of load and inlet air temperature inside the compressor on the electric efficiency of the CHP plant. Given the challenge of solving the tactical management model, we propose a heuristic algorithm. The heuristic works by solving the daily operational production scheduling problem, based on the final consumer's demand and on the electricity market price. The aggregate information from the operational problem is used to derive maintenance decisions at a tactical level.

4.1 Introduction

During the last decades, there has been an increasing trend in developing more economically and environmentally efficient energy production technologies. Undoubtedly, the need for coping with the climate change threat and for keeping the commitments taken up by several countries by signing the Kyoto Protocol, represent further

[1]The results of this chapter appear in Cordieri et al. [65]

key drivers towards pushing the changes the energy sector is undergoing. Considering the Italian context, *distributed energy generation* has been incentivized, resulting in an increasing decentralization of energy production plants, see Chicco et al.[6] for further details.

In the distributed energy production context, an important role has been played by *self-consumption*, meaning that a portion of the distributed energy generation is consumed in place. This option has been widespread lately as a consequence of its potential in improving the security of the energy supply. Therefore, self-consumption has been undertaken not just in the domestic field, but also in the industrial one, where this concept is even more important considering the massive consumption that most industrial processes need to handle.

The energy demand of industrial processes is usually the combination of various energy types such as heat and electricity. The most commonly adopted self-consumption framework, as for now, is coupling multiple interconnected energy production systems, see Illerhaus et al.[66]. This implies the installation of different technologies able to produce one or multiple energy types, to satisfy all energy needs.

It must be said that multiple interconnected energy production systems, even though very convenient, may be extremely challenging from a management point of view. The challenge comes principally from a need to achieve a perfect synchronization between the different energy production facilities, when operating the whole system. All the difficulties related to running an energy production plant, are extended to a group of plants. To achieve an optimal management of multiple interconnected energy production systems, a proper modeling of the system needs to be performed. Zooming inside the multiple interconnected energy production system, a further analysis needs to be done over one specific technology, which is the cogeneration of Combined Heat and Power (CHP). This technology can be frequently found in industrial power systems, because of its capacity to simultaneously provide different kinds of energy, and because it has shown itself as crucial in terms of efficiency in energy savings, see Illerhaus et al.[66]. Even though these facilities may be interesting especially when applied in multiple interconnected energy production systems configurations, scheduling their production and maintenance is challenging. Optimal management in this case is of extreme importance, to run CHP plants at best, and subsequently to meet the target profit expected during the investment phase.

Several studies centered on optimizing CHP plants' management have been conducted in the past. For example, Gardner et al.[67] and Chicco et al.[68] treated this electrical efficiency as a constant. As observed by Lozza[69], electric efficiency is non-linear with respect to the load at which the plant is operated, and according to the external environment's conditions of the site where the plant is located, in particular to the environment's air temperature. Therefore its simplification could

lead to an overestimation of what is the real functioning of the CHP plant. Another aspect of managing a CHP plant that has been neglected in past optimization models is the scheduling of maintenance operations. There are several kinds of maintenance operations, often requiring a partial periodic shutdown of the production operations. Therefore, optimizing the scheduling of such maintenance operations is fundamental. The maintenance activities are typically of a tactical nature, i.e., they need to be planned during the upcoming year. Thus embedding maintenance planning in the energy production schedules of multiple interconnected energy systems requires considering a tactical planning horizon, which is substantially longer than the typical daily planning horizon considered for operational energy production optimization problems.
The scientific aim of this work is to model and solve the tactical maintenance optimization problem encountered in multiple interconnected energy production systems. We based our models on a specific case study, with three energy production facilities (one CHP plant and two Dual Fuel boilers). We propose optimization models for both operational and tactical production planning. We implement a tactical management model for the maintenance operations' scheduling phase of the CHP plant, which is essential to reach a correct and complete understanding of the system. We specifically considered two cleaning options, i.e., online and offline. Furthermore include a piecewise linearization procedure of the efficiency variation curve as a function of load and inlet air temperature inside the compressor. Given the challenge of solving the tactical management model, we propose a computationally efficient heuristic algorithm. To do so, we develop a basic operational model for production scheduling based on the final consumer's demand, and on the electricity market price. The aggregate information from the operational problem is used to derive maintenance decisions at a tactical level. The remainder of this chapter is organized as follows. Section 4.2 presents a literature review of the topics discussed in this paper. Section 4.3 formally presents the tactical management of maintenance operations of multiple energy systems problem and the proposed solution method. Section 4.5 shows the computational results. Finally, Section 4.6 concludes and outlines research perspectives.

4.2 Literature review

As previously discussed, the use of multiple energy systems has recently become a commonly adopted solution in the energy production field. At the same time, it also raises a need to find proper tools to model its complex management, creating new interesting topics for the scientific community.
Mancarella and Chicco[70] use the *black-box-approach* to capture the relevant energy efficiency relationships (including off-design performance models), while reducing

the level of complexity. According to this approach, the system is reduced to its energy production part, which becomes the core of the problem, and it is set up to supply the time-varying demand.

Lahdelma and Hakonen[71] focus on the optimization of the single CHP plant's production scheduling problem. They model the hourly CHP operation as an LP problem, where the hourly electric power production and heat production of the CHP plant must be contained within a characteristic region of operation, assumed to be convex. Consequently, the production of the CHP plant for each time interval is found as a convex combination of the extreme characteristic points of this region of operation.

Ladhelma and Hakonen[71] has triggered further research in several directions. Kumbartzky et al.[72] start from Lahdelma and Hakonen's model to demonstrate how participating in the electricity market may be profitable for CHP plants, which are usually used for self-consumption. Wang et al.[73] extend the problem to a multiple energy system. The cost is allocated directly to the product, meaning heat and power, without differentiating between all of its components, such as fuel or maintenance costs. A similar assumption has been adopted in the work of Rong et al.[74]. This seems correct according to the time interval of at most one month at which the algorithm works. However, in reality, decisions such as maintenance operations are usually taken given a larger time interval, such as one year.

Milan et al.[75] focus mainly on the efficiency curves of the CHP plant. The authors seek to solve a non-linear model representing these curves, showing that the system's performance was affected considerably, when considering the effects of a variable efficiency. However, the solution found by Milan et al.[75] creates a non-linear problem, which is significantly more complex than linear problems.

Bischi et al.[76] present a data-driven MILP model for planning the short-term operation of combined cooling, heat and power (CCHP) energy systems. This work adds to previous studies a penalization of start-up operations of production facilities, and an effective handling of production units with non-linear performance curves. Bischi et al.[76] apply a piecewise linear approximation of performance curves considering a different number of intervals, that can vary with temperature during the planning horizon.

The previously presented approaches concentrated on short time intervals, neglecting the effect that the scheduling of maintenance operations may have on operating the system, especially on the CHP plant. In this sense, many studies and insights have led to a deep understanding of the real effects of maintenance operations on the CHP plant. Aretakis et al.[77] present a method to predict the impact of the compressor's cleaning process on the power plant's overall profit, focusing on an offline type of cleaning of the compressor. This way other types of cleanings are neglected, which has been proven to be sub-optimal from other studies, e.g. Meher-Homji[78].

Ogbonnaya[79] concentrated mainly on the consequences that an online cleaning has when conducted on a compressor, but proceeds further by considering a combination with offline cleaning. Even though this article does not develop an optimization model, it highlights the importance that a combination of compressor online and offline washing may have on the performance of the plant.
To the best of our knowledge, the tactical problem we introduce in this work is the first to simultaneously take into account the management of multiple interconnected energy systems, the impact of load and inlet air temperature inside the compressor on the electric efficiency of the CHP plant, and the maintenance operations' scheduling phase of the CHP plant.

4.3 Problem description and formulation

In this section, we present optimization models for multiple interconnected energy production systems. We present in section 4.3.3 a tactical management (TM) model that accounts for scheduling maintenance activities along with production operations. We include a piecewise linearization of the efficiency variation curve with load and inlet air temperature inside the compressor in section 4.3.1.
A simplified scheme of the system considered is depicted in Figure 4.1.

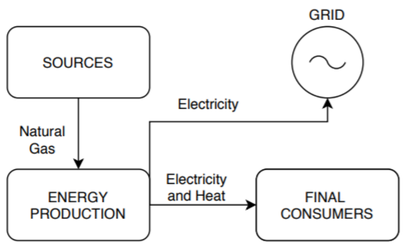

Figure 4.1: System studied

The system considered can be divided in three main parts: sources, utilities that produce electrical and thermal energy and final consumers. The main input, that has to be provided to the whole system in order to satisfy the final demand, is *natural gas*. The natural gas coming from the sources is processed inside the utilities in order to produce *electric energy* and *thermal energy* to satisfy the demand of the final consumers. In order to do so, three main components are currently used: a CHP plant, based on a Gas Cycle in combination with a Heat Recovery Steam Generator (HRSG), and two Dual Fuel Boilers. A further consideration needs to be done for electric energy. In fact, this final product represents a further income, since it can be sold on the electricity market and subsequently injected into the grid. This depends mainly on whether the production exceeds the self-consumption or not, coupled with the electricity market price. Similarly, the grid can be considered as a source of electric energy, whenever the production of the utilities does not meet the expected values.

The planning horizon is divided into $t \in \{0, ..., T\}$ hourly intervals. Note that this can be adjusted to meet the needs of the application of the model. We denote as K the set of final consumers and U the set of utilities that need to fulfill the demand. Moreover, $B \subseteq U$ represents those utilities that produce only thermal power. For each time interval the demand of user $k \in K$ is given in terms of electric energy P_k^t and thermal energy Q_k^t, measured as $[kWh]$. Several parameters are related to the thermodynamic characteristics of the system. The efficiency of utility $b \in B$, is denoted by η_b. The maximum and minimum daily energy production limits for utility $u \in U$ are $P_{u,max}$ and $P_{u,min}$, whereas the maximum and minimum daily energy production limits for utility $u \in U$ are $Q_{u,max}$ and $Q_{u,min}$.
The decision variable P_u^t quantifies the electric energy produced by the utility $u \in U$ in time t. The decision variable Q_u^t quantifies the thermal energy produced by the utility $u \in U$ in time t. Furthermore binary variable y_u^t takes the value of one if utility $u \in U$ is operating in t, and zero otherwise.
Based on Ladhelma et al. [71], considering the CHP plant, a set J_{CHP} of characteristic points is given. Each point $j \in J_{CHP}$ has coordinates in terms of electric energy p_j and thermal energy q_j, these four points determine the operational limits of the CHP plant. Namely, the operating values of thermal and electric energy of the CHP plant, Q_{CHP}^t and P_{CHP}^t, hence will be calculated as a convex combination of the points in J_{CHP}. In order to do this, it is necessary to introduce a continuous variable $x_j^t \in \{0, 1\}$, associated to each characteristic point of the feasible region at time $t \in \{0, ..., T\}$.
Let $V_{NG,u}^t$ be the continuous variable that represents the volumetric flow rate of natural gas consumed by each energy production utility $u \in U$ in time t, measured as $[Sm^3/h]$. Natural gas is the main fuel needed to supply each production plant, and is usually expressed in terms of primary thermal energy thanks to a parameter, the Lower Heating Value (LHV). The LHV represents the amount of energy obtainable by the use of that specific fuel and is expressed as $[MJ/Sm^3]$. We can then define the cost of natural gas according to the natural gas market as C_{NG} $[€/Sm^3]$. This cost is the result of an agreement between the plant operator and the natural gas market operator, and stays constant throughout the whole time period considered.
The system can either withdraw electric energy from the grid to compensate for a lack in electric energy production by the CHP plant, or it can sell the surplus of electric energy production to the grid. We denote as $P_{grid,in}^t$ the amount of electricity that is being withdrawn from the grid and is entering the system at time t. While $P_{grid,out}^t$ represents the amount of electricity that is being injected into the grid and exiting the system at time t. Both these variables are each linked to a

binary variable, respectively $w^t_{grid,in}$ and $w^t_{grid,out}$, that express whether or not the electricity is being withdrawn or injected in time t.
The price of electricity established by the electricity market at t is given by PUN^t. We recall that in the Italian context, the hourly electricity prices are essentially known one day in advance of the actual production day. Therefore, we assume them to be known parameters. Furthermore, since we aim to construct a tactical management model, we assume that any surplus production can be sold to the grid.
Other economic aspects that have been considered to evaluate the model are related to incentives. The incentives are calculated for every $t \in \{0, ..., T\}$ with respect to the energy savings, that the cogeneration of heat and power simultaneously creates. We denote the energy savings in period t by TEE^t. The revenue connected to each incentive produced at t, is given by R_{TEE} [€/TEE].

4.3.1 Electric efficiency variation according to load and temperature

The electric efficiency of a CHP plant can substantially change according to the inlet air temperature inside the compressor, and according to the load at which the plant is operated. Such changes are usually of a non-linear nature and can be expressed through various curves. Starting from the relationship between temperature and electric efficiency, Figure 4.2 shows exactly this concept extended for each load level at which the plant can be operated.

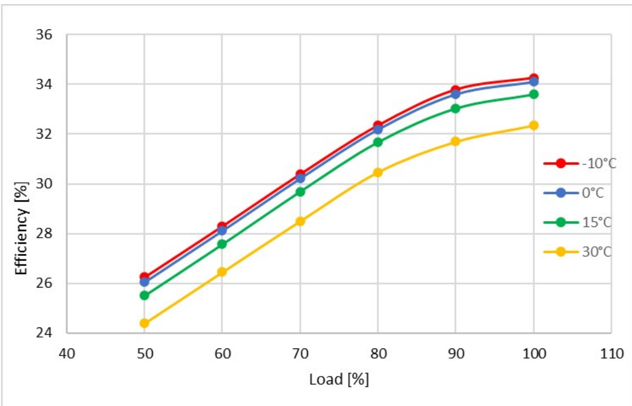

Figure 4.2: Efficiency correlation with inlet air temperature for each load level of the CHP plant

The data points corresponding to the curves in Figure 4.2 are given to the plant's operator as tabled values, where load levels and temperature values are the ones indicated on the plot. One must consider that the inlet air temperature inside the

compressor is dependent on external weather conditions of the site where the plant is located. This of course if an air treatment unit, such as a cooler, has not been installed before the compressor. Hence the inlet air temperature is usually a value known a priori, and is not affected by the decision-making process inside the optimization model.
It seemed correct not to include the temperature-efficiency correlation inside the optimization model, as a constraint. Instead, it has been implemented as a function, that we define as efficiency variations function (EVF). Given as input the inlet air temperature inside the compressor, the EVF calculates the relative electric efficiency-load curve. This curve is then introduced inside the optimization model as an input parameter. Figure 4.3 explains how the EVF actually works.

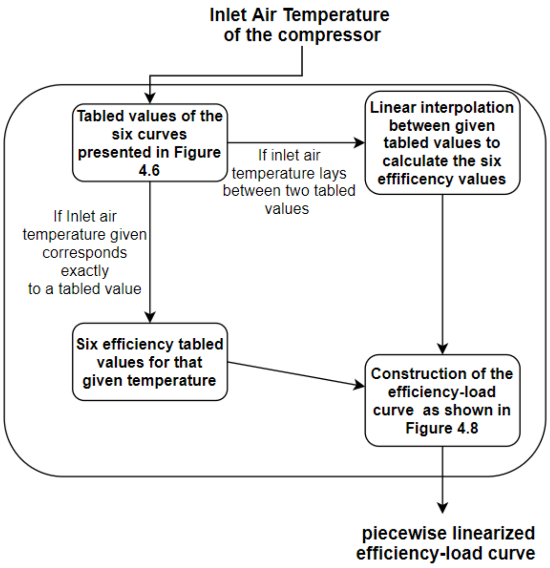

Figure 4.3: Process of the EVF

A last consideration needs to be made before proceeding further. Considering the electric efficiency of the CHP plant as a variable may result in non-linear constraints. In order to avoid this, the efficiency-load curves were actually transformed to correlate directly natural gas consumption $V^t_{NG,CHP}$ to load. What is obtained is a curve that relates a non-dimensional natural gas consumption $\frac{(V^t_{NG,CHP}\ LHV)}{P_{CHP,max}}$ to load. To model the piecewise linear efficiency variations we introduce the set of intervals of the EVF $d \in \{1, .., D+1\}$, where D is the number of breakpoints, and the parameters m_d, that represents the inclination of the piecewise linearization of the curve between $d-1$ and d for $d \in \{1, .., D+1\}$, and q_d that represents the intercept of the piecewise linearization of the curve between $d-1$ and d.
Moreover, we introduce L^t_d, which represents the decisional variable associated with

the piecewise linearization of the curve between $d-1$ and d in $t \in \{1, ..., T\}$, and z_d^t, that represent the binary variable connected to the piecewise linearization of the curve between $d-1$ and d in $t \in \{1, ..., T\}$.

4.3.2 Maintenance operations

This subsection will focus on maintenance operations on the compressor, in order to reduce the degradation of this component due to fouling. Maintenance operations are essential, in order to better model the real functioning of the CHP plant. We focus on two possible cleaning options for the compressor. The two options are online cleaning and offline cleaning, and are quite different in the way they must be executed, in their duration and in their impact on the CHP plant's performance.

We now discuss how the fouling phenomenon was included in the optimization model. According to Lozza [69], a constant degrading rate of performance of the CHP plant can be observed, with respect to its cumulative operating hours. The consumption calculated through the EVF does not consider the degrading phenomena of performance connected to fouling. In fact, one can say it represents a theoretical consumption for each period $t \in \{1, ..., T\}$. Therefore, from now on we will refer to it as $V_{NG,th}^t$. Based on real historical data of the considered system, the fouling phenomenon directly impacts the non-dimensional consumption curve. This results in an increase in non-dimensional consumption for every period $t \in \{1, ..., T\}$, $\frac{(V_{NG,CHP}^t \ LHV)}{P_{CHP,max}}$, of a constant rate denominated as ΔFl.

The considered online cleaning can be performed without turning off the CHP plant, but it still hinders its maximum electric energy production $P_{CHP,max}$ to $P_{reduced}$. An online cleaning activity takes two hours, once performed the CHP plant does not have to undergo other cleaning activities for a maximum period L_{on}, which in our case is of fifteen days.

The considered offline cleaning, once performed, involves the complete shut-down of the CHP plant for at least four hours. The time interval that has to pass between an offline cleaning and another maintenance operation (i.e., online cleaning or offline cleaning), is at most L_{off}, in our case sixty days. The added value of offline cleaning ΔOff, is greater than that of online cleaning ΔOn, measured on non-dimensional natural gas, $\frac{(V_{NG,CHP}^t \ LHV)}{P_{CHP,max}}$. Therefore, there exists a trade-off between the number of cleanings and the degrading rate of fouling.

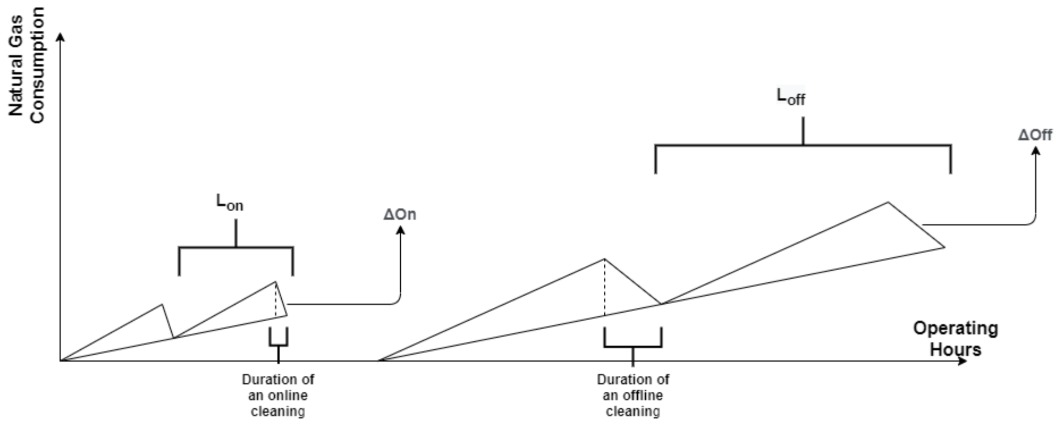

Figure 4.4: Effects of maintenance operations on non-dimensional consumption worsening due to fouling

The additional decision variables used in the mathematical formulation of the model are all binary variables and are defined as follows. Variable s^t refers to whether or not a maintenance operation is performed on the CHP plant in period t. Variable r^t indicates whether or not an online cleaning is performed on the CHP plant in t, while variable o^t indicates whether or not an offline cleaning is performed on the CHP plant in t. Finally, variable q^t takes the value of one if a maintenance activity occurs in t or if the most recent maintenance activity wasn't an online cleaning, while variable u^t indicates if a maintenance activity occurs in t, or if the most recent maintenance activity wasn't an offline cleaning.
Disruptions, including those for maintenance, generally have a physical impact also on the electrical network. However, in this work, we want to concentrate mainly on the effects on the power production part, as we use the network to deal with imbalances. Thus, we deliberately neglect such effects.

4.3.3 Tactical management model

Table 4.1 summarizes all sets, parameters and variables definitions discussed in this section. The TM model is thus stated as follows:

$$\text{[TM] maximize} \sum_{t\in T}\sum_{u\in U} C_{NG}V^t_{NG,u} + PUN^t(P^t_{grid,out} - P^t_{grid,in}) + R_{TEE}TEE^t \tag{4.1}$$

s.t.

$$P_{u,min}\; y^t_u \leq P^t_u \leq P_{u,max}\; y^t_u \;\forall t \in \{0,...,T\},\; u \in U \tag{4.2}$$

$$Q_{u,min}\; y^t_u \leq Q^t_u \leq Q_{u,max}\; y^t_u \;\forall t \in \{0,...,T\},\; u \in U \tag{4.3}$$

$$Q^t_b = \eta_b \; LHV \; V^t_{NG,b} \; \forall t \in \{0,...,T\}, \; b \in B \tag{4.4}$$

$$P^t_{CHP} = \sum_{j \in J_{CHP}} p^t_j \; x^t_j \; \forall t \in \{0,...,T\} \tag{4.5}$$

$$Q^t_{CHP} = \sum_{j \in J_{CHP}} q^t_j \; x^t_j \; \forall t \in \{0,...,T\} \tag{4.6}$$

$$\sum_{j \in J_{CHP}} x^t_j \leq y^t_{CHP} \; \forall t \in \{0,...,T\} \tag{4.7}$$

$$P^t_{grid,in} \geq \sum_{k \in K} P^t_k \; w^t_{grid,in} - \sum_{u \in U} P^t_u \; \forall t \in \{0,...,T\} \tag{4.8}$$

$$P^t_{grid,in} \leq M \; w^t_{grid,in} \forall t \in \{0,...,T\} \tag{4.9}$$

$$P^t_{grid,out} \leq \sum_{u \in U} P^t_u - \sum_{k \in K} P^t_k \; w^t_{grid,out} \; \forall t \in \{0,...,T\} \tag{4.10}$$

$$P^t_{grid,out} \leq M \; w^t_{grid,out} \forall t \in \{0,...,T\} \tag{4.11}$$

$$w^t_{grid,in} + w^t_{grid,out} \leq 1 \; \forall t \in \{0,...,T\} \tag{4.12}$$

$$\sum_{u \in U} Q^t_u = \sum_{k \in K} Q^t_k \; \forall t \in \{0,...,T\} \tag{4.13}$$

$$\sum_{u \in U} P^t_u + P^t_{grid,in} = \sum_{k \in K} P^t_k + P^t_{grid,out} \; \forall t \in \{0,...,T\} \tag{4.14}$$

$$TEE^t = 0,0086 K_{TEE} \; (\frac{P^t_{CHP}}{\eta_{e,r}} + \frac{Q^t_{CHP}}{\eta_{th,r}} - LHV \; V^t_{NG,CHP}) \; \forall t \in \{0,...,T\} \tag{4.15}$$

$$\frac{LHV \; V^t_{NG,CHP}}{P_{CHP,max}} \leq \sum_{d \in \{1,..,D+1\}} m_d \; L^t_d + q_d \; z^t_d \; t \in \{0,...,T\} \tag{4.16}$$

$$z^t_{CHP,d} \; d^t_{d-1} \leq L^t_d \leq z^t_{CHP,d} \; d^t_d \; \forall t \in \{0,...,T\}, \; d \in \{1,..,D+1\} \tag{4.17}$$

$$\sum_{d \epsilon \{1,..,D+1\}} z_d^t = y_{CHP}^t \ \forall t \in \{0, ..., T\} \tag{4.18}$$

$$\frac{P_{CHP}^t}{P_{CHP,max}} = \sum_{d \in \{1,..,D+1\}} L_d^t \ \forall t \in \{0, ..., T\} \tag{4.19}$$

$$\sum_{\tau \in (0,1,..L_{online}-1)} (1 - s^{t+\tau}) \leq L_{on} q^t + L_{off} u^t + (1 - q^t - u^t) M \ \forall t \in \{0, \ldots, T - L_{on} + 1\} \tag{4.20}$$

$$\sum_{\tau \in (0,1,..L_{off}-1)} (1 - s^{t+\tau}) \leq L_{off} u^t + (1 - u^t) M \ \forall t \in \{0, \ldots, T - L_{off} + 1\} \tag{4.21}$$

$$1 - s^t = q^t + u^t \ \forall t \in \{0, ..., T\} \tag{4.22}$$

$$s^t = o^t + r^t \ \forall t \in \{0, ..., T\} \tag{4.23}$$

$$r^t + q^t \leq 1 \ \forall t \in \{0, ..., T\} \tag{4.24}$$

$$o^t + u^t \leq 1 \ \forall t \in \{0, ..., T\} \tag{4.25}$$

$$P_{CHP}^t \leq P_{reduced} r^t + P_{max,CHP}(1 - r^t) \ \forall t \in \{0, ..., T\} \tag{4.26}$$

$$P_{CHP}^t \leq P_{max,CHP}(1 - o^t) \ \forall t \in \{0, ..., T\} \tag{4.27}$$

$$\begin{aligned} \frac{LHV \ V_{NG,CHP}^t}{P_{CHPmax}} &= \frac{LHV \ V_{NG,th}^t}{P_{CHPmax}} + \left(\frac{LHV V_{NG,CHP}^{t-1}}{P_{CHPmax}} - \frac{LHV \ V_{NG,th}^{t-1}}{P_{CHPmax}} \right) + \\ &- \Delta Off \ o^t - \Delta On \ r^t + \Delta Fl \ \forall t \in \{0, ..., T\} \end{aligned} \tag{4.28}$$

$$u^t \geq o^{t-1} - o^t \ \forall t \in \{0, ..., T\} \tag{4.29}$$

$$w^t \geq r^{t-1} - r^t \ \forall t \in \{0, ..., T\} \tag{4.30}$$

$$Temp^t \geq 8 r^t - (1 - r^t) M \ \forall t \in \{0, ..., T\} \tag{4.31}$$

$$\sum_{\tau \in (0,1)} r^{t+\tau} \geq 2(r^t - r^{t-1}) \forall t \in \{0, ..., T\} \tag{4.32}$$

$$\sum_{\tau \in (0,..,3)} o^{t+\tau} \geq 4(r^t - r^{t-1}) \forall t \in \{0, ..., T\} \tag{4.33}$$

The objective function (4.1) is the maximization of the plant's overall profit for the whole time period considered. The main costs that the plant has to face are connected to the cost of natural gas and to the cost of electricity, which has to be withdrawn from the grid whenever consumption exceeds production of the energy production utilities. The profit is a result of two main incomes, incentives and electricity sold to the grid.

Constraints (4.2) impose a lower and an upper bound to the electric energy production. While constraints (4.3) set a limit on the maximum and minimum thermal energy that can be produced by each facility when operated. Constraints (4.4) express the energy balance of the subset B, considering in this case a thermal efficiency that connects the outputs (Q_b^t) to the inputs (primary energy) of plant b.

Constraints (4.5) and (4.6) are used to calculate the production of the CHP plant as a convex combination of the points present inside the feasible operating region. While, constraints (4.7) limit the variables representing the points of the region to whether the plant is operated in $t \in \{1, ..., T\}$ or not.

Constraints (4.8) and (4.9) define and regulate the amount of electricity withdrawn from the grid that enters the system in each period. While constraints (4.10) and (4.11) define and regulate the amount of electricity produced from the CHP plant that can be sold to the grid because it is not needed by the final consumers. Constraints (4.12) regulate the fact that the grid cannot be simultaneously withdrawn and injected into the grid. The following constraints represent the overall energy balances that regulate the system. The main limit here is given by the demand of the final consumers, which must be satisfied in every $t \in \{1, ..., T\}$. This balance is divided into two different sets of constraints, one for thermal energy, as one can see in constraints (4.13), and the other for electric energy, as one can see in constraints (4.14). Constraints (4.15) define the value of incentives for each t when the CHP plant is working.

Similar to Froger et al. [80], constraints (4.16)-(4.19) impose the piecewise linear curves in the model.

Constraints (4.20) and (4.21) determine the maximum time interval that can pass between two cleanings, with respect to which type of maintenance operation has been performed as last.

Constraints (4.22)-(4.25), determine all the consistency constraints between the binary variables.

Constraints (4.26) and (4.27) are constraints related to maximum capacities of electric energy, at which the CHP plant needs to be limited when a certain kind of

cleaning is operated.
The real consumption of natural gas is determined through constraints (4.28). While constraints (4.29) and (4.30) determine the correlation between the binary variables of each cleaning. The last constraint (4.31) limits the minimum inlet air temperature inside the compressor $Temp^t$ at which an online cleaning can be performed, which is 8°C in our case. Under this value , there might be problems of water freezing on blades. Constraints (4.32) and (4.33) impose the minimum duration of each cleaning.

Table 4.1: Set, parameter and variable definitions of TM model

Sets	
$t \in \{1, ..., T\}$	Set of time intervals in which the planning horizon is divided into
$u \in U$	Set of utilities that produce electrical energy or thermal energy or both
$k \in K$	Set of final consumers
$j \in JCHP$	Set of characteristic points of the feasible region associated with the CHP plant
$b \in B \subseteq U$	Set of utilities that produce just thermal energy
$d \in \{1, ..D+1\}$	Set of intervals of the piecewise linearization of the efficiency curve, where D is the set of breakpoints
Parameters	
c_{NG}	Cost of natural gas expressed as €$/Sm^3$
PUN^t	Cost of electricity expressed as €/kWh for every t
R_{TEE}	Revenues associated to incentives expressed as €/TEE
LHV	Lower Heating Value of Natural Gas expressed as kJ$/Sm^3$
η_b	Efficiency of utility $b \in B$
$\eta_{e,r}$	Reference electric efficiency given by the electricity market
$\eta_{th,r}$	Reference thermal efficiency given by the electricity market
K_{TEE}	Coefficient given by electricity market
$P_{CHP,min}$	Minimum power boundary of the CHP plant, expressed as kWh
$P_{CHP,max}$	Maximum power boundary of the CHP plant, expressed as kWh
$Q_{b,min}$	Minimum power boundary of utility $b \in B$, expressed as kWh
$Q_{b,max}$	Maximum power boundary of utility $b \in B$, expressed as kWh
P_k^t	Electric energy flux needed each $t \in \{1, ..., T\}$ by $k \in K$,expressed as kWh
Q_k^t	Thermal energy flux needed each $t \in \{1, ..., T\}$ by $k \in K$,expressed as kWh
p_j, q_j	Coordinates of the characteristic points of the feasible operating region of the CHP plant
m_d	Inclination of linearization of the curve between $d-1$ and d for $d \in \{1, ..D+1\}$
q_d	Intercept of linearization of the curve between $d-1$ and d for $d \in \{1, ..D+1\}$
$P_{reduced}$	Maximum electric energy value of the CHP plant when an online cleaning is performed
L_{on}	Maximum period between an online cleaning and the next maintenance operation
L_{ff}	Maximum period between an offline cleaning and the next maintenance operation
ΔOn	Added value in terms of non-dimensional fuel consumption when an online cleaning is operated
ΔOff	Added value in terms of non-dimensional fuel consumption when an offline cleaning is operated
Variables	
x_j^t	Continuous variable associated to each characteristic point of set J_{CHP} in $t \in \{1, ..., T\}$
y_u^t	Binary variable that indicate whether $u \in U$ is producing in t
P_u^t	Electric energy flux produced in t by the utility $u \in U$
Q_u^t	Thermal energy flux produced in t by the utility $u \in U$
$P_{grid,out}^t$	Electricity flux injected to the grid in t
$P_{grid,in}^t$	Electricity flux withdrawn from the grid in t
$w_{grid,out}^t$	Whether or not electric energy is injected into the grid in t
$w_{grid,in}^t$	Whether or not electric energy is withdrawn from the grid in t
$V_{NG,u}^t$	Volumetric flow rate of natural gas consumed by each utility u in t
TEE^t	Incentives produced in t
$V_{NG,th}^t$	Theoretical volumetric flow rate of natural gas consumed by each utility u in t
L_d^t	Decisional variable associated with the piecewise linearization of the electric efficiency curve between $d-1$ and d in t
z_d^t	Binary variable connected to the piecewise linearization of the electric efficiency curve between $d-1$ and d in t
s^t	Whether or not a maintenance operation is performed on the CHP plant in t
r^t	Whether or not an online cleaning is performed on the CHP plant in t
o^t	Whether or not an offline cleaning is performed on the CHP plant in t
q^t	Whether or not a maintenance activity occurs in$t$ or if the most recent maintenance activity wasn't an online cleaning
u^t	Whether or not a maintenance activity occurs in t or if the most recent maintenance activity wasn't an offline cleaning

4.4 Heuristic for the tactical management model

As will be shown in Section 4.5.2, the TM model requires a substantial amount of computational time (e.g., more than 10 hours in our case study). Therefore, we now present a heuristic algorithm for the problem. The objective of the heuristic is to produce a high-quality solution in a relatively short time. The tactical model works with a planning horizon of one year divided into hourly intervals, thus leading to T=56760. Therefore, applying the TM model results in a rather large MILP. We observe that ignoring the maintenance decisions leads to a much simpler model to solve. This is due to the fact that the linkage between the periods in the TM model is primarily due to the maintenance decisions. Therefore, we propose a heuristic for the TM model based on aggregation principles. We denote this heuristic by HTM. We define the Operational model with Efficiency Variations OEV, as the TM model without maintenance decisions. Therefore, the OEV model is the TM model excluding constraints (4.20)-(4.33).

The basic idea of the HTM is to solve the OEV model on an hourly basis. The results are then aggregated on a daily basis. Once this step has been completed, the results obtained for each day are aggregated and used as parameters to solve the TM model for time set F, which is a set divided into daily intervals. An aggregate version of the TM model is then run on a daily planning horizon, the results from which indicate the days in which maintenance operations are to be performed. The TM model is then run on an hourly basis for those particular days, in order to schedule the maintenance activities. The heuristic algorithm is outlined in Figure 4.5. The algorithm starts by solving OEV (T), with i.e., T=56760. The results are then aggregated on a daily basis according to the procedure detailed in Figure 4.6. The TM model is then solved with the aggregated data, this is denoted by TM(F). We note that the planning horizon of TM(F) consists of 365 time steps. The solution of TM(F) will have days in which online cleaning is performed and days in which offline cleaning is performed. We denote the former by F' and the latter by F". Then an hourly version of TM is run for each day in F' and each day in F". The cost from these days is added to the cost of OEV based on the T set, but without considering the days included in sets F' and F" days, to yield a complete solution. In conclusion, the total profit will be calculated as the sum of the OEV T-based model's profit, plus the TM model's profit of days F' and F".

Fig. 4.5 shows the time sequence at which the aggregated algorithm works.

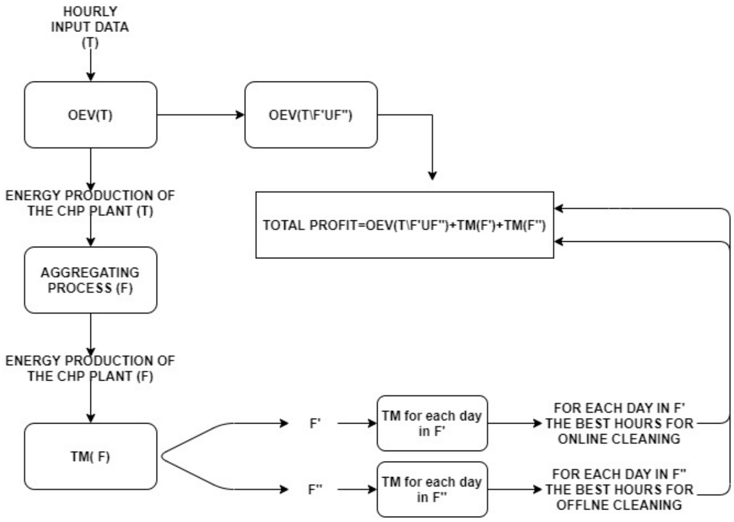

Figure 4.5: Heuristic algorithm outline

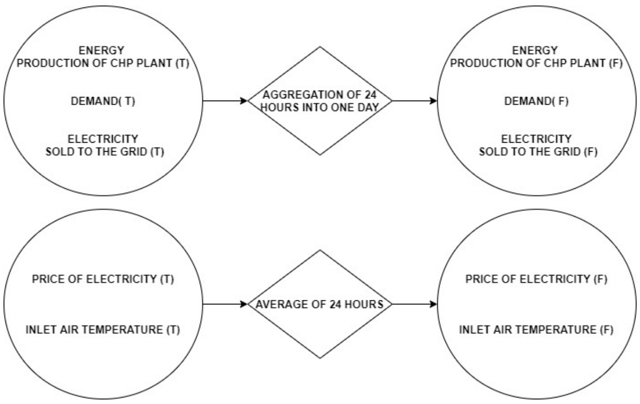

Figure 4.6: Aggregating procedure

4.5 Computational tests

To test our model we used CPLEX 12.9.0 to solve the MILP models through its Python API. All experiments were performed, using a single thread with 8 GB, on one computer having 4 cores and Intel(R) Core(TM) i5-7200U @2.50 GHz 2.71 GHz processor. The data used come from the case study described in section 4.3, which is an example of a self-consumption setting where the final consumer is represented by an industrial process. However, for confidentiality reasons, the results are distorted to be presented publicly.

In what follows, we discuss the historical data of the case study in section 5.1. In section 5.2 we present the results of the TM model and compare them to the case study. Finally, in section 5.3 we present the results of the heuristic algorithm.

4.5.1 An overview of historical data

In this section, an overview of how the considered system has been operated in the past will be presented.

The historical data regarding how the system has been operated in the past, takes into account also the real functioning of the electricity market, in terms of price and capacities. This means that not all the electric energy, which was bid on the electricity market has been accepted. This influences how the CHP plant and the whole system have been operated in the past.

The production levels established by the company are presented in Figure 4.7-4.8. We note that the CHP plant's production is not as stable and tends to adapt not just to demand but also to the electricity market's needs. This is evident, especially in Figure 4.9. At the same time one can see that as in the model, the flux of electric energy exiting the system to be injected inside the grid (Grid Out) tends to compensate for the fluctuations in demand to keep the CHP plant's production as stable as possible. The role undertaken by the flux of electric energy withdrawn from the grid entering the system is always the one to fulfill demand, whenever the CHP plant does not produce enough because of maintenance or other events that may hinder its production.

For what concerns the thermal energy production, as before the primary production is represented by the CHP plant, while the two boilers are used as a back-up to fulfill demand's needs.

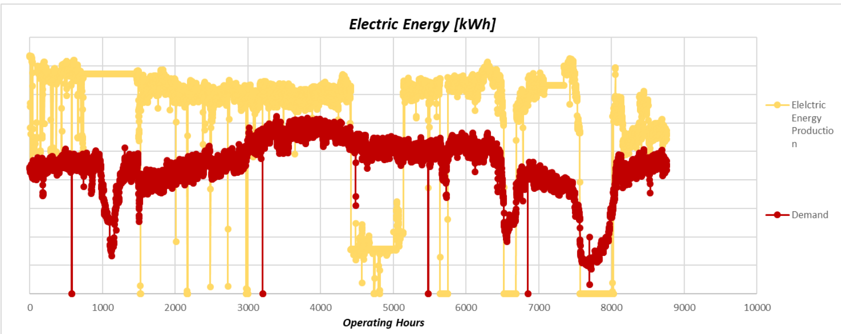

Figure 4.7: Real electric energy of historical data

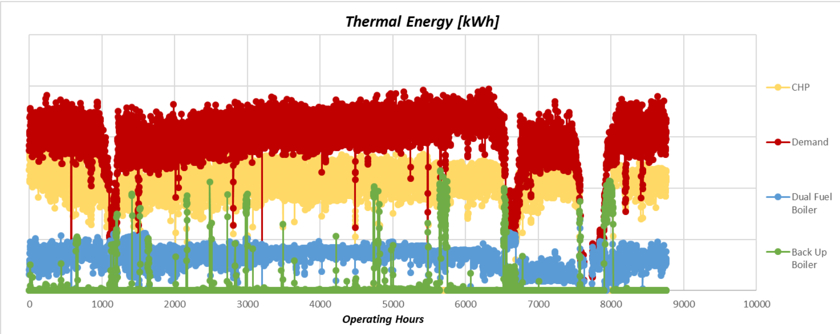

Figure 4.8: Real thermal energy of historical data

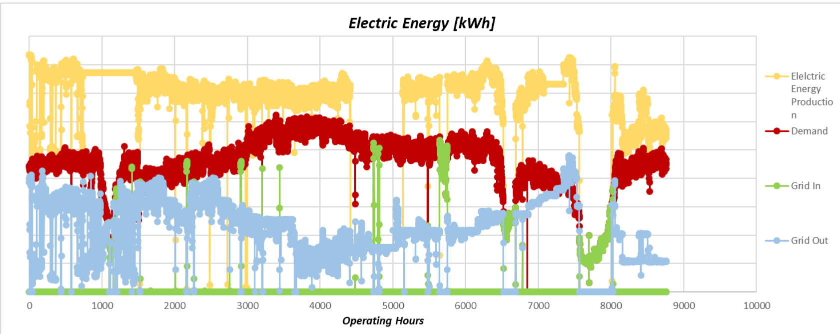

Figure 4.9: Real electric energy fluxes of historical data

4.5.2 Results from the tactical model

We run the TM model over a planning horizon of one year with an hourly planning interval (i.e., T=56760). The results are presented in Figures 4.10-4.13, and are summarised in Table 4.2. As can be observed in Figure 4.11, the TM model tries to set the level of electric energy produced at its maximum capacity. This is due to the attractive electricity prices on the market. In fact, as long as this value is favorable to sell, the electricity production stays at the maximum capacity level. Where the production is set to zero an offline cleaning is performed on the CHP plant, while where an online cleaning is performed the value of production is set at the value of its maximum reduced capacity. Figure 4.13 shows how the amount of electric energy exiting the system to be sold to the grid, compensates the variations in demand in order to keep the production as constant as possible. While, the amount of electric energy entering the system is used by the model to compensate for the lack of production during the maintenance operations, or is kept at minimum to minimize costs in the objective function.
Concerning the thermal energy production, the CHP plant is considered as the first source of thermal energy. While the two boilers are used as back-ups, to fulfill the amount of thermal energy not produced by the CHP plant, as shown in Figure 4.12.

We now focus on the results concerning the electric efficiency variations. The consumption adapts to the fluctuations of electric efficiency with respect to inlet air temperature inside the compressor and load. We tested also the TM model considering the electric efficiency as a constant, thus neglecting constraints (4.16)-(4.19). The results are compared in Figure 4.10.
The results connected to the TM model were obtained by setting the computational time to 10 hours, at which time the MILP gap was 0.22%.

TM model	
Computational time (h)	10
MILP gap (%)	0.22
Objective Function value (€)	2051446
Number of offline cleanings	6
Number of online cleanings	4
Difference in profit compared to an operational model (%)	10.66
Effects of considering the electric efficiency as a variable	
Average difference in terms of natural gas consumption (%)	16.5
Difference in profit (%)	7.82

Table 4.2: Main results obtained from the TM model

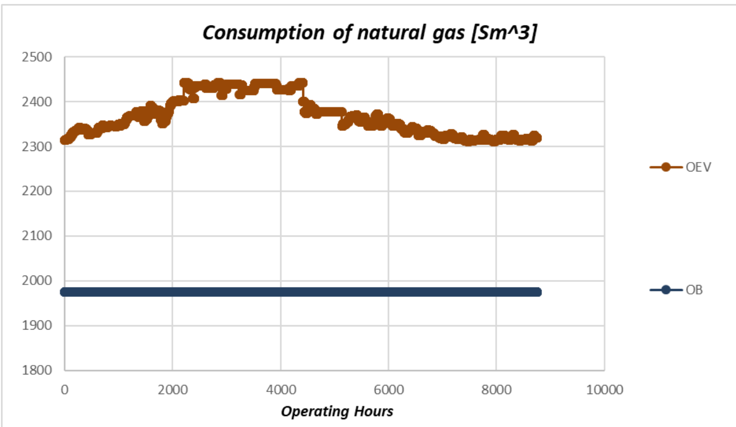

Figure 4.10: Comparison of the yearly natural gas consumption considering the electric efficiency of the CHP plant as a constant or as a variable

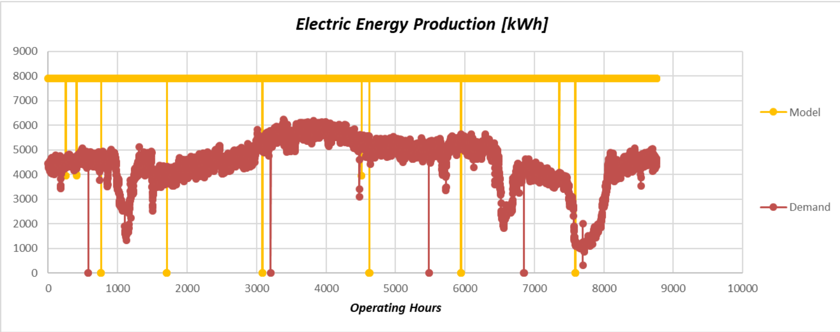

Figure 4.11: Electric energy production by the TM

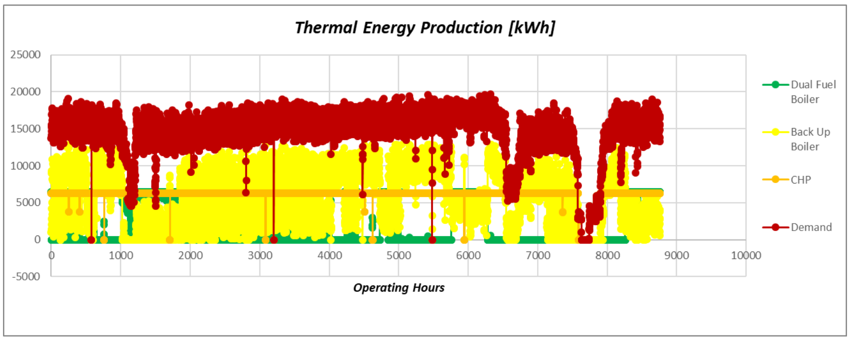

Figure 4.12: Thermal energy production by the TM model

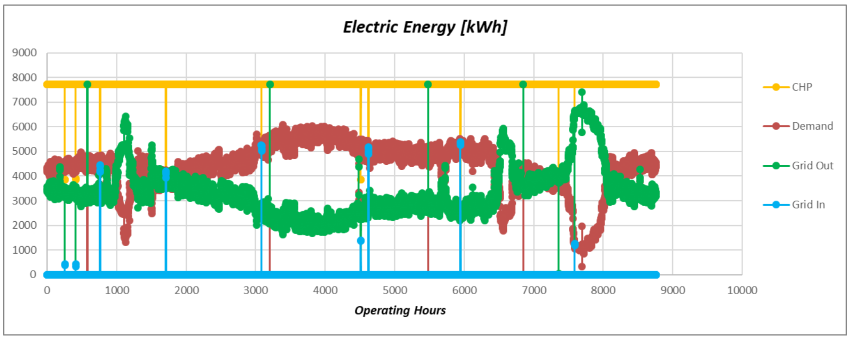

Figure 4.13: Electric energy fluxes by the TM model

We now focus on economic factors. Table 4.3 compares the monthly profits of the model's results and of the real functioning of the system. For confidentiality reasons, the data has been distorted. As one can see the difference between the two values is evident for each month.
The main difference in profit between the real functioning of the system considered and the model's results, is given by the amount of electric energy sold on the electricity market, but also by implementing the maintenance operations' scheduling inside the optimization model. In fact, the scheduling of cleanings is strictly

interconnected to the demand variations of the final consumers, and to the price of electricity. Therefore, if optimized it can improve the overall profit during the tactical time range.

	Model	Real Data
Number of offline cleanings	6	2
Number of online cleanings	4	10
	Difference in profit (%)	
Average	49	
March	24.6	
April	50.4	
May	40.4	
June	30.5	
July	5	
August	3.2	
September	28.6	
October	43.8	
November	38.2	
December	52.3	
January	75	
February	25.8	

Table 4.3: Comparison between TM model and real data

4.5.3 Results from the heuristic algorithml

To evaluate the quality of the solution obtained by the heuristic, we compared its performance with that of the TM model. These results are presented in Figure 4.14. We observed that the ATM model is coherent with the hourly TM model, proposing a combined solution of offline and online cleanings. Even though the two solutions are not exactly the same, they result in similar profits, where the difference is 3.61%.

Table 4.4: Comparison between maintenance operations' scheduling in Tm model and heuristic

	TM model	Heuristic
Number of offline cleanings	6	4
Number of online cleanings	4	6
Computational time	10 h with 0.22% gap	367 sec.

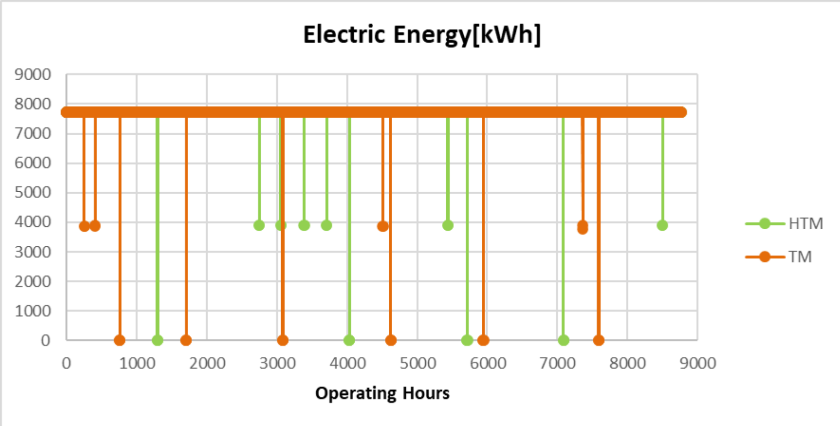

Figure 4.14: Comparison between maintenance operations' scheduling in TM model and heuristic

4.6 Conclusion

We proposed a tactical optimization model for the management of multiple interconnected energy systems. We proposed a model for the tactical setting, i.e., the TM model. The TM model is able to schedule maintenance operations of multiple interconnected energy systems for a planning horizon of one year. Including the electric efficiency variations in the tactical model, led to results that are more in line with the company's decisions. This improvement is evident when observing the natural gas consumption, which is more realistic.

Furthermore, given the challenge in solving the tactical management model, we proposed a heuristic algorithm to decrease the computation time of the tactical management model, reaching a difference in terms of profit of 3.61%. This result opens the possibility to extend the time range of the tactical management model from one year to several years, giving the chance to increase the planning horizon for the plant's operator.

At the same time it must be said that even though the production of the system has been calculated with respect to the hourly electricity price, this price has been considered as an input parameter. This is a valid approximation for tactical planning purposes but does not fully represent reality. Specifically, in the TM model we explicitly assumed the a priori knowledge of the electricity prices one year in advance. To relax this assumption we conducted an additional experiment, assuming a naive forecasting method for the electricity prices. Essentially we assumed that the price of electricity at a given period is precisely the price observed in the same period of the previous year. Running the TM model with this configuration led to a difference in terms of profit of 4.56%. Hence the TM model can be considered reliable also with a naive forecast based on historical data of the electricity prices of previous years.

Chapter 5

Conclusions

The aim of this thesis was to propose exact and heuristic algorithms for the integrated planning of multi-energy systems. First, a mathematical model for the generation expansion operations to optimize the performance of a Central Energy System (CES) system is proposed. Extensions (or updates) of the existing network were included in the model, to ensure compatibility with the network. All these decisions were evaluated both from an economic viewpoint, using the objective function of the problem, and from an environmental perspective, as specific constraints related to GHG gases (measured in CO2eq) emissions were imposed in the formulation. Two different instances were tested, to detect the effectiveness of the methodology proposed, using Gurobi as a solver and three different types of machines. The results showed the high dependency of the memory required to find an optimal solution, on the number of time steps and number of cores used to solve the problem. Given the complexity of the problem and the size of the instances of real scenarios, a heuristic may be necessary to create more competitiveness from a computational point of view.

Then, an algorithm for a bottom-up optimization model for solar organic Rankine cycle in the context of transactive energy trading is presented. This study first inspected the impact that this technology can have on the peer-to-peer trading application in renewable based community microgrids. Moreover, it investigated how different technological parameters of the solar ORC may affect the final solution. Finally, it studied the value of the solar ORC in the transactive energy trading context under different configurations and scenarios. The results highlight an overall gain, on average 16% in terms of operational costs. Since the aim of this study was to produce an optimization model for the operational management of the system, an investment costs analysis is not included. Future directions related to this work would be to concentrate on the integration of investment decisions. Moreover, the introduction of long-term storage systems could be another suggestion for future studies.

Finally, a tactical optimization model for the maintenance operations' scheduling phase of a Combined Heat and Power (CHP) plant is introduced. Two types of cleaning operations were analyzed, i.e., online cleaning and offline cleaning. Furthermore, a piecewise linear representation of the electric efficiency variation curve, accurately describing the impact of load and inlet air temperature inside the compressor on the electric efficiency of the CHP plant is included. Given the challenge of solving the tactical management model, a heuristic algorithm was developed. The heuristic first solves the daily operational production scheduling problem, based on the final consumer's demand and on the electricity market price. The aggregate information from the operational problem is used to derive maintenance decisions at a tactical level.
The models were tested on a specific case of study, with three facilities (one CHP plant and two Dual Fuel boilers). Compared to the operational basic model, the results found on electric efficiency variations are more in line with the actual functioning. The resulting profits are 7.82% lower than those obtained by the operational basic model. Moreover, developing a tactical management model for maintenance operations' scheduling led to more realistic results, with an estimated profit of 10.66% lower with respect to the operational model with electric efficiency variations. Therefore, in order to make decisions in the tactical planning horizon, the maintenance of the CHP plant is crucial. The proposed heuristic algorithm drastically improves the computation time of the tactical management model, reaching a difference in terms of profit of 3.61%. This result opens the possibility to extend the time range of the tactical management model from one year to several years.

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