

# POLITECNICO DI TORINO

Master's Degree in Ingegneria Energetica e Nucleare



**Politecnico  
di Torino**

Master's Degree Thesis

## Plug and Play model for the dispatch of Renewable Energy Sources in a MicroGrid framework: Deterministic and Stochastic Economic Optimization

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## **Abstract**

The increase of electricity consumption and the increase of Distributed Energy Sources in the electrical grid both introduce problems to the dispatch of electricity to the final consumers. The presence of sources whose production is related to the weather conditions also brings uncertainty to the definition of a dispatching strategy.

The aim of this thesis is to analyze a portion of the grid to define the dispatch strategy for supplying electricity to consumers with the use of a photovoltaic plant and a wind turbine, with the support of a battery and the grid, following the examples set by the literature. The concept of the model is of a Plug & Play perspective, meaning that the elements considered in the analysis could be connected or disconnected as desired. Pyomo and CPLEX were used to define an optimal solution, both in a deterministic and a stochastic way.





# Acknowledgements



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# Acronyms

## **ABM**

agent based modelling

## **ARMA**

autoregressive moving average model

## **BD**

bender decomposition

## **BESS**

battery electrical storage system

## **CC**

cycle charging

## **CCHP**

combined cooling heating power

## **CD**

combined dispatch

## **CHP**

combined heating and power

## **DER**

distributed energy resource

## **DG**

distributed generation

**DR**

demand response

**ED**

electricity demand

**EH**

energy hub

**ESS**

electrical storage system

**FC**

fuel cell

**FFS**

fast forward selection

**GA**

genetic algorithm

**GHG**

greenhouse gas

**GME**

gestore mercati energetici

**GO**

generator order

**GSE**

gestore servizi energetici

**HP**

heat pump

**HRES**

hybrid renewable energy system

**HS**

heat storage

**ILP**

interval linear programming

**IPCC**

intergovernmental panel on climate change

**IRENA**

international renewable energy agency

**LCOE**

levelized cost of energy

**LCOS**

levelized cost of storage

**LF**

load following

**LP**

linear programming

**LS**

load shedding

**MCS**

monte carlo simulation

**MG**

microgrid

**MILP**

mixed integer linear programming

**MINLP**

mixed integer non linear programming

**MPC**

model predictive control

**MT**

microturbine

**NSGAI**

non-dominated sorting genetic algorithm II

**NPC**

net present cost

**O&M**

operation and maintenance

**PCC**

point of common coupling

**PDF**

probability density function

**PEV**

plug-in electric vehicle

**PNIEC**

integrated national energy and climate plan

**POA**

plane of array

**PV**

photovoltaic

**RES**

renewable energy source

**SD**

self-discharge

**SoC**

state of charge

**WT**

wind turbine



# Chapter 1

## Introduction

According to the Intergovernmental Panel on Climate Change (IPCC), climate change is identified as changes in the state of the climate in the form of variation of its properties and that persists for an extended period or time [1]. Climate Change can be attributed to natural causes, such as volcanic activity, oceans circulation and variation in solar radiation, or to anthropogenic causes. To quantify the impact from Climate Change, the IPCC releases, every couple of years, an assessment report. In Assessment Report 5 [2], the authors stated that:

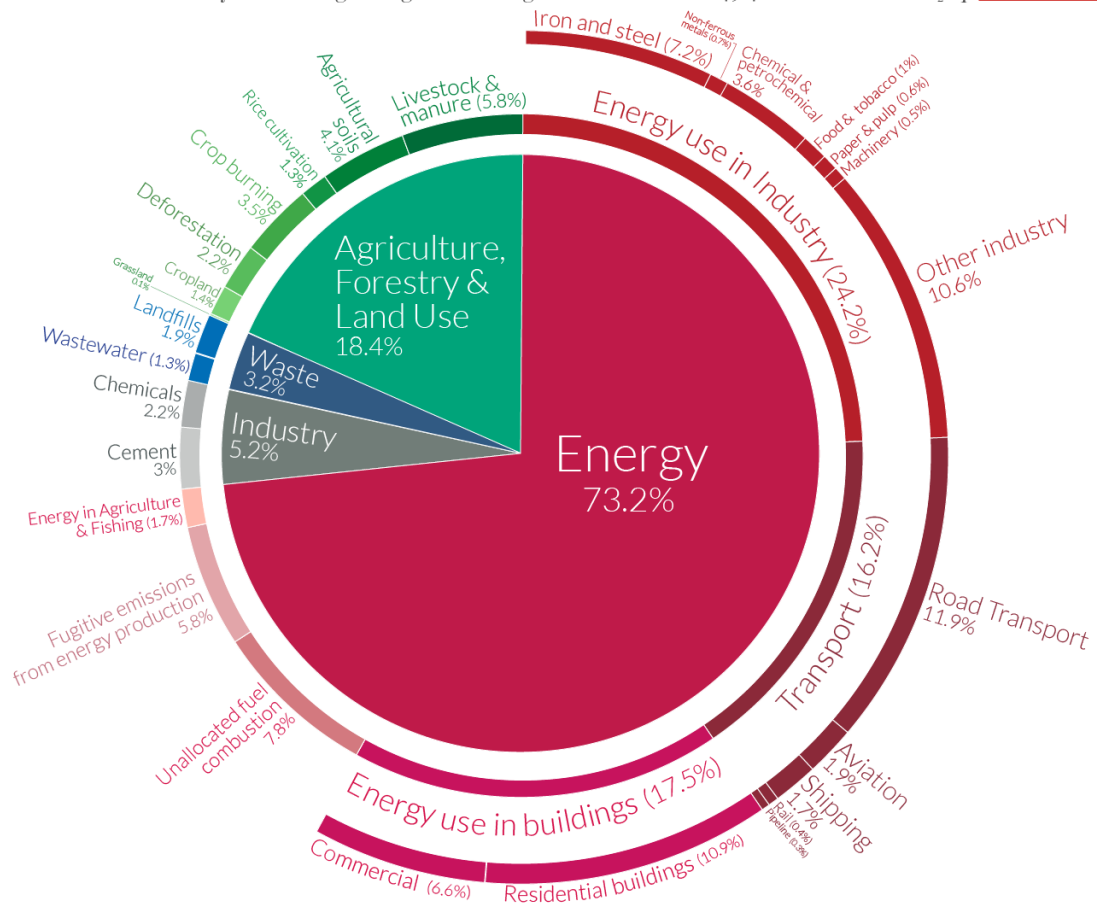
- Over the period between 1880 and 2021, the combined global average temperature of land and ocean surface has followed an increasing linear trend of  $0.85^{\circ}\text{C}$ ;
- The upper 75 m of the ocean water increased their temperature of  $0.11^{\circ}\text{C}$  per decade in the year between 1971 and 2010;
- Ocean surface salinity has also changed since 2050: high salinity regions have become more saline while low salinity one have become fresher;
- Due to the increase of  $\text{CO}_2$ , the ocean was subjected to acidification, since surface water's pH has decreased of 0.1, resulting in an increase of its acidity of 26%;
- Almost all around the world, the size of glaciers have continued to drop; also, in most regions, permafrost temperature have increased from the values they had in the 1980s due to the increase of surface temperature and to the variations in the snow cover;
- In 2010, the global mean sea level has increased of 0.19 m from the level it had than 100 years before (1901), reaching the value to 0.21 m.

The authors of [2] also analyzed the causes behind Climate Change, focusing on the increase of the emissions of anthropogenic Greenhouse Gases (GHG) since the pre-industrial values. The definition of GHG includes all those gases that are in the atmosphere, and contribute to the Greenhouse Effect that allows planet Earth to have the atmosphere it has, but that causes global warming when their concentration in the atmosphere is too high. These gases absorb and emit radiant energy at specific wavelengths within the spectrum of the radiation emitted by Earth's surface. Among these gases there are water vapor ( $\text{H}_2\text{O}$ ), carbon dioxide ( $\text{CO}_2$ ), nitrous oxide ( $\text{N}_2\text{O}$ ), methane ( $\text{CH}_4$ ) and ozone ( $\text{O}_3$ ) [2]. As can be seen from figure 1.1, the sector that is the main contributor to the emission of GHG is the energy sector.

## Global greenhouse gas emissions by sector

Our World  
in Data

This is shown for the year 2016 – global greenhouse gas emissions were 49.4 billion tonnes  $\text{CO}_2\text{eq}$ .



OurWorldinData.org – Research and data to make progress against the world's largest problems.

Source: Climate Watch, the World Resources Institute (2020).

Licensed under CC-BY by the author Hannah Ritchie (2020).

**Figure 1.1:** Industrial GHG emissions, subdivided by sector [3]

In the *Global Energy Review: CO<sub>2</sub> Emissions in 2021*, the International Energy Agency (IEA) [4] stated that, in 2021, CO<sub>2</sub> emissions reached the highest record for their annual value and that the biggest increase registered was the one caused by the electricity and heat production sector, responsible for 46% of the global increase in emissions. This variation is justified by the growth, in the same time period, of the electricity demand.

In fact, the Electrical Energy consumption, in recent years, has followed a general trend that is increasing every year. In 2019, in Italy the value of electricity consumption was of 319.6 TWh and, while the spread of COVID-19 impacted on different industrial sectors, leading to a decrease of 5.8% in 2020, then, in 2021, the consumption of electricity returned to 318.1 TWh, that is only 0.5% lower than the value of 2019 [5] [6].

Therefore, except for the year 2020, these trends of general increase of electricity lead to a necessity of increase of the generation of electricity.

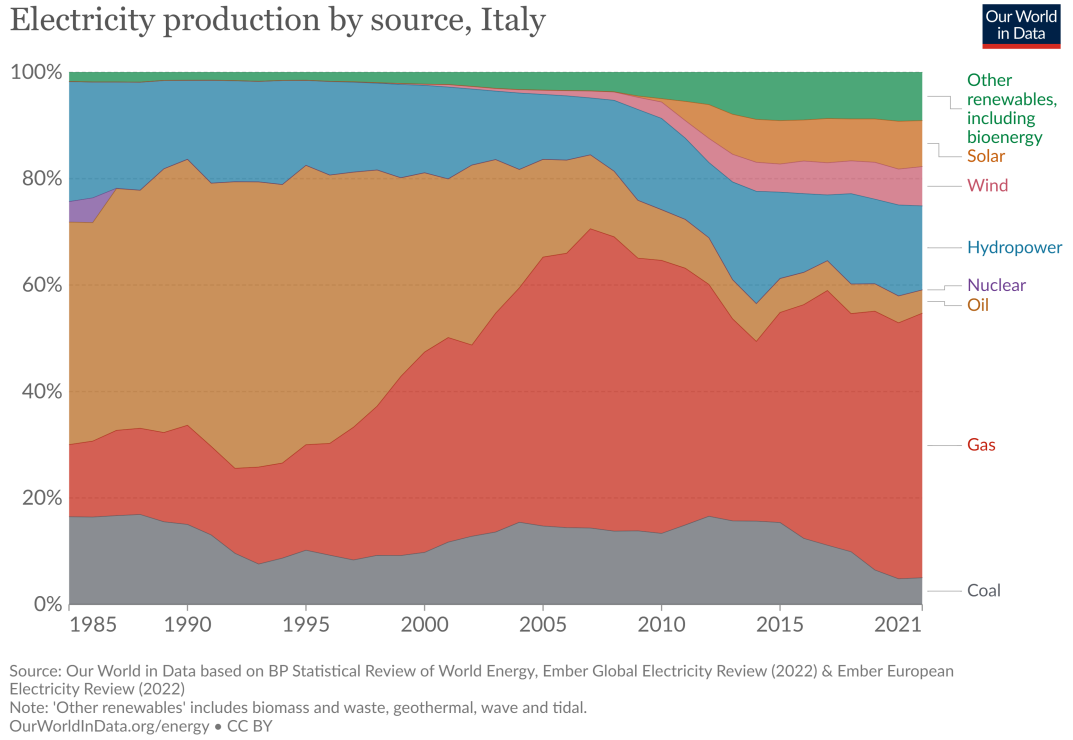
In the last 36 years, the Italian electricity mix changed following the trends as shown in figure 1.2. The use of coal indeed decreased in recent years, giving more space to less CO<sub>2</sub> emitting sources, like natural gas and hydropower. Still, natural gas is a fossil fuel and it still is, for definition, a resource that has quite an important environmental impact. In 2021, 40.91% of the electricity produced in Italy was derived from Renewable Energy Sources (RES) [7], where RES include hydropower, wind, solar, geothermal, modern biomass and wave and tidal power. As stated in the *Integrated National Energy and Climate Plan* (PNIEC) [8] from the Italian Government, the goal is to reach a share of 55% of RES in the electricity production within 2030.

To reach the goal set from the PNIEC [8], the *National Recovery and Resilience Plan* (PNRR) [9] includes a section dedicated to the investment to increase the self-consumption with the installation of new RES plants, especially in the framework of Energy Communities.

According to the European Commission, an Energy Community is citizen-driven local community organization that contributes to clean energy transition and to the increase of energy efficiency [10]. These organizations, usually, rely on the Distributed Energy Resources to supply their energy demand.

The International Energy Agency (IEA) defines the Distributed Energy Resources (DER) as energy resources of small size that are usually placed near the location in which electrical energy is used [11]. The traditional electrical system paradigm had four separated subsystems:

- centralized generation
- transmission system
- distribution system



**Figure 1.2:** Electricity generation mix in Italy for years 1985-2021 [7]

- utilization

With the increase of these small plants installed and connected to the grid, a paradigm shift from centralized to distributed generation is occurring. The emerging paradigm considers the presence of the generation subsystem also in the utilization one, as the figure of the prosumer is catching on. Prosumers are grid users that are both consumers and producers, since they have installed energy generation plants that usually can be attributable to DERs.

Furthermore, the transmission system shall shift from centralized to a Super Grid, that includes few high rated power plants, high voltage transmission of power might have to follow long distances and it should be operated centrally. Similarly, the distribution system has to change, from a decentralized system to a Smart Grid. Smart Grids have a high number of Distributed Generation (DG) plants, it can sustain a bidirectional power flow over the network and it should be operated in a dispersed way.

In the context of Smart Grids, there is the definition of MicroGrids (MG). A MG is defined as a group of electrical loads and DERs within defined electrical boundaries, that acts as a single entity with respect to the grid. A MG can operate in island

mode or in grid-connected mode, depending on the fact that is connected or not to the grid.

The increase of DER connected to the grid introduces issues related to the fact that most of these resources, such as photovoltaic power systems or wind turbines, are of unpredictable and intermittent nature, since they depend on weather conditions. Abrupt variations on the produced energy and therefore injected into the electricity grid may lead to stability problems, such as sudden variations on voltage and frequency values, that could be also worsened by the variation on the load. The changes in voltage and frequency can lead to power quality issues, then power outages could arise. Therefore, the definition of an optimal dispatch strategy is necessary to ensure the electrical grid stability and reliability.

A dispatch strategy is a set of rules that defines which generator or storage system would supply electricity to the load in a given time step. The optimization of a dispatch strategy can be performed according to different parameters.

In the first part of the following chapter 2, the state of the art in the literature concerning the optimization of the sizing of resource is illustrated, while in the second part (section 2.2) the optimization of the dispatch strategies will be discussed in detail. Then, in chapter 3, a MG composed by the load of 12 households, a photovoltaic power system, wind generator and a battery storage system, with the electrical grid support, is developed and simulated in two different weather conditions, to give a broader idea of how the dispatch strategy can change according to the season. The following chapter 4 introduces the uncertainty of time-depending parameters, such as wind speed, solar radiation, electricity demand and electricity market price, and defines a set of scenarios affected by uncertainty that are used as input to determine an optimal dispatch strategy. The MGs analyzed in both chapters 3 and 4 were developed in a plug-and-play type of framework, that allowed to easily change their configuration, to see how the different resources affect the dispatch of electricity.

# Chapter 2

## State of the art

The intention of this section is to present some existing literature concerning the use of optimization in the Energy systems.

In the energy sector, the types of optimization that can be performed can be subdivided according their purpose, that usually corresponds to different time periods in the life of an energy system. If the optimization is carried out with the aim of defining the design of a power generation plant, in terms of size and according to its location, then it is performed in the planning phase. Instead, if its purpose is to obtain a dispatch strategy in a system that consists of one or more power generation plants to supply a given load, the optimization will define which type of plant is working, for how long and in which operating conditions at every moment of a given period of time, then this is completed in the operational stage.

### 2.1 Planning stage optimization

The optimization performed in the planning stage aims at defining the optimal size of a given type of generation plant that is going to be installed at a given location to deal with an electricity demand. This is usually done with the objective of an optimal economic outcome, minimizing the investment costs for the realization of the plant. Performing the optimization in the planning stage considering the economic aspect of the project could also mean to take into account the expected operational costs that will be faced during the lifetime of the plant. While the investment costs include all the capital costs that are needed to design and realize the plant, the operational one are the costs the system will meet to generate power and to be able to fully operate during its useful timelife.

An example of planning economic optimization is presented in the first stage of the problem analyzed by Wu et al. [12]. Through the optimization, the optimal size of the system's components was defined, minimizing the expectation of the

total net-cost. The objective function of this optimization problem is composed by both the investment costs and the expected annual operational cost of the Distributed Energy Resources (DER). It is subjected, among other constraints, to a survivability requirement, that indicates whether the MicroGrid (MG) in question is resilient enough to survive a random outage. Therefore, in case the DERs operate in grid-connected mode, the optimization is performed with the main objective of minimizing of the operational costs, while, in case of a random outage that requires island-mode operation, the main goal is for the system to survive the outage. The uncertain parameters presented in this article are the load, the weather conditions, on which depends the power output from Renewable Energy Sources (RESs), the starting and ending time of a random outage and the State of Charge (SoC) of the battery in case a random outage occurs. These are represented by a vector and are solved in the first stage of the problem. Once the first stage is solved, the second stage aims at the minimization of the expected operational costs. Both stages of the problem were modelled as stochastic Mixed Integer Linear Programming (MILP) problems and are merged into a single equivalent deterministic MILP problem, solved by an open-source solver named Cbc (COIN-OR branch and cut). The proposed method was tested in a resource planning analysis for a U.S. military base, for which many details could not be divulged.

Another example comes from Boloukat et al. [13]. The authors aimed at obtaining the optimal combination of various technologies for a resource expansion planning, that maximizes the profit and the reliability and minimizes the costs. The model formulation is a Multi-objective MILP problem and Benders Decomposition (BD) is applied to simplify the solution of the problem. BD is used to subdivide the problem into a master investment problem and two sub-problems (in this case, operation and reliability). The master investment problem defines whether a given type of technology is installed and at which capacity, minimizing the investment cost. The operation sub-problem maximizes the profits of the technologies, as designed in the master problem, defining their optimal output, considering also a part of energy that could be sold to or bought from the grid and the charge and discharge of storage systems. The reliability sub-problem rearranges the output of the technologies when the operation of the system is not at the optimal point found in the other sub-problem. Often, this occurs in case of disturbances in the main grid that could isolate the MG. The uncertain nature of the RESs is included in this analysis with the use of Interval Linear Programming (ILP). ILP describes uncertainties as intervals and it is usually used when their distribution functions lack information. The solution to this optimization problem is found with the application of a specific algorithm. The case study was implemented on a MG composed of Photovoltaic panels (PV), Fuel Cells (FC), Wind Turbines (WT), diesel generator, a heat source, Heat Storage (HS) and Electrical Storage System (ESS). The optimization was performed in three different conditions:

- considering only the reliability of the grid and not the intermittency of the RES
- considering only the intermittency of the RES and not the reliability of the grid
- considering both grid reliability and RES intermittency

Also, Zhang et al. [14] performed the optimization in the planning stage through the minimization of the total cost of the energy system. Unlike the previous papers, in this article the demand is not simulated as a given fixed value subjected to a certain level of uncertainty, but it was described by an Agent Based Model. ABM generates uncertain demand scenarios for a community with different energy consuming activities and considering different types of households, based on probability models and demographic information. Probability functions related to the different types of behaviours of the occupants are considered, as well as two different settings for weekdays and weekends. Therefore, each run of the model could generate many different load profiles. K-means clustering approach is used to have a sufficient representation of the fluctuation of demand profiles and to make them suitable to be included in the system design optimization model. The optimization model is formulated as a Stochastic MILP problem, its objective is the minimization of the total cost of the energy system, expressed as the summation of the total costs of each scenario multiplied by the scenario probability. The total cost of each scenarios is given by the summation of the capital expenditures, the fuel costs and the maintenance costs, considering price variations related to both the season and the hour of the day. This simulation is applied to a case study of a residential community in Shanghai, China, that include 13 residential buildings and 1024 households. Said community is served by a Combined Heating and Power (CHP) unit, a boiler, an electrical chiller, an absorption chiller, a heat pump and a heat storage tank. The model is developed in GAMS and solved by CPLEX.

In [15], the optimal sizes of the components of two hybrid off-grid MGs are defined considering not only the minimum of  $CO_2$  emissions, Net Present Cost (NPC) and Levelized Cost of Energy (LCOE), but also according to five different pre-defined dispatch strategies that can be employed in meeting the load. These dispatch strategy are Generator Order (GO), Cycle Charging (CC), Load Following (LF), HOMER predictive dispatch and Combined Dispatch (CD) strategy and are analyzed using the HOMER software. With the GO dispatch strategy, there is a predefined order of generator combination that meets the demand. CC dispatch strategy has the generator operative at full capacity at all time it is required and the energy in surplus from meeting the load is used to charge the storage device. In LF, the operation of the generator is at a value enough to fulfill the load. The HOMER predictive dispatch already knows the load and the availability of the



resources due to forecasts. With CD, the least expensive optimal combination of generators indicates whether to apply LF or CC in every time-step. Frequency and Voltage stabilization constraints are considered to ensure MG systems stability. No stochastic behaviour of the RESs is included in this study. The objective function is the minimization of the sum of fuel costs as a quadratic function of the power output of each type generator employed. The simulation's MGs are composed of Diesel generators, PV systems, EESs and WTs. The dispatch simulations are performed with HOMER software, while the system performance and feasibility studies are performed in MATLAB Simulink.

The article from [16] considers the capacity design of off-grid Energy Hubs (EH). The capacity design of the components of the EHs is made of two phases. The first phase is a chance-constrained optimization problem that defines the capacity of the components, through the minimization of the NPC, with a certain value of virtual Load Shedding (LS). LS is performed by the system operator and consists of cutting unimportant parts of the load when the system faces some kind of emergency conditions, in this case when rare weather conditions that limit the RESs generation occur. The uncertainties related to solar and wind resources and to the load are considered in this part of the problem. The second phase of the capacity problem consists in the validation of the design defined in the first phase, through a set of deterministic multiperiod feasibility problems that use the true LS limit. The outcome of this phase defines a new value of the virtual LS limit, with which the first, and then again the second phase, is iterated. This iterative process allows to achieve a trade-off between reliability and cost. The chance-constrained optimization problem is reformulated as a robust model to allow a easier solution of the model, that is then solved as a Linear Programming (LP) problem, with the MATLAB-based CVX toolbox together with the Gurobi solver. This model is applied to an EHs composed of WT, PV panels, ESS, FC, CHP and an electrolyzer and Hydrogen tank as bulk energy storage. The EH peak demand is on 100 kW scale.

Most studies that handle the sizing of a MG do not usually include the possibility of changes in demand, technology, fuel and components price, including these values only as they are at the beginning of the project that lead to unrealistic results. Perera et al. [17] consider a standalone MG to visualize how three stages of changes condition the optimal design of the system. The MG is composed of PV panels, ESS, Biomass Gasification Combined Heat and Power unit (BGCHP) and Internal Combustion Generators (IGC). HOMER Pro is used to optimize the design in the three cases, that consist into different components' prices and demand profiles, and for which a comparison is made between the Cost of Energy and the percentage of Renewable energy penetration. The peak demand in the different stages are respectively 536 kW, 580 kW and 581 kW.

Wang et al. [18] analyse the optimization of the design of a integrated energy

system, meaning a system that couples different types of energy, in particular electrical, chemical and thermal energy. The sources of electrical energy are PV panels, WTs, CHP system and the public power grid to guarantee the backup for the system. Power-to-gas is employed to use the excess electricity and generated chemical energy. Finally, thermal energy comes from gas-source thermal generators, HPs and electricity-source thermal equipment. The objective function is composed of three goals:

- Minimization of the total economic cost
- Minimization of the total carbon dioxide emission
- Minimization of the comprehensive energy loss, to obtain the maximum comprehensive energy efficiency

The multi-objective function includes these objectives with the weighted sum method. The optimization is performed with the Genetic Algorithm (GA) in Matlab/Simulink software.

**Table 2.1:** Planning stage optimization in Energy systems

<i>Ref</i>	<i>Objective Function</i>	<i>Model</i>	<i>Solver</i>	<i>Uncertainties</i>			<i>Magnitude of Load</i>
				<i>Load</i>	<i>RES</i>	<i>Other</i>	
[12]	Total costs minimization	MILP (stochastic → deterministic)	Cbc (COIN-OR branch and cut)	✓	✓	<ul style="list-style-type: none"> <li>• Weather condition</li> <li>• Starting/ending time of random outage</li> <li>• Battery SoC (at random outage)</li> </ul>	Average 466 kW Peak 1648 kW
[13]	Profits and reliability maximization Costs minimization	Multi-objective MILP	Specific algorithm	-	✓	-	Min 2,323 MW in Winter Peak 4,925 MW in Summer
[14]	Total costs minimization	Stochastic MILP	GAMS model and CPLEX solver	✓	-	-	Average annual 2868 kWh (ABM estimate)

Table 2.1: Planning stage optimization in Energy systems (Continued)

Ref	Objective Function	Model	Solver	Uncertainties			Magnitude of Load
				Load	RES	Other	
[15]	Minimization of $CO_2$ emissions, NPC and LCOE, considering different dispatch strategies	-	HOMER and MATLAB Simulink	-	-	-	Load of 27.31 kW
[16]	Minimization of the NPC, given the LS value	Chance-constrained optimization problem	MATLAB+ based CVX toolbox and Gurobi solver	✓	✓	-	Peak about 100 kW
[17]	Minimization of Operational cost in different components' price and demand conditions	-	HOMER Pro	-	-	-	Peak 536 kW (Stage A) Peak 580 kW (Stage B) Peak 581 kW (Stage C)
[18]	Minimization of total economic cost, total $CO_2$ emissions and energy loss	-	GA in Matlab/ Simulink			-	Electrical 221 TJ Chemical 41 TJ Thermal 6 TJ

## 2.2 Operational stage optimization

When the optimization is performed in the operating stage, the size and location of the power generation equipment are usually already defined, at an optimal value or not, and the analysis aims at finding an optimal strategy to supply the load considering the use of different types of energy sources.

As presented by Wu et al. [19], the economic dispatch of a power system can be static or dynamic. Static economic dispatch defines a strategy considering only the operation of the system and the load as a constant value that changes with each independent period. Instead, with dynamic economic dispatch, the economic allocation of the generation is performed considering the knowledge of both present and future electricity demand, represented as a profile changing over several periods, allowing to have better coordination between different Distributed Generation (DG) systems. There are two cost-related objective functions that need to be minimized. One is the operating cost of the MG and the other is the pollutant treatment cost, and these are first investigated as individual objective functions and then together as the sum of the two costs. Normal Probability Distribution Function (PDF) is employed to describe the uncertainties related to the load and to the RESs power output. The paper in question found a dynamic economic dispatch for a simple MG (PV and WT, backup Diesel Engines, FC), that can operate either connected or disconnected from the main grid. When operating disconnected from the grid, there is an EES system to aid the demand supply, but in case the resources are still not enough to meet the load, parts of the demand that are considered unimportant can be interrupted (Load Shedding). The simulation is run and the dispatch strategy is defined for a 24 hours scenario, with time steps of 5 minutes. The model is solved in Visual C++ with Improved PSO (Particle Swarm Optimization) algorithm in combination with Monte Carlo Simulation (MCS) that determines whether the inequality related to the probability constraint of the spinning reserve is satisfied and, in case it is not, it considers a penalty function. PSO is based on the emulation of the behaviour of birds and fishes to initialize a set of candidate solutions to search for the optimal value. It is a meta-heuristic method, meaning that few or no assumptions are made.

Toopshekan et al. [20] developed a new dispatch strategy that reduces the cost of energy of the systems compared to the pre-prepared dispatch strategies usually used by HOMER (Hybrid Optimization Model for Multiple Energy Resources) software. These strategies are LF and CC. The former establishes that whenever a generator is operating, it produces just enough power to meet the demand, while with the latter the generator is always operating at full capacity and any excess power will be used to charge a battery system. The dispatch strategy developed in this article takes into account 24-h foresight of electrical load, wind speed, solar radiation and grid's cut-offs and it is developed to give information of a whole year.

It is applied to a hybrid system based in Tehran (Iran), that is composed by PV, WT, DGs and battery, and it is connected to the main grid. The comparison of the new dispatch strategy with LF and CC find that the former not only has a lower cost of energy than the pre-prepared strategies, but also has higher percentage of use of the RES, but this comes with the expense of a higher initial capital cost related to the different optimal system architecture defined for each strategy.

Zeng et al. [21] performed the economic optimization minimizing the costs while considering both the unit operating costs and the start-stop costs. Start-stop costs are related to the continuous turning on and off of the generation set. The optimization is simulated on a system composed by conventional thermal power plants, WT and PV. The model is a multi-scenario stochastic problem that is turned into a MILP problem to better find the solution. Load and RESs uncertainties are modelled starting from historical data with the Gaussian Autoregressive model and then Autoregressive Moving Average Model (ARMA) to have better fitted values. Quantile Regression is used to reduce the number of scenarios, considered with their quantile weights. The simulation time is of 24 hours, with 1 hour time-step. There are different types of scenarios to define the day-ahead dispatching schedule:

- Considering only the uncertainty of the RESs output
- Considering the uncertainty of both load and RESs output
- Considering no uncertainty
- Considering the uncertainty of both load and RESs output under different quantiles
- Considering the uncertainty of both load and RESs output with a traditional stochastic optimization method

The optimization from Daneshvar et al. [22] introduces, in the cost minimization objective function, a voice of cost related to the LS. The study applies the optimization to five different renewable-based EHs, in which the energy production comes from different combinations of RESs (WT and PV), EES and thermal storage and Combined Cooling Heating and Power (CCHP) unit. The uncertainties related to the solar radiation and wind speed are modelled with MCS approach and the Fast Forward Selection (FFS) is applied for scenario reduction. The case study is a 24 hours simulation with 1 hour time-step. The problem is modelled as a Mixed Integer Non Linear Programming (MINLP) problem and it is solved on GAMS with the use of DICOPT and SBB solvers.

Farsangi et al. present, in [23], a two-stage stochastic MINLP problem for the minimization of the operational costs of a MG, that can operate both connected to the main grid and in island mode, and in presence of a Demand Response (DR)

program. The DR program can be price based, meaning that the consumers change their habits according to the electricity price, and incentive based, meaning that the customers sign a contract that regulates the curtailment of their load in case of disturbances that cause the MG to operate in island mode. Both types of DR programs are included in the model. The uncertainties taken into account in the model are the electrical load, the market price of electricity, both modelled with Normal PDFs, the wind speed, modelled with the Weibull PDF and the solar radiation, with the Beta PDF. A MILP problem is employed to reduce the number of scenarios generated. The simulation is applied to three different cases:

- grid-connected without Demand Response programs
- grid-connected with Demand Response programs, considering maximum possible load shifting of 10% and 20%
- island condition with Demand Response programs, considering maximum possible load shifting of 10%

The MG for the validation of the model is served by PV, WT, CHP, thermal energy storage, FC and a Power generating unit. The loads are both thermal and electrical, Plug-in Electric Vehicles (PEV) are also included in the analysis. The model is modelled with GAMS and a ALPHA/ECP solver is employed.

Di Somma et al. [24] considered two objective functions in the optimization, one is economic and the other is environmental. The economic objective function was used to minimize the total energy cost of the DER system, while the environmental one is represented by the  $CO_2$  emissions related to the different technologies, that also need to be minimized. The simulations are performed first considering each of the two objective functions individually and then considering both together, varying the importance given to one of the two at the expense of the other. Both supply and demand side uncertainties were considered in the stochastic approach of the problem, they were modelled using Roulette Wheel mechanism and MCS method and were represented as 24h scenarios. The model is formulated as a Stochastic Multi-Objective Linear Programming problem. The three simulation cases are also solved in a deterministic way, without taking into account the uncertainties. The case study used to validate this model is based on a residential building composed of 50 apartments in Turin, served by CHP, PV, EES and considering that energy can be bought from and sold to the grid. The optimization was modelled and solved with CPLEX.

Other than the capacity design of the components of an off-grid EH, the paper from Geng et al. [16], presents also the definition of an optimal dispatch strategy of the optimally sized devices. The operation strategy is composed of a day-ahead optimal scheduling and of a real-time Model Predictive Control (MPC). The day-ahead scheduling is based on the forecast of the RESs generation and of the load and

aims at the minimization of the fuel cost and of LS. This optimization problem is reformulated as MILP through McCormick relaxation, and solved with the CVX toolbox and Gurobi solver. The real time MPC is a way to manage any deviation that might occur from what is defined in the day-ahead optimal schedule. The prediction horizon is of 4 hours with a 15 minutes time-step.

[25] present a security constraint multi-objective optimal dispatch for a grid-connected or islanded MG, based on the Pareto Concavity Elimination Transformation (PaCcET). There are two objective functions. The first one is to minimize the operation cost, including the one from DERs, and the cost related to the power exchange with the main grid when in grid-connected mode. The second one aims at improving the reliability through the decrease of the power exchange between the MG and the main grid and the reduction of the use of the EES when in island-mode operation. This second objective function includes also some penalty costs related to the LS of non-essential and essential loads. The proposed model is called Security-Constrained Multi-Objective Optimal Dispatch (SC-MOOD). This model is applied to a MG that consists into two dispatchable DERs, ESS and PV panels. This MG is simulation with DIgSILENT software and implemented in MATLAB. The uncertainties of PV generation and loads were not taken into account.

Zhang et al. [26] present an optimization for the definition of a dispatch strategy of a cluster of MGs. This optimization is a two-levels problem. The overall goals are the stability and the benefits from the MGs' cluster. The first level employs an improved PSO algorithm for the maximization of the MGs' benefits and for the minimization of the operation risk index. The benefits are defined as the incomes from the new energy consumed by the load and energy surplus on-grid minus the fuel costs and the electricity bought from the external grid, while the operation risk index represents the risks related to the load shortage and to the RESs overflow. Uncertainties related to wind, solar radiation and load are included in the operational risk index objective function and can be described as Gaussian PDF. The simulation period is of 24 hours and the time step is of 1 hour. The second level of the optimization aims at minimizing the power exchanged at Point of Common Coupling (PCC) and at minimizing the fluctuations of the DERs' generated power to reduce the impact of the MGs on the stability of the distribution network. Also, the power transmission losses, that occur when the distribution follows long-distance paths, need to be minimized. The number of iterations need to reach a solution with the Improved PSO is compared to the standard PSO and the Tabu Search (TS) algorithm.

Dynamic economic load dispatch (DELD) problem is faced in this paper [27] in the optimization of the power supply strategy of a system composed of Thermal power generators and WT generators. Load and wind power uncertainties are included in the scenario-based stochastic programming problem. The scenarios



are generated with MCS method and a scenario reduction technique is employed. The model developed is a nonsmooth non-convex optimization problem and it is solved with a modified Teaching-Learning-Based Optimization (TLBO), that is a metaheuristic algorithm inspired from the interactions between teacher and students and among students themselves in a classroom environment. The changes on this algorithm allow better solution quality, convergence speed, robustness and efficiency. The objective function of the problem in question is represented by the minimization of fuel consumption rate. The formulation includes constraints such as transmission power losses, valve point loading effects and ramp rate limits. The modified algorithm is tested considering five individual independent cases with different combinations of constraints. The simulation period is of 24 hours and the time step is of 1 hour.

The day-ahead scheduling of a islanded MG is proposed in [28]. Said MG consists of PV panels, a Geothermal generator and a Biomass generator. The objective function is represented as the minimization of the operating costs of the MG, considering the costs related to each generating unit. The PSO algorithm is employed in the solution of this problem. The time step is of 1 hour, but the simulation period could either be of 1 day or of 1 month. Solar energy is evaluated with the aid of statistical meteorological data and panels' properties. The results are compared to the one obtained from the use of the Harmony Search Algorithm instead of the PSO, finding that the solution is quite similar, but the computational time is lower with the PSO algorithm.

A two-step multi-objective scheduling problem based on cloud-edge computing is presented in [29]. A Central Energy Management System (CEMS) is employed for the day-ahead economical and environmental scheduling of a MG. The concept of two-step is included in the fact that the optimization is divided into two models: the global optimization model on cloud-side and the online local optimization model on edge-side. The first one is employed to find the global optimal day-ahead schedule using the forecast data, while the second one is used to correct what is computed in the first model. The first optimization model has two objective functions: an economic objective function that includes the minimization of fuel, Operation and Maintenance (O&M), start-up and depreciation costs and the maximization of the benefit from the main grid, and an environmental objective function that is the minimization of the air pollutants derived from the DGs. The objective function of the local optimization model is to minimize the correction on cost and emissions. Three different MGs are used to validate these models:

- Composed by microturbines (MTs), FC and ESS in island mode
- Composed by MTs, FC and ESS in grid-connected mode
- Composed by MTs, FC, ESS and WT in grid-connected mode

The optimization algorithm used to solve this problem is a Non-dominated Sorting Genetic Algorithm II (NSGAI), The global optimum obtained in the first step of the model is used as the initial population of the local optimization. For the electric load and the wind speed both forecasts and actual values are used.

**Table 2.2:** Operational stage optimization in Energy systems

<i>Ref</i>	<i>Objective Function</i>	<i>Model</i>	<i>Solver</i>	<i>Uncertainties</i>	<i>Simulation period</i>	<i>Time step</i>
[19]	Dynamic Economic Dispatch Costs minimization (considering Pollutant Treatment Cost)		Improved PSO, solved with Visual C++	Load and RESs modelled with Normal PDF MC simulation on the spinning reserve constraint	24 hours	5 minutes (288 periods)
[20]	Cost of Energy minimization		HOMER Pro MatLab Link	24 hours foresight on Load, Wind Speed and Solar Radiation	1 year	1 hour (8760 periods)
[21]	Unit Operating Cost and Start-Stop Cost minimization	Multi-scenario Stochastic problem $\rightarrow$ MILP		Load and RES, modelled from historical data with Gaussian Autoregressive model $\rightarrow$ ARMA $\rightarrow$ QR for scenario reduction	24 hours (Day-ahead)	1 hour
[22]	Cost minimization considering LS related cost element	MINLP	GAMS model DICOPT and SBB solver	Solar Radiation and Wind Speed, modelled with MCS FFS for scenario reduction	24 hours (Day-ahead)	1 hour
[23]	Operational Cost minimization with a DR program	Stochastic MINLP	ALPHAECOP with GAMS model	Wind speed $\rightarrow$ Weibull PDF Solar radiation $\rightarrow$ Beta PDF Load and market price $\rightarrow$ Normal PDF MILP for scenario reduction	24 hours	1 hour

**Table 2.2:** Operational stage optimization in Energy systems (*Continued*)

<i>Ref</i>	<i>Objective Function</i>	<i>Model</i>	<i>Solver</i>	<i>Uncertainties</i>	<i>Simulation period</i>	<i>Time step</i>
[24]	Economic OF (Cost minimization) Environmental OF ( $CO_2$ emissions minimization)	Stochastic Multi-Objective LP	CPLEX (Branch and Cut)	Solar radiation $\rightarrow$ Beta PDF Rank correlation between Solar radiation and electricity price Demand $\rightarrow$ RWM and MCS and FFS scenario reduction technique based on Kantorovich distance	24 hours	1 hour
[16]	Fuel cost and LS minimization	MPC $\rightarrow$ Stochastic MILP (through McCormick relaxation)	CVX toolbox and Gurobi solver	RESs generation and load	4 hours (for the real time MPC)	15 minutes
[25]	Minimization operation costs and improvement of the reliability (also penalty cost related to LS)	SC-MOOD	DIgSILENT software simulation and MATLAB	-	-	-

**Table 2.2:** Operational stage optimization in Energy systems (*Continued*)

<i>Ref</i>	<i>Objective Function</i>	<i>Model</i>	<i>Solver</i>	<i>Uncertainties</i>	<i>Simulation period</i>	<i>Time step</i>
[26]	1st level: maximization MGs' benefits and minimization operation risks 2nd level: minimization power exchanged at PCC and minimization DERs' power fluctuations		Improved PSO	Wind, solar radiation and load, modelled as Gaussian PDF	24 hours	1 hour
[27]	Minimization of the fuel consumption rate	Nonsmooth non-convex DELD optimization problem	Modified TLBO	Wind and load, modelled with MCS method and scenario reduction technique	24 hours	1 hour
[28]	Minimization MG operating costs	-	PSO, then compared to HSA	Statistical solar related data	1 day or 1 month	1 hour

**Table 2.2:** Operational stage optimization in Energy systems (*Continued*)

<i>Ref</i>	<i>Objective Function</i>	<i>Model</i>	<i>Solver</i>	<i>Uncertainties</i>	<i>Simulation period</i>	<i>Time step</i>
[29]	1 <sup>st</sup> ) step $\rightarrow$ Economic and Environmental dispatch 2 <sup>nd</sup> ) step $\rightarrow$ correction on the 1 <sup>st</sup> ) step	-	NSGAII	Forecasts for electric load and wind speed	24 hours (Day- ahead)	1 hour

This Chapter proposed a comprehensive review that highlights the main characteristics of the solutions analyzed in the literature. Both planning and operational stage models have been introduced. However, after careful consideration, it has been chosen to focus on a day-ahead optimization that minimizes the costs associated with the resources considered for the scenario. The framework introduced in this thesis allows to easily select the resources for the simulation in a plug-and-play fashion. In fact, the developed code follows the principle of modularity, i.e. according to the type of available resources, the optimized dispatch strategy can consider different types of setup MicroGrid under simulation. For the purpose of this thesis, the Renewable resources that have been considered are:

- Photovoltaic Plant
- Wind Turbine

Moreover, also a simple model of a Battery has been considered, in order to allow the system to charge it when there is exceeding RES production and to discharge it when it is needed to supply the load. The thesis does not limit itself to consider only one kind of optimization. Different users might have different requirements and focus their analysis on different topics, considering different resources or different sizes of installed resources.

Therefore, this thesis proposes a first MILP aimed at minimizing the electricity provision costs, in a context that considers a deterministic framework of a day in the past with defined values of Electricity Demand, Electricity Market Price, Wind Speed and Solar Radiation for a 24 hour time period. This was done with different configurations of the MG, giving the right importance to the plug-and-play aspect of the model.

In a second approach, probabilities studies have been introduced, so that the definition of the dispatch strategy could include the variability of the values of Electricity Demand, Electricity Market Price, Wind Speed and Solar Radiation, considered in the first part of the analysis. To do so, Probability Density Function have been introduced and used as input to a MILP that had the objective of reducing the number of scenarios related to the probability of said time-related variables (ED, MP, WS and SR), keeping a reasonable level of uncertainty. Then these scenarios are used as inputs to a MILP equal to the one in the first approach, defines a dispatch strategy with minimum operational costs for the MG.

In conclusion, the main features of the proposed framework are:

- the flexibility of the input
- the capability of easily adding new modules
- the possibility to choose the optimization
- the possibility to compare different configuration of the MG

## Chapter 3

# Deterministic approximation of the model

### 3.1 Model

The following chapter introduces the model that represents the plug-and-play framework. The first part of the chapter presents the resources that are included and defines the equations that describe the parameters related to those resources. Then, in the second part of the chapter, the plug-and-play model is used, coupled with a MILP, to define an optimal dispatch strategy in a deterministic approach, in which the variables that change in time come from the literature. Among these values, the Electricity Demand is represented by the aggregated load of 12 households, the Electricity Market Price comes from the *Gestore Mercati Energetici* (GME) website [30], and takes as a reference the year 2013. Also, the variables that depend on the weather conditions, that are the wind speed and the solar radiation, are taken in the year 2013 [31] [32].

For the purpose of this chapter, these time-related values were taken for a time period of 24 hours and, to have a more complete look on how the dispatching of electricity can change throughout the year, it is repeated for two different days, one that is representing of the summer season, and one for the winter season.

Moreover, a Battery Electrical Storage System (BESS) is considered, so that it can offer support to the RES in case the weather conditions would not be suitable for production, and in case of excess of RES production to charge it. The direction of these energy flows are related to economic convenience, since also the Electrical Grid takes part in the dispatch. In particular, the grid operates as a backup source of energy for when the RES production coupled with the battery is not enough, and as a "sink" that gathers the excess of RES production when it is higher than the load and the BESS is already fully charged. Furthermore, these rules also obey



to the economic advantage, therefore the MILP takes into account the costs related to the use of each resource.

## 3.2 Resource modelling

### 3.2.1 Wind Turbine

Following the line of reasoning of Farsangi et al. [23], the power from the WT is evaluated as represented in eq. 3.1.

$$P_{wind} = \begin{cases} 0 & \text{for } 0 \leq v_i < v_{cut\ in} \\ P_{rated} \cdot \left( \frac{v_i - v_{cut\ in}}{v_{cut\ out} - v_{rated}} \right)^3 & \text{for } v_{cut\ in} \leq v_i < v_{rated} \\ P_{rated} & \text{for } v_{rated} \leq v_i < v_{cut\ out} \\ 0 & \text{for } v_i \geq v_{cut\ out} \end{cases} \quad (3.1)$$

where  $v_i$  is the value of wind speed in the time step  $i$ ,  $v_{cut\ in}$  represents the cut-in speed, below which the wind turbine blades do not rotate and therefore the output power is zero,  $v_{cut\ out}$  is the cut-out speed, above which the turbine is stopped to maintain the structural integrity of the blades, for which again the output power is zero.  $v_{rated}$  is the rated speed, that represents the speed associated to the rated power of the wind turbine, and therefore the maximum output power. For  $v_i$  greater than the cut-in speed  $v_{cut\ in}$  and lower than the rated speed  $v_{rated}$ , the output power follows a cubic law, while when the wind speed is greater or equal to the rated speed  $v_{rated}$  the output power is constant and equal to the rated or nominal power of the wind turbine.

### 3.2.2 Photovoltaic Plant

On the other hand, the power from the PV plant is evaluated as

$$P_{PV} = S \cdot POA_{global} \cdot \eta_{mp} \quad (3.2)$$

where  $S$  is the area of whole PV system,  $POA_{global}$  is the global irradiance of the Plane Of Array (POA) and  $\eta_{mp}$  is the efficiency of the modules in the maximum power point.

These parameters are evaluated as

$$S = N_{PV\ cells} \cdot A_{cell} = \frac{P_{rated,tot}}{P_{rated,cell}} \cdot A_{cell} \quad (3.3)$$

$$T_{cell} = \frac{T_{amb} + (T_{c,NOCT} - T_{ex,NOCT}) \cdot \frac{POA_{global}}{G_{NOCT}} \cdot (1 - \frac{\eta_{mp,STC} \cdot (1 - \alpha_P \cdot T_{c,STC})}{\tau \cdot \alpha})}{1 + (T_{c,NOCT} - T_{ex,NOCT}) + \frac{POA_{global}}{G_{NOCT}} \cdot (\alpha_P \frac{\eta_{mp,STC}}{\tau \alpha})} \quad (3.4)$$

$$T_{amb} = T_{ex} + 0.05 \cdot POA_{global} \quad (3.5)$$

$$\eta_{mp} = \eta_{mp,STC} \cdot (1 - \alpha_P \cdot (T_c - T_{c,STC})) \quad (3.6)$$

### 3.2.3 Battery Electrical Storage System

Following the reasoning from Wu et al. [19], the BESS model includes the evaluation of the State of Charge of the storage system (3.7), that varies at each time step of the model and depends on the SoC of the previous time step. Equation 3.7 takes also into account the Self-Discharge  $SD_B$ , the charging/discharging energy of the BESS, that changes with time,  $E_{B,c}(t)$  and  $E_{B,d}(t)$ , the capacity  $Q_B$  and the efficiency  $\eta_B$ .

$$SoC_B(t) = \begin{cases} (1 - SD_B) \cdot SoC_{B,init} - \frac{E_{B,d}(t)}{Q_B \cdot \eta_B} & \text{for } t = 1 \\ (1 - SD_B) \cdot SoC_B(t-1) - \frac{E_{B,c}(t) \cdot \eta_B}{Q_B} & \text{for } t > 1; E_B \leq 0 \\ (1 - SD_B) \cdot SoC_B(t-1) - \frac{E_{B,d}(t)}{Q_B \cdot \eta_B} & \text{for } t > 1; E_B > 0 \end{cases} \quad (3.7)$$

Also, minimum and maximum values of both charging/discharging energy of the BESS and of the SoC are taken into account, according to the limit of the Battery system.  $SoC_{B,init}$  represents the initial State of Charge of the battery and it is set to 0.5 for all simulations that will follow in this work of thesis.

The energy exchanged with the BESS is given by the summation of discharged and re-charged energy to the battery (3.8).

$$E_B(t) = E_{B,d}(t) + E_{B,c}(t) \quad (3.8)$$

Where  $E_{B,d}(t)$  is the discharged energy from the battery into the load and it is defined to assume a value between zero and the maximum value of BESS charge, while  $E_{B,c}(t)$  is the energy flowing into the battery that assumes values between the minimum value of BESS charge and zero.

### 3.2.4 Electrical Grid

As already stated, the Electrical grid supplies energy to the framework when there is not enough electricity production from the RES and the BESS to supply the load or there is an economic advantage in buying electricity from the grid. On the other hand, the grid receives energy from the RES when their production is higher than the load and the BESS is already charged or it is not advantageous to charge it. These reasoning, without the economic part, that is largely explained later in the chapter, is summarized in the system of equations 3.9 below.

$$\begin{cases} \text{when } |E_{ED}(t)| > E_{PV}(t) + E_{WT}(t) + E_B(t) \rightarrow E_g(t) > 0 \\ \text{when } |E_{ED}(t)| < E_{PV}(t) + E_{WT}(t) + E_B(t) \rightarrow E_g(t) < 0 \end{cases} \quad (3.9)$$

As a reference, the electricity supplied by the grid is defined as positive, while the electricity injected into the grid is negative.

The economic advantage of buying and selling from the grid comes from the costs associated to these flows. In Italy, *Gestore Servizi Energetici* (GSE) provides different tariff mechanisms according to the needs and possibilities of the users. One of these is called *Scambio sul Posto* [33]. It is a form of self-consumption that takes place on-site and allows the prosumer to use the electrical network as a virtual storage for the produced electricity but not consumed right away.

In the context of this tariff mechanism, the electricity produced from the DERs is sold to the main grid at the Electricity Market Price, that assumes different values along the day and comes from the GME website [30].

### 3.3 Dispatch strategy optimization model

The balance of electricity of the MG is performed through the minimization of the operational costs. This is embodied in the objective function as represented in 3.10. The optimization is carried out with a time step of 1 hour, over a period of 24 hours, therefore considering the Day-Ahead market.

$$\min f = \sum_{t=1,2,\dots}^{T=24} p_{WT} \cdot E_{WT}(t) + p_{PV} \cdot E_{PV}(t) + p_{MP}(t) \cdot E_g(t) + p_B \cdot E_{B,d}(t) \quad (3.10)$$

The unit costs that participate to the objective function are the cost per unit of energy of the elements connected to the MG, respectively:

- $p_{WT}$  for the WT, that is represented by the WT Levelized Cost of Energy (LCOE), taken from the literature, more precisely from the International Renewable Energy Agency (IRENA) Power Generation costs of 2020 [34], for the onshore Wind power plants installed in Italy, equal to 0.062 \$/kWh;
- $p_{PV}$  for the PV, that is represented by the PV LCOE, also taken from the IRENA Power Generation costs of 2020 [34], for the residential sector PV installed in Italy, that is equal to 0.104 \$/kWh;
- $p_{MP}$  is the Market Price for electrical energy, it varies in time and it represents the cost for the electricity exchange with the Electrical Grid;
- $p_B$  is the cost related to the use of BESS, that is included only when the BESS is discharging, supplying energy to the load. This cost is assumed to be equal to the Levelized Cost of Storage for a Lithium-Ion battery for residential use, usually coupled with a PV system, from the version 7.0 of Lazard's Levelized Cost of Storage (LCOS) Analysis [35], that has the value of 0.621 \$/kWh. Meanwhile, the charging process is assumed to be free of costs, since it is performed only with the RESs connected to the MG

The values of LCOE and LCOS are converted from USD to Euro with an exchange rate of 0.88 €/€ [36].

The formulation also includes the energy balance, as for eq. 3.11, that forces the supply of the Electricity Demand (ED) with the available sources (PV, WT, BESS and electricity from the grid).

$$|E_{ED}(t)| = E_{PV}(t) + E_{WT}(t) + E_g(t) + E_B(t) \quad (3.11)$$

For what concerns the BESS model, there is a further constraint, that defines the circumstances of battery charge or discharge, that also cannot occur in the same time step. This is represented by the system of equation in 3.12 and 3.13.

$$\left\{ \begin{array}{ll} E_{B,c}(t) > |E_{ED}(t)|E + E_g(t) - (E_{PV}(t) + E_{WT}(t)) & \text{if } |E_{ED}(t)| < E_{PV}(t) + E_{WT}(t) \\ E_{B,c}(t) = 0 & \text{if } |E_{ED}(t)| > E_{PV}(t) + E_{WT}(t) \end{array} \right. \quad (3.12)$$

$$\left\{ \begin{array}{ll} E_{B,d}(t) < |E_{ED}(t)| + E_g(t) - (E_{PV}(t) + E_{WT}(t)) & \text{if } |E_{ED}(t)| > E_{PV}(t) + E_{WT}(t) \\ E_{B,d}(t) = 0 & \text{if } |E_{ED}(t)| < E_{PV}(t) + E_{WT}(t) \end{array} \right. \quad (3.13)$$

These last two constraints define that if the RESs' production is larger than the demand, then the battery could be charged, while when the electricity from RESs is smaller than the demand, the storage system could be discharged to supply it.

### 3.3.1 Applications of the model

The model introduced in the previous sections was first applied to a MG composed by the modelled resources, with the hypothesis of optimizing the electricity dispatch for a day in the year. Two days along the year were selected in ordered to have a generic idea of how the MG would behave in two different type of weather conditions. The first day that is analysed is July 1<sup>st</sup> 2013 (day 182) to represent a summer day, while the second one is December 14<sup>th</sup> 2013 (day 348), a winter day. The data concerning the PV panels, the WT and the BESS is summarized in the following tables (table 3.1, table 3.2 and table 3.3). The total PV rated power is assumed to be of 15 kW. This value was chosen based on the assumption that, on average, each of the household would install a PV system with rated power of 1.25 kW, or 5 of the households would install a PV system of 3 kW. The rated power of the WT comes from the assumption that the totality of the households would install a WT as a community, with a value of installed power of 10 kW. On the other hand, the rated capacity of the battery is of 25 kWh and its rated power of 6 kW.

**Table 3.1:**

PV parameters [37]

$P_{c,rated}$	0.283 kW
$A_c$	1.725 m
$n_{PVpanels}$	53
$T_{c,NOCT}$	45 °C
$T_{ex,NOCT}$	20 °C
$T_{c,STC}$	25 °C
$\tau\alpha$	0.9
$P_{tot,rated}$	15 kW
$p_{PV}$	0.09152 $\frac{\text{€}}{\text{kWh}}$

**Table 3.2:**

WT parameters [38]

$P_{rated,WT}$	10 kW
$v_{cutin}$	3 $\frac{\text{m}}{\text{s}}$
$v_{cutout}$	30 $\frac{\text{m}}{\text{s}}$
$v_{rated}$	10 $\frac{\text{m}}{\text{s}}$
$p_{WT}$	0.05456 $\frac{\text{€}}{\text{kWh}}$

**Table 3.3:**

BESS parameters [35]

$SD_B$	0.02 $\frac{\%}{\text{h}}$
$Q_B$	25 kWh
$\eta_B$	0.96
$SoC_{B,min}$	0.1
$SoC_{B,max}$	0.9
$E_{B,min}$	-6 kW
$E_{B,max}$	6 kW
$p_B$	0.54648 $\frac{\text{€}}{\text{kWh}}$

As already stated, for what concerns the information on the Market Price of electricity, the data is taken from the GME website [30] in the selected days. Also the information on wind speed and solar radiation are delimited to the selected days, respectively from the Visual Crossing website [31] and from the PVGIS tool [32]. The Electricity Demand is represented by the aggregated values of load from 12 households, this data is representative of one year of consumption and the selected days are taken from it.

## 3.4 Summer day (July 1<sup>st</sup>)

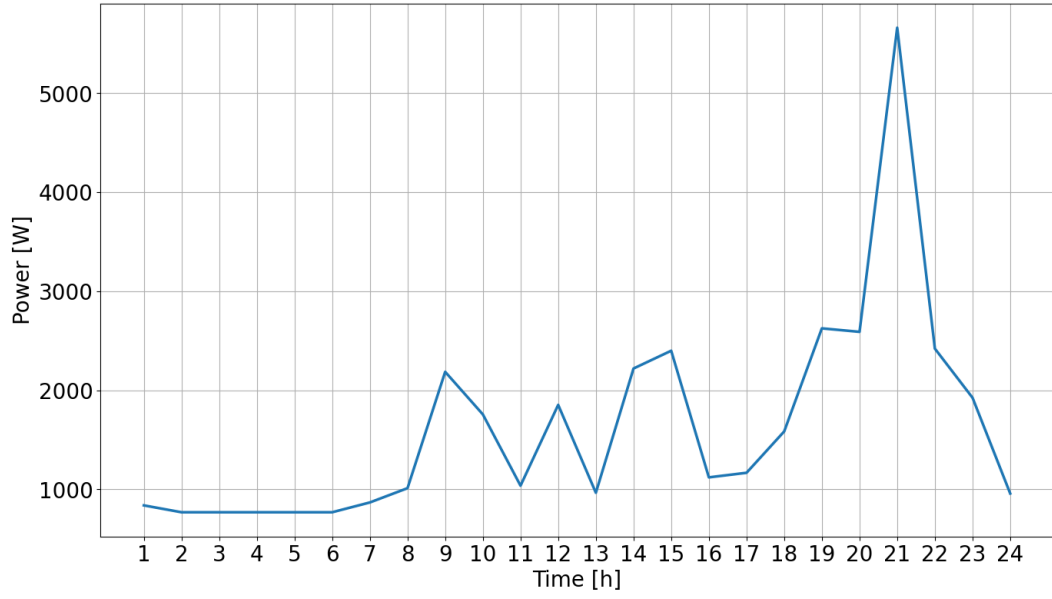
### 3.4.1 Input data

The following graphs represent the curves of 24 hours of data for respectively Electricity Demand (Figure 3.1), Market Price of Electricity (Figure 3.2), Wind Speed (Figure 3.4) and Solar Radiation (Figure 3.3) on said summer day of the year 2013.

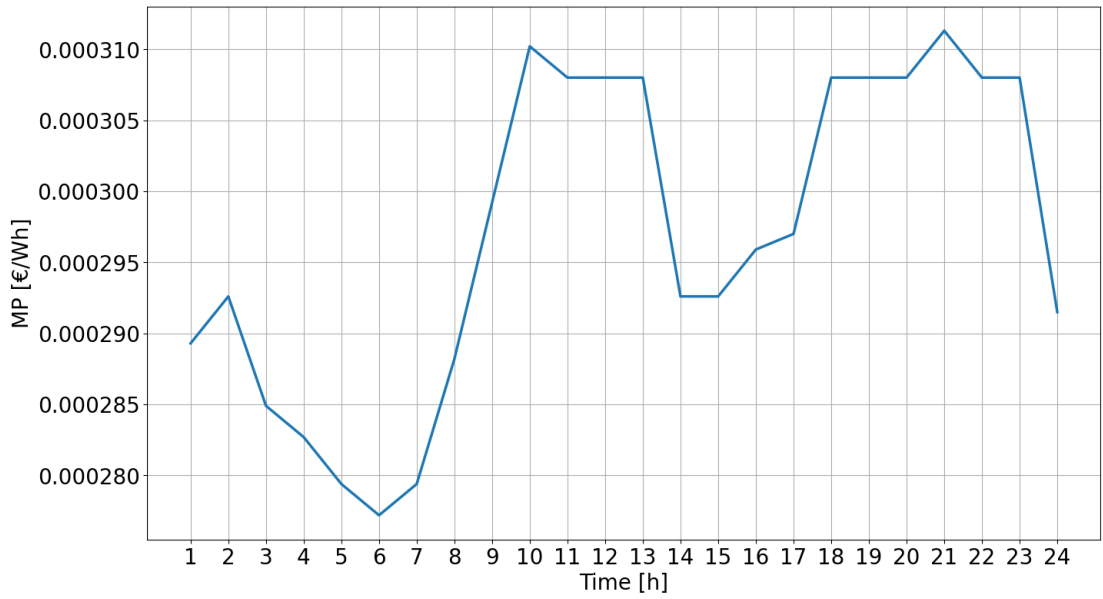
In figure 3.1, it can be clearly noted the increase of demand that typically occurs in the evening.

Figure 3.2 shows the electricity market price throughout the day, it is interesting to point out that the maximum price reached during this day is of  $0.0003113 \frac{\text{€}}{\text{Wh}}$ , that is equal to  $0.3113 \frac{\text{€}}{\text{kWh}}$ , meaning that is always lower than the cost associated to the BESS.

The power extracted from the PV panels is evaluated using the values from the



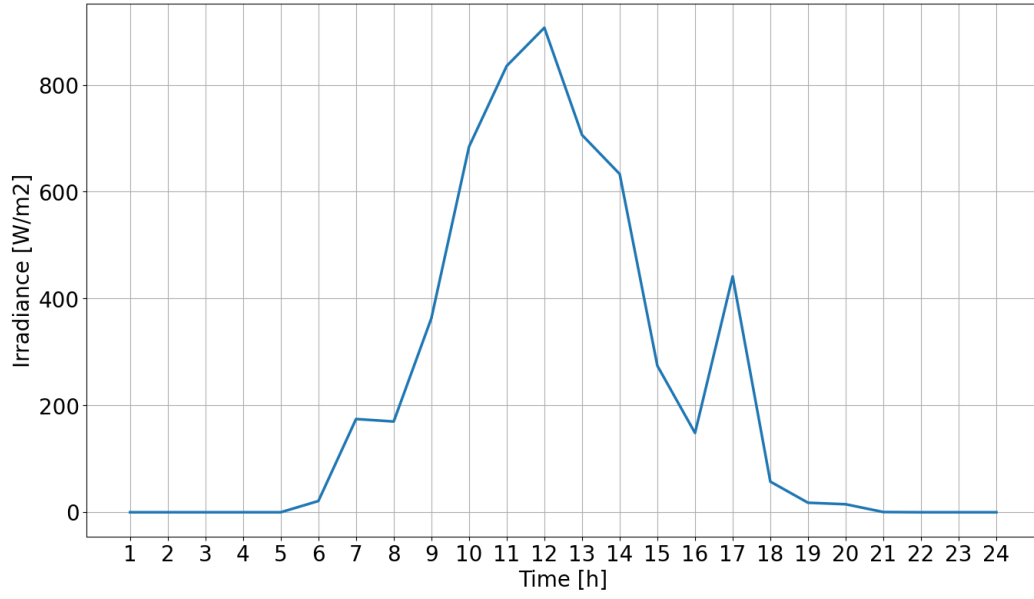
**Figure 3.1:** Electricity Demand for July 1<sup>st</sup> 2013



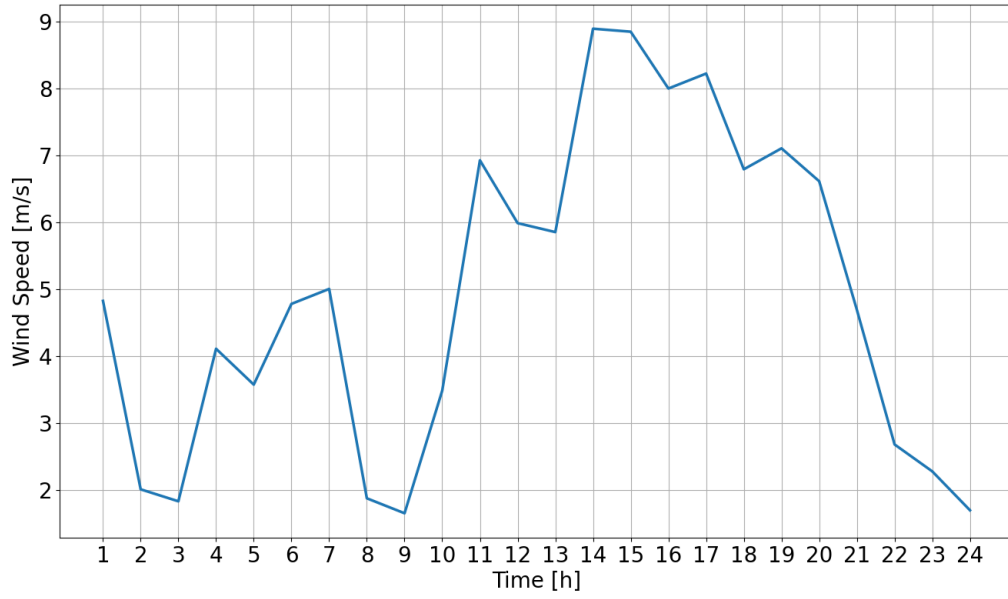
**Figure 3.2:** Electricity Market Price for July 1<sup>st</sup> 2013

curve represented in figure 3.3 as input to the model described in section 3.2.2. The resulting values of instantaneous power are represented in graph 3.5.

Similarly, the power extracted from the WT is evaluated using the values of



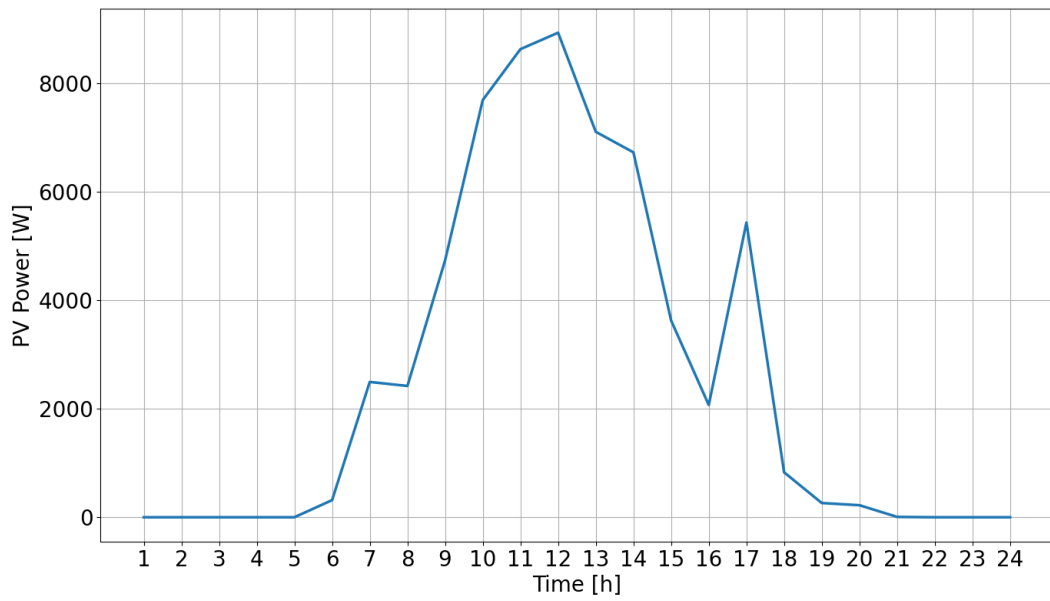
**Figure 3.3:** Solar Radiation for July 1<sup>st</sup> 2013



**Figure 3.4:** Wind Speed for July 1<sup>st</sup> 2013

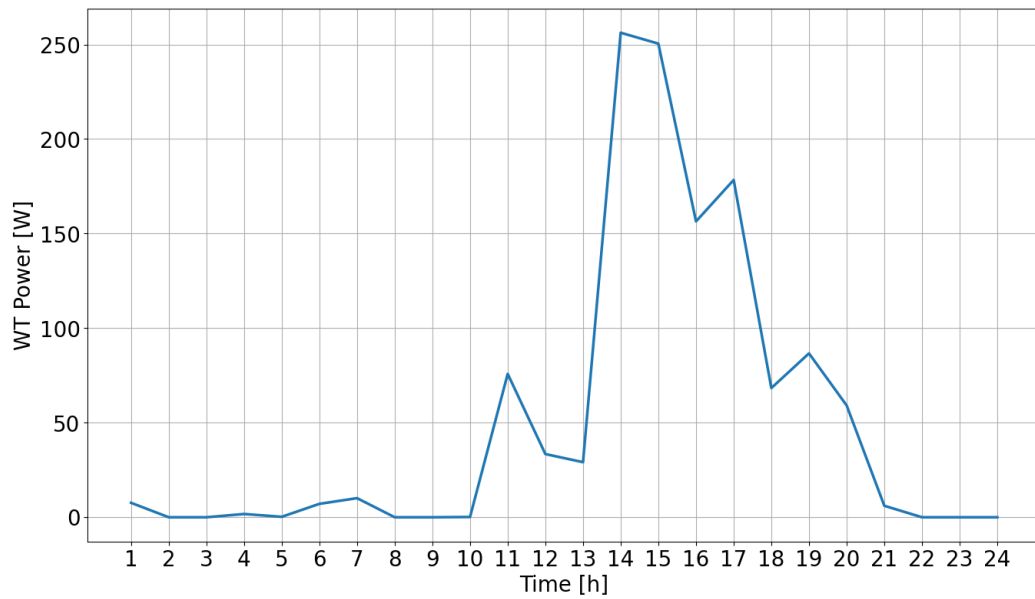
wind speed as represented in figure 3.4 as input to the model previously described in 3.2.1. The following graph (3.6) shows the instantaneous power curve for the WT. It is worth mentioning that the power from the WT is orders of magnitude





**Figure 3.5:** PV production for July 1<sup>st</sup> 2013

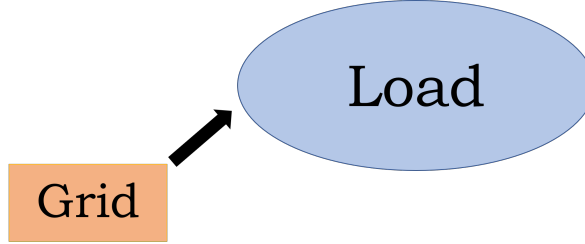
lower than the power extracted from the PV system.



**Figure 3.6:** WT production for July 1<sup>st</sup> 2013

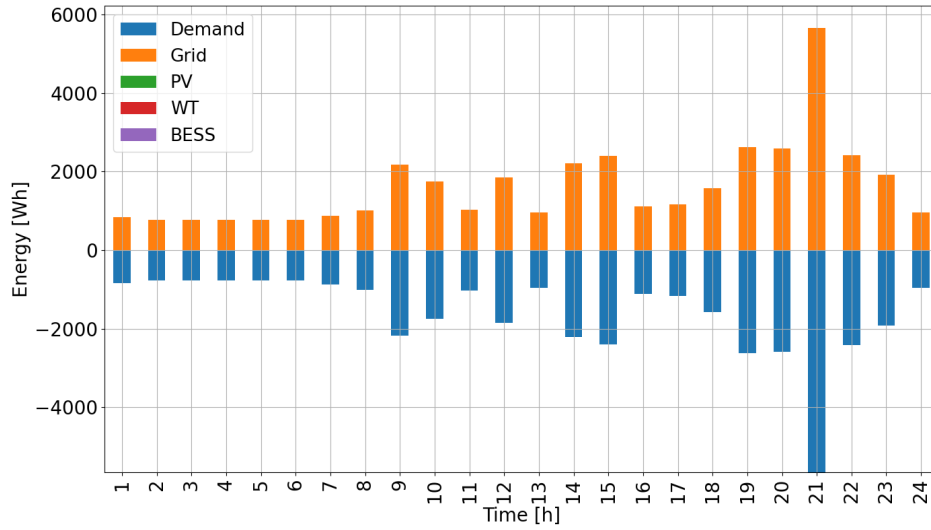
### 3.4.2 Results

With the data presented in the previous sections (3.3.1 and 3.4.1), the optimization model is first run considering a configuration without RES production and BESS support for the electricity supplying. Therefore, in this case, the whole ED is supplied by the grid as can be seen in the following block diagram of the MG 3.7.



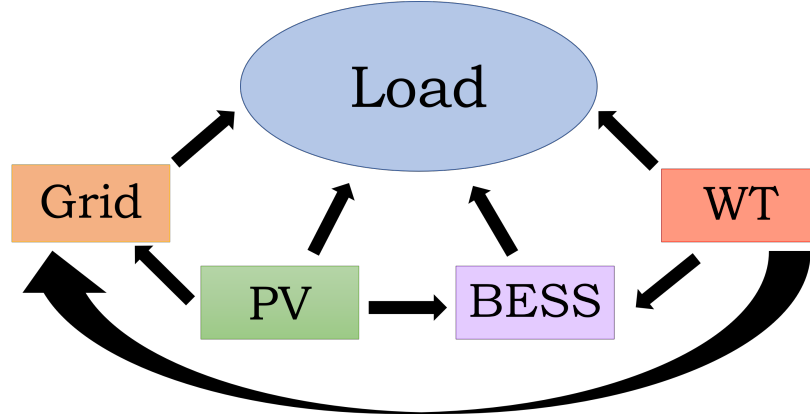
**Figure 3.7:** Representation of the MG with only the Grid supplying the Load

Since the totality of the electricity needed to supply the load is bought from the grid, as can be seen in the figure 3.8, the cost related to this dispatch strategy for the summer day is of 11.75€.



**Figure 3.8:** Electricity Demand dispatch with only the main grid on the summer day

Then, the framework is optimized in the case in which all renewable sources are connected as it is the BESS, as represented in figure 3.9.



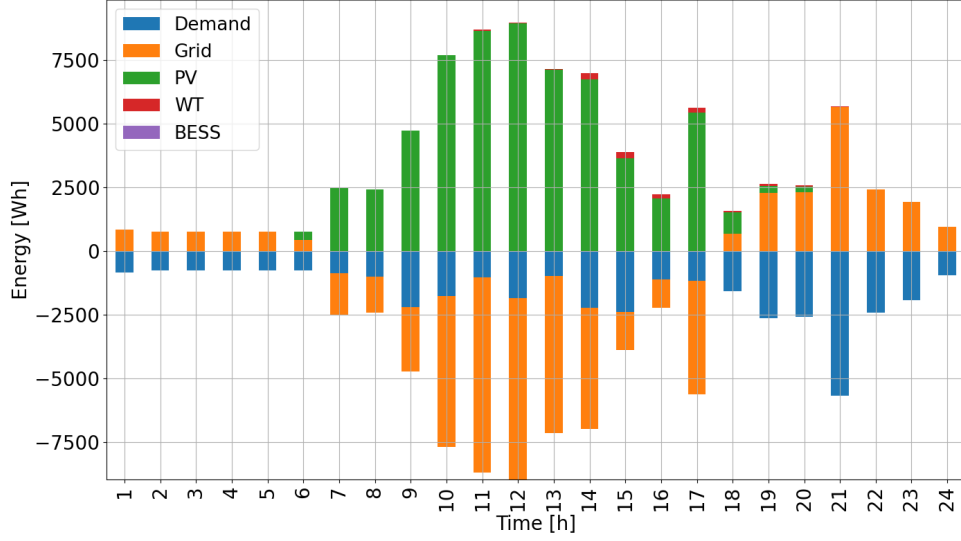
**Figure 3.9:** Representation of the MG with all resources and the BESS connected

The resulting curves are represented in Figure 3.10. To better understand the graph, it is worth mentioning that the ED is shown in blue and it is considered a negative value, while the available DERs, meaning WT and PV, are respectively represented in red and green and are considered positive. The power exchanged with the Electrical Grid is shown in orange and it is considered positive when it is extracted from the grid, therefore when it supplies energy to the load, while when energy is injected into the grid, its value is considered negative. This last case occurs only when the production of the RESs is higher than the ED and the amount of energy injected into the grid is given by the difference between what is produced from both WT and PV plants and the energy needed to supply the load, eventually reduced by the quantity supplied by the BESS. The steps in purple are representative of the energy flow exchanged with the BESS, in this case they are not showing since it does not participate to the dispatch strategy.

In the representation of the optimized MG dispatch strategy, in the first hours of this summer day, the ED is supplied by the grid, while starting from around 5 in the morning, the contribution of the PV plant increases due to the occurrence of daylight, and it supplies the load up until 20 in the evening, when the sun is set and the load is supplied by the grid. Since the production from WT is orders of magnitude smaller than the PV production, it only gives a small contribution to the ED supply briefly during the afternoon hours. It is worth mentioning that between 6 and 7 in the morning, the PV production gets much higher than the Electrical load, meaning that there is an injection of electricity in the grid for a value that is equal to the RES production net of the load, as can be seen up until 18 in the evening.

In this case, the BESS does not contribute at all to the energy balance, nor it is charged, due to the fact that there is not an economical convenience.

The optimized cost associated to this dispatch strategy is  $-1.45$  €. With respect to



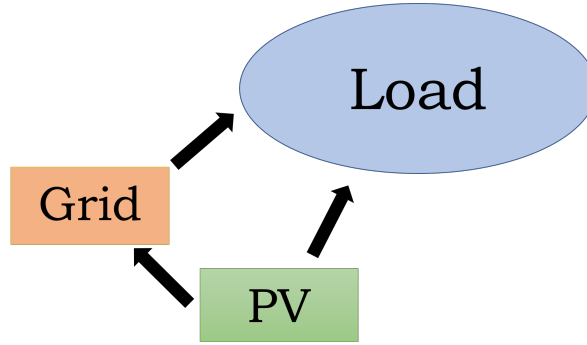
**Figure 3.10:** MG energy balance for the summer day

the case in which the load is entirely supplied by the main grid, there are savings of 112.34% for the single day, related to the fact that for the central part of the day, the system injects most of the PV production into the grid, earning from its sale.

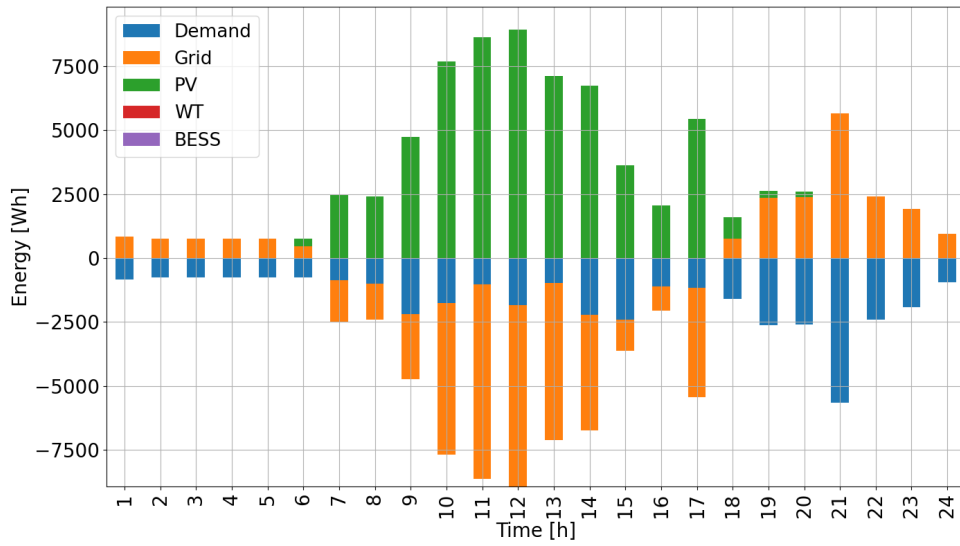
In the perspective of a Plug and Play model, the MG optimization is analyzed also in the cases in which respectively only the PV plant and only the WT are connected. In the circumstances of this summer day, unplugging the BESS would not be meaningful since it already does not contribute to the dispatch strategy.

In the framework in which the MG electricity demand would only be supplied by the PV and grid, the optimal dispatch strategy is shown in figure 3.12, while the representation of the MG can be seen in figure 3.11.

The absence of the WT does not make a great difference in the supply of the load, hence the cost of this optimal dispatch strategy is very similar to the original case,  $-1.15$  €. Comparing it to the case in which there is only the grid, the savings are 109.75%. The RES production still covers the whole demand, but convenience is slightly lower than the one in case with both PV and WT, due to the fact that in this configuration the quantity that can be injected into the grid is lower since there is not the WT production between 14 and 21 in the afternoon.

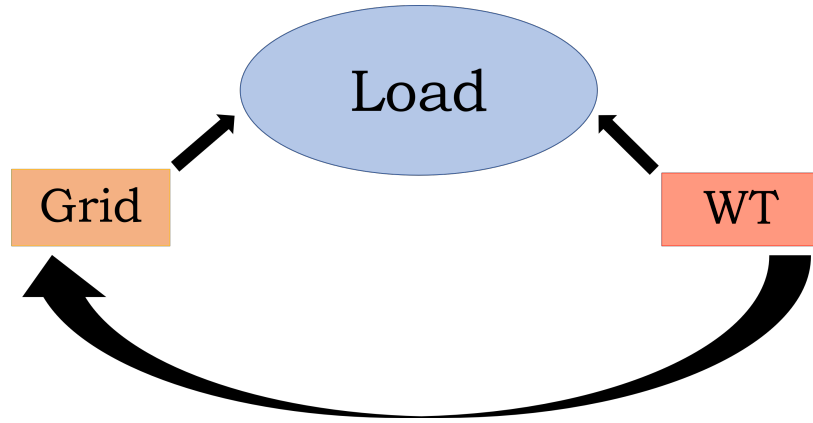


**Figure 3.11:** Representation of the MG with Grid and PV are supplying the Load

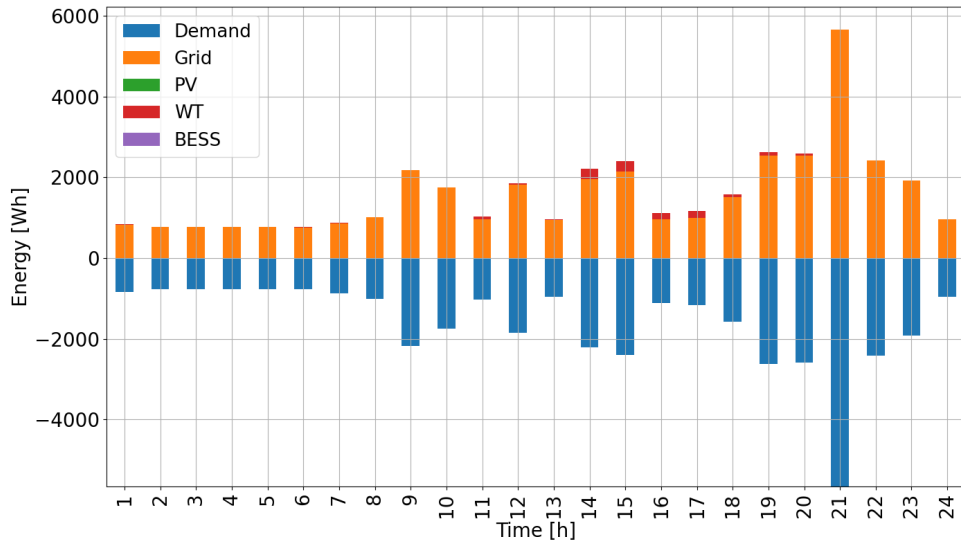


**Figure 3.12:** MG energy balance without WT for the summer day

More noteworthy it is the dispatch strategy without the PV system, as represented in figure 3.13. In this case, the ED is almost completely supplied by the grid. This explains the optimal dispatching cost to 11.45 €, with savings of only 2.55% compared to the case in which the ED is only supplied by the grid. The dispatch strategy is shown in figure 3.14. It can be seen that the WT contribution to the load supply is only present between 14 and 21 and its order of magnitude is much lower than the electricity demand's.



**Figure 3.13:** Representation of the MG with the Grid and the WT supplying the Load



**Figure 3.14:** MG energy balance without PV for the summer day

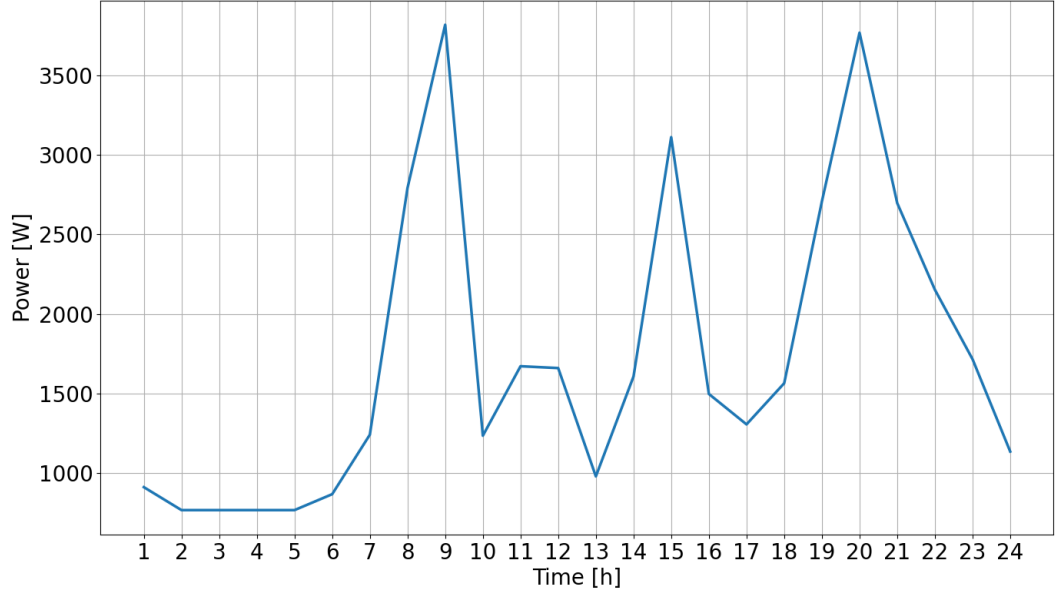
## 3.5 Winter day (December 14<sup>th</sup>)

### 3.5.1 Input data

Similarly to the summer day simulation, the data from a winter day, December 14<sup>th</sup> is used as an input to the model described in the previous sections.

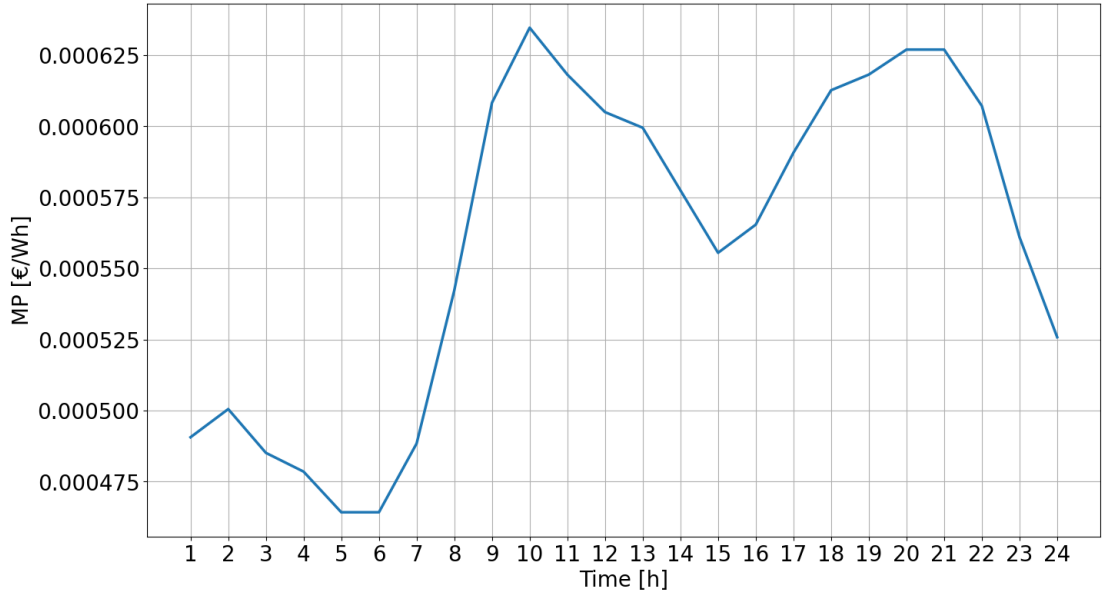
With respect of the summer day, the electricity demand, shown in figure 3.15, has

a peak value not only in the evening but also one in the morning and a smaller one in the first hours of the afternoon.

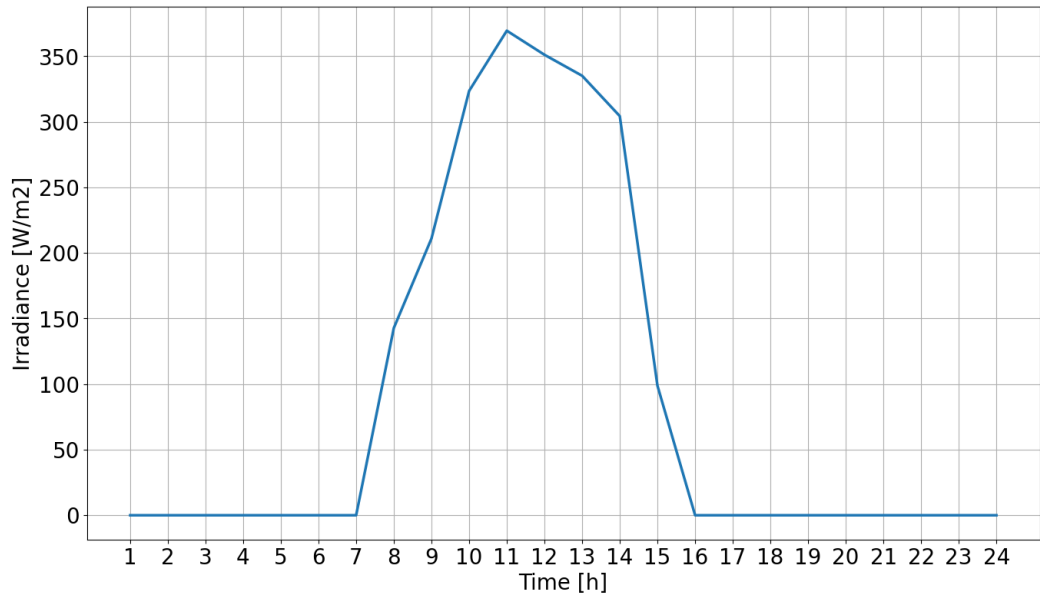


**Figure 3.15:** Electricity Demand for December 14<sup>th</sup> 2013

The maximum value of the market price on the winter day is higher than it was on the summer day, its value at 10 in the morning is of  $0.0006347 \frac{\text{€}}{\text{Wh}}$ , that is equal to  $0.6347 \frac{\text{€}}{\text{kWh}}$ , as shown in figure 3.16. This value is higher than the cost associated to the BESS, meaning that it will be moments during the day in which it might be more affordable to exploit the stored energy rather than buying it from the grid or employing the RES. The PV production and the WT production, evaluated as presented at the beginning of the chapter, are respectively represented in figure 3.19 and in figure 3.20. As expected, the PV production for the winter day is smaller compared to the one from the summer day. Instead the WT production is slightly higher during the winter day than the it is in the summer day.



**Figure 3.16:** Electricity Market Price for December 14<sup>th</sup> 2013

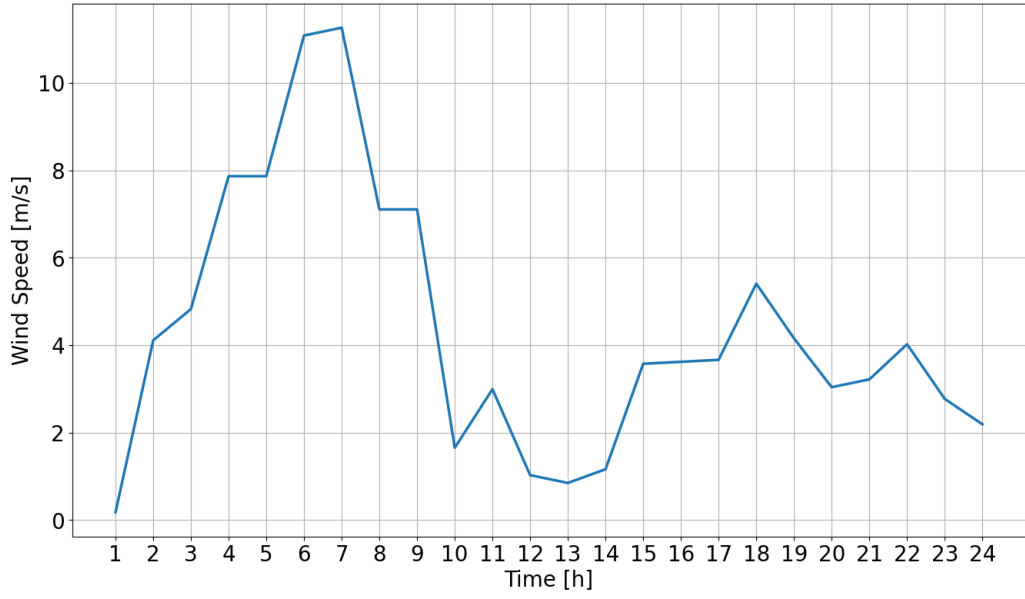


**Figure 3.17:** Solar Radiation for December 14<sup>th</sup> 2013

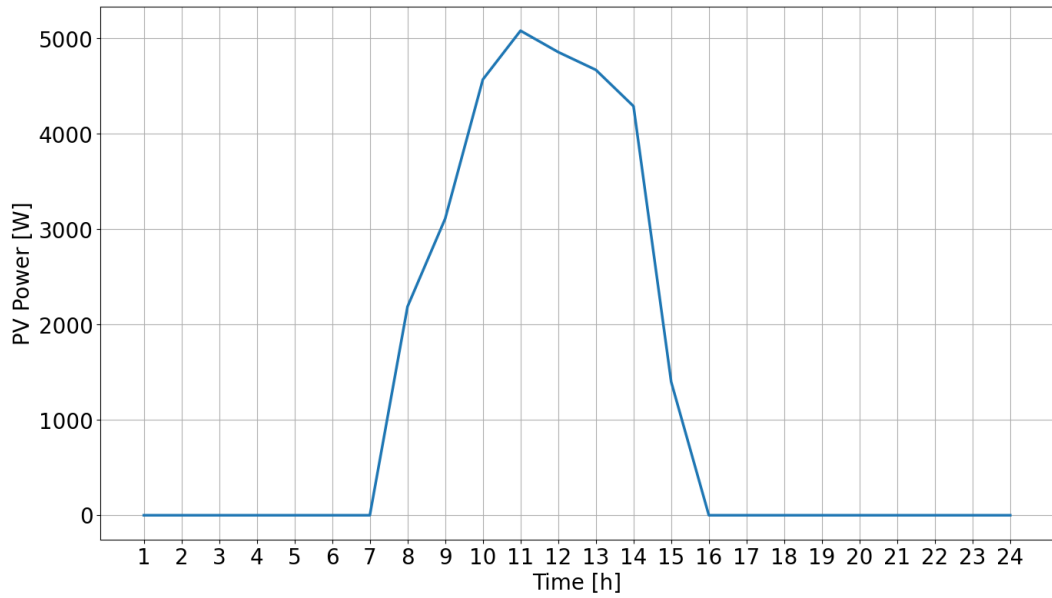
### 3.5.2 Results

The energy balance for the winter day, in the case in which there is only the main grid supplying electricity to the load and the BESS as support, is represented in





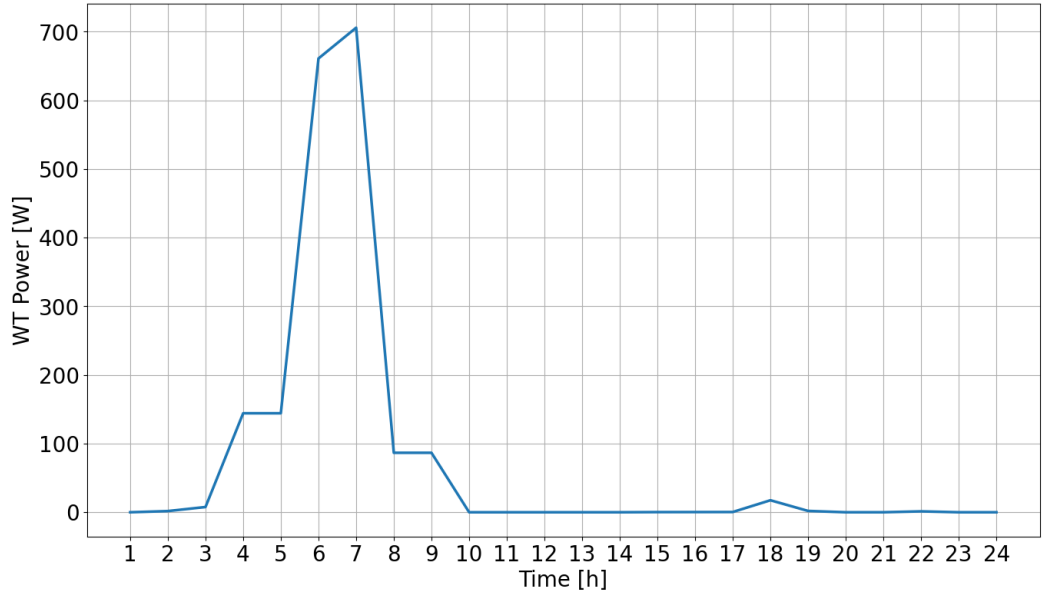
**Figure 3.18:** Wind Speed for December 14<sup>th</sup> 2013



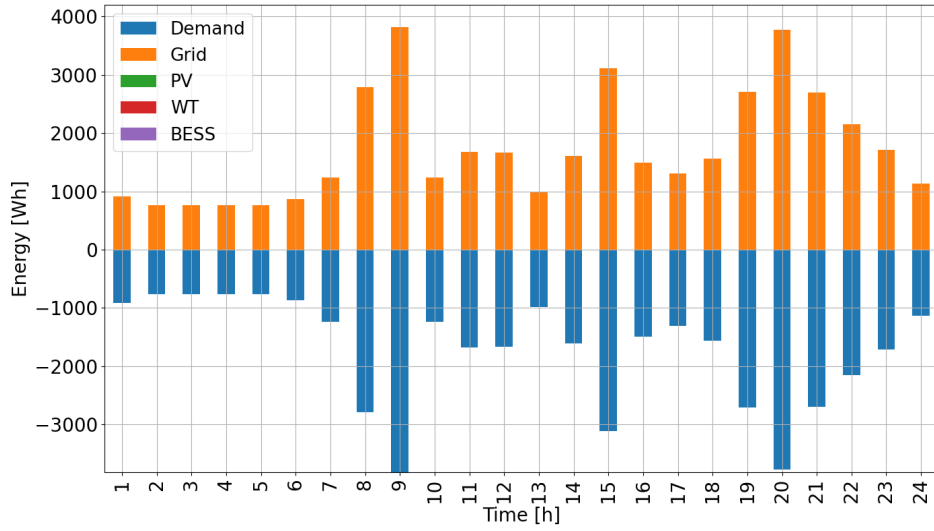
**Figure 3.19:** PV production for December 14<sup>th</sup> 2013

3.21. The cost associated to this dispatch strategy is of 24.00€.

The energy balance represented in Figure 3.22 shows the case in which all RESs and BESS are considered in the framework. Differently from the summer day, on this



**Figure 3.20:** WT production for December 14<sup>th</sup> 2013

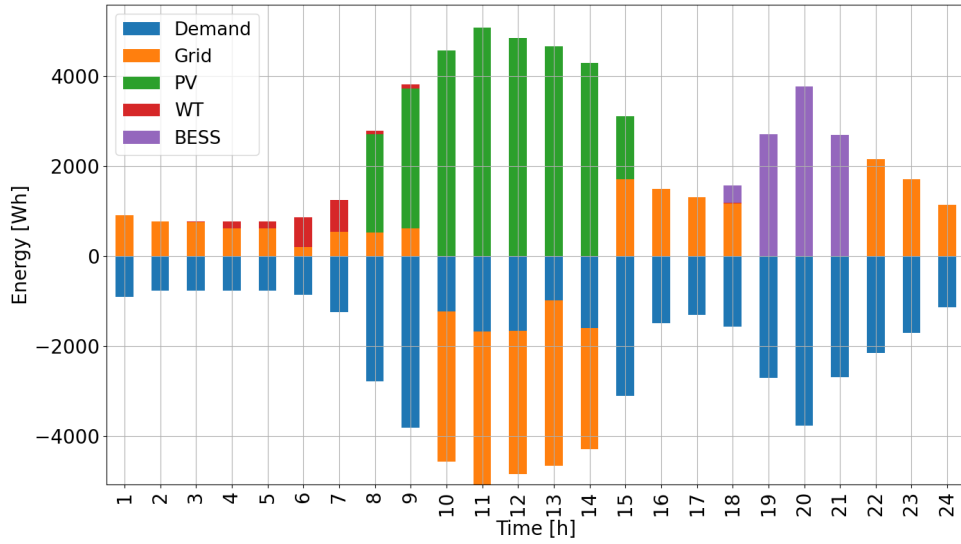


**Figure 3.21:** Electricity Demand dispatch with only the main grid for the winter day

day the BESS participates to the exchange of energy. The energy flow exchanged with the battery is considered positive when it is a source used to supply the load,

therefore when the BESS is discharging, and negative when the storage is charging. The charging of the battery is strictly related to the excess of production from the RES.

From the start of this winter day, the ED is entirely supplied with the contribution of the grid, until 3 in the morning, when the WT starts producing and it reduces the amount of electricity extracted from the grid until 8 in the morning, when the PV starts producing and it supplies part of the electrical load from 8 in the morning to 15. Between 10 and 14, the PV production is larger than the ED, therefore there is injection of electricity into the grid. The BESS contributes to the load, entirely or as a support for the grid, from 18 to 21. Then, in the last hours of the day only the grid is employed.



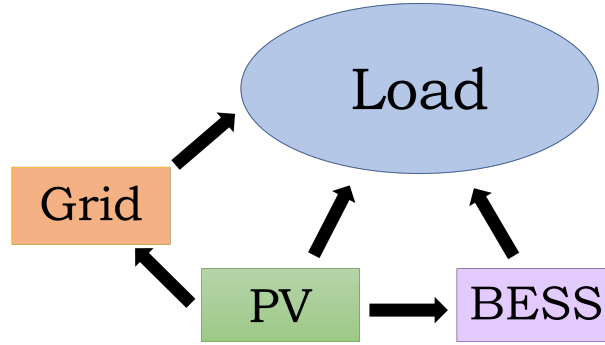
**Figure 3.22:** MG energy balance for the winter day with the use of RES and BESS

The minimized cost related to this dispatch strategy is 7.11 €. The use of this configuration in this case, saves 70.38% with respect to the case without RES and BESS. Therefore, even if for an extended period of time the PV produces more than what is need for the electrical load, so that electricity is injected into the grid, the related revenue is not enough to cover all the cost of energy supply that occur throughout the day.

Again, in the perspective of the Plug and Play model, the winter day was also simulated in case of a configuration without the contribution of respectively PV and WT. Differently from the summer day, here it is interesting to explore also the

cases without the BESS.

The configuration with the PV and the BESS is represented in figure 3.26, while the dispatch strategy is in figure 3.24. The main difference with the original

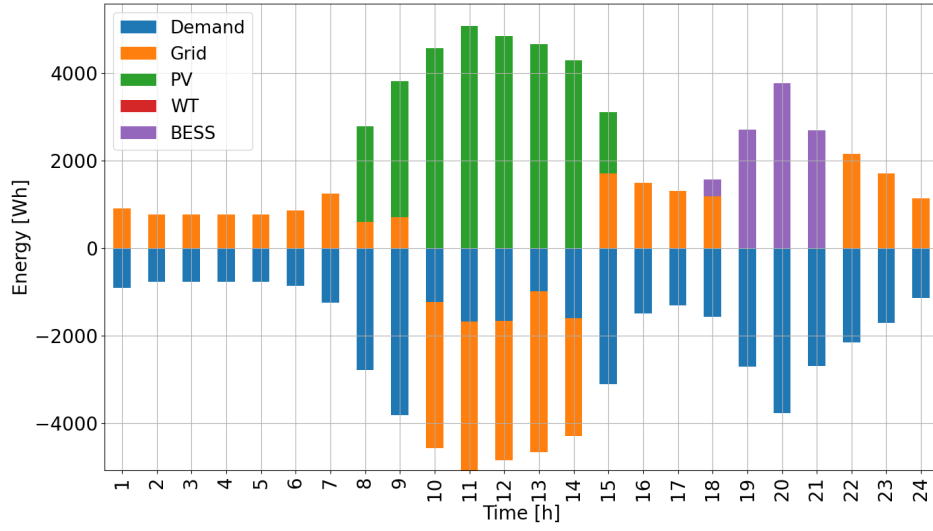


**Figure 3.23:** Representation of the MG with Grid, PV and BESS supplying the Load

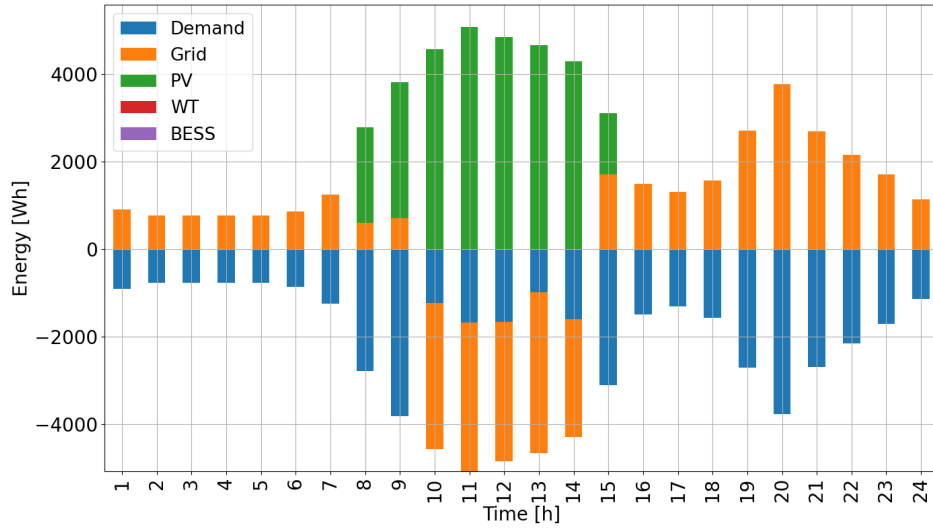
configuration can be noted in the first hours of the day, between 3 and 9, in which the electricity extracted from the grid is higher. The cost related to this arrangement is 7.91 €, as expected it is higher than the cost of the optimal dispatch with all the elements, but with respect to the case without RES there is not such a difference, since there is still 67.04% of savings compared to it. This is because the PV production is still large enough to sell electricity to the grid for most of the day and there is only an increase of electricity extraction from the grid in the morning when in the previous case there was the WT production.

If the BESS is also removed from the model, as shown in figure 3.25, the dispatch strategy's cost increases to 8.65 €, due to the increase of electricity extracted from the grid when there was the BESS discharge. Compared to the case in which there are only the main grid there is still 63.96% of savings for this configuration.

On the other hand, in case only the WT and BESS are present, as shown in figure ??, the cost of the optimal dispatch strategy is 22.44 €. Compared to the case of with only the main grid, the savings are quite small, only 6.5%. Apart from the grid, that it supplies electricity almost all day long, the BESS is discharging, not only between 19 and 21, but also between 10 and 11, as shown in figure 3.27. This can be explained by the fact that in those hours the MP of electricity is higher than the cost related to the storage discharge, meaning that there is a monetary convenience in discharging the BESS rather than buying electricity from the grid. It can be noted that the absence of the PV production highly affects the cost related to the supply of electricity and therefore the dispatch strategy. Again, removing also the BESS from the framework increases the cost up to 23.20 €, decreasing the savings with respect to the case with only the grid to 3.33%. In this case, the

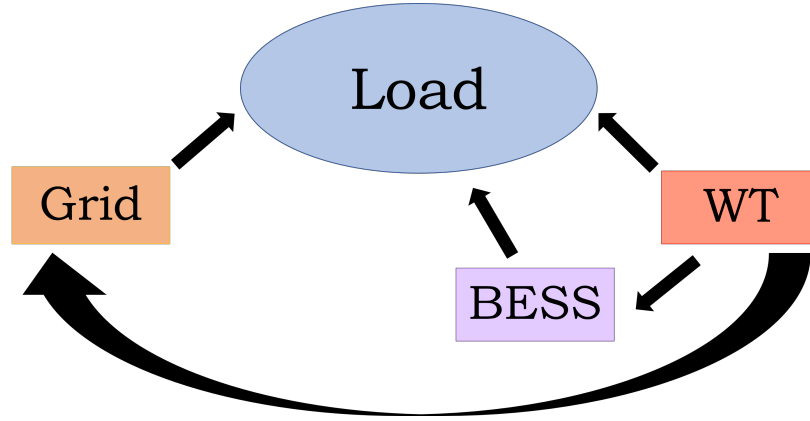


**Figure 3.24:** MG energy balance without WT for the winter day

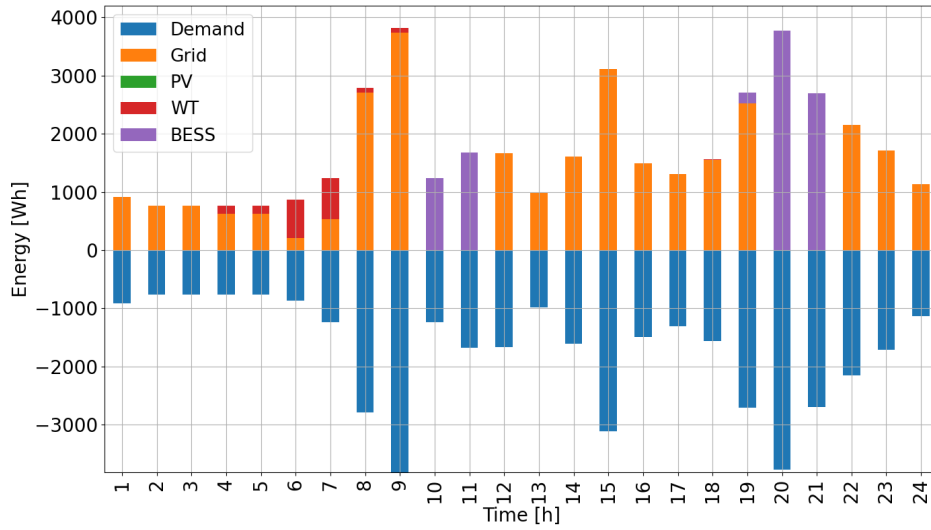


**Figure 3.25:** MG energy balance without WT and BESS for the winter day

electricity is extracted all the long from the grid and it is only reduced by the WT contribution between 4 and 9 in the morning.



**Figure 3.26:** Representation of the MG with Grid, WT and BESS supplying the Load

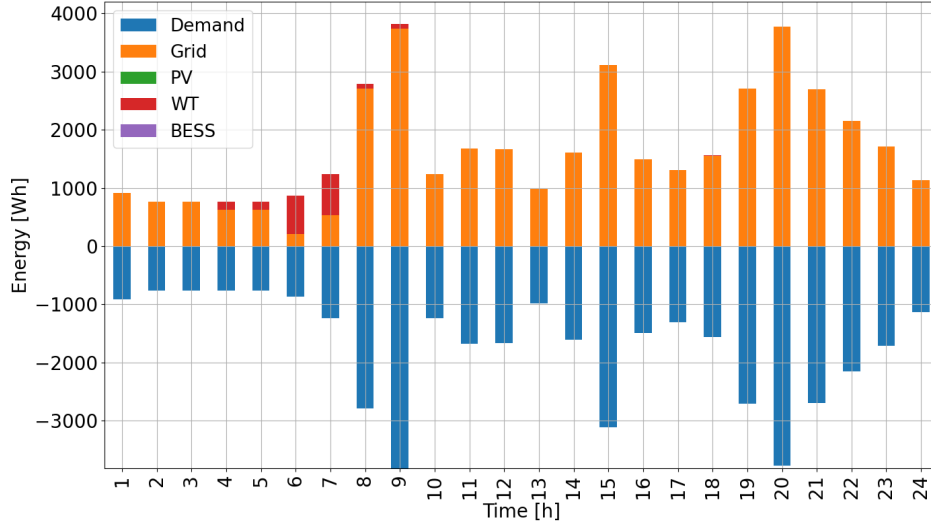


**Figure 3.27:** MG energy balance without PV for the winter day

### 3.6 Observations

In conclusion to this chapter, it can be stated that the component that affects the most the value of the costs related to the dispatch of electricity to the consumers is the PV system.

From these simulations it is clear that the employment of RES is advantageous to reduce the operational costs related to the dispatch of electricity, with particular



**Figure 3.28:** MG energy balance without PV and BESS for the winter day

mention to the PV power plants. Moreover, the supply of electricity still highly relies on the main grid, especially during the night. The BESS could be useful to store electricity when there is high production of RES and then to discharge it when the production is lower, therefore reducing the burden and the dependence on the electrical grid. At the moment, this is not worth doing, due to the fact that the cost associated to the storage, the LCOS, is still higher than the electricity Market Price, for most of the time.

The table 3.4 above summarizes the savings for each configuration analyzed in this

	<i>Grid</i>	<i>Grid + PV</i>	<i>Grid + PV + BESS</i>	<i>Grid + WT</i>	<i>Grid + WT + BESS</i>	<i>Grid + WT + PV + BESS</i>
<i>Summer day</i>	11.75€	-109.75%	-	-2.55%	-	-112.40%
<i>Winter day</i>	24€	-63.96%	-67.04%	-3.33%	-6.50%	-70.38%

**Table 3.4:** Comparison of savings in the different configurations for both summer and winter day

chapter, for both the winter and the summer day hypothesis. The highest savings come from the framework in which there are all the elements considered in the dispatch of electricity, but the storage system, all simulated in the summer day. In this case, the PV generation is high enough to completely cover the costs of operation and also to have a profit from operating the MG.

Anyway, even if the BESS does not seem to be convenient in the summer day, in

the winter configuration, increases the amount of savings in both cases in which the RES are employed singularly.



## Chapter 4

# Introduction of uncertainty

The scenarios presented in Sections 3.4.2 and 3.5.2 represent a good starting point to simulate interesting case studies. However, they do not consider any uncertainties in the input data. In more realistic scenarios, there might be the need to consider uncertainties in some of the variables. To this end, the parameters that could be affected by uncertainty would be the one related to time, therefore Solar Radiation, Wind Speed, Electricity Market Price and Electricity Demand.

Following the model from Farsangi et al. [23], the uncertain parameters are introduced in the model using PDFs. As already stated in section 2.2, PDFs were often represented in the literature to describe the probabilities related to uncertain variables. In particular:

- Wu et al. [19] employed the Normal PDF to describe the uncertainty related to the load and the RES power output, in particular WT and PV system;
- Farsangi et al. [23] used the Normal PDF to model the uncertainty from the load, and the authors used also to describe the market price of electricity. Meanwhile for the Wind speed, they employed the Weibull PDF, and for the solar radiation, the Beta PDF;
- according to Zhang et al. [26], The Gaussian PDF was better suited for the description of the uncertainty of wind speed, solar radiation and the load;
- Soroudi et al. [39] employed the Normal PDF for the electrical load uncertainty model, the Weibull PDF for the Wind speed and the Beta PDF for the solar radiation, in their article that analyzes the impact of DER production on the Distribution Network

For the purpose of this thesis, the Normal PDF was employed for the definition of the uncertainty related to the electricity Market Price and to the Electricity Demand, while the wind speed uncertainty was modeled by the Weibull PDF and the Beta PDF was used to describe the solar radiations’.

## 4.1 Uncertain parameters and probability model

Following the line of reasoning of Farsangi et al. [23], Wu et al. [19] and Soroudi et al. [39], the a Normal PDF was employed for both the electricity demand and the electricity market price, for which the formulation is presented in expression 4.1.

$$PDF(y) = \frac{1}{\sigma\sqrt{2\pi}} \cdot \exp\left(-\frac{(y - \mu)^2}{2\sigma^2}\right) \quad (4.1)$$

The Weibull PDF was selected for the wind speed as expressed in 4.2, following the reasoning from Farsangi et al. [23] and Soroudi et al. [39].

$$PDF(w) = \frac{k}{c} \left(\frac{w}{c}\right)^{k-1} \cdot \exp\left(-\left(\frac{w}{c}\right)^k\right) \quad (4.2)$$

with  $k = \left(\frac{\delta}{\mu}\right)^{-1.086}$  and  $c = \frac{\mu}{\Gamma(1+\frac{1}{k})}$

Then, as described by Soroudi et al. [39] and Farsangi et al. [23], the solar radiation is modeled by the Beta PDF as in expression 4.3.

$$PDF(sor) = \frac{\Gamma(\alpha + \beta)}{\Gamma(\alpha) \cdot \Gamma(\beta)} \cdot sor^{\alpha-1} \cdot (1 - sor)^{\beta-1} \quad (4.3)$$

Similarly to what presented in Chapter 3, the figures used to construct these PDF comes from the historical data, more precisely the hourly data for the whole year for the Market Price [30], Solar radiation [32] and Wind speed [31] was employed. The figures concerning the electrical load come from the same hourly aggregated load of 12 households as it was for Chapter 3.

By definition, each of the uncertain parameters has an associated probability. Since the uncertain parameters can have infinite values, and therefore the same number of related probabilities, the dispatch optimization model would have infinite inputs in the form of the PDFs of the variables affected by uncertainty. This would lead to high computational costs to define the optimal dispatch strategy. Therefore, the PDFs related to the uncertain parameters are divided into 7 sections, allowing the definition of 7 probabilities and related values for all uncertain parameters. The probabilities are evaluated as the integral of the Probability Density Function defined between the first and last value of each of the intervals that describe the variable as in expression 4.4).

$$p_{y,v_y} = \int_{y_{start}}^{y_{end}} PDF(y) dy \quad (4.4)$$

for  $v_y = 1, \dots, V_y$ , that are the uncertain parameters (PV, WT, MP and ED). While  $y$  is the value of the uncertain parameters and the intervals are defined as function of the mean value  $\bar{y}$  and of the standard deviation  $\sigma$  of the variables (eq. 4.5):

$$\bar{y} \pm a \cdot \sigma \quad (4.5)$$

where  $a$  is equal to 0.5, 1.5, 2.5, 3.5, and define the extremes of the intervals. The value of the uncertain parameter associated to each probability is calculated as the fraction between the integral of the PDFs between the extremities of an interval and the value of the associated probability:

$$x_{y,v_y} = \frac{1}{p_{y,v_y}} \cdot \left( \int_{y_{start}}^{y_{end}} y \cdot PDF(y) dy \right) \quad (4.6)$$

for  $v_y = 1, \dots, V_y$ .  $y_{start}$  and  $y_{end}$  represent the lower and upper values of said section, while the iteration over  $v_y$  considers each uncertain parameter.

In these last two equations (eq. 4.4 and eq. 4.6),  $y$  represents the uncertain parameter,  $p_{y,v_y}$  represents the probability associated with the parameter  $y$  for the scenario  $v_y$ .

Since the values of the selected uncertain parameters change throughout the day, the PDF are created taking as input data the 365 values of the year 2013 for each hour of the day, ending up with 24 PDFs for each of the uncertain parameters. In the figures below are represented the discrete PDFs respectively for the wind speed 4.1, the PV power 4.2, the market price 4.4 and the electrical load 4.3.

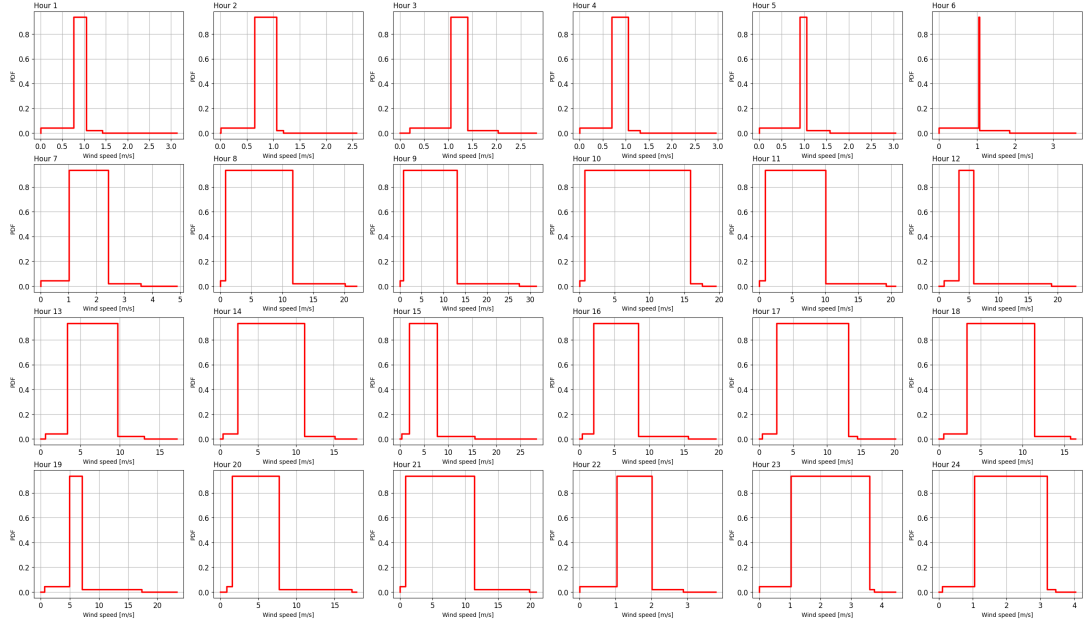


Figure 4.1: Wind Speed discretized PDFs for 24 hour time period

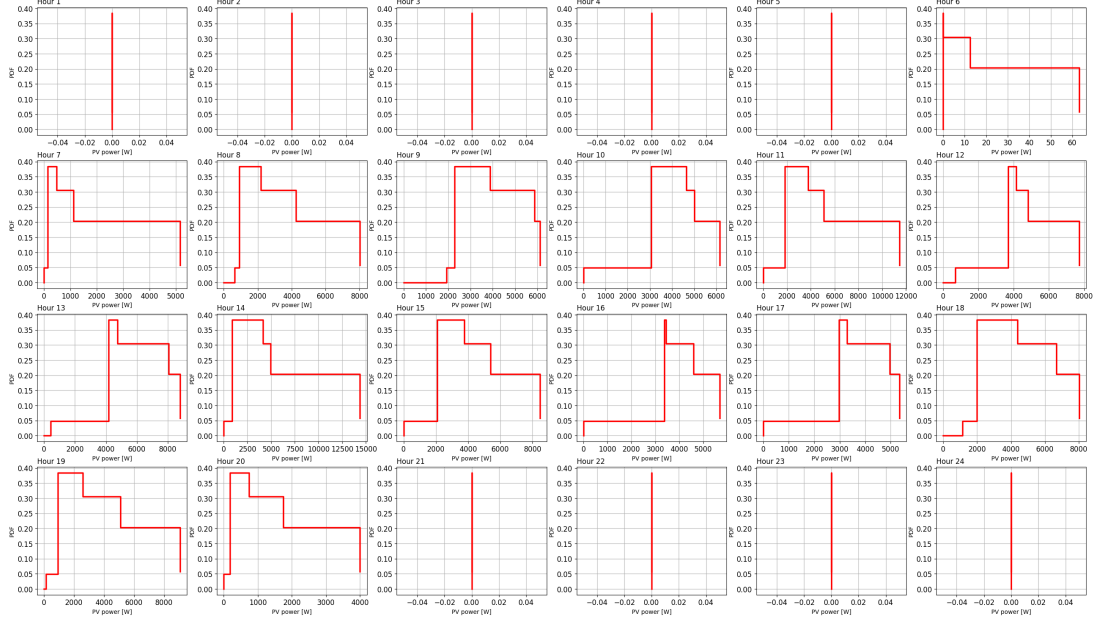


Figure 4.2: PV power discretized PDFs for 24 hour time period

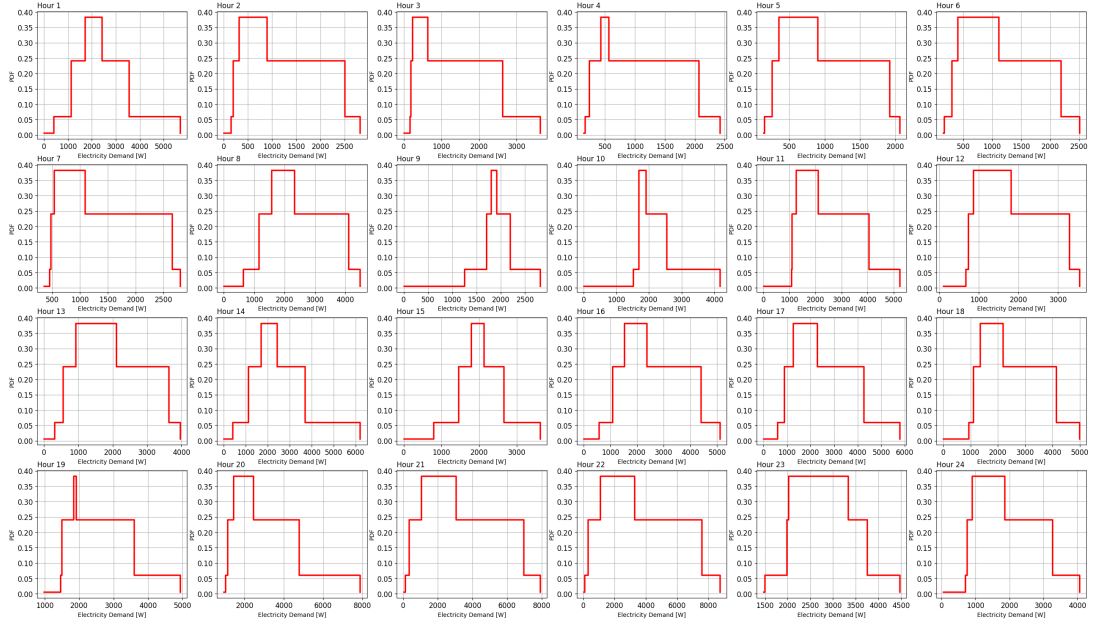


Figure 4.3: Electricity Demand discretized PDFs for 24 hour time period

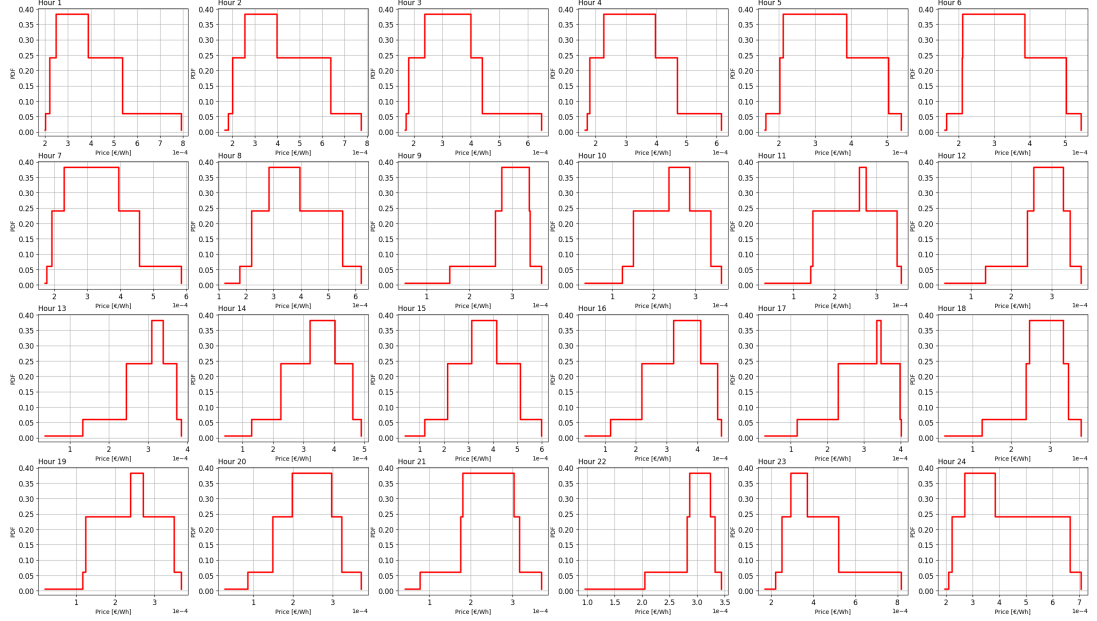


Figure 4.4: Market Price discretized PDFs for 24 hour time period

## 4.2 Reduction of number of scenarios

The use as input to the problem of 4 uncertain parameters, that could each be related to 7 values, would lead to  $7^4$  different scenarios, for a total of 2401 scenarios

each hour for 24 hours of time period that need to be simulated to define an optimal dispatch strategy. The computational burden of this high number of scenario is still large, even if only 7 probability are defined and considered. Therefore, a scenario reduction model is employed to manage the computational costs that this high number of scenarios would implicate. In the model developed from Farsangi et al. [23], a MILP optimization problem is employed to minimize the number of scenarios, while keeping a similar level of uncertainty for the whole model. This MILP model is composed as follows:

$$\min f = \sum_{v_1}^{V_1} \sum_{v_2}^{V_2} \sum_{v_3}^{V_3} \sum_{v_4}^{V_4} b_{v_1, v_2, v_3, v_4} \quad (4.7)$$

The objective function 4.7 aims at minimizing the number of scenarios employed through the minimization of the summation of the binary variable  $b_{v_y}$ , that represents an employed scenario when it is equal to 1, as later described in eq. 4.15.

$$\sum_{v_2}^{V_2} \sum_{v_3}^{V_3} \sum_{v_4}^{V_4} p_s(v_1, v_2, v_3, v_4) = p_{1, v_1} \text{ for } v_1 = 1, 2, \dots, V_1 \quad (4.8)$$

$$\sum_{v_1}^{V_1} \sum_{v_3}^{V_3} \sum_{v_4}^{V_4} p_s(v_1, v_2, v_3, v_4) = p_{2, v_2} \text{ for } v_2 = 1, 2, \dots, V_2 \quad (4.9)$$

$$\sum_{v_1}^{V_1} \sum_{v_2}^{V_2} \sum_{v_4}^{V_4} p_s(v_1, v_2, v_3, v_4) = p_{3, v_3} \text{ for } v_3 = 1, 2, \dots, V_3 \quad (4.10)$$

$$\sum_{v_1}^{V_1} \sum_{v_2}^{V_2} \sum_{v_3}^{V_3} p_s(v_1, v_2, v_3, v_4) = p_{4, v_4} \text{ for } v_4 = 1, 2, \dots, V_4 \quad (4.11)$$

$$\sum_{v_1}^{V_1} \sum_{v_2}^{V_2} \sum_{v_3}^{V_3} \sum_{v_4}^{V_4} p_s(v_1, v_2, v_3, v_4) = 1 \quad \forall v_1, v_2, v_3, v_4 \quad (4.12)$$

$$p_s(v_1, v_2, v_3, v_4) \leq b_{v_1, v_2, v_3, v_4} \quad \forall v_1, v_2, v_3, v_4 \quad (4.13)$$

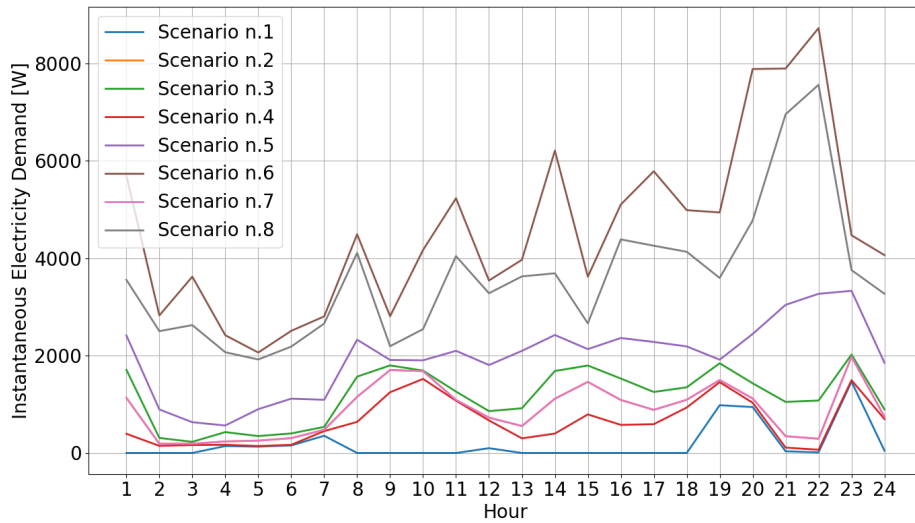
$$0 \leq p_s(v_1, v_2, v_3, v_4) \leq 1 \quad \forall v_1, v_2, v_3, v_4 \quad (4.14)$$

$$b_{v_1, v_2, v_3, v_4} \in [0, 1] \quad (4.15)$$

The expression 4.13 imposes the probability of the new scenario to be lower than the binary variable, meaning that, since probabilities are defined between 0 and 1, when the scenario is not selected, the probability is set to 0, while when the scenario is selected, the probability has to be lower than 1.

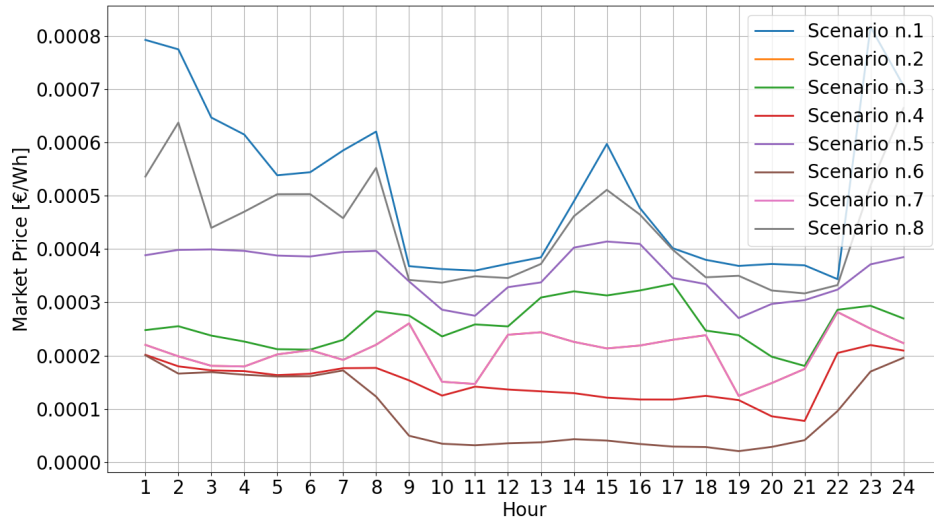
The other four constraints (4.8, 4.9, 4.10 and 4.11) have the purpose of keeping the value of probability of the new scenario for each of the variable equal to the probability of each of the values of the variable, keeping the value of uncertainty of the new scenarios equal to the one of the original problem. Equation 4.12 imposes that the sum of the probabilities of the new scenarios has to be equal to 1, while equation 4.14 defines the upper and lower limit of new scenarios' probabilities.

This MILP produces a reduced number of scenarios of probabilities for the 4 uncertain parameters, that have the same level of uncertainty of the original problem. In particular, 8 scenarios for each of the 4 uncertain parameters are obtained. In the following curves, the values of the parameters throughout the day are represented for each of the 8 scenarios selected by the MILP optimization problem. Figure 4.5 represents the ED scenarios, figure 4.6 represents the MP scenarios, figure 4.7 represents the PV power scenarios and figure 4.8 represents the WT power scenarios. Some of the curves might not be showing due to the fact that the same values could belong to more than one scenario. It could already be observed that the scenarios from the WT power are mostly all equal to zero, due to low wind speed.

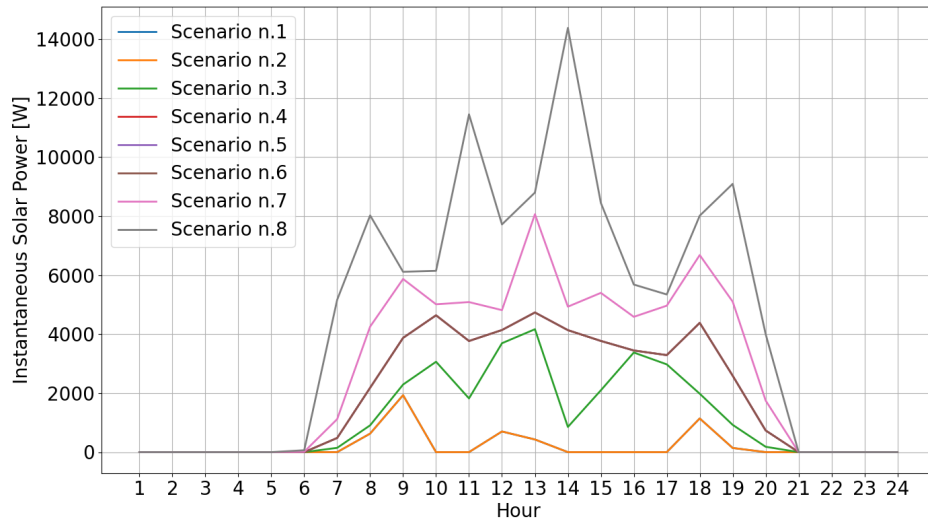


**Figure 4.5:** Electricity Demand scenarios over 24 hour time period

The obtained probabilities for each new scenario are shown in table 4.1.

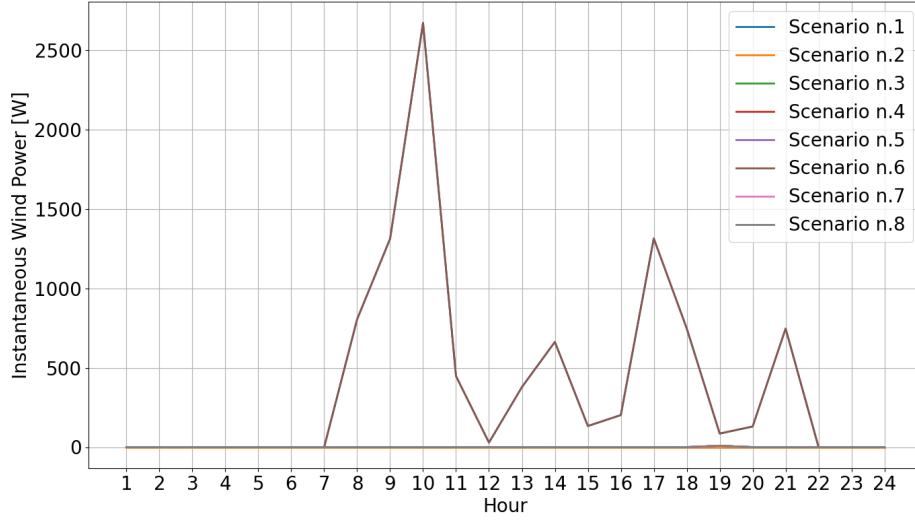


**Figure 4.6:** Market Price scenarios over 24 hour time period



**Figure 4.7:** PV power scenarios over 24 hour time period





**Figure 4.8:** Wind Power scenarios over 24 hour time period

<i>Scenario</i>	<i>Probability</i>
1	0.01
2	0.04
3	0.38
4	0.06
5	0.24
6	0.01
7	0.20
8	0.06

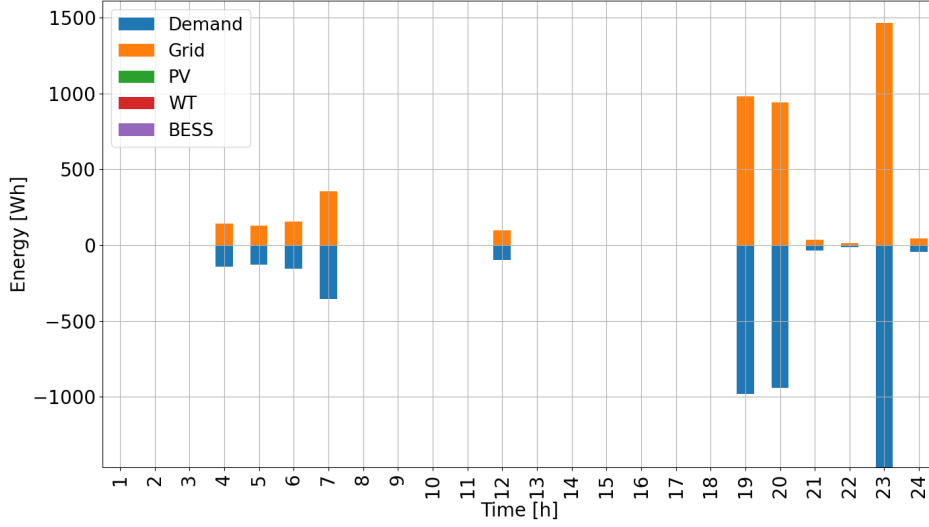
**Table 4.1:** Scenarios and related probability

### 4.3 Optimization of the MG dispatch strategy in a stochastic context

The values of each parameter for each of the scenarios is used as input to the model described in the previous chapter (3.1), producing 8 dispatching strategies, one for each of the new scenarios. The simulation was first run in the case in which no RES or BESS were employed in the electricity supply to offer a base for comparison for the dispatch strategies.

### 4.3.1 Scenario 1

The first scenario simulation in the framework with only the main grid to supply load has a related cost of 2.44€, and it is represented in figure 4.9. This value is not so high due to the fact that this scenario takes into account load values equal to zero for most of the day, also its probability of occurrence is 0.01.



**Figure 4.9:** Scenario 1 MG dispatch with only the main grid

The curves of the first scenario of the MG dispatch strategy in the case in which all RES and BESS are employed in the supply of electricity to the load are shown in 4.10. This scenario is represented by a low value of ED throughout the day, that is mostly supplied by PV and WT production. For most of the day, especially between 7 and 18 and again between 21 and 22, the production of the RESs is larger than the electrical load and therefore electricity is injected into the grid, generating a revenue. The BESS is discharged in the hours in which the RESs production is not present, therefore between 3 and 4, then between 6 and 9, and again in the evening, between 22 and 24.

The optimal value of operational cost of this dispatch strategy is  $-2.95$  €, which represent savings for 220.9% with respect to the case in which only the main grid is supplying the load. This high share of savings is justified by the fact that the RESs are producing electricity for the majority of the hours of the day and, since the load is low, almost all of the energy is sold to the main grid, generating a revenue.

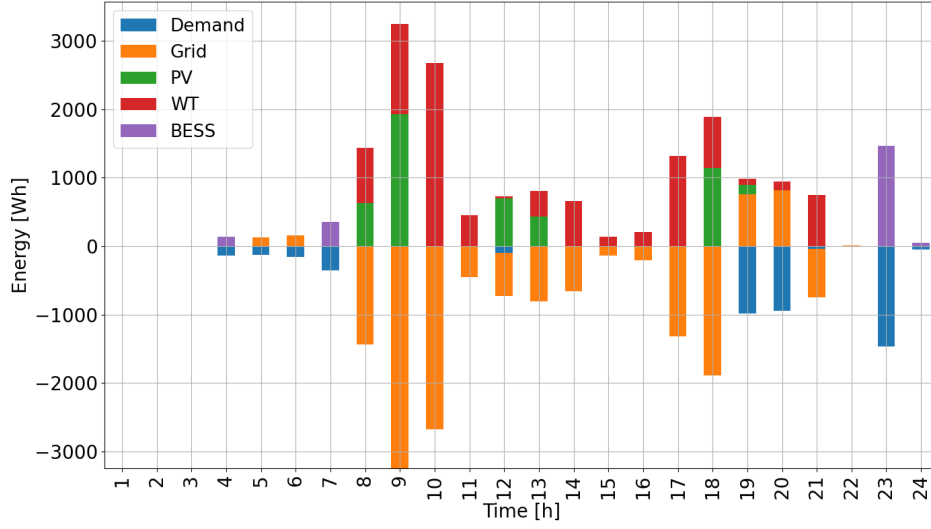


Figure 4.10: Scenario 1

### 4.3.2 Scenario 2

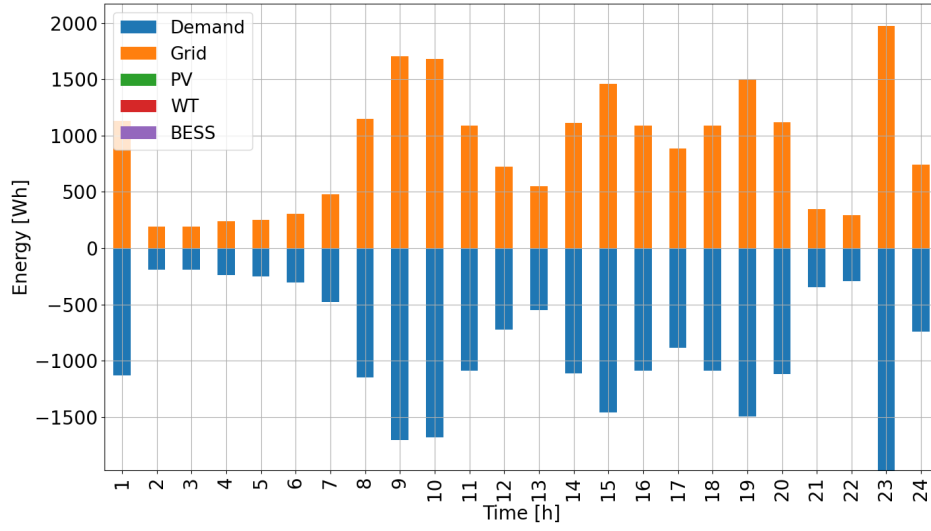
In case of Scenario 2, the figure 4.11 shows the configuration in which only the main grid is employed to supply electricity to the load. The optimal dispatch strategy cost related to this framework is of 4.41 €. The probability associated to this scenario is equal to 0.04.

In the case in which both RES and BESS are included the dispatch strategy, represented in 4.12, the production from the wind source is zero, and the BESS is neither charged or discharged. Differently from the first scenario, in some hours of the day, the electrical load reaches the order of magnitude of the PV production. Electricity is injected into the grid briefly at 9 in the morning and even less at 18. Other than these cases, the PV production only reduces the amount of energy needed from the grid to supply the load. The optimal operational cost related to this dispatch strategy is 3.66€, that represents 17.01% of saving with respect to the case that considers only the main grid.

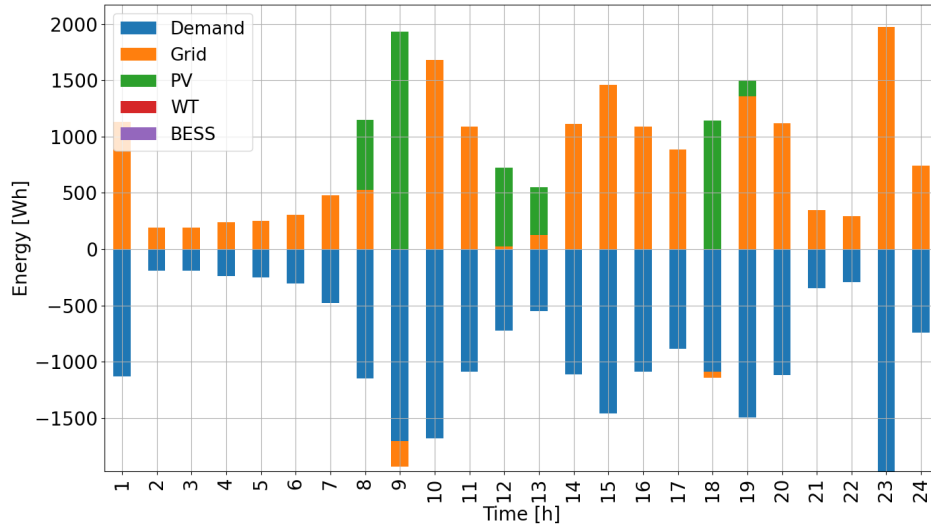
### 4.3.3 Scenario 3

Scenario 3 is associated to a probability equal to 0.38. The cost associated to the framework with only the main grid and the load is of 7.50 €. The curves related to this simulation are shown in figure 4.13

The introduction of the PV and WT energy source and the BESS leads to a MG

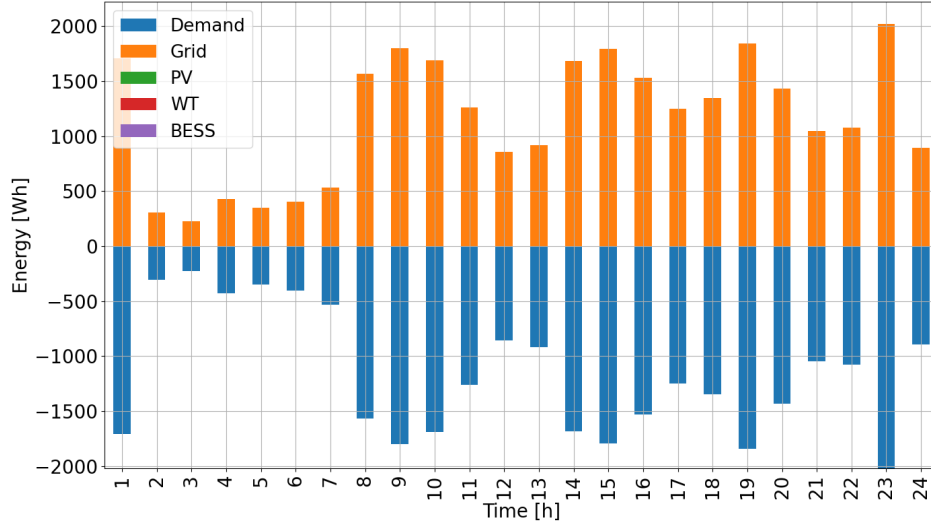


**Figure 4.11:** Scenario 2 MG dispatch with only the main grid



**Figure 4.12:** Scenario 2

dispatch strategy as the one shown in figure 4.14. In this case, the ED is entirely supplied by the energy from the grid from the start of the day until 6 and from 21 to 24. Then, in the central part of the day, it is supplied by the PV production,



**Figure 4.13:** Scenario 3 MG dispatch with only the main grid

that is high enough to also inject electricity into the grid for most of the time. Again the BESS does not participate at all to the dispatch strategy and the wind source is absent. The cost related to this optimal dispatch strategy scenario is 2.00 €. Therefore, the savings compared to the case with only the electrical grid are of 73.33%, meaning that even if the PV plant injects energy into the grid for about 8 hours throughout the day, it is not enough to cover entirely for the cost of supply the load with the grid during this day.

#### 4.3.4 Scenario 4

The 4<sup>th</sup> Scenario is related to a probability of 0.06. The case with only the electrical grid, shown in figure 4.15, has a cost of 2.22 €. When introducing the RES plants and the BESS, it can be seen that this scenario is characterized by a high production from the PV plant, as shown in figure 4.16, that allows to inject energy into the grid for 12 hours continuously. Again, the BESS and the WT do not contribute to the dispatch strategy. In the hours in which the solar radiation is not present, the load is supplied entirely by the electrical grid.

This scenario has an optimal cost is 0.39 €, the relative savings compared to the base case are of 82.43%. Even though many hours of the day are designated to injection of electricity into the grid, these sales are not enough to entirely cover the costs of dispatch for the day.

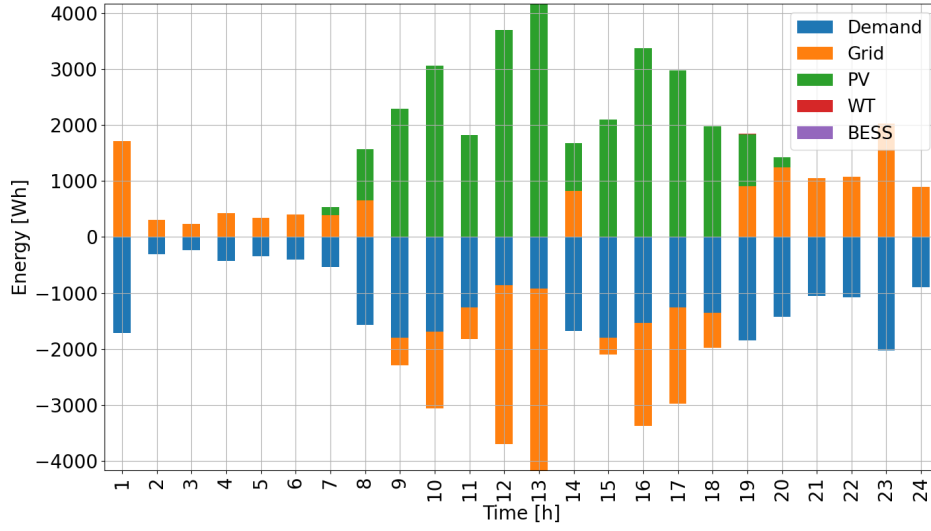


Figure 4.14: Scenario 3

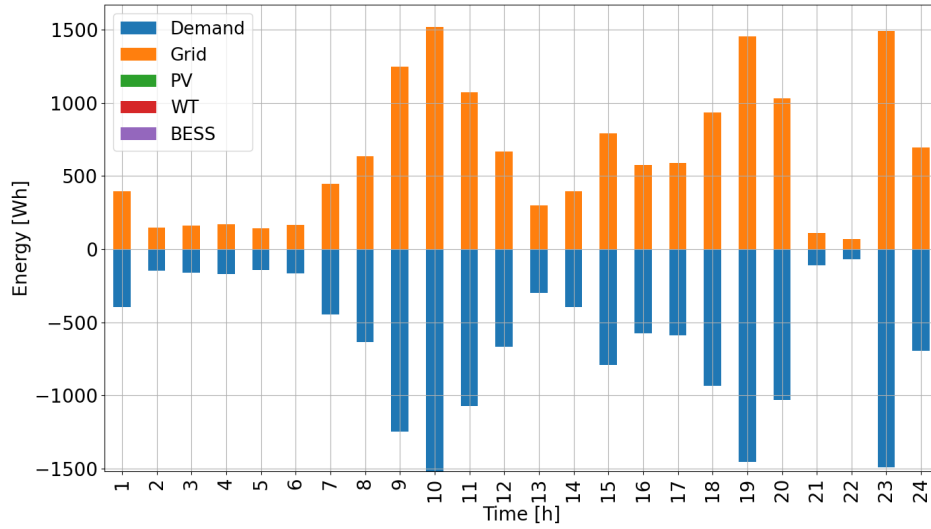
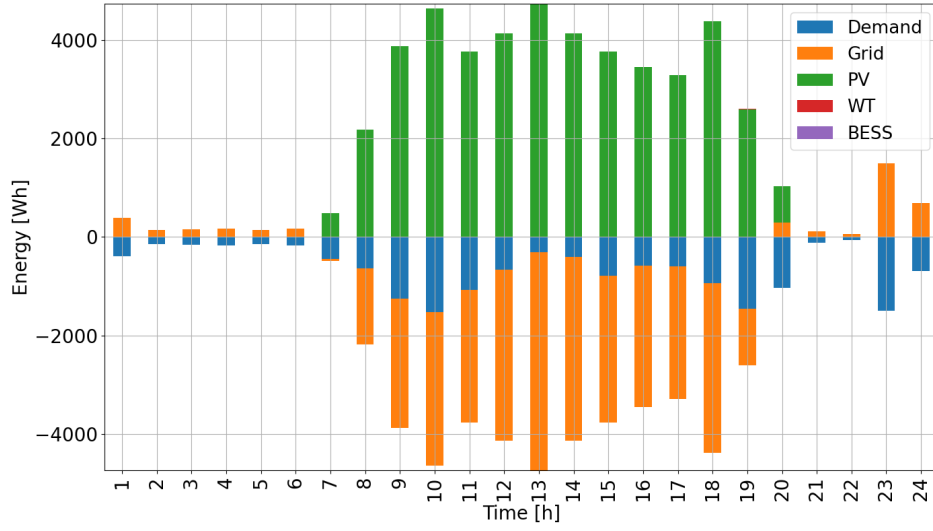


Figure 4.15: Scenario 4 MG dispatch with only the main grid

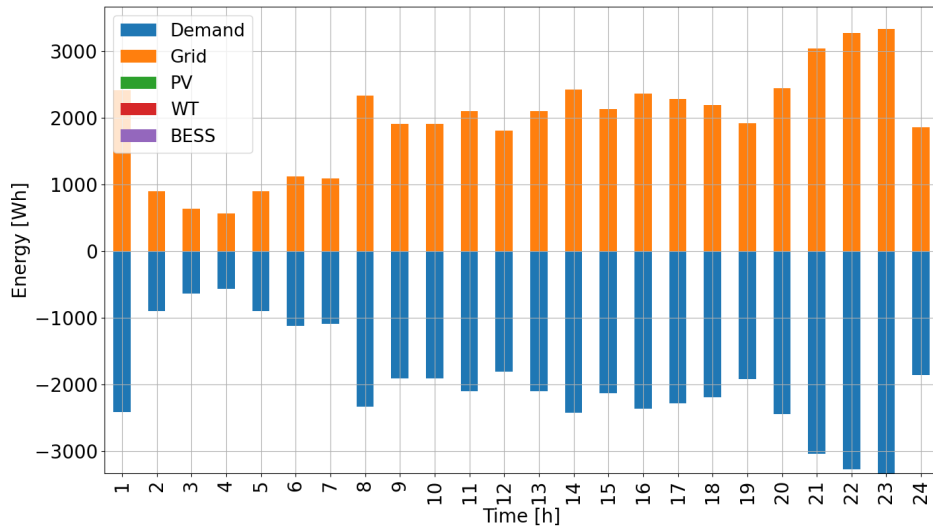
### 4.3.5 Scenario 5

Scenario 5 is characterized by a probability of 0.24. Figure 4.17 shows the simulation case of load supply entirely performed by the main grid. The associated cost is



**Figure 4.16:** Scenario 4

of 16.49 €. This scenario reaches higher values than the scenarios investigated before, up to more than 3000 Wh in the evening peak. As for the previous three



**Figure 4.17:** Scenario 5 MG dispatch with only the main grid

scenarios, in the framework with both RES systems and the BESS, in scenario

5 the BESS does not contribute to the optimal dispatch strategy and the WT production is zero, as shown in figure 4.18. The load is mostly supplied by the grid and the PV source. The solar resource also injects electricity into the network in the central hours of the day. The cost associated to this scenario is 4.87 €, with savings of 70.47% compared to the case without DERs. Even though the PV contribution is equal to the one in scenario 4 4.3.4, the savings are slightly lower because the load is in fact higher in this scenario, as can be clearly seen comparing the figures for both scenarios in the case with only the main grid, meaning figure 4.15 and figure 4.17.

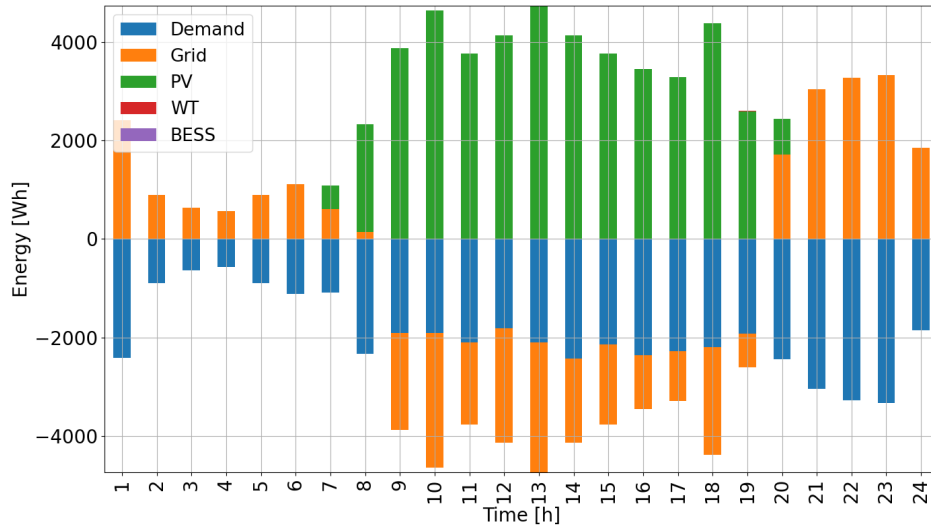
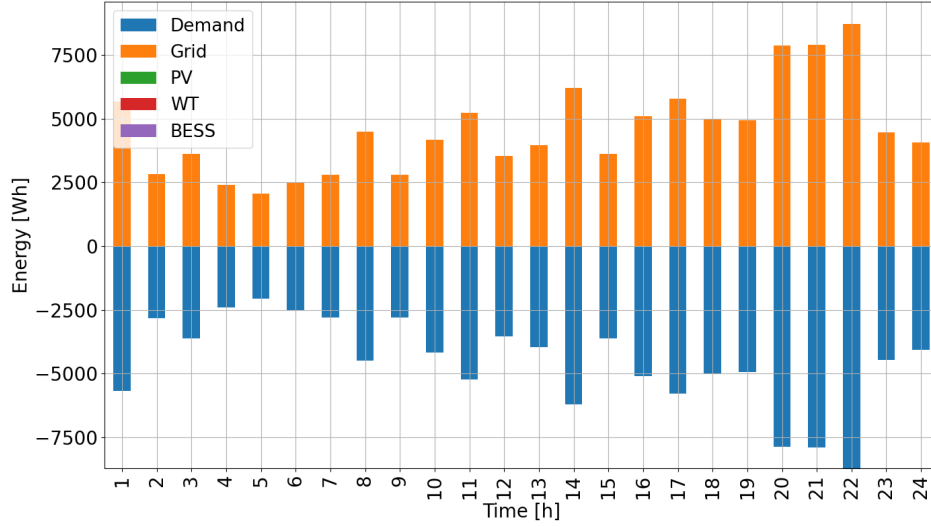


Figure 4.18: Scenario 5

#### 4.3.6 Scenario 6

Scenario 6 reaches the highest values of load compared to all the other scenarios, as shown in figure 4.19. The probability associated to this case is only 0.01, and the cost associated to the dispatch strategy considering only the main grid is equal to 9.05 €. In this scenario, after including the BESS and both RES, we can see that the WT contributes to the dispatch strategy, from 7 to 22, supporting the grid and the PV plant in the supply of the load. The BESS still does not participate. The amount of energy injected into the grid is quite low and concentrated in time step between 8 and 11 and 12 and 14, due to said high values of the ED. The cost associated to this dispatch strategy is 11.55 €, meaning that the introduction of the RES lead to higher costs of 21.30%. This increase is related to the fact that





**Figure 4.19:** Scenario 6 MG dispatch with only the main grid

when RES generate energy, the MG does not have the possibility to waste this energy, therefore it is obliged to either use it to feed the load or charge the battery or to inject it into the grid. In this framework, the cost related to the use of RES is higher than the MP when the solar and wind source are producing, but their participation to the dispatch strategy is inevitable, even if it is not economically convenient.

### 4.3.7 Scenario 7

Scenario 7 is represented by a probability of 0.20 and the costs of the configuration in case there is only the main grid, as presented in 4.21, are equal to 4.41 €. This scenario is characterized by the fact that it has very high PV production in the central part of the day. Again, the WT production is zero and BESS does not participate to the dispatch strategy. The grid takes over the electricity supply when the PV source is not available, therefore in the first and last hours of the day, while for the rest of the time the PV energy generation is high enough to sell electricity to the grid, net of the load. The costs related to this strategy is -3.60€, therefore with savings of 181.63%. This means that the PV system production is enough to cover the costs of operating this dispatch strategy and also to have a profit from the electricity sale.

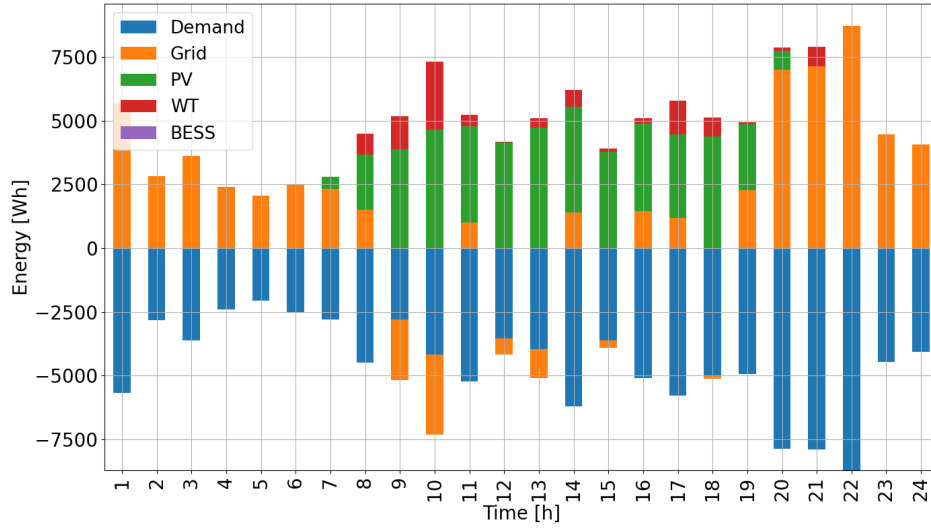


Figure 4.20: Scenario 6

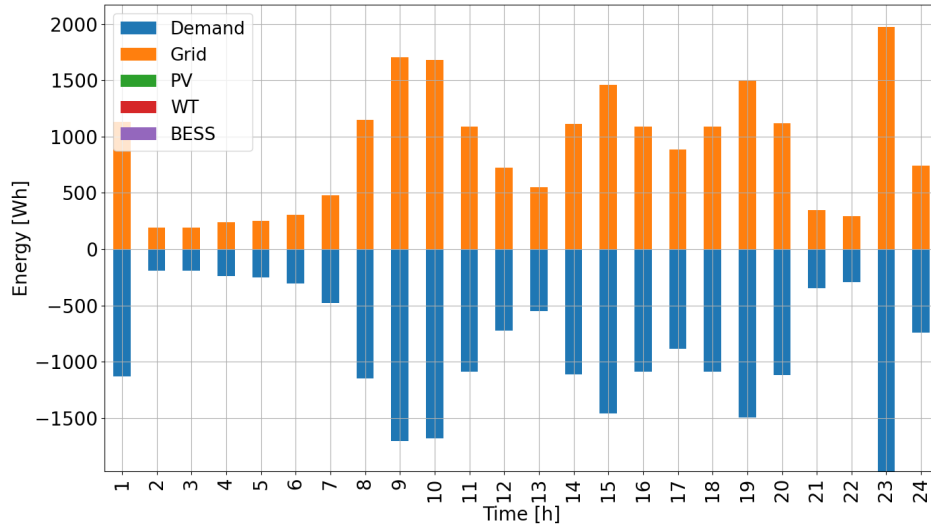
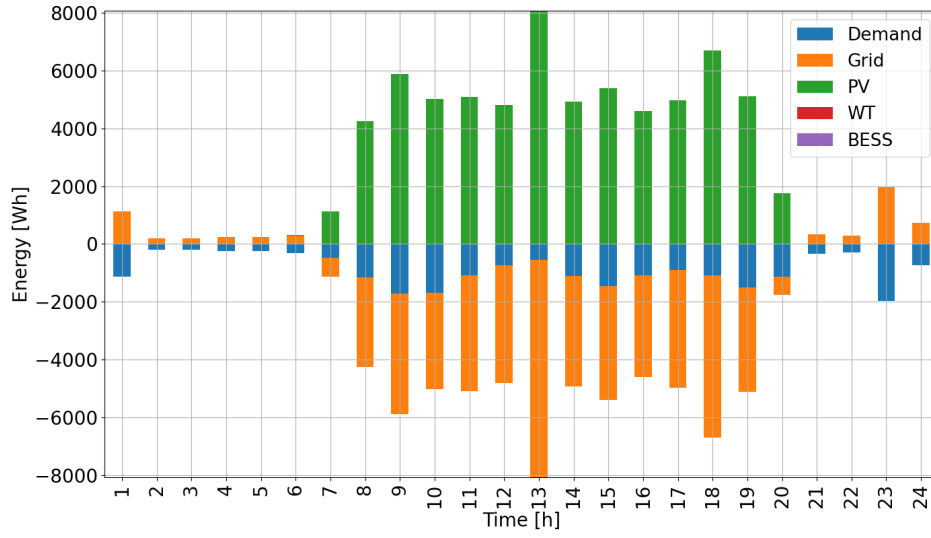


Figure 4.21: Scenario 7 MG dispatch with only the main grid

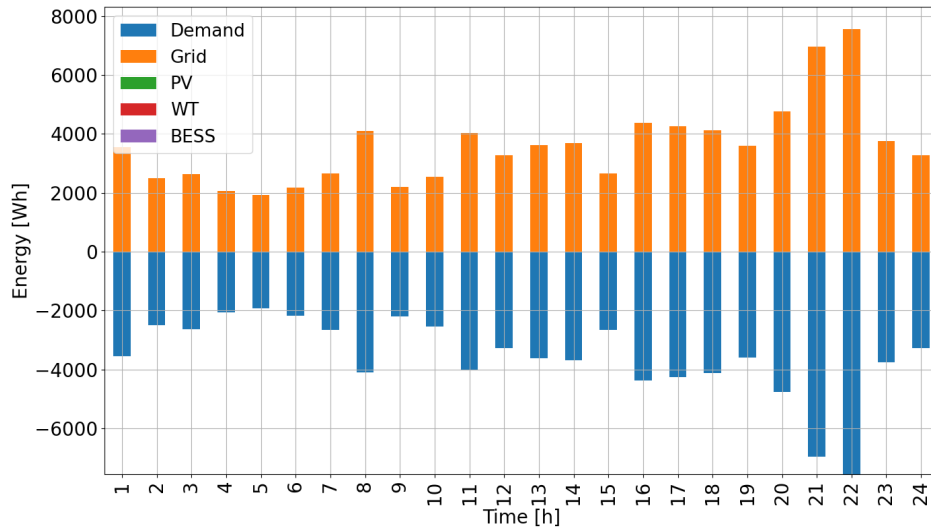
### 4.3.8 Scenario 8

The 8<sup>th</sup> and last scenario has a probability of 0.06 and its framework in case only the main grid is present is shown in 4.23 and the related operational cost is equal



**Figure 4.22:** Scenario 7

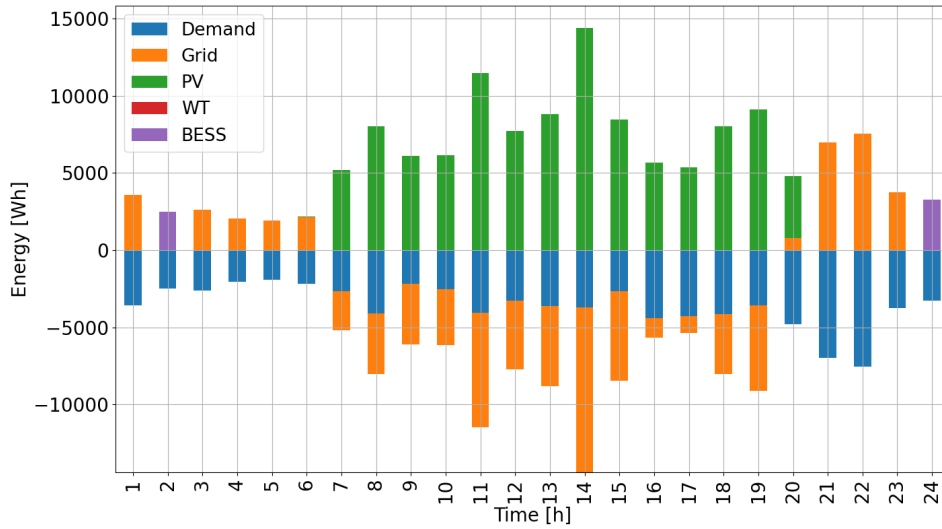
to 36.53€. As illustrated in figure 4.24, the introduction of RES and BESS shows



**Figure 4.23:** Scenario 8 MG dispatch with only the main grid

some contribution from this last element at 2 in the morning, and again at 24 in the evening. It can be noted that the PV production in this scenario is higher than

in all the other scenarios. When discharging, the BESS replaces the extraction from the grid, while during the day, between 7 and 20, the PV plant produces enough to supply the whole ED and also to inject electricity into the grid. The cost related to this scenario is 1.94€, with savings of 94.69%. Meaning that, even though the PV injects electricity into the grid for 15 hours throughout the day, the use of the BESS and the extraction of energy from the grid are more expensive than the revenue that comes from selling electricity.



**Figure 4.24:** Scenario 8

Table 4.2 summarizes the values of probability and the related savings or increase of cost for the use of RES and storage system for each of the 8 scenario generated.

Scenario	Probability	Grid only	With RES and BESS (% variation)
1	0.01	2.44€	-220.9%
2	0.04	4.41€	-17.01%
3	0.38	7.50€	-73.33%
4	0.06	2.22€	-83.43%
5	0.24	16.49€	-70.47%
6	0.01	9.05€	+21.30%
7	0.20	4.41€	-181.63%
8	0.06	36.52€	-94.69%

**Table 4.2:** Scenarios, related probability and cost variation with or without RES and BESS

## Chapter 5

# Conclusions

The flexibility of the plug-and-play model's inputs allowed to analyze different frameworks in which the MG operates. From chapter 3, the impact of the PV production on the dispatch strategy is highlighted, since there is a clear economic convenience in the inclusion of the solar resource in both the summer and winter days simulated in this context. In particular, for the summer day, there are savings up to almost 110% with respect to the case in which only the electrical grid serves the load, while for the winter day the savings are about 64%. On the other hand, the presence of the BESS does not widely affect the electricity dispatch, as it happens for the WT. The issue with the BESS is that the cost associated to it is, for most of the time, higher than the electricity MP, leading to low convenience in employing it. Further development in the electrical storage market could allow to decrease the cost associated to this element. Instead, the WT has small rated power, therefore its production is low.

A similar behavior is shown in chapter 4, in which the PV system is the RES that contributes more to the supply of electricity in all simulated uncertain scenarios and, therefore, brings more savings to the MG.

Future developments on this work of thesis could include:

- integrating this analysis with the plants sizing optimization, especially in the case of the WT
- the inclusion of grid constraints, in terms of voltage and frequency, in the dispatch strategy definition, so that power quality aspects could be included in the analysis
- the addition of the most recent incentives proposed by the Energy Authority in the economic optimization, so that this would better reflect the reality of operating a MG

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