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Methods for Optimal Microgrid Management

By

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Abstract

During the last years, the number of distributed generators has grown significantly and it is expected to become higher in the future. Several new technologies are being developed for this type of generation (including microturbines, photovoltaic plants, wind turbines and electrical storage systems) and have to be integrated in the electrical grid. In this framework, active loads (i.e., shiftable demands like electrical vehicles, intelligent buildings, etc.) and storage systems are crucial to make more flexible and smart the distribution system. This thesis deals with the development and application of system engineering methods to solve real-world problems within the specific framework of microgrid control and management.

The typical kind of problems that is considered when dealing with the management and control of Microgrids is generally related to optimal scheduling of the flows of energy among the various components in the systems, within a limited area. The general objective is to schedule the energy consumptions to maximize the expected system utility under energy consumption and energy generation constraints.

Three different issues related to microgrid management will be considered in detail in this thesis:

1. The problem of Nowcasting and Forecasting of the photovoltaic power production (PV). This problem has been approached by means of several data-driven techniques.
2. The integration of stations to charge electric vehicles in the smart grids. The impact of this integration on the grid processes and on the demand satisfaction costs have been analysed. In particular, two different models have been developed for the optimal integration of microgrids with renewable sources, smart buildings, and the electrical vehicles (EVs), taking into account two different technologies. The first model is based on a discrete-time representation of the dynamics of the system, whereas the second one adopts a discrete-event representation.
3. The problem of the energy optimization for a set of interconnencted buildings. In ths connection, an architecture, structured as a two-level control scheme has been developed. More precisely, an upper decision maker solves an optimization problem to minimize its own costs and power losses, and provides references (as

regars the power flows) to local controllers, associated to buildings. Then, lower level (local) controllers, on the basis of a more detailed representation of each specific subsystem (the building associated to the controller), have the objective of managing local storage systems and devices in order to follow the reference values (provided by the upper level), to contain costs, and to achieve comfort requirements.

Sommario

1. Introduction

The most versatile and widely used energy form is electricity, a resource accessible to more than 5 billion people around the world. The power grids that guarantee its availability are among the largest systems ever made, visible at night and even from space.

Today power generation comes essentially from large power plants mainly fuelled by fossil fuels, nuclear and hydroelectric power that operate through well-established transmission and distribution systems. Although these systems have offered efficient service around the world for over a century, the times are changing. Demand for energy is growing rapidly due to rapid social developments in many parts of the world, but also because modern digital economies increasingly depend on electricity availability. This dependence relationship imposes new structural developments in order to avoid network problems.

At the same time, modern societies have realized that, in order to combat climate change, it is necessary to reduce emissions. Optimum use of traditional sources has to underpin the development of production from non-traditional sources such as wind, solar, solar, geothermal, and biomass power plants. Thus, there is a great variety of energy sources whose integration and optimum use yield complex problems relevant to the design and management of electrical grids.

The impact of climatic conditions on the availability of wind and solar energy, together with the need to develop distributed facilities (e.g., domestic photovoltaic systems), further complicates the scenario, imposing the need for designing local networks capable of receiving and delivering electricity . In this connection, the power grid itself is used in new ways. Instead of serving relatively small geographic areas with links to other regions to ensure security of supply, networks are currently used as energy-efficient channels for longer distances.

Since they have not being designed to meet these needs, traditional power grids are therefore unable to provide long-term satisfactory performance. A global and widespread evolution is thus necessary.

The necessary measures include:

- the application of new design criteria and the use of advanced materials for equipment such as transformers and switches in order to improve the overall efficiency, safety and performance;
- the diffusion of electronic devices to optimize existing resources and improve network flexibility in case of interruptions;
- the use of storage technologies at all levels to mitigate peak demand and extend energy utilization produced from renewable sources;
- the use of more flexible transmission and distribution methods to balance supply fluctuations, increase efficiency and optimize performance;
- the integration of monitoring and control systems to prevent interruptions.

The term "smart grid", encompasses all these features in a single system by means of communication technologies that allow large data exchanges between Intelligent devices distributed in the electric system. Pike Research, one of the leading market research companies, estimates a global investment of around $ 200 billion in smart grid infrastructure over the period between 2010 and 2015[1].

Based on existing policies and trends, global energy needs will grow by 40% by 2030, with a consequent increase in emissions of carbon dioxide[2]. The scientific community is unanimous in believing that such an increase in emissions could have a significant impact on the economic, environmental and social level[3].

1.1 Context

Energy demand engines are demographic growth and rising living conditions in emerging markets, which will continue to increase fuel consumption. The challenge is to break the links between economic growth and energy demand and between energy production and carbon dioxide emissions.

The International Energy Agency (IEA) has defined a strategy for the next two decades to pursue these two goals through the decisive implementation of some low-carbon technologies. According to this approach, more than half of the savings would be due to the implementation of energy efficiency measures, while a fifth would result from the increase in the generation of energy from renewable sources.

Adapting the electricity supply system is a fundamental move, for two reasons: first, the generation of electricity represents the largest percentage of anthropogenic CO_2 emissions and is equal to 40% of global CO_2 emissions attributable to energy production . Second, the growth rate of electricity consumption is almost twice as much as the increase in overall energy consumption, so reducing emissions generated by energy production is increasingly urgent.

Thinking about power management reducing emissions at source is just one of the ways to reduce CO_2 levels. As highlighted in the IEA's analysis, improving energy efficiency is the most important means of setting a limit on primary energy consumption. The main goal of future networks is therefore to make energy efficient use, with the implementation of energy-saving technologies at every stage, from production to transmission and exploitation.

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[1] Pike Research, dicembre 2009. Cfr. http://www.pikeresearch.com/newsroom/smart-grid-investment-to-total-200-billion-worldwide-by-2015

[2] Agenzia Internazione per l'Energia (IEA), 2009. World Energy Outlook.

[3] IPCC (comitato intergovernativo per i cambiamenti climatici), 2007. The Fourth Assessment Report.

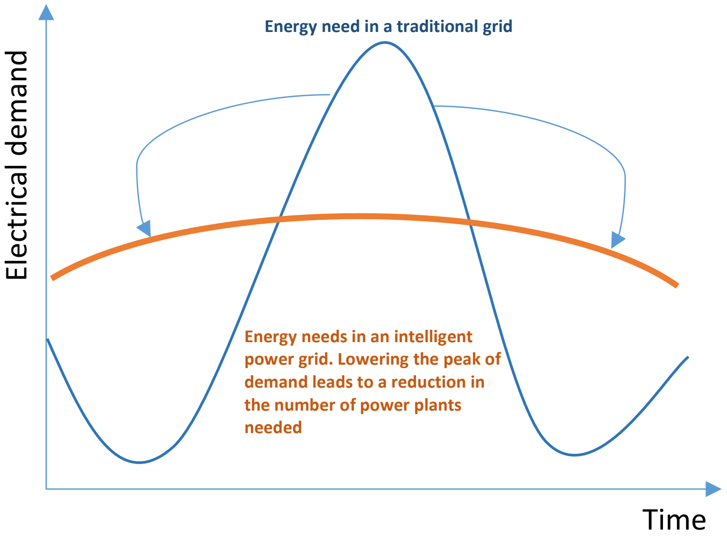

Figure 1: Smart grid vs traditional grid

In an intelligent electricity grid, demand-response technology is part of demand in times when the cost of energy is lower Figure 1 given that in a traditional power grid, peaks of the demand (in certain hours within the day) are partially satisfied by using power plants specially maintained in stand-by.

In 2016 Renewable Energy Sources (RES) generated more than 39%[4] of the electricity in Italy, and “Renewable energy technology, especially solar and wind, has made

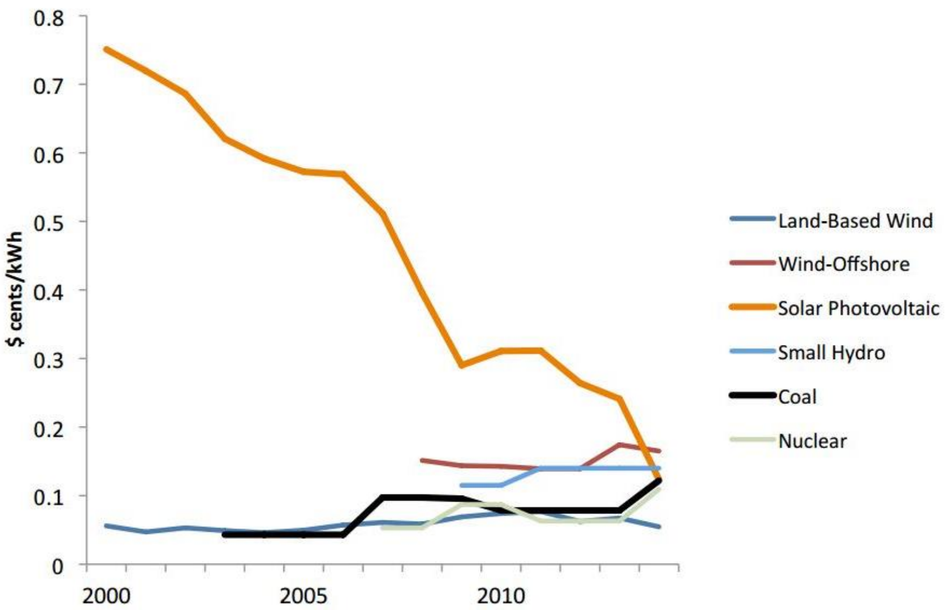

Figure 2: Energy production cost (WEF)[5]

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exponential gains in efficiency in recent years, enough to achieve economic competitiveness and, in an increasing number of cases, grid parity. For instance, the unsubsidized, levelled cost of electricity (LCOE) for utility-scale solar photovoltaic, which was highly uncompetitive only five years ago, has declined at a 20% compounded annual rate, making it not only viable but also more attractive than coal in a wide range of countries. By 2020, solar photovoltaic is projected to have a lower LCOE than coal or natural gas-fired generation throughout the world. Renewable infrastructure has moved much closer to utility-like investments and no longer presents frontier technology-like risks." [5] "These trends are relatively low-risk, with most necessary technologies already in development, and economies of scale continuing to be a self-reinforcing process. The fast adoption pace encourages supply expansion, which further reduces production costs and stimulates demand. "[6] Figure 2).

These trends have led to the concept of "Microgrid " and thus even of "Microgrid management ".

1.2 Development of photovoltaic

Figure 3: PV

The photovoltaic energy productions are characterized by the fastest growth, Figure 4 shows the PV installation evolution in the last 16 years. As it can be seen from this Figure 4, the solar power installed is given up to 75 GW in 2016; Furthermore, we can note the new investments of PV installation in China and in Japan.

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[5] Renewable Infrastructure Investment Handbook, Word Economic Forum
http://www3.weforum.org/docs/WEF_Renewable_Infrastructure_Investment_Handbook.pdf

[6] Renewable Infrastructure Investment Handbook, Word Economic Forum
http://www3.weforum.org/docs/WEF_Renewable_Infrastructure_Investment_Handbook.pdf

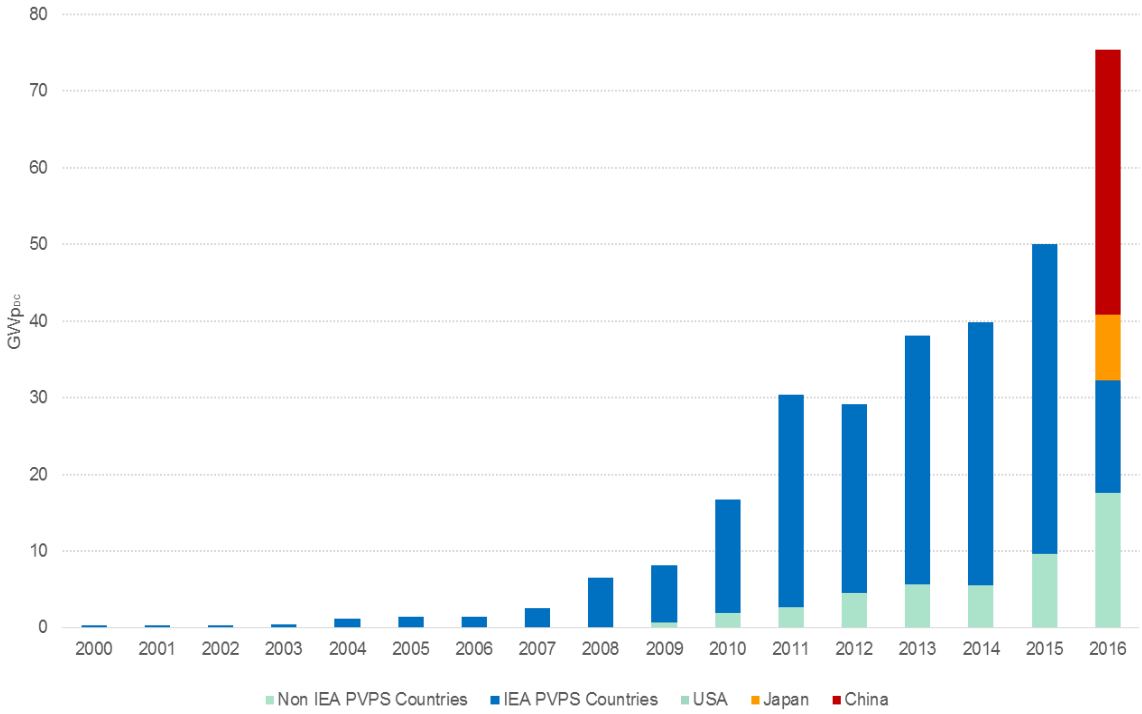


Figure 4: Evolution of annual PV installation[7]

This induces relevant investment that reflect in the installed PV price; indeed the installation cost has a radical decline in the world in the last year as show in Figure 2(orange line).

1.3 Grid evolution: Microgrid and Smart grid

The current model of a power grid is designed as a passive network whose unique function is that of carrying electricity in only one direction in a so called vertical system. Large power plants, fuelled mainly by fossil fuels, operate using and well-established distribution.

The convergence of several factors, mainly including the generation of electricity from renewable sources distributed over the territory, promotes the development of a new network concept. In this context, a major role is played by the distributed generation (DG) which offers more security and better performance due to the flexibility and the ability to integrate several other systems of monitoring and control.

The term smart grids incorporates all these features in one system through communications technologies that allow large data exchange between devices deployed in

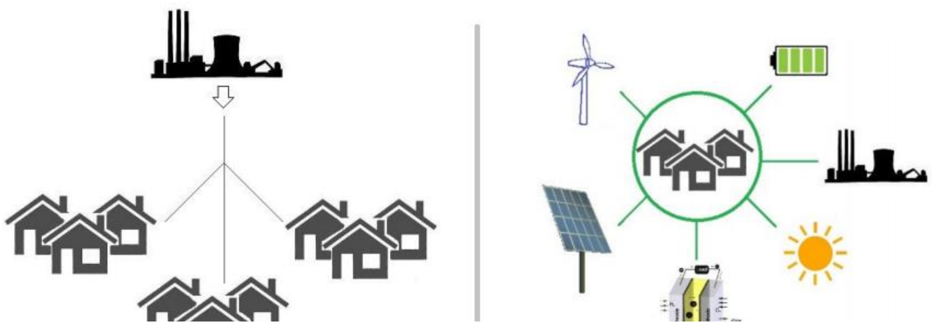


Figure 5: Vertical Generation and Distributed Generation

[7] http://w

the electrical system.

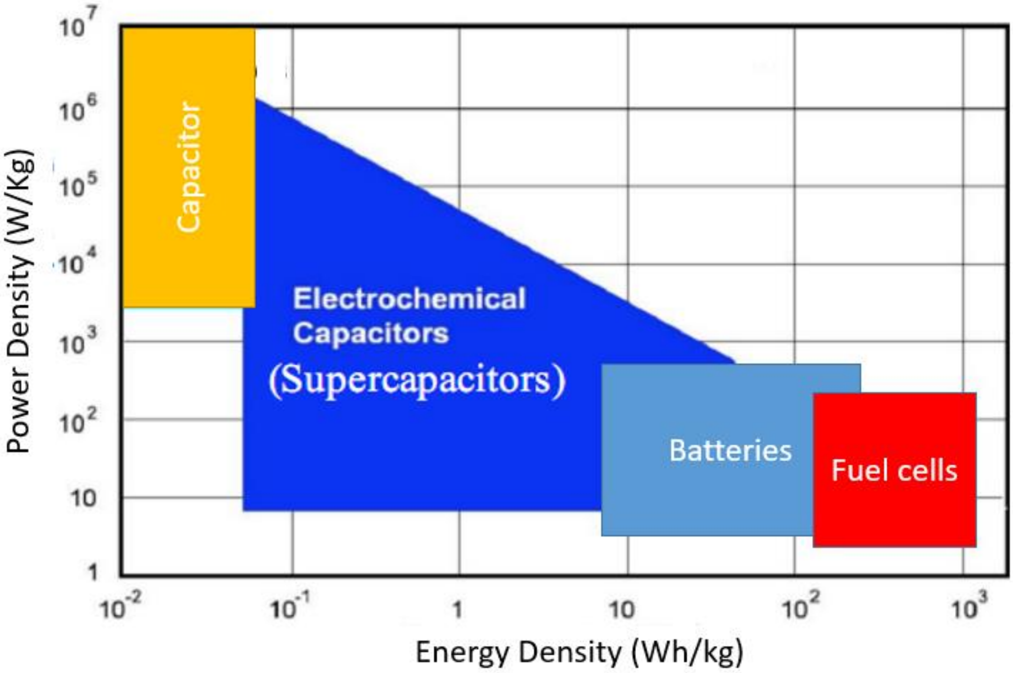
A power grid becomes smart when it integrates traditional technologies with innovative digital solutions that allow flexibility in its management. The key point of evolution is the shift from passive to active, so able to let bidirectional flows of energy allowing the interaction between producers and consumers. The “consumer” becomes “prosumer”. In fact, a single user of the system can, in different circumstances, be a feeder as well as a producer.

Energy management systems are vital tools used to operate optimally with smart applications. Automatic control of the grid is completely meaningless without a reliable identification of the state of the grid itself. A pervasive monitoring infrastructure made of sensor and communication devices has to be put in place. A typical smart grid configuration involves different actors that are all linked together through an intelligent management method, integrating different distributed and heterogeneous sources, either programmable or stochastic.

In detail, a microgrid is a low-voltage and small network connected to a distribution grid through the point of common coupling (PCC), and contains both distributed generations and loads. Several types of distributed energy resources (DERs) are used in a microgrid, such as microturbine (MT), fuel cell (FC) and energy storage system (ESS) as controllable units. Renewable energy, such as wind energy and photovoltaic, are also included in a microgrid as non-controllable units.

1.3.1 Development of Electrochemical Energy Storage

Storage technologies have a more and more important role in the future of power energy. Storage systems are often related to a voltage and power quality support, due to the high power dencity (Figure 6: Power density vs. energy density of various energy storage systemsFigure 6), but they also have to cope with the increasing use of renewable and intermittent energy sources, as wind and solar ones. Peaks and dips in demand can often be anticipated and satisfied by increasing or decreasing generation at fairly short notice. Storage systems may help the grid acting on the daily load curve by feeding the loads with “cheaper” energy accumulated during the not-peak hours.



1.3.2 Electrical vehicles

Figure 6: Power density vs. energy density of various energy storage systems

Electric vehicles can be integrated within smart grids since they represents not only a load but also a potential resource. In a not so futuristic vision, they can act as a distributed energy resources, since they can favour active short-response participation on storage resources by providing regulation services and power supply. In these circumstances, therefore the manager can also encourage owners towards avoiding to use the car during periods of high load so as to use the battery as storage admitting bidirectional flows based on demand energy network.

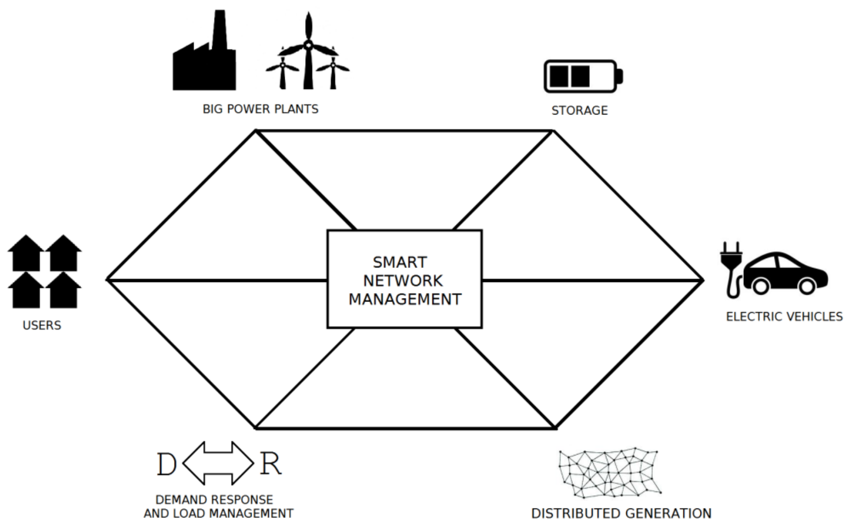


Figure 7: Smart metering and communication infrastructure

Furthermore, these systems riquires real-time accurate measurements and allow bidirectional power flow, enabling vehicle-to-grid (V2G) operation. In this system, plugged-in electric vehicles can communicate with the power grid to sell demand response services by either returning electricity to the grid or by throttling their charging rate and so representing a very flexible storage.

The motivation that underlies the V2G operating mode is the fact that cars spend most part of their day still in the parking lot. Therefore, at world average, since at any given time instant more than 90% of cars are parked about 20 hours out of 24, it is reasonable to consider the possibility that the batteries in electric vehicles are used to let electricity flow from the car to the electric distribution network and back. An electric car could exploit this actually dead period to offer to those who need it the residual energy stored in its battery.

The first step of V2G regards smart-charging strategies: batteries are charged during the off-peak times achieving different advantages also they do not contribute to raise the demand peak[8].

At large scale, it is reasonable to think about a realistic scenario in which electric cars for the majority of their life are parked. Thus, always connected to the power grid through static bidirectional converters, they are ready to absorb or transfer energy on their batteries. In this way, it is possible for them to absorb excess production of electricity and to return to the system in periods of greatest load. Thus, considering the huge amount of vehicles in the system, this yelds a massive energy reservoir distributed in the grid.

As previously mentioned, energy demand actually varies in time. It changes in the hot and in cold season for example and a peak demand can arise during certain phases of the day due to weather conditions, some sport events or other reason that involves the majority of people simultaneously. When a peak demand occurs, the national grid turns on the corresponding power stations to meet the increase demand and often relying on inefficient recovery-plants.

An income solution for the mitigation of this kind of events depends on energy demand management. When electricity demand begins to peak, network participants temporarily switch off or reduce consumes for a short periods of time until the demand returns to normal levels. This level of management is referred to Demand Response (Alessandrini, [15]).

Demand Response is a process that enables utilities to match electrical supply and demand and so avoid high costs due to the impact of peak events. It is defined as: “Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized”[9].

It corresponds to a wide range of actions which can be taken at the customer side of the electricity meter in response to particular conditions within the electricity system

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[8] Brinkman, Eberle, Formanski - Vehicle Electrification, Quo Vadis?
[9] Balijepalli, Murthy; Pradhan, Khaparde – Review of Demand Response under Smart Grid Paradigm - 2011

such as peak period network congestion or high prices events and it can be perfectly appropriate considering electric vehicles as a part of the system in which is possible to store energy.

1.4 Outline og the rest of the theis

Having so defined the framework within which the approaches presented in this thesis will be developed, it is now possible to outline the contents of the next chapters.

In the next chapter, the literature concerning microgrid management, with specific reference to the topics dealt with in this thesis, will be reviewed. In Chapter 3, the various components of a microgrid are described from a technical viewpoint and their integration into a real microgrid is considered.

When dealing with microgrid management problems, one of the preliminary most serious difficulties is the forecast of the power coming from (intermittent) renewable sources. For this reason, in chapter 4 a brief mention is made about a particular class of forecsting techniques falling within the framework of machine learning methods.

Chapters 5, 6 and 7 contain the main contributions of this thesis, relevant to two different kinds of problem. The first one (dealt with in chapters 5 and 6) is that concerning the optimal scheduling of charging of electrical vehicles integrated with the overall management of a microgrid. More precisely, in chapter 5 a discrete-time modelling of the system is adopted to state and solve the optimization problem, whereas in chapter 6 the dynamics of the system is modelled within a discrete-event framework.

The second type of problem (dealt with in chapter 7) is that relevant to the energy management of a set of buildings interconnected among themselves and with the main grid. A two-level optimization scheme is developed and applied for this purpose.

The effectiveness of the proposed approaches have been evaluated by considering real case studies. Namely, as regards the vehicle charging problems, data coming from an experimental microgrid set in the Savona Campus of the University of Genoa have been used. Instead, as rtegards, the energetic management of the buildings, a set of existing buildings in a district in Genoa have been considered.

2. Literature review

The main objective of this thesis is to develop a model and a management methodology that can help in reducing the production costs of energy, improving the efficiency, and reducing the environmental impact.

2.1 Optimal energy management of microgrid

In the new century, the electric power industry is facing unprecedented challenges arising from the continuous depletion of fossil fuels and the global worsening of environment. These challenges have spurred a great interest in integrating renewable energies into existing power systems. The development of the renewable energy sector, the concept of sustainable energy, and the use of technologies for distributed generation have focused attention on smart grids.

Another important class of systems to be considered in this connection are Microgrids. We can define Microgrids as low-voltage networks with distributed generation sources, local storage devices, and controllable loads that can operate either in an interconnected or isolated mode from the main grid (MG).

Microgrid deployment is becoming an increasingly attractive solution for electricity customers who cannot rely on supply of power from the main grid, and/or are seeking economic benefits from a locally generated power; one of the advantages offered by microgrids is to improve power system resiliency via local supply of loads and curtailment reduction.

Recent research on energy scheduling can be classified into three main streams: a) vehicles charging scheduling, b) building energy scheduling, and c) local-area energy scheduling.

The overall objective is to schedule the energy consumptions of the dynamic tasks to maximize the expected system utility under the given energy consumption and energy generation constraints. In the paper by C. Gong at al. [1] , the real-time local-area energy scheduling is considered, for a local-area power network with a single energy source and multiple energy consumers, and with both stochastic and deterministic energy demands.

A centralized scheduling model is adopted by Khodaei A. et al. [2] in which a master controller collects all the required information for microgrid scheduling and performs a centralized operation and control.

In the recent literature we also can find different papers dealing with the development of models for the simulation and optimization of microgrids with storage and renewable energies both at planning and operational level. Chen et al. [3] present a methodology for the optimal allocation and the economic analysis of an energy storage system in microgrids. Mohammadi et al. [4] present an optimized design of a microgrid in distribution systems with large penetration of dispersed generation units (among which PV, wind turbines and batteries).

Bracco et al. [5] consider an Energy Management System (EMS),based on a dynamic optimization model to minimize operating costs and CO2 emissions. This model is formalized and applied to the University of Genoa Savona Campus test-bed facilities consisting of a Smart Polygeneration Microgrid (SPM) and a Sustainable Energy Building (SEB) connected to this microgrid.

H. Dagdougui et al. [6] focus on the decentralized control of smart microgrids (SMGs), where each microgrid is modelled as an inventory system locally producing energy by wind/solar sources. The objective is to satisfy the internal demand, and to exchange power with its local energy storage technology, the main grid, and other similar microgrids of the region. In this framework, the problem faced in this paper is the optimization (minimization) of the costs of energy storage and power exchanged among SMGs.

Kamjoo et al.[7] present a method to determine the optimal size of HRES (hybrid renewable energy system) components is proposed, considering uncertainties in renewable resources. The method is based on CCP (chance-constrained programming) to handle the uncertainties in power produced by renewable resources. The design variables are wind turbine rotor swept area, the PV (photovoltaic) panel area and the number of batteries. The approach used in solving problems with CCP is based on the use of non-Gaussian joint distribution function that follow Gaussian distribution.

Besides, some paper can be founded in the literature that investigate about local energy scheduling for a micro grid with a semi-Markov discrete-time random process model renewable generation such as PV considered by Barnes et al. [8]. Another example is proposed by Zamo et al. [9] who present the results of a study about forecasting photovoltaic (PV) and electricity production for some power plants in mainland France.

The limit of the wind farm is different respect to PV,in fact, the limit is the dispatch ability of wind energy poses a challenge to its increased penetration. A technically feasible solution to this challenge is to integrate a Battery Energy Storage System (BESS) with a wind farm. This highlights the importance of a BESS control strategy. In view of this, some paper like that of Kou et al. [10] propose the application of a stochastic model predictive control scheme.

2.2 Optimal PV Energy production Forecasting and Nowcasting

The international increase in the use of renewable resources (RES) for power and energy production have led to an increasing attention on the PV power production performance. This significant result implies difficulties in the management of the grid because RES are intermittent, distributed over the territory, and difficult to forecast at the local scale. It is necessary to define new Energy Management Systems (EMSs) that are able to minimize costs and emissions related to power and energy generation on the basis of loads and RES forecasting. In the recent literature many papers show the need of the development of new EMSs for smart grids and microgrids [11], [12], [13]. In all such works, RES forecasting plays a crucial role for the definition of economically and environmentally sustainable operational strategies. In fact, the decision models used to schedule plants power production use forecasting of renewables and loads that are supposed to occur in the considered optimization horizon.

Forecasting methods can be broadly classified as physical or statistical. The physical approach uses solar and PV models to generate PV forecasts, whereas the statistical approach relies primarily on past data to train models, with little or no reliance on solar and PV models. From literature, it is clear that Numerical Weather Predictions (NWPs) models are operationally used to forecast the evolution of the atmosphere from about 6 hours onwards. Satellite-derived solar radiation images are a useful tool for quantifying solar irradiation at ground surface for large areas, but they need to set an accurate radiance value under clear sky conditions and under dense cloudiness from every pixel and every image. These limitations have set time series analysis as the dominant methodology for short-term forecasting horizons from 5 minutes up to 6 hours.

The power produced by a PV system depends critically on the variability of the weather. This variability of the power production may increase operating costs for the smart grid. In literature, many works are present that propose approaches for solar forecasting for PV applications for different time scales. Generally, articles differ for the approaches, data sets and application areas. For short-medium term forecasting, in literature, an Artificial Neural Networks (ANNs) methodology is applied to data obtained from a 750 W power capacity of solar PV panel. The main objective is that of determining the time horizon suitable to generate a prediction of the electricity production at small scale solar power system applications.

Bouzerdoum et al. [14] study a system in which the data used are the external temperature, the cell temperature and the solar irradiation, collected in 1 minute time horizon. They combine two well-known methods: the seasonal autoregressive integrated moving average method (SARIMA) and the support vector machines method (SVMs). An experimental database of the power produced by a small-scale 20 kWp GCPV plant is considered and the forecasted solar irradiance is used to estimate the power produced by the grid-connected PV system. The monitored climatic data are: the irradiance on the array plane, the module’s temperature and the external temperature at array side. With reference to the electrical data, the recorded quantities are: the string voltage, current and power, the AC power, the module and the frequency of the grid voltage, and the energy produced at DC and AC side.

Alessandrini et al. [15] propose the application of an analog ensemble (AnEn) method to generate probabilistic solar power forecasts. The AnEn is based on an historical set of deterministic numerical weather prediction model forecasts and observations of the solar power. The innovative aspect of the paper is the test of a new method for probabilistic PV energy forecast over the 0÷72 hours lead time interval. The proposed method has the advantage of not requiring an irradiance-to power conversion function. In fact, only the meteorological forecasted variables, global horizontal irradiance, cloud coverage, temperature, solar azimuth, solar elevation and photovoltaic power measurements are used for this application.

Trapero et al. [16] propose a univariate Dynamic Harmonic Regression model set up in a State Space framework for short-term solar irradiation forecasting. Time series hourly aggregated as the Global Horizontal Irradiation and the Direct Normal Irradiation are used. Hourly series of solar irradiation data were constructed, aggregating 1-minute ground-based solar irradiance data, which were recorded between January 2009 and December 2011 by the available weather station. The dataset contains 26280 observations.

Orwig et al. [17] develop standardized metrics, baselines, and target values to measure forecast accuracy improvement for a forecasting horizon of 24 hours, and assess that it is necessary to derive and predict several irradiance values including direct normal irradiance, diffuse irradiance, plane-of-array irradiance, and global horizontal irradiance from satellite imagery.

Bracale et al. [18] propose a new short-term probabilistic forecasting method to predict the probability density function of the hourly active power generated by a photovoltaic system. Firstly, the probability density function of the hourly clearness index is forecasted making use of a Bayesian auto regressive time series model (using also the cloud cover and humidity). Then, a Monte Carlo simulation procedure is used to evaluate the predictive probability density function.

Bacher et al. [19] propose a method for online forecasting in many applications and in this paper it is used to predict hourly values of solar power for horizons of up to 36 hours. The data used are 15 minutes observations of solar power from 21 PV systems located on rooftops in a small village in Denmark. The suggested method is a two-stage method where first a statistical normalization of the solar power is obtained using a clear sky model found using statistical smoothing techniques. Then forecasts of the normalized solar power are calculated using adaptive linear time series models. Both autoregressive (AR) and AR with exogenous input (ARX) models are evaluated, where the latter takes NWPs as input. The results indicate that for forecasts up to 2 hours ahead the most important input is the available observations of solar power, while for longer horizons NWPs are the most important input. The data covers the entire year 2006.

Chen et al. [20] propose a two stage simplified approach for forecasting power generation 24 hours ahead of using a radial basis function neural network (RBFNN). At first they apply Self-Organizing Map (SOM) to partition the data into three clusters using NWPs for daily solar irradiance and cloud cover.

Wolff et al. [21] use nearest neighbours regression and support vector regression for 1-hour ahead PV power forecast predictions based on measurements and numerical weather predictions. Pedro et al. [22] evaluate several univariated approaches using both statistical and computational intelligence methods including ARIMA, Neural Networks (NN) trained with both back propagation and genetic algorithms, and k-nearest neighbours. They found that NNs trained with genetic algorithm was the most accurate for hourly solar PV power prediction.

Nonnenmacher et al. [23] seek to evaluate and optimize NWPs based on direct normal irradiance (DNI) forecasts, predicting hourly average values of DNI, 12 and 36 hours ahead. Tao et al. [24] estimate, for a PV system without any complex meteorological instrumentation, an instantaneous power output of the solar network using Nonlinear Autoregressive Neural Network with External input (NARX). However, in reality radiation models of inclined surfaces were a prerequisite input to their NARX model, which is not always available. Al-Messabi et al. [25] used dynamic neural networks to predict power generation of these arrays they use in particular Focused Time Delay NN (FTDNN) and Distributed Time Delay NN (DTDNN). Bessa et al. [26] propose a vector auto regression based method to benefit from spatial-temporal dependencies of PV power. Using past observations from the neighboring locations and for forecast horizons less than 4 hours, up to 10% improvements in RMSE values are achieved. Liu et al. [27] propose a PV power forecasting model based on various meteorological data including AI and they validated the method through the analysis of the mean absolute percentage error between predicted values and measured values. In [28] a simple method is validated. They propose a forecasting method that mainly relies on mining data and finding days that are similar to the forecast day according to certain measures

While the term forecasting is of widespread use in everyday language, the term nowcasting belongs to the technical vocabulary of several research areas. Its adoption in a new context needs some clarification, as it is currently used with slightly different connotations, especially in very technical and specific fields. There is a general agreement that the term nowcasting appears in the meteorology literature, where it refers to the process of providing weather information and forecasts from zero to few minutes ahead [29], [30], [31], [32], [33]. In general, the term is used in a different sense from forecasting in terms of timeframe (forecasts are short-term predictions).

2.3 Microgrid and Electrical vehicle management

The integration of renewables, electrical vehicles and microgrids is getting more importance in the last few years. Also this interaction permits to reduce greenhouse gas emissions, increases the interactions between different systems and the reliability of the distribution networks.

In the recent literature, there are different papers that analyze smart grids management tools or EVs, but few of them consider Energy Management Systems (EMSs)[34] that integrate smart grids, the various modes of EVs charging and the definition in first-time of user be charged in a specific station (from the DSO, Distribution System Operator, point of view). In order to have a clear definition of the technologies that are present at world scale, Shamshiri et al. [35] present an overview of smart grids features and highlight the recent developments. Optimization models are crucial to achieve a reduction in electricity costs and to maximize investments. Monteiro et al. [36] show how significant reductions in electricity cost can be reached using proper approaches and develop a management architecture for the distributed micro-grid resource based on a multi-agent simulator that is able to optimize load scheduling. Nasrolahpour et al. [37] consider a microgrid and determine the optimal scheduling of each generator and the amount of controllable loads during a day including purchased energy from the main grid.

As one of the key factor of the modernization through future smart cities, the integration of electric mobility in the grid has been analyzed by different authors performing accurate models and reliable methods to manage properly EVs. Gonzalez et al. [37] summarize the most recent literature among the advantages of electric vehicles related to ancillary service for smart grids. Zhao et al. [38] presents the results of an investigation for the evaluation of different charging concepts and strategies. Delaimi et al. [39] propose a load management solution for coordinating the charging of multiple plug-in electric vehicles in a smart grid system. Allard et al. [40] compare the performance of different scenarios of smart charging and conventional charging applied to EVs, the implemented simulation model is based on the trend of Norway and so with a great integration of renewable and in particular wind energy.

Electric vehicles are equipped by efficient electric motors that are powered by high-density lithium ion batteries, which through chemical reactions generate electrical current; a typical drive for these vehicles is also composed by a DC/DC converter and an inverter that feeds the motor [41]. These motors allow bidirectional power flow. When there is a torque request from the traction system the power flow is from the battery to the wheels, otherwise during the regenerative braking the battery is recharged. The battery life is no more influenced only by the itinerary and the activity (for example pickup and delivering) [42] but also from the charging modes.

There are different types of charging stations: for example in [43] solar stations are taken into account, combining a PV system with electric vehicles also connected to the main grid. In particular, authors present a load scheduling model using data collected in two years. There are also different type of charging modes: the most used in smart grids are Smart charging and Vehicle to grid (V2G). Smart Charging concept represents a more flexible way of charging vehicles in order to modulate the feeding of the vehicles according to the grid necessities, for example during the peak hours. Instead, in V2G configuration, the power flow is bidirectional (from the grid to the vehicle and vice versa): the vehicle storage could help the microgrid to sustain the entire system if necessary or to regulate the voltage at the charging station node. These types of charging hav also some drawbacks: first of all, the creation of a fluctuating power demand. For this reason, the authors in [44] investigate a strategy to regulate the vehicle’s charge, considering different priority orders to reach the maximum flexibility, managing the power and consequently smoothing the demand curve. In [45] attention is focused on the active contribution, i.e., power modulation via different charging modes, of the electrical vehicles in the grid optimization considering the V2G mode. Differently, in [46] a mixed integer linear programming problem is formulated, with the objective of scheduling the charging of the vehicles, minimizing the energy costs and taking into account reliability and stability issues both as regards the microgrid and the customers.

The choice among different modes of charging influences not only the statement of the charging scheduling problems, but also the routing of electrical vehicles. For instance, in [47] a double layer smart charging algorithm for electrical vehicles (EVs) is presented, having the objective of allowing the single vehicle to reach the more suitable recharging station, limiting the transformer load and the total energy costs. In [48] the authors study different routing strategies to smooth microgrid's power fluctuations, caused by intermittent renewables and load, ensuring at the same time the grid power quality and the optimality of logistics services. Wang et al. [49] study the configuration of a system wherein EVs are connected to the smart grid as mobile distributed energy storage. Bracco et al. [50] present an overall EMS, based on a dynamic optimization model to minimize operating costs and carbon emissions considering different technologies as micro gas turbines, photovoltaic, concentrating solar systems, storages based on batteries technology.

Stochastic approaches are widely adopted to model the integration between electrical vehicles and power networks. In [51] a real case study is proposed, namely the distribution network from Zaragoza in Spain. The authors formulate a stochastic problem for energy resource scheduling including uncertainties of renewable sources, electric vehicles, and market prices. Also in [52] the scheduling problem is addressed, with the objective of maximizing the profit by charging the plugin electric vehicles within the low price time intervals as well as participating in ancillary service markets using stochastic programming. V2G technology could be integrated within a stochastic problem formulation as in [53], where uncertainties in the power flow are taken into account. The problem is solved by developing an algorithm based on bat metaheuristics.

Energy aggregators represent an effective tool that helps in the management of multiple devices connected together. In this connection, [54] formulates a stochastic model for day-ahead energy resource scheduling, integrated with the dynamic electricity pricing for electrical vehicles, to address the challenges brought by the uncertainty affecting demand and energy from renewable sources.

This type of problems includes models with many nonlinearities, and thus it is quite difficult to solve. As an example, [55] proposes three metaheuristic optimization techniques to solve the plug-in electric vehicle charging coordination problem in electrical distribution systems. These algorithm are based on tabu search, greedy randomized adaptive search procedure, and hybrid optimization. Such algorithms are developed with the objective of minimizing the operational costs, taking into account the objective of charging the electric vehicle batteries within a specific time interval. Similar approaches are followed in [56] and [57] for the same kind of problems. In particular, the application of genetic algorithms and particle swarm optimization techniques is described.

World organizations are encouraging national authorities to arrange more and more electric or hybrid vehicles. Mass deployment of EVs (Electrical vehicles) could be a good solution, but, unfortunately, a widely usage of EVs may cause technical problems [58].

The integration of a fleet of EV into an electric power grid introduces new issues in terms of the sustainability of the growing energy demand. Thiat is sufficient to conjecture that one day, with such an increasing demand, the available energy might become insufficient to host the recharge processes of too many EVs. Moreover, the adoption of many renewable energy sources (such as photovoltaic and wind) increases the unpredictability and the variability of the power production, leading to destabilize the grid [59], [60].

The interaction between microgrids and electrical charging stations could be a feasible solution to this problem [61], as smart microgrids have the capability to generate, distribute, and regulate the flow of electricity to consumers. In this connection, in [62] the authors consider a power system with an aggregator and multiple customers with EVs and propose novel electricity load scheduling algorithms, which, unlike what has been presented in previous works, jointly consider the load scheduling for appliances and the energy trading using EVs. In case of shortage of power generation, they automatically switch to use the energy stored in backup batteries or import electricity from neighboring microgrids or the power grid.

Electric power can be stored into storage systems and used later. For example, in [63] excess renewable power generation is used to produce hydrogen, which is stored in a refilling station. Instead, the authors of [64] presents a day-ahead scheduling framework for virtual power plant in a joint energy and regulation reserve markets. Impact of carbon dioxide emission of generators is taken into account by introducing a suitable penalty cost function. The presence of different uncertain parameters, regarding wind generation, EV owners' behavior, energy and market prices, and regulation up and down probabilities is considered using a point estimate method.

The overall load profile of the power grid, as well as of the microgrid, may change due to the introduction of EVs. Charging a large population of EVs has a significant impact on the power grid [65]. On the other hand, the introduction of EVs in the microgrid opens up opportunities to store and regulate power generated from highly intermittent energy generators.

Charging stations provide power supply for EV batteries. The deployment of complete infrastructures with complex equipment is unavoidable for promoting EVs. EVs need often many hours for charging. This means that the time spent for charging is long and consequently provokes long queues within these stations as well as intolerable waiting times. Thus, it is fundamental to develop and apply effective charging stations management policies. For instance, in [66], scheduling of EVs over charging stations is approached as an optimization problem, formulated as a linear programming problem. The paper proposes a decentralized control scheme for scheduling the flexible charging demand of plugin electric vehicles in residential distribution networks. This control scheme is designed for execution, by a multi-agent system, with two consecutive stages (first static and then dynamic scheduling).

Parking lots for EVs are increasing, in response to the growing number of this type of vehicles. Non-optimal operation of distributed generation sources and ineffective scheduling of EV charging stations can cause heavy economic problems for the lot owner and serious technical problems for the operator of the distribution network. In [68] the authors propose a fuzzy optimization model that aims at maximizing the PL's profit while satisfying EV owners' charging requirements. In [69] the EV-charge project is presented, with the objective of providing an effective solution by combining autonomous valet parking with e-mobility, introducing improved parking and charging comfort, thus simplifying the life of the customer and making more attractive the use of EVs. In [70] the vehicle scheduling problem is addressed following a discrete-event simulation approach. In particular, the car sharing model is treated by using a modeling approach based on the UML formalism for large systems.

Vehicle routing problem for EVs is dealt with in [71], where the authors consider a grid-connected microgrid model that consists of a logistic distribution system, where EVs depart from the depot, deliver the goods to multiple demand stations, and then return to the depot. On the basis of this model, the paper studies the coordinated dispatch strategies of EVs in order to smooth renewable energy and load fluctuations of the microgrid while ensuring the overall quality of logistics services.

In the recent literature, event driven approaches to EV-microgrids interactions, charging stations and parking lots management are presented in many works. In [72], the possibility of controlling the recharge processes of the vehicles' batteries in order to smooth the peak energy demand during critical periods has been investigated using an event driven optimization. In [73] the concept of park and-charge system is introduced. That allows the customers to park their electric vehicles at a parking lot, where the vehicles are charged during the parking time.

In this framework, another approach followed by some authors is that based on the development and application of model predictive control schemes. As an example, in [74] the authors seek for a suitable trade-off between the conflicting objectives of minimizing the net cost of buying energy and the error in the tracking of a reference aggregated charging power profile (following IEC 61851 standard). The same authors, in [75] and [76], consider the same problems in more complex scenarios. In particular, resources are coordinated according to the needs of maximizing self-consumption and minimizing the cost of energy consumption, within a contractual framework characterized by designed or market indexed pricing models.

In [77], a dual coordination mechanism is considered, which controls a cluster of devices at two different operational levels: market operation and real-time operation. In [78] the authors propose a hierarchical event driven multi-agent system framework to coordinate the scheduling of the charging process of electric vehicles. Finally, in [79] the authors propose a solution for the distributed dynamic assignment of a set of electric vehicles to a network of charging stations.

2.4 Residential Demand Response

Another important research topic about the microgrid management is that relevant to the so called smart buildings. Interconnected buildings can be seen as microgrids or districts that can share thermal and electrical power to satisfy comfort, economic and technical exigencies. Microgrid technology provides an opportunity and a desirable infrastructure to improve the efficiency of energy consumption in buildings, as assessed by [80] and [81]. Recent research shows that 20%–40% of building energy consumption can be saved through optimized operation and management, without changing the building structure and the hardware configuration of the energy supply system. Power consumption related to thermal appliance operation in a building, such as heating, ventilating, and air conditioning (HVAC) systems, represents a very important portion in load demand. The key to improve operation efficiency of building energy consumption is the coordination and the optimization of the operations of the various energy sources and loads. To attain these objectives, the development and the application of a suitable approach is required, which has to integrate dynamic models, intermittent renewables, active response mechanisms, real-time control of the distribution network, management of storage systems, and automatic measurement of energy consumption.

In this connection, in the recent literature, several works can be found related to BASs (Building Automation Systems) and EMSs (Energy Management Systems). However, very few of them, to the best of the authors' knowledge, are related to interconnected buildings. The scheduling problem of energy supply in buildings is considered in [82]. In this work, the objective is the minimization of the overall cost of electricity and natural gas necessary to satisfy the energy demand of a building, over a given time horizon, while satisfying the energy balance and complex operational constraints relevant to energy supply for equipment and devices. In many papers, approaches based on Model Predictive Control (MPC) are used for the management of buildings' energy consumption (see, e.g.,[83],[84],[85],[86] and [87]). MPC-based algorithms can be efficiently implemented and adapted to buildings of different sizes. Some papers consider a single element of the building, as in [88], where MPC strategies are developed to control the climate of a building where the room temperature has to satisfy comfort constraints. MPC is also applied in connection with building cooling systems and thermal energy storage systems. In these cases, it is proposed to optimally store the thermal energy in a tank by using predictive knowledge of building loads and weather conditions. In [89], the authors propose a model for the optimal design of distributed energy generation systems that satisfy the heating and power demand inside a small neighbourhood.

3. Distributed Energy Resources In Microgrids

This chapter focus on the MG components. Each component is modelled separately and the MG results from the combination of these components. The components that are considered in the model presented in ths thesis are: the photovoltaic energy source, the energy storage, the non-renewable sources for energy generation (e.g., a micro turbine), and the deferrable demand (for instance, the charging station for the electrical vehicles). In general, there is also a non-deferrable demand, but this does not require any specific model.

3.1 Introduction

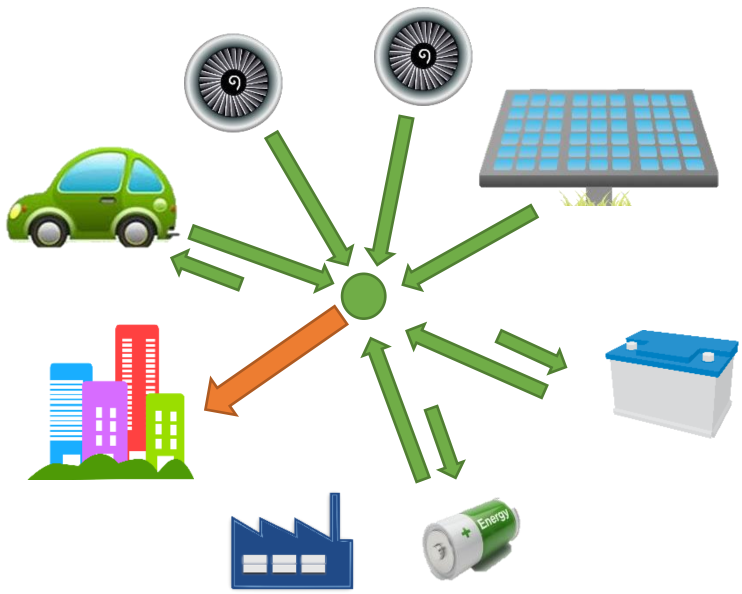
The management of MGs requires the intelligent exploitation of power and information by leveraging new technologies. The MG manager is no more a passive consumer of energy, but is capable of interacting with the real-time market by purchasing and selling energy on the basis of the results obtained by solving suitable optimization models.

An efficient MG management system has the following objectives:

- Combined Heat / Power (CHP) generation
- Coordination of supply and demand
- Minimization of transmission losses
- Integration of renewable energy sources
- Resilience to failures

The external issues that encourage the development of efficient MGs are:

- The necessity of reducing gaseous emissions (mainly CO2).
- The necessity of developing rational approaches to generation and exploitation of energy.
- The deregulation and the competiotion in the energy market.
- The increasing diversification of of energy sources.
- National and international regulations that favour the distributed generation of energy and the integration of heterogeneous sources.



3.2 The photovoltaic energy source

Photovoltaic (PV) electricity generation represents an attractive source of renewable energy, for distributed urban power generation, owing to the relatively small size and noiseless operation. Its application is expected to significantly grow all over the world.

PV generators are intrinsically modular; in other terms, they offer the advantage of allowing the possibility of adding further units in order to meet a possible increasing demand. The photovoltaic cell is a small size current generator. The most widely used material for its construction is silicon, which can be, depending on its molecular structure, monocrystalline, polycrystalline amorphous power, in descending order of conversion efficiency.

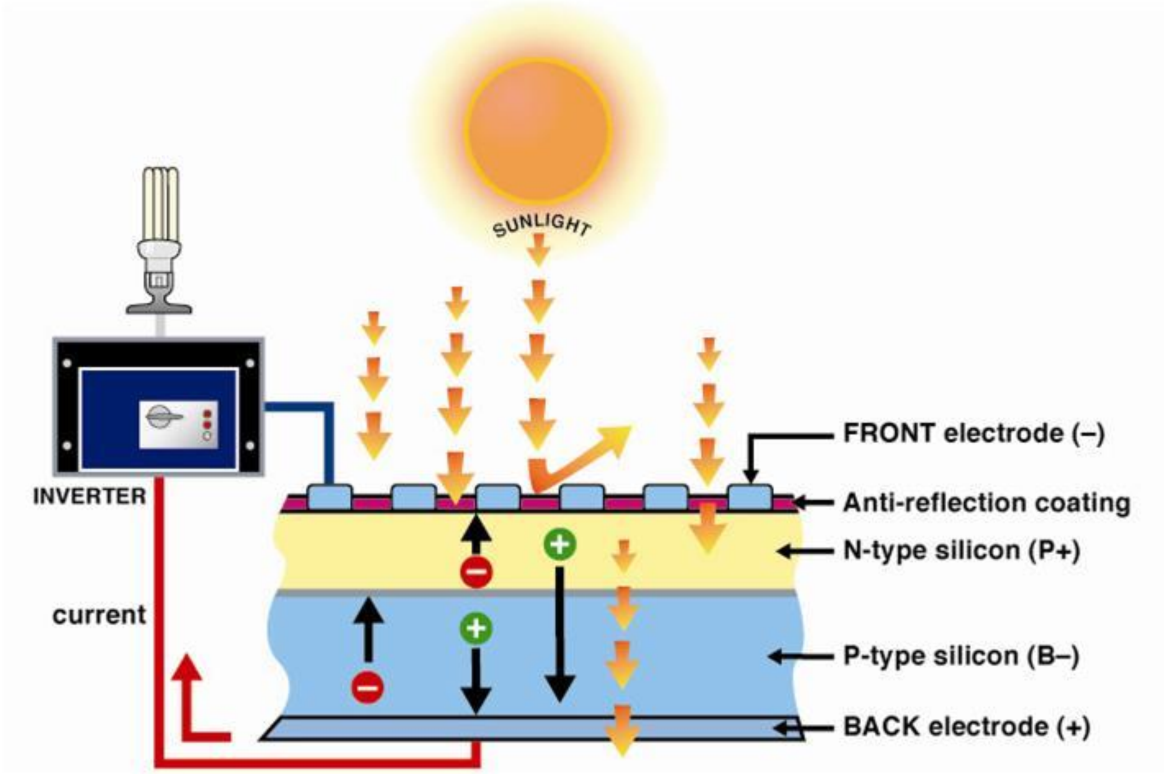


Figure 8 Cells Photovoltaic transformation

The Solar Cell is the basic building block of Solar PV technology. These cells are wired together to form a module (PV Solar Panel). The PV Modules gather solar energy in the form of sunlight and convert it into direct current (DC) electricity. An inverter can convert this DC power into alternating current (AC power). Figure 8 shows the basic process of photovoltaic convection.

The performance of the photovoltaic cell depends on a set of context-specific variables, operating conditions and climatic conditions in which the device is acting. The productivity of the cell is strictly correlated by its capability of intercepting solar radiation and the temperature it reaches, which, in turn, is influenced by various atmospheric issues that will be discussed in chapter 4. Note that the relation of energy with radiation is directly proportional, instead the relation with temperature is inversely proportional.

Clearly, electrical power production is not constant over time. Besides to intermittency, the additional difficulty of forecasting PV power production represents a real challenge as regards the development of efficient and reliable MG management systems.

3.3 Energy Storage

The function of the storage is that of accumulating energy in high production periods in order to satisfy the demand in low production periods. In case of excess production, the system charges the batteries, while in the absence of power, the network is either powered by the energy drawn from the batteries or by the energy bought from the grid.

More specifically, the energy storage in a micro grid has the following functions:

- To allow the storage of energy (within a range of a few MWh)
- To attenuate the load power ramp
- To allow for peak shaving

Figure 9 Energy storage example

3.4 Microturbines

Micro turbines (MTc) are small high-speed gas powered generation systems. The World's first turbine was set at Neuchatel in 1939 by Brown-Boveri. The thermal efficiency in 1939 was 18%, whereas today is ranges from 47% to 60%. The maximum shaft post-war power was 4MW, whereas today is 450MW.

The micro turbines have lower efficiency in respect to the normal ones, for the blade and for construction technical aspect. In Figure 10 a schematic reprersentation of a MTc is provided, showing the following elements:

- Compressor
- Generator
- Combustion chamber
- Radial turbine
- Diffuser
- Recuperator.

The compressor increases the pressure of the air which passes through the recuperator, and the combuster, where it is superheated; then it is finally delivered to the turbine casing. Then, the exhaust product exiting from the turbine passes through a recuperator, where further heat is extracted to be used in the preheating process of air entering the combuster chamber. This reduces the fuel needed in the combuster. Finally, the generator converts mechanical energy into electrical energy.

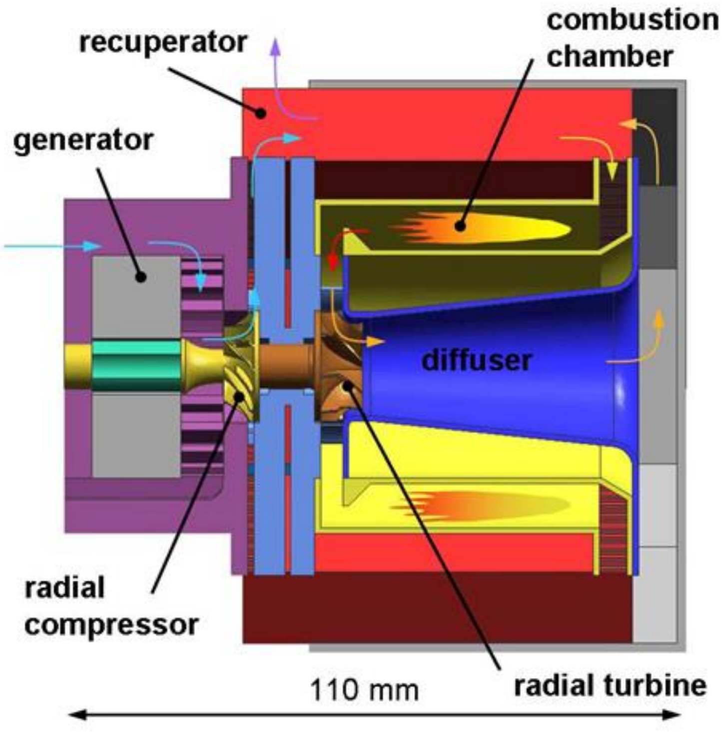


Figure 10 Micro tubina gas

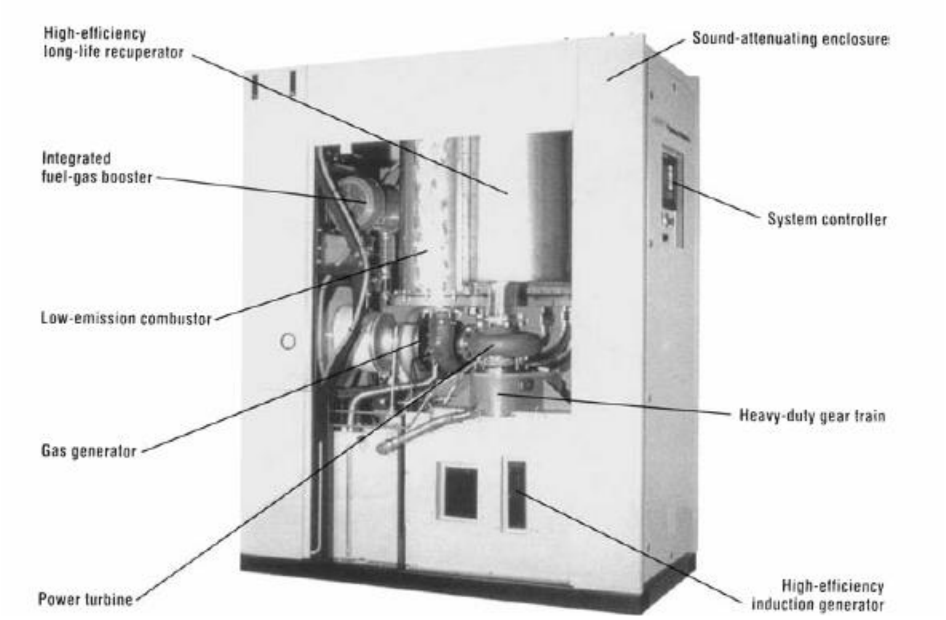


Figure 11 A cogeneration micro-turbine system package example

3.4.1 Turbines Modelling

In this thesis the model adopted for the microturbine is that reported in [5].

3.5 Deferrable demand: Electrical vehicle charging

In the last decades, the investment on the electric batteries produce an increase of the hybrid and electrical vehicles, which represent for a micro grid an external unpredictable but deferrable demand. From this arises the importance of the research as regards, for instance, optimal scheduling and smart charging of vehicles.

3.5.1 How the electrical vehicle works

The electric vehicles uses the electric motor for the traction using energy from a system of electric batteries with considerable advantages in terms of reliability, safety, quietness and emissions reduction. Some years ago, the most used technologies were lead acid batteries and DC brush motors. Today, ignoring the most exotic technologies, lead has been replaced by lithium and DCbrush motors by either DC brushless or induction motors.

The main parameters that describe the characteristics of an electrochemical accumulator are:

- Capacity: It is measured in Ampere-hours [90] and represents the amount of energy that can be stored. The capacity is given by the product of the current intensity and the time required for the battery to become discharged. For example, a battery with capacity of 1 Ah can deliver a current of 0.1 amps for ten hours before to discharge. However the real capacity is dependent on the rate of discharge, capacity decreases with increasing current demand, for this reason, a 1 Ah battery usually fails to provide 1 Amp for one hour.

- Rated voltage: it is the average voltage between the positive and negative terminals when the battery delivers current. To get the energy in Watt-hours multiply the capacity for the rated voltage.
- Specific energy: it is the energy that can be supplied from the accumulator per unit of mass (Wh/kg) or per unit of volume (Wh/dm3).
- Rated power: value obtained by multiplying the rated voltage and the discharge current. A significant parameter of the batteries for the electric vehicle is the specific peak power, which identifies the ability of acceleration of the electric vehicle. It is defined as the power per unit of weight that the storage system is capable to support for 30 seconds with a value of the DOD (see below) by 80%, that is, with low battery.
- Depth Of Discharge (DOD): is the amount of energy that has been withdraw from the battery, it is expressed as a percentage in relation to the nominal capacity of the battery. For instance if 30 Ah has been consumed from a battery of 100 Ah, DOD is 30%.
- State Of Charge (SOC): represents how much energy is stored in the battery. It is the complement of DOD, as the one increases the other decreases, DOD = 30% then SOC = 70%.
- Energy efficiency: is the ratio between the energy absorbed during the recharging phase and the energy delivered during the discharge.

Lead acid batteries have always been the cheapest and most common traction batteries available. However, they have a too low specific energy (20-40 Wh/kg) and thus they cannot guarantee a sufficient autonomy to the vehicle. Medium-long recharging times are also required and environmental conditions may change rated features[10].

The nickel-cadmium batteries are the most prevalent after the lead. They are robust and with higher performances than lead. In particular, the specific energy can be up to 50 Wh/kg. However, the presence of cadmium has severely limited the spread due to his high toxicity. In fact, the disposal of cadmium requires a very accurate process of re-

[10] David Linden, Thomas Reddy – Handbook of batteries

covery and recycling in order to avoid the contamination of the environment. In order to reduce the environmental impact of such batteries, recently cadmium was replaced by metal hydrides. In this way, it is also possible to attain higher values of the specific energy, about 80 Wh/kg. Such batteries are nowadays used on hybrid vehicles but the high cost of the raw material and the poor performance in the plug-in vehicles limit their penetration in the market.

Among the newest technologies of accumulation (that are continuously under development) one of the most promising are the lithium-ion accumulators. These batteries can be built in a variety of shapes and sizes, in order to efficiently fill the available space in the devices that make use of them. The specific energy can be more than 200 Wh/kg, that is, very high in comparison to the other technologies. Thanks to this high energy density they are one of the most popular types of rechargeable batteries for portable electronics, land and aerospace applications.

In the general configuration of a Li-ion rechargeable battery the cathode receives electrons during discharge and vice versa supplies them during charging, the anode instead provides electrons during discharge and vice versa receives them during charging.

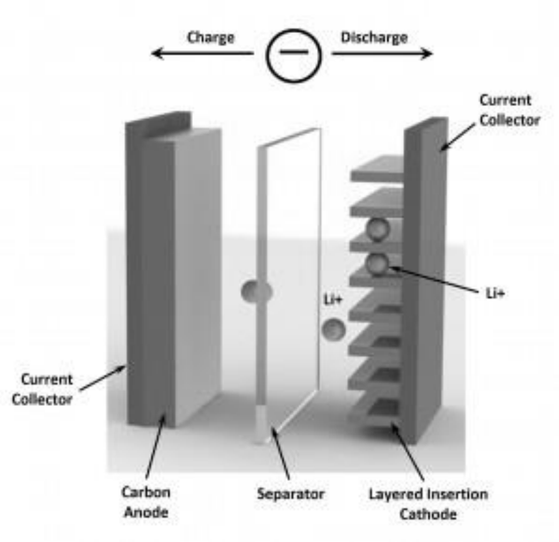


Figure 12: Li-ion battery

When the cell is completely discharged all the lithium is present is in the cathode. During the charging process a lithium ion is extracted from the metal oxide constituting the cathode and transferred to the anode through the external circuit. The metal of the cathode is then oxidized. At the anode, lithium ions are trapped and reduced to lithium when they acquire electrons provided by the external circuit.

Instead, during the discharging process, the Li placed in the matrix of graphite at the anode is oxidized, releasing electrons while the lithium ions migrate through the electrolyte to the cathode

A good point of Li-ion batteries is the small memory effect. This effect describes the specific problem affecting batteries that gradually lose their maximum energy capacity if they are repeatedly recharged after being only partially discharged. The battery appears to remember the smaller capacity causing them to hold less charge and it is a proper characteristic of lead acid and nickel based batteries.

Apart from the high price, one of the main disadvantages of this kind of batteries is that are subject to aging, even if not in use. Anyway those are not considered fully mature since manufacturers are constantly improving lithium-ion batteries.

The battery storage opened up infinite possibilities and is fundamental for electric vehicles. All these types of batteries are carefully managed through the system of monitoring and management (BMS). A Battery Management System is used to check the batteries during charge and discharge. When the vehicle requires power, the BMS manages the discharging phase of the battery.

Among the basic variables monitored by the BMS, the main ones there are:

- the voltage, significant for feeding the loads,
- the state o charge (or the depth of discharge), necessary to evaluate the autonomy of the vehicle,
- the cells temperature, in order to avoid failures.

-

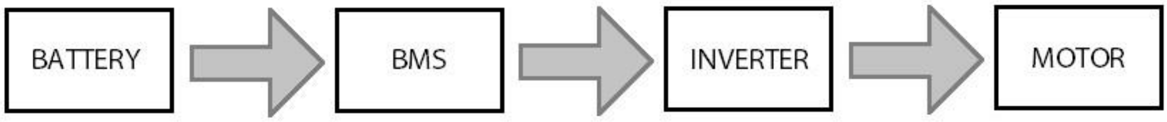


Figure 13 Storage kit in EV

In the charging phase BMS continuously controls power and current flows. Charging each cell is like filling a glass of water without spilling. As the glass fills up, the flow is reduced to catch every last drop. In battery terms, this means reducing current in order to balance cell voltage, ultimately tapering down to a trickle as it nears full. In fact, even using fast charging systems, it is quick to reach up to 80% of the SOC, while from 80% to 100% the charging time increases because the current delivered to batteries is reduced.

As regards propulsion, newest EVs can be motorized by two types of engines: DC brushless or AC induction motor. DC brushless motors are also known as electronically commutated motors. The machine is made by a stator and a rotor. The rotor includes two or more permanent magnets that generate a DC magnetic field. In turn, this magnetic field enters the stator core that is made up of thin stacked laminations and interacts with currents flowing within the windings to produce a torque interaction between the rotor and stator.

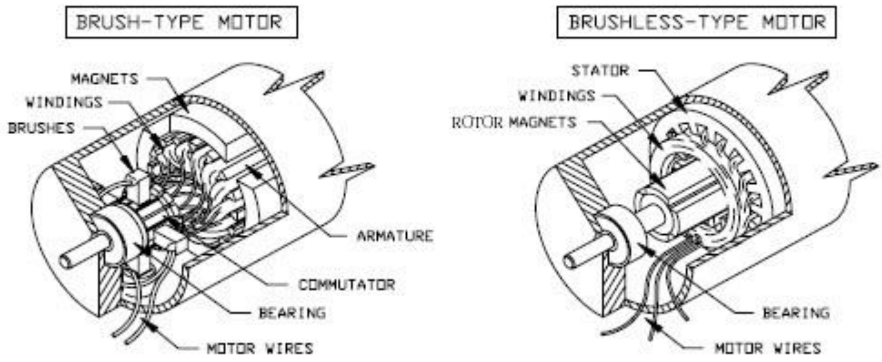


Figure 14 comparison between brushed and brushless motor

BLDC (Brushless DC electric motor)motors are synchronous machines that are powered by a DC electric source via an integrated control device called inverter. By switching the power supply, the inverter commutates the DC signal in the stator windings producing an AC electric signal to drive the motor. In this context, AC is not a sinusoidal waveform, but rather a bi-directional current with no restriction on waveform. In this way, the magnets on the rotor follows the magnetic field generated by the controller in the stator windings. The controller in DC motors changes the orientation of the DC current in the stator windings (that is why the motor is also called electronically commutated motor). The rotor's speed is synchronized to the speed of the commutation thanks to the magnets. Additional sensors and electronics control the inverter output amplitude and waveform (and therefore percent of DC bus usage/efficiency) and frequency (i.e. rotor speed). As the rotor rotates, it is necessary that the magnitude and polarity of the stator currents be continuously varied in order to keep the torque constant and make the conversion of electrical to mechanical energy efficient.

In an AC induction motor the stator is virtually identical to that in a DC brushless motor. In fact, both have three sets of "distributed windings" that are inserted within the stator core. The essential difference between the two machines is the rotor. Unlike the DC brushless rotor, the induction rotor has no magnets, just stacked steel laminations with buried peripheral conductors that form a shorted structure.

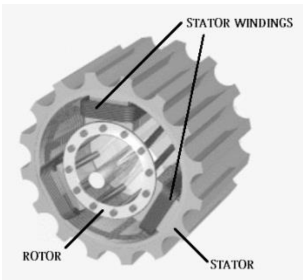


Figure 15 AC induction motor

Currents flowing in the stator windings produce a rotating magnetic field that enters the rotor. In turn, the frequency of this magnetic field is seen by the rotor as equal to the difference between the applied electrical frequency and the rotational frequency of the rotor itself (that is why the machine is called asynchronous). Accordingly, an induced voltage exists across the shorted structure that is proportionate to the speed difference between the rotor and electrical frequency. In response to this voltage, currents are produced within the rotor conductors that are approximately proportionate to the voltage, hence to the speed difference. Finally, these currents interact with the original magnetic field to produce forces components that yield desired rotor torque.

While 3-phase induction motors have great utility, they also have some severe limitations as they cannot operate in DC. Only by making use of an inverter, it becomes possible to power an induction machine from a battery or other DC source. Moreover, since shaft speed is proportionate to line frequency, speed regulation becomes possible simply by adjusting the inverter frequency.

Both DC brushless and induction drives use motors having similar stators. Both drives use 3-phase modulating inverters. The only differences are the rotors and the inverter controls. When making use of digital controllers, the only differences are related to control. In fact, DC brushless drives require an absolute position sensor, while induction drives require only a speed sensor.

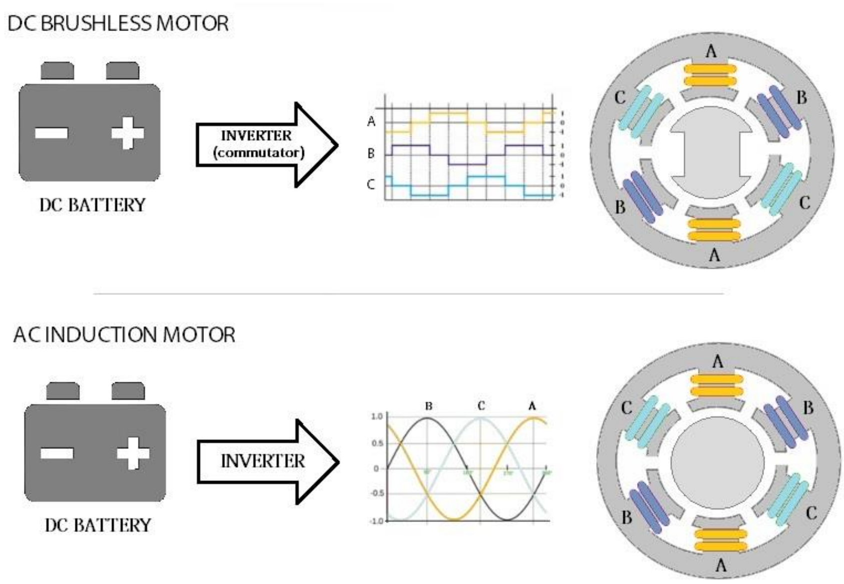


Figure 16 DC brushless motor and AC induction motor

One of the main differences between the two motors is that considerably less rotor heat is generated with the DC brushless drive. Thus, rotor cooling is easier and peak point efficiency is generally higher for this drive. The DC brushless drive can also operate at unity power factor, whereas the best power factor for the induction drive is about 85 percent. This means that the peak point energy efficiency for a DC brushless drive will typically be a few percentage points higher than for an induction drive.

Induction machines are more difficult to control. The control laws are more complex and difficult to manage. Achieving stability over the entire torque-speed range and over temperature is more difficult with induction than with DC brushless. Also torque performance is low compared with DC machines.

Anyway for manufacturing the permanent magnets of the rotor the so called rare earth are required, for this reason rotors are really expensive and the also difficult to handle due to very large forces that come into play when anything ferromagnetic gets close to them. This means that induction motors will likely retain a cost advantage over permanent magnet machines. Also, due to the field weakening capabilities of induction machines, inverter ratings and costs appear to be lower, especially for high performance drives.

Back in the 1990s most of all the electric vehicles were powered by DC brushless drives. Today all hybrid cars are powered by DC brushless drives. The reason is that the hybrid usually don't need to be plugged-in but the battery are charged directly by an internal engine. Thus, they don't need any inverter to convert the AC current from the grid to feed the battery that needs DC voltage and then those feed the motor that requires DC as well.

The manufacturers offer different solutions, often related to the economic feasibility or special requirements. DC brushless drives will likely continue to dominate in the hybrid markets and that induction drives will likely maintain dominance for pure electrics.

Proving that the electric drive is technically reliable, environmentally friendly and affordable, possible solution available on market are Figure 17:

- Hybrid Vehicle (HV)
- Electric Vehicle (EV)
- Plug-in Hybrid Vehicle (PHV)
- Fuel Cell Hybrid Vehicle (FCHV)

Hybrid Vehicle (HV)	HYBRID SYNERGY DRIVE	HV CO_2
Electric Vehicle (EV)	ELECTRIC DRIVE	EV ø
Plug-in Hybrid Vehicle (PHV)	PLUG-IN HYBRID	PHV CO_2
Fuel Cell Hybrid Vehicle (FCHV)	FUEL CELL HYBRID	FCV H_2O

Figure 17 Types of EV on market

3.5.2 Electrical vehicle models

To model the EV charging we define the following terms:

- $x_{sveh,i}(t)$ is the state of charge a t time t
- $P_{G\rightarrow v,i}(t)$ the power flow to vehicle i (unrestricted in sign) during time interval (t, t+1),
- Δt the length of the time discretization interval
- $cap_{veh,i}$ is the battery capacity of vehicle *i*.

Then, the following equation can be used to represent the dynamics of the state of charge of each vehicle in percent, express the result as a percentage:

$$x_{sveh,i}(t+1) = \left(x_{sveh,i}(t) + P_{G\rightarrow v,i}(t) \frac{\Delta t}{cap_{veh,i}} 100 \right) \quad i = 1..N; t = 1..T-1 \qquad (3.1)$$

Then, the following constraint must be introduced to impose that the value of the state of charge of each vehicle is between a minimum and a maximum value

$$x_{sveh\ min} \leq x_{sveh,i}(t) \leq x_{sveh\ max} \quad i = 1..N; t = 1..T \qquad (3.2)$$

4. PV Production NowCasting

4.1 Introduction

As previously mentioned, the forecasting (and nowcasting) of the variables affecting and conditioning the behaviour of the microgrid is of extreme importance to ensure acceptable performances for the entire system. In this chapter, specific methodologies will be mentioned and their application to data useful to predict the power from renewables (PV) within a microgrid will be discussed. The purpose of this chapter is not that of presenting the developmente of new methodologies, but rather that of clarifying which methods, among those available in the literature, have been adopted in order to provide forecasts of the variables of interest. Actually, the forecasting of the production of power from PV is of utmost importance for the statement of the problems considered in the next three chapters of this thesis. For details about the methods mentioned here, the reader can refer to the paper by Oneto, Laureri et al. [106] which presents and compares the various approaches that have been used.

4.2 Data Driven NowCasting and Forecasting

For the development of a model for the PV nowcasting and/or forecasting, it is necessary to consider a a variable $v_1(t)$ (the solar power generation) which can be measured at a particular frequency, and other possible correlated variables $\{ v_1(t), v_2(t), v_3(t), \dots \}$ (for instance, external temperature, solar radiation, etc.) which can be measured generally at different frequencies, from time t_0 onwards. The goal is to predict the value of $v_1(t)$, from $t = t_0$ to $t = t + \delta^+$ (with δ^+ being the length of the future horizon like 1 day, 2 days ect., that will be referred to as *prediction horizon*). Besides, for some of the correlated variables (external temperature, humidity, etc.) forecasted sequence of values $\{ \widehat{v_2}(t), \widehat{v_3}(t), \dots \}$ (e.g. from the national weather services) may be available over the considered prediction horizon. Note that here and in the following we use the notation $v_1(t)$ to represent the whole sequence of values of variable v_1, from the present time instant t_0 till the end of the prediction horizon. The considered problem may be put within the classical framework of multivariate regression problems [90], [91].

In the conventional regression framework [93], a set of data $D_n = \{(x_1; y_1); \dots ; (x_n; y_n)\}$, with $x_i \in X \in \mathbb{R}$ and $y_i \in Y \in \mathbb{R}$, are collected from the field. Then, the goal is to identify the unknown model $\mathfrak{G}: X \rightarrow Y$ through a model $\mathfrak{M}: X \rightarrow Y$ chosen by an algorithm $\mathcal{A}_{\mathcal{H}}$ defined by its set of hyperparameters $\mathcal{H}$ [106]. The accuracy of the model $\mathfrak{M}$ in representing the unknown system $\mathfrak{G}$ can be evaluated using different measures of accuracy [94], [95]. In particular, given a set of fresh data $T_m = \{(x_1; y_1),\dots,(x_m; y_m)\}$, the model will predict a series of outputs $\{ \widehat{y_1}, \dots, \widehat{y_m}\}$ given the inputs $\{x_1; \dots; x_m\}$. Based on these outputs it is possible to compute these performance indicators [95]:

- Mean Absolute Error: $MAE = \frac{1}{m}\sum_{i=1}^{m}|y_i - \hat{y}_i|$
- Mean Absolute Percentage Error: $MAPE = \frac{100}{m}\sum_{i=1}^{m}|(y_i - \hat{y}_i)/y_i|$
- Mean Square Error: $MSE = \frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2$

- Normalized Mean Square Error: $NMSE = \frac{1}{m\Delta}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2\ with\ \Delta = \frac{1}{m}\sum_{i=1}^{m}(y_i - \overline{y_i})^2$ and $\overline{y_i} = \frac{1}{m}\sum_{i=1}^{m} y_i$
- Relative Error Percentage: $REP = 100\sqrt{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2 / \sum_{i=1}^{m} {y_i}^2}$
- Pearson Product-Moment Correlation Coefficient:

$$PPMCC = \frac{\sum_{i=1}^{m}(y_i - \bar{y})(\hat{y_i} - \bar{y})}{\sqrt{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}\sqrt{\sum_{i=1}^{m}\left(y_i - \bar{\hat{y}}\right)^2}}\ with\ \bar{\hat{y}} = \sum_{i=1}^{m}\hat{y_i}$$

These measures of accuracy canbe used for testing and comparing the effectiveness of the different models. Actually, the MAPE will not be adopted since the true value of the energy production is zero during the night and so it leads to a division by zero that is not possible to handle smootly.

In our case, in order to map the PV nowcasting and forecasting problems into a regression model, the input space X is assumed to be composed by:

- $v_1(t)$ for $t \in [t_0 - \delta^-,\ t_0)$ (a sequence of the past values of the variable of interest)
- $\{\ v_2(t), v_3(t), \ldots\}$ for $t \in [t_0 - \delta^-,\ t_0)$
- for the possible correlated variables for which we have also the forecasted values we add $\{\ \widehat{v_2}(t), \widehat{v_3}(t), \ldots\}$ for $t \in [t_0,\ t_0 + \delta^+]$

For what concern instead the output space $\mathcal{Y}$, two different scenarios must be distinguished.

In the nowcasting scenarios $Y = v_1(t_0)$. This model can be useful for detecting anomalies in the behavior of the power generating units. For example at certain time t_0 with a given external conditions (external temperature, solar radiation, etc.) they should generate, based on the nowcasting model, a certain amount of power and instead the actual generation is lower; this may indicate the presence of some failure in the system.

In the forecasting scenarios, $Y = v_1(t_0 + \delta^+)$ with $\delta^+ > 0$. This model can be useful to predict the amount of energy that the solar power generation system will generate. This information is extremely important in order to properly set the management optimization problem for the micro grid.

The mapping of the the solar power generation problem into a multivariate regression problem is depicted in Figure 188.

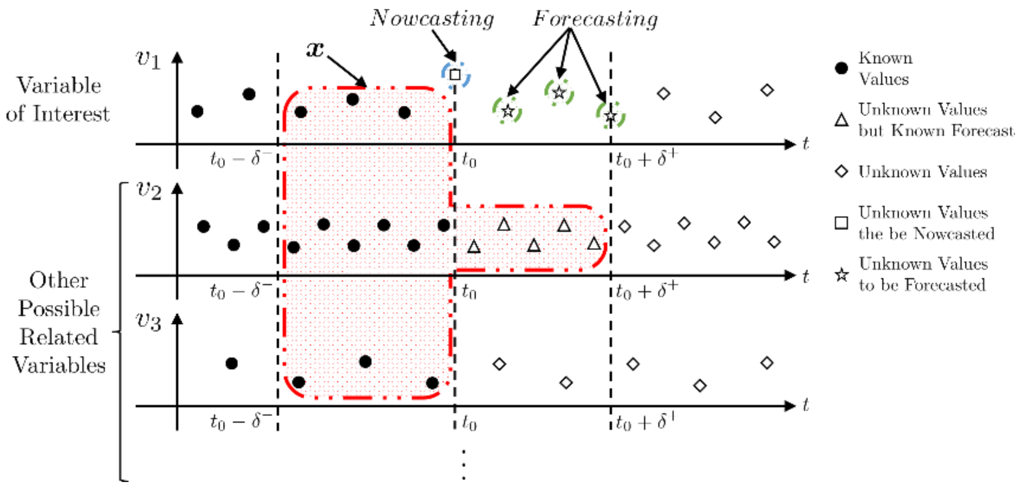


Figure 18: Mapping of the solar power generation problem into a multivariate regression problem.

We have compared the performances of three differente "state of art" data driven techniques (Kernel Methods, Extreme Learning Machine, and Random Forests) over different time horizons.The considered methos are briefly mentioned below.

A. Kernel Methods

Kernel methods are a family of machine learning algorithms. They represent the solution in terms of pairwise similarity between input examples [78]. Kernel methods consistently outperform previous generations of learning techniques. They provide a flexible and expressive learning framework that has been successfully applied to a wide range of real world problems even though, recently, novel algorithms, such as Deep Neural Networks [80] and Ensemble Methods [82], have become increasingly interesting [78].

B. Extreme Learning Machine

The Extreme Learning Machine approach [106] was introduced to overcome problems posed by the back-propagation training algorithm [108]: potentially slow convergence rates, critical tuning of optimization parameters, and the presence of local minima that call for multi-start and re-training strategies. ELM was originally developed for the single-hidden-layer feedforward neural networks [109] and then generalized in order to cope with cases where ELM is not neuron alike.

C. Random Forests

Random Forests (RF) was proposed in [97], where Breiman tried to give an answer to these questions: How do we build these simple classifiers? How many simple classifiers do we have to combine? How can we combine them? Is there any theory which can support us in making these choices? Actually, combining the output of several classifiers may result in a much better performance than using any one of them alone [97, 112]. Indeed, many state-of-the-art algorithms search for a weighted combination of simpler classifiers [113]: Bagging [97], Boosting [114] and Bayesian approaches [115] or even NN [116] and Kernel methods such as SVM [95].

Random Forests (RF) of tree classifiers is one of the state-of-the-art algorithm for classification which has shown to be one of the most effective tool in this context [117]. RF combines bagging to random subset feature selection. In bagging, each tree is independently constructed using a bootstrap sample of the dataset. The RF algorithm adds an additional layer of randomness to bagging. In addition to constructing each tree using a different bootstrap sample of the data, RF changes the way how the classification trees are constructed. In standard trees, each node is split using the best division among all variables. In RF, each node is split using the best among a subset of predictors randomly chosen at that node. Eventually, a simple majority vote for clarification task or the average response for the regression ones is taken for prediction. In [97] it is shown that the accuracy of the final model depends mainly on three different factors: how many trees compose the forest, the accuracy of each tree and the correlation between them. The accuracy for RF converges to a limit as the number of trees in the forest increases, while it rises as the accuracy of each tree increases and the correlation between them decreases. RF counterintuitive learning strategy turns out to perform very well compared to many other classifiers, including NN and SVM, and is robust against overfitting [97].

4.3 Forecasting and Nowcasting Models: the Savona Campus Smart Polygeneration Microgrid: Case Study

The Savona Campus SPM is a low voltage grid with a ring topology. It is characterized by an EMS that includes a monitoring system communicating with devices in field and local controllers, and an optimization model that, on the basis of renewable resources forecasts, provides the optimal schedule of plants. The SPM of the University of Genoa (Figure 19) includes:

- three gas turbines with high efficiency cogeneration (160 kWe, 284 kWth) powered with natural gas;
- one photovoltaic plant (80 kWp); three thermodynamic solar systems equipped with Stirling engines (3kWe, 9 kWth);
- one absorption chiller (H2O/LiBr) with buffer tank;
- one electric storage system based on the Na-NiCl2 (capacity 100kWh);
- two charging stations for electric vehicles;
- a supervisory software that manages all production plants and storage systems.

This solar farm provides between 17% and 20% of the power consumed in the area. The Campus is spread over an area of approximately 50000 m^2 and hosts a canteen, a cafe, a library, some residence halls, offices, classrooms, laboratories, a tennis court, a football field, a gym and some green areas. Specifically, different kinds of demands are present: electrical power for lights, instrumentation, and heat pumps, thermal power for heat and cool. The necessary power is provided by all the above reported technologies and by the external grid. The energy consumptions of the Savona University Campus are: 962 MWh/year (electricity consumption), 1426 MWh/year (thermal consumption). The primary energy consumption is 299 ton/year and the annual CO_2 emission are 714 ton CO_2/year. The energy bill is about 275 kW/year. During the day, the PvPP (Photovoltaic Production Power) varies according to the season and weather conditions.

We have made use of data collected from Savona Campus SPM PvPP System, which has a peak power of around 80 kW and comprises a number of equal PvPP modules of about 170 W. This solar farm provides between 17% and 20% of the power consumed daily by the Campus. The analyses and forecasts here presented are based on the available measurements from May 2014 and September 2015.

The following kinds of data are collected every minute:

- true power delivered by the PvPP system to the grid;
- solar radiation;
- the temperature of the PvPP panel;
- the predicted PvPP by the SPM's EMS (1 hour and 1 day ahead).

Instead, the external temperature is registered every 15 minutes.

Moreover, from the Nautical Institute [121], the following parameters are registered at each hour:

- relative humidity;
- wind speed;
- wind direction;
- sea level atmospheric pressure.

Regarding the weather forecast, the climate data were provided by the [112], the forecast data are:

- solar radiation;
- external temperature;
- relative humidity;
- wind speed;
- wind direction;
- sea level atmospheric pressure.

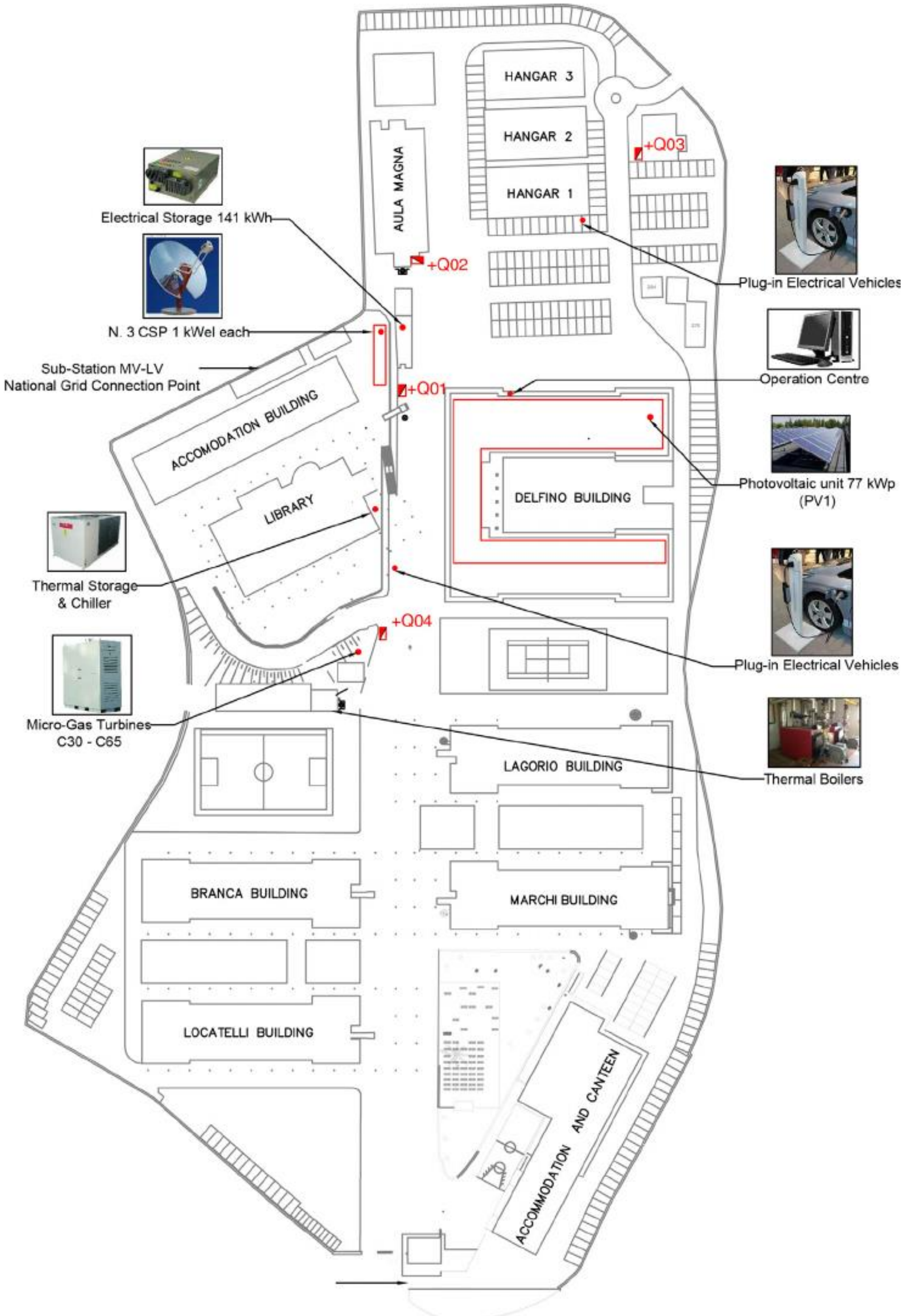


Figure 19: Savona Campus of the University of Genoa: the SPM

This means that, according the above general formalization, our variable of interest is represented by PvPP, while, for all the other variables, we possess both the actual value and the forecasted one and we can therefore map all these variables into a regression problem based on the model (nowcasting or forecasting) we want to build.

Finally we also run the optimization model described in [5] by using both the forecasts obtained by the above described method and by the presently available method used in the EMS of the SPM (as regards the values of renewable power). In particular, we have used data relevant to March 24, 2015. Regarding loads, for the specific case study, the daily consumes have a peak power of 280 kW for electrical demand and of 940 kW for the thermal demand.

Namely, we have considered the application of the predictive control scheme developed in [5] using three different data sets: a) the real data for PvPP collected on the field, a posteriori; b) the forecasts provided by the presently used model; c) the forecasts provided by the above described model. In this way, we can compare the energy cost and the CO_2 emissions obtained in the three cases.

The control variables of the optimization problem are represented by the power production from fossil fuel plants (i.e. gas microturbines), power exchange with the storage, and the external grid. Instead, the state variable is the state of charge of the battery.

The objective function is represented by costs due to operational management and emissions, while constraints include production technologies and storage system's models, as well as the models for electrical and thermal power distribution. All equations are detailed in [5].

4.4 Results

The experiments have been run within two different scenarios:

I. Nowcasting: we make the nowcast of the PvPP in the next 1 hour;
II. Forecasting: we make the forecast of the PvPP 1, 2, 3, 4, 5, 6 and 7 days ahead.

Moreover, two methodologies have been exploited for nowcasting and forecasting purposes:

- Present Model (AM): in this case, the presently used prediction system [123], which is based on a physical model of the microgrid, has been exploited;
- Data Driven Model (DDM): in this case, the data driven techniques described in Section 4.3 have been exploited and aim at improving the AM

In Figure 20 the patterns of the three sequence of values (real data, predictions provide by the AM model, and predictions provided by the DDM model) are represented.

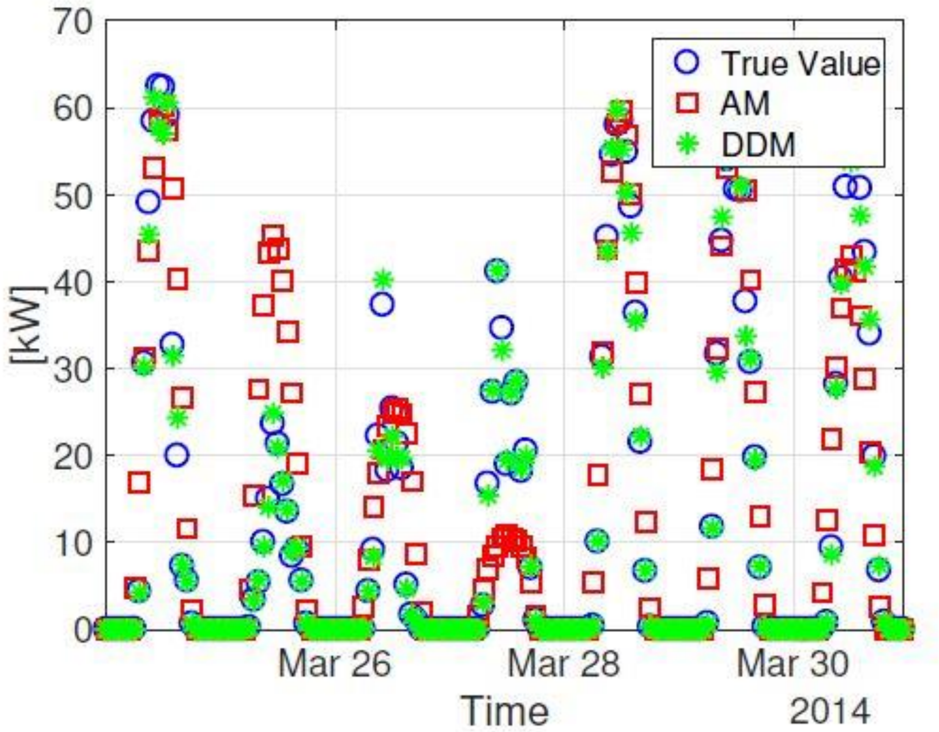


Figure 20: Comparison of the AM with DDM 1-day ahead forecasting performance in a week of 2015.

The performances of the two prediction models have been compared by analysing the differences, for the two considered performance objectives, between what is obtained by using each of the prediction models, and what is obtained by using real data, when applying the considered control optimization scheme.

In Table 1, the above differences are shown, as regards the application of the two prediction models, referring to the data for March 24, 2015.

Table 1: Additional costs and CO_2 $_2$ emissions due to the use of the AM PvPP or the DDM PvPP with respect to ideal case when the True PvPP is available for March 24, 2015.

	AM PvPP	DDM PvPP
Additional Costs [Euro/day]	15.61	1.70
Additional CO_2 emissions [Kg]	33.4	3.5

From Table 1 it is possible to see an appreciable save in costs and CO_2 emissions due to the use of the DDM with respect to the AM.

5. Optimal control in a microgird: Electrical vehicles charching demand response discret time model

A tipicaly external electrical demand in a microgrid is the charging demand of electrical vehicles. Indeed EVs market is growing and the charging infrastructure too, often supported by local governments. Some of the "future" problem can be the peak of demand and the case for charging management. In fact, "demand response can rappresent an opportunity for consumers to play a significant role in the operation of the electric grid by reducing or shifting their electricity usage during peak periods in response to time-based rates or other forms of financial incentives. Demand response programs are being used by some electric system planners and operators as resource options for balancing supply and demand." [11]

5.1 Energy Management System

The proposed optimization model can be used within a general Energy Management System for the optimal operation of a portion of a grid (i.e, microgrids, districts, etc.) in which EVs are integrated both as a shift-able load (for demand response programs) and as a power generator (when the V2G option is activated). Data in field and meteorological forecasting are stored in a monitoring system that is linked to the proposed optimization model, which in turn provides the optimal schedule for plants in the microgrid that is automatically sent to hardware in field. Specifically, a new model is proposed in which the state of charge of the vehicles is included in the microgrid optimization problem and it is linked with the decisions related to the desired arrivals and departures. Electric vehicles recharge their batteries by drawing electricity from the grid by means of appropriate charging systems. The charging infrastructure can be used if the power necessary for charging is available and it is possible due to the interaction through vehicles and distribution network and defining the best compromise between the power required by the customers and the power available at stations. To allow the optimization of the charging process, it is required that the distributor be in charge of directly monitoring, managing and controlling the charging of electric vehicles by the use of appropriate devices and algorithms. In the present work, the users' preferences as well as grid's constraints are managed by the proposed EMS as shown in the sequel.

Specifically, in this thesis, the vehicles' owners (i. e., the customers) communicate to the microgrid's decision maker their desires of charging vehicles within a specific time window. The microgrid manager has the responsibility of satisfying the customers' requests (both in terms of the amount of recharge and of service timeliness) while avoiding to spend too much to produce or acquire the necessary energy. The task of the microgrid manager has thus to be conveniently formalized as an optimization problem to be solved in real time, using all available information. Figure 24 shows the considered system: a

[11] U.S. Department of Energy https://energy.gov/oe/activities/technology-development/grid-modernization-and-smart-grid/demand-response

central controller has to manage production from fossil fuels, power exchange with batteries, EVs and the external grid, on the basis of the forecasting of renewable power production and (non-deferrable) electrical demand.

The formalized decision problem requires the knowledge of a considerable amount of information (daily load curve, production from renewable resources) and refers to the determination of several decision variables. Such variables must specify the power production from production plants, storages and electric vehicles charging/discharging processes and power purchase exchange with the external grid. In fact, the model is representative of a decision maker that has a complete control on the considered grid and that has to satisfy several demands, aiming at optimizing his/her own revenues/costs.

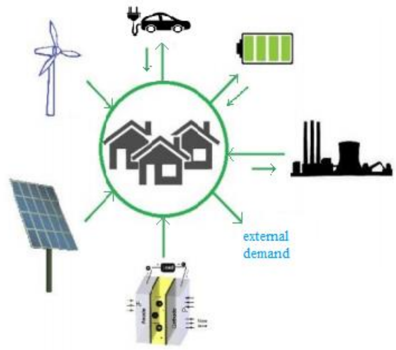


Figure 21: Smart Grid scheme

As regards the scheduling of the charging of the EVs, with respect to the existing literature, the original contribution of this work is the formalization of an optimization problem for a smart grid with a deferrable demand represented by the charging process of electrical vehicles. The cost to be optimized for the considered problem includes the economic cost of energy production/acquisition (energy can be acquired from the main grid) and the cost relevant to the delay in the satisfaction of the customers' demand. The latter cost is represented as a tardiness cost. We will consider two different models: in the first one, the demand of any electrical vehicle is considered as determined, whereas in the second model, the vehicle electrical demand is considered as a function of the charging cost (that is, the demand is assumed to be elastic).

5.2 The first model (rigid energy demand)

The system model and the optimization problem will be developed in the following within a discrete-time setting. For this reason, a constant time discretization interval has been selected, equal to 15 minutes. The length of the optimization horizon is equal to T time discretization intervals.

A generic power flow variable *P(t)* will represent a power flow within time interval *(t, t+1)*, whereas a generic state variable x(t) will represent the value of that variable just at time instant t.

5.3.1 The constraints affecting the system behavior

It is assumed that there is a single charging facility, and that only a vehicle can be served by this facility in each time interval.

Thus, there is the basic need to introduce a set of binary variables, each of them referring to a certain vehicle and to a certain time interval. Namely, we define

$$\delta col_i(t) = \begin{cases} 1 & if\ the\ vehicle\ is\ charging \\ & in\ time\ interval\ (t, t+1) \\ 0 & otherwise \end{cases}$$

$i = 1, \ldots, N; t = 1, \ldots, T-1$

Where *N* is the number of vehicles.

At this point, a first set of constraints has to be introduced to represent the dynamics and the behavior of the vehicle charging system.

Let Tin_i and Tf_i represent the time intervals in which the charging process of vehicle i begins and is concluded, respectively.

Then, the following constraints are introduced in order to impose that the charging process of each vehicle is accomplished within a given time window.

$$Tin_i \geq Trel_i \qquad i = 1, \ldots, N \tag{5.1}$$

$$Tf_i \leq T - 1 \qquad i = 1, \ldots, N \tag{5.2}$$

Constraint (5.1) imposes that the time interval at which the recharging process of the generic vehicle i begins is not lower than the release time (interval) of that vehicle, that may be thought as the time interval in which the vehicle arrives at the recharging facility.

Constraint (5.2) imposes that the recharging process is completed within the considered time horizon. Note that no deadline is introduced for the recharging of vehicles, apart for the common constraint represented by (5.3).

The following constraint is introduced to prevent that more than a single vehicle is charging at the same time (this is equivalent to say that only a single charging facility is present in the system, and that this facility can charge only one vehicle at a time).

$$\sum_{i=1}^{N} \delta col_i(t) \leq 1 , \qquad t = 1..T-1 \tag{5.3}$$

Another constraint to be introduced is

$$\delta col_i = \begin{cases} 0 & if\ t \leq Tin_i\ or\ \ t \geq Tf_i \\ 1 & else \end{cases} \qquad i = 1..N; t = 1..T-1 \tag{5.4}$$

Constraint (5.4) links the decision variables δcol_i, Tin_i, Tf_i so that their meaning is consistent with the statement of the problem. In other words, constraint (5.4) does not allow the vehicle charging before the initial time Tin_i and after the final time Tf_i .

Additional constraints that is necessary to introduce are

$$x_{sveh,i}(Tin_i) = x_{sveh,i_{in}} \qquad i = 1..N \tag{5.5}$$

$$x_{sveh,i}(t) = \begin{cases} x_{sveh,i_{out}} & if \quad t \geq Tf_i \\ x_{sveh,i}(t) & else \end{cases} i = 1..N; t = 1..T \tag{5.6}$$

In (5.5) and (5.6) $x_{sveh,i}(t)$ represents the state of charge of vehicle *i* at time instant *t*. Constraint (5.5) imposes that the energy storage level of vehicle *i* remains at the same (initial) level, $x_{sveh,i_{in}}$ (that is assumed known), until the charging process begins. Constraint (5.6) imposes that the energy level must be, at any time $t \geq Tf_i$, equal to ($x_{sveh,i_{out}}$), that is, the energy level required for that vehicle.

Then, the following constraint represents the dynamics of the state of charge of each vehicle express the result as a percentage of the sample:

$$x_{sveh,i}(t+1) = \left(x_{sveh,i}(t) + P_{G\rightarrow v,i}(t) \frac{\Delta t}{cap_{veh,i}} 100 \right) \qquad i = 1..N; t = 1..T-1 \tag{5.7}$$

being $P_{G\rightarrow v,i}(t)$ the power flow to vehicle *i* (unrestricted in sign) during time interval *(t, t+1)*, Δt the length of the time discretization interval and $cap_{veh,i}$ is the battery capacity of vehicle i.

The following constraint imposes that the value of the state of charge of each vehicle is between a minimum and a maximum value

$$x_{sveh\,min} \leq x_{sveh,i}(t) \leq x_{sveh\,max} \quad i = 1..N; t = 1..T \tag{5.8}$$

A further constraint is required in order to limit the value of the power flow to (or from) each vehicle

$$-P_{max} * (\delta col_i(t)) \leq P_{G\rightarrow v,i}(t) \leq P_{max} * (\delta col_i(t)). N; t = 1..T-1 \tag{5.9}$$

Note that the power exchange with the vehicle is bi-directional. That is to say, each vehicle can be used also as an additional storage element.

In addition to the constraints relevant to the vehicles, further constraints are to be taken into account in order to represent the dynamics of the rest of the microgrid.

A power constraint bounds the power flow that can be obtained from non-renewable sources (mainly, fossil fuels)

$$0 \leq P_{NRIN}(t) \leq P^{Max}{}_{NRIN}(t); \;\; t = 1..T-1 \tag{5.10}$$

Another constraint is used to bound the (bi-directional) power exchange of the microgrid with the main grid

$$-P^{MAX}{}_{MG\rightarrow G} \leq P_{MG\rightarrow G}(t) \leq P^{MAX}{}_{MG\rightarrow G} \;\; ; \;\; t = 1..T\text{-}1 \tag{5.11}$$

In (5.11) $P^{MAX}{}_{MG\rightarrow G}$is absolute value of the maximum power flow and $P_{MG\rightarrow G}(t)$ is the power flow within time interval(t, t+1)from the main grid to the microgrid.

A constraint is introduced in order to bound the (bi-directional) power flow to (from) the storage element in the microgrid:

$$-P_{G\rightarrow S}{}^{MAX} \leq P_{G\rightarrow S}(t) \leq P_{G\rightarrow S}{}^{MAX} \;\; t = 1..T-1 \tag{5.12}$$

where, $P_{G\rightarrow S}{}^{MAX}$ is absolute value of the maximum power flow within time interval (t, t+1).

The following constraint on the energy level of the storage element has also to be taken into account

$$x_S^{min} \leq x_S(t) \leq x_S^{max} \quad t = 1..T \tag{5.13}$$

where $x_S(t)$ is the energy level of the storage element at time instant t.

The following storage state equation has to be taken into account in the statement of the optimization problem:

$$x_S(t+1) = x_S(t) + P_{G\rightarrow S}(t)\Delta t \quad t = 1..T \tag{5.14}$$

Finally, the power balancing constraint has to be fulfilled, namely

$$P_R(t) - P_{G\to S}(t) + P_{MG\to G}(t) - \sum_{i=1}^{N} P_{G\to v,i}(t) + P_{NRIN}(t) - P_{EXT}(t) = 0$$

$$t = 1..T-1 \tag{5.15}$$

where $P_{EXT}(t)$ is the non-deferrable (external) power demand that has, in any case, to be satisfied in time interval (t, t+1).

5.3.2 The overall optimization problem

The following cost function must be minimized

$$min\{\sum_{t=0}^{T-1} \beta P_{NRIN}(t)\Delta t + \sum_{t=0}^{T-1} \beta_{PURCHASE}(t) \cdot \max\{P_{MG\to G}(t), 0\}\, \Delta t - \sum_{t=0}^{T-1} \beta_{SELL}(t) \cdot \max\{-P_{MG\to G}(t), 0\}\, \Delta t + \sum_{i=1}^{N} \alpha_i \max\{Tf_i - Tdd_i, 0\}\} \tag{5.16}$$

where:

- β is the unit cost for producing power from non-renewable sources;
- $\beta_{PURCHASE}(t)$ is the unit purchase prize from the main grid, in time interval (t, t+1);
- $\beta_{SELL}(t)$ is the unit selling prize from the main grid, in time interval (t, t+1);
- Tdd_i is a given value providing the due-date of vehicle i, that is, the time interval within which the charging of the vehicle should be completed;
- α_i is a tardiness weighting coefficient for vehicle i.

Note that the overall cost to be minimized is composed by the sum of economic costs and tardiness costs.

The optimization problem thus consists in the minimization of (5.16) under constraints from (5.1) to (5.15).

5.3 Case Study for the first model.

In this section, we present a case study in order to show the benefits obtained by the use of optimal vehicle scheduling. Real data have been used for a portion of the Savona Municipality. The vehicle demand is composed by 4 electrical vehicles (*N*=4) connected to a grid-connected microgrid, with PV and wind power production, residential demand, production from natural gas, electrical batteries and charging stations. The four case study considers a large time horizon of *T*=95 time units (for a time interval of 15 minutes) 24 hours. In the Figure 22 there are show Electrical Demand and PV Energy Production that are the data used in the following scenarios.

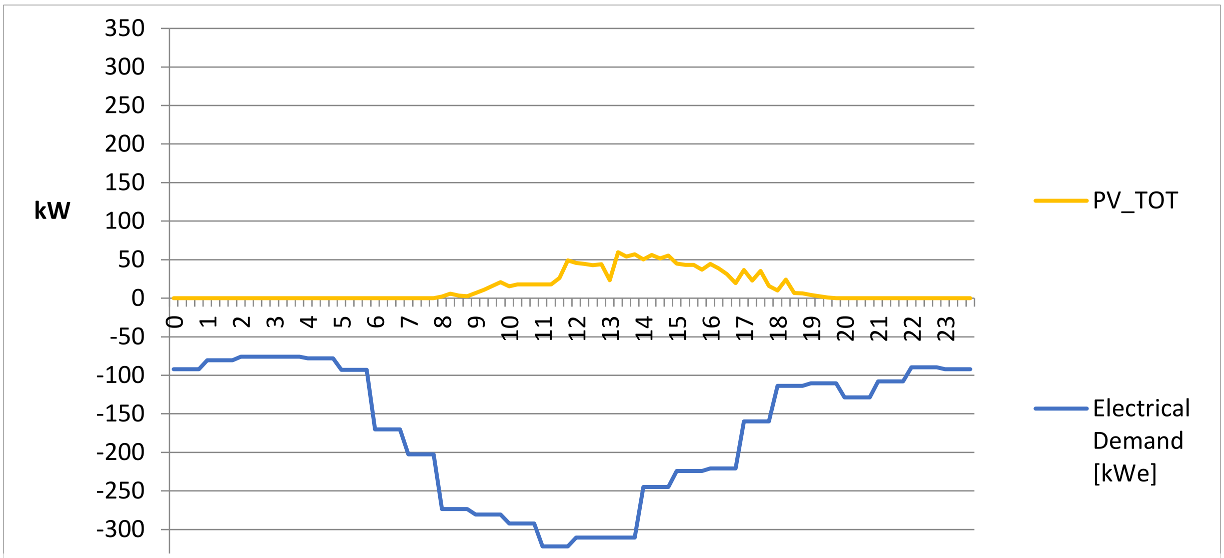


Figure 22:PV Power Prudution and Electrical Demand

The optimal schedule of production plants, storage systems and EVs is obtained by solving the optimization problem (5.1)-(5.16) by the use of Lingo optimization software tool [10], computational time 20 miutes.

Four cases have been considered with the aim of testing the proposed model and comparing different possible scenarios that may occur when dealing with EVs. The following parameters have been changed for the i-th vehicle: $C_{veh,i}$ (vehicle capacity), Treli (release time: when the vehicle arrives), $T_{dd,i}$ (due-date: when the user wishes to receive the vehicle charged), $x_{sveh,i_{in}}$ state of charge of the vehicle that is arriving), $x_{sveh,i_{out}}$ (final state of charge that the user wishes for the vehicle). Specifically:

<u>Scenario 1.</u>

In this scenario, all vehicles have the same capacity, release time and desired state of charge. In fact, attention is here focused on the different state of charge of the vehicles that arrive. That is: $\mathrm{C_{veh,i}}$ ={52,52, 52, 52}; $T_{rel,i}$={30,30, 30, 30}; $x_{sveh,i_{in}}$ = {10, 15, 20, 25}; $x_{sveh,i_{out}}$ = {80, 80, 80, 80}; $T_{dd,i}$={ 55, 55, 55, 55}. The optimal solution, as it is shown in Figure 24, corresponds to charging first the EV battery with a lower request of energy. The resulting state of charge for all vehicles is reported in Figure 23.

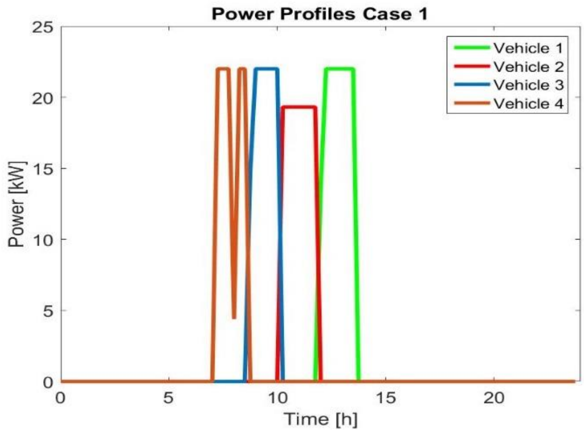


Figure 24: Vehicle power profile in Scenario 1

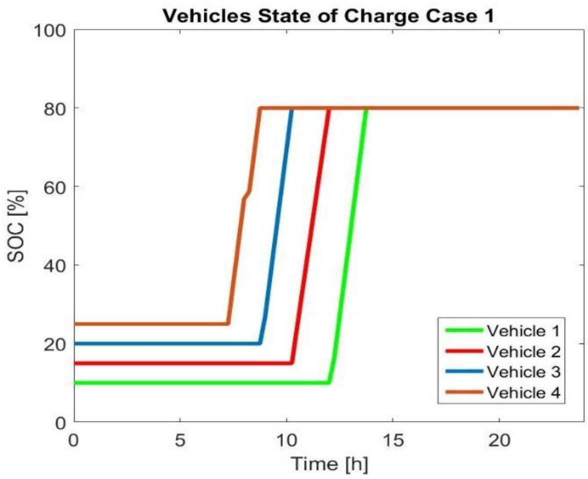


Figure 23: Vehicles' state of charge in Scenario 1

<u>Scenario 2.</u>

in this scenario, the only parameter that is different for the four vehicles is the due-date, while the other ones are considered the same. That is: $C_{veh,i}$ ={52,52, 52, 52}; $T_{rel,i}$= {30, 30, 30, 30}; $T_{dd,i}$={55, 45, 40, 35}; $x_{sveh,i_{in}}$ = {20, 20, 20, 20}; $x_{sveh,i_{out}}$ = {80, 80, 80, 80}. The optimal "schedule" is reported: the EV battery with the nearest due date is charged as first.

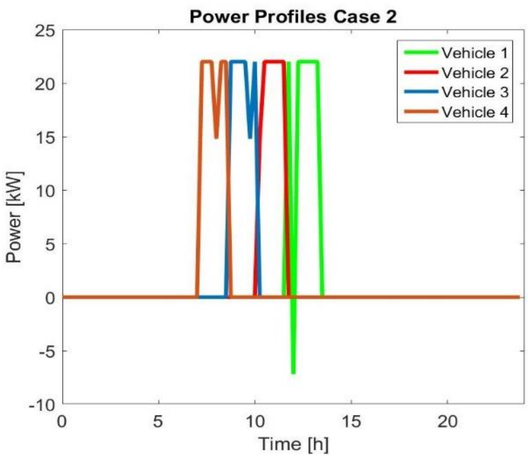


Figure 25: Vehicle power profile in Scenario 2

Figure 26 reports the corresponding state of charge.

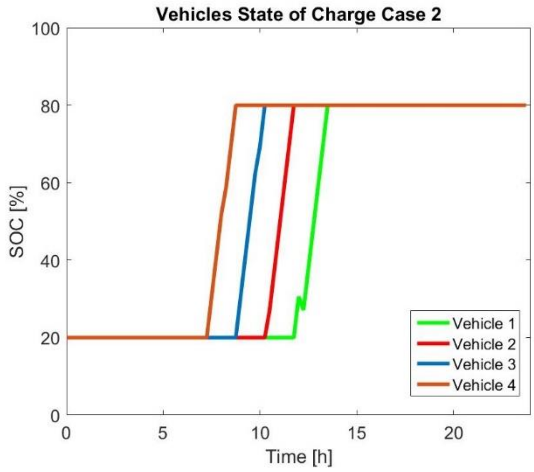


Figure 26: Vehicles' state of charge in Scenario 2

Scenario 3.

In this scenario, the only different parameter (with respect to case I and case II) among vehicles is the release time. That is: $C_{veh,i}$ ={52, 52, 52, 52}; $T_{rel,i}$={50, 45, 35, 30}; $T_{dd,i}$={ 55, 55, 55, 55}; $x_{sveh,i_{in}}$ = {20, 20, 20, 20}; $x_{sveh,i_{out}}$ ={ 80, 80, 80, 80}. As shown in Figure 27, the vehicle with the lowest release time is served as first. The corresponding state of charge for each vehicle is shown in Figure 28. It can be noted than, in this case study, the vehicle 1 gives back energy to the grid (as it is possible this model).

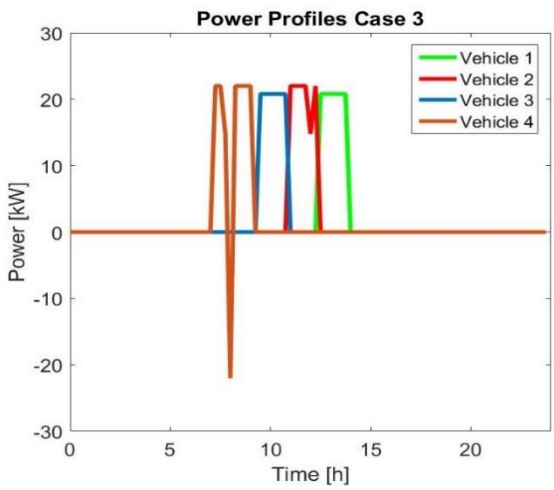


Figure 27: Vehicles' power profile in Scenario 3

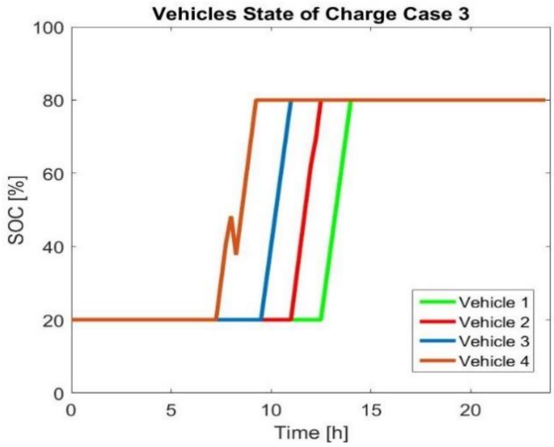


Figure 28: Vehicles' state of charge in Scenario 3

Scenario 4.

In this case both release times and due-dates are different. That is: $C_{veh,i}$ ={52, 52, 52, 52}; $T_{rel,i}$={45, 40, 35, 30}; $T_{dd,i}$={45, 45, 40, 55}; $x_{sveh,i_{in}}$={20, 20, 20, 20}; $x_{sveh,i_{out}}$ ={ 80, 80, 80, 80}. The optimal schedule, shown in Figure 29, is the same as in Scenario 3. Thus, the most influencing parameter is the release time as compared with the due-date. The state of charge of each vehicle is shown in Figure 30.

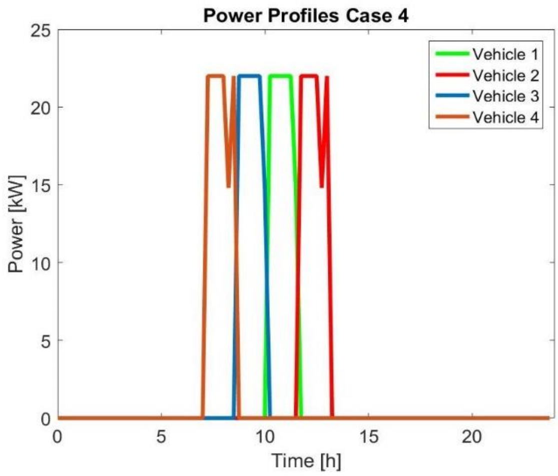


Figure 29: Vehicles' power profile in Scenario 4

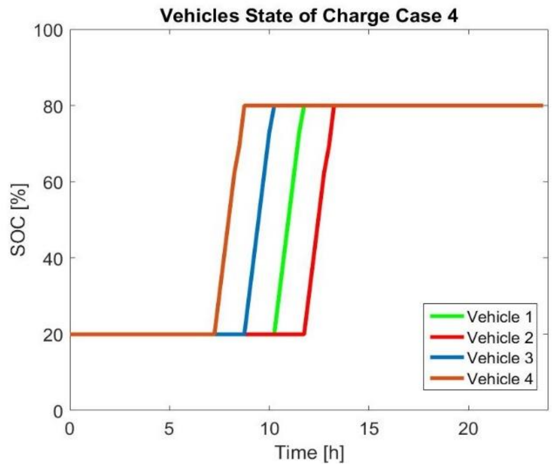


Figure 30: Vehichles' state of charge in Scenario 4

It is important to note that, in this chapter, attention is focused on EVs. However, since the chosen decision variables are also related to production levels, and power exchange with the batteries and the external grid, each optimal solution includes also an optimal schedule for such components. As an example, Figure 31 shows the active power flows of the overall microgrid in Scenario 2.

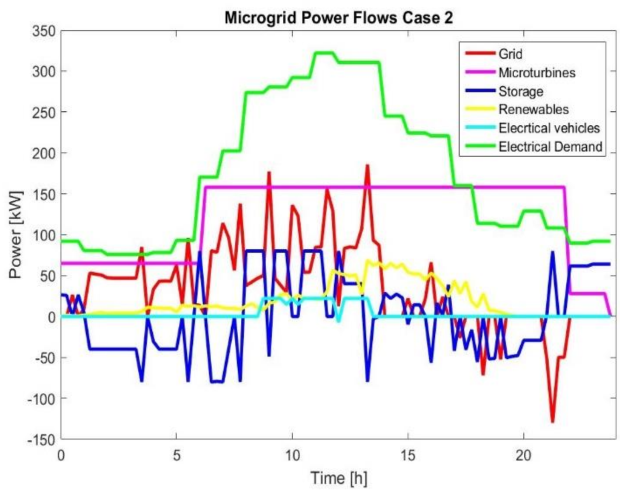


Figure 31: Microgrid power flows

5.4 The second model (elastic demand)

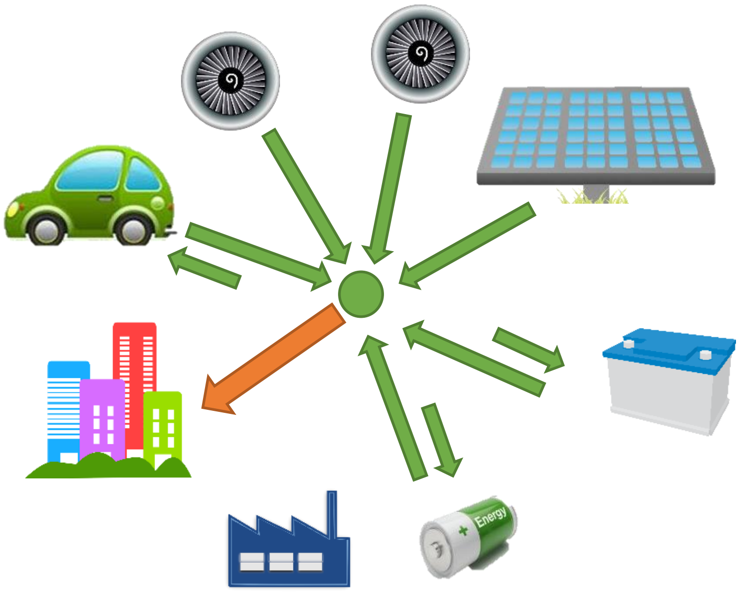


Figure 32: Microgrid design

In this section a second model will be considered in which the demand is a function of the prices. To improve the readability, the problem will be completely reformulated, with respect to the case of rigid demand, even if some of the variables will have an analogous meaning.

5.4.1 The considered variables

<u>*The state variables.*</u>

The state of the considered system is made of the following information:

- the state of charge of the two storage systems [kWh] (i.e., $x_{sl}(t_k)$ related to a lithium battery and $x_{ss}(t_k)$ for a sodium battery, both with capacity of 40[kWh]);
- the state of charge of vehicle i [kWh] $x_{sveh,i}(t_k)$ for i=1,…, N.

Here again, all variables are considered in discrete time instants t_k, k=0, 1, 2,… The length of the discrete time interval will be denoted as Δt, while the overall optimization horizon is (t_0, t_T) and consists of T time intervals.

<u>*Variables and data relevant to the set of vehicles.*</u>

The charging process of a vehicle has an integer duration, namely

- $\left(t_{c_i}, t_{c_i+1}\right)$ is the time interval in which vehicle i begins its charging process;
- (t_{f_i}, t_{f_i+1}) is the time interval in which vehicle i concludes its charging process.

In Figure 33 an example, concerning the charging of two different vehicles is represented.

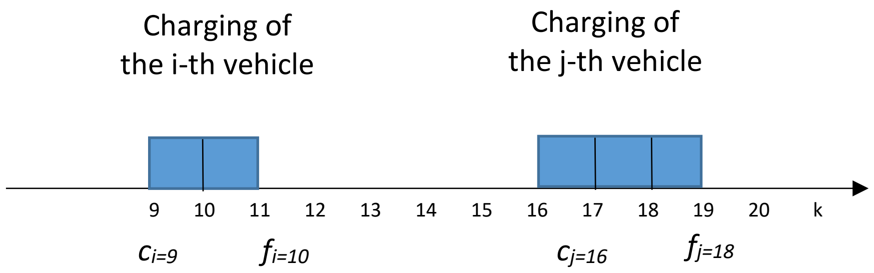


Figure 33: Charging of two different vehicles

Each vehicle *i, i=1, ..., N,* is characterized by the following a-priori information:

- $D_{i,max}$ [kWh] is the aspiration level of the amount of energy to be acquired by the vehicle e; this is the maximum amount of the energy request by the vehicle;
- (t_{rel_i}, t_{rel_i+1}) is the release time interval (this may be thought as corresponding to the time interval in which the vehicle is made available for the charging state process);
- (t_{dd_i}, t_{dd_i+1}), that is, the time interval at which the charging process of the vehicle should be concluded. In particular, t_{dd_i+1} is the due-date of the charging of vehicle i. A tardiness with respect to a due date induces the payment of a penalty cost;
- α_i [€/h] is the unit (tardiness) penalty cost.

In the formalization of the problem, the possible reduction is considered of the actual energy demand by vehicle i (from the value $D_{i,max}$ down to zero), depending to the prices for the charging service.

More specifically, it is assumed that the actual demand of vehicle *i*, namely D_i, is determined on the basis of the *unit charging cost* $Gric_i$ [€/kWh] through the application of the *elastic demand function* represented in Figure 34.

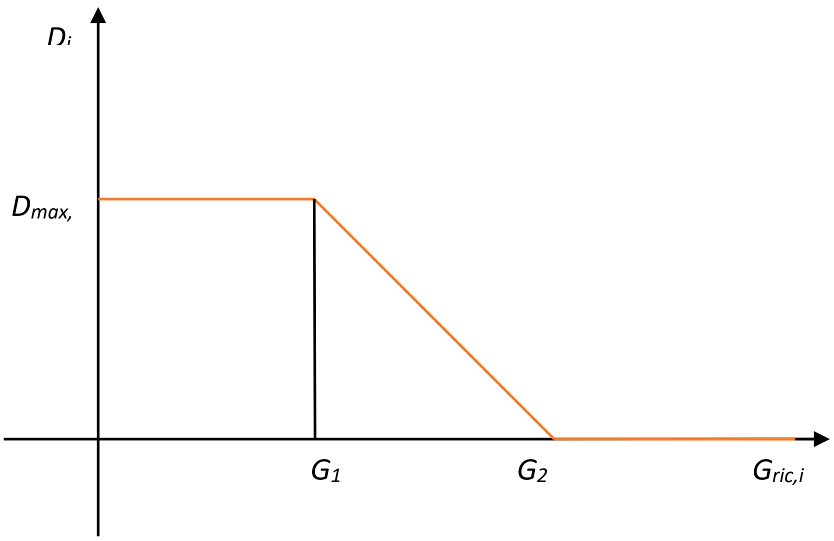


Figure 34: The elastic demand function

The function expressing the actual is given by the following expression where G_1 and $G_2$are given constants, assumed independent from *i*.

$$D_i = \begin{cases} D_{max,i} & if \;\; Gric_i \leq G_1 \\ \frac{D_{max,i}}{G_1 - G_2}(Gric_i - G_2) & if \;\; \mathrm{G}_1 < Gric_i \leq \; G_2 \\ 0 & if \; Gric_i > \; G_2 \end{cases} \qquad i = 1, \ldots, N$$

Obviously, it may turn out that the actual number of vehicles requiring the charging service is reduced, with respect to the initial number of N, as some of them require zero demand. The charging cost $Gric_i$ for vehicle i is determined as the product between of the unit cost for purchasing energy from the main grid in the time interval (t_{rel_i}, t_{rel_i+1}) and the value of a function $\theta(t_{rel_i})$, namely

$$Gric_i = \; \theta\left(t_{rel_i}\right) \cdot \beta_{PURCHASE}\left(t_{rel_i}\right) \qquad\qquad i = 1, \ldots, N \tag{5.17}$$

The values of function $\theta(t_{rel_i})$, for any possible (discrete) value t_{rel_i}, are determined in order to smooth service request peaks.

Here again, we use the notation:

- $\beta_{PURCHASE}(t_k)$ = unit purchase price from the main grid, in time interval (t_k, t_{k+1});
- $\beta_{SELL}(t_k)$ is the unit selling price to the main grid, in time interval (t_k, t_{k+1}).

The sequences $\beta_{PURCHASE}(t_k)$ and $\beta_{SELL}(t_k)$, $k = 0,1,..T-1$ are considered as given, whereas the sequence $\theta(t_k)$, $k = 0,1,..T-1$ consists of decision variables whose value has to be determined through the solution of an optimization problem.

The decision variables of the problem.

In the problem formulation, we introduce the possibility that the decision maker (that is, the microgrid manager) declares the impossibility of providing service to a certain vehicle. This possibility is modelled through the introduction of the binary decision variables ε_i , where ε_i = 1 means that the service is provided, whereas in case ε_i = 0 the vehicle is not served. In addition, we have to impose that ε_i = 0 when D_i=0, that is, when the actual demand of the customers corresponding to vehicle i becomes equal to zero, that is, when $Gric_i \geq G_2$.

In addition, for each time interval (t_k, t_{k+1}), k=0,1,2,…T-1, the decision maker has to find the optimal value of the following variables [kW]:

- $P_{G\to v,i}(t_k)$, the power flow from the microgrid to the i-th vehicle, unrestricted in sign, i=1,2,3,…N;
- $P_{eng1}\ (t_k)$, $P_{eng2}\ (t_k)$, the power flows from the two engines to the microgrid;
- $P_{sl\to G}\ (t_k)$, the power flow from the lithium storage to the microgrid, unrestricted in sign;
- $P_{ss\to G}\ (t_k)$, the power flow from the sodium storage to the microgrid, unrestricted in sign;
- $P_{MG\to G}\ (t_k)$, the power flow from the main grid to the microgrid, unrestricted in sign.

In the above notation, the orientation of the arrow in the subscript relevant to the variables representing power flows identifies the direction in which the power flow (if unrestricted in sign) is considered as positive.

Besides, in addition to the above variables, it is worth defining the set of the binary variables $\delta_i(t_k)$, k=0,1,2,…,T-1, i=1,2,…, N, where $\delta_i(t_k) = 1$ if vehicle i is connected to the charging station in time interval (t_k, t_{k+1}) and 0 otherwise.

Summing up, the decision variables of the problem are:

- $P_{G\to v,i}(t_k)$,$P_{eng1}(t_k)$, $P_{eng2}(t_k)$,$P_{sl\to G}(t_k)$, $P_{ss\to G}(t_k)$, $P_{MG\to G}(t)$ $\quad k = 0,1,..T-1$
- ε_i $\quad i$=1,2,…,N
- c_i, f_i $\quad i$=1,2,…,N
- $\delta_i(t_k)$ $\quad k = 0,1,..T-1$; i=1,2,…,N
- $\theta(t_k)$ $\quad k = 0,1,..T-1$

5.4.2 The constraints affecting the system behavior

Constraints representing the system state evolution.

The following storage state equations have to be taken into account in the statement of the optimization problem:

$$x_{sl}(t_{k+1}) = x_{sl}(t_k) - P_{sl\to G}(t_k)\cdot\Delta t \qquad k = 0,1,..T-1 \tag{5.18}$$

$$x_{ss}(t_{k+1}) = x_{ss}(t_k) - P_{ss\to G}(t_k)\cdot\Delta t \qquad k = 0,1,..T-1 \tag{5.2.3}$$

$$x_{sveh,i}(t_{k+1}) = x_{sveh}(t_k) + P_{G\to v,i}(t_k)\cdot\Delta t \qquad i = 1..N; \quad k = 0,1,..T-1 \tag{5.19}$$

Constraints affecting the vehicle charging process.

Next, we consider the constraints relevant to the dynamics of the charging process. First, it is necessary to prevent that more than a single vehicle is connected to the charging station, in the same time interval, namely

$$\sum_{i=1}^{N}\delta_i(t_k) \le 1 \qquad i = 1..N; \quad k = 0,1,..T-1; \tag{5.20}$$

Moreover, we must impose that the time interval at which the charging starts should be greater than or equal to the release time interval:

$$c_i \ge rel_i \qquad i = 1..N; \tag{5.21}$$

Besides, we have to impose that the charging process (if any) must finish before the end of the time horizon

$$f_i \le T-1 \qquad i = 1..N; \tag{5.22}$$

A further constraint has the function of relating the state of the charging station with the time interval during which the charging of a vehicle i takes place:

$$\delta_i(t_k) = \begin{cases} 0 & if\ t_k \le t_{c_i-1},\ or\ t_k \ge t_{f_i+1}\ or\ if\ D_i = 0 \\ \varepsilon_i & else \end{cases}$$
$$i = 1..N; \quad k = 0,..T-1; \tag{5.23}$$

The above constraint allows the connection of a vehicle only when the demand expressed by the vehicle is not zero and the microgrid manager agrees for the service. In this case, the vehicle is connected only during time interval (t_{c_i}, t_{f_i+1}).

Another constraint prevents the service with no demand, that is

$\varepsilon_i = 0$ when D_i=0, that is, when $Gric_i > G_2$ $\qquad i = 1..N$ (5.24)

Besides, it is necessary to introduce a constraint that prevents that a vehicle departs from the station before reaching the desired state of charge (that is, without having received an amount of energy equal to its demand D_i. To this end, it is sufficient to enforce

$$x_{sveh,i}(t_k) = \begin{cases} x_{sveh,i_{in}} + \quad D_i \quad\quad if \quad t_k \geq t_{f_i+1} \quad\quad and\ \varepsilon_i = 1 \\ \quad\quad\quad\quad x_{sveh,i}(t_k) \quad\quad\quad\quad else \end{cases}$$

$$i = 1..N; k = 1,..T \tag{5.25}$$

At time instant $t_k = t_{rel_i}$, the state of charge has to be equal to the given initial value, that is

$$x_{sveh,i}(t_{rel_i}) = x_{sveh,i_{in}} \quad\quad i = 1..N; \tag{5.26}$$

<u>*Constraints expressing upper and lower bounds.*</u>

The evolution of the system state variables is constrained by upper and lower bounds, namely

$$x_{sveh\,min,i} \leq x_{sveh,i}(t_k) \leq x_{sveh\,max,i} \quad\quad i = 1..N; \quad k = 1,..T \tag{5.27}$$

where $x_{sveh\,min,i}$ and $x_{sveh\,mmax,i}$ are lower and upper bounds, respectively, for the state of charge of vehicle i.

Similarly, constraints bounding the value of the state of charge of the storage elements have to be taken into account:

$$x_{ss}^{min} \leq x_{ss}(t_k) \leq x_{ss}^{max} \quad\quad k = 1,..T \tag{5.28}$$

$$x_{sl}^{min} \leq x_{sl}(t_k) \leq x_{sl}^{max} \quad\quad k = 1,..T \tag{5.29}$$

where symbols have an obvious meaning.

In addition, a series of constraints has to be considered in order to bound the values of the power flows which are considered as decision variables in the model:

$$-P^{max}{}_{G\to v,i}\delta_i(t_k) \leq P_{G\to v,i}(t_k) \leq P^{max}{}_{G\to v,i}\delta_i(t_k)$$

$$i = 1..N; \quad k = 0,1,..T-1 \tag{5.30}$$

$$-P_{MG\to G}{}^{max} \leq P_{MG\to G}(t_k) \leq P_{MG\to G}{}^{max} \quad\quad k = 0,1,..T-1 \tag{5.31}$$

$$0 \leq P_{eng1}(t_k) \leq P^{max}{}_{eng1} \quad\quad k = 0,1,..T-1 \tag{5.32}$$

$$0 \leq P_{eng2}(t_k) \leq P^{max}{}_{eng2} \quad\quad k = 0,1,..T-1 \tag{5.33}$$

$$-P_{G\to ss}^{max} \leq P_{G\to ss}(t_k) \leq P_{G\to ss}^{max} \quad\quad k = 0,1,..T-1 \tag{5.34}$$

$$-P_{G\to sl}^{max} \leq P_{G\to sl}(t_k) \leq P_{G\to sl}^{max} \quad\quad k = 0,1,..T-1 \tag{5.35}$$

where all symbols have a straightforward meaning. Note that we have taken into account that some of the power flows are bi-directional.

Finally, the power balancing constraint has to be fulfilled for any time instant, namely

$$P_R(t_k) + P_{S\to G}(t_k) + P_{MG\to G}(t_k) - \sum_{i=1}^{N} P_{G\to Vi}(t_k) - P_{EXT}(t_k) + P_{eng1}(t_k) + P_{eng2}(t_k) = 0 \quad\quad k = 0,1,..T-1 \tag{5.36}$$

where $P_{EXT}(t_k)$ is the non-deferrable (external) power demand that has, in any case, to be satisfied in time interval (t_k, t_{k+1}) and $P_R(t_k)$ is the forecasted power flow from renewable sources in the same interval.

5.4.3 The overall optimization problem

The overall cost to be minimized is composed by the sum of economic production costs plus net energy buying costs (from the grid) and the overall weighted tardiness cost.

Thus, the optimization problem consists in the following minimization of (5.37) under constraints from (5.16) to (5.36).

$$min\left\{\sum_{k=0}^{T-1}\gamma P_{eng1}(t_k)\Delta t+\sum_{t=0}^{T-1}\gamma P_{eng2}(t_k)\Delta t+\sum_{t=0}^{T-1}\beta_{PURCHASE}(t_k)\cdot \max\{P_{G\to MG}(t_k),0\}\Delta t-\sum_{t=0}^{T-1}\beta_{SELL}(t_k)\cdot\max\{-P_{MG\to G}(t_k),0\}\Delta t+\sum_{i=1}^{N}\varepsilon_i\cdot\alpha_i\cdot\max\{t_{f_i}-t_{dd_i},0\}-\sum_{i=1}^{N}\varepsilon_i\cdot\theta\left(t_{rel_i}\right)\cdot\beta_{PURCHASE}\left(t_{rel_i}\right)\cdot D_i\right\} \quad (5.37)$$

where γ is the unit cost for producing power from engines (this cost is assume to be equal for the two engines). Note that the last term in the cost function to be optimized corresponds to the revenue for the microgrid manager coming from the service provided to the customers.

5.5 Case Study: second model

First, let us provide, in Table 1, the values of the parameters of the elements of the microgrid.

Plant	[kW]
Engine 1	$P^{Max}{}_{eng1}=30$
Engine 2	$P^{Max}{}_{eng2}=65$
Storage (Na-Ni)	$P^{max}_{G\to ss}=40$
Storage (Li-Ion)	$P^{max}_{G\to sl}=40$
Electric vehicle storage	$P^{max}{}_{G\to v,i}=22$
Main grid	$P_{MG\to G}{}^{max}=1000$
γ	0,237

Table 1: Power flow data

We have considered an optimization horizon consisting of 96 time intervals, each ones of 15 minutes, that is, on the whole, corresponding to 24 hours. Thus Δt =0.25h .

In Figure 35, the patterns (obtained by real field-sensors measurements) of the known *non-deferrable* demand and of the renewable energy power are represented, over the whole optimization horizon. Unit cost ($\beta_{PURCHASE}(\cdot)$) and benefit ($\beta_{SELL}(\cdot)$) for the power exchanged with the external grid are the following.

$$\beta_{PURCHASE}(t)=\begin{cases}0.2\dfrac{€}{kWh} & 0\le t\le 36\ or\ 81\le t\le 95\\ \dfrac{0.26€}{kWh} & 37\le t\le 80\end{cases}$$

$$\beta_{SELL}(t)=0.15\frac{€}{kWh}\qquad for\ any\ t$$

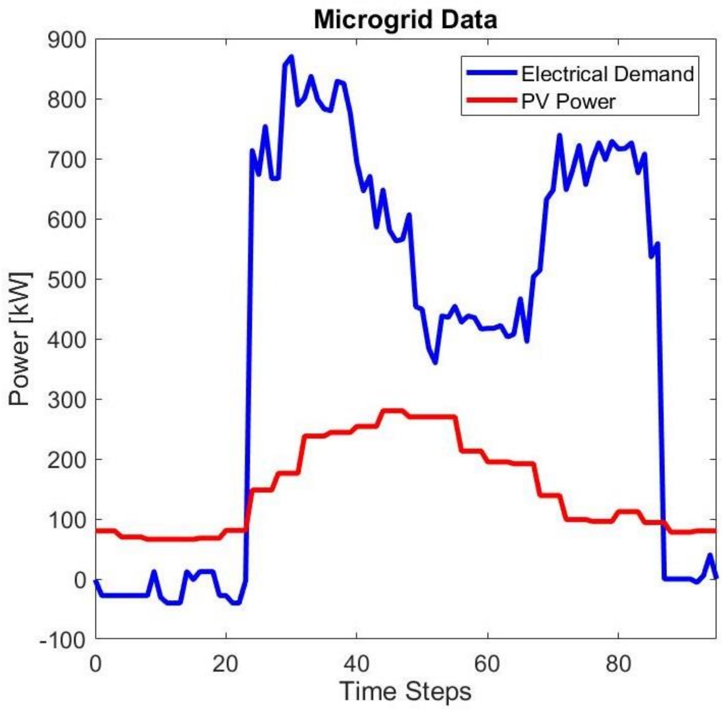


Figure 35: Electrical demand, PV power production

Several demand scenarios are considered in connection to the above described system.

For all cases, the optimization problem presented in the previous section has been solved by using Lingo optimization software tool [10]; the run times are about 60 minutes.

<u>Scenario 1</u>

In this case, we consider different 3 vehicles. All related data are summarized in Table 2.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3
rel_i	40	35	65
dd_i	65	59	79
$D_{max,i}$ [kWh]	30	30	30
$x_{sveh,i,in}$ [kWh]	5	5	5
α_i [€/h]	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 2: Data for the first scenario

The results obtained are shown in Figure 36.

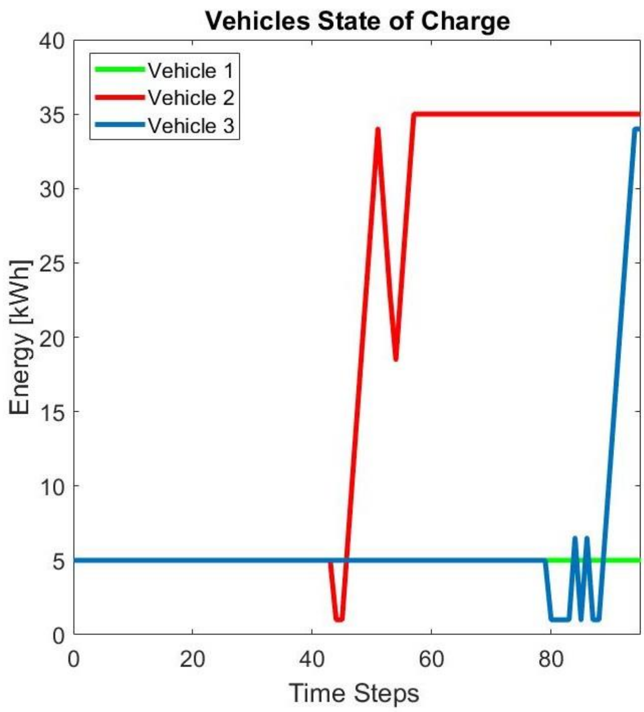


Figure 36: The evolution of the state of charge of the three vehicles (Scenario 1)

Specifically, Figure 36 shows the state of charge of the three vehicles. It can be noted that vehicle 1 is not charged at all (i.e., the state of charge remains the same), while the other two vehicles are both charged and discharged (i.e., vehicle to grid is performed and the EVs serve also as temporary energy sources).

The values of the most relevant decision variables are reported in Table 3.

Table 3: First scenario output

Vehicle output	**Vehicle 1**	**Vehicle 2**	**Vehicle 3**
$\boldsymbol{\theta(t_{rel})}$	2	2	2
$\boldsymbol{c_i}$	56	44	80
$\boldsymbol{f_i}$	61	54	96
$\boldsymbol{D_i}$ **[kWh]**	30	30	30
$\boldsymbol{\varepsilon_i}$	1	1	1

We can note from these results that in this scenario no vehicle reduces its demand with respect to Dmax,i, and that all services are provided by the microgrid manager. Besides, the charging process of each vehicle is completed without going beyond the corresponding due-date.

The plot of the state of charge of the two storage elements is provided in Figure 37.

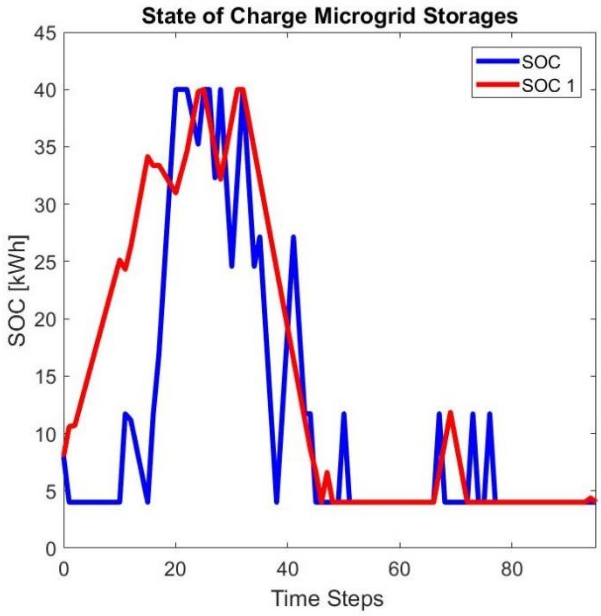


Figure 37:The evolution of the state of charge of the two microgrid storages

Finally, the various power flows in the system are represented in Figure 38.

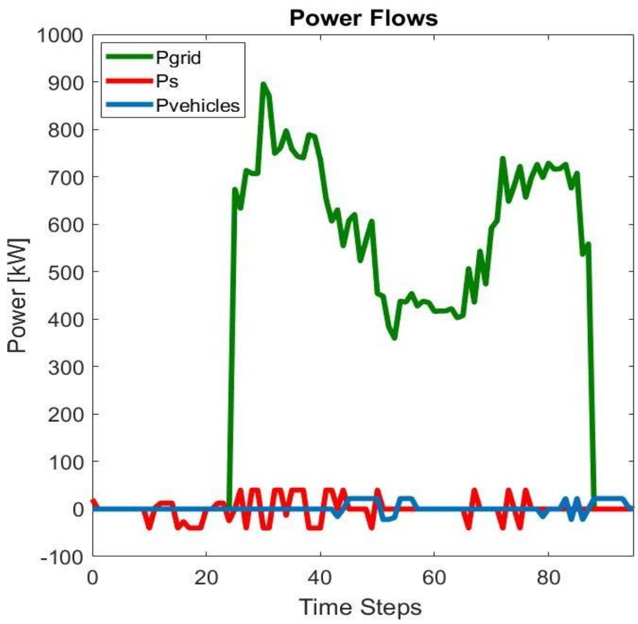


Figure 38: Power flows in the microgrid (Scenario 1). Ps is the sum of P_(sl→G) (t_k) and P_(ss→G) (t_k). Pvehicles is the sum of power flows P_(G→v,i) (t_k) for all i.

Note that in the time intervals 25-35 the microgrid buys energy from the grid, to be able to satisfy a large energy demand in intervals 30-60. This anticipation is due to the fact that time intervals 36-80 are characterized by the highest purchase cost of energy from the main grid.

Scenario 2.

Let us consider now a second scenario in which only the parameter reli of vehicle 3 has been changed with the previous basic scenario.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3
rel_i	40	35	67
dd_i	65	59	79
$D_{max,i}$[kWh]	30	30	30
$x_{sveh,i,in}$[kWh]	5	5	5
α_i [€/h]	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 4: Vehicle data Second scenario

In this case, the demands of the three vehicles are all equal to 30 KWh, as in the previous scenario. However, the micro grid manager decides against servicing vehicle 3.

In Figure 39 the patterns of the state of charge of the three vehicles are reported.

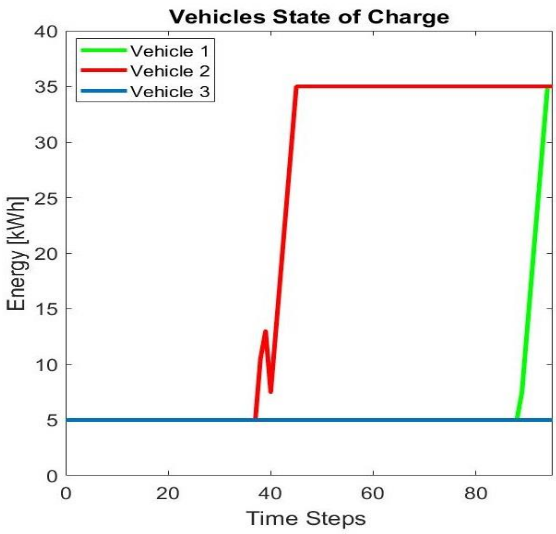


Figure 39: The evolution of the state of charge of the three vehicles (Scenario 2)

The values of the most relevant decision variables are reported in Table 5.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3
$\theta(t_{rel})$	2	2	0
c_i	38	89	-
f_i	46	95	-
D_i[kWh]	30	30	0
ε_i	1	1	0

Table 5: Second scenario output

Scenario 3.

In the third scenario, the maximum demand of vehicle 1 is changed with respect to the Scenario 2, as reported in Table 6.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3
rel_i	40	35	67
dd_i	65	59	79

$D_{max,i}$[kWh]	10	30	30
$x_{sveh,i,in}$[kWh]	5	5	5
α_i [€/h]	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 6: vehicles data Third scenario

In Figure 40, the patterns of the state of charge of the three vehicles are reported.

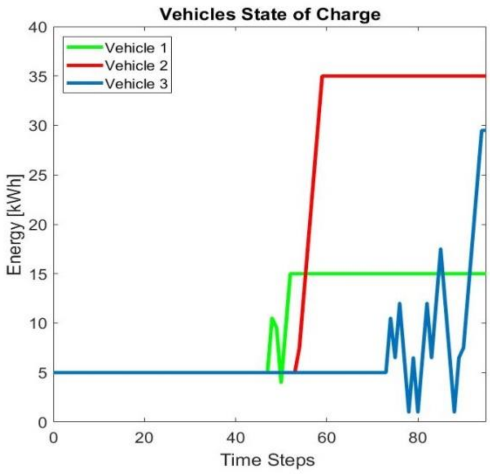


Figure 40:The evolution of the state of charge of the three vehicles (Scenario 3)

Note that, with a lower demand from vehicle 1, the micro grid manager accepts to charge even vehicle 3.

The values of the most relevant decision variables are reported in Table 7.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3
$\boldsymbol{\theta(t_{rel})}$	2	2	2
$\boldsymbol{c_i}$	48	54	74
$\boldsymbol{f_i}$	53	60	95
D_i[kWh]	10	30	30
$\boldsymbol{\varepsilon_i}$	1	1	1

Table 7: Third scenario Output

Scenario 4.

Let us consider now a fourth scenario in which the parameters rel_ihave been changed with respect to the first scenario, for all vehicles, reducing the time intervals allowed for charging.

All data concerning vehicles, for the fourth scenario, are summarized in Table 8.

Vehicle data	Vehicle 1	Vehicle 2	Vehicle 3
$\boldsymbol{rel_i}$	50	55	67
$\boldsymbol{dd_i}$	65	59	79
$Dmax_{,i}$[kWh]	30	30	30
$x_{sveh,i,in}$[kWh]	5	5	5
α_i [€/h]	0.1	0.3	0.1
G_1, G_2 [€/kWh]	0.5, 0.6	0.5, 0.6	0.5, 0.6

Table 8: Data vehicles Fourth scenario

In Figure 41 the patterns of the state of charge of the three vehicles are reported.

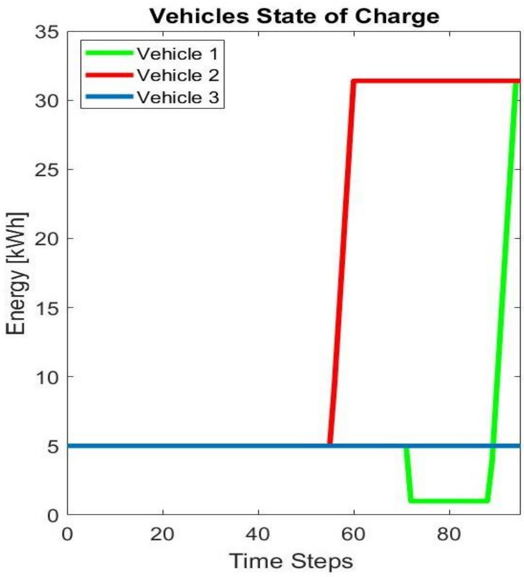


Figure 41: The evolution of the state of charge vehicles of the three vehicles (Scenario 4)

Note that the demands of vehicles 1 and 2 are reduced, with respect to D_{max}. Besides vehicle 3 is not served.

Vehicle output	Vehicle 1	Vehicle 2	Vehicle 3
$\boldsymbol{\theta(t_{rel})}$	2	2	3
$\boldsymbol{c_i}$	72	65	-
$\boldsymbol{f_i}$	95	61	-
D_i[kWh]	26.4	26.4	0
$\boldsymbol{\varepsilon_i}$	1	1	0

Table 9: Fourth scenario output

6. Optimal control in a microgird: Electrical vehicles charching demand response discrete event model

6.1 Introduction

The formalization of the problem provided in the previous chapter, within a discrete-time setting, suffers from a serious drawback, since the number of decision variables grows as the number of the time intervals increases. Thus, in order to keep the problem tractable, it is necessary, in discrete-time modelling, either to limit the number of the time intervals by adopting a suitably large discretization step (thus giving rise to a rough approximation of the dynamics of the real system) or to limit the length of the optimization horizon (thus leading to possible “myopic” control schemes, unable to make use of all available forecasts). Actually, none of these choices is satisfying and for this reason one is led to consider the possibility of a discrete event approach, in which events (which are responsible of the changes of the state of the system) are exactly tracked at the time instants at which they take place, without any approximation.

In fact, in the literature concerning the sequencing and scheduling of services, a discrete event formalization is mostly preferred to a discrete-time one. However, there is an intrinsic difficulty in following this approach in the case of problems, like the one considered in the previous chapter, whose statement is basically conditioned by forecasted information (power coming from renewables and non-deferrable demand) that is intrinsically provided in discrete time. In this case, the forecasted information is typically represented in discrete-time, so it is necessary to find some way to convert these forecasts in some information that is dependent on the time instants at which the discrete events affecting the systems behavior (customer arrivals, completion of services, etc.) occur. This point will be detailed in the following.

6.2 The Model

The problem considerec in this section falls within the broad class of scheduling problems. Such problems refer to the assignment, sequencing and timing of a given set of jobs (or customers) to a given set of resources (or machines) that have to provide a certain service for these jobs. There is a great variety of scheduling models in the literature. For most of them, the solution of the scheduling problem requires to specify three kinds of decisions:

Assignment decisions (i.e., which jobs are assigned to the various available resources);

Sequencing decisions (i.e., once assignment decisions are taken, how to order the services of the jobs assigned to each of the resources);

Timing decisions (i. e., in which time intervals the various services are accomplished).

It is worth noting that for *nonregular* optimization objectives (i.e., those corresponding to the case in which some advantage may be obtained by delaying some completion time) the last decisions (timing) are not trivial.

Besides, it is apparent that the three kinds of decisions are strictly interconnected, as the optimization (scheduling) problem has to be solved as a whole and cannot be decomposed into three separate decision phases.

When dealing with the specific scheduling problem considered in this chapter, since one single service station is considered (which is assumed to be capable of charging a single vehicle at a time), it is apparent that the assignment decisions are trivial, since all jobs (vehicles) are assigned to the same resource. In addition, it is assumed that *the service sequence is given* , that is, the vehicles are charged following the order of their arrivals. Thus, the only decisions that have to be taken are those concerning the timing of services. However, the problem is not trivial, as the service (charging) time intervals are themselves decision variables, as clarified in the following.

The following pictures represent the scheme of the considered system and define the considered power flows.

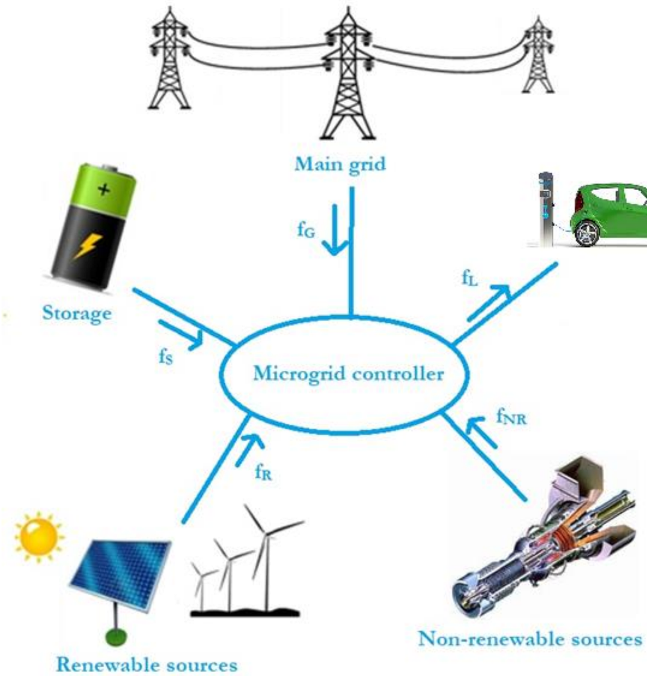


Figure 42: System related power flows

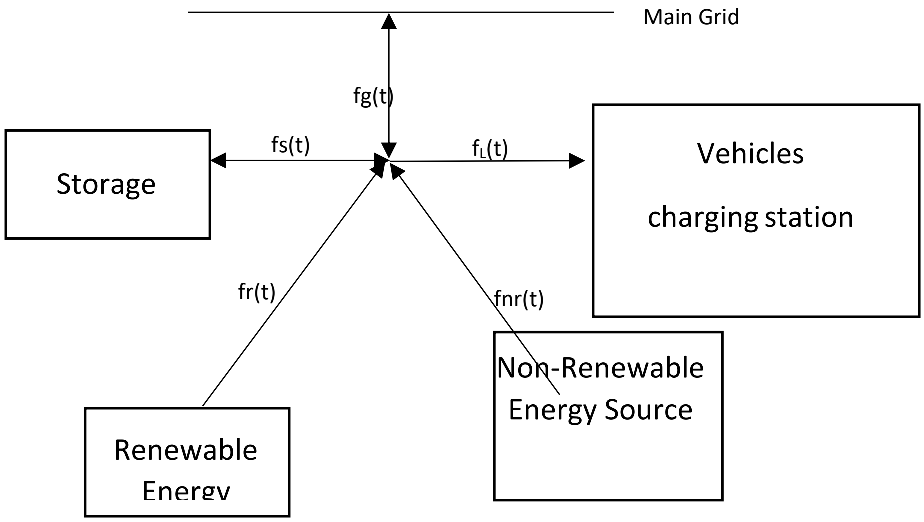
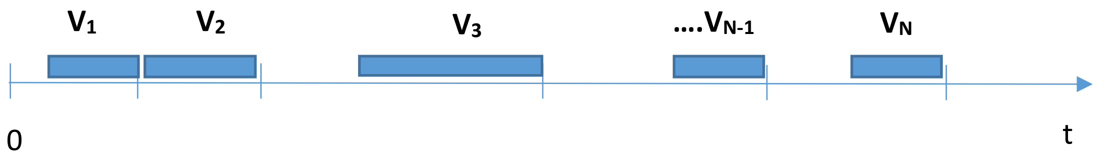
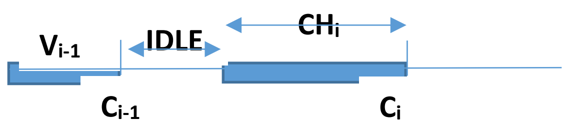


Figure 43: Microgrid

As the service sequence is given, the vehicles can be identified according to their order of arrivals



The model is assumed as *non-preemptive* (that is, the service cannot be interrupted and resumed). Moreover, the power flow is only towards vehicles (that is, no vehicle can be used as a temporary storage). The time interval between the completion time instants (= the instants at which the charging is completed) of two subsequent jobs (=vehicles) can be partitioned as follows:



where:

- C_i = completion time (of the charging) of the *i-th* vehicle;
- CH_i = charging time (interval) for the *i*-th vehicle;
- $IDLE_i$ = idle time interval before the charging of the *i-th* vehicle.

It is assumed that, in any case $IDLE_i$ must be greater than or equal to a minimum value. This minimum value can be considered as equal to the minimum necessary set-up time.

It is also assumed that, for each vehicle V_i, the following information is given a priori:

- *Release time* ***rt****$_i$*: time instant at which the vehicle becomes available for service;
- *Due date* ***dd****$_i$*: time instant at which the service for the vehicle should be completed; it serves to define and evaluate the tardiness cost;
- *Dead line* ***dl****$_i$*: time instant at which the service must be completed. It serves to define a constraint of the problem;

- *Energy request* $\boldsymbol{ER_i}$: amount of energy required for charging the vehicle;
- *Penalty coefficient* $\boldsymbol{\alpha_i}$ for unitary tardiness: it is the cost paid for a unit delay (with respect to the due date dd_i) in providing the required energy to vehicle V_i (per unit of energy required). It is expressed in [€/(kWh*h_{DELAY})].

In addition to what has been previously specified, the following assumptions are made:

- the values of the powers $f_G(\mathrm{t}), f_{NR}(\mathrm{t})$ are kept constant within each time interval (C_{i-1},C_i). Such constant values are denoted as $f_{G,i}(\mathrm{t}), f_{NR,i}(\mathrm{t})$, respectively.
- the value of the power $f_L(\mathrm{t})$ is kept constant within each time interval (C_{i-1}-CH_i,C_i), that is, during the charging of vehicle V_i. This constant value is denoted as $f_{\mathrm{L},i}(\mathrm{t})$, respectively.
- the selling and buying prices (to and from the main grid, respectively) are given functions *SP(t)* and *BP(t),* for $t \geq 0, t \in \Re$. However, such prices are considered as "frozen" at time instant C_{i-1}, for the whole time interval *(C_{i-1},C_i).* That is to say, the formulation of the cost to be minimized will be provided in the assumption that

$$SP(t) = SP(C_{i-1}) \quad for \quad C_{i-1} < t \leq C_i$$
$$BP(t) = BP(C_{i-1}) \quad for \quad C_{i-1} < t \leq C_i$$

On the basis of the previous assumptions and considerations, the basic state equation of the system, describing the dynamics of the state of charge of the storage element *x(t)* is

$$\dot{x} = -f_S(\mathrm{t})$$

That can be represented, within a discrete-event setting, as

$$x(C_i) = x(C_{i-1}) - \bar{f}_{S1,i} IDLE_i - \bar{f}_{S2,i} CH_i \qquad 6.1)$$

where

$\bar{f}_{S1,i}$: the average value of $f_S(\mathrm{t})$ within time interval *(C_{i-1},C_{i-1}+$IDLE_i$);*

$\bar{f}_{S2,i}$: the average value of $f_S(\mathrm{t})$ within time interval *(C_{i-1}+$IDLE_i$, C_i).*

In the following, $x(C_i)$ will be denoted as simply x_i, for the sake of brevity.

The power balance equation

$$f_L(t) = f_G(t) + f_S(t) + f_R(t) + f_{NR}(t) \tag{6.2}$$

cannot be imposed as a constraint for every time instant. The only way to impose a balance equation constraint is that of considering two integral constraints (for each vehicle), namely

$$0 = f_{G,i}(t) + f_{S1,i}(t) + f_{R1,i}(t) + f_{NR,i}(t) \quad \text{within time interval} \quad (C_{i-1}, C_{i-1}+IDLE_i) \tag{6.3}$$

$$f_{L,i}(t) = f_{G,i}(t) + f_{S2,i}(t) + f_{R2,i}(t) + f_{NR,i}(t) \quad \text{within time interval} \quad (C_{i-1}+IDLE_i,\ C_i) \tag{6.4}$$

The average value of the power coming from the renewable source within the interval *(C_{i-1},C_{i-1}+$IDLE_i$)* is given by:

$$\bar{f}_{R1,i}(t) = \frac{\int_{C_{i-1}}^{C_{i-1}+IDLE_i} f_R(t)dt}{IDLE_i} \tag{6.5}$$

Instead, the average value of the power coming from the renewable source within the interval *(C_{i-1}+$IDLE_i$, C_i)* is given by:

$$\bar{f}_{R2,i}(t) = \frac{\int_{C_{i-1}+IDLE_i}^{C_i} f_R(t)dt}{CH_i} \tag{6.6}$$

Obviously, $f_R(t)$ is assumed as known, thus terms $\bar{f}_{R1,i}(t)$, $\bar{f}_{R2,i}(t)$ can be easily expressed as a function of *C_{i-1},C_i,$IDLE_i$*, which are among the decision variables of the problem.

The cost function to be minimized is

$$\min \sum_{i=1}^{N} \{ BP(C_{i-1})(C_i - C_{i-1}) f_{G,i}^{+} - \mathrm{SP}(C_{i-1})(C_i - C_{i-1}) f_{G,i}^{-} + CNR \cdot f_{NR,i}^{i=1} \cdot (C_i - C_{i-1}) + \alpha_i \cdot tard_i \cdot ER_i \}$$
(6.7)

where *CNR* is the unit cost [€/kWh] for generation of not-renewable energy.

The minimization in (6.7) has to be carried out taking into account constraints (6.1), (6.2), (6.3), (6.4), (6.5), (6.6) (written for *i*=1,…,*N*), and the following further constraints:

$$f_{G,i} = f_{G,i}^{+} - f_{G,i}^{-} \qquad \text{i=1,…,N} \qquad (6.8)$$

$$C_i \le dl_i \qquad \text{i=1,…,N} \qquad (6.9)$$

$$C_i - CH_i \ge rt_i \qquad \text{i=1,…,N} \qquad (6.10)$$

$$IDLE_i \ge \varepsilon \qquad \text{i=1,…,N} \qquad (6.11)$$

$$IDLE_i = C_i - CH_i - C_{i-1} \qquad \text{i=1,…,N} \qquad (6.12)$$

$$f_{L,i} CH_i = ER_i \qquad \text{i=1,…,N} \qquad (6.13)$$

$$tard_i \ge C_i - dd_i \qquad \text{i=1,…,N} \qquad (6.14)$$

$$f_{G,i}^{+} \le F_g^{MAX} \qquad \text{i=1,…,N} \qquad (6.15)$$

$$f_{G,i}^{-} \le F_g^{MAX} \qquad \text{i=1,…,N} \qquad (6.16)$$

$$x_{MIN} \le x_i \le x_{MIN} \qquad \text{i=1,…,N} \qquad (6.17)$$

$$-F_{S,\mathrm{MAX}} \le \overline{f}_{S1,i} \le F_{S,\mathrm{MAX}} \qquad \text{i=1,…,N} \qquad (6.18)$$

$$-F_{S,\mathrm{MAX}} \le \overline{f}_{S2,i} \le F_{S,\mathrm{MAX}} \qquad \text{i=1,…,N} \qquad (6.19)$$

$$f_{\mathrm{L,MIN}} \le f_{\mathrm{L},i} \le f_{\mathrm{L,MAX}} \qquad \text{i=1,…,N} \qquad (6.20)$$

$$f_{\mathrm{NR},i} \le f_{\mathrm{NR,MAX}} \qquad \text{i=1,…,N} \qquad (6.21)$$

Note that in the above formulation C_0 is assumed equal to 0, and also x_0 is assumed as given.

All variables are understood to be not negative, but $f_G(t)$ and $f_S(t)$, which have to be declared as free in the statement of the optimization problem.

6.2 Application

In this section, we present a case study in order to show the result obtained by the use of a dicrete event formulation of the problem. Real data have been used for a portion of the Savona Municipality. The vehicle demand is relevant to 4 electrical vehicles (N=4) connected to a grid-connected microgrid, with PV and wind power production, production from natural gas, electrical batteries and charging stations.

The optimal schedule of production plants, storage systems and EVs is obtained by solving the optimization problem (6.1)-(6.11) by use of Lingo optimization software tool [10], run time less than 2 minutes.

6.2.1 Case study

In the case study the power coming the renewable source is assumed as known, but time-varying over the optimization horizon.

We consider system (data reporting in Table 12) with 4 different vehicles, all related data are summarized in Table 11.

Table 11: Vehicle Event driven Datas Casa Study

Vehicle data	***Vehicle 1***	***Vehicle 2***	***Vehicle 3***	***Vehicle 4***
dd	***1.5***	***2***	***2.5***	***1.5***
dl	***1.5***	***3***	***4***	***5***
ER	***100***	***80***	***100***	***100***
tard	***0***	***0.2***	***0.7***	***1.2***
Cnr	***0.13***	***0.13***	***0.13***	***0.13***
$X_{in}(0)$	***20***	***20***	***20***	***20***

Table 12: System Event driven Datas Casa Study

System data	
X_{max}	***100***
X_{min}	***10***
f_{Gmax}	***100***
f_{Smax}	***50***
f_{Lmax}	***100***
f_{Lmin}	***150***
F_{NRmax}	***50***
C_0	***0***
α	***0.1***

In the following *Figure 44* the original (piece-wise linear) pattern of the power from renewable is represented. This pattern comes from some forecasting technique. A dotted line represents the best third-order polynomial interpolation, obtained by standard tools, which can be used to compute the definite integral over a given time interval. Claearly, other kinds of interpolating functions could have been used, but, in our opinion, the quality of the proposed approximation is fairly acceptable.

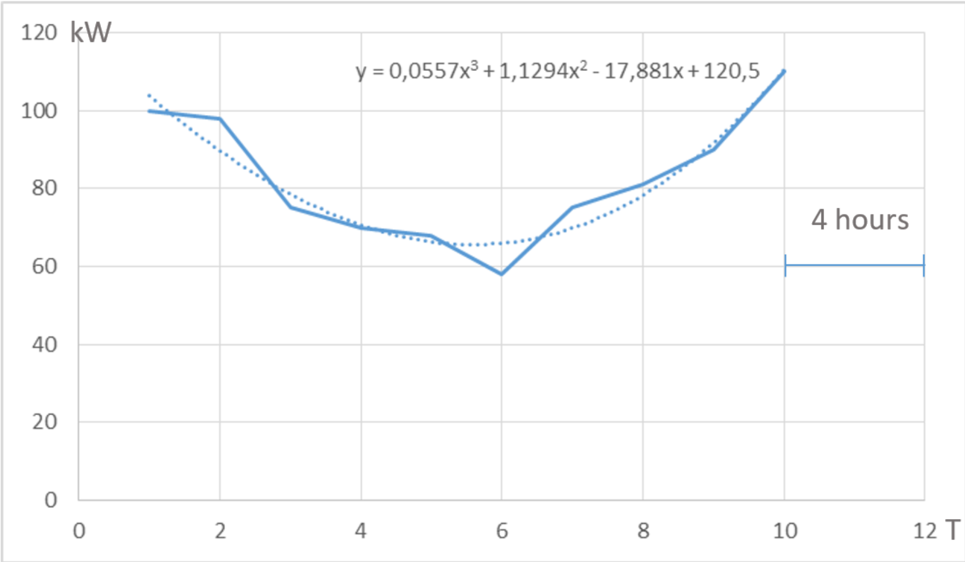


Figure 44: Renewable Power Function per point and its polynomial approximation

Using the third-order approximation

$$fr(x) = a_0x^3 + a_1x^2 + a_2x + a_3$$

it is possible to express the two average values in (6.5) and (6.6) as functions of the decision variables of the problem.

Where $a_0 = 0{,}0557\ \mathrm{kWh/t\hat{}3}$ $a_1 = 1{,}1294\ \mathrm{kWh/t\hat{}3}$ $a_2 = -17{,}881\ \mathrm{kWh/t\hat{}3}$ $a_3 = 120{,}5\ \mathrm{kWh/t\hat{}3}$.

The aim of the algorithm is still to minimize to cost of a charging station. The optimal cost obtained is 23.94 euros.

The results obtained are summarized in Table 13.

Table 13: Event driven Resluts Case study

Vehicle output	***Vehicle 1***	***Vehicle 2***	***Vehicle 3***	***Vehicle 4***
Idle	***0,23***	***0,27***	***0,26***	***0,33***
C	***0,90***	***1,70***	***2,70***	***3,70***
rt	***0,05***	***0,33***	***0,50***	***1,00***
CH	***0,67***	***0,53***	***0,74***	***0,67***
X	***10,00***	***10,00***	***10,00***	***10,00***
f_G	***-12,77***	***0,00***	***0,00***	***0,00***
f_{s1}	***-100,00***	***-100,00***	***-100,00***	***-100,00***
f_{s2}	***50,00***	***50,00***	***34,41***	***50,00***
Fnr	***0,00***	***0,64***	***12,65***	***23,19***
f_l	***150,00***	***150,00***	***134,41***	***150,00***
Optimal Value	***23,9476***			

In Figure 45 the vehicle charging scheduling is represented. The due dates are not always fulfilled, because it is more convenient to pay a penalty for the tardiness than to buy energy from the grid.

Figure 45: Time horizon results for Charging Vehicle case study

Figure 46 f_G Power flow in the time intervals

Figure 46 rapresents the power flow from the microgrid to main grid. Instead, Figure 47 shows che power flow f_{NR} over the optimization horizon.

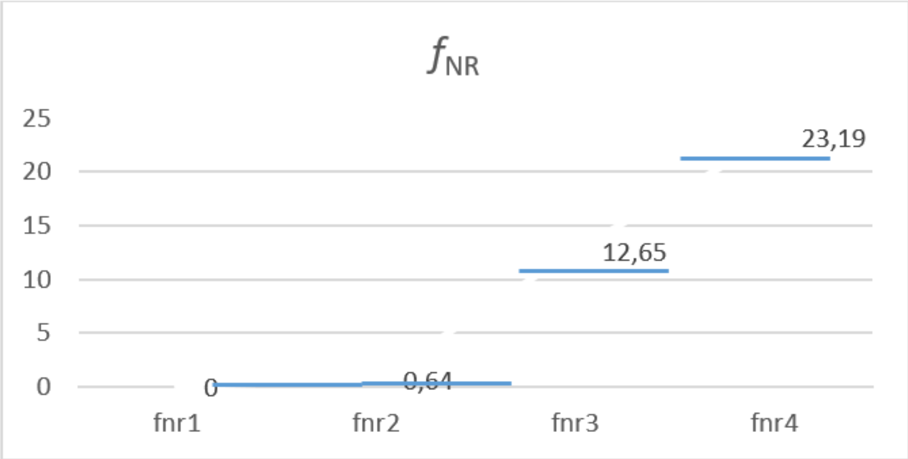


Figure 47 f_{NR} Power flow in time intervals

7. Optimal integration of interconnected buildings

7.1 Introduction

In this chapter, another kind of problem is faced. In this case, a system is considered that is composed by different buildings connected to the same grid that has a unique connection with the external grid. Each building is supposed to have access to some individual intermittent production from renewable resources (wind and photovoltaic). Besides, each building includes a storage system and can exchange power with the other buildings. Heat pumps are used to produce the thermal power that it is necessary to guarantee the desired temperature necessary to ensure a certain comfort level. In fact, each building can be seen as a microgrid like in [36]. In the present tratment, the thermal model of each building is also considered, by introducing a state equation to represents the temperature variation of that building over time.

Two decision levels are here considered because of the presence of different interacting decision makers with different objectives and different information. In the considered scheme, an Upper level Decision Maker (UDM) is responsible for all decisions regarding the interaction with the main grid. The UDM has the objective of minimizing costs (or maximizing benefits) due to the purchase (sales) of electrical energy from (to) the external grid, and power losses. Besides, the presence of several Lower Level Decision Makers (LDM) is assumed, each of which is responsible of a single building (for any LDM, the objective is that of optimizing the behavior of the corresponding building). In this scheme, the UDM emulates the behavior of the LDMs, to obtain a satisfactory solution for the whole system. Then, the LDMs try to track the optimal results provided by the UDM while maintaining a reasonable comfort and containing costs. It is important to note that the aim of this work is not that of modelling in detail the technologies and the distribution systems. For example, storage systems and temperature variation inside buildings are described through the use of simple linear dynamic models drawn from the literature ([124],[5]). For the solution of the UDM decision problem, an approach similar to the ones presented in ([122],[123]) is here applied to the case of interconnected buildings. Results have been derived for a case study in the Genoa Municipality (Italy).

7.2 The bi-level control scheme

The considered control architecture is depicted in Figure 48. The UDM defines and solves a decision problem in order to provide reference values to local users, minimize costs and losses, and respect power flow constraints.

Before the process starts, the UDM receives data from the LDMs (i.e., pres-

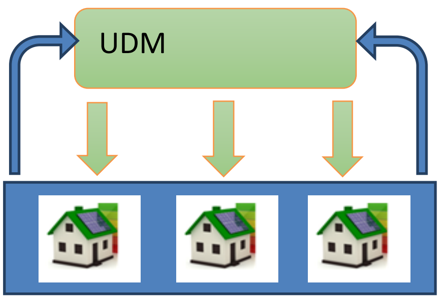


Figure 48: The proposed architecture.

ence/absence of storage systems, renewables, inhabitants, etc.), analyzes and collects other available data (local users behaviour in the previous days, forecasts of external temperature and renewables availability, structural data on buildings coming from a GIS-based database, etc.). Instead, the LDMs receive reference values from the UDM, do not have information on the electrical grid and on other users, and have more detailed information on the rooms inside the buildings, occupancy, possibility to perform demand response programs, etc. Each LDM tries to track its own pattern determined by the UDM, and to minimize its own costs. If both UDM and LDMs are satisfied from the solution, the procedure stops. Otherwise, a further interaction between the UDM and the LDMs is required.

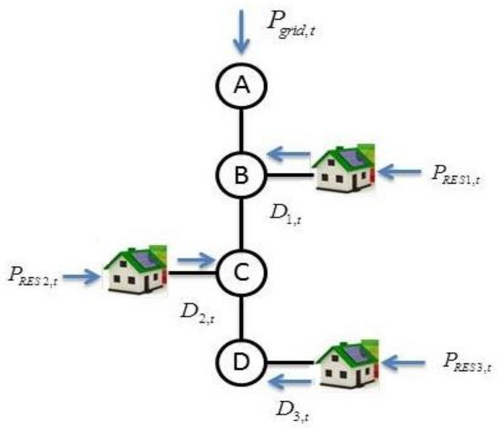


Figure 49 The considered system

The considered physical system is characterized by three interconnected buildings, whose energy demand has to be satisfied by renewable resources and power taken from the external grid, as represented in Figure 49.

Thermal power is produced through heat pumps by using electrical power. The objective of the UDM is to minimize costs (benefits) due to the purchase (sales) of electrical energy $P_{grid,t}$ from (to) the external grid, and power losses $P_{loss,t}$. More specifically, the considered objective function is

$$J = \sum_{t=0}^{T-1} \left[C_{u,t} \max(P_{grid,t}, 0) + B_{u,t} \min(P_{grid,t}, 0) + C_{u,t} P_{loss,t} \right] \tag{7.1}$$

being the power exchange with the external grid in time interval *(t, t+1), t=0,…,T-1*, , the electrical losses due to the exchange of power in the network $C_{u,t}$ unit costs for buying energy from the external grid, and $B_{u,t}$ the unit price for selling power to the external grid.

The State of Charge (*SOC*) dynamics of the storage systems of the various buildings can be represented in percente by the following equations:

$$SOC_{j,t+1} = a_{j,t} SOC_{j,t} - \frac{\eta_j P_{S,j,t} \Delta t}{CAP_j} \quad j=1,..,B,\ t=0,…,T\text{-}1 \tag{7.2}$$

$$\eta_j = \begin{cases} \eta_{c,j} \quad if \quad P_{S,j,t} > 0 \\ 1/\eta_{d,j} \quad otherwise \\ \end{cases} \qquad j=1,...B \tag{7.3}$$

Where CAP_j is the capacity of the storage in building j, *B* is the number of buildings, $\eta_{c,j}, \eta_{d,j}$ are efficiency parameters in charging and discharging modes $a_{t,j}$ is a loss coefficient due to the internal losses and Δ is time interval (hr). Instead, $P_{S,j,t}$ is the power (unrestricted in sign) drawn by the storage (kWel) of the j-th building , and *SOCj,t* is the building battery state of charge.

The power balance equation of each building is given by

$$P_{RES,j,t} + P_{S,j,t} - L_{j,t} = D_{j,t} \quad j = 1,\dots B \quad \text{t=0,...,T-1} \tag{7.4}$$

$$L_{j,t} = q_{j,t} + D_{f,j,t} \qquad j = 1,\dots B \quad \text{t=0,...,T-1} \tag{7.5}$$

where $P_{RES,j,t}$ is the power from renewables for each building *j*, $L_{j,t}$ is the electrical load for the j-th building, $q_{j,t}$ the electrical power provided to heat pumps in the j-th buildind, $D_{f,j,t}$ the forecasted electrical load of each building, and $D_{j,t}$ the power exchanged between each building and the main grid.

It is now necessary to take into account the power flow equations, for active and reactive power, which affect the power exchanges between nodes connected within the same grid. These equations for low voltage AC grids are here expressed in per unit values because (as suggested by literature) this method offers computational simplicity by eliminating units and expressing system quantities as dimensionless ratios:

$$p_{h,k,t} = \frac{P_{h,k,t}}{S_b} \qquad h,k = 1,\dots,N, h \neq k, t = 0,\dots,T\text{-}1 \tag{7.6}$$

$$q_{h,k,t} = \frac{Q_{h,k,t}}{S_b} \qquad h,k = 1,\dots,N, h \neq k, t = 0,\dots,T\text{-}1 \tag{7.7}$$

being *h, k* two generic nodes within the node set *N*. One or more building can be connected to the same node of the grid. In (7.7) S_b is the power base, that is, a constant power with respect to which all powers are expressed, *N* is the number of nodes, $p_{h,k,t}$ and $q_{h,k,t}$ are the active and reactive powers, respectively, expressed in p.u.. Active and reactive power between nodes *(h, k)* are given by

$$p_{h,k,t} = \frac{r_{h,k}(v_{h,t})^2}{\left(r_{h,k}\right)^2 + \left(\hat{r}_{h,k}\right)^2} - \frac{v_{h,t}v_{k,t}\left(r_{h,k}\cos(\bar{\delta}_{h,k,t}) - \hat{r}_{h,k}\sin(\bar{\delta}_{h,k,t})\right)}{\left(r_{h,k}\right)^2 + \left(\hat{r}_{h,k}\right)^2} \quad h,k = 1,\dots,N, h \neq k,$$

$$t=0,\dots,T\text{-}1 \tag{7.8}$$

$$q_{h,k,t} = \frac{\hat{r}_{h,k}(v_{h,t})^2}{\left(r_{h,k}\right)^2 + \left(\hat{r}_{h,k}\right)^2} - \frac{v_{h,t}v_{k,t}\left(\hat{r}_{h,k}\cos(\bar{\delta}_{h,k,t}) + r_{h,k}\sin(\bar{\delta}_{h,k,t})\right)}{\left(r_{h,k}\right)^2 + \left(\hat{r}_{h,k}\right)^2} \qquad h,\ k=1,\ldots,N, h \neq k,$$

t=0,…,T-1 (7.9)

where $\bar{\delta}_{h,k,t} = \delta_{h,t} - \delta_{k,t}$, $r_{h,k}$ and $\hat{r}_{\mathrm{h,k}}$ are resistance and reactance parameters for the link (*h, k*), respectively, $v_{h,t}$ and $\delta_{h,t}$ are the voltage and the phase at node *h*, respectively. The balance equation for active power at each node inside the main grid is given by:

$$\sum_{j \in A_h} D_{j,t} + \sum_{\substack{k=1 \\ h \neq k}}^{N} P_{h,k,t} = 0 \qquad h=1,\ldots,N,\ t=0,\ldots,T\text{-}1 \tag{7.10}$$

where A_h is the set of buildings connected to the node *h*. It is important to note that an equation similar to (7.10) is valid for the node of connection with external grid. At this node, no buildings are connected and the contribution $D_{j,t}$ is substituted with $P_{grid,t}$. Equations similar to those expressed by (7.4), (7.5) and (7.10) are formalized for reactive power but they are here not reported for the sake of brevity. The power losses at each branch could be evaluated as follows

$$P_{loss,t} = \sum_{h \in N} \sum_{k \in N} R_{\mathrm{h,k}} \left(\frac{\sqrt{Q_{\mathrm{h,k},t}^2 + P_{h,k,t}^2}}{v_{h,t}} \right)^2 \quad h \neq k,\ t=0,\ldots,T\text{-}1 \tag{7.11}$$

Moreover, the following bounds must be imposed:

$$-Y_{h,k,t} \le P_{h,k,t} \le Y_{h,k,t} \quad h,\ k=1,\ldots,N,\ h \neq k,\ t=0,\ldots,T\text{-}1 \tag{7.12}$$

$$SOC_{\min,\mathrm{j},t} \le SOC_{\mathrm{j},t} \le SOC_{\max,\mathrm{j},t} \quad j=1,\ldots,B \quad t=0,\ldots,T\text{-}1 \tag{7.13}$$

$$v_h^{MIN} \le v_{h,t} \le v_h^{MAX} \qquad h=1,\ldots,N \quad t=0,\ldots,T\text{-}1 \tag{7.14}$$

$$\left(Q_{grid,t}\right)^2 + \left(P_{grid,t}\right)^2 \le \left(S_{grid}^{MAX}\right)^2 \qquad t=0,\ldots,T\text{-}1 \tag{7.15}$$

$$\left(QD_{\mathrm{j},t}\right)^2 + \left(L_{\mathrm{j},t}\right)^2 \le \left(S_{load,\mathrm{j}}^{MAX}\right)^2 \quad j=1,\ldots,N \quad t=0,\ldots,T\text{-}1 \tag{7.16}$$

$$\left(Q_{RES,t}\right)^2 + \left(P_{RES,t}\right)^2 \le \left(S_{RES,\mathrm{j}}^{MAX}\right)^2 \quad j=1,\ldots,B \quad t=0,\ldots,T\text{-}1 \tag{7.17}$$

$$\left(Qs_{j,t}\right)^2 + \left(Ps_{\mathrm{j},t}\right)^2 \le \left(S_{STO,\mathrm{j}}^{MAX}\right)^2 \quad j=1,\ldots,B \quad t=0,\ldots,T\text{-}1 \tag{7.18}$$

$$\left(Q_{h,k,t}\right)^2 + \left(P_{h,k,t}\right)^2 \le S_{h,k}^{MAX} \quad h,k=1,\ldots,N,\ h \neq k,\ t=0,\ldots,T\text{-}1 \tag{7.19}$$

where:

- $Y_{h,k,t}$ is the power limit for power that flows in the grid;

- $SOC_{\min,j,t}$, $SOC_{\max,j,t}$ are bounds related to storage systems capacity;
- v_h^{MIN} and v_h^{MAX} are lower and upper bounds for voltage at node *h;*
- $S_{grid,j}^{MAX}$, $S_{RES,j}^{MAX}$, $S_{load,j}^{MAX}$, $S_{STO,j}^{MAX}$, $S_{h,k}^{MAX}$ represent maximum apparent power for production, grid connection, renewables, load, power exchange with storage, and power flows, respectively;
- $Q_{grid,t}$, $QD_{j,t}$, $Q_{RES,t}$, $Qs_{j,t}$, $Q_{h,k,t}$ are reactive powers.

It is supposed that the UDM has no detailed information about the temperature in the rooms in each building. Thus, a single variable $T_{j,t}$ is used to represent the temperature of the overall building j. The dynamics of such a temperature is simply represented as in Yao et al. (2015)

$$T_{j,t+1} = T_{j,t} + \frac{\Delta}{C_j}[\eta_s q_{j,t} - \frac{1}{\tilde{R}_{th,ext,j}}(T_{j,t} - T_{ext,t})] \qquad j=1,\ldots,B,\ t=0,\ldots,T-1 \tag{7.20}$$

where C_j is the thermal capacitance in building *j* (J/K), $T_{ext,t}$ is the external temperature (K), $q_{j,t}$ the thermal power provided by heat pumps, $\tilde{R}_{th,ext,j}$ is the resistance between building *j* and the external environment, and η_s is a known conversion parameter. The following upper and lower bound constraints have to be fulfilled:

$$T_{j,MIN} \le T_{j,t} \le T_{j,MAX} \qquad j=1,\ldots,B, \quad t=0,\ldots,T-1 \tag{7.21}$$

The UDM must provide reference values to buildings in order to minimize the costs of the whole system. To this end, it emulates the local users behaviour, on the basis of its available information. Then, an analytical solution for the LDMs' decision problem is obtained and inserted as a constraint in the UDM decision problem.

Local users are supposed to follow references given by the UDM. In particular, their objective function is given by

$$\min = \hat{J} = \sum_{t=0}^{T-1} \sum_{j=1}^{J} \alpha(T_{j,t} - \tilde{T}_{j,t})^2 + \beta(q_{j,t} - \tilde{Q}_{j,t})^2 + \lambda(SOC_{j,t} - SOC_{j,t}^*)^2 + \sigma(\mathrm{D}_{j,t} - \tilde{\mathrm{D}}_{j,t})^2 \tag{7.22}$$

where $\tilde{Q}_{j,t}$ are the reference patterns for the power to building j to satisfy thermal demand (kWth); $SOC_{j,t}^*$ is the reference value for the state of charge of the storage system in building j; $\tilde{T}_{j,t}$ is reference value for temperature, $\tilde{\mathrm{D}}_{j,t}$ is the reference value for power exchanged between the main grid and building j; α, β, λ, σ are weighting factors. All other symbols have been already defined.

The following equations must be taken into account in the UDM optimization problem:

$$SOC_{j,t+1} = SOC_{j,t} - \frac{\eta_j P_{S,j,t} \Delta}{CAP_j} \qquad j=1,\dots B, \quad t=0,\dots,T-1 \qquad (7.23)$$

$$P_{RES,j,t} + P_{S,j,t} = q_{j,t} + D_{f,j,t} + D_{j,t} \qquad j=1,\dots B, t=0,\dots,T-1 \qquad (7.24)$$

$$T_{j,t+1} = T_{j,t} + \frac{\Delta}{C_j}[\eta_s q_{j,t} - \frac{1}{\tilde{R}_{th,ext,j}} \; (T_{j,t} - T_{ext,t})] \qquad j=1,\dots B, t=1,\dots,T-1 \qquad (7.25)$$

where C_j is the thermal capacitance in building j (J/K), $T_{ext,t}$ is the external temperature (K), $\tilde{R}_{th,ext,j}$ is the resistance between building j and the external environment.

The optimization problem given by equations (7.22)-(7.25) can be expressed in the following form:

$$\min \quad \hat{J} = \frac{1}{2}\sum_{t=0}^{T-1}[(\underline{x}_{t+1} - \underline{x}_t^*)'Q(\underline{x}_{t+1} - \underline{x}_t^*) + (\underline{u}_t - \underline{u}_t^*)'R(\underline{u}_t - \underline{u}_t^*)] \qquad (7.26)$$

s.t.

$$\underline{x}_{t+1} = A\underline{x}_t + B\underline{u}_t + C\underline{z}_t \qquad t=0,\dots,T-1 \qquad (7.27)$$

where

$$\underline{x}_t = col[T_{j,t}, j=1,\dots,B \;, SOC_{j,t,} \, j=1,\dots,B] \qquad t=0,\dots,T-1 \qquad (7.28)$$

$$\underline{u}_t = [P_{S,j,t}, {}_{j=1,\dots,B}, P_{grid,j,t}, {}_{j=1,\dots,B}, q_{j,t}, {}_{j=1,\dots,B}, \mathrm{D}_{j,t}, {}_{j=1,\dots,B}] \quad t=0,\dots,T-1 \qquad (7.29)$$

$$\underline{z}_t = [P_{RES,j,t}, \mathrm{D}_{f,j,t}, j=1,\dots,B, T_{ext,t}] \qquad t=0,\dots,T-1 \qquad (7.30)$$

$$\underline{x}_t^* = \left[\tilde{T}_{j,j=1,\dots,B} SOC^*_{j\dots j=1,\dots,B}\right]; \qquad t=0,\dots,T-1 \qquad (7.31)$$

$$\underline{u}_t^* = [\tilde{Q}_j, {}_{j=1,\dots,B}, \tilde{\mathrm{D}}_j, {}_{j=1,\dots,B}] \qquad t=0,\dots,T-1 \qquad (7.32)$$

and where matrices Q and R are suitably defined positive definite (diagonal) matrices, defined through the weight coefficients in the expression (7.22) of the cost. Besides, the structure and parameters of matrices *A, B* and *C* in (7.27) can be derived from the dynamical equations representing the behaviour of the state of charge of the storage in the buildings and the (average) temperature for each building.

The optimal control law for this control problem can be found using an approach like the one in [36]

$$
\begin{aligned}
\underline{u}_k &= -(R + B' K_{k+1} B)^{-1} B' K_{k+1} A \underline{x}_k \\
&+ ((R + B' K_{k+1} B)^{-1} B' K_{k+1} B R^{-1} B' - R^{-1} B') g_{k+1} \\
&- (R + B' K_{k+1} B)^{-1} B' K_{k+1} B \, \overline{u}_k + \\
&\overline{u}_k - (R + B' K_{k+1} B)^{-1} B' K_{k+1} C \underline{z}_k
\end{aligned}
\quad k=0,\ldots,T\text{-}1 \qquad (7.33)
$$

where K_k and g_k , k=0,…,T-1, can be found through the following backward recursions

$$
K_k = Q + A(K_{k+1} - K_{k+1} B (R + B' K_{k+1} B)^{-1} B' K_{k+1}) A \quad k=0,\ldots,T\text{-}1 \qquad (7.34)
$$

$$
\begin{aligned}
g_k &= -A(K_{k+1} - K_{k+1} B (R + \\
&B' K_{k+1} B)^{-1} B' K_{k+1}) B R^{-1} B' g_{k+1} + A g_{k+1} + \\
&A(K_{k+1} - K_{k+1} B (R + B' K_{k+1} B)^{-1} B' K_{k+1})(B \overline{u}_k + C \underline{z}_k) - Q_i \underline{\overline{x}_k}
\end{aligned}
\quad k=0,\ldots,T\text{-}1 \qquad (7.35)
$$

initialized with $K_T = Q$ and $g_T = -Q \underline{\overline{x}}$. Δ

Thus, the solution to the UDM optimization problem is given by equations (7.33)-(7.35).

7.2.1 The Local User Optimization Problem

The local users have more information on the buildings and may decide to apply demand response programs. Each consumer follows the references coming from the UDM, has more detailed information, system and decision problem. The storage state equations (7.2) have to be taken into account as constraints to the optimization problem. The dynamics of the temperature is in this case given by:

$$
\begin{aligned}
T_{i,j,t+1} &= T_{i,j,t} + \frac{\Delta}{C_{i,j}} [\eta_s q_{i,j,t} - \frac{1}{\tilde{R}_{th,ext,i,j}} \tilde{A}_{i,j,ext} (T_{i,j,t} - T_{ext,t}) \\
&- \sum_{\substack{k=1 \\ k \neq i}}^{I} \frac{1}{\tilde{R}_{th,i,j,r}} \tilde{A}_{i,j,r} (T_{i,j,t} - T_{r,j,t})]
\end{aligned}
$$

$$
i=1,\ldots I, \; j=1,\ldots,B, \; r=1,\ldots I, \; t=0,\ldots,T\text{-}1 \qquad (7.36)
$$

where $C_{i,j}$ is thermal capacitance of room *i* in building *j* (B/K); $T_{ext,t}$ is the external temperature (K); $\tilde{R}_{th,ext,i,j}$ is the resistance between room *i* in building *j* and the external environment; $\tilde{R}_{th,i,j,r}$ is the resistance between room *i* and room *r* in building j. $\tilde{A}_{i,j,r}$ is the generic element of the adjacency matrix: it is equal to 1 if room *i* of building *j* is adjacent to room *r* and 0 otherwise; $\tilde{A}_{i,j,ext}$ is a coefficient equal to 1 if room j is adjacent to external environment, and 0 otherwise; $q_{i,j,t}$ is the thermal power (kWth) (unrestricted in sign) provided by heat pumps to room *i* in building j. Clearly, $q_{j,t} = \sum_{i=1}^{I} q_{i,j,t}$, where *I* is the number of rooms); $T_{i,j,t}$ is temperature (K) in room i of building j at time instant t.

The power balance equation is given by:

$$P_{RES,j,t} + P_{S,j,t} = \tilde{L}_{j,t} + D_j \qquad j=1,\ldots,B,\ t=0,\ldots,T-1 \tag{7.37}$$

$$\tilde{L}_{j,t} = L_{b,t} + P_{veh,j,t} + P_{wash,j,t} + q_{j,t} + P_{loss,j,t} \qquad j=1,\ldots,B,\ t=0,\ldots,T-1 \tag{7.38}$$

where $P_{veh,j,t}$, $P_{wash,j,t}$, $P_{loss,j,t}$ are the power of electrical vehicles, washing machines and the electrical losses inside the house, which, for the sake of simplicity, is a percentage of the brown goods load $L_{b,t}$.

It is important to note that local users can shift the power demand of their devices, while following reference values for power exchange with the external grid. The following constraints hold for the scheduling of electrical vehicles and washing machines

$$\sum_{t=0}^{T-1} P_{veh,j,t} \geq \tilde{P}_{ev,j} \qquad \text{j=1,…,B} \tag{7.39}$$

$$P_{wash,j,t} = \delta_{j,t} \bar{P}_{wash,j} \qquad \text{j=1,…,B, t=0,…,T-1} \tag{7.40}$$

$$\sum_{t=0}^{T-1} P_{wash,j,t} \geq P_{washTOT,j} \qquad \text{j=1,…,B} \tag{7.41}$$

$$\delta_{j,t+1} = \begin{cases} 1 \quad if \quad \delta_{j,t} = 1 \quad and \quad P_{wash,j,t} < P_{washTOT,j} \\ 0 \quad if \quad \delta_{j,t} = 1 \quad and \quad P_{wash,j,t} \geq P_{washTOT,j} \\ \delta_{j,t+1} \quad if \quad \delta_{j,t} = 0 \end{cases}$$

$$\text{j=1,…,B, t=0,…,T-1} \tag{7.42}$$

where $\tilde{P}_{ev,j}$, $\bar{P}_{wash,j}$, $P_{washTOT,j}$ are daily electrical demands for electrical vehicles and washing machines.

The total cost for a building is given by:

$$C_{TOT,\mathrm{j}} = \sum_{t=0}^{T-1} D_{j,t} C_{u,j,t} \qquad \text{j=1,…,B} \tag{7.43}$$

$$C_{TOT,\mathrm{Min,j}} < C_{TOT,\mathrm{j}} < C_{TOT,\mathrm{Max,j}} \qquad \text{j=1,…,B} \tag{7.44}$$

where are the $C_{TOT,\mathrm{Min,j}}$ and $C_{TOT,\mathrm{Max,j}}$ the minimum and maximum cost, respectively, that the LDM *j* considers to be sustainable, and $C_{u,j,t}$ the unit cost for power in building j.

The LDMs' objective function tracks values coming from the aggregator. That is,

$$\min = \hat{J} = \sum_{t=0}^{T} \left(\mathrm{D}_{j,t} - \tilde{D}_{j} \right)^{2} \qquad \text{j=1,...,B} \qquad (7.45)$$

7.3 Case Study

The proposed two level architecture has been applied to a case study: 3 buildings in the district of Sampierdarena (Municipality of Genoa) have been selected. All buildings have been divided in five rooms (or thermal zones, i.e., areas with homogeneous thermal characteristics). The developed decision models for UDM and LDMs have been solved by the use of the optimization package Lingo (www.lindo.com) [10], computation time 20 minutes.

The UDM decision problem is nonlinear while the LDMs decision problems are quadratic with binary and continuous decision variables. Thus, different initializations have been used to solve the optimization problems. The external temperature (°C) and renewables availability (kW) are reported in Figure 50 and Figure 51, respectively.

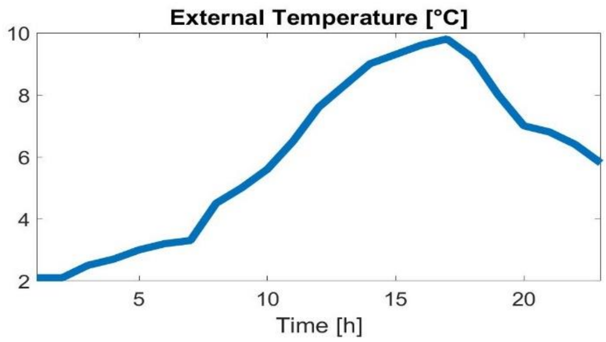
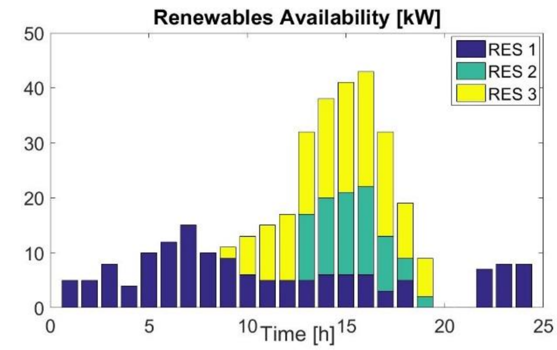


Figure 50: External Temperature

Figure 51: Renewables availability in the three buildings (RES1, RES2, RES3)



7.3.1 Solution of the UDM decision problem

First, the UDM decision problem has been solved and the reference patterns for local users have been found. The overall objective function is equal to 636 €.

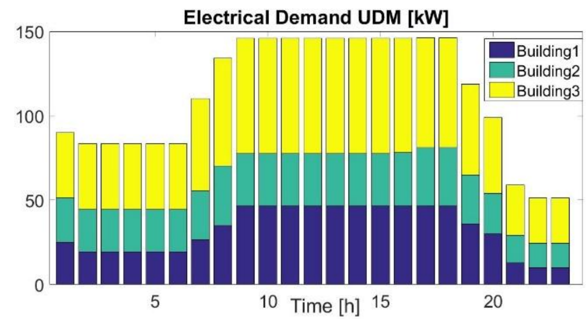


Figure 52: Electrical Demand from UDM.

Figure 52 reports the optimal values for the power Dj,t that the UDM provides to the three buildings. Instead, Figure 53 shows power flows at nodes A (connection point to the main grid) and B (connected to building 1), by using the notation of Figure 49. Specifically, PAB is power from node A to node B, PBA and PBC are power flows from node B (to node A and node C, respectively). It is important to note that the power exchanged between these two nodes (PAB and PBA) are approximately equal but opposite in sign. This means that power losses are very low and that the power flow equations are solved in a correct way.

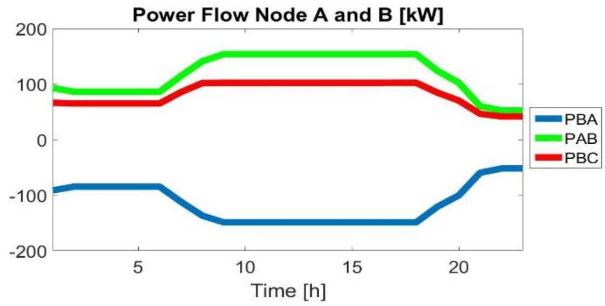


Figure 53. Power exchange at nodes A and B.

7.3.2 Solution of the LDM decision problem

Then, the LDMs' optimization problems have to be solved, taking into account reference patterns from the UDM. For the sake of brevity, in the following, only results for building 1 are reported. The value of the objective function of the LDM is equal to zero. This means that the obtained solution satisfies both the UDM and the LDM. The evolution of the state of charge of the battery is represented in Figure 54. Such a behavior mainly depends on the UDM reference values, on fixed demands, and, consequently, on when it is better to schedule the deferrable demand.

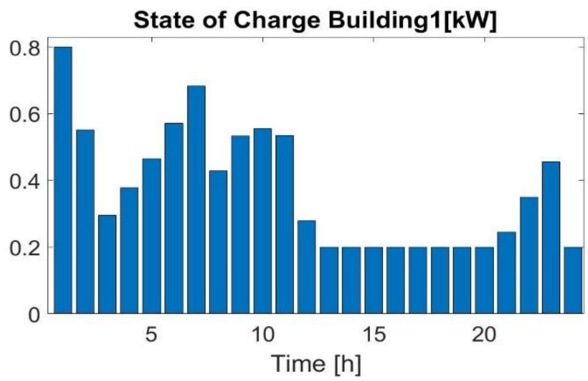


Figure 54. Battery state of charge.

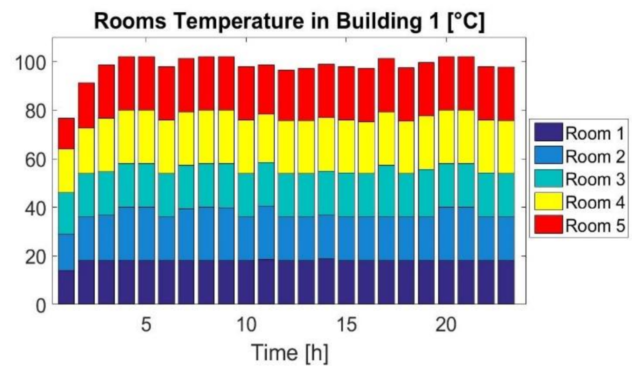


Figure 55. Temperature over time for rooms in building 1.

Finally, the temperature variation for the rooms in building 1 is shown in Figure 55. It can be seen that all rooms stay within temperature upper and lower bounds and that they have a similar behaviour, even though around a different average temperature.

Conclusions

Optimization and control problems related to the management of smart grids cover a wide range of possible topics. In this thesis, some of them have been considered in some detail, and possible approaches for the solution of such problems have been developed.

A considerable attention has been devoted to the analysis of problems relevant to optimal scheduling of the charging of electric vehicles. This problem has been analyzied within two different settings: discrete-time and discrete-event.

In the discrete-time case, the dynamics of the system has been represented by representing, for each sampling interval, the change in the values of the state variables determined by the power flows in the microgrid. In this way, it is possible to precisely track the patterns of the (forecasted) renewable power and exterenal nondeferrable demand. It is also possible to model the demand of the vehicles as an elastic demand (i. e., the quantification of the demand depends on the current prices of energy). The behaviour of the microgrid manager (that has the responsibility of providing the required service to the vehicle owners) can also be represented with several degrees of freedom. Namely he/she can adjust prices, in order to discourage high recharging demands, and even refuse service to some vehicle. More important, the service sequence is not determined in advance, but it is a result of the solution of the overall optimization problem (whose formulation takes into account the due dates of the various service requests, and thus the tardiness costs). In this way, the determination is allowed not only of the optimal timing, but also of the optimal sequencing of the services.

On the whole, the interest of the discrete-time problem formulation is that of allowing to follow an approach within which the vehicle charging scheduling problem and the optimal management of the entire microgrid are viewed in an integrated framework. Hovever, a serious difficulty arises when the number of the discretization intervals becomes too high and then the number of decision variables of the problems reaches values that prevent determining the solution within acceptable computational times.

For the above reason, a further approach has been introduced for the scheduling problem referred to the charging of the electrical vehicles, still integrated with the management of the overall microgrid. This second approach is characterized by the adoption of a discrete-event modelling of the dynamics of the considered system. This choice allow to greatly reduce the number of decision variables (thus yielding more acceptable computational times), but requires to know in advance the service sequence of the vehicles. This sequence may be, for instance, a priori determined on the basis of the First-Come-First-Served rule. Thus, the scheduling problem that is considered within this approach refers only to timing optimization, as the service sequence has already been fixed.

Further research in this direction should be oriented towards the development of approaches allowing a discrete-event formulation of the problem, but letting the service sequence be a part of the solution of the optimization problem.

Anaother class of problems considered in this thesis is that relevant to the integrated management of a set of buildings connected within the same grid and capable of exchanging power among them and with the main grid. For this kind of problem, a two-level approach has been developed in which, at the highel level, an “upper-level” decision maker solves a problem in which each building is taken into account by means of a simplified model. Instead, at the lower level, the “local” controllers (one for each building) try to track the reference behaviour obtained (for each of them) by the upper level controller, by use of a mode detailed model for the building.

All approaches have been applied to real case studies in the Provinces of Genoa and Savona. In both cases, satisfactory results have been obtained, as regards the quality of the obtaind performances, as well as with reference to the required computational times.

References

[1] Chen Gong, Xiaodong Wang, Weiqiang Xu, And Ali Tajer Distributed Real-Time Energy Scheduling In Smart Grid: Stochastic Model And Fast Optimization Ieee Transactions On Smart Grid, Vol. 4, No. 3, (2013)

[2] Amin Khodaei, Member, Ie, Resiliency-Oriented Microgrid Optimal Scheduling, Ieee Transactions On Smart Grid, Vol. 5, No. 4, (2014)

[3] Chen C, Duan S, Cai T, Liu B, Hu G. Optimal Allocation And Economic Analysis Of Energy Storage System In Microgrids. Ieee Trans Power Electron (2011);26:2762–73

[4] Mohammadi M, Hosseinian Sh, Gharehpetian Gb. Optimization Of Hybrid Solar Energy Sources/Wind Turbine Systems Integrated To Utility Grids As Microgrid (Mg) Under Pool/Bilateral/Hybrid Electricity Market Using Pso. Sol Energy (2012);86:112–25.

[5] Stefano Bracco, Federico Delfino, Fabio Pampararo, Michela Robba, Mansueto Rossi A Dynamic Optimization-Based Architecture For Polygeneration Microgrids With Tri-Generation, Renewables, Storage Systems And Electrical Vehicles Energy Conversion And Management, Volume 96, 15 May 2015, Pages 511–520

[6] Hanane Dagdougui And Roberto Sacile, Decentralized Control Of The Power Flows In A Network Of Smart Microgrids Modeled As A Team Of Cooperative Agents. Ieee Transactions On Control Systems Technology, Vol. 22, No. 2, March 2014

[7] Azadeh Kamjoo*, Alireza Maheri, Ghanim A. Putrus Chance Constrained Programming Using Non-Gaussian Joint Distribution Function In Design Of Standalone Hybrid Renewable Energy Systems,Energy 66 (2014) 677,688

[8] Arthur K. Barnes, Student Member, Ieee, Juan C. Balda, Senior Member, Ieee, And Andrés Escobar-Mejía A Semi-Markov Model For Control Of Energy Storage In Utility Grids And Microgrids With Pv Generation, Ieee Transactions On Sustainable Energy, Vol. 6, No. 2, April (2015)

[9] A M. Zamo, O. Mestre, P. Arbogast , O. Pannekoucke Benchmark Of Statistical Regression Methods For Short-Term Forecasting Of Photovoltaic Electricity Production Part I: Deterministic Forecast Of Hourly Production, Solar Energy 105 (2014) 792–803

[10] Peng Kou ,Feng Gao , Xiaohong Guan, Stochastic Predictive Control Of Battery Energy Storage For Wind Farm Dispatching: Using Probabilistic Wind Power Forecasts Renewable Energy 80 (2015) 286e300

[11] K. Rahbar, J. Xu, and R. Zhang, “Real-time energy storage management for renewable integration in microgrid: An off-line optimization approach,” IEEE Transactions on Smart Grid, vol. 6, no. 1, pp. 124–134,2015.

[12] K. A. Alobeidli, M. H. Syed, M. S. El Moursi, and H. H. Zeineldin, “Novel coordinated voltage control for hybrid micro-grid with islanding capability,” IEEE Transactions on Smart Grid, vol. 6, no. 3, pp. 1116–1127, 2015.

[13] D. Arcos-Aviles, J. Pascual, L. Marroyo, P. Sanchis, and F. Guinjoan, "Fuzzy logic-based energy management system design for residential grid-connected microgrids," IEEE Transactions on Smart Grid, 2016.

[14] M. Bouzerdoum, A. Mellit, and A. M. Pavan, "A hybrid model (sarima–svm) for short-term power forecasting of a small-scale grid-connected photovoltaic plant," Solar Energy, vol. 98, pp. 226–235, 2013.

[15] S. Alessandrini, L. Delle Monache, S. Sperati, and G. Cervone, "Ananalog ensemble for short-term probabilistic solar power forecast,"Applied Energy, vol. 157, pp. 95–110, 2015.

[16] J. R. Trapero, N. Kourentzes, and A. Martin, "Short-term solar irradiation forecasting based on dynamic harmonic regression," Energy, vol. 84,pp. 289–295, 2015.

[17] K. D. Orwig, M. L. Ahlstrom, V. Banunarayanan, J. Sharp, J. M. Wilczak, J. Freedman, S. E. Haupt, J. Cline, O. Bartholomy, H. F Hamann, B. M. Hodge, C. Finley, D. Nakafuji, J. L. Peterson, D. Maggio, and M. Marquis, "Recent trends in variable generation forecasting and its value to the power system," IEEE Transactions on Sustainable Energy, vol. 6, no. 3, pp. 924–933, 2015.

[18] Bracale, P. Caramia, G. Carpinelli, A. R. Di Fazio, and G. Ferruzzi, A bayesian method for short-term probabilistic forecasting of photovoltaic generation in smart grid operation and control," Energies, vol. 6,no. 2, pp. 733–747, 2013.

[19] P. Bacher, H. Madsen, and H. A. Nielsen, "Online short-term solar power forecasting," Solar Energy, vol. 83, no. 10, pp. 1772–1783, 2009

[20] C. Chen, S. Duan, T. Cai, and B. Liu, "Online 24-h solar power forecasting based on weather type classification using artificial neural network," Solar Energy, vol. 85, no. 11, pp. 2856–2870, 2011.

[21] B. Wolff, E. Lorenz, and "Statistical learning for short-term photovoltaic power predictions," in Computational Sustainability, 2016.

[22] H. T. C. Pedro and C. F. M. Coimbra, "Assessment of forecasting techniques for solar power production with no exogenous inputs," Solar Energy, vol. 86, no. 7, pp. 2017–2028, 2012.

[23] L. Nonnenmacher, A. Kaur, and C. F. M. Coimbra, "Day-ahead resource forecasting for concentrated solar power integration," Renewable Energy, vol. 86, pp. 866–876, 2016.

[24] C. Tao, D. Shanxu, and C. Changsong, "Forecasting power output for grid-connected photovoltaic power system without using solar radiation measurement," in International Symposium on Power Electronics for Distributed Generation Systems, 2010.

[25] N. Al-Messabi, Y. Li, I. El-Amin, and C. Goh, "Forecasting of photovoltaic power yield using dynamic neural networks," in International Joint Conference on Neural Networks, 2012.

[26] R. J. Bessa, A. Trindade, and V. Miranda, "Spatial-temporal solar power forecasting for smart grids," IEEE Transactions on Industrial Informatics, vol. 11, no. 1, pp. 232–241, 2015.

[27] J. Liu, W. Fang, X. Zhang, and C. Yang, "An improved photovoltaic power forecasting model with the assistance of aerosol index data," IEEE Transactions on Sustainable Energy, vol. 6, no. 2, pp. 434–442, 2015.

[28] Y. Zhang, M. Beaudin, R. Taheri, H. Zareipour, and D. Wood, "Dayahead power output forecasting for small-scale solar photovoltaic electricity generators," IEEE Transactions on Smart Grid, vol. 6, no. 5, pp 2253–2262, 2015.

[29] R. Rasmussen, M. Dixon, F. Hage, and J. Cole, "Weather supportto deicing decision making (wsddm): A winter weather nowcasting system," Bulletin of the American Meteorological Society, vol. 82, no. 4, p. 579, 2001.

[30] Z. Sokol, "Nowcasting of 1-h precipitation using radar and nwp data,"Journal of Hydrology, vol. 328, no. 1, pp. 200–211, 2006.

[31] K. A. Browning and C. G. Collier, "Nowcasting of precipitation systems,"Reviews of Geophysics, vol. 27, no. 3, pp. 345–370, 1989.

[32] J. Shao and P. J. Lister, "An automated nowcasting model of road surface temperature and state for winter road maintenance," Journal of applied meteorology, vol. 35, no. 8, pp. 1352–1361, 1996.

[33] Z. Sokol and P. Peˇsice, "Comparing nowcastings of three severe convective events by statistical and nwp models," Atmospheric Research, vol. 93, no. 1, pp. 397–407, 2009.

[34] Liu, L., Kong, F., Liu, X., Peng, Y., Wang, Q., "18. A review on electric vehicles interacting with renewable energy in smart grid", 2015, Renewable and Sustainable Energy Reviews 51,4574, pp. 648-661

[35] M. Shamshiri, Chin Kim Gan, Chee Wei Tan "A review of recent development in smart grid and micro-grid laboratories", IEEE International, Power Engineering and Optimization Conference (PEDCO) Melaka, Malaysia, 2012, pp. 367-372.

[36] J. Monteiro, J. Eduardo, P.J.S. Cardoso, J. Semiao, "A distributed load scheduling mechanism for microgrids", IEEE International Conference on Smart Grid Communications, 2014, pp. 278-283.

[37] E. Nasrolahpour, M. Doostizadeh, H. Ghasemi, "Optimal management of micro grid in restructured environment", Second Iranian Conference on Renewable Energy and Distributed Generation (ICREDG), 2012, pp. 116- 120.

[38] E. Gonzalez-Romera, Barrero-Gonzalez, E. Romero-Cadaval, M.I. Milanes-Montero, "Overview of Plug-in Electric Vehicles as Providers of Ancillary Services", 9th International Conference on Compatibility and Power Electronics (CPE), 2015, pp. 516-521.

[39] Zhao, Awater, Schafer, Breuer, Moser, "Scenario-based evaluation on the impacts of electric vehicle on the municipal energy supply systems", IEEE Power and Energy Society General Meeting, 2011, pp. 1-8.

[40] Deilami, Masoum, Moses, Masoum, "Real-Time Coordination of Plug-In Electric Vehicle Charging in Smart Grids to Minimize Power Losses and Improve Voltage Profile", IEEE Transactions on Smart Grid, (Volume:2 , Issue: 3), 2011, pp. 456-467.

[41] S. Allard, Phen Chiak See, M. Molinas, O.B. Fosso, J.A. Foosnas, "Electric Vehicles Charging in a Smart Microgrid Supplied with Wind Energy", IEEE PowerTech (POWERTECH), Grenoble, 2013, pp. 1-5.

[42] Abousleiman, R., Al-Refai, A., Rawashdeh, O., "Charge capacity versus charge time in CC-CV and pulse charging of li-ion batteries", 2013 SAE Technical Papers.

[43] Ehsani, M., Gao, Y., Gay,S.,E., Emadi,A."Modern Electric, Hybrid Electric, and Fuel Cell Vehicles: Fundamentals, Theory, and Design",2005, CRC press.

[44] Ha, D.-L., Guillou, H., Martin, N., Cung, V.-D., Jacomino, M., "Optimal scheduling for coordination renewable energy and electric vehicles consumption" 2016, 2015 IEEE International Conference on Smart Grid

[45] Khemakhem, S., Rekik, M., Krichen, L., "A flexible control strategy of plug-in electric vehicles operating in seven modes for smoothing load power curves in smart grid", 2017, Energy 118, pp. 197-208.

[46] Laureri, F., Puliga, L., Robba, M., Delfino, F., Odena Bultò, G., "An optimization model for the integration of electric vehicles and smart grids Problem definition and experimental validation", 2016, IEEE 2nd International Smart Cities Conference: Improving the Citizens Quality of Life, ISC2 2016 – Proceedings.

[47] Tushar, M.H.K., Assi, C., Maier, M., Uddin, M.F., "Smart microgrids: Optimal joint scheduling for electric vehicles and home appliances", 2014, IEEE Transactions on Smart Grid.

[48] Yagcitekin, B., Uzunoglu, M. "A double-layer smart charging strategy of electric vehicles taking routing and charge scheduling into account", 2016, Applied Energy.

[49] Yang, H., Pan, H., Luo, F., Qiu, J., Zhang, P. , Lai, M., Dong, Z.Y. "Operational Planning of Electric Vehicles for Balancing Wind Power and Load Fluctuations in a Microgrid", 2016, IEEE Transactions on Sustainable Energy PP (99), 7577880.

[50] W. Xiaojun, T. Wenqi, H. JingHan, H. Mei, J. Jiuchun, H. Haiying, "The Application of Electric Vehicles as Mobile Distributed Energy Storage Units in Smart Grid", Asia-Pacific Power and Energy Engineering Conference (APPEEC), 2011, pp. 1-5.

[51] S. Bracco, F. Delfino, F. Pampararo, M. Robba, M. Rossi, "A dynamic optimization-based architecture for poly-generation micro-grids with trigeneration, renewables, storage systems and electric vehicles", Energy Conversion and Management 96, 2015, pp. 511-520.

[52] Soares, J., Fotouhi Ghazvini, M.A., Borges, N., Vale, Z., "A stochastic model for energy resources management considering demand response in smart grids", 2017, Electric Power Systems Research 143, pp. 599-610.

[53] Alipour, M., Mohammadi-Ivatloo, B., Moradi-Dalvand, M., Zare, K., "9. Stochastic scheduling of aggregators of plug-in electric vehicles for participation in energy and ancillary service markets", 2017 Energy 118, pp. 1168-1179

[54] Tabatabaee, S., Mortazavi, S.S., Niknam, T., "11. Stochastic scheduling of local distribution systems considering high penetration of plug-in electric vehicles and renewable energy sources", 2017, Energy 121, pp. 480-490.

[55] Soares, J., Ghazvini, M.A.F., Borges, N., Vale, Z., "Dynamic electricity pricing for electric vehicles using stochastic programming ", 2017, Energy 122, pp. 111-127.

[56] Arias, N.B., Franco, J.F., Lavorato, M., Romero, R., Metaheuristic optimization algorithms for the optimal coordination of plug-in electric vehicle charging in distribution systems with distributed generation, 2017, Electric Power Systems Research 142, pp. 351-361.

[57] Janjic, A., Velimirovic, L., Stankovic, M., Petrusic, A., "17. Commercial electric vehicle fleet scheduling for secondary frequency control", 2017, Electric Power Systems Research 147, pp. 31-41

[58] Jian, L., Zheng, Y., Shao, Z., "High efficient valley-filling strategy for centralized coordinated charging of large-scale electric vehicles" , 2017, Applied Energy 186, pp. 46-55.

[59] Carpinelli, G., Mottola, F., Proto, D., Varilone, P., Minimizing unbalances in low-voltage microgrids: Optimal scheduling of distributed resources, 2017, Applied Energy 191, pp. 170-182.

[60] Mortaz, E., Valenzuela, J., Microgrid energy scheduling using storage from electric vehicles, 2017, Electric Power Systems Research 143, pp. 554-562

[61] Kim, B.-G., Ren, S., Van Der Schaar, M., Lee, J.-W., "Bidirectional energy trading and residential load scheduling with electric vehicles in the smart grid", 2013; IEEE Journal on Selected Areas in Communications 31(7), 6547831, pp. 1219-1234.

[62] Alavi, F., Park Lee, E., van de Wouw, N., De Schutter, B., Lukszo, Z., "Fuel cell cars in a microgrid for synergies between hydrogen and electricity networks", 2017 Applied Energy 192, pp. 296-304.

[63] Shayegan-Rad, A., Badri, A., Zangeneh, A., "Day-ahead scheduling of virtual power plant in joint energy and regulation reserve markets under uncertainties", 2017, Energy 121, pp. 114-125.

[64] *Faria, R., Moura, P., Delgado, J., De Almeida, A.T., "Managing the charging of electrical vehicles: Impacts on the electrical grid and on the environment", 2014; IEEE Intelligent Transportation Systems Magazine 6(3),6861516, pp. 54-65.*

[65] *Mkahl, R., Nait-Sidi-Moh, A., Gaber, J., Wack, M., "An optimal solution for charging management of electric vehicles fleets", 2017 ; Electric Power Systems Research 146, pp. 177-188.*

[66] *Jannati, J., Nazarpour, D., Optimal energy management of the smart parking lot under demand response program in the presence of the electrolyser and fuel cell as hydrogen storage system, 2017; Energy Conversion and Management 138, pp. 659-669.*

[67] *Faddel, S., Al-Awami, A.T., Abido, M.A., Fuzzy Optimization for the Operation of Electric Vehicle Parking Lots, 2017, Electric Power Systems Research 145, pp. 166-174.*

[68] *Timpner, J., Wolf, L., "Design and evaluation of charging station scheduling strategies for electric vehicles", 2014; IEEE Transactions on Intelligent Transportation Systems 15(2),6651804, pp. 579-588.*

[69] *Clemente, M., Fanti, M.P., Iacobellis, G., Ukovich, W. "A discrete-event simulation approach for the management of a car sharing service", 2013; Proceedings - 2013 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2013 6721828, pp. 403-408.*

[70] *Simonov, M., Attanasio, A., "Cooperative recharge method of connected electric vehicles in smart grid", 2012; Proceedings - 2012 International Conference on Connected Vehicles and Expo, ICCVE 2012 6519597, pp. 329-334.*

[71] *Kong, F., Xiang, Q., Kong, L., Liu, X., "On-Line Event-Driven Scheduling for Electric Vehicle Charging via Park-and-Charge", 2017; Proceedings - Real-Time Systems Symposium 7809844, pp. 69-78.*

[72] *Di Giorgio, A., Liberati, F., Canale, S., "IEC 61851 compliant electric vehicle charging control in smart grids", 2013; 2013 21st Mediterranean Conference on Control and Automation, MED 2013 - Conference Proceedings 6608892, pp. 1329-1335.*

[73] *Di Giorgio, A., Liberati, F., "Near real time load shifting control for residential electricity prosumers under designed and market indexed pricing models", 2014; Applied Energy 128, pp. 119-132.*

[74] *Di Giorgio, A., Liberati, F., Canale, S., "Electric vehicles charging control in a smart grid: A model predictive control approach", 2014 ; Control Engineering Practice 22(1), pp. 147-162.*

[75] *De Craemer, K., Vandael, S., Claessens, B., Deconinck, G., "An event-driven dual coordination mechanism for demand side management of PHEVs" 2014; IEEE Transactions on Smart Grid 5(2),6565418, pp. 751-760*

[76] *Azar, A.G., Jacobsen, R.H., "Agent-based charging scheduling of electric vehicles", 2017; 2016 IEEE Online Conference on Green Communications, OnlineGreenComm 2016 7805408, pp. 64-69.*

[77] Fanti, M.P., Mangini, A.M., Pedroncelli, G., Ukovich, W., "A framework for the distributed management of charging operations", 2014; 2014 IEEE International Electric Vehicle Conference, IEVC 2014

[78] Amini, M.H., Moghaddam, M.P., Karabasoglu, O., "Simultaneous allocation of electric vehicles' parking lots and distributed renewable resources in smart power distribution networks",2017 Sustainable Cities and Society 28, pp. 332-342.

[79] Colson, C.M., Nehrir, M.H,(2009). "A review of challenges to real-time power management of microgrids," IEEE Power Energy Soc. Gen. Meet., pp.12-50,Calgary, AB, Canada.

[80] Katz,B.S., "Educating the smart grid," (2008) IEEE Energy2030 Conf., pp. 17–18, Atlanta, GA.

[81] Guan, X., Xu, Z., Jia, Q.-S., (2010) "Energy-Efficient Buildings Facilitated By Microgrid" IEEE Transactions On Smart Grid, vol. 1, No. 3, pp. 243.

[82] Fan, C., Xiao, F., Wang, S.(2014). "Development of prediction models for next-day building energy consumption and peak power demand using data mining techniques" Appl. Energy,vol. 127, pp. 1–10.

[83] Avci, M., Erkoc, M., Rahmani, A., Asfour, S (2013). "Model predictive HVAC load control in buildings using real-time electricity pricing," Energy Buildings, vol. 60, pp. 199–209.

[84] Yao, J., Costanzo, G.T., Zhu, G., Wen, B.(2015) "Power admission control with predictive thermal management in smart buildings" IEEE Transactions on Industrial Electronics 62 (4), pp. 2642-2650

[85] Gondhalekar, R., Oldewurtel, F .,Jones, C.N.(2013) "Least-Restrictive Robust Periodic Model Predictive Control Applied To Room Temperature Regulation," Automatica, vol. 49, pp. 2760–2766.

[86] Lee, K.-h., Braun, J.E.(2008) "Model-based demand-limiting control of building thermal mass," Building Environ., vol. 43, no. 10, pp. 1633–1646.

[87] E. Izgi, A. Öztopal, B. Yerli, M. K. Kaymak and A. D. Şahin, "Short–mid-term solar power prediction by using artificial neural networks," Solar Energy, vol. 86, no. 2, pp. 725-733, 2012.

[88] Mehleri, E.D., Sarimveis, H., Markatos, N.C., Papageorgiou, L.G. "A mathematical programming approach for optimal design of distributed energy systems at the neighbourhood level," Energy, vol. 44(1), pp. 96-104.

[89] Ma, Y., Borrelli, F., Hencey, B., Packard, A., Bortoff, S.. (2009) "Model predictive control of thermal energy storage in building cooling systems," Proc. IEEE CDC, pp. 392–397.

[90] F. Takens, Detecting strange attractors in turbulence. Springer, 1981.

[91] N. H. Packard, J. P. Crutchfield, J. D. Farmer, and R. S. Shaw, “Geometry from a time series,” Physical Review Letters, vol. 45, no. 9, p. 712, 1980.

[92] V. N. Vapnik, Statistical learning theory. Wiley New York, 1998.

[93] J. Shawe-Taylor and N. Cristianini, Kernel methods for pattern analysis. Cambridge university press, 2004.

[94] L. Ghelardoni, A. Ghio, and D. Anguita, “Energy load forecasting using empirical mode decomposition and support vector regression,” IEEE Transactions on Smart Grid, vol. 4, no. 1, pp. 549–556, 2013.

[95] L. Breiman, “Random forests,” Machine learning, vol. 45, no. 1, pp 5–32, 2001.

[96] D. Anguita, A. Ghio, L. Oneto, and S. Ridella, “In-sample and out-of-sample model selection and error estimation for support vector machines,” IEEE Transactions on Neural Networks and Learning Systems, vol. 23, no. 9, pp. 1390–1406, 2012.

[97] M. Fernández-Delgado, E. Cernadas, S. Barro, and D. Amorim, “Do we need hundreds of classifiers to solve real world classification problems?” JMLR, vol. 15, no. 1, pp. 3133–3181, 2014.

[98] N. Cristianini and J. Shawe-Taylor, An introduction to support vector machines and other kernel-based learning methods. plus 0.5em minus 0.4emCambridge university press, 2000.

[99] J. Smola and B. Schölkopf, “A tutorial on support vector regression,” Statistics and computing, vol. 14, no. 3, pp. 199–222, 2004.

[100] W. S. Lee, P. L. Bartlett, and R. C. Williamson, “The importance of convexity in learning with squared loss,” IEEE Transactions on Information Theory, vol. 44, no. 5, pp. 1974–1980, 1998.

[101] L. Rosasco, E. De Vito, A. Caponnetto, M. Piana, and A. Verri, “Are loss functions all the same?” Neural Computation, vol. 16, no. 5, pp. 1063–1076, 2004.

[102] G. Lugosi and K. Zeger, “Nonparametric estimation via empirical risk minimization,” Information Theory, IEEE Transactions on, vol. 41, no. 3, pp. 677–687, 1995.

[103] D. Anguita, A. Ghio, L. Oneto, and S. Ridella, “In-sample model selection for support vector machines,” in International Joint Conference on Neural Networks, 2011.

[104] L.ONETO F. LAURERI M.ROBBA F.DELFINO D.ANGUITA "Data-Driven Photovoltaic Power Production Nowcasting and Forecasting for Polygeneration Microgrid" IEEE Systems Journl, 2017

[105] Davide Anguita, Alessandro Ghio, Luca Oneto and Sandro Ridella “A learning machine with a bit-based hypothesis space,” in European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, 2013.

[106] Tikhonov and V. Y. Arsenin, Methods for solving ill-posed problems. plus 0.5em minus 0.4emNauka, Moscow, 1979.

[107] S. Ridella, S. Rovetta, and R. Zunino, "Circular backpropagation networks for classification," IEEE Transactions on Neural Networks, vol. 8, no. 1, pp. 84–97, 1997.

[108] D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning representations by back-propagating errors," Cognitive modeling, vol. 5, no. 3, p. 1, 1988.

[109] F. Bisio, P. Gastaldo, R. Zunino, and E. Cambria, "A learning scheme based on similarity functions for affective common-sense reasoning," in International Joint Conference on Neural Networks, 2015.

[110] G.-B. Huang, H. Zhou, X. Ding, and R. Zhang, "Extreme learning machine for regression and multiclass classification," IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 42, no. 2, pp. 513–529, 2012.

[111] G. Lever, F. Laviolette, and F. Shawe-Taylor, "Tighter pac-bayes bounds through distribution-dependent priors," Theoretical Computer Science, vol. 473, pp. 4–28, 2013.

[112] R. E. Schapire, Y. Freund, P. Bartlett, and W. S. Lee, "Boosting the margin: A new explanation for the effectiveness of voting methods," The Annals of Statistics, vol. 26, no. 5, pp. 1651–1686, 1998.

[113] Gelman, J. B. Carlin, H. S. Stern, and D. B. Rubin, Bayesian data analysis. plus 0.5em minus 0.4emTaylor & Francis, 2014.

[114] M. Bishop, Neural networks for pattern recognition. plus 0.5em minus 0.4emOxford university press, 1995.

[115] Anguita, A. Ghio, L. Oneto, and S. Ridella, "Selecting the hypothesis space for improving the generalization ability of support vector machines," in International Joint Conference on Neural Networks, 2011, pp. 1169–1176.

[116] M. Fern´andez-Delgado, E. Cernadas, S. Barro, and D. Amorim, "Do we need hundreds of classifiers to solve real world classification problems?" JMLR, vol. 15, no. 1, pp. 3133–3181, 2014.

[117] Efron, "Bootstrap methods: Another look at the jackknife," The Annals of Statistics, vol. 7, no. 1, pp. 1–26, 1979.

[118] Hernández-Lobato, G. Martínez-Muñoz, and A. Suárez, "How large should ensembles of classifiers be?" Pattern Recognition, vol. 46, no. 5, pp. 1323–1336, 2013.

[119] G. Biau, "Analysis of a random forests model," JMLR, vol. 13, no. 1, pp. 1063–1095, 2012.

[120] S. Bernard, L. Heutte, and S. Adam, "Influence of hyperparameters on random forest accuracy," in International Workshop on Multiple Classifier Systems, 2009.

[121] Coraddu, L. Oneto, F. Baldi, and D. Anguita, "Ship efficiency forecast based on sensors data collection: Improving numerical models through data analytics," in OCEANS 2015-Genova, 2015.

[122] *Delfino, F., Minciardi, R., Pampararo, F., Robba, M. (2014). "A Multilevel Approach for the Optimal Control of Distributed Energy Resources and Storage", IEEE Transactions on Smart Grid, Special Issue on Control Theory and Technology in Smart Grid, pp. 2155-2162.*

[123] *Figueiredo, J., Sá Da Costa, J, (2012)"A SCADA system for energy management in intelligent buildings", Energy and Buildings, Vol. 49, pp. 85–98, Bune .*

[124] *Minciardi, R, Robba, M., "A Bi-level Approach for the Stochastic Optimal Operation of Interconnected Microgrids", IEEE Transactions on Automation Science and Engineering, 2018*