



A Contribution Towards Predictive Control for Energy Management in Micro-grids Systems: Application into a Smart and Energy Efficient Buildings

Elmouatamid Abdellatif

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Chouaib Doukkali University

Faculty of sciences

PhD Thesis in

Energy Engineering and Automation

Presented by

Abdellatif EL MOUATAMID

A thesis submitted in fulfillment of the requirements for the degree of
PhD of Chouaib Doukkali University

A Contribution Towards Predictive Control for Energy Management in Micro-grids Systems: Application into a Smart and Energy Efficient Buildings

Presented on December 30, 2020 in front of the jury members:

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Dedication . . .

à mes parents ; j'espère que ce travail soit une prière pour mes parents et pour l'âme de mon père qui nous a quittés pendant la préparation de cette thèse. Ce travail est le fruit des sacrifices de mes parents et de leurs efforts fournis jour et nuit pour mon éducation et mon bien être

à ma famille

à mes collègues

à mes encadrants

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The Framework of the Thesis Work

This thesis's work is carried out within the project MIGRID (Towards Smart Grids: Renewable Energy Integration into Smart Buildings), funded NAS ([National Academy of Sciences](#)) under USAID PEER ([Partnership for Enhanced Engagement in Research](#)) program, Cycle 5 - 398 (2017-2020).

MIGRID involves two Moroccan universities ([Chouaib Doukkali University](#), [Al-Akhawayn University in Ifran](#)) and one US university ([University of Houston](#)). Its main objective is the development and the deployment of Smart Grids technology in Morocco, via the promotion of Renewable Energy Integration into Smart Buildings.

ABSTRACT

The general context of this thesis concerns the integration of RESs (Renewable Energy Sources) into smart MGs (micro-grids) for buildings in order to support the continuous growth of buildings' electricity demands. However, their intermittent nature and unpredictable variability represent the main challenge of their efficient and seamless integration into buildings. Energy storage systems are considered among the most promising technologies that could balance RESs production with buildings' energy consumption. Electrochemical (batteries) storage systems are the most deployed in buildings. This is due to their multiple advantages, mainly modularity, cleanliness, and high efficiency. However, the unpredictable and discontinuous nature of the power production and consumption make the power management in MG systems a difficult task. Therefore, intelligent control strategies are required for efficient energy management in MG systems.

This thesis focuses on the development and deployment of an intelligent and predictive control strategy for energy balance in MG systems. A predictive control approach, named MAPCASTE (Measure, Analyze, Plan, ForeCAST, and Execute), is developed and deployed in real-sitting scenarios. Mainly, MPC (Model Predictive Control) and GPC (Generalized Predictive Control) have been investigated in order to carry out the proposed MAPSASTE. This later was deployed and evaluated by assessing its effectiveness for energy management in MG systems. In particular, modeling, simulation, experimentation, and performance assessment of the deployed MG system, together with the developed control approach, have been performed. Experimentations have been conducted using a real MG platform, which was deployed in the frame of two research & development projects.

Keywords: *Micro-grid systems, energy management, predictive control, renewable energy sources, battery storage system, information and communication technologies, IoT/Big-Data.*

Résumé

Le contexte général de cette thèse concerne l'intégration des sources d'énergie renouvelables (RES) dans les micro-réseaux (MG) afin de faire face à la croissance continue de la demande en électricité des bâtiments. Cependant, le caractère intermittent et la variabilité imprévisible des RESs représentent le principal défi à relever afin de permettre leur intégration efficace dans les bâtiments. Les systèmes de stockage d'énergie sont considérés parmi les technologies les plus prometteuses qui pourraient équilibrer la production des RES avec la consommation d'énergie. Les systèmes de stockage électrochimiques (batteries) sont les plus déployés dans les bâtiments. Cela est dû à leurs multiples avantages, principalement la modularité, la propreté et le rendement élevé. Cependant, la nature imprévisible et discontinue de la production et de la consommation d'énergie rend la gestion de l'énergie dans les systèmes MG une tâche difficile. Par conséquent, des stratégies de contrôle intelligentes sont nécessaires pour une gestion efficace de l'énergie dans ces systèmes.

Dans la présente thèse, une approche de contrôle intelligent et prédictif est proposée afin de permettre une gestion efficace d'énergie dans les systèmes MG. Cette approche, nommée MAPCASTE (Mesurer, Analyser, Planifier, ForeCAST et Exécuter), est développée et déployée dans des scénarios réels. Principalement, les techniques MPC (Model Predictive Control) et GPC (Generalized Predictive Control) ont été étudiés afin de réaliser l'approche MAPSASTE. Cette dernière a été déployée et son efficacité pour la gestion de l'énergie dans les systèmes MG est évaluée. En particulier, la modélisation, la simulation, l'expérimentation et l'évaluation des performances du système MG déployé, ainsi que l'approche de contrôle développée, ont été effectuées. Des expérimentations ont été menées sur une plateforme MG, qui nous avons déployée dans le cadre de deux projets de recherche.

Mots clés : *Système micro-réseaux, gestion de l'énergie, contrôle prédictif, sources d'énergie renouvelables, système de stockage batterie, technologies de l'information et de la communication, IoT / Big-Data.*

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LIST OF ACRONYMS

AC	Alternative Current
AIC	Akaike Information Criterion
ANN	Artificial Neural Network
ARIMA	AutoRegressive Integrated Moving Average
ARX	Auto Regressive model with eXternal inputs
BIC	Bayesian Information Criterion
C/D	Charge/Discharge
CARMA	Controller Auto-Regressive Moving-Average
CAS	Collective Adaptive Systems
CC	Central Controller
CCS-MPC	Continuous Control Set MPC
D/R	Demand/Response
DC	Direct Current
EEBLab	Energy Efficient Building Laboratory
EM	Energy Management
FCS-MPC	Finite Control Set MPC
FL	Fuzzy Logic
GPC	Generalized Predictive Control
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information and Communication technologies
IGBT	Insulated Gate Bipolar Transistor
IGDT	Information Gap Decision Theory
IoE	Internet of Electricity
IoS	Internet of Services
IoT	Internet of Things
LC	Local Controller
LPPT	Limited Power Point Tracking
LSTM	Long Short-Term Memory
MAB	Multi-Agent-Based
MAE	Mean Absolute Error
MAPCASTE	Measure, Analyze, Plan, ForeCAST, and Execute
MG	Micro-Grid
MILP	Mixed Integer Linear Programming
ML	Machine Learning

MPC	Model Predictive Control
MPPT	Maximum Power Point Tracking
MQTT	Message Queue Telemetry Transport
MSE	Mean Square Error
NLP	Nonlinear Programming
NZEB	Net Zero Energy Building
OCV	Open Circuit Voltage
OSS-MPC	Optimal Switching Sequence MPC
OSV-MPC	Optimal Switching Vector MPC
PID	Proportional Integral Derivative
PMSG	Permanent Magnet Synchronous Generator
PV	Photovoltaic
RES	Renewable Energy Sources
RTU	Remote Terminal Units
SCADA-EMS	Supervisory Control and Data Acquisition-Energy Management System
SG	Smart Grid
SoC	State of Charge
SVM	Space Vector Modulation
TEG	Traditional Electrical Grid
WT	Wind Turbine

General Introduction

According to recent statistics from the International Energy Agency, the global energy demand grew fast pace during the last decades. This exceptional increase is due mainly to the robust economy and high heating and cooling needs. For that, fossil sources are still the most suitable solution to tackle the constant rise in energy consumption. As a result, global energy-related CO₂ emissions rose by 1.7% to 33.5 Gigatonnes in 2019 causing an increase in the greenhouse effect and global warming. However, electrical energy is considered as the “fuel” of the future with a global electricity demand growing by 4.4% in 2019 to more than 23000 (TWh). Face to this increase in the global electricity demand, more urgent actions are needed to develop all clean energy solutions and to improve efficiency, especially the building sector, which represents 20% of the total energy consumption. However, recent studies predict a drop in global energy demand of 5% in 2020 due to the impacts of the health crisis Covid-19 pandemic (IEA, 2020), as shown in Figure 0.1. Especially for the main energy sources, the consumption of petroleum and coal is expected to decline by 8% and 7% respectively.

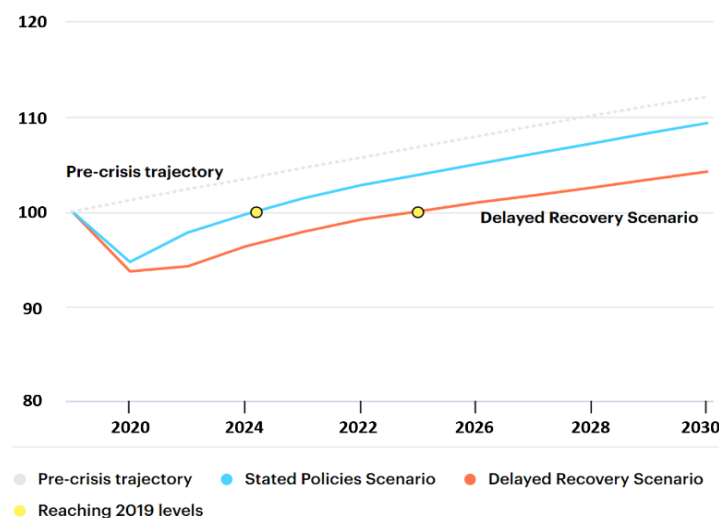


Figure 0.1. Global primary energy demand growth by scenario, 2019-2030 (IEA, 2020)

The international energy agency also expects demand will not be returned to pre-coronavirus levels. It will account for less than 20% of energy consumption by 2040, for the first time since the industrial revolution. The agency suggested that it is the best period to make more efforts to never become to traditional energy sources revolution. In this way, only structural changes, in the power production and consumption methods, can improve the revolution towards clean energy sources. Previously, electrical energy was produced almost exclusively from pollutant sources in centralized environments and consumed completely in decentralized locals. For environmental and economic reasons, this old structure of energy

production generated more greenhouse gas and it required the establishment of a network to transport the energy produced in a few production plants to the final consumers. Therefore, the consumers are encouraged to develop decentralized means of electricity production based on the use of RESs in order to increase the energy efficiency of production, which contributes to producing “cleaner” energy.

Mainly, renewable energies come from solar, wind, water stream (hydraulic), wood energy, and from other plants or urban waste (biomass). Mostly, solar and wind energy are considered as the main renewable sources that are more reliable, safe, and very easy solutions for being integrated in buildings. However, the integration of renewable energy into buildings can cause challenges and impacts for the system operation. Three main types of problems could appear concerning RESs integration:

- RESs have a significant cost and consume a lot of energy in their fabrication. To compensate for this ecological debt and to maximize profitability, the production of these sources should be maximized. In fact, wind energy is the energy extracted from the wind using an aero generator device, such as a WT. Among RESs, wind power is, currently, the best in terms of economic profitability. By considering the energy and materials necessary for the construction and assembling equipment, the deployment of one MW of WT on a windy site avoids an annual injection of 2000 tons of CO₂ in case if the electricity produced came from fossil sources. In addition, a 2.5 MW WT has a lifecycle of around 20 years under normal operating conditions and can produce, in just two to three months, all the energy consumed for its realization. However, the cost of this installation is expensive and cannot be insured by a simple consumer. In fact, dimensioning a small turbine should be combined with other solutions like PV panels. However, solar energy constitutes the easily exploitable energy in a very strong evolution in the two types that are PV and thermal energy. The inconvenience of PV systems is their yield of 3 to 15% and their significant investment cost/energy produced ratio. According to the German Ministry of the Environment (BMU) report, PV systems need 2 to 5 years to amortize the energy consumed for their construction, including the cost of manufacturing and assembly. To maximize the efficiency of RESs, hybrid PV and wind systems have been developed.

- Storage devices are the most critical component of the system, having a very limited life depending on charge-discharge cycles and being to be changed when the yield decrease. For that, a good control strategy to manage the D/R of the storage devices is needed. For example, by considering the different factors that can damage the batteries, the yield of the

installation can be increased and the profitability of the system will be more significant. However, the environmental conditions of the batteries, cyclic life, depth discharge, temperature, and recharge rate are the different factors that can cause fast damage to the batteries. In fact, the batteries will be changed more frequently and automatically in the long term, the profitability of the installation decreases due to the high cost of the storage devices (batteries).

- The main limitation of RESs is that they depend entirely on weather conditions, which have a stochastic nature and very changeable behaviors during the day and the season. Mainly, the production is limited during some periods that cannot have a coincidence with the consumption periods and the generated power should be stored or injected during peak production. For example, the PV system generates power during sunny days, the consumers can use the power generated totally or partially and the surplus could be stored to be used during the night. Moreover, during the night or cloudy day, the system cannot satisfy the demand and the consumer should have other sources to accumulate the energy need. For the wind generation, the production is very variable compared to the PV systems due to the variable nature of the wind speed and direction for the same period. However, this stochastic nature of the weather conditions generates a large variability on the RESs production and a time lag between the electrical power production and real consumption. Generally, this factor decreases the flexibility and the reliability of the system and the balance of the power flows will be more complex.

Face to these problems, a hybrid system of RESs can be used to increase the reliability of the system (Figure 0.2). However, it requires efficient sizing, modeling, and analysis of its components together with intelligent platforms in order to ensure the balance between production and consumption (D/R control), while maintaining the storage devices in their good state of health. At the same time, the building is connected to the TEG to ensure the power to the loads if the RES cannot satisfy the demand. Such systems require a good strategy for monitoring, control, and effective management. In fact, the management of these hybrid systems of RES requires the use of ICT for developing intelligent control strategies. For instance, in the context of buildings management, an MG consists of household appliances (Loads) connected by an energy network (e.g., RES, storage devices, TEG), and by a communication infrastructure allowing the interaction between the different components of the MG system (Figure 0.2).

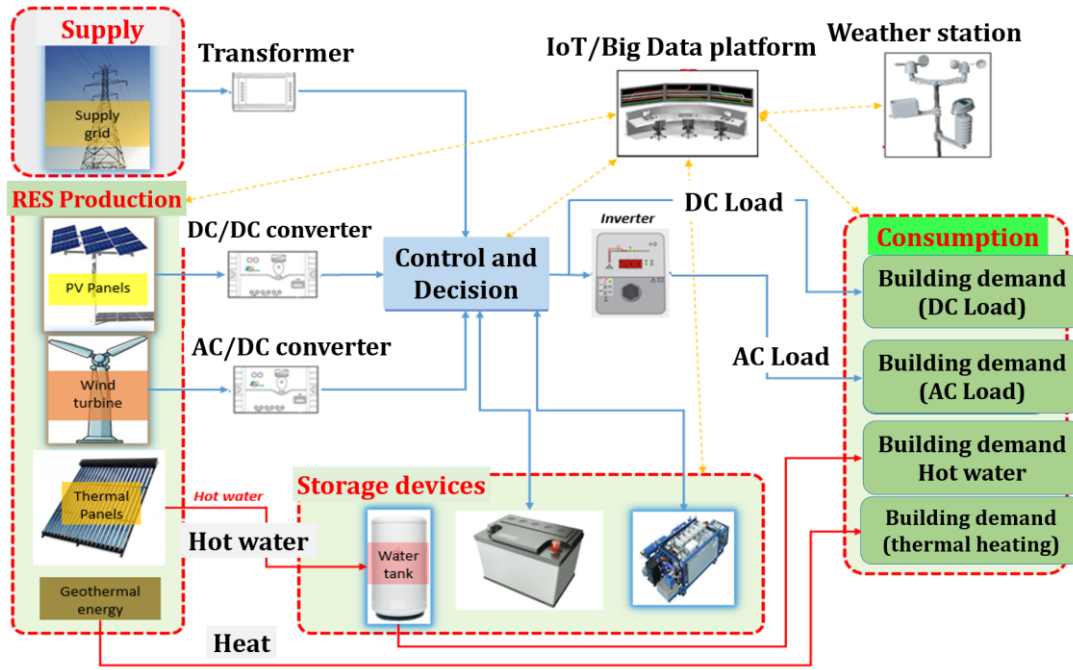


Figure 0.2. A holistic system architecture of RES and data monitoring platform

In our studies, and in order to take the abovementioned constraints into account, we consider that the MG system can be structured in one vertical and three horizontal layers. The first horizontal layer concerns all architectural design aspects and the building's envelope (e.g., orientation, insulation materials). The second layer focuses on the integration and the control of all passive/active systems (e.g., HVAC, lighting), while the third layer concerns the integration and the management of hybrid RESs system (e.g., solar energy, wind). A vertical layer has been incorporated, and includes recent technologies (e.g., IoT/Big-data, wireless communications). It is worth noting that this work is a part of the work we are undertaking under MIGRID project, which aims to develop techniques and tools for sizing, modeling, simulation, and experimentation of a smart MG system. As shown in Figure 0.2, this system is mainly developed and deployed for investigating innovative approaches in the context of energy efficiency in buildings.

The work described in this dissertation concerns the third layer by investigating RESs connection, integration, and management. In this layer, the aim is to determine, on-the-fly, the best energy assignment plan as well as a good compromise between energy production and energy consumption in order to increase the energy efficiency of buildings while keeping at maximum as possible the occupants' comfort. Unfortunately, the unpredictable and discontinuous nature of the power production and consumption make the power management in the MG system a difficult task in order to satisfy the control constraints and to maximize a

ratio between user satisfaction and cost. Moreover, such systems require a good strategy for monitoring, control and effective management.

In this dissertation, an intelligent predictive control approach, named MAPCASTE (Measure, Analyze, Plan, ForeCAST, and Execute over knowledge base) is investigated and developed to perform an instantaneous equilibrium of the D/R balance. In fact, the developed approach should be able to predict, estimate, and control the interaction between power production, storage devices, and building demands. However, integrating RES into the MG systems requires real-time tracking of the amount of expected consumption (Demand) and the amount of produced energy (Response) in order to smooth electricity flow and avoid blackouts. Therefore, a holistic platform, including RES, storage devices, IoT/Big-Data platform, and context-awareness control, have been developed and deployed. More precisely, a hybrid system of RES is developed with the different layers that constitute the MG system concept. This hybrid system is connected to an advanced metering infrastructure using the recent IoT/Big-data technologies for measurement, data monitoring, and processing. The RESs (e.g., PV system, WT) coupled with storage systems (e.g., batteries) are modeled, simulated, and experimented. This aspect of modeling is important because the overall efficiency of the control algorithm will depend on the ability of the model to monitor simultaneously the evolution of the multi-source energy system and the consumption of the building. From the simulation model, experiments are carried out to validate the obtained results.

In summary, the main contributions of this work are as follows:

- A Demand/Response control strategy is developed to balance the power flows between RES (e.g., PV, WT), storage devices (e.g., batteries), and the utility grid. For this part, the work focuses on two approaches. The first approach concerns the classical control approaches (e.g., On/Off, PID). Most of these methods are based on real-time data processing to generate control actions according to predefined rules and fixed schedules. The second approach concerns the control predictive approaches. For these approaches, different constraints and optimization functions are modeled and integrated in order to generate the control actions. In this work, a MPC control strategy is developed to control the whole system. The deployed predictive control strategy approach manages the MG in order to maximize the usage of the RES and to minimize the usage of the utility grid by considering the storage devices' limits. Simulations and experimentations have been conducted to study the usefulness of the platform and the effectiveness of the proposed D/R control approaches. Therefore, the GPC model is

integrated based on the deployed MPC strategy, and the usefulness of this new predictive control is presented to minimize the electricity bill for consumers.

- A platform that integrates IoT/Big-data technologies is developed for data monitoring and real-time processing. In this platform, different sensors are installed in the MG for data measurement (e.g., current, voltage, power, temperature). Data collected from these sensors need to be processed in real-time in order to figure out the right control decision according to actual situations (e.g., occupancy, energy consumption-production patterns, and weather conditions data). Furthermore, these data have to be stored for further analysis, especially for developing predictive control strategies using ML (machine learning) algorithms. In addition, the platform integrates both IoT/Big-data technologies for data acquisition and data processing/visualization.

This Dissertation is structured into five chapters as follows. In the first chapter, actual statistics for energy demand are presented together with the principal problems encountered in the TEG. It analyzes the challenges for the actual electrical network and presents the benefits that can be ensured by integrating the concept of the MG system in the traditional electrical networks. The chapter presents the context of the MG buildings system, which is a complex and major energy consumer node.

The second chapter presents a state of the art of control approaches associated with the energy balance in MG systems. Principally, this study is carried out in order to define the suitable control approach for MGs for EM in buildings by identifying the interconnection method and the main components of the system. Classification of approaches is also given in order to shed more light on the need for predictive control for EM in MGs. A general overview of the main predictive control approaches for EM systems is introduced.

In chapter three, the concept of the MG system is presented with the different main layers that constitute the MG structure. In fact, the different energetic components are modeled in order to have both real and experimental MG system modeling offering the possibility to test and validate the studied control approaches. Moreover, an MG system infrastructure is developed together with a platform for data gathering, monitoring, and processing. We put more emphasize on MG systems as crucial infrastructures for leveraging energy-efficient and smart buildings by developing and deploying a holistic IoT/Big-Data platform in which sensing and actuation tasks are performed according to the actual contextual changes.

In chapter four, simulation and experiment results are presented to validate the different components in our deployed MG system together with naïve control scenarios. The aim is to show the usefulness of this holistic platform for monitoring, data processing, and control in energy-efficient buildings. An MG system platform is deployed and validated with a control card for EM approaches deployment. This MG is used to validate and to deploy the different scenarios presented in this work. It is named EEBLab located at the International University of Rabat, in Morocco. The EEBLab MG system is used actually as a research platform for MG systems development and test of research works.

Chapter five focuses on the development of a model predictive control strategy, named MAPCASTE, for energy balance in MG systems. This later was deployed and evaluated by assessing its effectiveness for EM in MG systems. In fact, the main aspect of the proposed MAPCASTE approach is to measure, in real-time, the main input control parameters; analyzing and processing data, predicting future behaviors, forecasting suitable commands to reach the desired setpoint depending on the predefined constraints and objective functions, and correcting the errors depending on the real measurements. The main objective is to connect efficiently the electricity generators and consumers by predicting the most suitable actions for energy flow management. More precisely, based on energy production and consumption profiles as well as the availability of energy storage systems, the proposed control strategy selects the best suitable energy source for supplying the building's loads. The electricity price is integrated as a cost function to be minimized while respecting the defined constraints. Simulations have been conducted and results are presented to validate the proposed predictive control approach by showing its effectiveness for MG systems control. The powerful of the MAPCASTE for the EM system was shown by minimizing the electricity bill.

Finally, general conclusions and perspectives are presented. This part gathers the most relevant results and the main contribution of the thesis. The main challenges and ongoing works are presented concerning the implementation of the proposed control strategies.

Chapter 1: Micro-Grid Systems for Smart and Energy Efficient Buildings

1. Introduction

The past decades have seen strong growth in global energy demand, in particular gas, oil, and electricity. Electricity is one of the main resources for modern economic development and it is providing a rising share of energy services. Demand for electricity is set to increase as a result of rising household demand, with the electrification of transport (e.g., electrical vehicle) and increasing demand for digitally connected devices and air conditioning systems (Figure 1.1). Furthermore, the increase in electricity demand was one of the key reasons why global CO₂ emissions from the power sector reached a high record in the past decades. Innovative solutions and actions should be developed, especially for high electricity consumers, in order to reduce greenhouse gas emissions. For instance, the consumption in buildings has increased and it accounts currently for over 40% of total energy consumption due to increased demand for building services and indoor environmental quality (e.g., heating, cooling) (Cao, Dai, & Liu, 2016). A significant energy saving can be, however, achieved if buildings are correctly constructed, controlled and operated.

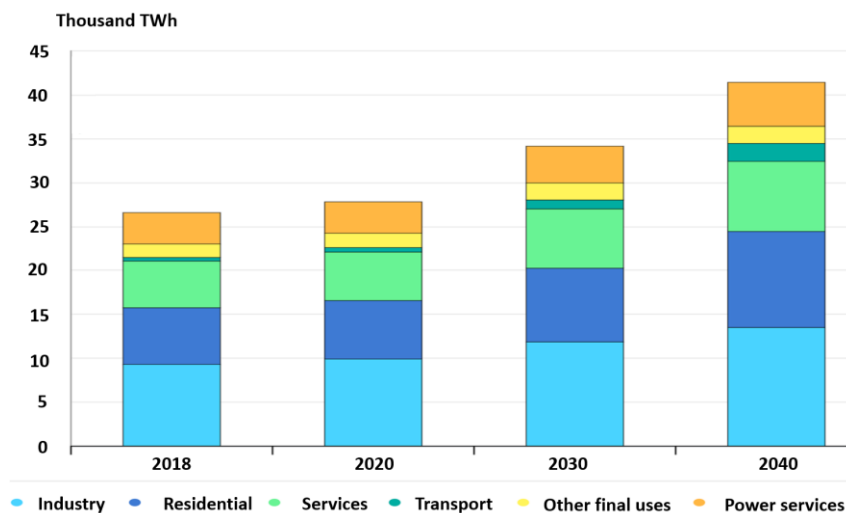


Figure 1.1. Electricity demand by sector, 2018-2040 (International Energy Agency, 2019)

RESs are considered as the main solution to decrease electricity consumed from TEG. The share of these sources to the global electricity demand is increased constantly (Figure 1.2). Unfortunately, the unpredictable and discontinuous nature of these renewable energies makes these RES difficult to control and manage. Therefore, it is necessary to characterize as precisely as possible the production of these sources. The influence of unpredictable and

discontinuous nature can be diminished by coupling two or more RESs (e.g., solar thermal energy, PV, wind, hydraulic, biomass). In some locations, the wind is more stable and almost permanent and the WT can produce significant power. For other places, sunny days are relatively more important along the year and the PV system can be more efficient. For that, a hybrid system of RES that combines several sources together with storage devices (e.g., batteries, fuel cells) is highly recommended. The objective of this system is to combine the advantages and the best operational characteristics of each energy source in order to increase the reliability and the flexibility of the whole system.

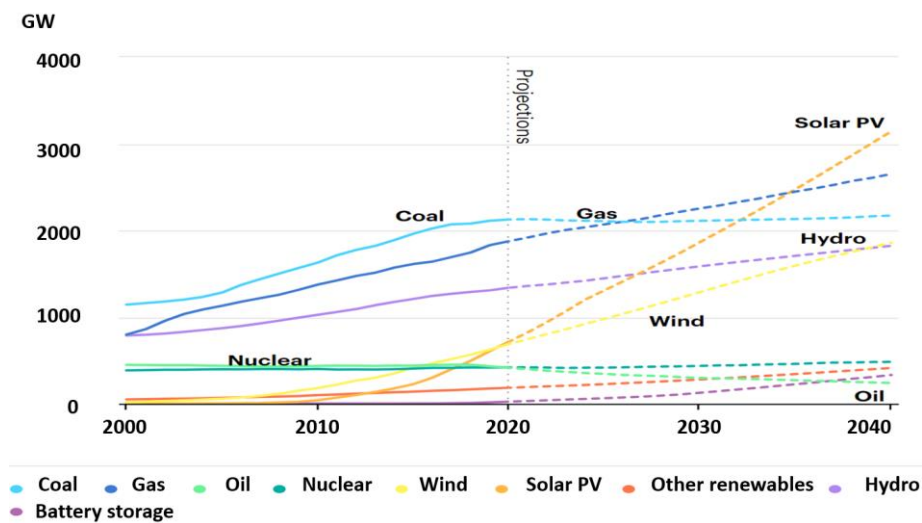


Figure 1.2. The international installed power generation capacity by source, 2000-2040
(International Energy Agency, 2019)

However, due to the intermittent and irregular nature of the RES production and the limit of storage devices, the electric grid could be integrated in order to eventually ensure the power demands while ensuring the quality and the reliability of electrical services. This simple hybrid system needs to be automatically controlled accordingly. In fact, D/R control approaches are required for balancing the intermittent RES generation while handling the delay, which might occur between the power production and the actual building's consumption. In fact, a controllable building that integrates these elements together with the TEG is known as MG systems.

In this chapter, the concept of MG buildings systems is presented by highlighting the need for integrating hybrid systems of RESs together with EM for efficiently operating and controlling the MG systems.

2. The traditional electrical grid problems

This section is dedicated to the TEG structure and the problems related to energy transport, distribution, and consumption. The aim is to show the usefulness of the new concept of MG systems.

2.1. Traditional electrical grid structure

For technical, environmental and economic reasons the current production of electrical energy is geographically distributed. While consumers are, at the same time, grouped and concentrated at some distributed locations. In order to supply energy to customers, electricity networks are established between these two units. Electricity is amplified at the high voltage on the transport network and regularly it becomes medium on the distribution networks in order to be, finally, on low voltage for the end consumer (Figure 1.3).

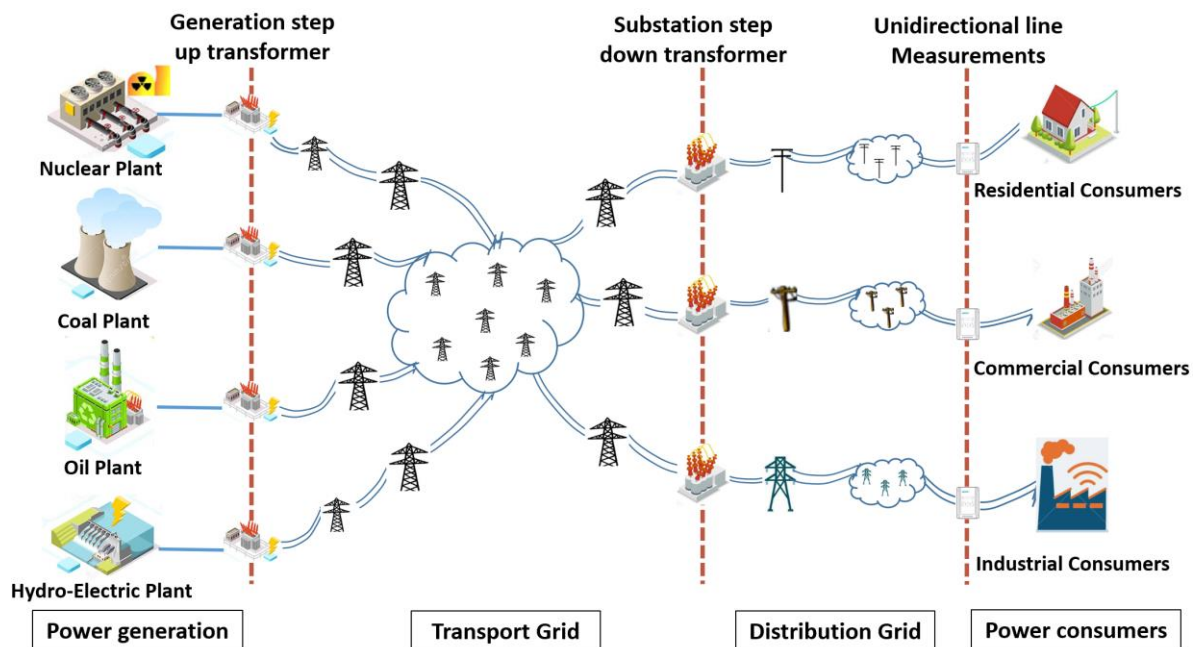


Figure 1.3. TEG system architecture

The major objective of this structure of the electricity network is to maintain a permanent balance between electricity consumption and production. While the structure of this electrical network is well organized, it suffers, however, from different problems that can be simplified as follows:

- **Electrical distance:** to understand the structure of the electrical network, we need a measure of electrical connectivity distance. This electricity transport distance is variable depending on the consumer's location, voltage, the section of the line, and its power. These

parameters combined to generate a “voltage drop” proportional to the section and the length of the line. The voltage drop is closely related to the losses ([Hines et al., 2010](#)).

- Voltage drop: its origin is mainly due to the heating of the cables that are used to transport higher currents and to the natural resistance of the cable as well. A visible “voltage drop” is generated at the end of the receiver line. The transformer at the end of the line generally compensates these falls causing a loss of power. For example, on a 300 km line, a “voltage drop” of 450 V is observed, depending on the section and the length of the line. For a 6000 V line, it corresponds to a “voltage drop” of 7.5%, which is not negligible. This “voltage drop” will be 600 V, for a 225 kV line, presenting 0.2% of the initial voltage and it is partially negligible. The problem is that the line voltage cannot exceed a limit due to the materials used for cables’ insulation ([Salvador, 2012](#)).

- Frequency: in an electrical network, active and reactive power has to be in balanced condition with the power demanded by the consumers including the losses in the transport lines. The unbalance condition that happens from power production is not equal to the demanded power. The unbalance between both elements causes a deviation of the system frequency from its setpoint value (50/60Hz). Maintaining the frequency at the selected values is a critical issue because all the elements of the network are sized and optimized to work at the same value (50 or 60 Hz). If the frequency is above or below this threshold value, the losses on the network increase and the machines can probably be damaged causing a blackout of the whole system.

- Cable resistance: the current limit is imposed by the section of the cable of the line that can act as a resistance. It heats and expands when it is crossed by a high current and it can generate enormous problems for the electrical network. This phenomenon rises exponentially when the upper load limit is exceeded and it can cause a blackout of the whole network ([Granizo et al., 2018](#)).

2.2. The increase of residential sector demand

Energy demand from buildings continues to rise due to the robust development of household appliances and to the HVAC systems usage (Figure 1.4). Various techniques could be used to increase the energy efficiency of buildings. The envelope and the design of the building could improve the thermal performance of buildings. The second key aspect is related to the control of active equipment (e.g., lighting, HVAC) and services ([Berouine,](#)

Ouladsine, & Bakhouya, 2019a; Lachhab et al., 2018b) (Figure 1.5). Recently, many studies have shown the necessity of integrating and deploying RES in buildings.

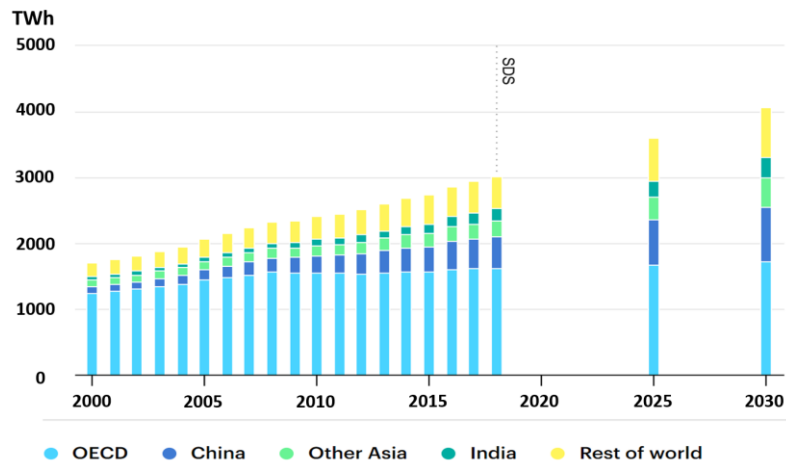
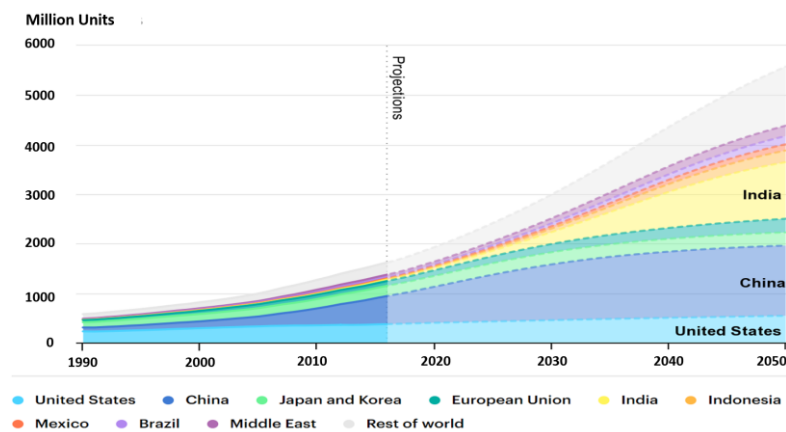
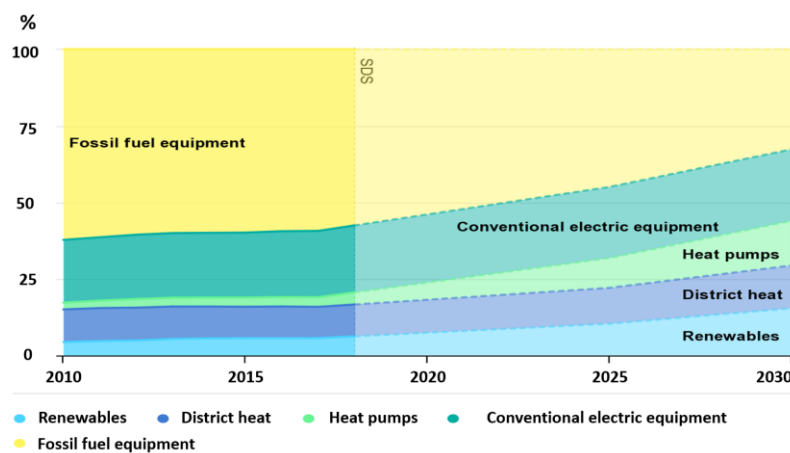


Figure 1.4. Power consumption for household appliances by region, 2000-2030 (International Energy Agency, 2019)



a)



b)

Figure 1.5. a) Global air conditioner stock; b) Heating technology sales (International Energy Agency, 2019)

The aim is to increase significantly the energy efficiency in buildings and to minimize the consumption from the TEG. This topic is one of the main focuses of regional, national, and international energy policies. For example, the European Commission has adopted the “20-20-20” strategy, which focuses on three principles: 20% reduction of greenhouse gas emissions, 20% decrease of electrical energy demand by increasing energy efficiency, and 20% share of the RES production in total energy consumption compared to 1990 levels. The project is extended to 2030 with new objectives and charges (European Commission, 2020a, page: 4) (Figure 1.6). However, despite the willingness of integrating these systems, still many issues have to be addressed, especially the EM for their seamless integration with buildings.

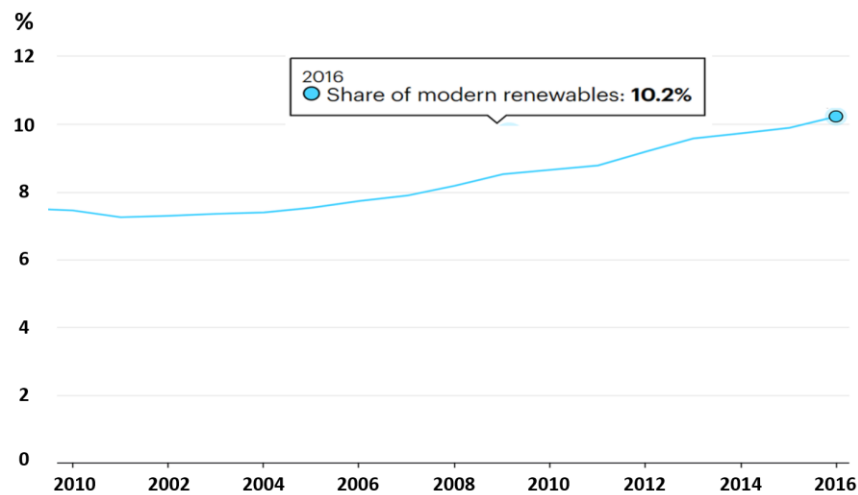


Figure 1.6. RES share in the final energy consumption for residential sector (International Energy Agency, 2019)

2.3. Peak of demand

Due to the variability of the electricity consumption profile during the day and season, peak periods of consumption can be produced as a result of the variable nature of the potential demand. This major problem of the electricity network operation generates significant problems of the whole system operation, especially, frequency and voltage variability. For the proper grid's operation, the operator must constantly balance production and consumption of both active and reactive power, in order to maintain the frequency and voltage amplitude close to their nominal values. In fact, maintaining the frequency on the nominal value is a crucial issue because all the elements of the electrical network are sized and optimized to work at the selected frequency (50 or 60 Hz). On the electrical network, an excess of power results in an increase in voltage and frequency, which is not desirable. To regulate this situation, a balance must be ensured between the produced and consumed power. Certainly, a difference between

the supply and electricity demand causes braking or acceleration of the alternators, which produce the voltage of the electrical network. For the alternators, the voltages produced have a frequency proportional to the speed of rotation and three cases can be mentioned (Figure 1.7): *i)* the power consumption is higher than power production, in this case, the frequency decreases compared to the nominal value; *ii)* the power consumption is lower than the power production and the frequency increases compared to the nominal value; *iii)* a balance between power production and power consumption, in this case, the frequency is established to the nominal values.

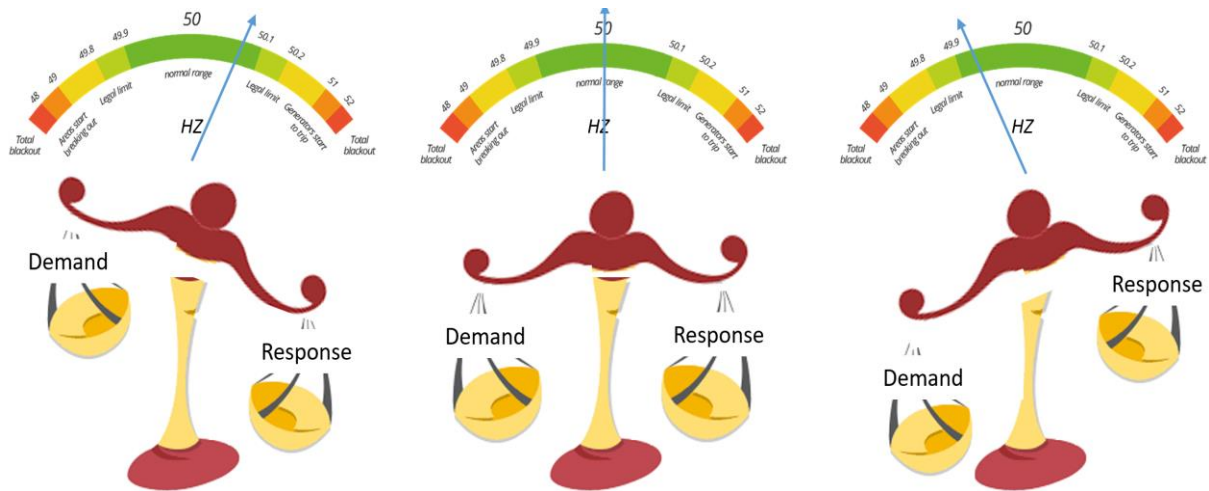


Figure 1.7. Frequency variability depending on power D/R variability

Moreover, this frequency variability is due to the voltage variability between the generators and consumers. For that, matching electricity generation precisely to the consumer on a second-by-second basis is the main challenge and the overriding principle of operation of any large-scale electricity network. The failure to manage this issue will result in a blackout of the network. To tackle these problems, the operators look to balancing services by controlling the alternators. However, in the TEG, the operators do not have any control or management of power consumption; they can only interact with the power production variability. Therefore, the residential consumption present generally two interesting peaks demand observed during the daily consumption curve, as shown in Figure 1.8. The daily consumption curve, as depicted in Figure 1.8, shows two peaks of demand, one in the morning and the second in the evening. This daily electricity consumption curve is a daily reflection of our lifestyles, which also depends on the season of the year. Especially in winter, over 24 hours, electricity consumption represents a peak in the morning, with an increase from 06:00 AM to 08:00 AM.

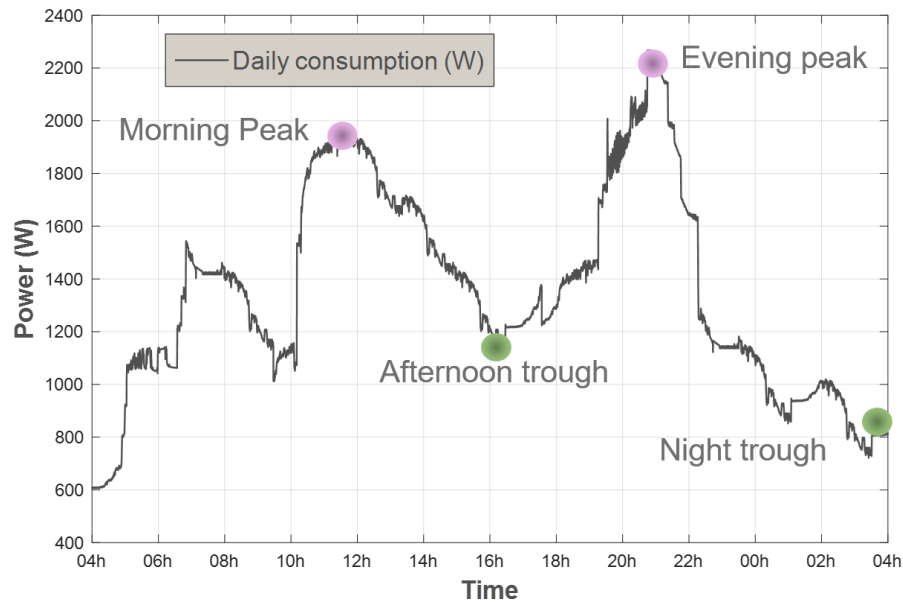


Figure 1.8. Daily consumption example from the installed EEBLab

At this hour, daytime life restarts its rhythm, the peoples switch ON the light, operate household appliances for breakfast, and take shower. As shown in the curve, the morning pear covers the noon period and a dip in the afternoon is observed. Around 07:00 PM, it is the evening peak and, therefore, the consumption increases to the maximum due to the different activities and household operations (e.g., TV, HVAC, lighting). During these peaks, the operators should manage this variability of consumption by interacting in the generator's operation and a forceful possibility of a blackout is present.

3. Local energy production: renewable energy sources and storage

3.1. Renewable energy benefits and challenges

The development and the exploitation of renewable energies have improved significantly in the past decades years due to the capability of RES to meet the rising power demands and reduce environmental pollution. Renewables, including solar, wind, hydraulics, biomass, and others, are at the center of the transition to fewer greenhouse gas emission sources and more sustainable energy systems. Generally, this decentralized electricity, which is produced from RESs, provides greater security to supply the power to consumers when the main energy source is unavailable. RESs are locally integrated into buildings allowing an additional energy source to be added to the system and can replace some (or all) of the energy coming from the network (TEG). However, a system for electricity generation, which depends entirely on the RESs, is not reliable due to the available nature of these renewable sources, which cannot be

constantly assured. This electrical generating system involves natural phenomena that are replenished constantly, such as sunlight and wind. In fact, the fundamental issues that should be addressed to improve the deployment of these sources can be summarized in the following sub-sections.

3.1.1. Production delay

The RES power production cannot be adapted to the consumption profile of users during the day. Generally, the peak demand is displayed during the morning and the evening periods as mentioned in the previous sections. During this time, the RESs power generations (especially the PV production) are not available and other sources are required. In addition, during peak production, the generated power cannot be consumed totally by the demand and should be stored or injected in the TEG.

3.1.2. Sources not guaranteed

The RESs depend entirely on weather conditions and unfortunately, we cannot guarantee the presence of the sun or wind. For that, other guaranteed sources should be installed together with storage systems. In fact, a good sizing of storage devices is required, but for a large scale, this solution makes the installation more expensive. However, storage devices are the most critical component of the system, having a very limited life depending on charge-discharge cycles and being changed when the yield decreases.

3.1.3. Service quality

PV system and wind power installations do not offer kinetic energy due to the electronic technologies used for the different equipment for PV and for wind power installations, which, therefore, tends to increase the frequency and voltage variation rates. Mainly, RESs should offer the possibility of power frequency adjustment to ensure safety and good quality to the electricity injected in the TEG. When the presence of these sources is massive on an electrical network, the characteristics make it more difficult to maintain the stability of the system and can be incompatible with the dynamic of the security management of the electrical network. Moreover, PV and wind installations present rapid variations in their production. This instability requires the use of intelligent and predictive control strategies in order to adjust in real-time the D/R balance.

3.1.4. Installation cost

RESs equipment consumes a lot of energy in their fabrication and the cost of these solutions stays a little higher compared to other traditional generators. Unlike traditional technologies, the efficiency of renewable technologies is generally very specified by the environmental constraints and more the sources are worked at their maximum more the profitability of the system will be maximized. Therefore, comparisons should be made based on optimal usage conditions. For example, RESs energy is locally delivered and the cost should be compared to the delivered energy from traditional sources including transport and distribution cost. However, the cost difference still favors fossil fuel technologies than RESs due to their higher cost. Mainly, significant policy actions enhanced levels of investment in research and development to minimize the RESs production cost by developing other technologies for PV and wind systems.

3.1.5. Difficult to predict

The weather conditions have a direct effect on the RESs power generation and the stochastic nature of these inputs parameters (e.g., temperature, irradiance, wind speed) makes it difficult to predict the output of the system (power generation). Research work focusing on the power forecast is one of the main solutions that can be used to minimize the effect of the different RES problems. For example, the very short-term forecast can be used to avoid the cut of electricity in a local installation range by interacting with the storage devices. The aim is to make more stable the variability of the frequency and the voltage. In addition, a short-term forecast can be used to optimize the production planning of the different means of the system, in particular, start/stop actions for hydraulic inventory management policies, which take normally a long time to interact with the electricity demand variability. Moreover, a long-term forecast makes it possible to anticipate potential breaks in D/R balance by adjusting the operating program of the various production sources. It can be used to design correctly the economic strategies for a country, to guarantee the electricity offer and to plan the maintenance time for large scale PV and WTs installations.

Actually, to maximize the efficiency of the RES, hybrid PV and wind systems have been developed. The objective of this system is to combine the advantages and the best operational characteristics of each energy source. However, the integration of storage systems is recurred to reduce the intensity of different problems. In the next section, different storage systems that can be combined with RES are presented by focusing on those that are used in our deployed MG system.

3.2. Benefits of electrical energy storage systems

Different kinds of technical and technological solutions are proposed face to the intermittent problem of RES. The integration of storage systems is considered as one of the effective solutions to eliminate or to minimize the intensity of the different mentioned problems. The electrical energy storage systems can balance the variability and the intermittency of power supply for a system, which is based partially or totally on RESs power generation. They can help to eliminate some fundamental services problem in an electrical network, such as frequency and voltage stability.

The necessity of an energy storage system is to provide flexibility and improve the reliability of renewable energy systems. It is one of the main solutions to balance the energy supply and demand for RES systems. In fact, the deployment of an energy storage system is not only for balancing the power flow but also for reducing significantly the cost of the electricity bill. However, in a TEG network, the peak demand periods are managed by starting up fuel, coal, or nuclear plans. For decentralized electricity generation systems, the storage systems can be used locally to supply power during peak demand. In addition, electrical equipment can deteriorate due to the intermittent production of electricity from RES. For that, using storage devices, the service quality can be ensured on the distribution network by adjusting the frequency and voltage variability. Moreover, according to the size and to the technical specifications, storage systems can offer warranties in terms of power predictability, stability, or even provide a programmable energy dispatch while ensuring the system services, which are required for the proper functioning of electrical systems. For example, the power generated by the fuel-cells in an MG system varies on voltage and frequency and the use of batteries is recommended to stabilize this variability and to ensure some quality to the electrical service.

In the current context of renewable energies development, storage systems, therefore, appear as an essential solution to promote the insertion of the predictive control for EM and to improve energy efficiency. It is also a solution to increase the safety and flexibility of systems, which are connected to the electrical network by regulating the frequency and voltage variability caused by the power D/R variability. Especially, for the predictive control strategies, energy storage promotes an important role in energy balance with the possibility to have decentralized storage that can be controlled centrally. Furthermore, the cost optimization function can be integrated into the control strategies for EM-based storage devices. This

minimization of cost bill can be achieved by charging the storage system during the periods of least demand and discharging during the peak demand. Generally, different services can be rendered by the storage systems as illustrated in Figure 1.9.

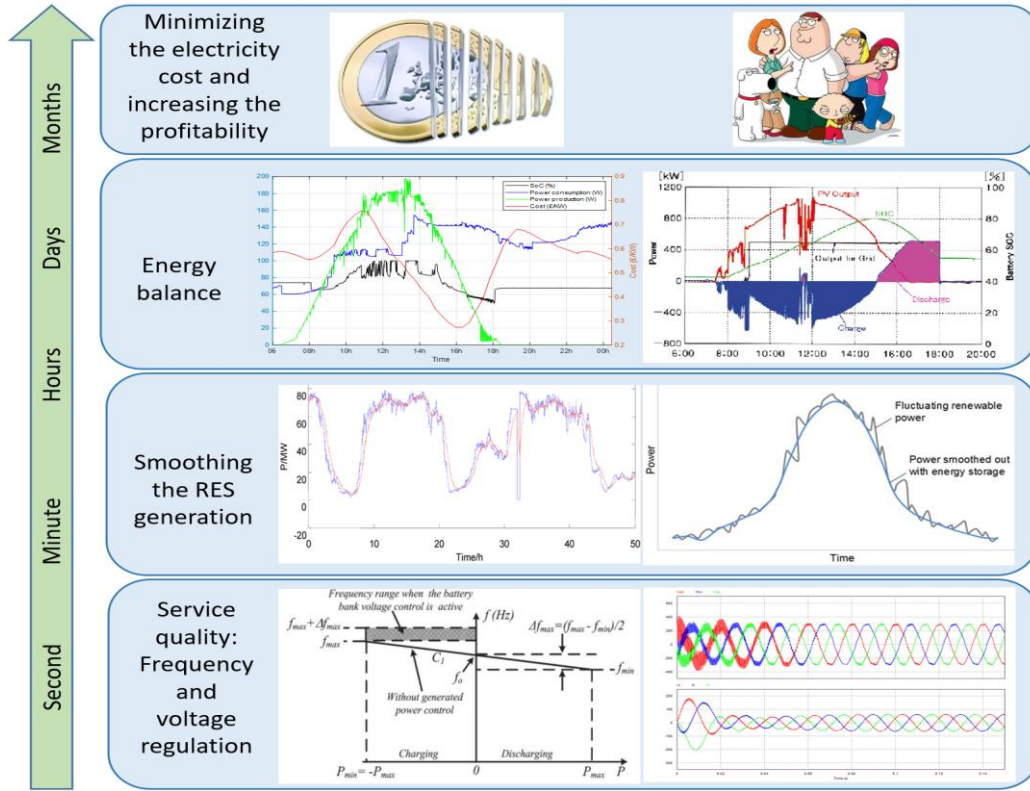


Figure 1.9. Storage systems usefulness for RES deployment

It is recommended to conduct more research work in order to reduce the costs of the different kinds of storage devices, which should make it possible to respond to significant deployment challenges and to increase the profitability of the system as well. However, it is required for the EM control strategies to consider the state of health of storage devices (e.g., batteries) by minimizing as much as is possible the cycle of C/D while keeping a good service quality for consumers.

4. Towards smart MG systems

4.1. MG system as a part of smart grid system

The integration of RESs for large-scale of electrical energy production has recently accelerated because of evident climate change, insufficiency of fossil resources, and greenhouse gas emissions. RES are clean and eco-friendly sources and their abundance and renewable nature are among the most important factors for their integration into SG networks.

However, these green energy sources come with new challenges, mainly their seamless integration with existing electrical networks. In addition, another important challenge for this new electricity infrastructure is real-time monitoring and data processing, which requires new ICT-based infrastructures (Figure 1.10). The main aim is to ensure sustainable and reliable renewable energy generation systems (Berouine et al., 2019b; Kabalci & Kabalci. Y, 2019). Therefore, this integration of ICTs, energy distribution systems, as well as distributed energy generation systems (e.g., RESs), creates what is commonly named “Smart Grid” (SG). In fact, SG represents the new smart electrical network, since it brings the flexibility to integrate new electrical services, such as electrical vehicles, and enables consumers to be energy producers by integrating RESs using a bidirectional communication network (Asaad et al., 2019). This depends mainly on the fast advances in ICT-based infrastructures covering then all aspects of the electricity grid and its associated services. In fact, due to the development of IoT infrastructures and their related intelligent services, the electricity grid has new capabilities to monitor, manage, and control its components and then takes advantage of sophisticated bidirectional interactions. Moreover, the ICTs integration enables various smart and automatic services, such as smart metering infrastructure, smart control and management for D/R balance, advanced electricity marketing, and intelligent energy storage for electrical vehicles integration.

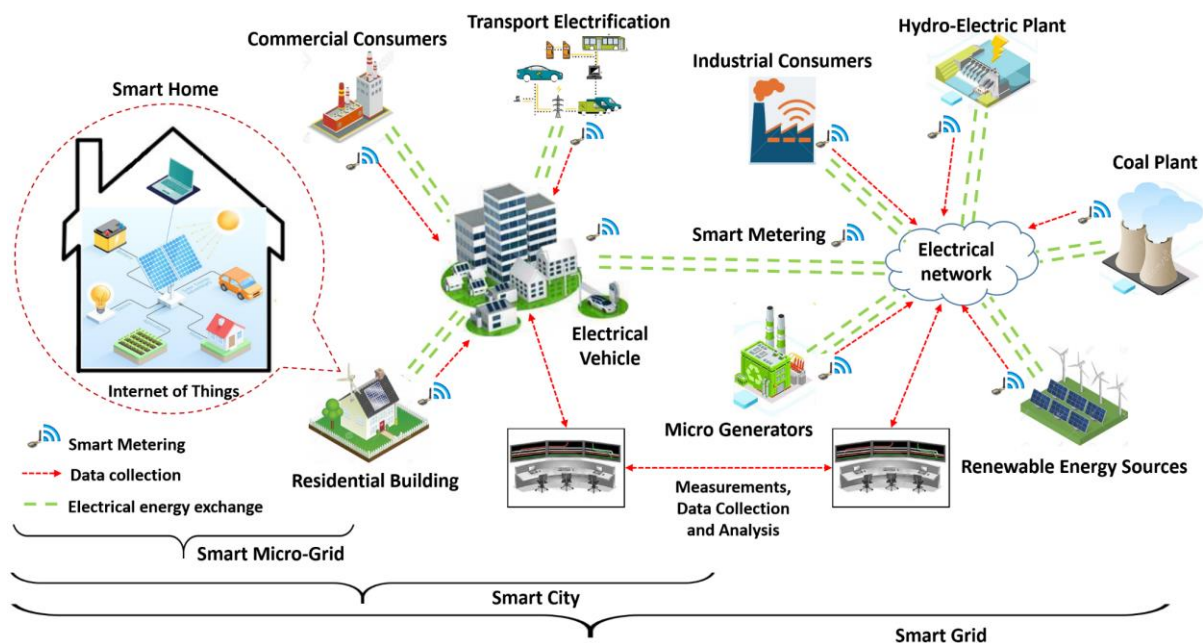


Figure 1.10. Global architecture: From SG to smart MG

However, despite this progress, some research work stated that the SG is experiencing new challenges. Mainly, it is able to manage only electrical energy neglecting other existing

types of energy (e.g., thermal, chemical, and electrochemical). In addition, the SG is based on the actual infrastructures of power distribution grids, which are limited by the unidirectional exchange of the electricity (Wang et al., 2017). Therefore, face these challenges; other concepts have been developed together with the revolution of SG, such as the IoE, the IoT, and the IoS, as mentioned in Figure 1.11 (Tsiatsis et al., 2018). Especially, the development and the emergence of smart MG systems could resolve some of the abovementioned SG challenges. MG could simplify the management of electrical energy, from centralized to distribute EM. In addition, in MG systems, different types of energy can be managed locally with the possibility to interconnect different MGs in a distributed manner.

Depending on the scale of the system, numerous definitions for MG systems have been proposed. For two European projects, named “Microgrids” and “More Microgrids”, the MG system is considered as a basic feature of future active distribution networks and it is composed of more than one building (Kanchev, 2014). For instance, in Greece, the “Kythnos Island Microgrid” is composed of 12 houses connected to a solar PV plant and battery bank. The PV plant comprises 10 kW of PVs for energy generation, a nominal 53-kWh for the battery bank, and a 5-kW diesel generation. A second PV plant of about 2 kW, mounted on the roof of the control system building, is connected to 32-kWh of the battery bank in order to provide power for monitoring and communication (Hatziargyriou et al., 2007).

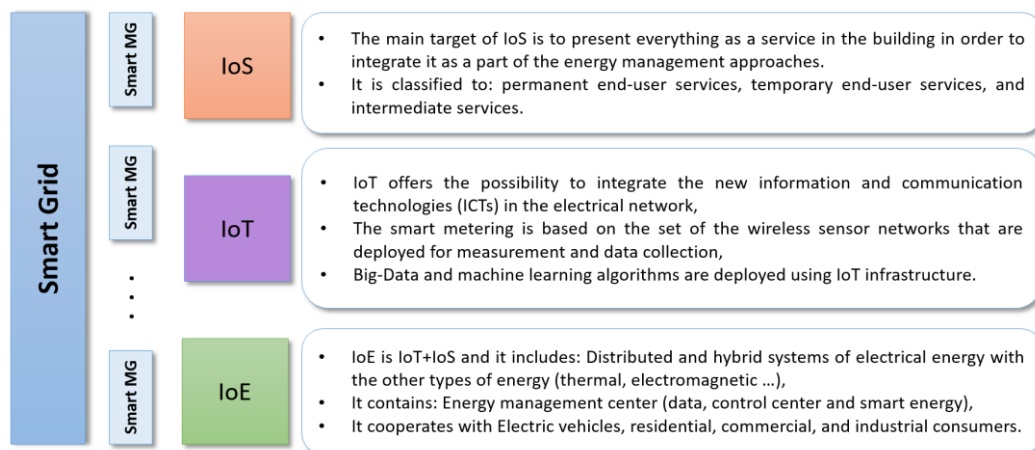


Figure 1.11. SG and smart MG presented as a combination of IoE, IoT and IoS

Another system in Germany for “More Microgrids” project, named “MVV Residential Demonstration”, is installed at Mannheim-Wallstadt. The project prepares about 20 families for a continuous long-term field test site that are considered as one MG. In fact, the first goal of the experiment is to involve customers in load management. For that, 30 kW of PV is already installed. Based on PV power availability information from their neighborhood, the

families shifted their consumption when it is possible to use directly solar energy. As a result, participating families shifted their consumption significantly from the typical residential evening peak toward hours with the higher solar insolation, and from cloudy days toward sunny days ([Hatziaargyriou et al., 2007](#); [European Commission, 2020b](#)).

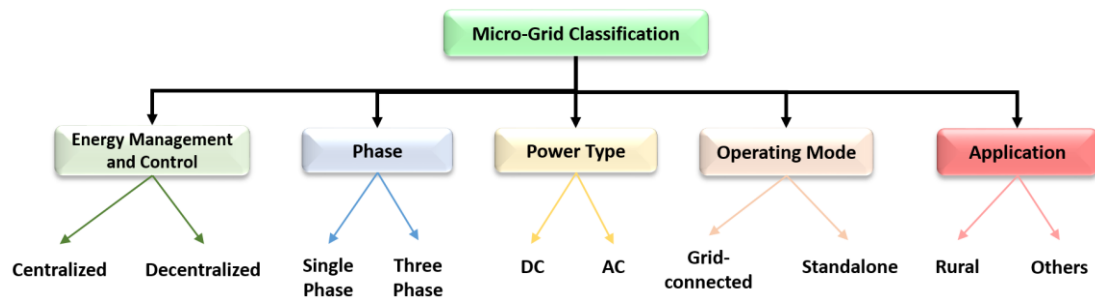
In the United States, there are many projects in universities and military bases already developed with an estimated global market rise from about 3.2 GW in 2019 to 15.8 GW by 2027 (including all types of MG systems, as it is depicted in Figure 1.12), where only the United States accounted for almost 35% of this market in 2018 ([Microgrid Knowledge, 2020](#)). The most well-known researches and development project, named “Consortium for Electric Reliability Technology Solutions” (CERTS), is developed for the power system reliability of emerging technology in MG systems. The project is provided for relatively small sites ($\sim <2$ MW at the peak) and it is delivered for a research platform, which is considered as an MG installed in a laboratory at the University of Wisconsin, Madison ([Consortium for Electric Reliability Technology Solutions, 2020](#)). Another interesting international standard is Japan, which sets ambitious targets for increasing the contribution of RESs in MG systems. In fact, the research funding and management agencies of the Ministry of Economy, Trade, and Industry have started different MG projects. Mainly, a recent project named “Integrating renewables into the Japanese power grid by 2030” is involved. In this project, Japan’s Renewable Energy Institute (REI) and “Agora Energiewende” attempt to integrate renewables energy into Japan’s power grids without endangering grid stability, the study also promotes data transparency. International experience has shown, however, that a number of technical measures, not yet widespread in Japan, can be safely implemented to improve grid stability ([Renewable Energy Institute, 2018](#)).

4.2. MG system types and benefits

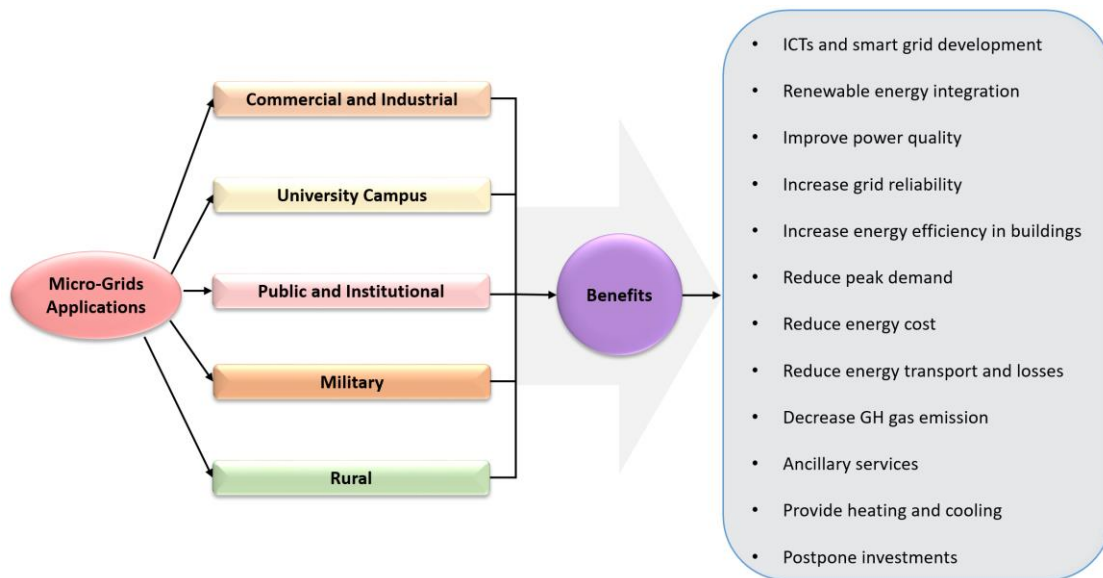
4.2.1. MG system types

A large part of research projects considers large-scale buildings and RESs plants as MG systems. For instance, according to the MG operation mode, different types of MG systems are classified as depicted in Figure 1.12.a. Similarly, by considering the applications and the objectives ([Guimaraes, 2020](#)), another classification is presented in Figure 1.12.b. Other academic researches present the MG system as a single building, which integrates ICTs infrastructure, RESs, and energy storage with the electrical power grids. For instance, in ([Zhang, Gatsis, & Giannakis, 2013](#); [Dagdougui, Ouammi, & Sacile, 2017](#)), the MG systems

are defined as smart power systems that are grouped together within a limited geographic area. They include loads, distributed generation units, and energy storage systems (batteries, electric vehicles, hydraulic storage, etc.). The main advantage of MG is to enable customers to have both a bidirectional communication platform and control devices to manage their energy needs and excesses. In addition, with an adequate communication structure, it is possible to shape the users' load demand curves by means of D/R strategies.



a)



b)

Figure 1.12. MG system types and benefits

Other works present the MG as a systematic and efficient approach for managing the power system by integrating all distributed generating sources into a micro-power system (Kumar, Zare, & Ghosh, 2017; Fathima et al., 2018). For example, in (Kumar, Zare, & Ghosh, 2017), authors defined the MG system as a low-voltage power network with distributed energy generation (e.g., PV arrays, micro-wind turbines, fuel cell, energy storage), which offers better control capability over network operation. It is considered as a solution to meet the local energy demand by connecting distributed power generation to distribution networks,

such as local substations without further expansion of costly centralized utility grids. In addition, the United State Department of Energy (DOE) defines an MG as follows: “An MG is a group of interconnected loads and distributed energy sources within clearly defined electrical boundaries that act as a single controllable entity with respect to the grid” (Chauhan & Chauhan. K, 2019).

4.2.2. MG system benefits

Distributed energy resources is a new structure of electricity network that improved the concept of MG system, in which the classical consumers are becoming a producer of electricity with the possibility to store locally the electricity. Mainly, the hybrid system notices the energetic layer of an MG system while combining this layer with communication and envelope layers presents the MG system concept. The hybrid system of RESs combines several sources connected together with energy storage devices and the utility grid in order to deal with the problem of renewable energy intermittent power. The main objective of this system is to profit from the advantages and the best operational characteristics of each energy source. Generally, a hybrid system of RESs is connected to an energy storage system using an identified interconnection topology. Depending on the location and on the dimensioning of the components, it can be autonomous (standalone) or connected to the TEG (grid-connected). For the MG system, PVs panels, small or medium-sized WTs, and batteries are the most components that are used to provide the power demanded by consumers (Figure 1.13).

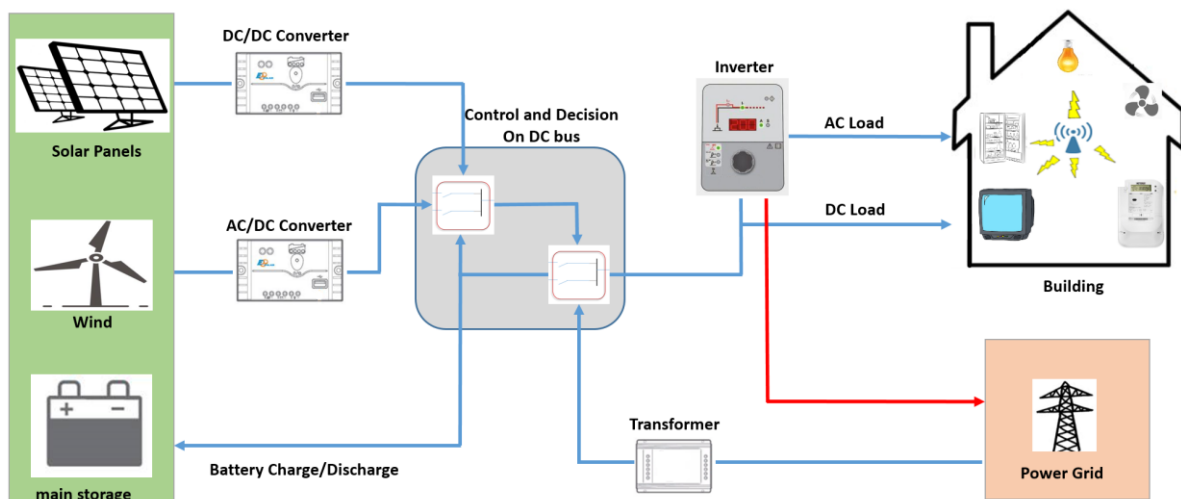


Figure 1.13. Hybrid system of RESs

The integration of different RESs in a hybrid system, as mentioned above, is a significant approach towards realizing reliable, secure, and efficient electrical power systems for

buildings. However, in order to ensure the proper integration of the hybrid system into buildings and especially in the MG system, different standards and requirements are developed to normalize the usage of this architecture. For example, the standards IEC 61000 and EN 50160 are defined in Europe and IEEE C37.95, IEEE 37.118, and IEEE 1547 in the US ([Elmouatamid et al., 2020a](#)). These standards present the principal requirements and criteria concerning the secure integration and protection of the MG system.

4.3. MG systems for smart buildings

For our specific definition, the MG systems for smart buildings can be seen as socio-technical systems that integrate different heterogeneous entities (e.g., sensors, actuators, lighting, HVAC, occupants, RES, storages), which could interact dynamically and in a collective manner to balance between energy efficiency, occupants' comfort, sustainability, and the adaptability. More precisely, making buildings more energy-efficient while ensuring occupants' comfort require incorporating mechanisms and techniques, which allow entities interacting in order to perform suitable actions (e.g., turning On/Off HVAC and lighting, balancing the fluctuation between power production and consumption) as shown in Figure 1.14. As stated in ([De Florio et al., 2013](#); [Bakhouya et al., 2017](#); [Lachhab et al., 2017a](#)), systems operating in dynamic environments with these capabilities are qualified as socio-technical CAS. These systems should learn and evolve by performing distributed decisions at different temporal and spatial scales while self-organize when entities join or leave the collective (e.g., occupants' number and presence). For instance, platforms for buildings' EM could react to the dynamic changes (e.g., buildings occupants' preference, number, presence) for lowering energy consumption while making occupants' life more comfortable and consequently, increasing the energy efficiency in buildings. Mainly, one of the most important factors that define the "Smart Buildings" is the adaptability. It is defined as the characteristic of buildings to use information gathered from a range of sources to prepare the building for a particular event before that event has happened (e.g., predictive control, occupants forecasting) ([Elkhouchi et al., 2018a](#)). The adaptability allows the differentiation between previous generations of buildings and Smart Buildings. In fact, using IoT/Big-Data technologies, the buildings gather data externally (e.g., weather conditions, RES production) and internally (e.g., occupancy, loads consumption) to adapt its operations depending on the context-awareness principles.

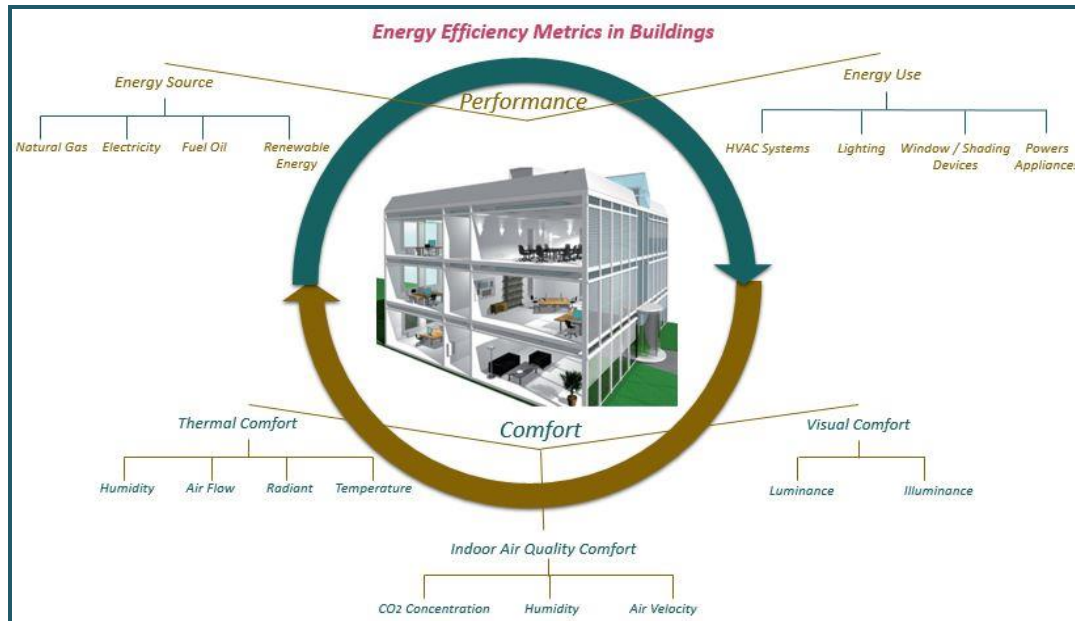


Figure 1.14. Energy efficiency and occupants' comfort metrics (Bakhouya et al., 2017)

The collected data is used to develop ML algorithms that are used to forecast the actions, which are required to perform and operate different buildings' services. For example, the forecast of weather conditions can be used to predict the RESs production, which allows flexible management of energy D/R. In addition, by measuring the energy production/consumption and by forecasting the occupant's activities, the adaptive buildings modify the starting time of temporary end-user services (e.g., washing machine service, cooking service). However, these above-mentioned aspects represent the main factors to develop the concept of "Micro-Grid" systems. It is due to the capabilities of recent ICTs techniques (e.g., ML, IoT) to forecast future events, which are required to develop efficient EM approaches.

4.4. International MG standards

The MG concept is relatively new and the regulatory framework is still under development. It should be standardized for being integrated into the existing electrical grid network. In this way, several research groups within the International Electro-technical Commission (IEC) are working on the question of standardizing systems that use renewable energies. The standards consider the power quality (e.g., frequency, voltage, harmonic noise), the components (e.g., inverters, converters), the architecture and design of MG, and the size of the integrated renewable sources (e.g., generated power, low-voltage, medium voltage). In addition, the MG systems should respect the existing electrical norms and their deployments.

Especially, for MG that are connected to the electrical network, the inverter should ensure the electricity quality avoiding then the injection of noise in the utility grid.

4.4.1. International standards for distributed energy integration

Realizing specific technical standards are difficult and the standards concerning RESs integration have some differences in different worldwide locations due to the different operational methods, the EM strategies, and the different penetration levels and types of RESs and storage devices. For instance, in the United States, the IEEE-1547 series of standards covers all aspects related to the interconnection of distributed energy resources with the electrical grid. These standards impose requirements on the quality of the energy produced in terms of voltage, frequency, and harmonics. It provides requirements relevant to the interconnection and interoperability performance, operation, testing, safety, maintenance, and security considerations. The first revision of 1547 assembles several participants whose investor affiliations, manufacturers and integrators, test labs, research groups, and academia. The full revision of 1547 issues, concerns, and updates are being coordinated with corresponding standards and codes, such as the Nippon Denki (NEC) and Underwriters Laboratories (UL) safety standards. This full revision included participants from various states, covering all United States regions and some other regions, such as the United Kingdom, Canada, and Japan (Basso, 2014; Gaiceanu, Arama, & Ghenea, 2020; IEEE Standards Association, 2020). Therefore, depending on the MG topologies, buses (Table 1.1), and electricity architectures, different standards are considered, as presented in (Moussa et al., 2019; Yamashita, Vechiu, & Gaubert, 2020).

Table 1.1. Voltage-level standards in DC and AC bus of MG

Micro-Grid buses	Normalized voltage levels	Micro-grid applications	Principal standards
DC	48V	Standalone systems	IEC-60038 and IEEE-2030.10
	380V-400V	Grid-connected systems	IEC-60038
		Commercial and industrial buildings	
AC	1500V	Commercial and industrial buildings	IEEE Std 1709
	230V and 400V	MG connected to the TEG	IEEE-1547

Alike the USA, several works in European Renewable Energy Council (EREC) are urged to improve new integration standards of distributed energy resources. The standardization of the system helps the power system operators to share experiences with manufacturers and

developers in order to internationalize their items and consequently normalize the system for future deployment while avoiding the alteration between electricity participants. The main European standards applicable to MG systems are EN-50160 and IEC-61000.

These standards describe and specify the main characteristics of the voltage supplied by a low-voltage, medium-voltage, and high-voltage AC public network under normal operating conditions. They describe the limits and levels of the voltage characteristics that can be expected at each delivery point of the public network ([BUILD UP, 2020](#); [European renewable energy council, 2020](#); [Hannan et al., 2020](#)). Table 1.2 summarizes the United States and European standards that are appropriate to the deployment of MG systems.

Table 1.2. International standards for distributed energy integration in MG systems

Standards	Description	Standards specifications
IEEE-1547 (US)	Requirements on power quality and distributed energy sources integration in the electrical grid.	<ul style="list-style-type: none"> Integration, protection system design and operation of distributed system.
IEEE-1547.4 (US)	It includes the planning and operation of the MG systems (IEEE Standards Coordinating Committee 21, 2020). The SCC21 develops a guide to help the operators, the specialists, and the manufacturers to use the technical aspects of the MG operation and implementation.	<ul style="list-style-type: none"> Control/monitoring and application guide. Interconnection requirement for distributed system higher than 10 MVA. Testing and measurement techniques.
IEC-61850-7-420 IEC-61968-9 EN-13757-4 & 5	This series of standards concerns: Communications for distributed energy resources, meter reading and control, radio mesh meter bus, wireless meter bus.	<ul style="list-style-type: none"> Rules and guidelines regarding the connection with secondary distribution networks (Hannan et al., 2020). Studies on the impact of DES interconnection.
IEC-60364-1	Recommendations for human safety, guaranteeing the safety of persons against life dangers, verification of electrical installation of Nominal-Voltages.	<ul style="list-style-type: none"> Recommended practice for establishing procedures and methods.
IEC-61851	Electrical vehicle integration in MG, charging station regulations for single-phase (levels up to 250V) and three-phase (levels up to 480V).	<ul style="list-style-type: none"> Ideal grid-consumer connection configurations. Supply methods and loads considerations.
IEEE-C37.95 (US)	It is a guide for grid-consumer interconnection with a number of different protective information. It covers applications involving service to a consumer that normally requires a transformation between the utility's supply voltage and the consumer's utilization voltage.	<ul style="list-style-type: none"> Time tags and synchronization applications. Verification methods of standards compatibility with measurements.
IEEE-C37.118 (US)	Standard for Phasor Synchronization with power system and data transformation for the grid system operating and interconnection.	<ul style="list-style-type: none"> Phasor Synchronised definition and measurement unit methods.
IEEE-2030.10	DC energy providers for off-grid system, communication protocols, recommendation for low DC voltage designated to standalone systems.	<ul style="list-style-type: none"> Specify the main voltage characteristics at the PCC in low, medium and high voltages during steady-state operation.
IEEE-2030.7	EM system, control level associated to the proper operation, configuration, and regardless topology.	<ul style="list-style-type: none"> Determine the power frequency, harmonics, voltage unbalance, voltage variation and flicker limits at PCC.

IEEE Std 1709	Power quality recommendation and voltage tolerances for Medium-Voltage DC bus.	<ul style="list-style-type: none"> • Describe the indicative values for some power quality events.
IEEE Std 115	Electromagnetic compatibility and regulations about power quality limitations for AC and DC buses.	<ul style="list-style-type: none"> • Electromagnetic compatibility levels.
EN-50160 (Europe)	It describes and specifies the main characteristics of the voltage supplied by AC public network under normal operating conditions of distribution systems.	<ul style="list-style-type: none"> • Integrity requirements and safety functions. • Requirements for safety and protection.
IEC-61000 (Europe)	It contains specifications for Electromagnetic compatibility (emission standards, immunity, installation, testing and measurement techniques), it is required to keep interference between electronic devices under control to reduce disturbance and improve immunity in residential, industrial, and commercial environments.	<ul style="list-style-type: none"> • Short interruptions, voltage sags and voltage variation protection tests. • Mitigation methods and installation guidelines. • Progress on constructing high-performance buildings (near-zero energy buildings).
ISO 52000-1	Standard for energy performance of buildings, which establishes a systematic and comprehensive structure for assessing building energy performance.	<ul style="list-style-type: none"> • Regulations to define the concept of (NZEB) Net Zero Energy Building.
ISO 52003-1		
ISO 52010-1		
ISO 52018-1		
ISO 52016-1	Efficient thermal energy in MG, important response time for HVAC to respect building thermal-zone standards, such as the estimation of energy needed for heating and cooling.	

However, despite this progress in deploying MG systems and advancing standards, still their integration into existing and smart buildings requires efficient and holistic management platforms. Especially, the integration of recent IoT/Big-data technologies for real-time monitoring and data processing in order to develop new predictive control approaches, which allow ensuring the sustainability and the reliability of these new energy generation systems.

4.4.2. Communication technology used for MG system

The ICTs have a fundamental role in the performance of MG systems operation and its practical deployment. In an MG system, a large number of distributed components, such as the end-users, generators, and energy storage systems, require a reliable, sophisticated, and fast communication infrastructure to reach the mandatory of such systems. Therefore, effective communication systems should be normalized to enable real-time exchange of data in MG systems in order to collect the necessary information used for the EM of the system. Mainly, the communication technologies that are used actually in MG systems can be classified into two categories, wired and wireless technologies. Table 1.3 presents the different communication technologies, which can be used in the MG system with the specified international standards.

Table 1.3. Communication technologies for MG building systems

	TYPE	TECHNOLOGY	STANDARD	CONTROL LEVEL APPLICATION	ADVANTAGE	DISADVANTAGE
WIRED	Power line	PLC	ISO/ IEC 14908-3	Primary and Secondary (Smart home and smart buildings)	<ul style="list-style-type: none"> • Easy interfacing and programming • High bandwidth • High reliability • Robust against cyber attack • Fast rate • Less signal degradation • Long life • Fast response and convergence time • Can handle extensive data • Remote terminal units (RTU) connection is possible • Preferred for centralized EM systems 	<ul style="list-style-type: none"> • The number of connected devices is limited to physical connections • Expensive implementation • High risk of Single Point of Failure • Difficult to expand the network • Repeater required for long distance • Difficult in error debug • Skilled operator is required
	Serial	RS-232, RS-422, RS-485	IEC-61968 IEC-61970	Secondary (Smart home, smart buildings)		
	Ethernet	Ethernet IEEE 802.3		Primary, Secondary, and Tertiary (Smart home, smart buildings, and cities)		
	Bus-based	CANBus		Primary, Secondary (Secondary Smart home, smart buildings)		
		Modbus		Primary, Secondary (Smart home, smart buildings)		
		Profibus	IEC61850	Primary, Secondary, (Smart home, smart buildings)		
	SCADA	PLC RS Ethernet IEEE 802.3	IEEE STD. 1815- 2012, IEEE 60870	Primary, Secondary, and Tertiary (Smart Microgrids, Smart buildings)		
WIRELESS	WLAN	Wifi	IEC61850	Primary, Secondary, and Tertiary (Smart home, smart buildings, and cities)	<ul style="list-style-type: none"> • Less interference • Can serve multiple services connectivity 	<ul style="list-style-type: none"> • Not robust against cyber attack • High power consumption
		Lifi	IEC61850	Primary, Secondary (Smart home, smart buildings)		
		Bluetooth	IEEE 802.15.1	Primary (Smart home)	<ul style="list-style-type: none"> • Less interference • Cost-effective 	<ul style="list-style-type: none"> • Not robust against cyber attack • Less privacy • Lower bandwidth • Short transmission range
		ZigBee	IEC-61968 IEC-61970	Primary, Secondary (Smart home, Smart buildings)	<ul style="list-style-type: none"> • Self-organization property • Self-healing property • Large number of devices can be connected 	<ul style="list-style-type: none"> • Not robust against cyber attack • Less privacy • Low transmission rate
		WiMax	IEEE 802.16j/m	Primary, Secondary, and Tertiary (Smart home, smart buildings, and cities)	<ul style="list-style-type: none"> • Suitable for AMI • Suitable for centralized and decentralized structure 	<ul style="list-style-type: none"> • High installation cost • Interference problem is affected by weather • Not robust against cyber attack
	Cellular networks	3G	IEC61850	Primary, Secondary (Smart cities)	<ul style="list-style-type: none"> • Easy upgrade • Handy in nature • High bandwidth compared to other 	<ul style="list-style-type: none"> • Higher initial cost • Vulnerable in nature
		4G		Tertiary (Smart cities)		

		5G		Tertiary (Smart cities)	wireless technologies • Adaptable automation applications	to	
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The common standard, which is used for power system automation and communication technologies in MG systems, is the IEC-61850 standard (Dede et al., 2016). It is an international standard for substation automation and a part of the International Electrotechnical Commission's Technical Committee 57 (TC57) architecture for electric power systems (Parhizi et al., 2015). Its main benefit is to guarantee a normalized communication structure among MG systems. The standard describes the exchange information and the data-frame structure in an MG system communication. The family of this standard results in improvements in both costs and the performance of utility grids. Therefore, the communications systems in MG provide a means to exchange information and monitor the different elements for control and protection purposes.

4.5. MG system architecture

The main advantage of MG is to enable customers to have both a bidirectional communication platform and control devices to manage their energy needs and excesses. In addition, with an adequate communication structure, it is possible to shape the users' load demand curves by means of D/R strategies. The MG is considered as a solution to meet the local energy demand by connecting distributed power generation to distribution networks, such as local substations without further expansion of costly centralized utility grids. Therefore, the architecture of a hybrid system of RES is an important issue that needs to be considered when the different sources are deployed together in order to supply the power to the loads. Different topologies can be defined depending on the nature of the delivered energy AC or DC, and the nature of the loads to be supplied. Generally, they are three main configurations, which are DC/Bus configuration, AC/Bus configuration, and AC/DC configuration. In fact, according to the integration of this hybrid system, different studies have been focused to improve the control strategies for optimal EM in the MG (Kenzelmann, 2012; Veneri, 2017). The study of a control strategy must begin with a study of the interconnection architecture of the sources and the AC/DC bus installation.

4.5.1. DC bus topology

In DC common bus topology, all energy generators and storage devices of the system are connected to a DC bus through the appropriate electronic converters (AC/DC, DC/DC).

Generally, it is used when the power is generated and consumed locally without transport or distribution network, which is the case for the MG. In this type of topology, the phase and frequency control is not considered and the transmission system is stable. Additionally, the frequency and voltage synchronization and reactive power management issues are eliminated making the operating system easier than that in the AC. In fact, batteries are the main element of the DC bus and act as a buffer element, for current peaks, and for short-term energy storage. For that, a charge controller is used to generate the power to the batteries. Mainly, in this architecture, the system supplies the power to the loads by a centralized inverter and the energy flow is bidirectional (Figure 1.15). When it is needed, the electrical network is connected separately to the loads. This configuration offers more flexibility for controlling each generator.

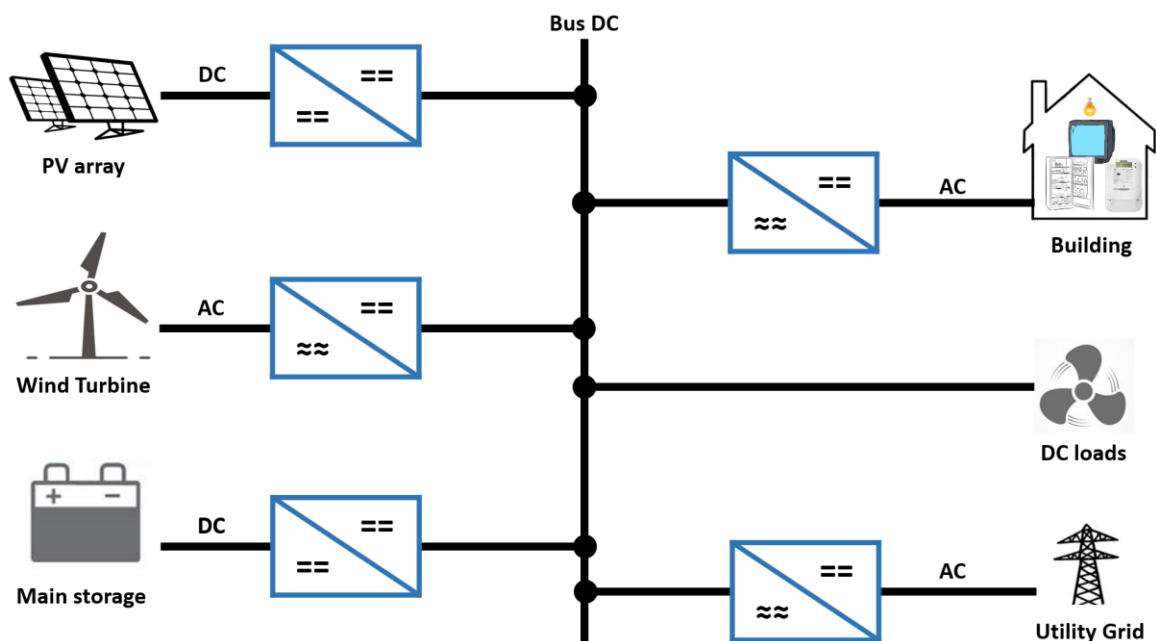


Figure 1.15. The DC topology

However, the RES output power is typically DC power, which should be converted into AC power to supply the electricity to the existing AC loads. Consequently, the AC/DC/AC energy conversion for some generators leads to low efficiency and power losses. Usually, the power is transmitted to the batteries before the conversion to AC power. For that, the batteries must have a large capacity and they are constantly subjected to C/D cycles. In addition, one interface is linked to the AC loads and a failure of the inverter causes a total cut of the electrical supply. To avoid this problem, multiple synchronized inverters should be installed, which increases the installation cost.

4.5.2. AC bus topology

The AC bus topology is the main solution, which is used actually in electrical systems. In this topology, all energy generators and storage devices of the system are connected to an AC bus through the appropriate electronic inverter (AC/AC, DC/AC) (Figure 1.16). This solution is more suited for the large transport and distribution network due to the low loss of energy during the transport phase for a long distance. Due to the distributed nature of the power generators in the TEG, and due to the necessity to transport the energy to consumers, this choice is judicious.

In this topology, the interconnection point with the electrical network requires the use of special and expensive equipment to connect the RES with the main utility grid, which is known as the Point of Common Coupling to adapt the high and medium or low voltage lines. Generally, a three-phase AC bus is commonly employed as the point of common coupling. On the other hand, in some cases, AC must be reconverted to DC because some equipment uses DC power. In addition, the voltage and frequency of the AC topology must be regulated in very strict limits in order to ensure the stable operation of the whole system.

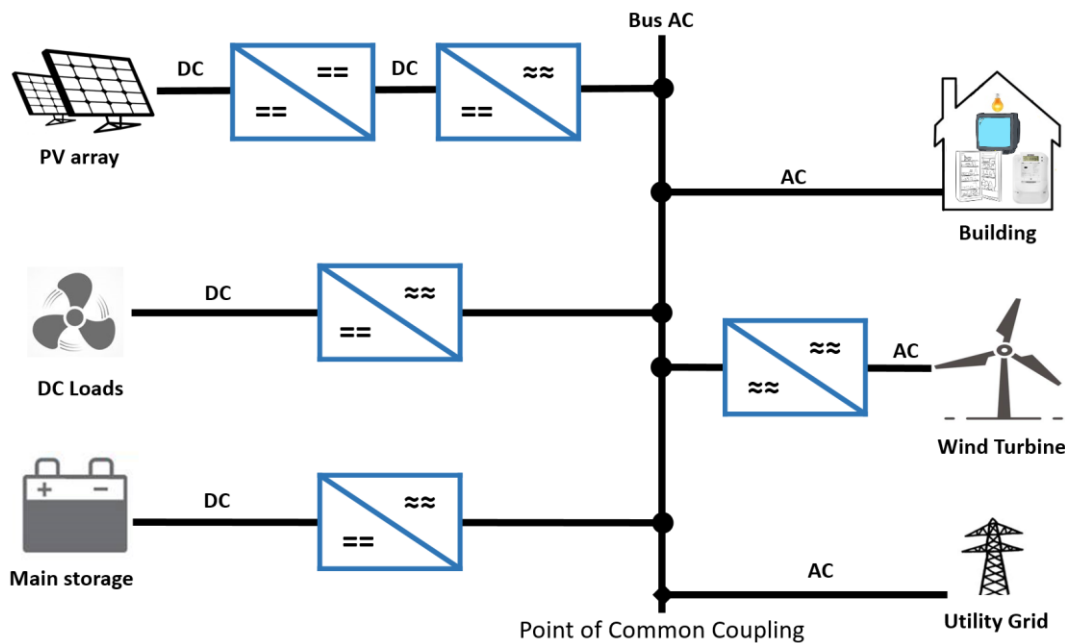


Figure 1.16. The AC topology

4.5.3. DC/AC coupling topology

The DC/AC coupling configuration has higher performance compared to the previous configurations. In this configuration, RESs generators can supply the power directly to the AC loads using an inverter. At the same time, these sources are connected to the batteries for

eventually storing extract energy. In fact, when there is a surplus of energy from RESs, it can charge the batteries or inject them in the TEG. Also, the bidirectional inverter can supply the loads or charge the batteries depending on the deployed control strategy. This topology does not require RESs and energy storage dimensioning due to the possibility to inject or to extract, partially or totally, the energy to the TEG, which increases the system efficiency and reduces the installation cost. For high performances of the system, this topology is used and generally, the DC bus is used for coupling the RES inside the MG system together with the storage system while the AC bus is used to interconnect the whole MG to the TEG as depicted in Figure 1.17.

This configuration allows connecting each generator or loads (DC or AC) to the corresponding bus, then to exchange the power between the buses by a bidirectional DC/AC inverter. However, by comparing the conversion efficiency, the DC bus is more efficient than the AC bus when energy storage is involved in power flow due to fewer conversion levels. For example, for a PV generation to the battery charging case, the power in an AC Bus is converted through DC/DC to DC/AC in order to reach the AC bus, and it is converted through AC/DC charge controller for the storage process. Therefore, the DC bus eliminates these losses, which are caused by DC/DC, DC/AC, and AC/DC conversions. Moreover, for the transmission efficiency, a significant feature of DC transmission is planned, especially for MG systems installation, because there is no reactive power and as result, the transmission losses, caused by reactive power in AC systems, are eliminated. In addition, the same amount of real power delivered by a DC line tends to produce less copper loss than AC over the same line resistance (Veneri, 2017). For an AC power line, the voltage amplitude and the frequency angle should be regulated simultaneously. Consequently, as the AC grids are three-phase systems, sophisticated techniques should be employed to manage the unbalanced components (voltage, frequency), which principally come from the vast adoption of single-phase of the MG equipment and loads in a low voltage power system. Unlike the AC power system, for DC power, a constant DC voltage can ensure the stability of the installation. These essential factors indicate better controllability for DC MG systems over AC.

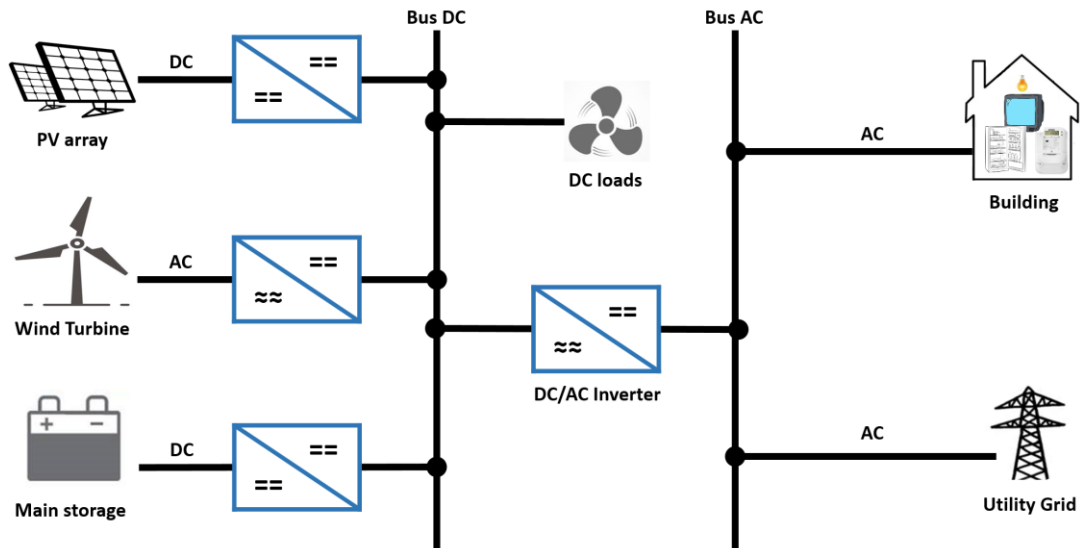


Figure 1.17. DC/AC coupling topology

4.6. Operational modes of Micro-grid system

MG systems are designed to operate efficiently and resiliently since they are not only dedicated to a high penetration level of RESs and storage systems but also due to their capability to operate in isolated mode when RESs can satisfy the demand or during the faults, which occur in the main electrical network. Therefore, MG systems offer greater reliability and efficiency for the electrical network system, especially by locally controlling the generated power while improving the energy quality, as well as smoothing the power curve by the deployed storage devices. In addition, the losses of energy, which are caused by the transport and distribution system to the end-consumer, are reduced and, consequently, the blackouts of electricity, created by the peak demand, can be avoided.

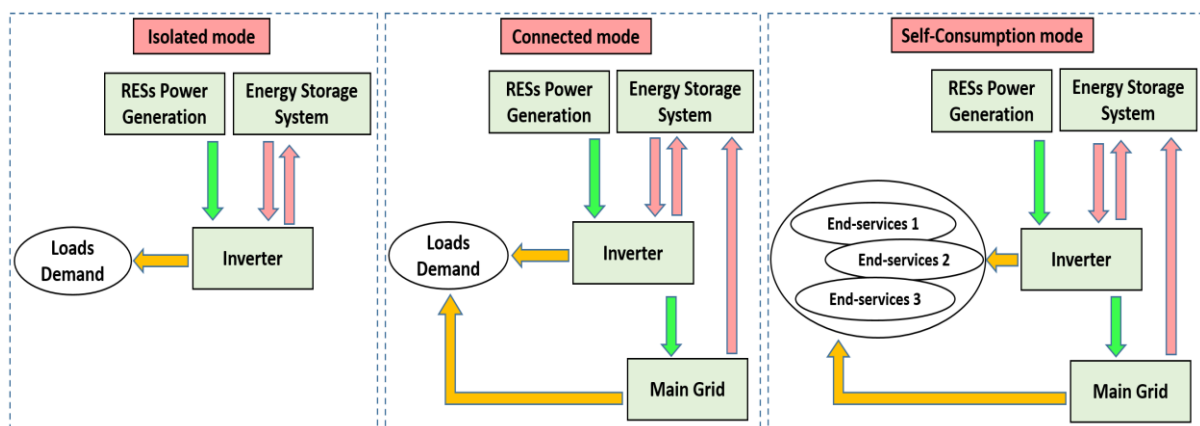


Figure 1.18. The MG system operating modes

However, MG systems are operated, as shown in Figure 1.18, into two distinctive modes: grid-connected and islanded modes ([Guimaraes, 2020](#)). Other literature works consider another mode, named self-consumption mode, by controlling buildings' services, i.e., identifying those that can be connected to the main grid ([Bridier, 2016](#)).

4.6.1. Isolated mode

For isolated mode, named standalone mode, the RESs production and storage devices are dimensioned in order to satisfy totally the demand. Generally, another source is integrated, such as diesel motors, to satisfy the demand during the low or the absence of RESs generation. This mode is useful in critical applications, such as the isolated site that requires a high cost for electricity transport and distribution. For isolated sites, it is necessary and practical that the hybrid system has total autonomy requiring the use of storage systems not only to smooth the variable nature of RESs but also to ensure the power availability and the continuous supply of energy. However, energy storage represents a very significant part of the cost and maintenance of the MG installation, and the lifetime of storage devices is much lower than PV panels, the WT, and the converters. For that, good strategies are required for sizing the storage devices and the RESs generation. Several works are presented in the literature to dimension the optimal configuration for isolated sites according to the weather conditions including technical and economic characteristics of all specific MG components ([Abbes, 2012](#); [Aristizábal et al., 2019](#); [Mekontso et al., 2019](#); [Al-Ghussain et al., 2020](#)). In addition, the island mode is studied in various research projects of MG systems ([Nichols et al., 2006](#); [Bellido et al., 2018](#)). The specific standards IEEE Std 1547.4-2011 is the only international reference for MG systems, which are operating in island mode ([IEEE, 2011](#)).

4.6.2. Grid-connected mode

Unlike isolated mode, the grid-connected mode is considered as the major key for RESs integration in buildings in order to develop the concept of “Smart Grid” and consequently the MG systems. A real MG system is connected to the electrical network to increase the reliability of the production system and to realize the main objective of such systems. This mode offers a high benefit for both energy and financial cost by reducing the size of the installation (e.g., battery capacity, number of PV panels) on the one hand, and by integrating the cost of energy in the management strategies on the other hand. In fact, the majority of hybrid systems, connected to the electrical grid, have a limited capacity of energy storage systems that are used to reinforce the power quality and to smooth the RESs generation. In

this case, they are dimensioned to ensure the power during the failure of TEG or during the perturbed RESs production periods, and as results minimizing the size of storage devices. However, the architecture of MG connected mode necessitates certainly the inclusion of inverters, both to convert, when necessary, from direct to alternating currents and to provide some level of frequency and voltage control as well. Principally, the inverter is the interface that provides the interconnection to the electrical network by respecting the norms of power quality (e.g., frequency, voltage) and by deploying the EM strategy. Moreover, the inverter supplies the power to the loads offering then the possibility to charge the storage systems, to extract or inject the electricity from/to the electrical network, and to serve potentially heterogeneous sources without loss of synchronization, propagation of harmonics, or loss of system stability.

It is worth noting that we have considered the connected mode of MG systems as the main architecture of our deployed MG system. This mode is more adaptable for the actual structure of buildings by offering the possibility to develop the actual building as an MG system. This issue is studied by a set of research projects and several testsite are deployed by considering the connected mode of MG systems ([Hirsch, Paraga, & Guerrero, 2018](#); [Castro, 2020](#); [Energy Networks Australia, 2020](#); [Microgrid Knowledge, 2020](#)).

4.6.3. Self-consumption mode

Another mode, named self-consumption, depends strongly on the concept of “internet of services” in buildings by coupling the two other operating modes. It requires a high integration of ICTs and IoT/Big-Data technologies to predict and control efficiently the different components and services of the system. In fact, by deploying ML algorithms, the internal and external parameters can be forecasted to control and manage powerfully the power system (i.e., production, consumption) while keeping a high comfort for the building’s occupants. Mainly, in MG systems, the services can be decomposed into three main categories: *i)* permanent end-user services, its energetic assignment plan covers the whole time range; generally, these services produce directly comfort to occupants; *ii)* temporary end-user services, the time range of these services can be modified by the EM system (e.g., modification of the starting time of a washing machine service, cooking service); *iii)* intermediate services, which produce electrical power to the whole end-users by managing the previous end-user services with the energy production services (e.g., RES, storage devices, grid).

Therefore, the self-consumption mode modifies the starting time of temporary end-user services (e.g., electrical vehicle C/D, washing machine service, cooking service) and the buildings can be supplied by electricity from both RESs and electrical network at the same time. In addition, in a given situation, the control strategy can switch some services that consume a high level of energy to the electrical network while keeping the RESs connected only to defined building's loads. This operating mode is more useful to ensure a continuous supply of electricity to some principal services that are not designed to support the cut of electricity (e.g., data-center, networking equipment, IoT/Big-Data platforms). Data centers are considered as one of the best examples of an industry with relatively established plans for the blackouts of electricity. For example, the Great East Japan Earthquake on March 11th 2011 killed more than 15 000 people, destroyed 4 nuclear generation plants, and left several million people without electricity and no critical damage to data centers were reported ([International Electro-technical Commission, 2014](#)). Furthermore, by coupling the IoT, IoE, and IoS concepts, the household equipment can interact with EM strategies in order to minimize the cost of energy while avoiding the cut of electricity during the failure of the energy sources. For example, by considering the electrical vehicle as a service in the building, the control strategy can use its battery as a source of energy during the night by considering that the electrical vehicle is a smart service, which can communicate its SoC and its targets to the communicated system ([Veneri, 2017](#)). Different literature works are realized to develop this new concept of service control in buildings ([Basu et al., 2011](#); [Tsiatsis et al., 2018](#); [Kabalci & Kabalci, Y, 2019](#); [Birleanu & Bizon, 2020](#)).

5. System optimization and control constraints in MG systems

The main constraint for MG system is being able to supply, as much as possible, the energy demanded by consumers from renewable sources. The control strategy should be able to smooth the large variations of energy production and consumption, while keeping a good state of health of the energy storage with high service quality. For that, two main aspects must be considered to deploy the control approaches and to improve the system operation: *i*) the EM, which includes decisions and actions related to the energy flow and cost for a scale of several minutes, hours, or days; *ii*) the control for energy quality and power maximization for a scale of the second or millisecond and it concerns frequency/voltage stability and power maximization for the different installed sources (e.g., PV, wind). The main objective is the development of an intelligent EM strategy for EM, towards smart MG systems.

Therefore, one of the main constraints is the optimization criterion that should be considered to minimize the cost of the kilowatt-hour (kWh) of electricity production. In this type of criterion, the initial equipment costs are not the only parameters that should be considered. The studies of this criterion take a long time to be analyzed during the lifetime of the system by considering the different parameters that can influence the installation cost. The global costs over the lifetime of the installation are also considered, including future maintenance, the electricity costs, the replacements of certain parts of the system (e.g., batteries, regulators). Principally, the calculation of the life-cycle cost for the system is an economic calculation form, which allows a direct comparison of various and envisaged solutions. However, to establish a valid study of the cost optimization, the analysis period is the longest lifetime of the system operation. During this time, different criteria are considered: *i)* initial investment/capital including the buying of equipment and installation of the system; *ii)* maintenance and operation, some maintenances are necessary each year for a good operation of the system; *iii)* the cost of electricity including the price spent annually to supply electrical power from the TEG; *iv)* replacement costs of each component having a shorter service life than the whole system.

In another case, system dimensioning has an important role in cost optimization. In fact, some studies considered that the dimensioning of the equipment (e.g., PV panels, batteries) in order to have an autonomous system is the main key to increase the profitability of the installation. Practically, it is more profitable when an intelligent and predictive control strategy is deployed. For example, it is possible to install a high number of PV panels and batteries to have an autonomous system and, consequently, a high installation cost. The work presented in (Stoyanov, Notton, & Lazarov, 2007) showed that it is not desirable to configure the system with a storage capacity greater than three days of autonomy because beyond this value the impact of increasing the capacity becomes negligible. However, it will be more profitable by deploying a control strategy for EM to make switching decisions that consider the electricity cost and the C/D battery cycle. An intelligent and predictive control strategy can manage the system in order to plan the optimal consumption period. For example, the control strategy could charge the batteries when the electricity price is cheap for being used during morning peak consumption. Furthermore, when the price is expensive the batteries could be discharged by supplying the power to consumers while the surplus can be injected into the grid. The next chapter presented a state of the art of the main control approaches that are used for EM in MG systems. A comprehensive description of control and optimization

methods is highlighted, particularly to identify the most common and effective method for EM in MG systems.

6. Conclusions

Demand for electricity is increased due to the development of the industry, the electrification of transport, the rise of household demand, and the increase in demand for digitally connected devices and air conditioning systems. For that, solutions and actions should be developed for higher consumers of the electricity with the aim to minimize the electrical energy demands. For instance, buildings are one of the main consumers of electricity and if they are correctly constructed, controlled, and operated, a significant energy saving can be attained. One of the main solutions to minimize the energy demanded from the utility grid is RESs integration. In this chapter, actual statistics for energy demand are presented together with the principal problems encountered in the TEG. As a solution, a hybrid RESs system is proposed to reduce or eliminate the problems caused by the transport and the destruction of electricity in TEG. This hybrid system contains different renewable generators connected to energy storage systems. It allows producing locally a part of energy in order to minimize the consumption from TEG. The different components of the system are detailed and the main topologies for RES interconnection are presented especially for the MG systems. However, the management of these hybrid systems of RES requires the use of information and communication technologies (ICT) for developing intelligent control strategies. The integration of hybrid RESs system with ICT infrastructures allowed the emergence of the new concept named micro-grid (MG). Therefore, control approaches should be developed for the reliable and efficient operation of MG system. The use of ICT in the MG system allows the deployment of intelligent and predictive control strategies, which can predict the suitable actions to balance the Demand/Response of electricity by considering multiple objective functions and constraints. These control approaches can be deployed to manage the energy in the MG system in order to keep a high service quality for consumers and the maximum profitability of the systems.

Chapter 2: Review of Control and Energy Management Approaches in Micro-Grid Systems

1. Introduction

Proper management of energy flow in the MG system must be carried out in order to improve the global performances of the system, to minimize the cost of the electrical bill, and to extend the lifetime of its components (e.g., converters, batteries, fuel cells). In general, EM approaches involve an objective function, which could be used to maximize the efficiency of the hybrid RES system and to minimize energy consumption while improving the consumers' quality of services. For instance, an EM control strategy that considers only the availability of the electricity can be developed to switch, at each time, from RES to storage devices or to the TEG without considering the electricity price or the profitability of the system. In other cases, control strategies can interact with the generators by limiting the power generation. The aim is to ensure the electrical quality of services and, consequently, minimize the profitability of the installation. However, despite that these strategies could reach the defined objective, they might decrease the performance of other criteria like batteries' lifetime, the system's installation cost, and profitability.

Actual commercial inverters provide high-performance energy balance by interconnecting RESs, energy storage systems, and the utility grid, by taking into consideration only a single-objective function. This later is mainly implemented in order to increase the availability of the electricity for building's loads. With a limited configuration, the inverter can use batteries or the TEG at any moment without taking into account other constraints, such as the electricity cost and the C/D cycle of the batteries. For instance, high and frequent cycles of C/D of batteries could decrease their performance, while reducing the system's profitability. EM strategies that are deployed in the actual inverters use "if-else" statements to perform real-time decisions. For instance, the defined setpoint values (i.e., control inputs) cannot be adjusted according to predictive variations of RESs production, load demand, and battery SoC. Such EM strategies are considered as "passive strategy" in their decisions and actions ([Higueta, 2017](#)). Control strategies incorporating multiple-objective functions are, therefore, required for efficient EM (i.e., ensuring electricity availability) while taking into consideration operational constraints (e.g., costs, reliability, and flexibility). In fact, "active strategies", for EM should be developed in order to adapt the setpoint values accordingly. These strategies could use intelligent and predictive control techniques together

with recent IoT/Big-data technologies (e.g., data monitoring, data analysis, data mining, ML) for efficient EM in hybrid RESs systems. In this chapter, control structures and strategies, from literature, are presented by highlighting their advantages and drawbacks in the context of MGs for smart buildings.

2. Control architectures

In hybrid energetic systems or MG systems, distributed and hybrid RESs generators (e.g., PV panels and WTs) are used to produce clean energy (e.g., solar, wind) while energy storage systems are installed to compensate the fluctuation between RESs generation and load consumption. These hybrid systems can operate either on grid-connected or standalone modes depending on desired and fixed objectives. However, while the penetration of these distributed generators is continuously growing, new EM approaches are required for their seamless integration within the existing electricity network. Table 2.1 presents recent literary works concerning the deployment of hybrid systems. As highly stated in Table 2.1, batteries are the most used devices for energy storage.

Table 2.1. Survey through collection of EM for hybrid MG system

<i>Ref</i>	<i>Grid</i>	<i>DG</i>	<i>PV</i>	<i>WT</i>	<i>Biomass</i>	<i>FC</i>	<i>Hydrogen</i>	<i>Battery</i>	<i>Diesel</i>	<i>Super-capacitor</i>	<i>EV</i>
(Indragandhi et al., 2018)		✓	✓	✓		✓		✓			
(Zhang et al., 2018)			✓	✓		✓		✓			
(Ghaffari & Askarzadeh, 2020)		✓	✓			✓	✓		✓		
(Dali et al., 2010)	✓		✓	✓				✓			
(Zhang et al., 2020)								✓		✓	✓
(Chandan et al., 2020)						✓		✓		✓	✓
(Sandgani & Sirouspour, 2017)	✓	✓	✓	✓				✓			
(Zheng et al., 2018)	✓	✓	✓	✓	✓			✓			
(Lin et al., 2016)	✓	✓	✓	✓				✓			
(Li, Roche, & Miraoui, 2017)			✓			✓	✓	✓			
(Mazzola et al., 2015)			✓	✓	✓			✓			
(Rabiee et al., 2016)	✓	✓	✓	✓		✓		✓			✓
(Dash & Bajpai, 2015)		✓	✓			✓		✓			

Therefore, the deployment of an EM approach should be able to enhance the dynamic response of distributed energy resources under different operating conditions and maximize

the usage of RESs power generation, while ensuring stability when one or more sources are connected or disconnected into/from the system. In this way, different approaches from the literature have been proposed for EM (Table 2.2). As shown in this Table, the most suitable control strategies could be selected according to fixed constraints and objective functions. These control strategies can be classified into three main categories: centralized, decentralized, and hierarchical control, as mentioned in Figure 2.1. These control strategies are presented in the rest of this section.

Table 2.2. Hybrid system control overview, approaches and contributions

<i>Ref</i>	<i>Main objective</i>	<i>EM approach</i>	<i>MG scale</i>	<i>Control structure</i>
(Elkazaz et al., 2020)	Authors present an EM system to minimize the daily operating cost of an MG and maximize the self-consumption of the deployed RES by selecting the best setting for a central battery storage system based on a defined cost function.	Convex Programming, Model Predictive, and Rolling Horizon Predictive Control	Medium	Hierarchical
(Ghaffari & Askarzadeh, 2020)	A method is developed to size an off-grid PV/diesel/FC hybrid energy system in order to optimize the number of system components with respect to the cost minimization of the installation.	Crow search algorithm	Large	Hierarchical
(Kuznetsova et al., 2015)	An analysis of EM system of an MG using a robust optimization taking the uncertainties of wind power and solar power generations and energy consumption into consideration.	Agent-based modelling	Large	Decentralized
(Zhang et al., 2018)	A methodology for modeling and optimally sizing a hybrid system for renewable energy considering two energy storage devices: hydrogen and batteries.	Wavelet transform, Neural network and FL	Large	Not specified
(Zheng et al., 2018)	A deterministic constrained optimization and stochastic optimization approaches to estimate the uncertainties in biomass-integrated MG supplying both heat and electricity. The work developed an economic linear programming model with a sliding time window to assess design, scheduling of biomass-combined power and heat based MG systems.	Linear programming model with a sliding time window	Small	Decentralized
(Lin et al., 2016)	An MG energy management strategy by considering RES integration into the distribution network. The time-of-use, other technical constraints, and an enhanced bee colony optimization is proposed to solve the daily economic dispatch of MG systems.	Enhanced bee colony optimization	Small	Centralized
(Aghdam et al., 2018)	A method known as contingency-based EM for system of MGs. A stochastic optimization is proposed according to various scenarios of the	Contingency-based EM	Large	Hierarchical

	contingencies.			
(Arcos-Aviles et al., 2017)	A fuzzy EM approach is deployed to smooth the power flow of an MG containing heat and power unit. The aims is to use the surplus of electrical power of the MG for storing in electrical energy storage systems and ensuring the water temperature of the thermal storage system in the desired value in order to supply residential buildings.	Fuzzy energy management strategy	Medium	Not specified
(Sandgani & Sirouspour, 2017)	An EM method is deployed in an MG system containing energy storage devices and renewable energy based distributed generators in grid-connected MG. In the studied approach, the neighboring MG share the capacity of their distributed resources and energy storage devices aiming at reducing the operational costs.	Lexicographic programming, Linear programming, Receding horizon control	Large	Hierarchical
(Marzband et al., 2016)	An algorithm for EM system of an MG using multi-layer ant colony approach pointing on determining the optimum point of operation for local distributed energy generation with least electricity production cost. The studied algorithm has the capability of analyzing the constraints related to economic and technical aspects of the problem.	Multi-layer ant colony approach	Medium	Not specified
(Olivares et al., 2014)	A model predictive control technique to determine the optimal operation of the MG system using an extended horizon of evaluation and recourse. The EM problem is decomposed into Unit Commitment and Optimal Power Flow problems in order to avoid a mixed-integer non-linear formulation.	Model predictive control	Large	Centralized
(Li, Roche, & Miraoui, 2017)	Authors proposed a combined EM and sizing methodology, formulated as a leader follower problem. The leader problem focuses on sizing and aims at selecting the optimal size for the MG components. The problem is solved using a genetic algorithm and the follower problem is formulated as a unit commitment problem and is solved with a mixed integer linear program.	Mixed integer linear program	Small	Centralized
(Dash & Bajpai, 2015)	Authors proposed an EM approach to divert excess energy of PV to the electrolyzer.	Linear Programming	Small	Centralized
(Helal et al., 2017)	The operating cost of MG is minimized, while considering droop controlled active and reactive power dispatch of AC side MG as a constraint.	Mixed integer nonlinear programming	Small	Centralized

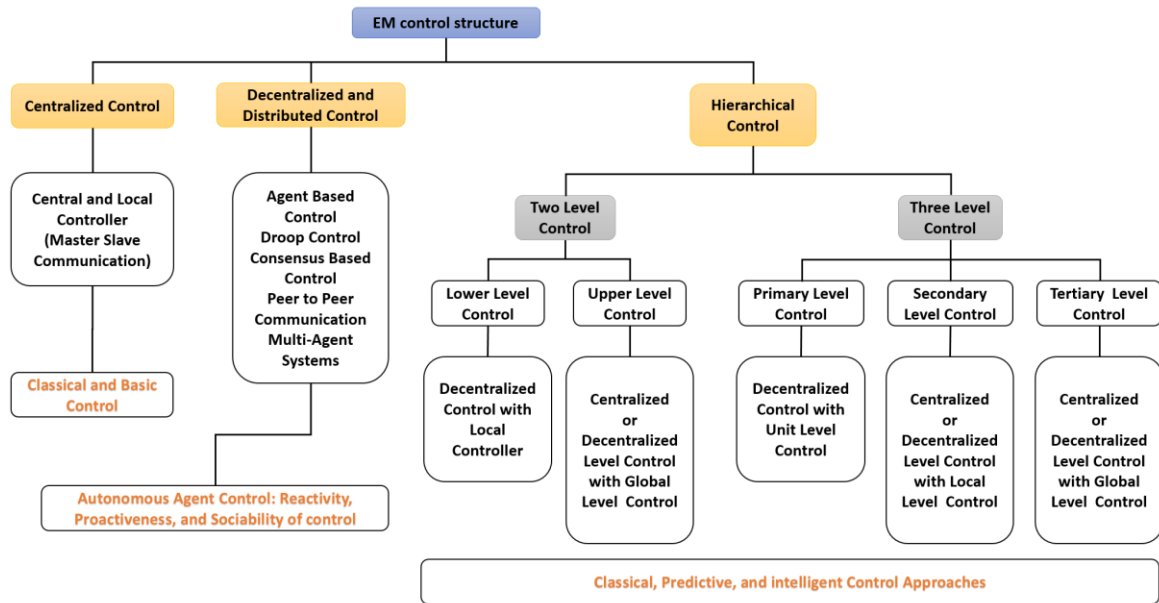


Figure 2.1. Control structure for energy management in MG systems

2.1. Centralized control

Centralized control approaches use a single CC, which is characterized by a high performance computing unit and secure communication infrastructure in order to manage different entities of the system (e.g., RESs, Storage systems, TEG). Each entity uses an LC in order to communicate and directly interact with the CC. Moreover, by using recent communication and computing technologies (e.g., IoT, Big-Data), the CC is able to monitor, collect, and analyze in real-time data. This allows all entities to collaborate with the central EM controller while ensuring a flexible MG operation in both grid-connected and standalone mode (Figure 2.2). The CC collects data, such as RESs energy production, energy consumption pattern, the energy price from market operators, and weather condition and then executes the optimal and efficient system's control. Numerous research works, for literature, have developed and deployed centralized EM strategies. For instance, in (Tsikalakis & Hatziargyriou, 2007), authors proposed a centralized controller in order to optimize the operation of MG by maximizing the production of distributed RESs generators while establishing energy transfer back and forth with the main utility grid. The efficiency of the proposed solution on the MG system is investigated by considering a typical case network operating under various market policies and spot market prices.

Moreover, authors in (Olivares et al, 2014) developed a centralized EM system for a standalone MG system based on model predictive control method in order to reduce the

computational loads. In fact, the studied problem is solved iteratively by NLP and MILP techniques. Other centralized control strategies are summarized in Table 2.2. However, despite that centralized strategies are easy to implement, they showed their limit, especially when dealing with large-scale hybrid systems (Warnier et al., 2017).

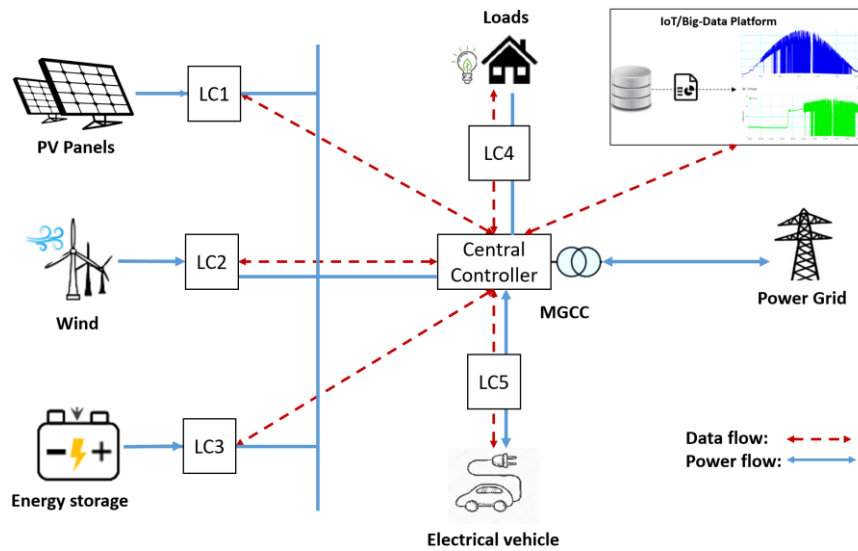


Figure 2.2. Centralized control structure

2.2. Decentralized control

Unlike centralized strategies, in decentralized control, each entity is considered autonomous by using an LC. This means that groups of entities are controlled separately by a leader. In literature, the terms decentralized and distributed controls are often used in place of each other (Kermani et al., 2020; Yamashita et al., 2020). The distributed control can be considered as a decentralized control in which LCs use local measurements, such as frequency and voltage values, to elect the leader entity. They are also allowed to share information with neighbors. For a distributed control, LCs do not only use local measurements but also are able to send and receive the required information to other LCs (Pourbabak et al., 2019). In decentralized control approaches, limited local connections are required and the control decisions are made based only on local measurements (Figure 2.3). It does not require a high-performance computing unit and high-level connectivity (Senjyu et al., 2005).

As depicted in Figure 2.3, each LC operates individually on managed energy sources, storage systems, and loads without central control. The control decisions are determined locally based on local measurements, which are shared among controllers using peer-to-peer communication. However, monitoring, processing and data visualization is considered critical in order to coordinate various distributed controllers and then achieve a global operation goal.

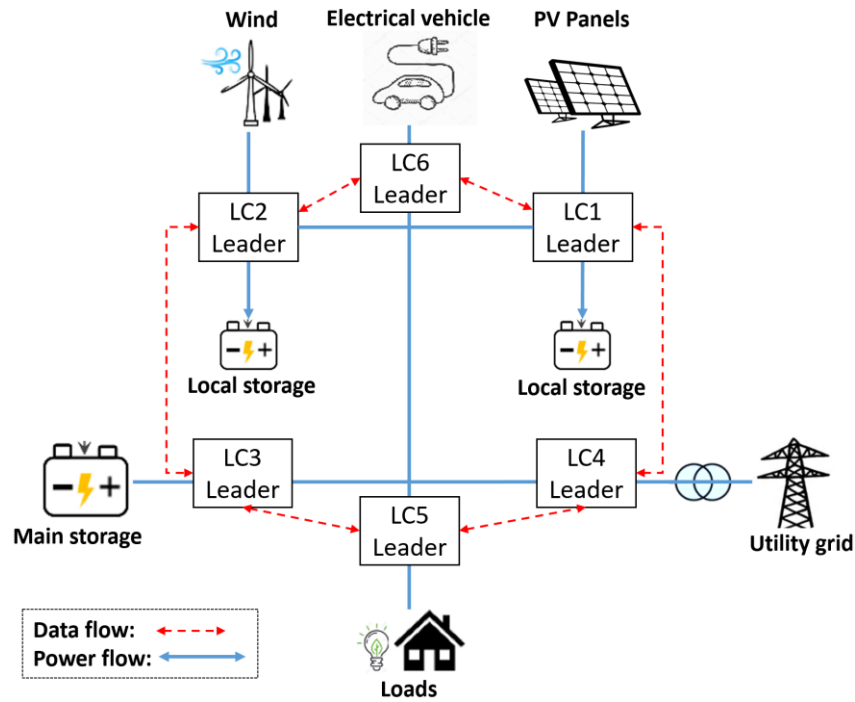


Figure 2.3. Decentralized control structure

This process is standardized by the norm IEC-61968 for a single building EM system and by IEC-61850 for interoperability between building MG systems (Liu et al., 2016; Aftab, Hussain, & Ali, 2019). Depending on the communication network availability, the decentralized control can be classified into three operation modes: *i) fully dependent*, in which the distributed controllers generate local control decision while communicating information with each other via a CC, *ii) partially independent* operation mode, in which LCs communicate with each other and share information with the CC in order to generate central decisions, *iii) fully independent* operation mode, in which the distributed controllers communicate directly with each other and independently from the CC (Celik et al., 2017). However, despite the flexibility of these operational modes, the decentralized control structure presents low performances compared to centralized control (Feng et al., 2017; Espín-Sarzosa et al., 2020; Rathor & Saxena, 2020; Yamashita et al., 2020). This is due to the low response time and the incomplete information about the total MG system installation.

2.3. Hierarchical control

Hierarchical control is mainly proposed for SG systems. In fact, the extended geographic areas of these systems, the extensive communication and computation requirements made the implementation of fully centralized approaches a difficult task. At the same time, the higher coupling between the different LCs requires a maximum level of coordination, which cannot

be achieved by decentralized control structures. However, a compromise between the fully centralized and decentralized control structures is realized by providing hierarchical control structures (Molzahn et al., 2017; Van et al., 2020), according to three control levels: primary, secondary, and tertiary, as depicted in Figure 2.4.

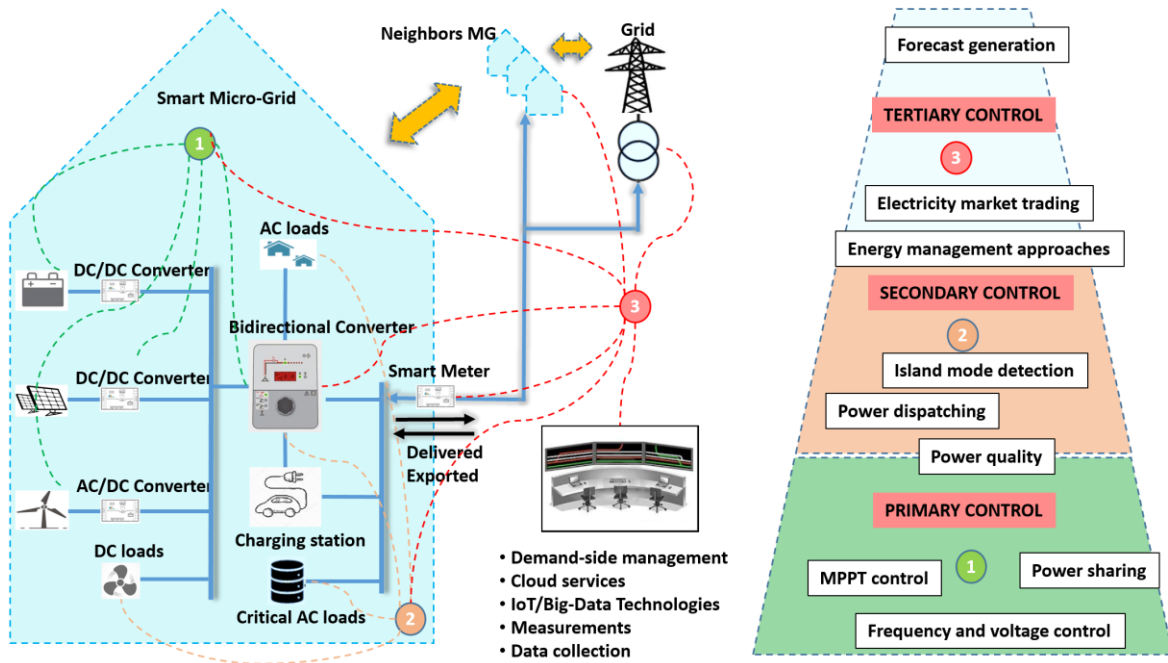


Figure 2.4. Hierarchical control structure

The primary control level stabilizes the voltage and frequency generated from each source in order to respect the limits required by the standards (Elmouatamid et al., 2020a; Elmouatamid et al., 2020b; Gaiceanu et al., 2020). In addition, the primary control level detects the operating mode of MG systems offering then the ability to operate in grid-connected and standalone modes (Prabaharan et al., 2018). For the secondary control level, the MG voltage and frequency are restored after the system's load variation. The aim is to ensure and enhance, within the required standards values, the power quality. It allows the synchronization between the MG systems and the main electrical network (González-Romera et al., 2020). The main objectives of tertiary control are the power flow control in the grid-connected mode, ensuring the optimal operation in both modes like capacitance and inductance (Guerrero et al., 2012). Figure 2.5 includes the structures of each level of the hierarchical control. The control levels differ in the response time frame speed in which they operate as well as the infrastructure requirements, especially for the communication, which is normalized by the standards IEC-61850-7-420 and EN-13757-4 (Elmouatamid et al., 2020).

Table 2.3. Control architectures for hybrid system, advantages and inconveniences

<i>Control structure</i>	<i>Advantages</i>	<i>Inconveniences</i>
<i>Centralized</i>	<ul style="list-style-type: none"> • Strong controllability and real-time observability of the whole MG system; • Provides strong supervision and wide control of the whole system; • Mature and established approaches for control of many systems; • Suitable for small size MG systems where the collected information is performed by low bandwidths communication (Sahoo et al., 2017); • Suitable for the internal control in MG system; • Global optimization of all entities of the same MG; • Offers high-performance computing unit and a secure communication infrastructure; • Holds the control strategy that considers the MG entirely; it depends on the simple architecture of the system to build a global knowledge making the EM control easier to be deployed; • Straightforward implementation, the CC allows economic implementation and it is easy to maintain; • Optimal decision is guaranteed. 	<ul style="list-style-type: none"> • The failure of the CC affects the whole system operation; • Heavy computation burden is a technical barrier for the deployment; • Not well designed to support plug-and-play functionalities of a large number of entities; • Need a high level of connectivity due to the direct interaction of each entities with the central; • Requiring high processing unit for the CC; • More prone to failures since only one unit regulates the voltage and leads to reduce life span of Battery bank stack (Kumar et al., 2019); • Poor scalability and responsible for shorter battery life (Cupelli et al., 2016); • Since all information is collected and handled at one CC, the computational burden increases making the control less effective for real-time communication requirements; • Reliability is degraded for the whole system.
<i>Decentralized</i>	<ul style="list-style-type: none"> • Distributed processing system with autonomous control capability; • Peer-to-peer nodes communication, allowing greater flexibility of operation, and avoiding single-point failure; • Higher reliability due to the redundancy of controllers and communication; • Distributed generators are controlled by independent controllers through their local variables offering redundancy communication link; • Insufficient information about other entities of the MG systems; • Droop control strategy is usually used to avoid circulating currents between the converters without the use of digital communication link; • Avoiding single-point failure, enhancing the expandability, and allowing greater flexibility of operation; • High privacy for the entities and less amount of information; • Reduction of the computational need and releasing the traffic on the communication network; • Reduces computational burden and increases reliability and robustness; • Easy realization of plug-and-play functionality. 	<ul style="list-style-type: none"> • Incomplete information about the overall MG status; • Voltages and currents average regulation requires more data transmission through the MG; • Local optimization in EMS is not able to provide a global solution for operating cost minimization of the total MG; • The distributed processing does not guarantee global optimal results for the whole MG system; • A high complexity of implementation compared to centralized and hierarchical control; • Load dependency problem, responsible for the circulating currents in distributed generators, accuracy of load sharing can be achieved with the compromise of deviation in the voltages compared to their rated values; • Unsuitability for non-linear loads due to harmonics and inability to achieve coordinated performance of multiple components with different characteristics, and poor transients performance; • Requires effective synchronization and strong communication to achieve synchronicity; • Requires fast periodical reconfiguration.

Hierarchical	<ul style="list-style-type: none"> • More suitable for DC MG systems; • The voltage and the current are regulated locally by the source converters; • Flexible regulation of the system voltage within acceptable intervals; • Economic power dispatch among the converters, between the MG, the utility grid as well as the neighboring-MG; • Synchronous generators with the same frequency for all over the grid; • The operation constraints are dispatched to different levels reducing the processing time; • Improving the current mismatches among the controllers; • Combining the previous control structures; • Optimal decision is possible. 	<ul style="list-style-type: none"> • The distributed generators should participate in voltage regulation and frequency control; • Some generators operates in limited power mode while supplying only the power planned by the electricity market; • The distributed generators are responsible for adjusting the differences between the planned demand and the actual loads, therefore, the demand should be forecasted to plan correctly the output of the generators; • Adjacent layers coordination is required; • There is no transfer of information and energy if there is a communication fault in the upper layer; • Less computation burden.
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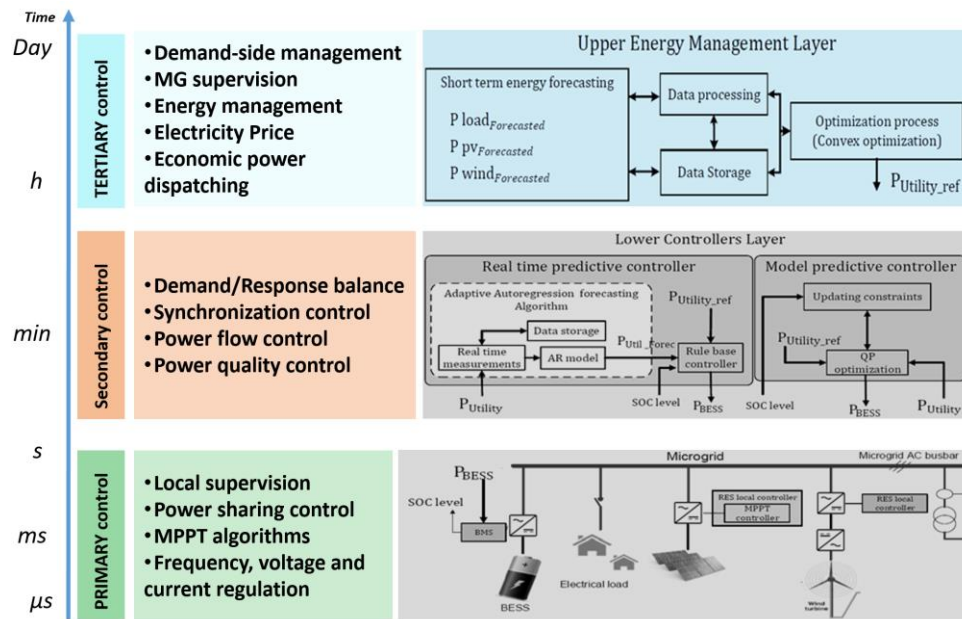


Figure 2.5. Hierarchical control levels

The hierarchical control can be implemented in parallel in both centralized and distributed structure. The advantages and disadvantages of each control structure are presented in Table 2.3.

3. Control strategies

The deployment of more than one energy source in the MG systems requires the use of efficient control strategies/approaches for managing energy flow. This requires the development and the deployment of EM systems. EM systems should be able to coordinate effectively the energy sharing and trading among all electrical networks while supplying loads according to the operational conditions and economic constraints with secure, reliable, and efficient power system operation. In fact, optimization techniques, for D/R, demand-side

management, and power quality management, are needed to achieve different EM system objectives while satisfying multiple constraints, such as electricity price minimization and occupants' comfort maximization, as mentioned in Figure 2.6.

The concept of EM system is not new and began with the first electrical networks, known as “Energy Control Center”. In the past decade, the electrical network is developed and new challenges have been evolved, consequently, new ICTs are deployed in order to improve the electrical power sector. The EM system is also developed to be renamed as a SCADA-EMS, which is charged to deploy various control techniques like services control, distributed management systems, and demand-side management (Rathor & Saxena, 2020). With the deployment of RESs, the EM system should be capable to create an energy balance between the variable demand and the stochastic RES generations in an efficient manner. It could have a control center, which is capable to supervise, monitor, manage, and optimize the operation of distributed generators, diversify consumers and the transport/distribution facility of the electricity. Actually, the EM system is not limited to the classical control objective but is developed to work for real-time applications, predictive control scheduling, and transmission security management.

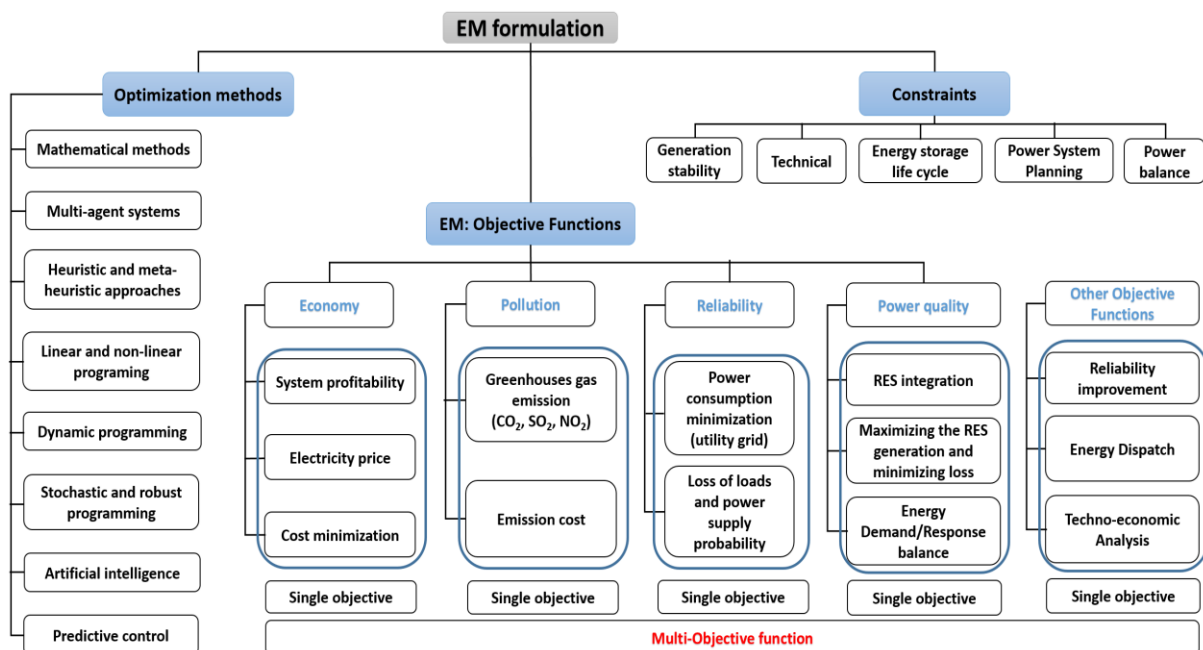


Figure 2.6. Objective functions, constraints and optimization methods for optimum operation of MG systems

Several approaches have been proposed and use diversified objective functions and constraints while using optimization methods for efficient EM, as depicted in Figure 2.6.

3.1. Objective functions and constraints

The deployment of EM control strategies specifies the main objective functions, which could be related to the operation cost, pollution, reliability, and power quality (Li, Roche, & Miraoui, 2017; Cannata et al., 2019; Jiménez-Fernández et al., 2019; Hannan et al., 2020). For instance, the main aim of using economic objective functions is to minimize the electricity price. Different formulations are studied for cost minimization in MGs. For instance, in (Liu, Y., et al., 2014), authors proposed an EM strategy for electricity cost minimization in residential MG, which is constituted by multiple households with distributed energy resources. This EM strategy considers predefined purchasing/selling decisions, at each time slot, for reducing the electricity cost as well as scheduling decisions for the shifted loads. In (Kamboj et al., 2016), authors formulate cost minimization as a dynamic economic load dispatch problem. A meta-heuristic algorithm is introduced and compared with other methods, such as differential evolution algorithm, genetic algorithm, and particle swarm optimization. The work presented in (Haidar et al., 2020), proposed an optimal strategy by evaluating the performance of different hybrid MG systems. A mathematical model is studied for sizing the component of the MG in order to meet the lowest possible cost while maximizing load demand under varying weather conditions. In (Elkazaz et al., 2020), authors present an EM system to minimize the daily operating cost of an MG while maximizing the self-consumption of the deployed RES by selecting the best setting for a central battery storage system according to a defined cost function. A simple comparison is made to show the advantages of two different layer controllers: rolling horizon predictive controller and model predictive controller. Another interesting work is presented in (Corchero et al., 2014), in which the authors introduced an optimization model for managing a residential MG, which contains RESs and a charging spot with a “vehicle-to-grid” system.

The deployment of EM approaches, which consider the pollution factor as an objective function, take time for being validated since the whole procedure should consider the life cycle of the different deployed equipment. In fact, every new energy source technology, which is promoted as being “renewable” or “sustainable”, is subject to an energy balance analysis in order to calculate the net energy yield. The energy analysis does not consider only the data for present generation systems, but also for the probable improvements in production and energy system technology (Alsema, 2012). The equivalent CO₂, generated during the fabrication of each component, should be calculated and compared to the equivalent energy, which is generated during its life cycle. While we consider that this energy is generated by

traditional sources in order to estimate the equivalent CO₂ emission and by comparing these two elements of CO₂ generation, the profitability of the system concerning the pollution objective can be defined. For example, authors ([Mason et al., 2006](#)) studied the life cycle of the balance system component of 3.5 MW_p multi-crystalline PV installation. The life cycle and the boundary conditions are calculated for each component of a PV installation (e.g., PV metal support, aluminum frames). Authors in ([Alsema, 2012](#)) present estimations of the energy requirements for manufacturing PV systems and evaluate the energy balance for an example of the PV system applications. The work investigated the effects of future developments in PV generation technology in order to assess the long-term predictions of PV system as a candidate for a sustainable energy supply and for CO₂ mitigation. Authors considered the energy payback time to estimate the CO₂ mitigation potential and conclude that 90% of greenhouse gas emissions during the PV system life cycle are caused by the energy used during system manufacturing and not during the system operation.

Alike economic and pollution aspects, the term reliability covers different aspects concerning the system operation cost, profitability, failure and maintenance, and productivity. Consequently, as mentioned above, RESs have a significant cost and consume a lot of energy in their fabrication. In order to maximize the profitability and system's reliability, the production of these sources should be maximized. Therefore, the main aim is to maximize the use of renewable energy generation, minimizing the loss of energy, keeping the storage energy system in a good state of health, and ensuring a safe and efficient supply of energy to the loads. In this way, ([Jafari et al., 2020](#)) presented an electricity market strategy for reliability enhancement of islanded multi-MG systems. A techno-economical objective function is deployed to account the profit of MG owners and to enhance the reliability of the system as well. Distribution functions are used for probabilistic modeling of RESs and loads and an electricity market strategy is proposed to improve the profit of the MG owners. However, the power quality, in particular the power loss, is still the main issue for the system's reliability and, therefore, several works propose suitable EM methods and control techniques to minimize the power loss in MG systems. For instance, in ([Yenealem et al., 2020](#)), the authors integrated an MG with static synchronous compensator controller in order to ensure a higher power flow with an enhanced voltage profile and reduced power loss. They conclude that a static synchronous compensator controller raises the capacity of the distribution line and contributes to voltage profile improvements and power loss reduction.

Similar works consider the concept of power loss minimization as stated in (Maknouninejad et al., 2014; Shieh et al., 2019; Barakat et al., 2020).

After defining the system's constraints together with objective functions, suitable optimization methods are required to ensure accordingly the exchange of the power flow between the installed RESs/storage and the MGs on the one hand, and between MGs and the utility grid on the other hand. The rest of this section is dedicated to an overview of the main methods from literature.

3.2. Optimization and control methods

Numerous research works are carried for MG control according to the system's topologies, structures, and operation modes (Ontiveros et al., 2017; Shayeghi et al., 2019; Rathor & Saxena, 2020). For example, optimization and control methods should manage the stochastic nature of the installed RES generators by ensuring a reliable supply of power to consumers, while keeping the storage system, the electricity bill, and the occupants comfort at the acceptable operating conditions.

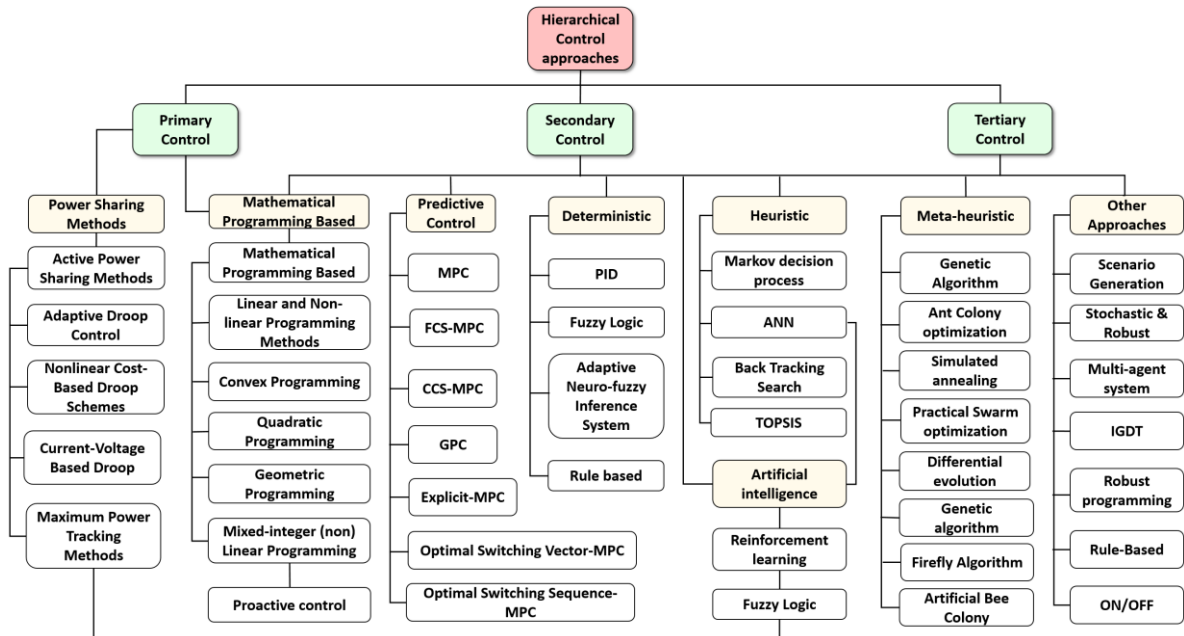


Figure 2.7. Control approaches for energy management systems

Figure 2.7 presents a proposed classification of MG control methods commonly used in MG operations. A brief description of each method is presented in the rest of this section. Furthermore, various steps should be specified, as depicted in Figure 2.8, for EM in MG.

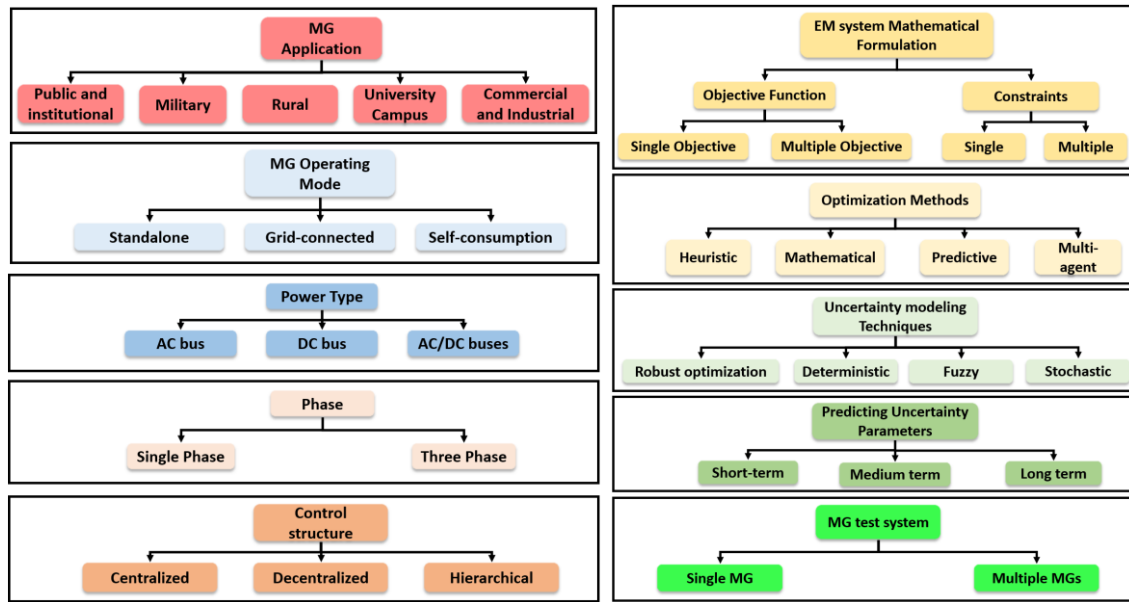


Figure 2.8. MG and EM system specification and underlying construction steps

3.2.1. Predictive control methods

Recently, predictive control approaches have been proposed for advanced systems' control according to defined constraints. Their aim was to develop predictive controllers for efficient energy flow in MG systems. These controllers could forecast future actions and decisions, but they require forecasted inputs' values (e.g., power consumption/production). With recent progress in IoT and Big-data technologies together with ML, it is now possible to deploy sensors for gathering contextual data (Elmouatamid et al., 2019a). These data could be processed and used for predicting n-step-ahead values. Therefore, the forecasted values are the main inputs for generating the most suitable and future actions by predictive control approaches (Elmouatamid et al., 2019b; Elmouatamid et al., 2019c).

MPC and GPC are the well-known approaches having the capabilities of predicting future events and forecasting right control decisions accordingly. In fact, they have the ability to incorporate optimization mechanisms, which allows integrating the system's constraints and disturbances in forecasted control decisions. For instance, the GPC is widely used in advanced control applications, such as in EM and buildings' automation systems (Buyak et al., 2017; Rahmani-Andebili et al., 2017). For example, the work presented in (Hemmati et al., 2017), introduced a home EM system for battery storage and PV systems. The proposed planning, for the optimal operation strategy, is expressed as a stochastic mixed-integer nonlinear programming. The power generated by the PV system is considered as an uncertain parameter and modeled by a probability distribution function. The battery storage system is used to store

energy during off-peak/low-cost hours and discharge energy during on-peak/high-cost hours. However, the main limitation of this EM strategy is the passive reaction of the system with the cost and the peak demand variability. It is programmed by a fixed time interval that presents predefined periods of on-peak and high-cost and it is not defined by an active function for the interactive variability of the cost and the electricity demand. Moreover, authors ([Rahmani-Andebili et al., 2017](#)) proposed an adaptive and dynamic optimization technique based on the stochastic MPC approach. The proposed EM approach is applied for distributed energy resources scheduling problem for a set of smart homes with different sources of energy. Its aim is to address the uncertainty and variability issues of the PV power generation. This study is designed for large-scale smart houses by taking into consideration their cooperation with their neighbors. Another interesting work is presented in ([Bordons et al., 2019](#)), in which authors proposed an EM system using the MPC where a simple state-space model is used for the performance modeling of an MG system. This work considered the RESs power production and the consumption as measured disturbances parameters for the EM system. Therefore, the storage systems and the cost are modeled as constraints for the MG system, which are solved by the state-space equations. In addition, other works are presented in the literature, which refer to optimal control of RES in MG systems considering hybrid storage systems, as detailed in ([Petrollese et al., 2015](#)). In ([Negenborn et al., 2009](#)), the authors used the MPC for optimal control of distributed energy resources with a battery storage system. In other works, the MPC is used for EM of MG systems that are connected to the charging station for electrical vehicles ([Mendes et al., 2016](#); [Garcia-Torres et al., 2018](#); [Chen et al., 2020](#)). Generic MPC models are introduced in ([Bozchalui et al., 2012](#); [Parisio et al., 2014](#)) for economic optimization in MG systems.

It is worth noting that the MPC family was proposed for electronic power, and especially for power converter control. The GPC is one of the CCS-MPC (Continuous Control Set MPC) methods that calculate a continuous control command in order to generate the desired output of the power converter. The CCS-MPC models have a lower computational cost than the other existing methods like FCS-MPC (Finite Control Set), OSV-MPC (Optimal Switching Vector), and OSS-MPC (Optimal Switching Sequence) ([Bordons et al., 2015](#)). It can be used for long predictive horizon problems by calculating the control actions beforehand and then limiting the online computation burden. Mainly, the calculation time is the main factor for the deployment of MPC control families. In past decades, the development of computing units and the integration of ICTs and ML algorithms for power electronic applications encourage

the use of predictive control for the power converter. For instance, in (Linder et al., 2005; Rodriguez et al., 2007), an FCS-MPC is used for the current control of three-phase inverter. It is studied in (Gregor et al., 2009) for multiphase inverter, in (Lezana, Aguilera, & Quevedo, 2008; Cortes et al., 2010) for multilevel inverter, and in (Correa et al., 2009; Vargas et al., 2010) for matrix converter. For more details, we refer readers to an interesting review, which is related to predictive control applications in power electronics (Vazquez et al., 2014). These approaches offer the possibility to integrate multiple objective functions and constraints with the possibility of its integration in the different control levels. Mainly, with the integration of the new ICT, the predictive control can be developed to present high performance for control commands and actions prediction. In addition, the use of ML algorithms to forecast the control input parameters offers more reliability and flexibility to the predictive control approaches.

3.2.2. Classical approaches

Many EM optimization approaches are based on classical approaches, such as mixed-integer linear and nonlinear programming. These approaches can be considered as efficient methods for the MG system's control according to the specified objective and constraints. For instance, authors in (Sukumar et al., 2017) proposed an MG EM system for power-sharing, power trading with the main grid, continuous run, and on/off mixed-mode based on linear programming optimization method. In this study, on/off mode is solved by a MILP solution approach, which optimizes the operation of MG with respect to the operation mode of the main grid, fuel cell, and energy storage system. The work presented in (Nemati et al., 2018) developed a real-coded genetic algorithm and a MILP-based method to schedule the unit commitment and economic dispatch of MG units. The work considers the voltages limits, equipment loadings, and unit constraints in its formulation and the proposed algorithm deploys a flexible set of sub-functions, intelligent convergence behavior, as well as diversified searching approaches and penalty methods for constraint violations. At the same, a method is investigated to deal with the constraints of the MILP algorithm for handling the nonlinear network topology constraints. Another interesting work is presented in (Shekari et al., 2019), authors present a MILP-based approach for managing electrical and heat demands in a multiple MG environment. The proposed strategy considers different energy converters and storages, distributed energy generators, and electricity/heat storage units for optimal scheduling of MG including technical and economic ties between electricity and natural gas systems. The deployed algorithm is developed based on AC power flow, while the deployed

model respects reactive power and voltage security constraints allowing the MG system to minimize the operation cost. Moreover, several other works are presented using these approaches as presented in (Helal et al., 2017), in which operating cost of MG is minimized using MINLP while considering, as a constraint, droop controlled active and reactive power dispatch of AC side MG. In (Panwar et al., 2017), an EM approach for MG is proposed under the operation system of transformer nominal operation and voltage security. Three objective functions of customer benefits, load leveling, and network losses are studied.

Generally, the objective function and constraints, deployed in linear programming methods, are linear functions with whole-valued and real-valued decision variables. This family of approaches is often used for system analysis and optimization as it presents a flexible and powerful method for solving large and complex problems, such as distributed generation and MG systems.

Dynamic programming methods are used to solve more complex problems that can be sequenced and discretized. The studied problems are usually fragmented into sub-problems that are optimally solved, while, the obtained solutions are super-imposed to develop an optimal solution for the original problem (García Vera et al., 2019). Therefore, the rule-based methods are generally used to implement the EM system because they do not require any future data profile to make a decision, thus making them more suitable for real-time applications. For example, authors in (Bukar et al., 2020) presented a rule-based EM system, in which a rule-based algorithm is used to implement the priority of RES usage and manage the power flow of the proposed MG components. A nature-inspired optimization algorithm is used to optimize the MG system's operations for long-term capacity planning. The main goal of the proposed objective function is to minimize the cost of energy in MG systems as well as the deficiency of power supply probability. Other works proposed rule-based methods to control and optimize the energy flow in MG systems. For example, the work presented in (Merabet et al., 2016) developed a control algorithm to provide power compatibility and EM for different resources in the MG. A real-time control system is used to validate, experimentally, the hybrid system in the MG. Results showed that the proposed approach provides stable operation of the MG subsystems under various power generation and consumption conditions. In (An & Quoc-Tuan, 2015), a method is studied to build the optimal EM for the MG-connected system, which includes energy trading cost with the main grid and battery aging cost. The authors used a dynamic programming algorithm to minimize the cash flow of the system while maximizing the power supply from the main grid.

Alike other classical methods, a dynamic programming algorithm can be considered as a mathematical optimization method, which can be used to simplify a complicated problem to simpler sub-problems for being solved in a recursive manner. They are able to provide optimal decisions; however, they required high computational cost, which makes them difficult to be implemented in embedded devices.

3.2.3. Heuristic and meta-heuristic approaches

Heuristic and meta-heuristic approaches are used in many disciplines, such as in telecommunications and transportation systems. Recent studies have developed EM approaches for MG systems. For instance, in (Papari et al., 2017), authors introduce a heuristic method for optimal operation and EM of DC MG systems. The studied problem is formulated in form of a single-objective optimization problem by focusing only on cost minimization. Authors in (Khan et al., 2019a) proposed a meta-heuristic based system by integrating the harmony search algorithm and the enhanced differential evolution. To ensure that the power consumption does not exceed a fixed threshold value during peak periods, multiple knapsacks are used and the proposed system outperforms the existing meta-heuristic techniques in terms of cost and peak to average ratio. (Chen et al., 2011) proposed an economical model for energy storage system together with a real coded-genetic algorithm model for MG systems operating in a grid-connected mode. The developed algorithm maximizes the present cost of an energy storage system over its lifespan based on its capital, energy arbitrage revenue, operation cost, and maintenance cost. In (Radosavljević et al., 2016), an optimal EM system is proposed for a grid-connected MG system based on a genetic algorithm, which considers the electricity price, power consumption, and the uncertainty of RESs generation. The work showed that the particle swarm optimization method is more efficient in terms of finding the best solution to the studied optimization function in comparison with genetic algorithm and combinatorial particle swarm optimization. A deterministic EM problem is solved, in the work presented by (Marzband et al., 2014), via a multi-period gravitational search algorithm. In (Aghajani et al., 2015), a multi-objective particle-swarm-optimization algorithm is used to solve the EM system problem, considered as a multi-objective problem. However, in (Alavi et al., 2015; Rabiee et al., 2016) the EM system problem is solved by single-objective using particle swarm optimization based algorithms.

Generally, heuristic optimization approaches use exploratory methods, in a reasonable time, to solve the optimization problems; however, they are unable to assure optimality of the obtained results (Khan et al., 2016a).

3.2.4. Artificial intelligent methods

Artificial neural networks are examples of artificial methods. They are considered stochastic methods, which could be used to solve optimization problems for the system having random variables. For MG systems, RESs have a variable nature caused by the weather conditions, which affect the power generation. An example, authors (Motevasel et al., 2014) presented an expert system for EM in MG systems using neural networks in order to predict the power generation of the installed RESs. In (Solanki et al., 2017), the authors proposed a mathematical model for smart load management in a standalone MG system. The studied loads are modeled by neural networks and predictive control is used to manage the energy according to predicted load variation. In (Venayagamoorthy et al., 2016), an EM system for an MG system, connected to the utility grid, is presented with the main objectives to maximize the use of renewable energies while minimizing carbon emission. Two neural networks are used to model the proposed EM system using evolutionary adaptive dynamic programming and learning concepts. For the deployed neural networks, one is used for the management strategy, and the other is used to check the optimal system's performance. Authors in (Li et al., 2013) used a neural network to control a bidirectional rectifier/inverter. A dynamic programming algorithm is implemented and it is trained using back propagation through time. The deployed neural networks show a high ability to trace rapidly changing reference commands for frequency and voltage, and satisfying control requirements for a faulted power system. The neural network controller used in this work is performed and studied under typical vector control conditions. Authors in (Wang et al., 2019) proposed a Lagrange-programming neural networks method for efficient control and management of the MG system with the main objective to minimize the overall cost of MG. In this work, the load is classified into different categories of controllable load, thermal load, price sensitive load, and critical load, while, variable neurons and Lagrange neurons are combined to obtain optimal scheduling of MG operation.

Mainly, neural networks can control, optimize, and identify the system's parameters, in online or offline applications. Unlike the previous approaches, neural networks can solve problems with nonlinear data in large-scale MG systems, because of their ability to solve the

system's stability via self-learning and prediction capabilities ([Mahmoud et al., 2017](#); [Roslan et al., 2019](#)).

Alike neural networks, FL method is considered as one of the non-linear techniques that are used for power regulation with power electronics-based converters. This intelligent control consists of a fuzzifier, rule evaluator, and a defuzzifier; while, a set of rules known as rule-base and database is considered for the control strategy deployment. Mainly, the FL method is used to control space vector PWM based three-phase rectifier and it is used with intelligent techniques-based Droop-Control to manage multiple distributed energy DC-MG systems ([Diaz et al., 2014](#)). For instance, in ([Kakigano et al., 2012](#)), the authors proposed a voltage control technic using FL based centralized controller with gain scheduling control for DC-MG with electric-double-layer-capacitor as energy storage. A fuzzy-based control strategy, proposed in ([Agnoletto et al., 2016](#); [De Nadai et al., 2017](#)), is capable to determine small voltage and frequency steps regulations to improve the performance of Droop-Control by diminishing the mismatch in the common bus without heavy communication links. This work considers the frequency and voltage as variables uncoupled and then correct each one separately by considering that the voltage is local and the frequency is global variables of the system. The proposed fuzzy method changes the frequency and the voltage reference values in the droop equation of the Voltage Sources Inverters to correct its variation. In ([EI-Bidairi et al., 2018](#)), FL and a meta-heuristic algorithm known as Grey-Wolf optimization are used to optimize the interconnection between multiple MG systems. The main aims of this method are to minimize both the costs for the generators units and the emission levels of the fossil fuel sources. Several works studied the use of FL for EM in MG systems. In ([Jafari et al., 2018](#)), a mode transition strategy is deployed to smooth the mode variation and a fuzzy controller is used to determine the operation mode of coupled MG system with 20 different grid-connected and standalone MG systems. The FL is also considered as a deterministic algorithm for frequency and voltage regulation in both primary and secondary control levels and it is characterized by low computational cost and easiness of implementation. In the literature, FL is the most deterministic approaches used together with PI controller.

MAB control approaches are generally used in MGs because they are decentralized while allowing multiple interacting agents to follow their specified rules and goals and to perform autonomously dedicated functions ([Dou et al., 2015](#)). The principal element of MAB methods is the agent, which can be a virtual or physical entity situated in a specified system (e.g., buildings, MG). It is capable to autonomously react depending on the changes in the system's

environment (Mao et al., 2014; Sahoo et al., 2017). In (Khan et al., 2019b), a comprehensive description of different optimization techniques applied to EM is highlighted, and a comparison with other techniques is realized including MAB. Authors in (Raju et al., 2017), presented an EM-based on the differential evolution algorithm, developed in JADE (Java Agent Development Environment) for grid outage. The proposed MAB approach showed its efficiency in minimizing load's uncertainty as well as the generation costs from the intermittent nature of RESs generation. The approach also considered the price variation in the utility grid, and the critical loads are considered while selecting the best solution. In (Anvari-Moghaddam et al., 2017), a fault-tolerant multi-agent control approach is proposed for coordinated energy and comfort management in integrated buildings and MG systems. Several cooperative agents are presented and trained in order to reach global coordination, to satisfy related constraints, and to meet the system's objectives. The integrated buildings and MG systems are mathematically formulated as a multi-objective optimization problem, which is solved under different operating conditions. Other interesting research works, which consider the MAB control approaches for EM in MG systems, are presented in (Karavas et al., 2015; Kofinas et al., 2018; Samadi et al., 2020).

The usage of the MAB method is rapidly growing in power systems, especially for EM in MG systems. MABs, combined with system modeling, make the arrangements of MG units autonomously directed making the scheme more intelligent and protective. The deployment of MAB control in the MG system considers each agent as an intelligent unit, which can communicate with their neighboring agents in a collaborative way to determine future control actions to achieve the common objective. The communication with neighboring agents requires the deployment of advanced ICTs in order to benefit from the advantage of such approaches.

Despite the efficiency of the abovementioned methods, still real-time and predictive control approaches are required for intelligent EM in smart MG systems.

4. Comparison of control approaches for MG systems

The choice of an EM approach is an essential requirement for reliable and stable operation of the MG system. Depending on the characteristics of the deployed system (e., topologies, operation modes, structure), EM can be selected. However, the deployment of an approach does not signify that the others are not reliable, while the studied constraints and the fixed objective of the control strategy are the main issues in order to identify the utility of the

deployed method. In the rest of this section, the advantages and the disadvantages of different control techniques are presented (see Table 2.4).

Table 2.4. Brief comparison of control approaches

<i>Control approach</i>	<i>Application</i>	<i>Advantage</i>	<i>Disadvantage</i>
Model predictive control (Vazquez et al., 2016; Castilla et al., 2020; Vazquez et al., 2014)	<ul style="list-style-type: none"> Reliable for power sharing between MG and the utility grid Hybrid AC/DC coupled MG 	<ul style="list-style-type: none"> Robust against uncertainty Power smoothing Multiple control objective and constraint functions are implemented for the same control strategy Optimal control 	<ul style="list-style-type: none"> Requiring the use of advanced ICTs Control parameters information should be defined in advance
Adaptive droop (Augustine et al., 2015; Djebbri et al., 2020)	<ul style="list-style-type: none"> Hybrid system of RESs Parallel DC/DC converter Heavy loading conditions 	<ul style="list-style-type: none"> The different operation modes eliminate the overload conditions between generator unites, storage devices, and utility grid; Minimizing circulating current. 	<ul style="list-style-type: none"> Difficult to select the proper voltage levels Generating interconnection resistances between the installed converter and requiring information about the DC bus Control parameters should be known in advance.
Artificial neural networks (Moon et al., 2019; Reynolds et al., 2019)	<ul style="list-style-type: none"> Distributed power generation units Multiple MG system interconnection 	<ul style="list-style-type: none"> The approach can control, optimize, and identify the system's parameters in online or offline applications Solve problems with nonlinear data approaches in large-scale systems in MG Solve the system's stability and fault tolerance via self-learning and prediction 	<ul style="list-style-type: none"> Complexity of the model structure Experimental interpretation of the model is difficult (black boxes) Difficult to determine the best network structure in case of adding or raising units from the MG topology Possibility only on stable system structure
Distributed cooperation control (Huang et al., 2014; Liu et al., 2018; Xing et al., 2019)	<ul style="list-style-type: none"> The control is optimal for DC-MG system Improving voltage levels for DC-MG 	<ul style="list-style-type: none"> Flexible, robust, and, extensible Optimal coordination control and improved voltage profile 	<ul style="list-style-type: none"> Less security for the communication system Frequency response nature cannot be visualized
Conventional droop (Huang et al., 2010; Peyghami et al., 2019)	<ul style="list-style-type: none"> Reliable for DC-MG Linear loads Inductive transmission lines 	<ul style="list-style-type: none"> Easy implementation for the primary control 	<ul style="list-style-type: none"> Voltage regulation is not ensured The voltage drop across the bus resistance causing a current sharing degradation Active and reactive power bandwidth variation of the controllers affects the voltage and frequency controls
FL based control (Erdinc et al., 2019)	<ul style="list-style-type: none"> Reliable for primary control 	<ul style="list-style-type: none"> Improved voltage and frequency regulation 	<ul style="list-style-type: none"> Requiring a high processing unit

2009; Abd-El Baset et al., 2020)	<ul style="list-style-type: none"> • Voltage and frequency regulation 	and power sharing for multiple MG	<ul style="list-style-type: none"> • Errors methods adopted for the participation function and time consuming process
Multi-agent based control (Khan et al., 2016b; Prinsloo et al., 2018; Xiong et al., 2020)	<ul style="list-style-type: none"> • Distributed power generation units • Multiple MG system interconnection 	<ul style="list-style-type: none"> • The group of agents can address larger problems than any individual is capable to do in MG system • Redundancy and economies of large scale • The ability to meet global constraints • Flexibility to work in uncertain environments under unforeseen conditions 	<ul style="list-style-type: none"> • Potential for conflicts; need for increased agent sophistication • Short term benefits may not outweigh organization construction costs for the installed MG systems • Requiring a high connectivity between agents and the LC • The agent should operate at the same parameters of the other agents, especially for voltage and frequency regulation

A good approach must consider the stochastic nature of different control parameters, the installation cost, the components lifetime, the distributed resources, and the reliable and safe operation of the MG system. In fact, the deployment of an EM control strategy requires the classification of the whole system into different levels, while, each level should operate by coordinating with the other levels from the sources (e.g., maximum power point tracking) to the end consumers, which can be a local consumer or a neighboring MG consumer. Nowadays, smart components are installed for each source and for each MG system, which can cooperate with them due to the new ICTs. Especially, the actual inverters can execute different control strategies from the source power regulation to the interconnectivity to the utility grid or to the neighboring MG. In addition, the inverters can be installed for a large scale of MG systems creating clusters of data and electricity exchange, while, these inverters could be connected to the internet in order to store the historic data in the cloud. Mainly, the main objective function for each inverter is ensuring continuous power supply to the consumers, without considering the lifetime of the battery storage system or the cost of electricity. In this context, the development of an EM control strategy that considers the electricity price variation and minimizes the battery C/D cycle is required. These two issues allow the maximization of the system profitability by minimizing the electricity bill and avoiding a frequent replacement of battery storage in an MG system. The main idea is to develop an intelligent and predictive control strategy that can control optimally the distributed resources in the MG by considering multiple constraints and objective functions at the same time.

5. State of the art synthesis and our contribution

Control strategies, generally, use single-objective function procedures (e.g., maximizing the quality of the services). Without considering different operating constraints, these procedures are easier to implement and to deploy in real-sitting scenarios. Moreover, control strategies, which take into consideration only the energy availability within MG components (e.g., energy sources, storage devices, traditional electric grid), could be implemented by simple algorithms. These algorithms implement procedures that switch, at each time, from RES to either storage devices or to the TEG. For instance, actual commercial inverters are able to manage efficiently the interconnection between RESs, energy storage systems, and the utility grid by incorporating a single-objective function. In particular, the MG system's EM takes into consideration only the availability of the electricity for being supplied to buildings loads. The inverter can use once either batteries or the utility grid without taking into account other parameters, such as the actual electricity cost as well as batteries C/D cycles. However, high batteries C/D cycles, in a limited time, could decrease their performances, which impact the profitability of the system. In other cases, controllers can interact, in real-time, with energy sources generators (e.g., solar, wind) in order to limit the power generation (LPPT). The aim is to ensure the quality of the electrical services (e.g., frequency, voltage), and consequently minimizing the profitability of the MG system's components. Despite their advantages, they could have, however, negative impacts on the batteries' lifecycle and system's profitability. Therefore, context-awareness principles and predictive analytics could be exploited for developing context-driven control approaches.

Our thesis's contribution to the current state of knowledge aims to develop context-driven control approaches for EM of MG systems in the context of smart buildings. Mainly, a predictive control approach, named MAPCASTE (Measure, Analyze, Plan, foreCAST, and Execute), is developed and deployed in real-sitting scenarios for EM in MG systems (see Figure 2.9). Unlike the control approaches from literature, MAPCASTE considers multiple objectives functions, which take into consideration batteries C/D cycles as well as the electricity price forecasting. The main aim is to ensure, in an optimal way, the continuous electricity supply from different installed sources (e.g., RESs, batteries, TEG) to the building's services. The proposed approach is based on predictive control models, which are able to generate a sequence of future control actions over a prediction horizon.

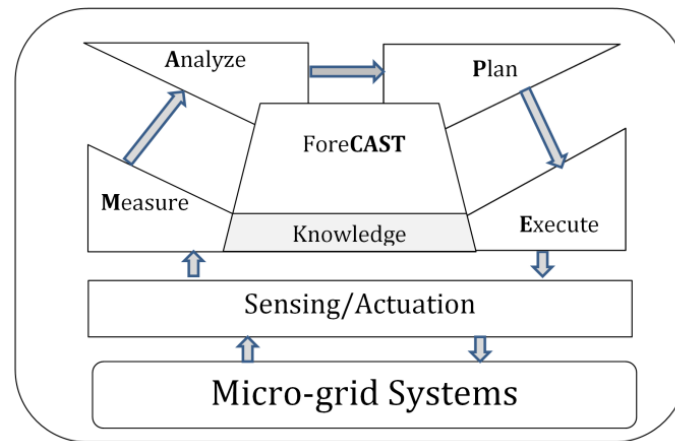


Figure 2.9. The proposed control approach schemes with operation process

However, in order to carry out the MAPCASTE, several forecasted inputs values are required, mainly the power production/consumption and batteries SoC. This requires an advanced metering infrastructure, which allows measuring and predicting all input values. Therefore, an MG was deployed together with an IoT/Big data platform in order to conduct experiments and validate developed models. The deployed MG system contains RESs and battery storage systems, which are connected together with the TEG in order to supply the electrical energy to the building's loads (e.g., lighting, ventilation). The IoT/Big data platform was developed and deployed in order to allow measuring and forecasting RESs power generation, loads consumption, and batteries SoC. Sensing/actuating components with a control card are installed in order to monitor and manage the whole MG system offering the possibility to test the developed control techniques in the real context.

6. Conclusions

The EM and the optimization control in MG systems are becoming multiple objectives “management/optimization” function to be satisfied by solving simultaneously technical, economic, and environmental problems. Therefore, several approaches (e.g., exact, stochastic, and predictive) have been proposed for EM. These approaches are chosen based on their practicality, reliability, and resource availability in the MG environment. This chapter reviewed recent research work related to EM in MG systems. In particular, we focused on different control approaches that have been proposed to efficiently operate MG systems including centralized, decentralized, and hierarchical management structures. A comprehensive description of control and optimization methods is highlighted, particularly to identify the most common and effective method for EM in MG systems. Predictive control

showed to be a good candidate since it integrates optimal control, multivariable processes and it is a flexible control scheme that allows easy inclusion of system constraints and optimization functions. It is robust against uncertainty and power smoothing problems, thus, multiple control objective and constraint functions can be implemented for the same control strategy. However, despite the power of these predictive control techniques, their deployment in real-sitting scenarios requires a holistic platform that integrates MG components together with all equipment for measuring and predicting important input data. With recent technological advances in microprocessors, data analysis, and ML, predictive control can be seen, therefore, as a promising alternative for EM in MG systems. In the frame of this thesis, the MG system's modeling, together with experimental platforms are developed and deployed for being used in conducting both simulations and experimentations for performance evaluation of the proposed control approaches.

Chapter 3: The Deployed Micro-grid System Integrating Renewable Energy Sources: IoT/Big Data Platform and used Models

1. Introduction

The decentralization of energy production, via the integration of RESs, makes the electrical system more complex and more difficult to control in order to keep a suitable electricity balance (i.e., D/R). Consequently, the transition from unidirectional to bidirectional interconnection and from centralized to decentralized energy production requires the use of smart equipment (e.g., smart metering, smart inverter, smart transformer) (Llorente et al., 2012). This equipment should be able to interact with different building's services taking into consideration its surrounding environment. In this context, an MG system is defined as an “intelligent building” that can produce, consume, and store locally the electrical energy. The MG, via a well-established ICT-based infrastructure, can interact with consumers, with neighboring MGs, and with the TEG. The main objective of such systems is to connect efficiently the producers and consumers of electricity with a high level of security, stability, and continuity of energy supply (the increase of services quality). As a result, the MG has the possibility to smoothen the electrical peaks demand in the electrical network, which represents a major challenge for the TEG. It also allows for managing the electricity flows by considering economic and environmental constraints. Accordingly, the electricity bill can be minimized by avoiding peaks demands and, therefore, the consumption can be maximized from RESs while minimizing subsequently the carbon impact. Therefore, as state above, the interaction of different buildings' components needs to integrate ICT-based infrastructures for data collection, analysis, and processing. This integration of ICT together with RES and storage has enabled the emergence of “Micro-Grid” systems (Ali et al., 2013). MG systems remain important and necessary building blocks for the development of SG systems as well as smart cities applications and services (Hatziargyriou , 2014).

In this chapter, a new holistic architecture of smart buildings is presented by improving the main layers of MG systems. This architecture is proposed in order to integrate all buildings' aspects with the main trade-off is to minimize energy consumption while maintaining a suitable occupants' comfort. In fact, an MG system is structured into three layers following the proposed holistic architecture. More precisely, we shed more light on the MG system's components modeling in order to have a real platform with its virtual models

offering the possibility to validate our system by comparing simulation and experimentation results. In addition, another layer is added to integrate recent IoT/Big-Data technologies for data gathering, processing, and control.

2. MG layers structure for energy efficient buildings

As shown in Figure 3.1, our MG system is structured into three horizontal layers: passive building layer (e.g., building envelope and insulation, architecture design), active building systems layer (e.g., HVAC system, Lighting), and RESs system layer (e.g., PV, wind, storage). These layers are monitored by one vertical layer for communication and ICTs integration. This layer integrates mainly an IoT/Big-Data platform in order to measure, analyze, predict, and forecast actions depending on the actual and predicted context.

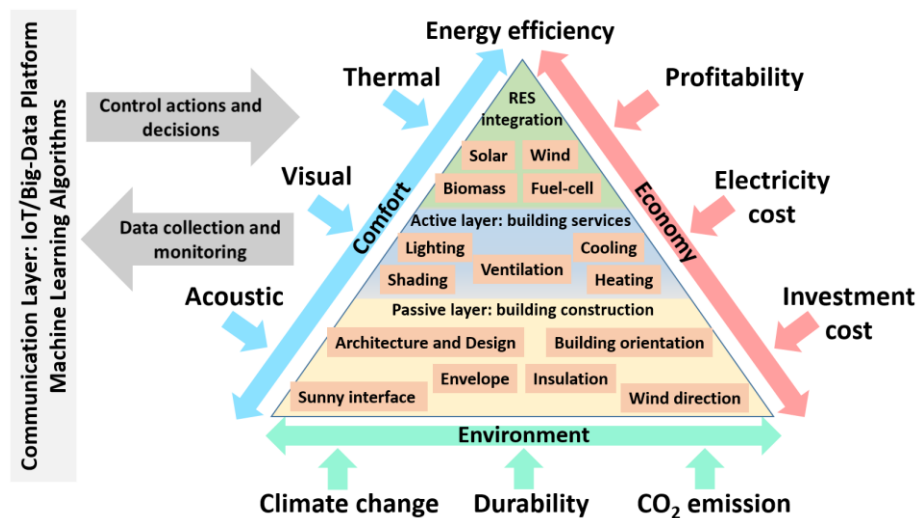


Figure 3.1. The main MG system's layers for smart and energy-efficient buildings

In particular, our MG system is a smart and active building that combines ICTs/Big-data infrastructure, RESs/storage systems, EM/control strategies, and electrical power grids. This new concept of a building is more interactive for both consumers and energy producers. In fact, consumers will reduce the cost of their energy consumption based on the used control approaches, which take into account the real-time cost of the power and the predictive power generation, for efficient D/R management (Elmouatamid et al., 2020b). In addition, the household equipment (e.g., refrigerators, washing machines, microwaves, lighting) are becoming intelligent devices, which may be actively controlled using IoT devices, as well as adjusted and controlled by interacting with other systems (e.g., power generation, EM system). Moreover, this MG structure offers the possibility to integrate new buildings' services, such as electrical vehicles, which can be used as a storage device to compensate the

energy in the building by integrating the “Grid-to-Vehicle & Vehicle-to-Grid” techniques. Mainly, the main component of the energetic system is presented in Figure 3.2, which is installed in our deployed MG system.

In the next sections, we focused on the modeling of each components of MG layers, especially for RESs, storage devices, and ICTs/Big-data infrastructure.

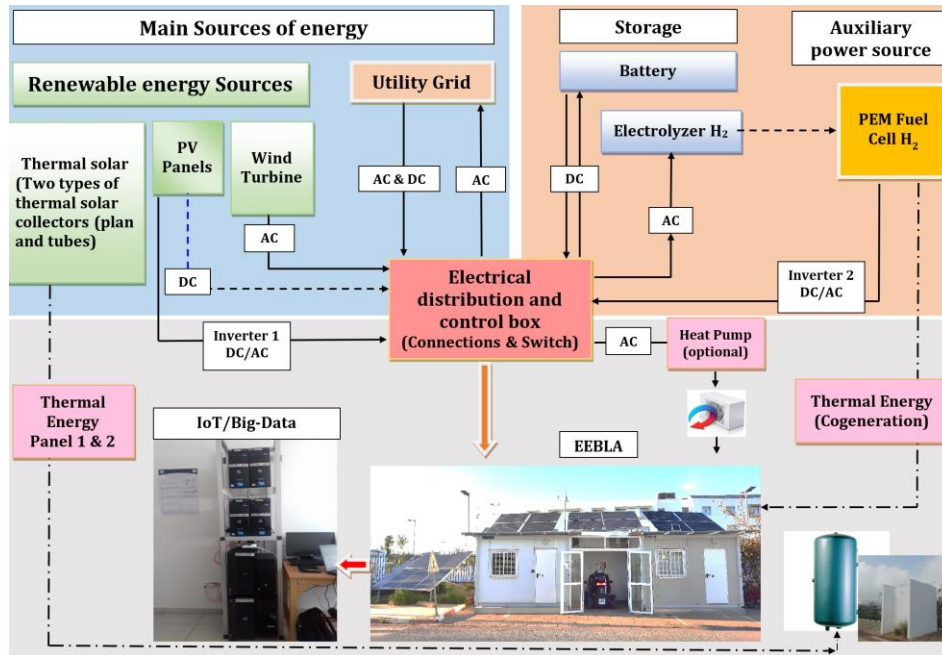


Figure 3.2. The holistic model of the deployed MG system

3. Renewable energy sources modeling

3.1. Photovoltaic systems and electrical energy production

The PV module is the interface that converts sunlight into electricity. The sunlight can be converted directly into electricity using PV panels or indirectly by concentrating the solar radiation to heat water that can be also used to provide electrical power. In fact, PV technologies use semiconductor materials to convert sunlight directly into electricity. The electronic component that is used to generate electricity is the PV cell. They are grouped together to form a PV panel that can produce current directly from solar radiation (Seyedmahmoudian et al., 2013). A PV plant is usually composed of several PV panels; it contains decades of panels for a building or thousands for a power plant. The majority of PV installations are connected to the distribution networks (low voltage). However, the high penetration of the PV system in the MG system is encouraged due to the simplicity of the installation and the clean nature that they have. In this section, the mathematical models are

presented for each RESs units based on the studies that are realized in (El mouatamid et al., 2017).

3.1.1. Photovoltaic cell modeling

The PV system is integrated as a main RES in MG systems together with WT in order to supply the power to the loads. For that, the system should be modeled and characterized by mathematical equations for easy and efficient integration into simulation tools. In fact, modeling this system requires taking weather data (e.g., temperature, irradiance) as input variables. Various mathematical models are developed to characterize the highly nonlinear behavior resulting from semiconductor junctions that constitute the solar cell. In our study, we consider the single diode model (Habbati et al., 2014). Principally, to describe a single diode model, three equivalent circuit models can be defined as shown in Figure 3.3: the ideal PV cell model, the PV cell with series resistance, and PV cell with series and shunt resistances.

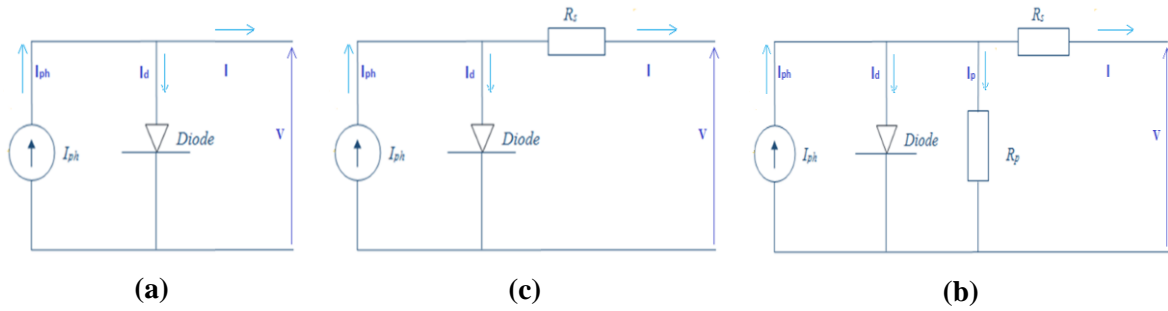


Figure 3.3. PV cell equivalent circuit model; a) Ideal single diode model, b) PV cell with series resistance, c) PV cell with series and shunt resistances

For Figure 3.3.a, the ideal single diode model does not take into consideration the internal losses of the current due to the resistance of the electrical wires. A diode is connected in anti-parallel with the light generated current source. The generated current I is obtained by Kirchhoff law:

$$I = I_{ph} - I_d, \quad (3.1)$$

where, I_{ph} is the photocurrent generated by the incidence of light, and I_d is the current through the diode, which is proportional to the reverse saturation current I_o and it is presented by the following equation:

$$I_d = I_o \cdot \left[\exp \left(\frac{V}{N_s \cdot n \cdot V_t} \right) - 1 \right], \quad (3.2)$$

where V is the diode voltage, N_s is the number of PV cell connected in series, n is the ideality factor of the cell and it depends on PV cell technology, V_t is the thermal voltage presented by equation (3.2.a), k is the Boltzmann constant ($1.38 \times 10^{-23} \text{ J K}^{-1}$), q is the electronic charge ($1.602 \times 10^{-19} \text{ C}$), and T_{op} is the PV cell temperature (K).

$$V_t = \frac{k \cdot T_{op}}{q} \quad (3.2.a)$$

To develop the accuracy of the model, Figure 3.3.b presents a PV cell model with series resistance R_s . For a real model, it is impossible to neglect the resistance of the wires, which can be integrated into the previous saturation current equation and it can be written as follows:

$$I_d = I_o \cdot \left[\exp \left(\frac{V + I \cdot R_s}{N_s \cdot n \cdot V_t} \right) - 1 \right], \quad (3.3)$$

However, in reality, leakage of current has occurred between the terminals of the PN junction of the PV cell. As mentioned in Figure 3.3.c, this leakage of current is modeled by a shunt resistance R_p . By applying Kirchhoff law, the current will be expressed by the following equation:

$$I = I_{ph} - I_o \cdot \left[\exp \left(\frac{V + I \cdot R_s}{N_s \cdot n \cdot V_t} \right) - 1 \right] - \frac{V + I \cdot R_s}{R_p}, \quad (3.4)$$

In equation (3.4), both sides contain the unknown current parameter I , which is a typical implicit transcendental equation. This implicit equation can be resolved by the Newton iteration method, which is based on some approximation for the unknown parameters (Shinong et al., 2020).

3.1.2. Parameters calculation

The chosen PV cell model is the single diode model with both series and shunt resistances in order to obtain a better accuracy of the model. For the studied model, we consider that the unknown parameters are I_{ph} , I_o , R_s , and R_p . To calculate these parameters,

some known equilibrium operation points are used. For instance, the photocurrent I_{ph} is defined by:

$$I_{ph} = [I_{sc} + K_i (T_{op} - T_{ref})] \cdot \frac{G}{G_{ref}}, \quad (3.5)$$

where, I_{sc} is the short circuit current, K_i is the short circuit temperature coefficient at I_{sc-ref} ($T_{ref} = 25 + 273 \text{ K}$, $G_{ref} = 1000 \text{ w/cm}^2$), G and T_{op} present respectively the operational irradiance and temperature. According to the equation (3.1), the PV cell current at the standard test conditions is obtained by equation (3.5.a). In fact, by considering that the PV cell is short-circuited ($V=0$), we have: $I_{sc,ref} = I_{ph,ref}$ and the photocurrent depends on the input parameters of weather condition (Temperature, Irradiance).

$$I = I_{ph,ref} - I_{o,ref} \cdot \left[\exp\left(\frac{V}{N_s \cdot n \cdot V_{t,ref}}\right) - 1 \right] \quad (3.5.a)$$

For the reverse saturation current I_o , it is proportional to the cube of the PV cell temperature and it is presented by equation (3.5.b) as follows:

$$I_o = I_{rs} \cdot \left(\frac{T_{op}}{T_{ref}}\right)^3 \cdot \exp\left[N_s \cdot \left(\frac{1}{T_{ref}} - \frac{1}{T_{op}}\right) \cdot \frac{E_g \cdot q}{K \cdot n}\right] \quad (3.5.b)$$

where E_g is the band gap energy of the semiconductor and I_{rs} is formulated by equation (3.5.c).

$$I_{rs} = I_{sc} \cdot \left[\exp\left(\frac{V_{oc} \cdot q}{K \cdot n \cdot T_{ref} \cdot N_s}\right) - 1 \right] \quad (3.5.c)$$

Since the value of E_g is not provided by the datasheet of the PV cell manufacturer, in our study I_o is calculated using the equation presented in (Villalva et al., 2009) as follows:

$$I_o = \frac{I_{ph,ref} + K_i (T_{op} - T_{ref})}{\exp\left(\frac{q \cdot (V_{oc,ref} + K_u (T_{op} - T_{ref}))}{K \cdot n \cdot T_{op} \cdot N_s}\right)}, \quad (3.6)$$

In this equation, the different parameters can be calculated using the known values provided by the manufacturer. The K_i and K_u are respectively the short circuit current temperature coefficient and the open-circuit voltage temperature coefficient for the PV, which

we have used in this practical application. Regarding the series and the shunt resistances determination, they can be approximated from the slopes of the I-V curve at V_{oc} and I_{sc} , respectively. The resistance at V_{oc} is best proportional to the series resistance R_s , but it is larger than the parallel resistance. R_p is represented by the slope at I_{sc} . Typically, the resistances at I_{sc} and at V_{oc} will be measured and noted by the manufacturer.

3.2. Wind energy production

The WT is a source of energy that depends principally on the wind speed. It is considered as one of the most significant clean energy sources. The transformation of this energy into electricity is ensured through WTs, which can cover a wide range of power depending on the needs and the type of generation chosen. For example, offshore WTs can have several tens of meters in height in order to generate several megawatts of electricity, which makes them interesting solutions to generate electricity for a national network. Other WTs, not exceeding ten meters and they are more suitable for domestic usage, producing a few hundred or thousands of watts. They must be installed in open spaces to improve their production, especially for safety reasons. They are therefore perfectly adequate for an isolated structure, such as a farm, where space is available.

Several WT structures exist, which can be chosen according to the generated power, the range of wind speeds, and the desired dimensions. Two types of architecture are to be distinguished, Horizontal Axis-WT and Vertical Axis WT. Mainly, various research works on vertical axis WT were carried. Actually, more research works focus on horizontal axis WT, which is more efficient at large scales. In fact, the horizontal axis WT is highly developed and used in all current large-scale wind farms. In this section, the horizontal axis WT, which was deployed in our MG system is modeled and characterized for seamless integration into buildings.

3.2.1. Wind turbine modeling

An aerodynamic generator study is important to simulate correctly the implemented WT. In fact, due to the velocities of the air behind the WT, the power recovered from a WT is less than the power of the wind. It then defines what is called a power coefficient C_p as being the ratio of the mechanical power produced by the aerodynamic system of the wind P_t divided by the kinetic power of the wind P_p . The mechanical power produced by the turbine is given as follows:

$$P_t = C_p \cdot P_v = \frac{1}{2} C_p \cdot \rho \cdot S \cdot v^3 = \frac{1}{2} C_p \cdot \rho \cdot \pi \cdot R^2 \cdot v^3, \quad (3.7)$$

where S is the area swept by the turbine, v is the wind speed, R is the radius of the blades, ρ is the density of the air ($\rho = 1.225 \text{ kg/m}^3$) in standard test conditions. It is important to note that the ratio between the turbine speed and the wind speed is expressed by equation (3.7.a) as follow:

$$\lambda = \frac{\Omega_t \cdot R}{v} \quad (3.7.a)$$

where Ω_t represents the turbine rotation speed. Moreover, the power coefficient C_p depends on the pitch angle and the number of blades constituted the aerodynamic generator. It can be estimated by equation (3.7.b):

$$C_p = 0.5716 \left(\frac{116}{\lambda_i} - 0.4\beta - 5 \right) e^{\frac{-21}{\lambda_i}} + 0.0068 \lambda \quad (3.7.b)$$

The expression of λ_i is presented by equation (3.7.c) as follow:

$$\lambda_i = \frac{1}{\lambda + 0.002\beta} - \frac{0.003}{\beta^3 + 1} \quad (3.7.c)$$

According to the BETZ theory, only 59% can be recovered from the wind power as mentioned in Figure 3.4.

The mechanical torque C_t obtained from the mechanical power can be formulated as follows (equation (3.7.d)):

$$C_t = \frac{P_t}{\Omega_t} \quad (3.7.d)$$

Furthermore, a multiplier is required for the mechanical transmission between the turbine and the electrical generator. This multiplier transforms the slow speed generated by the rotor of the WT into high-speed power and low torque used by the electrical generator. This multiplier transmission can be molded by:

$$\begin{cases} J = J_{turbine} + J_g + J_{tree} \\ J \frac{d\Omega_g}{dt} = C_t - C_{em} - f \cdot \Omega_g \end{cases} \quad (3.8)$$

where C_{em} presents the electromagnetic torque produced by the generator, Ω_g is the speed of the generator, Ω_t is the speed of the turbine, f is the coefficient of viscous friction of the generator, J presents the total inertia of the wind energy conversion system, $J_{turbine}$ is the inertia of the turbine, J_g is the inertia of the generator, and J_{tree} presents the moment inertia of the tree.

On another hand, the productivity of the WT depends on the number of the blade that influences directly on the turbine speed. For a horizontal axis WT, the variability of λ is presented, which corresponds to the ratio of the tangential speed at the blade divided by the wind speed. As shown in Figure 3.4, the three-blade rotor is the only WT, which is able to recover the extreme possible power. For the two-blade and one-blade rotor, they rotate faster and λ move towards high values but with a low C_p .

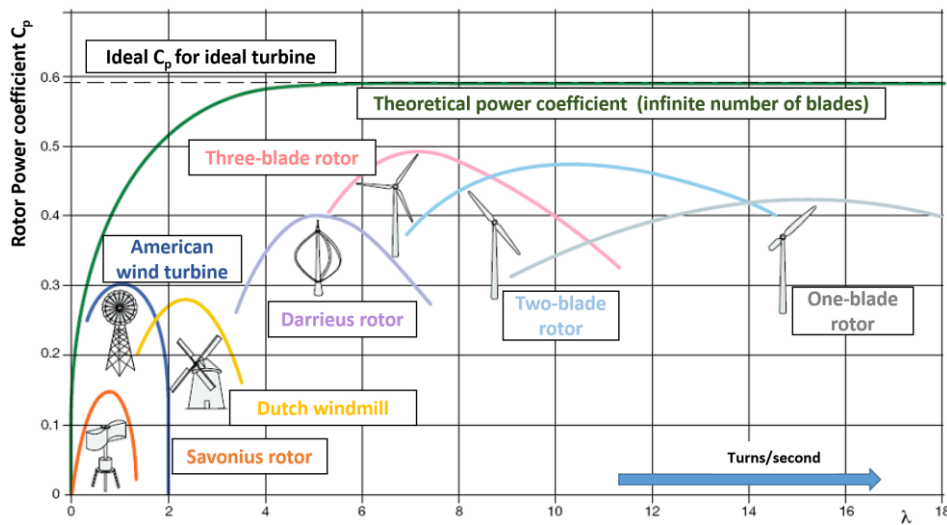


Figure 3.4. The power coefficient C_p average for different types of WT (Ebrahimipour et al., 2019)

3.2.2. Permanent magnet synchronous generator

The MG system we have deployed in our study contains, as mentioned above, a horizontal axis WT with three-blade rotor, which can be characterized using the PMSG. For the small scale of power production, PMSG is the generator the most popular due to its simplicity of employment and control. The model of PMSG can be expressed by equation (3.9) (Singh et al., 2013; Rabeh et al., 2018).

$$\begin{cases} V_d = -R_s i_d - L_d \frac{di_d}{dt} + p\omega_r L_q i_q \\ V_q = -R_s i_q - L_q \frac{di_q}{dt} + p\omega_r (-L_d i_d + \psi_f), \\ \psi_d = L_d i_d + \psi_f \\ \psi_q = L_q i_q \end{cases} \quad (3.9)$$

where ψ_f represents the flux of the permanent magnet, i_d (resp. i_q) is the current in the axis d (resp. q) of the stator, V_d (resp. V_q) is the voltage of the axis d (resp. q) of the stator, L_d (resp. L_q) is the inductance of the axis d (resp. q) of the stator.

We also adopt a smooth-pole PMSG in which $L_d = L_q = L_s$. Therefore, the electromagnetic torque is characterized by equation (3.10).

$$C_{em} = \frac{3}{2}p(\psi_d i_q - \psi_q i_d) = \frac{3}{2}p(\psi_d i_q + (L_d - L_q) \cdot i_d \cdot i_q) = \frac{3}{2}p\psi_f i_q, \quad (3.10)$$

However, balancing the production and demand of energy in MG systems is based on the measurement of the wind power generation, which is not controllable and cannot be predicted perfectly. For that, this modeling of the WT is an essential step to simulate properly the whole hybrid system. Simulation and experimental results are compared in order to validate the usefulness of the model using the same weather conditions and the same WT parameters provided by the manufacturer.

3.3. Energy storage

Generally, energy storage is categorized as thermal, mechanical, magnetic, kinetic, electrical, chemical, and electrochemical technologies. For electrochemical technologies, according to the different requirements, various kinds of storage technologies are used (e.g., batteries, electrolyzer-fuel cells system) with specific characteristics, such as the maximum current, the minimum voltage, the rated voltage and current, the capacity of electrical energy and power, and also the weight and volume. For MG systems, different constraints (e.g., the volume, the safety, the cost) should be considered to select the more profitable storage technologies with easier usage of the deployment.

3.3.1. Batteries as electrochemical energy storage

The battery is one of the oldest forms of electrical energy storage. It is an electrochemical generator, which stores electricity in the form of chemical energy. Generally, the function of

electrochemical energy storage is to transform the energy released by electrochemical reactions into electrical energy. This energy conversion process is ensured by one or more electrochemical cells, which consist of a compilation of two electrodes with active materials: a positive electrode (anode) and a negative electrode (cathode), liquid electrolyte, cell connectors, separators, and usually containers. Through the electrochemical reactions at the two electrodes, the electrochemical generators produce a flow of electrons during the discharging phase using an external circuit (Figure 3.5). These reactions can be reversible, allowing the generator to be charged by applying an external voltage through the two electrodes. Depending on the reversibility of the process, electrochemical generators can be classified into two categories: irreversible electrochemical reaction (Primary battery) in which the generator is discharged only once and permanently, and the reversible electrochemical reaction (Secondary batteries or accumulators) in which the generator can be recharged applying an external source of energy to return the electrodes into their initial state.

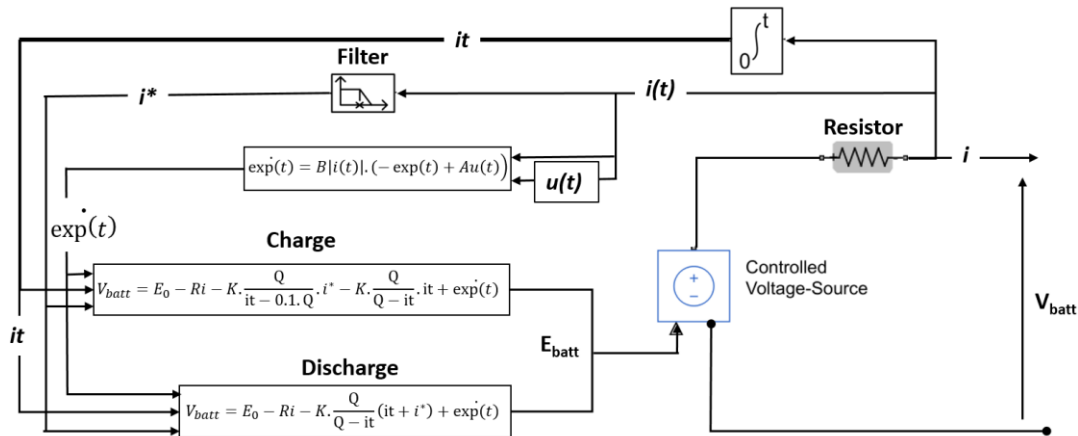


Figure 3.5. The deployed battery modeling

However, different rechargeable batteries technologies are deployed for RESs energy storage in the MG system. They are commonly the most used and the most suitable for electrical energy storage in the domestic sector and in small RES plants, due to the easier installation and the less cycling when compared to other technologies. In fact, several types of batteries energy storage are available on the market including Lead–Acid, Nickel–Cadmium, Lithium-Ion, Nickel-Metal hydride, Sodium-Sulfur, and Zinc-Bromine. These batteries have a large storage capacity for long discharge times (up to several hours) with a rate of 70 to 90% (Bridier et al., 2016). On another hand, the major challenges of these technologies are the cost and the lifetime cycle, limited by the chemical degradations of the reactions. For that, several research works are focused on electrochemical batteries, in particular Lithium-Ion. The

electrolyte materials are the main key for researchers to develop other batteries that are less expensive and have a high lifetime cycle. For example, researchers in the French Network on Electrochemical Energy Storage have developed a Sodium-Ion battery with high characteristics comparable to Li-ion (density of 90 Wh/kg and a lifetime of more than 2000 cycles). The advantage of sodium is that it is more abundant (2.6% compared to 0.06% for lithium) and therefore less expensive to produce ([National Center for Scientific Research, 2020](#)). Other researchers aim to improve the C/D batteries process and new technology is developed based Silicon-Oxide electrodes, which increase by 20% the performance of Li-Ion batteries ([Park et al., 2015](#)).

Nowadays, Li-Ion batteries are widely the most expensive and they are used generally for portable usage, which requires a low capacity. For that, other rechargeable batteries are used for large scale energy storage systems. Mainly, Lead-Acid batteries are used for domestic usage due to its low cost compared to other solutions. In fact, the Lead-Acid batteries are the oldest and the most commonly used type of rechargeable battery. Although, they have the lowest energy/volume ratio after the Nickel-Iron batteries and they have a low energy/weight ratio. This technology has the ability to generate a high flow of current due to the construction of cells that maintain a large power/weight ration. Basically, the Lead-Acid is consisted by connecting a series of cells, which contain a positive electrode (lead oxide) and a negative electrode (lead), immersed in an electrolyte solution (sulfuric acid) and separated by a cell divider. Besides, Lead–Acid battery has a low expected lifetime (5–15 years), a low C/D cycle and a negative influence on the environment by generating toxic remnants ([Chen et al., 2009](#)). For these reasons, the management of the C/D cycle of the battery is a worrying subject because it is important to control its usage in order to maximize its lifetime.

Due to the abovementioned reasons, this energy storage system is considered in our study and a description of their modeling is described in the following section. Furthermore, Lead–Acid battery is used actually, for a large scale of RES applications, especially the gel battery, because of their low cost and because the industry today is very established to recycle the Lead.

3.3.2. Battery modeling

Lead-Acid batteries are used to store exceed of energy generated by the RESs during the low peak demand periods. In order to use more efficiently this type of battery, the characterization and the determination of the SoC is a very important task before their

integration within MG systems. Typically, the battery modeling and characterization is a required step to identify battery's parameters and study their behavior and performance for seamless integration in MG systems. It is important that the model must characterize more precisely its response to various operating conditions. In our deployed MG system, the SoC of the batteries is used as an input parameter to the deployed control strategies. However, the dynamic behavior of battery modeling is a complex process due to the different phenomenon that can influence its electrical and electrochemical characteristics. For example, the SoC of the Lead-Acid battery could be determined by measuring the concentration of the electrolyte through the specific gravity method, which is almost impossible experimentally. Typically, several battery models are studied in order to develop a specific model, which can be used to follow the evolution of the battery parameters during its operation (Tremblay et al., 2009; Boulmrharj et al., 2018). There are mainly three types of models used to represent the temporal behavior of the battery: electrochemical models, equivalent electrical circuit models, and black-box models. In this section, a battery dynamic model is presented, which is easy to use and to extract the dynamic model parameters from the battery datasheet. The model takes into account the OCV as a function of SoC, which is the more interesting parameters for the control. Generally, the Lead-Acid battery voltage is presented as a function of the capacity by the curve presented in Figure 3.6, which is obtained using the Matlab-Simulink model for a given Lead-Acid battery (12V, 100Ah).

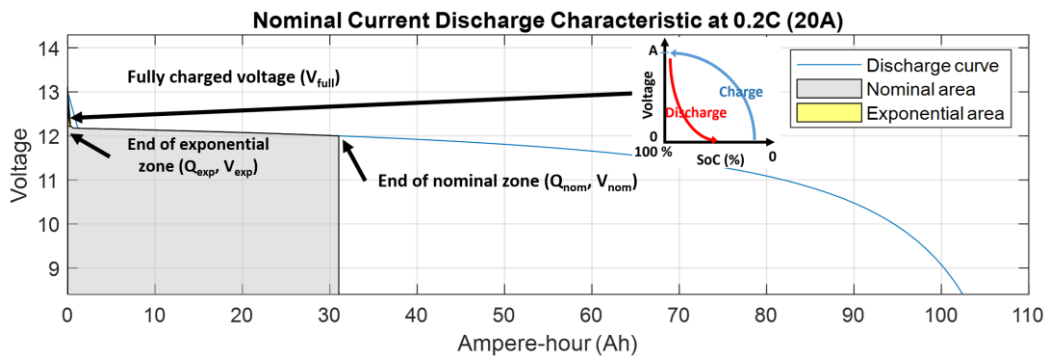


Figure 3.6. Lead-Acid battery discharge characteristic

As is shown in Figure 3.6, the nominal zone of a Lead-Acid battery presents a high part of the curve. For that, to increase the lifetime of the battery, it is obligatory to consider the parameters mentioned by the battery datasheet (e.g., fully charged voltage, minimum SoC). Moreover, a procedure for characterizing the parameters of a battery model comprises two stages: carrying out tests on the battery and identifying the value of each parameter from experimental data. For the proposed model, the term concerning the polarization resistance is

integrated and the polarization voltage term is added to represent the OCV behavior more precisely (i.e., the non-linearity relationship between the OCV and the SoC) as already validated in (Boulmrharj et al., 2018). The battery voltage variability is expressed by equation (3.11) and equation (3.12) respectively in both discharge and charge processes.

$$V_{batt} = E_0 - Ri - K \cdot \frac{Q}{Q - it} (it + i^*) + \exp(t), \quad (3.11)$$

$$V_{batt} = E_0 - Ri - K \cdot \frac{Q}{it - 0.1 \cdot Q} \cdot i^* - K \cdot \frac{Q}{Q - it} \cdot it + \exp(t) \quad (3.12)$$

where V_{batt} is the battery voltage, E_0 is the battery constant voltage, R is the internal battery resistance, i is the battery current, it is the actual battery charge, i^* is the filtered current, K is the polarization constant, Q is the battery capacity, and $\exp(t)$ is an expression that represents the exponential zone voltage.

A controlled voltage source is used to model the OCV of the battery and it is connected in series with a constant resistance as mentioned in Figure 3.5. In fact, the accuracy of this battery model is the use of a filtered current i^* flowing through the polarization resistance presented by equation (3.12.a).

$$P_{Resistance} = K \cdot \frac{Q}{Q - it} \quad (3.12.a)$$

In addition, during the exponential zone, the OCV varies non-linearly with the SoC and this hysteresis phenomenon between the charge and the discharge can be represented by the non-linear dynamic system expressed by equation (3.13), where B is the exponential zonetime constant inverse and A is the exponential zone amplitude. The exponential voltage ($\exp(t)$) depends on the initial value ($\exp(t_0)$) and the C/D mode ($u(t) = 1$ for charge mode, and $u(t) = 0$ for discharge mode) that depends on the battery current mode (discharge ($i > 0$) and charge ($i < 0$)). The C/D processes is implemented using the model depicted in Figure 3.5.

$$\exp(t) = B|i(t)| \cdot (-\exp(t) + Au(t)) \quad (3.13)$$

It is worth noting that our aim is to integrate this battery model in our simulated MG system using the same real battery parameters. This allowed comparing both simulations and

experimentations results. This model is also used to estimate the essential parameter for our study (SoC), which is required to develop context-driven approaches for EM management and control for multi-energy source installations.

3.3.3. Wide range of energy storage systems

Depending on the type and the scale of the deployed MG system, various solutions of energy storage can be deployed. Mainly, pumped hydro-electricity storage was generally implemented for large-scale and long-term energy storage. The system consisted generally of two interconnected reservoirs located at different elevations, a turbine to generate electricity when the water returning to the low elevation, and a device that is used to pump water to the high elevation. In fact, during off-peak demand periods, large quantities of water are pumped into the high elevation storage using the surplus of electricity, which is converted to hydraulic potential energy. Afterward, during peak demand, a turbine is used to generate electricity by converting the potential energy to electricity. This system needs usually a large landmass to store the water. For large-scale production, this technique can use rivers, ocean, or also massive lakes as the lower reservoir. It can be used for long-term energy storage in large plants of RESs.

Electrical energy storage is another family, which includes different technologies like capacitors and super-capacitors. Mainly, without chemical reaction, this technology stores directly electrical energy into electric current using an inductor (coil) made from a superconducting material. The super-capacitors offer very high capacitance in a small array, which can be released very quickly. They are suitable for short term and high-power demand applications. In particular, this technology has a high cycle life and it is more suitable for applications requiring a constant and continuous mode of operation. It is used to solve voltage and frequency stability and power quality problems for the electrical network and for the large industrial customers.

Chemical energy storage is a more used technology, which is realized through accumulators by alternating the C/D phases and by a double function of gaze storage and electricity generation. The accumulators are fabricated from several methods (e.g., nickel–cadmium, lead–acid, nickel–iron, sodium–sulfur, lithium–ion, and lithium–polymer). These systems are used generally for short-term energy storage and the minimum discharge period of the electrochemical accumulators rarely reaches below a few minutes. They are more useful for portable systems, and they are used to ensure the power security for permanent

applications (e.g., renewable energy in isolated areas, emergency network backup) (Ibrahim et al., 2008).

It is worth noting that one of the main emerging technologies for chemical energy storage in MG systems is the fuel-cells hydrogen storage, which is realized by a fuel-cell system. It is a means of restoring electrical energy to produce hydrogen through the water electrolyzer. The system uses separate processes for hydrogen production, storage, and use and it includes three main components: *i*) the electrolyzer, used to produce hydrogen and oxygen from water by consuming an electric current during the off-peak demand, *ii*) the fuel-cells, which uses the stored hydrogen and oxygen from the air to release energy peak demand periods, *iii*) the hydrogen tank, which is used to store the hydrogen generated by the electrolyzer.

Hydrogen fuel-cell storage systems are receiving increasing attention for the actual researches, especially for their integration with RES. In particular, the stochastic nature and the variable production of RES produce fast power fluctuations that can cause incomplete separation of the gases from the electrolyte, and consequently, the H_2 and O_2 are mixed in the electrolyte. Therefore, the integration of the fuel-cells system into MGs should be coupled to other storage devices systems like batteries in order to maximize the efficiency and to avoid the damage of this expensive solution of storage. It is worth noting that this type of energy storage is not considered in this work, it was investigated in other works under the project MIGRID. We focus mainly on batteries, their modeling, and integration within our MG system.

4. Experimental platform of MG systems: EEBLab

Approaches developed in the frame of this dissertation are deployed and tested in real-sitting scenarios in our MG systems.

4.1. Data sensing and communication

The building's transition to smart the MG system requires the distribution of the communication as well as a distribution management system. For instance, the IEEE Standards Association approved the OpenFog Reference Architecture, developed by the OpenFog Consortium, including Intel, Cisco Systems, Microsoft, Dell, ARM Holdings, and Princeton University, as an official standard, under the name of IEEE 1934 (Chiang et al., 2016), for IoT communication in MG systems. The standard classifies the interaction of interconnected units for streaming and real applications into three classes: *i*) Machine-to-

Machine, in which any component can send/receive data or command to/from any other one using the capabilities of IoT, ii) People-to-Machine, the users can control each machine, which can be adapted depending on the occupants' comfort, and iii) People-to-People, in which users can exchange data through a cooperation mechanism. In the MG system, communication among all devices is required aiming to improve the effectiveness and reliability of the system's operations. In our studies, sensors are used to collect contextual data, which are submitted to our remote platform for storage or further analytics. Mainly, current and voltage sensors are installed to gather data from RESs, storage devices, and load consumption. Actuators are deployed for operating actions that are generated by the energy flow controller. It is worth noting that sensors are devices or integrated circuits used to detect specific physical parameters by converting sensed values to electrical signals, which are readable by microcontrollers. Mainly, three types of sensors outputs can be specified, current loop output, voltage output, and digital output. The sensors based on current loop output are calibrated over a specified range against various engineering units to convert the real value, such as the temperature, pressure, and current, to an equivalent current value measured by the deployed microcontroller. The output of the individual calibration certificate is compared to a mathematical manipulation made to obtain the absolute value. The loop's operation is straightforward in which the sensor's output signal is first converted to a proportional current, with the less current (generally on mA) presents the sensor's zero-level output and the high current represents the sensor's full-scale output. For example, the 4-20mA current loop is a very robust sensor-signaling standard, while, the current loops are ideal for data transmission because of their characteristic insensitivity to electrical noise. Therefore, the voltage output sensors can have various voltage outputs (5V, 10V, from -5V to +5V and more) that are calibrated over this range against various units. The output is compared to the individual calibration certificate for the specified measurement range for which the sensor is selected. Generally, there are two types of voltage output signals, differential and single-ended measurements. The differential voltage signal is "floating", meaning that has no reference to the ground. The measurement is taken as the voltage difference between the two wires. The benefit of this method is noise elimination because the noise is added to both wires and can then be filtered out by the common-mode rejection of the data acquisition system. For single-ended measurement, it considers as the voltage difference between a wire and the ground. The noise is only on the positive wire and as a result, it is still measured along the output voltage of the sensor. Mainly, transmitting the sensor's output as a voltage over a long distance has several drawbacks. The transmission for long distances produces corresponding lower

voltages at the end receiver due to the wiring and the interconnecting resistance. Also, the voltage devices are sensitive to the noise pickup for which the shielded wires are used to minimize this noise.

However, many sensors use a digital signal rather than analog signals of voltage and current. Face to the noises and the measurement perturbs, it is more robust. The two most common digital communications are RS-232 and RS-485. The RS-485 is more used because it only specifies the electrical characteristics of the generator and the receiver. It does not specify or recommend any communications protocol, only the physical layer. Modbus, Profibus, Canbus, and SDI 12 are all examples of communication protocols employing the RS-485 style signal. Therefore, the major advantage of the RS-485 system is that sensors can be transported; meaning that each sensor has its own individual address and many can be all attached to one cable. This means that multiple sensors only use up one port on the data logger saving considerably on cable and data logging costs. Long distances are achievable but the distance is a function of the cable and supply voltage. The longer the cable the greater the signal attenuation will be and so the length is not infinite. Signal attenuation also increases with the frequency of data transfer and the achievable distance diminishes with the data rate.

Therefore, the deployed MG is equipped with a component for measuring power consumption and production. In fact, a set of current and voltage sensors have been installed for power measurement as shown in Figure 3.7. The system contains a switch controlled by an Arduino, which allows collecting the data from different sensors. Furthermore, the system contains a micro-computer (Raspberry pi) for collecting data from different sensors. In fact, sensors transmit analog signals to the microcontroller, which converts them into numerical data. For example, a voltage sensor is used to measure the output PV voltage with an accurate range that considers the maximum voltage of the PV installation. For that, a tension divider bridge is used to convert the values from zero to 5V, which is the Arduino accurate range. In fact, the Arduino program converts obtained values to tension data. Moreover, the Arduino transmits these data to the Raspberry for activating the right action according to the deployed control algorithm. Data are then transmitted to the IoT/Big-data platform for visualization and storage. As shown in Figure 3.7, these data could be used for further analysis (e.g. power forecasting).

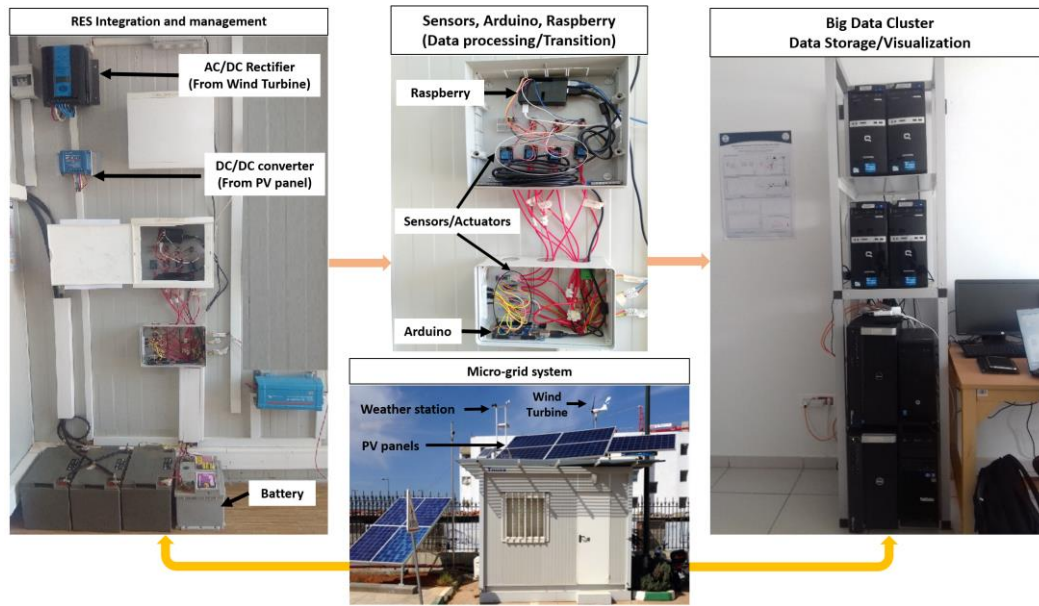


Figure 3.7. Monitoring platform architecture

Next section introduces our MG system's architecture. In particular, we highlighted the necessity of integrating recent IoT/Big-Data technologies for gathering external and internal data, which have been used to generate predictive actions (e.g., regulating the room temperature by forecasting building's occupancy, ventilation speed variation according to the forecasted CO₂, intelligent and predictive control of energy flows management using forecasted power production, consumption, and battery SoC).

4.2. IoT/Big-data platform for data collection

The aim was to develop a research testsite integrating the different components of an MG system, which is used to test and integrate control strategies for predicting, estimating, and controlling the interaction between power production, storage, and building's demands. As shown in Figure 3.7, the system integrates PV panels, WT, batteries, and the TEG connected together in order to supply electricity to the building's services according to actual contexts. The system is monitored by an IoT/Big-Data platform, which is used to collect, analyze, and store the data for EM and control strategies development. Moreover, several scenarios are deployed in order to develop a research platform that considers the concept of MG systems with the different components of the different layers.

Real-time and context awareness information could be exploited for developing predictive and adaptive context-driven control approaches using recent IoT and Big-data technologies together with real-time and ML algorithms (Elkhoukhi et al., 2019; Hadri et al.,

2019). A platform that uses context-driven technologies, as well as complex-event processing technologies, is deployed for data monitoring and processing in order to develop intelligent and predictive control strategies for EM in MG systems. The platform is composed of four main layers, sensors/actuators layer, data acquisition, data processing, and data visualization/storage together with further services and applications for context-driven control (Figure 3.8).

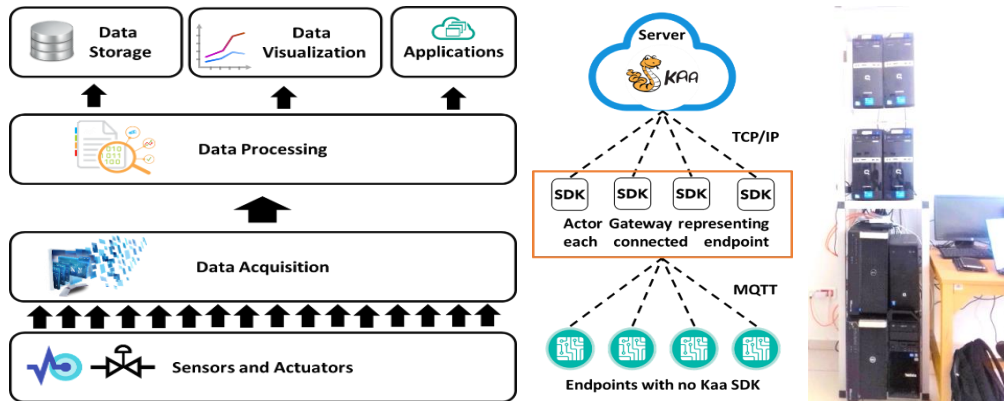


Figure 3.8. IoT/Big-Data platform architecture

The MG is mainly equipped with a component for measuring the different necessary parameters (e.g., current, voltage, temperature, wind speed), for interacting with the passive and the active equipment, for regulating the comfort for the occupancy, and for managing the power production and consumption. In fact, a set of sensors is installed depending on the desired scenarios. In addition, the first layer includes the actuators that are used to receive and to execute different commands, which are generated by the control strategies for EM or for equipment and services control. Regarding the data acquisition layer, a Kaa application is developed (i.e., IoT technique) ([Kaa, IoT technique, 2020](#)) which is used to receive data from deployed sensors. We have also used MQTT, which is a publish-subscribe-based protocol for IoT applications. For data processing and storage, Storm services are used ([Storm, Apache Storm, 2020](#)). Mainly a topology composed of Spouts and Bolts was designed and developed to allow receiving and processing streaming data from sensors. The spouts receive the data from the Kaa application, and then transmit it to the Bolts for processing and storage into the database (e.g., MongoDB) for further in-depth analysis. The services layer includes real-time visualization and storage together with the control of active equipment and RESs power production and consumption monitoring and management. The platform was used for data gathering and processing of internal and external building's context. For instance, it was used to build occupant information (e.g., number, presence, behavior, activities), since is a major

input for control approaches in energy-efficient buildings (e.g., active systems control) (Elkhoukhi et al., 2018b). In fact, comprehensive fine-grained occupancy information could be integrated to improve the performance of occupancy-driven control of HVAC, lighting, and ventilation systems. A platform for real-time detection of occupants' is deployed. The platform was adopted by including real-time ML component with the main aim is to analyze, explore, and predict the occupancy information in buildings. However, these predicted values are then used for efficient control of active equipment and for predicting the electricity consumption behavior, which is used for EM.

4.3. Weather station

Regarding the external context, we have deployed a weather station. In fact, for several scenarios, we need to gather internal and external context data. We have built a weather station near the WT and PVs in order to have as precisely as possible the data concerning wind speed, direction, irradiation, temperature, and humidity. The weather station was deployed and used to collect the data for real-time visualization and processing for further usage by other building's services and applications. All these data are gathered and processed in real-time using our IoT and Big-data platform, as depicted in Figure 3.9.

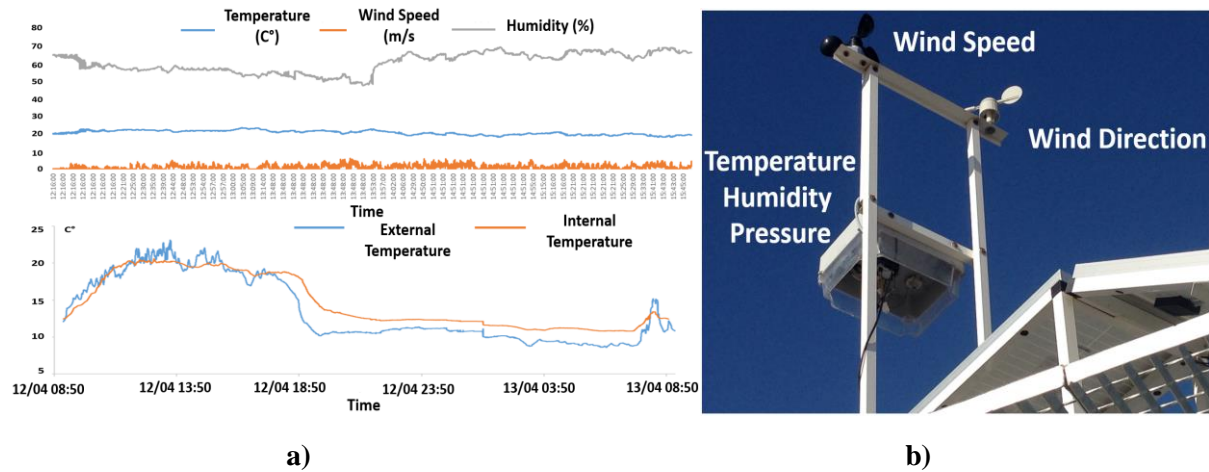


Figure 3.9. a) Internal/external temperature b) weather monitoring

Weather data are collected in order to validate the results obtained from simulations and experimentations by using the same input parameters. For example, radiance and temperature are measured together with the PV power during the same day. Radiance and temperature are used as input parameters to the mathematical PV model, which is developed for conducting simulations and validate experimentations' results using similar contextual data.

4.4. Building envelope

This part concerns the passive layer, which allows reducing energy consumption by developing less-energy-consuming equipment and materials in buildings. Emerging devices, which use natural forces without using electricity, such as natural lighting, room relocation, natural ventilation, could be used to increase insulation. In fact, the architecture design, buildings envelope, and orientations can influence energy reduction. Therefore, the passive design must be considered in the phase of construction in order to reduce the final energy use of the building.

As part of our studies, a work is realized by focusing on the thermo-mechanical characterization of our EEBLab, which mainly consists of galvanized steel, of which expanded polyurethane is injected into the walls and the roof. As well as two types of internal insulation are adapted, namely chipboard for the floor and polyurethane for the roof. The main aim is to thermally study the behavior of the EEBLab, in order to propose good material for the insulation and consequently minimizing the use of the HVAC system for heating and cooling.

4.5. Active/Passive equipment control

This part concerns the MG system active layer that allows the deployment of context-driven control approaches in order to improve energy consumption. In this layer, the electrical energy can be minimized by optimizing the operation times of the active equipment (e.g., HVAC, ventilation systems) while maintaining occupants' comfort within good air quality and suitable thermal comfort ([Berouine et al., 2019a](#)). In fact, the ventilation systems are normally installed in buildings to improve the air quality by injecting fresher air from outside into inside buildings. These systems automatically act on behalf of occupants by ensuring good indoor air quality, especially in cold or hot periods, or when there are no windows. In fact, the ventilation controller performs this task by adjusting fresh air as much as needed based on actual indoor CO₂ concentration. The aim is to improve the optimal balance between energy efficiency and indoor air quality. For that, a ventilation control system was deployed, which maintains the indoor CO₂ concentration at the comfort set-point with an efficient and minimal ventilation rate and energy consumption ([Lachhab et al., 2018a](#)).

Another study puts more emphasis on developing efficient control approaches in order to deliver acceptable occupants' comfort while maintaining optimal energy consumption.

Control approaches are investigated for controlling the deployed HVAC system in our EEELab ([Lachhab et al., 2017b](#)). A control card is deployed in order to interface between all HVAC components and the control device. It allows the regulation of temperature and ON/OFF control of the HVAC system by adjusting the inside ventilator and the compressor based on the desired schedules (heating, conditioning, or only ventilation). The deployed IoT/Big-Data platform is used to measure the hourly electricity consumption of the HVAC system, which is used in our study as a load to test the EM control strategies.

Generally, the HVAC is the most used system for thermal comfort regulation in buildings and is considered as the highest electricity consumer. For that, renewable sources of thermal energy are required to minimize the electricity mainly used for heating, cooling, and air conditioning. In this perspective, we have deployed a geothermal platform ([Kharbouch et al., 2018](#)), an earth-to-air heat exchanger system that could be used for building cooling and heating. In fact, this clean and sustainable source can be deployed and used to minimize the usage of HVAC systems. The system is installed to extract heat from the ground for either cooling or heating purposes. It is basically a buried pipe, deployed at a certain depth in the ground, where air exchanges heat with soil. This system is deployed in the side area of our EEELab and the pipelines are installed inside a trench of 5m in length, 2m width, and 1.5 depth. Different sensors are installed as well in order to measure and control the temperature exchange in order to investigate the performance and the effectiveness of the system in terms of power consumption and comfort.

It is worth noting that, under MIGRID project, the platform was used in different scenarios, especially those related to building envelope and active/passive systems layers. For instance, in the second layer, the electrical energy can be minimized by optimizing the operation times of the active equipment (e.g., HVAC, ventilation systems), while maintaining occupants' comfort within a good air quality and suitable thermal comfort.

4.6. RESs integration

Despite the importance of the modeling and simulations, the deployment of real a MG system for conducting experiments is required in order to study and assess the accuracy of these models. The system contains mainly energy sources (PV and WT), storage devices (batteries) and loads, which are coupled together in our deployed MG system using our developed control card (Figure 3.10).

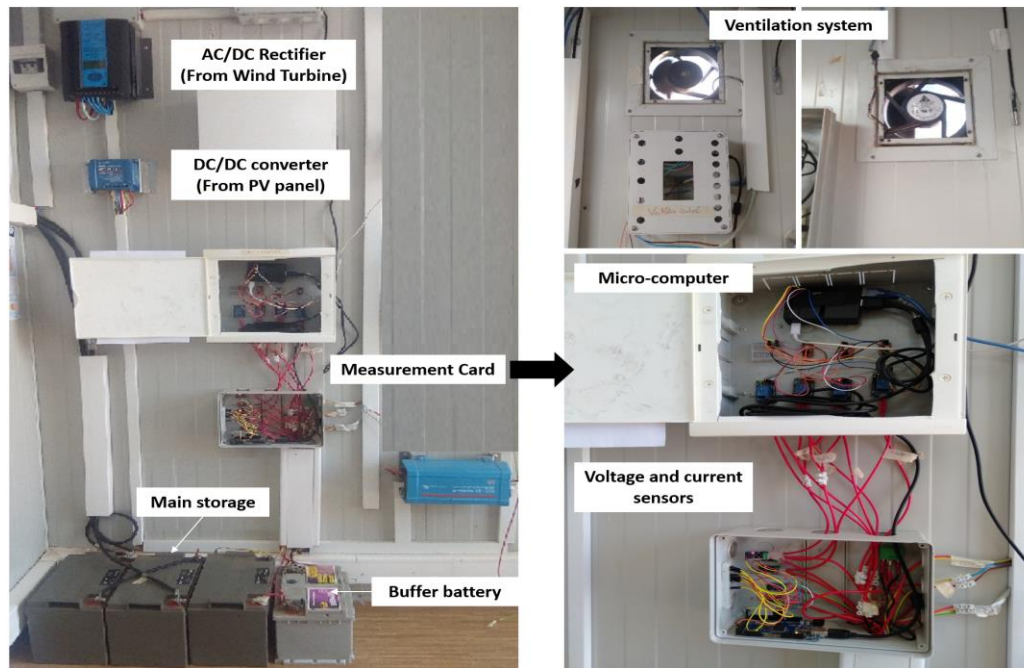


Figure 3.10. The hybrid system of RESs installed in our EEBLab

However, for the RESs installation, the installed PV panels are over-dimensioned in order to consider in the future works the possibility to interconnect multiple MG systems for the energy exchange. The main components are presented in Table 3.1. However, the system is performed by adding more sources and technologies in order to create multiple interconnected MG systems. In addition, the possibility to inject the electricity, into the utility grid, is envisaged by integrating the electrical vehicle as an energy storage system solution. The deployed MG system is depicted in Figure 3.11. The details of RESs integration with EM control approaches are presented in the next chapters.

Table 3.1. The main electrical components of EEBLab

<i>Components</i>	<i>Number</i>	<i>Characteristics</i>
DC bus	--	24V
PV panels	8	Polycrystalline, 270Wp,
Wind turbine	1	PMSG, 420W, nominal wind speed: 14.5 m/s, starting speed: 2.0 m/s
Battery	4	Gel, 110Ah/12V, recommended maximum depth discharge: 40%
Power inverter	1	Operating battery voltage: 19-33V; Nominal power: 2200W; Peak power: 3000W, efficiency: 94%.
Charge controller	1	Nominal battery voltage: 12V, 24V, 48V; nominal charge current: 85A; Maximal PV power: 2400W for 24V; efficiency: 96.5%.
Loads	--	Two computers (240W), HVAC system (2000W), 3 lamps (180W), two fans (60W). The system has the possibility to supply the electricity to another test site that contains cooking plate (1500W), 4 lamps (200W), freezer (80W).
Grid-connected	Yes	Only extraction
Electrical vehicle	1	Twizy 45; 5 horse; battery type: Lithium ion; battery capacity: 6.1 KWh



Figure 3.11. EEBLAB: the deployed energy efficient building laboratory

5. Conclusions

The main aim of the work presented in this chapter is to shed more light on the usefulness of developing an integrated platform in order to enable the deployment of smart MG systems in energy-efficient buildings. The MG platform connects the building's components using sensing/actuating, IoT, and Big Data technologies in order to leverage real-time gathering, data processing, and predictive control. RESs and battery storage devices are modeled in order to have both real and virtual MG platforms offering the possibility to validate the studied scenarios by simulations and experimentations. It was used for validating the proposed models and results mainly by investigating, *i)* the efficient connection, integration, and the management of different RES and storage devices, *ii)* the suitable dimensions for energy production and storage devices, *iii)* different possible D/R and predictive algorithms, *iv)* context-aware driven control of deployed equipment, e.g., lighting and HVAC systems. Methods that allow smart management with predictive analytics are investigated to be integrated into the platform prototype to handle this type of complex systems.

Chapter 4: The Deployed Micro-grid System Integrating Renewable Energy Sources: Experimental Evaluation and Validation

1. Introduction

In the frame of this thesis, we aimed to develop a research MG system, which is used to test and integrate control strategies for predicting, estimating, and controlling the interaction between power production, storage, and building's demands. The system is monitored by an IoT/Big-Data platform for collecting and data processing. Two MG systems have been deployed during the period of this dissertation. The first one is named EEBLab (International University of Rabat, Sala-Eljadida, Morocco), in which the testing scenarios are realized for the components validation and the control scenarios testing. The second MG system is a smart Green-Building, which is deployed during an international competition named "Solar Decathlon Africa" (Green Energy Park, Benguerir, Morocco). The two platforms are actually used as a research platform.

In this chapter, the simulation and the experimental validation of the different components for the MG system are realized and basic control strategies are deployed to show the usefulness of the deployed system to monitor the MG platform. In fact, the deployed IoT/Big-Data platform is used to collect the data that is used to control our deployed control card for EM. Case studies are presented concerning the deployment of an EM control strategy for energy balance in an MG system of RESs, storage devices, and the utility grid. The hybrid MG platform was deployed, several scenarios have been tested and evaluated, and preliminary results showed the usefulness of the platform for efficient management of buildings components. The platform is further enhanced by developing other ongoing scenarios, especially, for predictive control strategies.

2. RESs deployment and validation

2.1. PV panels

A model of PV panel is deployed in Matlab-Simulink using the same parameters that are noted by the manufacturer for the real PV panels. The PV panel's behavior was verified using both simulations and experimentation and by using real radiation and temperature data. The PV characteristics used in both simulations and experiments are described in Table 4.1.

Table 4.1. PV Characteristics

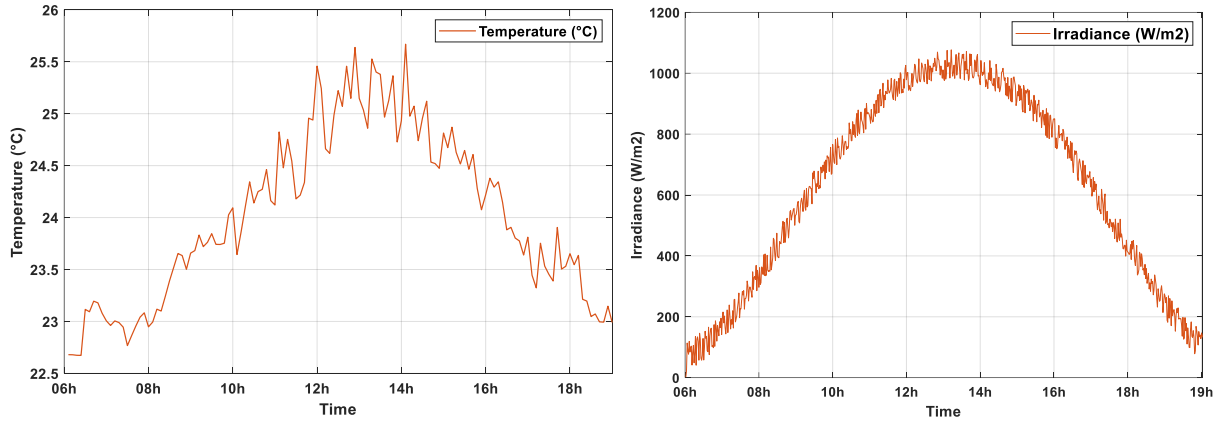
Standard test condition at:

Solar irradiance 1000 W/m^2 ; Cell temperature 25°C , Air mass 1.5

Characteristics	Value
Cell type	Polycrystalline 156*156 mm
Nominal power	270 W
Number of cells	60 (6*10)
Open circuit voltage (V_{oc})	38.4 V
Short-circuit current (I_{sc})	9.06 A
MPP voltage (V_{MPP})	31.1 V
MPP Current (I_{MPP})	8.69 A
Module efficiency	16.29 %
Operating temperature	-40°C to $+85^\circ\text{C}$
Maximum system voltage	1000V DC
Maximum series fuse rating	15 A

The deployed weather station (presented in chapter four) collected the input parameters for the same day of the experimentation. Therefore, one panel is used to validate the model, while, our proper card is deployed to measure the generated current and voltage from the PV. The system contains mainly energy sources (PV), storage devices (batteries), and a load (ventilation system). The PV is used to charge the battery, which in turn supplies the ventilation system. The deployed ventilation system is installed in order to ensure that the PV panel could generate its maximum power at each moment. Mainly, the testing scenario is equipped with a DC/DC converter, which implements an MPPT. The main function of the MPP-tracker is to adjust the panel output voltage/current into a value that matches the maximum energy needed by a given load. In our study, we consider that the deployed DC/DC converter ensures the good MPPT algorithms operation that is deployed by the manufacturer. We need also weather conditions (irradiance, temperature, solar panel tilt, and orientation) as input variables. Experiments have been conducted during different scenarios. The tilt of the panel was set to 30° with a southerly orientation ([El mouatamid et al., 2017](#)).

Figures 4.1.a and 4.1.b show respectively the temperature and the irradiation profile, of May 10th, 2020 (06:00 PM to 06:00 AM), collected in our test site (Morocco, Sala-aljadida, International University of Rabat). This data is used as input parameters to the developed simulation model.



(a) (b)

Figure 4.1. Real data during 12 hours, (a) Temperature, (b) Irradiance

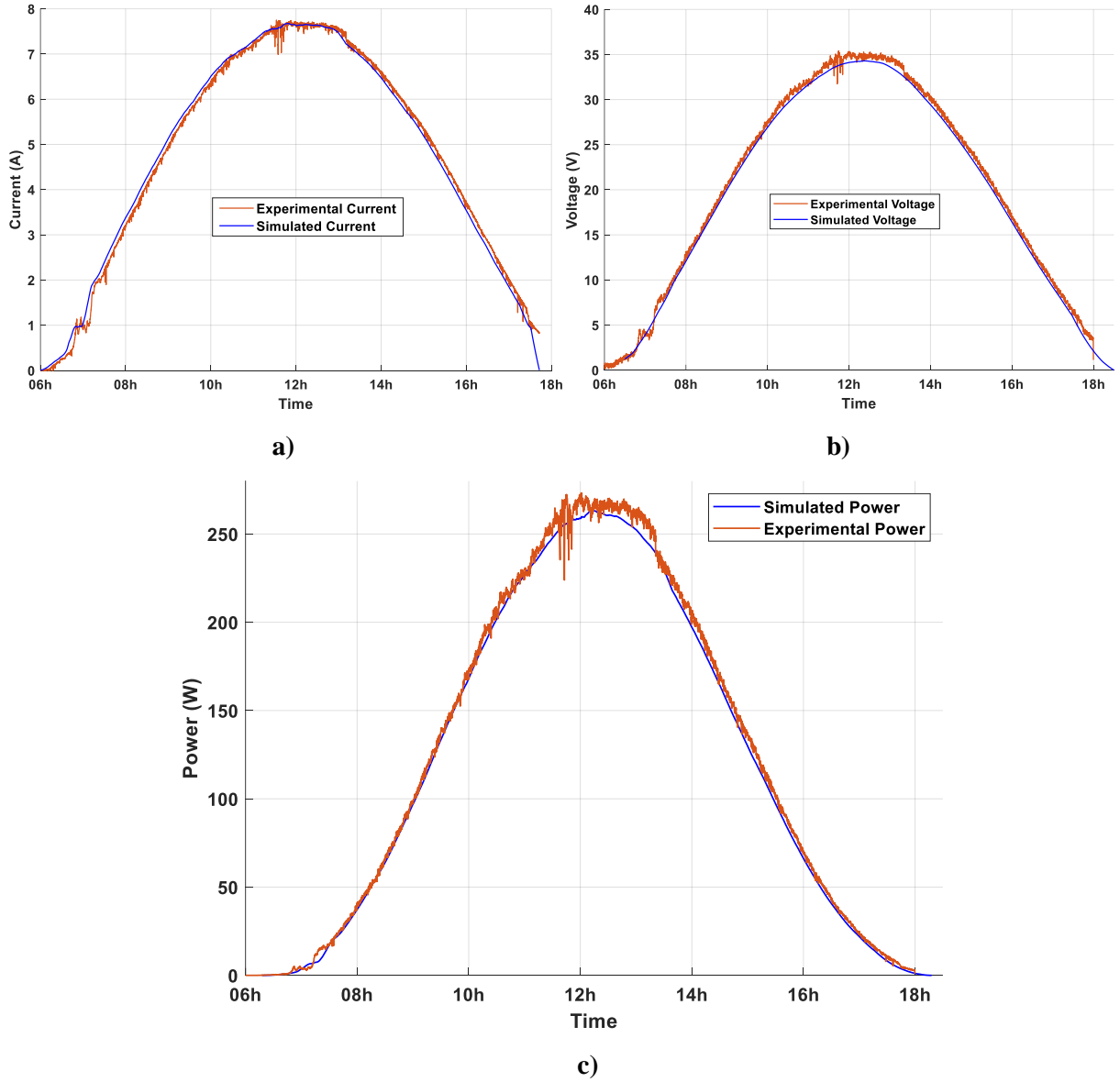


Figure 4.2. Simulation and experiment data, a) PV current, b) PV voltage, c) PV power

Figure 4.2.c shows the PV production for 12 hours. These data are presented here to first verify the PV model used for conducting experiments, and then to study the usefulness of the IoT/Big-Data platform for real-time data monitoring and processing. Obtained results, as shown in Figure 4.2, confirm the efficiency of the PV model in capturing the contextual environment in which the PV is deployed and tested as well. We have evaluated the current, the voltage, and the power generated using simulations and experiments in order to show the accuracy of the proposed model. The current obtained by simulations (blue curve) is compared with the measured one (red curve) as shown in Figure 4.2.a. Figure 4.2.b shows the comparison between the voltage values obtained by simulation (blue curve) and these obtained by experimentation (red curve). These results validate the studied module of the PV. Therefore, the deployed measurement system is used to measure the total PV power production for the solar park that is installed in our MG system. The power generated from the PV panels is an interesting input parameter for the control strategies, which are developed in our study. While, in the deployed MG system, eight panels are installed in order to supply the power to different equipment in the laboratory.

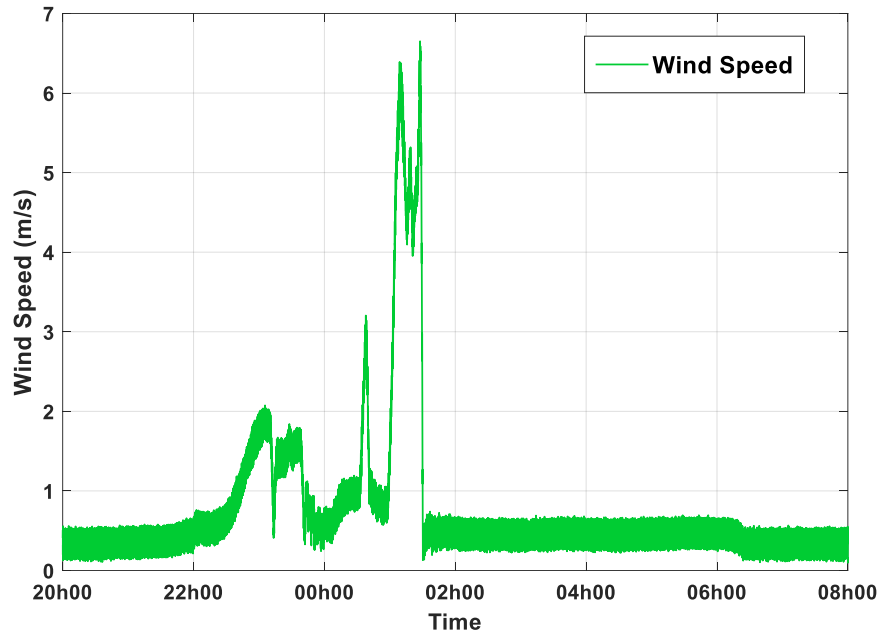
2.2. Wind turbine

The MG system includes also a horizontal axis WT with three-blade rotor. The installed WT generates an AC power, while, the deployed control card and the bus topology that is deployed in the MG system operate on DC bus topology. For that, a rectifier is installed in order to convert the generated power to DC power, which is coupled in a hybrid system with the PV panels, while, the same battery storage system is used for both PVs and WT. Therefore, a measurement card is installed in order to collect wind power generation. The installed weather station collected the wind speed, which is used to simulate the deployed model for the WT in order to compare and validate both simulation and experimental results. Table 4.2 describes all the parameters used for the deployed WT.

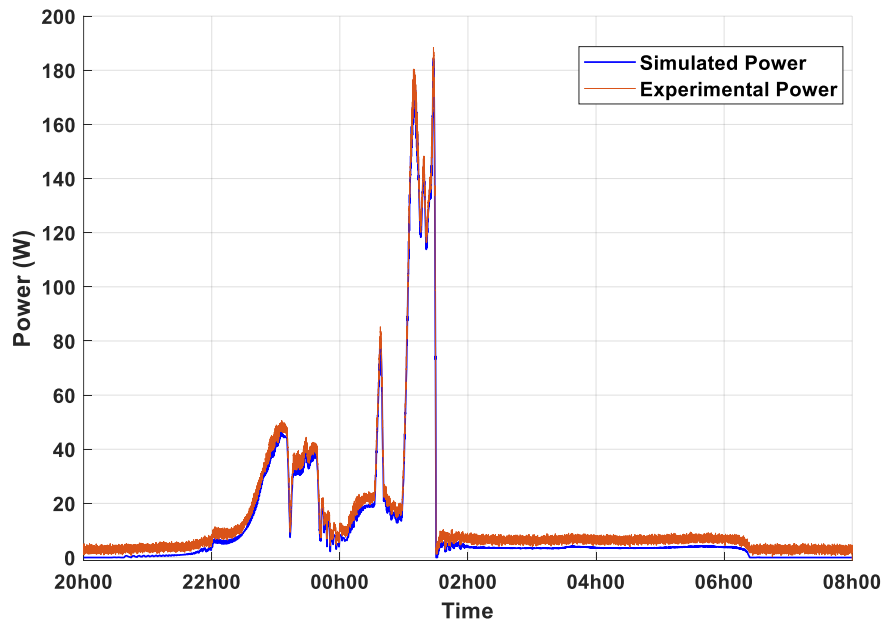
Table 4.2. Parameters of the wind-turbine conversion system

<i>Parameters</i>	<i>Values</i>
<i>Ls</i>	1.25mH
<i>Rs</i>	0.9 Ω
<i>p (pair of pole)</i>	19
<i>ψ_f Flux of the permanent magnetic</i>	0,09 Wb
<i>Maximum power</i>	420 W
<i>R Radius of the blades</i>	0,575 m
<i>J(inertia)</i>	5 Kg.m.s ⁻²
<i>f Coefficient of viscous friction of the generator</i>	0,06 Kg.m ² s ⁻²
<i>Power rate</i>	420W

In this section, simulation and experimental results are compared to show the accuracy of the proposed model, especially with a variable wind profile collected according to the local weather station, which is installed in our MG system (Morocco, Sala-aljadida, International University of Rabat) as shown in Figure 4.3.a.



a)



b)

Figure 4.3. WT generation scenario, a) Wind speed profile, b) Simulation and experiment power generation

The measurement card is installed to collect the data from the WT and the weather station collected the equivalent wind speed and direction that are used in the simulation to generate the equivalent behavior of power generation using the deployed mathematical model (Figure 4.3.b). However, the system is installed in a site where the wind speed has only a limited number of days when it exceeds the rated speed of the WT to levels, which allow giving an important production, due to different existing obstacles. For that, the power generated by the WT is less than the power generated by the solar park installed in the MG. Hence, it is coupled with PV panels in order to study a global control strategy for a hybrid system of RESs. Moreover, unlike the PV panels' generation, the WT has variable production in the order of a few seconds due to the highly variable nature of wind speed as mentioned in Figure 4.4. For that, the wind power is converted to DC power in order to be coupled with the batteries to smooth its behaviors, while, to have reliable control scenarios in the DC bus.

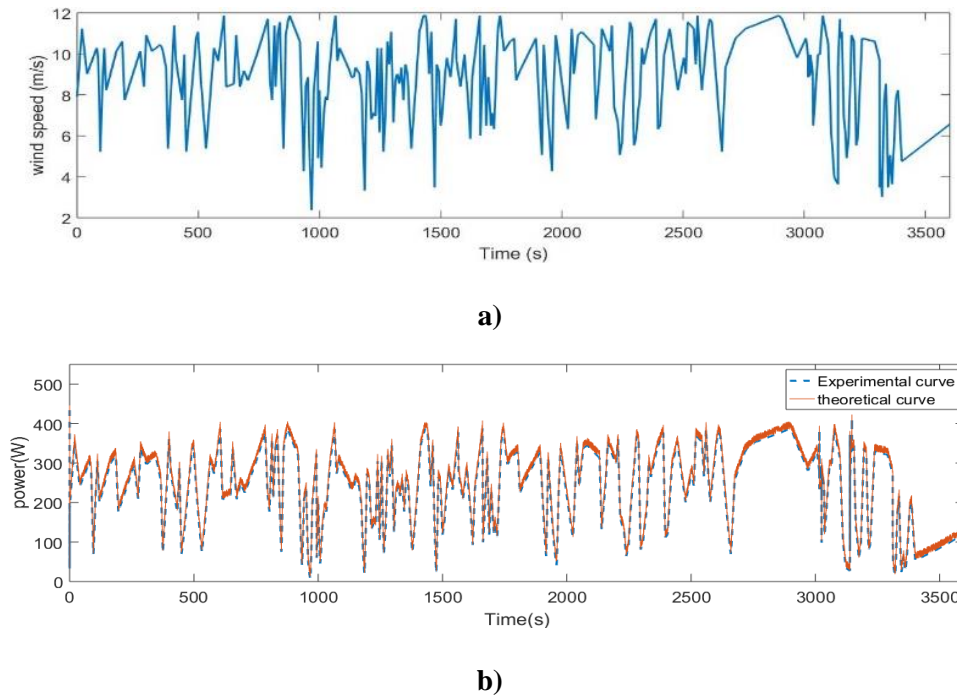


Figure 4.4. a) Wind speed variation during one hour, b) The equivalent wind power generation

2.3. Battery storage device

The use of storage devices in the MG system is motivated by the intermittent nature of RESs and the need to regulate the power quality (e.g., frequency, voltage) generated by these generators. The main aim is to store the surplus of the produced power during the peak production for possible usage when there is no production and keeping, at the same time, a maximum state of health for the storage devices. Therefore, a set of batteries are installed in

our deployed MG system due to their benefits (e.g., fast response, modularity, and good energy efficiency). For that, a platform to study, model, and experiment the batteries is required. This platform offers the possibility to monitor the used battery for better SoC estimation. These parameters are required to develop and deploy control strategies for EM in MG systems. In fact, a battery model is designed to estimate and predict the batteries' performance and behavior because the SoC is used as a critical parameter for our control strategy.

Electrical-circuit models (e.g., the first-order RC model, the second-order RC model) are commonly used for batteries' behavior estimation. These models are composed of a voltage source, resistors, and capacitors, which can simulate its dynamic behavior. They become more and more accurate when the model's order increases (i.e., RC networks). Therefore, in order to determine the battery characteristics, an instrumentation platform is first developed using recent sensing/actuating equipment for gathering important battery's parameters, which are then used for building a model for the battery deployed in our EEBLab (Figure 4.5).

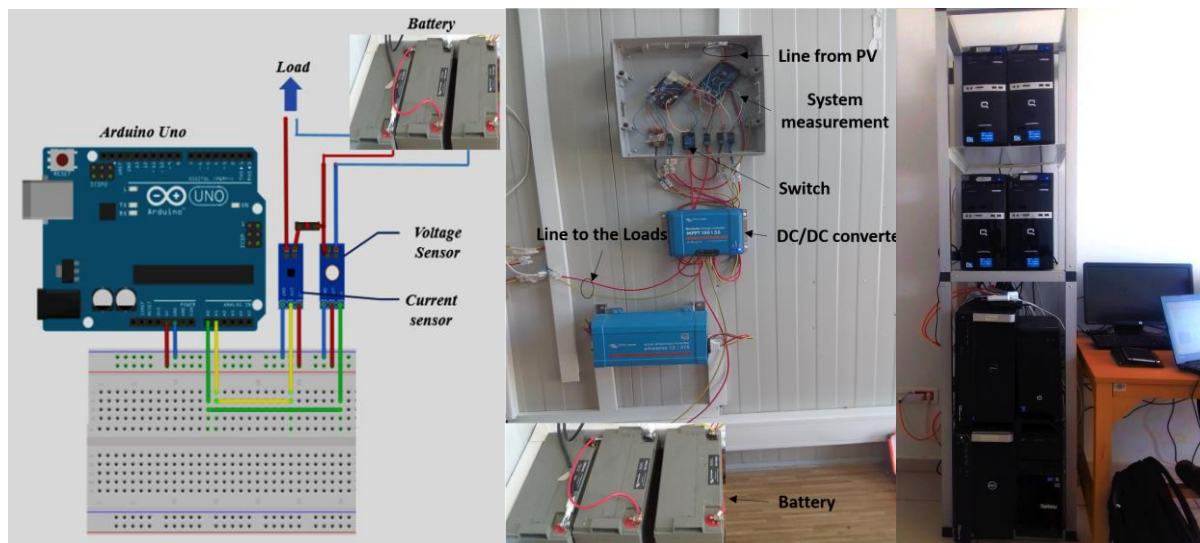


Figure 4.5. Battery characterization system (Naitmalek et al., 2019)

It is composed of a Lead-acid battery and a set of sensors to extract the battery's voltage and current. The sensors are connected to an acquisition board (e.g., Arduino) used to collect the data, and then send them to a cluster for processing and storage. The developed platform provides other information about the estimation of the battery's SoC by the Coulomb Counting method. After validating the battery model, it is integrated into our MG for simulations and experiments. In fact, the deployed model is based on the voltage and current measurement, while, the SoC is estimated using the behavior of the battery voltage variation.

Therefore, the obtained result is compared to the experimental SoC variation. These results show that the SoC and voltage curves have the same behavior due to the mapping function we have used for SoC estimation using the battery's voltage. Experimentally, a mapping function of the battery's voltage is used for SoC estimation. This mapping function attaches each voltage value to an equivalent SoC. The battery's voltage range is defined as follows, the battery is charged during a time period until the voltage is stabilized and the obtained voltage value is attached to 100% of SoC. As shown in Table 4.3, this voltage value is about 14.4V. Therefore, Figure 4.6 presented the voltage variation, which is presented by the manufacturer of the battery for the first use in the specified condition.

Table 4.3. Parameters of the deployed battery

Output voltage	12 V
Rated Capacity	110 Ah
Float charge voltage	13.5-13.8 @ 25°C
Cyclic charge voltage	14.1-14.4 @ 25°C
Recommended maximum depth discharge	50%
Cycle life	1800 (depth discharge 30 %) 750 (depth discharge 30 %) 500 (depth discharge 30 %)

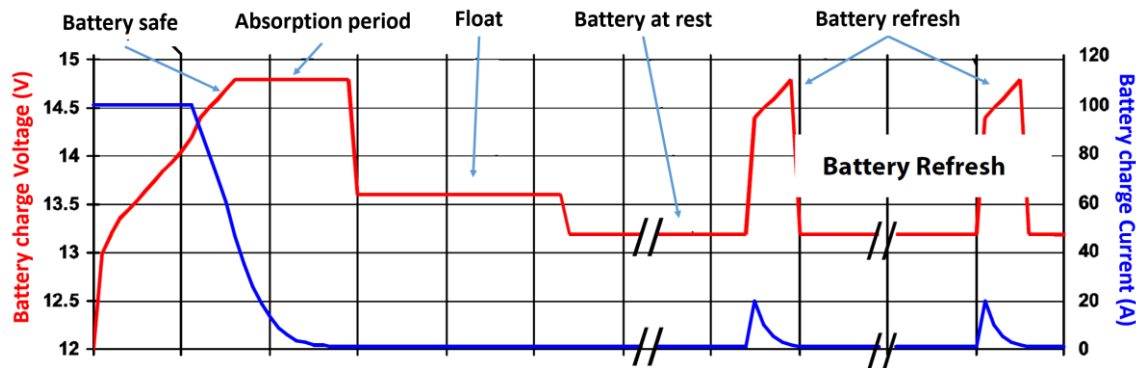


Figure 4.6. Battery voltage characterization for four charging steps

However, the battery used in this experimentation is degraded, this why the voltage stabilizes around 14.25V, which is considered 100% in this case. Moreover, the battery is discharged continuously when supplying the ventilation system. When the current reaches zero, the battery voltage was stabilized on 7.5V, and then this value is attached to 0% of SoC. The obtained voltage range is used to estimate the SoC based on this mapping function, which is implemented and deployed on the Arduino. Figure 4.7 shows the SoC variation using both simulations and experimentations and results confirm their accordance over time with slight differences.

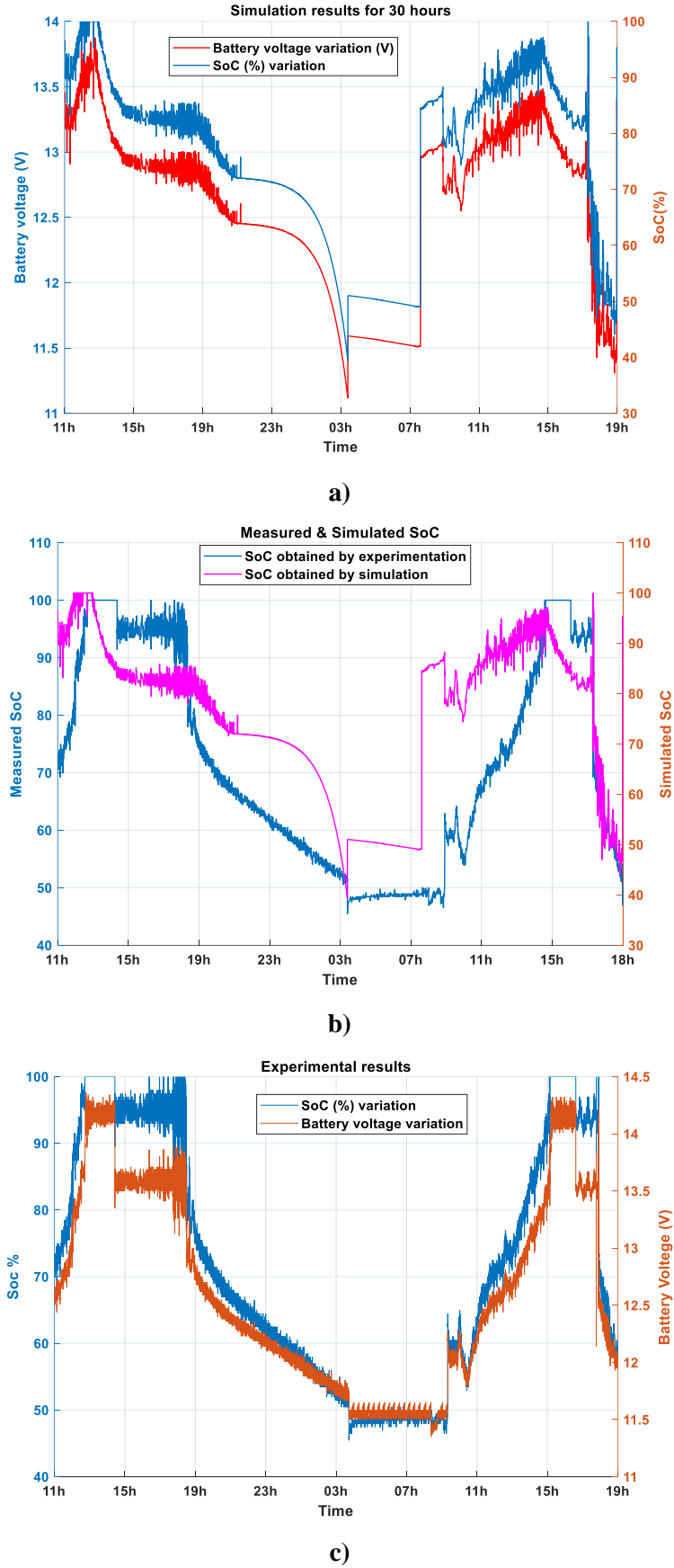


Figure 4.7. a) SoC estimation from voltage variation, b) The deployed battery modeling validation, c) The battery SoC estimation using the measured voltage by our deployed platform

The error depends on the stability of the data variability because the SoC measurement based on the voltage variability is not always a suitable method for SoC estimation. The battery voltage varies depending on the connected loads to the batteries. The main aim is to use the SoC as input control parameters but is studied carefully by another dissertation in the same project (Boulmrharj et al., 2018).

As shown in Figure 4.7.c, the blue curve presents the battery SoC variability estimated using the measured battery voltage (orange curve). During this scenario, the battery C/D current and voltage are measured and collected using our deployed IoT/Big-Data platform. The measured parameters are used to estimate the SoC variability. Therefore, the SoC is a key parameter for the EM strategies in the MG systems. In fact, as depicted in Figure 4.7, from 11:00 AM to around 07:00 PM, the battery is charged by the surplus generated from the RESs. During the night, from 07:00 PM to around 04:00 AM, the battery generates the power to the load because the PV generation is unavailable. However, the battery is at rest from 04:00 AM to around 08:00 AM because the SoC reaches the regulated threshold value, which is fixed by the EM strategy, in order to avoid a deep-discharge of the battery.

For the different scenarios, the proposed IoT/Big-Data platform could be used to measure different parameters in the MG system. Depending on the studied scenario, suitable sensors are selected and can be connected to this platform for data collection, monitoring, and processing. Mainly, the measured parameter is used to control efficiently the deployed MG system. In the next section, naïve control strategies are presented to show the usefulness of the deployed system in managing the energy flow, while, proposing a good infrastructure to deploy other intelligent and predictive control strategies. These predictive control strategies are presented in the next chapter. The rest of this section is dedicated to the scenarios related to RES and storage devices integration and control.

3. Real-time control scenarios for EM in MG system

3.1. RESs coupling and control card deployment

The work focused on the deployment of control strategies for EM in MG system that concerns the tired layer of the proposed study presented in Figure 2.1. After the deployment of the whole components of the MG system, this simple hybrid system, however, needs to be automatically controlled accordingly. In fact, D/R control approaches are therefore required for balancing the intermittent RES generation and the delay might occur between the power

production and the actual building's consumption. The main aim is to develop a control card to test the different studied control strategies for EM. Unlike existing systems, which are used as a black-box to collect and manage the energy in MG, the deployed control card allows us to measure, monitor, manage, and deploy our algorithms (El Mouatamid et al., 2017; Elmouatamid et al., 2018). In fact, the developed card can be seen as an embedded EM system for optimal energy usage according to the actual context (Figure 4.8). Therefore, different objective functions can be taken into account when optimizing and designing a control strategy, like the smoothing of the production, the continuity of the power generated to the consumer, the energy cost, and the C/D cycle of the batteries (Elmouatamid et al., 2019b). For that, a control strategy should be deployed to satisfy the constraints designed by the optimization functions. The main communication infrastructure is employed for total energy measurement and management purposes. This infrastructure provides the autonomous operation with the required measurements, decisions, and control by collecting data through the sensors and producing the commands for the Hw/Sw card, which is connected to the control switches used in the hybrid system (Elmouatamid et al., 2019a).

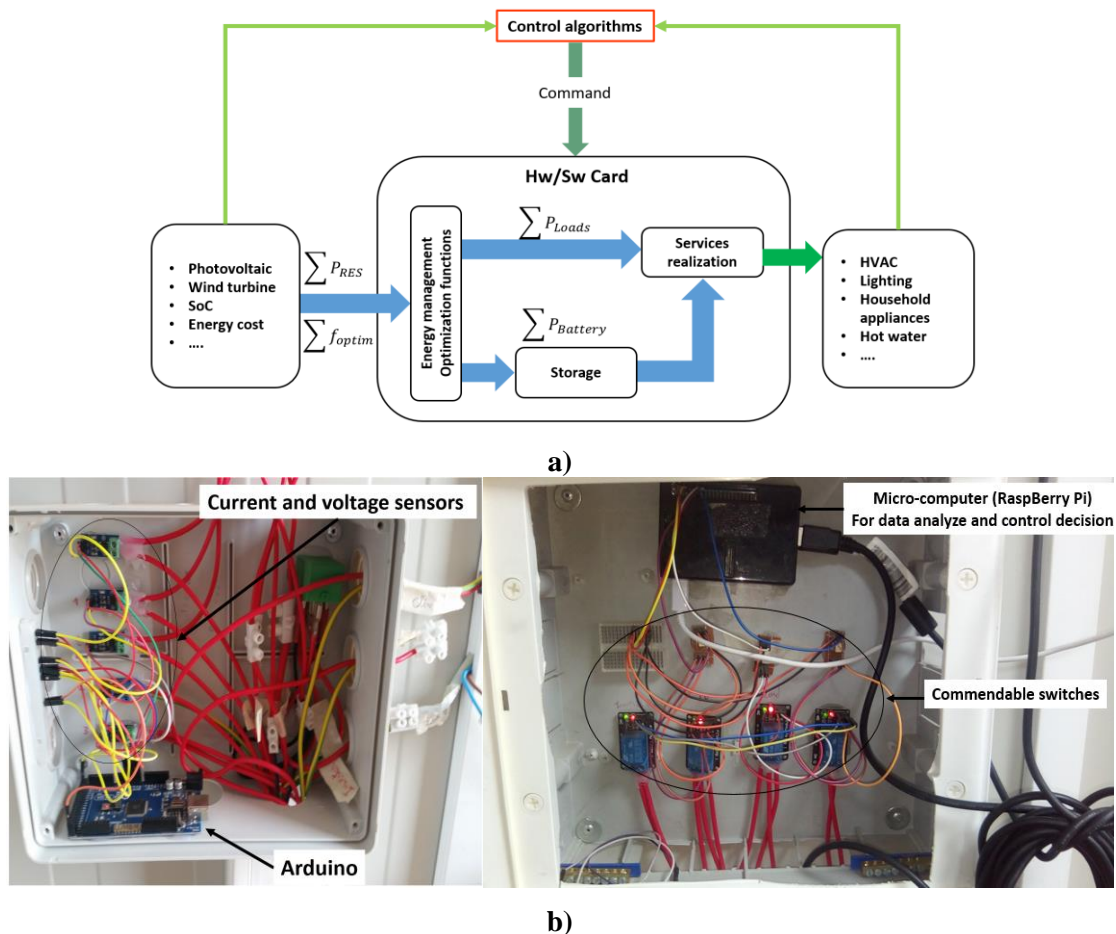


Figure 4.8. a) Schematic view of the control card, b) The deployed Hw/Sw control card (Elmouatamid et al., 2019a)

For the data measurement, the control card collects the main control parameters (e.g., PV, WT, power consumption) to execute suitable actions depending on the predefined scenarios. However, the power generated by the WT is less than the power generated by the PV, and it is almost zero during the night. During the period of production of the WT, the PV can satisfy the demand and the WT is used to charge the batteries, as shown in Figure 4.9.

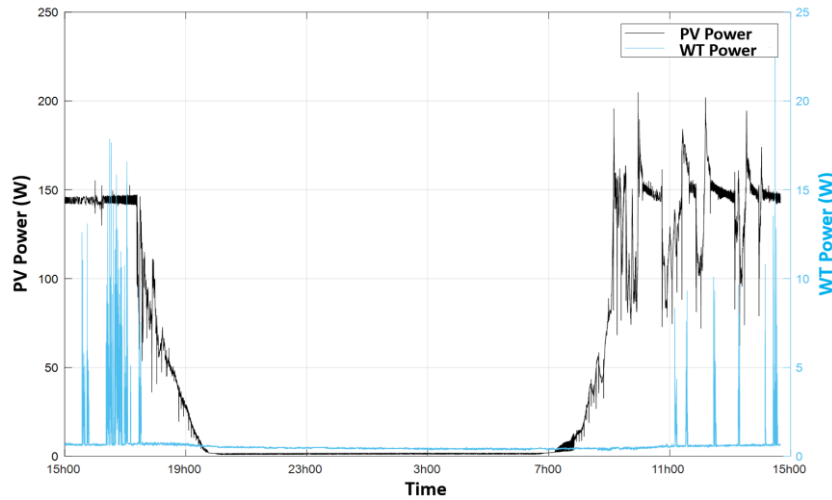


Figure 4.9. PV-WT power generated during 24 hours

Moreover, a case study is presented for a large-scale installation in which the developed control card and the IoT/Big-Data platform are used to measure and store the data collected by the deployed current and voltage sensors for the total installed RESs, battery storage system, and load consumption. As shown in Figure 4.10, the green curve presents the power generated from the eight PV panels for 24 hours. This power is calculated by measuring the PV current and voltage variability during the day, which depends on the weather conditions (e.g., temperature, irradiance) changeability. At the same time, the battery SoC is calculated using our battery characterization system installed in the MG system. Moreover, the power consumption is measured and stored for the same period. These parameters are the main input for the EM strategy. Mainly, to ensure a high level of reliability and flexibility of the power supply demanded by the consumer in an optimal way, a preliminary control strategy for a hybrid system is presented in this section. In fact, a real hybrid system is deployed in our EEELab for conducting experiments. Preliminary results are presented to show the usefulness of the control strategy for balancing the D/R according to the actual weather condition (production) and the occupancy (consumption). The installed MG system together with the IoT/Big-Data platform is tested and validated. Therefore, the main aim is to develop our proper control card in which we can deploy different control strategies and predictive approaches based on ML algorithms using the collected data from the deployed MG system.

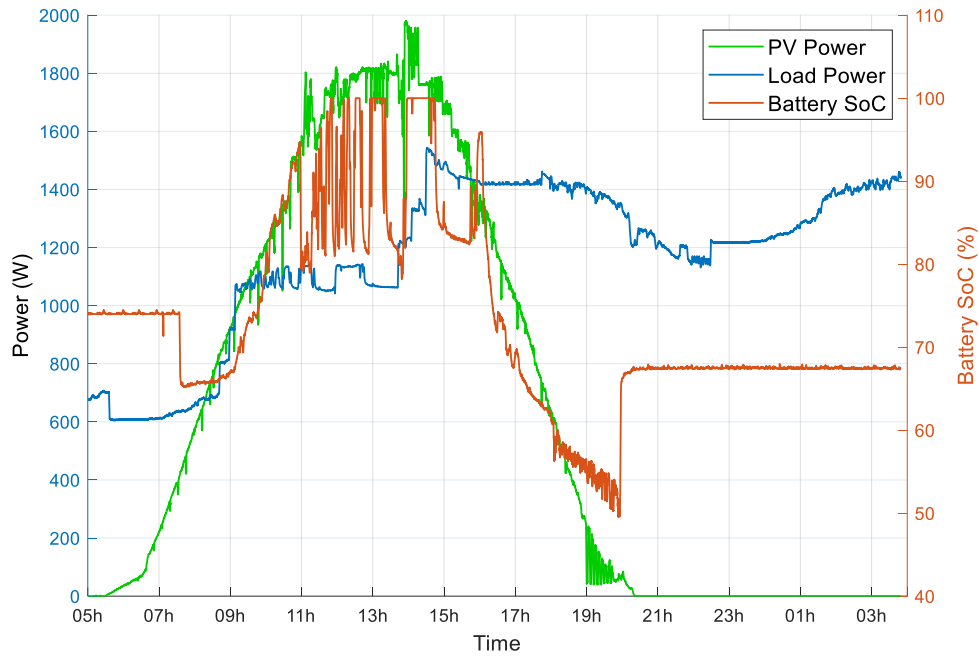


Figure 4.10. Power measurement scenario in our deployed MG system platform

3.2. PV-battery-grid control scenario

One of the main objectives of our studies is to minimize the C/D cycle of the battery in a deployed MG system by deploying a control strategy that considers the battery cycle in its operation. The control strategy proposed in this scenario is only to validate the operation modes of the deployed system and it is presented as follows. As described in the abovementioned sections, the estimated SoC together with power production/consumption values are used as input parameters to the proposed controller in order to select the best suitable switching mode. It allows managing the connection between the load and the battery, on one hand, and between the load and the electric grid on other hand. In fact, four modes are considered as shown in Table 4.4.

Table 4.4. Operating mode of the batteries

Mode	Battery connection		SoC
	Charging	Discharging	
0	OFF	OFF	Battery at rest
1	ON	OFF	$SoC < SoC_{min}$
2	OFF	ON	$SoC > SoC_{max}$
3	ON	ON	$SoC_{min} < SoC < SoC_{max}$

For instance, the control algorithm starts first by computing the SoC and the power of the PV. If the estimated SoC is about 100%, the control stops charging and the ventilators are powered by the battery. Otherwise, a threshold value is used to select between the battery and

the utility grid. If the SoC value is above this threshold, the control selects the battery as the main power supplier; otherwise, the control checks the PV power to refine the decision. If it is below a fixed threshold value, the load is powered by the grid; otherwise, it will be powered by the battery. It is worth noting that the deployed prototype includes a ventilation system composed of two ventilators operating with 24 Watts of maximum power. This means that the choice of the threshold values of the switching between the battery and the grid needs to consider the load power. The EEBLab includes also other equipment, mainly lighting, HVAC, and other variable components. It is to notice that the experimental scenarios are realized for a limited number of PV panels in order to balance its power generation with the WT on the one hand, and due to the measurement components limits that we have.

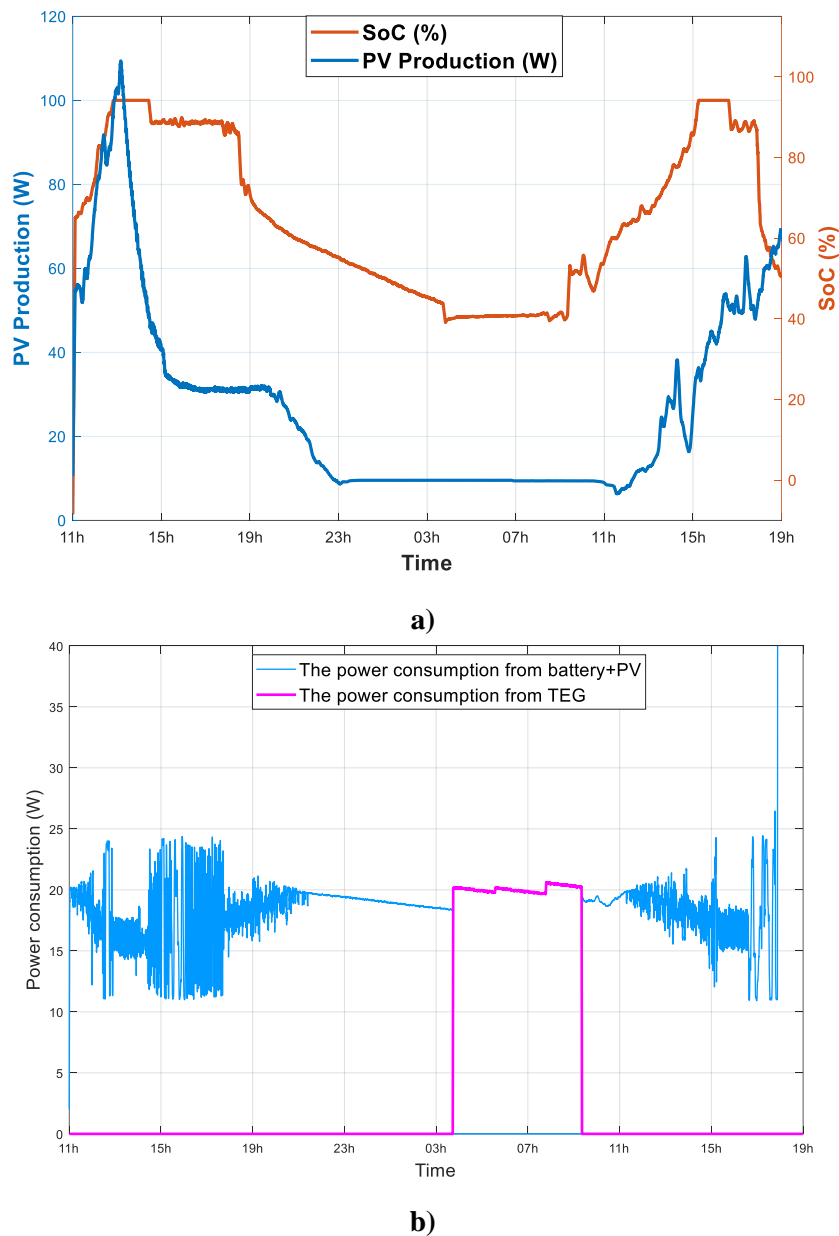


Figure 4.11. a) Production and SoC variation b) Consumption from battery-grid and SoC status

Figure 4.11.a shows the power generated by the deployed PV panel and the variation SoC as well. From 11:00 to 15:00, the PV is used to charge the battery and supply the ventilation system. Around 15:00, the battery started to discharge because the PV production is less than the required power. From 20:00 to 03:00, the ventilators are only supplied by the battery and the PV production is almost negligible. Between 03:00 and 08:00, the system switched to the electric grid, and we can see that during this period the battery and the PV current are almost zero.

It is worth noting that the consumption is measured using three current sensors. The first sensor is installed between the regulator and the ventilators, the second is installed between the ventilators and the transformer, which provides the power supplied from the grid, and the third one is installed after the other two sensors for data validation. The aim is to confirm the right behavior of the control strategy as depicted in Figure 4.11.b. At a certain time (around 15:00), the production became low, and therefore the ventilators are powered by the battery. Around 03h00, the SoC decreased to reach the threshold value, and the system switched from the battery to the electric grid throughout the night. At 08:00, the SoC exceeded the threshold value and the system switched back to be powered by the battery.

In this scenario, a preliminary control strategy is introduced for EM in the MG system, which aims to supply, in an optimal way, the power demands. A control card is developed and deployed for real-testing of control approaches. Another interesting point is the integration of the IoT/Big-data platform for real-time data collection, processing, and analysis. These data are used for real-time MG control by balancing the power demand and response according to the actual context.

3.3. PV-WD-battery-grid control scenario

PVs and WT are deployed in the EEELab and connected together with storage devices to supply different AC/DC equipment. To ensure the power when we have bad weather conditions or during the night, the system is connected to the traditional grid. The Hw/Sw control card implements the control approach for EM in the MG system. Real-time data processing is used in this scenario to gather data from weather station, power production, and power consumption. The control approach uses these data to extract the actual context in order to select the best suitable action for either storing extra energy, or supplying directly the building equipment from the PV/Wind/Batteries, or from the electric grid. In this study, the

architecture is consists of two batteries, a buffer battery with less capacity, and the main battery storage system with high capacity as is depicted in Figure 4.12.

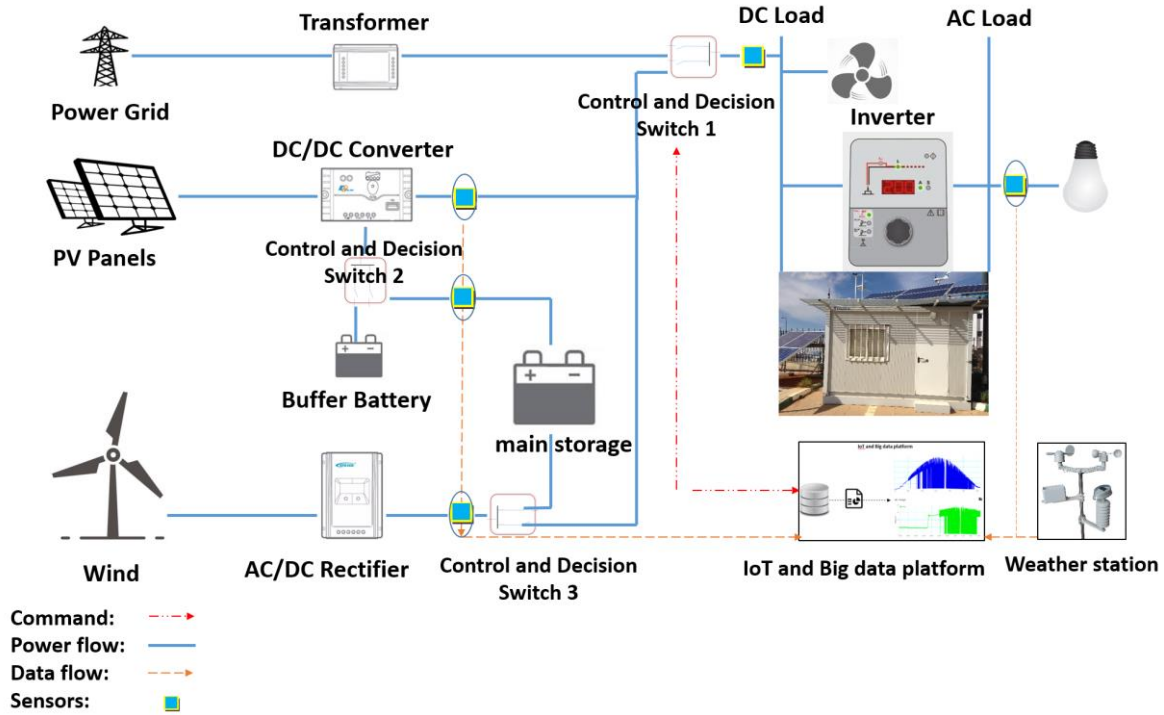


Figure 4.12. The test scenario architecture

When the loads are connected directly to the PV, to WT, or to PV/WT, the buffer battery can smooth the power if there are sudden variations in the weather conditions. The main storage is used to store the power from the sources and to generate power when the production is less than the loads demands.

The developed card can be seen as an embedded EM system for optimal energy usage according to the actual context. In fact, the PV (resp. WT) system produces the electric power only during sunny (resp. windy) days, but the high power consumption appears to be around midday and during the moment of sunset. During the day, the aim is to use all the energy produced from RESs and to avoid high charging and discharging cycles of the batteries. Also with the EM system, a priority is defined between the PV system and WT to supply the loads. For example, it is preferable to supply the loads by the PV system and use the WT to charge the battery because the radiation is more stable than the wind speed. We can calculate the power produced from each source during a period to define the sources' priority and to minimize the loss of power supply probability. The total energy produced by the RESs (equation 4.3) is the summation of E_{PV} and E_{WT} , respectively produced by the PV and WT during one day and can be expressed by equation (4.1) and (4.2), and the maximum power

demanded by the storage can be calculated by equation (4.4). The total energy calculated for each source can be taken into account, as the input parameter, to design the control strategies.

$$E_{PV} = \int_0^{24h} P_{PV}(t)dt \quad (4.1)$$

$$E_{WT} = \int_0^{24h} P_{WT}(t)dt \quad (4.2)$$

$$E_{RES} = E_{PV} + E_{WT} \quad (4.3)$$

$$E_{Bat} = E_{RES} - \int_0^{24h} P_{Consumption}(t)dt \quad (4.4)$$

Different objective functions can be taken into account when optimizing and designing a control strategy, like the smoothing of the production, the continuity of the power generated to the consumer, and C/D cycle of the batteries. For that, a control strategy is designed to satisfy the loads demands (lighting, ventilation system) throughout the day and night by using the PV, WT, batteries, and utility grid. The main communication infrastructure is employed for the total energy measurement and management purposes. This infrastructure provides the autonomous operation with the required measurements, decisions and controls by collecting data through the sensors and producing the commands for the Hw/Sw card connected to the control switches used in the hybrid system.

The proposed strategy could control the deployed MG system according to the following cases: *i)* the power generated by the PV system has priority in satisfying power demand by loads over that delivered by the WT or by the batteries, because in the testing site there is more radiation during the day than wind, *ii)* if the power generated by the PV system is higher than the loads demand, the PV system is connected directly to the loads using a buffer battery, which allows balancing the power delivered to the load (Figure 4.12: switch 2), in this case, the power generated by the WT is used to charge the main battery, *iii)* if the electric power generated by the PV system is less than power demand, PV and WT supply the power to the loads (Figure 4.12: switch 2, 3), *iv)* if the load demand exceeds the power generated by PV/WT combination, the difference is supplied by the main storage (Figure 4.12: switch 2), *v)* if the power generated by PV/WT is less than the demand and the SOC of the battery is less than 60 % (to avoid a deep discharging), the power is supplied by the traditional grid (Figure 4.12: switch 1), during this time PV/WT power is used to charge the main storage. The flowchart of the main control strategy is illustrated in Figure 4.13.

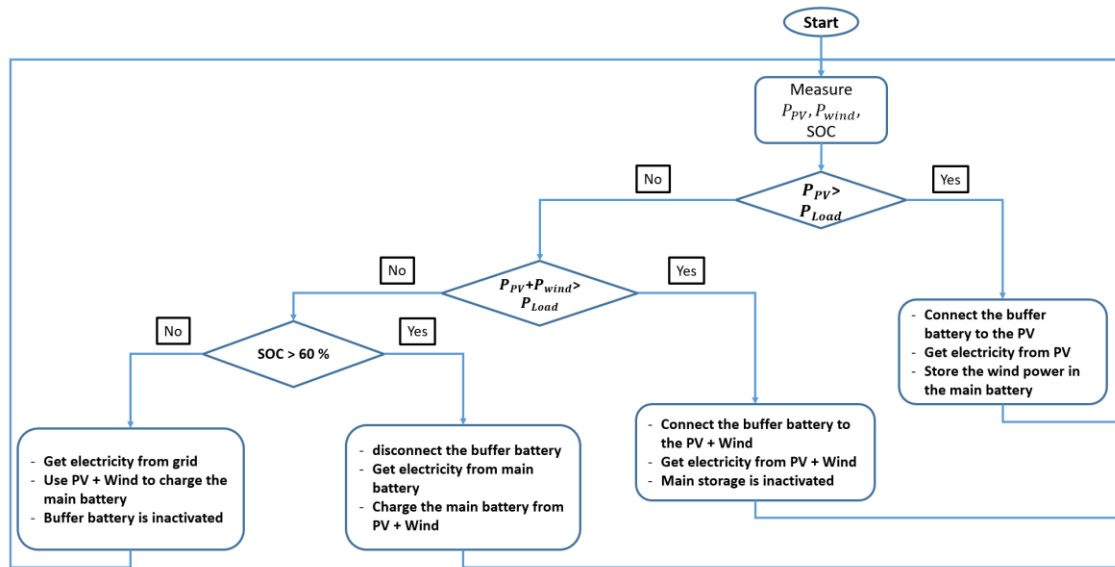


Figure 4.13. Flowchart of the power flow management

In order to validate the behavior of the control strategy and the functionality of the hybrid system, experimental results have been extracted. The main objective is to minimize the electricity consumption from the traditional grid while maximizing the production of renewable energy. A real system is presented to extract the data to confirm the usefulness of the EM system control. The measurements of the power exchanged in the main elements of the Hybrid system are presented. Figure 4.14 shows the real hybrid system installed for this scenario.

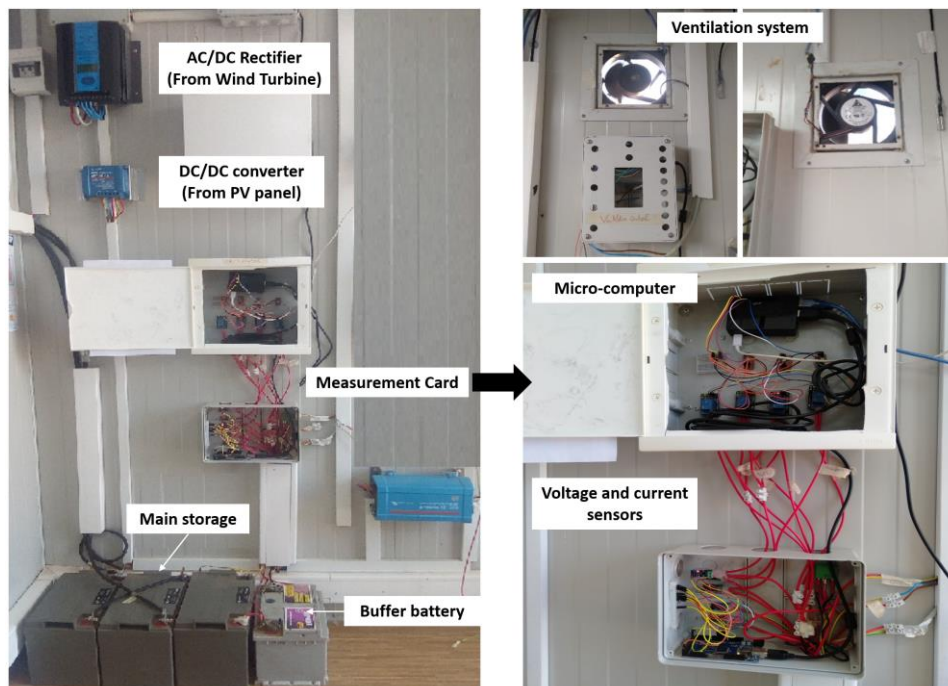


Figure 4.14. Hybrid system implemented in the EEBLab

3.3.1. Buffer battery

The buffer battery is used when the renewable energy generators are directly connected to the load. The capacity of this battery is less than the main battery storage. As shown in Figure 4.15, the C/D current of this buffer battery is low. From 7:00 AM to around 10:00 AM, the PV production is less than the power demand, for that, the buffer battery is disconnected and the battery current is zero. From 10:00 AM to around 18:00 PM we have some peak due to the variable production during this period.

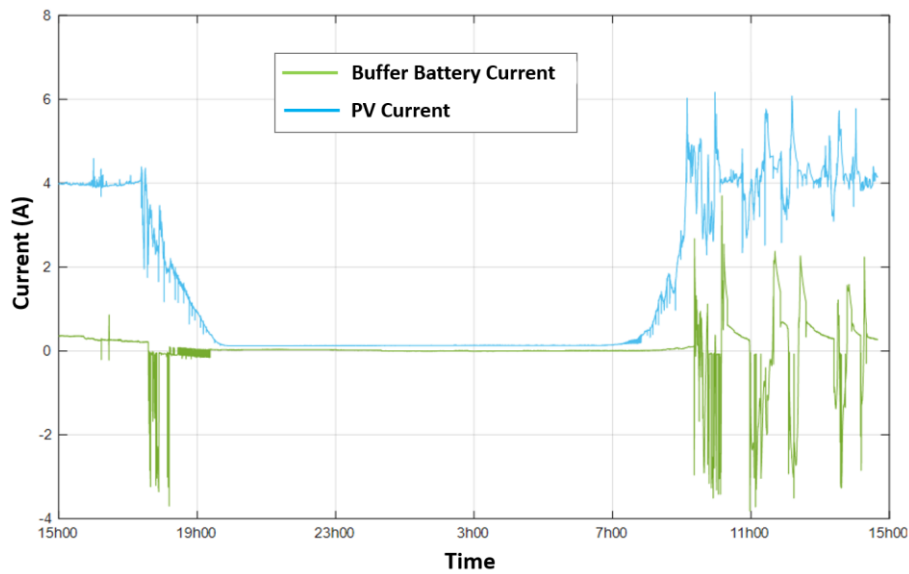


Figure 4.15. Buffer battery current variation

3.3.2. Main battery storage

The batteries used in the main storage have a large capacity. When the power production is higher than the power consumption, these batteries are connected to the RES just for charging. For that, in Figure 4.16 we can see that from 07:00 AM to 18:00 PM the current is positive, the batteries are charged. At the same time, the power supplied to the consumer is ensured by the PV and the WT. As shown in Figure 4.16, from 18:00 PM to 20:00 PM the power produced by the RESs is less than the power consumed in the building, and the main battery storage is connected to complete the power needs. During the night, the RESs generations are around zero and the main storage is discharged, for that we can see in Figure 4.17.a that the system switched from the RESs to the traditional grid in order to ensure the power to the loads. The inverter is used to generate the total power from different RESs and storage devices to the loads.

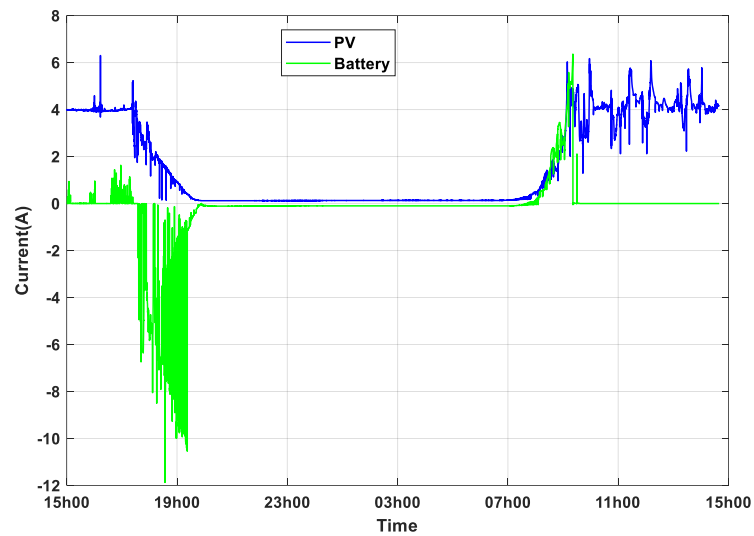


Figure 4.16. Main storage C/D current variation with PV production

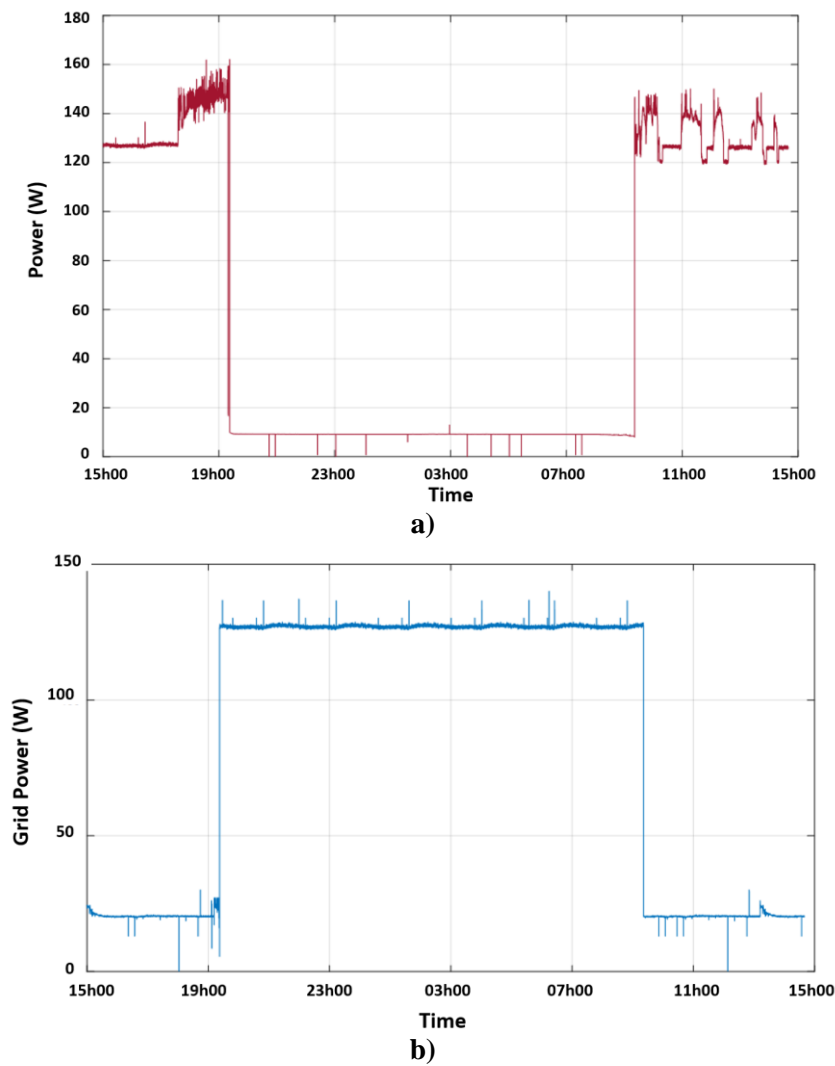


Figure 4.17. a) The power generated from RESs to the loads, b) Power consumed from traditional grid

3.3.3. Grid power

As mentioned above, the traditional grid is used to ensure the power to the building when the power production is zero and the storage is discharged. During the 24 hours of the experimentation, the batteries are discharged around 20:00 PM and started charging around 07:00 AM. Figure 4.17.b shows that during this period the power generated by the traditional grid is equal to the power consumption (Lighting, ventilation system). The obtained results from both simulations and experimentations showed the usefulness of the introduced platform as well as the effectiveness of the proposed control strategy in managing the power flows.

4. Conclusions

The main aim of the work presented in this chapter is to validate the deployed MG system components with the developed control card for EM. The MG platform connects the building's components using sensing/actuating, IoT/Big-Data technologies in order to leverage real-time gathering and data processing for RESs production, battery SoC variation, and loads consumption. The platform was deployed, several scenarios have been tested and evaluated, and results showed the usefulness of the platform for efficient management of buildings components. In fact, control strategies based on real-time data collection are deployed to control the power flow for a real MG system. The proposed control strategy permits to connect multi-energy sources (e.g., PV, wind) and storage devices together with the TEG. Simulation and experiment results are presented to validate the different used models as well as the interconnection of all MG system components. These latter are used to investigate and evaluate the effectiveness of the proposed predictive approaches using both simulations and experimentations.

Chapter 5: A Predictive Control Strategy for Energy Management in Micro-grid Systems

1. Introduction

Studies conducted in the previous chapter, showed that energy consumption could be efficiently reduced by deploying MG systems (Elmouatamid et al., 2020a). The aim is to minimize the electrical bill's cost while extending the lifetime of the system's components (e.g., converters, batteries, fuel-cells). Generally, an EM system incorporates control strategies and functions, which maximize the MG system's efficiency and minimize energy consumption. The work presented in this chapter introduces an intelligent and predictive control strategy, named MAPCASTE (Measure, Analyze, Plan, foreCAST, and Execute), for EM in MG systems, as depicted in Figure 5.1. MPC and GPC have been investigated in order to carry out the proposed MAPSASTE. This later was deployed and evaluated by assessing its effectiveness for EM in MG systems (Elmouatamid et al., 2020b). In fact, the main aspect of the proposed MAPCASTE approach is to measure, in real-time, the main input control parameters; analyze the data for ML algorithms training, prediction of the future behaviors, forecasting the suitable commands to reach the desired setpoint depending on the predefined constraints and objective functions, and correcting the errors depending on the real measurements.

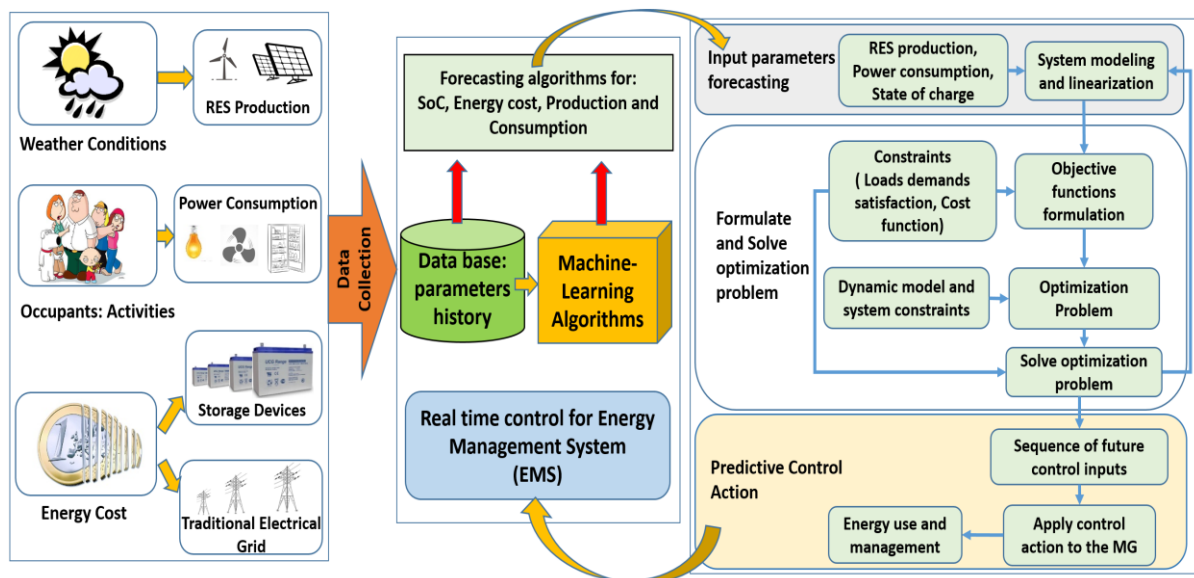


Figure 5.1. EM schemes with GPC operation process

In this chapter, forecasting models are first presented for predicting the power production and consumption in MG systems together with the battery SoC. A control strategy is then implemented to balance the D/R by taking into account the forecasted and real-time values. Therefore, a hierarchical control approach is proposed to manage the energy flow in MG systems. More precisely, an EM system is deployed based on model predictive control in order to manage the operation of such MG and in particular its interaction with the main electricity grid. A power converter is then modeled and controlled by a GPC model in order to ensure the interaction with the grid. An optimization function with dedicated constraints is modeled for both secondary and tertiary layers. For the second layer, the C/D cycle of the battery and the maximum power extracted from RESs are designed as the main constraint to be optimized by the GPC model, while for the tertiary layer the electricity price is integrated as an input parameter for the control.

2. Power forecasting for MG systems

The variability and the uncertain nature of power production and consumption make the system more difficult to control. In fact, weather conditions influence the production of RESs while occupancy influences power consumption. Therefore, the development of accurate short term forecasts are needed for seamless integration of RES (e.g. PV system, WT) together with the TEG in MG systems. This section presents a forecasting model for predicting the power production and consumption in MG systems together with the battery SoC. A control strategy is then implemented to balance the D/R by taking into account the forecasted and real-time values. Based on the data collected from a real MG system, simulation results are presented to show the effectiveness of power forecasting for MG control.

2.1. Classification of power forecasting techniques

Different ML methods can be used to forecast the power production and consumption using the historical behavior of data. The forecasting can be able to minimize the consumption from TEG by maximizing the RES generation, in consequence reducing the electricity cost. An accurate forecast is used to reduce the uncertainties of the RES integrated into MG by implementing control strategies based on the forecast values. Different techniques can be implemented for load and PV power forecasting: exponential smoothing, multiple regression, stochastic time series, statistical models, and artificial intelligence.

Many methods have been proposed in the literature; however, selecting the best suitable ones to be used for MG control is required. In fact, power forecasting is an integral process in the planning and the control of electric utilities in the MG system. It is frequently identified as an important tool to address the uncertainty and the variability of power production and load consumption in the MG with a large RES integration. Some forecast algorithms need a high quantity of data to be trained and to have a low error (e.g. ANN, LSTM) (Breiman et al., 2001; Nottona et al., 2013; Rana et al., 2015; Pedro et al., 2017). Generally, these algorithms need a long training time to be stabilized and to be executed; it can be used for medium and long-term forecasting cases. In addition, based on the time series analysis, a classification can appear (Figure 5.2). In another way, other algorithms can be trained by a low quantity of data to forecast a very short or short term in the future (e.g. ARIMA, ARX). During a given period, the algorithms calculate the error between the observed and forecasted values in order to ensure that the error does not increase more than the threshold limits. While the application area is an interesting point to define the categories and the algorithms of the forecast to implement. For the control, the time horizon can be very-short, from a few minutes to one hour or more ahead to make decisions. For that, an algorithm, which demands a few time to be trained, can be selected. For example, the control strategy can switch from PV panels and batteries to the traditional electric grid if the forecasted values show that in a few moments the RES cannot satisfy the demand. This decision can be implemented based on the forecasted values obtained during a few minutes. Therefore, the integration of the price as an input parameter to the control strategy needs a few hours ahead of the forecast values to stabilize the system.

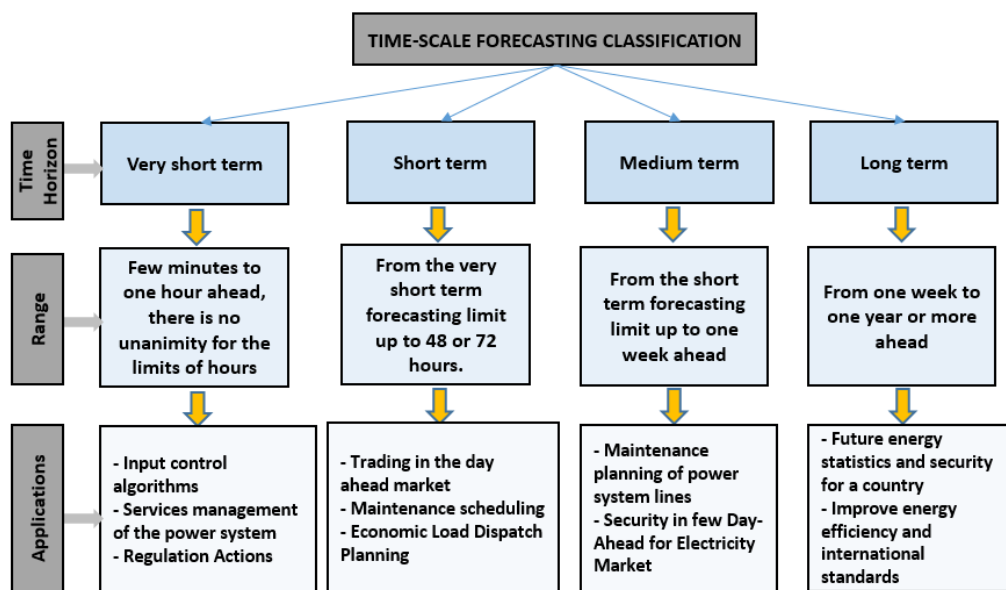


Figure 5.2. Time scale forecasting classification

The electricity price varies during the time by considering the peak of the consumption and production. Another classification can be used by considering the stability of the data used to train the algorithm and the variability of the values to forecast. Figure 5.3 shows a basic classification of the methods that can be implemented to forecast the RES generation and the load consumption based on the data type used to train the algorithms (i.e., stationary or no-stationary).

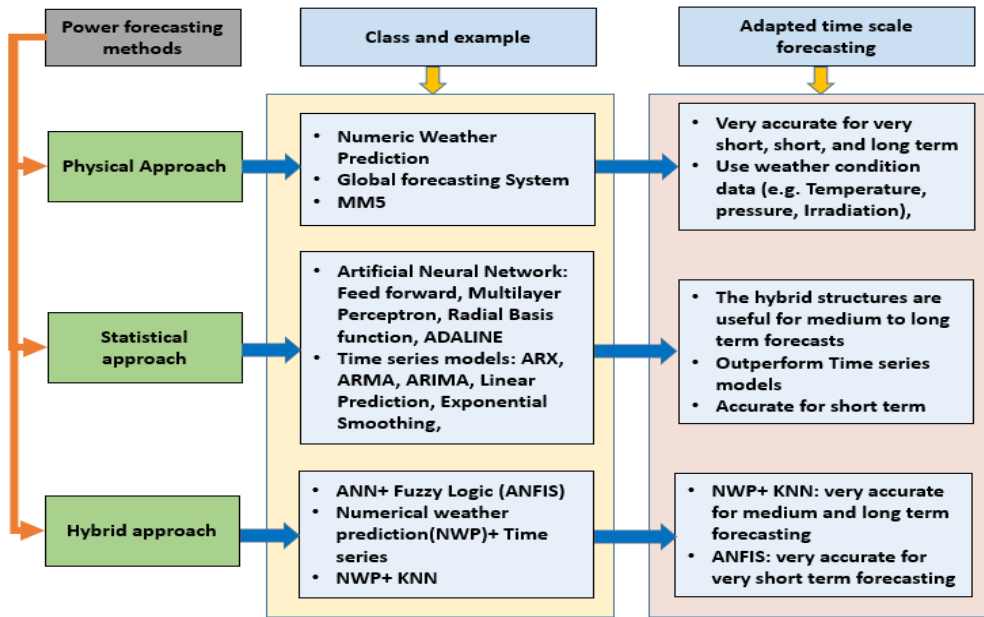


Figure 5.3. Power forecasting methods

2.2. Deployed forecasting technique

Statistical models approaches, as stated above, do not need internal functionality information from the system, which generates the value to forecast. It is a data-driven approach that is able to extract relationships on previous data in order to forecast the future behavior of the values. However, the quality of historical data is essential for an accurate forecast, a large historical of data is typically required. These approaches benefit from the capability of correcting systematic errors associated with the measurement of inputs (Graditi et al., 2016). They include the regressive methods, which estimate a relationship between dependent (e.g. temperature, irradiation) and independent parameters (e.g. model temperature, wind speed).

ARIMA is one of the popular linear models in time series forecasting due to its statistical properties as well as Box Jenkins methodology in the model building process (Box GEP et al., 2008). It is one of the most useful approaches used to analyze the non-stationary time-series,

by integrating two approaches for stationary time series, autoregressive (AR), moving average (MA), and combined AR and MA (ARMA) series. The application of the ARIMA method has a fundamental impact on the study of the non-stationary time series analysis due to Box and Jenkins approach, which includes five iterative steps (Mbamalu et al., 1993) (Figure 5.4), as described below.

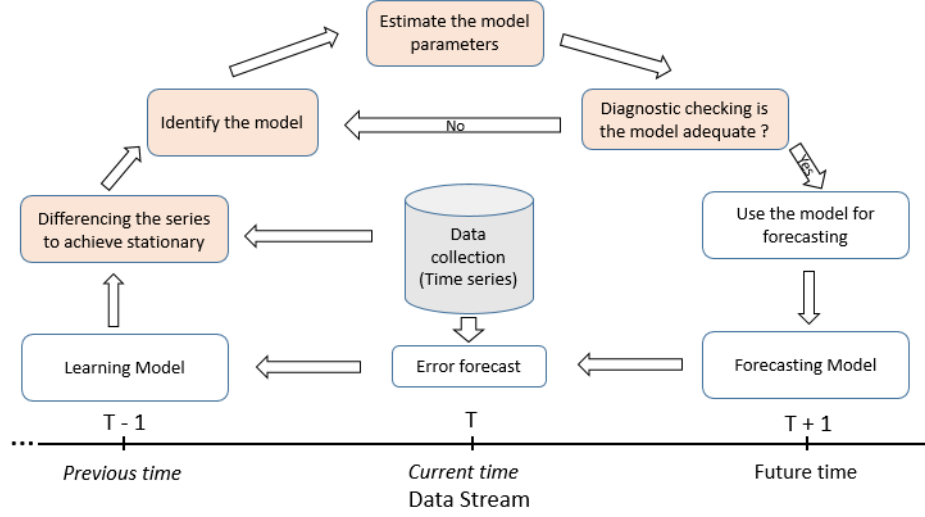


Figure 5.4. Different iterative steps of ARIMA model

Differentiation step, in this phase general ARIMA models is presented to model the data. The general formulation is presented by equation (5.1) (Alfares et al., 1999):

$$\varphi_p(B)\Phi_{sp}(B^l)\Delta^d\Delta_l^{sd}X_t = \Theta_{sq}(B^l)\theta_q(B)\epsilon_t \quad (5.1)$$

where B represents the back-shift operator ($B: B^{-1}(X_t) = X_{t-1}$ and $B^{-l}(X_t) = X_{t-l}$), this function can contain factors of polynomial functions presented by equation (5.1.a) as follow:

$$\begin{aligned} \varphi_p(B) &= 1 - \sum_{l=1}^p \varphi_l B \\ \theta_q(B) &= 1 - \sum_{l=1}^q \theta_l B \\ \Phi_{sp}(B^l) &= 1 - \sum_{m=1}^{sp} \Phi_{ml} B^l \\ \Theta_{sq}(B^l) &= 1 - \sum_{n=1}^{sq} \Theta_{nl} B^l \end{aligned} \quad (5.1.a)$$

where, the non-seasonal operators are $\varphi_p(B)$ and $\theta_q(B)$ and the seasonal operators are $\Phi_{sp}(B^l)$ and $\Theta_{sq}(B^l)$. The terms $\Delta^d = (1 - B)^d$ and $\Delta_l^{sd} = (1 - B^l)^{sd}$ are respectively the

non-seasonal and seasonal differencing operator. X_t is the power at the actual time t , and ϵ_t represents the error at the period t .

Identification step is the estimated procedures applied to a data to find the best ARIMA model by determining appropriate parameters (p, q) and d , in order to obtain the stationary time series. It is a critical step to build an ARIMA $(p, d, q)(sp, sd, sq)$ model, where AR: p is the auto-regression order of the model, which indicates the number of parameter φ , and I : d is the degree of differencing to make a stationary data X of the model, and MA: q is the order of the moving average aspect, which indicates the number of the model parameter θ , sp is the seasonal AR order, which indicates the number of parameter Φ , sq is the seasonal MA order, which indicates the number of parameter Θ , and sd is the number of times the data series needs to be seasonally differenced in order to indicate a seasonally stationary series. Estimation step, once the model is specified to obtain the stationary time series, the model parameters are estimated in such a way that the error is minimized. Its parameters are estimated from the conditional least squares methods, based on the values estimated during the identification step. The last step of ARIMA model's building is the diagnostic checking, after the identification and the estimation of the model parameters, this step checks if the model is a good fit for the data, the assumptions about the errors (also known as the residuals) are satisfied, then determines if the autocorrelation is zero or insignificant. If the model is inadequate, a new model should be identified by the different steps of parameter estimation and model verification.

The idea with ARIMA model is that the finale residual should look like white noise and verify if there is information available in the data to extract. In each step of ARIMA modeling (AR, I, MA), time-series data is passed through these three parts to produce less residual. The sequence of three steps for ARIMA analysis is started by the integrated step, in this step the model subtracts time series with its lagged series in order to extract trends from the original series data. The differencing order is used to subtract the data; equation (5.2) presents the differencing order one and two.

$$\left. \begin{aligned} (d = 1): X'_t &= X_t - X_{t-1} \\ (d = 2): X'_t &= X_t - X_{t-1} - (X_{t-1} - X_{t-2}) \end{aligned} \right\} \quad (5.2)$$

The formula is used to remove the trend in order to make data stationary on average but it is not stationary on variance. In order to produce reliable forecasts through ARIMA models, we need to make the series stationary on variance. For this reason, the original time series data

is transformed by a logarithmic function. The following equation represents the process of log transformation mathematically (equation (5.3)).

$$X_t'' = \log_{10}(X_t) - \log_{10}(X_{t-1}) \quad (5.3)$$

After the time series data is transformed in the integrated step, the influence of the previous observed values on the current values is extracted in the autoregressive step. This is done by developing a regression model with the time-lagged period values as predictor variables. Equation (5.4) presents the general form for the regression model.

$$X_t = \varphi_1 X_{t-1} + \varphi_2 X_{t-2} + \dots + \varphi_p X_{t-p} + \epsilon_t \quad (5.4)$$

Concerning MA step, the influence of the previous period's error terms on the current period's error is extracted. MA part of ARIMA is developed with the simple multiple linear regression values with the lagged error values as predictor variables (equation (5.5)).

$$X_t = \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} \quad (5.5)$$

ARIMA model is defined by coupling the three models (*AR*, *I*, *MA*). The values of ARIMA should firstly be defined by optimizing a metric of interest, such as partial correlation and autocorrelation of the series, AIC and BIC values. The idea is to choose a model with minimum AIC and values. AIC is a measure of the quality of fitting an estimated model. It is based on the concept of entropy, which is a measure of the information lost when a mathematical model is used to describe the actual data. The AIC can be defined by equation (5.6).

$$AIC = \log Z + \frac{2n}{N} \quad (5.6)$$

where N is the number of values in the estimation data set, n is the number of the estimated parameters, and Z is the loss function.

It is worth noting that another key factor that should be taken into consideration is the precision of the model. To measure the accuracy of the predictions, the errors between the forecasted values and actual data are analyzed. Two indicators are used, MAE and the MSE. These two indicators have been used to evaluate the accuracy of the obtained model to be used for forecasting.

$$MAE = \frac{1}{N} \sum_{t=1}^N |X_t - F_t| \quad (5.7)$$

$$MSE = \frac{1}{N} \sqrt{\sum_{t=1}^N (X_t - F_t)^2} \quad (5.8)$$

2.3. Control strategy based on forecasting method and simulation results

The proposed strategy could control the deployed MG system, which contains a PV panel connected to battery storage in order to ensure the power to a ventilation and lighting systems. In this case study, the control strategy is based on the forecasted values to make control decision according to the following cases: i) the power generated by the PV system has priority in satisfying power demand by loads over that delivered by the TEG or by the batteries, ii) if the power generated by the PV system is higher than loads demand, the PV system is connected directly to the loads, iii) if the electric power generated by the PV system is less than demand, power will be supplied from the PV and the main storage, v) if the power generated by PV is less than the demand and the SoC of the battery is less than 40 % (to avoid a deep discharging), the power will be supplied by the traditional grid, during this time PV power is used to charge the main storage.

In fact, during the day the PV production is used to ensure the power to the loads and to charge the battery as well. As shown in Figure 5.5.a, from 01:00 PM to thereabouts 08:00 PM the irradiation decreases, during this time the battery starts to discharge in order to ensure the power to the loads together with the PV panel. Moreover, during the night only the battery is used to supply the power to loads, but when the SoC reaches the threshold value the control strategy switches from RES to the TEG. In addition, the power consumption data are collected and the ARIMA model is deployed to forecast the consumption during the same period for the test. In fact, the consumption depends on the occupant's activities in the building. As shown in Figure 5.5.c, the consumption variety is due to the ventilation speed variety, which depends on the indoor CO₂ concentration. The previous data are used to train ARIMA, which starts to forecast the consumption around 01:00 AM and the obtained results are compared to the real data.

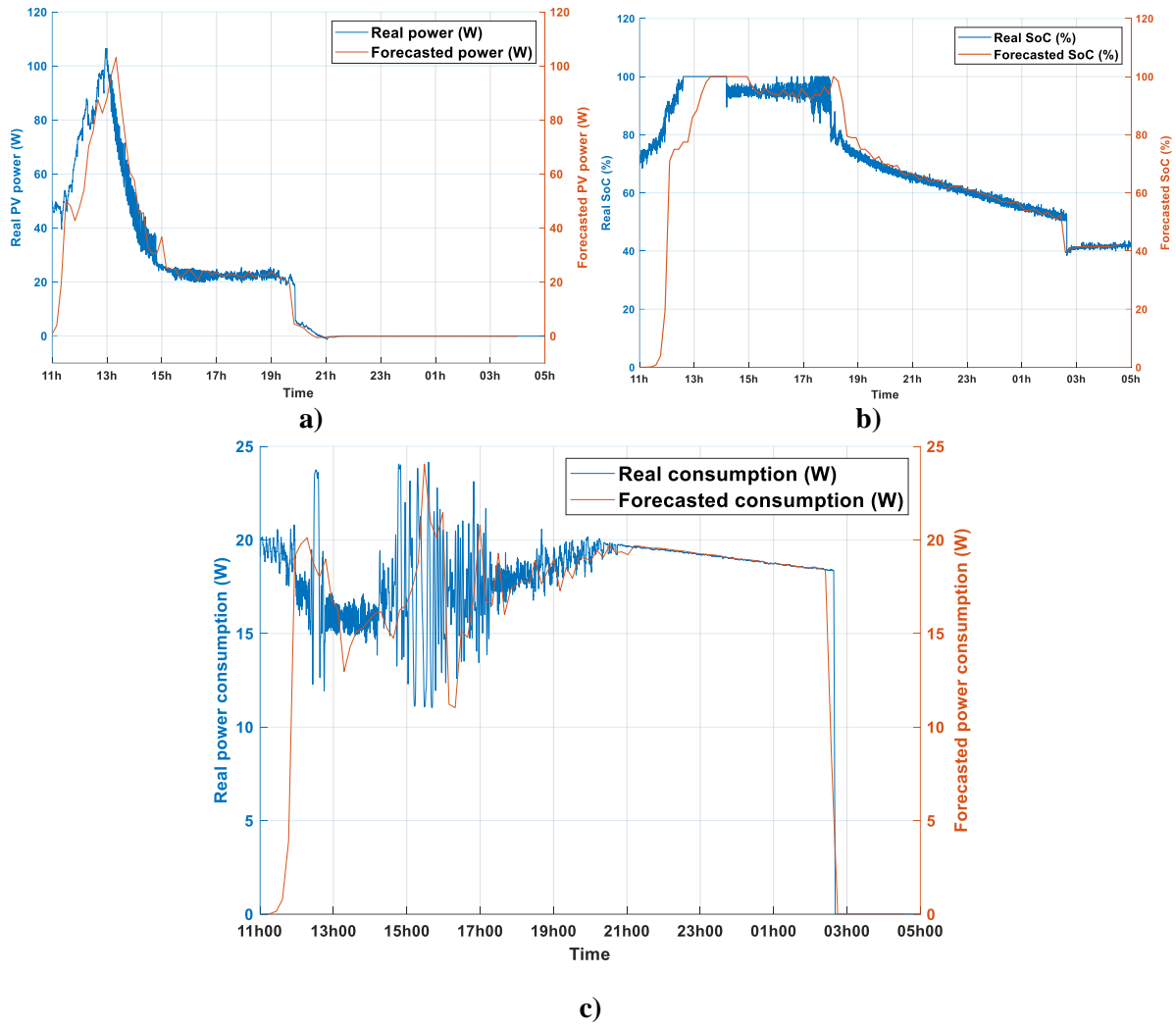


Figure 5.5. a) Forecasting and real PV power, b) Forecasting and real SoC, c) The real and the forecasted power consumption

The input parameters used for this control strategy are the PV power production, load consumption, and SoC of the battery. For that, a dataset of the PV power production, load consumption, and SoC is used to train the implemented ARIMA forecasting algorithm. The obtained algorithm is used to forecast the control strategy input parameters. Figure 5.5.a presents the forecasting power together with the real power of the PV, the values are obtained a few minutes before the real-time values. The same for the SoC of the battery, Figure 5.5.b shows that around 2:30 AM the control strategy switches from RES to the traditional grid because the forecasting value obtained shows that the threshold value of the SoC will be attended (Figure 5.6.b). For that, the SoC remains constant at 50% from 2:30 AM to the end of the simulation.

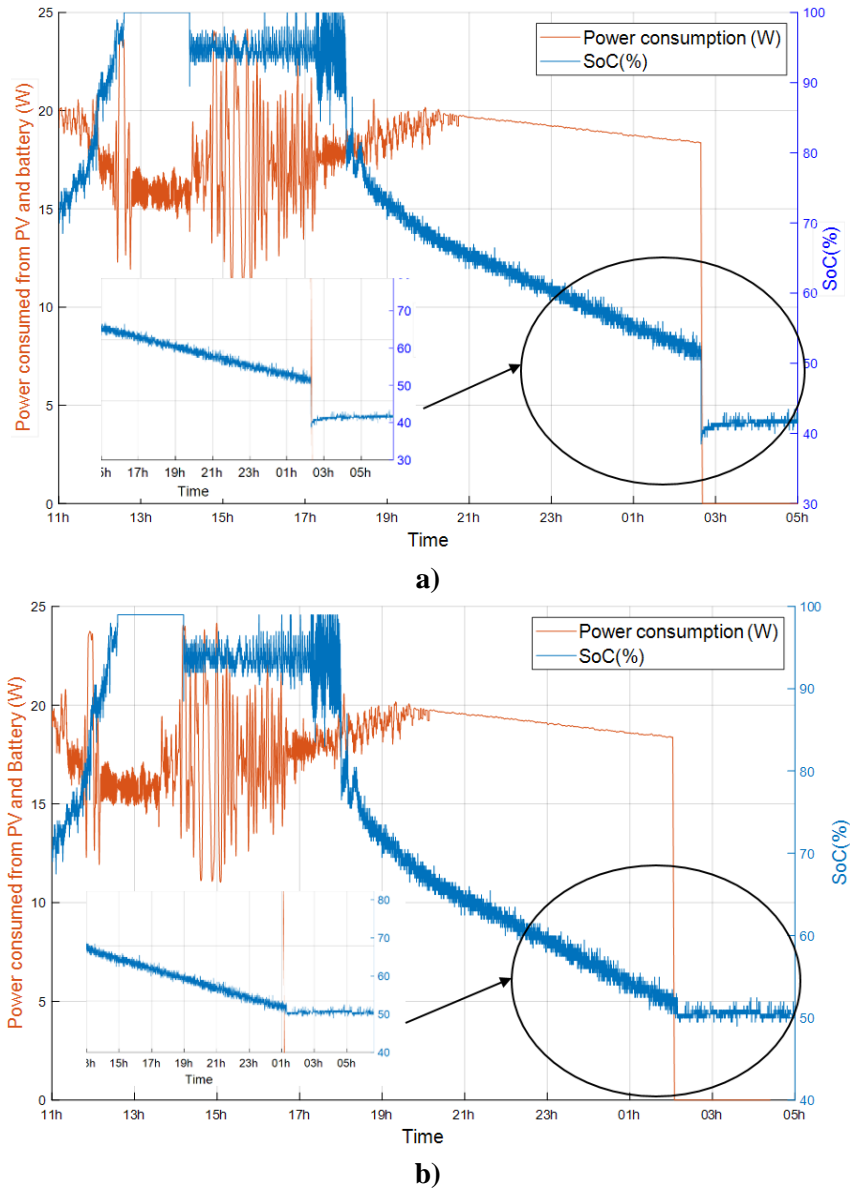


Figure 5.6. Control decision: a) The switching moment based on real-time values, b) The switching moment based on forecast values

Therefore, the battery is discharged to 40% around 3:00 AM (Figure 5.6.a) when the control strategy is based on the real-time values of the SoC. Figure 5.6.a shows the switching moment of the control strategy based on the real data obtained. Around 3:00 AM the battery is discharged and the system switches at this moment when the threshold value of the SoC is obtained, from the RES to the TEG. The same model is simulated using the forecast values like input parameters to the control strategy. Figure 5.6.b shows that the control strategy switches from PV and battery to the traditional grid when the threshold value of the SoC is obtained by the forecasting algorithm. In this case, the switching moment is obtained before the switching (Naïve approach) moment obtained in the case when the real values are used as input parameters. In fact, a predictive control strategy allows for avoiding possible blackouts

in the MG. The system is able, via the forecasting process, to process future values, which allow deciding on the best suitable source before getting in these blackouts situations.

In another scenario, the deployed algorithm computes at each time the different parameters based on the minimum AIC. As shown in Table 5.1.a, the minimum AIC is calculated and the equivalent ARIMA parameters are selected. For that, the ARIMA steps are realized in order to predict future values by maximizing the accuracy between the predicted and the real values. In fact, to measure the prediction accuracy, the errors are calculated by comparing the predicted and the real values (Table 5.1.b).

Table 5.1. The minimum AIC, b) The errors for ARIMA parameters determination

a)						
ARIMA(0, 0, 1)x(0, 1, 0, 12)12 - AIC:62710.84745637427						
ARIMA(0, 0, 1)x(0, 1, 1, 12)12 - AIC:62753.61460619093						
ARIMA(0, 0, 1)x(1, 0, 0, 12)12 - AIC:62714.03259053544						
ARIMA(0, 0, 1)x(1, 0, 1, 12)12 - AIC:62720.49716196509						
ARIMA(0, 0, 1)x(1, 1, 0, 12)12 - AIC:62671.88138477944						
ARIMA(0, 0, 1)x(1, 1, 1, 12)12 - AIC:62695.284563062145						
ARIMA(0, 1, 0)x(0, 0, 0, 12)12 - AIC:-3234.553093513031						
ARIMA(0, 1, 0)x(0, 0, 1, 12)12 - AIC:-3659.388317612963						
ARIMA(0, 1, 0)x(0, 1, 0, 12)12 - AIC:15472.320320780986						
ARIMA(1, 0, 1)x(0, 1, 1, 12)12 - AIC:9679.542874411818						
ARIMA(1, 0, 1)x(1, 0, 0, 12)12 - AIC:-10955.736960633389						
ARIMA(1, 0, 1)x(1, 0, 1, 12)12 - AIC:-10852.704233932041						
ARIMA(1, 0, 1)x(1, 1, 0, 12)12 - AIC:181.01318158835284						
ARIMA(1, 0, 1)x(1, 1, 1, 12)12 - AIC:443.1730259998549						
ARIMA(1, 1, 0)x(0, 0, 0, 12)12 - AIC:-17301.58083630186						
ARIMA(1, 1, 0)x(0, 0, 1, 12)12 - AIC:-17921.721669614883						
ARIMA(1, 1, 0)x(0, 1, 0, 12)12 - AIC:2209.839536935602						
ARIMA(1, 1, 0)x(0, 1, 1, 12)12 - AIC:-17185.339012788172						
b)						
	coef	std err	z	P> z	[0.025	0.975]
ar.L1	0.9869	0.000	2027.760	0.000	0.986	0.988
ma.L1	0.4186	0.002	224.696	0.000	0.415	0.422
ar.S.L12	-0.5821	0.002	-258.078	0.000	-0.587	-0.578
sigma2	0.0590	0.000	316.822	0.000	0.059	0.059

The prediction of the power generation and the electricity demand can be used to calculate the battery SoC and the predicted parameter is used as input to the control strategy. During the day, the PV panels generate the power to the loads, charge the battery, and the surplus is transmitted to a resistance, which is considered as the grid injection. As shown in Figure 5.7.a, for 48 hours the PV power production is collected. For the first day, from 02:00 PM to around 06:00 PM and due to the bad weather conditions, the PVs generation decreases. During this period, the battery supplies the power to the load accumulating the need for power caused by the decrease of PV generation (Figure 5.7.b). Moreover, during the night, only the batteries generate electricity to supply the load, and when the SoC is at its minimum, the control strategy switches from RES to the TEG.

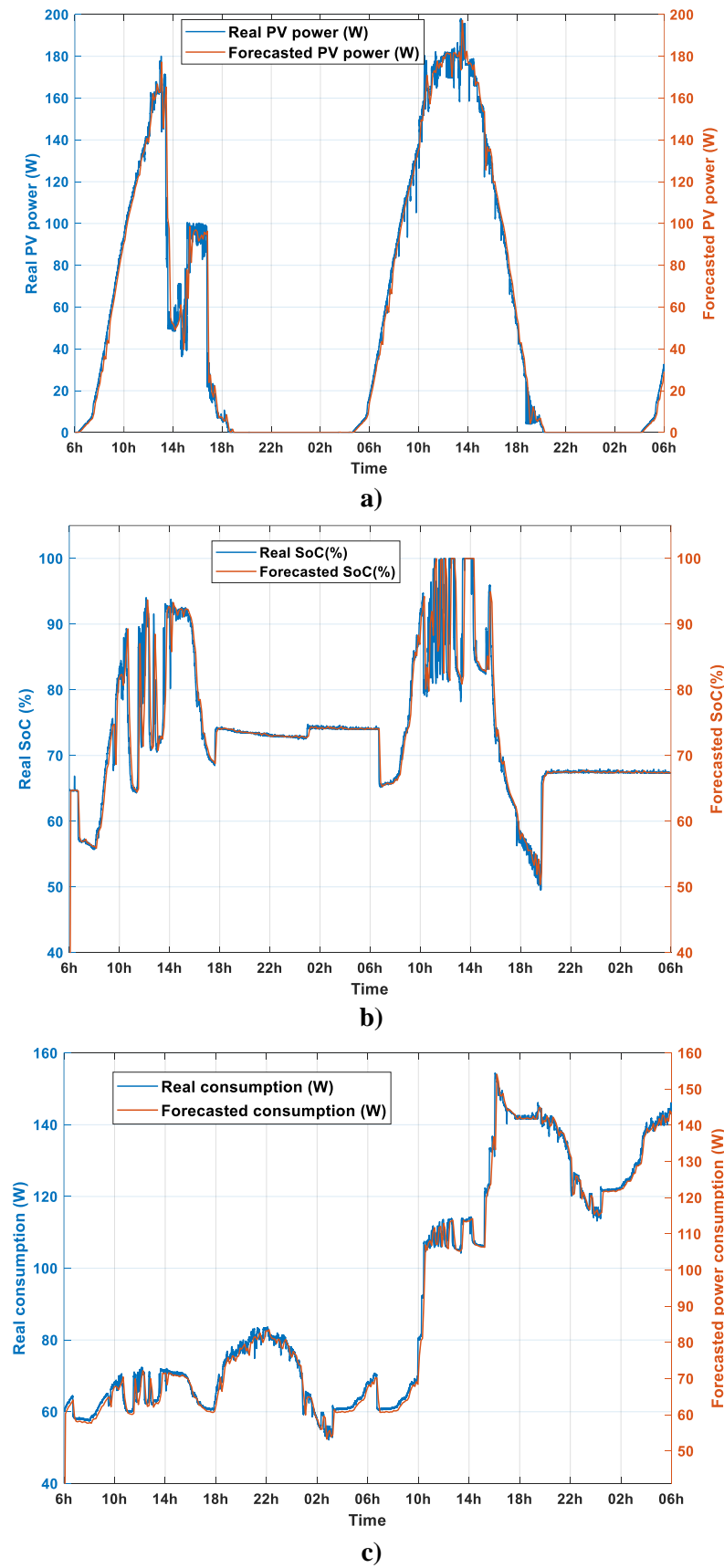


Figure 5.7. a) Predictive and real PV generation, b) Predictive and real SoC, c) Predictive and real loads consumption

In addition, to forecast the power consumption during the same period of the tests, the ARIMA model is deployed using the real data-set of power consumption. It is worth noting that the occupants' activities influence power consumption. As shown in Figure 5.7.c, the energy demand behavior varies due to lighting and the ventilation speed's variation, which is mainly influenced by occupants' activities. The ARIMA model is trained using the gathered data and then the obtained model is used to forecast the desired parameters' values.

Figure 5.7.a illustrates the power forecast (orange curve) with the real PVs generation (Blue curve). For each instance, the deployed ARIMA model generates a value with a timestamp of about three minutes. The same for the battery SoC, Figure 5.7.b indicates that around 06:00 PM the control approach switches from renewable energy to the TEG because the battery SoC reaches the threshold value as predicted. At the same time, the power consumed from RES was measured (Figure 5.7.c), the orange curve presents the power consumption generated by ARIMA model and the blue curve is the real power consumption. The Obtained results are used as inputs for the MPC in order to predict the suitable action by respecting the predefined constraints ($P_{load} = P_{pv} \pm P_{bat}$).

As described above, the predictive control approach is able to balance the power generated from a PV panel using battery storage in order to ensure the power to the load. The input parameters used in the control strategy are the PV power production, SoC of the battery, and the load power consumption. These input parameters are forecasted and the values obtained for a very short term are used as input parameters to the control strategy. In the rest of this chapter, we carry out the MAPCASTE approach using model predictive control, the MPC and GPC, using the abovementioned forecasting method of power consumption and production including the battery's SoC.

3. MPC-based control for energy balance in MG Systems

A ML algorithm, as described in the previous section, was deployed to predict future values, which are used by the control strategy. In this section, an MPC strategy is developed to solve the optimal constraints function by computing efficient management actions. It presents an essential control approach that can be used to predict and forecast the suitable actions in MG systems according to the system's constraints. More precisely, the main objective is the development of an intelligent and predictive control strategy for EM in the MG system based on an MPC model. To reach this aim, the following studies are realized. An EM approach based on the MAPCASTE principles is introduced for MG system's control, the

controllable system and the operational constraints are modeled by a state-space equation for MPC deployment, a data-monitoring platform is installed for real-time data forecasting in order to carry out the MAPCASTE control loop. The effectiveness of the deployed control approach is studied in real-sitting scenarios using our MG system.

3.1. MG modeling and control approach

The deployed control approach considers the batteries SoC evolution in order to keep the operating costs of the whole system at a reasonable level. For this aim, the deployed batteries are modeled and simulated using the OCV model with resistance. As mentioned in equation (5.9), the OCV is written as an SoC function.

$$V_{bat}(t) = OCV(SoC(t)) + R \cdot I_{bat}(t) \quad (5.9)$$

The dynamic voltage of the *Ohmic* resistance R and the OCV present the behavior of the battery voltage variability. This equation can be stated as follows:

$$Y(t) = a \cdot SoC(t) + R \cdot I \quad (5.10)$$

where I represents the C/D battery current, a is a factor defined by the experimental battery characterization using the least-squares method, and R presents the *Ohmic* resistance. By considering that the battery current is null during the full charged mode of the battery, we can then calculate the SoC by exploiting directly the battery's voltage variability. In fact, equation (5.10) can be presented as follows:

$$Y(t) = SoC(t) \quad (5.11)$$

Moreover, using the Coulomb method, the SoC can be formulated as the nominal capacity C ratio and is accumulated on the operation period τ . It is calculated by the current flow-rate measurement and integration over the interval of time (equation (5.12)).

$$C(t + \tau) = C(t) + \Delta C \quad (5.12)$$

We can use the measured battery C/D current I_{bat} together with the actual $SoC(t)$ in order to estimate the future values $SoC(t + 1)$ by applying equation (5.13). In this work, the measured I_{bat} is implemented to train the ML algorithm and the forecasted current is used to calculate the SoC. The deployed predictive control approach uses input prediction values to generate the feed-forward.

$$SoC(t + 1) = SoC(t) + I_{bat}(t) \cdot \Delta t / C \quad (5.13)$$

The main aim is to manage the C/D current based on the control strategy. Therefore, the MPC adjusts the I_{bat} by considering the variability of RESs generation and loads demand in order to define the operation mode: battery charging, battery discharging, or battery-at-rest. The constraints of the model are presented by equation (5.14), where P_{pv} is the PV panels' generation, P_{load} is the loads' consumption, P_{bat} and P_{grid} represent respectively the power extracted or generated from batteries, and the power extracted from the TEG.

$$P_{load} = \begin{cases} P_{pv} \pm P_{bat} ; & \text{if } P_{pv} \geq 0 \text{ and } SoC > SoC_{min} \\ P_{grid} ; & \text{if } P_{pv} < P_{load} \text{ and } SoC < SoC_{min} \end{cases} \quad (5.14)$$

In fact, the control strategy specifies a discharge limit to avoid battery deep-discharge when the RESs production is unavailable and the battery is at its minimum SoC. Moreover, the batteries store the surplus of the PV panels generation according to the following cases: the battery starts charging during the peak production ($P_{load} < P_{pv}$), it starts to supply the loads when the demand surpasses the PV panels' production ($P_{load} > P_{pv}$), and finally the battery is at rest if the SoC is at the fixed threshold and the PV power generation is unavailable ($SoC < SoC_{min}$ and $P_{pv} = 0$) or the battery SoC is at the maximum. To keep the SoC at its maximum as much as possible, the optimization function can be represented by the given objective function E_N (equation (5.15)), which should be minimized within a future horizon n .

$$E_N = SoC_{max} \begin{pmatrix} 1 \\ \vdots \\ 1^n \end{pmatrix} - \begin{pmatrix} SoC(t) \\ \vdots \\ SoC(t + n) \end{pmatrix} \quad (5.15)$$

The problem constraints that should be satisfied are formulated in equation (5.16) as follow:

$$\begin{cases} SoC_{min} < SoC_k(t + k) < SoC_{max} \\ P_{pv} \pm P_{bat} = P_{load} \end{cases} \quad (5.16)$$

Now, the MPC strategy could be designed based on the formulated constraints and the above-mentioned equations, which we have defined for managing the power exchange in the MG system. In fact, for our system modeling, the $SoC(t)$ is considered as the system state equation. The equation (5.11) expression can be rewritten in the state equation form as follow:

$$x(k+1) = Ax(k) + BU(k) \quad (5.17)$$

where $x(k)$ represents the system state for $A = 1$. In this case, the I_{bat} is the systems' input. The equality could be interpolated to n-steps-ahead to obtain the following representation (equation (5.18)):

$$\begin{cases} x(k+2) = A^2x(k) + ABU(k) + BU(k+1) \\ x(k+3) = A^3x(k) + A^2BU(k) + ABU(k+1) + BU(k+2) \\ \vdots \\ x(k+n) = A^n x(k) + A^{n-1}BU(k) + \dots + BU(k+n-1) \end{cases} \quad (5.18)$$

The matrix form for this representation could be written as follows:

$$\begin{pmatrix} x(k+1) \\ \vdots \\ x(k+n) \end{pmatrix} = \begin{pmatrix} A \\ \vdots \\ A^n \end{pmatrix} x(k) + \begin{pmatrix} B & 0 & \dots & 0 \\ AB & \ddots & \ddots & \vdots \\ \vdots & \ddots & B & 0 \\ A^{n-1}B & \dots & AB & B \end{pmatrix} \begin{pmatrix} U(k) \\ \vdots \\ U(k+n+1) \end{pmatrix} \quad (5.19)$$

This equation takes the following form:

$$\bar{X} = \bar{A} x(k) + \bar{B}U(k) \quad (5.20)$$

The observation equation could be interpolated to n steps as follows:

$$\begin{pmatrix} y(k+1) \\ \vdots \\ y(k+n) \end{pmatrix} = \begin{pmatrix} CA \\ \vdots \\ CA^n \end{pmatrix} x(k) + \begin{pmatrix} CB & 0 & \dots & 0 \\ CAB & \ddots & \ddots & \vdots \\ \vdots & \ddots & CB & 0 \\ CA^{n-1}B & \dots & CAB & CB \end{pmatrix} \begin{pmatrix} U(k) \\ \vdots \\ U(k+n+1) \end{pmatrix} \quad (5.21)$$

$$\text{This representation is equivalent to: } \bar{Y} = \bar{C}x(k) + \bar{D}\bar{U} \quad (5.22)$$

The following variation of the input vectors is considered as follows,

$$\begin{cases} U(k) = U(k-1) + \Delta U(k) \\ U(k+1) = U(k) + \Delta U(k+1) = U(k-1) + \Delta U(k) + \Delta U(k+1) \\ \vdots \\ U(k+n-1) = U(k-1) + \Delta U(k) + \Delta U(k-1) + \dots + \Delta U(k+n-1) \end{cases} \quad (5.23)$$

The matrix form for this representation is:

$$\begin{pmatrix} U(k) \\ U(k+1) \\ \vdots \\ U(k+n) \end{pmatrix} = \begin{pmatrix} 1 \\ \vdots \\ 1^n \end{pmatrix} U(k-1) + \begin{pmatrix} 1 & 0 & \dots & 0 \\ 1 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 1 & \dots & 1 & 1 \end{pmatrix} \begin{pmatrix} \Delta U(k) \\ \Delta U(k+1) \\ \vdots \\ \Delta U(k+n+1) \end{pmatrix} \quad (5.24)$$

This representation is equivalent to:

$$\bar{U} = I_1 U(k-1) + I_2 \Delta \bar{U}(k) \quad (5.25)$$

Equations (5.25) and (5.20) can be combined to obtain the following predictive model (equation (5.26)):

$$\bar{X} = \bar{A} x(k) + \bar{B} I_1 U(k-1) + \bar{B} I_2 \Delta \bar{U}(k) \quad (5.26)$$

Combining equations (5.19) and (5.20), the predictive observation model is presented as follows:

$$\bar{Y} = \bar{C} x(k) + \bar{D} I_1 U(k-1) + \bar{D} I_2 \Delta \bar{U}(k) \quad (5.27)$$

The constraint function to optimize is represented by the equation (5.28), which is equivalent to the command $\Delta \bar{U}(k)$ to reduce the error. In fact, the battery is used to absorb or generate the power satisfying the energy balance (D/R). At the same time, it is more important to keep the battery at its maximum SoC_{max} when it is possible.

$$Y_{ref} = [SoC_{max}(k+1), SoC_{max}(k+2), \dots, SoC_{max}(k+n)] \quad (5.28)$$

Finally, the error is formulated by equation (5.28.a) by considering the desired regulation, which is required to reach by the control model.

$$E = Y - Y_{ref} \quad (5.28.a)$$

Then, to get the control series ΔU , the criterion function to optimize is represented by the following:

$$J = \frac{1}{2} (E Q E^T + \Delta \bar{U} R \Delta \bar{U}^T) \quad (5.29)$$

where Q and R are, respectively, the error and the inputs' variation covariance matrices. A priori is choosing for the diagonal matrix R to ensure the algorithm convergence. The control approach manages the system to generate the values that minimize the J while respecting the constraint (equation (5.16)). As illustrated in Figure 5.8, by respecting the constraints, the deployed MPC controls the battery charged/discharged state accordingly. The MPC controller either charges the batteries, absorbing the PV panels' production surplus or discharges the batteries to ensure the power demand to the consumers.

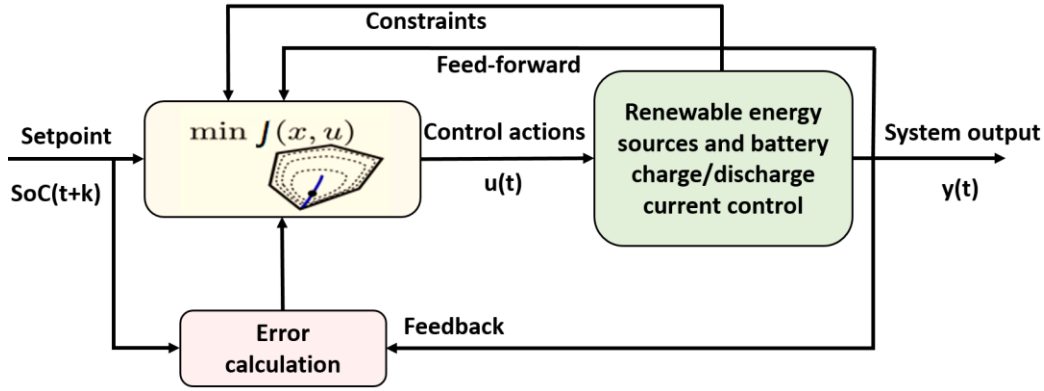


Figure 5.8. A schematic view of the predictive control model

Mainly, by considering the constraints, the TEG is integrated and it is used when the battery SoC extends the limit value and the PV panels' production cannot satisfy completely the demand. The SoC is considered as an input parameter to the MPC model, it is calculated by predicting the battery C/D current using the deployed ARIMA algorithm. The battery current is also obtained by the prediction of the PV panels' generation as well as the load consumption.

3.2. MPC strategy deployment and validation

As described early, we are aiming to deploy the MAPCASTE closed-loop for MG management. A platform was deployed to allow sensing and analyzing data generated by sensors. The stored data are used to train the ARIMA model and the predicted values are used as inputs for the control strategy. In fact, input parameters are predicted using ARIMA while control actions' forecasting are computed using the MPC controller. These two last phases are described in this section together with the performance evaluation.

The deployed MG system is used to collect real data, which are used to validate the results for both the MPC and a PID controller. As stated above, this system contains RESs (e.g., PV, grid), storage systems, and active loads (e.g., lighting, ventilators). The PV panels charge the batteries, which in turn provide the power to the lighting and ventilation systems. However, during the night or cloudy days, the batteries discharge and the operation of the loads is ensured from the TEG. So, to ensure efficient MG management, the control approach uses the predicted values (from the ARIMA model) to forecast the control decisions. The following cases are obtained: i) the PV power production has the priority to generate the electricity in order to satisfy the loads over the TEG and the storage devices; ii) the PV panels supply directly the electricity to the loads when it is more important than the loads' demand,

iii) when the PV generation could not satisfy the loads' demand, PV and the main battery storage supply the power to the loads, v) if the battery SoC is less than 50 % and the RESs generation is less than the loads demand, then the system switches to the TEG. During this period the PV panels charge the main energy storage.

Essentially, the aim of the proposed MAPCASTE is to optimize the batteries' C/D current according to electricity production and consumption. In fact, the MPC controller allows balancing the power flows accordingly. In order to show the effectiveness of the MAPCASTE, results obtained when using the MPC are compared with those obtained from a PID controller. Mainly, the PID model is deployed in the charge controller in order to regulate the PV power production. Unlike PID, the MPC strategy forecasts suitable actions for either switching to the batteries or to the TEG. It's worth noting that the PV system is simulated with the same input parameters for real a scenario (e.g., irradiance, temperature) with the same load demand variability. In addition, a model for the deployed battery is characterized in order to be integrated into the simulation. The duty cycle of the charge controller and the converter are controlled by the commands that are generated by the MPC bloc depending on the predicted context of the PV power generation, the battery SoC, and the load consumption. The predictive commands are generated and shifted by the forecast time horizon compared to the real command obtained by the PID control. Moreover, the C/D current variability depends on the PV panels' generation and the demand variability. In fact, the battery SoC influences directly to the battery current; more the battery is charged more the current decreases. In this scenario, the battery C/D current is the setpoint for the MPC and the PID model (Figure 5.9). It is calculated by the predictive C/D current, which depends mainly on the PV panels' production and power consumption as well.

Figure 5.9 presents the real variability of the C/D current during two days (orange curve). Around 02:00 PM, the batteries start to discharge supplying the power to the load depending on the constraints presented in equation (5.16). Almost at 06:00 PM, the minimum SoC is reached, and during the night, the control/card switches from RESs to the TEG. In the morning, the RES start producing the electricity, which is used mainly to supply the power to the load, the surplus is used to charge the battery. In fact, the obtained results are used as a setpoint for the MPC and the PID model in order to calculate the SoC.

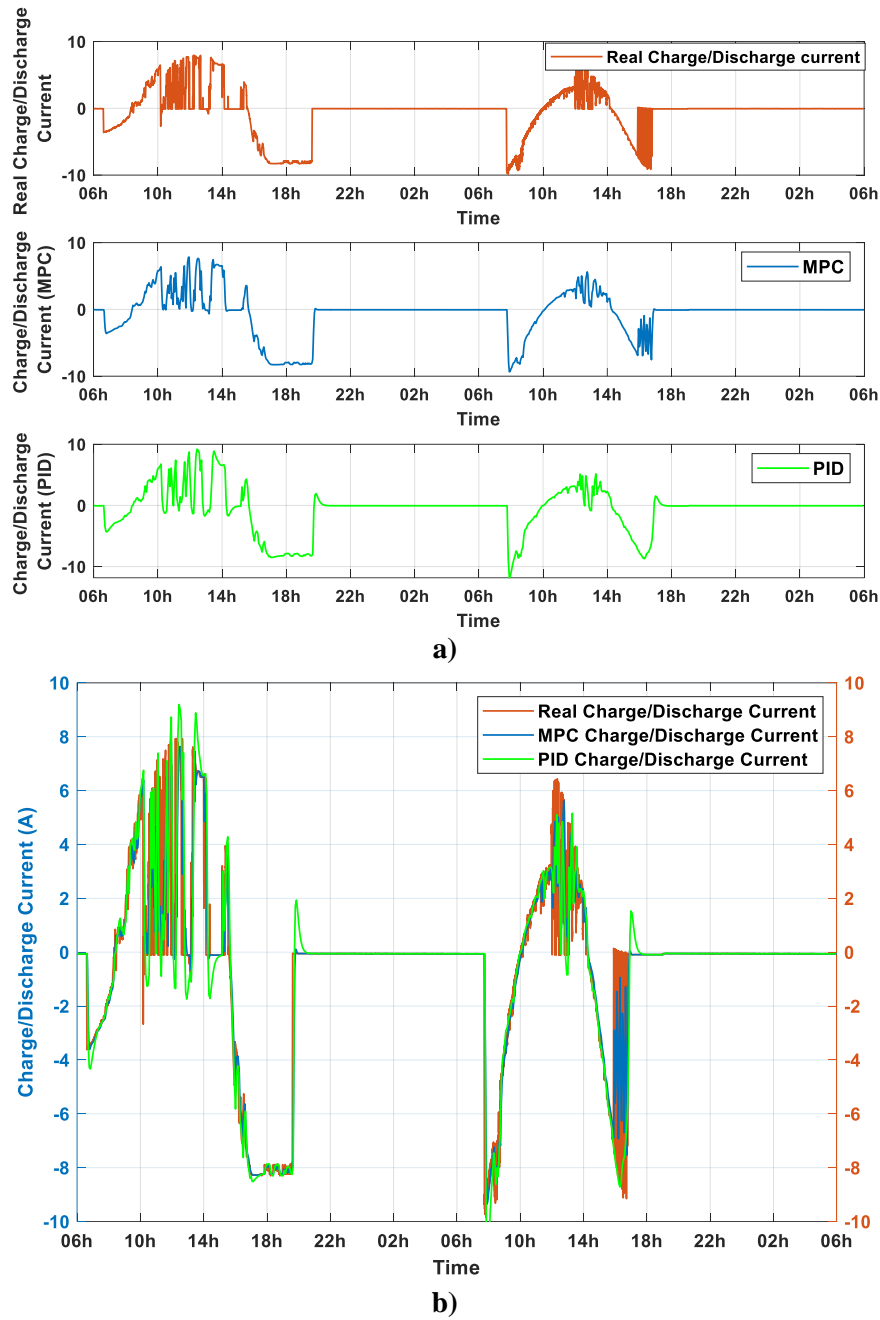


Figure 5.9. a) Battery C/D current variability, b) Comparison of the current for the different methods

Figure 5.10 presents the SoC obtained by the MPC (blue curve) and the PID (green curve). The SoC variability is presented depending on the MPC and PID controller command, which is required to reach the desired SoC. Moreover, the ML algorithm predicts future values with insignificant errors. Through the deployment of this model, the current is generated and it is used to predict the future SoC desired at each time. The MPC model uses the SoC to forecast future control actions depending on the operational context. As shown in Figure 5.10.b, during sudden change of the values, the PID presents an interesting peak for the

transit regime. Unlike the PID, the MPC forecasts the corresponding power to generate or to extract from storage devices avoiding a sudden change of the current. For that, the MPC presents a stable regime compared to the PID (Figure 5.10.a).

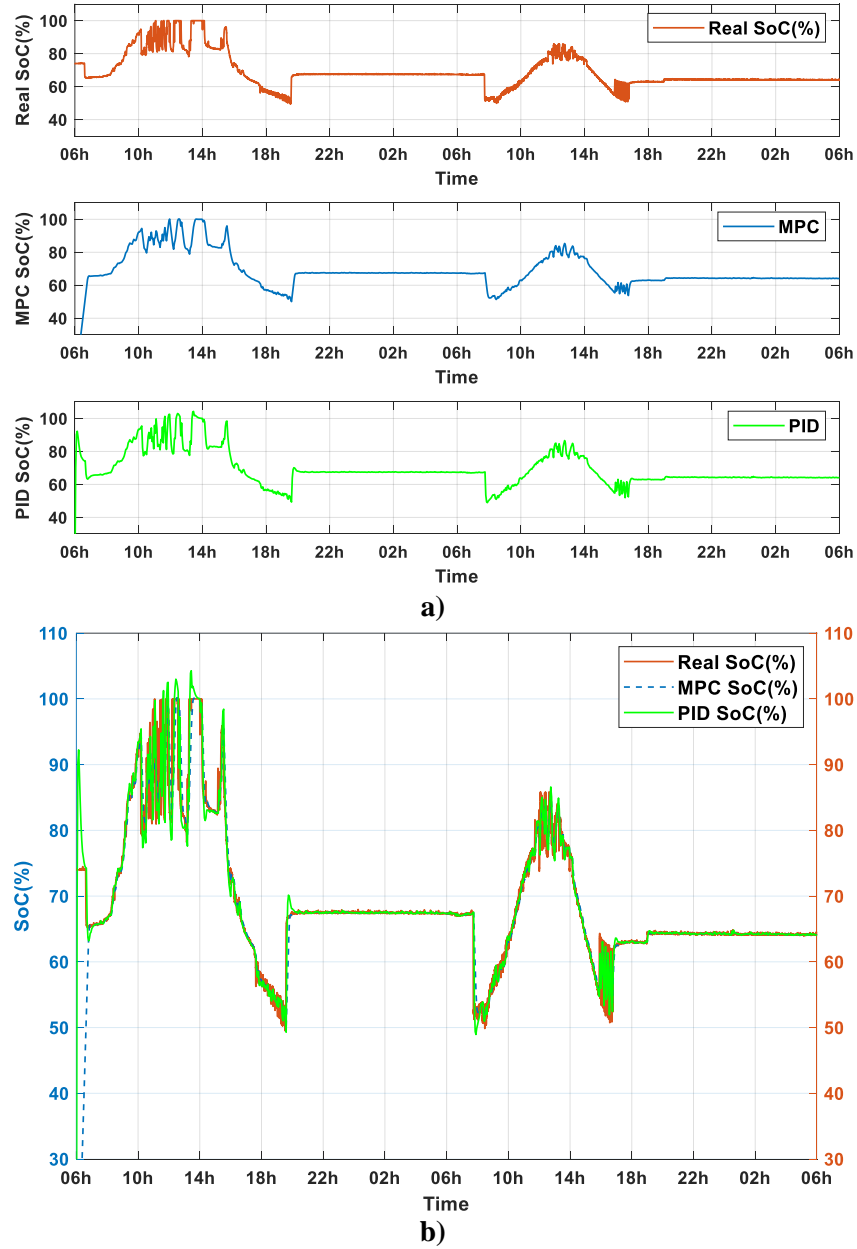


Figure 5.10. a) SoC variability for the different methods, b) The obtained SoC comparison for the different methods

As stated by the abovementioned results, the proposed predictive control approach manages the MG by maximizing the usage of the RES while considering the storage devices' limits. In fact, the MPC strategy forecasts future actions to control the C/D currents of the battery, by considering the specific variability of power production and loads' consumption. The optimization function and the constraints are presented for the proposed MPC strategy

and the obtained results illustrate the utility of the model for efficient control of the MG compared to the PID control.

Next section will enhance the MPC by considering its generalized version (GPC) by including additional constraints, in particular, the electricity price forecasts. Therefore, the energy price is an interesting exogenous for both the consumer and the central grid. Firstly, as most known, the main challenge for the actual grid is the “electricity blackouts” that are generally caused by high demands during the “peak hours” (e.g., morning, evening). Within this context, the electricity operators use the price as penalties for the consumer to avoid “peak demand” during some periods. Thus, the energy price has become an exogenous factor for the grid by minimizing the consumption during the period when the price is expensive, which is equivalent to the “peak demand period”. Secondly, a consumer that has RESs installation with a storage system can locally manage the energy flow depending on electricity price. For a given scenario, the consumer can use the central grid avoiding then the use of the local storage system, which will be kept at its maximum for usage during the high price periods.

4. MG system modeling for GPC integration

4.1. GPC modeling, constraints and objective functions

The GPC is a predictive approach that allows computing and predicting the suitable actions for being performed according to forecasted and contextual information/constraints of MG systems. It can be classified with advanced process control families with less variation in process variables. Its main concept, as depicted in Figure 5.11, is described as follows. Based on a predefined model of the MG system, optimal future actions (controls/commands) are computed to reach the desired setpoint according to the defined constraints and optimization functions. These functions consider future error, constraints, and control parameters.

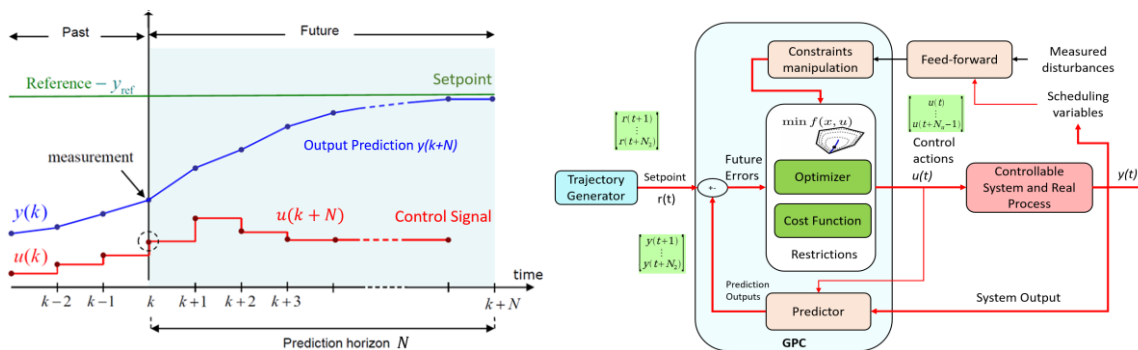


Figure 5.11. A schematic view of GPC concept and control mechanism

As described in Figure 5.11, the predictor generally calculates, for each instant t , the predictions of the dynamic evolution of the process $[y(t+1), \dots, y(t+N)]^T$ throughout the defined horizon, N -steps ahead. This prediction is based on the dynamic parameters, which are measured at t , as well as the future control system's regulation $[u(t), u(t+1), \dots, u(t+N)]^T$, along the prediction horizon N . The future control actions are then generated in order to optimize the desired cost function by resolving, at each defined time step, the predefined constraints. The designed cost function keeps the system's output at $(t+k)$ as close as possible to the defined setpoint. This setpoint dictates the output evolution accordingly. Generally, the cost function takes the form of a quadratic function of the errors between the predicted output and the setpoint (Ławryńczuk, 2014).

For GPC integration within the MG system, we focus only on secondary and tertiary control. The former control considers that the EM supervises the MG system by gathering the required data from its entities, mainly RES, batteries, and loads. It mainly manages the energy for both grid-connected and islanded modes with the reliable and secure operation. Accordingly, the controllable units of the studied MG system, in both modes, are modeled by a state-space equation, described in equation (5.30), where $x(t)$ is the system state, $u(t)$ is the vector of manipulated variables, $y(t)$ is the output vector, and A , B , C are respectively the system matrix, the control matrix, and output matrix.

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) \\ y(t) = Cx(t) \end{cases} \quad (5.30)$$

In the secondary layer, we have incorporated the GPC within the EM in order to generate suitable control actions for efficient power D/R balance. More precisely, the batteries SoC is controlled by the GPC strategy according to the variability of predicted power production, power consumption, and electricity cost. In fact, the power generated by the RESs and the power consumption are considered as disturbances sources for the MG system during its operation. Therefore, batteries SoC could be modeled by a state-space equation while the variability of these controllable parameters is considered as a result of the disturbances variation described as follows:

$$P_{bat} = \begin{cases} P_{RES} - P_{load} ; & \text{if } 0 \leq P_{RES} \text{ and } SoC_{min} < SoC \leq SoC_{max} \text{ (Charge)} \\ P_{load} ; & \text{if } P_{RES} = 0 \text{ and } SoC_{min} < SoC \text{ (Discharge)} \end{cases} \quad (5.31)$$

where P_{bat} is the power generated or extracted from the battery, P_{RES} is the power generated by RES, P_{load} is the load demand, SoC_{min} is the minimum batteries SoC (to avoid a deep discharge), and SoC_{max} is the SoC when the batteries are fully-charged.

Generally, the controller cannot manipulate the disturbances of the system. Hence, in our GPC model, the RES power generation and the load consumption are represented as measured system disturbances. These disturbances can be computed using actual measured power production/consumption, which are in turn affected by external disturbances (e.g., weather conditions, occupant's activities). The deployed IoT/Big data platform, as stated above, could handle this task by forecasting these disturbance parameters (i.e., RES, load power), and consequently, minimizing the GPC prediction errors (Elmouatamid et al., 2019b; Elmouatamid et al., 2019c).

In fact, if the disturbances can be measured or predicted, their influence on the system's output can be included in the GPC model. This allows anticipating their effect on the control command. Alike any predictive control model, the GPC can reject disturbances according to the feedback mechanism. In this way, the GPC can inherently include a feed-forward effect. Therefore, the $d(t)$ disturbances' effect is added to the state-space formulation (equation (5.30)) and the equivalent dynamic model is then written in equation (5.32), where B_d is the matrix, which quantifies the effect of the disturbances on the system states, and $d(t) = P_{RES} - P_{load}$ combines the disturbances into one variable.

$$\begin{cases} x(t+1) = Ax(t) + Bu(t) + B_d d(t) \\ y(t) = Cx(t) \end{cases} \quad (5.32)$$

As stated above, the main aim of the GPC is to control the battery charging/discharging power. In fact, the GPC regulates the battery state in order to reach the operating goal (i.e., D/R balance) and to make the right decision: *charge*, *discharge*, or *battery-at-rest*. At a first step, these decisions are made depending on the conditions, which are mentioned in equation (5.31). It is worth noting that for modeling the SoC dynamics, the disturbances could be indirectly integrated into the control variables. More precisely, the future values $SoC(t+1)$ can be calculated by accumulating the actual $SoC(t)$ and the battery C/D current, as described in equation (5.13).

Alike the secondary control, which manages the energy for both grid-connected and islanded modes with reliable and secure operation, the tertiary control tackles all issues related to the interconnection between the MG system and the utility grid. It mainly adjusts the power

setpoint in order to manage efficiently the power flows by having the possibility to interconnect multiple MG systems. This control layer is mainly considered at the same time as a part of the main grid and the MG. Under this control, several constraints could be included as a cost function for the efficient management of MG systems. Examples are the electricity price (i.e. the cost for purchasing electricity from the utility grid), the system's profitability (i.e. daily operation costs of the battery storage system and RESs), and the revenue related to the excess energy, which is injected to the utility grid (i.e., selling energy to the neighboring MG systems).

In this work, the electricity price is considered as a fundamental constraint, which is shared between the secondary and the tertiary control layer. In fact, by interpolating this constraint in both layers, the control actions must be generated according to the electricity price variability. The cost function variability used in our work follows the energy price, as presented by the European Foundation (Grigg et al., 1990). In fact, the following control strategy is adopted. When the electricity price is inexpensive, the control strategy could charge the batteries from the main grid for being used during the morning peak consumption, otherwise, the batteries and RESs could be used to supply the power to the building's loads while the surplus can be injected to the grid. Mainly, when the price is less than a defined threshold value, a simple conditional control strategy could be deployed to balance the power flow by providing the priority to RESs and the utility grid than batteries, otherwise, the batteries and the RESs have the priority to supply the building's loads, as shown in Figure 5.12.

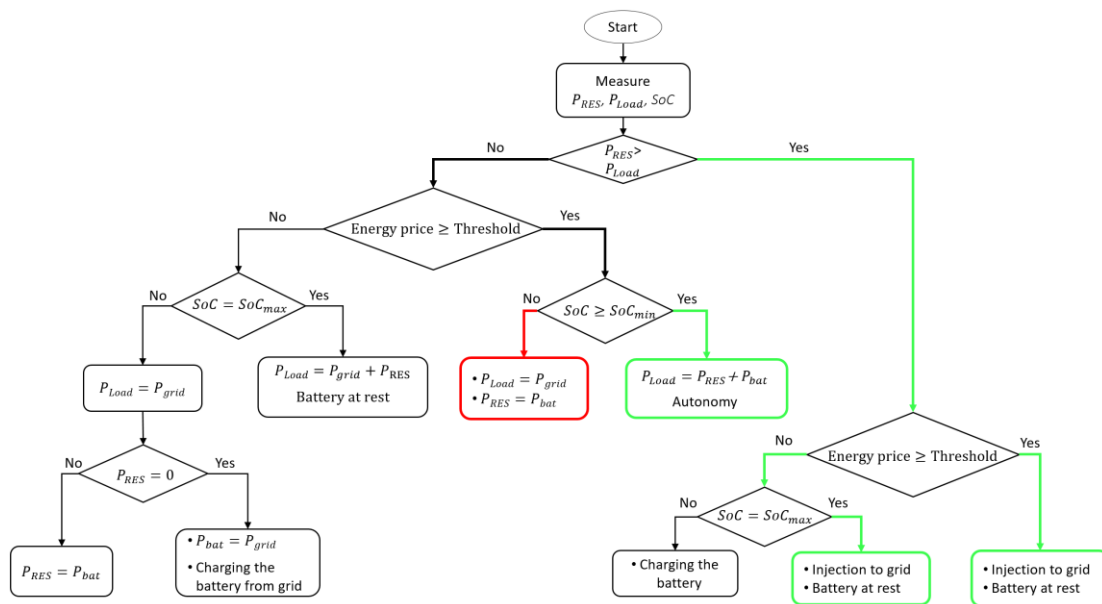


Figure 5.12. EM and control strategy

In all cases, the battery can be charged from either RESs or TEG according to the daily electricity price variation. In order to include the above-mentioned constraints into the GPC, we use an incremental model by considering $\Delta u(t) = u(t) - u(t - 1)$ as the control decision variable, and, therefore, the state-space equation could be presented as in equation (5.33), where the new state vector is $z(t) = [x(t), u(t - 1)]^T$ and the matrices M , N , and Q are obtained by comparing equations (5.32) and (5.33).

$$\begin{cases} z(t + 1) = Mz(t) + N \Delta u(t) + N_d d(t) \\ y(t) = Qz(t) \end{cases} \quad (5.33)$$

In this state-space equation (5.33), the prediction includes the estimated disturbances (i.e. RESs production, load consumption). The GPC original algorithm is extended to include the cases of measurable disturbances and change in the predictor. In fact, by considering a system that operates around a practical setpoint, the single-input single-output of the system plant can be described by equation (5.34), after linearization, as follows:

$$A(z^{-1})y(t) = z^{-d}B(z^{-1})u(t - 1) + C(z^{-1}) \cdot \frac{e(t)}{\Delta} \quad (5.34)$$

where $e(t)$ is a zero mean white noise, d is the dead time of the system, and the polynomials, in the backward shift operator z^{-1} , A , B , and C are presented by:

$$\begin{aligned} A(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_{na} z^{-na} \\ B(z^{-1}) &= b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_{nb} z^{-nb} \\ C(z^{-1}) &= 1 + c_1 z^{-1} + c_2 z^{-2} + \dots + c_{nc} z^{-nc} \end{aligned} \quad (5.35)$$

This model is known as a CARMA, in which the disturbances are non-stationary. Therefore, the main objective of predictive control is to predict future control actions $u(t)$, $u(t + 1)$, and $u(t + i)$ in such a way that the future system's output is driven to reach the setpoint. The GPC model consists of applying a sequence of control actions in order to minimize a defined multi-objective cost function. It is worth noting that this vector is generated by an ML algorithm, which is mainly used to forecast the RESs power generation and load consumption (Elmouatamid et al., 2019b; Elmouatamid et al., 2019c). Consequently, the GPC predictor can reject the effect of these disturbances, along the horizon N , by providing a feed-forward effect. Within this context, the prediction is generated by considering only the cost function, which is modeled by the electricity price as well as the cost associated with the energy used in order to keep the batteries' SoC at its maximum. Therefore, the constraint defined for the tertiary level control can be written as follows:

$$J = \sum_{j=1}^{N_c} |u(t+j-1)|_{Q_1}^2 + \sum_{j=1}^{N_c} |\Delta u(t+j-1)|_{Q_2}^2 + \sum_{j=1}^{N_c} |y(t+j|t) - y_{ref}(t+j)|_R^2 \quad (5.36)$$

The first term of equation (5.36) represents the cost related to the energy supplied to the building's load by RESs and storage devices. The matrix Q_1 is generally diagonal and its values depend on the defined priority, which is set-up to control energy sources, as stated above (Figure 5.12). The second term considers the variability of the electricity price along the prediction horizon N . It mainly represents the cost optimization function for the GPC. The third term is responsible for setpoint tracking errors; at each moment, the main aim is to regulate the equality $I_{bat} = I_{RES} - I_{load}$ by regulating the battery current while respecting, as much as possible, the constraint described by equation (5.15). However, keeping the SoC at its maximum is highly desirable in order to avoid high cycles of C/D, which could have a direct impact on batteries' state-of-health. This constraint is, however, not mandatory for the MG system's operations. Therefore, the elements of the matrix R will be smaller than other matrix elements. Accordingly, the optimal solution of equation (5.36) could be obtained by solving a quadratic programming problem, as presented in (Camacho et al., 2013).

It is worth noting that the control strategy decisions are generated for a DC MG bus, but the main grid is, however, an AC power system. Thus, a voltage source inverter is required to convert the DC voltage into AC voltage. This will allow generating efficiently the control actions by the above-mentioned GPC model. The next section focuses on the MG synchronization issue by providing a single-phase power converter model.

4.2. Single-phase modeling for MG synchronization

The simulated MG system is connected to the utility grid by a bidirectional interface. The aim is to have a complete scenario in order to study the usefulness of the GPC-based control strategy. However, the converter is one of the power electronic devices, which requires time's latency in the order of tens to hundreds of microseconds in order to operate efficiently (Vazquez et al., 2016). This technical constraint could be avoided using the GPC for predictive control. In fact, in order to compute the predictive output parameters (e.g., voltage, current), a state-space equation is required to generate equivalent duty cycle impulse. As depicted in Figure 5.13, the simulated model is, therefore, represented by a closed-loop configuration of a single-phase MG system. The system is modeled by a DC voltage source and other electronics components, which act as an interface between RESs and the AC utility

grid. Usually, an IGBT is used as a voltage source inverter due to its fast switching speed, which is represented by $V_{sw} = \tau(s)V_{dc}$, where V_{dc} meant for the deployed DC voltage sources, and $\tau(s)$ is the duty ratio, which is controlled by the GPC model.

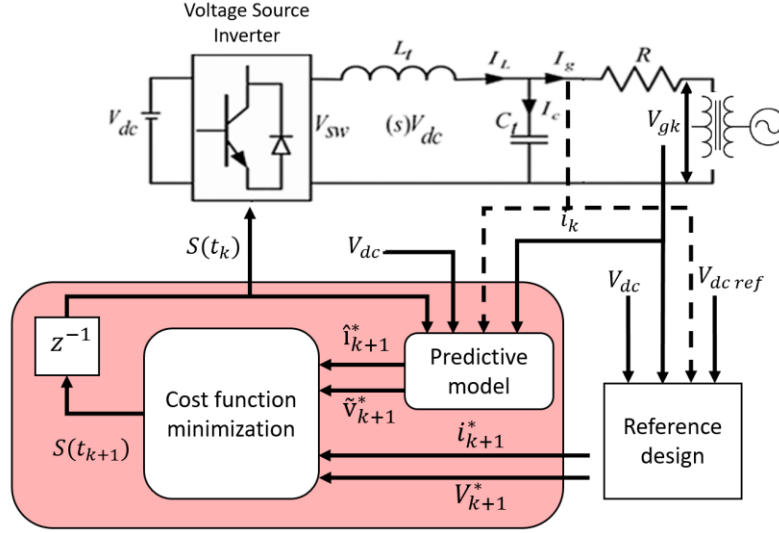


Figure 5.13. Single-phase MG system

The main objective of this system's model is to convert the DC power generated by RESs to AC power while controlling the active and reactive power in order to have an equal power of both DC and AC sides. In fact, the voltage through the inductor of the single-phase MG is described by equation (5.37.a) (see Figure 5.13).

$$V_L = L \frac{dI_L}{dt} \quad (5.37)$$

By considering V_{sw} as the switching voltage, the equation can be written as follows:

$$\frac{dI_L}{dt} = \frac{V_L}{L} = \frac{V_{sw} - V_g}{L} \quad (5.37)$$

where, V_g is the voltage through the capacitor, which acts as an MG voltage, and I_L is the current across the inductor. By deploying the Laplace Transform, we obtain:

$$I_L(s) = \frac{V_L(s)}{sL} = \frac{V_{sw}(s) - V_g(s)}{sL} \quad (5.38)$$

Moreover, the grid voltage of the single-phase is written as: $C \frac{dV_g}{dt} = I_c$, where I_c is the current across the capacitor. So, we obtain the following equations:

$$\frac{dV_g}{dt} = \frac{1}{c} I_c \quad (5.39)$$

The system state-space equation for a linear time invariant is:

$$\begin{cases} \frac{dx(t)}{dt} = Ax(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad (5.40)$$

From equations (5.37) and (5.39), we obtain respectively the system state matrix, the input variable, and the disturbances matrix: $x = \begin{bmatrix} I_L \\ V_g \end{bmatrix}$, $u = [V_{sw}]$, and $d = I_g$. The duplication of this presentation with equation (5.40), we obtain equation (5.41) as follows, where, $y = V_g = [0 \ 1] \begin{bmatrix} I_L \\ V_g \end{bmatrix}$ represents the output of the system.

$$\frac{d}{dt} \begin{bmatrix} I_L \\ V_g \end{bmatrix} = \begin{bmatrix} 0 & -\frac{1}{L} \\ \frac{1}{c} & 0 \end{bmatrix} \begin{bmatrix} I_L \\ V_g \end{bmatrix} + \begin{bmatrix} I_L \\ 0 \end{bmatrix} V_{sw} + \begin{bmatrix} 0 \\ -\frac{1}{c} \end{bmatrix} I_g \quad (5.41)$$

Generally, the GPC-based controller computes, for each sampling time, a sequence of actions that minimize the defined cost function. Only the first action is applied to the controllable system by solving the open-loop optimal control problem. This process is repeated, at every sampling time horizon, for remaining actions. In our case, the GPC strategy is applied to the current's control of a power converter, as described in the block diagram of Figure 5.13. For instance, when the predictive time horizon is 1, the optimal control action $S(t_k)$, calculated at t_{k-1} , is applied to the converter. The measured current i_k and voltage $V_{dc\ ref}$ are used by the reference design model in order to generate the reference current i_{k+1}^* and voltage V_{k+1}^* . The predictive model allows then computing the predicted current \hat{i}_{k+1}^* and voltage \tilde{V}_{k+1}^* . Furthermore, the defined references and the predicted current and voltage values are used to improve the cost function, and consequently generating the optimal control action $S(t_{k+1})$ for being applied at t_{k+1} . However, the main problem, which could face this predictive approach, is its deployment in actual inverters for real-time control. This is due mainly to the considerable processing time delay, which is required to generate predictive values. This delay must be considered in the design of the power controller, and consequently, the delay compensation is a practical method that is used to solve such problem (Cortes et al., 2011). Within this context, we consider a single-phase system, which is interfaced with the utility grid, as depicted in Figure 5.13. Therefore, the predicted current vector \hat{i}_{k+1}^* is calculated, during a sampling time T_s , by a discrete-time model, which is a function of the

measured currents i_k , the inverter voltage V_{gk} , and the electromotive force $\tilde{e}(k)$. This current vector is described as follows:

$$\hat{i}_{k+1}^* = \left(1 - \frac{RT_s}{L}\right) i_k + \frac{T_s}{L} (V_{gk} - \tilde{e}(k)) \quad (5.42)$$

Moreover, as stated in (Larrinaga et al., 2007; Cortes et al., 2011), the three-phase is presented by seven different voltage vectors. To simplify the presentation, the system is represented by three values of β in order to have only three possible trajectories for i_β , in particular for a single-phase system. Figure 5.14 highlights the problem related to the processing delay, especially for ideal and practical cases.

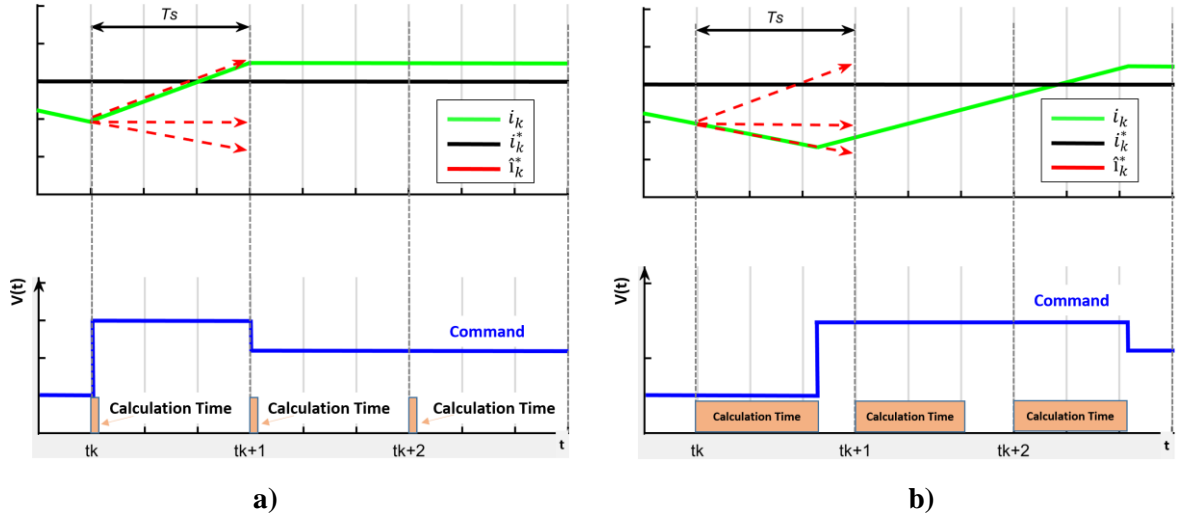


Figure 5.14. Predictive control operation, a) Ideal case: calculation time is negligible, b) Practical case: calculation time is significant

In Figure 5.14, the red curve represents the predicted current, as mentioned in equation (5.42), the green curve is the actual current, which is obtained by minimizing the cost function, and the black line is the considered current reference. Depending on the processing speed and the sampling frequency, the time is significant between the parameters' measurement and the application time (including the time for prediction) of the new control action. For an ideal case, the processing time, spent by the microcontroller, is insignificant and the predictive control model operates as shown in Figure 5.14.a. In fact, at the present time t_k , the current is measured and the optimal action is immediately calculated, consequently, the control action, which minimizes the error at the time t_{k+1} , is generated and applied at time t_k . For that, the output reaches the reference current correctly on time t_{k+1} . Practically, the calculation time is significant compared to a given sampling time of the

model. As a result, a delay is created between the measurement time and the application of the predicted control action. Figure 5.14.b shows that during the time T_s (between t_k and t_{k+1}) the previous state continues to control the system, accordingly, the voltage vector, which is selected at time t_k , continues to be applied after t_{k+1} . In this way, the next action is selected considering the measurement in t_{k+1} and it will be applied near to t_{k+2} . This makes the current oscillate around the reference, which then increases the “current ripple”.

As a solution to this problem, the delay compensation method for the predictive control is proposed in order to take into account the calculation time. In fact, the calculated control action, at time t_k , is applied at the sampling time t_{k+2} , as shown in Figure 5.15. The measured current at t_k is used as the starting point for the next switching state and the predicted current for the delay compensation is calculated by equation (5.43), where \hat{i}_{k+1}^* is the previous prediction of the current, and $V_{g(k+1)}$ presents the actuation to be evaluated.

$$\hat{i}_{k+2}^* = \left(1 - \frac{RT_s}{L}\right) \hat{i}_{k+1}^* + \frac{T_s}{L} (V_{g(k+1)} - \tilde{e}(k+1)) \quad (5.43)$$

Accordingly, the cost function uses the predicted current \hat{i}_{k+2}^* in order to calculate, at the next sampling time, the switching state. This single-phase modeling is simulated in order to synchronize the MG system with the electrical grid, while the surplus of RESs power generation is injected through a power converter controlled by the GPC model. The obtained results are reported in the next section.

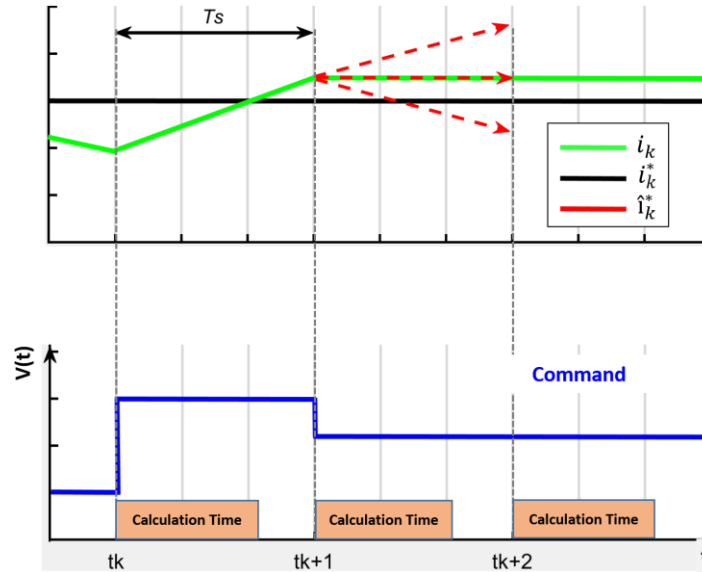


Figure 5.15. Predictive control with significant calculation time: operation of delay compensation method

5. Results and performances evaluation

The MG system is composed, as already described, of RESs and batteries in order to supply clean energy to the building's load. It is also connected to the utility grid and could operate in either connected or standalone modes. More precisely, two RESs have been considered, solar and wind. In fact, PV panels and a WT are deployed to generate a maximum power of 1KW and 1.5KW respectively. These RESs generators are connected to a battery storage system in order to supply the building's load with continuous power. A variable behavior of power demand is used to simulate the load consumption presenting two peak-demand periods.

Furthermore, the MG system couples both DC and AC buses. In fact, the power generated from RESs is converted to DC power due to its robustness face to the power quality problems (e.g., reactive power, harmonics). An EM system is deployed using the GPC model in order to generate control actions accordingly (Figure 5.12) while minimizing the predefined cost function. The GPC-based predictive control model is also used to control the power converter in order to ensure the quality of power while converting DC to AC power before being injected into the utility grid.

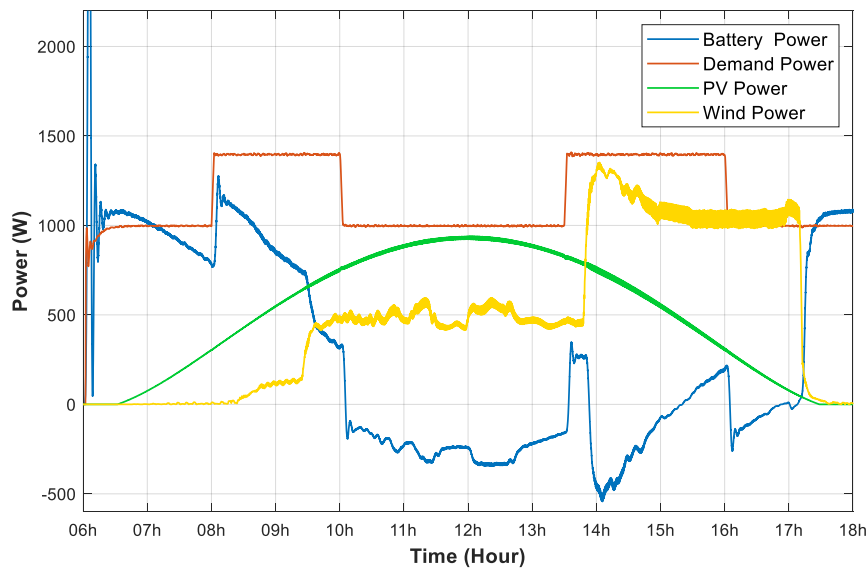
For performance evaluation, four main scenarios have been considered by conducting a sensitivity analysis of the GPC-based control strategy according to different situations. The first scenario is dedicated to investigating the operational capability of the MG system when coupling different RES and batteries with the developed EM system. In this scenario, we have considered that initially batteries are fully charged, while in the second scenario batteries are initially discharged and the threshold value of the electricity price is already fixed. The third scenario augments the second scenario by a further constraint regarding the electricity price by using a dynamic threshold value according to the peak-demand periods. The fourth scenario simulates the complete behavior of the MG system and the GPC-based control according to the electricity price by favoring the usage of RESs and storage devices while minimizing the usage of the electrical grid. In addition, batteries could be charged from the electric grid, especially when the electricity price is lower. Table 5.2 below summarizes the characteristics of the MG system's entities and initial conditions. It is worth noting that in all scenarios, the battery discharging (resp. charging), as well as the extracted (resp. injected) power from (resp. to) the utility grid, have positive (resp. negative) sign in all experimental results, presented in the rest of this section.

Table 5.2. MG system parameters

Description	Value
DC bus voltage	320V
AC bus voltage	240V
System frequency	50Hz
DC link capacitance	2.2 μ F
LC Filter inductance	0.4 μ H
LC Filter capacitance	6.85 μ F
Load capacitance	100mH
Load inductance	1pF
Battery capacity	150Ah
Maximum PV power	1KW
Maximum wind power	1.5KW

5.1. EM scenarios using GPC control approach

In the first scenario, a GPC model is integrated to regulate the battery C/D according to the constraints, which are presented by equations (5.31) and (5.29) (i.e., the batteries are initially fully charged). In this scenario, the controller manages the power production/consumption by interacting with the batteries by performing the actions presented in Figure 5.12. In this case, batteries are first used to supply the building's load, especially when the RESs cannot satisfy demand. The operational behavior of the MG system is depicted in Figure 5.16. As shown, around 07:00 AM, the PV panels start to generate the power (green curve), which is accumulated with the batteries' power (blue curve) in order to ensure the power to the load. Around 08:30 AM, the WT starts to generate the power (yellow curve) together with the PV and batteries. At 10:00 AM, the RESs (i.e. PV and WT) generation is becoming higher than the power demand, and the surplus is used to charge the batteries.

**Figure 5.16. GPC control for autonomous operation mode**

It is also shown that the GPC-based model took into consideration the objective function (equation (5.15)) by keeping, as much as possible, the batteries SoC at its maximum. From 10:00 AM to 05:00 PM, batteries power is again accumulated with the power generated from RESs in order to supply the building's load, while around 05:00 PM, the power generated from RESs is almost negligible and, therefore, batteries are the most powerful supplier.

In summary, during this scenario, the MG system is tested in order to show its capability to operate within the variable RESs generation while respecting the abovementioned constraints, which are incorporated within the GPC-base control model. As demonstrated, without considering the electricity price, the MG system is operated in the autonomous mode and the GPC controller manages efficiently the variable production of RESs by interacting with the storage system. In fact, the proposed GPC model could ensure the island mode detection by managing the power dispatching tasks, which are handled by the secondary layer.

As stated above, the second scenario is mainly dedicated to evaluate the MG system's behavior when batteries are initially discharged. Since RESs generations and load demand are considered as measurable system disturbances, and only the electricity price is uncontrollable, the operational behavior MG needs to be adapted, by the GPC-based control, in order to supply the building's load. In this scenario, we consider that the same RESs and loads behaviors are used, but by having the possibility to extract or inject the electricity from or to the grid. The GPC controller is designed to manage the switching between batteries and the grid without controlling the power generated by RESs. As shown in Figure 5.17, RESs are considered generating the maximum power using the MPPT of the first control layer (green curve for PV generation and yellow curve for WT generation). Under this scenario, the electricity price is taken into account as the main constraint for the tertiary control layer (equation (5.36)) for managing the interconnection between the MG system and the utility grid. As defined in equation (5.36), the Q_1 matrix elements represent the priority between the RESs, the batteries, and the utility grid for supplying the power to the building's load while minimizing the cost function, which represents the electricity price variability.

As is depicted in Figure 5.17, the consumption (orange curve) is the setpoint willing to reach by the GPC model. The aim is to accumulate the RESs power generation, batteries, and the utility grid while minimizing the cost function, which is embedded in the GPC-based control.

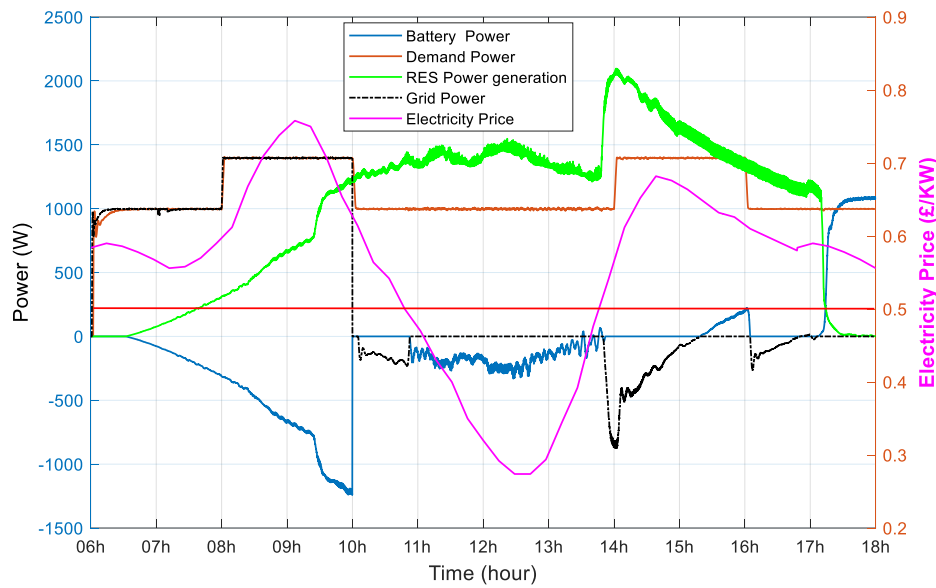


Figure 5.17. EM scenarios based on GPC model controller for grid-connected mode and static setpoint

At the starting time, the batteries are discharged and the RESs generation is null, though the controller uses the utility grid for supplying the building's load. As clearly mentioned in Figure 5.17, from 06:30 AM to 10:00 AM, the RESs generation (green curve) is less than the power demand, consequently, and according to the control diagram of Figure 5.12, the power generated by RES is only used to charge the batteries. Therefore, the building's load is completely supplied by the utility grid (black curve). It's worth noting that, the operational behavior needs to be avoided in MG systems, as also indicated in Figure 5.12. More precisely, during this period, the electricity price is higher than the defined threshold value, but the RESs generation is less than the load demand while the batteries are not at the maximum. However, the GPC model could not operate efficiently, since it needs to satisfy firstly the constraint defined for the secondary control layer while using the RESs power generation in order to charge the batteries, keeping their SoC at a maximum level. At 10:00 AM, the RESs generation is higher than the power demand. In this case, the energy excess is managed according to the electricity price variation. In fact, during the following periods, 10:00 AM-11:00 AM, 02:00 PM-03:00 PM, and 04:00 PM-05:00 PM, the electricity price (pink curve) is higher than the threshold value (red curve). Therefore, the surplus is injected into the grid in order to increase the prosumers' profitability by selling the energy at a high price. From 11:00 AM to around 01:00 PM, the electricity price is less than the threshold value; in this case, the surplus is used to charge the batteries instead to inject it into the utility grid. Therefore, the batteries will be charged and could supply the building's load, as shown during the period

from 03:00 PM to around 04:00 PM. They are also used for supplying the load even after 05:00 PM despite that their SoC is not at the minimum. To summarize, in this second scenario, a fixed threshold value (red curve in Figure 5.17) of the electricity price is integrated as a cost function for being minimized by the GPC-based control. In fact, the GPC manages the power between the RESs, the batteries, and the utility grid according to the defined priority as well as the constraints for the secondary and the tertiary layers.

Unlike the second scenario, in the third scenario, a dynamic threshold value is used for the electricity price by considering the peak-demand periods. In fact, the electricity price is an interesting exogenous for both prosumers and the utility grid operators. For instance, it could be used by the grid operators as penalties for the consumers, avoiding then the peak-demand. In fact, the consumers can efficiently manage their consumption by using, for example, programmable machines, which could be controlled by integrating the “Internet of Things” technologies, or by the deployment of intelligent and predictive control strategies. Moreover, in the MG system, the proposed GPC model can locally manage the RESs generation and storage devices. For the studied scenario, the electrical grid is used only during some periods, mainly when the electricity price is inexpensive. Batteries SoC is kept at its maximum for being used during periods with high electricity prices, and consequently, the electricity bill is minimized. Furthermore, the high electricity demand from the grid is minimized avoiding then the generation of peak-demand. As shown in Figure 5.18, at the starting time, the RESs start charging the batteries and the grid generates the power for supplying the building’s load. From 06:00 AM to 08:00 AM, the MG system operates like in the second scenario. However, during the morning peak-demand period (from 08:00 AM to 10:00 AM), the electricity price (pink curve) increases to reach the maximum, although the batteries start to generate the electricity to the load in order to avoid using the utility grid, having the highest price. During the periods (from 10:00 AM to around 02:00 PM), which show the lowest electricity price, the RESs (green curve) supply the power to the load while the surplus is managed in a similar manner as the previous scenario. In the afternoon (from 02:00 PM to 04:00 PM), there is a peak-demand, as shown by the orange curve (Figure 5.18). In this period, the surplus generated by RESs is injected into the grid while the batteries are used to supply the building’s load (especially when RES generation is low), respecting then the electricity price variation and the battery SoC constraints.

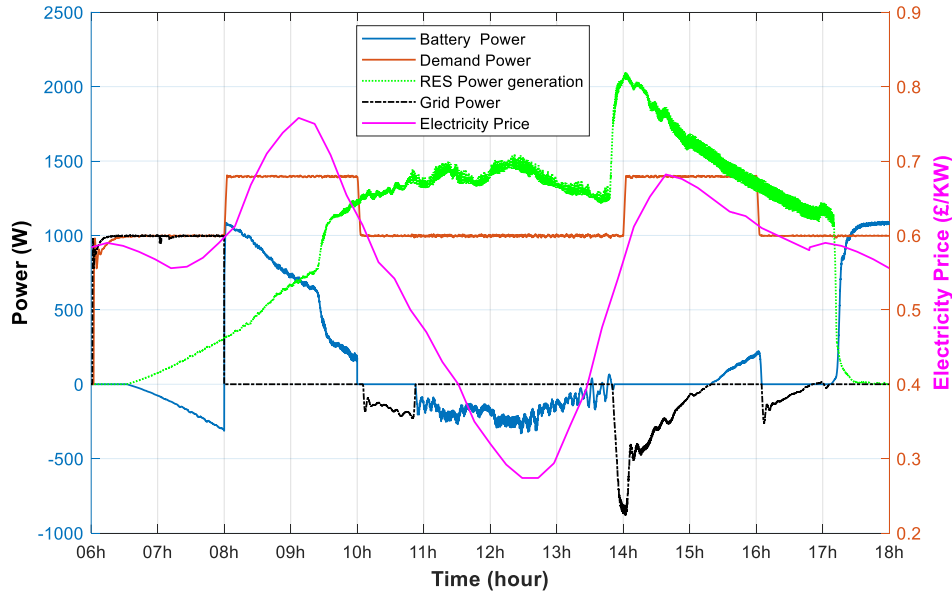


Figure 5.18. GPC controller for grid-connected mode and dynamic setpoint

In summary, from the results, depicted in Figure 5.18, the deployed GPC model manages the energy flow according to the defined constraints, which related to the secondary layer (equation (5.29)). It also handles efficiently the cost function related to the tertiary layer (equation (5.36)).

The fourth scenario is mainly included to investigate the MG system behavior taking into consideration all constraints defined in equation (5.36). The aim is to maximize supplying the building's load from RESs and batteries, especially when the electricity price is expensive. This priority is selected depending on the elements of the diagonal matrix Q_1 presented in equation (5.36). In addition, the action selected by the GPC model during a giving prediction horizon N considers the variability of electricity price, which is presented by the second term of the equation (5.36). Thus, the sources selected to generate the electricity to the loads should be capable to generate the equivalent energy in order to reach the selected setpoint presented in the third term of the equation (5.36), while the setpoint is presented by the electricity consumption variability.

In this scenario, the GPC model for EM is deployed during 24 hours with the main aim is to show the utility of this model in minimizing the electricity bill. Two cases are considered in order to make a comparative study regarding the electricity cost. For the first case (Case 1), as described in Figure 5.19.a, we have considered a dynamic threshold value for the electricity price, in a similar way as the third scenario. In the second case (Case 2), as depicted in Figure

5.19.b, we consider that the EM system can use the electrical grid to charge the batteries, mainly when the electricity price is inexpensive.

As already known, batteries are used during the night when the RESs power is unavailable, especially for the PV panels. As shown in Figure 5.19.a, around 05:00 PM the RESs generation becoming insignificant (green curve for PV power, and yellow curve for the wind power). Consequently, the batteries start generating the power (blue curve) to the loads (orange curve). When the batteries are used, their energy is accumulated with the WT in order to satisfy the requested power. However, at 08:00 PM, the batteries' SoC reached the minimum threshold value (to avoid a deep-discharging) and the WT cannot satisfy alone the energy demand. In this case, the utility grid is used to supply the electricity to the building's loads, while the power, which is generated by the WT, charges the batteries, from 08:00 PM to around 02:00 AM. During the rest of the night, the batteries are not fully charged, and, therefore, the load is supplied by the utility grid while the batteries remain at rest. In the morning, starting from 06:00 AM to 12:00 AM, the RESs generation is less than the load's demand. In this period, as shown in Figure 5.19.a, the power generated by the RESs is entirely stored in the batteries, while the building's load is supplied by the utility grid. However, from 12:00 AM to 04:00 PM, the RESs generation is higher than the building's load demand. During this period, and because the electricity price is low, the surplus is then used to charge the batteries. From 04:00 PM to 05:00 PM, the surplus is, however, injected into the utility grid. The aim is to profit from the high electricity price by selling it, and then reducing the electricity bill for consumers.

Regarding the second case, as presented in Figure 5.19.b, we consider that the batteries can be charged at night from the utility grid, especially when the electricity price is lower. The system operates like in case 2. Though, at 02:00 AM, the utility grid charges the batteries because the electricity price is low and the batteries SoC should be kept at its maximum for being used during the morning in order to avoid the peak-demand. Unlike the first case, the building's load is supplied, during this peak-demand, only by both the batteries and RESs, without using the utility grid.

To summarize, the abovementioned scenarios focused on the performance evaluation of the GPC-based control for EM in MG systems. We put more emphasis on the operation behavior of the considered MG system following a cost function and the system's constraints. The next sub-section will focus on the benefit of the GPC-based control of the electricity price.

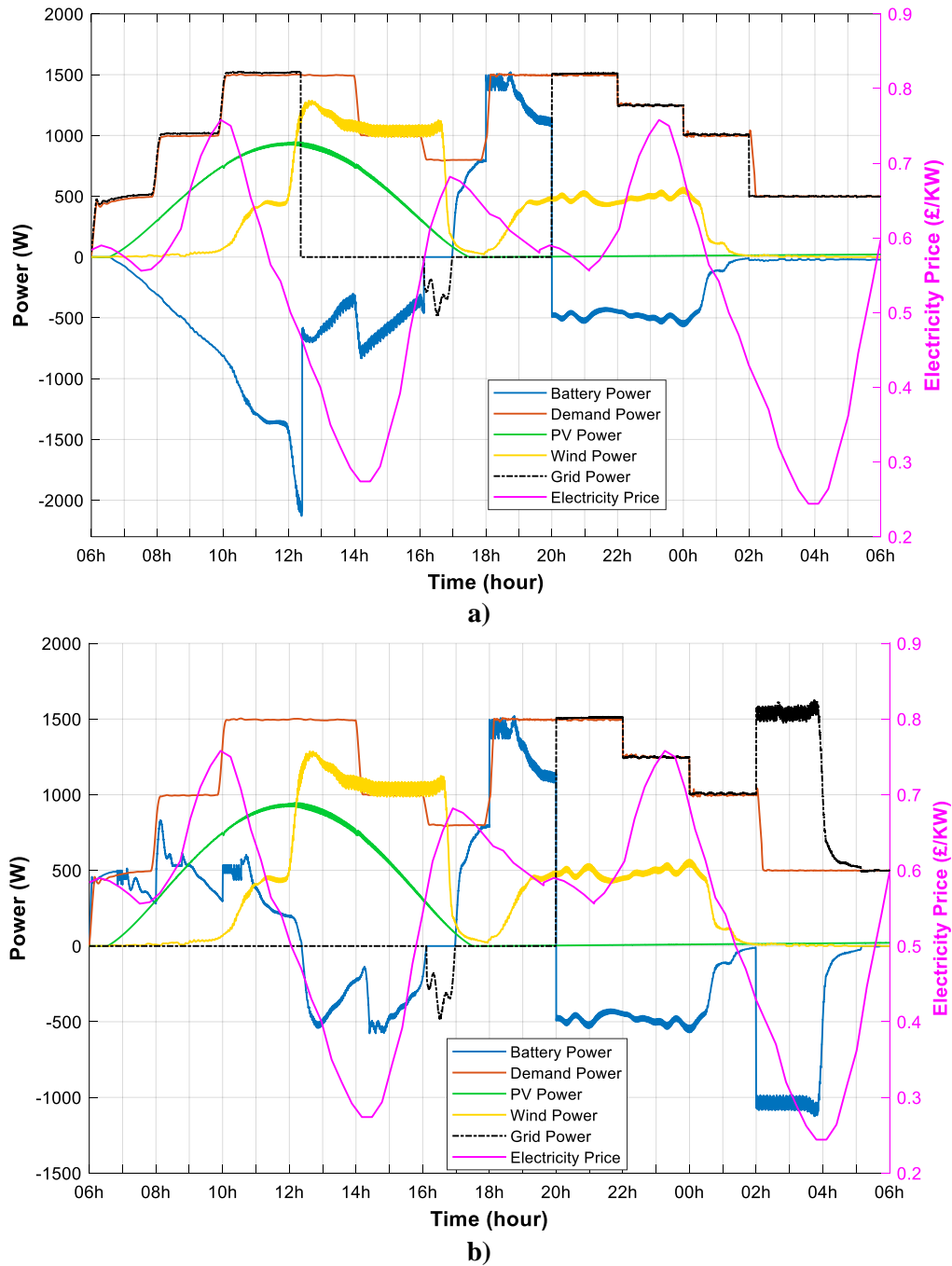


Figure 5.19. EM scenarios based on GPC model, a) Case 1: without battery-grid interaction, b) Case 2: with battery-grid interaction

5.2. The benefit of GPC model on the electricity price

In this section, the profit of electricity price is computed for the fourth scenario and in both cases (1&2, Figure 5.19), since they represent the entire system's operations. In this study, the kilowatt-hour is calculated for the power, which extracted or injected into the utility grid, as well as the power used to charge or discharge the batteries. It's worth noting that the RESs generate the maximum power at each moment without limiting the power by the LPPT

algorithms. In the studied scenarios, the possibility to charge the battery from the grid was integrated as an important element in the proposed EM strategy for the MG system.

Table 5.3. Electricity price benefit for case 1

<i>Time</i>	<i>Battery</i>		<i>Grid</i>	
	<i>Cost Average</i> (€)	<i>Power Average</i> (KWh)	<i>Power Average</i> (KWh)	<i>Equivalent Cost</i> <i>exchange</i>
<i>06h-07h</i>	0.58	-0.02	0.41	0.24
<i>07h-08h</i>	0.56	-0.19	0.50	0.28
<i>08h-09h</i>	0.6	-0.44	0.98	0.59
<i>09h-10h</i>	0.72	-0.69	1.00	0.73
<i>10h-11h</i>	0.70	-1.05	1.48	1.05
<i>11h-12h</i>	0.57	-1.35	1.48	0.84
<i>12h-13h</i>	0.45	-1.13	0.54	0.25
<i>13h-14h</i>	0.33	-0.46	0	0
<i>14h-15h</i>	0.28	-0.67	0	0
<i>15h-16h</i>	0.43	-0.47	0	0
<i>16h-17h</i>	0.63	-0.04	-0.28	-0.18
<i>17h-18h</i>	0.66	-0.65	0	0
<i>18h-19h</i>	0.62	-1.42	0	0
<i>19h-20h</i>	0.59	-1.17	0	0
<i>20h-21h</i>	0.58	-0.49	1.48	0.85
<i>21h-22h</i>	0.58	-0.45	1.48	0.85
<i>22h-23h</i>	0.68	-0.47	1.22	0.83
<i>23h-00h</i>	0.74	-0.51	1.22	0.90
<i>00h-01h</i>	0.61	-0.35	0.99	0.59
<i>01h-02h</i>	0.49	-0.05	0.98	0.48
<i>02h-03h</i>	0.37	-0.02	0.47	0.17
<i>03h-04h</i>	0.27	-0.02	0.47	0.12
<i>04h-05h</i>	0.29	-0.02	0.47	0.13
<i>05h-06h</i>	0.48	-0.0.2	0.47	0.22
<i>Total</i>	--	-5.71 KWh	15.36 KWh	8.97 €

However, a high cycle of the batteries' C/D could play a major role in decreasing the batteries' state-of-health. The GPC-based control manages the power flow in order to keep, as much as possible, the battery SoC at its maximum (equation (5.28)). This avoids a high cycle of C/D and a deep-discharge of batteries, which causes the degradation of their state-of-health. Regarding case 1, batteries can only be charged from RESs production. They are mainly used to compensate the power generated for supplying the building's load according to the constraints, which are set in the deployed GPC model. As presented in Tables 5.3 & 5.4, the cost average, the battery power average, and the grid power average are calculated for each hour during the system's operation period. In fact, the negative average power represents the equivalent power, which is used to charge the batteries, while the positive value is the equivalent power, which is generated from the batteries in order to supply the electricity to the load. By comparing this factor in both cases, the batteries have a total battery power-average equal to "-5.71KWh" and "-0.0042KWh" respectively for cases 1 and 2.

Table 5.4. Electricity price benefit for case 2

<i>Time</i>	<i>Cost Average (€)</i>	<i>Battery</i>	<i>Grid</i>	
		<i>Power Average (KWh)</i>	<i>Power Average (KWh)</i>	<i>Equivalent Cost exchange</i>
<i>06h-07h</i>	0.58	0.45	0	0
<i>07h-08h</i>	0.56	0.38	0	0
<i>08h-09h</i>	0.6	0.60	0	0
<i>09h-10h</i>	0.72	0.41	0	0
<i>10h-11h</i>	0.70	0.50	0	0
<i>11h-12h</i>	0.57	0.25	0	0
<i>12h-13h</i>	0.45	-0.20	0	0
<i>13h-14h</i>	0.33	-0.36	0	0
<i>14h-15h</i>	0.28	-0.40	0	0
<i>15h-16h</i>	0.43	-0.37	0	0
<i>16h-17h</i>	0.63	-0.01	-0.26	-0.16
<i>17h-18h</i>	0.66	0.65	0	0
<i>18h-19h</i>	0.62	1.42	0	0
<i>19h-20h</i>	0.59	1.17	0	0
<i>20h-21h</i>	0.58	-0.49	1.51	0.87
<i>21h-22h</i>	0.58	-0.45	1.51	0.87
<i>22h-23h</i>	0.68	-0.48	1.25	0.85
<i>23h-00h</i>	0.74	-0.51	1.25	0.92
<i>00h-01h</i>	0.61	-0.35	1.01	0.61
<i>01h-02h</i>	0.49	-0.05	1.01	0.49
<i>02h-03h</i>	0.37	-1.04	1.54	0.57
<i>03h-04h</i>	0.27	-1.02	1.51	0.40
<i>04h-05h</i>	0.29	-0.10	0.59	0.17
<i>05h-06h</i>	0.48	-0.004	0.50	0.24
<i>Total</i>	--	-0.0042 KWh	11.42 KWh	5.85 €

For case 1, this is due to the high usage of the utility grid, and consequently, the batteries receive maximum power from the RESs without considering the electricity price variation, especially during the day. However, in case 2, the batteries can be charged from the electrical grid, mainly when the electricity price is inexpensive. In fact, the negative average of the power grid represents the equivalent power, which is injected into the grid from RESs, while the positive average is equivalent to the power, which is extracted from the grid in order to satisfy the load demand. As depicted in Table 5.3, in case 1, “15.36 KWh” of energy is used from the grid, representing an equivalent of “8.97€” for 24 hours, while in case 2, only “11.42KWh” of energy is extracted from the grid, which is equivalent to “5.85€” for the same period.

Therefore, different factors are considered in order to manage the energy flow in the MG system. In order to maximize its profitability, for all studied scenarios, the RESs generate maximum power at each moment. When RESs cannot satisfy the demand, the grid and the batteries’ power are efficiently managed in order to avoid the degradation of batteries state-of-health, while minimizing the electricity bill. In summary, the above-mentioned results show

the usefulness of the GPC-based control in minimizing the electricity bill for the consumer by integrating the electricity price as main an important factor for EM of MG systems. However, the power quality as well the timely decision, which is provided by the GPC-base control, has to be assessed. The next sub-section focuses on evaluating and assessing these two important factors.

5.3. Power quality for GPC controller

Computing and processing for providing timely decisions and actions are most important, especially in systems requiring real-time predictive control. For instance, as stated above, a delay is created between the measurement time and the application of the predicted control action. In fact, between two moments (t_k and t_{k+1}), the previous state continues to control the system, and consequently, the voltage vector, selected at time t_k , continues to be applied after t_{k+1} . This makes the power oscillates around the reference, and then the “current ripple” increases. Therefore, by using the GPC controller for the tertiary control layer, the predictor calculates, for each instant t_k , the predictions of the dynamic evolution of the process $[y(t+1), \dots, y(t+N)]^T$, throughout the prediction horizon N . This prediction is based on dynamic parameters, which are measured at this moment, as well as on future control regulation $[u(t), u(t+1), \dots, u(t+N)]^T$, along the prediction horizon N . As depicted in Figure 5.20, the orange curve represents the output power, which is generated by the inverter according to GPC-based control, while the blue curve represents the power, which is generated by the inverter according to a PID controller.

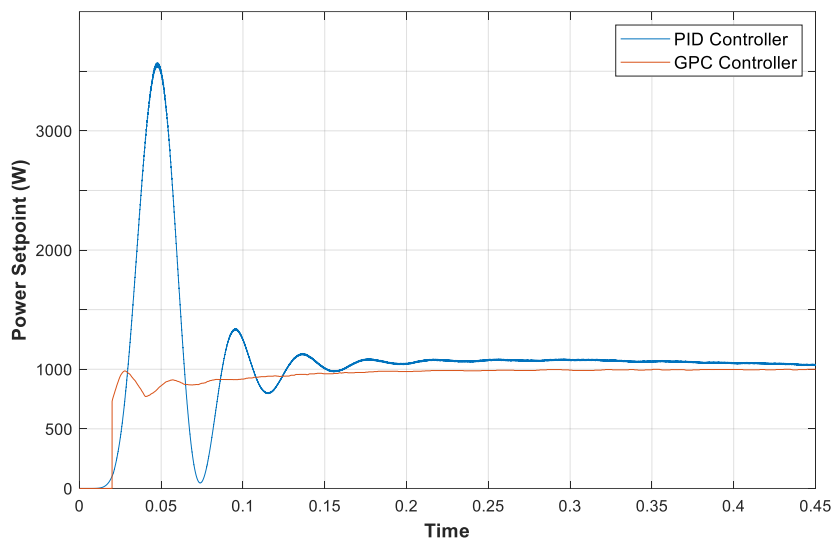
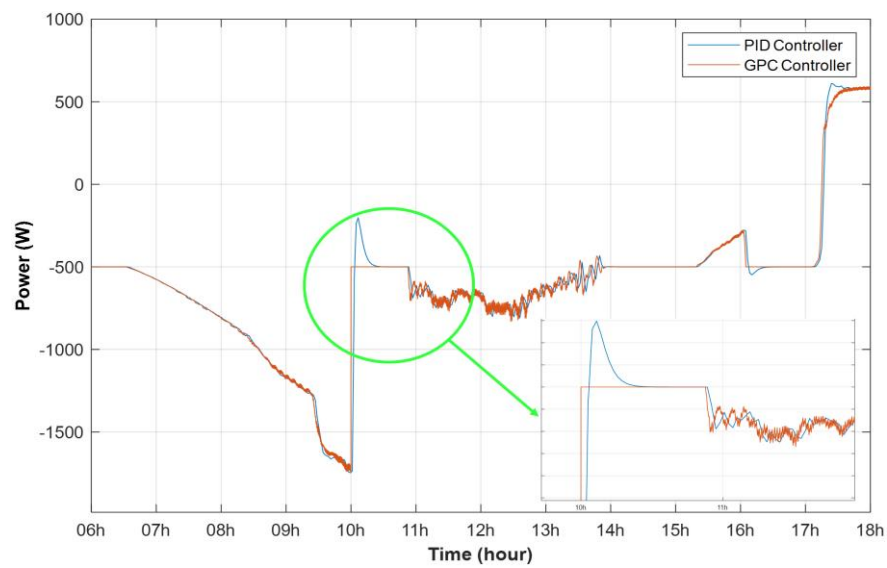
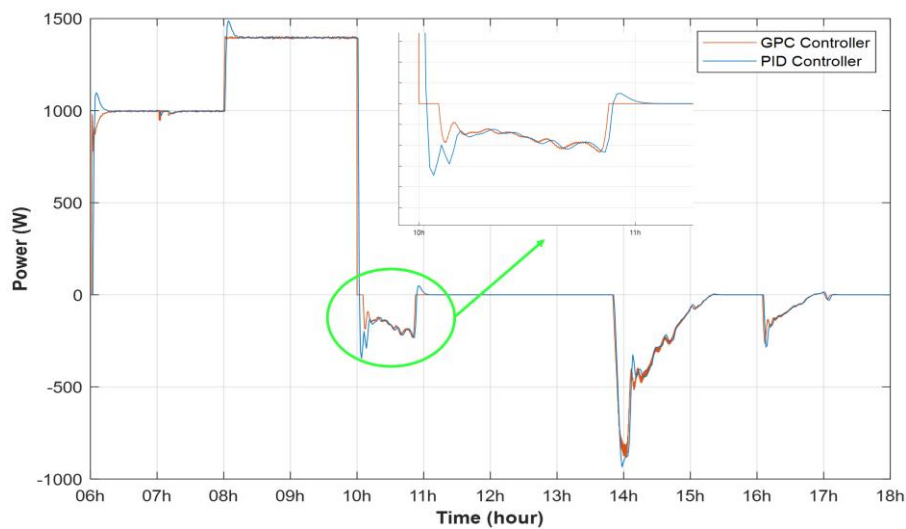


Figure 5.20. Power regulation for GPC and PID controller

As shown in Figure 5.20, unlike the PID controller, which takes a few moments to reach the setpoint regulation (1000W of load consumption), the GPC controller generates the future control actions by keeping the system's output as close as possible to the setpoint. In fact, the GPC controller shows more system's stability during the switching moments. Moreover, the control strategy decision by the GPC-based control is mainly generated for the secondary and tertiary control layer. In fact, the GPC manages the system for the secondary control layer by taking the right action on batteries C/D according to the detected mode, autonomous, grid-connected. As shown in Figure 5.21, the PID controller takes more time to converge to the desired references, especially during switching moments.



a)



b)

Figure 5.21. Power regulation for GPC and PID controller, a) Battery power regulation, b) Grid power exchange

Since the PID is based on a feedback control mechanism (i.e., cannot generate future actions) and the studied constraints cannot be modeled for real-time control, we present only the result when the PID is applied for the grid-connected mode with a static setpoint. Unlike PID, the GPC controller is based on a feed-forward control mechanism, which allows it to generate future actions according to a predefined cost function and constraints. As depicted in Figure 5.21.a, the regulation of batteries C/D decision is more stable at the switching moments and without a significant “current ripple”. Similarly, high switching performances are presented for the interconnection with the electrical grid (Figure 5.21.b). This is due to the delay compensation method, which is used by the GPC-based control. Furthermore, the GPC model gives an exact solution to an approximated optimization problem by calculating the voltage reference to the inverter.

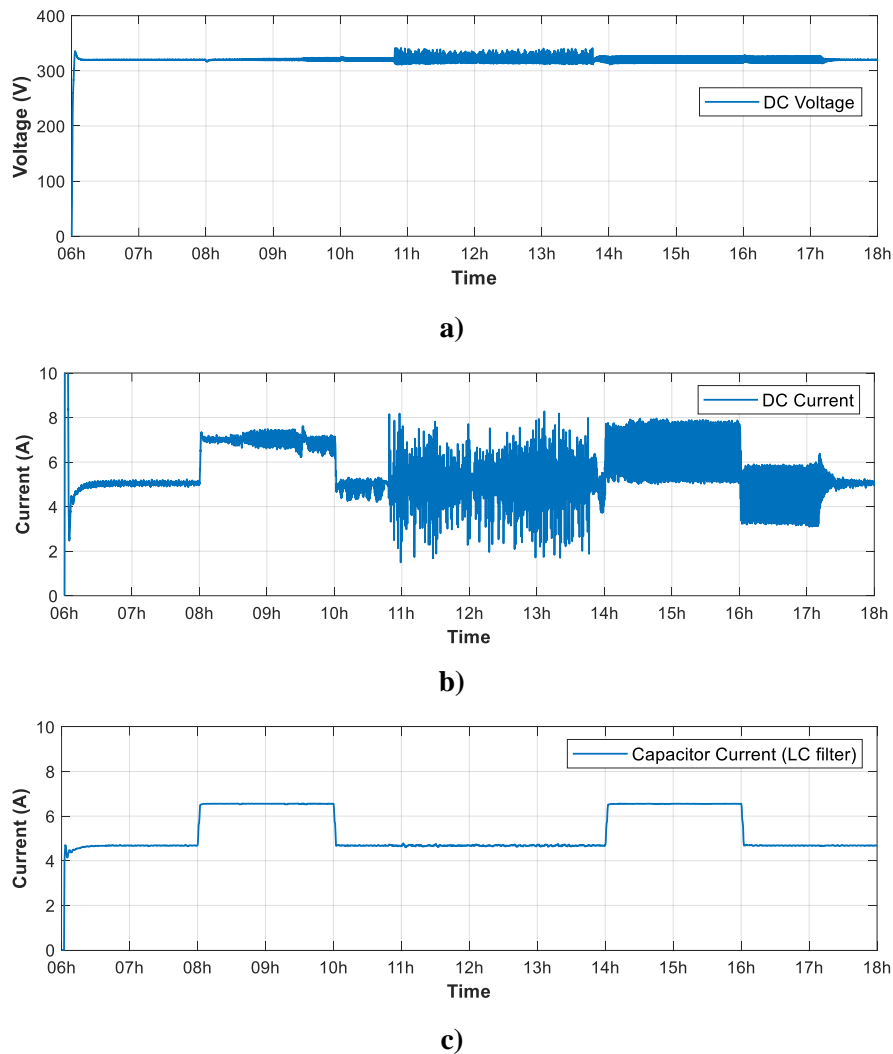


Figure 5.22. Current and voltage regulation, a) DC bus voltage, b) DC bus current, c) the current across the filter capacitor

However, this voltage is generated by a PWM or SVM technique. As presented in Figure 5.13, the power circuit of a grid-connected converter is represented by a smoothing inductor. The main objective of the GPC model is to calculate, for the inverter, the reference of the output voltage for each connected source and load or injection of power to the grid. For the controller, the main variables are the DC voltage/current, the grid voltage/current, and the load voltage/current. The inverter should be able to regulate the output depending on the parameter variation of the DC bus. The output of the system is modeled by equation (5.43), in which the output voltage and current are regulated following the references that are generated by the GPC-based control. Figure 5.22 presents the obtained regulation of voltage and current for the deployed power converter depending on the DC voltage variation. Figure 5.22.a, b, and c present respectively the DC voltage, the DC current, and the current across the LC filter capacitor.

The active power filter essentially consists of a voltage source inverter and a DC bus connected to a capacitor while the AC bus is connected to the main grid through an LC filter. Mainly, for each load connected to the AC bus, the converter should be capable to generate suitable current and voltage. For the studied scenarios, the voltage and frequency of the grid are set as 240V and 50Hz respectively. Depending on the deployed loads used for our scenarios, Figure 5.23.a presents the current variation and Figure 5.23.b presents the voltage, which is measured at the output of the inverter.

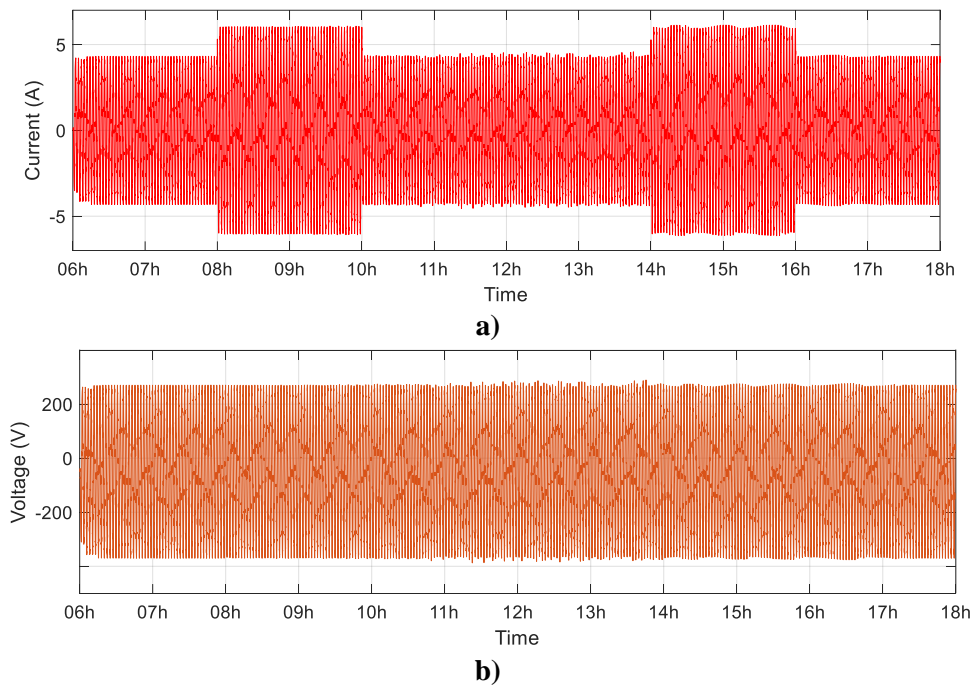


Figure 5.23. a) Load current variation, b) Load voltage variation

The frequency spectrum is presented for the AC bus voltage and current and for the load voltage as shown in Figure 5.24. Depending on the equation (5.40) dynamics, the voltage-source-inverter output is chosen as the control signal and the final switching sequence is generated through a PWM technique. The performance is analyzed for an RLC load, which is deployed for simulation purposes. Thus, the converters must ensure the stability of the energy injected into the utility grid, according to the rules established by the operators (IEEE Standard Association, 2018).

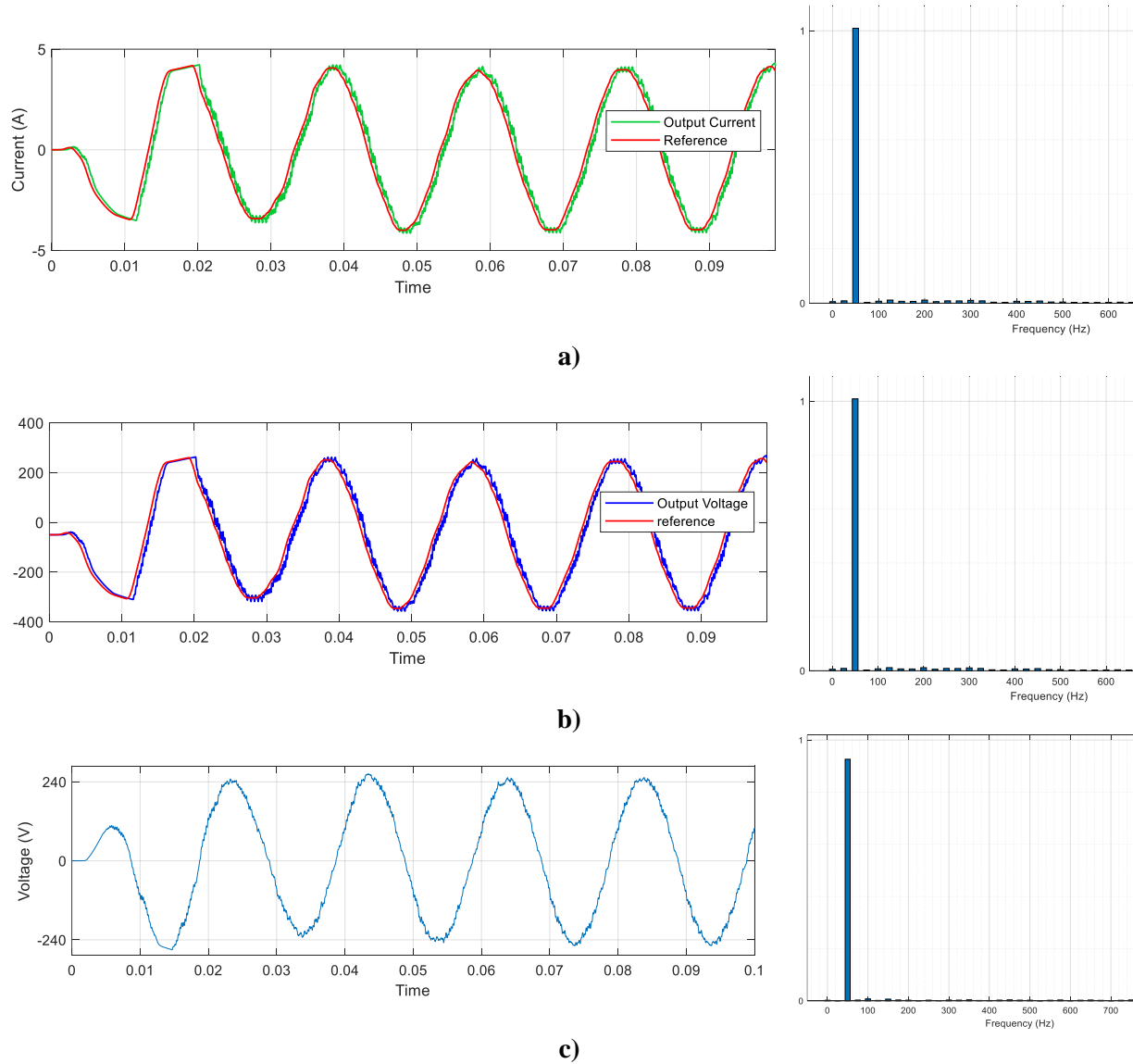


Figure 5.24. Frequency spectrum, a) Inverter output current, b) Inverter output voltage, c) Load voltage

It is worth noting that, in power electronics, the state feedback regulators do not guarantee a good performance in terms of rapid recovery and low harmonic distortion of the

output, especially when the system is affected by disturbances and variations in parameters. However, the use of a feed-forward technique improves the transient response and minimizes, even remove harmonic disturbances. Better performance of this type of controllers is achieved, as shown in Figure 5.24. The output tracks the reference voltage and current with good behavior by ensuring the stability of the system's frequency at 50Hz for harmonic loads. Furthermore, the GPC provides an explicit solution for unconstrained predictive control. It is also able to handle the problem of mismatch between the model and the deployed load.

6. Conclusions

This chapter introduced an intelligent and predictive control strategy, named MAPCASTE, for EM in MG systems. MPC (Model Predictive Control) and GPC (Generalized Predictive Control) have been investigated in order to carry out the proposed MAPCASTE. This later was deployed and evaluated by assessing its effectiveness for EM in MG systems. In fact, the main aspect of the proposed MAPCASTE approach is to measure, in real-time, the main input control parameters; analyze the data for ML algorithms training, prediction of the future behaviors, forecasting the suitable commands to reach the desired setpoint depending on the predefined constraints and objective functions, and correcting the errors depending on the real measurements. In fact, ML algorithms classifications are presented for power forecasting in MG systems. In addition, an EM system, based on MPC and GPC principles, is developed for being deployed in the secondary and the tertiary control layers. In fact, the secondary layer focused on power regulation and energy D/R balance. An optimization function was defined, for this level. State-space equations are presented for the controllable MG system's entities depending on the constraint, which is defined in the tertiary control layer. Therefore, the tertiary control focused only on power dispatch and economic aspects. Within this context, the electricity cost is used as a constraint to control the batteries C/D. Indeed, the electricity price is integrated as a cost function to be minimized while respecting the defined constraints. The controller manages the power between the RESs, the batteries, and the utility grid depending on the operational constraints of the EM strategy. The powerful of the MAPCASTE for the EM system was shown by minimizing the electricity bill.

General Conclusions and Perspectives

Conclusions

In this dissertation, an intelligent and predictive control strategy for EM (energy management) in MG (micro-grid) systems has been developed, deployed, and tested. The aim was to define an appropriate predictive control approach for EM, which allows an optimal control and scheduling operations of hybrid renewable energy sources. In fact, by first studying the environmental and global energy context, the concept of MG systems for buildings is introduced. The need to integrate RESs into the building is studied, by highlighting important problems that need to be tackled for efficient EM. Therefore, a concise state of the art is presented by introducing the main control approaches, which have been proposed for EM in hybrid RESs systems. Principally, this study is carried out in order to define the suitable control approach by identifying the interconnection method and the main components of the studied MG system. Modeling of the different components of the hybrid energy system is realized following a specific problems classification, especially, for MG systems. Moreover, an MG system infrastructure is developed together with a platform for data gathering, monitoring, and processing. We put more emphasis on MG systems as crucial infrastructures for leveraging energy-efficient and smart buildings by developing and deploying a holistic IoT/Big-Data platform in which sensing and actuation tasks are performed according to the actual contextual changes. The developed platform integrates the new information and communication technologies making the buildings more intelligent. It was used for validating the proposed models and results mainly by investigating, i) the efficient connection, integration, and the management of different RES and storage devices, ii) the suitable dimensions for energy production and storage devices, iii) different possible demands/responses and predictive algorithms, iv) context-aware driven control of deployed equipment (e.g., lighting and HVAC systems).

A predictive control strategy is then developed, named MAPCASTE, for measuring, analyzing, predicting, and forecasting actions in order to ensure efficient and optimal operation of MG systems. The control strategy is based on machine-learning algorithms to predict main input parameters, which are used for forecasting suitable actions. The main objective is to connect efficiently the electricity generators and consumers in order to predict the most suitable actions for energy flow management. More precisely, based on energy production and consumption profiles as well as the availability of energy storage systems, the proposed control strategy selects the best suitable energy source for supplying the building's

loads. It manages efficiently the usage of energy storage and utility grid while maximizing RESs power generation. Simulations and experimentations have been conducted and results are presented to validate the proposed predictive control approach by showing its effectiveness for MG systems control, in particular the system's profitability and energy cost minimization.

Perspectives

Ongoing works focuses on the development of smart converters according to the thesis findings. In fact, the actual commercial inverters offer the possibility to manage the power flows between different power sources, loads, energy storage systems, and utility grid with high performances. However, these inverters are limited generally to a single objective function, which is the satisfaction of the loads demand without considering other operating constraints, like the electricity price and the battery state-of-health. Moreover, the integration of new IoT/Big-data technologies to the actual inverter improved the performance of the system to control and predict the suitable actions for EM and control. Mainly, the integration of machine-learning algorithms is required to analyze the data and to predict the actions for EM in MG systems. In this way, the development of smart inverter enhanced the possibility to integrate multiple objective functions and operating constraints that can be integrated in the EM approaches. Therefore, the deployment of predictive control strategies in real scenarios requires the use of open access power converter. For that, we are deploying our proper power inverter in order to have the ability to conduct real-testing of predictive control strategies with specific constraints and multiple objective functions. Moreover, the development of predictive control strategies improves the actual MG building systems by offering the possibility to interconnect multiple MG systems with the possibility to exchange power. The deployment of smart inverter offers the possibility to create MG networks using IoT/Big-data technologies. In this context, a platform for MG2MG energy and data exchange will be developed based on the predictive control deployed in the smart inverters.

Two ongoing theses have already started, the first one deals with the first perspective by including other constraints and objective functions for being integrated into our developed inverter, while the second thesis will focus on the development of distributed EM for MG2MG.

Author's Publications

Journal papers

- [1] Elmouatamid, A., Ouladsine, R., Bakhouya, M., El kamoun, N., Zine-Dine, K., & Khaidar, M. (2020). *Review of Control and Energy Management Approaches in Micro-Grid Systems*. In Smart Grids and Microgrids. Energies.
- [2] ELMOUATAMID, A. (2020). *MAPCAST: an Adaptive Control Approach using Predictive Analytics for Energy Balance in Micro-Grid Systems*. International Journal of Renewable Energy Research (IJRER), 10(2), 945-954.
- [3] Elmouatamid, A., NaitMalek, Y., Bakhouya, M., Ouladsine, R., Elkamoun, N., Zine-Dine, K., & Khaidar, M. (2019). *An energy management platform for micro-grid systems using Internet of Things and Big-data technologies*. Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering, 233(7), 904-917.
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Chapter books

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