OPTIMAL ENERGY MANAGEMENT OF A MICROGRID SYSTEM

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Dedication

To my dearest mother,

Whatever I do or say to you, I cannot thank you as I should, your affection covers me, your benevolence guides me and your presence close to me has always been my source of strength to face the different obstacles.

To my dearest father,

You have always been close to me to support and encourage me. May this work reflect my gratitude and affection.

To my dearest brother Nabil,

For your presence, your love, your sacrifices and your encouragement throughout my university career. Thank you.

To my dearest brother Khierdinne and my dearest sister Meriem,

May the god give you health, happiness, courage and especially success.

Abstract

A smart management strategy for the energy flows circulating in microgrids is necessary to economically manage local production and consumption while maintaining the balance between supply and demand. Finding the optimum set-points of the various generators and the best scheduling of the microgrid generators can lead to moderate and judicious use of the powers available in the microgrid. This thesis aims to apply an energy management system based on optimization algorithms to ensure the optimal control of microgrids by taking as main purpose the minimization of the energy costs and reduction of the gas emissions rate responsible for greenhouse gases. Two approaches have been proposed to find the optimal operating set-points. The first one is based on a uni-objective optimization approach in which several energy management systems are implemented for three case studies. This first approach treats the optimization problem in a uni-objective way where the two functions price and gas emission are treated separately through optimization algorithms. In this approach the used methods are simplex method, particle swarm optimization, genetic algorithm and a hybrid method (LP-PSO). The second situation is based on a multiobjective optimization approach that deals with the optimization of the two functions: cost and gas emission simultaneously, the optimization algorithm used for this purpose is Pareto-search. The resulting Pareto optimal points represent different scheduling scenarios of the microgrid system.

Keywords:
Renewable Energies, Microgrid, Hybrid Energy System, Energy Management System, Optimization Algorithms, Set-points, Cost, Emissions.

Resumo

Uma estratégia de gestão inteligente dos fluxos de energia que circulam numa microrrede é necessária para gerir economicamente a produção e o consumo local, mantendo o equilíbrio entre a oferta e a procura. Encontrar a melhor programação dos geradores de microrrede pode levar a uma utilização moderada e criteriosa das potências disponíveis na microrrede. Esta tese visa desenvolver um sistema de gestão de energia baseado em algoritmos de otimização para assegurar o controlo ótimo das microrredes, tendo como objetivo principal a minimização dos custos energéticos e a redução da taxa de emissão de gases responsáveis pelo com efeito de estufa. Foram propostas duas estratégias para encontrar o escalonamento ótimo para funcionamento. A primeira baseia-se numa abordagem de otimização uni-objetivo no qual vários sistemas de gestão de energia são implementados para três casos de estudo. Neste caso o problema de otimização é baseado na função preço e na função emissão de gases. Os métodos de otimização utilizados foram: algoritmo simplex, algoritmos genéticos, *particle swarm optimization* e método híbrido (LP-PSO). A segunda situação baseia-se numa abordagem de otimização multi-objetivo que trata a otimização das duas funções: custo e emissão de gases em simultâneo. O algoritmo de otimização utilizado para este fim foi a Procura de Pareto. Os pontos ótimos de Pareto resultantes representam diferentes cenários de programação do sistema de microrrede.

Palavras-chave:
Energias Renováveis, Microrrede, Sistema de Energia Híbrida, Sistema de Gestão de Energia, Algoritmos de otimização, Custo, Emissões.

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List of abbreviations

AC	Alternative Current
AFSA	Artificial Fish Swarm Algorithm
BFGS	Broyden Fletcher Goldfarb Shanno
BPSO	Binary Particle Swarm Optimization
CAES	Compressed Air Energy Storage
$\mathbf{CO_2}$	Carbon Dioxide
DC	Direct Current
DE	Differential Evolution
DFP	Davidon Fletcher Powell
DG	Distributed Generators
DMS	Demand Management System
DOD	Depth Of Discharge
EMS	Energy Management System
ESS	Energy Storage System
EU	European Union
GA	Genetic Algorithm
GHG	Greenhouse Gas Emissions

HES	Hybrid Energy System
HS	Harmony Search
IEA	International Energy Agency
IR	Infra Red
LP	Linear Programming
MG	Microgrid
MILP	Mixed Integer Linear Programming
MPPT	Maximal Power Point Tracking
MTOE	Million Tonnes of Oil Equivalent
NLP	Nonlinear Programming
$\mathbf{NO}_x$	Nitrogen Gas
PSO	Particle Swarm Optimization
PV	Photovoltaic
RES	Renewable Energy Sources
SM	Simplex Method
$\mathbf{SO}_2$	Sulphur Dioxide
SOC	State Of Charge
STEP	Stations for Energy Transfer by Pumping
UPS	Uninterruptible Power Supply
UV	Ultra Violet
WT	Wind Turbine

List of symbols

Δ_t	Operation Time
η_{bat}	Battery Efficiency
η_{conv}	Converter Efficiency
η_c	Charging Efficiency
η_d	Discharging Efficiency
η_s	Overall Efficiency of Photovoltaic Panels
γ	Temperature Coefficient
C_T	Total Cost
E_M	Total Emissions
G	Global Irradiation
N_{pv}	Number of Photovoltaic Panels
N_{wt}	Number of Wind Turbines
P_{conv}	Power of Converter
P_c	Maximum Charging Rate
P_d	Maximum Discharging Rate
P_g	Power Exchanged With the Network
P_n	Nominal Power
P_{pv}	Power Produced By a Photovoltaic Panels
P_{wt}	Power Produced by the Wind Turbine
S	Surface

T_0	Outside Temperature
v	Instantaneous Wind Turbine Speed
v_d	Start-up Speed of the Wind Turbine
v_i	Wind Speed Measured at $10m$
v_m	Cut-off Speed of the Wind Turbine
v_n	Rated Wind Turbine Speed
B_{xi}	Hourly Power Prices
EF_{xi}	Emission Rates
G_{best}	Best Position of the Particles
P_{besti}	Best Position of a Particle
U_i	Operation Mode
v_i	Particle Velocity Vector
X_i	Particle Position Vector

Chapter 1

General Introduction

1.1 Introduction

The considerable increase in popuation is followed by inflation in demand, human energy consumption can become a large-scale problem, the main trouble is the growing consumption of electrical energy which leads to the rising of electricity cost also to environmental effects if it continues to be produced only from conventional sources. According to the International Energy Agency (IEA), in 2018 the production of electricity based on fossil fuels (gas and oil) was estimated at 64% of the total electricity production in the world, while the contribution of renewable sources was estimated at only 26% (hydroelectricity 16%, wind 5%, biomass 3%, solar 2%) and 10% of the production was from nuclear power plants, the world has experienced a historic peak in greenhouse gas emissions related to this fossil fuel-based production, with 33.1 billion tons of CO_2 being released into the atmosphere, as a result, in 2018 the planet's temperature was more than $1°C$ warmer than the 19th-century average according to the U.S. space agency (NASA). Therefore, several efforts were made in this area by orienting towards production with renewable energies, especially in the point of view of the challenge that the world community has declared against global warming. Even though they are inexhaustible and available, the stochastic effect of renewable energies leads to innovative methods to get the best benefit from them. Using these sources as decentralized generators is the better option for reducing greenhouse gas (GHG) emissions and losses in the energy transport system.

To increase the penetration of renewable energies and solve the problems posed in the conventional electrical scheme such as transmission losses in the transport and distribution networks, the microgrid concept has been introduced to ensure reliable production on a small scale, by making the place of consumption a place of production. The operation of the microgrid (MG) generators requires an energy management system (EMS) allowing optimal control. Based on optimization approaches, the management system aims to reduce the billing cost of the microgrid consumers as well as the reduction of the greenhouse gas emission rate followed by this production, while ensuring the comfort of the users. A local production from several energy sources gives place to the concept of a microgrid.

1.2 Motivations

The optimal management of a microgrid system economically and environmentally is a research area that has grown especially after the objective established by the European Union (EU) to confront climate change in the framework for action on climate and energy for the period of 2021-2030. Following the increase of 2018, the EU has set three objectives: the reduction of greenhouse gas emissions by at least 40%, increasing the contribution of renewable energy to at least 32% and improving energy efficiency by at least 32.5%. However, the optimal management will encourage the deployment of a microgrid system that represents a real opportunity to increase the attractiveness towards renewable energy production and therefore achieve the objectives set by the european community.

1.3 Literature Review

The replacement of a big single electrical grid by a set of manageable microgrids is a new form of maintaining energy systems, a microgrid community is composed of small distributed generation units based on renewable energy production on the one hand and storage systems on the other hand, connected to the grid in some cases. However, an energy management system is responsible for the efficient operation of the microgrid. It introduces reliable communication between all distributed generation units and guarantees a low energy price and emission rate. The work performed in this thesis is mainly based on the optimal management of the energy supplied by distributed generators. The storage system is therefore considered to be a production unit and not only back-up system.

The microgrid tends to operate in both island and grid-connected mode. Determining an optimal share of the energy produced by the distributed generation units available in a microgrid is a challenge that has become one of the most interesting and important research topics. several works have been proposed in this context, various management vision and strategy were already adopted, researchers in [23] as well as [24] developed programming of distributed generators by mixed-integer linear programming (MILP) method. In [25] a genetic (GA) algorithm was proposed to achieve an optimal operational optimization strategy for hybrid energy systems. In [26] the author proposed a new approach based on an artificial fish swarm (AFSA) algorithm to solve the problem of optimal scheduling of available sources in a microgrid community. In [27] four optimization approaches have been developed and compared for microgrid source scheduling which are: the direct search method, particle swarm optimization (PSO), lambda logic and lambda iteration, the PSO has shown better performance in the adopted management strategy. In [28] the author presented day-a-head optimised scheduling using a harmony search (HS) and differential evolution (DE) algorithms. In [29] an optimal real time energy management allowing to minimise costs and emissions also to encourage the power coming from renewable generators by using binary particle swarm optimization (BPSO) method. In [30] the author proposes optimal energy management in the presence of high penetration of renewable energy, this system tended to minimize the microgrid running and worst-case transaction costs, along with the utility of the dispatchable loads while considering the stochastic nature of distributed generators. In [31] the author proposed an energy management strategy for a smart city based on load scheduling, two PSO algorithms were developed in two steps to find the optimal operating set-points. The first PSO algorithm led to the optimal set-points powers of all microgrid generators that can satisfy the non-shiftable needs of the smart city demand with a low operating cost, while the second PSO algorithm aimed at the scheduling of the shiftable city demand to avoid peak hours when the operating cost is high.

1.4 Objectives

The work presented in this thesis has several objectives mainly :

1. The development of a smart energy management system (EMS) based on optimization approaches to ensure optimal control and management of a microgrid system.

2. Study of the problem through two optimization approaches: Uni-Objective and Multi-Objective.

3. Development and comparison of energy management systems based on several uni-objective optimization algorithms: linear programming (LP) based on simplex method, two evolutionary algorithms: Particle swarm optimization (PSO) algorithm and the genetic algorithm (GA), also, a hybrid method (LP-PSO).

4. Treatment of three study cases in the uni-objective approach to illustrate the relation between price and gas emission.

5. Development of an energy management system based on multi-objective optimization algorithm: Pareto Search.

6. The comparison of both uni-objective and multi-objective methods to find a reliable energy management system model.

1.5 Thesis Structure

The work presented in this thesis is organized into six chapters :

Chapter 1 (Introduction), addressed to show the general idea of the problem, the motivations that led to its treatment, the expected objectives of the thesis and the structure followed in its writing.

Chapter 2 (State of the Art of Multisources Systems) aims to describe the position of the world community towards renewable energies and the importance of moving towards microgrids, also gives a description of hybrid systems and multi-source systems with the importance of their implementation, with a characterization of the different divisions that can compose a microgrid system.

Chapter 3 (Energy Management and Optimization Approaches) is composed of two parts. the first part describes the concept of energy management in microgrids and the different energy management systems already proposed in literature. The second part treat the uni-objective and multi-objective optimization methods that will be implemented in the proposed energy management system.

Chapter 4 (Modelisation and Problem Formulation) define on one hand the modelisation of the different sources which constitute our microgrid, and on other hand, the implementation of the mathematical models for both uni-objective and multi-objective methods used to ensure optimal management of the microgrid.

Chapter 5 (The Proposed Energy Management System) describes the different energy management systems proposed in different study cases based on the two optimization approaches: uni-objective and multi-objective.

Chapter 6 (Results and Discussion) contains the results achieved by the implementation of energy management systems based on the optimization approaches for different study cases using the $MATLAB$ platform, the results of both uni-objective and multi-objective approaches are interpreted and justified in order to finally establish an energy management system that guarantees optimal scheduling of microgrid generators while respecting economic and environmental constraints.

The last chapter conclude the study and propose guidelines for futur works.

Chapter 2

State of The Art of Multisources Systems

2.1 Introduction

The part of renewable energies is growing in the world community due to their high environmental and economical benefits (reduction of greenhouse gases, global warming), they are inexhaustible, available and environment-friendly sources [32]; it's a solution to the increasing of energy demand problem. Mainly, renewable energies represent a useful alternative for the electrification of isolated or difficult access sites; however, the main conflict that delays the deployment of renewable sources is their intermittent effect because of their main dependence on meteorological conditions which are frequently variable and cannot be precisely predicted. In order to obtain a permanent production, a combination of several renewable sources, a storage system, conventional back-up systems, and sometimes the main grid is crucial, for example in a hybrid system which contains the photovoltaic (PV) and wind turbines sources (WT): the wind can ensure a minimum production at night when the production from the solar panels is absent, and inversely, in good weather condition, the solar panels can ensure more regular production than that of the wind turbine [33]. So, to have a reliable multi-source system, it is important to take into account two challenges, the first one is the optimal sizing that ensures the energy autonomy of the site, by maximizing the power collected by the energy sources, while the second challenge is related to the optimal management of power production and consumption [34]. In this chapter, the state of the art of multi-source systems is presented. The first part starts by describing the current state of renewable energy and the world's position towards it; also presents the different types of generation based on renewable energy systems. Moreover, it explains the need for a transition from conventional grids to smart grids by a comparison between the structure and advantages of the two entities. Finally, several configurations of hybrid systems that build a microgrid system are presented to choose the most suitable for the MG proposed in this project.

2.2 Context

Climate issues such as the greenhouse emissions effect (GHG) require the development of new alternative energy sources. Renewable energies offer a better option for the environment in order to reduce global warming, carbon dioxide emissions and pollution. This is leading to global awareness of energy issues.

2.2.1 World Energy Issues

In 2017, the International Energy Agency (IEA) declared 14035 Mtoe (million tonnes of oil equivalent) of world energy production, with 2652,615 Mtoe corresponding to the world electricity production; this amount represents 64% of the total electricity production, on the other hand, only 26% of the total production comes from renewable sources and the rest from nuclear energy.

However, awareness must be obligatorily adopted due to the environmental risk suffered by our ecosystem which could lead to a large increase in natural disasters. In fact, this requires the limitation of greenhouse gases (GHG) emission mainly caused by the combustion of fossil resources (oil, gas, coal). Moreover, to cover the growth of energy demand, several solutions have been proposed by the world community, the first one consists of searching for new fuel sources to be extracted from the soil, this latter raises many ecological questions which make it contradictory with the recommendation of the energy transition, the second one encourages investment in nuclear power, it's indeed an efficient production issue, but it can produce harmful effects in the long term as the one caused by of disaster of Fukushima on 2011 which caused long term ecological effects through radioactive waste [35]. Ultimately, the last solution that is the most reasonable, concerns the orientation towards the idea of energy-saving and clean energy. This motion is in accordance with the recommendations of energy efficiency and energy transition, therefore the use of renewable energy sources such as solar, wind and geothermal energy is the best option for the reduction of gases responsible for global warming [36].

2.2.2 The Current World Position Towards Renewable Energies

Global energy investments in renewable energy have reached a new record as shown in Figure 2.1. This progress has taken place even as the cost of fossil fuels has fallen. In terms of net investment in new electricity generation capacity, renewable energies have once again surpassed fossil fuels. Global investment in new renewable energy capacity over the current ten-year period, from 2010 to 2020 reached 350 trillion, with more gigawatts of installed solar power capacity than any other generation technology. This decade of investment has quadrupled renewable energy capacity from 414 GW to 1650 GW. As a result, 12.9% of the total world electricity in 2018 was generated by renewable energy sources, avoiding the emission of 2 billion tons of CO_2 into the air [37].

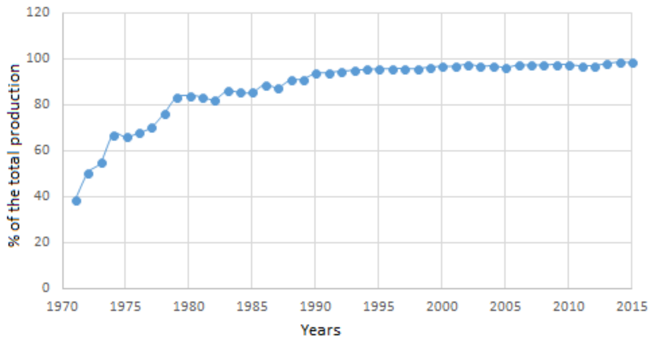


Figure 2.1: Global investment in renewable energy (2007-2017) [1].

Figure 2.2 and Figure 2.3 show a considerable increase in the combined capacity of solar PV and wind systems in 2017 compared to 2007. In 2008 in the Kyoto protocol, the european union (EU) imposes a strategy for member states with targets to be achieved by 2020, called the 20/20/20 strategy. It consists of reducing greenhouse gas emissions by 20%, reduces consumption by 20% and increase the penetration of renewable energies in production to 20% [38], but the Kyoto protocol did not fully achieve its intended objectives. In 2018 the world has experienced a historic peak in greenhouse gas emissions related to fossil fuel-based production, with 33.1 billion tons of CO_2 being released into the atmosphere. As a result, the planet temperature was more than $1°C$ warmer than the 19th century average according to the U.S. space agency (NASA). Therefore, another objective was established by the EU to confront climate change in the framework for action on climate and energy for the period of 2021-2030. Following this increase of 2018, the EU has set three objectives: the reduction of greenhouse gas emissions by at least 40%, increasing the contribution of renewable energy to at least 32% and improving energy efficiency by at least 32.5%.

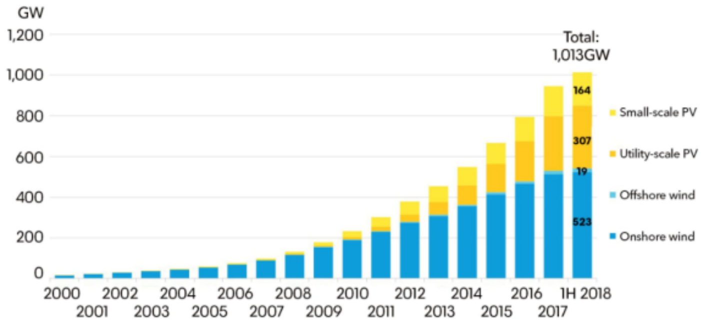
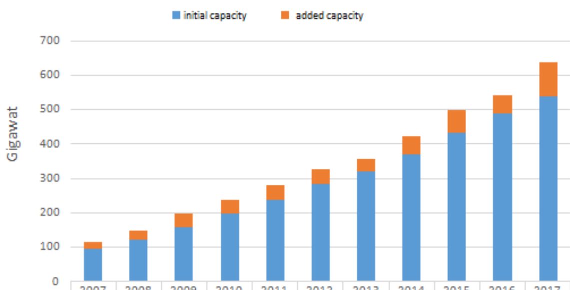


Figure 2.2: Global wind and solar installations, cumulative to June 30,2018 [1].



	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
added capacity	20	27	38	39	41	45	36	52	64	55	98
initial capacity	94	121	159	198	238	283	319	370	433	487	539

Figure 2.3: Total wind energy capacity and annual additions (2007-2017) [1].

2.3 Towards a Smart Grid

The smart grid is an electricity distribution system that uses software technologies to optimize and coordinate the generation, distribution and consumption of electricity in order to improve energy efficiency and system reliability. New technologies will also allow savings to be made by smoothing consumption points through the use of distributed generation, in this way, the power supply to consumers will be more reliable and the cost of electrical energy can be reduced. The deployment of smart grids will also be one of the catalysts for increasing the share of renewables sources in the energy mix [39].
The penetration of generators based on renewable energies in the electricity grids of current distribution is often limited for technical reasons [40]. In an electrical system, generation is at all times linked to the demand for electricity users. Knowing that demand is variable and cannot be controlled except in special cases (e.g. by direct load control, clearing, load shedding,

...), production must adapt instantaneously to demand in order to preserve the stability of the system. Smart grids will make it possible to act on demand through smart meters, able to move certain loads overtime on arrival of a signal tariff. This interaction between producers, distributors and consumers, through a computer network and local aggregators, will allow reaching a better adaptation of consumption to instantaneous production capacities than the use of decentralised storage [41].

Some plants have an irregularity (renewable energy sources), some plants can be started up more quickly, others require a very long start-up or shutdown time (nuclear), thermal and hydroelectric power stations have an operating range for which production is optimal and corresponding to optimal performance, all of these specificities are taken into account by the dispatching during operational planning. However, the increasing inclusion of decentralised generation (most often non-pilotable) will require a change in management of all the networks, from this point of view, the aggregation of distributed generation, the use of energy storage devices and load control is the next step in the evolution of power grids [42]. This means that the intelligence of the network will also be decentralised to the distribution networks and in particular to local levels of observation and management. In the following, a comparison between an intelligent network and a traditional network will show the main differences.

2.3.1 Conventional Electricity Grid

Electricity generation will be provided by big power plants controlled by a dispatching center of the transport network. The operator of the transmission system receives information for consumption from transformer stations and operators of the distribution networks. Decentralised generation is perceived by network operators as a passive load of negative power, it is not controlled and the power generated is estimated uniquely on the basis of forecasts. Once the distributed generation exceeds the power consumption on one branch of the network, this can cause local difficulties at all other levels of the power system [43]. The Figure 2.4 represents the structure of a classical scheme.

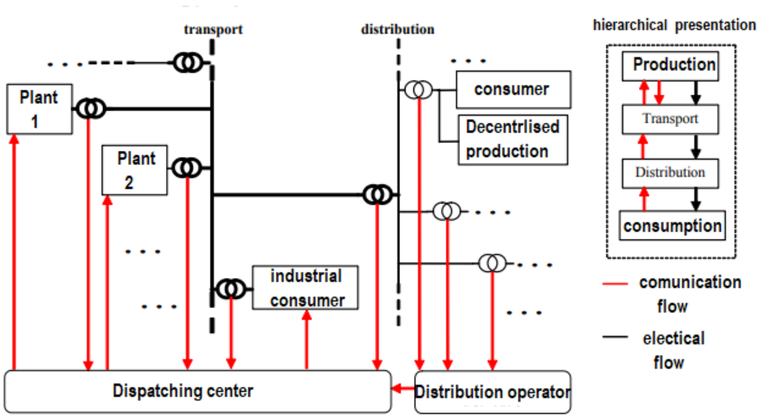


Figure 2.4: Traditional structure of the electrical system [2].

2.3.2 Smart Grid

Distributed generation and consumption are locally controlled by central controllers, each local set of distributed generators, loads and storage devices appears to the distribution system operator as a single entity that can behave either as a consumer or as a producer of electrical energy. In this way, it is easier to forecast consumption and production with a small horizon and thus the information that the other actors in the power system receive would be more which allows optimizing the whole power system [44]. The Figure 2.5 represents the structure of a smartgrid scheme.

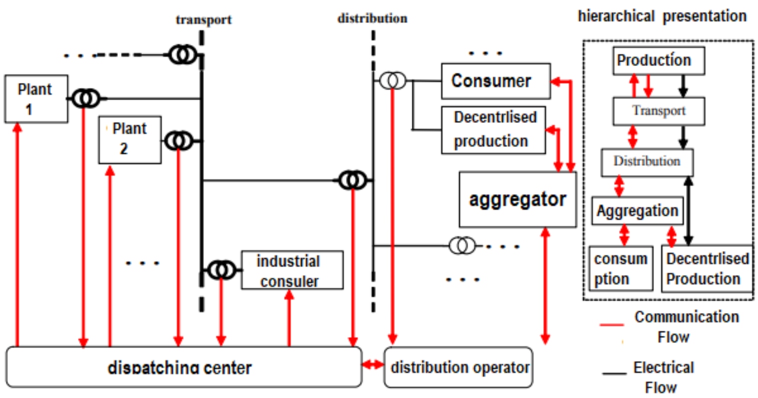


Figure 2.5: Structure of the smart grid [2].

2.4 Multiple Types of Power Supply

The power grid is defined as a set of infrastructures that transport the flow of electrical energy from the production centers to the consumption centers. The classic transmission scheme has been modified several times following the appearance of micro and nano-grid systems, which have led to an optimised infrastructure used.

2.4.1 Interconnected Networks Generation

The electrical model classically used in the generation for industrial countries consists mainly on the implementation of power grids, derived generally from gas, thermal and nuclear power plants, this type of network has a path from generation to consumption as follows: at the output of the generating station, the average voltage is raised to a very high voltage by means of high-voltage transformers in order to be transported through the very high voltage lines, then a high-voltage network takes over to deliver electricity to large industrial customers, and to consumption areas, also the medium and low-voltage networks supply the residential areas and then homes and other small structures respectively, however, an integration of renewable sources is allowed and the interconnection between the different networks of the neighbouring countries is favoured (for example the case of the EU). Interconnections play a major role in Europe's energy strategy for a sustainable electricity grid, allowing greater integration of renewable energies and guaranteeing access to electricity for everyone at all times with the best price [45], interconnections offer the possibility of importing electricity from a neighbouring country in the event of a strain on the national supply, which constitutes an economically efficient solution. They avoid the need to invest in additional capacity to ensure the security of supply and make it possible to mutualise production investments with neighbouring countries [46].

2.4.2 Microgrid Generation

This type of generation consists in creating durable, continuous and sustainable electrical energy to participate in the global energy transition. This solution is scalable and satisfies the energy needs of isolated groups of buildings or even isolated villages with low population density. It is based on the principle of hybridisation by the conception of a small scale network called microgrid [36]. To increase the penetration of renewable energies and solve the problems posed in the conventional electrical scheme such as transmission losses in the transport and distribution networks, the microgrid concept has been introduced to ensure reliable production on a small scale, by making the place of consumption a place of production. The microgrid is defined as a low-voltage distribution network including various distributed generators (micro-turbines, fuel cells, photovoltaic, wind turbines, among others), together with storage devices and controllable loads that can operate interconnected or isolated from the main distribution network, microgrids become a component of smart grids, where a load management system is used to balance generation and consumption. It can effectively optimise and improve the efficiency of energy consumption and provide flexibility, controllability and economic efficiency of power system operation. The reliability and the control of the microgrid are improved under an energy management system, Figure 2.6 illustrates an example of a microgrid system devices.

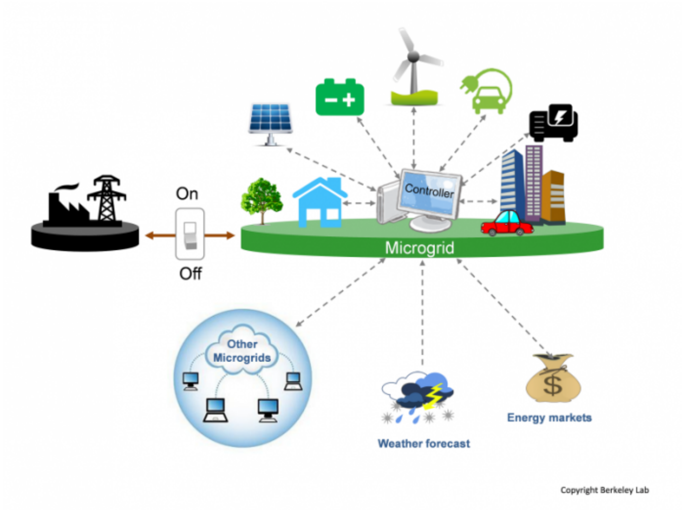


Figure 2.6: A typical microgrid system devices [3].

2.4.3 The Stand-Alone Generation

When the region to be electrified is low-populated and away from the main grid, the solution of off-grid generation is the best solution for the power supply of a house or community of residence. The first challenge is to make an optimal sizing to ensure continuity of supply whatever the weather conditions and demand. The sources of production must be chosen small to be installable and maintainable by a private person, this is why photovoltaic panels, small wind turbines are the most suitable. Besides, it is preferable to place the production sources close to the installation in order to minimize line losses. In this case, storage systems are mandatory to constitute a production reserve and maintain the balance in case of energy lack, the storage system is sized in such a way as to ensure a good autonomy to the installation, and to ensure continuity in the days when there is a lack of production. In some cases, diesel generators or fuel cells can be used to maintain the balance between supply and demand, therefore, the consumer depends on his ability to obtain fuel. This type of generation is also called: Nanogrid generation.

2.4.4 Decentralised Generation

Also known as "dispersed" or "distributed", it is the production of electrical energy using small power plants connected to low-voltage and, more rarely, medium-voltage networks. Distributed generation is based on renewable energy sources, but in some cases, it can also be produced with conventional generators (diesel units and micro gas turbines in cogeneration). This production has increased considerably in recent years due to various factors, the main one being the liberalisation of energy markets in the vast majority of countries [47], however, the independent power producer can sell its electricity on power markets; depending on the country, different systems exist: bilateral contracts, pool system or single buyer. Another factor that contributes to the increase in the use of distributed generators is the development and increasing position of renewable energy on a large scale in the global energy community due to the strong political desire to increase energy independence and reduce greenhouse gas emissions and pollutants. Studies show that distributed generation can benefit all types of households levels and for all actors in the power system [13]:

1. Consumers can lower their electricity bills by producing a part of their energy locally.
2. coordination between decentralised generators and co-management of distribution networks during peak hours can be a major challenge, introduce more flexibility and therefore investment in strengthening small networks.
3. Reduction of losses due to the proximity of generators and consumers.
4. Distributed generation is also beneficial for consumption sites far from the distribution network, whose consumption does not justify the installation of large power generators.
5. With distributed generation devices, the reliability of power supply to the critical loads can be increased.

The main requirement of distributed generation is that production must exceed consumption, but due to the intermittent effect of the renewables sources, this can pose a problem for the stability of the distribution network. Another problem is local overvoltages on the grid and difficulties in predicting the power available at any given time. It is also important to note that dispersed generators inject energy behind protection devices (located in distribution stations), which may, in some scenarios, cause them to spontaneously trigger [39]. The solution to these problems is the clustering of renewable energy based generators, storage systems and small generators dispersed in virtual power plants or microgrids. The implementation of these distributed generators on a microgrid scale will provide generation reserves to satisfy fluctuating demand, which in some cases may be cheaper than in the balancing market.

2.5 Distributed Generators Used in Microgrids

Different energy sources are exploitable in a microgrid, two conditions are required in order to improve their use, the first is the possibility of absorbing the demanded power with easy maintenance of generator, the second is to ensure economic reliability compared to a conventional source used or the main grid connection.

2.5.1 Wind Energy

The first possible source is wind energy. Clean and renewable, it is available in abundant quantities all over the planet. In recent years, wind power has become the main source of electricity from renewable sources, excluding hydropower, with more than $593\,TWh$ produced worldwide in 2019. The transformation of this energy into electricity is done by wind turbines, which can cover a large range of power depending on the needs and the type of generation chosen. For example, offshore wind turbines can be several tens of meters high to generate several MW [48], other types of lower height that do not exceed tens of meters are adapted for domestic use, located close to the places of supply in order to create hundreds to thousands of watts.

2.5.1.1 Wind as an Energy Source

The wind is an inexhaustible resource, free and available everywhere described by the movement of atmospheric air produced by the non-uniform solar radiation on the surface of the earth, the sun heats the earth unevenly, which creates zones of different temperatures and atmospheric pressure all around the globe, from these pressure differences, air movements are born, this latter represents the wind. If a heat evaluation of the globe is made, a surplus of energy at the equator and a deficit at the poles can be observed, which leads to a transfer of heat from the equator to the poles, so the mass of heated air at the equator cools down in the poles. As a consequence, this displacement will give rise to the wind, it is described by the laws of fluid mechanics. The earth receives through the sun a power of $1.74 \times 10^{17}\,W$ only 1 to 2% of this energy is converted into wind energy. However, wind variation in a given site is an important criterion that must be carefully considered when implementing a wind turbine system [49].

2.5.1.2 Wind Characterisation

For the implementation of a wind power system, two criteria are carefully studied: the average wind speed and its regularity. The average wind speed is calculated for a period of 10 minutes, The second factor is the wind distribution, it's an essential criterion because it varies according to height and over time, a stable wind close to its average speed does not have the same effect on wind turbines as an irregular wind that receives peaks and turbulence, this latter is the primary cause of wind turbine damage and tiredness. In the proximity of an obstacle or the surface, the wind loses its power. It is therefore important to take measurements at the height of the blades [50].

Variations in wind speed at any given site are plotted on a graph called "The Weibull Distribution" as shown in Figure 2.7. This graph is constructed from measurements of average wind speed taken every 10 minutes; the values obtained are distributed into different wind speeds, then, the Weibull density probability function curve can be plotted to analyze the majority part of the wind blowing on the site as well as the analysis of the wind character by determining Weibull parameter values k and c, they are important decision parameters for the choice of the wind turbines systems to be installed on the study site [51].

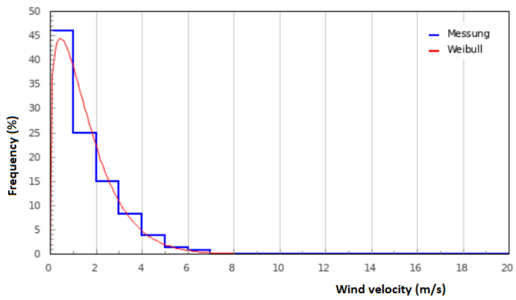


Figure 2.7: Histogram of wind speed variation distribution [4].

The area under the curve is defined by:

$$f(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left(-\frac{v}{c}\right)^{k} \tag{2.1}$$

with :

- v: Is the wind velocity.

- k: Is the Weibull form factor, it indicates the form of the wind distribution and its value is between 1 and 3, as the value is smaller, the wind speed is more variable. When the k value is close to 3, it corresponds to a constantly variation of wind speed, which is required when are looking to open a wind farm site.

- c: Is the Weibull scale factor expressed in (m/s), it is proportional to the average wind speed.

2.5.1.3 Types of Wind Turbines

There are two types of wind turbines, vertical-axis wind turbines and horizontal-axis wind turbines, which are the most common. the horizontal-axis wind turbines are the most widely used at present compared to those with a vertical axis because they are less expensive, besides, they are less exposed to mechanical stress [52], they consist of several blades for generating a driving torque to drive the rotation. The number of blades varies between 1 and 3, the three-blade rotor is the most widely used because it is a compromise between the power coefficient, the cost and rotation speed of the wind sensor [53]. Horizontal-axis turbines are generally placed facing the wind by a mechanism of orientation or by a phenomenon of natural dynamic equilibrium assured by a rudder in the case of a leeward turbine. The Figure 2.8 present onshore three-blade horizontal axis wind turbine.

Figure 2.8: Onshore three-blade horizontal axis wind turbine [5].

The second type concern the vertical axis wind turbines, devised in two types, the first one is the savonius type, characterized by a low efficiency compared to conventional blade wind turbines, it has the advantage of working with all wind directions, the second is darrieus type, they are the most adapted in buildings and their efficiency is relatively low. The vertical axis wind turbines allow eliminating the limits introduced by the size of the blades and their rotation speed [54]. Figure 2.9 present vertical type of wind turbines: Savonius and Darrieus.

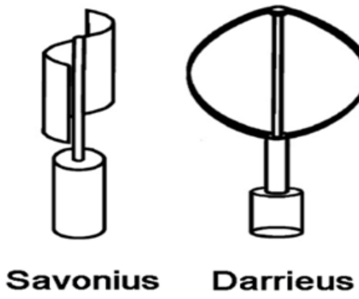


Figure 2.9: Vertical type of wind turbines: Savonius and Darrieus [6].

2.5.2 Solar Energy

Solar energy is the energy served by the irradiation from the sun, directly or diffusely through the atmosphere, considered as one of the solutions to the problems of fossil fuel exhaustion on the planet. The sun sends irradiation to the earth's surface that each year represents about 8400 times the energy consumption of humanity. This corresponds to an instantaneous received power of 1 kilowatt peak per square meter (kWp/m^2) distributed over the entire spectrum from UV to IR. The deserts of our planet receive in 6 hours more energy from the sun than humanity consumes in a year. The solar source is at the origin of three types of energy: photovoltaic solar energy, solar thermal energy and thermodynamic solar energy [7]. Figure 2.10 shows the distribution of the different types of solar-based energy sources.

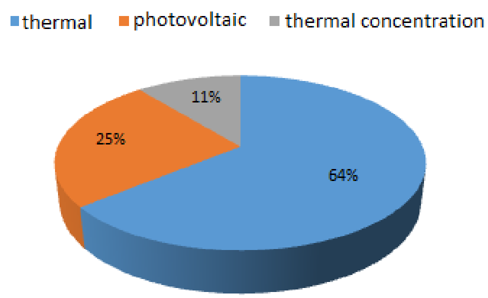


Figure 2.10: The distribution of the different types of energy based on solar energy [7].

2.5.2.1 Photovoltaic Solar Energy

Photovoltaic solar energy is derived from the conversion of sunlight into electricity inside semiconductor materials such as silicon, which are coated with a thin metal layer. These photosensitive materials have the property of releasing their electrons under the influence of external energy, the energy is delivered by photons, which is a fundamental component of light that hit the electrons and release them, as a result, an electric current is created, then this produced electricity is either available in direct form or stored in batteries (decentralised electrical energy) or in electricity injected into the grid, all depending on the type of design and for which the installation is intended. The photovoltaic solar generator is made up of photovoltaic modules themselves composed of photovoltaic cells connected to each other [8]. The performance of a photovoltaic system depends on the orientation of the solar panels and the insolation zones in which they are located

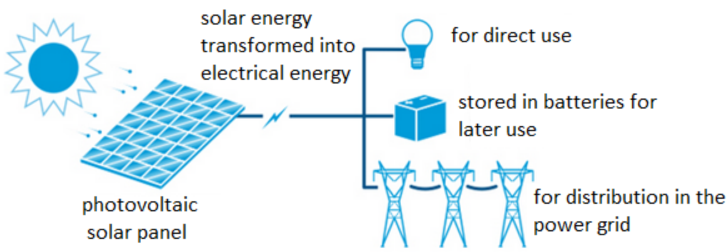


Figure 2.11: Conversion of photovoltaic solar energy into electrical energy [8].

2.5.2.2 The Components of a Photovoltaic System

The components of a photovoltaic system depend on the type of application, either isolated or connected to the electricity grid.
For a stand-alone installation, the main components to ensure a reliable configuration are:

1. Photovoltaic panels
2. DC/DC converter for MPPT operation
3. Charge controller
4. Storage system
5. An inverter for supplying a possible AC load

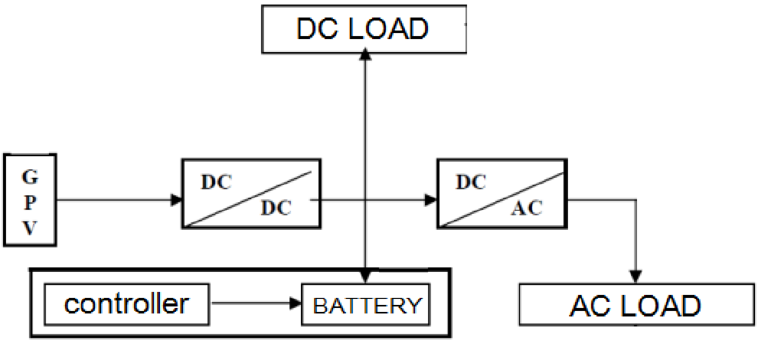


Figure 2.12: Synoptic representation of the structure of a photovoltaic system with storage system [9].

For an installation connected to the main grid, the system components are:

1. Photovoltaic panels
2. DC/DC converter for MPPT operation
3. Charge controller
4. Switching and protection unit for DC power supply
5. Synchroniser
6. DC/AC converter
7. Switching and protection unit for AC power supply

The necessity of the storage system depends on the type of injection into the main grid, if it is an injection of all the energy production, it is not necessary to use storage batteries, instead, if it is an injection of energy surplus, part of it will be stored for domestic use and the rest will be injected into the public grid.

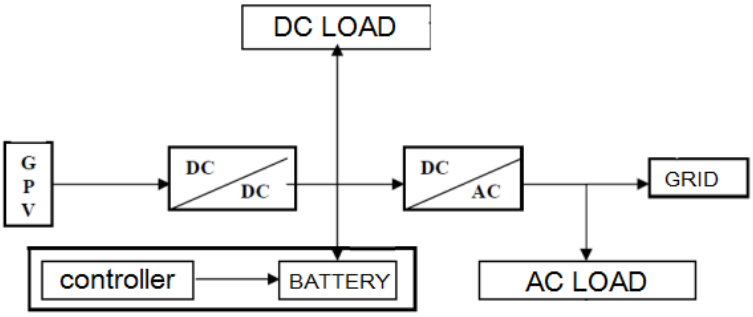


Figure 2.13: Synoptic representation of the structure of a grid-connected photovoltaic system [9].

2.5.3 Micro Turbines

Microgas turbines are small combustion gas turbines with power output ranging from 30 kW to over 200 kW [55]. The installation of micro-turbines is cheaper than building power plants with their distribution lines, especially in regions that have reached the limit of available electrical power, remote areas and countries with low electrification [56]. The microturbine is widely used in microgrids due to its interesting advantages:

- Flexibility in the case of additional loads.
- Ability to improve availability and security of supply.
- Ability to cut peak power demand, allowing savings in the cost of energy and the possibility of reselling the energy produced.
- Ability to compensate for reactive energy and to attenuate harmonics.

Finally, its flexibility to operate in grid-connected or stand-alone mode as well as the possibility of adapting it to an emergency power supply when it is associated with an electrical energy storage devices.

2.5.3.1 Principle of Operation

The microturbine is composed of: an envelope, a compressor, a collector, a combustion chamber, a turbine and an electrical system: permanent magnet synchronous machine, frequency converter, filters, supervision and control. The turbine wheel drives the compressor wheel, the compressor pushes the air into the combustion chamber where natural gas is added for combustion. The compressed and heated air expands through the turbine causing the conversion of thermal energy into mechanical energy on the turbine shaft, which directly connects the compressor and the permanent magnet synchronous machine which allows the production of electrical energy [10]. The operation process is described in the schematic of Figure 2.14.

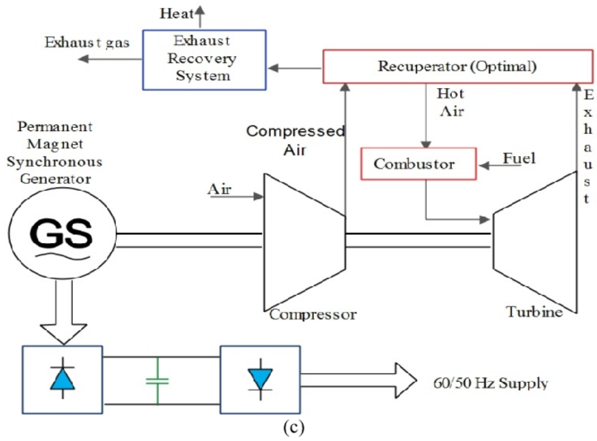


Figure 2.14: Micro-turbine explanation diagram [10].

2.5.4 Storage System

Energy storage consists on preserving a quantity of energy for later use, it is a key to current issues, either to optimize energy resources or to promote access to them, it responds to multiple objectives, this allows for an adjustment between production and consumption i.e. achieving in real time a balance between the quantity of energy generated and the quantity required by consumers. On the other hand, when demand is greater than production, this disequilibrium is re-established by the restitution of the energy present in the storage elements. However, in order to deal with the intermittent nature of renewable energies and their fluctuating production. The existence of an auxiliary system, mainly storage, which will lead to a flexible system is essential [57].

2.5.4.1 Form of Storage of the Energy Produced

The storage of electricity requires several stages of transformation which gives several forms of storage, mainly [58]:

1. **Mechanical Energy**: Stations for energy transfer by pumping (STEP), compressed air storage (CAES) and flywheel.

2. **Electrochemical and Electrostatic Energy**: Battery, capacitors and superconductors.

3. **Thermal or Thermo-mechanical Energy**: Sensible heat, latent heat and energy by sorption.

4. **Chemical Energy**: Hydrogen and methanation.

5. **Electromagnetic Energy**: Coil, superconducting and supercapacitance.

Figure 2.15 shows that the technologies allowing the management of high powers for long periods mainly concern STEP, CAES and heat. Massive energy storage is mainly stationary storage, but some mobile batteries can also store quantities of energy in the order of a few tens of MWh. These batteries are used as energy reserves, unlike UPS (Uninterruptible Power Systems) batteries, which deliver a short pulse in continuous operation (to start an emergency generator, for example).

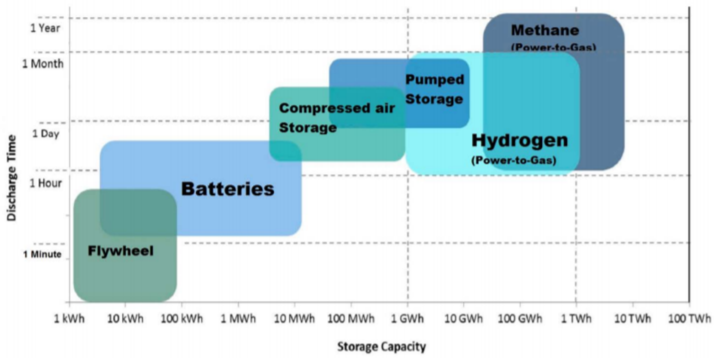


Figure 2.15: The different storage technologies according to their power and discharge time [11].

2.5.4.2 Most Recommended Option for Microgrid System

The storage mode chosen is the electrochemical battery, it constitutes a combination of electroche mical cells that can store electrical energy in chemical form, and then restitute it partially for later, due to the reversibility of the reactions involved. These reactions consist of oxidation and reduction at the electrodes, the current circulating in the form of ions in the electrolyte and in the form of electrons in the circuit connected to the battery. The energy capacity of the battery, which is expressed in watt-hours, depends on the quantity and nature of the chemical elements in the cell. Batteries are often the most expensive components of an electrical conversion system. Therefore, it is important to take care of them through proper use and monitoring. However, good energy management and knowledge of the battery parameters is essential [59, 60].

2.5.4.3 Storage Capacity

Battery capacity is a measure of the charge stored by the battery expressed in Ah, and is determined by the mass of active material contained in the battery. The capacity represents the maximum amount of energy that can be extracted from the battery under certain specified conditions. The energy present in the battery can be described by the energetic capacity as the product between the voltage in volts and the electric capacity in Ah, it is expressed in Wh [12].

2.5.4.4 Depth of Discharge and State of Charge

The life span of batteries is expressed in the number of cycles mainly related to the depth of discharge DOD, this is another way of inducing the state of charge of the battery, if the battery is fully charged the $DOD = 0\%$, if the battery is not fully charged then the depth of discharge is expressed in relation to the amount of energy consumed, if the battery is fully discharged the $DOD = 100\%$, in other words, this is the energy extracted from a fully charged battery. For example, a 100 Ah battery, which discharges by 20 Ah, corresponds to a depth of discharge of 20%. The maximum depth of discharge DOD_{max} is the value of the energy that can be extracted from the battery without damaging the battery. The useful capacity C_u is related to the nominal capacity C_n by the following equation:

$$C_u = C_n \times DOD_{max} \tag{2.2}$$

Another way to determine the charge level of a battery is to determine the state of charge of the battery, also expressed as a percentage. The state of charge is the remaining capacity of the battery estimated by the ratio of the currently available charge quantity Q to the total quantity Q_{tot}. The state of charge SOC is given by the following equation:

$$SOC = \frac{Q}{Q_{tot}} \tag{2.3}$$

Manufacturers often recommend not to go below a certain state of charge (about 30% or 40%) to avoid damage to the battery due to excessive discharge. The minimum state of charge can be expressed by the following equation:

$$SOC_{min} = 100 - DOD_{max} \tag{2.4}$$

A charge and discharge constitute a cycle. In solar energy, a cycle is defined as 24 hours, another way to locate the status of a battery is to indicate the state of charge. The *SOC* is an indication of the charge level of a battery; the indication is given as a percentage.
In the diagram of Figure 2.16, a practical example that shows the state of charge of the batteries for a solar system over a few days, it is remarkable that in this system a cycle appears every 24 hours. The cycle starts when the battery is full, the battery is discharged and then the battery is recharged. This cycle ends when the battery is full again.

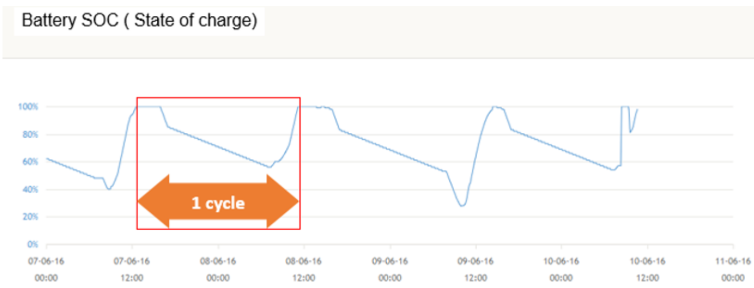


Figure 2.16: Battery cycle depending on state of charge [12].

2.6 Microgrids Based on Hybrid Power Systems

Microgrid electricity production using renewable energy sources offers greater reliability of supply to consumers while respecting the environment. However, the random nature of these sources requires the establishment of rules for the sizing and use of these systems in order to exploit them in the best possible way. Considering their respective seasonal characteristics, the energies (solar and wind) do not compete with each other but on the contrary, they can mutually enhance each other. This is why a microgrid based on hybrid system composed of these two energy sources is often proposed, which consists of the optimal exploitation of the complementarity between them.

2.6.1 Definition of Hybrid Systems

The problem of variable and non-guaranteed power produced by renewable energy sources can be solved by coupling the supply sources and creating a hybrid energy system (HES). The hybrid system is an electrical system comprising more than one energy source, at least one of them is renewable and include storage devices [61]. From a general point of view, the energy system of a given microgrid can be considered as a hybrid system.

2.6.2 Classification of Hybrid Systems

Hybrid systems are classified according to several criteria. The most common are presented as follows:

2.6.2.1 According to Operating Mode

Hybrid systems can be classified into two groups. The first group concerns the hybrid systems working in parallel with the electricity grid, also called grid-connected systems, these systems help to satisfy the load of the country's electrical system. While the second work in isolated mode to satisfy the needs of consumers located in sites that are far from the main grid: mountain huts, islands, isolated villages, etc [17].

2.6.2.2 According to The Structure of the Hybrid System

Three factors can be taken into account in the classification according to the structure of the system. The first factor is the presence or absence of a conventional energy source, this source can be a diesel generator, a micro gas turbine, and/or in some cases power plant. The second possible factor is the presence of storage devices which can ensure the satisfaction of loads during periods of absence of primary resources, storage units can be electrochemical batteries, electrolysers with hydrogen reservoirs, or flywheels. The last factor is related to the type of renewable energy sources used, the system may contain one or a combination of several renewable energy sources, indeed, it is important to take into account the potential of the site before implementing the hybrid system and choose the most appropriate architecture [17].

2.6.2.3 According to The Power Range

Hybrid systems are also classified by their power range in low, medium and high power as indicated in the following Table:

Table 2.1: The classification of the hybrid system by power range [17].

Power of the Hybrid System (kW)	Applications
low ≤ 5	Stand-alone systems
$5 <$ Average ≤ 250	Isolated microgrids
high > 250	Large isolated grids

2.6.3 General Diagram of Hybrid System

The Figure 2.17 shows the general architecture of a hybrid system. An electric bus is common and linked to all the elements that are connected, These elements are grouped and classified according to their electrical function: the generating elements or sources, the load elements and the storage elements.

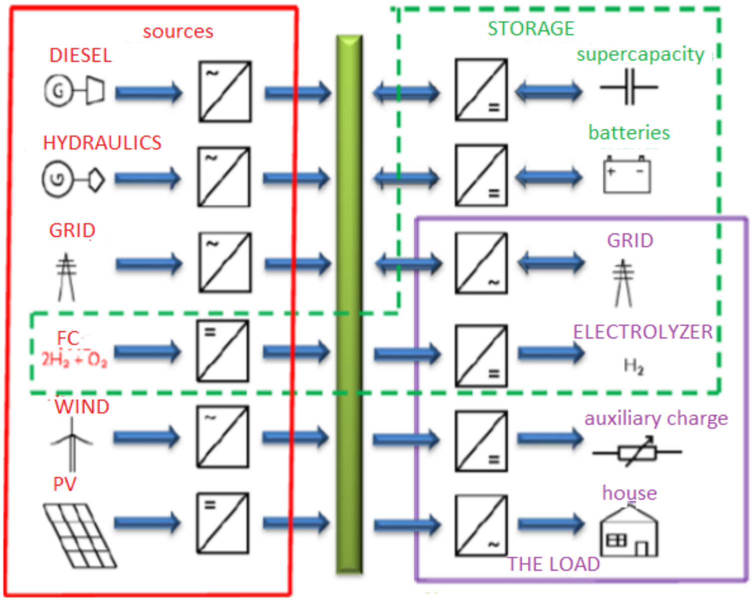


Figure 2.17: Hybrid System Diagram [13].

2.6.4 Advantages of Hybrid Systems

Hybrid systems are designed to provide energy for a large number of communities in isolated areas, particularly in developing countries where connection to the national grid is not economically and technically viable. The advantages of hybrid systems based on renewable energy sources are as follows [17]:

1. Two or more renewable energy sources can be integrated into a system, based on their local potential.
2. There are no greenhouse gas emissions produced by the renewable energies of a hybrid system.
3. Modular, easy to install and in the majority of cases, does not need to be designed for domestic use.

4. Hybrid systems are cheaper than large systems and less complex than conventional systems.

5. The hybrid system is best adapted for off-grid electrification.

6. The source for the hybrid system is abundant, free and inexhaustible so the electrical energy produced by these systems is independent of the price of fuel.

2.7 Configuration of the Microgrid System

For microgrid systems there are three principal possible configurations, DC bus architecture, AC bus architecture and AC/DC bus architecture.

2.7.1 DC Microgrid

This technology was born from the need to couple AC consumers with DC generators, in addition, to charge the battery on the DC side. These configurations plants serve to supply remote consumers. In this case, the power supplied by each source is centralised on a DC bus. Therefore, AC production systems use rectifiers. The control system is relatively simple, which is a great advantage for this architecture, but it has low efficiency due to batteries and losses in the converter [62]. The Figure 2.18 represents the synoptic diagram for the architecture of a DC hybrid system [14].

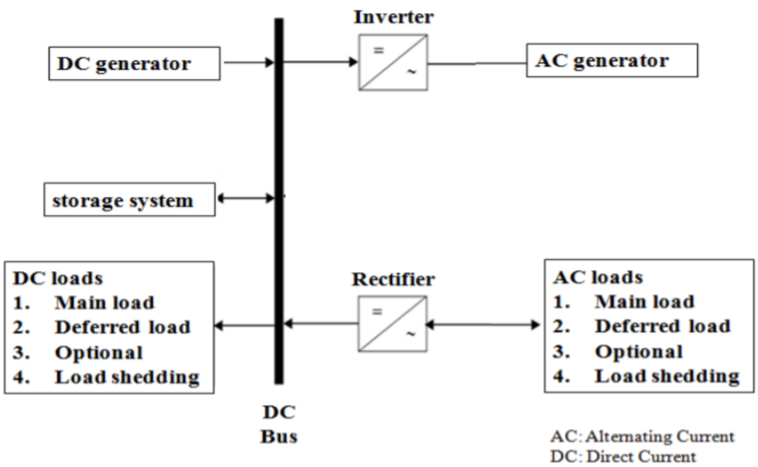


Figure 2.18: Synoptic diagram of a DC microgrid [14].

2.7.2 AC microgrid

A coupling of all the consumers and all the generators on the AC side makes it possible to create flexibles systems composed of modular components. Depending on the application and the available energy sources, it is possible to integrate differentes energy sources, both renewable and conventional. In addition, the system can be easily expanded by adding components or electrical generators to meet increasing energy needs [62]. The decoupling of the different production sources will make it possible to operate independently of each production source, also the possibility of increasing and reducing the voltage with a simple passive device (transformer) is an important advantage for this type of architecture. The efficiency of the whole system is low, because of a certain part of energy lost due to batteries and losses in the converters. The connection of all sources on an AC bus complicates the control system. From an implementation point of view, this system is relatively complicated due to the parallel operation (synchronization problem). The Figure 2.19 represents the synoptic diagram for the architecture of an AC hybrid system [14].

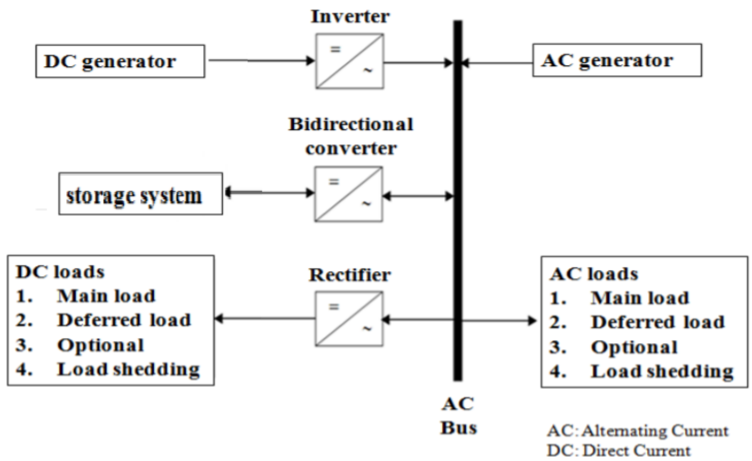


Figure 2.19: Synoptic diagram of a AC microgrid [14].

2.7.3 DC/AC Microgrid

In the two-bus configuration, renewable energy sources can supply one part of the load with AC and the other part with DC. Both buses must be connected by a bi-directional converter. The generator and the inverter can operate independently or in parallel. When the load is low, either can generate the necessary energy. However, both sources can operate in parallel during peak loads; the nominal power of the generator and inverter can be reduced without affecting the capacity of the system to supply peak loads. but the realisation of this system is relatively complicated because of the parallel operation of the inverter which must be able to operate in autonomous and non-autonomous modes by synchronizing the input voltages with the output voltages of the generator [62]. The architecture of DC/AC hybrid system is shown in the Figure 2.20 [14].

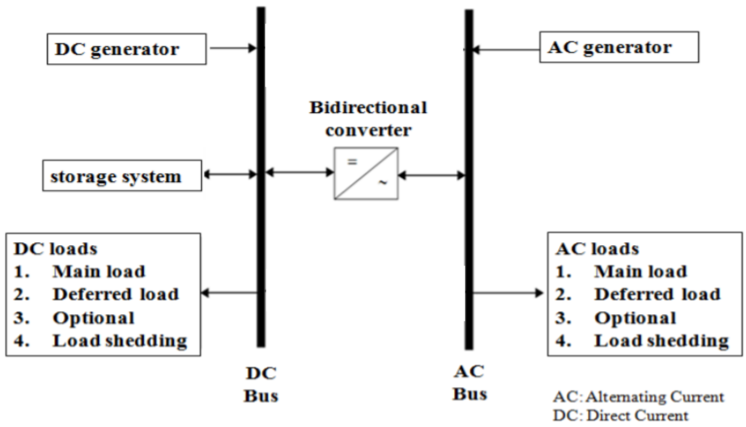


Figure 2.20: Synoptic diagram of a DC/AC microgrid [14].

Chapter 3

Energy Management and Optimization Approaches

3.1 Introduction

The association of distributed generators (DG), energy storage systems (ESS) and controllable loads close to the energy consumers gave place to a small scale network called microgrid. The stochastic behavior of renewable energy sources, as well as the demand variation, can lead in some cases to problems related to the reliability of the microgrid system. On the other hand, the market-price of electricity from mainly non-renewable sources becomes a concern for a simple consumer due to its high costs. So, to manage the microgrid in an optimal way, economically and environmentally, a smart energy management system is installed to allocate the optimal power set-points for the microgrid generators. The work proposed in this project consists of developing an energy management system (EMS) to ensure the optimal management of the microgrid. The management is based on a control monitor that ensures optimal control every hour by extracting from each energy sources the optimal power points taking into account the minimisation of the cost and emissions, However, the development of the management algorithm will not be possible without the use of optimizations approaches certainly necessary for the optimal control of the microgrid. In this chapter, the notion of energy management in microgrids is defined by making a description of the EMS works already proposed in this research area, on the other hand, the notion of battery control and load control are introduced. The second part of this chapter will explain the optimization approaches used in the energy management systems proposed for this thesis.

3.2 Energy Management Problem in Microgrids

Aggregation of renewable energy sources at the local level as a hybrid energy system (SHE) gives rise to the microgrid. However, achieving a reliable balance between supply and demand when using a large renewable energy system can be difficult, therefore an energy management strategy is necessary in this case. This section treats the notion of energy management in the different components of the microgrid.

3.2.1 The Principle of Energy Management

The definition of energy management is very broad, it is used in different fields. In some cases, this expression of energy control replaces that of energy management. It is also a large concept which refers to all the techniques that aim to reduce consumption in a building, or even in a country, it has a wide scope and that is why the two concepts of **(energy management)** and **(energy control)** are often confused [16].

The term control includes voltage and frequency regulation. More precisely, local control of the protection level including primary voltage and frequency regulation, on the other hand, in electrical engineering, the term energy management is not framed by a precise definition but it differs according to the field of application, there are three fields of application: production and storage; transport and distribution; and consumption. For simplification, Figure 3.1 presents the different classes of energy management in an electrical system.

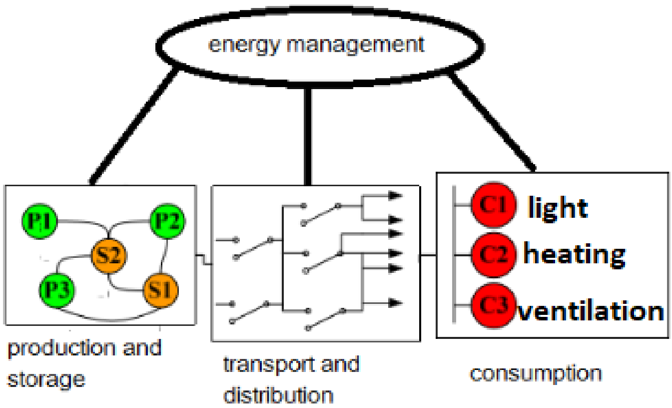


Figure 3.1: Application fields of energy management in electrical engineering [15].

This classification is based on the three main areas traditionally studied in electricity, note however that storage is usually considered as a separate area, it is grouped with the field of production because in the case of electricity production in a decentralized system by a hybrid

system, production and storage are linked and energy management is involved in these two areas, in this part, the energy management must allow for example to produce electrical energy reliably while respecting the constraints of the elements of production or storage [63].
For the management in the transport and distribution part, mainly designs the optimal routing of the energy, for example, in the case of a meshed network, this makes it possible to ensure the reliability and distribution of energy transit over the various lines available, so as to avoid overloading particular lines and to reduce line losses. Finally, the main objective of energy management on the consumption side is to reduce or defer users' consumption while minimizing the impact on people's comfort. This is the level at which the smart meters proposed by the big companies are used. Depending on the field of application, energy management aims to satisfy very different objectives [64].

3.2.2 Energy Management of Production in Microgrids

In order to control each element that constitutes the microgrids, an energy flow management system must be set up on a simple system composed of a PV generator and a battery, the simplest energy system must allow for example to extract the maximum power from the solar panels also to protect the battery in case of overload, if necessary, other more advanced rules can be used in particular to ensure minimum cycling of the battery. In general, good management must ensure that the load is permanently supplied. Other objectives may be set at a later stage, e.g. the fault tolerance of a component, maximising efficiency, the reduction of the cost operation, but the energy management will not be able to go beyond the physical limits of the elements, if the sizing of the system has been incorrectly done, even efficient energy management will not improve it [16, 65].
For a good explanation of energy management in microgrid systems, a fluidic analogy is known to make the concept easier to understand, the connection between the different elements by a bus can be imagined as a water reservoir that is supplied with water from different sources, some of them predictable and controllable and others not, such as intermittent sources. This tank will be emptied by the different loads of the consumers. It is also assumed that the storage systems are present and can, if required, pump the water or release part of it, the aim being to maintain a constant water level in the tank in order to ensure sufficient pressure to the users, by analogy this means maintaining a constant voltage in the bus in order to ensure a permanent power supply to the load, so that the energy management system can control the storage systems and distributed generators to ensure the reliability of the installation on the one hand, and an optimized operating cost on the other hand through the installed management systems. This vision has been adopted in the city of Vienna for the management of the power

grid on a larger scale, as shown in Figure 3.2.

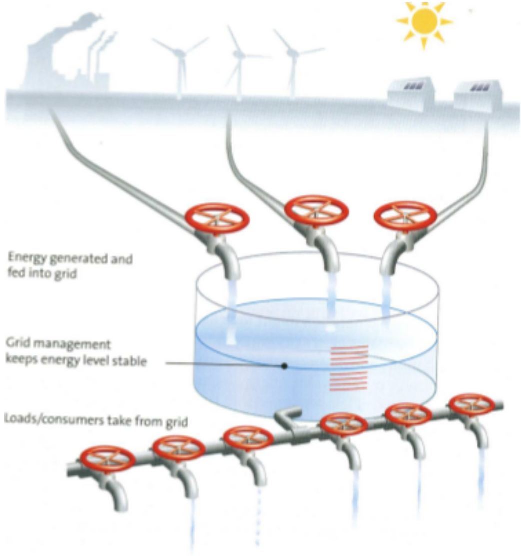


Figure 3.2: Fluidic analogy of energy management [16].

3.2.3 Storage Management in Microgrids

In order to obtain optimal energy and maximum efficiency from the microgrid, it is necessary to set up an energy transfer management system, which allows the optimization of each system component operation while preserving the norms of their operating range [17]. However, two important storage management strategies should be explained. The first one is ***the short-term storage strategy*** also called "Peak Shaving Strategy", allows to filter out fluctuations in renewable energies and load. When there is a consumption peak, the battery intervenes and covers this need, this strategy contributes to reducing the start/stop cycles of diesel generators and therefore preserves fuel consumption. The other strategy is ***long-term storage*** also called "Cycle Charge Strategy", used to supply the load for a longer period of time, especially where the potential is insufficient. For example, the diesel generator is switched off until the state of charge of the batteries reaches the minimum level. Once this threshold is reached, the diesel generator is restarted and remains in operation until the batteries are recharged and reach the maximum level. This strategy also contributes to the reduction of start/stop cycles of diesel generators and thus preserves fuel consumption. However, this strategy quickly depletes the charge/discharge life cycle of the batteries.

3.2.4 Transport and Distribution in Microgrids

The use of distributed generators and storage systems at the local level in a microgrid system will reduce the investment in transmission lines and therefore bring an economic gain, on the other hand, such type of distribution will reduce transmission losses at the line level. However, transmission and distribution lines in microgrids do not require appropriate management such as production and consumption parts.

3.2.5 Load Management in Microgrids

The load management strategy is based on the principle of using loads to vary energy demand. In this way, loads are connected and disconnected in order of priority. Figure 3.3 shows a load priority example. This strategy can also be short or long term.

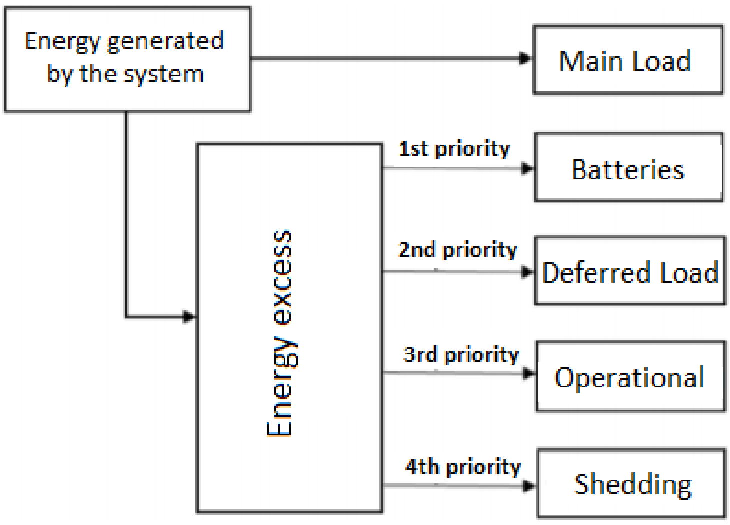


Figure 3.3: Diagram of load priority [17].

The short-term load control strategy connects and disconnects system loads taking into account the peaks of certain fixed bus frequency limits. The loads are therefore connected in a progressive manner, according to the frequency variations. The role of the load shedding is to help for the regulation of the frequency of the network in cases of excess energy, by varying its power according to the frequency deviation [66]. While, ***long-term load control strategy*** ensures energy balance for long periods of time. Loads should only be connected when their priority regime is high, for example, shiftable and optional loads usually have a reduced priority for part of the day [67].

3.3 Classical Approach For Energy Management in Microgrids

When an energy management system is designed, the system is generally considered as a set, first of all, it should be consider that this set is composed of different elements that often have very different characteristics and constraints, so it is important to take into account the constraints of each element and the physical limit of operation for each one. As a result, complexity arises when the number of elements and constraints that make up the system increase. In practice, the classic approach of energy management in microgrids is carried out by a central controller in which a program is developed according to a supervisory approach. The realisation of the program is based on a long "If ... else if ....then" control structure, which gives rules for example if the battery is empty then charge it, In our case, this classical vision will depend on the state of charge of the battery, which is always a primordial condition, and on the power available in the other components of the microgrid system, i.e. the maximum power that can be delivered by each one of them. The unit prices represent a suitable condition for the batteries to be charged when the price of electricity is low. The total energy price of the microgrid and emission rate are then optimised by means of optimization algorithms that will be detailed in the rest of this chapter, this will allow a good management of the power flow, i.e. ensuring system reliability and balance between consumption and production, also having the lowest energy billing price for microgrid consumers, this classical approach is very popular in the field of energy management; of course, if it is well designed, it ensures a constant power supply to the load, as mentioned above, always within the physical limits of the different components, but this approach requires the designer of the energy management system to be exhaustive in the testing of the control structures, if an event occurs that is not taken into account by the system, it could be dangerous for the proper functioning of the configuration, however, the management algorithm must take into account all the scenarios that may occur during the operation of the system [16].

3.4 Optimization Problem

An optimization problem is principally defined by one or several objective function(s) to be optimized in a search space including a set of solutions or configurations made up of different values taken by the decision variables limited by a set of constraints.

The variables of the problem can be of various nature (real, integer, boolean, etc.) and express qualitative or quantitative data. The objective function represents the goal of the decision maker. The constraint set defines conditions on the search space that the variables must satisfy. These constraints are often inequality or equality constraints and generally allow limiting the research region (feasible solutions). The optimal solution to the problem is to find the point or set of points in the search space where the objective function has the extreme value (minimum or maximum). The result is called the optimal or optimum value [21].

3.5 The Uni-objective Optimization

When only one objective (criterion) is given, the optimization problem is uni-objective. In this case, the optimal solution is clearly defined, it is the one that has the optimal value (minimum, maximum). Formally, solving an optimization problem lies in finding an optimal point noted by (S^*) of the set of potential solutions to the problem noted by (W) that optimizes (minimizes or maximizes) the value of the objective function ($f(x)$) while respecting the constraints under study.

$$\begin{aligned} \min_{x} \quad & f(x) \\ s.t. \quad & g_i(x) = 0, \quad i \in I \\ & h_j(x) \leq 0, \quad j \in D \end{aligned} \tag{3.1}$$

In most optimization problems, restrictions are imposed by the characteristics of the problem. These restrictions must be satisfied in order to consider an acceptable solution. This set of restrictions, called constraints, describes the dependencies between the decision variables and the problem parameters. These constraints c_j are usually formulated by a set of inequalities or equalities of the form [68]:

$$C_j(x_1, x_2, ..., x_n) \leq 0 \tag{3.2}$$

According to the character of the objective function as well as constraints, two types of optimization problems can be defined: linear and non-linear optimization.

3.6 Linear Programming

Linear programming represents optimization problems whose objective function and constraints are of linear form. it represents the core of optimization, solving a problem of this nature is the easiest to solve. Many problems encountered in engineering have a linear character which makes it an efficient solving tool, an important part of the decision problems that managers encounter

in practice are undoubtedly linear optimization problems or linear programs, in mathematics, many real problems of operations research can be expressed as an LP problem. For this reason, a large number of algorithms for solving other optimization problems are based on the solution of linear problems [69].
According to William baumaul, linear programming is a mathematical technique for optimizing (maximizing or minimizing) a linear objective function under constraints in the form of linear inequalities. It aims at selecting among different actions the one that will most likely achieve the desired objective [70].
Robert dorfman and Paul Samuelson add that linear programming is a method of determining the best course of action to achieve given objectives in a situation of limited resources. It is therefore a method of solving an economic problem, either in the context of a global economy, in the public sector, or in a particular enterprise [71].
Linear programming problems are written as follows:
$\exists A \in R^{m*n}$, $b \in R^m$ known by $m \leq n$, and $C = (c_1, .., c_n)^T$ getting the vector $X = (x_1, .., x_n)^T$ such that [72] :

$$\begin{aligned} \min_{x} \quad & f(x) = CX = \sum_{i=1}^{n} c_i x_i \\ s.t. \quad & Ax = b \\ & x \geq 0 \end{aligned} \tag{3.3}$$

With f representing the objective function, $Ax = b$ and $x \geq 0$ are the constraints, the set of $x \in R^n$ such that $Ax = b$ is an affine variety whose intersection with the set of $x \leq 0$ forms a convex set, often noted U, called the feasible region, each of the points of the feasible region characterizes a feasible solution among which at least one minimizes the objective function: this is the optimal solution, located at one of the vertices of the feasible region U, obtained by using the simplex algorithm [73, 74].
The modeling of a linear optimization problem is devised in three steps:

1. The determination of decision variables: the decision variables are also called real problem variables.

2. Constraints can be assimilated to an obstacle, such as technical, scientific, economic, and law of nature limitations.

3. The objective or economic function, is a function that allows to determine the optimum (maximum profit) or (minimum cost), the goal of the optimization problem is to maximize or minimize this function to the optimum, by different methods such as the graphical

method or simplex method.

In most real problems, there are more than two variables to be determined. An algebraic procedure for solving linear programs with more than two variables is ***simplex method***. An application of this procedure has been used to solve programs with a little more than a few thousand variables. The standard formatting consists of introducing additional variables (one for each constraint) in order to rewrite the inequalities ($\leq$) as equalities. Each of these variables represents the number of unused resources. They are called gap variables. The simplex algorithm is an iterative process that progresses in an evolutionary direction: it moves from a basic feasible non-optimal solution to another solution with a better target value. In this way, one avoids going through all the feasible base solutions, the number of which is usually prohibitive. To check the non-optimality of a solution, a simple test will be performed. Moreover, thanks to the simplex algorithm, one will be able to detect, if necessary, that the optimum is infinite [75]. For our case, the simplex method is more adapted to our problem because of the linear character of the problem and the type of constraints. The Figure 3.4 represents the flowchart for solving linear problems with simplex method.

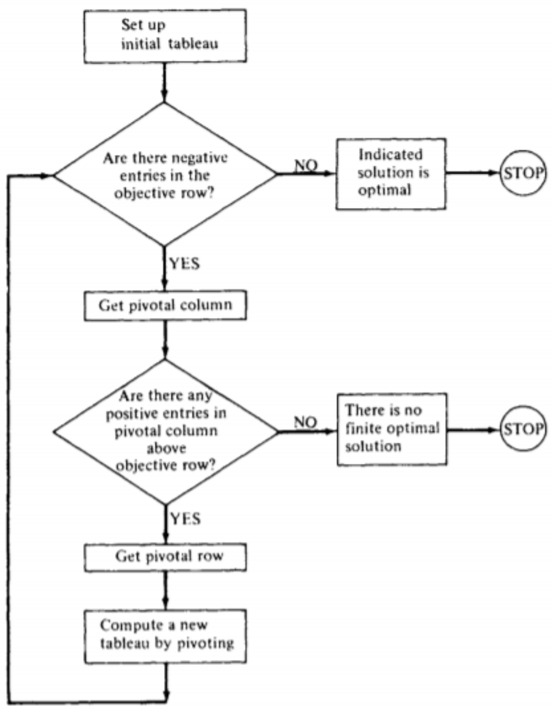


Figure 3.4: LP resolution flowchart with simplex method [18].

The literature has evoked other approaches to solve linear optimization problems. Among them, in [76] a graphical method has been proposed, in [77] authors has used the Least Cost Method to solve the transportation problems.

3.7 Nonlinear Optimization

The nonlinear optimization also called nonlinear programming (NLP) deals mainly with optimization problems that have a nonlinear objective function or/and constraints, provided that the functions that define the problem can be differential several times for the establishment of theoretical tools such as the optimality conditions. In order to solve this type of problem two main approaches are adopted, the first is based on deterministic methods that treats a specific type of problem with conditions that need to be verified, and the other is a solution to special problems based on random nature, known as stochastic methods. In the rest of the chapter the two approaches are introduced and explained [78].

3.7.1 Deterministic Methods

As their name suggests, for a given problem and for a given starting point, these methods always have the same procedure. This branch can be divided into two sub-families on which the most usual is the gradient method.
The exploration of the optimum is directed using calculations based on the partial derivatives of the objective function, allowing a rapid orientation in the direction of the nearest optimum. Several techniques are illustrated in the literature, including the steepest descent method [79], the Newton or quasi-Newton methods (BFGS or DFP) [80, 81] and the Levenberg-Marquardt methods [82]. In spite of the fast convergence, the disadvantage of the gradient methods lies mainly in the convergence trap in some local convergences, at the same time, the gradient methods are applicable to continuous problems, therefore they don't allow to take into accounts directly possible discrete parameters such as the number of photovoltaic panels or the number of wind turbines.

3.7.2 Meta-heuristic Methods

The use of exact methods is not always possible for a given problem because of the objective function complexity, or the number of solutions, or computation time, among others. To deal with these obstacles, mathematicians have developed approximative methods, called Meta-heuristics. The term *heuristic* derives from the ancient greek "heuristic" and signified find. It qualified all that is used for discovery and exploitation [83]. These methods only use the values of the objective function. They explore the space of the solutions by successive tests by looking for the most favorable directions. They are based on a random prospection of the solution space using probabilistic transition rules. Thus, for distinct optimizations with the same starting configurations, the path to the optimum can be different. Among the stochastic algorithms commonly used for energy management are genetic algorithm (GA) and particle swarm optimization (PSO) that is chosen in this study case in order to compare it with a linear programming algorithm (LP) based on simplex method [24].

3.8 Particle Swarm Optimization

The Particle Swarm Optimization (PSO) method is inspired by the dynamics of animals moving in compact groups e.g. swarms of bees, grouped flights of birds, movement of fish groups, the PSO depends on a population of simple agents called particles, each particle is considered as a potential solution to the problem. And each particle has Position (position vector), Velocity (velocity vector) and memory allowing it to remember its performance (in position and in value) and the best performance achieved by the adjacent particles (informant), each particle has a group of informants, historically called its neighborhood.
The particles communicate with each other throughout the search space in order to build a solution to the problem posed and by taking advantage of their collective experience. In the beginning, the particles do not know the location of the minimum, so they have to fly over the whole search space, the search mechanism is based on two principles:

1. **The law of communication**: it is to inform the measure elaborated by each particle to the other agent present in the swarm.
2. **The law of learning** : when the particles exchange their value they can cooperate and learn that the location of the other party is better and therefore find the best value of the whole swarm called global minimum.

Based on these two principles, the solution of optimization problems can be achieved by using the intelligence of the swarm [84].
Each particle is a candidate to solve the optimization problem, the whole of the agents constitutes the swarm, the search space is the space of all possible solutions of the optimizat ion problem. In the search space, the particle i of the swarm is modelled by its position vector with the dimension of the swarm n : $X_i(t) = \{x_1(t), x_2(t), ..., x_n(t)\}$ and velocity vector $V_i(t) = \{v_1(t), v_2(t), ..., v_n(t)\}$ [19, 84].
This particle i is not alone, but it is a member of swarm, the particles interconnect and learn from each other by the principle of communication and learning with respecting the optimization

constraints, in addition to the position and the velocity, each one of the particles has a memory of its best position or experience, it is said personnel best $P_i(t)$, there is also the best experience of all the swarm noted $g(t)$, it belong to all particles which are in the swarm. [19, 84]. The mathematical model that describe the mechanism of PSO algorithm can be expressed as follow:

$$\begin{cases} X_i(t+1) &= X_i(t) + V_i(t+1) \\ V_i(t+1) &= C_0 V_i(t) + C_1 r_1 [P_i(t) - X_i(t)] + C_2 r_2 [g(t) - X_i(t)] \end{cases} \tag{3.4}$$

where C_0, C_1 and C_2 represent the positive constant of velocity weighting, acceleration weighting of the cognitive component, acceleration weighting of the social component, respectively. while r_1 and r_2 are random values in the range $(0, 1)$ to bring a stochastic character to the algorithm. The movement of the particle is influenced by the following three components as shown in Figure 3.5 [84]:

- **Inertia component**: the particle has a tendency to follow its current direction of movement.
- **The cognitive component**: the particle has a tendency to move to the best site through which it has already passed.
- **Social component** : the particle tends to follow the direction of the best value reached by the whole swarm.

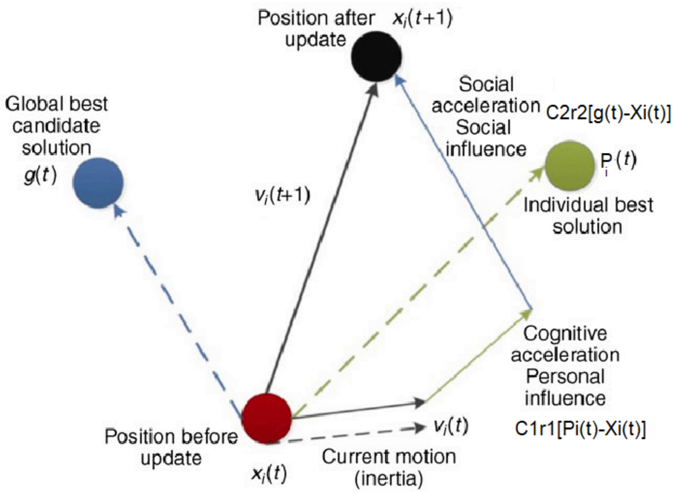


Figure 3.5: PSO search mechanism in multidimensional search space [19].

The two values P_i and g, are updated at each iteration until the global minimum is reached, the best personal position, $P_i(t)$, associated to the particle i is the best position the particle has visited since the beginning of evolution $P_i(t) = \min\{X_i(1), ..., X_i(t)\}$. The best global position at the moment t, is defined as $g(t) = \min_i P_i(t)$ [84]. Figure 3.6 represents an explicative flowchart of the PSO algorithm:

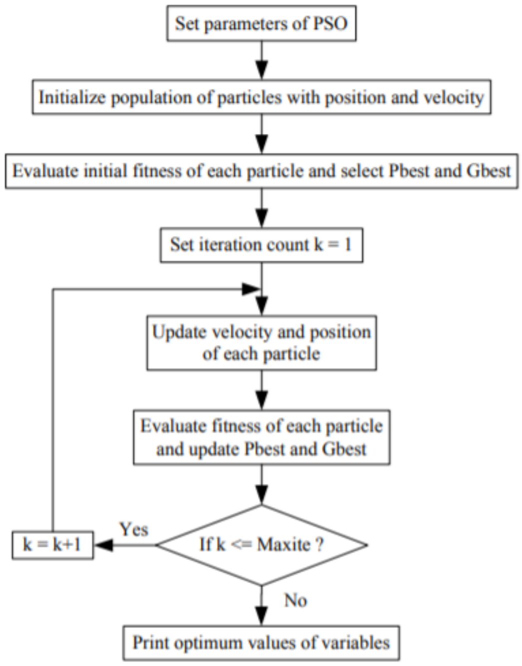


Figure 3.6: Flowchart of PSO algorithm [19].

3.9 Genetic Algorithm

Genetic Algorithm (GA) is a metaheuristic based on a population of potential solutions. Its mode of operation is based on the biological principles of natural selection which coordinate the survival of the samples that are best adapted to their environment [85]. The GA starts with a set of solutions randomly initialized in space. The individuals here are represented by their design variables, they are named as chromosomes. The chromosomes of the initial population are used to produce a new population, going through the different genetic operators, mainly: crossover, mutation and selection. This is motivated by the hope of making a new population better than the previous one [86, 87].

The crossover acts on the two-parent chromosomes to produce two other chromosomes, hoping that the two new chromosomes will be better than the previous ones, this is achieved if the good genes of the latter are the ones that are combined. Figure 3.7 summarises the crossover procedure, in this case, it is a unitary crossover [88].

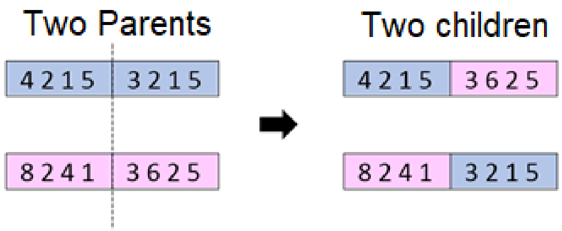


Figure 3.7: Crossover process.

The mutation is a genetic operator that enables new genetic characteristics to be offered to the chromosome directly by mutating one or more of its genes as shown in Figure 3.8. It is generally used after the crossover [88].

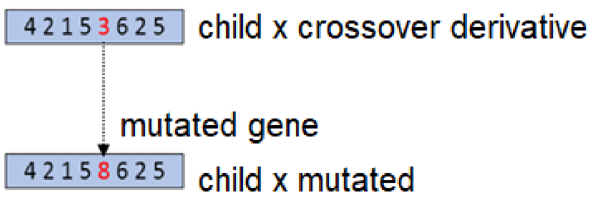


Figure 3.8: Mutation process.

Figure 3.9 below represents the flowchart of evolution of the genetic algorithm.

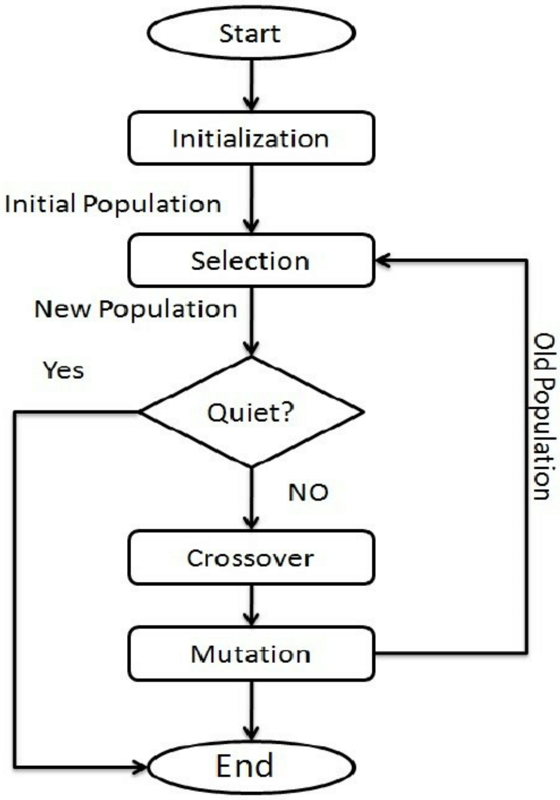


Figure 3.9: Flowchart of the genetic algorithm [20].

The best individual of the last population it is the proposed solution. The algorithm can be stopped when the population is no longer evolving. This is described by a weak variation of the objective function during several generations.

3.10 The Multi-Objective Optimization

Many optimization problems involve the optimization of different objectives simultaneous, often conflicting. This is case of our problem, aims to optimize, simultaneous, two criteria: cost and gas emissions. In fact, for a problem with two contradictory objectives, the optimal solution is a set of points corresponding to the best possible compromise. In this case of two objectives to be optimized, any improvement of one of the objectives is due to the determinants of the other, so the optimal solution or close to the optimum will be the compromise between the two [89]. The multi-objective problem has the particularity of being much more difficult to deal with than the uni-objective because: the difficulty lies in the absence of order relationship between the solutions. When there is a set of solutions, one may be better than the other on certain objective. There is not a single solution but rather a set of solutions called Pareto optimal set

that are a trade-off between the different objectives to be optimized.
In order to identify the best compromises, an order relationship is defined between these elements which is the dominance relationship in the sense of Pareto, and the set of the best compromises is called the Pareto front. The area of compromise or the set of effective solutions constitutes a balance in the sense that no improvement can be made on one objective without degradation of at least another objective [21].

3.10.1 Mathematical Definition of a Multi-Objective Problem

Multi-objective optimization problem consists in searching for the best solutions that minimize a number m of functions, called objective functions, $f_{mj}(x)$ with $j \in M = \{1, ..., m\}$, with respect to a vector x, which is the vector of n parameters: $x = (x_1, .., x_n)^T$ by satisfying the constraints that define the set Ω [90]:

$$\begin{aligned} \min_x \quad & F(x) = (f_1(x), f_2(x), f_2(x), ..., f_m(x))^T \\ s.t \quad & x \in \Omega \subseteq R^n \end{aligned} \tag{3.5}$$

where, m is the number of objectives functions ($m \geq 2$), x is the set of feasible solutions.
The concept of Pareto dominance is crucial to compare any two points in the feasible region; a solution x is said to dominate another solution y (denoted by $x \leq y$) if and only if x is partially less than y on the set Ω, i.e, $\forall i \in \{1, ..., m\}$ [91]:

$$x \preceq y \iff f_i(x) \leq f_i(y) \tag{3.6}$$

3.10.2 Solving Multi-objective Problems

Multi-objective problem solving falls under two quite different disciplines, indeed solving a multi-objective problem can be divided into two phases [21]:

1. **The search for the best compromise solutions** : This is the multi-objective optimiza tion phase.

2. **The choice of the solution to be retained** : This is the task of the decision-maker who, from among the set of compromise solutions, must extract the one(s) it will use. It is a multi-objective decision and it calls for decision theory.

Multi-objective problems have the particularity of being much more difficult to deal with than their uni-objective equivalent. The optimization results of a multi-objective problem is a set of solutions, the concept of the optimal solution becomes less relevant in that case. The optimal or good quality solution is no longer a single solution but a set of solutions compromised between the different objectives to be optimized.

3.10.3 Pareto Optimality

In the 19th Century, Vilfredo Pareto, an Italian mathematician, formulated the following concept: in a multi-objective problem, there is such a balance that one cannot improve one objective without deteriorating at least one of the other objectives. Pareto approaches directly use the notion of dominance in the selection of the generated solutions. The main advantage of these approaches is the simultaneous optimization of contradictory objectives. To identify these best compromises that define an orderly relationship between these elements, the most famous and most used is the dominance relationship in the Pareto sense. The set of the best compromises is called the Pareto front, the compromised surface, or the set of effective solutions. The Pareto front is the set of compromise solutions. In the following Figure, points A and B are two points of the Pareto front: A does not dominate B, B does not dominate A, but both dominate point C. The goal of multi-objective optimization is to determine the Pareto front for a given problem [21].

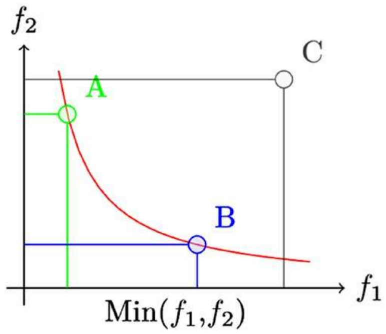


Figure 3.10: Pareto front [21].

3.11 Pareto Search Algorithm

In the multi-objective part presented in this thesis, Pareto Search Algorithm has been used as an optimization approach in the energy management system. in the following, an overview of this method is presented.

Pareto Search Algorithm is a direct multiple search algorithm, uses pattern search on a set of points to search iteratively for non-dominated points [92]. It inspired by the search/poll paradigm of direct-search methods of directional type and uses the concept of Pareto dominance to maintain a list of non dominated points by satisfying all bounds and linear/non-linear constraints at each iteration [93].

The pattern search attempt to find the best match i.e, the solution that has the lowest error value in the multidimensional analysis space of possibilities. The Pareto Search Algorithm uses several intermediate quantities and tolerance in its research mechanism [93].

At each iteration, the algorithm is organized around a search step and a polling step, which represent a significant factor in the obtaining of convergence results. The search step is used to improve algorithmic performance. The polling step establishes a local search around one of the non-dominated points chosen by the search step, which represents an iteration point or polling center [92, 93]. In the two steps: search and poll, a temporary list is first created, it stores all the points of the current iteration list and all the points evaluated around this step. This list is further filtered by removing all dominated points and keeping the non-dominated points. A trial list L_{trial} is then extracted from this filtered list of non-dominated points and must necessarily include all the non-dominated points that belong to the iterative list considered in the previous iteration [94, 95].

Pareto Search Algorithm Steps

1. **Initialization**:

   To create the initial set of points, Pareto-search Algorithm generates random points satisfying the problem bounds.

2. **Poll to Find Better Points**:

   Pareto-search algorithm polls points from iterates, with the polled points inheriting the associated mesh size from the point in iterates. The algorithm uses a poll that maintains feasibility concerning bounds and all linear constraints. The score of a feasible point is the vector of objective function values of that point while the score of an infeasible point is the sum of the nonlinear infeasibilities.

   Pareto-search algorithm polls each point in iterates. If the polled points give at least one non-dominated point concerning the incumbent (original) point, the poll is considered a success. Otherwise, the algorithm continues to poll until it either finds a non-dominated point or runs out of points in the pattern.

3. **Stopping Conditions**:

   For three or fewer objective functions, Pareto-search Algorithm uses volume and spread as stopping measures. For four or more objectives, Pareto-search Algorithm uses distance and spread as stopping measures.

Chapter 4

Modelisation and Problem Formulation

4.1 Introduction

After overviewing the concept of energy management systems (EMS) and describing the different optimization approaches that can be used, now it needs to choose the architecture of the microgrid and choose the sources that build the system. According to the available sources, it was considered that the microgrid system is made up of two renewable sources mainly (wind power and photovoltaic energy), an energy storage system and a micro-turbine system, with the whole connected to the main grid.
In this chapter, first, the modeling will be defined for each one of the sources that constitute the microgrid, and choose an architecture that can be suitable for the system allowing the management in the most optimal way. The second part of the chapter will deal with the mathematical formulation of the problem in uni-objective and multi-objective approach.

4.2 Elaboration of Energy Source Models

The production of electricity from renewable energies is constantly increasing. Some authors [96, 97] have shown that its integration into the national grid with a management system is more than necessary, in order, for example, to reduce the use of conventional power plants based on fuel and allowing a simple consumer to be an actor in energy production (prosumer). With a potential that is still under-exploited, solar photovoltaic, wind and hydropower offer real economic and ecological advantages. On the other hand, the complementary that they offer in terms of daily energy production leads to systems based on their mutual combination or with other conventional energy sources. This gives to these systems architectures that require very little storage. These systems are hybrid in their constitution and operation. They can be decentralised or interconnected to the national grid. Hybrid systems are known as a viable alternative for the provision of energy [98]. The current section deal with the modeling of the sources constituting the microgrid under study.

4.2.1 Modeling of Wind Generator

Wind energy, a freely available source of energy, the electrical energy is produced by the rotation of the blades of the wind turbine which are placed on a tower at a considerable height, several factors have to be taken into account when designing the wind turbine model such as the power curve of the wind turbine, the efficiency of the generator and the efficiency of the mechanical transmission. In some cases, the choice of the model is made according to the wind speed distribution on the chosen site.
As the wind is stochastic event, a wind turbine has no control over its generated power. Therefore, power generation by wind turbines depends on the availability of wind speed that varies with heights. The wind speed measured at anemometer height needs to be converted to hub heights by the following power law equation [99]:

$$\frac{V_z}{V_i} = \left(\frac{h_z}{h_i}\right)^x \tag{4.1}$$

with V_z and V_i are the wind speeds at the hub height h_z and at the reference height h_i respectively. x is an exponent of the power law which is a function of both the atmospheric stability in the layer on which x is determined to be valid and the underlying surface characteristics, for example, x is equal to 1/7 for open terrain.
The power generated by wind turbines is a function of wind velocity [100], and a piece-wise function relates the relationship between the wind speed and output power as follows:

$$\begin{cases} P_{WT} = 0 & v_f < v \\ P_{WT} = P_{WT_n} \times \dfrac{V^3 - V_c^3}{V_r^3 - V_c^3} & v_c < v < v_r \\ P_{WT} = P_{WT_n} & v_r \leq v \leq v_m \\ P_{WT} = 0 & v \leq v_c \end{cases} \tag{4.2}$$

where P_{WT_n} is the nominal electrical power, v_r is the rated wind speed, v is the value of the wind speed, v_c is the cut-in wind speed, and v_f is the cut-off wind speed.
The power curve of a wind generator is illustrated in Figure 4.1 in which power generation begins at the v_c and stops at the v_f. The output power increases non-linearly between v_c and

v_r and remains to its rated generation until wind speed reaches v_f. The wind generator does not produce any power after the cut-off wind speed due to safety reasons.

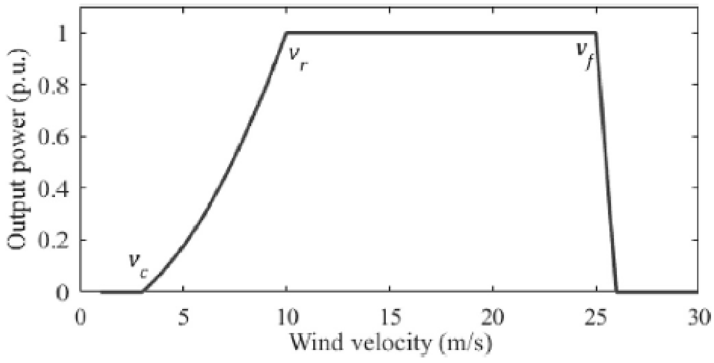


Figure 4.1: Example of Power curve for wind generator [22].

The total output power for a number of wind turbines can be expressed as follows:

$$P_W = N_{WT} \times P_{WT} \tag{4.3}$$

where N_{WT} is the number of wind generators.

4.2.2 Modeling of the Photovoltaic Generator

The power generated by photovoltaic (PV) panels from sunlight is known as solar power. In PV panels, sunlight is converted into DC electricity. In solar power generation, the size of the PV panels and solar irradiation, which determines the amount of direct and defused energy on an earth's surface. The solar irradiation is on W/m^2, varies from place to place [101]. To obtain efficient energy transfer, the PV panels should be operated with the maximum power point tracking (MPPT) mode. The output power of the PV panels depends on their size and efficiency, and can be calculated as a function of solar irradiation with the assumption of operation at MPPT mode as follows [22]:

$$P_s = \eta_s \times A \times SI[1 + \gamma(T_0 - 25)] \tag{4.4}$$

where η_s is the overall efficiency, A is the area of PV panels, SI is the Solar irradiation. The T_0 is the outside temperature, γ is the temperature coefficient of the maximum output power generally represented as a negative percentage per $^{\circ}C$ or $^{\circ}K$

For a number of solar generators, the total output power can be extracted as follows:

$$P_{pv} = N_s \times P_s \tag{4.5}$$

where N_s is number of solar generators.

4.2.3 Modelling of Converters

In a multi-source production system, the converters have various functions such as the ability to synchronise with the grid, the current control, the Maximal Power Point Tracking (MPPT) control and the detection of islanding situation. In our multi-sources system, converters, including DC/DC and DC/AC conversions. In order to model this conversion, there are two approaches [102]: the European approach (*eur*) [103] and the American approach (*cec*)[104].

$$\eta_{eur} = 0.03\eta_{5\%} + 0.06\eta_{10\%} + 0.13\eta_{20\%} + 0.10\eta_{30\%} + 0.48\eta_{50\%} + 0.20\eta_{100\%} \tag{4.6}$$

$$\eta_{cec} = 0.04\eta_{10\%} + 0.05\eta_{20\%} + 0.12\eta_{30\%} + 0.21\eta_{50\%} + 0.53\eta_{75\%} + 0.05\eta_{100\%} \tag{4.7}$$

where $\eta_{(5\%,10\%...100\%)}$ is the efficiency at a specified output power of the converter P_{conv}, given as a percentage of the nominal power P_n, as follows:

$$\eta_{\%} = 100\frac{P_{conv}}{P_n}. \tag{4.8}$$

4.2.4 Modeling of the Energy Storage System

To optimize the operational planning of a microgrid, a proper model must be developed for the energy storage system (ESS) [105]. As indicated in Section 2.5.4.1, there are several forms of energy storage, these latter have different characteristics, including response times, storage capacities and peak current capabilities, which are applied for different purposes with different time-scales. Electrochemical batteries are selected in this study due to their popularity of storing electrical energy for a long time.

The ESS system used in microgrids consists of a multitude of identical batteries, connected in series to increase the voltage level and in parallel to increase the current level [106], the energy stored in the ESS is used as the state variable by the management system. In battery modeling, several factors are necessary to describe its behavior such as capacity and charge/discharge rate, in order to increase the lifespan of the storage system, deep discharges are avoided, so batteries are delimited by their minimum and maximum capacity, respectively E^{min} and E^{max} with :

$$E^{min} \leq E(t) \leq E^{max} \tag{4.9}$$

$$\begin{cases} E(t+1) &= E(t) - \Delta_t P_c(t)\eta_c, \qquad \text{charging} \\ E(t+1) &= E(t) - \dfrac{\Delta_t P_d(t)}{\eta_d}, \qquad \text{discharging} \end{cases} \tag{4.10}$$

where $P_c(t)$ and $P_d(t)$ are the charging and discharging powers of the battery at time t, respectively; $E(t)$ and Δ_t are the storage energy at time t and the interval of time, and η_c and η_d are the charging and discharging efficiency, respectively.
The limitations for charge and discharge power of the battery are given as follow:

$$\begin{cases} -P_c(t)\eta_c \leq P_c^{max} & \text{charging} \quad (P_c(t) < 0) \\ \dfrac{P_d(t)}{\eta_d} \leq P_d^{max} & \text{discharging} \quad (P_d(t) > 0) \end{cases} \tag{4.11}$$

where P_c^{max} is the maximum charging rate and P_d^{max} is the maximum discharging rate.

Battery control is a crucial issue that must be taken into account when managing the microgrid, so the energy storage system can only be operated as one of the following modes at a time:

1. **Charge modes:** the battery can be charged from the grid and/or renewable energy sources with an energy quantity which is not beyond the charging rate.

2. **Discharge modes:** the battery supplies energy to loads when prices are high with an energy quantity within the battery discharging rate.

3. **Inactive modes:** there is no activity of the battery energy in this mode as the grid utility and microgrid directly supplies the electricity to loads at certain hours in order to consider economical perspectives.

4.2.5 Electrical Grid

For the purpose of simplicity, the purchase and selling prices of electricity are determined in real time designated by $B_g\,(Euro/kWh)$. In real-time pricing, the rate varies through time as a function of market wholesale prices that are modified in relation to electricity demand, i.e., peak demand indicates a high rate of electricity use [107].
The import and export power at time t is denoted as P_g in kW, with the following interpretation:

- P_g(t) > 0 if power is imported from the grid.
- P_g(t) < 0 if power is exported to the grid.

In the preceding paragraphs, the modeling of the different microgrid components was elabora ted. However, the photovoltaic system, the wind turbine and the storage system which are connected to the main grid with the micro-turbine allow building a microgrid. The rest of this chapter is dedicated to the mathematical formulation of the optimization problem for optimal energy management in the microgrid.

4.3 The Problem Formulation

Energy management in the microgrid system is usually formulated as an optimization problem. In this section, the mathematical formulation of the optimization model for optimal energy management in a microgrid is studied. The models will allow to the optimal energy production setpoints for each source of the system. Two objective functions are proposed, the first is the economic function and the second is the environmental function. In this chapter two optimization approaches are studied in two optimization ways: uni-objective and multi-objective approach.

4.3.1 Cost Evaluation

The choice of the cost function is the most relevant approach. It depends on several parameters mainly the type of architecture of the microgrid. Several functions have already been used, in [**?**] the cost of exploitation from the distributed resources and the storage system was considered constant during the day and the buying and selling price of the main network was different, while in [105], [108] and [109], the cost of the distributed resources and the storage system was considered dynamic throughout the day, also the cost of selling / buying energy supplied by the grid or injected varies during the day, the main objective of the cost function is to satisfy the demand of load during the day in a most economical way. So, in each hour t the cost can be calculated as:

$$C(t) = \sum_{i=1}^{N_g} U_i(t) P_{DGi}(t) B_{DGi}(t) + \sum_{j=1}^{N_s} U_j(t) P_{SDj}(t) B_{SDj}(t) + P_g(t) B_g(t) \tag{4.12}$$

where N_g and N_s are the total number of generators and storage devices, respectively. The $B_{DGi}(t)$ and $B_{SDj}(t)$ represents the bids of i^{th} DG unit and j^{th} storage device at hour t. $P_g(t)$ is the active power which is bought (sold) from (to) the utility at hour t and $B_g(t)$ is the bid of utility at hour t. $U_i(t)$ and $U_j(t)$ are the Operation mode of the i^{th} generator and the j^{th} storage device (ON or OFF), respectively.

4.3.2 Emission Evaluation

In addition to the operating cost, the aspect of greenhouse gas emissions is also taken into consideration. The emission objective function consists of the atmospheric pollutants such as nitrogen oxides NO_X, sulfur dioxide SO_2, and carbon dioxide CO_2. The mathematical formulation of total pollutant emission in kg can be expressed as:

$$EM(t) = \sum_{i=1}^{N_g} U_i(t) P_{DGi}(t) EF_{DGi}(t) + P_g(t) EF_g(t) \tag{4.13}$$

where $EF_{DGi}(t)$ and $EF_g(t)$ are emission factors which described the amount of pollutants emission in kg/MWh for each generator and utility at hour t, respectively. Each value considers the sum of the amount of pollutants, namely carbon dioxide, sulfur dioxide and nitrogen oxides. The total quantity of emissions in kg can be determined by the way of the following function [110]:

$$EM = \sum_{t=1}^{T} EM(t) \tag{4.14}$$

4.3.3 Constraints

The optimization problem proposed for ensuring an economically and environmentally optimal operation of the microgrid is limited by technical constraints that are necessary to achieve a reliable operation of the system, these are explained below.

4.3.3.1 Power Balance Constraints

The total power generation has to satisfy the total demand (including storage) and transmission losses. The active power balance is the precondition for a stable operation, in terms of frequency stability. The transmission losses are considered numerically low, being neglected in this study. Thus, the power balance constraint assumes the following form:

$$\sum_{i=1}^{N_g} P_{DGi}(t) + \sum_{j=1}^{N_s} P_{SDj}(t) + P_g(t) = P_L(t) \tag{4.15}$$

being $P_L(t)$ the total electrical load demand at hour t. And knowing that the power of the battery $P_{SDj}(t)$ can be positive in case of discharging or negative in the case of charging where it is considered as a load.

4.3.3.2 Electrical Limits of Generators Constraints

For a stable operation, the active power output of each DG is limited by lower and upper bounds as follows:

$$P_{DGi}^{min}(t) \leq P_{DGi}(t) \leq P_{DGi}^{max}(t) \tag{4.16}$$

$$P_{SDj}^{min}(t) \leq P_{SDj}(t) \leq P_{SDj}^{max}(t) \tag{4.17}$$

$$P_{g}^{min}(t) \leq P_{g}(t) \leq P_{g}^{max}(t) \tag{4.18}$$

where $P_{\cdot}^{min}(t)$ and $P_{\cdot}^{max}(t)$ are the minimum and the maximum powers of the distributed generator (DG) or storage device (SD) and the grid (g) at the time t, respectively.

4.3.3.3 Storage System Limits Constraints

Battery must remain within the limits of its capacity and its (charging/ discharging) is limited by a maximum rate that must not be exceeded

$$E^{min}(t) \leq E(t) \leq E^{max}(t) \tag{4.19}$$

$$\begin{cases} -P_c(t)\eta_c \leq P_c^{max} & \text{charging,} \quad P_c(t) < 0 \\ \dfrac{P_d(t)}{\eta_d} \leq P_d^{max} & \text{discharging,} \quad P_d(t) > 0 \end{cases} \tag{4.20}$$

where $E^{min}(t)$ and $E^{max}(t)$are the minimum and maximum energy levels of the battery, P_c^{max} and P_d^{max} are the maximum rate of charge/discharge of the battery that be must respected in each operation.

4.3.4 Uni-Objective Approach

The proposed microgrid is composed of renewable sources (photovoltaic and wind-turbine) non-renewable sources (micro-turbine) and storage devices with the totality coupled to the main grid. The choice of the cost function is the most pertinent decision to make. In fact, several models have been proposed in the literature, such as the one proposed in [105] where the total operating cost of the distributed energy resources and the cost of sale/purchase of energy supplied by, or injected, into the grid are considered dynamic. This function also takes into

account the cogeneration cost, the starting cost of the fuel cell and the charging/discharging cost of the storage batteries.
The main purpose of the cost function is to provide the load requirements during the day in an economical way. In the addressed case, the formulation of the problem is not far away from [105], where the study contains several cases, for this reason, the mathematical formulation of the uni-objective problem must take into account several aspects such as the exchange of energy by the microgrid with the main grid as well as the choice of the constraints on the distributed generators of the microgrid and the storage system.
The microgrid under study consists of three main parts: the main network based on centralized production, also decentralized production based on photovoltaic, wind-turbine, micro-turbine, and the third part concern the storage system. The goal is to manage the microgrid system in order to have the optimal energy price and reduced emissions rate, the management will be based mainly on three necessary factors:

1. The nominal hourly power available from each source (renewable or conventional).
2. The hourly unit price for each source of the microgrid system.
3. The state of the charge of the storage system.

The goal of the proposed energy management system is to find the optimal set-points of distributed generators, storage system and the amount of exchanging power with the utility grid while respecting the economical and environmental constraints.
The optimization problem can be written as follows:

$$\min CT = \min \sum_{t=1}^{T} C(t) \tag{4.21}$$

The optimization is done using five algorithms, two evolutionary algorithms (PSO & GA), linear programming (LP) based on simplex method and a mixed approach (LP-PSO).

4.3.5 Multi-Objective Approach

The multi-objective approach characterises the simultaneous optimization of the two independent criteria (economic and environmental), as seen previously. This approach consists in having the harmonisation of the two parameters, i.e. a compromise between the two objectives by satisfying the constraints of the problem, the mathematical formulation is described in the following section.

The mathematical formulation is similar to the previous ones of the uni-objective case, in fact, the parameters of the objective function are similar to the previous, and the problem is defined as follows:

$$\begin{cases} \min f_1 & = & \min\Big(\sum_{i=1}^{N_g} U_i(t)P_{DGi}(t)B_{DGi}(t) + \sum_{j=1}^{N_s} U_j(t)P_{SDj}(t)B_{SDj}(t) + P_g(t)B_g(t)\Big) \\ \min f_2 & = & \min\Big(\sum_{i=1}^{N_g} U_i(t)P_{DGi}(t)EF_{DGi}(t) + P_g(t)EF_g(t)\Big) \end{cases} \tag{4.22}$$

The problem will be solved using Pareto search algorithm based on the direct multi-search principle.

Certainly, the result will represent a compromise between the two aspects: for a very deep decrease of the cost, a considerable increase of greenhouse gases will be obtained, for that reason, the improvement of one of the objectives is done at the instance of the other objective, by this hypothesis, the results of a multi-objective problem do not represent a unique optimal point but a set of points called Pareto-optimal, the set of different points that represent scenarios.

Chapter 5

The Proposed Energy Management Systems

5.1 Introduction

The concept of integrating distributed energy resources and energy storage systems into a microgrid has become one of the main challenges in the field of power generation, the microgrid can operate either in isolated mode or connected to the main grid. The simultaneous operation of the renewable sources (of a stochastic behavior) and the main network (which supports a considerable load) and the electrical load of a variable character, are controlled using an energy management system whose main role is to identify the optimal power that can be exploited by the microgrid satisfying the energy needs of the microgrid consumers.

In this work, the elaboration of a management strategy makes it possible to reduce the energy bill of the consumer by ensuring the balance between production and consumption. This work also makes it possible to compare several scenarios and several optimization strategies adopted either by linear programming (simplex method) or by evolutionary algorithms (in this case PSO GA).

On the other hand, another approach based on multi-objective optimization has been proposed (based on the Pareto search principle) where both criteria cost and gas emission are simultaneou sly optimized. With this strategy, it is possible to establish several scheduling scenarios through the resulting non-dominant points after solving the optimization algorithm. Each point represents the compromise between the two criteria: cost and gas emission. In the work proposed in this study, the power values delivered by the renewable generators as well as the unit energy price are similar to [31] and [105]. Indeed, the configuration of the microgrid is taken identical. This chapter represents a description of the different energy management systems proposed to control the energy flows of microgrid generators.

The optimization model adopted in this work can be described in Figure 5.1.

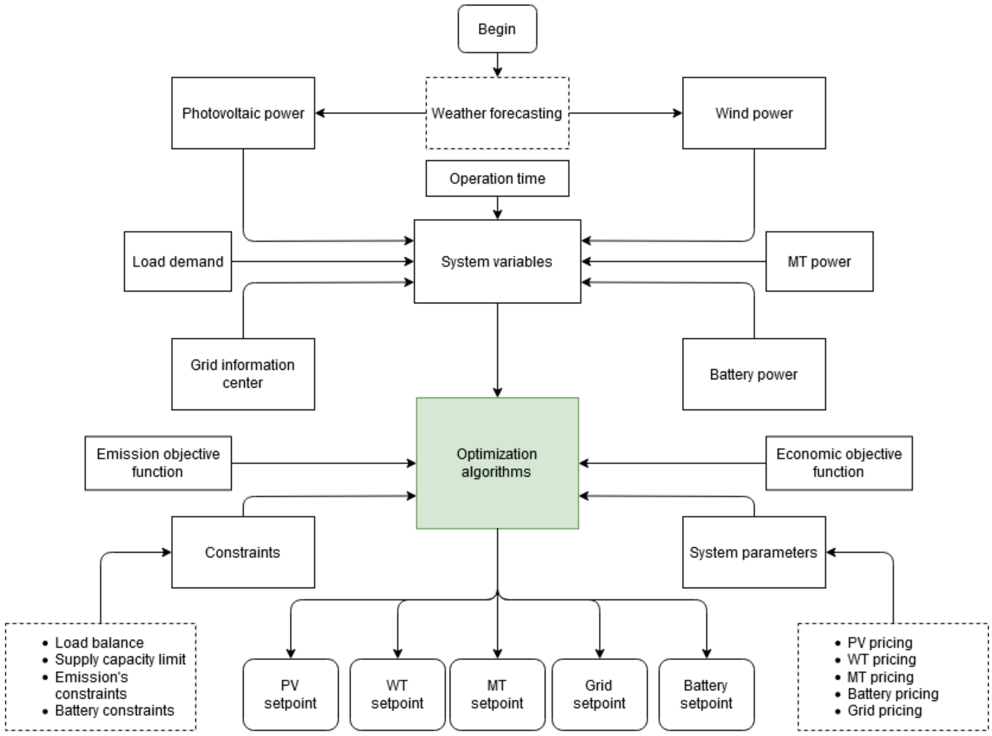


Figure 5.1: Microgrid optimization model.

The concept of optimal energy management in a microgrid is formulated as an optimization problem, including economic and environmental functions. Under technical constraints and economic parameters, the energy management system allows delivering the optimal power set-points ensuring an optimal distribution of the energy flow inside the microgrid.

5.2 Microgrid Description

The system proposed in this study consists of a combination of photovoltaic generators, a wind turbine farm and a conventional micro-turbine system. Because of the stochastic effect of renewable sources and the limited capacity of the micro-turbine, it is proposed to add a storage system. The microgrid is connected to the main grid, even so, it may have the possibility to be explored off-grid, in case of not required, malfunction or failure of the main grid, the connection is ensured through a transformer and common coupling point (PCC) as indicated in Figure 5.2 [111]. By this way, the main grid acts as a buffer, when the sources and the exploitation procedures into the microgrid are not enough. So, regarding the economic and environmental criteria and conventional sources, renewable energy sources can provide energy for loads and/or charge the battery. Excess energy, after satisfying the local loads demands

(including the battery), can be fed into the main grid to reduce the total operating cost of energy and gas emissions rate, also this energy excess can be exchanged with other microgrids. The battery energy cannot be sold to the main grid for reasons of safety, reliability and continuity [112]. The energy management system (EMS) will allows optimal scheduling of the distributed generators (DG) and the energy storage system (ESS) by taking into account the economic and environmental aspects as main constraints. The capacity of the battery is considered to provide for a 1-hour local charge. The management system will operate according to the available power (without exceding their limits) and considering the dynamic hourly energy unit prices for each one of the sources as it is displayed in Table A.1 (that is presented in appendix A).
The following Figure illustrates a simplified diagram of the microgrid architecture

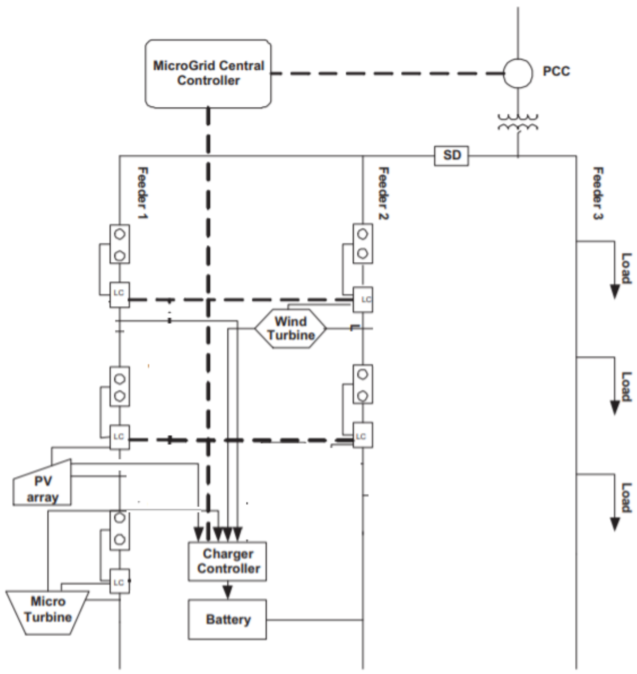


Figure 5.2: Microgrid architecture.

The state of charge of the storage system is also one of the decision variables that the energy management system follows to operate and manage the different charging and discharging processes inside the microgrid. The cases of the charging/discharging of the storage system are described according to its state of charge as follows:

1. In case ($SOC_{Battery}(t) = SOC_{max}$): The storage system will be considered as a source with the four other sources and its operation is made according to the amount of energy

demanded and its price under the hour of demand, knowing that its discharge is limited by a maximum discharge rate which must not be exceeded according to the constraint 4.3.3.3.

2. In case ($SOC_{Battery}(t) = SOC_{min}$): In this case, the storage system will require a certain quantity of energy from the cheapest sources of the microgrid, in order to charge it according to the limit value of its maximum charge rate, the storage system will be considered as a load by the microgrid in this situation.

3. In case ($SOC_{min} < SOC_{Battery}(t) < SOC_{max}$): According to the tariff of the storage system two cases can occur:

   - In case where the price of the energy storage system is the most expensive and the energy demanded by the microgrid consumers can be largely delivered by the other sources, the storage system will continue to be charged with this remaining energy, i.e. charging the batteries with the remaining energy in the cheapest way within the limits of the maximum charge rate, but if the energy supplied by the distributed generators is insufficient, the energy from the storage system will be used as a compensation source of energy to satisfy the electric power balance constraint, described on Equation 4.15.
   - In the case where the price of energy delivered by the storage system is cheaper compared to other sources, the storage system will behave as a source that can deliver maximum energy equal to the maximum limits of its discharge rate.

5.3 Uni-objective Approach

The central control of the microgrid requires an energy management system. The microgrid presented in this work is composed of the distributed resources, the storage system and the main grid, their simultaneous operation requires an energy management system, on which the main function is to determine in an autonomous way, the optimal quantity of energy that will be supplied by the microgrid and the main grid to satisfy the demand in terms of the energy required by the load per hour while ensuring the lowest cost of energy and reducing emission rates. In this section, several energy management systems are presented to deals with the different cases that may be encountered.

5.3.1 Case Study One: Optimal Energy Management of a Microgrid using Data (A)

In this study it was used the data obtained in [105]. The target point in this study case is the determination of the power set-points calculated by the energy management system based on the optimization problem described above, to solve this latter, several methods are proposed in this study case: one linear programming method: Simplex Method (SM); and two evolutionary algorithms: particle swarm optimization algorithm (with two implementations - one based on swarm intelligence (PSO1) with an improved (PSO2)) and genetic algorithm (GA); finally the study presents a mixed approach (LP-PSO).
The strategy of the LP-PSO algorithm consists of a PSO algorithm combined with the simplex method, where the particles departures are fixing by introducing the decisive variables of the LP as the search starting point. The starting vector generated is the vector that is constituted of decisive variables obtained by the compilation of the simplex method (SM), the iterative process of this method is shown in the flowchart of Figure 5.3.

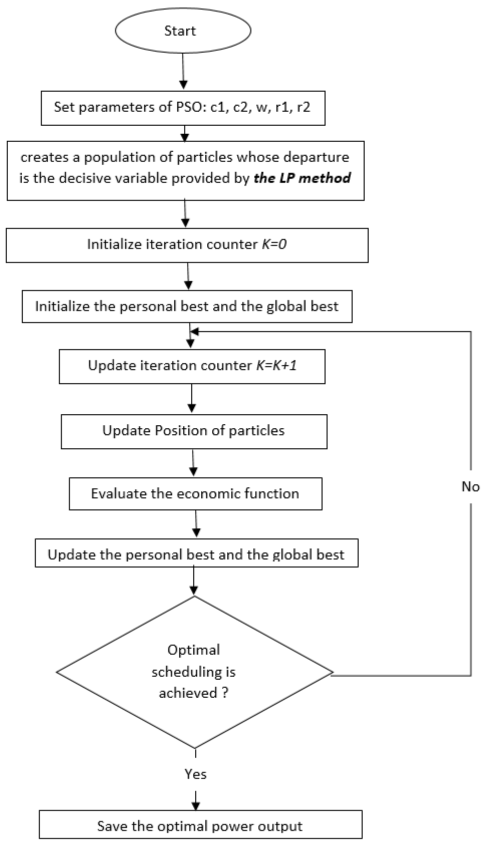


Figure 5.3: Flowchart of the hybrid method (LP-PSO) for the first study case.

Using the optimization model described in Figure 5.1, the energy management system allows to obtain the best power profile of the microgrid generators to achieve an optimal energy price, then in second place, the evaluation of emissions is ensured by the Function 4.12 using as input: the emissions factors presented in Table 5.2 and the optimal power values obtained from the total cost minimization results. The optimal management operation is achieved through the implementation of an optimal management strategy based on a uni-objective optimization approach as defined at Section 4.3.4.

The microgrid proposed in this case consists of two renewable sources (photovoltaic and wind turbine), a micro-turbine, a storage system and the main grid. The power values delivered by the renewable generators as well as the unit energy price are similar to [105].

Figure 5.4 shows the daily demand of microgrid consumers.

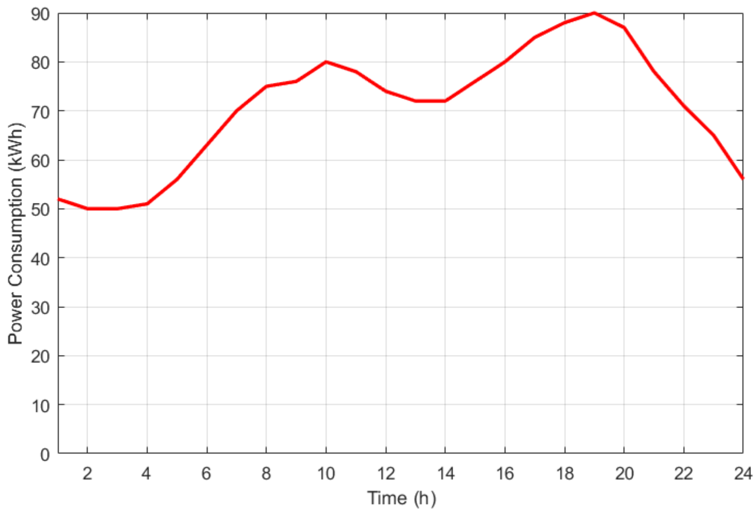


Figure 5.4: Daily consumption profile for the first study case.

Figure 5.5 represents the profile of renewable sources power available inside the microgrid system.

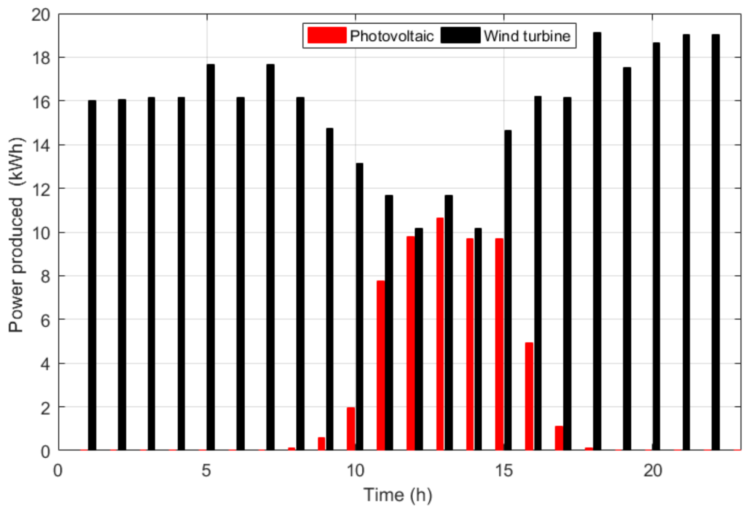


Figure 5.5: The daily power profile from renewable energy sources for the first study case.

The next table presents the power limits of the microgrid generators as well as the maximal power exchanged with the main grid with values in kWh.

Table 5.1: Maximum and minimum limits for microgrid production units for the first study case.

MG system	Min power (kW)	Max power (kW)
P_{GR}	0	90
P_{WT}	0	20
P_{PV}	0	25
P_{MT}	6	30
P_{ESS}	-25	30

Greenhouse gas emission (GHG) factors of the polluting sources are shown in Table 5.2.

Table 5.2: Emission factors.

EF	MT(Kg/MWh)	Grid(Kg/MWh)
CO_2	724	922
NO_X	0.2	2.295
SO_2	0.00136	3.583

The main target of the first study case is to compare the reliability of the optimization algorithms (SM), (PSO), (GA) and mixed (LP-PSO) with justification and to choose the best of them to be used in the next study case, which aims for the analysis of different purposes.

5.3.2 Case Study Two: Optimal Energy Management of a Microgrid through a maximal exploitation of renewable energy sources using Data (B)

In the second case, the data are obtained from [31]. The energy management system operates in the same way as in Study Case One, which is the reduction of the energy bill with a reduced emission rate during a 24-hour day. The target issue in this second study case is the determination of the bi-directional energy exchanging between the microgrid and the main grid. The remaining renewable energy not used to supply the consumers of the microgrid or to charging the battery storage system will be sent to the main grid.
The characteristics of the microgrid used in this phase are similar to the one proposed in [31], the Figure 5.6 represent the average daily power profile delivered by the wind turbine and the photovoltaic systems.

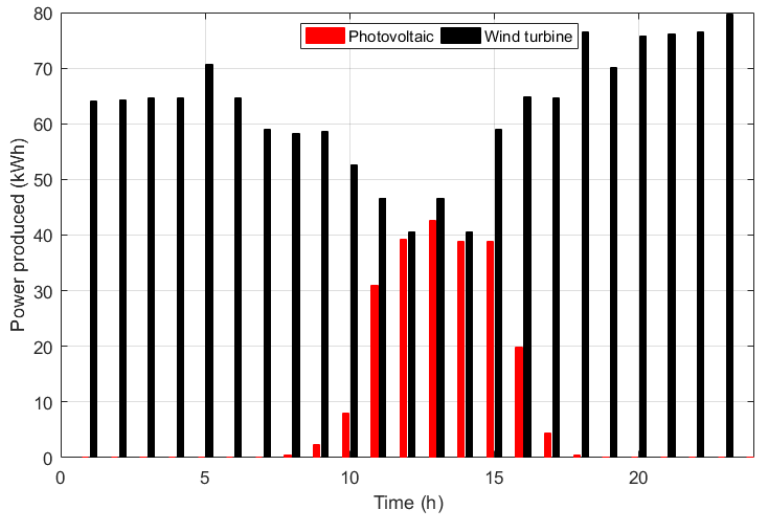


Figure 5.6: The daily power profile from renewable energy sources for the second study case.

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The consumption profile of the microgrid community is shown in the figure 5.7

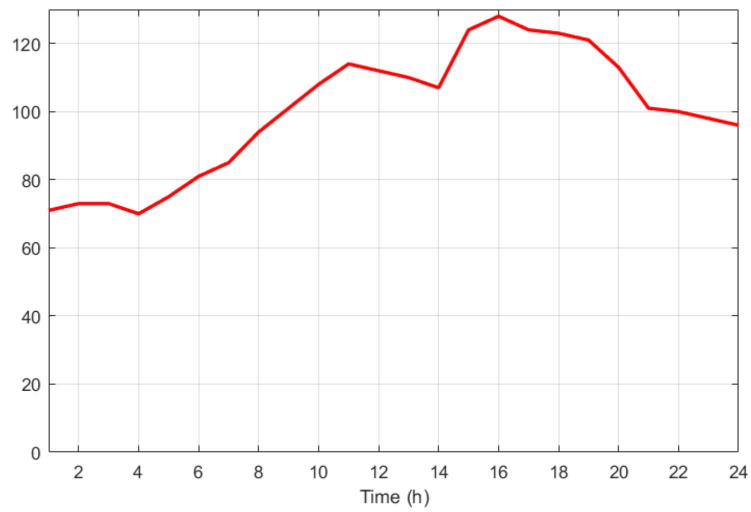


Figure 5.7: Daily consumption profile for the second case.

The power limits of the microgrid generators are displayed on the following table :

Table 5.3: Maximum and minimum limits for microgrid production units for the second study case.

MG system	$P_{min}(kW)$	$P_{max}(kW)$
P_{GR}	0	90
P_{WT}	0	80
P_{PV}	0	40
P_{MT}	6	30
P_{ESS}	-10	20

Greenhouse gas emission (GHG) factors of the polluting sources are taken similar to that of the first study case.
Two management approaches are compared in this study:

1. **Approach one** : Operating the distributed generators of the microgrid as well as the storage system and the main grid at their optimal point that ensures the lowest possible energy cost, the remaining energy after feeding all microgrid consumers will be used to charge the storage system when needed, otherwise, if the storage system cannot perform this operation, this remaining energy is lost.

2. **Approach two** : Operating a part of the distributed generators (photovoltaic and wind turbine) at their maximum power point, a part of them will be used with the other

sources of the microgrid in order to ensure the lowest energy cost to the consumers, the remaining energy from renewable sources will be used first of all to ensure the charging of the battery, in case this energy is not needed by the storage system, this remaining energy will be exchanged with (injected to) the main grid.

The objective of this study is to identify the impact of energy exchange between micro grid and main grid by injection from renewable sources on the minimization of energy costs and the reduction of emissions. The optimization algorithm that has demonstrated the best performance from the four algorithms introduced in the first study case , will be adopted on the EMS of the second case.

5.3.3 Case Study Three: Optimal Energy Management of a Micro-grid through load scheduling

The third study case is a proposition of an energy management system according to the type of load that exists in the microgrid. The data are obtained from [31]. The types of loads in the proposed microgrid are smart home loads, composed of a main fixed part called a non-shiftable load, and a secondary part comprising shiftable load that could be shed to avoid a high price of energy at the consumption peaks. The behavior of non-shiftable and shiftable load are shown in Figure 5.8. The loads are connected through sensors and communication technologies, in an internet of things (IoT) based approach, allowing the sensing and transmitting of real-time data, which enables decision-making according to specified objectives. This gives to the customer the possibility to program their demand, independently, by taking as reference the instantaneous operating cost delivered by the manager of the microgrid.
For this purpose several strategies have already been proven to be effective in load scheduling: the use of fuzzy logic for the optimal management and loads programming in a smart house [113], and many other meta-heuristics such as genetic algorithm in [114], PSO in [115] have allowed moderate consumption scheduling. Also, an artificial neural network (ANN) algorithm based forecasting model has been developed in [116]. After the load analysis, the most common approach is to perform load shedding to avoid consumption peaks and, consequently, excessive costs. In [31] a PSO algorithm was proposed for this task, achieving a better performance when compared with standard management.

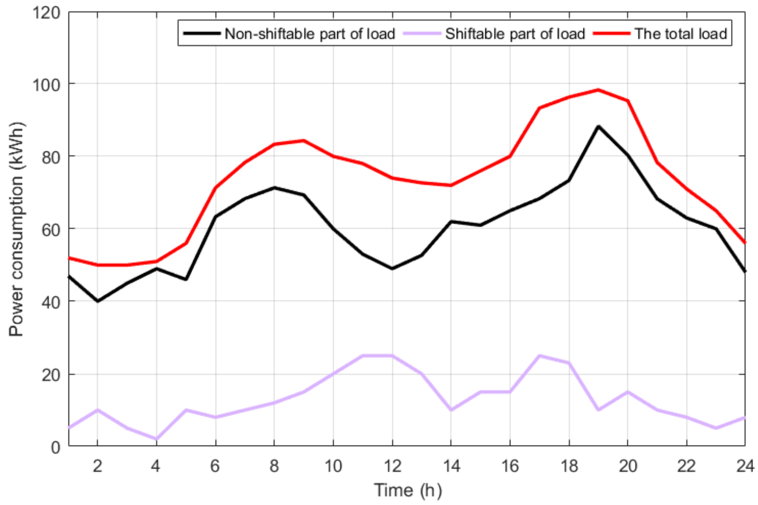


Figure 5.8: Hourly load distribution for the third study case.

The Figure 5.9 present the architecture of the microgrid.

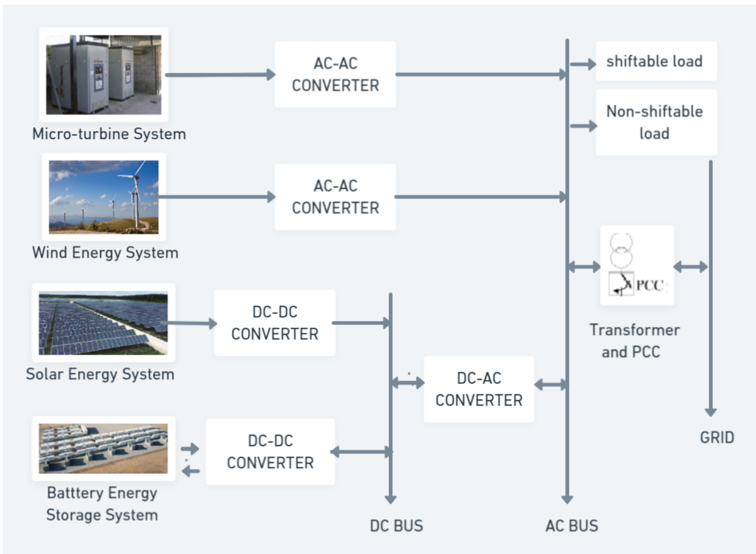


Figure 5.9: Microgrid configuration.

The contribution of this study is to ensure the supply of both shiftable and non-shiftable devices, instantaneously, i.e., assuring feeding the essential loads when needed, while assuring the minimisation of the operation costs. A storage system was introduced in the microgrid system to optimise the operating costs and ensure a minimum (GHG) emission rate followed by the production of DG. This operation is ensured by an EMS, based on a mixed optimization method (LP-PSO). To demonstrate the influence link (price-emission) two scenarios have been proposed. The first takes into account the optimization of energy costs as a primary goal, while the second takes the environmental effect by increasing the use of renewable energy sources. In order to be economically and ecologically reliable, two constraints must be considered in the optimization problem associated to the costs and emissions issues. The proposed microgrid is composed of two conventional sources (microturbine and the main grid) responsible for GHG emissions mainly CO_2, SO_2, and NO_x with different rates. The energy management program proposed in this study is established considering two types of loads. The non-shiftable part can be fed mainly by the two renewable sources PV's and WT's, the microturbine and the grid. The shiftable part is provided by the storage batteries as the first priority with the remaining power from the previous four sources after feeding the non-shiftable part of the load. The energy management system (EMS) depends mainly on a mixed optimization using linear programming (LP) based on the simplex method, and a particle swarm optimization (PSO) method. In order to consider both economic and environmental criteria, two management policies are proposed:

- **Scenario 01** : The supply of non-shiftable part of the load, is supported by the four main generators previously identified: photovoltaic, wind-turbine, microturbine and main grid, depending on the state of charge of the storage system, the supply of the shiftable part of the load is provided by the storage battery as a first priority. But, in the case where the storage system has reached its minimum state of charge, the compensation is provided by the remaining power after supplying the non-shiftable part of the load.

- **Scenario 02**: This approach will mainly take into account the environmental criterion. Although the power supply of the non-shiftable loads is provided by the four main sources, the supply of the shiftable loads is assured by the ESS, but in case the state of discharge of the battery bank is achieved, the lack will be compensated by the remaining power from renewable sources: photovoltaics and wind turbines, if the energy from renewable sources is insufficient for this operation, the non-supplied part will be shifted out to off-peak hours.

It should be noted that the pricing of energy from the storage system is not delivered by the energy manager each hour, but the energy price is considered to be the same as that used for charging when it was relatively low.

5.4 Multi-objective Approach

In the multi-objective approach, the metrological data, the power limits of the distributed generators, as well as the characters of the storage system, are taken similar to the first study case of the uni-objective approach, however, the results achieved from the multi-objective situation will be compared with it.

This approach consists of proposing several management scenarios based on the result of the non-dominant points, i.e. the best compromises between the two entities: cost and emission obtained by the Pareto search algorithm explained in chapter three.

Chapter 6

Results and Discussion

6.1 Introduction

This chapter contains the simulation results using the $MATLAB$ programming platform after applying (EMS) to the three study situations of the uni-objective approach and for the situation of the multi-objective approach. The results are interpreted in accordance with the objective described in the previous chapter. The presentation of results is in graphical form and the numerical values are in tabular form in the appendix A.

6.2 Uni-Objective Situation: Case Study One

The first study case represents the energy management of a microgrid using an energy managem ent system (EMS) based on optimization approaches presented previously used to solve the energy management problem described in Section 5.3.1, the purpose of this phase is to analyze and compare the reliability of the energy management system for each optimization algorithm: PSO, GA, SM and a mixed approach LP-PSO dedicated to solve the optimal set-point of the microgrid generators.The results of each method are presented and analyzed in the following. In this study case, the energy from the grid is delivered in a unidirectional way, i.e. the energy is sold from the grid and delivered to the microgrid, otherwise, the inverse operation is not permissible.
Taking into account the available power and energy prices (Table A.1), the EMS allows having the optimal set-points of the distributed generators and the storage system through optimization algorithms as shown in Figure 5.1. In this way, the operation cost is minimized and the emissions are evaluated.
Table 6.1 represents the values of the total energy cost and the total quantity of emissions

emitted by the microgrid using the energy management system proposed for each one of the optimization algorithms, the algorithmic performance is indicated by the simulation time and the precision of the results.

Table 6.1: Comparison between results for the first study case.

Results \ Algorithms	SM	PSO1	PSO2	GA	LP-PSO
Total Price (Euro)	143.05	144.96	143.05	143.05	143.05
Total Emissions (kg)	1353.73	1351,40	1353.73	1353.73	1353.73
Simulation time (sec)	3.12	0.040	0.031	5.62	0.038

According to the results presented in Table 6.1, the operating cost for SM, PSO2, GA and for the hybrid LP-PSO is 143.0492 *Euro*, for PSO1=144.9574 *Euro*, the performance of the PSO2 in the compilation rapidity as well as the precision are remarkable. First of all, the addressed problem and constraints in this study are linear. This judges the performance of the SM compared to PSO1, the convergence of the optimal setpoints of SM (Table A.2) are more accurate than that resulting from the PSO1, this benefit is reflected in total resulting operation price of SM. According to Table A.3, the PSO1 is converging very close to the global optimum but with a certain degree of error compared to the precision of SM, the accumulation of these small errors will become significant in the total operation cost per day. The advantage of this meta-heuristics is the possibility to solve any kind of problem (linear or non-linear).

From a convergence point of view, it was remarkable that the decisive variable values of the PSO1 were close to the optimum, but did not represent the global optimality. By definition in the search principle of the PSO algorithm, the starting point of the particles are random and translates between the lower and upper limit of the problem. The hybrid LP-PSO will make it possible to fix the departures of the particles by introducing the decisive variables of the LP as the search starting point. The starting vector generated is the vector that is constituted of decisive variables obtained by the compilation of the simplex algorithm, by this way, the problem of precision is solved, and the result converges towards the global optimum. Simulation results have demonstrated the reliability of this method, although the results of LP-PSO are similar to LP, PSO2 and GA because of the linear nature of the problem under study, the LP-PSO will be reliable also in the case of non-linearity. In terms of simulation time, the adapted PSO2 showed that is faster than PSO1, LP-PSO and GA.

Starting from the importance of the PSO which is intended to work for any type of linear or nonlinear problem, another PSO algorithm was developed to achieve better accuracy than the classical PSO1, where the initial particles were randomly initiated between lower and upper problem limits. A new approach of particle initialization was followed by fixing the departure of the particles using the upper limits vector of the problem, in fact, by adopting this method the search space of particles is reduced i.e. the size of the swarm is limited. The global optimum was obtained with precision in a fast simulation time as indicated in Table 6.1, this approach is indicated as PSO2.

The algorithmic performances of the Genetic Algorithm (GA) have given good results in terms of precision, knowing that the stopping condition is taken similar to that of the PSO which is the reaching of the global optimum and with the same starting condition; the path to the optimum by the genetic algorithm is much slower than that of the PSO, this is judged by the very large search space generated by the GA mechanism following their genetic operators like crossover and mutation, in PSO particles update themselves with the internal velocity. Besides, the information-sharing mechanism in PSO is significantly different than the genetic algorithm, it should be noted that in the case of the genetic algorithm, the *MatLab* GA toolbox was used.

Figure 6.5, represents a comparison between the hourly energy tariffs obtained by the energy management system for 24 hours operation, as previously indicated, the results of PSO2, SM, GA, LP-PSO are identical which reflects the similarity in the daily total energy price, the difference of the PSO1 values is also presented by the price curve, the prices are in (euros/kWh).

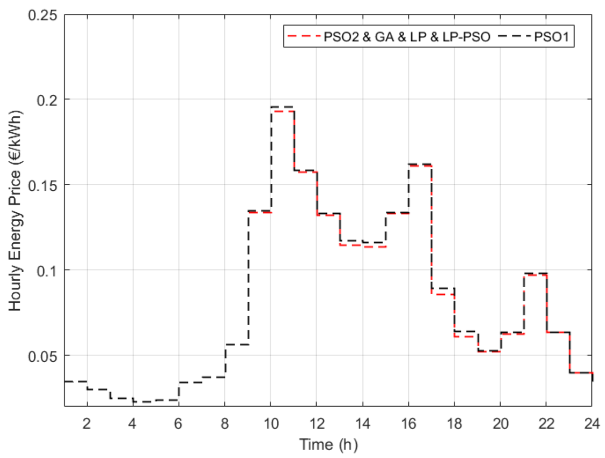


Figure 6.1: Comparison of the energy unit price obtained by EMS.

Figure 6.2 presents the comparison between the price of energy obtained by the implementation of the energy management system and the other energy unit prices of the microgrid generators.

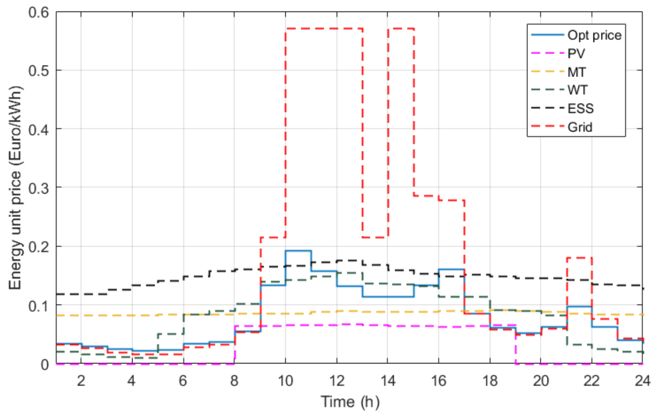
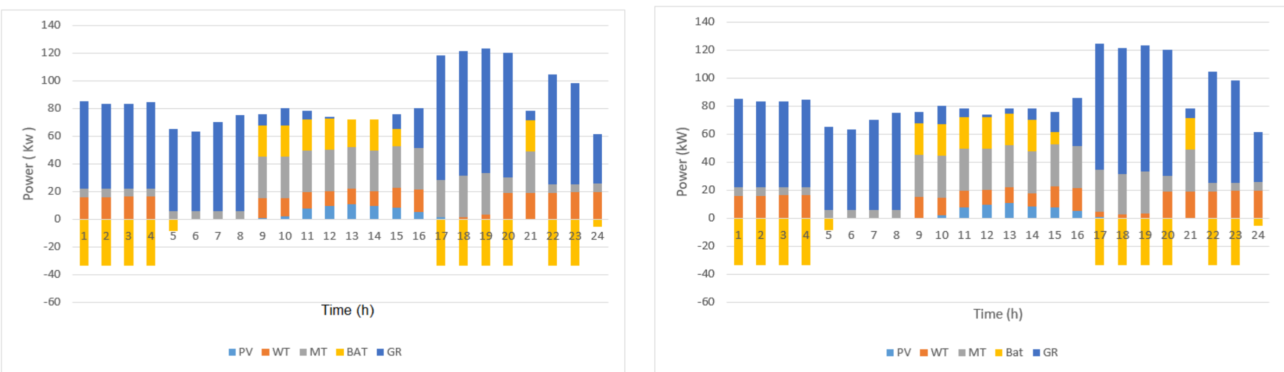


Figure 6.2: Comparison of the optimal price from the EMS and the unit prices of the MG generators.

Figures 6.3a and 6.3b represent the optimal set-points of the distributed generators obtained by the energy management system, according to Figure 6.3a it is remarkable that the results of the algorithms PSO2, SM, LP-PSO and GA are identical which judges the reason of having confusing graphs, contrary to the PSO1 in Figure 6.3b which gives different results compared to the previous algorithms.



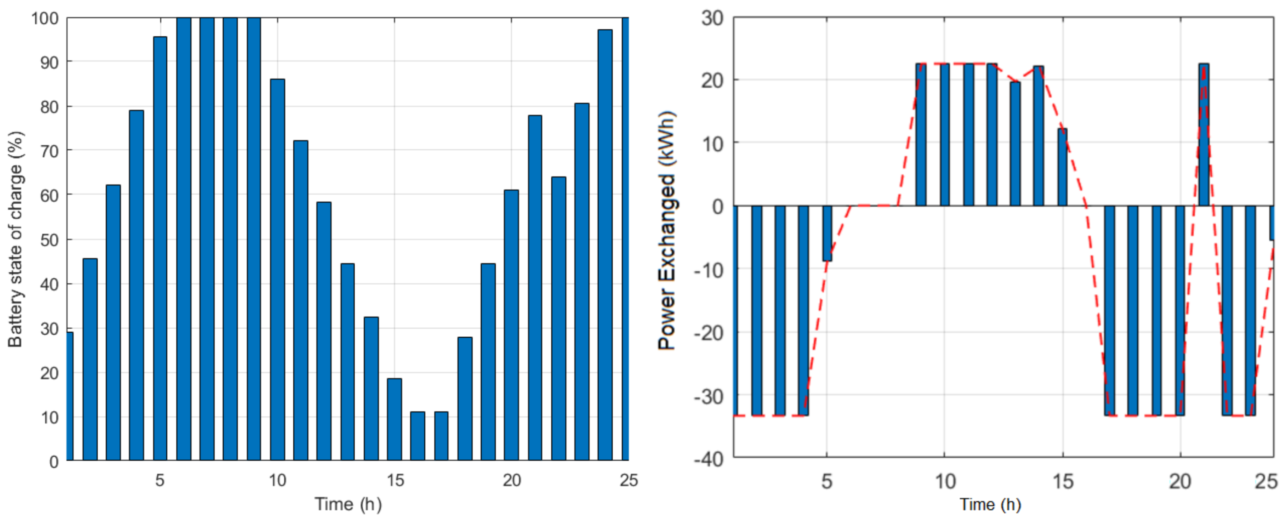
(a) SM, PSO2, GA, LP-PSO.

(b) PSO1.

Figure 6.3: Hourly dispatching set-points of the microgrid generators.

According to the sources scheduling of the proposed microgrid in this part, it is remarkable that the photovoltaic source is fully exploited during the day due to its low price compared to the other four sources, the wind source is widely exploited during the night due to its low price at this time. This reflects the flexibility and complementary between these two renewable sources. The storage system chosen has the following parameters: $E^{max}(t)$ =180 kWh, n_c = 90 %, n_d=90 %, $E(1)$=52 kWh, the characteristics of the storage system are illustrated by its

charge/discharge operations within the limits of the rate. The charging of the storage system is ensured during the part of the day where the consumption is lower, characterized by low unit energy costs, and the battery delivers energy to compensate for the lack during the day.
Figure 6.4a shows the energy variation of the battery farm of the proposed microgrid during 24 hours of operation, the values are in %.
Figure 6.4b illustrates the daily energetic exchange of batteries with the microgrid, the negative value represents the energy used for the charging process while the positive corresponds to the energy delivered by the storage system to the microgrid consumers.



(a) Battery state of charge. (b) Exchanged energy with the microgrid.

Figure 6.4: Storage system performances.

It is possible to observe that, during the hours of high consumption, the price of the grid is high, in this case, the use of the storage system takes part to compensate for the lack of energy and reduces the use of energy from the utility, that's why the use of the battery is remarkable during the day when the price of the grid is high, the storage system follows its charging process during the night when the consumption of the microgrid is less high. So, the batteries will take advantage to be charged as shown in Figure 6.4a. For maintenance and safety reasons, the micro turbine is present all day long, either by its minimum power of 6 kW or by its power delivered to compensate for the lack of energy that should be supplied to the microgrid consumers. Figure 6.2 represents the hourly unit price of the kWh obtained after the implementation of the management strategy, it is clear that the energy price delivered by the microgrid was saved and therefore the user will have a price of energy much lower than that of the conventional grid. This result is one of the benefits obtained from the implementation of

microgrids.
Figure 6.5 presents the impact of the results obtained by the optimization algorithm used in the energy management system (EMS) on the variation of emissions during the day, considering that the emissions are evaluated by using the optimal power set-points, the impact of the algorithm on the total energy cost will also be reflected on the variation of emissions, the values are in kg/kWh.

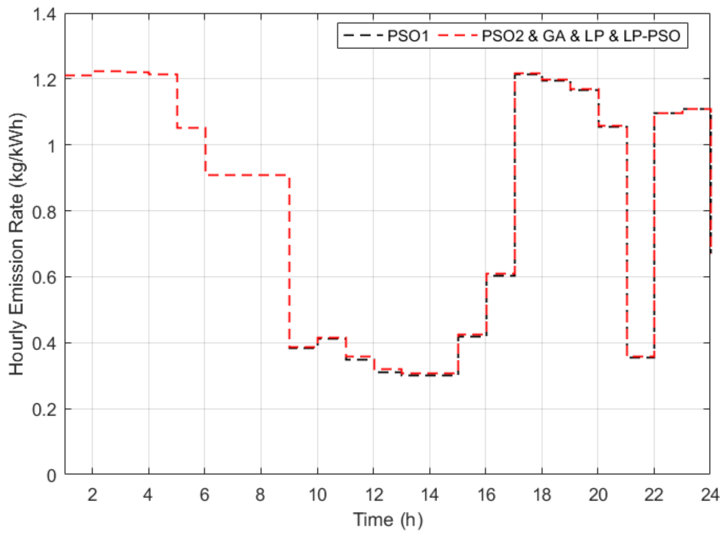


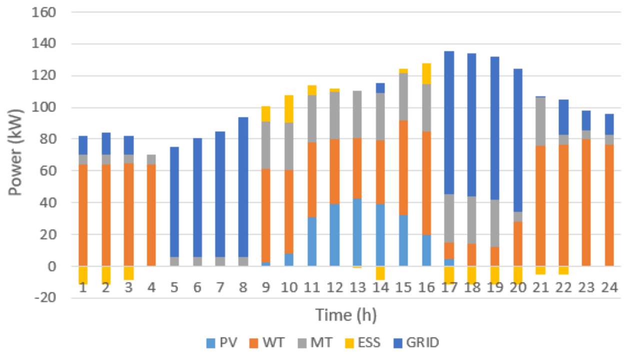
Figure 6.5: Comparison of the emissions obtained by EMS.

It is possible to conclude that the quantity of emissions is directly related to the two sources: the main grid and the micro-turbine, responsible for the emissions of greenhouse gases, according to Figure 6.5 it is clear that emissions are higher at night because of the low prices of the grid during this period which encourages its use to supply the consumers of the microgrid and take advantage of it to charge the storage system. So, for the minimization of the cost during this period, i.e. to use the cheapest source which is the principal grid, the emissions will be increased significantly.

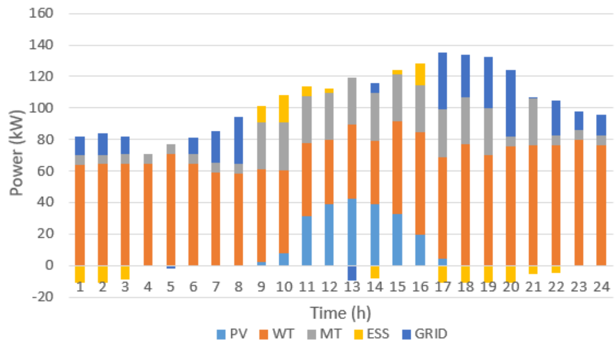
6.3 Uni-Objective Situation: Case Study Two

The objective of the management system is to reduce the energy costs over a 24-hour day, the target point in this study case is to demonstrate the impact of the energy exchange between the microgrid and the main grid (injection). The remaining renewable energy not used to supply the microgrid consumers and to charge the battery storage system will be sent to the main grid.

After the algorithmic performances demonstrated by the PSO2 in the first case study, this later will be used as an optimization tool in the management program for this second study case.
In order to highlight the objective envisaged, the power and consumption data are chosen of important values and taken similar to that of the microgrid proposed in [31], the exchange of energy (microgrid to the grid) is allowed only by renewable generators of the microgrid (photovoltaic and wind turbine), because of environmental considerations, the energy of the micro-turbine source is not injected. And to increase the lifespan of the storage system, the excess storage battery is also undelivered to the main grid.
Two approaches have been proposed and compared in order to conclude the injection impact and energy exchange between the microgrid and the main grid. The first one consists of satisfying the local needs of the microgrid consumers and ensuring the charging of the storage system in case of need, the scheduling of the sources is effected in an optimal way. While in the second approach, the renewable generators are set at their maximum operating point, part of this energy with the other three sources of the microgrid is destined to satisfy the local consumers of the microgrid and the surplus of this energy is used to ensure the charging of the storage system in case of need. The remaining part of the renewable sources is injected into the main grid.
Figures 6.6a and 6.6b represent the optimal set-points of microgrid generators for the two proposed scenarios, with and without injection.
According to the results obtained from the approach of Figure 6.6a, it is remarkable that the sources are scheduled at their optimal set-points, such that the source with the cheapest price is favored over the others, also according to the scheduling of this microgrid, it is noticeable that a large part of the energy from renewable sources is remaining, from where it will neither be used to satisfy local needs (to supply microgrid consumers or used to charge batteries) nor be exchanged with the main grid. So, an estimated energy quantity of $484.5156\,kW$ will be lost without being profited.
The approach of Figure 6.6b represents a bi-directional communication between the microgrid and the main grid, the power points of the renewable sources are at their maximum value.



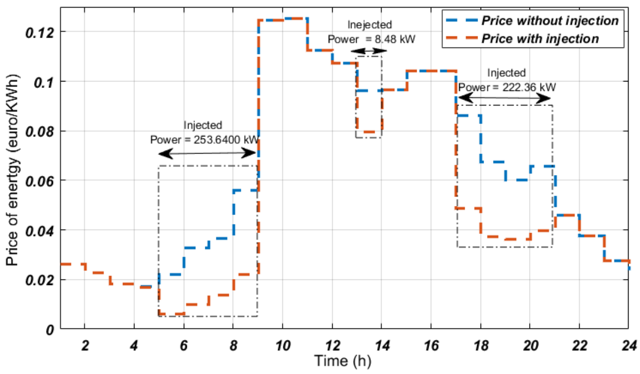
(a) First approach.



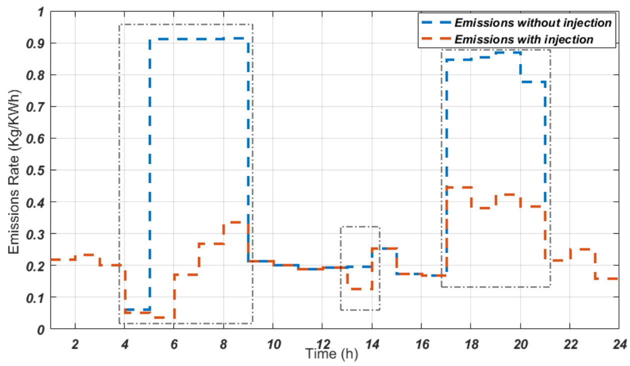
(b) Second approach.

Figure 6.6: Hourly dispatching set-points of the microgrid generators.

Figure 6.7a represents the comparison of the energy price for the two proposed scenarios, the values are in $(Euro/kWh)$. It is remarkable that the energy exchange operation has reduced the total energy costs of the microgrid.
It can be seen from 6.7b that in the case of energy injection. the emissions were considerably reduced as a consequence of reducing the use of conventional sources based on fuel in the main grid by taking the renewable energy delivered by the microgrid as a means of compensation and reduction of fuel consumption.



(a) Energy price comparaison.

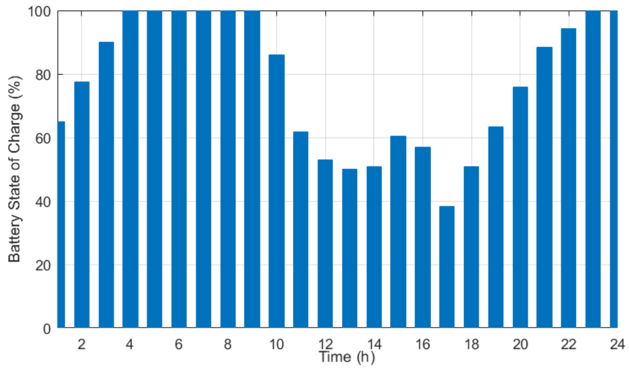


(b) Emissions comparison.

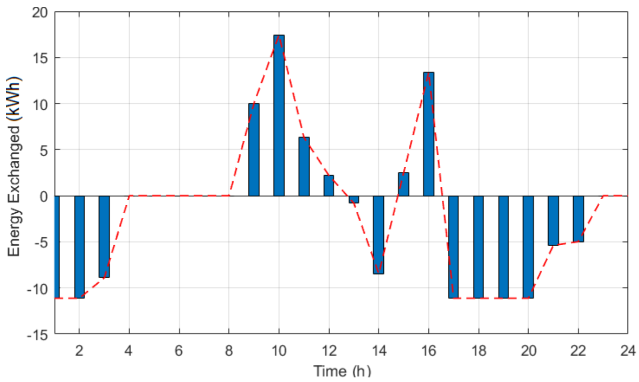
Figure 6.7: Prices and emissions comparison.

Figure 6.8a represents the energy variation of the microgrid storage system described by its state of charge in %.
It is possible to observe that the batteries are mainly used to compensate for the lack of energy during the day, the charging process of the storage system is done during the night following the reduced energy prices during this period, this can be justified by Figure 6.8b that illustrates

the daily energetic exchange of batteries with the microgrid, the negative value represents the energy used for the charging process while the positive corresponds to the energy delivered by the storage system to the microgrid consumers.



(a) Battery state of charge.



(b) Exchanged energy with the microgrid.

Figure 6.8: Storage system performance.

Figure 6.9 represents the energy exchange operation between the two entities (grid and microgrid) as well as the billed power which corresponds to the difference between the two types of energy (injected & exploited).

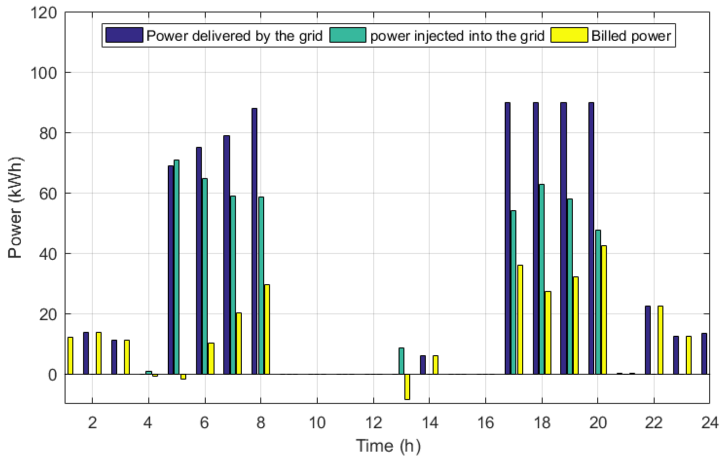


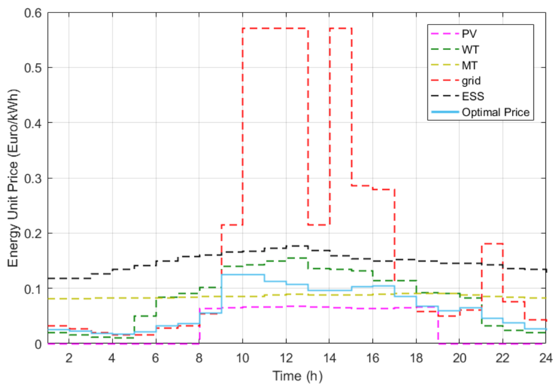
Figure 6.9: The power supplied by the grid, the power injected and the power payed during one day.

Table 6.2 represents the comparison of the total price and emissions between the two proposed approaches: with energy injection and without injection of the remaining renewable energy into the main grid.

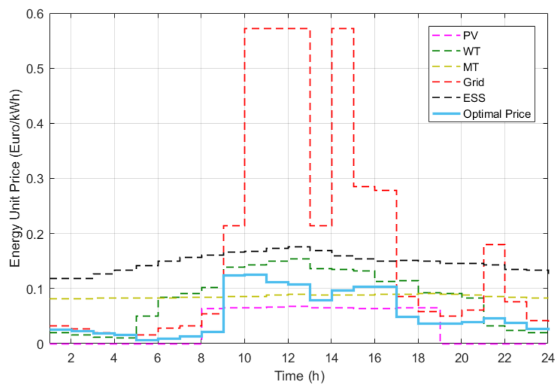
Table 6.2: Comparison between results for the second study case.

Results \ Approaches	Approach 01	Approach 02
Total Price (Euro)	164.32	140.15
Total Emissions (kg)	1020.50	570.88

The two Figures 6.10a & 6.10b shows the hourly energy price per kWh obtained by the implementation of the energy management system for both proposed approaches.



(a) First approach



(b) Second approach

Figure 6.10: Comparison of the optimal price from the EMS and the unit prices of the MG generators.

According to the obtained results, it can be seen that the renewable sources are fully exploited, with no loss of their production. The excess of renewable energy production after satisfying the local needs of the microgrid allowed to ensure the charging of the storage system with success in such a way that at the end of the day, the battery was fully charged, also a quantity of 481.5156 kW was delivered to the main grids, this allowed to reduce the total energy bill of the microgrid to 140.1505 $Euro$ and to reduce emissions at 570.8807 kg. After injecting these sources into the grid, which is considered to produce only from conventional sources, the power extracted from fossil-based power plants will be reduced, consequently, the emissions from these large power plants will be reduced also. This approach will therefore allow us to take full advantage of the local energy of the microgrid by eliminating any loss, also it is an awareness-raising approach due to the contribution to the reduction of greenhouse gases responsible for global warming. The results that are shown in Table 6.2 and Figures 6.10a and 6.10b demonstrate the impact of this approach. The convergence characteristics of the optimization algorithm PSO2 are not discussed in this case study since it is the same analysis as the previous case.

6.4 Uni-Objective Situation: Case Study Three

The main purpose of the energy management system is to reduce the cost of energy and emission rate. In the two previous study cases, the source scheduling takes mainly into account the unit costs of the hourly energy delivered by the microgrid manager as well as the power limits of the generators. The third study case considers also the load scheduling, the loads are controlled to avoid a possible overload leading to a high energy price and emission rate in the consumption peaks, the energy management system for this case was clearly explained in the previous chapter. The proposed microgrid is composed of renewable sources and non-renewable sources, the renewable sources are: photovoltaic (PV) and wind-turbine (WT), the non-renewable sources are the micro-turbine (MT) and the storage system. The totality coupled to the main grid allows the exchange of energy between these two entities. Two scenarios are proposed to supply the microgrid consumers. The first takes into account the economic criterion and the second the environmental criterion, both of them allow to illustrate the price/emissions relation.
After cost minimisation by means of objective function 4.12, the quantity of emissions is evaluated by the second function 4.14. Load demand, energy production from renewable sources are presented respectively in Figures 5.8 and 5.5. The main grid can exchange with the microgrid a maximum power of $95\,kW$. To reduce the number of start-up/shutdown and for maintenance reason, the micro-turbine (MT) is present at all times either by its minimum power of $6\,kW$ or by the necessary power of load that is limited to $30\,kW$. The battery is used to supply the shiftable part of the load, its maximum capacity is $15\,kWh$.
The application of the energy management system allowed the calculation of the optimal set-points for the distributed generator (DG) and storage system (ESS) of the microgrid through the combined LP-PSO strategy. There is a balance between supply and demand, i.e. that every hour the sum of the optimal points is equal to the power demand from the microgrid consumers. Table A.1 present the DG and grid bids according to [31]. All values are in $Euro/kWh$.
Figures 6.11a and 6.11b represent the optimal power set-points for the two proposed scenarios in order to demonstrate the price/emissions correlation. Considerable use of renewable resources is observed in the second scenario illustrated by their higher set-point than the first scenario.

(a) First scenario.

(b) Second scenario.

Figure 6.11: Hourly dispatching set-points of the microgrid generators.

According to the available powers and daily energy bids of Table A.1, it is clear that the photovoltaic power is fully exploited because of its encouraging price, but the presence of this source depends on its potential that is available only during the day. So, this allows wind energy to be exploited. The advantage with this source is that it is potentially available during the night and its price is relatively low during this period which justifies its wide use.
Figure 6.12 shows the energy exchanged by the battery to supply the shiftable loads parts, it also shows the energy supplied by the microgrid to charge the storage system, the charging process is indicated by negative values.

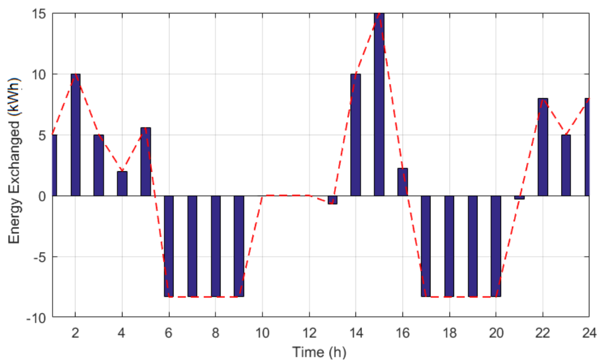
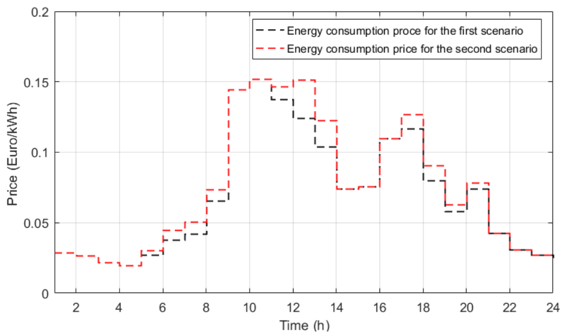


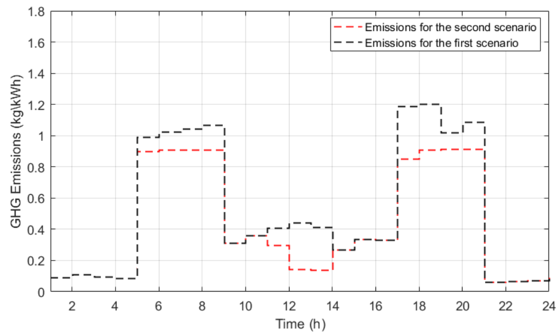
Figure 6.12: Energy exchange of the batteries with the microgrid during the day.

During the day, the insufficient power of the photovoltaic source leads to compensation by one of the two conventional sources: from the grid or the microturbine, depending on their unit operating price. The use of the storage system is intended to supply, as a priority, the shiftable part of the load. The management of charge and discharge is ensured by the PSO algorithm while respecting the battery limit constraints. In [31] the shiftable part of the load is driven at times when the energy price is low. This will lead to the discontinuation of some home-application when they are part of the shifted load, and therefore, the comfort of the users can be affected. Instead of shifting the load to times when the energy price is low, this cheaper energy can be used for charging the energy storage system that supplied as first priority the part of load supposed to be shifted.

Figure 6.13b represents emissions comparison for the two proposed scenarios, the value are in (Kg/kWh) and Figure 6.13a represents an energy price comparison for the two proposed scenarios, the values are in $(Euro/kWh)$.



(a) Energy price comparison.



(b) Emissions comparison.

Figure 6.13: Prices and emissions comparison.

The evaluation of the emissions is obtained for both scenarios, where the emissions come mainly from the production of micro-turbine and from the main grid considering that its production comes only from fossil resources.

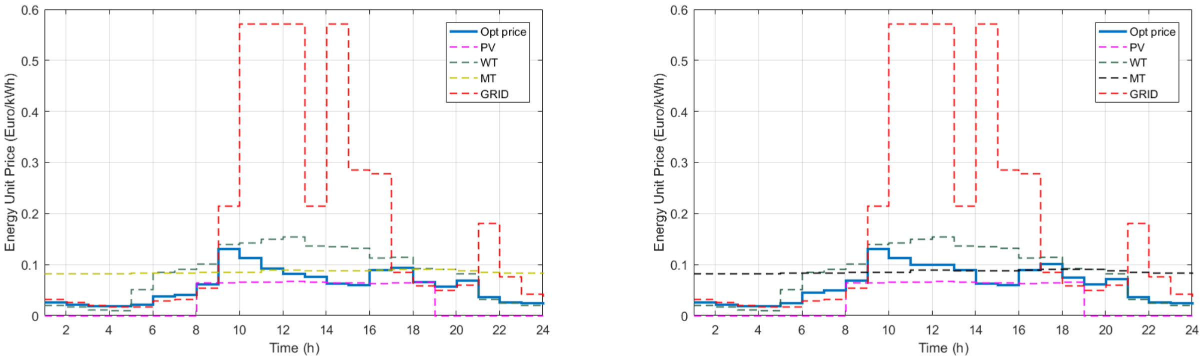
Table 6.3 presents the results of the total energy cost and the total quantity of emissions released from the microgrid and obtained by the energy management system developed for the two proposed scenarios.

Table 6.3: Comparison between the two scenarios.

Scenarios / Results	Total operation cost (Euro)	Total emissions (Kg)
01	102.6873	843.403
02	109.4177	786.5389

Figures 6.14a and 6.14b illustrates the hourly unit price of energy obtained by the implementation of the energy management system compared with the hourly energy prices of each distributed

generator of the microgrid as well as the main grid.



(a) First scenario. (b) Second scenario.

Figure 6.14: Comparison of the optimal price from the EMS and the unit prices of the MG generators.

As illustrated by the results of the optimal setpoints and Figure 6.12, during the hours when the energy price was relatively low, it can be seen that the battery is being charged at the limits of its maximum charge rate (the charging of the storage system is shown by negative values), by adopting this approach, the total price of energy was reduced to 102.68 $Euro$, by comparing with that of [31] which equaled to 106.87 $Euro$.
Taking into account the environmental aspect, the second scenario increases the use of green renewable sources (photovoltaic, wind turbine) and reduces the use of the conventional one (micro-turbine, main-grid). For the reduction of emissions, it is observed that the price has increased to 109.41 $Euro$ and emissions have been reduced to 786.5 kg. An inverse relation is consequently obtained between the price and the emissions. This will lead to go towards the second approach of multi-objective optimization: where price and emissions are both target to be optimized, i.e. a dependent optimization relation between the two objectives. Different to the uni-objective approach that gave an optimal point, the multi-objective optimization will deliver a set of optimal solutions (Pareto front), that will represent scenarios, of which the best compromise between price and emission is selected to schedule the distributed generators of the microgrid.

6.5 Multi-objective Situation

The multi-objective optimization model described in the previous chapter is applied for the management of the microgrid composed of two renewable sources (photovoltaic and wind

turbines), two conventional sources (the micro-turbine and the main grid) and a storage system, the power data are taken similarly from case study one of the uni-objective approach, the main grid will exchange energy with the microgrid in a uni-directional way (from the main grid to microgrid), an inverse operation is not allowed. The total capacity of the battery farm is estimated at E^{max}= 180 kWh with a charge/discharge efficiency of $n_c = n_d = 0.9$, this latter is considered initially at a power of $E(1) = 52\,kWh$, the micro-turbine is present during all the operation process of the microgrid, either by a minimum power of $6\,kW$ or by the power required for the load, the total power that the main grid can provide for the microgrid is $90\,kW$.
The principal function of the management system is to an ensure optimal control of the microgrid, respecting mainly the technical constraints of the problem such as : the continuity without interruption of the power supply and exceeding the the power limits. A demand over the limits could deteriorate the technical characteristics of the microgrid generators.
On the other hand, the management system proposed in this section will ensure economical energy scheduling and reduced emissions; these two criteria have been formalised by a multi-objective function allowing to give results through an optimization search algorithm called: Pareto-search, the results obtained represent the compromise between the price of energy and the quantity of emissions emitted from conventional generators.
The results presented in the Table 6.4 are non-dominant points obtained by the optimization of the multi-objective (cost/emission) function, the values of the total energy prices are in $Euro$, and the total quantity of emission in kg, these points represent scenarios discussed in the rest of this section.
Table 6.4 presents the set of non-dominanted solutions obtained by the implementation of the optimization algorithm in the energy management system. These results represent the best trade-off between the two targets under minimisation.

Table 6.4: The non-dominanted point obtained.

Scenarios	Total Energy Cost (Euro)	Total Emissions (Kg)
01	161.0118	1.2795×10^3
02	159.9786	1.2809×10^3
03	159.7697	1.2823×10^3
04	158,5841	$1{,}2872 \times 10^3$
05	157.5630	1.2984×10^3
06	156,7201	1.3120×10^3
07	155,8556	$1{,}3239 \times 10^3$
08	155.3164	1.3387×10^3
09	154.9797	1.3524×10^3

The non-dominated points are classified in Pareto front as shown in Figure 6.15. All these points represent several scheduling scenarios for the distributed generators of the microgrid, the energy storage system and energy exchanged between the main grid and the microgrid.

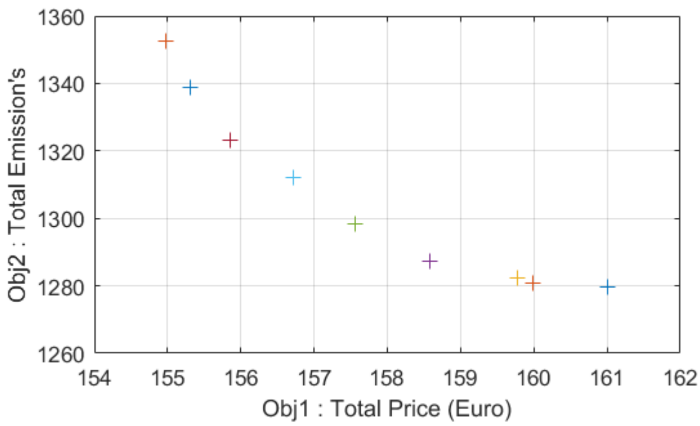


Figure 6.15: Pareto front for non-dominant solutions.

According to the trade-off obtained from the non-dominated points, two cases are highlighted, the best environmental trade-off and the best economic trade-off representing scenarios 1 and 9 presented in Tables 6.5 and 6.6 respectively.

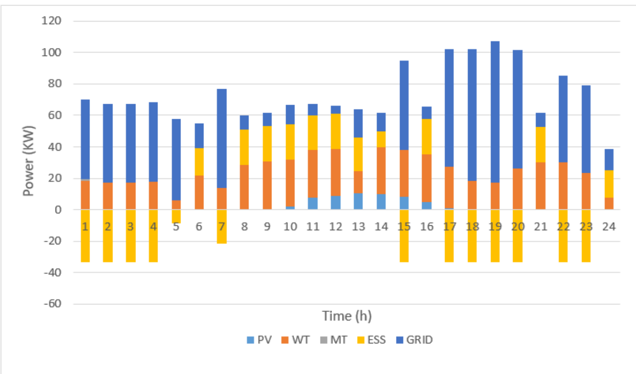
Table 6.5: Comparison of results considering the economic criterion.

Scenarios	Total Energy Cost (euro)
The worst	161.0118
The average	157.5630
The best	154.9797

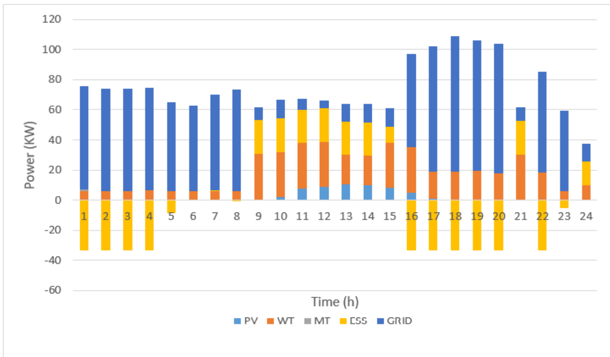
Table 6.6: Comparison of results considering the environmental criterion.

Scenarios	Total Emissions (Kg)
The worst	1.3524×10^3
The average	1.2984×10^3
The best	1.2795×10^3

Figures 6.16a and 6.16b show the optimal power set-points of the microgrid generators respectively for the best environmental and economic situation



(a) Best environmental solution.



(b) Best economical solution.

Figure 6.16: Hourly dispatching set-points of the microgrid generators.

Figure 6.17 shows the two power profiles of the energy storage system of the microgrid corresponding to two scenarios presented previously.

It is possible to verify that, for both cases, the energy storage system is mainly used to compensate for the lack of energy during peak hours.

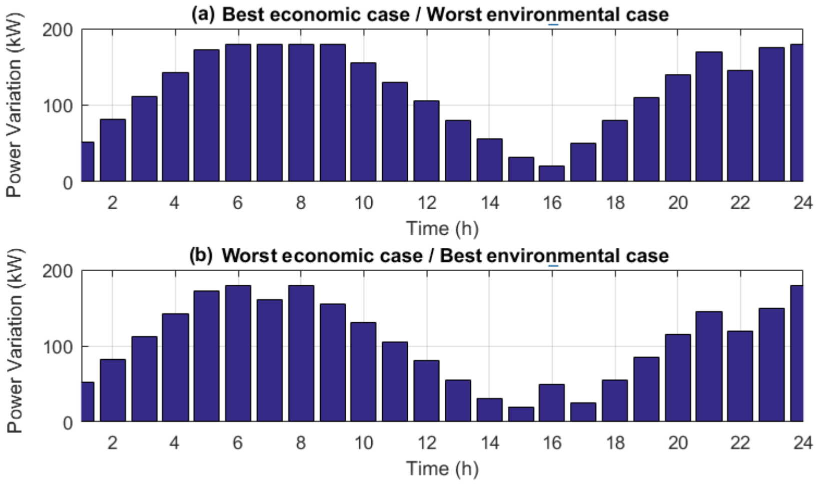


Figure 6.17: Storage system power variation considering (a) scenario 1 and (b) scenario 9.

Figure 6.18 illustrates the daily power exchange of the energy storage system with the microgrid. The areas below the zero axes represent the energy during the charging process while the remaining areas represent the energy delivered to the microgrid. The null values, between 6 and 8 am from the best economic scenario (Figure 6.18(a)), indicate the inactive mode of the energy storage system, which translates that the energy of the storage system has reached its maximum limit E^{max}, and therefore the energy storage system stop charging.

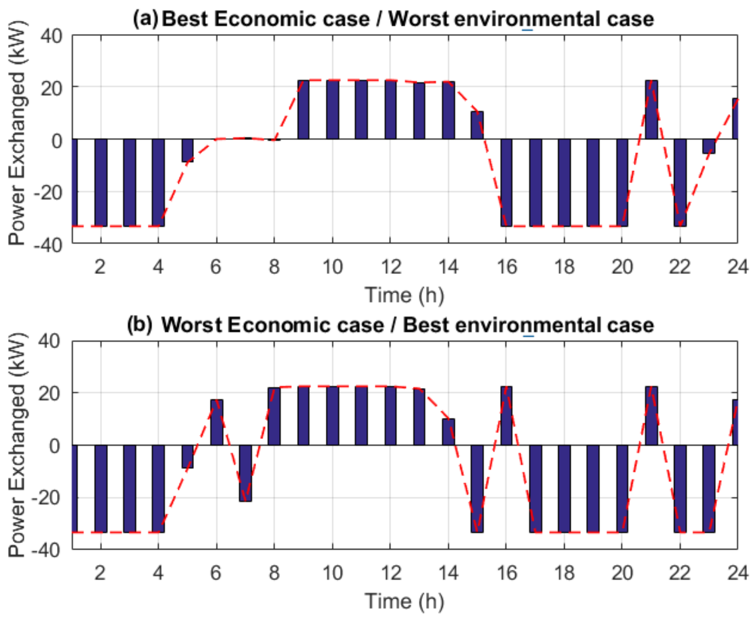


Figure 6.18: Power exchange of the batteries with the microgrid during the day considering (a) scenario 1 and (b) scenario 9.

Based on the analysis of the non-dominated points, the discussion is divided into two cases, the first one mainly characterize the economic criterion, while the second one is related to the environmental criterion, discussed hereinafter.

6.5.0.1 Economic Criterion

Table 6.5 characterizes the classification of the prices according to three states: best, average, and worst, identifying scenarios one, five, and nine, respectively. It is possible to observe that the best point for the price is evaluated at $154,97$ *euro*, with a total quantity of GHG emission equal to 1.3524×10^3 kg. It can be noticed that for an improvement of the economic criterion, the environmental one has been deteriorated. According to the results obtained from the microgrid generators scheduling, illustrated in Figure 6.16b, it is outstanding that the optimal set-points for the microgrid generators with the lowest energy prices are the most important. The main grid is delivering energy to the microgrid during the night period when consumption is reduced and therefore the energy price is low. This energy is mainly used to charge the storage system, as shown by the battery set points in Figure 6.16b (charging is indicated by negative values). During the day, the use of the photovoltaic source is important due to its low price, whereas wind energy is moderately exploited. When cost of energy provided by the main grid is high, the consumption is supported by the micro-turbine in first place, and with the storage batteries according to their price, state of charge and discharge rate limits. The grid is considered as the last resource considering its high cost, *ie* during peak hours, the power from the main grid is not envisaged.
However, the first scenario takes mainly into account the economic criterion by favoring the cheapest sources and considering the fact that the environmental criterion will not be much affected since it is a simultaneous optimization of two objectives.

6.5.0.2 Environmental Criterion

Table 6.6 characterizes the classification of emissions according to three states best, average and worst case, identifying scenarios nine, five, and one, respectively. The best point for emissions is evaluated at 1.2795×10^3 kg, with a total energy price equal to $161,01$ *euro*. It can be noticed that for an improvement of the environmental criterion by 5.39 %, the economic criterion is deteriorated by 3.75%. According to the results presented in Table A.8 and Figure 6.16a, the hourly set-points from renewable sources (wind turbines and photovoltaic) are the most important. The photovoltaic source is fully exploited during the day due to its encouraging price, and being non-polluting also the wind source is considerably exploited to reduce the use of conventional sources responsible for greenhouse gas emissions (GHG). On the other hand,

the use of conventional sources is classified according to the emission factor, the lack of energy is compensated by the micro-turbine due to its reduced emission factor compared to that of the main grid, for this reason, their set-points are important comparing with the previous case which takes into account much more the economic criteria. Furthermore, the main grid is less interrogated since it is considered as a strong emission source. The purpose of battery discharging is to compensate the lack of energy and limit the energy exchange from the main grid to the microgrid to reduce greenhouse gas emissions responsible for global warming.
Indeed, the second case will take into consideration the scheduling of the microgrid product ion sources while favouring the environmental aspect without affecting the economic aspect illustrated by the total cost of energy.

The performance of the energy management system (EMS) based on the Pareto-search Algorithm is demonstrated by the non-dominant points obtained which represent trade-off cases between cost and emissions, allowing the achievement of several scenarios and offering several choices to the grid operator for the scheduling of the microgrid generators taking as reference the points located in the Pareto front.

6.6 Comparison Between Uni-objective and Multi-objective Results

The difference between the two approaches lies in the treatment of the problem, as previously mentioned, the uni-objective approach minimises energy costs, in other words: it takes the cost function as main target to be optimised and the emissions are represented consequently on which their evaluation is done by another function using the set-points obtained after the energy cost optimization. From a mathematical point of view, the results obtained from the uni-objective optimization represent a single optimal point, ensuring a global minimum through one of the deterministic or stochastic optimization approaches presented previously, according to the three study cases presented in the uni-objective approach, an inverse relationship between price and emissions was observed. This result led us to address the problem of energy management in the microgrid using a multi-objective optimization approach whose cost and gas emission criteria are simultaneously optimised.
The minimisation of the two criteria simultaneously (getting minimum for both) seems to be impossible but the compromise between the two was obtained by non-dominanted points located on a Pareto front ensuring the optimality between the two targets cost and emissions, however, several scenarios can be proposed by the microgrid operator to plan these distributed generators, storage system and predict the energy purchased from the main grid when needed, also the

energy sold to the main grid in case that the interaction between the two entities microgrid and the main grid is bi-directional. From the point of view of algorithmic performance, the proposed optimization algorithms for optimising the energy cost in the uni-objective approach was faster compared to the Pareto search algorithm dedicated to the multi-objective optimization, this is reasonable since in the second approach the target is to search for several non-dominanted points representing the compromise between cost and emissions in a feasible search space, while the first approach the target was to find a single optimum which is represented by the objective function representing the lowest energy cost.

Chapter 7

General Conclusion and Perspectives

General Conclusion

In this thesis, several energy management strategies in a microgrid were proposed using an energy management system (EMS) based on optimization approaches for optimal operation of distributed generators while evaluating the technical, economic, and environmental aspects of these operations. In this way, the hourly energy pricing decreases until the energy bill is obtained at the lowest possible cost.
The energy management in a microgrid system is formulated as an optimization problem. For this purpose, the work of this thesis was divided into two main parts, the first one treats the solution of the problem in a uni-objective way. In this regard, three study cases were investigated to solve the most common management problems encountered in works developed in this line of research. The first study case was oriented towards a mathematical study through the development of an intelligent management strategy based on linear and non-linear optimization methods where five optimization algorithms were developed and implemented in the energy management system, including two evolutionary algorithms, Particle Swarm Optimization (PSO) & Genitic Algorithms (GA) on which a technique was proposed to make them more robust and precise whatever the parameters of the problem under study, also linear programming (LP) optimization approach based on the simplex method (SM) was implemented. Finally, a hybrid method (LP-PSO) was developed to analyze its impact on the energy management system. The improved PSO named PSO2 has shown the best performance in terms of accuracy and convergence rapidity. This is why this optimization approach was adopted in the management system proposed in the second study case, which aimed to highlight the economic and environmental impact that the exchange of energy between a microgrid and the rural grid could bring. Simulation results have proved the impact that could be generated

by injecting energy excess from renewable energy sources in the utility on both economically and environmentally ways. considering that the majority of distributed generators used in the microgrid are of non-controllable character and mainly dependent on weather conditions, a management approach based on load controllability was developed in the last study case, the work was a continuity of a recently published paper without a storage system and without connection to the main grids. Therefore, our task consisted of providing the microgrid with an intelligent energy storage system. After that, connecting the two entities microgrid and main grid with proposing our energy management system based on a hybrid optimization method (LP-PSO), the comparison of the two works have shown the reliability of the proposed energy management system based on the proposed optimization approach on the final price of energy as well as on the rate of GHG emissions.
Following the inverse relation obtained between the two parameters (cost and gas emissions) in the uni-objective part, the second part of the thesis treated the problem of microgrids energy management in a multi-objective way considering the simultaneous optimization of the economic and environmental parameters, the optimization algorithm adopted was the Pareto search algorithm, based on the direct multi-search (DMS) principle. In contrast to the uni-objective part characterized by a unique point of convergence representing the global optimum, the multi-objective treatment gave a set of trade-offs between parameters to be optimised, called non-dominant point implemented in a Pareto front representing a set of scenarios. In this part, the microgrid manager will be the main decision-maker about which scenario is going to be selected considering both economic and environmental aspects.

Perspectives

The integration of renewable energy sources with information and communication (ICT) technologies into microgrid systems have opened the way to smart cities, however, the intermittent nature of RES leads to moments of temporary failure of energy management systems. Indeed, the integration of forcasting models with a demand management side (DMS) systems will improve the efficiency of the microgrid allowing for more reliable energy management systems. The latter will be a future work proposed as a continuation of this thesis.

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Appendices

Appendix A

Numerical Results

A.1 energy unit Price

Table A.1: The hourly energy unit prices of distributed generators, energy storage system and main grid.

Time (h)	PV (€/kWh)	WT (€/kWh)	MT (€/kWh)	Battery (€/kWh)	GRID (€/kwh)
01;00	0	0.021	0.0823	0.1192	0.033
02:00	0	0.017	0.0823	0.1192	0.027
03:00	0	0.0125	0.0831	0.1269	0.020
04:00	0	0.011	0.0831	0.1346	0.017
05:00	0	0.051	0.0838	0.1423	0.017
06:00	0	0.085	0.0838	0.15	0.029
07:00	0	0.091	0.0846	0.1577	0.033
08:00	0.0646	0.110	0.0854	0.1608	0.054
09:00	0.0654	0.140	0.0862	0.1662	0.215
10:00	0.0662	0.143	0.0862	0.1677	0.572
11:00	0.0669	0.150	0.0892	0.1731	0.572
12:00	0.0677	0.155	0.09	0.1769	0.572
13:00	0.0662	0.137	0.0885	0.1692	0.215
14:00	0.0654	0.135	0.0885	0.16	0.572
15:00	0.0646	0.132	0.0885	0.1538	0.286
16:00	0.0638	0.114	0.09	0.15	0.279
17:00	0.0654	0.110	0.0908	0.1523	0.086
18:00	0.0662	0.0925	0.0915	0.15	0.059
19:00	0	0.091	0.0908	0.1462	0.050
20:00	0	0.083	0.0885	0.1462	0.061
21:00	0	0.033	0.0862	0.1431	0.181
22:00	0	0.025	0.0846	0.1385	0.077
23:00	0	0.021	0.0838	0.1346	0.043
00:00	0	0.017	0.0831	0.1269	0.037

A.2 uni-objective results

A.2.1 numerical results of the first study case

Table A.2: Optimal power set-points for the firs study-case using SM and PSO2 and GA and (LP-PSO) method.

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	16.0133	6	-33.3333	63.32	52
02:00	0	16.08	6	-33.3333	61.2533	50
03:00	0	16.16	6	-33.3333	61.1733	50
04:00	0	16.1733	6	-33.3333	62.16	50
05:00	0	0	6	-8.8889	58.8889	51
06:00	0	0	6	0	57	63
07:00	0	0	6	0	64	70
08:00	0	0	6	0	69	75
09:00	0.59	14.7333	30	22.5	8.1767	76
10:00	1.9800	13.16	30	22.5	12.36	80
11:00	7.7500	11.6667	30	22.5	6.0833	78
12:00	9.8	10.1468	30	22.5	1.5532	74
13:00	10.65	11.6667	30	19.6833	0	72
14:00	9.7	10.146	30	22.1540	0	72
15:00	8.12	14.6467	30	12.1627	11.0706	76
16:00	4.9500	16.2133	30	0	28.8367	80
17:00	1.1	0	27.2333	-33.3333	90	85
18:00	0.1	1.2333	30	-33.3333	90	88
19:00	0	3.3333	30	-33.3333	90	90
20:00	0	18.6493	11.6840	-33.3333	90	87
21:00	0	19.04	30	22.5	6.46	78
22:00	0	19.03	6	-33.3333	79.3033	71
23:00	0	19.3330	6	-33.3333	73.0003	65
00:00	0	19.6900	6	-5.5556	35.8656	56

Table A.3: Optimal power set-points for the firs study-case using PSO method.

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	16.0133	6	-33.3333	63.32	52
02:00	0	16.08	6	-33.3333	61.25333	50
03:00	0	16.16	6	-33.3333	61.1733	50
04:00	0	16.1733	6	-33.3333	62.16	50
05:00	0	0	6	-8.8889	58.8889	51
06:00	0	0	6	0	57	63
07:00	0	0	6	0	64	70
08:00	0	0	6	0	69	75
09:00	0.3576	14.6848	29.9823	22.4610	8.5142	76
10:00	1.9148	12.5053	29.9690	22.4348	13.1761	80
11:00	7.7358	11.64	29.9995	22.4732	6.1515	78
12:00	9.7986	10.0716	29.9870	22.4306	1.7122	74
13:00	10.6289	11.6662	29.9588	22.4320	3.3142	72
14:00	8.0985	9.8576	29.9923	22.4730	7.5786	72
15:00	7.9557	14.5146	29.9509	9.1309	14.4480	76
16:00	4.9077	16.2132	29.9986	0.1489	34.7316	80
17:00	1.0035	3.3301	29.9999	-33.3333	89.9999	85
18:00	0.0358	2.5170	28.7815	-33.3333	89.9990	88
19:00	0	3.3652	29.9682	-33.3333	90	90
20:00	0	18.6418	11.6917	-33.3333	89.9999	87
21:00	0	18.9552	29.9523	22.4275	6.6650	78
22:00	0	19.03	6	-33.3333	79.3033	71
23:00	0	19.3330	6	-33.3333	73.0003	65
00:00	0	19.6900	6	-5.4466	35.7566	56

A.2.2 numerical results of the second study case

Table A.4: Optimal power set-points for the second study-case (first approach).

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	64.04	6	-11.1111	12.0711	71
02:00	0	64.32	6	-11.1111	13.7911	73
03:00	0	64.64	6	-8.8889	11.2489	73
04:00	0	64	6	0	0	70
05:00	0	0	6	0	69	75
06:00	0	0	6	0	75	81
07:00	0	0	6	0	79	85
08:00	0	0	6	0	88	94
09:00	2.36	58.6	30	10.04	0	101
10:00	7.92	52.64	30	17.44	0	108
11:00	31	46.68	30	6.32	0	114
12:00	39.20	40.60	30	2.20	0	112
13:00	42.60	38.20	30	-0.8000	0	110
14:00	38.80	40.60	30	-8.4444	6.0444	107
15:00	32.48	59	30	2.52	0	124
16:00	19.80	64.84	30	13.36	0	128
17:00	4.4	10.7111	30	-11.1111	90	124
18:00	0.40	13.7111	30	-11.1111	90	123
19:00	0	12.1111	30	-11.1111	90	121
20:00	0	28.1111	6	-11.1111	90	113
21:00	0	76.16	30	-5.3778	0.2178	101
22:00	0	76.44	6	-4.9827	22.5427	100
23:00	0	79.72	6	0	12.28	98
00:00	0	76.6	6	0	13.40	96

Table A.5: Optimal power set-points for the second study-case (second approach).

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	64.04	6	-11.1111	12.0711	71
02:00	0	64.32	6	-11.1111	13.7911	73
03:00	0	64.64	6	-8.8889	11.2489	73
04:00	0	64.68	6	0	-0.68	70
05:00	0	70.72	6	0	-1.72	75
06:00	0	64.68	6	0	10.32	81
07:00	0	58.92	6	0	20.08	85
08:00	0	58.24	6	0	29.36	94
09:00	2.36	58.6	30	10.04	0	101
10:00	7.92	52.64	30	17.44	0	108
11:00	31	46.68	30	6.32	0	114
12:00	39.20	40.60	30	2.20	0	112
13:00	42.60	46.68	30	-0.8000	-8.48	110
14:00	38.80	40.60	30	-8.4444	6.0444	107
15:00	32.48	59	30	2.52	0	124
16:00	19.80	64.84	30	13.36	0	128
17:00	4.4	64.60	30	-11.1111	36.1111	124
18:00	0.40	76.52	30	-11.1111	27.1911	123
19:00	0	70.12	30	-11.1111	31.9911	121
20:00	0	75.80	6	-11.1111	42.3111	113
21:00	0	76.16	30	-5.3778	0.2178	101
22:00	0	76.44	6	-4.9827	22.5427	100
23:00	0	79.72	6	0	12.28	98
00:00	0	76.6	6	0	13.40	96

A.2.3 numerical results of the third study case

Table A.6: Optimal power set-points for the third study-case (first scenario).

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	41	6	5	0	52
02:00	0	34	6	10	0	50
03:00	0	39	6	5	0	50
04:00	0	43	6	2	0	50
05:00	0	0	6	5.5556	44.444	51
06:00	0	0	6	-8.3333	65.3333	63
07:00	0	0	6	-8.3333	72.3333	70
08:00	0	0	6	-8.3333	77.3333	75
09:00	2.36	51.9733	30	-8.3333	0	76
10:00	7.92	42.080	30	0	0	80
11:00	31	17	30	0	0	78
12:00	39.2	4.8	30	0	0	74
13:00	42.6	0.0859	30	-0.6859	0	72
14:00	38.8	0	23.20	10	0	72
15:00	32.48	0	28.52	15	0	76
16:00	19.8	27.9778	30	2.2222	0	80
17:00	4.4	0	6	-8.3333	82.9333	85
18:00	0	0	6	-8.3333	90.3333	88
19:00	0	0	6	-8.3333	92.3333	90
20:00	0	0	6	-8.3333	89.3333	87
21:00	0	72.2743	6	-0.2743	0	78
22:00	0	57	6	8	0	71
23:00	0	54	6	5	0	65
00:00	0	42	6	8	0	56

Table A.7: Optimal power set-points for the third study-case (second scenario).

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	41	6	5	0	52
02:00	0	34	6	10	0	50
03:00	0	39	6	5	0	50
04:00	0	43	6	2	0	50
05:00	0	4.444	6	5.5556	40	51
06:00	0	8	6	-8.3333	57.3333	63
07:00	0	10	6	-8.3333	62.3333	70
08:00	0.400	11.6	6	-8.3333	65.3333	75
09:00	2.36	51.9733	30	-8.3333	0	76
10:00	7.92	42.080	30	0	0	80
11:00	31	25	22	0	0	78
12:00	39.2	25	9.8	0	0	74
13:00	42.6	20	10.0859	-0.6859	0	72
14:00	38.8	0	23.20	10	0	72
15:00	32.48	0	28.52	15	0	76
16:00	19.8	27.9778	30	2.2222	0	80
17:00	4.4	25	6	-8.3333	57.9333	85
18:00	0.400	22.6	6	-8.3333	67.3333	88
19:00	0	10	6	-8.3333	82.3333	90
20:00	0	15	6	-8.3333	74.3333	87
21:00	0	72.2743	6	-0.2743	0	78
22:00	0	57	6	8	0	71
23:00	0	54	6	5	0	65
00:00	0	42	6	8	0	56

A.3 Multi-objective Results

Table A.8: Optimal power set-points for the best environmental solution of multi-objective situation.

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	16,013	18,441	-33,3333	50,878	52
02:00	0	16,08	17,408	-33,3333	49,845	50
03:00	0	16,16	17,368	-33,3333	49,805	50
04:00	0	16,173	17,861	-33,3333	50,299	51
05:00	0	7,372	6	-8,8889	51,517	56
06:00	0	8,16	21,562	17,343	15,937	63
07:00	0	14,34	14,066	-21,4109	63,004	70
08:00	0,1	15,206	28,487	22,124	9,08	75
09:00	0,59	14,0898	30	22,5	8,82	76
10:00	1,98	13,16	30	22,5	12,36	80
11:00	7,75	10,816	30	22,5	6,935	78
12:00	8,534	8,079	30	22,5	4,887	74
13:00	10,65	8,33	13,643	21,611	17,767	72
14:00	9,7	10,146	30	10,264	11,89	72
15:00	8,12	14,6467	30	-33,3333	56,566	76
16:00	4,95	14,245	30	22,5	8,305	80
17:00	1,1	16,1467	26,074	-33,3333	75,013	85
18:00	0,0997	19,117	18,246	-33,3333	83,871	88
19:00	0	16,053	17,28	-33,3333	90	90
20:00	0	18,65	26,37	-33,3333	75,314	87
21:00	0	16,361	30	22,5	9,134	78
22:00	0	19,0297	30	-33,3333	55,303	71
23:00	0	19,333	23,28	-33,3333	55,72	65
00:00	0	17,341	7,41	17,59	13,691	56

Table A.9: Optimal power set-points for the best economical solution of multi-objective situation.

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	9,923	6	-33,3333	68,733	52
02:00	0	9,29	6	-33,3333	68,044	50
03:00	0	9,318	6	-33,3333	68,015	50
04:00	0	9,673	6,299	-33,3333	68,361	51
05:00	0	0	6	-8,8889	58,888	56
06:00	0	0	6	0	57	63
07:00	0	0	6	0,3594	63,64	70
08:00	0	1,697	6	-0,4437	67,746	75
09:00	0,591	4,089	30	22,5	8,82	76
10:00	1,98	13,16	30	22,5	12,36	80
11:00	7,75	10,815	30	22,5	6,935	78
12:00	8,534	8,0787	30	22,5	4,887	74
13:00	10,65	8,329	19,642	21,6109	11,767	72
14:00	9,7	8,353	19,95	21,9197	12,075	72
15:00	8,12	14,65	30	10,4693	12,763	76
16:00	4,949	16,213	30	-33,3333	62,17	80
17:00	1,1	16,1467	17,7308	-33,3333	83,35581	85
18:00	0,0996	12,49	18,741	-33,3333	90	88
19:00	0	17,0249	19,263	-33,3333	87,044	90
20:00	0	16,455	18,048	-33,3333	85,829	87
21:00	0	16,36	29,99	22,5	9,1394	78
22:00	0	19,029	18,183	-33,3333	67,12	71
23:00	0	10,903	6	-5,5556	53,653	65
00:00	0	18,752	10,119	15,3223	11,807	56

Appendix B

Algorithms Pseudo Codes

B.1 PSO Algorithm

Algorithm 1: Pseudo code for the optimisation process with PSO algorithm

Input : P_{pv}, P_{WT}, P_{MT}, P_{ESS}, P_{grid}, P_{load}, B_{pv}, B_{WT}, B_{MT}, B_{grid}, B_{ESS}, $f(P_., B_.)$

Output: $Setpoint_{pv}$, $Setpoint_{WT}$, $Setpoint_{ESS}$, $Setpoint_{MT}$, $Setpoint_{grid}$

Initialisation : n_{pop}, n_{it}, n_{var}, c_1, c_2, ω, lb, ub
PSO;
for $i \leftarrow 1$ **to** n_{it} **do**
  Initialisation : $\overrightarrow{x_i}(t)$, $\overrightarrow{x_{Best}}$, $\overrightarrow{v_i}(t)$, $\overrightarrow{G_{best}(t)}$
  for $j \leftarrow 1$ **to** n_{pop} **do**
    $\overrightarrow{x_i}(t+1) = \overrightarrow{x_i}(t) + \overrightarrow{v_i}(t+1)$
    $\overrightarrow{v_i}(t+1) = c_0.\overrightarrow{v_i}(t) + c_1.r_1.\overrightarrow{P_i}(t) - \overrightarrow{x_i}(t) + c_2 r_2(\overrightarrow{G_{best}}(t) - \overrightarrow{P_i}(t))$
    if $f(\overrightarrow{x_i}(t)) < f(\overrightarrow{x_{Best}}(t))$ **then**
      $\overrightarrow{x_i}(t)) = f(\overrightarrow{x_{Best}}(t))$ `// Position evaluation`
      if $f(\overrightarrow{x_{Best}}(t)) < f(\overrightarrow{G_{Best}})$ **then**
        $f(\overrightarrow{G_{best}}) = f(\overrightarrow{x_{Best}}(t))$ `// Evaluation of the best global`
      else
        return
      end if
    else
      return $j = j + 1$
    end if
  end for
  $G_{solution} = f(\overrightarrow{G_{best}})$ `// Best solution of iteration i`
end for
return $i = i + 1$

B.2 Genetic Algorithm

Algorithm 2: Pseudo code for the optimisation process with Genetic Algorithm (GA)

```
Input  : P_pv, P_WT, P_MT, P_ESS, P_grid, P_load, B_pv, B_WT, B_MT, B_grid, B_ESS, f(P., B.)
Output: Setpoint_pv, Setpoint_WT, Setpoint_ESS, Setpoint_MT, Setpoint_grid
Initialisation : n_pop, n_generation, n_it, n_var, η_croisement, η_mutation, β, γ, σ, lb, ub
AG;
for i ← 1 to n_it do
    Initialisation : x_i(t)                      // Initialization of the parent chromosomes
    for j ← 1 to n_pop do
        Selection;
        C_Prob = exp(−β ∗ c)
        Crossover;
        for k ← 1 to n_generation/2 do
            P_1 = roulette wheel(C_Prob)
            P_2 = roulette wheel(C_Prob)
            (x_k1, x_k2) = Crossover(P_1, P_2)
        end for
        Mutation;
        for l ← 1 to n_generation do
            x_l = Mutation(x_k)
            if f(x_l) < f(x_Best) then
                x_solution = x_l                 // Best solution of the iteration l
            else
                return
            end if
        end for
        n_pop = n_generation
    end for
    C_ost = f(x_solution)                        // Best price for the best solution
end for
return i = i + 1
```

Appendix C

The Articles

C.1 Article 01

Title: Smart Microgrid Management: a Hybrid Optimisation Approach.

Journal: Energy, Sustainability and Society.

Situation: On process.

RESEARCH

Smart Microgrid Management: a Hybrid Optimisation Approach

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Abstract

Background: The association of distributed generators, energy storage systems and controllable loads close to the energy consumers gave place to a small-scale electrical network called microgrid. The stochastic behavior of renewable energy sources, as well as the demand variation, can lead in some cases to problems related to the reliability of the microgrid system. On the other hand, the market price of electricity from mainly non-renewable sources becomes a concern for a simple consumer due to its high costs.

Method: In this work, an energy management system was developed based on an innovative optimization method, combining linear programming, based on the simplex method, with particle swarm optimisation algorithm. Two scenarios have been proposed to characterise the relation price versus gas emissions for optimal energy management. The objective of this study is to find the optimal setpoints of generators in a smart city supplied by a microgrid in order to ensure consumer comfort, minimising the emission of greenhouse gases and ensure an appropriate operating price for all smart city consumers.

Results: The simulation results have demonstrated the reliability of the optimisation approach on the energy management system in the optimal scheduling of the microgrid generators power flows, having achieved a better energy price compared to a previous study with the same data.

Conclusion: The energy management system based on the proposed optimisation approach gave an inverse correlation between economic and environmental aspects, in fact, a multi-objective optimisation approach is performed as a continuation of the work proposed in this paper.

Keywords: Microgrid; Smart Sustainable Cities; Energy Management System; Particle Swarm Optimisation; Linear Programming

1 Introduction

The considerable increase in population is followed by inflation in demand and human energy consumption can become a large-scale problem. The main problem is the consumption growing of electrical energy which leads to the rising of electricity cost and also to environmental impact mainly when the energy is from conventional sources. According to the International Energy Agency (IEA), in 2018 the production of electricity based on fossil fuels (gas and oil) was estimated at 64% of the total electricity production in the world, while the contribution of renewable sources was estimated at only 26% (hydroelectricity 16%, wind 5%, biomass 3%, solar 2%) and 10% of the production was from nuclear power plants. The world has experienced a historic peak in greenhouse gas emissions related to fossil fuel-based production, with 33.1 billion tons of CO_2 being released into the atmosphere. As a result, in 2018 the planet's temperature was more than $1°C$ warmer than the 19^{th} century average according to the U.S. space agency (NASA). Therefore, the world community made several efforts by orienting the production from renewable energies, especially in the challenge of decreasing global warming [1]. Even though they are inexhaustible and largely available, the stochastic effect of renewable energies leads to innovative methods in order to get the best benefit from them. The utilization of these sources as decentralised generators are the better option for reducing greenhouse gas (GHG) emissions and losses in the energy transport system [2, 3].

To increase the penetration of renewable energies and solve the problems associated with the conventional electrical system such as losses in the transport and distribution networks, the microgrid concept has been introduced to ensure reliable production on a small scale, by making the place of consumption a place of production [4, 5].

The microgrid is defined as a low-voltage distribution network including various distributed generators (micro-turbines, fuel cells, photovoltaic, wind-turbines, among others), together with storage devices and controllable loads that can operate interconnected or isolated from the main distribution network. Microgrids become a component of smart grids, where a load management system is used to balance the energy generation and consumption [6, 7]. The optimal energy management system can effectively optimize, improve efficiency, provide flexibility, controllability and economic viability of power system operation [8].

A local production from several energy sources gives place to the concept of multi-source. The optimal management of a multi-source system economically and environmentally is a growing research area especially after the objective established by the European Union (EU) to confront climate change in the framework for action on climate and energy for the period of 2021-2030. The key targets are: reduction of greenhouse gas emissions by at least 40% (from 1990 levels), increasing the contribution of renewable energy to at least 32% of final energy consumption, and improving energy efficiency by at least 32.5%. Several management systems strategies have already been proposed, for instance, the authors in [9, 10] developed a mixed-integer programming (MILP) method to deal with the optimal energy control of distributed generators for a small microgrid. In [11] a genetic algorithm (GA) was proposed to achieve an optimisation strategy for hybrid energy systems. In [12] the author proposed a new approach based on an artificial fish swarm algorithm (AFSA) to solve the problem of optimal planning of available sources in a microgrid community. In [13] four optimisation approaches have been developed and compared for microgrid source scheduling. The author used the direct search method, particle swarm optimisation (PSO), lambda logic, and lambda iteration. The PSO showed better performance between the four adopted management strategies. In the work performed in [14] the author presented day-ahead optimised scheduling using a harmony search (HS) and differential evolution (DE) algorithms. In [15] an optimal real-time energy management strategy was developed to minimise costs and gas emissions and also to encourage renewable generation, by using the binary particle swarm optimisation method (BPSO). In [16] the author proposes optimal energy management in the presence of high penetration of renewable energy, a novel model was introduced to deal with the challenging constraint of the supply-demand balance raised by the intermittent nature of renewable energy sources. In this study, the conventional generation costs, utilities with adjustable loads, distributed storage costs were taken into and, additionally, the worst-case transaction cost was included in the objective function.

Seyed et al. had proposed in [17] a distributed energy management system to program the central and local controllers of the microgrid, taking into account the optimal power flows via an Alternate Multi-Multiplier Direction (ADMM) method.

In [18] the author proposed an energy management strategy for a smart city taking into account the demand schedule, the latter had considered that the load is composed of two parts, one fixed and the other shiftable. For optimal energy management, the author had proposed two PSO algorithms used in two steps to ensure optimal scheduling of distributed generators. The first PSO algorithm allowed to determine the optimal power setpoints of all micro-grid generators that can satisfy the fixed demand needs in the smart city with a reduced operating cost, while the second PSO algorithm allowed to schedule the changing demand of the city in order to avoid peak hours characterized by a high operating cost.

Initial integration of information communication technology (ICT) into city operations have promoted telicity, information city, and digital city concepts. Later, the conception of IoT has founded the smart cities, which support the city operations intelligently with minimal human interaction [19]. However, smart cities and sustainable cities have given rise to the 'smart sustainable city' referred to a city that is supported by the pervasive presence and massive use of ICT technology, enable the city to control available resources in a safe, sustainable and efficient way to improve economic and societal outcomes [20, 21]. In this context, the work presented in this paper consists of an architecture extension of the one proposed in [18] by adding a storage system to the distributed generators of the microgrid destined to supply a smart city (photovoltaic system, wind generator, and micro-turbine) with a connection of the entire microgrid with the utility grid. A combined management strategy between linear programming (LP) based on the simplex method and particle swarm optimisation (PSO) has been adopted to ensure optimal dispatch of the microgrid sources, according to the load-demand of the smart city, while ensuring an optimal energy cost and considering the minimization of GHG emissions. This study presents an innovative optimization approach proposed to ensure optimal energy management in microgrids using energy storage and load control devices, essential pillars that contribute to the development and evolution of microgrids.

This paper is organised as follows. Section 2 presents an overview of a microgrid community. In Section 3 the energy storage system is modeled. In Section 4, the problem formulation is presented and the objective function with constraints are formulated. Section 5 explains the adopted energy management strategy with a description of the optimization algorithms used. Simulation results for two scenarios of the energy management system are performed and compared in Section 6. Section 7 concludes the study and proposes guidelines for future works.

2 Microgrid Description

The system proposed in this study consists of a combination of photovoltaic generators, a wind turbine farm and a conventional micro-turbine system. Because of the stochastic effect of renewable sources and the limited capacity of the micro-turbine, it is included a storage system in order to ensure the continuous balance between supply and demand and minimize the amount of curtailed energy from renewable resources. The microgrid is connected to the main grid, even so it may have the possibility to be explored off-grid, in case of not required, malfunction or failure of the main grid, the connection is ensured through a transformer and common coupling point (PCC) as indicated in Figure 1. By this way, the main grid acts as a buffer, when the sources and the exploitation procedures into the microgrid are not enough. So, regarding the economic and environmental criteria, renewable energy sources can provide energy to loads and/or charge the battery. Excess energy, after satisfying local demands, can be fed into the main grid to reduce the total operating costs and reduce the emissions from conventional generation, or it can be exchanged with other microgrids.

In this study case, the battery is dimensioned to assist local load for one hour and the stored energy cannot be sold to the main grid for safety reasons, reliability, and continuity [22]. The energy management system (EMS) will allow optimal scheduling of distributed generators (DG) and the energy storage system (ESS) by respecting economic and environmental constraints.

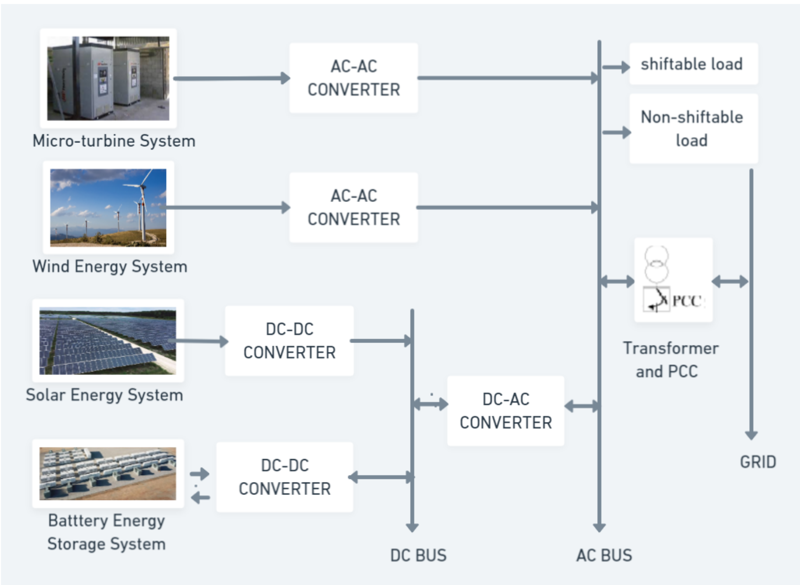

Figure 1 The architecture of the microgrid

The power limits for each DGs and storage device are shown in Table 1, where P_g represents the power delivered by the main grid, P_{WT}, P_{PV} and P_{MT} are the power delivered by the wind turbine, photovoltaic system and micro-turbine, respectively. Finally, P_{SD} is the energy associated to the storage device. The main grid can exchange with the microgrid a maximum power of 95kW. In order to reduce the number of start-up/shutdown and for maintenance reasons [18], the micro-turbine (MT) is present at all times either by its minimum power of 6kW or by the necessary power of load that is limited to 30kW. The battery is used to supply the shiftable part of the load, being its maximum capacity of 15kWh.

Table 1 Maximum and minimum limits for microgrid production units

Microgrid system	P_g	P_{WT}	P_{PV}	P_{MT}	P_{SD}
P_{min}(kW)	0	0	0	6	-7.5
P_{max}(kW)	95	80	40	30	15

Figure 2 shows the daily variation of the power delivered by the renewable generators, namely photovoltaic and wind turbine. The determination of the optimal size of distributed generators is beyond the scope of this paper, therefore the power data delivered by the distributed generators are taken similar to the microgrid proposed in the study [18].

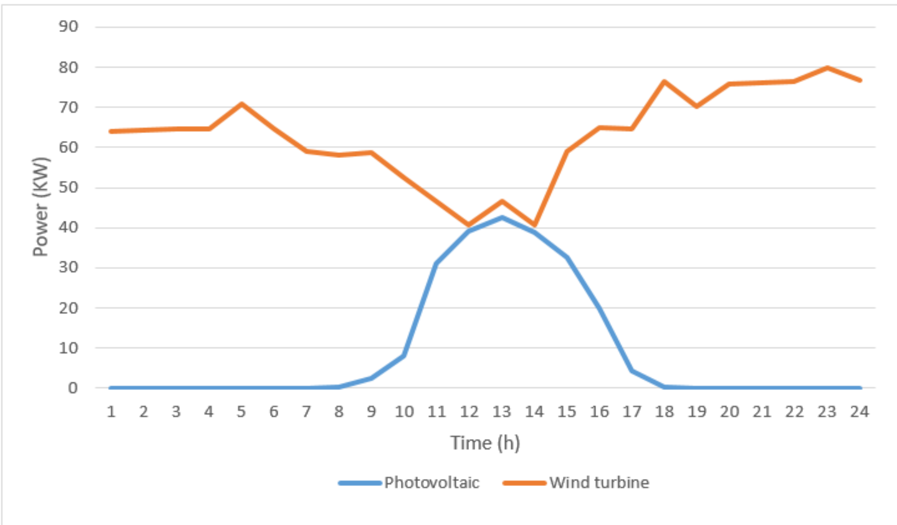

Figure 2 The daily power profile from renewable sources [18]

The types of loads in the proposed microgrid are smart home loads, composed of a main fixed part called a non-shiftable load, and a secondary part comprising shiftable load that could be shed to avoid a high price of energy at the consumption peaks. The behavior of non-shiftable and shiftable loads is shown in Figure 3. The loads are connected through sensors and communication technologies, in an internet of things (IoT) based approach, allowing the sensing and transmission of real-time data, which enables decision-making according to specified objectives. This gives to the customer the possibility to program their demand, independently, by taking as reference the instantaneous operating cost delivered by the manager of the microgrid [23]. For this purpose several strategies have already been proven to be effective in load scheduling: the use of fuzzy logic for the optimal management and loads programming in a smart house [24], and many other metaheuristics have allowed moderate consumption planning such as Genetic Algorithm, as proposed in [25], and PSO presented in [26]. Also, an Artificial Neural Network algorithm based forecasting model was developed in [27]. After the load analysis, the most common approach is to perform load shedding to avoid consumption peaks and, consequently, excessive costs. In [16] a PSO algorithm was proposed for this task, achieving a better performance when compared with standard management.

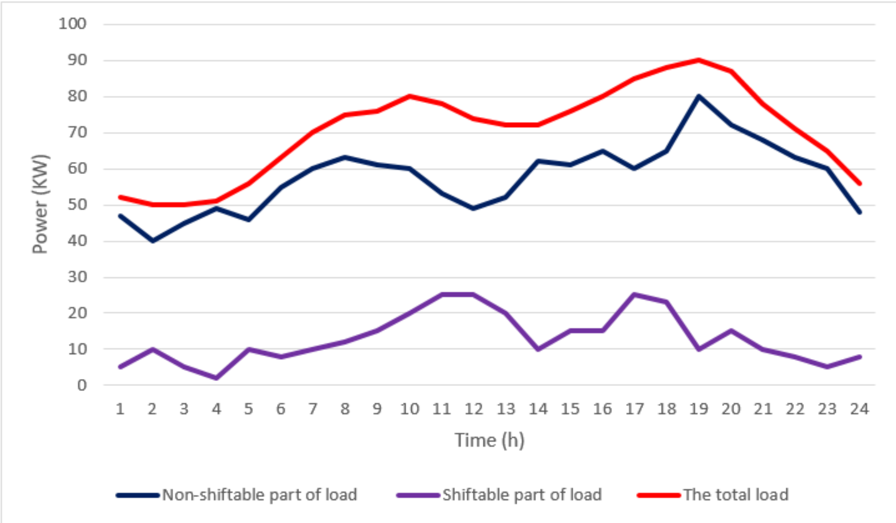

Figure 3 Hourly Load Distribution [18]

The contribution of this paper is to ensure the supply of both shiftable and non-shiftable devices, instantaneously, i.e., assuring feeding the essential loads when needed, while assuring the minimisation of the operation costs. A storage system was introduced in the microgrid system to optimise the operating costs and ensure a minimum GHG emission rate followed by the production sources. This operation is ensured by an energy management system (EMS), based on a mixed optimisation method (LP-PSO). To demonstrate the influence link between price and emission, two scenarios are proposed. The first scenario takes into account the optimisation of energy costs as a primary goal, while the second one takes the environmental effect by increasing the utilization of renewable energy sources.

3 Modeling of the Energy Storage System

To optimise the microgrid scheduling, a proper model must be developed for the energy storage system (ESS) [28]. However, there are several types of storage systems: supercapacitors, electrochemical batteries, superconducting magnetic energy storage, compressed air energy storage and flywheel energy storage [29]. These devices have different characteristics, including response times, storage capacities, and peak current capabilities, which are applied for different purposes with different time-scales [30]. Electrochemical batteries are selected in this study due to their popularity of storing electrical energy for a long time and capacity.

The ESS system used in this microgrid consists of a bank of electrochemical batteries, connected in series to increase the voltage level and in parallel to increase the current level [31]. The energy stored in the ESS is used as a state variable by the management system. To properly model the ESS, several factors must be considered, such as the capacity and charge/discharge rates. In order to increase the lifespan of the storage system, deep discharges should be avoided. So, considering that $E(t)$ represents the battery stored energy at time t, the charging and discharging operations are given by:

$$\begin{cases} E(t+1) = E(t) - \Delta_t P_c(t)\eta_c, & \textit{charging mode} \\ E(t+1) = E(t) - \dfrac{\Delta_t P_d(t)}{\eta_d}, & \textit{discharging mode} \end{cases} \quad (1)$$

where $P_c(t)$ and $P_d(t)$ are the charging and discharging powers of the battery at time t; Δ_t is the interval of time considered, and finally, η_c and η_d are the charging and discharging efficiency.

4 Problem Formulation

The proposed management system aims to find the optimal power operation points for distributed generators, storage systems, and the main grid concerning economic and environmental constraints.

4.1 Cost Minimization

The definition of the cost function is the most relevant approach. It depends on several parameters, mainly the type of architecture of the microgrid [32]. Several functions have already been used, in [33] the cost of exploitation from the distributed resources and the storage system were considered constant during the day and selling/buying prices of the main grid were different, while in [28, 34, 35], the cost of the distributed resources and the storage system was considered dynamic throughout the day. Also, the cost of selling/buying energy supplied by or injected into the grid varies during the day, being the main objective of the cost function to satisfy the load demand during the day in the most economical way. So, in each hour t the cost can be calculated as:

$$C(t) = \sum_{i=1}^{N_g} U_i(t) P_{DGi}(t) B_{DGi}(t) + \sum_{j=1}^{N_s} U_j(t) P_{SDj}(t) B_{SDj}(t) + P_g(t) B_g(t) \quad (2)$$

where N_g and N_s are the total number of generators and storage devices, respectively. $B_{DGi}(t)$ and $B_{SDj}(t)$ represent the bids of i^{th} DG unit and j^{th} storage device at hour t. $P_g(t)$ is the active power which is bought (sold) from (to) the utility grid at hour t and $B_g(t)$ is the electricity price of the utility grid at hour t. $U_i(t)$ and $U_j(t)$ are the operation mode of the i^{th} generator and the j^{th} storage device (ON or OFF), respectively. The energy bids of the elements that constitute the microgrid as well as the hourly grid electricity price are know parameters defined according to [18], while P_{DGi}, P_{SDj} and P_g are the variables that are identified to solve the following problem :

$$CT = \min C(t) \tag{3}$$

4.2 GHG Emissions Evaluation

Emissions include the polluting gases responsible for the greenhouse effect such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon dioxide (CO_2) [34]. Table 2 presents the emission factors for non renewable sources as defined in[28].

Table 2 Emission factors [28]

EF	Micro-turbine (Kg/MWh)	Grid (Kg/MWh)
CO_2	724	922
NO_X	0.2	2.295
SO_2	0.00136	3.583

The quantity of GHG Emissions at time t is given by:

$$EM(t) = \sum_{i=1}^{N_g} U_i(t)P_{DGi}(t)EF_{DGi}(t) + P_g(t)EF_g(t) \tag{4}$$

where $EF_{DGi}(t)$ and $EF_g(t)$ are GHG emission factors which described the amount of pollutants emission in kg/MWh for each generator and utility grid at hour t, respectively.

The total quantity of GHG emissions in kg during a period of time T, can be determined by:

$$\text{EMT} = \textstyle\sum_{t=1}^{T} EM(t) \tag{5}$$

4.3 Power Balance Constraint

The total power generation has to meet the total demand (including storage) and transmission losses. The active power balance is the precondition for a stable operation, in terms of frequency stability. The transmission losses are considered numerically low, being neglected in this study. Thus, the power balance constraint assumes the following form:

$$\sum_{i=1}^{N_g} P_{DGi}(t) + \sum_{j=1}^{N_s} P_{SDj}(t) + P_g(t) = P_L(t) \tag{6}$$

being $P_L(t)$ the total electrical load demand at hour t. And knowing that the power of the battery $P_{SDj}(t)$ can be positive in case of discharging or negative in the case of charging where it is considered as a load.

4.4 Electrical Limits of Generators Constraint

The generators must not operate beyond their limits and, in addition, the energy exchanged between the microgrid and the main grid are limited. The active power output of each DG and the main grid are limited by lower and upper bounds as follows:

$$P_{DGi}^{min}(t) \leq P_{DGi}(t) \leq P_{DGi}^{max}(t) \tag{7}$$
$$P_{SDj}^{min}(t) \leq P_{SDj}(t) \leq P_{SDj}^{max}(t) \tag{8}$$
$$P_{g}^{min}(t) \leq P_{g}(t) \leq P_{g}^{max}(t) \tag{9}$$

where $P_{.}^{min}(t)$ and $P_{.}^{max}(t)$ are the minimum and the maximum powers of the distributed generator (DG), storage device (SD) and the grid (g) at the time t, respectively.

4.5 Storage System Limits Constraint

Battery must remain within the limits of its capacity and its charging/ discharging is limited by a maximum rate that must not be exceeded

$$E^{min}(t) \leq E(t) \leq E^{max}(t) \tag{10}$$

$$\begin{cases} -P_c(t)\eta_c \leq P_c^{max} & \text{charging mode,} \quad P_c(t) < 0 \\ \dfrac{P_d(t)}{\eta_d} \leq P_d^{max} & \text{discharging mode,} \quad P_d(t) > 0 \end{cases} \tag{11}$$

where $E^{min}(t)$ and $E^{max}(t)$ are the minimum and maximum energy levels of the battery, respectively, and P_c^{max} and P_d^{max} are the maximum rates of charge/discharge of the battery that must be respected in each operation.

5 Proposed Management System

In order to be economically and ecologically reliable, two constraints must be considered in the optimisation problem associated to the costs and emissions issues. The proposed microgrid is composed of two conventional sources (micro-turbine and the main grid) responsible for GHG emissions mainly CO_2, SO_2, and NO_x with different rates. The energy management program, proposed in this study, is established considering two types of loads: non-shiftable and shiftable. The non-shiftable part can be fed by the two renewable sources PV's and WT's, the micro-turbine and also the grid. The shiftable part is provided by the storage batteries as the first priority with the remaining power from the previous four sources after feeding the non-shiftable part of the load. The energy management system (EMS) depends mainly on a mixed optimization using linear programming (LP) based on the simplex method, and a particle swarm optimization (PSO) method.

In order to consider both economic and environmental criteria, two management scenarios are proposed:

Scenario 01: The supply of non-shiftable part of load, is supported by the four main generators previously identified: photovoltaic, wind-turbine, micro-turbine and grid,

depending on the state of charge of the storage system. The supply of the shiftable part of load is provided by the storage battery as a first priority. But, in the case where the storage system has reached its minimum state of charge, the compensation is provided by the remaining power after supplying the non-shiftable part of the load.
Scenario 02: This approach will mainly take into account the environmental criterion. Although the power supply of the non-shiftable loads is provided by the four main sources, the supply of the shiftable loads is assured by the ESS, but, in the case that the battery bank achieves its minimum state of charge, the lack will be compensated by the remaining power from renewable sources: photovoltaics and wind turbines, if the energy from renewable sources is insufficient for this operation, the non-supplied part will be shifted out to off-peak hours.

5.1 Optimisation Techniques

This study presents two optimisation techniques to solve the problem presented in section 4, the simplex method and the Particle Swarm Optimization (PSO) approach, detailed below.

5.1.1 Simplex Method

The simplex method is an algorithm for solving linear optimisation problems, its procedure consists of moving from a feasible solution to another, at each step, by improving the value of the objective function. The method is completed after a finite number of these transitions [36].

Two characteristics of the simplex method have led to its acceptance as a computational tool. The first one is the robustness of the method which allows solving any linear problem: it detects redundant constraints in the optimisation problem; it identifies cases where the objective value is unlimited; it solves problems with multilocal solutions; it is a self-initiated method used either to generate an appropriate and feasible solution or to show that the problem has no feasible solution. On the other hand, the simplex method offers much more than optimal solutions. It shows how the optimal solution depends on the problem data (cost coefficients, constraint coefficients and righthand-side data) [36].

5.1.2 Particle Swarm Optimization Algorithm

The PSO is a stochastic optimisation technique that finds the optimal solution using a population strategy iteratively to improve a candidate solution. This method was originally developed by Eberhart and Kennedy in 1995 and it is based on the dynamic behavior of animals moving in compact groups [37]. PSO depends on a population of simple particles where each particle is considered as a potential solution to the problem [38]. The particles communicate between them in all search space to build a solution to the problem posed, by taking advantage of their collective experience. Each particle has a memory of its best position or experience, known as best personal value (P_i), and also the best experience of all the particle swarm denoted as global best ($G_.$) [39].

First of all, a random number of particles are evaluated in the search region, then each particle changes its position in this space according to its current location (X_i), previous velocity (V_i), best personal value (P_i) and global best value (G). With some random perturbations, the velocity of each particle is modified iteratively according to the best position. The next step starts again after updating the position (X_i) of each particle. In this process, the swarm as a whole can find the optimal solution [22]. As the particles interact with each other, they progress towards the optimal solution as expressed in Equation (12) [40].

$$\begin{cases} X_i(t+1) &= X_i(t) + v_i(t+1) \\ v_i(t+1) &= C_0 v_i(t) + C_1 r_1 (P_i(t) - X_i(t)) + C_2 r_2 (G(t) - P_i(t)) \end{cases} \tag{12}$$

The personal best $P_i(t)$ and the global best $G(t)$, are updated at each iteration until the global minimum is reached, $r1$ and $r2$ are random parameters between $[0,1]$. The personal best $P_i(t)$, associated with the particle i, is the best position that the particle has visited since the beginning of the evolution. Considering a minimisation function, $f(x)$, the best personal position at the moment, $t+1$, is calculated as follows:

$$\begin{cases} P_i(t+1) &= P_i(t), \quad f(X_i(t+1)) \geq f(X_i(t)) \\ P_i(t+1) &= X_i(t+1), \quad f(X_i(t+1)) < f(X_i(t)) \end{cases} \tag{13}$$

The best global position at time t is defined as follows:

$$G(t+1) = min_i(P_i(t+1)) \tag{14}$$

5.2 Energy management system procedure

The importance of linear programming is illustrated in the first part of execution of the energy management program by using the simplex method as an optimal scheduling tool for the distributed generators that supply the non-shiftable loads. The main highlighted constraint is the assurance of continuous power supply to these loads by the three microgrid distributed generators: photovoltaic, wind turbine, micro-turbine and main grid, while respecting the power limits of each one of them, respectively, (P_{DGi}^{max}) and (P_g^{max}). In the second step, the PSO is intended to manage the charging and discharging process of the storage system dedicated to supply the shiftable part of the load while respecting the limits constraints (4.5). The initial departure points of the PSO particles are the optimal set point values delivered by the linear programming (LP) algorithm used to schedule the generators of the microgrid to feed the non-shiftable part of the load. Figure 4 illustrates the process of the proposed energy management system.

6 Numerical Results and discussion

This section presents the numerical results of the EMS applied to reduce the cost and the GHG emissions in a time span of 24 h of operation. The microgrid comprises three power sources, two being renewable, the photovoltaic system, the wind turbine, and a non-renewable source, a micro-turbine. Additionally, the microgrid comprises an energy storage system and it is also connected to the utility grid,

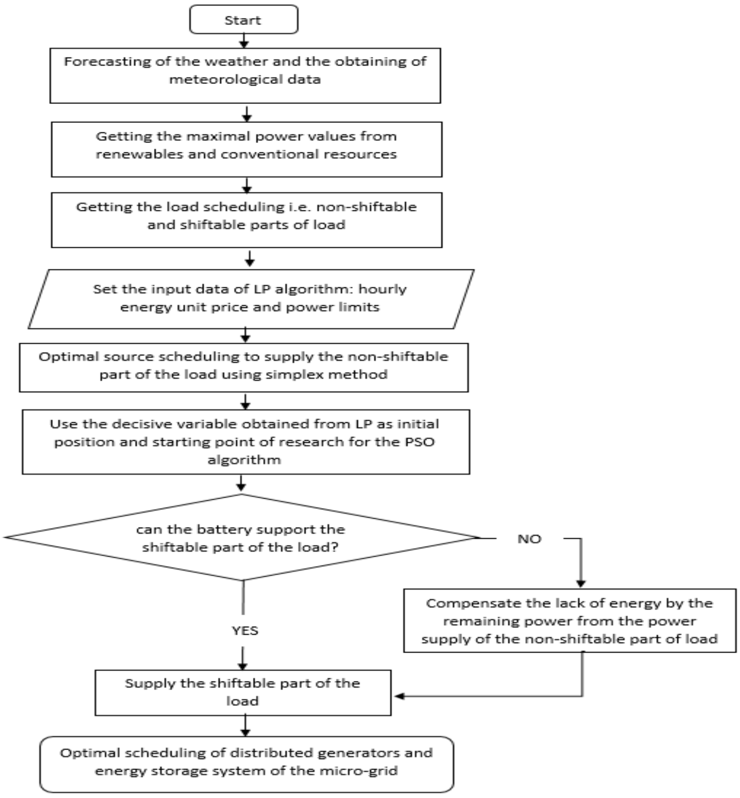

Figure 4 Flow-chart of the proposed energy management system

which may act as a buffer, supplying or absorbing the energy from the imbalances into the microgrid loads and sources.

Two scenarios are proposed to supply the microgrid consumers. The first takes into account the economic criterion and the second the environmental criterion, both of them allow to illustrate the price/emissions relation, as described in the previous section.

After cost minimisation by means of objective function (3), the quantity of emissions is evaluated by the second function (5). The application of the energy management system allowed the calculation of the optimal setpoints for the distributed generator (DG's) and storage system (ESS) of the microgrid through the combined (LP-PSO) strategy (Figure 4), assuring a power balance between supply and demand, i.e, at all times, the sum of the optimal power points generated by the microgrid sources and the main grid is equal to the power demand from the microgrid consumers and the energy required for charging the storage system in case of need.

The parameters of the selected PSO are as follows: search dimension = 1, population size = 60, number of iteration = 100, $c1$ = 2, $c2$ = 2 and w = 0.78, the performance and reliability of the optimisation algorithms are proven by the good choice of the optimal power set points.

Tables 3 and 4 present the solutions found for the first and second scenarios identifying the energy sources and considering the load needs for each hour (all values are in kW) and PV, WT, MT and ESS represent the optimal power setpoints of the microgrid generators and storage system obtained by the implementation of the energy management system.

The results of Table 3 show that for each hour, the setpoints of the cheapest sources are the most important, while in Table 4 we remark a high use of renewable sources.

Table 3 Optimal scheduling of DGs and storage for the first scenario. Total operation cost= 102.69 Euro. Total emissions= 807.40 kg.

Time	PV	WT	MT	ESS	GRID	LOAD
01	00	41	06	05	00	52
02	00	34	06	10	00	50
03	00	39	06	05	00	50
04	00	43	06	02	00	51
05	00	00	06	5.5556	44.444	56
06	00	00	06	-8.3333	65.3333	63
07	00	00	06	-8.3333	72.3333	70
08	00	00	06	-8.3333	77.3333	75
09	2.36	51.9733	30	-8.3333	00	76
10	7.92	42.080	30	00	00	80
11	31	17	30	00	00	78
12	39.2	4.8	30	00	00	74
13	42.6	0.0859	30	-0.6859	00	72
14	38.8	00	23.20	10	00	72
15	32.48	00	28.52	15	00	76
16	19.8	27.9778	30	2.2222	00	80
17	4.4	00	06	-8.3333	82.9333	85
18	00	00	06	-8.3333	90.3333	88
19	00	00	06	-8.3333	92.3333	90
20	00	00	06	-8.3333	89.3333	87
21	00	72.2743	06	-0.2743	00	78
22	00	57	06	08	00	71
23	00	54	06	05	00	65
24	00	42	06	08	00	56

Table 4 Optimal scheduling of DGs and storage for the second Scenario. Total operation cost=109.42 Euro. Total emissions= 672.87 kg.

Time	PV	WT	MT	ESS	GRID	LOAD
01	00	41	06	05	00	52
02	00	34	06	10	00	50
03	00	39	06	05	00	50
04	00	43	06	02	00	51
05	00	4.444	06	5.5556	40	56
06	00	08	06	-8.3333	57.3333	63
07	00	10	06	-8.3333	62.3333	70
08	0.400	11.6	06	-8.3333	65.3333	75
09	2.36	51.9733	30	-8.3333	00	76
10	7.92	42.080	30	00	00	80
11	31	25	22	00	00	78
12	39.2	25	9.8	00	00	74
13	42.6	20	10.0859	-0.6859	00	72
14	38.8	00	23.20	10	00	72
15	32.48	00	28.52	15	00	76
16	19.8	27.9778	30	2.2222	00	80
17	4.4	25	06	-8.3333	57.9333	85
18	0.400	22.6	06	-8.3333	67.3333	88
19	00	10	06	-8.3333	82.3333	90
20	00	15	06	-8.3333	74.3333	87
21	00	72.2743	06	-0.2743	00	78
22	00	57	06	08	00	71
23	00	54	06	05	00	65
24	00	42	06	08	00	56

According to the available power and daily energy bids, it is clear that the photovoltaic power is fully exploited because of its encouraging price, but the presence of this source depends on its potential that is available only during the day. So, this gives the opportunity for wind energy to be exploited. The advantage with this source is that it is potentially available during the night and its price is relatively low during this period which justifies its wide use.

During the day, the insufficient power of the photovoltaic source leads to compensation by one of the two conventional sources: from the grid or the micro turbine, depending on their unit operating price.

The LP method is responsible for the scheduling of the microgrid generators needed to supply the non-shiftable part of the load by the mean of the energy management system. The use of the storage system is intended to supply as a priority the shiftable part of the load. The management of the battery charge/discharge, as well as the supply of the shiftable part of the load, is ensured by the PSO algorithm while respecting the battery limit constraints.

In [18] the shiftable part of the load is driven at times when the energy price is low. This will lead to the disconnection of some home-application when they are part of the shifted load, and therefore, the comfort of the users can be affected. Instead of shifting the load when the energy price is low, the cheaper energy can be used for charging the ESS, this energy will be used to power the shiftable part of the load. The parts of loads that were supposed to be shifted will be maintained and powered by the energy of the battery, which price depends on the low prices of the sources used to charge it. Therefore, get the best benefit from the cheapest energy sources available on the microgrid.

The dispatching optimal power setpoint of microgrid generators for the first and the second scenarios are illustrated in figures 5 and 6, respectively.

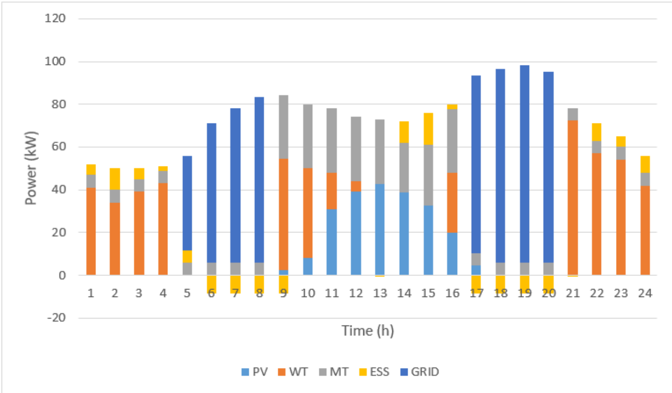

Figure 5 Hourly dispatch set-points of microgrid generators for the first scenario.

During the hours when the energy price is relatively low, it can be seen that the battery is being charged at the limits of its maximum charge rate (the charging of the storage system is shown by negative values). By adopting this approach, the total price of energy comparing with results presented in [18] was reduced to 102.69 Euro.

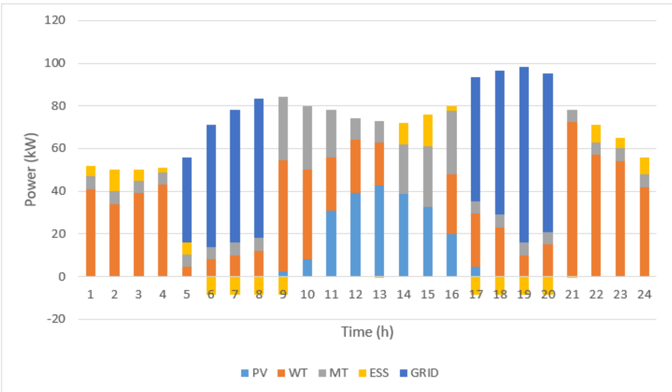

Figure 6 Hourly dispatch set-points of microgrid generators for the second scenario.

Figure 6 and Table 4 describe the power flow behavior in the microgrid for the second scenario explained previously. It should be noted that the setpoints of the energy from the main grid and micro-turbine have been reduced while the set points of the renewable sources: photovoltaic and wind energy are more important due to their massive exploitation imposed by the strategy of the energy management system (EMS) that promotes the environmental aspect in this part. Therefore, the rate of greenhouse gas emissions has been significantly reduced.

Figure 7 illustrates the comparison of the hourly variation of the energy prices for a 24 h operating time in the microgrid obtained by the scheduling elaborated by the energy management system based on the hybrid optimization approach LP-PSO for both scenarios. It can be seen that the hourly variation of energy prices for the first scenario is lower than the second one. This behavior results from the different management strategies elaborated in the two scenarios, since during the day, the management system of the first scenario will favour the use of energy from sources with a reduced energy price according to the load demand by the consumers and the energy required for charging the storage system. while the management system of the second scenario aims at encouraging a higher use of renewable sources in order to reduce the increase of GHG emissions.

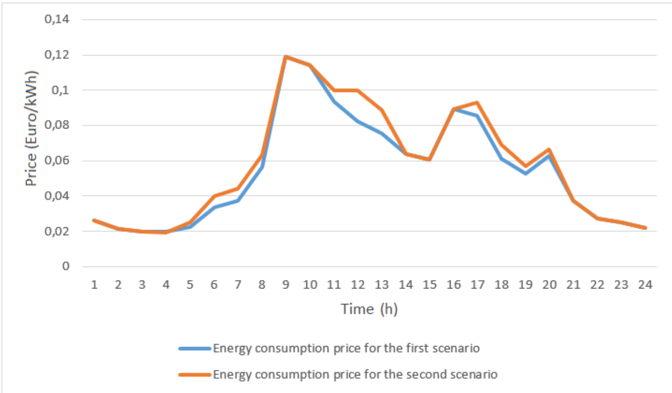

Figure 7 Day profile of the obtained operating cost.

The evaluation of the emissions is obtained for both scenarios. Figure 8 shows a comparison of the hourly variation in greenhouse gas emissions (GHG) for the two scenarios proposed in the microgrid. The emissions come mainly from the energy produced by the micro-turbine and the main grid, which is considered produced from fossil resources. The management system in the second scenario encourages the use of renewable sources, which results in a considerable reduction in GHG emissions as can be seen in Figure 8.

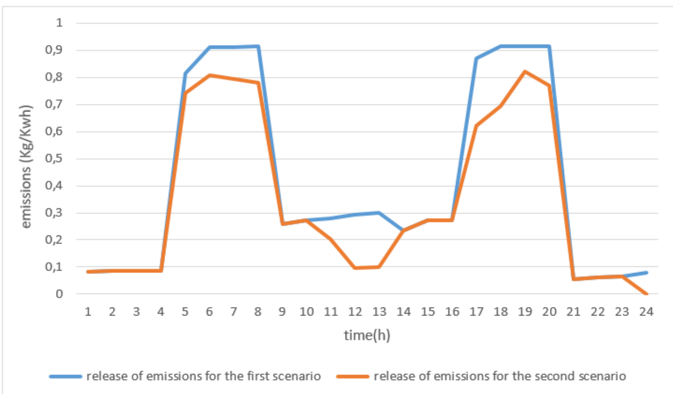

Figure 8 Daily profile of the obtained emissions.

For the reduction of emissions, it is observed that the price has increased to 109.42 Euro and GHG emissions have been reduced to 672.87 kg per day. So, the inverse relation is consequently obtained between the two criteria. This will go towards the second approach of multi-objective optimisation where price and emissions are both targeted to be optimised, i.e, a dependent optimisation relation between the two objectives.

Table 5 Comparison between both scenarios.

scenario	Total operation cost (Euro)	Total emissions (kg)
01	102.69	807.40
02	109.42	672.87

7 Conclusions and Future Work

In this paper, an energy management system has been proposed for the optimal scheduling of the microgrid generators taking into account the controllability of scheduled loads. The configuration of the microgrid represents an extension of the architecture proposed in [18], the management system takes as main targets the optimisation of the price and the reduction of the GHG emission rate, by using a hybrid optimisation approach LP-PSO strategy. The results demonstrate the reliability of the proposed energy management system (EMS) in the optimal scheduling of the microgrid generators power flows, having achieved a better energy price compared with the previous study with the same data, presented in [18]. The uni-objective approach gave an inverse relation between economic and environmental constraints. Starting from this result, a multi-objective approach is going to be presented as future work by taking the price and emissions as a dependent optimisation target. Differently to the uni-objective approach that gave an optimal point, the multi-objective optimisation will deliver a set of optimal solutions (Pareto front), that will represent scenarios, of which the best compromise between price and emission is selected to give the optimal scheduling of microgrid generators.

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C.2 Article 02

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Optimization Methods for Energy Management in a Microgrid System Considering Wind Uncertainty Data

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Abstract. Energy management in the microgrid system is generally formulated as an optimization problem. This paper focuses on the design of a distributed energy management system for the optimal operation of the microgrid using linear and nonlinear optimization methods. Energy management is defined as an optimal scheduling power flow problem. Furthermore, a technical-economic and environmental study is adopted to illustrate the impact of energy exchange between the microgrid and the main grid by applying two management scenarios. Nevertheless, the fluctuating effect of renewable resources especially wind, makes optimal scheduling difficult. To increase the results reliability of the energy management system, a wind forecasting model based on the artificial intelligence of neural networks is proposed. The simulation results showed the reliability of the forecasting model as well as the comparison between the accuracy of optimization methods to choose the most appropriate algorithm that ensures optimal scheduling of the microgrid generators in the two proposed energy management scenarios allowing to prove the interest of the bi-directionality between the microgrid and the main grid.

Keywords: Microgrid, Energy Management System, Optimization Algorithms, Set-points, Wind Forcasting, Artificial Neural Network

1 Introduction

Renewable energy sources (RES) are currently being deployed on a large scale to meet the requirements of increased energy demand, mitigate the environmental pollutants, and achieve socio-economic benefits for sustainable development [1]. In counterpart, renewable energy sources suffer from several obstacles, mainly their intermittent nature, which makes difficult to precisely predict their production [2]. However, to address this problem, an aggregation of (RES) at a local level as a hybrid energy system (HES) gives rise to the microgrid (MG) concept. Achieving a reliable power balance between supply and demand can be difficult when using a large renewable energy system, this is why an energy management strategy is necessary in the case of a microgrid [3].

Hossein et al [29], have classified energy management systems in microgrids into four categories according to the type of backup system used, including non-renewable energy sources, energy storage system (ESS), demand-side management (DSM) and hybrid systems.

Microgrids are low-voltage (LV) distribution networks that contain a set of distributed generators (DGs), storage devices and controllable loads operating in islanded mode or interconnected to the main distribution network as a controlled entity [8], usually based on a central controller that enables the optimization of their functioning during an interconnected operation by optimizing the production of local DGs and electricity exchanges with the main distribution network.

The microgrid control operation contains three main levels, the first level characterizes the micro sources controller (MSC) which uses the local information to control the voltage and frequency in transit condition. The two others levels concern the microgrid system controllers (MGSC) and the distribution management system (DMS) that are responsible for the maximization of the microgrid value and the optimization of its operation by using the market prices of electricity in order to quantify the power that the MG should draw from the distribution system [10].

The deployment of these systems offers many advantages for both the user and the electricity provider. For the user's application, the microgrid can improve the quality of the network and reduce the operation cost. From the electric utility provider implementation of distributed generation systems with the ability of reducing the power flow on transmission and distribution lines, reducing losses and costs for additional power [9], as well as contributing on the reduction of greenhouse gas emissions. Microgrids are capable to increase the dependability, economy, offering clean generation of electrical energy and its supply to sustain the consumer's satisfaction. The incorporation of RES in the MG system has developed to generate, distribute and supervise the electrical power, in order to obtain the optimal combination [28]. Hence, several research works have been developed in the area of microgrid energy management. The authors of [11] developed optimal energy management of microgrid system considering it as being as optimal scheduling of power flow, in [12] authors treat the energy management issues by the mean of an economic objective function using a matrix real-coded genetic algorithm (MRC-GA). The linear programming (LP) algorithm was used in [13] to manage the microgrid for the purpose of minimizing the daily operating cost. In [14] Kerboua et al proposed a particle swarm optimization (PSO) algorithm for the energy management strategies of smart cities using load scheduling. In [15] a genetic algorithm (GA) was used for an advanced EMS model able to determine the optimal operating strategies regarding to energy costs minimization and pollutant emissions reduction. Other authors have considered the energy management in microgrid as a multi-objective optimization problem considering both economic and environmental aspects, in [4] a multi bacterial foraging optimization (MBFO) was proposed for the optimal energy dispatch of a microgrid system. In [16] a multi-objective particle swarm optimization was proposed (MOPSO) for management and optimal distribution of energy resources, for the same purpose a nondominated sorting genetic algorithm (NSGA) was adopted on [17].

Further to its remarkable development in the field of renewable energies, according to the Portuguese Renewable Energy Association (PREA), in 2019, the wind power production in Portugal was estimated at 5429 MW. Infact, this represents an encouraging statistic to increase wind production capacity in the country. As a matter of fact, wind generation in microgrid systems represents an important resource, but its widely fluctuating effect makes it scheduling with other distributed energy resources more difficult. However, a wind forecasting model allowing the prediction of the available capacity of wind generation in the microgrid is important to improve the reliability of the system, to do this, several models have been proposed in the literature. Liang et al proposed in [18] a wind-velocity prediction model based on the previous values of the velocity using two-layer artificial neural networks with a back propagation algorithm for short-term wind speed forecasting. In [19] the authors established the development of an artificial neural network-based wind power forecaster and the integration of wind forecast results into unit commitment (UC) scheduling considering forecasting uncertainty by the probabilistic concept of the confidence interval. In [20], a prediction model was proposed using a hybrid Kalman filter with an artificial neural network (KF-ANN) based on the linear autoregressive integrated moving average (ARIMA). In [21] the authors proposed several prediction models based on ANN uses multiple local meteorological measurements together such as wind speed, temperature and pressure values, the results allowed to analyze and compare the effect of using several local variables instead of wind speed only.

This article proposes optimization methods for energy management in a microgrid system considering wind uncertainty. In order to predict the hourly wind energy production during the day, a multilayer neural network algorithm is proposed, the performances of the model are evaluated according to the mean squared error (MSE) value. On the other hand, energy management is formulated as a uni-objective optimization problem. To allocate the power set-points for the optimal scheduling of microgrid generators, five optimization methods are proposed and compared: linear programming (LP) based on simplex method, two particle swarm optimization (PSO) algorithms, genetic algorithm (GA) and a hybrid approach (LP-PSO). Finally, two management scenarios are proposed to illustrate the economic and environmental impact of energy exchange between the microgrid and the main grid.

The remaining parts of the paper are organized as follows: Section 2 describes the wind forecasting model. In section 3 the architecture, as well as the operation of the microgrid, are presented. The storage system has been modeled in section 4. The operation of the energy management system, the optimization problem and these constraints are explained in Section 5. In Section 6, we present and discuss results obtained under the computational simulations. Section 7 concludes the study and proposes guidelines for future works.

2 Wind Forecasting Model

Wind energy is one of the most energy-efficient ways to produce electrical power in a microgrid. The wind farms require a continuous and sufficient wind speed for proper electricity production [22]. However, to improve the reliability and quality of the microgrid, a wind speed forecasting model based on ANN neural network is proposed in this article. The wind speed is predicted accurately by ANN using multiple local meteorological measurements. The proposed ANN model uses the previously recorded wind speed and temperature together weighted by W_{ij} to predict the future value of wind speed as illustrated in Fig. 1.

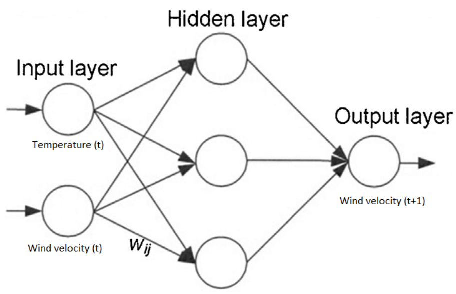

Fig. 1. Structure of the ANN model

The real data are collected by using a data monitoring system which can record 5 minutes' time interval sensor measurement. The data are measured by the meteorological station of the laboratory at the Polytechnic Institute of Bragança (latitude: 41° 47' 52.5876°" N - longitude: 6°° 45' 55.692" W) from January 1, 2019, to December 31, 2019. Figures 2 and 3 shown the data of wind and temperature.

Wind speed data of five-minute intervals between January 1, 2019, and December 31, 2019, are obtained as an input representing 103104 samples of which 90% are used for training, 5% for testing, and 5% for validation. The ANN structure has two layers. Feedforward back propagation is handled as a network type. The transfer function is take in a sigmoid. Because the Levenberg –Marquard algorithm has fast convergence, this latter is handled by the learning process for all ANN structure. The performances of the model are measured using the mean

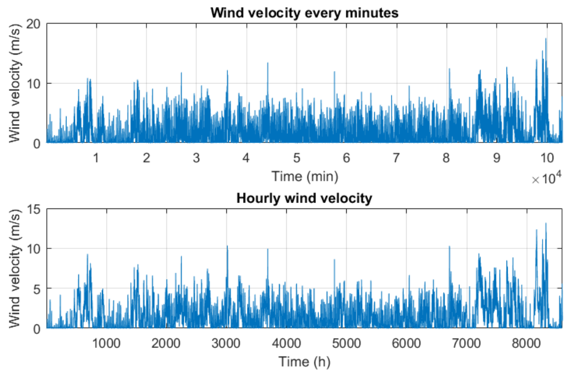

Fig. 2. Pattern of wind speed data in five minutes' interval in Polytechnic Institute of Bragança

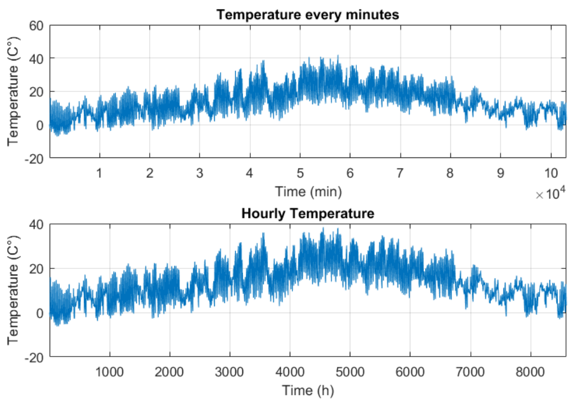

Fig. 3. Pattern of temperature data in five minutes' interval in Polytechnic Institute of Bragança

square error (MSE) value as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x_i})^2 \quad (1)$$

where n is the number of periods of time, x_i is the desired neural network output value associated to the wind velocity, and $\bar{x_i}$ is the estimated value obtain by neural network associated to the wind velocity.

3 Microgrid Architecture

The chosen microgrid consists of two renewable sources photovoltaic (PV) and wind-turbine (WT), a conventional source micro-turbine (MT) and an energy storage system (ESS) in addition to the load. The latter are interconnected via two buses (DC and AC) through the bidirectional inverter. The MG system is connected to the main grid. The exchange of energy between the microgrid and the main grid is mutual in a way that the main grid supplies (sells) energy when its unit price is cheap, and absorbs (buys) surplus energy from renewable generators.

The real-time energy management of different elements of the microgrid is mainly based on the unit cost of energy per kWh by satisfying the load balance constraint while minimizing the cost. Fig.4 shows the microgrid architecture adopted in this study.

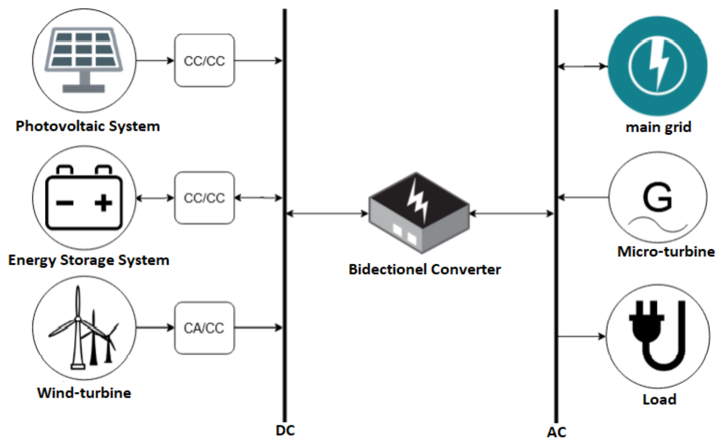

Fig. 4. Microgrid Architecture

The power limits of the microgrid generators are presented in Table 1.

Table 1. Maximum and minimum limits for microgrid production units

MG system	Min power (kW)	Max power (kW)
P_{gr}	0	90
P_{WT}	0	20
P_{PV}	0	25
P_{MT}	6	30
P_{ESS}	-25	30

The daily photovoltaic and wind production power profiles are shown in Fig.5 [4].

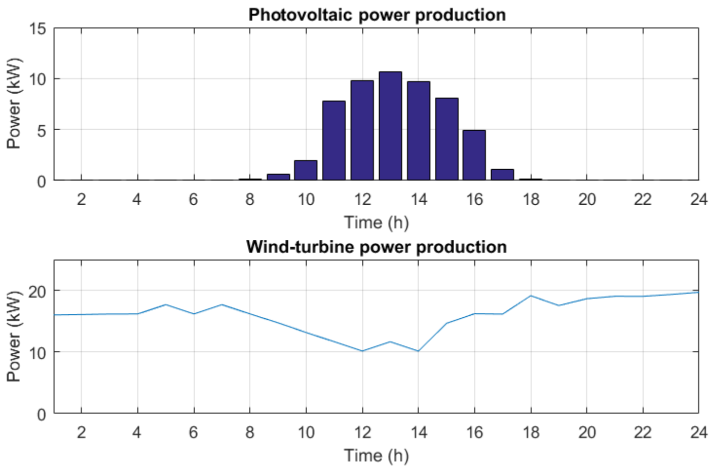

Fig. 5. Photovoltaic and wind energy production profile

The average daily consumption for the community of the microgrid is illustrated in Fig.6.

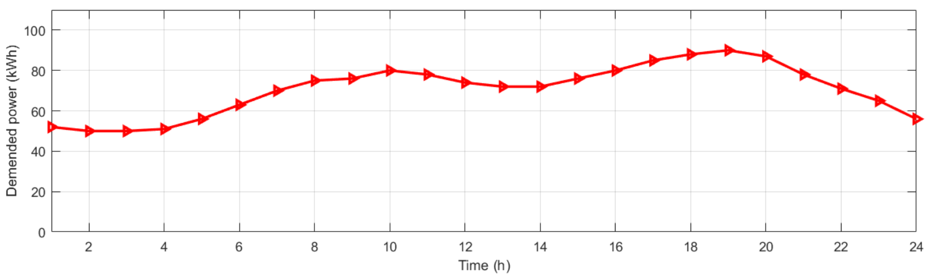

Fig. 6. Daily profile of the microgrid demand

4 Energy Storage System Modelling

The development of microgrids with an energy storage system (ESS) has been a subject of considerable research in recent years [23]. To ensure reliable, resilient, and cost-effective operation of the microgrid, the ESS must have a proper model with a correct type choice. Several types of energy storage systems can be used in a microgrid system, each storage type has different characteristics, including response times, storage capacities and peak current capacities, which are addressed at different applications and different time scales [24].

In the literature, electrochemical batteries have shown the best performance in microgrid systems as well as their ability to store electrical energy for a long period of time [25]. Within this context, an ESS composed of electrochemical batteries is introduced in this study, a complete mathematical model is used to simulate the states of charge and discharge of the ESS.

Several factors are necessary to describe the battery behavior, such as capacity and charge/discharge rate [26]. To increase the lifespan of the battery energy system (BES), deep discharges must be avoided, considering that $E(t)$ represents the battery stored energy at time t, the energy flows entering (Charging mode) or exiting (discharging mode) from the battery at each time step t are computed as follows:

$$\begin{cases} E(t+1) = E(t) - \Delta_t P_c(t)\eta_c, & \text{charging mode}, \\ E(t+1) = E(t) - \frac{\Delta_t P_d(t)}{\eta_d}, & \text{discharging mode}, \end{cases} \tag{2}$$

where $P_c(t)$ and $P_d(t)$ are the charging and discharging powers of the battery at time t; Δ_t is the interval of time considered, and finally, η_c and η_d are the charging and discharging efficiency.

For the reliable operation, battery must remain within the limits of its capacity and its charging/ discharging is limited by a maximum rate that must not be exceeded

$$E^{min}(t) \leq E(t) \leq E^{max}(t) \tag{3}$$

$$\begin{cases} P_c(t)\eta_c \leq P_c^{max} & \text{charging mode}, \quad P_c(t) < 0 \\ \dfrac{P_d(t)}{\eta_d} \leq P_d^{max} & \text{discharging mode}, \quad P_d(t) > 0 \end{cases} \tag{4}$$

where $E^{min}(t)$ and $E^{max}(t)$ are the minimum and maximum energy levels of the battery, respectively, and P_c^{max} and P_d^{max} are the maximum rates of charge/discharge of the battery that must be respected in each operation.

5 Energy Management System Operation

In this section, the optimization model of the energy management system adopted for the proposed microgrid will be presented. The state variables to be optimized in this case are the output powers of the different generators, the storage system and the main grid. The goal is to determine the power set-points of all microgrid generators by formulating the management problem as an objective function to be optimized. Indeed, five optimization methods are proposed in this study including linear programming (LP) based on the simplex method, two particle swarm optimization (PSO) algorithms, a genetic algorithm (GA), and a hybrid (LP-PSO) algorithm. Besides, greenhouse gas emissions (GHG) released during an operational day will be evaluated through an environmental function.

The optimization model used in the energy management system is illustrated in Fig.7.

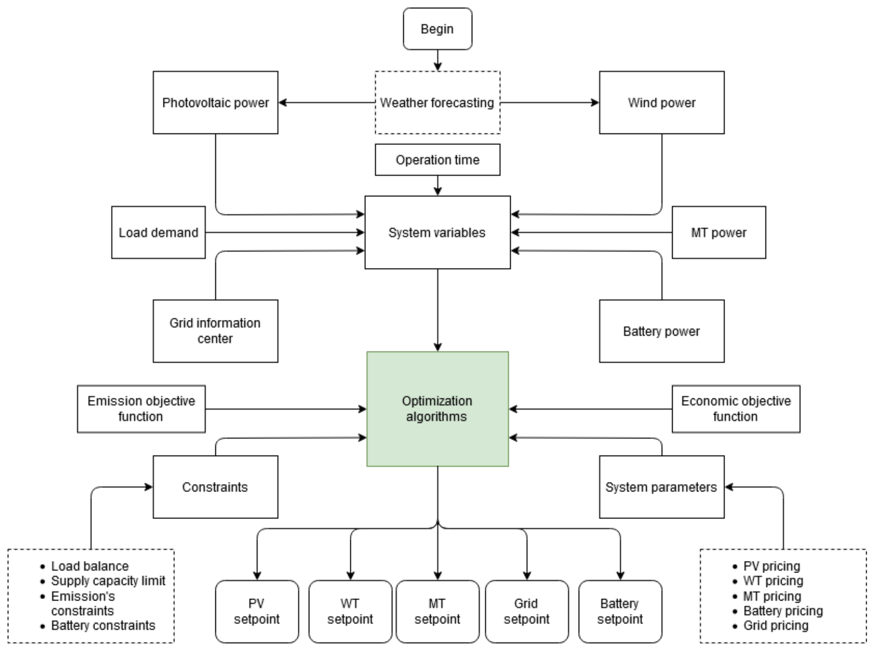

Fig. 7. Microgrid optimization model

The purpose of the microgrid operator is to manage the system in order to find the optimal daily profiles for each source of the microgrid that will allow us to obtain the lowest possible daily energy price, the management will be based mainly on three essential factors:

1. The nominal hourly power $P_x(t)$ available in each source x (renewable or conventional) in each hour t.
2. The hourly energy unit price $B_x(t)$ for each generator of the microgrid system.
3. The state of charge $SOC(t)$ of the energy storage system.

The energy management system (EMS) problem intent to find the optimal set-points of the distributed generators, the storage system and the amount of energy exchanged with the power grid taking into account the economic and environmental constraints.

5.1 Problem formulation

Energy management in the microgrid system is formulated as an optimization problem based on economic and environmental objective functions as described as follows.

Energy Price Evaluation The choice of the cost function is the most relevant issue for the optimization problem. It depends on several parameters mainly the type of architecture of the microgrid. Several functions have already been used, in [4] the cost of exploitation from the distributed resources and the storage system was considered constant during the day and the buying / selling price of the main network was different. In [5], [6] and [7], the cost of the distributed resources and the storage system were considered dynamic throughout the day, also the cost of selling / buying energy supplied by the grid or injected varies during the day. In this case, the main objective of the cost function is to satisfy the demand of load during the day in a most economical way. So, in each hour t the cost function $(C(t))$ can be calculated as:

$$C(t) = \sum_{i=1}^{N_g} P_{DGi}(t)B_{DGi}(t) + \sum_{j=1}^{N_s} P_{SDj}(t)B_{SDj}(t) + P_g(t)B_g(t) \tag{5}$$

where N_g and N_s are the total number of generators and storage devices, respectively. The $B_{DGi}(t)$ and $B_{SDj}(t)$ represents the bids of i^{th} DG unit and j^{th} storage device at hour t. $P_g(t)$ is the active power which is bought (sold) from (to) the utility at hour t and $B_g(t)$ is the bid of utility at hour t.

Emissions Evaluation In addition to the operating cost, the aspect of greenhouse gas emissions is also taken into consideration. The emission objective function consists of the atmospheric pollutants such as nitrogen oxides NO_X, sulfur dioxide SO_2, and carbon dioxide CO_2. The mathematical formulation of total pollutant emission in kg can be expressed as:

$$EM(t) = \sum_{i=1}^{N_g} P_{DGi}(t)EF_{DGi}(t) + P_g(t)EF_g(t) \tag{6}$$

where $EF_{DGi}(t)$ and $EF_g(t)$ are GHG emission factors which described the amount of pollutants emission in kg/MWh for each generator and main grid at hour t, respectively. Table 2 presents the emission factors for non renewable sources as defined in [4].

The energy management optimization problem can be defined as follows:

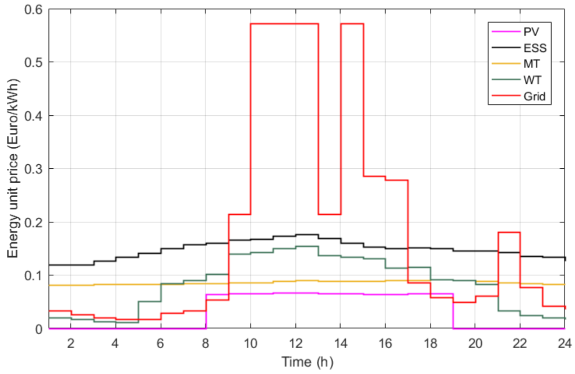

Fig. 8. The unit energy prices of the MG generators and the main grid

Table 2. Emission factors

EF	Micro-turbine (kg/MWh)	Grid (kg/MWh)
CO_2	724	922
NO_X	0.2	2.295
SO_2	0.00136	3.583

$$\min_{(P_{DGi},P_{SDj},P_g)} \sum_{i=1}^{N_g} P_{DGi}(t)B_{DGi}(t) + \sum_{j=1}^{N_s} P_{SDj}(t)B_{SDj}(t) + P_g(t)B_g(t) \quad (7)$$

$$s.t. \qquad \sum_{i=1}^{N_g} P_{DGi}(t) + \sum_{j=1}^{N_s} P_{SDj}(t) + P_g(t) = P_L(t) \quad (8)$$

$$P_{DGi}^{min}(t) \leq P_{DGi}(t) \leq P_{DGi}^{max}(t) \text{ for } i = 1, ..., N_g, \quad (9)$$

$$P_{SDj}^{min}(t) \leq P_{SDj}(t) \leq P_{SDj}^{max}(t) \text{ for } j = 1, ..., N_S, \quad (10)$$

$$P_g^{min}(t) \leq P_g(t) \leq P_g^{max}(t) \quad (11)$$

where the total price is calculated by $CT = \sum_{t=1}^{T} \min C(t)$ and the total quantity of emissions in kg can be determined by $EM = \sum_{t=1}^{T} EM(t)$. Equation (8) represents the total power generation needs to satisfy the total demand. The Equations (9) - (11) are the simple bounds associated to the decision variables.

5.2 Management Operation

Several management systems have been presented in the literature, [27] have proposed a multi-objective operational strategy of a microgrid for a residential application. In this context, the economic and environmental aspects have been formulated as a multi-objective problem with non-linear constraints. For this purpose, the terms of operating cost, maintenance cost, start-up cost, and the cost of CO_2, SO_2, NO_X emissions are taken into account. In this study, the management is developed as a uni-objective optimization problem whose main goal is to optimize the economic aspect. However, the environmental aspect will be evaluated but will not be taken into account in the optimization process. Therefore, the aim is to select the cheapest power in a given hour and to allocate it to the load, ensuring the energy balance required by the consumer while obtaining the cheapest possible daily energy bill. During this process, the storage system is managed in detail as follows:

- **In case of ($E(t) = E^{max}$):** The storage system will be considered as the main source with the four other sources (Photovoltaic, wind, micro-turbine, and grid), its energy supply will be operated according to the quantity of energy requested and its unit energy price per hour. It should be noted that the discharge rate is limited by a maximum quantity that must not be exceeded according to the constraints presented before.

- **In case of ($E(t) = E^{min}$):** The storage system will require a certain amount of energy for the charging process from the cheapest sources in the microgrid at a given time. In this situation, the storage system will be considered as a load by the microgrid. If all unit energy prices of the different generators are considerably high, and the load is satisfied, the charging process of the storage system will not happen at this time and will wait until the energy prices are sufficiently low.

- **In case of ($E^{min} < E(t) < E^{max}$):** Depending on the energy unit price of the storage system, two cases can occur:

  1. In the event that the price of the energy delivered by the storage system is the most expensive and the energy demanded by microgrid consumers can be largely satisfied by other sources, the storage system will continue to be charged and its energy will not participate in supplying the load. But, if the energy supplied by the various generators is insufficient, the energy from the storage system will be used as a compensating energy source to satisfy the energy balance constraint.

  2. Otherwise, if the price of the energy delivered by the storage system is cheaper compared to other sources, the storage system will participate in supplying the load and provide maximum energy equal to the limit of its discharging power rate.

The objective of the management system presented in this paper is to reduce the energy bill over a 24-hour day. The target point in this study case is the determination of the power set-points calculated by the five optimization methods. The remaining renewable energy not used to power the microgrid consumers and to charge the battery storage system will be sent to the main grid. In fact, we present the two scenarios proposed for this purpose:

- **Scenario 01**: The energy surplus from the different RES of the microgrid is used to cover the energy needs of the storage system while preserving the economic aspect by choosing the times when the price is the cheapest. However, if the batteries become fully charged, the energy surplus will be considered as energy loses. During this management, we will take into account the optimal price retained from the optimization as well as the rate of GHG emissions resulting from the energy operations performed by the microgrid.
- **Scenario 02**: The energy from the different renewable energy resources is used to cover the energy needs of the storage system in order to charge it while preserving the economic aspect by choosing the times when the energy prices are relatively low. However, if the batteries prove to be fully charged, the energy surplus from renewable sources in this case will be distributed and sold to the grid with the same purchase energy prices. During this management, we will evaluate the optimal price retained from the optimization procedures as well as the rate of GHG emissions resulting from the energy operations achieved by the microgrid. In addition, the power of the renewable energy generators (photovoltaic and wind) in this case are fully exploited, in order to highlight the impact of the energy injection to the main grid and its economic-environmental consequences.

6 Results and Discussions

6.1 Wind Forecasting Results

The proposed multi-layer neural network algorithm is trained by using “nntool” predefined function in $MATLAB$. The feed-forward network with a back-propagation algorithm assures the adjusting of weights which is determined at the offline training. The Table 3 illustrates the characteristics of the network.

Fig.9 represents the mean squared error, the best MSE obtained is 0.48 in the ninth epoch.

To evaluate the reliability of the prediction model proposed in this paper, Fig.10 illustrates a comparison of the results obtained by the wind forecasting model based on the artificial neural network and the real wind speed results. According to this latter, the prediction speed follows the real speed, on the other hand, some deviation occurs between values due to the stochastic character of the problem under study which has already been deduced from the MSE value.

Table 3. ANN characteristics

Type of network	feed-froward
Hidden layer activation function	sigmoid
Back-propagation algorithm	Levenberg-Marquardt
Performances	Mean squared error
Number of hidden neurons	10
Number of samples	103104
Training samples	90 %
Testing samples	5 %
Validation samples	5 %

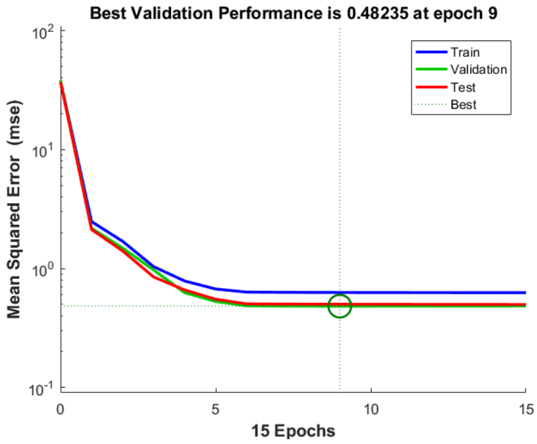

Fig. 9. The mean squared error of the network

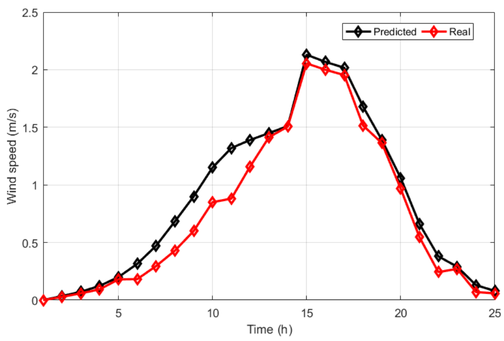

Fig. 10. Comparison of hourly forecasted wind speed with real data

6.2 Optimization methods comparison

The objective of the energy management system is to reduce the energy microgrid consumer bill over a 24-hour day. The target point in this section is the determination of the power set-points calculated by the energy management system based on optimization algorithms.

The optimization problem is represented by a linear objective function and constraints, for its treatment, five optimization methods was applied, namely, the linear programming LP based on the simplex method, two variants of particle swarm optimization PSO algorithm with different starting conditions, the first noted PSO1, whose particle starting point represents a random value that translates between the problem bounds while in the second one noted PSO2 a new approach of particle initialization has been proposed by fixing the particle starting point using an upper bounds vector of the problem. The fourth method used for the treatment of the problem is a hybrid LP-PSO, it is an innovative optimization strategy whose goal is to improve the performance of the PSO for optimal treatment of the management problem characterized by a linear optimization function. The approach adopted in this method lies on the use of linear programming as a technique for generating the initial starting points of the swarm particles, the PSO continues with those particles the search for the optimum to deliver the optimal set-points to ensure the minimization of the energy price evaluation function. And finally, a genetic algorithm GA was used in the management system to be compared to the four methods explained above. The performances of each method are presented in Table 4.

Table 4. Algorithmic performances

Results	LP	PSO1	PSO2	GA	LP-PSO
Total Price (Euro)	143.0492	144.9574	143.0492	143.0492	143.0492
Total Emissions (kg)	1353.7329	1351.4000	1353.7329	1353.7329	1353.7329
Simulation time (sec)	3.120	0.040	0.031	5.620	0.038

Taking into account the available power illustrated in Fig.5 as well as the microgrid energy unit prices illustrated in Fig.8, the EMS allows to have the optimal set-points of the distributed generators and the storage system through one of the optimization algorithms LP, PSO1, PSO2, GA and LP-PSO as shown in Table 4.

According to the results presented in Table 4, the operating cost for LP, PSO2, GA and the hybrid LP-PSO is 143.0492 $Euro$, on the other side for PSO1 was 144.9574 $Euro$.

A comparison is made between the performances of the optimization methods used to solve the energy management problem. According to the Tables 5 and 6, it is noted that in the five programs the cheapest source at a given hour has the most important set point without exceeding the power limits shown in Table 1.

Table 5. Optimal power set-points using LP and PSO2 and GA and LP-PSO method

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	16.0133	6	-33.3333	63.32	52
02:00	0	16.08	6	-33.3333	61.2533	50
03:00	0	16.16	6	-33.3333	61.1733	50
04:00	0	16.1733	6	-33.3333	62.16	50
05:00	0	0	6	-8.8889	58.8889	51
06:00	0	0	6	0	57	63
07:00	0	0	6	0	64	70
08:00	0	0	6	0	69	75
09:00	0.59	14.7333	30	22.5	8.1767	76
10:00	1.9800	13.16	30	22.5	12.36	80
11:00	7.7500	11.6667	30	22.5	6.0833	78
12:00	9.8	10.1468	30	22.5	1.5532	74
13:00	10.65	11.6667	30	19.6833	0	72
14:00	9.7	10.146	30	22.1540	0	72
15:00	8.12	14.6467	30	12.1627	11.0706	76
16:00	4.9500	16.2133	30	0	28.8367	80
17:00	1.1	0	27.2333	-33.3333	90	85
18:00	0.1	1.2333	30	-33.3333	90	88
19:00	0	3.3333	30	-33.3333	90	90
20:00	0	18.6493	11.6840	-33.3333	90	87
21:00	0	19.04	30	22.5	6.46	78
22:00	0	19.03	6	-33.3333	79.3033	71
23:00	0	19.3330	6	-33.3333	73.0003	65
24:00	0	19.6900	6	-5.5556	35.8656	56

The optimal power set-points of the LP, PSO2, LP-PSO, and GA showed in Table 5 converged to the global optimum, opposite to PSO1 where the setpoints showed in Table 6 do not represent the global optimum (convergence to local optimality) due to the nature of the optimization problem, this convergence with a certain error influenced the total daily energy price.

The linear nature of the optimization problem judges the reliability of linear programming LP based on the simplex method. The adoption of the LP-PSO method also delivered optimal results but in terms of convergence rapidity it was not the best method, in fact, the PSO2 has demonstrated the best performances compared to the four other optimzation methods in terms of accuracy and rapidity convergence of optimal power set-points.

The performances of the genetic algorithm GA has given good results in terms of precision, knowing that the stopping condition is taken similar to that of the PSO which is the reaching of the global optimum and with the same starting condition; the path to the optimum by the genetic algorithm is much slower than that of the PSO, this is judged by the very large search space generated by the GA mechanism following their genetic operators like crossover and mutation, in PSO particles update themselves with the internal velocity. Besides, the information-sharing mechanism in PSO is significantly different than the genetic algorithm.

Table 6. Optimal power set-point using PSO1 method

Time (h)	PV (kWh)	WT (kWh)	MT (kWh)	Battery (kWh)	GRID (kWh)	Load (kWh)
01:00	0	16.0133	6	-33.3333	63.32	52
02:00	0	16.08	6	-33.3333	61.25333	50
03:00	0	16.16	6	-33.3333	61.1733	50
04:00	0	16.1733	6	-33.3333	62.16	50
05:00	0	0	6	-8.8889	58.8889	51
06:00	0	0	6	0	57	63
07:00	0	0	6	0	64	70
08:00	0	0	6	0	69	75
09:00	0.3576	14.6848	29.9823	22.4610	8.5142	76
10:00	1.9148	12.5053	29.9690	22.4348	13.1761	80
11:00	7.7358	11.64	29.9995	22.4732	6.1515	78
12:00	9.7986	10.0716	29.9870	22.4306	1.7122	74
13:00	10.6289	11.6662	29.9588	22.4320	3.3142	72
14:00	8.0985	9.8576	29.9923	22.4730	7.5786	72
15:00	7.9557	14.5146	29.9509	9.1309	14.4480	76
16:00	4.9077	16.2132	29.9986	0.1489	34.7316	80
17:00	1.0035	3.3301	29.9999	-33.3333	89.9999	85
18:00	0.0358	2.5170	28.7815	-33.3333	89.9990	88
19:00	0	3.3652	29.9682	-33.3333	90	90
20:00	0	18.6418	11.6917	-33.3333	89.9999	87
21:00	0	18.9552	29.9523	22.4275	6.6650	78
22:00	0	19.03	6	-33.3333	79.3033	71
23:00	0	19.3330	6	-33.3333	73.0003	65
24:00	0	19.6900	6	-5.4466	35.7566	56

6.3 Comparison of the two scenarios

Following the algorithmic performances illustrated by the PSO2, this latter will be used as an optimization tool in the energy management system (EMS) for the two scenarios described above. The rest of the paper presents the economic and environmental results of the two proposed scenarios.

Table 7. Results of both scenarios

Scenarios	Scenario 01	Scenario 02
Total Price (Euro)	143.0492	137.6627
Total Emissions (kg)	1353.7329	1246.1000

Scenario 1 The results obtained in Fig.11 are the optimal power set-points for the different energy sources of the microgrid, the sum of these values in a given hour t is equal to the power value of the load for the same hour t. The cheapest source in a given hour has the highest set-point without exceeding these power limits. The second cheapest source is added to it and so on until the power balance constraint is verified. In this way, the operating cost is minimized and the emissions are evaluated.

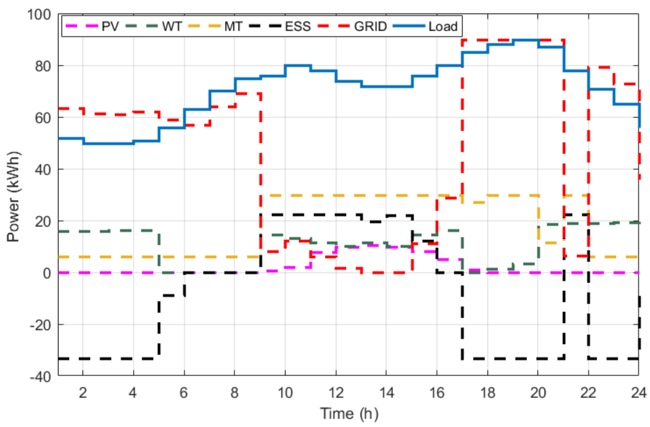

Fig. 11. Optimal power setpoints obtained in the first scenario

The charging of the storage system is ensured during the part of the day when consumption is low and characterized by low energy unit costs. Otherwise, the battery provides energy to compensate the deficit during the day. In this study case, the energy from the grid is supplied unidirectionally, i.e. the energy is only sold from the grid and delivered to the microgrid, reverse operation is not allowed. For maintenance and safety reasons, the micro-turbine is present all day long either by its minimum power of $6\,kW$ or by its delivered power to compensate the energy deficit that should be supplied to the microgrid consumers.

Fig.12 presents the hourly unit prices of the optimal energy flows from the various sources and the optimal price obtained by the energy management system in function of the operating hours during the day.

It is remarkable that the photovoltaic source is fully exploited during the day because of its low price compared to the other four sources and the wind source is widely exploited during the night because of its low price as well. However, during peak hours, the grid price is very high, in this case, the use of the storage system allows to compensate the energy deficit and reduce the dependence on the main grid. This demonstrate the importance of the battery during the day when

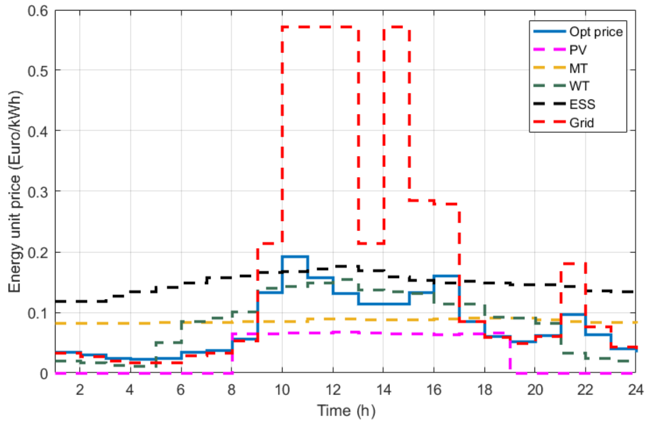

Fig. 12. The unit prices of the powers resulting from the optimal management and the optimal billing prices for the first scenario

the grid price is high. The storage system itself follows its charging process during the night when the consumption of the microgrid is smaller and the energy unit price is low. Fig.13 illustrates the daily energy exchange of the batteries with the microgrid. It is well observed that when batteries demand energy, the *SOC* increases, and when they supply energy, the *SOC* decreases.

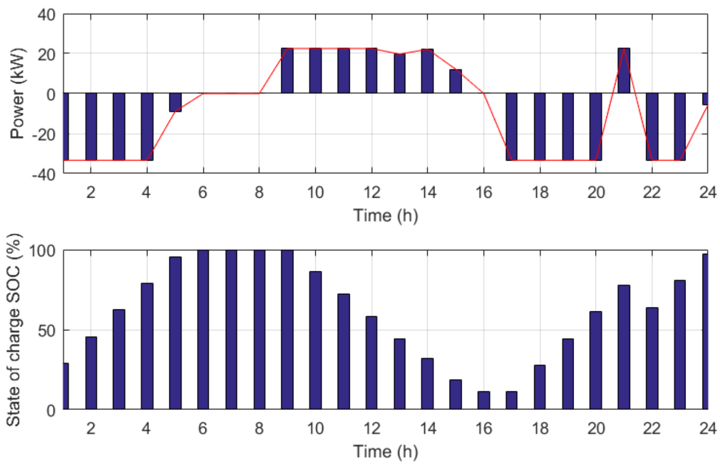

Fig. 13. The energy exchange of the batteries with the microgrid during the day

The emissions quantity is directly related to the two sources: the main grid and the micro-turbine, which are responsible for greenhouse gas emissions. According to Fig.14, it is clear that emissions are higher during the night due to the reduced unit prices of the grid and thus the primary operation of the microgrid is to supply consumer and take advantage to charge the ESS system.

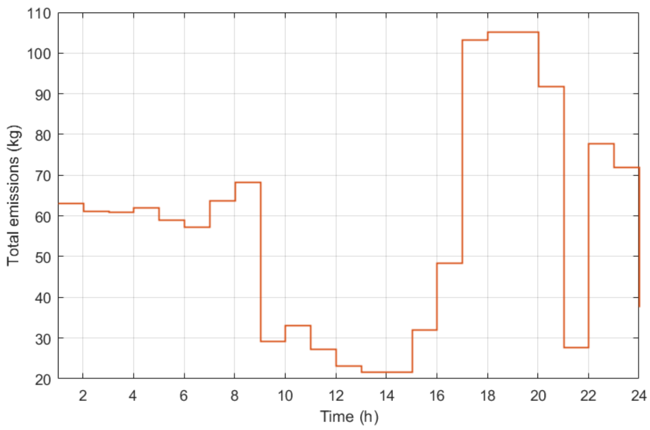

Fig. 14. The total daily emissions due to the use of fossil sources in the microgrid without injection

Scenario 2 According to the results obtained in Table 7 and Fig.15, it can be seen that the renewable sources are fully exploited, no loss of power is caused. The excess energy, after satisfying the local needs of the microgrid, allowed the successful charging of the storage system in such a way that at the end of the day the battery was fully charged. In addition, an amount of $116,0529\ kW$ was also delivered to the main grid, which reduced the total daily energy bill of the microgrid to $137.6627\,Euro$, and reduced GHG emissions to $1246.1\,kg$.

It is remarkable that the photovoltaic and wind energy sources are fully exploited during the day, in order to take advantage of the benefits of injecting green energy into the main grid, thus reducing the energy bill and the rate of GHG emissions. The power management of the other sources seems identical to the first scenario, except for the main grid that is modified due to its price, which remains very high during the day compared to the micro-turbine and the storage system.

The grid provides precise power to meet the load requirements. However, this energy is not fully counted in the energy bill, and the power injected during a given hour is subtracted and compensates for the energy that is supposed to be

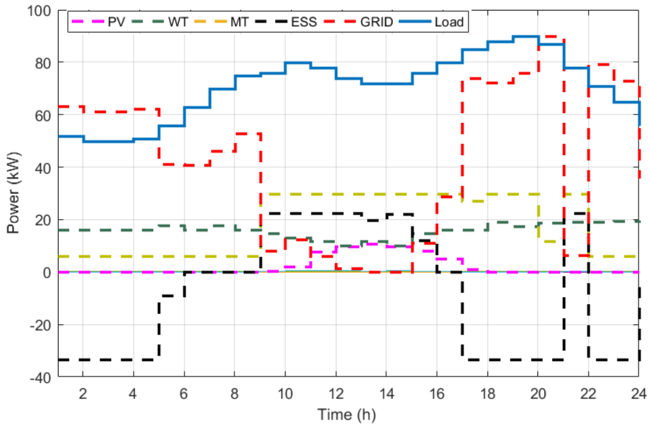

Fig. 15. Optimal power setpoints obtained in the second scenario

supplied by the network. In this way, during consumption billing, only the power paid will be considered.

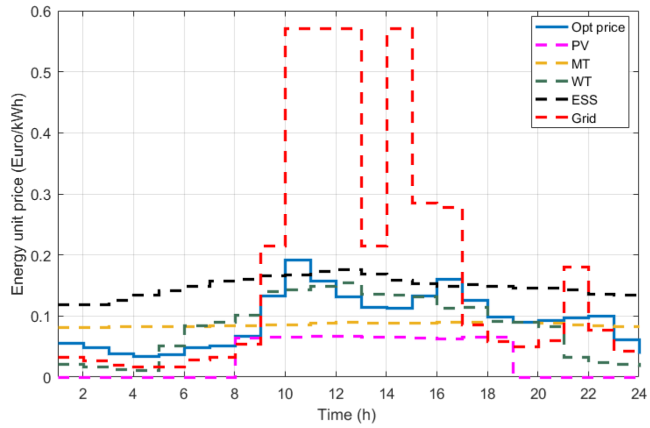

Fig. 16. The unit prices of the powers resulting from the optimal management and the optimal billing prices

Fig.17 shows the power supplied by the grid, the power injected, as well as the power taken into account in the billing.

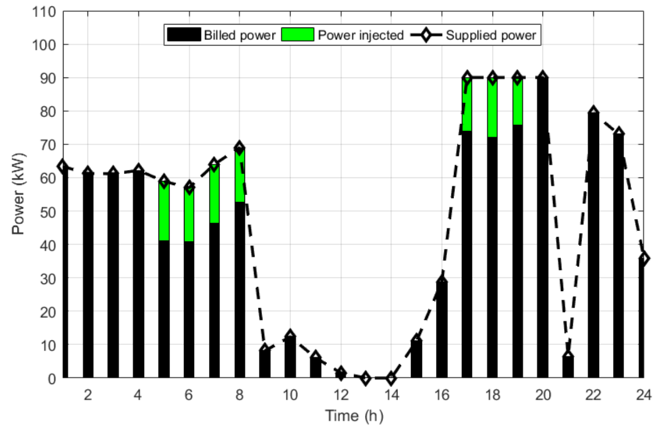

Fig. 17. The unit prices of the powers resulting from the optimal management and the optimal billing prices for the second scenario

The quantity of emissions is directly related to the two sources: the main grid and the micro-turbine, which are responsible for greenhouse gas emissions. According to Fig.18, it is clear that emissions are higher during the night due to the reduced unit prices of the grid and thus the primary operation of the microgrid, taking advantage of this to recharge the storage system. The emission rate, in this case, remains lower than the first scenario.

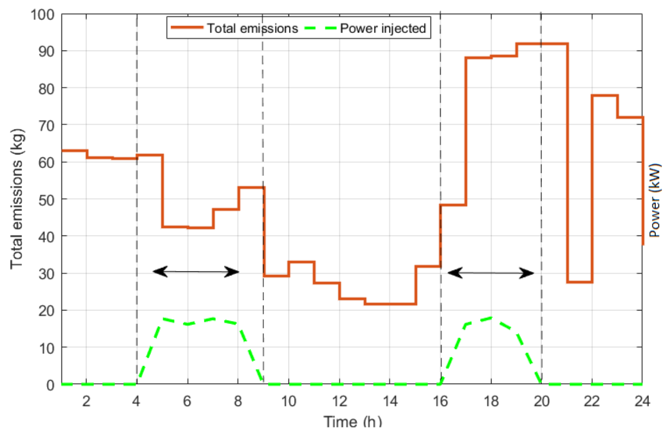

Fig. 18. The total daily emissions due to the use of fossil fuel sources in the microgrid with injection

7 Conclusion and Future Works

This study investigated the problem of energy management in microgrid systems by considering the impact of the wind speed intermittent aspect on wind turbine power production. For that matter, a prediction model based on the artificial intelligence of neural network (ANN) has been developed to ensure a forecast of the wind velocity parameter, the performance of the model was evaluated by the mean squared error (MSE) value. On the other hand, this work showed a comparison between several optimization methods used by the energy management system (EMS) proposed for the optimal dispatch of energy inside a microgrid, ensuring a reduced energy cost. In particular, five optimization approaches were proposed, including two versions of Particle Swarm Optimization (PSO) algorithm, a Genetic Algorithm (GA), Linear Programming (LP) based on the simplex method, and finally a hybrid approach (LP-PSO), all programmed in the $MATLAB$ software. However, the proposed PSO has shown a high level of performance. Two scenarios were adopted to assess the technical-economic and environmental impact of bi-directional interconnection between the microgrid and the main grid. In fact, the low energy price and the reduced rate of emissions have made it possible to present one of the important advantages that a microgrid could bring in the reduction of the energetic cost as well as in the contribution to the reduction of the greenhouse gases (GHG) emissions responsible for the global warming. Differently to the uni-objective approach that gave an optimal point, a multi-objective optimization approach will be developed as future work on which an energy management system is dedicated to ensuring the optimal scheduling of the distributed generators and the energy storage system accompanied by a moderate exchange between the MG and the main grid while considering the simultaneous optimization of both economic and environmental criteria. The results will deliver a set of optimal solutions (Pareto front), that will represent scenarios, in which the best Trade-off between price and emission is selected by the microgrid operator to give the optimal scheduling.

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C.3 Article 03

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Optimal Energy Management of Microgrid Using Multi-objective Optimisation Approach

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Abstract. The use of several distributed generators as well as the energy storage system in a local microgrid require an energy management system to maximize system efficiency, by managing generation and loads. The main purpose of this work is to find the optimal set-points of distributed generators and storage devices of a microgrid, minimizing simultaneously the energy costs and the greenhouse gas emissions. A multi-objective approach called Pareto-search Algorithm based on direct multi-search is proposed to ensure optimal management of the microgrid. According to the non-dominated resulting points, several scenarios are proposed and compared. The effectiveness of the algorithm is validated, giving a compromised choice between two criteria: energy cost and GHG emissions.

Keywords: Microgrid· Power Management · Energy Management System · Multi-objective Optimisation · Pareto-search Algorithm

1 Introduction

An upcoming fossil fuel shortage is estimated in the coming years, on the other hand, problems related to global warming due to the increase in greenhouse gases (GHG) emissions have affected the world especially after the major peak in 2018 due to the massive use of fossil resources in power generation. About 64% of the world's production was based on oil and gas, however, 33.1 tons of CO_2 was released into the atmosphere [1]. According to the U.S. space agency (NASA) the average temperature of the earth surface has increased by $1°C$ compared to the average of the 19th century [2]. As a result of this environmental conflict, a challenge was made by european union member states in the framework for action on climate and energy for the period 2021-2030. Three objectives have been set: reducing greenhouse gas emissions by at least 40%, increasing the contribution of renewable energies to at least 32% and improving energy efficiency by at least 32.5% [3].

Nowadays there is an upward tendency for using small power systems, able to bring the energy production near to the consumption. In this type of system, the most important sources are renewable based (e.g, photovoltaic panels, wind turbines, etc.), due to their low environmental impact, in combination with diesel generators in order to obtain the necessary mix able to assure the balance between production and consumption. These small power-producing networks called microgrids need a distributed and autonomous power generation control [4]. Nevertheless, the dispatch problem is transversal to all power systems [5], in particular in the autonomous isolated microgrids with limited power sources.

A microgrid is based on the interconnection of small modular generation (micro-turbines, fuel cells, photovoltaic, among others), combined with storage devices (flywheels, energy capacitors or electrochemical batteries) and loads, some of them controllable, at low voltage distribution systems [6]. The operation of micro-sources in the network is complex but it can provide distinct benefits to the overall system performance if it is managed and coordinated efficiently [7].

The use of microgrids has become an attractive option for power utility companies since they can help to improve the power quality and power supply flexibility. Also, they can provide spinning reserves and reduce transmission and distribution costs. Moreover, they can be used to feed the customers in the event of an outage in the main grid [8].

Following this interest in microgrids, several works have been performed to ensure optimal management. Researchers in [9] proposed a genetic algorithm (GA) approach to solve the problem of electric power dispatch using a model that describes the load demand and environmental requirements. In [10] a multi-team particle swarm (MTPSO) algorithm is proposed to solve the microgrid schedule problem. The algorithm is based on swarm information to update the velocity (position) with faster and more stable convergence, the simulation results show that the proposed algorithm gives a better global search ability than the classic PSO. Real-time PSO-based energy management of a stand-alone hybrid wind, micro-turbine, and energy storage system is presented in [11], with the results being compared to sequential quadratic programming (SQP). The computation results show the reliability of the proposed PSO for energy management strategy in hybrid systems. However, due to the pollutants emission of fossil fuel generators, the economic objectives are not sufficient for optimal operation of the microgrids. Therefore, to achieve the best solutions, environmental and economic objectives must be considered simultaneously. Many researchers have considered both cost and gas emissions to schedule the output power of distributed generators in the microgrids. In [12] authors have converted the gas emissions objective to a constraint and have solved the problem as a single objective, but to find the Pareto optimal solutions, this method is not efficient. An improved modified bacterial foraging optimisation (MBFO) algorithm is proposed in [13] to solve the multi-objective problem for expert energy management of a microgrid considering wind energy uncertainty in such a way that the total operating costs and the net emissions are simultaneously minimized. Authors in [14] present an expert multi-objective adaptive modified particle swarm optimisation (AMPSO) algorithm for optimal operation of a typical MG with renewable energy sources to solve the multi-operation management problem in the microgrid, the numerical results indicate that the proposed method demonstrates superior performances and shows dynamic stability and excellent convergence.

The work proposed in this article consists in developing an energy management system dedicated to the scheduling of the distributed generators and the energy storage system of the microgrid considering the simultaneous optimisation of the economic and environmental criteria. The Pareto-search algorithm based on the direct multi-search method is proposed as an optimisation approach in the energy management system. The results allow to have a set of solutions called non-dominated solutions or optimal Pareto solutions. The Pareto solutions represent the compromise between the two criteria to be optimised: costs and GHG emissions. Finally, the obtained scenarios are analyzed and compared in order to have multiple scheduling choices while respecting the economic and environmental constraints.

The remaining of the paper is organized as follows: Section 2 presents the architecture of the proposed microgrid. In Section 3 the storage system is modelled. Section 4 formulates the multi-objective optimisation problem together with the related constraints and explains the concept of multi-objective optimisation. the Pareto-search Algorithm is presented in Section 5. Section 6 deals with the analysis and discussion of the results obtained after the implementation of the energy management system based on the Pareto-search Algorithm. Finally, Section 7 concludes the study and point out some further studies.

2 Microgrid Description

The proposed microgrid comprises two renewable sources: photovoltaic (PV) and wind-turbine (WT) additionally, it has a micro-turbine (MT), and an energy storage system (ESS). The microgrid can be explored connected to the main grid, which will act as a buffer if needed, or it can be explored off-grid, when internal resources are enough to satisfy the demand or even in case of a malfunction or failure of the grid. The connection is ensured through a transformer and common coupling point (PCC) as indicated in Fig.1.

For a reliable operation process considering the economic and environmental constraints of the proposed management system, renewable energy sources can provide energy to loads and/or charge the battery. Excess energy, after satisfying local demands, can be fed into the main grid, reducing the total operating energy costs and GHG emissions from conventional generation, or it can be exchanged with other microgrids.

Regarding the energy storage system, it is assumed an exploitation mode able to contribute to its lifespan, avoiding deep discharges and reducing the number of charges-discharges cycles. Additionally, this work considers that the exchange of energy from the storage system to the main grid is not allowed.

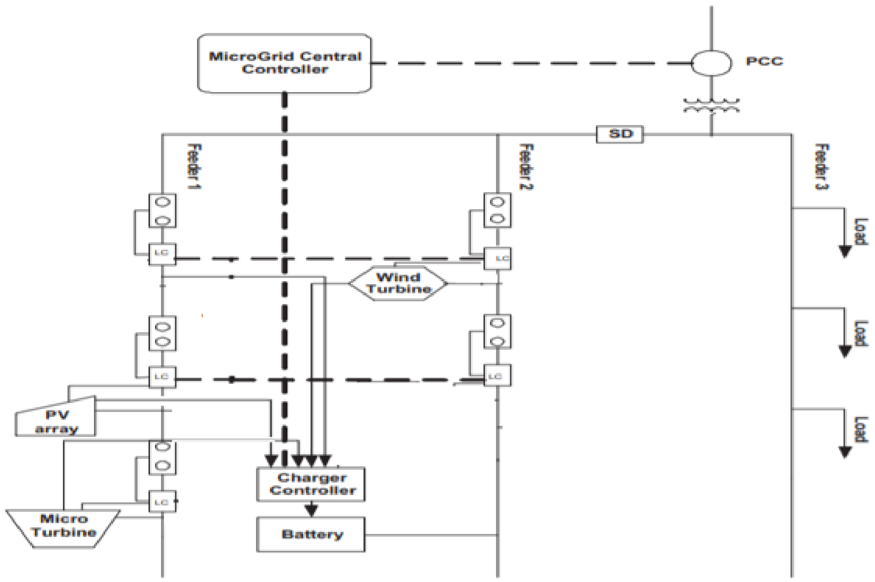

Fig. 1. The architecture of the microgrid

The energy management system will ensure the optimal control of the sources according to the dynamic market prices in a time span of 24 h. The load and power sources profiles of the microgrid proposed above are the same as the ones previously considered in [13]. The maximum power that can be produced by the photovoltaic panels is 10 kW and the maximum power of the wind turbine generator is 20 kW. To reduce the number of startup/shutdown, consequently, the maintenance requirements, the micro-turbine can operate in a power range from 6 kW to 30 kW. The maximum power exchanged with the main grid is limited to 90 kW. The energy storage system is designed to assure the load for a maximum time period of 1 h. Under this hypothesis, the total capacity of the energy storage system is $E^{max} = 180\,\text{kWh}$, and it is considered an initial situation given by $E(1) = 52\,\text{kWh}$. Fig.2 illustrates the principle scheme for the operation of the microgrid energy management system.

Fig.3 (a) and (b) show the maximal hourly power delivered by the renewable generators for a time span of 24 h. Fig.4 presents the variation of the hourly consumption of the microgrid under the same period of time.

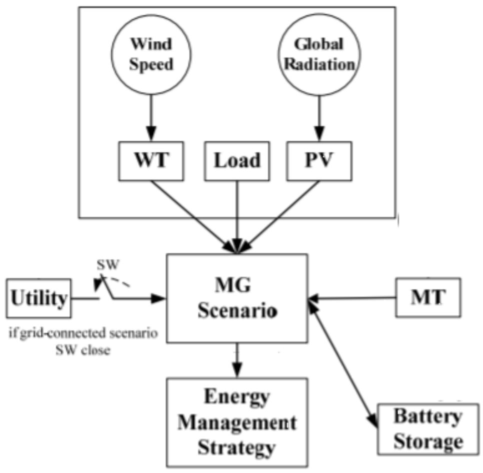

Fig. 2. The principle of the management strategy.

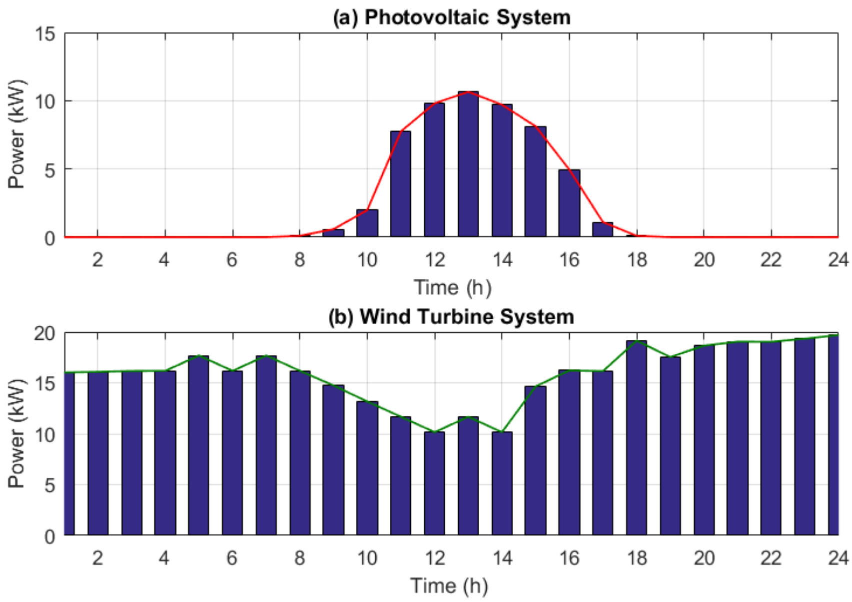

Fig. 3. The daily power profile from (a) PV system, (b) WT system.

3 Modeling of the Energy Storage System

The energy storage system has an important role in a microgrid exploitation because it allows the flexibility needed to assure the balance between the produc-

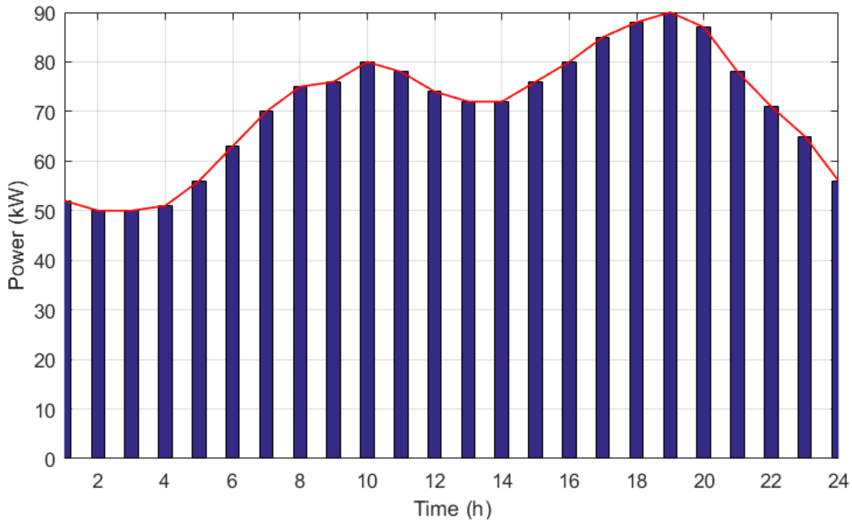

Fig. 4. The daily load profile.

tion and consumption, in the presence of variations of either loads or intermittent sources. Taking into account the microgrid storage requirements, the most appropriate storage form is the electrochemical battery [15]. This ESS is chosen for its long-term storage capacity and for the ease of bidirectional flow and fast power response, allowing a good frequency adjustment source in a microgrid to provide real-time dynamic balance. It has a positive significance for improving the power quality of the microgrid and ensuring stable operation [10]. In order to have reliable modeling of this ESS, several parameters have to be taken into account such as the nominal capacity and the rate of charge/discharge, this later is used to limit the deep discharge of the battery leading to a higher lifespan. Therefore, the battery usage is delimited by their minimum and maximum capacity allowed, respectively E^{min} and E^{max} with:

$$E^{min} \leq E(t) \leq E^{max} \tag{1}$$

The energy available in the battery is an important technical parameter to provide data support for the microgrid management, for instance, the quantity of energy at time $t+1$ is related to the value at time t, and the charge and discharge energy of the battery can be expressed as follows [16]:

$$\begin{cases} E(t+1) = E(t) - \Delta_t P_c(t)\eta_c, & charging\, mode \\ E(t+1) = E(t) - \frac{\Delta_t P_d(t)}{\eta_d}, & discharging\, mode \end{cases} \tag{2}$$

where $P_c(t)$ and $P_d(t)$ are the charging and discharging power of the battery at time t, $E(t)$ and Δ_t are, respectively, the stored energy at time t and the interval of time considered and, finally, η_c and η_d are the charging and discharging efficiency, respectively.

Battery control is a crucial issue that must be taken into account when managing the microgrid, so the energy storage system (ESS) can only be operated as one of the following modes at a time [17]:

- **Charge mode**: the battery can be charged from the grid, micro-turbine, and/or renewable energies with an energy quantity that is not beyond the charging rate.
- **Discharge mode**: the battery delivers a quantity of energy without exceeding the limit rate of discharge to supply the microgrid consumers if the prices of Kwh are high.
- **Inactive mode**: the battery will not perform any of the above two operations (charge/discharge), since the grid utility and the microgrid provide electricity directly to the loads during certain hours in order to consider economic and/or environmental features.

4 Optimisation Problem

The problem of optimal scheduling of distributed microgrid generators and storage system is defined as a problem of allocating optimal power generation set points, in such a way that the operating cost and the net emission of pollutants from conventional sources in the microgrid are minimized simultaneously while satisfying all constraints imposed by the energy management system (EMS). The mathematical model of the problem can be presented in the following sections.

4.1 Objective functions

Objective 1: Operating Cost Minimization The definition of the operating cost function depends on several parameters, mainly the architecture of the microgrid. The cost of the distributed resources and the storage system is considered dynamic throughout the day, also the cost of selling/buying energy supplied by or injected into the grid varies during the day, being the main objective of the cost function is to satisfy the load demand during the day in the most economical way. So, in each hour t, for a time span of 24 h of operation, the objective function can be expressed as follows [18]:

$$C(t) = \sum_{i=1}^{N_g} U_i(t) P_{DGi}(t) B_{DGi}(t) + \sum_{j=1}^{N_s} U_j(t) P_{ESSj}(t) B_{ESSj}(t) + P_{Grid}(t) B_{Grid}(t) \tag{3}$$

where N_g and N_s are the total number of generators and storage devices, respectively. $B_{DGi}(t)$ and $B_{ESSj}(t)$ represent the bids of i^{th} DG unit and j^{th} storage device at hour t. $P_{Grid}(t)$ is the active power which is bought (sold) from (to) the utility grid at hour t and $B_{Grid}(t)$ is the bid of the utility grid at hour t.

$U_i(t)$ and $U_j(t)$ are the operation mode of the i^{th} generator and the j^{th} storage device (ON or OFF), respectively. Table 1 present distributed energy resources, storage and grid bids.

The optimisation model of the first objective function can be written as follows:

$$f_1 = \sum_{t=1}^{T} \min C(t) \tag{4}$$

The optimisation model will lead to find P_{DGi}, P_{ESSj} and P_{Grid}, *i.e*, the optimum set points of distributed generators, energy storage system and main grid respectively that ensures a low total energy price in each hour t.

Table 1. The hourly unit prices of the distributed generators, storage system and main grid of the proposed microgrid (Euro/kWh) [13]

Time (h)	PV	WT	MT	ESS	GRID
01:00	0	0.021	0.0823	0.1192	0.033
02:00	0	0.017	0.0823	0.1192	0.027
03:00	0	0.0125	0.0831	0.1269	0.020
04:00	0	0.011	0.0831	0.1346	0.017
05:00	0	0.051	0.0838	0.1423	0.017
06:00	0	0.085	0.0838	0.15	0.029
07:00	0	0.091	0.0846	0.1577	0.033
08:00	0.0646	0.110	0.0854	0.1608	0.054
09:00	0.0654	0.140	0.0862	0.1662	0.215
10:00	0.0662	0.143	0.0862	0.1677	0.572
11:00	0.0669	0.150	0.0892	0.1731	0.572
12:00	0.0677	0.155	0.09	0.1769	0.572
13:00	0.0662	0.137	0.0885	0.1692	0.215
14:00	0.0654	0.135	0.0885	0.16	0.572
15:00	0.0646	0.132	0.0885	0.1538	0.286
16:00	0.0638	0.114	0.09	0.15	0.279
17:00	0.0654	0.110	0.0908	0.1523	0.086
18:00	0.0662	0.0925	0.0915	0.15	0.059
19:00	0	0.091	0.0908	0.1462	0.050
20:00	0	0.083	0.0885	0.1462	0.061
21:00	0	0.033	0.0862	0.1431	0.181
22:00	0	0.025	0.0846	0.1385	0.077
23:00	0	0.021	0.0838	0.1346	0.043
24:00	0	0.017	0.0831	0.1269	0.037

Objective 2: GHG Emissions Minimization The environmental footprint from atmospheric pollutants is considered the second objective. Emissions in-

clude the polluting gases responsible for the greenhouse gas effect such as nitrogen oxides (NO_x), sulfur dioxide (SO_2), and carbon dioxide (CO_2). Table 2 presents the emission factors as defined in [13].

Table 2. Pollutants emission factors [13]

EF	Micro-turbine (Kg/MWh)	Grid (Kg/MWh)
CO_2	724	922
NO_X	0.2	2.295
SO_2	0.00136	3.583

The mathematical formulation of the second objective can be described as follows [13]:

$$EM(t) = \sum_{i=1}^{N_g} U_i(t) P_{DGi}(t) EF_{DGi}(t) + P_{Grid}(t) EF_{Grid}(t) \tag{5}$$

where $EF_{DGi}(t)$ and $EF_{Grid}(t)$ are GHG emissions factors describing the amount of pollutants emission in kg/MWh for each distributed generator and utility grid at hour t, respectively.

The optimisation model of the second objective function can be written as follows:

$$f_2 = \sum_{t=1}^{T} \min EM(t) \tag{6}$$

The optimisation model will lead to find P_{DGi} and P_{Grid}, *i.e*, the optimum set points of distributed generators and main grid, respectively, that ensures a low total emission amount in each hour t.

4.2 Constraints functions

Power Balance Constraint Total demand (including storage) and transmission losses must be covered by the total power generation. The active power balance, in terms of frequency stability, is the precondition for a stable operation. The losses in transmission are considered numerically small, being ignored in this article. The condition of the power balance assumes the following form:

$$\sum_{i=1}^{N_g} P_{DGi}(t) + \sum_{j=1}^{N_s} P_{ESSj}(t) + P_{Grid}(t) = P_L(t) \tag{7}$$

being $P_L(t)$ the total electrical load demand at hour t. Moreover, the power of the energy storage system $P_{ESSj}(t)$ can be positive in case of discharging or negative in the case of charging.

Electrical Limits of Generators Constraint The microgrid distributed generators must not operate beyond their limits, and the energy exchanged between the microgrid and the main grid is also limited. Each DG and main grid's active power output is limited by the lower and upper limits, as follows:

$$P_{DGi}^{min}(t) \leq P_{DGi}(t) \leq P_{DGi}^{max}(t) \tag{8}$$

$$P_{SDj}^{min}(t) \leq P_{ESSj}(t) \leq P_{ESSj}^{max}(t) \tag{9}$$

$$P_{g}^{min}(t) \leq P_{Grid}(t) \leq P_{Grid}^{max}(t) \tag{10}$$

where $P_{.}^{min}(t)$ and $P_{.}^{max}(t)$ are the minimum and the maximum powers of the distributed generator (DG), energy storage system (ESS) and the grid (Grid) at the time t, respectively.

Storage System Limits Constraint The battery must maintain within the limits of its capacity and limited by a maximum rate (charging/discharging) that must not be exceeded.

$$E^{min}(t) \leq E(t) \leq E^{max}(t) \tag{11}$$

$$\begin{cases} -P_c(t)\eta_c \leq P_c^{max} \quad charging\, mode, \quad P_c(t) < 0 \\ \dfrac{P_d(t)}{\eta_d} \leq P_d^{max} \; discharging\, mode, \, P_d(t) > 0 \end{cases} \tag{12}$$

where $E_{min}(t)$ and $E_{max}(t)$ are the minimum and maximum energy levels of the battery, P_c^{max} and P_d^{max} are the maximum rate of charge/discharge of the battery that be must respected in each operation.

4.3 The multi-objective optimisation problem

Many real optimisation problems require the simultaneous optimisation of different and often conflicting objectives, characterized by the term of multi-objective optimisation. The solution to these multi-criteria optimisation problems is not a unique optimal point, but a set of solutions called the non-dominated, indifferent, or Pareto-optimal solutions, corresponding to the best possible compromise, since, one particular solution is not the best with regard to all the objectives. Generally, in a multi-objective optimisation problem, different objective functions must be simultaneously optimised taking into account a set of equality and inequality constraints, as follows [19]:

$$\min F = \{f_1, f_2\} \tag{13}$$

where F is a vector composed by the two objective functions (cost emissions) defined on Section 4.1. The minimization problem defined on (13) is subject to the constraints defined in previous Section 4.2.

Assuming that the two solutions to the multi-objective problem are x_1 and x_2, the two solutions may have one of two properties: one dominates the other, or none dominates the other. In a minimization problem, without loss of generality, a solution x_1 dominates x_2 if both following two conditions are satisfied [18]:

$$\exists i \in 1, 2 : f_i(x_1) < f_i(x_2) \tag{14}$$

The non-dominated set of solutions is referred as the optimal set called the Pareto front. On the other hand, to establish the acceptability of each solution to be included in the non-dominated solutions repository, the concept of Pareto dominance is used.

5 Pareto-search Algorithm

The Pareto search algorithm is a direct multiple search algorithm that uses pattern searches on a set of points to iteratively search for non-dominated points [20]. It is based on the search/polling model of direct directional search methods and uses the concept of pareto dominance to keep a list of non-dominated points by satisfying all linear/nonlinear bounds and constraints at each iteration [21]. The pattern search is intended to find the best correspondence *i.e* , the solution with the smallest error value in the multidimensional possibility analysis space. The Pareto search algorithm employs a number of intermediary and tolerance variables in its search mechanism. [21].

At each iteration, the algorithm is structured along a search step and a probe step, which are important considerations for achieving convergence results. The searching step is used to improve the performance of the algorithm. The polling step performs a local search around one of the non-dominated points chosen by the search step, which constitutes an iteration point or interrogation center. In both steps, search and polling, a provisional list is first generated, which keeps all the points of the actual iteration list and all the estimated points around this step. This list is then filtered by removing all dominated points and retaining the non-dominated points. A trial list L_{trial} is then retrieved from the filtered list of non-dominated points and must eventually contain all non-dominated points that are part of the considered iteration list in the preceding iteration [21] [22]. The steps of the Pareto search algorithm are explained as follows.

1. **Initialization** To generate the starting set of points, Pareto-search algorithm will produce a set of random points that satisfies the bounds of the problem. .
2. **Poll to Find Better Points**
   The Pareto search algorithm interrogates the points of the iterates, with the interrogated points inheriting the associated mesh size of the point in the iterates. The algorithm uses a query that keeps the feasibility relative to the limits and all linear constraints. If the model has non-linear constraints, the Pareto search computes the feasibility of each interrogated point and keeps the unfeasible points score separate from the feasible points value.

The score of a feasible point is the vector of values of the objective function of this point while the score of an infeasible point is the sum of the nonlinear infeasibilities.
The Pareto search algorithm interrogates each point by iterations. If the interrogated points result in at least one non-dominated point compared to the existing (original) point, the interrogation is considered as successful. Otherwise, the algorithm continues to interrogate until it reaches an undominated point or there are no more points in the model.
3. **Stopping Conditions**
For three or less objective functions, the Pareto search algorithm uses volume and spread as stopping criteria. For four or more, the Pareto search algorithm employs distance and spread as stopping parameters.

6 Numerical Results and Discussion

The energy management system (EMS) proposed in this work consists in the scheduling of the microgrid production sources by taking into account the simultaneous minimization of both cost and GHG emission criteria through the Pareto-search optimisation algorithm.

Table 3 presents the set of non-dominanted solutions obtained by the implementation of the optimisation algorithm in the energy management system. These results represent the best trade-off between the two targets under minimisation.

Table 3. The non-dominanted solutions obtained by Pareto-search Algorithm

Scenarios	Total Energy Cost (euro)	Total Emissions (kg)
01	161.0118	1.2795×10^3
02	159.9786	1.2809×10^3
03	159.7697	1.2823×10^3
04	158,5841	$1,2872\times10^3$
05	157.5630	1.2984×10^3
06	156,7201	1.3120×10^3
07	155,8556	$1,3239\times10^3$
08	155.3164	1.3387×10^3
09	154.9797	1.3524×10^3

The non-dominated points are classified in Pareto front as shown in Fig.5. All these points represent several scheduling scenarios for the distributed generators of the microgrid, the energy storage system and energy exchanged between the main grid and the microgrid.

According to the trade-off obtained from the non-dominated points, two cases are highlighted to illustrate the energy management process of the energy storage system, the best environmental trade-off and the best economic trade-off,

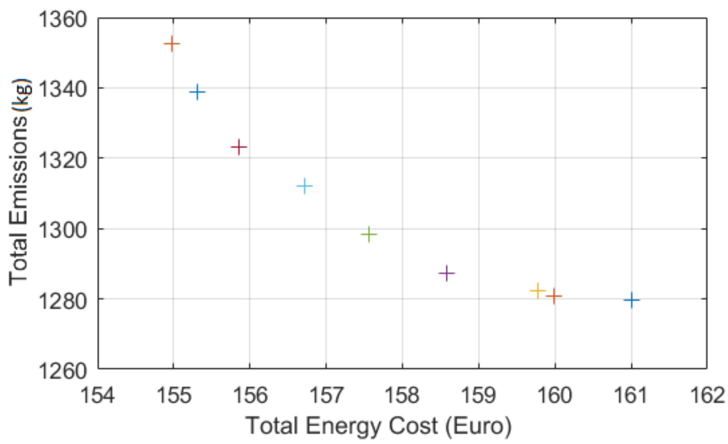

Fig. 5. Pareto front.

scenarios 1 and 9, respectively. Fig.6 show the two power profiles of the energy storage system of the microgrid corresponding to those scenarios. It is possible to verify that, for both cases, the energy storage system is mainly used to compensate the lack of energy during peak hours.

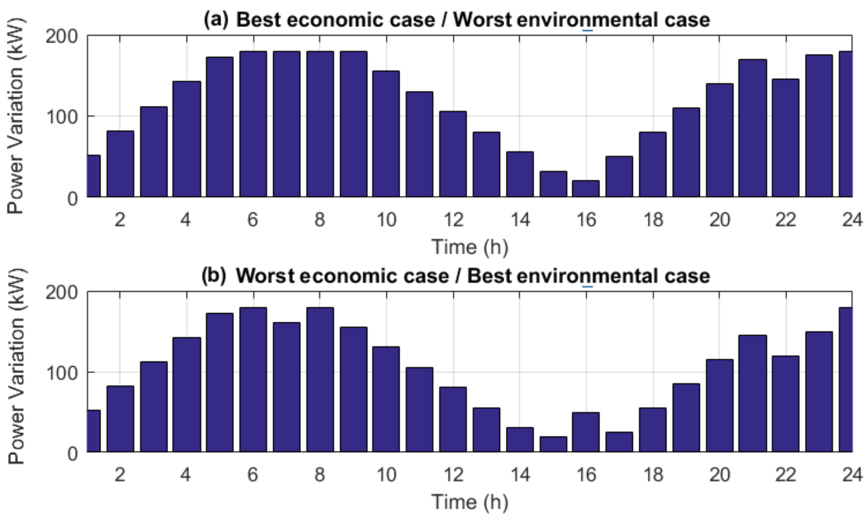

Fig. 6. Storage system power variation considering (a) scenario 1 and (b) scenario 9.

Fig.7 illustrates the daily power exchange of the energy storage system with the microgrid. The areas below the zero axes represent the energy during the charging process while the remaining areas represent the energy delivered to the microgrid. The null values, between 6 and 8 am from the best economic scenario (Fig.7(a)), indicate the inactive mode of the energy storage system, which translates that the energy of the storage system has reached its maximum limit E^{max}, and therefore the energy storage system stop charging.

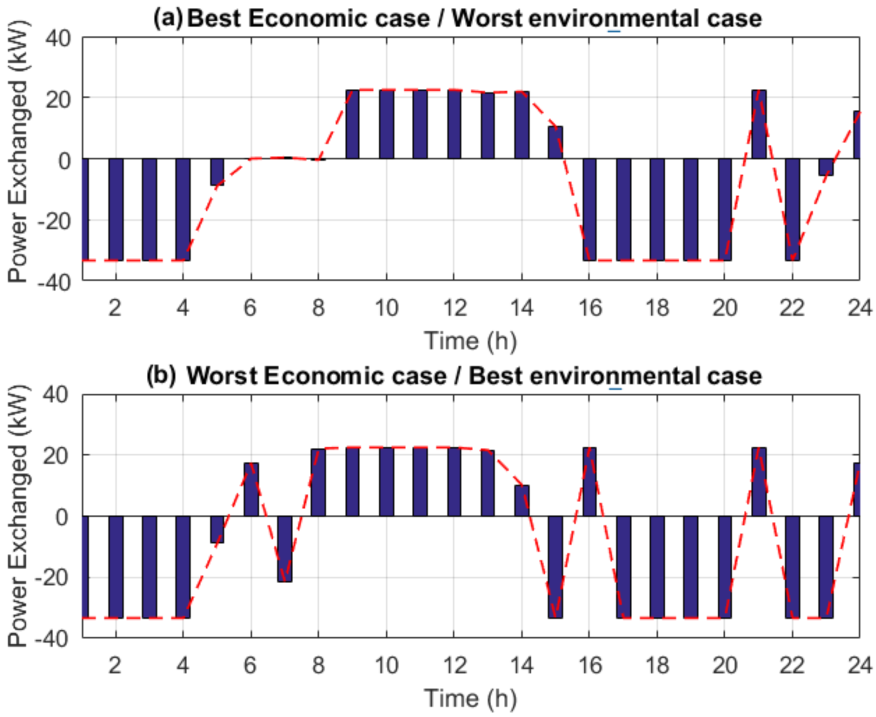

Fig. 7. Power exchange of the batteries with the microgrid during the day considering (a) scenario 1 and (b) scenario 9.

Based on the analysis of the non-dominated points, the discussion is divided into two cases, the first one mainly characterize the economic criterion, while the second one is related to the environmental criterion, discussed hereinafter.

6.1 Economic criterion

Table 4 characterizes the classification of the prices according to three states: best, average, and worst, identifying scenarios one, five, and nine, respectively.

Table 4. Comparison of results considering the economic criterion

Scenarios	Total Energy Cost (euro)
The worst	161.01
The average	157.56
The best	154.97

It is possible to observe that the best point for the price is evaluated at 154, 97 *euro*, with a total quantity of GHG emission equal to 1.3524×10^3 *kg*. It can be noticed that for an improvement of the economic criterion, the environmental one has been deteriorated. According to the results obtained from the microgrid generators scheduling, illustrated in Fig.8, it is outstanding that the optimal set-points for the microgrid generators with the lowest energy prices are the most important. The main grid is delivering energy to the microgrid during the night period when consumption is reduced and therefore the energy price is low. This energy is mainly used to charge the storage system, as shown by the battery set points in Fig.8 (charging is indicated by negative values). During the day, the use of the photovoltaic source is important due to its low price, whereas wind energy is moderately exploited. When cost of energy provided by the main grid is high, the consumption is supported by the micro-turbine in first place, and with the storage batteries according to their price, state of charge and discharge rate limits. The grid is considered as the last resource considering its high cost, *ie* during peak hours, the power from the main grid is not envisaged.

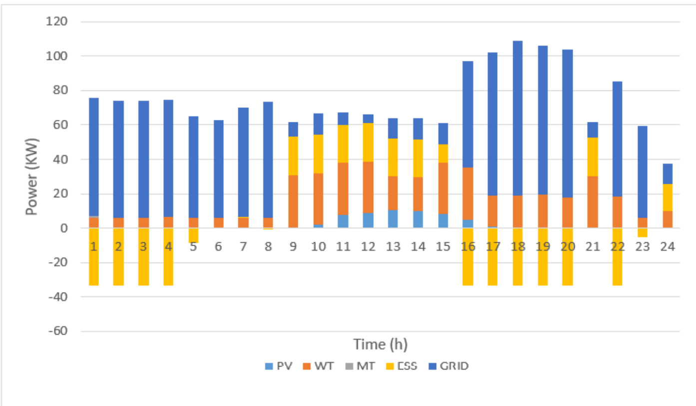

Fig. 8. Hourly dispatching set points of generators considering the best economical solution of multi-objective situation.

However, the first scenario takes mainly into account the economic criterion by favoring the cheapest sources and considering the fact that the environmental criterion will not be much affected since it is a simultaneous optimisation of two objectives.

6.2 Environmental criterion

Table 5. Comparison of results considering the environmental criterion

Scenarios	Total Emissions (Kg)
The worst	1.3524×10^3
The average	1.2984×10^3
The best	1.2795×10^3

Table 5 characterizes the classification of emissions according to three states best, average and worst case, identifying scenarios nine, five, and one, respectively.

The best point for emissions is evaluated at 1.2795×10^3 kg with a total energy price equal to $161,01$ *euro*. It can be noticed that for an improvement of the environmental criterion by 5.39 %, the economic criterion is deteriorated by 3.75%. According to the results presented in Fig.9, the hourly set points from renewable sources (wind turbines and photovoltaic) are the most important. The photovoltaic source is fully exploited during the day due to its encouraging price, and being non-polluting also the wind source is considerably exploited to reduce the use of conventional sources responsible for greenhouse gas emissions (GHG). On the other hand, the use of conventional sources is classified according to the emission factor, the lack of energy is compensated by the micro-turbine due to its reduced emission factor compared to that of the main grid, for this reason, their set-points are important comparing with the previous case which takes into account much more the economic criteria. Furthermore, the main grid is less interrogated since it is considered a strong emission source. The purpose of battery discharging is to compensate the lack of energy and limit the energy exchange from the main grid to the microgrid in order to reduce greenhouse gas emissions responsible for global warming. The second case will take into consideration the scheduling of the microgrid production sources while favoring the environmental aspect without affecting the economic aspect illustrated by the total cost of energy.

The performance of the Energy Management System (EMS) based on the Pareto-search Algorithm is demonstrated by the non-dominant points obtained which represent trade-off cases between cost and emissions, allowing the achievement of several scenarios and offering several choices to the grid operator for the scheduling of the microgrid generators taking as reference the points located in the Pareto front.

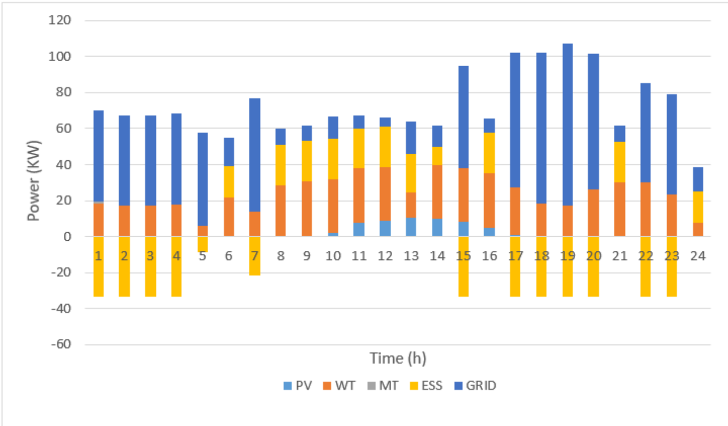

Fig. 9. Hourly dispatching set-points of generators considering the best environmental solution of multi-objective situation.

7 Conclusions and Future Work

In this paper, an energy management system based on a multi-objective optimisation approach has been proposed to solve the problem of optimal energy management in microgrids. Both economic and environmental aspects were simultaneously considered and optimised through the Pareto-search Algorithm. The results present a set of non-dominated solutions placed on a Pareto front, allowing the achieving of several microgrid scheduling scenarios. The proposed methodology provides a set of effective Pareto-optimal solutions respecting the technical-economic and environmental considerations of the problem under study and offering to the microgrid operator a variety of options for selecting an appropriate energy allocation scenario based on environmental or economic considerations. The wind turbine represents one of the permanent producers of the microgrid, however, this latter faces several obstacles, mainly the fluctuating effect. A wind speed forecasting model to predict the available capacity of wind energy production in the microgrid is important to improve the reliability of the system, to do that, a forecasting model based on the Artificial intelligence of the Neural Network (ANN) is proposed as future work. In the same context, another algorithm based on artificial intelligence will be proposed to ensure the demand scheduling of a smart city under economic and environmental considerations to further optimise the management of the microgrid and increase its efficiency.

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