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

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January 15, 2021

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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 to predict the future value of wind speed as illustrated in Figure 1.

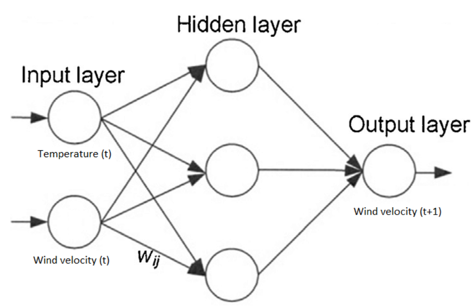

Fig. 1. Structure of the ANN model

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 square error (MSE) value as:

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

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.

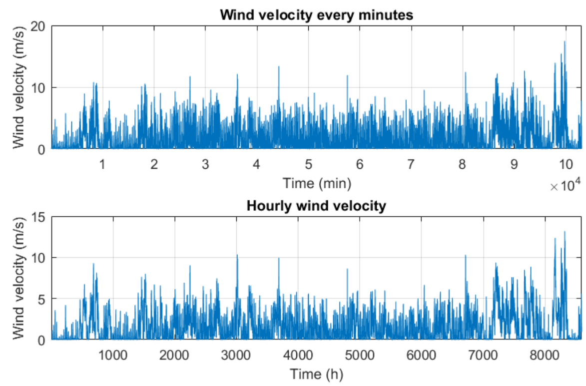

Fig. 2. Pattern of wind speed data in five minutes' interval in Polytechnic Institute of Bragança

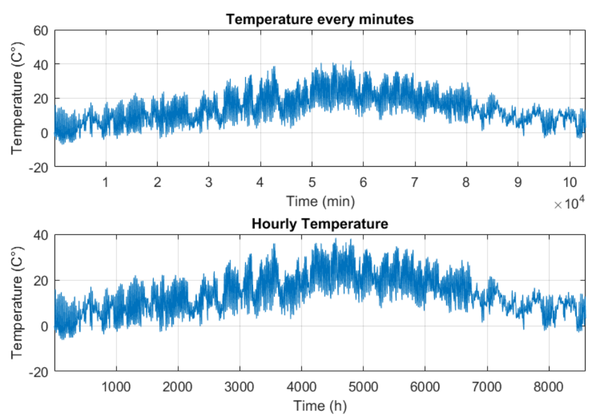

Fig. 3. Pattern of temperature data in five minutes' interval in Polytechnic Institute of Bragança

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. Figure 4 shows the microgrid architecture adopted in this study.

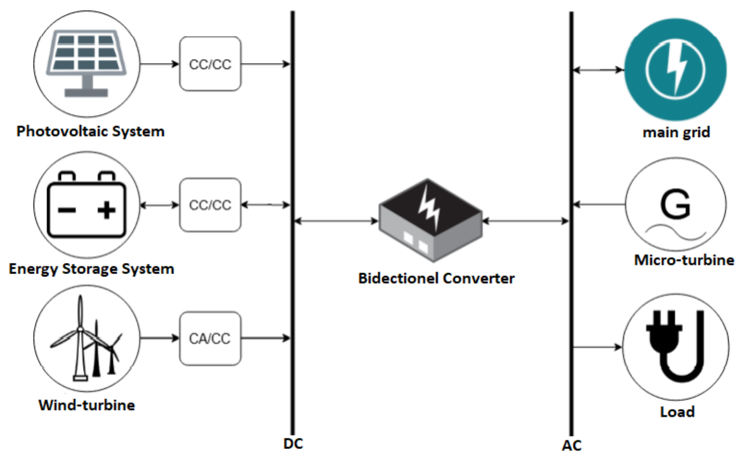

Fig. 4. Microgrid Architecture

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 Figure 5 [4].

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

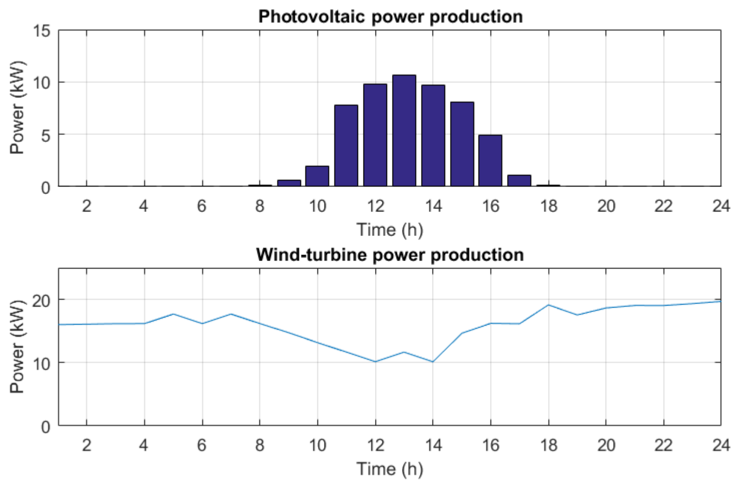

Fig. 5. Photovoltaic and wind energy production profile

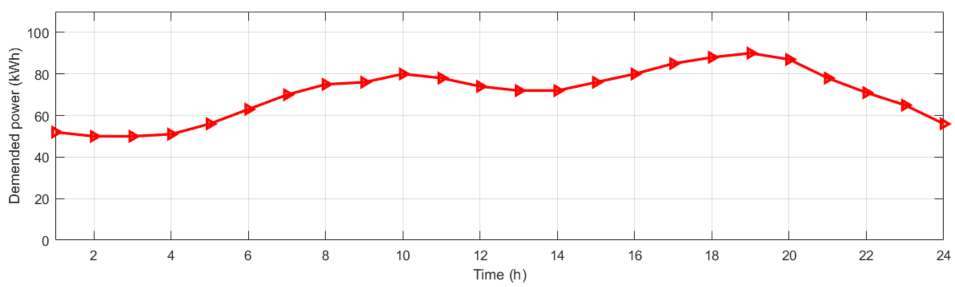

Fig. 6. Daily profile of the microgrid demand

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 Figure 7.

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

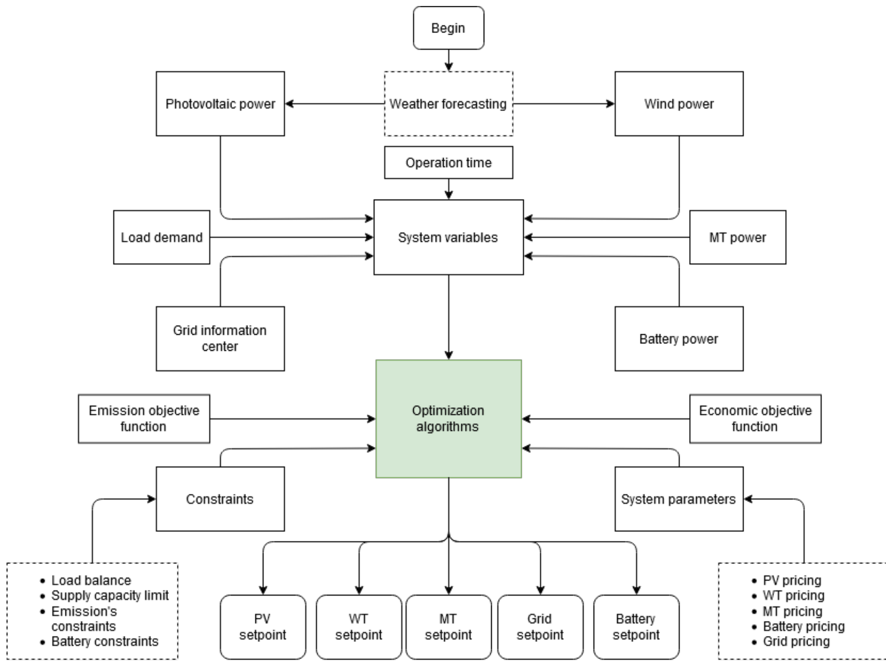

Fig. 7. Microgrid optimization model

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.

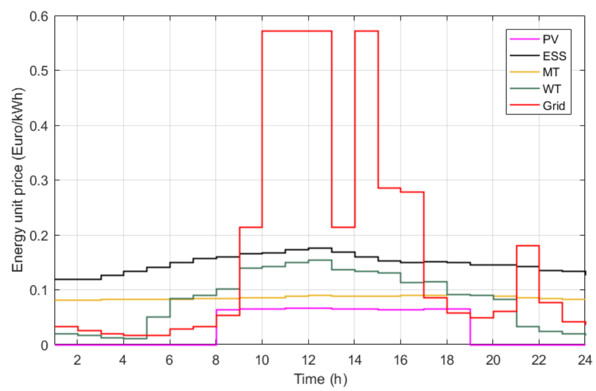

Fig. 8. The unit energy prices of the MG generators and the main grid

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].

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

The energy management optimization problem can be defined as follows:

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

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

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

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

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

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.

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 %

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

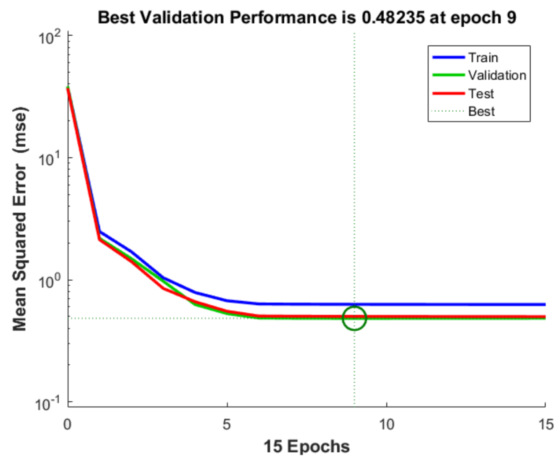

Fig. 9. The mean squared error of the network

To evaluate the reliability of the prediction model proposed in this paper, Figure 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.

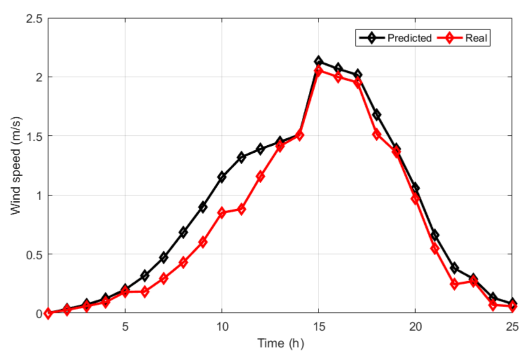

Fig. 10. Comparison of hourly forecasted wind speed with real data

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 Figure 5 as well as the microgrid energy unit prices illustrated in Figure 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 Figure 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.

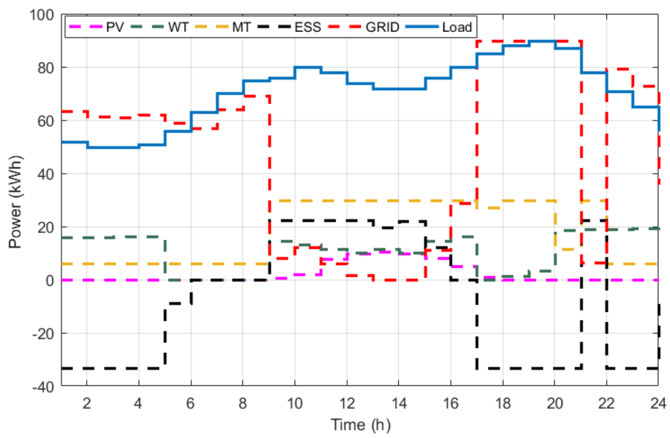

Fig. 11. Optimal power setpoints obtained in the first scenario

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.

Figure 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

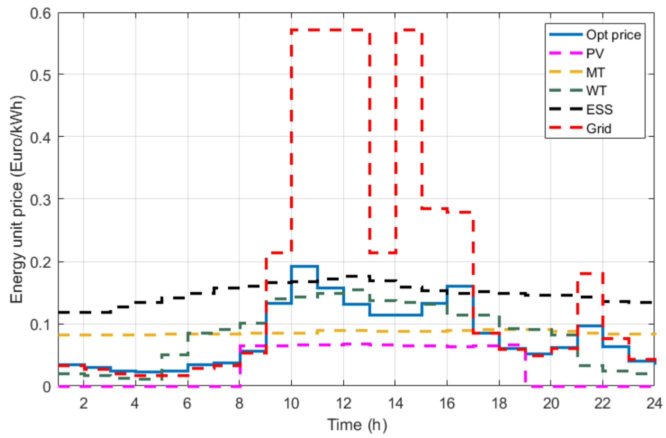

Fig. 12. The unit prices of the powers resulting from the optimal management and the optimal billing prices for the first scenario

when 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. Figure 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.

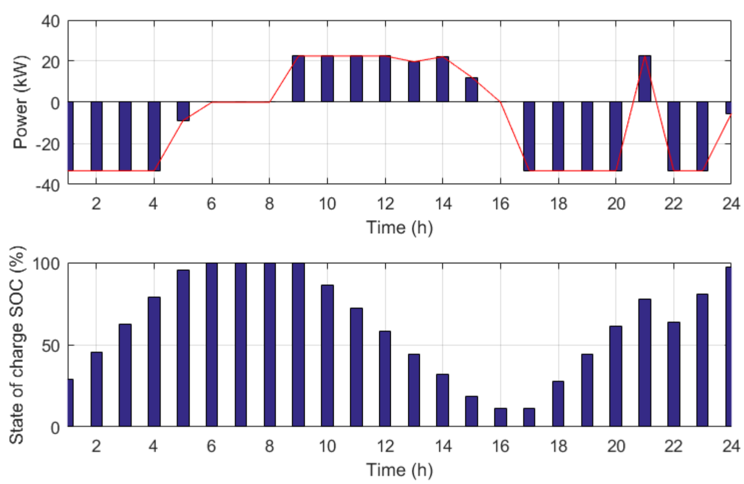

Fig. 13. The energy exchange of the batteries with the microgrid during the day

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 Figure 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.

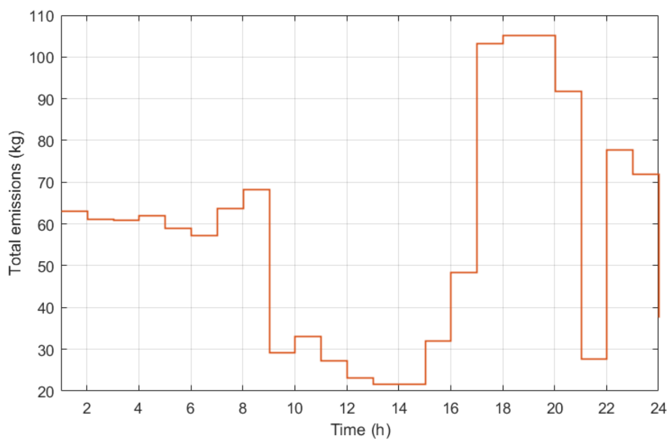

Fig. 14. The total daily emissions due to the use of fossil sources in the microgrid without injection

Scenario 2 According to the results obtained in Table 7 and Figure 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

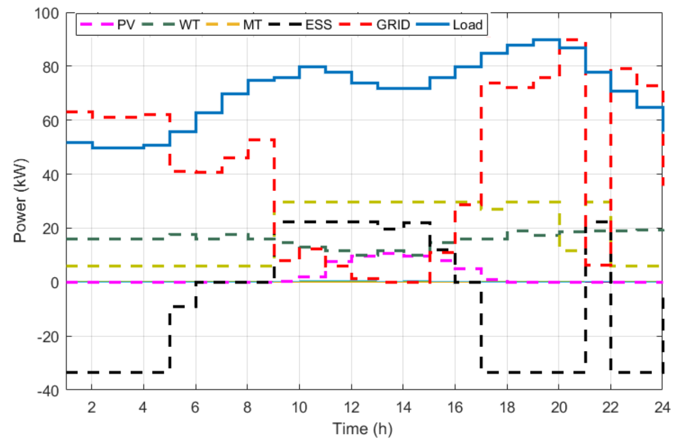

Fig. 15. Optimal power setpoints obtained in the second scenario

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

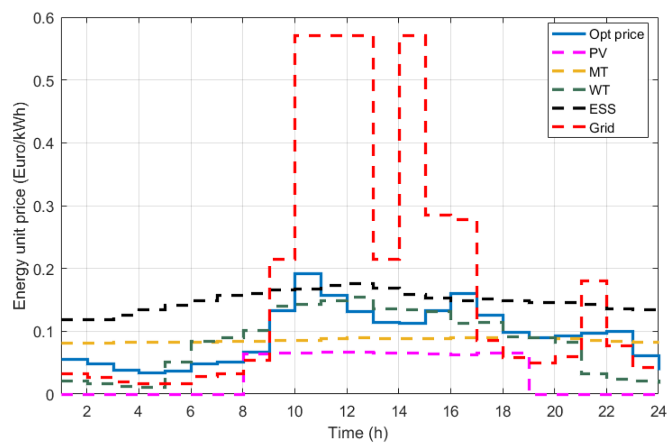

Fig. 16. The unit prices of the powers resulting from the optimal management and the optimal billing prices

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

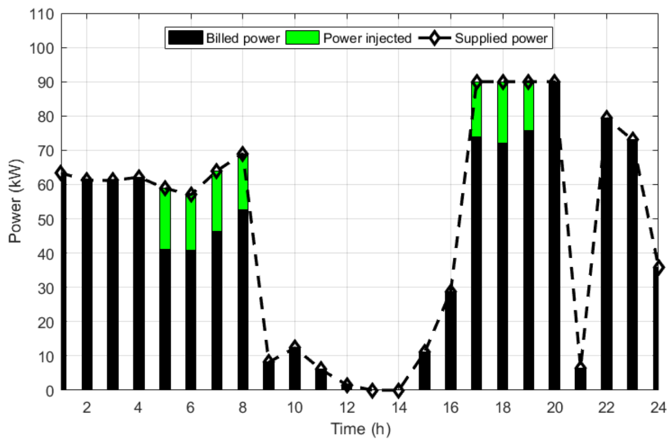

Fig. 17. The unit prices of the powers resulting from the optimal management and the optimal billing prices for the second scenario

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 Figure 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.

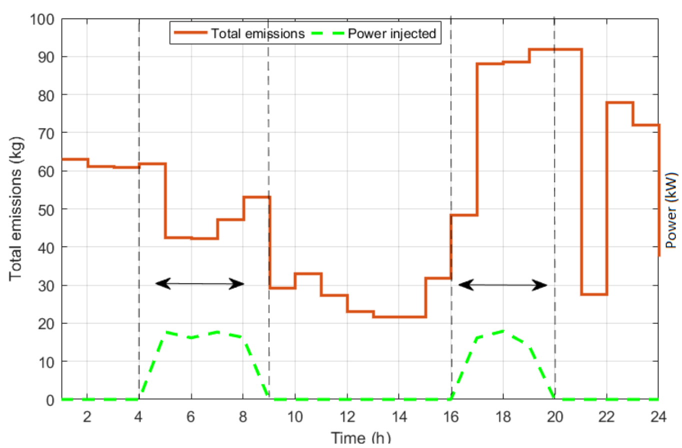

Fig. 18. The total daily emissions due to the use of fossil fuel sources in the microgrid with injection

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.

References

1. M. F. Zia, E. Elbouchikhi, M. Benbouzid, Microgrids energy management systems: A critical review on methods, solutions, and prospects, Applied energy 222 (2018) 1033–1055. .
2. J. Vlachogiannis, Probabilistic constrained load flow considering integration of wind power generation and electric vehicles, IEE Transaction On Power System 24 (2005) 1808–1817.
3. H. Hua, Y. Qin, C. Hao, J. Cao, Optimal energy management strategies for energy internet via deep reinforcement learning approachs, Applied Energy 239 (2019) 598–609.
4. M. Motevasel, A. R. Seif, Expert energy management of a micro-grid considering wind energy uncertainty, Energy Conversion and Management 83(2014) 58–72.
5. A. Dukpa, I. Duggal, B. Venkatesh, L. Chang, Optimal participation and risk mitigation of wind generators in an electricity market, IET renewable power generation 4 (2) (2010) 165–175.

6. B. Hartono, R. Setiabudy , Review of microgrid technology, in: 2013 international conference on QiR, IEEE, 2013, pp. 127–132.
7. W. Shi, X. Xie, C.-C. Chu, R. Gadh, Distributed optimal energy management in microgrids, IEEE Transactions on Smart Grid 6 (3) (2014)1137–1146.
8. C. Chen, S. Duan, T. Cai, B. Liu, G. Hu, Smart energy management system for optimal microgrid economic operation, IET renewable power generation, 5(3), (2011) 258–267.
9. S. Chakraborty, M. D. Weiss, M. G. Simoes, Distributed intelligent energy management system for a single-phase high-frequency ac microgrid, IEEE Transactions on Industrial electronics 54 (1) (2007) 97–109.
10. K.Abdelfettah, F.Boukli, K. A. Mourad. Particle Swarm Optimization for Micro-Grid Power Management and Load Scheduling , International Journal of Energy Economics and Policy 10.2 (2020): 71-80.
11. X. Zhang, R. Sharma, Y. He, Optimal energy management of a rural microgrid system using multi-objective optimization, in: 2012 IEEE PES innovative smart grid technologies (ISGT), IEEE, 2012, pp. 1–8.
12. A. G. Tsikalakis, N. D. Hatziargyriou, Centralized control for optimizing microgrids operation, power and energy society general meeting, IEEE, 2011, pp. 1–8.
13. G. Aghajani, N. Ghadimi, Multi-objective energy management in a microgrid, Energy Reports 4 (2018) 218–225.
14. A. Ouammi, Y. Achour, D. Zejli, H. Dagdougui, Supervisory model predictive control for optimal energy management of networked smart greenhouses integrated microgrid, IEEE transactions on automation science and engineering 17 (1) (2019) 117–128.
15. F. Zhang, K. Cho, J. Choi, Y.-M. Lee, K. Y. Lee, A study on wind speed prediction using artificial neural network at jeju island in korea ii, in: 2011IEEE 54th International Midwest Symposium on Circuits and Systems(MWSCAS), IEEE, 2011, pp. 1–4.
16. K. Methaprayoon, C. Yingvivatanapong, W.-J. Lee, J. R. Liao, An integration of ANN wind power estimation into unit commitment considering the forecasting uncertainty, IEEE Transactions on Industry Applications 43(6) (2007) 1441–1448.
17. R. Adnan, F. A. Ruslan, Z. M. Zain, et al., New artificial neural network and extended kalman filter hybrid model of flood prediction system, in:2013 IEEE 9th International Colloquium on Signal Processing and its Applications, IEEE, 2013, pp. 252–257.
18. U. B. Filik, T. Filik, Wind speed prediction using artificial neural networks based on multiple local measurements in eskisehir, Energy Procedia 107(2017) 264–269.
19. Y. Kumar, J. Ringenberg, S. S. Depuru, V. K. Devabhaktuni, J. W. Lee,E. Nikolaidis, B. Andersen, A. Afjeh, Wind energy: Trends and enabling technologies, Renewable and Sustainable Energy Reviews 53 (2016) 209–224.
20. M. Faisal, M. A. Hannan, P. J. Ker, A. Hussain, M. B. Mansor, F. Blaabjerg, Review of energy storage system technologies in microgrid applica-tions: Issues and challenges, IEEE Access 6 (2018) 35143–35164.
21. X. Tan, Q. Li, H. Wang, Advances and trends of energy storage technology in microgrid, International Journal of Electrical Power Energy Systems44 (1) (2013) 179–191.
22. E. Chemali, M. Preindl, P. Malysz, A. Emadi, Electrochemical and electrostatic energy storage and management systems for electric drive vehicles: State-of-the-art review and future trends, IEEE Journal of Emerging and Selected Topics in Power Electronics 4 (3) (2016) 1117–1134.

23. R. Tian, S.-H. Park, P. J. King, G. Cunningham, J. Coelho, V. Nicolosi,J. N. Coleman, Quantifying the factors limiting rate performance in battery electrodes, Nature communications 10 (1) (2019) 1–11.
24. D. Zhang, S. Evangelisti, P. Lettieri, L. G. Papageorgiou, Economic and environmental scheduling of smart homes with microgrid: Distribured energy resources operation and electrical tasks, Energy conversion and management 110 (2016) 113–124.
25. M. Elsied, A. Oukaour, H. Gualous, R. Hassan, Energy management and optimization of the multisource system based on the genetic algorithm, IEEE 23rd International Symposium on Industrial Electronics ISIE 2014.
26. Whei-Min, Chia-Sheng, T. Ming-Tang, Energy management strategy for microgrids by using enhanced bee colony optimization, energies 9 (2015) 1–16.
27. A. Quoc-Tuan, L. Ngoc. Tung, Optimal energy management strategies of microgrids, IEEE Symposium Series on Computational Intelligence (2016).
28. M.Waseem, J.Wang, L.Xiong, S.Huang, Architecture of a Microgrid and Optimal Energy Management System, Multi Agent Systems-Strategies and Applications (2020).
29. H.Shayeghi, E.Shahryari, M.Moradzadeh, P.Siano, A survey on microgrid energy management considering flexible energy sources. Energies (2019) 1-26.