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An intelligent energy management system for optimum design and real-time operation

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ABSTRACT

Planning and management of distribution networks has become a very difficult task, especially with the strong expansion of renewable energy sources (RES) which are intermittent in nature. Maintaining fluidity and reliability of real-time decisions while taking into consideration uncertainties related to production and increasing the profit of distribution network operators is the objective of the system proposed in this work. It is an intelligent energy management system dedicated to the management of grid-integrated RES and battery energy storage systems (BESS), composed of: i) a real-time control and data acquisition model, ii) a model for forecasting the intermittent parameters of RES based on neural networks, iii) a long-term planning model based on the optimal placement and size of RES and BESS, and iv) an hourly planning model for scheduling the energy distribution between energy sources. The non-dominated sorting genetic algorithm and the entropy-TOPSIS method (technique for order of preference by similarity to ideal solution) form the basic block of this model. To evaluate it, a modified IEEE 33 bus network was used for testing and the results, for short-term scheduling, proved that the system succeeds in maximizing profits and significantly minimizing CO_2 emissions, in addition to power losses and voltage drops.

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1. INTRODUCTION

– Motivation and background

All over the world, a major transition in the energy field has emerged due to the increase in CO_2 emissions and the cost of electrical energy; renewable energy sources (RES) replace fossil fuel energy with a competitive cost and zero CO_2 emissions [1]. This is the strategy of Morocco, located in North Africa, which has reviewed its development strategy much like other countries and changed its orientation by starting to invest more and more in renewable energy projects, given its geographical position and its significant potential in terms of solar and wind resources [2]–[4].

As key drivers of energy transition and sustainable development, renewable energies such as wind turbines (WT) and photovoltaic panels (PV) pose several challenges due to their stochastic and intermittent nature [5]. Battery energy storage systems (BESS) can be a promising solution to manage the intermittent nature of RES since their cost has decreased by 45% between 2012 and 2018 [5], and it is still decreasing. BESS can guarantee a variety of services in the network; it can regulate and control voltage, reduce reverse power flows, guarantee power in the event of an interruption, and smooth production [6]. The integration of

RES with storage offers several advantages to the network. In order to get the maximum possible benefit during the installation, their planning is of major importance [7].

Decentralization, digitalization and decarbonization (3D) are the three pillars for the green energy of the future [8]. It is the 3Ds that have redefined the world of energy and paved the way for a smart, reliable and increasingly independent grid. With the integration of smaller and dispersed RES and BESS into the grid, reliance on large generation plants will be limited, which will also lead to reduced CO_2 emissions and transmission losses. Moreover, effective monitoring and management of these decentralized generation sources will help ensure the system efficiency in the midst of complex changes in the energy market. This is the concept of energy management.

Energy management systems (EMS) are defined as systems that monitor and control the electrical network by receiving data collected from sensors installed in this network, exploiting them for optimization purposes and sending the results back to the network as soon as possible [9]. The energy management concept includes all optimal decisions planned and implemented to ensure energy availability at minimum cost. It is a very important concept that is supposed to help distribution network operators (DNO) to face the challenges of energy costs, uncertainties related to production and load variations [10]. Hence the need to develop a robust intelligent energy management system equipped with artificial intelligence techniques and information technology capabilities in order to overcome these challenges.

– Literature review

In the literature, several researchers were interested in the energy management problem. Mazidi *et al.* [11] proposed an optimization model for day-ahead dispatch of renewable sources, which aims to minimize operating costs and takes into consideration uncertainties related to the load and wind production. Nikmehr and Ravadanegh [12] used particle swarm optimization (PSO) algorithm and imperialist competition algorithm (ICA) in order to minimize the operating cost of microgrids. The results obtained showed that an optimal sharing of power between the main network and the microgrid reduces these costs significantly. An energy management strategy based on a hybrid algorithm has been proposed, in [3], for a grid-integrated residential system to optimize daily operating costs and CO_2 emissions. Aghdam *et al.* [13] proposed a procedure for energy management between multi-microgrid systems which takes into consideration the stochastic character of renewable energies and the cost of degradation of batteries. El Kazaz *et al.* [14] have developed a two-layer energy management model that optimizes the daily network operating cost.

Energy management has also been the center of interest of [15] where an energy management system based on three services has been proposed; a demand forecasting service, a voltage profile forecasting service and a management constraint service. Chen *et al.* [16] in turn, have proposed a model of energy management in distribution networks taking into account the uncertainties of production. For economic optimal operation and improved system quality, power losses and nodal voltage deviation have been optimized. Reihani *et al.* [17] conducted an extensive study on the use of BESS to show their effectiveness in managing energy from intermittent sources. It has been found that proper BESS charge/discharge planning can ensure system efficiency. Jozwiak *et al.* [18] carried out an analysis of the load demand for boats in Ballen Marina to optimize the cost of energy for sailors and the cost of energy exchanged with the main grid. This proved the important role of demand flexibility analysis as a key element in the energy system. An energy management model has also been developed for microgrids, in [19], to minimize main grid imports and minimize cash flow. Azoug *et al.* [20] proposed an efficient hybrid energy system after demonstrating the effect of efficient use of renewable energy sources on system efficiency. Kothai and Jayapal [21] developed a cost management system for grid-connected PV-wind system scheduling with storage for cost minimization and un-interruption of power.

– Contribution and paper structure

The system proposed in this work is a system that promotes the strong insertion of renewable energies and BESS as well, while limiting imports from the main grid. Made up of several complementary modules, the system is based on a two-level planning model:

a) Long-term planning (over the lifetime of the equipment) through the optimal placement and size of PV, WT and BESS.
b) Short-term planning which consists of the daily operation of production units and the charging/discharging behavior of BESS. The model is based on two parallel modes, real-time scheduling and day-ahead scheduling. This model optimizes four objective functions; two of a technical nature, one economic and the other environmental.

A secure real-time acquisition architecture, based on the internet of things (IoT), has been proposed in order to guarantee end-to-end communication between the EMS and the network. The proposed system respects the notion of 3D; decentralization is guaranteed during the optimal location of RES and BESS and the notion of de-carbonization is investigated during the optimal daily operation of the network. As for digitization, it is highlighted by the exploitation of IoT technologies for an effective exchange of data.

This paper is structured as follows: the general architecture of the proposed system is described in section 2. The mathematical modeling of loads, RES and BESS is introduced in section 3. Section 4 is devoted to the sizing and long-term planning of a hybrid system made up of WT, PV, and BESS. The daily planning of this hybrid system is formalized and detailed in section 5. And section 6 contains the general conclusion of this work.

2. DESCRIPTION OF THE PROPOSED SYSTEM

In addition to the main grid, PV, WT and BESS can also support the load. These units can interface with the grid through electronic power converters. The objective of this system is to promote the insertion of these sources in a decentralized way and limit imports of energy from the main network. Figure 1 presents the energy management system proposed in this work. The system includes the following modules:

- An IoT-based real-time acquisition and control module that collects real-time data from RES and BESS, stores it in a database as historical data, and displays it on the EMS interface. This module is also capable of sending execution orders to the network.
- A forecasting module that uses historical data to forecast production and demand 24 hours in advance.
- A long-term planning module which intervenes at the time of the installation of production sources by planning their optimal size and position.
- A short-term planning module that is capable of developing an optimal energy distribution plan for a time step of one hour.

In order to exchange data and decisions between RES, BESS, loads and EMS, each unit must be equipped with a Raspberry Pi via sensors installed in the field. The Raspberry Pi will exchange data and decisions with the broker using the message queuing telemetry transport (MQTT) application protocol. All generating units, loads, and EMS are MQTT clients that publish or subscribe to the MQTT broker in order to send or access data. A robust, efficient and reliable communication network is therefore necessary to transmit information and instructions in real-time between the various equipment and the EMS and a robust encryption technique must be used in order to secure the communication. In this work, an end-to-end communication system based on a virtual private network (VPN) concentrator with 4G cellular network (4th generation) was proposed to be added to the system in order to guarantee remote communication between the MQTT broker and MQTT clients, in addition to a VPN tunnel created by OpenVPN in order to secure the exchange of data. OpenVPN uses certificates and encryption algorithms to secure data from end to end. Forecast parameters, optimization results and real-time collected data will be displayed on a human-machine interface (HMI).

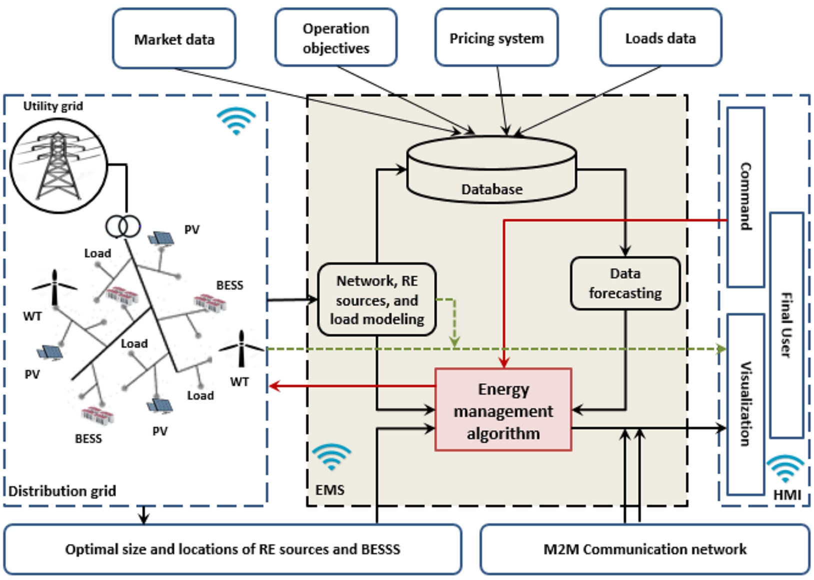


Figure 1. The proposed energy management system

For the two-level scheduling model, the resolution of the optimization problem is done using the non-dominated sorting genetic algorithm II (NSGA-II). An algorithm combining performance and robustness and part of the most dominant evolutionary algorithms in the field of multi-objective optimization. It is the most studied algorithm in scheduling since 2014 [22]. NSGA-II is based on the notion of non-dominance, which makes it possible to assign the solutions of a population to the different Pareto fronts and is characterized by a high diversity of results, thanks to the congestion distance and elitism. It has been used for both long-term and short-term planning, in this work, all long with entropy-TOPSIS method (technique for order preference by similarity to ideal solution) which is used to classify the optimal-Pareto solutions. Entropy-TOPSIS is a hybrid method that determines the weights in an objective way using entropy and classifies the solutions by TOPSIS. It has proven its effectiveness when compared to other several classification methods [23]. The flowchart of the two-level planning model, developed in this work, is shown in Figure 2.

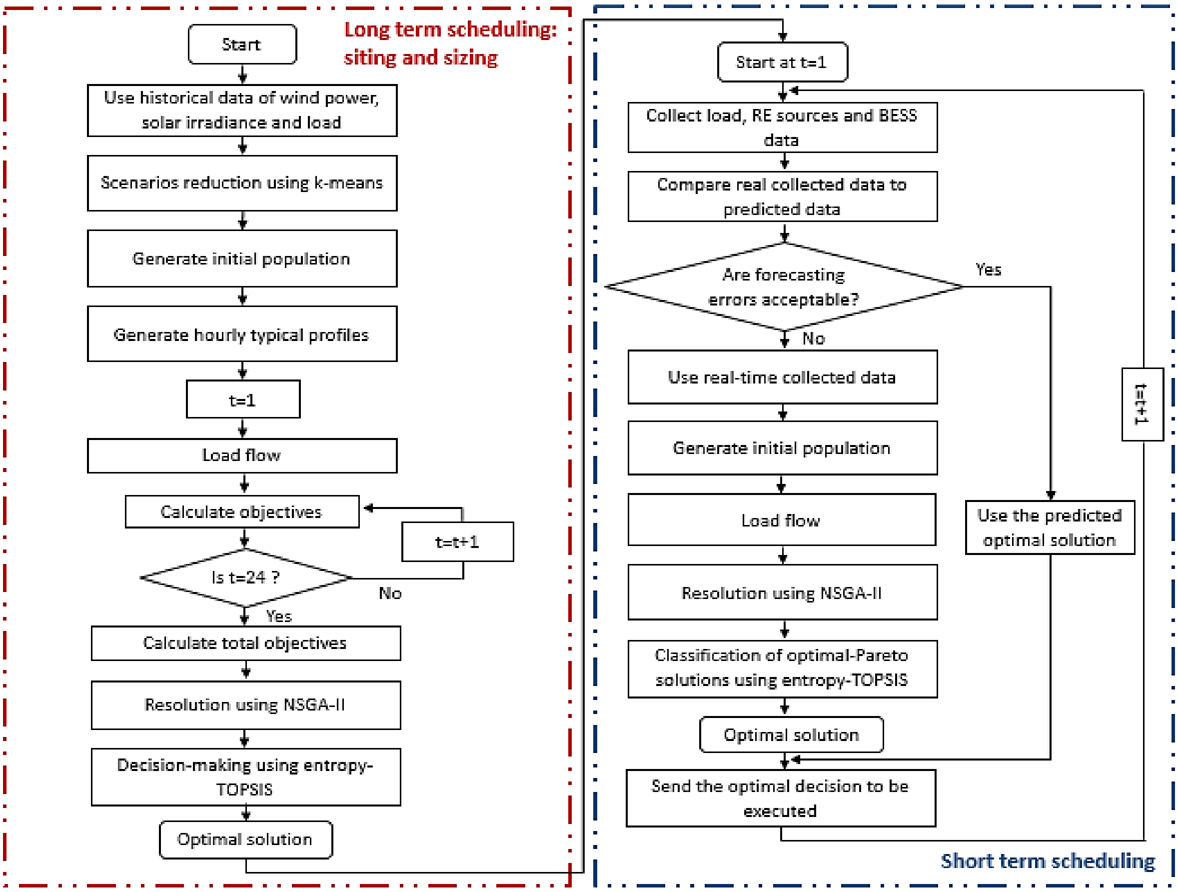


Figure 2. The two-level scheduling solution flowchart

3. MATHEMATICAL MODELING OF THE HYBRID SYSTEM

Planning and properly evaluating the performance of a hybrid production system requires the modeling of its various components. The optimization of the location and size of the hybrid system as well as the planning of the energy distribution in the network strongly depend on the mathematical models of the components of this system. It is a step of great importance that consists in developing a mathematical model which describes the system in the most representative and precise way. The hybrid system, in this work, consists of a PV/wind/storage system integrated into the distribution network. In this section, mathematical modeling of photovoltaic and wind power generation, load power and stored energy is presented.

3.1. Load modeling

The uncertainties related to the variation of the load can be represented according to the type of load (industrial, commercial, residential). In this article, all three types were considered, each at a specific percentage. The percentage of each type of load during a 24 h period and at each node of the IEEE 33 bus network were taken from [24]. Therefore, the load can be modeled as in (1) and (2).

$$P_i(t) = P_{L,i} \times [f_C(i).C_{p,C}(t) + f_I(i).C_{p,I}(t) + f_R(i).C_{p,R}(t)] \quad (1)$$

$$Q_i(t) = Q_{L,i} \times [f_C(i).C_{q,C}(t) + f_I(i).C_{q,I}(t) + f_R(i).C_{q,R}(t)] \quad (2)$$

Where P_i and Q_i are the active and reactive powers for the mixed load at node i. $P_{L,i}$ and $Q_{L,i}$ are the active and reactive load powers at each node i. f_C, f_I and f_R are respectively the proportions of the commercial, industrial and residential load of each node and $C_{p,C}$, $C_{q,C}$, $C_{p,I}$, $C_{q,I}$, $C_{p,R}$ and $C_{q,R}$ are the coefficients that represent the proportions of the commercial, industrial and residential load for each time interval for active and reactive load powers, respectively. The typical load profile generated within a 24 h interval is represented in Figure 3.

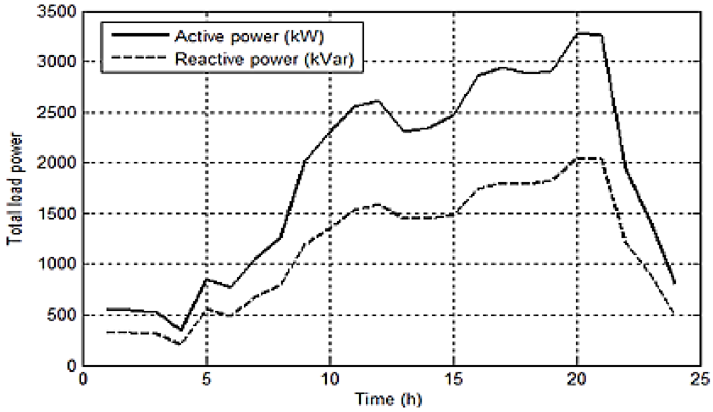


Figure 3. Typical load profile

3.2. The photovoltaic system modeling

The output photovoltaic power P_{PV} is expressed, in (3) and (4), as a function of the standard photovoltaic power $P_{PV,stc}$ and solar irradiance G [25].

$$P_{PV} = P_{PV,stc} \times f_{PV} \times 1 + \alpha_p \times (T_c - 25) \times \frac{G}{1000} \quad (3)$$

$$T_c = T_a + G\ \frac{T_{c,NOCT} - T_{a,NOCT}}{G_{T,NOCT}} \quad (4)$$

Here, T_c and T_a are, respectively, the temperature of the photovoltaic cell and the average ambient temperature (°C) and f_{PV} and α_p are the PV derating factor (%) and the temperature coefficient (%/°C), respectively. $T_{c,NOCT}$ is the nominal operating cell temperature NOCT (°C), $T_{a,NOCT}$ is the ambient temperature at which the NOCT is set, and $G_{T,NOCT}$ is the solar irradiance at which the NOCT is defined.

3.3. The wind turbine modeling

The choice of the appropriate model for calculating wind power is of great importance. The most simplified model that expresses the relationship that links wind power (P_{WT}) to wind speed (v_W) [26] is formalized in (5).

$$P_{WT} = \begin{cases} 0 & v_w \le v_{ci}\,;v_w \ge v_{co} \\ P_{WTr} \times \frac{v_w - v_{ci}}{v_r - v_{ci}} & v_{ci} \le v_w \le v_r \\ P_{WTr} & v_r \le v_w \le v_{co} \end{cases} \quad (5)$$

Where P_{WTr} is the rated output power of the wind turbine and v_r, v_{co} and v_{ci} are the rated speed, cut-out speed and cut-in speed of the wind turbine, respectively in m/s. Historical wind speed data is measured at a reference height of 10 m by anemometer. The power law is therefore used to convert the wind speed from the reference height to the hub height of the wind turbine [27], as in (6) and (7).

$$v = v_0 \left(\frac{h}{h_0}\right)^{\alpha} \quad (6)$$

$$\alpha = \frac{0.37 - 0.088 \ln (v_0)}{1 - 0.088 \ln (\frac{Z_0}{10})} \quad (7)$$

v_0 and v are wind speeds at anemometer height and hub height, respectively (m/s). h_0 is the anemometer height (m) and h is the hub height (m). α is the power law exponent and Z_0 is the roughness length (m).

3.4. The battery energy storage system modeling

Lithium-ion batteries are selected in this work for their better performance and their longer life cycle, in addition to their cost which is decreasing over time. BESS is used to support the load during peak hours (generally between 4 p.m. and 10 p.m.), when there is no photovoltaic or wind power or when it is insufficient. The state of charge (SoC) of the BESS at time t as a function of its state of charge at time t-1 [14] is expressed in (8).

$$SoC(t) = SoC(t-1) + \eta_{ch} \times \frac{P_{ch}(t)}{P_{BESSr}} - \frac{P_{dis}(t)}{\eta_{dis} \times P_{BESSr}} \tag{8}$$

Where P_{BESSr} represents the rated power of BESS, P_{dis} and P_{ch} are the discharging and charging powers of the BESS at time t, and η_{ch} and η_{dis} represent the charging and discharging efficiencies respectively.

4. LONG-TERM SCHEDULING: OPTIMAL LOCATION AND SIZE

In this work, a two-layer planning model was proposed, providing long-term planning and daily scheduling. In this section, it is about long-term planning. The objective is to optimize the locations and sizes of BESS, WT and PV systems integrated into the distribution network, simultaneously, in order to minimize investment costs, voltage drops and active power losses.

4.1. Typical generated solar irradiance and wind speed profiles

Solar irradiance and wind speed data (at 10 m) for five years were collected (43,776 hours) for a location in the city of Casablanca in Morocco in order to estimate and model the uncertainties linked to PV and WT. Simulation with such a number will require enormous time, hence the need to generate a daily typical profile that is the most representative by reducing all these scenarios. The k-means algorithm [28] was used to group the data into several clusters, each cluster being characterized by a centroid and a probability of occurrence. The profile with the lowest distance from the centroid and the highest probability of occurrence is the one selected as the typical profile. Figure 4 represents the normalized typical profiles of solar irradiance and wind speed. The per-unit system associates the values of irradiance and wind speed with their maximum value and compares it with their real values. These typical data will be used to calculate the wind and photovoltaic powers at each instant t (using (3)-(7)).

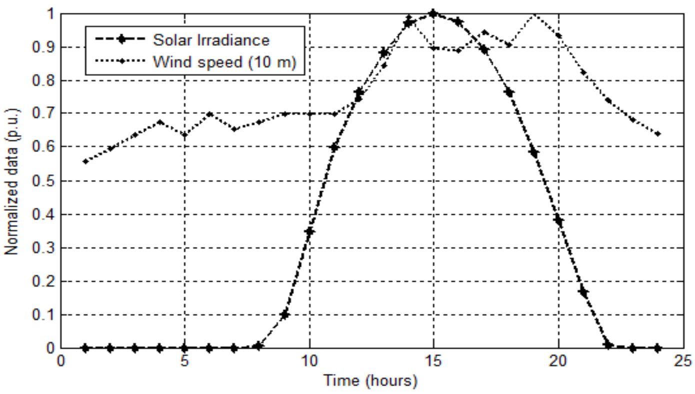


Figure 4. Normalized typical data of wind speed and solar irradiance

4.2. Formulation of the multi-objective problem

In the literature, several works have confirmed that the advantages of integrating RES and BESS in the network are numerous, either at the economic or technical level. In order to have the maximum benefit without disruption of the network during their installation, their coordination in terms of location and size is a very important issue [29]. For optimal sizing of PV, WT and BESS, the network is assumed to be in stand-alone mode and only these sources can support the loads. The location and size problem is solved simultaneously for PV, WT and BESS. All sources integrated into the network are assumed to be type III with a power factor of 0.85. The optimization problem is formalized in order to minimize the following objective functions:

4.2.1. Total active power losses

Active power losses, in distribution networks, constitute the highest percentage in the electrical system [29]. Minimizing these losses is one of the main objectives of DNO while guaranteeing a stable and continuous supply to end customers [23]. The daily power losses P_{Loss}^{d} are to be minimized in this problem and are formalized in (9) and (10).

$$P_{Loss}^{d} = \sum_{t=1}^{24} P_{Loss}(t) \tag{9}$$

$$P_{Loss}(t) = \sum_{\substack{i=1 \\ i \neq j}}^{n} \sum_{j=1}^{n} R_{i,j}\, I_{i,j}^{2}(t) \tag{10}$$

P_{Loss} represents the hourly active power losses, $R_{i,j}$ is the line resistance, $I_{i,j}$ is the current passing through this line and n is the number of nodes in the network.

4.2.2. Voltage drops

The distribution system voltage may vary when the network is subject to many changes, causing voltage drops which may have negative effects on the system operation [23]. The average daily voltage drops $\Delta V_{d,mean}$ are expressed as a function of the nodal voltage V_i in (11) and (12).

$$\Delta V_{d,mean} = \frac{1}{24} \sum_{t=1}^{24} V_d(t) \tag{11}$$

$$V_d(t) = \frac{1}{n} \sum_{i=1}^{n} \left(V_i(t) - V_{mean}(t)\right)^2 \tag{12}$$

V_d and V_{mean} are the hourly voltage drops and the average voltage at each instant t, respectively.

4.2.3. Total investment cost

The total investment cost is one of the objectives to be minimized in the long-term planning problem. This total cost C_T includes the capital cost of RES and BESS and their operation and maintenance costs, as in (13)-(17).

$$C_T = \frac{1}{365} \times [C_{RES} \times CRF_{RES} + C_{BESS,T} \times CRF_{BESS}] \tag{13}$$

$$C_{RES} = (C_{PV} + C_{O\&M,PV}).P_{PVr} + (C_{WT} + C_{O\&M,WT}).P_{WTr} \tag{14}$$

$$C_{BESS,T} = (C_{BESS} + C_{O\&M,BESS}).E_{BESS,r} \tag{15}$$

$$CRF_{RES} = \frac{r(1+r)^{y}}{(1+r)^{y}-1} \tag{16}$$

$$CRF_{BESS} = \frac{r_{BESS}(1+r_{BESS})^{y_{BESS}}}{(1+r_{BESS})^{y_{BESS}}-1} \tag{17}$$

C_{RES} and $C_{BESS,T}$ represent total investment costs of RES and BESS respectively. C_{PV}, C_{WT} and C_{BESS} are the investment costs of PV, WT and BESS, respectively. $C_{O\&M,PV}$, $C_{O\&M,WT}$ and $C_{O\&M,BESS}$ are the operation and maintenance costs of PV, WT and BESS respectively. P_{PVr} and P_{WTr} are the rated powers of PV and WT and $E_{BESS,r}$ is the rated capacity of BESS. r and r_{BESS} are the discount rates for RES and BESS and y and y_{BESS} represent the lifetime of RES and BESS respectively. CRF_{RES} and CRF_{BESS} are the capital recovery factors that convert initial costs to an annual basis for RES and BESS respectively.

4.2.4. Constraints

The equations formulated above are subject to equality and inequality constraints formalized in (18)-(22). The constraints expressed in (20)-(22) are valid also for reactive powers.

$$0.95 \leq V_i(t) \leq 1.05 \tag{18}$$

$$SoC_{min} \leq SoC(t) \leq SoC_{max} \tag{19}$$

$$P_{min} \leq P_{PVr}, P_{WTr} \leq P_{max} \tag{20}$$

$$E_{min} \leq E_{BESS,r} \leq E_{max} \tag{21}$$

$$P_{grid}(t) + P_{PV}(t) + P_{WT}(t) + P_{BESS}(t) = P_{load}(t) + P_{Loss}(t) \tag{22}$$

P_{BESS} is the BESS power at time t, SoC_{min} and SoC_{max} represent the minimum and maximum state of charge of BESS and P_{min} and P_{max} are the minimum and maximum powers generated by RES. E_{min} and E_{max} are the minimum and maximum capacities of battery systems, P_{grid} is the power delivered by the main grid and P_{load} is the total load power.

4.3. Simulation and results

In this work, the 12.66 kV IEEE 33 bus test network was used to test the proposed model and the typical load profile shown in Figure 3 was used in the simulation. The NSGA-II algorithm was used for solving the multi-objective problem and the entropy-TOPSIS method was deployed for the classification of optimal-Pareto solutions. The technical parameters of RES and BESS and investment costs used in this study are presented in Table 1 and Table 2. The results of the simulation are presented in Table 3 and Figure 5.

Table 1. RES and BESS economic data [30]–[32]

Costs	PV	WT	BESS
Investment cost	1020 (€/kW)	1350 (€/kW)	458 (€/kWh)
O&M cost (% of investment cost)	1.7	3	2
Lifespan (years)	25	25	15
Discount rate (%)	4.5	4.5	10

Table 2. Technical data of RES and BESS [33]

Equipment	Technical parameters	
PV	T_a (°C)	19
	$T_{a, NOCT}$ (°C)	20
	$G_{T, NOCT}$ (W/m^2)	800
	α_p (%/°C)	-0.48
	f_{PV} (%)	95
WT	v_{ci} (m/s)	3
	v_{co} (m/s)	25
	v_r (m/s)	11.5
BESS	SoC_{min} (%)	10
	SoC_{max} (%)	90
	η_{ch}	0.95
	η_{dis}	0.95

Table 3. Optimal location and size results

Equipment	PV 1	PV 2	WT 1	WT 2	BESS 1	BESS 2
Size	782 (kW)	755 (kW)	764 (kW)	742 (kW)	4.251 (MWh)	3.3449 (MWh)
Location (bus)	15	31	23	28	7	19

It is quite clear, from Figure 5, that the concept of decentralization is respected. Instead of depending 100% on the main grid with very high-power losses and voltage drops, with decentralized RES and BESS throughout the network and close to the consumer, these losses and voltage drops will decrease considerably, as shown in Table 4, without forgetting their positive impact on the environment. Other evolutionary algorithms, well known in the literature for their performance, have been applied to solve this planning problem and have been compared in terms of results and computational time. These algorithms are NSGA-III, SPEA2 (strength Pareto evolutionary algorithm 2) and MOEA/D (multi-objective evolutionary algorithm based on decomposition). More details about these algorithms are provided in [34].

The results, presented in Table 4, show that NSGA-II, compared to other algorithms, gives better results in a reduced computational time for this specific problem. Thanks to its non-dominated sorting properties and crowding distance, NSGA-II forms a diversified and distributed Pareto front in addition to its rapid convergence. Even though NSGA-III is a more developed version of NSGA-II, but it doesn’t always outperform it [35]. Optimal sizes and locations found by NSGA-II were able to achieve significant reductions, when compared to the base case (where only the main grid supports loads), in terms of daily power losses with a value of 82.97%, compared to 70% for NSGA-III, 76.37% for SPEA2 and 76.3% for MOEA/D.

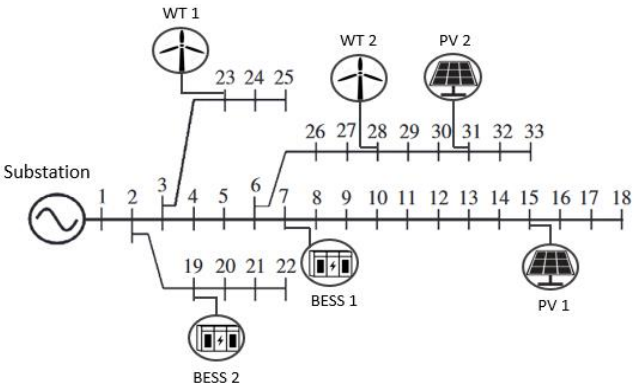


Figure 5. The optimal location results in the IEEE 33 bus network

Table 4. Comparison results of optimization algorithms

Methods	P_{Loss} (kW)	V_{mean} (p.u.)	Cost (€)	Simulation time (s)
NSGA-II	253.29	1.98 e-5	1959.53	4037.43
NSGA-III	445.11	5.63 e-5	1959	5155.1
SPEA2	351.50	4.93 e-5	1945.14	4902.37
MOEA/D	366.60	4.98 e-5	1971	4287

5. SHORT-TERM SCHEDULING: ENERGY MANAGEMENT

Unlike long-term scheduling, discussed in the previous section, which consists of planning the location and size of production units over a long period of time, short-term planning is a decision-making procedure that aims to ensure the correct operation of the distribution network in a short period of time. The objective of the short-term planning layer, in this work, is to determine the operation and decisions of the system with respect to the energy distribution in order to optimize the profit of network operators, CO_2 emissions, power losses and voltage drops.

5.1. Formulation of the multi-objective problem

The objective of short-term energy scheduling is to efficiently manage the energy distribution between the available sources in the network in order to optimize specific objective functions. The dynamic economic dispatch must be ensured every moment trying to limit energy imports from the main grid and improve energy production from RES. In this problem, the decision vector is a binary vector of 9 elements:

$$X = [x_1\ x_2\ x_3\ x_4\ x_5\ x_6\ x_7\ x_8\ x_9] \quad (23)$$

The first two elements are dedicated to PV 1 and PV 2 and they either take 1 when these two PV systems inject power into the grid or 0 otherwise. Likewise, x_3 and x_4 are devoted to WT. x_5 and x_6 are for BESS 1 and BESS 2 and they are 1 if these systems inject into the network and 0 otherwise. For x_7 and x_8, their value is 1 if BESS 1 and BESS 2 are charging and 0 otherwise. x_9 is devoted to the main grid. This vector is generated randomly in order to optimize the functions expressed in (10) and (12), in addition to the objective functions below, subject to the constraints expressed in (18)-(19) and (22).

5.1.1. The profit of the distribution network operators

During each hour, the DNO profit P_r is a function to be maximized in order to guarantee the financial gains to the distribution network operators. The profit is expressed as the difference between the cost of the energy sold C_{sell} and the cost of the energy bought C_{buy} by DNO, as in (24)-(27).

$$P_r(t) = [C_{sell}(t) - C_{buy}(t)] \times \Delta t \quad (24)$$

$$C_{sell}(t) = P_{ch}(t)\ C_{BESS,sell} + P_{load}(t)\ C_{load,sell}(t) + P_{excess}(t)\ C_{excess,sell}(t) \quad (25)$$

$$C_{load,sell}(t) = C_{Com,sell}\ .f_C(i).C_{p,C}(t) + C_{Ind,sell}.f_I(i).C_{p,I}(t) + C_{Res,sell}.f_R(i).C_{p,R}(t) \quad (26)$$

$$C_{buy}(t) = P_{PV}(t)\ C_{PV,buy} + P_{WT}(t)\ C_{WT,buy} + P_{dis}(t)\ C_{BESS,buy} + P_{grid}(t)\ C_{grid,buy}(t) \quad (27)$$

Where $C_{BESS,sell}$ is the cost of selling energy to BESS to charge it (€/kWh), $C_{load,sell}$ is the cost of selling electricity to customers at time t (€/kWh), P_{excess} is the excess power in the network (kW), $C_{excess,sell}$ is the cost of exporting excess power to the main grid (€/kWh) and $C_{PV,buy}$ and $C_{WT,buy}$ are the purchased costs of photovoltaic and wind power (€/kWh), respectively. $C_{BESS,buy}$ represents the cost of purchasing energy from BESS (€/kWh), $C_{grid,buy}$ is the cost of purchasing energy from the main grid at time t (€/kWh) and Δt is the time step (1 h). $C_{Com,sell}$, $C_{Ind,sell}$ and $C_{Res,sell}$ are costs of the energy sold to commercial, industrial and residential clients, respectively.

5.1.2. Carbon dioxide emissions

Emissions reduction is one of the challenges facing distribution network operators. This reduction leads to amazing improvements in air quality [9]. In this work, only carbon dioxide (CO_2) is considered, as being the largest cause of global warming. It was assumed that 100% of the energy provided by the main grid is generated from coal power plants. This is justified by the great participation of coal in the production of electricity in Morocco [36]. These emissions E_{CO2} are expressed in (28) and (29).

$$E_{CO2}(t) = P_{grid}(t) \times E_{g,CO2} + P_{RES}(t) \times E_{RES,CO2} + P_{BESS}(t) \times E_{BESS,CO2} \quad (28)$$

$$P_{grid}(t) = P_{load}(t) - \sum(P_{PV}(t), P_{WT}(t), P_{BESS}(t)) \quad (29)$$

$E_{g,CO2}$, $E_{RES,CO2}$ and $E_{BESS,CO2}$ represent the equivalent CO_2 emissions emitted by the main network, by RES and by BESS, respectively, and are presented in Table 5. P_{RES} is the power generated by RES.

Table 5. Equivalent CO_2 emissions per kWh for each source

	Main grid	PV	WT	BESS
kg CO_2 eq/kWh	1.06 [37]	0	0	0

5.2. Numerical results

5.2.1. System data

In order to validate the model, the test was done for the modified IEEE 33 bus test network, shown in Figure 5, with the locations and sizes found in the previous section. Due to the lack of real data, the load profile used in this test is presented in Figure 3. A summer day was selected to test the model, solar irradiance and wind speed data for this day are presented in Figure 6. Electricity selling tariffs in Morocco for residential and commercial customers and purchasing tariffs from RES and BESS are listed in Table 6. Time-of-Use (TOU) electricity tariffs are used for industrial customers and the main grid, as shown in Figure 7.

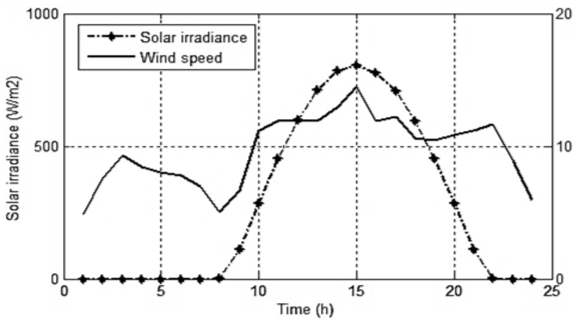


Figure 6. Wind speed and solar irradiance data for a sunny day

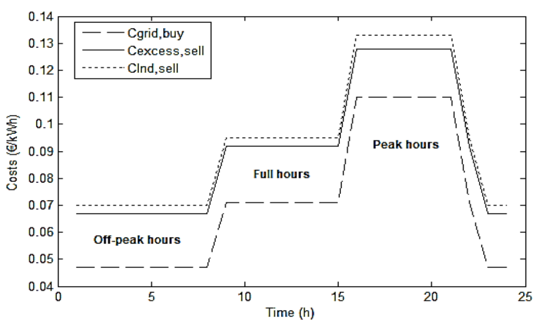


Figure 7. TOU purchasing and selling tariffs to the main grid and industrial customers

Table 6. Purchasing and selling tariffs

	$C_{PV,buy}$	$C_{WT,buy}$	$C_{BESS,buy}$	$C_{BESS,sell}$	$C_{res,sell}$	$C_{com,sell}$
Cost (€/kWh)	0.062	0.039	0.1	0.045	0.15	0.16

5.2.2. Data forecasting

Non-linear autoregressive (NAR) neural networks were used to predict the data in Figure 6. Figure 8 presents the prediction results. NAR neural networks are used to solve nonlinear time series problems. They can be described as in (30).

$$y(t) = f(y(t-1), y(t-2), y(t-3), \ldots\ldots, y(t-d)) \tag{30}$$

d past values are used to predict y over time. d is defined as feedback delays and f is approximated after determining optimal biases and weights during training. The value of d is 24 and 120 for solar irradiance and wind speed respectively. The mean square error (MSE) performance function found is 0.0017 W/m^2 and 0.0018 m/s for solar irradiance and wind speed and R^2 regression values are 0.966 and 0.985, respectively.

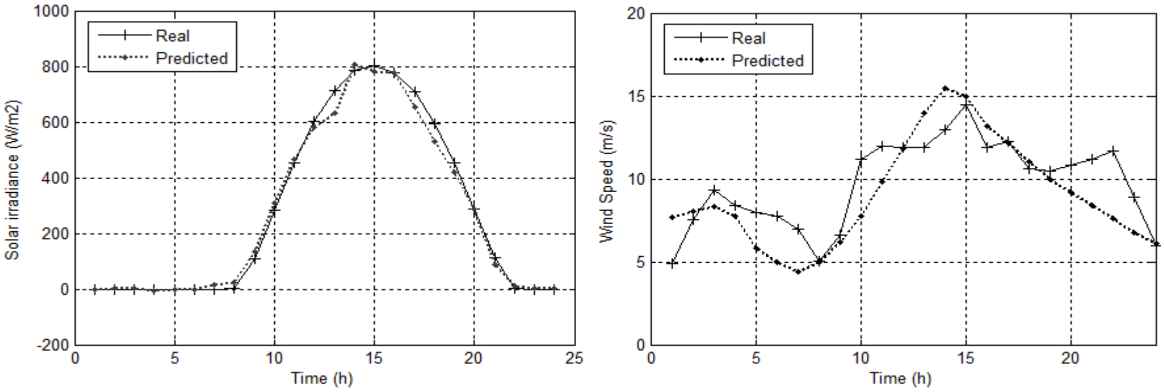


Figure 8. Actual vs. predicted wind speed and solar irradiance

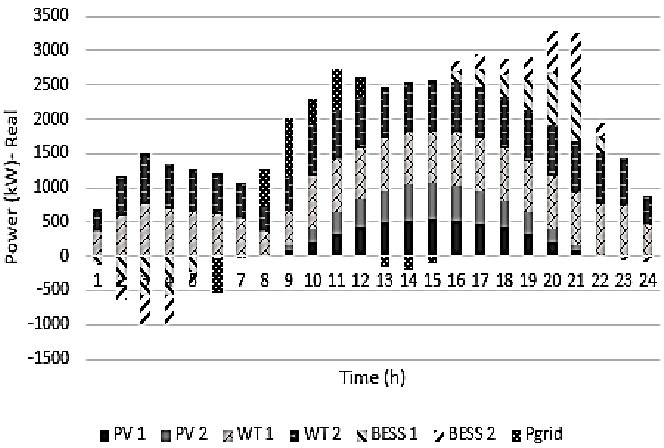
5.2.3. Simulation results

Figure 9 shows the participation of each unit in supporting the load at each instant. It represents the optimal decisions taken by the energy management algorithm for real-time decision-making (case 1) and day-ahead scheduling (case 2) which is based on forecasts at the 24-hours horizon. The initial state of charge (at $t = 0$) in this test is 50%.

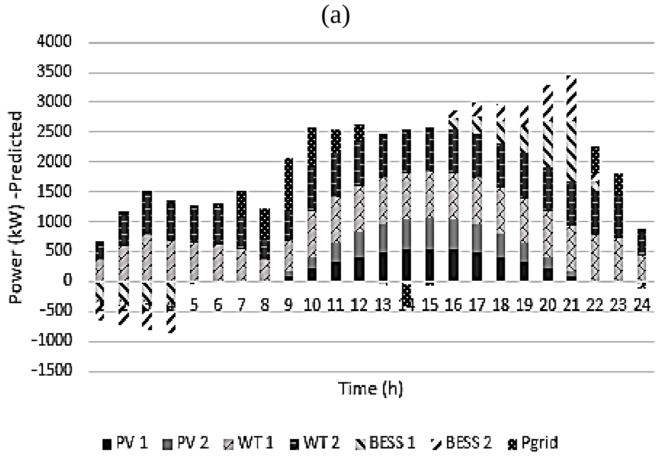
Due to forecast errors, it is noticeable, from Figure 9, that there is a difference between decisions based on data collected in real-time and those based on forecasts. From 1:00 a.m. to 5:00 a.m., for both cases, only wind turbines WT 1 and WT 2 were supporting the load and the excess of energy was stored in BESS 1 and BESS 2. For case 1, the algorithm decided to continue to support the load using both wind turbines and to charge both BESS at 6:00 a.m. and 7:00 a.m. For case 2, the main grid compensated for the lack of power due to forecast errors during these hours and until 12:00 p.m. The main grid started to intervene in case 1 from 8:00 a.m. to 12 p.m. From 1:00 p.m. to 3:00 p.m., PV 1, PV 2, WT 1 and WT 2 supported the load and the surplus was sold to the main grid (for both cases). Both BESS, fully charged, started to discharge from 4 p.m. to 10 p.m. and the load power for the rest of the day was supplied by wind turbines with support from the main grid for case 2 (10 p.m. and 11 p.m.). Battery systems started to be charging again at 23:00 p.m. for case 1 and at 12 a.m. for case 2. Figure 10 illustrates the behavior of BESS 1 and BESS 2 at each instant. It is quite clear that the two BESS discharge only during peak hours and the algorithm proceeded to charge them from the excess energy coming from RES outside these hours. In addition, supplying the load power during the day mainly by RES with the main grid support for few hours was the algorithm's optimal decision which gave less power losses, voltage drops and CO_2 emissions with higher profit.

For both cases (real and forecasted), battery energy storage systems have almost the same behavior but with different charging and discharging powers depending on the excess power from RES at each instant and on the charging power. It is noteworthy that the state of charge of the two BESS is always kept within the limits in order to avoid the systems degradation. Table 7 presents objective functions for each case compared to the base case (where only the main grid supports loads). In order to highlight the importance of adding storage to the system, a comparison was made between the PV/WT hybrid system with BESS (for case 1) and without BESS (for the same case) in terms of total daily power losses, average voltage drops, profits and CO_2 emissions, as presented in Table 8.

From Table 7, it is clear that for all hours, all objective functions have been improved compared to the base case. These are the most optimal results among all possible solutions. Even with forecasting errors, case 2 remains better than the base case and better than all the other possible solutions, with significant gains. It can be concluded that the integration of WT, PV and BESS using a robust energy management system has many advantages for distribution system operators. These advantages are summed up in a reduction of power losses and CO_2 emissions, in addition to an increase in profits and a great improvement in the voltage profile. Considerable gains have been made across all objectives, as shown in Figure 11 and Figure 12. The advantages brought by the integration of BESS were underlined by the results listed in Table 8. By comparing it to the system containing only PV and WT (without BESS), the system with BESS was able to record better gains in terms of voltage drops, CO_2 emissions and power losses while keeping almost the same profit for DNOs.



(a)



(b)

Figure 9. Optimal energy distribution decisions for (a) case 1 and (b) case 2

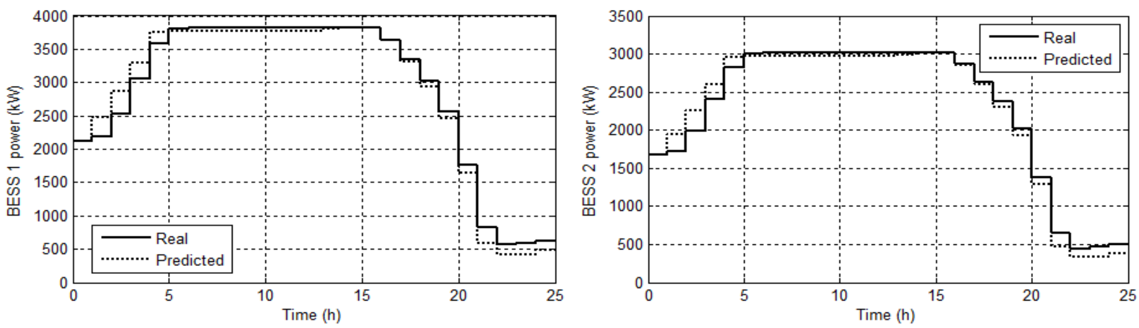


Figure 10. Power stored in BESS 1 and 2

Table 7. Optimization results of short-term planning

t	Real				Predicted				Base case			
	P_{Loss} (kW)	Var (V)	Pr (€)	E_{CO2} (kg)	P_{Loss} (kW)	Var (V)	Pr (€)	E_{CO2} (kg)	P_{Loss} (kW)	Var (V)	Pr (€)	E_{CO2} (kg)
1	1.63	4.46 e-6	42.1	0	6.22	1.04 e-5	45.29	0	3.99	1.85 e-5	36.92	582.1
2	5.81	9.83 e-6	45.09	0	7	1.14 e-5	45.65	0	3.99	1.85 e-5	36.92	582.1
3	10.81	1.54 e-5	37.24	0	8.12	1.18 e-5	36.23	0	3.81	1.79 e-5	27.16	554.7
4	9.58	1.4 e-5	31.85	0	7.61	1.11 e-5	31.10	0	1.63	7.49 e-6	23.08	366.4
5	5.45	1.11 e-5	89.38	0	2.82	8.41 e-6	86.94	0	10.11	4.34 e-5	80.06	901
6	6.05	9.86 e-6	86.84	0	2.17	8.25 e-6	68.62	87.26	8.26	3.66 e-5	63.11	816.9
7	4.30	1.35 e-5	102.67	0	5.07	2.38 e-5	98.24	477.73	15.27	6.71 e-5	93.91	1116.6
8	7.70	3.87 e-5	113.34	584	6.81	3.25 e-5	112.81	557.3	21.57	9.62 e-5	107.75	1332.2
9	13.92	6.4 e-5	159.13	894	13.81	6.08 e-5	156.53	953.72	54.85	2.54 e-4	125.3	2137.9
10	8.82	1.92 e-5	190.5	416	8.97	2.22 e-5	181.51	690.9	72.73	3.4 e-4	138.62	2447.6
11	8.78	7.5 e-6	220.3	438	8.67	6.71 e-6	220.5	419.06	90.61	4.17 e-4	166.4	2709.9
12	9.04	6.57 e-6	227.92	297	8.91	5.63 e-6	227.69	323.75	95.55	4.37 e-4	172.3	2766.6
13	13.81	4.16 e-5	229.83	0	11.11	2.32 e-5	224.14	0	74.20	3.29 e-4	169.7	2446.8
14	15.68	5.54 e-5	227.79	0	17.74	6.87 e-5	242.3	0	75.86	3.41 e-4	165.9	2484.2
15	14.36	4.68 e-5	224.22	0	13.68	4.21 e-5	223.53	0	83.95	3.84 e-4	164.28	2615.8
16	12.6	2.66 e-5	272.45	0	12.58	2.65 e-5	272.41	0	114.4	5.22 e-4	112.6	3036.9
17	12.03	1.78 e-5	276.46	0	11.43	1.33 e-5	274.03	0	121.5	5.5 e-4	118.9	3121
18	10.62	9.01 e-6	269.86	0	10.36	6.57 e-6	266.7	0	117.8	5.29 e-4	118.2	3056.2
19	10.32	5.29 e-6	264.57	0	10.56	6.34 e-6	262.9	0	122.1	5.47 e-4	119.48	3085.6
20	17.09	2.81 e-5	274.8	0	17.08	2.81 e-5	274.4	0	157.3	7.07 e-4	134.5	3479.3
21	23.62	6.87 e-5	262.7	0	25.74	7.76 e-5	251.3	0	155.7	7.02 e-4	131.9	3452
22	11.17	4.11 e-5	160.4	0	13.19	6.23 e-5	154.7	466.11	53.86	2.43 e-4	124.9	2065.1
23	7.73	2.46 e-5	128.44	0	7.66	3.53 e-5	125.2	385.7	27.4	1.22 e-4	116.99	1483
24	2.77	8.68 e-6	64.84	0	2.9	8.77 e-6	65	0	8.79	4.02 e-5	57.96	854.3

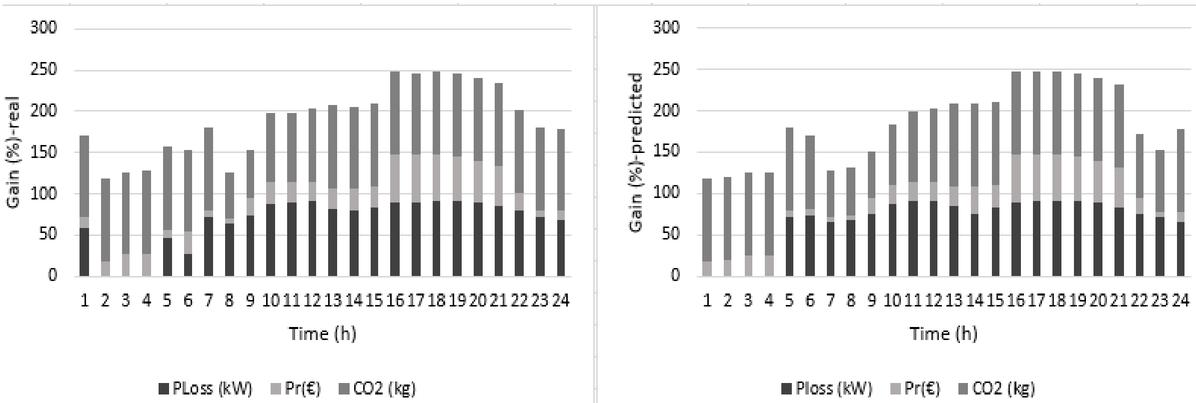


Figure 11. Gains in terms of power losses, profits and CO_2 emissions

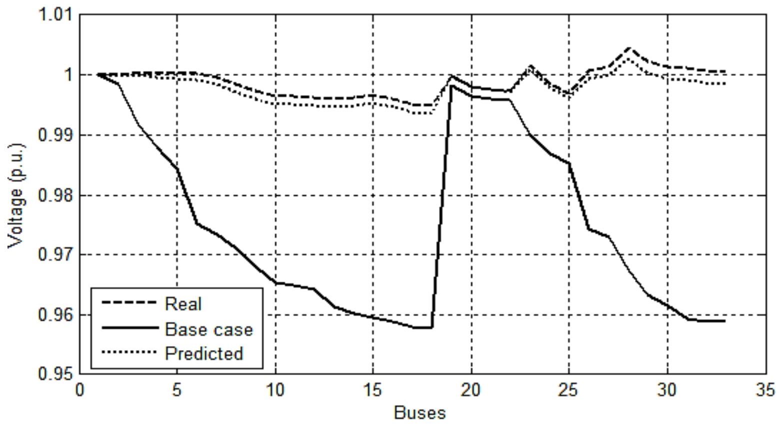


Figure 12. The average nodal voltage

Table 8. The total daily objective functions comparison (with and without BESS)

Objective functions	Base case	With BESS	Without BESS
Daily power losses (kW)	1495.5	243.69	302.57
Daily average voltage drops (pu)	2.82 e-4	2.45 e-5	3.69 e-5
Daily profits (€)	2606.84	4002.72	4032.3
Daily CO_2 emissions (kg)	47494.2	2629	8494.4

In most research work, researchers carry out the energy scheduling based on forecasts or what is called optimal day-ahead dispatch. In this work, the proposed system takes into consideration the two modes in parallel; real-time and day-ahead scheduling. The estimated response time of the real-time scheduling system, proposed in this work, does not exceed 2 minutes, which falls within the definition of real time [38]. This time includes the acquisition and control time and the optimization and classification time. The decisions estimated 24 hours in advance will serve to support any delay at the system level and also to detect errors in the measurement sensors. If the forecast errors are minimal and the predicted data matches the data collected in real-time, the predicted decision will be executed immediately without running the algorithm another time, in order to save execution time.

The proposed model can achieve considerable gains for both real-time and day-ahead scheduling. Forecast errors, which must be within the limits, did not impact the gains expected by the DNO. The NSGA-II algorithm, modified in this work, has proven its robustness and performance for a large number of objectives, knowing that several algorithms lose their performance when increasing the number of objectives. Depending on the constraints and functions to be optimized, the algorithm makes the appropriate and optimal decision at each instant in order to increase benefits for network managers.

6. CONCLUSION

This paper proposes an intelligent energy management system based on NSGA-II and entropy-TOPSIS and dedicated to the acquisition, modeling, long-term and short-term scheduling and control of the distribution network in the presence of RES and BESS. The proposed system is based on a secure communication architecture that guarantees the acquisition of data from sensors installed in the field and the sending of execution orders from the EMS to the network. The collected data is used to model the energy sources on the one hand and to forecast their parameters on the other hand. Long-term planning is done only once before the installation of RES and BESS in order to optimize the total investment cost, voltage drops and power losses. Daily scheduling is also part of the system tasks which aims to optimize hourly power losses, voltage drops, DNO profits and CO_2 emissions. A test was performed for a modified IEEE 33 bus network for the two planning models and the obtained results have proven their effectiveness. For long-term planning, the optimal solution proposed by the system significantly minimizes power losses, voltage drops and total investment cost. Significant gains were also recorded, for short-term planning, in terms of profits, voltage drops and power losses and a very significant reduction in CO_2 emissions has been observed. This paper proposes an integral solution for energy management in distribution networks based on real-time and day-ahead scheduling as complementary tasks for more accuracy and less execution time.

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