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Battery Storage Systems Control Strategies with Intelligent Algorithms in Microgrids with Dynamic Pricing

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Abstract: The current microgrid (MG) needs alternatives to raise the management level and avoid waste. This approach is important for developing the modern electrical system, as it allows for better integration of distributed generation (DG) and battery energy storage systems (BESSs). Using algorithms based on artificial intelligence (AI) for the energy management system (EMS) can help improve the MG operation to achieve the lowest possible cost in buying and selling electricity and, consequently, increase energy conservation levels. With this, the research proposes two strategies for managing energy in the MG to determine the instants of charge and discharge of the BESS. A heuristic method is employed as a reference point for comparison purposes with the fuzzy logic (FL) operation developed. Furthermore, other algorithms based on artificial neural networks (ANNs) are proposed using the non-linear autoregressive technique to predict the MG variables. During the research, the developed algorithms were evaluated through extensive case studies, with simulations that used data from the PV system, load demands, and electricity prices. For all cases, the AI algorithms for predictions and actions managed to reduce the cost and daily consumption of electricity in the main electricity grids compared with the heuristic method or with the MG without using BESSs. This indicates that the developed power management strategies can be applied to reduce the costs of grid-connected MG operations. It is important to highlight that the simulations were executed in an adequate time, allowing the use of the proposed algorithms in dynamic real-time situations to contribute to developing more efficient and sustainable electrical systems.

Keywords: energy management; uncertainty; energy markets; microgrids; dynamic electricity pricing

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1. Introduction

The traditional electric power system comprises equipment and infrastructure that generate electric energy through centralized structures and transmission over long distances to connect the distribution and reach the final consumer [1], as shown in Figure 1a.

The current electrical power system has evolved with advanced technologies to increase efficiency, reliability, and security in electrical energy supply. Among these technologies, we can highlight: the automation and digitization of control systems, the use of renewable energy sources (RESs), the development of an energy storage system (ESS), and the implementation of intelligent solutions for load management and loss reduction [2,3], as shown in Figure 1b. This leads, in addition to lower losses in transmission lines, to bidirectional power flows [4]. It is important to emphasize that ESSs have a fundamental role in the development of this model of the electric power system. One change is using information and communication technology (ICT) [5] for more active system consumers.

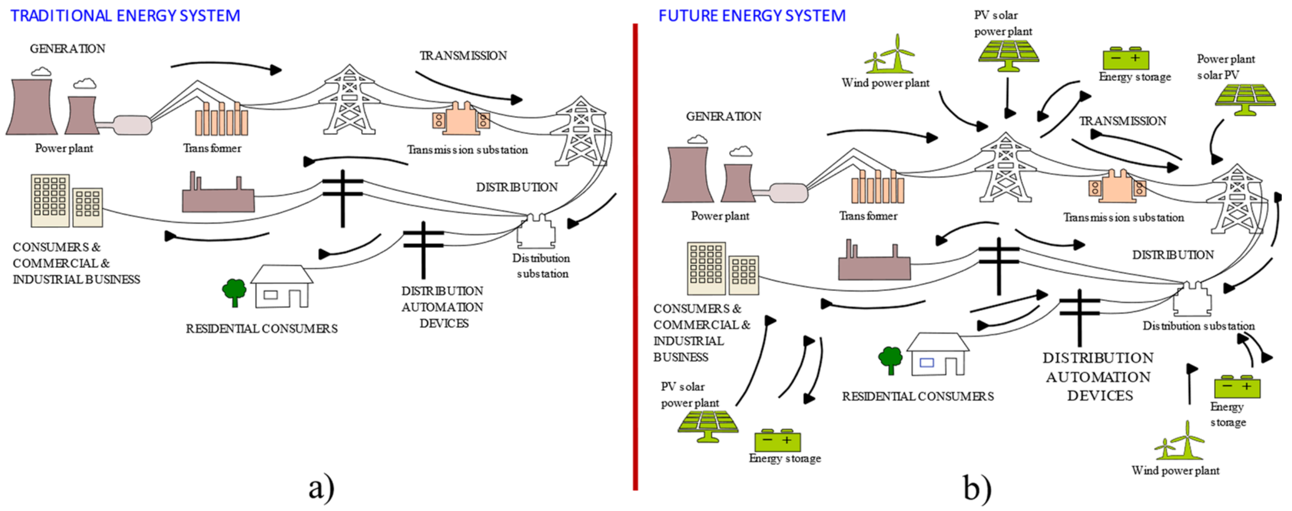

Figure 1. Traditional electrical systems compared to the current electrical system. In (**a**) a traditional electricity distribution system is presented, and letter (**b**) a future electricity distribution system is presented.

From this perspective, how MG has been widely accepted through the combination of various resources, such as PV panels, wind turbines, diesel generators, and energy storage systems (ESS), and controllable loads, which operate together to provide reliable and sustainable electricity to local consumers [6]. It is an alternative to centralized power generation systems, which depend on large power plants and high-voltage transmission lines to supply electricity to remote areas. With MGs, it is possible to supply electricity more efficiently and with a high level of reliability [7–9]. The result of this is the more active distribution side that participates in the operation of the electrical system. This can bring benefits in incorporating RES, optimizing operations, ensuring a reliable energy supply, and addressing related challenges to non-dispatchable renewable sources (NDRS), bidirectional energy flows, and more active consumers [10].

There are benefits to energy management at MG, and its challenges ensure stability and reliability in the electrical system. The energy management system (EMS) can include technologies such as monitoring sensors, energy control systems, data analysis software, and load management strategies. These technologies allow MG operators to monitor energy demand in real-time and optimize available energy, providing reliable, sustainable, cost-effective power that responds to continuous or spikes in power demand [11].

To achieve the objectives, algorithms of ANNs are developed through the non-linear autoregressive technique for forecasting the variables, and through the FL, make decisions regarding the purchase or sale of electricity to maximize energy efficiency and reduce costs. The MG of the simulations uses a PV generation system, variable loads, and a BESS. The proposed EMS is capable of the following:

- To avoid increasing simulation processing, incorporate a battery model that does not include the simulation degradation process. However, it is essential to emphasize that the battery model used in the simulation is realistic enough to provide accurate results in the management of the purchase and sale of electricity, quality of voltage levels, and frequency in the bars;
- Consider the variable and uncertain nature of PV generation, the unpredictable inputs and outputs of loads at the distribution level, and the price of electricity in the dynamic scenario for a daily operation;
- Present simultaneous solutions for multiple desired objectives, with the minimization of daily operating costs, the improvement of the use of generated PV energy, and the improvement in the use of the battery, keeping it within its operational limits;
- Present suggestions for prediction algorithms, with ANN training being carried out using data from the next day's schedule and control and operation simulations for

the purchase/sale of electricity in MG in a dynamic pricing scenario. With these algorithms, achieving an adequate balance between control accuracy to provide electrical power quality indices and low computational effort to develop an efficient and sustainable EMS is possible;
- Apply a method of short-term nature in the forecast horizon for making decisions on the purchase or sale of electrical energy.

Methods based on artificial neural networks (ANNs) can be performed for forecasting retail electricity price costs for day-ahead planning [12] based on historical data to achieve a better overall performance of the MG operation compared to heuristic methods. The research [12] investigates the effect of RES prediction errors on MG energy management using a predictive control model. This research proposal includes several adequate resources to meet the forecasting requirements. Some of these characteristics are presented below and with objectives similar to those [13,14]:

- It is developed in ANN with a non-linear autoregressive technique formulated and trained for forecasting the variables of load, PV-generated power, and electricity price. The controller uses the FL code to make decisions regarding purchasing or selling electricity. In this way, the proposed resolution algorithms can be tuned and implemented to effectively deal with the restrictions associated with the particularities of the MG;
- Dynamic operation. These algorithms are suitable for making real-time EMS control decisions.

The presentation of simulation results shows the effectiveness of predictions with ANN algorithms with non-linear autoregressive technique and FL for decision making in the purchase or sale of electricity, where data with the time of purchase were successfully used—considerably appropriate simulation about the simulation interval of 24 h.

This manuscript is organized as follows. Section 2 addresses some important literature reviews related to smart grid implementation. Section 3 describes the structure of the system and the heuristic and proposed algorithms for the EMS. Section 4 presents the model, parameters, data, the proposed forecast module, and the results collected in clear and partially cloudy sky scenarios. Section 5 presents the analysis of simulated results. Finally, conclusions are drawn in Section 6.

2. Challenges of Implementing Modern and Intelligent Grids

Before transforming a conventional grid structure into a modern, intelligent, sustainable, and efficient grid, it is necessary to follow several steps, like using DGs built with RESs. In addition, the problems caused by the high amount of DG with PV generation can be reduced by installing a BESS: greater consumer participation, increased use of ICT, and the development of new control systems.

Although several definitions of MG exist in the literature, all the main characteristics are maintained. In this thesis, we adopted the definition established by CIGRÉ [15]:

> "MGs are electricity distribution systems containing distributed loads and energy resources (such as distributed generators, storage devices or controllable loads) that can be operated in a controlled and coordinated manner, both while connected to the main power grid and while islanded."

The correct management of local energy generation and storage results in the reduction in losses in distribution lines. In addition, distribution systems with DG and local BESSs reduce dependence on grid load flow problems. To take advantage of the full potential of MG, we face several technical challenges mentioned in the current literature, such as:

Stability: The operation of the MG can result in voltage and frequency oscillations, compromising the grid's stability in the transition from connected to islanded control modes [16]. Therefore, in order to effectively solve these challenges, it is important to guarantee the adjustments in a precise way for the operation of the MGs [8,17].

Low inertia: MGs do not have inherent stability and can face several instabilities caused many times in situations of grid formation without the installation of SG and high concentrations of NDRS in conditions to operate in island mode. To avoid these problems, implement BESSs with the appropriate controls or reinstall the SG [7,18].
Uncertainties: MGs are subject to variations caused by environmental conditions. Therefore, forecasting methods are implemented to ensure accuracy in meeting demand about present generations and decisions regarding the purchase and sale of electricity, according to prices [17].
Bidirectional power flow: The characteristics are different from the conventional grid, as the power flows in generation at the distribution level are bidirectional, generating complications for protection [16,18];
Coordination between entities: Because there are several challenges from factors such as energy balancing, failure rates of equipment installed in the MG, variations in installed loads, uncertain generations and dependent on renewable sources, and weather forecasts, it is extremely important to use communication compatibility between components installed in the MG [14].

The MG Control

Control plays a crucial role in modern MG operations. In this context, it is important to emphasize that:

- The MG system must address the challenges above to ensure reliability and economy;
- It is essential to ensure a smooth transition between operating modes;
- Mains connected or island operating modes are desirable for the system, including voltage and frequency regulation;
- To achieve the goals of decreasing MG operating costs, it is necessary to develop and implement advanced control strategies that meet the specific requirements of MG, allowing efficient and optimized operation in different operating conditions.

There are several control approaches to managing the operation of modern MG, as illustrated in Figure 2. These approaches can be categorized as follows:

Centralized control: A central controller sends signals to each controllable agent based on data from the MG components and the external grid, as shown in Figure 2a.
Decentralized control: In this configuration, local control of each MG unit is carried out independently, without exchanging information with other units, except for a few lead agents who transmit and receive information through a center. This is represented in Figure 2b.
Distributed control: When local controllers use a communication grid to exchange information and seek a cooperative solution to the general control problem, we have a distributed approach, as shown in Figure 2c.
Hierarchical control: This approach seeks a balance between a fully centralized and fully decentralized control architecture. It involves implementing a hierarchical control scheme in which centralized and decentralized methods can be used at each level of the hierarchy [16,17,19,20]. These different control architectures offer flexibility in MG management, allowing adaptation to the specific needs of each system. Choosing the appropriate control approach will depend on the MG characteristics, performance requirements, and operational constraints.

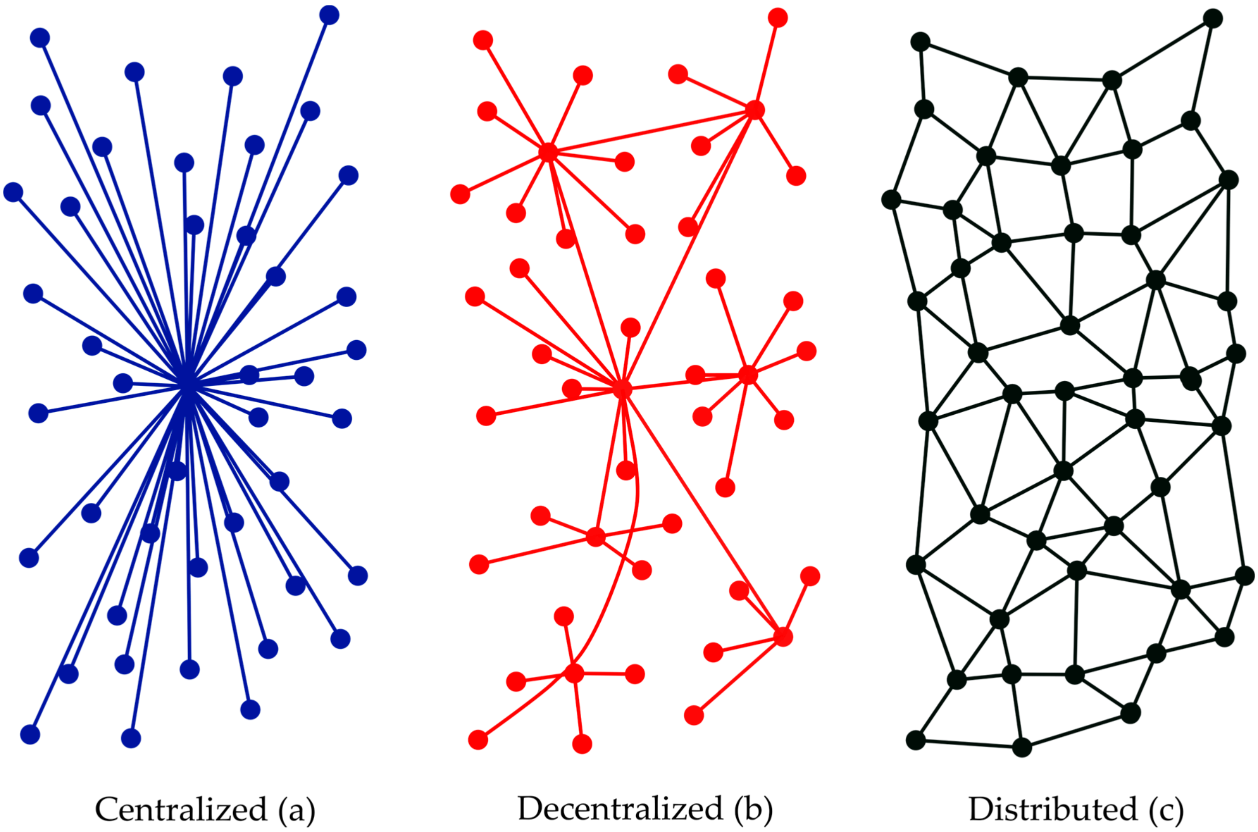

Figure 2. A comprehensive view of control architectures covering centralized, decentralized, and distributed configurations [21].

To deal with different timescales of the variables present in an MG, the hierarchical strategy is accepted as an approach recognized as a standard for MG [17,22–24] due to the need to deal with different time scales in these systems. In this article, we adopt the representation illustrated in Figure 3, where the hierarchical control strategy is built by the following classes, each one with different and specific response times for MG control:

- Regarding the interfacing of the converters present in the MG, the primary control is decentralized and consists of controllers located in the energy converters. This control layer is responsible for functions that provide fast response, power sharing, and detection for island operating conditions;
- Being slower than the speed of the primary control layer, the secondary control aims to correct steady-state deviations, correcting the frequency and voltage levels according to the reference levels programmed in the primary controller. Thus, this layer must synchronize and exchange energy with the main grid;
- At a high level and dedicated to evaluating the long-term operation of the MG, tertiary control is considered the "top layer". This layer, through intelligence, introduces the advance in the MG operation, being able to consider optimization, resources, demand forecasts, and adaptations to environmental conditions.

As per the description provided on MG control, this research focuses on EMS. Under current conditions, various surveys and the definitions of this system within the hierarchical control structure may vary from one survey to another. It is evident from the control structure of Figure 3 that both secondary and tertiary levels are used in the EMS, as shown in [23–25]. However, it is presented in [26] that the electric power management functions in the secondary controller since the tertiary control is only used for conditions in operation modes connected to the grid.

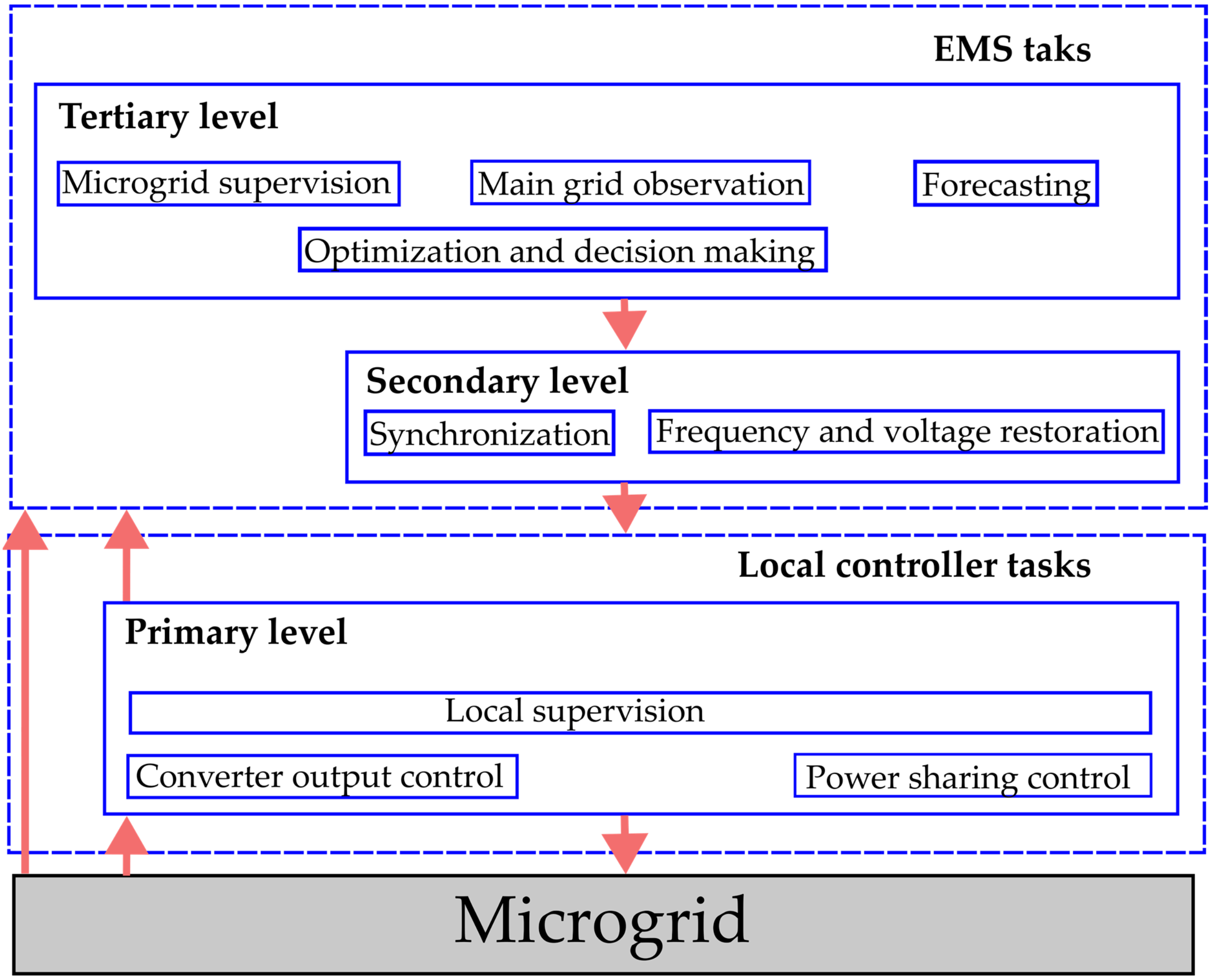

Figure 3. Organization (hierarchy) in layers of the control system for an MG [23].

3. Aspects Related to the EMS and the MG

This section first defines MG and gives an overview of typical control approaches to MG operation. Then, the EMS is presented to define its role within the MG control scheme. Finally, an analysis of energy management strategies is conducted in order to identify an appropriate one for the control of the MG method addressed in this document.

3.1. The MG and the Current Energy System

The MG is a small electrical system that can work either dependent on the main grid or autonomously in isolated mode. It connects the connection to the main grid occurs through the point of common coupling (PCC), covering local control systems, distributed generation (DG), distributed ESSs, and controlled or non-controlled loads. Furthermore, an MG has electrical limits and behaves as a single controlled entity concerning the main grid [7,27]. Figure 4 shows an example of an MG.

MG also favors the installation of RES, such as wind turbines, PV generators, and small-scale hydropower on a small scale [27,28]. In addition, the ability to switch to an isolated mode of operation during mains failures and emergencies significantly increases the reliability of the MG.

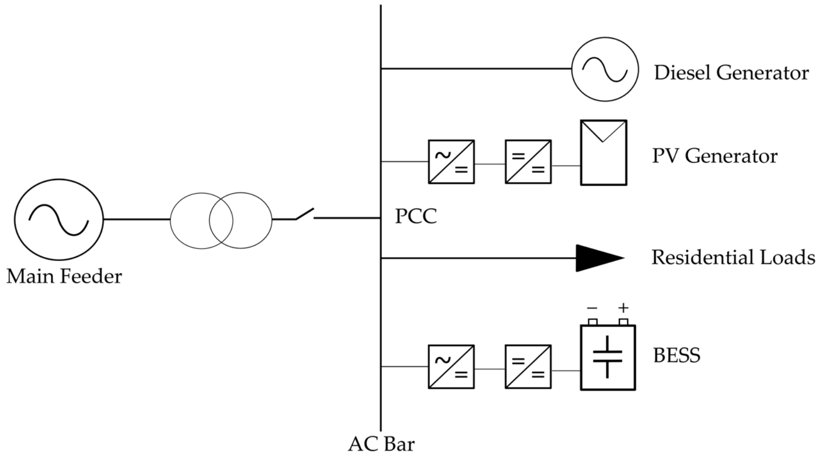

Figure 4. Example of a basic MG-AC composed of generators, BESSs, power electronic converters, and loads.

3.2. The EMS of MG

One of the essential elements for the optimal functioning of an MG is the proper use of the EMS. EMS makes use of ICT to ensure efficient coordination between MG units and to provide reliable, sustainable, high-quality, and economically viable electricity [29]. To achieve this goal, the EMS performs several functions, including data collection and monitoring, data analysis, forecasting, and real-time control, as exemplified in Figure 5.

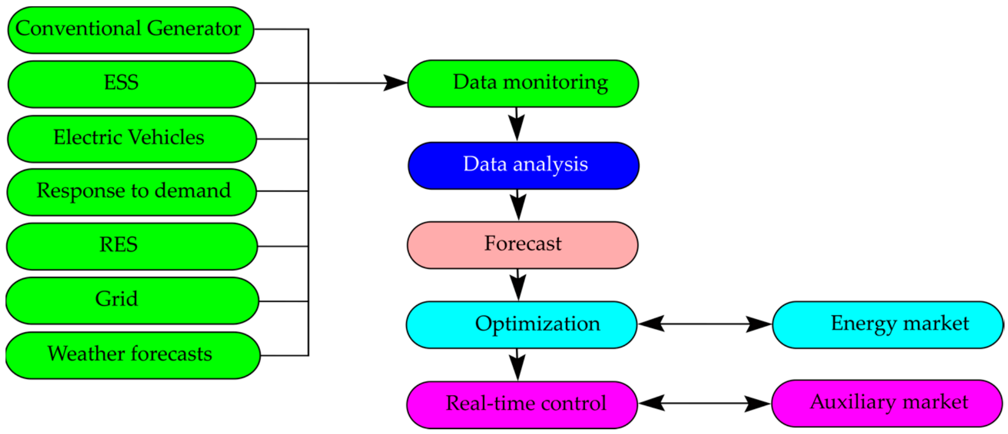

Figure 5. MG power management functions [30].

Power management functions play a crucial role in optimizing the operation of MGs. EMS uses historical and forecast data to monitor and analyze the operation of MG units, improve performance, and address system constraints. These data are used to adjust the forecasting and optimization models, improving the planning and execution of the purchase and sale of electric energy. Furthermore, the analysis of this information can help to maximize the energy efficiency of the MG and to develop new control and more accurate prediction code to estimate [31]:

- Loads;
- PV generation;
- Electricity prices.

This research explores methods that lead to an improved operation of the MG, using AI algorithms as the main actors for the central EMS present in the MG control structure. Thus, implementing such appropriate algorithms becomes essential for realizing the real-time control of the MG. The addressed data play a fundamental role in advanced decision-making strategies to improve MG through the monitoring and evaluating of the sets of information collected from data that are predicted by the techniques used. Therefore, achieving improved operation of the MG is achieved through these useful decision-making tools, employing the improved output to perform real-time control of the MG [4].

3.3. Energy Management Methods

There are different approaches adopted in EMS for MG, ranging from the use of heuristic algorithms to the application of optimization techniques. In Sections 3.4 and 3.6, two methods used are considered in this research; heuristics and AI-based. For the latter, it is worth highlighting the use of the set of approaches of predictive algorithms through the ANN with the application of the non-linear autoregressive technique and FL for decision making regarding the purchase or sale of electricity at the lowest market cost. The purpose of this analysis is to present the defined manner to order the performance of the BESS in the connected MG that is considered.

3.4. The Heuristic Method

Heuristic algorithms are a category of methods used in power management in MG. They are known to be easy to implement and computationally efficient, making them a popular option for smaller-scale MG [32].

The heuristic method, hysteresis band control (HBC), is one of the most used energy management systems in MG [32]. This method, described in studies such as [33,34], uses a hysteresis band to control the operation of the BESSs, with limits established according to the state-of-charge (SoC) level. The HBC is incredibly efficient when only one SAEB is used to handle power generation and demand balances in the MG, as long as the SoC is within the limits range. When the SoC reaches one of the thresholds, the BESS is disconnected, making it necessary to use other units or external power. This approach is agile, straightforward, and appropriate for real-time management.

The heuristic algorithms are often used as a benchmark to evaluate the behavior of newly proposed methods. In [35], an example presents an algorithm based on rules to control hybrid MGs, where the users can easily understand the results. Furthermore, in [36], a heuristic-based method is one of four power management approaches to regulate an MG to minimize the energy consumption of the MG. Although the heuristic algorithm resulted in cost savings, it was outperformed by other strategies in terms of overall performance.

Therefore, the main characteristics of heuristic algorithms are [14,32]:

- Facility;
- Computational processing speed.

Despite this, the solutions offered by heuristic algorithms are only sometimes excellent, and they have a short-term limited nature, as they only consider the current time. Furthermore, including too many details and additional features in the algorithm can make the problem too complex to be solved using conventional heuristic methods.

3.5. Developed Heuristic Algorithm

Figure 6 illustrates the scheme of the heuristic algorithm, where the transmission of energy flow signals is represented by Figure 7. The algorithm receives energy and power data from the EMS. This information is used to define the level of available net energy. Initially, the resulting energy signal is observed. If it is negative, it indicates that the amount of solar PV energy is insufficient to supply the loads, requiring the battery supply for the service. However, it is important to observe whether this discharge violates the minimum load restriction of the EMS or if the power exceeds the maximum discharge limit. Thus, the loads must be supplied by the main feeder. However, if the net energy is positive, it indicates a surplus of PV energy available, which can be used to power the battery. However, this operation is only allowed if the EMS has yet to reach its maximum limit and the battery has yet to be charged to the upper level of the maximum charge limit.

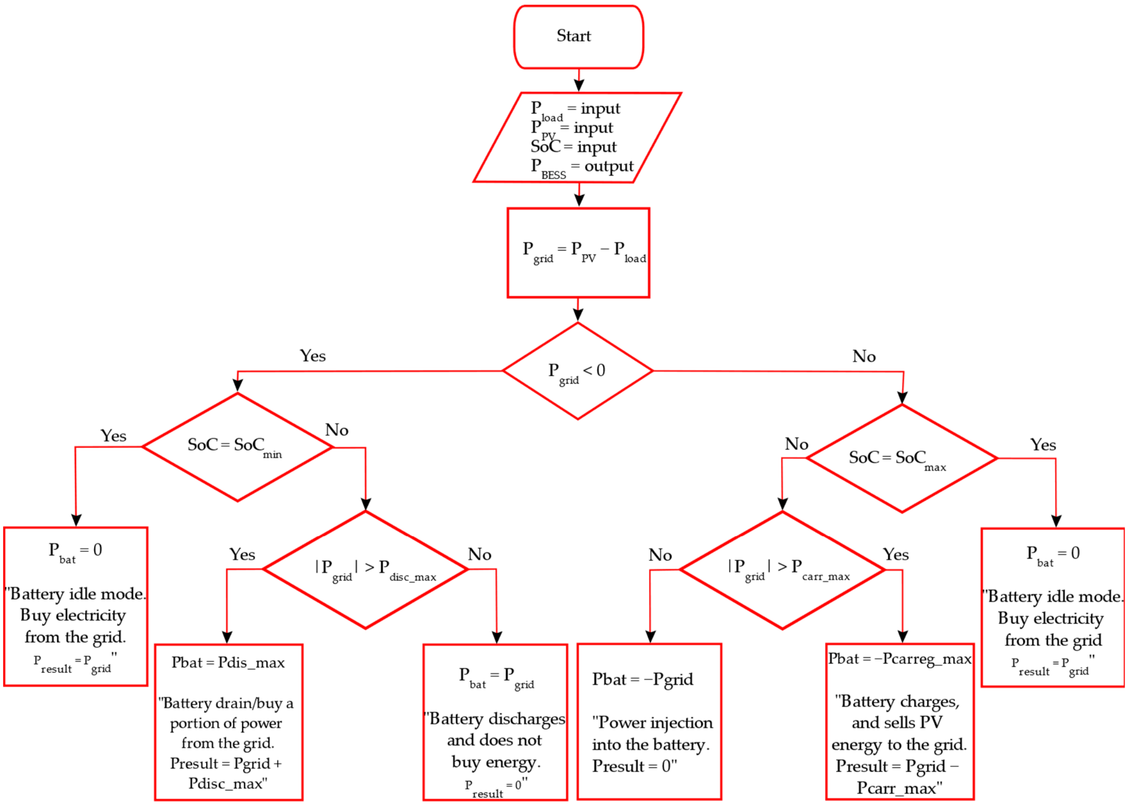

Figure 6. Heuristic algorithm flowchart.

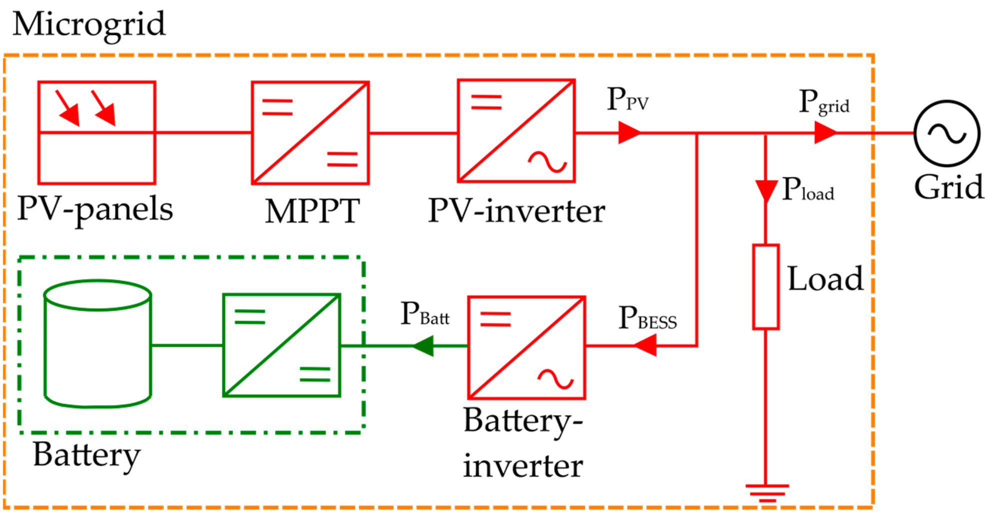

Figure 7. The illustration of the positive sign convention for energy flows in the MG [37].

3.6. The AI Method

There are several investigations on time series in the literature. The authors of [38] suggested a generalized approach to predicting solar and wind power generation. The same perspective in [39] uses a recurrent ANN to predict the PV power generated over the next 24 h while using historical PV power and temperature forecast. The work presented in [40] proposes a hybrid one-day-ahead PV power forecasting model.

Therefore, the second research method is to develop AI-based algorithms composed of algorithms for predictions of the following MG variables: load demand (kW), generated power PV (kW), and the value of the electricity price of the grid (R$/kWh), and another to carry out decision making related to the purchase and sale of electricity with regard to reduce the total electricity price consumption and increase the level of sustainability of the MG, with a smaller amount of power consumed.

3.6.1. The ANN with the Non-Linear Autoregressive Model for Predicting the Variables

High variations with short transient periods characterize time series applications. This fact makes it challenging to proper time series using a linear mode. However, a non-linear approach can be used. An ANN with a non-linear autoregressive model, as used for time series conditions, is referred to as a discrete, non-linear, autoregressive model, as shown in [28,29]:

$$y(t) = h(y(t-1), y(t-2), \ldots, y(t-p)) + \varepsilon(t) \tag{1}$$

$y(t)$ are the predicted values;
$h()$ is the set of the variable;
$y(t-p)$ are the delay values of the variable;
p are the delays;
$\varepsilon(t)$ represents the approximation error.

The future values of a time series $y(t)$ are predicted only from the values of this series. The function $h(\ )$ is unknown, and ANN training aims to improve this function by optimizing the network weights and neuron biases. The term $\varepsilon(t)$ already represents the approximation error of the series y in time t. It is essential to highlight that in this model, only one series is involved.

According to [41], "the topology of a non-linear autoregressive network is shown in Figure 8. The values of p are the feedback delays. The number of hidden layers and neurons per layer are optimized through a trial-and-error procedure to obtain the best-performing network topology". However, by reducing the number of neurons, it can affect the generalization capacity of the network. On the other hand, when increasing the number of neurons excessively, the program becomes very demanding in terms of processing speed. This research uses a hidden layer composed of 15 neurons, with three numbers of delays p, and an output layer, as shown in Figure 9. The software used was Matlab R2019b ntstool, a non-linear autoregressive network time series application.

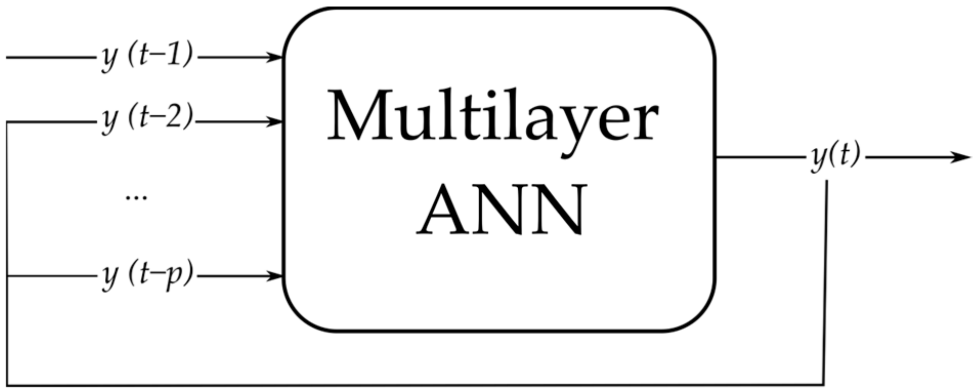

Figure 8. Non-linear autoregressive network.

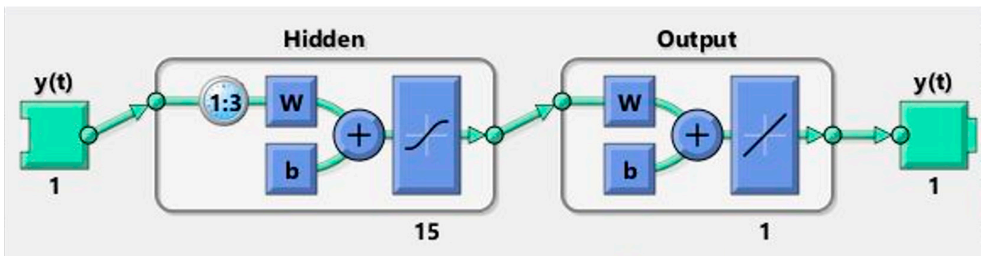

Figure 9. Proposed ANN model for forecasts.

The learning rule, according to [42], "of the non-linear autoregressive network is the Levenberg–Marquardt backpropagation (LMBP) procedure. This training function is usually the fastest backpropagation-type algorithm. The Levenberg–Marquardt algorithm was designed to approximate the second-order derivative without the need to calculate the Hessian matrix to increase the training speed". Depending on the conditions, the Hessian matrix can be approximated according to the first equation below, and the gradient can be calculated according to the second equation below according to [43].

$$H = J^T J \tag{2}$$

$$g = J^T e \tag{3}$$

J is the Jacobian matrix that contains the first derivatives of the network errors in relation to weights and bias;

e is a vector of network errors in all training samples;

H is the Hessian matrix;

g is the gradient vector.

The research by [44] shows that "to estimate the Jacobian matrix, the study uses a standard backpropagation algorithm to approximate the Hessian matrix. This approach is more straightforward than calculating the Hessian matrix. The LMBP algorithm uses this approach in the Newton-type update described in Equation (4)".

$$x_{k+1} = x_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{4}$$

x_{k+1} is the updated estimate of the solution in the (k + 1)-th iteration of the Levenberg–Marquardt algorithm;

x_k is the current estimate of the solution in the k-th iteration;

J^T is the transpose of the Jacobian matrix;

J is the Jacobian matrix that includes the first derivatives of the respective network errors in relation to weights and bias. It is calculated using the standard backpropagation technique;

μ is the regularization parameter, also known as the damping factor. It controls the importance of regularization in the parameter update. When μ is zero, the method becomes the pure Newton's method, using the approximate Hessian matrix. When μ is large, the method approaches gradient descent with a smaller step size;

I is the identity matrix;

e is a vector of the network's errors.

It should be noted that this method uses the Jacobian matrix for the calculations. It is important to highlight that the mean sum of squared errors is assumed as the performance function. Therefore, when using the residual sum of squares, they should be used in networks, according to Equations (5) and (6), where:

$$SSE = \sum_{i=1}^{n} (\hat{y}_i - y_i)^2 \tag{5}$$

$$MSE = \frac{SSE}{n} \tag{6}$$

y_i represents i-th data sample;

$\hat{y}_i$ are the approximate data obtained by the network for the value of y_i;

n is the number of data samples for training the network;

SSE is the sum of squared errors;

MSE is the mean squared error.

To help create the network, the MATLAB® Neural Network Time Series application is used with the non-linear autoregressive network (NAR) model for predicting the variables function, which allows visualizing and training dynamic neural networks to solve autoregressive network problems non-linear and non-linear autoregressive with exogenous non-linear time series. The definition of the percentage divisions of the data of the sets:

- Training (70%);
- Validation (15%);
- Test (15%).

3.6.2. FL for Decision Making—Model Architecture

This subsubsection describes the FL model. First, the architecture of the FL model for decision making is presented. In addition, a detailed presentation of the development of each step of the model's architecture is commented on, along with a discussion and evaluation. The methodology for creating the FL (adapted from [45]) is shown in Figure 10.

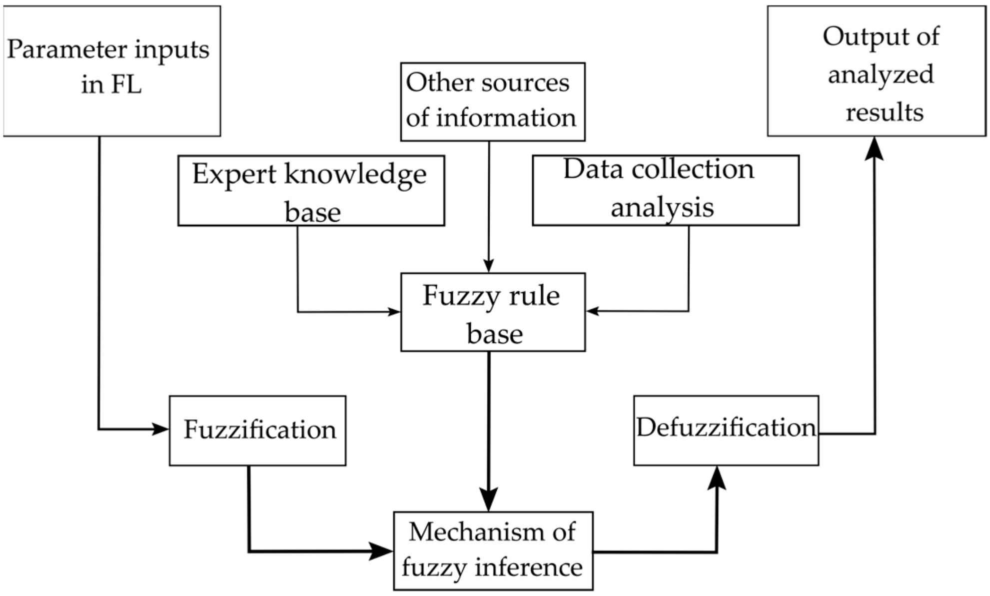

Figure 10. The methodology of realization of the proposed model in FL [45].

This section develops the knowledge base for creating the methodology shown in Figure 10.

In order for the model to be easily interpretable, manageable, and modifiable, a structure is developed integrating the FL with input modules referring to:

- Energy demand forecast;
- Forecast of electricity price values;
- Forecast of PV-generated power;
- BESS SoC.

A fuzzy structure with four input modules and one output module, as shown in Figure 11, is chosen due to the ease of changes in membership curves and rulebase adjustments. The model changes the only output referring to the BESS's performance from the input variables' different levels according to the if-then rule base of the Mamdani fuzzy inference system [34].

The methodology shown in Figure 10 is chosen after careful research of different structures. To implement the factors in the proposed model, the FL controller is developed to meet the structure, as shown in Figure 11, using Matlab's Fuzzy Logic Toolbox software. The FL controller receives four input variables, which through the FL controller rule base, define only a single value language output for BESS performance. This makes the model easily interpretable and flexible and simplifies the process of user evaluation and calibration. The FL controller can respond to different values of input variables, as described in more detail in the next subsubsection.

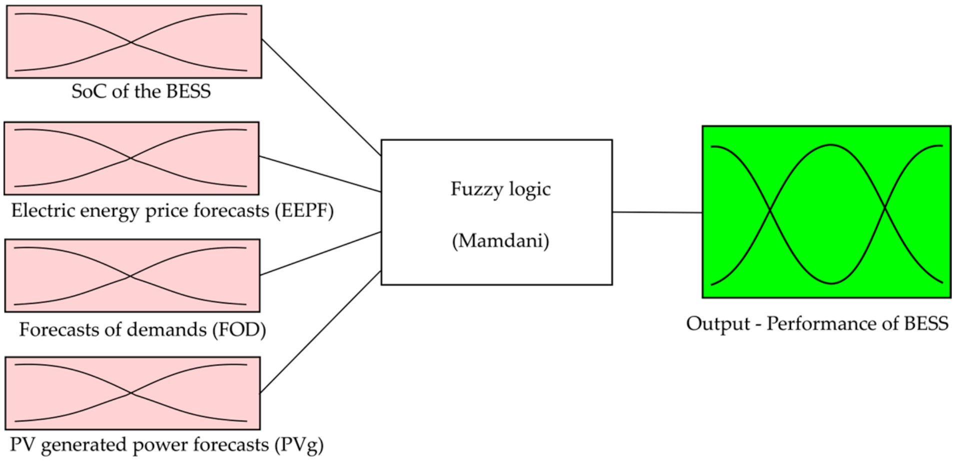

Figure 11. Adopted example of Mandani-type fuzzy inference with four input modules and one output module (drawn figure inspired by Matlab's Fuzzy Logic Toolbox in Matlab R2019b software).

3.6.3. The Fuzzy Ruleset

A set of rules for the state inference mechanism must be defined to evaluate fuzzy input parameters. The set of rules seen in Table 1 shows the 16 specific rules used for the defuzzification process comprising the rule base with the AND type connection.

Table 1. Adopted FL controller rule base.

SoC	EEPF	FOD	PVg	Output
Low	Low	Low	Low	Low
Low	Low	Low	High	Low
Low	Low	High	Low	Low
Low	Low	High	High	Low
Low	High	Low	Low	High
Low	High	Low	High	High
Low	High	High	Low	Medium
Low	High	High	High	High
High	Low	Low	Low	Low
High	Low	Low	High	Low
High	Low	High	Low	Low
High	Low	High	High	Low
High	High	Low	Low	High
High	High	Low	High	High
High	High	High	Low	High
High	High	High	High	High

SoC = State of charge of the BESS; EEPF = electric energy price forecasts; FOD = forecasts of demands; PVg = photovoltaic generated power forecasts.

4. The Adopted Model and Results

This section presents an evaluation of the control developed with several case study simulations during the daily simulation period when using PV generation data [46] with a clear and partially cloudy sky, load demand [46], and Nordpool electricity price profiles [47]. Section 4.1 presents the parameters, data, and prediction method used in the simulation process. Section 4.2 presents, comments, compares, and discusses the results of four simulation cases to analyze the developed method's performance and the algorithms' effects on the MG regarding voltage, frequency, and operational limits.

4.1. Variables, Information, Predictions, and Programs Used

For the simulation referring to obtaining the data, the parameters used in the MG refer to the next day's price schedule and electricity billed data from Nordpool in France, referring to 10 November 2022. In particular, this model comprises the 14-bar CIGRÉ one.

The blocks of this library of MG simulations were made in variable step phasor-type solution 60 Hz Simulink MATLAB® R2019b, and for the vectorization of the images, the Coreldraw® program was used.

4.1.1. The CIGRÉ 14-Bar

The reference scheme used in the research is the CIGRÉ model for medium voltage with 14 nodes [7,48], illustrated in Figure 12. The operational versatility of this model ensures the simulation of the actuation of switches S1, S2, and S3. However, switches Sa and Sb combine the branch line distributor with the downstream loads, being stepped down to medium voltage via Ta and Tb. The D1/Yg (delta/grounded star) were combined at Nodes 1 and 12, with the required electrical power supplied to the other loads present in the model.

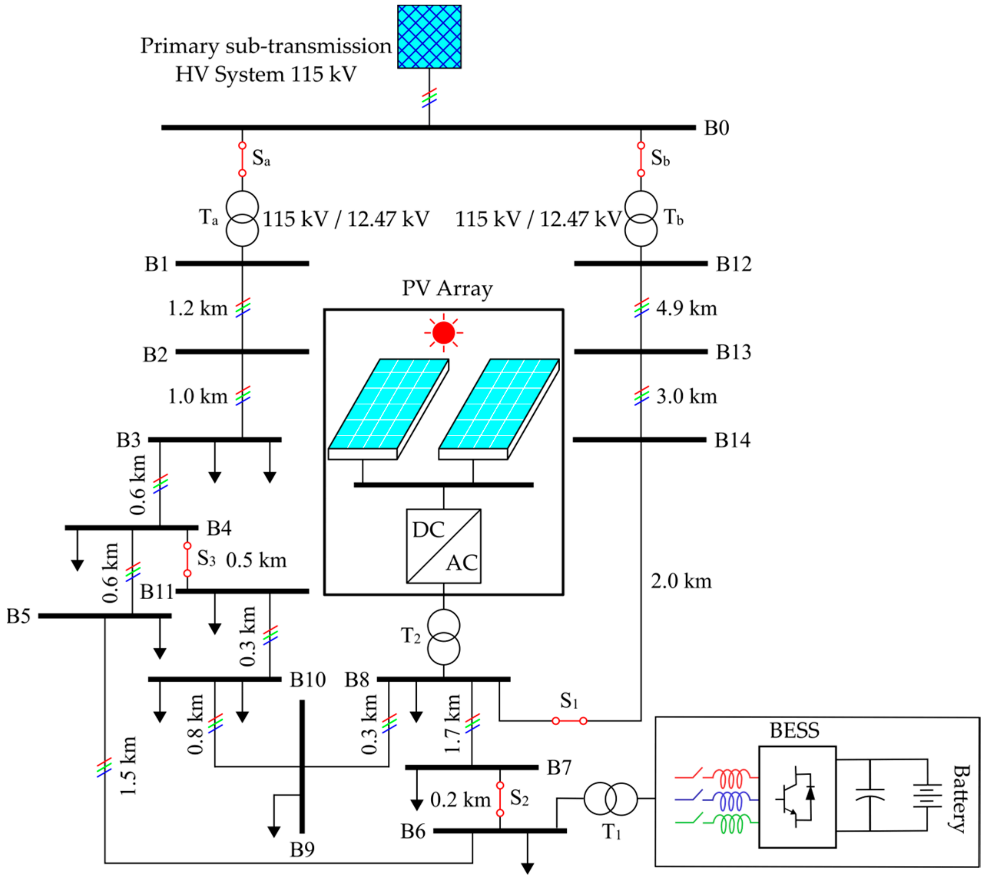

Figure 12. The 14-bus model used.

In Bus 6, a BESS with a nominal power of 400 kW is installed; in Bus 8, a PV system with an installed power of 250 kW is installed. Both are connected to the medium voltage line at 12.47 kV through transformers T1 and T2. The following sections provide data and parameters adopted.

4.1.2. The Parameters

Table 2 lists the data configured for the BESS and PV systems installed in the MG. The simulation considers the daily period to investigate and evaluate the algorithm's ability to operate the MG with time in clear and partially cloudy skies.

Table 2. MG data employed in system simulation.

Parameter	Value
MG voltage (Vrms)	12,470
Nominal frequency (Hz)	60
Battery type	Lithium-ion
Rated power (kW)	400
Rated capacity (kWh)	2500
Overall system efficiency (%)	95.5
Upper charge limits (%)	80
Lower charge limits (%)	20
SoC to recharge (%)	11
Initial state of charge (0–100%)	50
Initial active Cmds (kW)	400
Maximum PV power (kW)	250
Simulation type	Phasor

SoC range is limited to maximize battery life to avoid deep discharge or equipment overload events. Some experiments show that charging lithium-ion batteries to 85% provides a longer lifespan than charging them to 100% [49]. Fully discharged batteries are also not recommended because many cell chemistries cannot tolerate deep discharges, and cells can be permanently damaged if fully discharged. Therefore, the minimum and maximum limits of SoC considered in this research are 20% and 80%, respectively. Appendix C presents the battery model used in the simulations [46].

SoC range is limited to maximize battery life to avoid deep discharge or equipment overload events. It is important to inform you that, according to [4], "Some experiments indicate that charging Li-ion batteries to 85% provides a longer battery life than charging fully to 100%. Fully discharging batteries is also advised against, as many chemical cells cannot withstand deep discharges, which can result in permanent damage to the cells. Therefore, the lower and upper SoC limits considered in this study are 20% and 80%, respectively". Appendix C presents the battery model used in the simulations [46].

4.1.3. The Data

The simulation process considers the PV generation data for the clear and partially cloudy sky situation, as shown in Figure 13. It is defined for the clear and partially cloudy sky situation:

- Clear sky: Refers to a sky without significant clouds or with few scattered clouds. In this condition, solar irradiance reaches the Earth's surface without major obstructions, resulting in high irradiation levels to increase the generated PV power;
- Partially cloudy sky: This condition occurs when clouds cover part of the sky while other areas remain unobstructed. Solar irradiance can vary depending on the amount and density of the clouds with a decrease in the generated PV power.

These datasets have a variable time resolution of approximately 1441 points, and then a transition is used of the data to a rate of 86,104 points for better resolution.

The demand adopted in the model comprises variable loads installed along the bars, according to the 14-bar CIGRÉ model. Figure 14 shows the adopted load curve.

Cost data referring to the next day's electricity price schedule and real-time billing data are collected from the Nordpool French area from 10 November 2022 [47] and converted into real currency (R$). These data are of the dynamic billing type and have a resolution of one hour, and is represented in Figure 15. In this type of dynamic billing to buy electricity from the main grid, the cost per kWh depends on the time of use of that kWh and its value at that instant. For comparison purposes, the price received for the sale of energy to the main grid was assumed to be equal to the purchase price in all cases, excluding any fees, charges, or taxes applied at the national level.

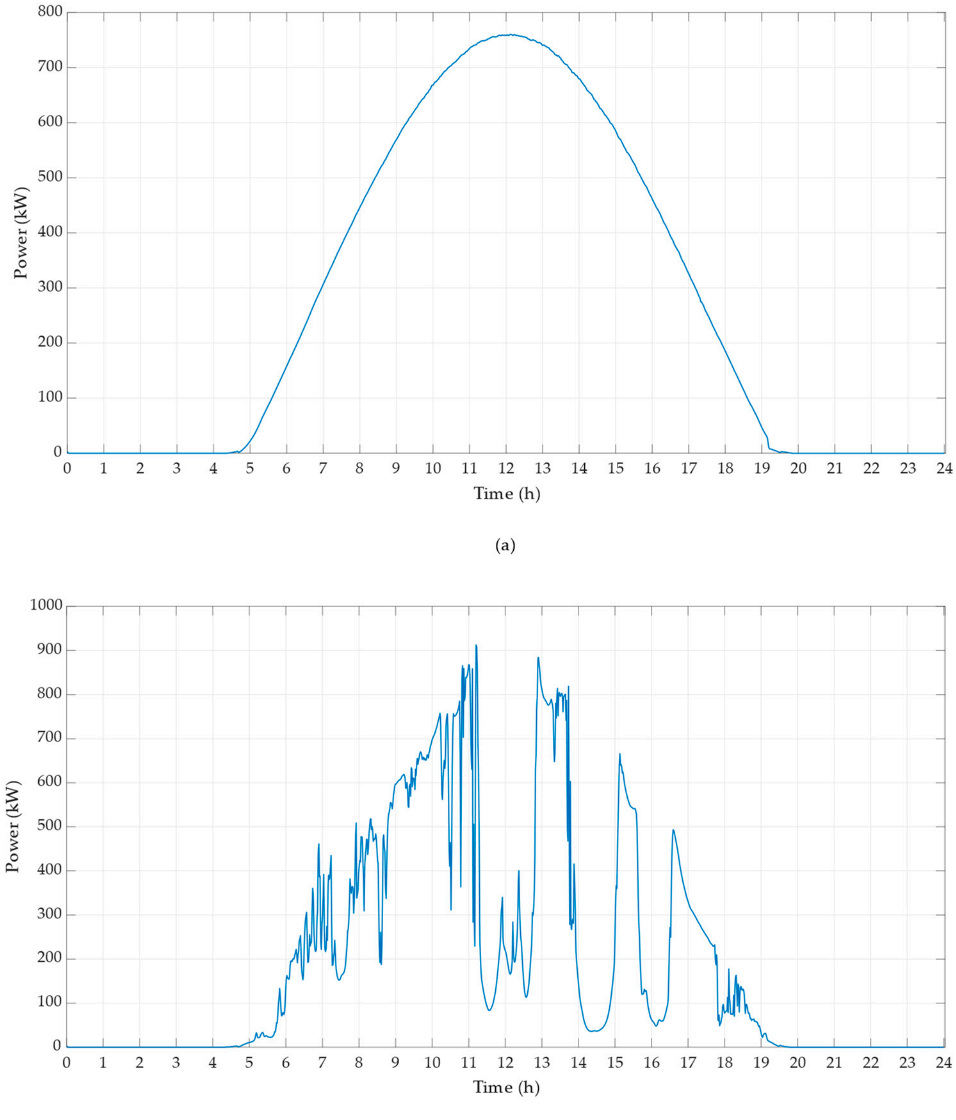

Figure 13. PV generator power data. (**a**) The situation with the sky clear, and (**b**) the partially cloudy sky.

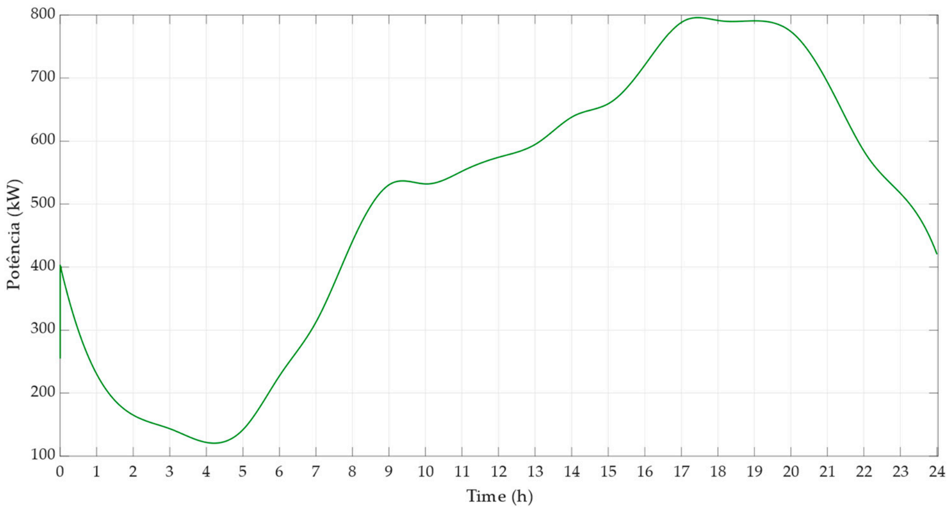

Figure 14. The curve refers to the variable loads adopted.

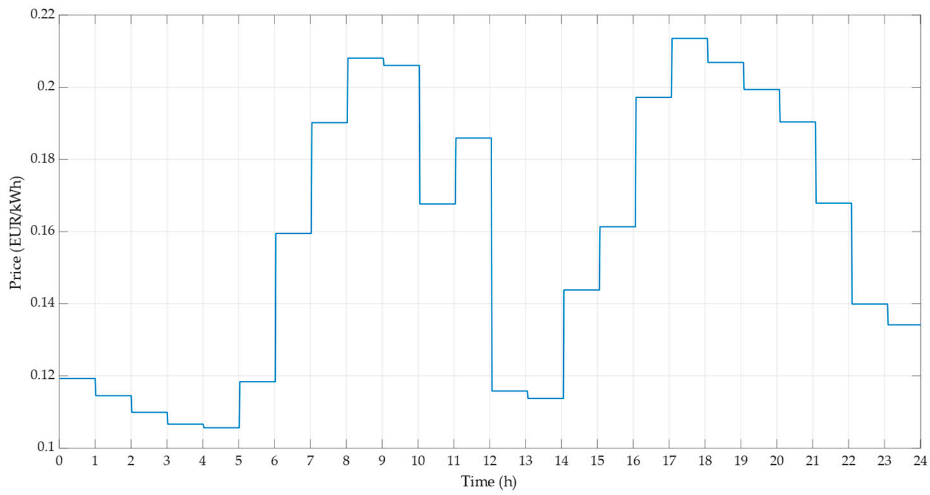

Figure 15. The dynamic charging prices adopted in the case studies.

4.1.4. The Modules for Forecasting the Variables

The energy management system needs to know the PV, load, and electricity price data presented in Section 4.1.3 in advance. Therefore, the proposal allows the implementation of a forecasting module to forecast these outputs. Other PV and demand curves are used [46], and the schedule cost curve for the next day [47] for network training. Figure 16 shows the prediction modules connected to the FL input.

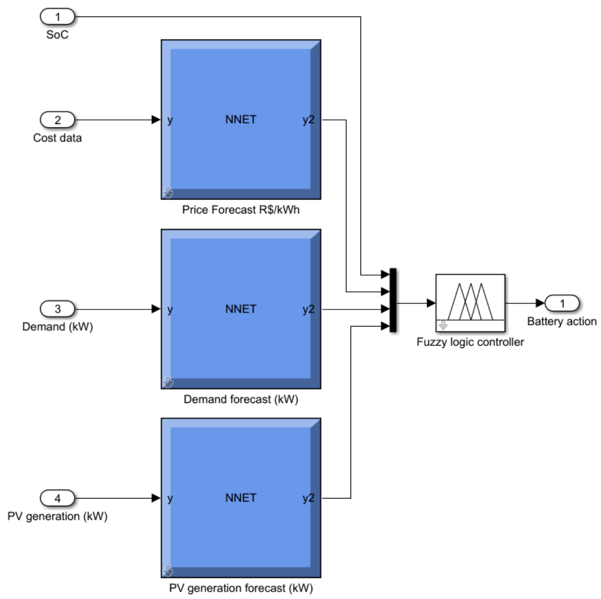

Figure 16. Modules for forecasting demand variables (kW), prices (R$/kWh), and PV-generated power (kW). And modules input into the FL controller (blocks modeled for Simulink).

The curves used for training are presented in Appendix A. It is important to highlight that the RNA training data forecast electricity prices for the Nordpool French area [47], the values billed for a previous weekday (9 November 2022). The other data are also different from those used in the simulations to better generalize the ANN for applications in other MG conditions with dynamic pricing. The prediction results are shown in Appendix B. It is important to highlight that the data refer to a day with the data resolution defined following Section 4.1.3.

4.2. Case Study Scenarios

In order to evaluate the effectiveness of the developed energy control system and the MG model in different situations, the following scenarios were designed and simulated:

- Case 1: Heuristic method for the clear sky;
- Case 2: Proposed method for the clear sky;
- Case 3: Heuristic method for the partially cloudy sky;
- Case 4: Proposed method for the partially cloudy sky.

The following subsubsections provide simulation results for the proposed cases. All were simulated for one day, and numerical results were plotted in the same time interval for all studied variables. A daily consideration of the resolution takes place during the graphical representation of the state of charge (SoC) of the battery, the electricity prices, and the powers generated by the photovoltaic (PV) system. Finally, the total costs and amount of energy consumed from the grid for each case are used to compare the types of algorithms discussed in the manuscript.

4.2.1. Cases 1 and 3 of Reference Applied the Heuristic Method for Precise and Partially Cloudy Sky Conditions

Two heuristic scenarios are incorporated in the case studies, aiming to provide a broader basis for comparison, where the results of AI algorithms can be contrasted with those of heuristic algorithms based on simple rules. Thus, the advantages of using an energy management technique based on AI for programming the BESS action are highlighted. The heuristic algorithm is detailed in Section 3.4. Figures 17 and 18 show the simulation results of the heuristic cases of the clear and partially cloudy sky for 24 h.

4.2.2. Cases 2 and 4, Proposed Methods Applied for Clear and Partially Cloudy Sky Conditions

Cases two and four incorporate the precisions by showing how well the FL algorithm and the forecasts of the trained ANN deal with changes in variables throughout the day under clear and partially cloudy sky conditions. The curves for the simulation results of the proposed algorithm for the 24 h are shown in Figures 19 and 20.

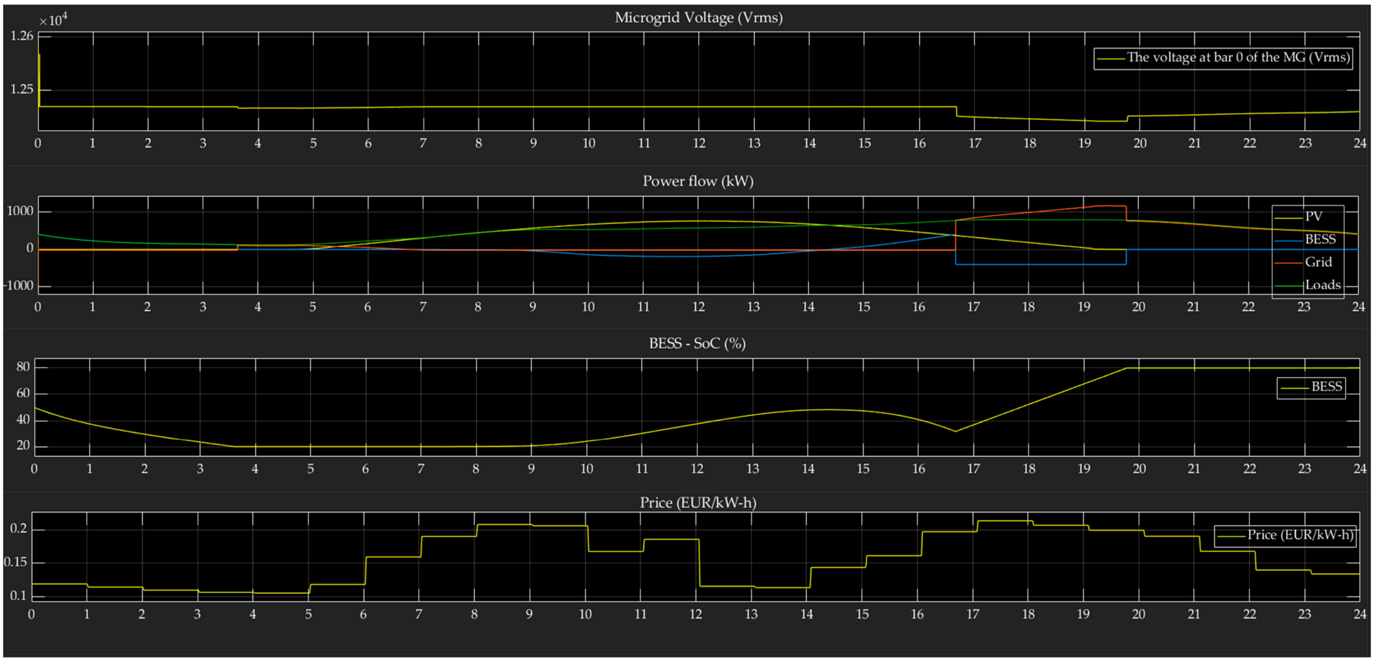

Figure 17. Results of the heuristic reference case for the simulation period with a clear-sky day.

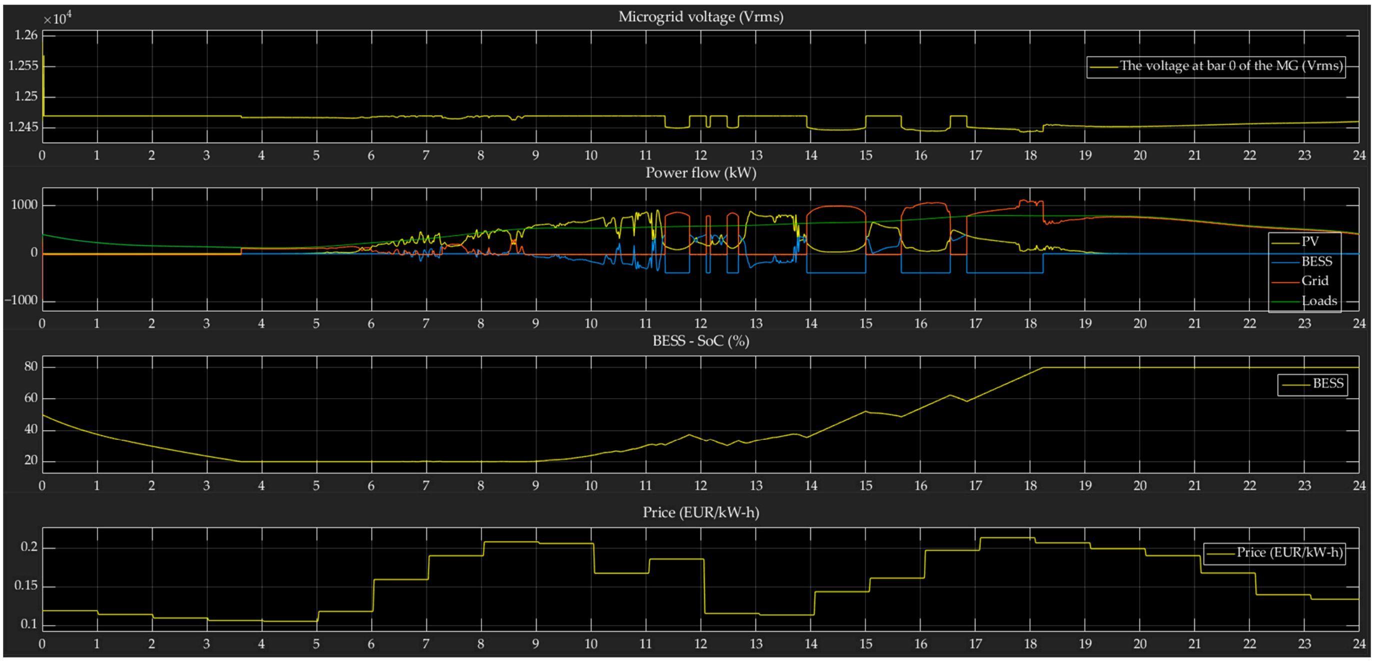

Figure 18. Results of the heuristic reference case for the simulation period with partially cloudy sky day.

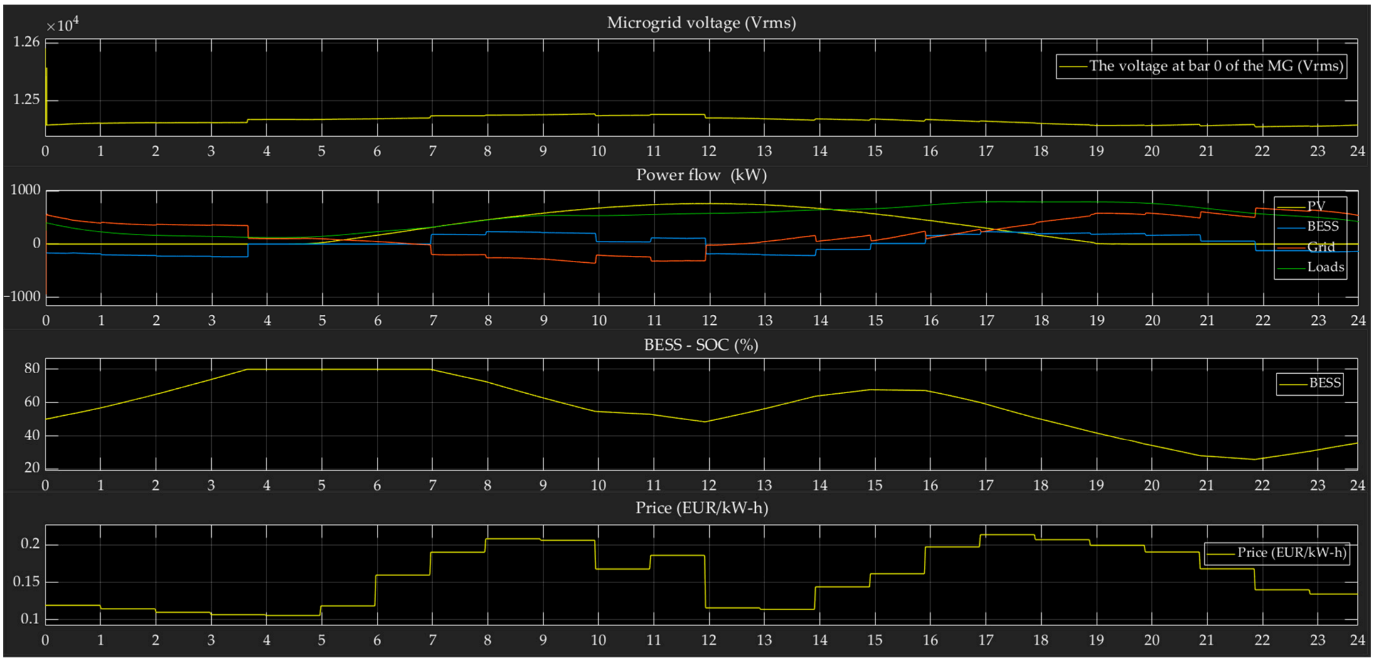

Figure 19. Results of the case with the proposed model for the simulation period with a clear-sky day.

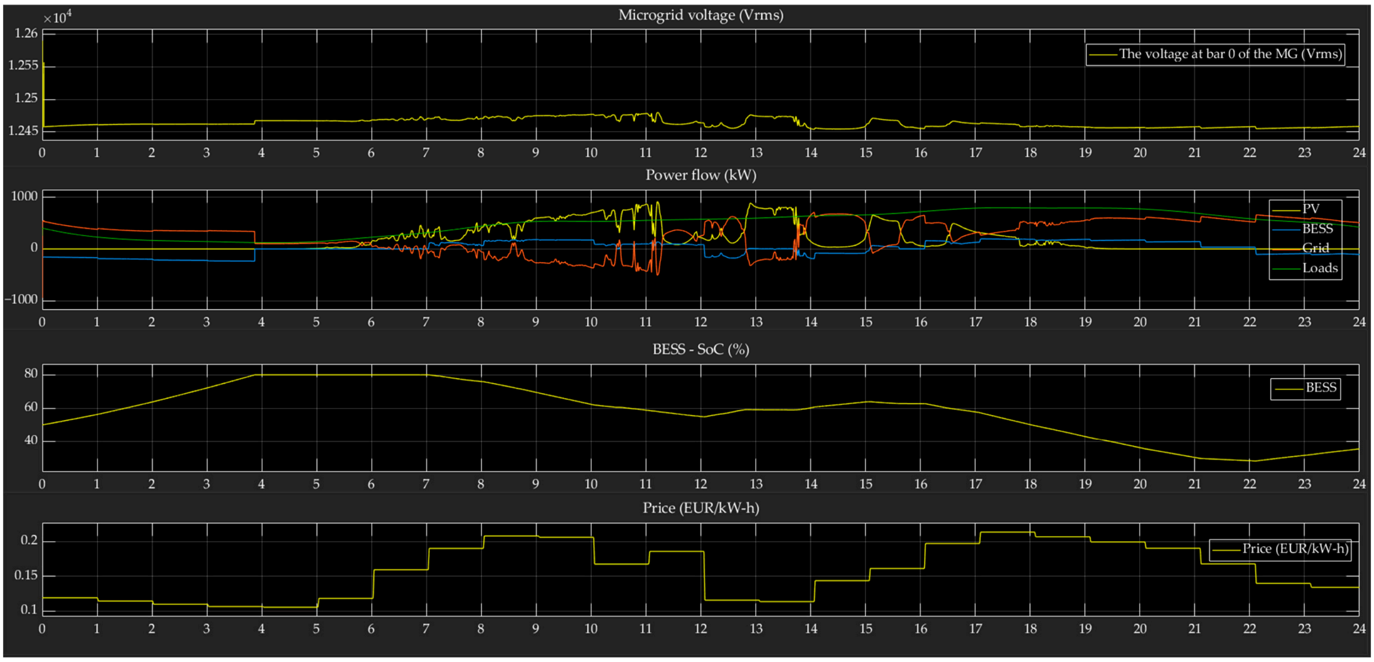

Figure 20. Results of the case with the proposed model for the simulation period with partially cloudy skies.

5. Analysis of the Results of the Four Cases

This section discusses the simulations' results in the four cases presented in Section 4.2 and then compares costs and use of electricity consumed from the main feeder between the algorithms in situations of a clear and partially cloudy sky.

5.1. Discussion of Cases 1 and 3 with the Heuristic Method

It is observed in Figure 17, the behavior of the case study for the clear sky, when starting the simulation without PV generation, the battery supplies energy demanded by the loads until the moment of 03:40, where the minimum limit of SoC is reached. After an idle period, it is verified that the battery is charged when there is an excess of PV energy available, from 9:00 a.m. to approximately 2:25 p.m., which is expected because, after this interval, the defined rules do not allow the batteries to charge from the mains in these conditions. Then, after a brief period of discharge, from approximately 14:26 to approximately 16:45, there is a period for charging the batteries from the mains up to their maximum SoC limit (80%), which implies the idle battery for the remainder of the day.

In Figure 18, a similar behavior at the beginning of the simulation was detected. However, when starting the PV power generation in the clouded sky situation, a behavior change is observed, with the batteries being charged at the instants in which the excesses of PV power occur about the power demanded by the loads. The main feeder operates in the absence of generated PV power. As in the case of Figure 17, the day ends with the batteries idle and at their maximum SoC limit (80%).

5.2. Discussion of Cases 2 and 4 with the Proposed Method

As shown in Figure 19, the difference in the performance of the EMS with the FL algorithm compared to the results of the reference method is remarkable. From Figure 19, referring to the clear sky, it is observed that at the beginning, the battery charge until approaching the limit SoC limit (80%) at 05:55; this occurs due to the low value of the electricity price on the market, remaining in this period until 07:00. Then, with a gradual price increase, two slopes in the discharge curve are observed at approximately noon, where a quick loading occurs until 14:10. Then, there is a brief idle period of the battery, to start at 16:00 the discharge process due to the high price of electricity in the market until

20:50 reaching the 50% SoC level. Then, after the idle period, around 23:00, the recharge process is resumed due to the decrease in the price of electricity in the market.

Figure 20 presents similar results due to the variation in electricity market prices being the same in both simulations.

5.3. Comparison between the Heuristic and Proposed Algorithms

This section investigates the effects of variations in the cost value in reais (R$) and the use of grid energy (kWh) over the 24 h of simulation for clear and partially cloudy sky scenarios. Figure 21 shows the results for three conditions simulated with a clear sky:

- Heuristic method;
- Proposed method with AI;
- Without using BESSs.

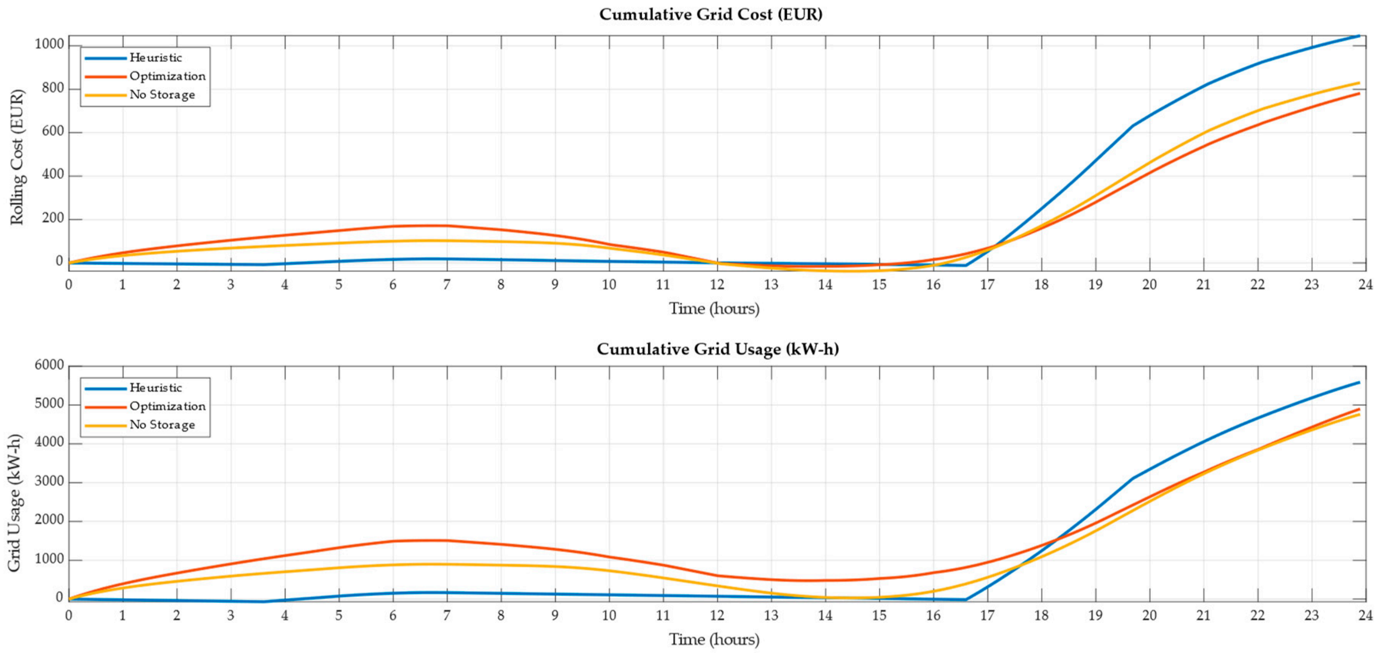

Figure 21. Comparison of methods used clear sky.

Table 3 shows the cumulative cost results in over 24 h with clear skies for both methods. It is essential to highlight that the difference between the two methods is approximately 25.36%.

Table 3. Total cost results for the two methods under the clear-sky condition.

Cost in Simulations	Value (EUR)
EMS cost with heuristic method	1046.6575
EMS cost with AI method	781.2258

Figure 22 shows the results for the three conditions simulated with a partially cloudy sky:

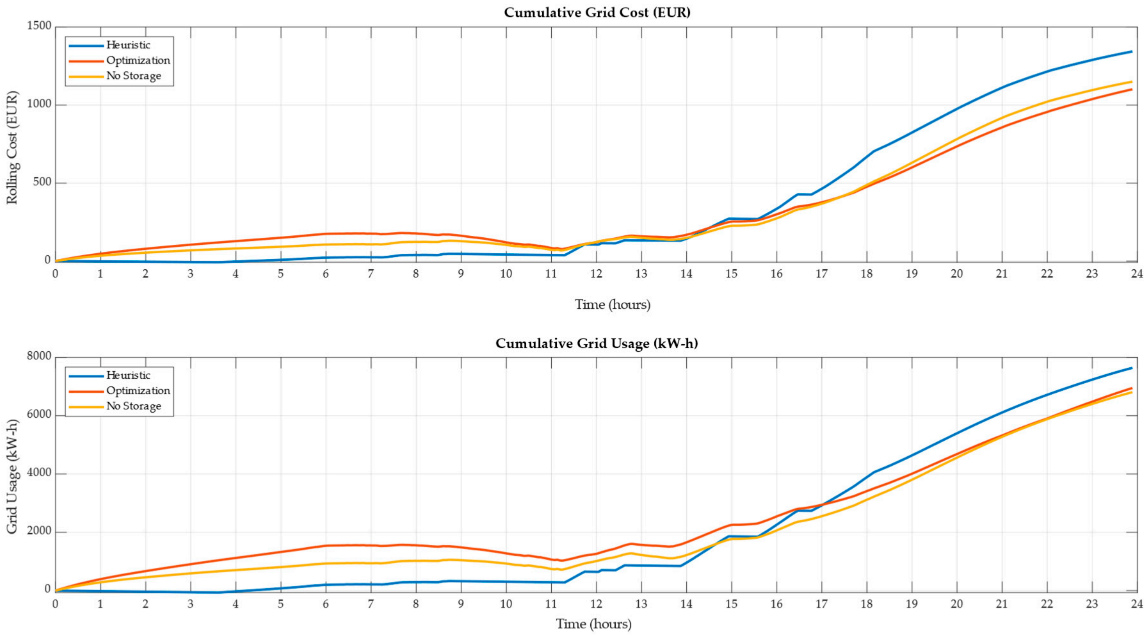

Figure 22. Comparison of methods used in partially cloudy skies.

Table 4 shows the results of accumulated costs over 24 h with partially cloudy skies for both methods. It is essential to highlight that the difference between the two methods is approximately 18.04%.

Table 4. Results of total costs for the two methods in the partially cloudy sky condition.

Cost in Simulations	Value (EUR)
EMS cost with heuristic method	1343.4049
EMS cost with AI method	1101.0664

It can be that in clear-sky scenarios, the economy and sustainability are more excellent. It is important to highlight that the cases using the proposed algorithm ended the day with around 55% SoC, unlike those using the heuristic algorithm that ended the day with 100% SoC, influencing these final cost values.

6. Conclusions

This manuscript focused on implementing an EMS for a grid-connected MG was proposed. The main purpose of the investigation was to try a management strategy that integrates the ANN with a non-linear autoregressive model for predictions of the variables with the FL programming to make decisions regarding the purchase or sale of electricity to assume a suitable decision due to the dynamics of the variables involved in the MG, updating the model at each integration step.

Based on the investigation, it was concluded that EMS within an MG framework using AI is an acceptable approach to reducing costs. The literature review generated guidelines and suggestions for developing the proposed EMS methodology.

Then, a simulation platform developed to test power management strategies in an MG using MATLAB/Simulink is presented. This platform was created by modifying and combining existing models, followed by a grid-connected MG that includes a PV system, static and variable demand, and a battery without the inclusion of the degradation model. In addition, phasor resolution techniques were used to increase simulation speed and provide sufficient detail for analysis. It is important that the model only supports the grid-connected operation mode, and future research may explore modifying the model to include the islanding mode of operation.

In addition, in the simulation platform developed for MG, two energy management strategies were integrated: forecasting algorithms using a non-linear autoregressive model to make predictions of the variables, combined with FL to make energy purchase or sale decisions, and a heuristic control system for comparison purposes. The proposed algorithm adopted the future behavior of the system, considering energy generation through PV panels, load demand, and electricity prices in order to determine MG operations based on FL. It is important to emphasize that the algorithm did not take battery degradation into account, as this aspect is beyond the scope of this research. Standard algorithms can be applied and improved for other MGs.

Finally, the implementation of the suggested approach was studied through a comprehensive case study over a 24 h simulation duration operating PV and demand data from Mathworks and electricity price profiles from Nordpool. For all scenarios, the proposal managed to reduce the daily price of energy taken from the main grid compared to the heuristic algorithm. It is worth noting that, different from the proposed algorithm, the heuristic term or day with the SoC does not have a maximum level of 80% defined in the program. In addition, depending on the selected configurations, the results revealed that the proposed algorithms were able to select the reference values for the battery power in a manner that:

1. Minimizes the energy bought at peak hours;
2. Maximizes self-consumption of locally made photovoltaic energy;
3. Created adequate service to the battery by holding it within its limitations and reducing its degradation.

Therefore, the development is a flexible algorithm that can be adjusted by counting on the overall management purpose. Furthermore, the 24 h simulation period was completed within an adequate runtime.

Based on the paragraphs above, this article achieved its general objective: to design an efficient EMS for an MG connected to the main grid, solving problems of scenarios for clear and partially cloudy sky days within a predictive structural model.

Author Contributions: G.H.A. designed the study, performed the experiments, and wrote the manuscript; F.A.M.M. contributed to the experiments and elaborated the manuscript; G.C.G. project organization and administration. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Figure A1 shows the curve referring to the data used for training the ANN load demand forecasts for the MR.

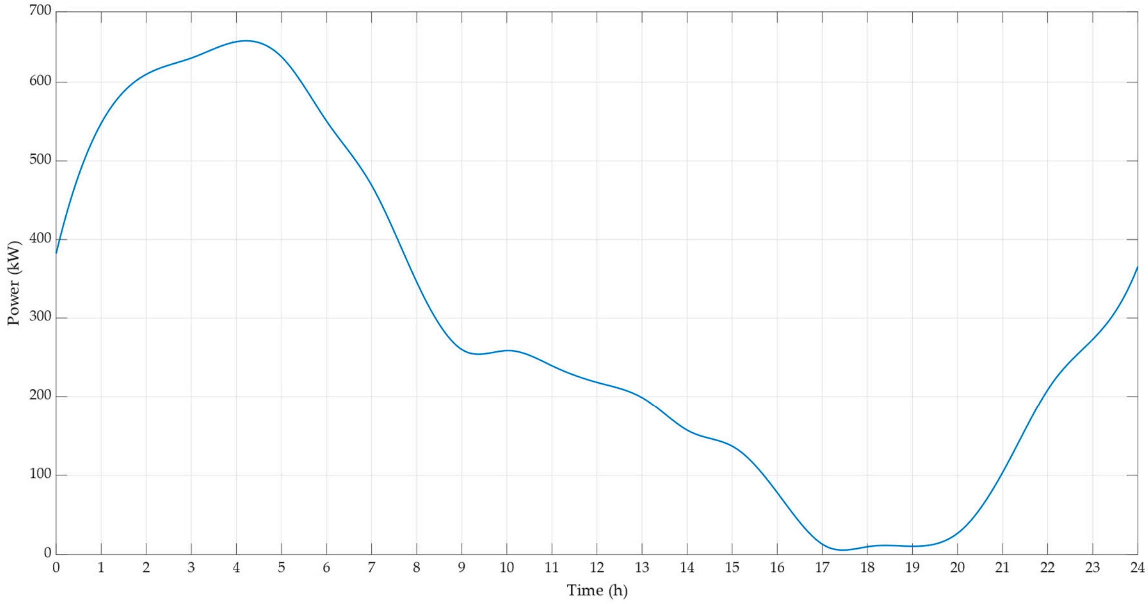

Figure A1. Load curve for training ANN predictions.

Figure A2 presents the curve referring to the data used in training the ANN forecasts of the clear-sky day for generating PV electric energy.

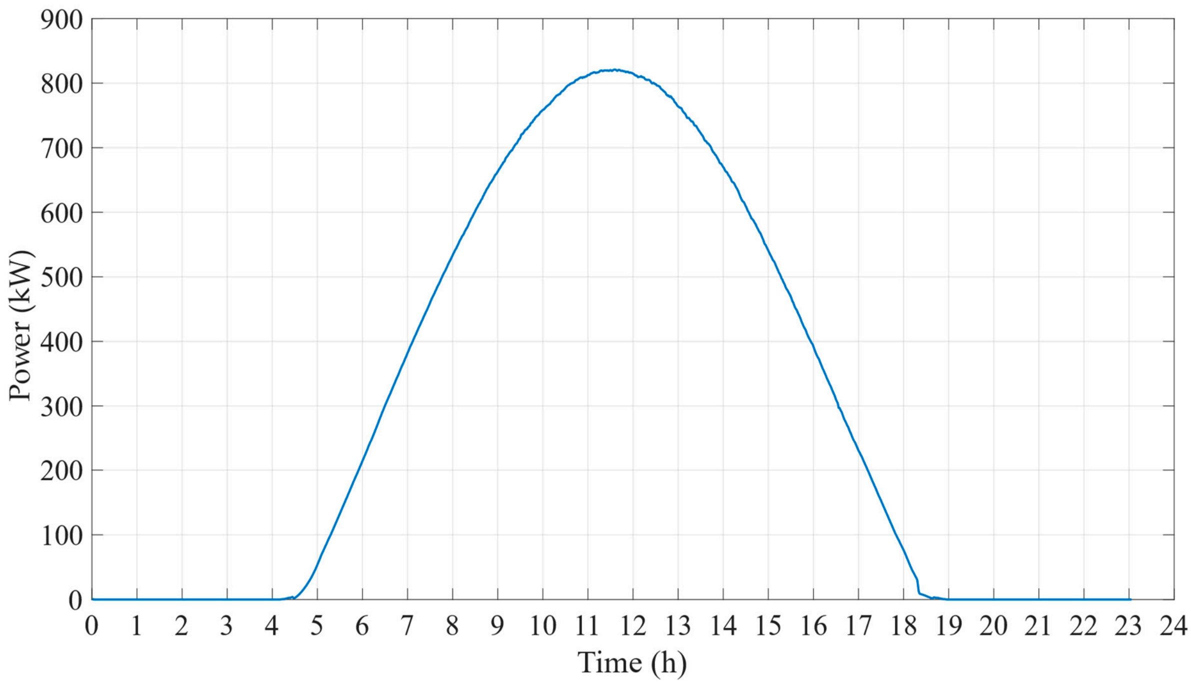

Figure A2. Clear-sky day curve for training ANN predictions.

Figure A3 presents the curve referring to the data used in training the ANN forecasts of the cloudy sky day for generating PV electric energy.

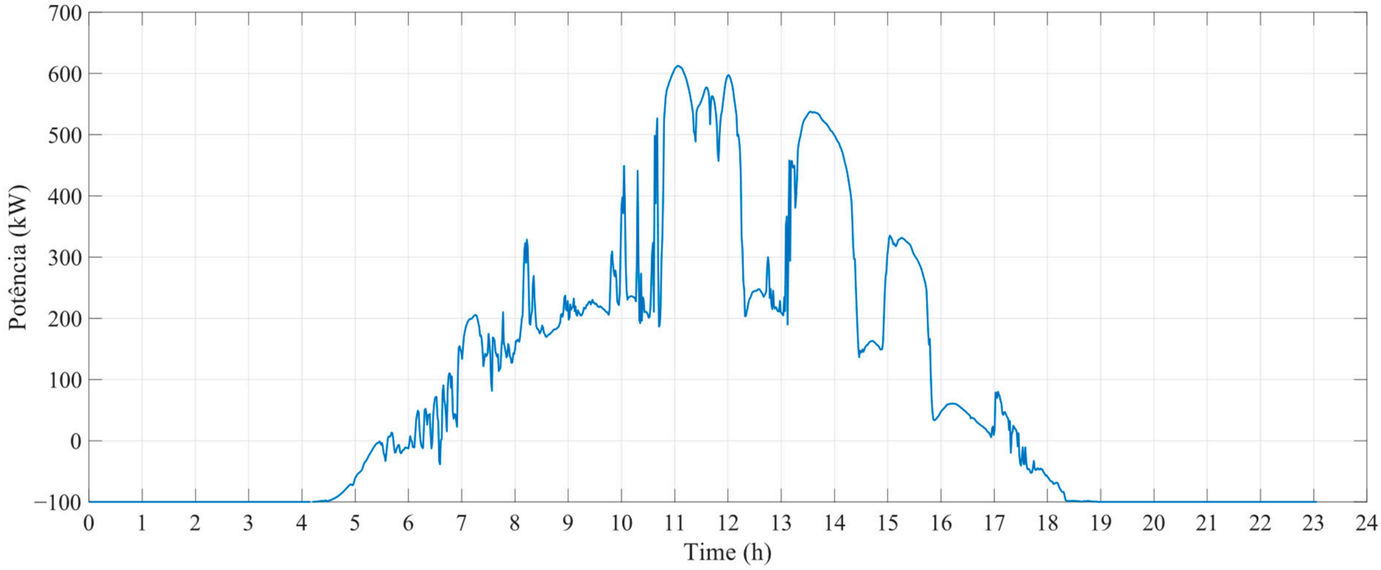

Figure A3. Cloudy sky day curve for training ANN predictions.

Figure A4 presents the curve referring to the data used in the training of the ANN forecasts of electricity prices on 9 November 2022.

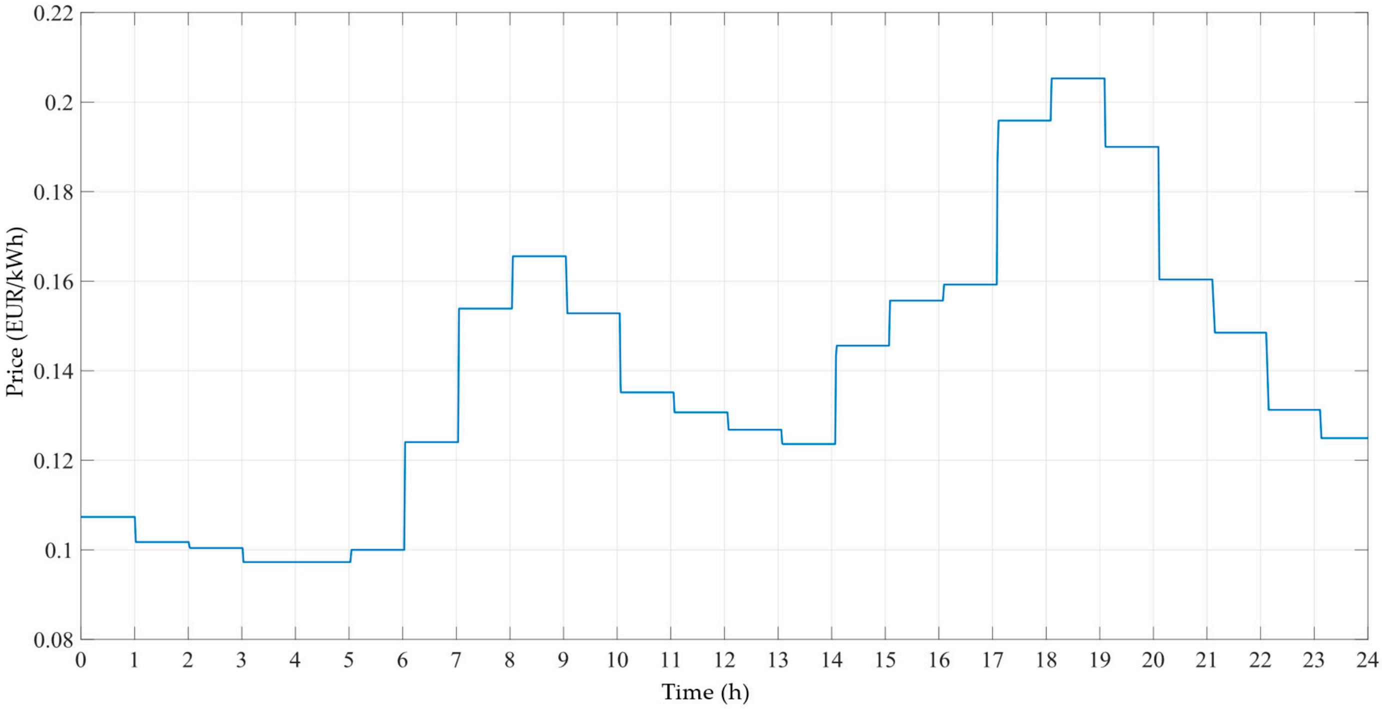

Figure A4. The dynamic charging prices adopted for training ANN predictions.

Appendix B

Figure A5 shows the forecasts for the load demand.

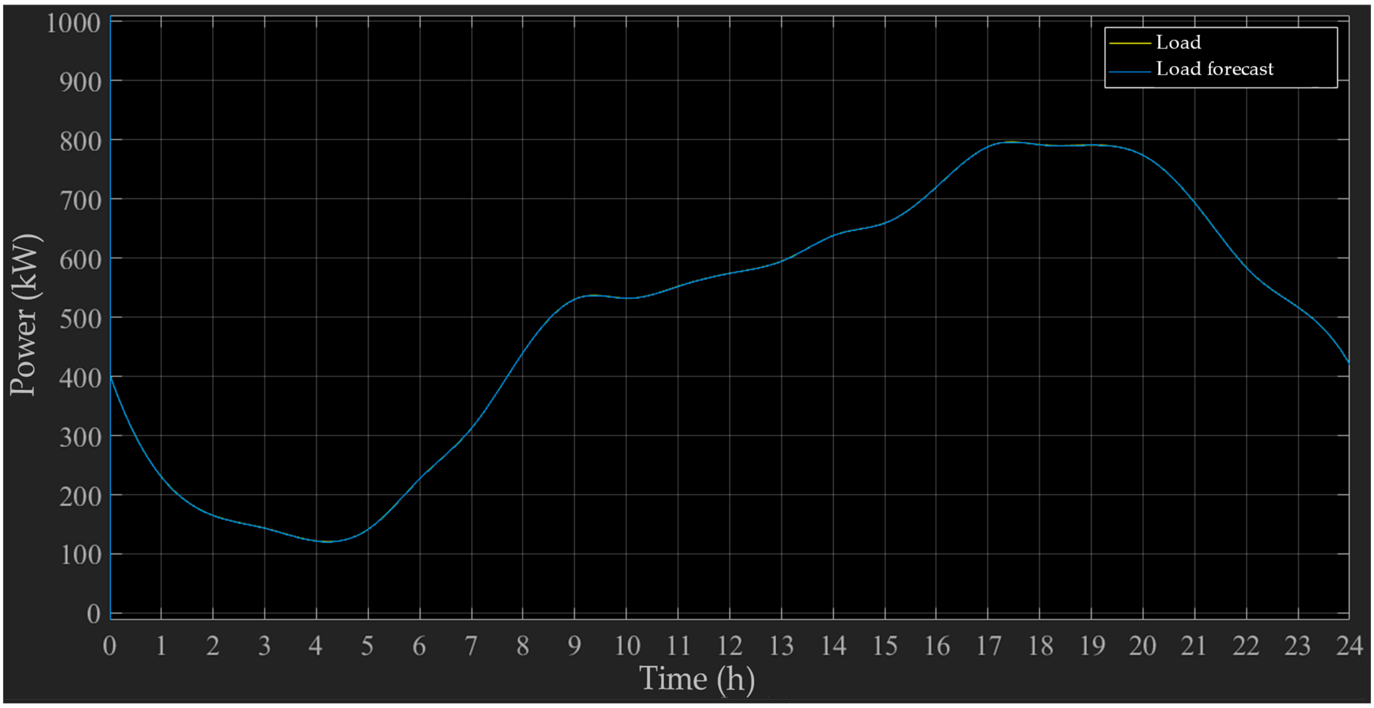

Figure A5. Previsions of the load with the trained RNA.

Figure A6 shows the forecasts for PV electrical generation on a clear-sky day.

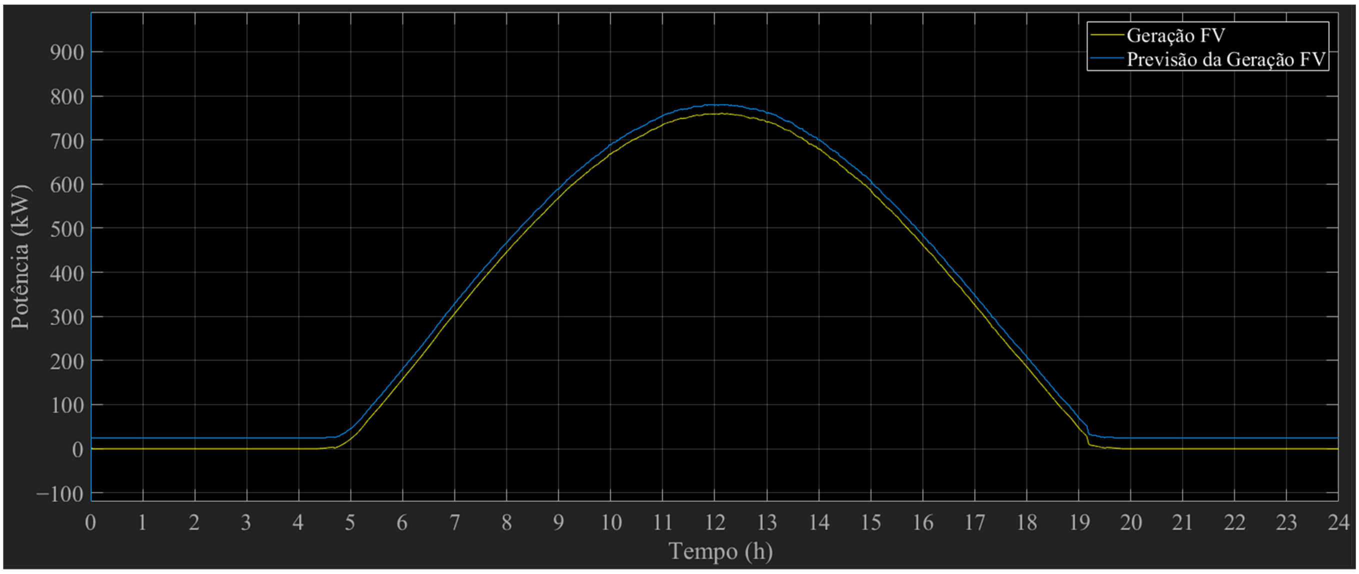

Figure A6. Previsions of PV Generation on a clear-sky day with the trained RNA.

Figure A7 shows the forecasts for PV electrical generation on a cloudy sky day.

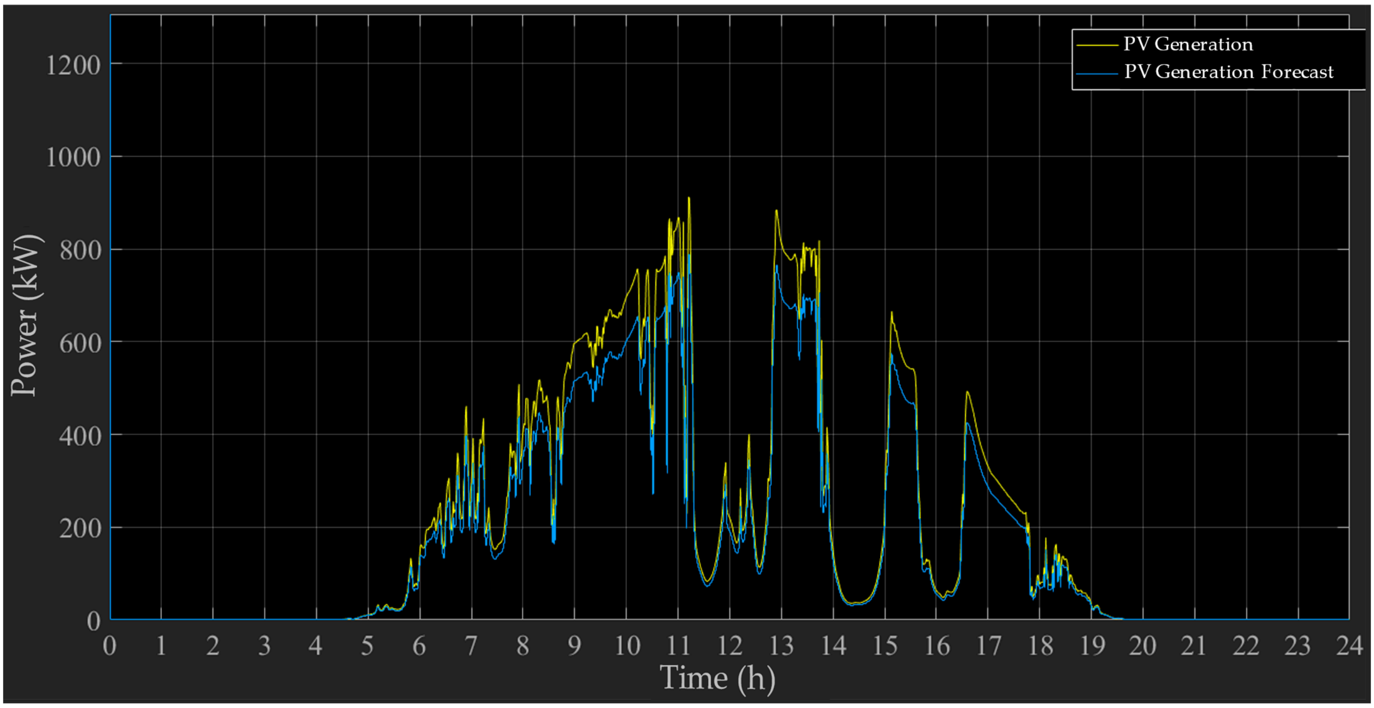

Figure A7. Previsions of PV generation on a cloudy sky day with the trained RNA.

Figure A8 shows the forecasts made for electrical energy prices.

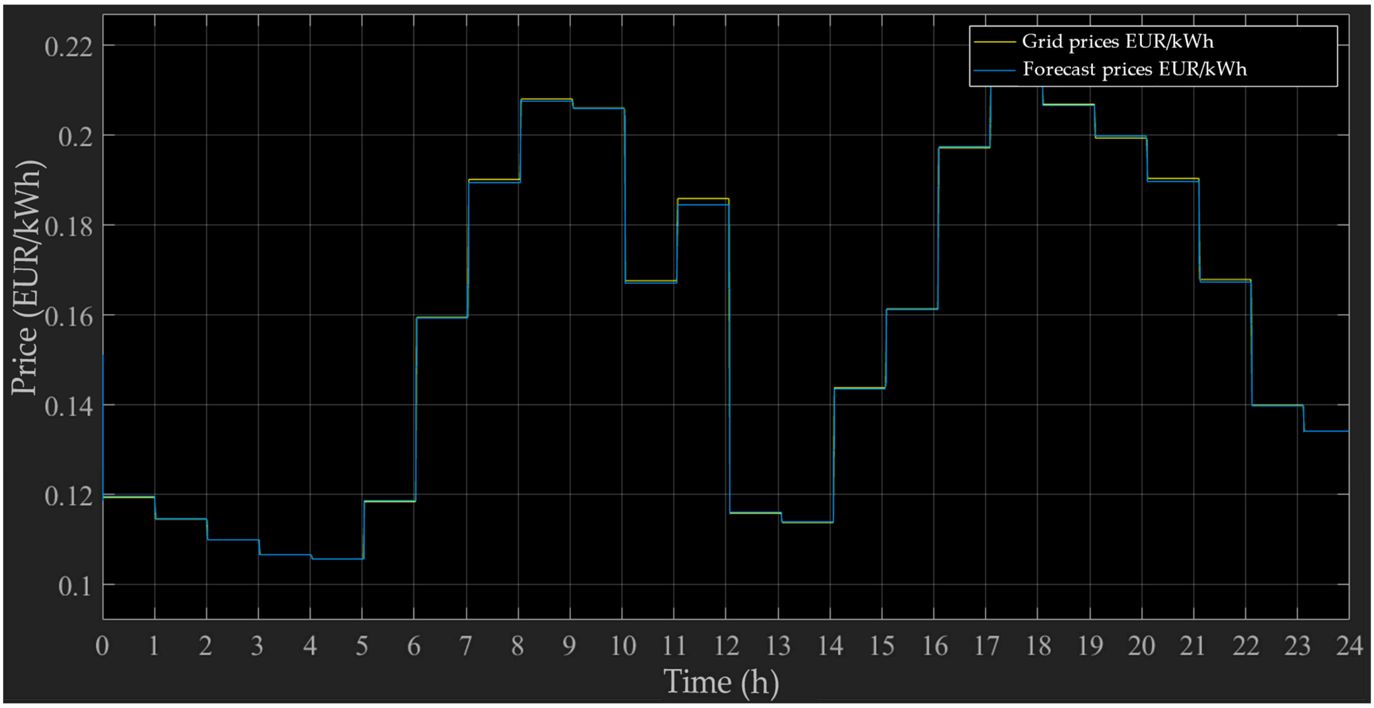

Figure A8. Electricity cost forecasts by means of trained RNA.

Appendix C

This appendix presents the battery model used [46].

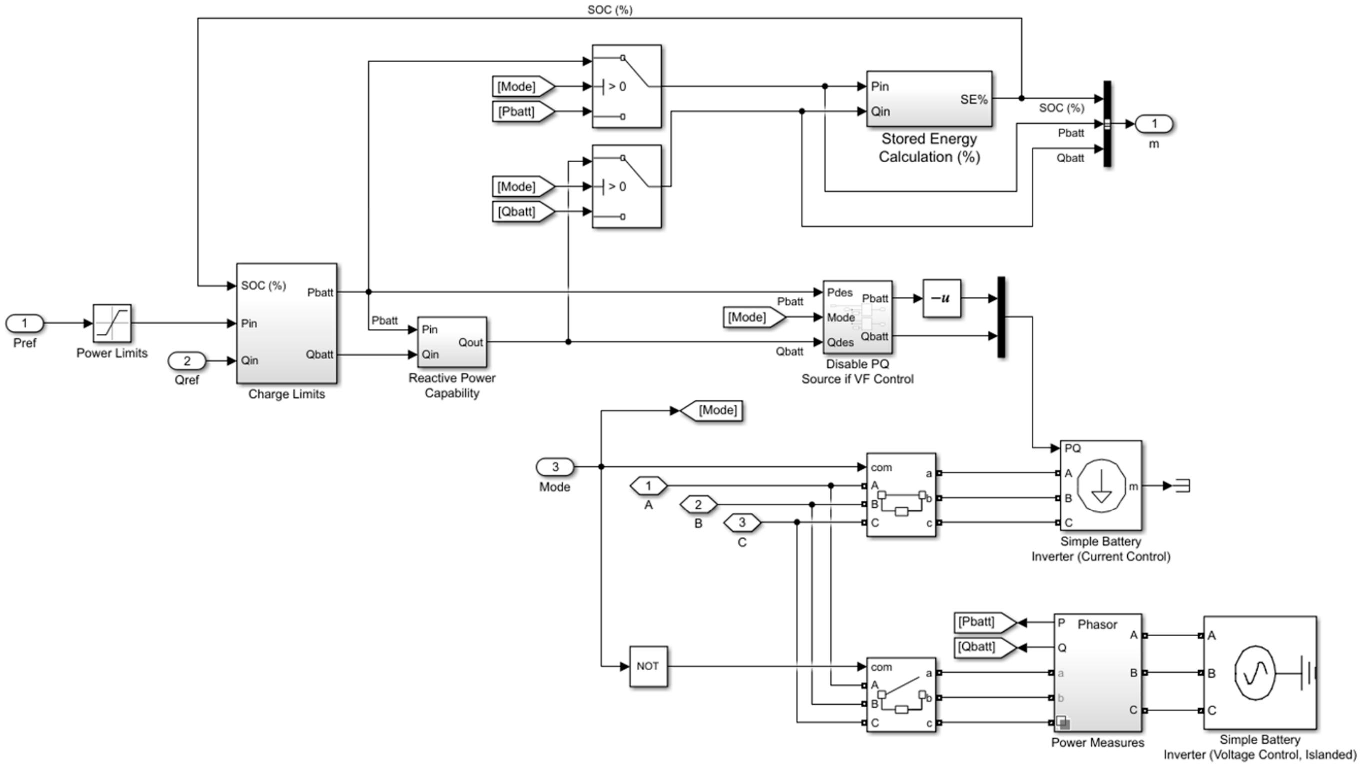

Figure A9. Battery model used [46].

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