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Real-Time Energy Management System for Microgrids

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HIGHLIGHTS

- An approach using AI techniques is proposed to evaluate real-time versus dispatch on a microgrid.
- Artificial Neural Network is used to predict load and renewable generation operation point on a microgrid.
- A novel approach with three-dimension analysis for deviation between day-ahead dispatch and real-time is presented.
- Adjustments in operation point are performed using fuzzy logic or MILP according to deviation between dispatch and real-time operation points.

Abstract: Microgrids (MD) is a new technology to improve efficiency, resilience, and reliability in the electricity sector. MD are most likely to have a clean energy generation, but the increase of microgrids with this kind of generation brings new challenges for energy management (EMS), especially concerning load uncertainties and variation of energy generation. In this context, this study has the main objective to propose a method of how to attend this matter, verifying the difference between the day before and real-time. The EMS proposed analyses the MD in real-time, calculating the deviation between dispatched and what was predicted to happen in the operation point in a three-dimensional analysis approach, considering renewable energy generation, battery State of Charge (SOC) and load curve. The system categorized the deviation in three possible quantities (small, medium, or high) and it acts accordingly. For the Next Operation Point predictor are used an artificial neural network (ANN) methodology. For the Decision Support System, it's used a fuzzy logic system to adjust the next operation point, and it uses a mixed-integer linear programming (MILP) approach when the deviation is too high, and the dispatched operation is unfeasible. Simulations with real data and information of a pilot project of MD are carried out to test and validate the proposed method. Results show that the methodology used to attend the matters of uncertainties and variation of energy generation. A reduction of operational cost is observed in the simulations.

Keywords: Microgrid; Real-time; Energy Management System; Fuzzy logic; Artificial Neural Networks.

INTRODUCTION

In the last couple of decades, it has been observed a great rise in electrical energy demand all around the world, bringing concern about how to attend to this demand with a low environmental cost [1]. Researchers, government authorities, and the private sector are uniting efforts to implement and strengthen new technologies in the electric sector to improve efficiency, resilience, and reliability in this sector, such as distributed generation, battery energy storage systems, electric vehicles, and microgrids.

Microgrids (MD) can be defined as a group of interconnected loads (controllable or not) and distributed energy resources (DER) with defined electrical boundaries that act as a single controllable entity and can operate both grid-connected and island mode. DER, such as distributed energy storage systems (DES) and distributed generators (DG), may increase the quality and reliability of electric energy on the MD and the resilience of the wider grid [2-3]. However, these DER bring new challenges concerning energy management to the utility grid and to the MD itself, increasing interest in research about energy management systems (EMS).

Stluka and coauthors [4] presents an approach of energy management optimization taking into account utility and demand-side objectives trying to achieve a point that is good for both sides. The problem is formulated separately for the utility and MD, but the optimization is realized with both as a unity. The proposed method is tested in a real MD and it's observed a reduction in energy annual costs.

A two-layer strategy has been proposed in [5–8] on which variation of energy generation with solar and wind resources is taken into consideration. In Jiang and coauthors [5], the first layer is responsible for planning the MD, generating an optimal dispatch for the given situation, while the second layer acts in real-time trying to adjust with possible technical restrictions that may arise. Hu and coauthors [6] compares a system with two layers with a classic optimal dispatch using a mixed-integer linear programming system for the task to manage the energy resources of an MD. In Wang and coauthors [7] a high penetration of renewable resources is considered to the EMS proposed, on which the second layer finds and adjusts errors between what was planned the day before and what is happening in real-time. In Zeng and coauthors [8] the real-time layer also considered load and energy prices uncertainties using dynamic programming and artificial neural networks.

Also, some studies focus only on real-time EMS [9–12]. In Subramanian and Garcia [9] was developed some algorithms that take into account the dispatch of interruptible loads and DES, seeking a reduced operational cost. In Rahbar and coauthors [10] minimize operational cost is also pursued, but that is possible by reducing the use of utility energy and optimizing the energy flow of DES, assuming to know in advance the energy consumption and generation on the MD in a given finite time interval. In Dehgahnpour and Nehrir [12] is proposed EMS using Nash Bargain Solution on which there is a controller for each DER with particular objective functions and restrictions and based on these. Different scenarios with demand response programs are considered to test the proposed method.

Other studies have shown a system with a third layer inserted in between the day before layer and real-time layer, called the intra-day layer (13). This intra-day layer has the objective to reduce the divergence between what was planned the day before and real-time information, using the data collected by the intra-day layer to obtain more accurate predictions in the real-time layer, improving operation in MD. A Model Predictive Control (MPC) approach was developed in Perez and coauthors [14] considering both connected and islanded mode. The authors assure an optimal system operation for both modes, seeking to reduce impacts of peak demand and utility energy costs in connected mode and improvements in continuity indicators while in islanded mode.

An economic analysis was conducted in de Lara Filho and coauthors [15] intended to reduce energy costs in a public university in Brazil. A computational tool was used to optimize the contracted demand and simulate annual savings with three different possibilities: Demand Side Management strategies; use of the free market; and a PV generation system. All three possibilities result in expressive annual savings.

In Machado and coauthors [16] a comprehensive overview of research topics and recent developments in microgrid operation are presented, aiming to present a broad vision of the distribution system based on MDs operation at all its levels. First, a multi-objective optimization is presented aiming to minimize operational costs as well as maximize battery life span. Second, is presented the interaction between MDs and theirs DERs, and the distribution network was modeled representing the grid operation as a unity. Also, a collaborative optimization for multiple MGs operating together is presented. At last, a theoretical MD operation framework through decentralized energy markets is discussed as well.

The main objective of the present study is to propose a method for a real-time energy management system for microgrids, aiming to reduce the divergence between the day-ahead dispatch and real-time operation, especially concerning load uncertainty and photovoltaic variation of energy generation. A load and energy generation predictor is developed using artificial neural networks to predict the next operation point. Simulations are carried out using information from a real MD and these are used to evaluate the proposed method under different scenarios.

This works presents a new approach to calculate deviation between day-ahead dispatch and real-time data. A three-dimension deviation calculation, considering renewable energy generation, battery State of Charge (SOC) and load curve, is used to analyzed possible divergence that appears, carrying the inspection of the operation point in a global way. The EMS will perform its action based on the calculated deviation, and adjustments in operation point are performed using fuzzy logic or MILP according to deviation between dispatch and real-time operation points.

This paper is organized with the following section. Material and Methods brings all the information, data, and methods used to develop the EMS, also detailing all parts of the proposed system. Results present the main results obtained from the simulations of scenarios and a discussion about them is carried out. The conclusion summarizes the results obtained and brings the final considerations.

MATERIAL AND METHODS

For the development of this study, real measured data and documents were used, such as the load profile of a commercial building, meteorological data provided by an Itaipu Binacional's research project, and information about a real MD located at the Ballroom from Barigui Park, in Curitiba. The MD has a photovoltaic generation with a capacity of 32,64 kWp, a DES is composed of three lithium phosphate batteries with a unit capacity of 9.6 kWh (total of 28,8 kWh), with a nominal power of 2.9 kW and a charge and discharge current of 100 A.

The meteorological data includes irradiance (W/m²), ambient temperature (°C), the temperature of the photovoltaic module (°C), and wind speed (m/s). Data were collected in the city of Foz do Iguaçu, Paraná, Brazil, for 11 months, with a ten-minute interval. The load data were first presented in [17] and it consists of three load profile curves, namely: working days load profiles; Saturdays load profile; Sundays and holidays load profile. Each profile is represented as a curve in

Figure ***1***,

Figure **2** and

Figure **3**, respectively.

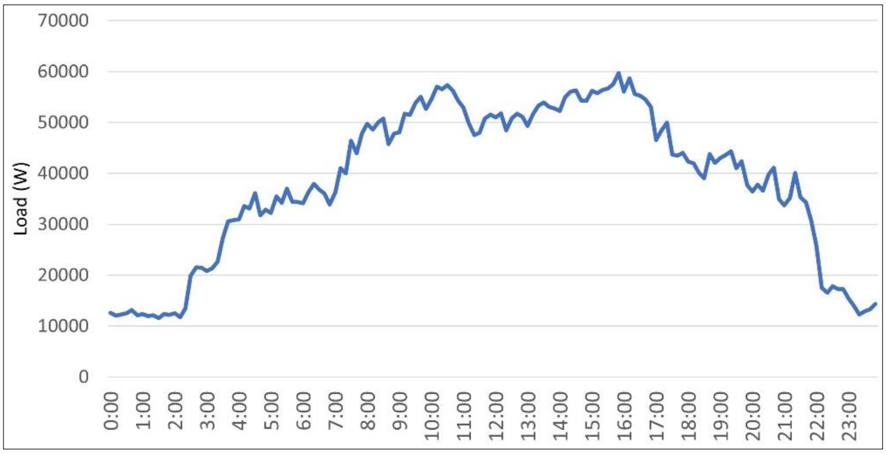

Figure 1. Working day load profile. Adapted from [17]

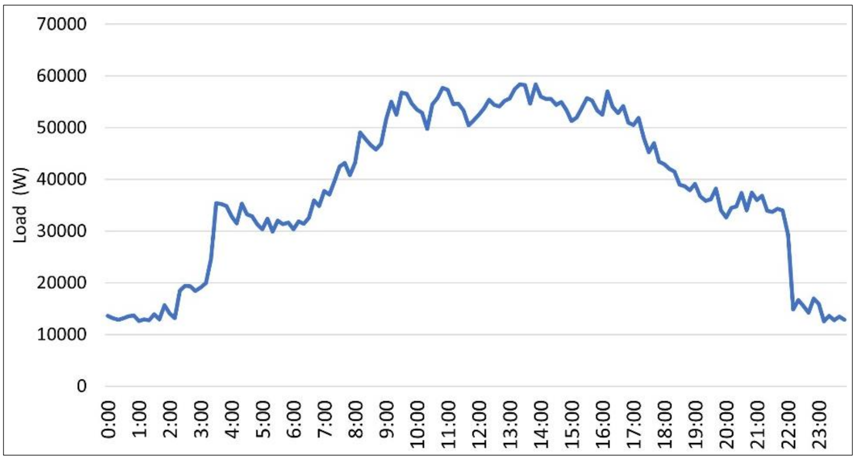

Figure 2. Saturdays load profile. Adapted from [17]

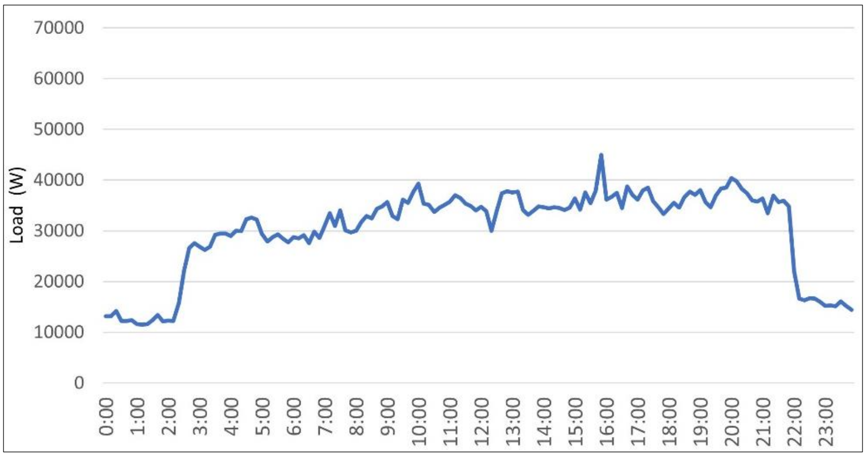

Figure 3. Sundays and holidays load profile. Adapted from [17]

To reconcile the quantity of load data and meteorological data, a load emulation was carried out based on the three load curves presented. A curve fitting was necessary to adapt the monthly energy consumption on the MD in the study. The energy consumption used for it is shown in Table 1.

Table 1. Energy Consumption used for the MD

Month / Year	Monthly energy consumption (kWh)	Month / Year	Monthly energy consumption (kWh)
January / 2019	1843	July / 2019	2507
February / 2019	2285	August / 2019	2731
March / 2019	3012	September / 2019	2821
April / 2019	2938	October / 2019	3080
May / 2019	2570	November / 2019	3383
June / 2019	2763	December / 2019	2663

Since the load profiles only dictate the loads for one day, the next step was to generate all days of the year using the 2019 calendar. To generate different days with the same initial data, it was inserted a noise with a daily variation of zero and a maximum variation of 5% for each measurement, according to the equation (1), in which x is the original value of load, RB is the white noise with normal distribution and x' is the new value of load for each interval.

$$x' = x + (0.05 \cdot x \cdot RB), \tag{1}$$

With the data presented, it was possible to implement, test, and validate the management system as it is described in the sections ahead. The EMS for MD proposed consists basically of three parts, namely: next operation point forecaster; decision support system; and optimization system. The flowchart in
Figure ***4*** summarizes how the system works.

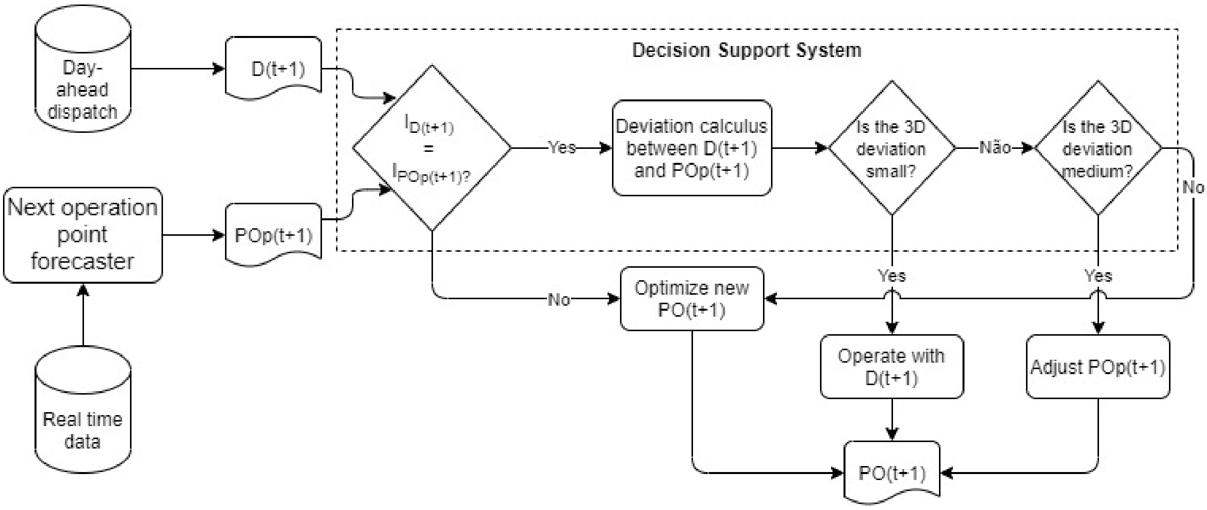

Figure 4. Microgrid Energy Management System flowchart

The day-ahead dispatch was carried out using an adaptation of the model proposed in [18]. Since the original model is for a one-hour time interval, it was necessary to change some information and part of the code so it could generate a dispatch with 10 minutes intervals data.

Next Operation Point (NOP) Forecaster

The NOP Forecaster has the objective to predict the operation point of the microgrid in the next interval, which is ten minutes from the present time. For such task, the forecaster is fed with real-time weather and load data, and it's divided into four different parts: load forecaster; energy generation forecaster; DES forecaster; and islanding events. The first two parts consist in predicting time series and it was used methods of Artificial Neural Networks (ANR). The DES forecasting was carried out using a deterministic method and islanding events are received and passed out to the Decision Support System. A flowchart of the NOP Forecaster is presented in
Figure ***5***.

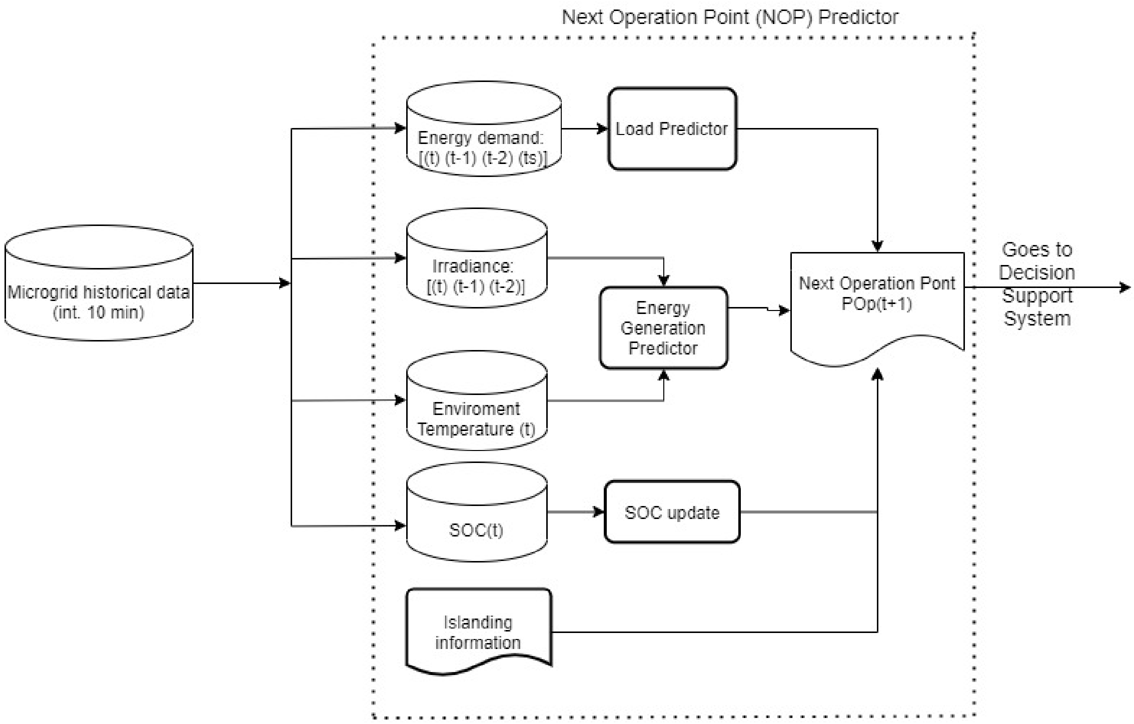

Figure 5. Next Operation Point Forecaster Flowchart

Load Forecaster was implemented using a Feedforward ARN with multiple layers, in which the input layers receive load data from the last three operation points as well as information about the time and day of the week. The output layer gives a medium value of load for the next time interval ($t + 1$), and this value is used to obtain the energy demand for $t + 1$.

Energy generation forecaster first must predict the next irradiation that is going to happen. For that purpose, it was used a Feedforward ANN with multiple layers, with data from the last three operation points and information about the time of the day in the input layers. The result of this is an estimating value of irradiance (G) for $t + 1$, used for calculation of energy generation (E_{PV}), as shown in Equation 2 [19]. The constants A_{mod}, n, η, P_r are respectively the module area, the number of modules, the module efficiency, and the loss coefficient (usually 75%).

$$E_{PV} = \frac{10}{60} \cdot \frac{1}{1000} \cdot G \cdot (A_{mod} \cdot n) \cdot \eta \cdot P_r, \tag{2}$$

The energy generation estimation is only correct if the weather conditions are the same as the NOCT standards. To avoid errors in this estimation, the temperature of the module is calculated (Equation 3) and used to correct the energy generation in Equation 4 [20].

$$T_{mod} = T_a + (T_{NOCT} - 20) \cdot \frac{G}{G_{NOCT}} \tag{3}$$

$$E_{PV_C} = E_{PV} - \frac{k}{100} \cdot (T_{mod} - T_a) \cdot E_{PV}, \tag{4}$$

T_{mod}, T_a and T_{NOCT} are respectively calculated temperature of the module for the given conditions, environment temperature, and module temperature in NOCT standards conditions. The constant k is the module's temperature coefficient.

The last estimation is concerning the state of charge (SOC) of the DES. To do so must be know the SOC in the present and what will be charge/discharge rate in the current time interval (t). Thus, it's determined according to Equation 5. Note that is the amount of energy flow in the battery and that negative values mean that the battery is discharging. The charge/discharge limits must be provided to the system and must be equal to the maximum output power for the DES divided by six, thus having the value in units of energy in 10 minutes intervals.

$$SOC(t + 1) = SOC(T) + \frac{\Delta E}{C}, \tag{5}$$

For islanding information, a check is made between what was planned in the day-ahead dispatch and what is happening in real-time. This verification is carried out by the Decision Support System. With all those information, it's possible to generate the predicted NOP ($PO_p(t + 1)$), containing information on energy demand, energy generation, SOC, and islanding data for the next time interval.

Decision Support System (DSS)

With the predicted NOP available, it's possible to carry out some comparisons between the predicted NOP and the day-ahead dispatch. The data are received in packages only for the next time interval and are processed accordingly. To generate a better result, the continuous variables (energy demand, generation, and SOC) were normalized individually and the islanding information will be represented by a binary variable.

The islanding information is the first one to be checked since a mismatch between dispatch and NOP will jeopardize the whole planning made on the day before. In that manner, the DSS makes a comparison between what was planned ($I_{D(t+1)}$) and what is the islanding situation of the MD ($I_{POp(t+1)}$). If there's a match, the DSS will proceed to the calculation of deviation. If not, the system will proceed to optimize a new operation point for the next time interval.

The deviation between the dispatch and the NOP information is used as a parameter for the DSS to make a decision. This works proposes a method for verifying the deviation between dispatch and predicted NOP in three dimensions analyses, aiming to save computational work, being the distance in between the two points with the normalized variables. Figure 6 shows an example of this deviation on which the line represents the linear distance between the two points and X, Y and Z represent energy demand, energy generation, and SOC, respectively. According to the value of the deviation, the DSS may proceed in three different ways. For a small deviation (Deviation < 0.05), the MD will operate with what was planned in day-ahead dispatch, considering that this difference will not interfere as much in the planning. In case of a medium deviation (0.05 < Deviation < 0.25), it's considered that these differences will impact the operation of the MD, requiring adjustments in the operation point. For larger deviation, the system will decide for the same situation as a not predicted islanding, optimizing a new operation point.

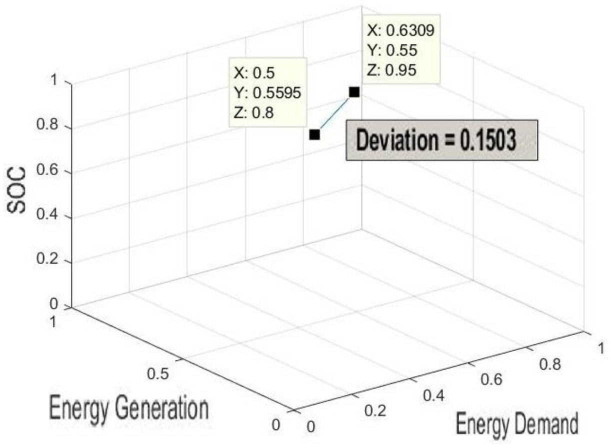

Figure 6. Three dimensions deviation example

For the adjustment of operational point, the system now will analyze each of the variables individually to discover what caused the divergence calculated in the 3D deviation. For that purpose, a Fuzzy inference system (Mamdami method) was implemented with three input Fuzzy sets, one for each individual calculated deviation, which allows 27 rules covering all possible situations, having as output two fuzzy sets, which are related to the DES charge and discharge rate and the MD controllable loads. For the first, the defuzzified output gives an alternative charge/discharge rate, according to Equation 6.

$$SOC_{adj.} = SOC_{previous} + \left(aBat \cdot \frac{2,4}{28,8}\right), \quad (6)$$

For the controllable load, the defuzzified output relates to a percentage amount of the controllable loads that will be turned off. Controllable loads were considered binary variables, which could be activated or not Four load groups were considered, with their powers of 1000 W, 750 W, 1500 W, and 1250 W. To optimize this selection of loads to be cutoff and taking into account the value given by the Fuzzy System, there is a MILP optimization process that minimizes the number of groups that will be disconnected.

Optimization System

The optimization system will be used in two different situations: first, mismatch in islanding information; second, when the deviation is high. In both cases, the MD may be connected to the utility power grid or be island mode and for that reason, optimization must be separated into two types: when connected to the utility power grid, the system will try to minimize operation costs; when the MD is an island, it will optimize the use of DES in order avoid curtailment. For both types, it was used a MILP approach, described mathematically in this subsection.

When the MD is connected to the utility power grid, the energy demand can be attended with the energy generated in the photovoltaic power plant, the DES, or by the utility company. However, the system must try to optimize operation costs, always choosing the energy source with the lowest cost possible. For that matter, the MILP problem seeks to minimize the cost (Equation 7) in which P_1, P_2 and P_3 is the quantity of energy supplied by the PV generation, by the DES, and by the utility company respectively. Letter a to d are binary decision variables for the controllable loads on which if the value is 1 it means that there was a curtailment of a certain controllable load. UC stands for the utility energy cost. This objective function is subject to the restriction on equations 8, 9, and 10.

$$min(Z) = 0,496825 \cdot P_1 + 0,51321 \cdot P_2 + UC \cdot P_3 + 10 \cdot a + 10 \cdot b + 10 \cdot c + 10 \cdot d, \quad (7)$$

s.t.

$$P_1 = E_{PV_C}, \quad (8)$$

$$P_1 + P_2 + P_3 + a \cdot cc_1$$
$$+ b \cdot cc_2 + c \cdot cc_3 + d \cdot cc_4 \geq demanda, \quad (9)$$

$$0 \leq SOC - \frac{P_2}{28,8} \leq 1, \quad (10)$$

The other possible situation is when the MD is an island and it's completely disconnected from the utility grid. In this case, the MD must manage its resources trying to minimize possible outage or load curtailment, making the MILP problem simpler, as shown in equations 11, 12, and 13.

$$max(Z) = P_2 - (a \cdot cc_1 + b \cdot cc_2 + c \cdot cc_3 + d \cdot cc_4),$$

s.t.

$$P_2 \leq 2{,}4, \tag{12}$$

$$P_2 + a \cdot cc_1 + b \cdot cc_2 + c \cdot cc_3 + d \cdot cc_4 \leq demanda, \tag{13}$$

RESULTS

In this section are shown the simulation results of the MD EMS. First are presented some results obtained in the NOP Forecaster. Secondly, simulations with different scenarios are presented for the DSS and Optimization System in a way that all possible outcomes can be addressed. At the end of the section are presented some results of a full-day simulation.

NOP Forecaster

The first part of the NOP forecaster is the load forecast. The training for this ANN took 795 epochs and its best performance was 0.0047 in mean squared error (mse). In Figure 7 it's possible to compare the original data set (blue solid curve) and the set generated by the ANN (orange dashed curve). It's possible to see that the network predicts nicely smooth fluctuations throughout the day, having some difficulties detecting some load peaks.

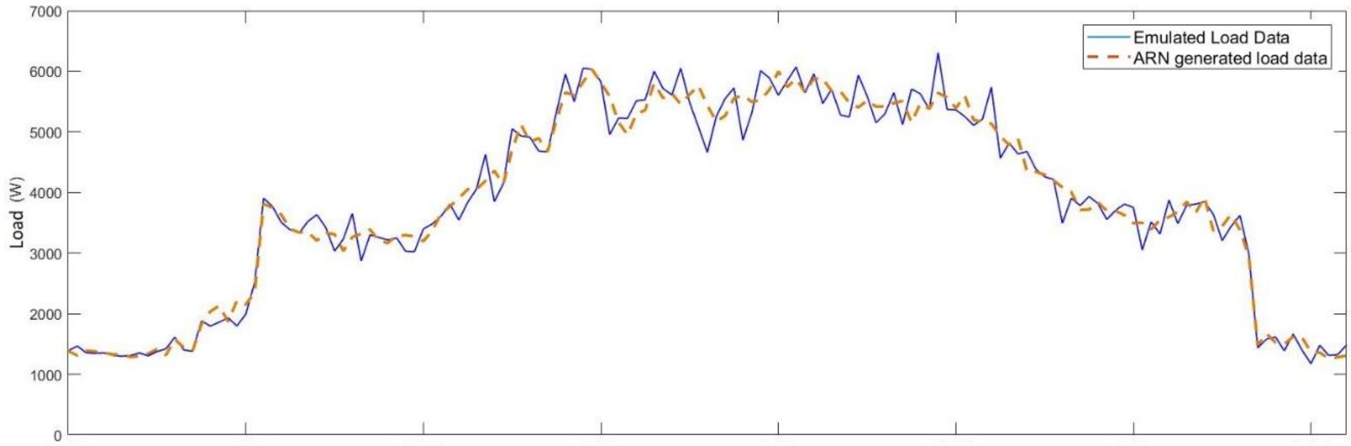

Figure 7. Comparison between emulated load profile and ARN load profile.

For the generation forecaster, it was used ANN to predict the irradiance in the next time interval. After the training (113 epochs and mse of 0.0207) it was compared the original data with the data generated by the ANN. In Figure 8 it's possible to see the result of two different days: the first one with several variations throughout the day and the other with almost no variations. Analyzing the curve on the right, for a day without external disturbances, the network can return very accurate results, practically bypassing the curve of real data. The same cannot be observed during abrupt variations, in which the network manages to trace a pattern, but does not respond so quickly that it returns such precise responses. This problem should be solved using a shorter time interval for the data used in this ANN.

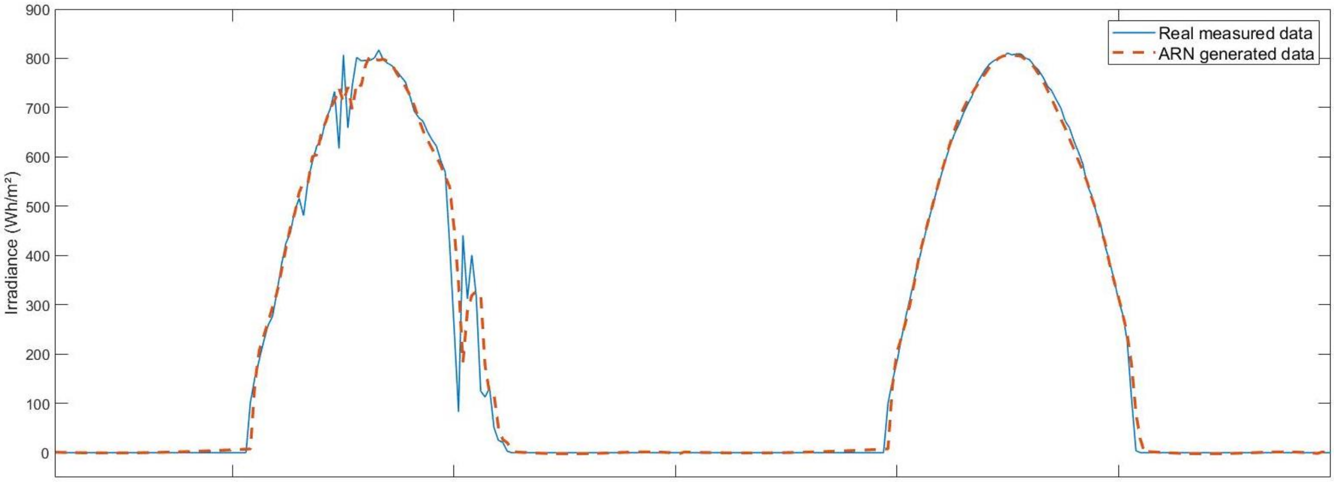

Figure 8. Comparison between measured and ARN predicted irradiance

Scenarios Results

For the simulation of the DSS and the optimization system, it's proposed eight different scenarios that cover all possible outcomes in the MD operation. The simulation results will be divided into two groups of four to facilitate its presentation and discussion. In the first group, it will be the situation with small and medium deviations, and in the second group only the ones with high deviation.

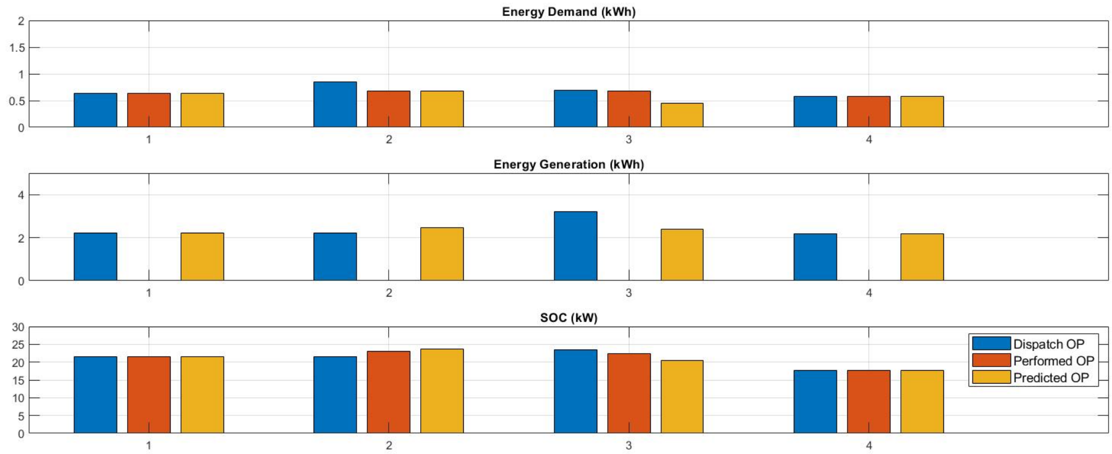

Figure 9. Scenarios 1 to 4.

In scenario 1, there's a deviation of 0.0095, meaning a small deviation. For that reason, the performed operation point will be the same as what was planned on the day-ahead dispatch. For scenario 2, the system finds a larger deviation equal to 0.1961 (medium deviation), making it necessary to adjust the operating point. This deviation is due to a higher-than-expected demand with also an increase in power generation. To adjust this issue, the DSS adjusts operation by using the extra power generated to charge batteries.

In scenario 3, there are considerable divergences in two of the magnitudes, with the generation being smaller than planned and the SOC also having a lower value. Despite a different situation from scenario 2, the DSS will also choose for the adjustment of the predicted OP. The difference lies in the fact that the adjustment will be charging the DES and controllable load curtailment.

Scenario 4 would be the one considered perfect, with zero deviation. However, the probability of this point happening is very remote, especially due to the variation of the energy generation and some unpredictable aspects of the load that can hardly be predicted a day in advance.

For the simulation of the optimization system, four scenarios are presented. This situation happens in two different situations: islanding information mismatch (unscheduled islanding, for example); the second is when the calculated deviation is greater than 0.25, characterizing a high deviation.

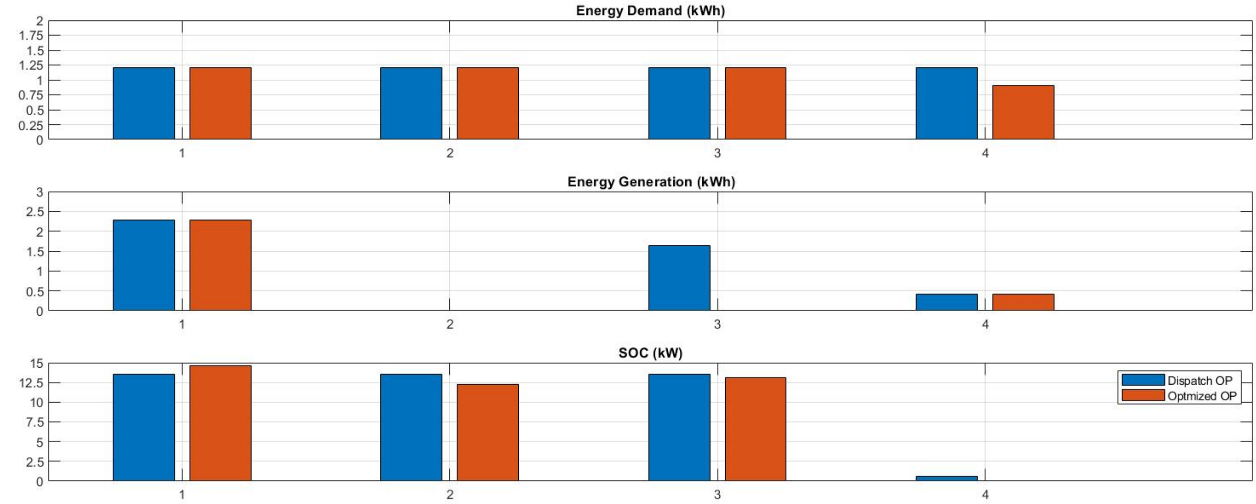

Figure 10. Scenarios 5 to 8

Scenario 5 consists of having a power generation greater than the load in the observation period. In this case, the generation is sufficient to meet the entire energy demand and, in addition, use the spare energy to load the storage system. Scenario 6 is that there is a null generation, despite the load being greater than zero. In this case, the system only has one way of meeting the demand, which is through battery discharge. This scenario is complemented by the next two.

Both scenarios 7 and 8 have the situation in which the generation is smaller than the load, diverging only in terms of the SOC on DES, which will interfere with the result obtained. In scenario 7, there is enough SOC to meet the spare load, while in 8, the SOC is insufficient. In the latter, a controllable load curtailment will be carried out to meet the maximum demand power possible.

With this simulation, it was possible to see that the proposed EMS react to the scenarios as expected and planned in the flowchart presented in

Figure ***4***. The next step was to make the EMS run in a full-day simulation. The results are presented in the next subsection.

Full-day Simulation

For the full-day simulation, a day-ahead dispatch with a ten-minute interval was needed so it could be the other set of data that the EMS needed to carry on the real-time management. Figure 11, Figure 12 and Figure 13 shows the optimal dispatch used, on which the intervals are numbered from 1 to 144. It's possible to see that the dispatch only uses the DES when the tariff is higher, reducing the utility bill. During the day, the energy generation overcomes energy demand, and the surplus energy is absorbed by the utility and the MD receives energy credits for it. In the other periods of the day, since the energy tariff is lower, the dispatch uses the utility to meet MD's energy demand. Also, the DES only discharges at a one percent rate for each period.

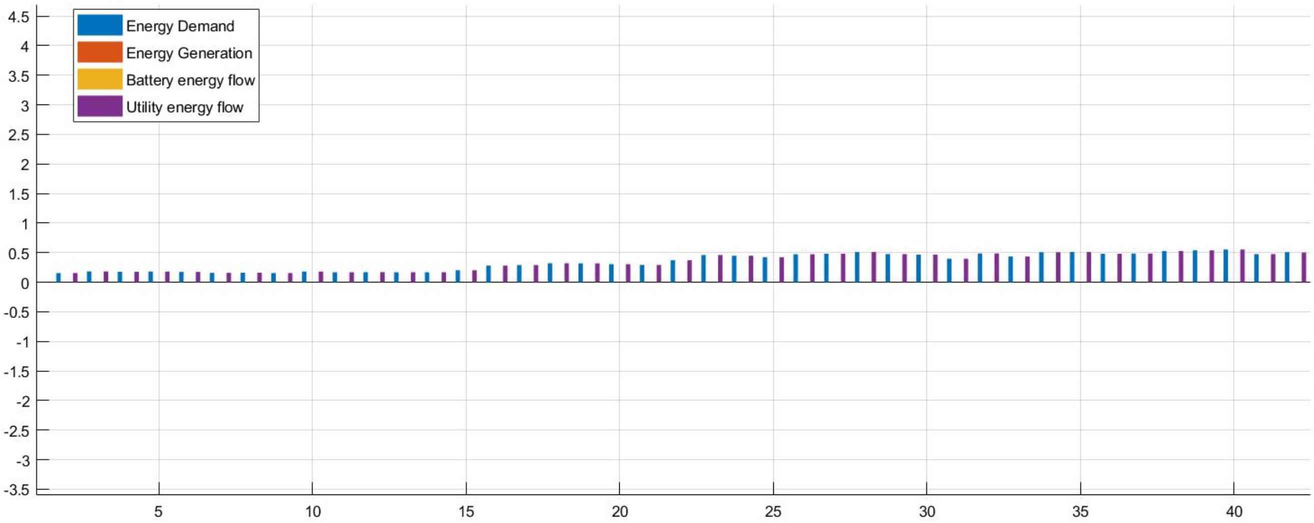

Figure 11. Day-ahead dispatch energy balance – Low load period.

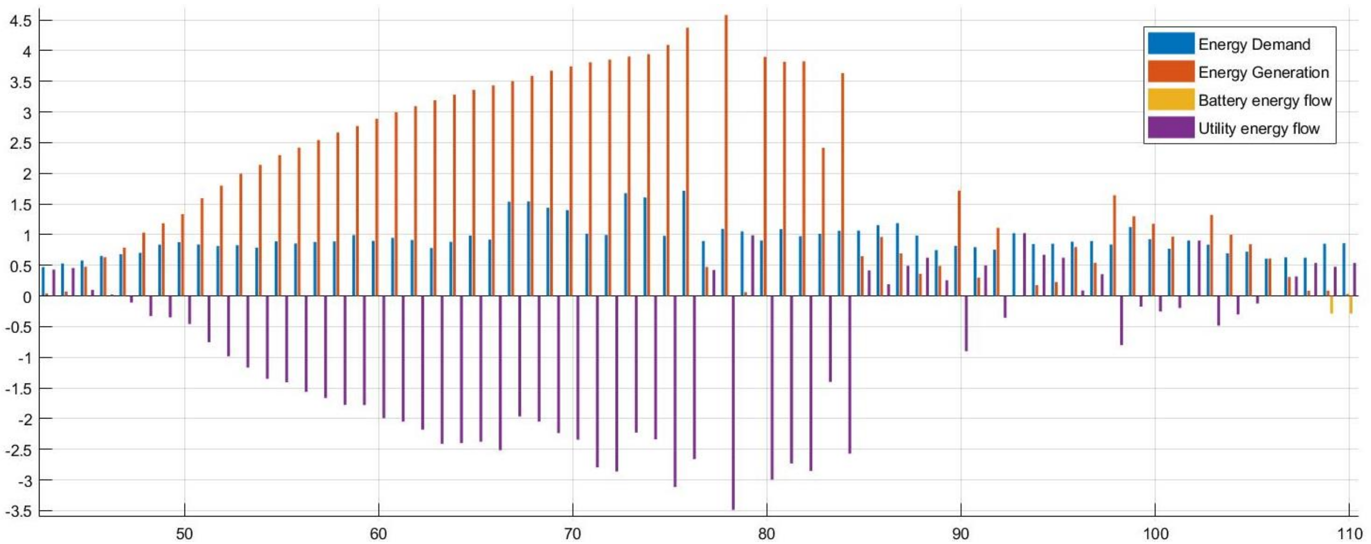

Figure 12. Day-ahead dispatch energy balance – PV generation period.

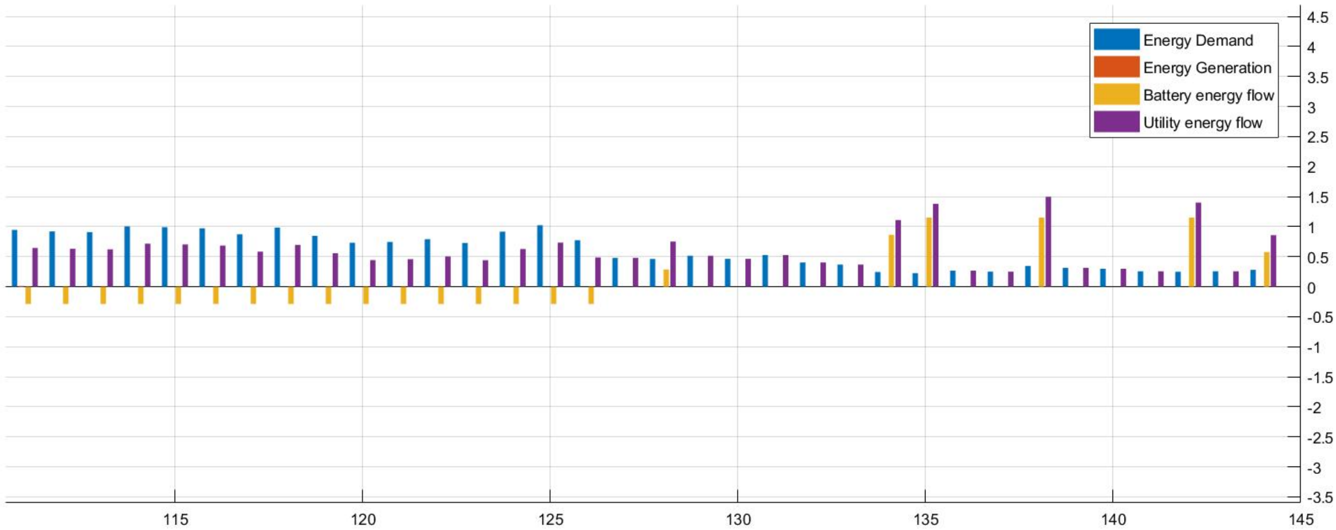

Figure 13. Day-ahead dispatch energy balance – night time.

With the dispatch data set, and with the EMS in place, the simulation was carried out for the 144 points of the full day. Previously performed OPs are used to predict the NOP. For every single point, the deviation calculus is carried out, and then it is verified its magnitude, so the EMS makes its decision.

Figure 14, **Figure 15**, **Figure 16**, bring the intervals on which happened a small, medium, and high deviation. The small deviations happened at the end of the night and at dawn where there is no PV generation and load uncertainties are smaller.

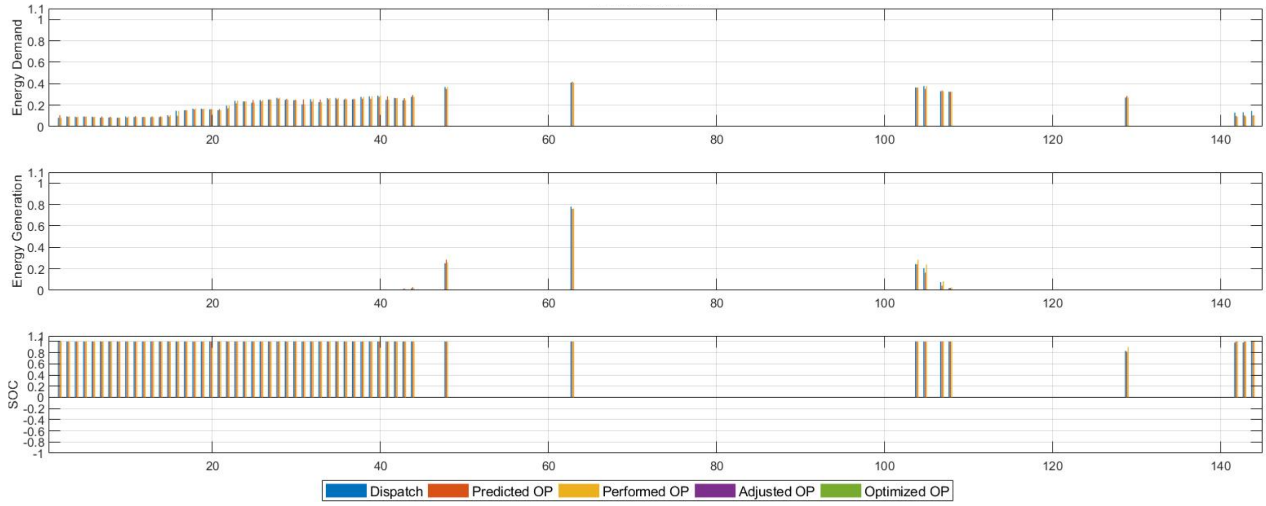

Figure 14. Small Deviation points

The medium deviation occurs throughout the day, on which load and generation are more responsible for the bigger value of deviation. When energy tariffs are higher (109 to 126), the systems adjust the DES discharging rate so it can reduce even more the utility bill and avoid load curtailment, which will only happen in case MD is disconnected from the wider grid and energy demand is greater than what the DES can provide in the 10 minute-interval.

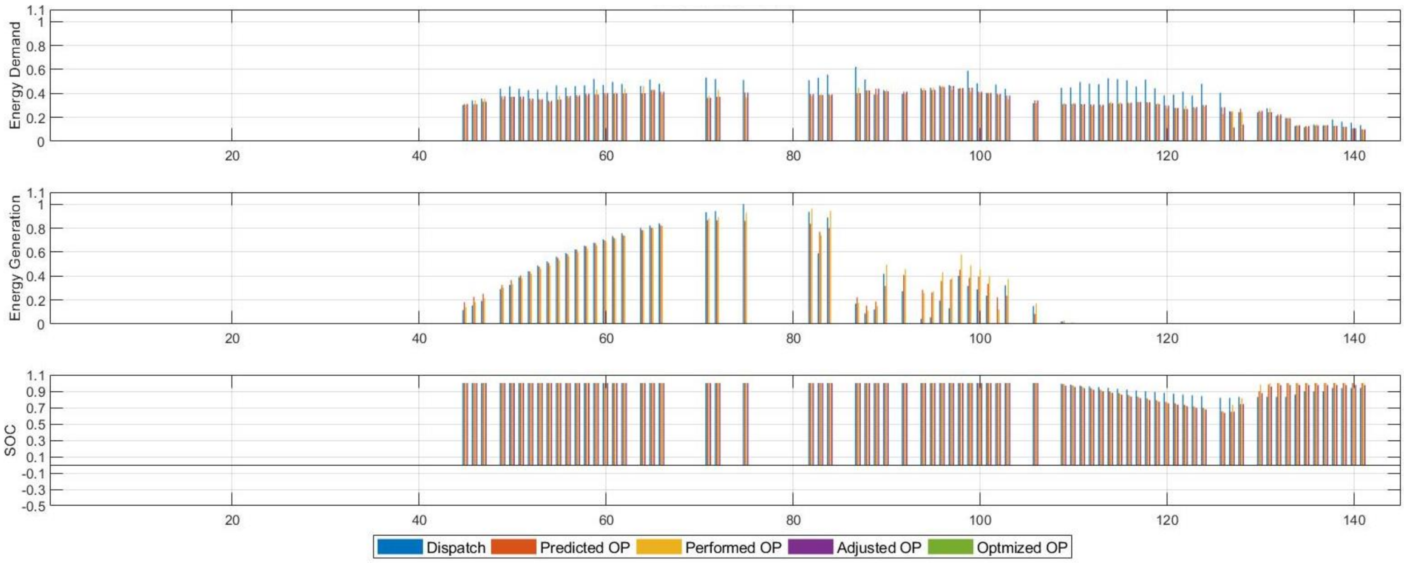

Figure 15. Medium deviation points

High deviation occurs especially because of the uncertainty with the load during the day, where the performed energy in certain periods where halved in comparison to what was planned in day-ahead dispatch. This way, the optimization system was called to generate a new operation point.

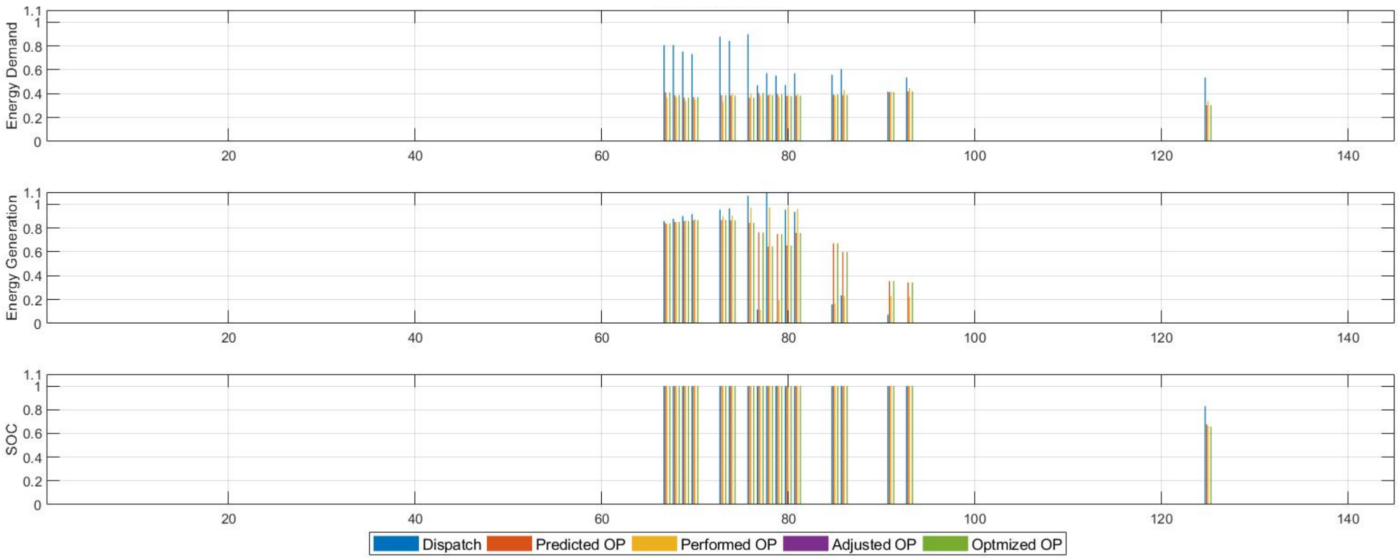

Figure 16. High deviation points

Regardless of the deviation encounter, the utility flow is used to perform the load balance in real-time. In **Erro! Fonte de referência não encontrada.** Figure 17, Figure 18 and Figure 19 it's possible to see the new energy balance with the MD's performed operation points. The differences between this and the one presented in **Erro! Fonte de referência não encontrada.** Figure 11, Figure 12 and Figure 13 are in the intervals where it was encountered a medium or high deviation. When the tariff is in higher prices, the EMS made the DES discharging rate a little higher to reduce the utility bill cost for the MD. After the prices reduce (after 126) there is a huge amount of energy flow coming from the utility to the MD to be used to charge the DES again. During the day there are some divergences between the planned and performed generation as well. That was correct by DSS.

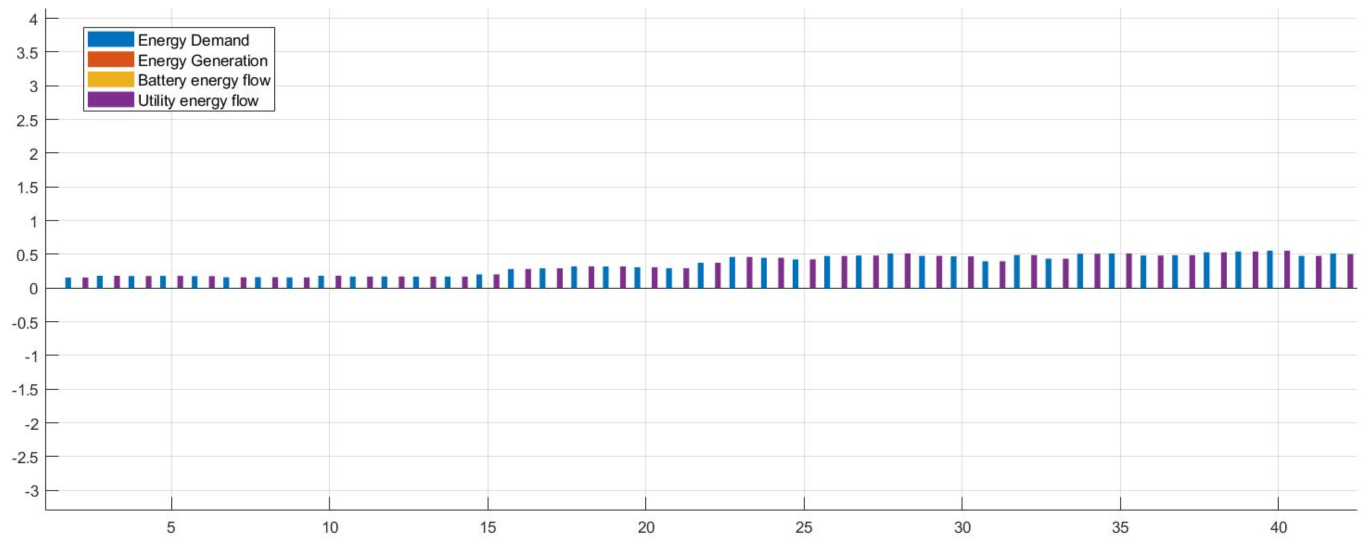

Figure 17. Performed Operation Point energy balance – Low load period.

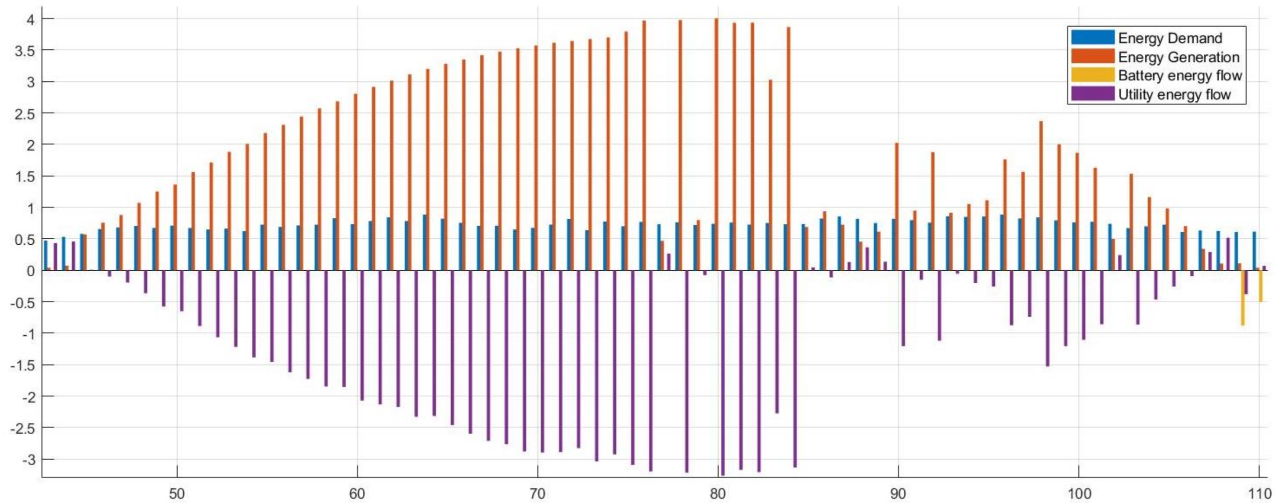

Figure 18. Performed Operation Point energy balance – PV Generation period

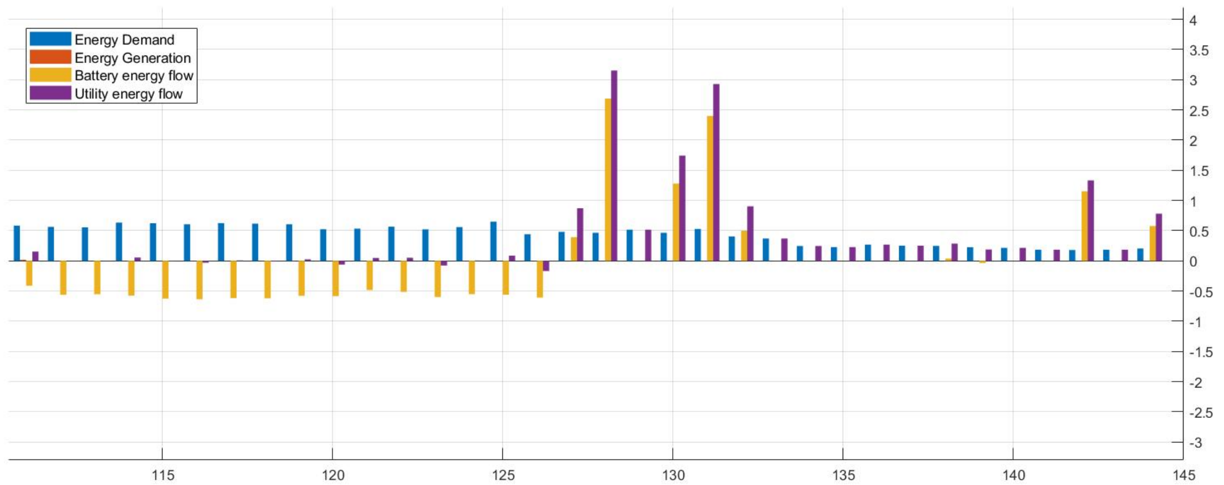

Figure 19. Performed Operation Point energy balance – Night Period.

DISCUSSION

In the small deviation situations (Figure 20) it's possible to see that the energy balance of what was performed by the MD is the same as the planned dispatch. The reason for that is that the EMS understands that a small deviation will not interfere in the operation of the MD, so no action is taken.

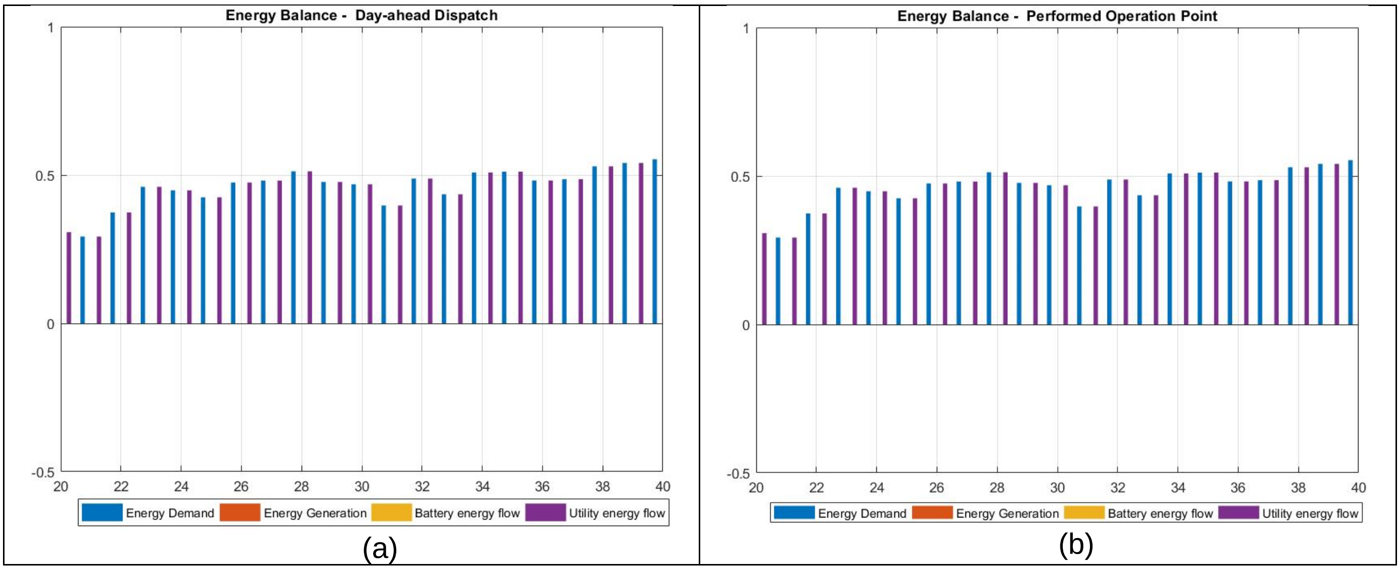

Figure 20. Small deviation Discussion. (a) Day-ahead dispatch. (b) Performed Operation Point.

For the medium deviation (Figure 21) is possible to see that there is a difference in energy demand, due to the load uncertainties, making it almost halved. The EMS increases the discharge rate to reduce to almost zero the need for the utility energy in this period on which the energy tariff is higher and consequently, reducing operational costs. After the tariff returns to the low value, there's a huge amount of energy coming from the utility grid to charge the DES back again. The EMS has chosen a way to meet the needs for energy at a lower operational cost.

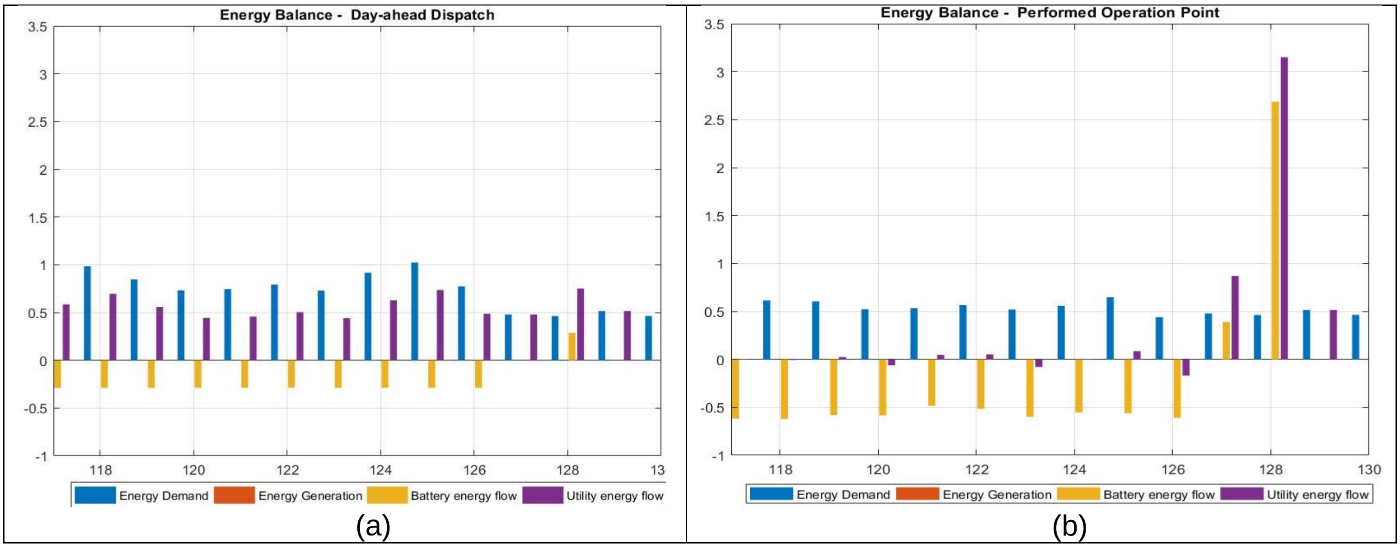

Figure 21. Medium deviation discussion. (a) Day-ahead dispatch. (b) Performed Operation Point.

In Figure 22, points 80 to 84 happen high deviations situations, caused by the great differences in load prediction as well. The optimization system searches for the best way to attend this matter, meeting energy demand with MD's generation and the surplus energy is injected on the utility grid in exchange for energy credits.

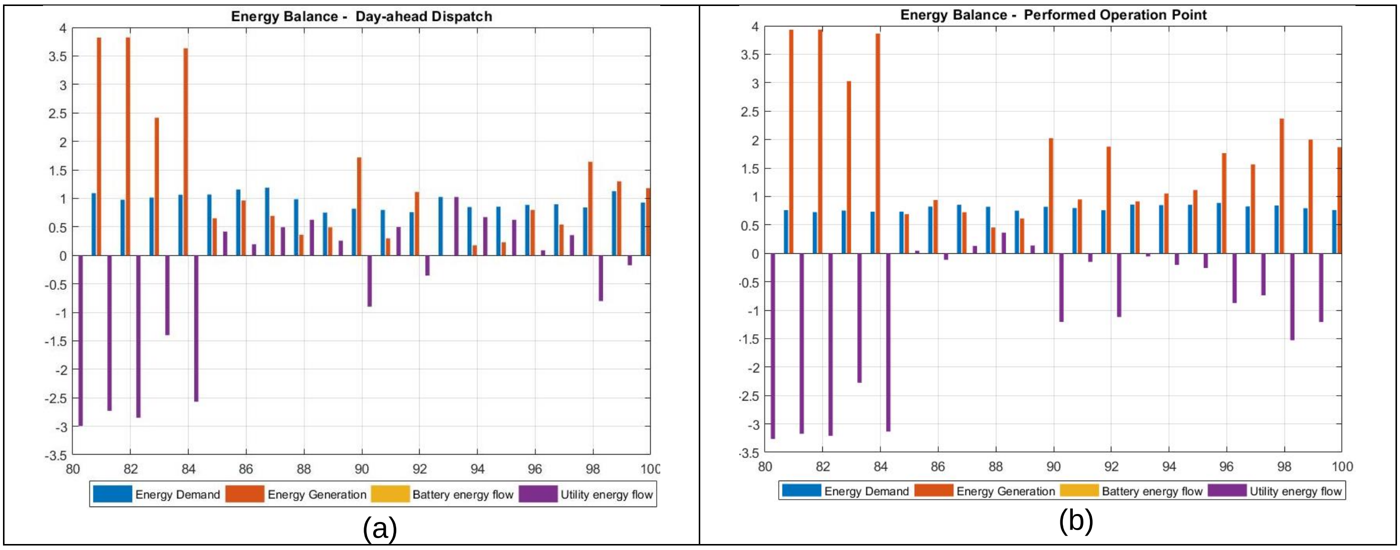

Figure 22. High Deviation discussion. (a) Day-ahead dispatch. (b) Performed Operation Point.

CONCLUSION

The main objective of the present study was to propose a method for a real-time energy management system for microgrids that could overcome possible divergence between what was planned on the day-ahead dispatch and real-time operation, especially in terms of load uncertainty and variation of energy generation on PV systems. The proposed method achieves this matter by analyzing the MD collect data ten minutes before operation, calculating the deviation, and acting accordingly to this deviation size and how much it makes planned operation in day-ahead unfeasible.

The NOP predictor has shown to be a powerful ally to real-time energy management since it has the task only to predict the next operation point 10 minutes from in the future, its predictions errors are really small, helping in solving the uncertainties and variation of energy generation problems encounter in EMS with only a day-ahead management tool. Also, the three-dimension deviation way of categorizing the divergence and serving as a measure of how much the system must act on the operation point showed to be a good way to treat this divergence as well.

The simulation of eight possible scenarios was carried out to show that the system can cover all possible outcomes that could happen during an MD daily operation. Finally, a full-day simulation was carried out, using real data, and comparing it with a day-ahead dispatch. This way was possible to test and validate the proposed method, and it's possible to see that the uncertainties are carried out nicely by the system, changing the MD operation point to get a better result and even reducing operational cost.

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