Stochastic Unit Commitment in Microgrids: Influence of the load forecasting error and the availability of energy storage

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Abstract

A Stochastic Model for the Unit Commitment (SUC) problem of a hybrid microgrid for a short period of 24 hours is presented. The microgrid considered in the problem is composed of a wind turbine (WT), a photovoltaic plant (PV), a diesel generator (DE), a microturbine (MT) and a Battery Energy Storage System (BESS). The problem is addressed in three stages. First, based on the historical data of the demanded power in the microgrid, an ARMA model is used to obtain the demand prediction. Second, the 24-hour-ahead SUC problem is solved, based on generators' constraints, renewable generation and demand forecast and the statistical distribution of the error in the demand estimation. In this problem, a spinning reserve of the dispatchable units is considered, able to cover the uncertainties in the demand estimation. In the third stage, once the SUC problem has been solved, a case study is established in real time, in which the demand estimation error in every moment is known. Therefore, the objective of this stage is to select the spinning reserve of the units in an optimal way to minimize the cost in the microgrid operation.

Keywords: Microgrid, Distributed generation, Energy storage sources, Unit commitment problem.

Nomenclature

- Acronyms:

MT	Microturbine
DE	Diesel Engine
PV	Photovoltaic unit
WT	Wind Turbine
BESS	Battery Energy Storage System
SOC	State Of Charge

- Index:

i	unit index
t	time index

- Parameters:

a_i, b_i and c_i	Operation and manteinance costs of dispatchable unit i.
P_{max_i}	Maximum generation capacity of unit i.
P_{min_i}	Minimum generation capacity of unit i.
P^c_{max}	Maximum charging rate of the BESS at time t.
P^d_{max}	Maximum discharging rate of the BESS at time t.
SOC_{max}	Maximum state of charge of the BESS.
SOC_{min}	Minimum state of charge of the BESS.

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- Parameters:
  - η_c Battery charging efficiency.
  - η_d Battery discharging efficiency.
  - P_t^d Power demanded at time t.
  - r_i^{up} Spinning reserve cost in unit i.
  - μ_t Mean of the distribution of the demand forecast error at time t.
  - σ_t Standard deviation of the demand forecast error at time t.
  - w_t Demand forecast error at time t for a study case.

- Variables:
  - $P_{i,t}$ Power given by unit i at time t.
  - SOC_t State of charge of the BESS at time t.
  - $R_{i,t}^{up}$ Up spinning reserve of the dispachable unit i at time t.
  - R_t^{up} Up spinning reserve of all the dispachable units at time t.
  - $R_{i,t}^{down}$ Down spinning reserve of the dispachable unit i at time t.
  - R_t^{down} Down spinning reserve of all the dispachable units at time t.
  - $\delta_{i,t}$ (binary) On/Off status of generator i at time t.
  - $\hat{P}_t^d$ Demand forecast.

1. Introduction

The International Committee of Large Electrical Networks (CIGRE) defines microgrids as: electrical distribution systems that contain distributed energy resources and loads (generators, storage devices and controllable loads) that can operate in a controlled way connected to the main network or isolated [1]. They make it possible to respond to the need to supply energy to isolated cities, islands or specific consumption, contributing to the improvement of service reliability, and to reduce losses and enhance the stability of the system [2], [3].

Recently, several forms of energy storage with relative intensity have been studied, including: electrochemical batteries, air compressors, supercapacitors, flywheels and magnetic superconductors [4]. The energy storage system (ESS) is considered an indispensable element of a reliable microgrid because it provides significant benefits to the operation of microgrids both in isolated and grid-connected operation modes [5]. In the isolated operation mode, the ESS can be used to ensure the balance between generation and load, reduce the operating cost by storing energy during the low-price period and discharging the accumulated energy during the high-price period, reducing the peak loads [3].

In particular, the battery energy storage system (BESS) has proven to be an efficient technology for applications related to power management and power quality in microgrids, e.g., covering consumption peaks [6], participating in active power control [7], flattening the load curve [8], participating in the frequency control [9], voltage control [10] and working as a reserve in the microgrid [11], [12]. Therefore, the selection of the optimal size and the operation strategy, including the BESS loading/unloading cycle, is a priority to obtain the maximum benefit in the operation of the microgrid.

The Unit Commitment (UC), initially determines the programming of the units that must start and stop in order to respond to the required demand [13]. Once the UC has been carried out, the economic dispatch (ED) is responsible for assigning to the programmed units power to generate and to cover the demand in the most economical way, while satisfying the physical constraints of the generating units (power balance, power generation limits) [13] [14]. Stochastic unit commitment (SUC) is presented as an alternative to deterministic models. Moreover, it addresses the problems of uncertainties in the system, associated with the generation of renewable energy and the demand [15], [12],[16].

Because of the differences between traditional generation systems and microgrids, new and different approaches and methods of solution to the problems of ED and UC have been proposed. The minimization of operating costs and CO_2 emissions are presented in [17], [18]. In [17], the model does not include intermittent renewable energy resources and the economic dispatch is solved through a quadratic programming approach. In [18] energy storage devices are incorporated and an optimization methodology based on heuristic approaches is proposed. In [12] an optimization problem is proposed for a hybrid micro-grid in which the exchange of energy between the BESS and the electrical network is decided through a mixed integer quadratic programming problem. Restrictions on generation reserves are also considered for frequency control in [16].

Current research on microgrids is directed towards the following topics [19]:

1. Planning and dispatch of units for the supply of the demand, taking into account the associated uncertainty and the required reserve levels.

2. The reliable and economical operation of microgrids with high penetration of intermittent generation, specially in isolated operation.

Based on the preliminary work presented in [20], this paper proposes to address the optimal operation of an isolated microgrid in the short term, 24 hours ahead, by selecting the scheduling that produces the greatest savings in fuel consumption. In addition, the analysis presented focuses on a robust approach to the problem, adapting to the uncertainty in demand, obtaining valid results in operation up to more than 99% of cases. The contribution of this study can be summarized as follows:

1. It is proposed to solve the operation planning of a microgrid, in the short term, considering the uncertainty in the demand forecast.

2. A three-stage problem is proposed:

   (a) First, based on the historical data of the demand, an ARMA technique is used to obtain an appropriate estimation of the 24-hour curve. Furthermore, considering the historical data, it is possible to adjust the prediction error to a normal distribution.

   (b) Second, we propose a planning stage in which, based on the estimated demand curve and the most probable prediction of renewable generation, the SUC problem is solved. In this problem, we consider a spinning reserve in the dispatchable units able to cover the estimation error in most cases.

   (c) Finally, an operation stage is considered. In this stage, we consider a real study case in which the value of the demand prediction error is known. The aim of this stage is to decide which dispatchable unit will cover the demand prediction error. Note that the SUC problem was solved in the previous stage and therefore the status on-off of the dispatchable units is known.

3. Finally, the impact that the variation of the parameters of the battery bank has on the problem is quantified.

The article is organized as follows. Section 2 presents the demand prediction model. In Section 3, the SUC problem is formally stated. Section 4 describes the structure of the microgrid considered and introduces some simulations in order to show the effectiveness of the proposed method. Finally, Section 5 presents some conclusions and remarks.

2. Uncertainties Modeling and Load Forecasting

The historical data of the load forms time series that can be used to predict the future electrical demand in a microgrid (see for instance [21] and [22]).

The ARMA model is a combination of an autoregressive model (AR) and moving averages (MA) used to predict the future behavior of a signal $y(t)$ based on the historical data, and is formulated as follows:

$$y(t) = \sum_{i=1}^{p} \Phi_i y_{t-1} + \sum_{j=0}^{q} \theta_j \varepsilon_{t-j} \tag{1}$$

where Φ_i are the coefficients of the autoregressive model, θ_j are the coefficients of the moving average term, ε_{t-j} are the prediction errors that are adjusted by the average of the normal distribution function and standard deviation of the sample and $y(t)$ is the signal to be estimated. This model suggests that the value for any point in the time series is a linear combination of the p previous values of the load and the q previous values of the errors.

In this study, two-year historical demand data have been used to obtain the coefficients in (1) and the hourly samples. In order to fix the values of p and q, the Akaike's Information Criterion (AIC) [21] has been used. The values obtained for these parameters are $p = 6$ and $q = 5$.

The result of this algorithm is the prediction of the demand of the microgid for the next 24 hours. In order to know the accuracy of the method, some simulations are run and the result is compared with known demand historical data. Thus, we can define ε as the error in the demand forecast, calculated by using:

$$\varepsilon = \frac{\text{predicted value} - \text{real value}}{\text{predicted value}} \times 100 \tag{2}$$

The error at each hour is adjusted to a normal distribution[1], which allows to apply the $3\,\sigma$ criteria. This criteria provides a reliability band of 99,73%. That is, the real value of the demand error will be in the band defined by $[\mu_t - 3\,\sigma_t, \mu_t + 3\,\sigma_t]$ in the 99,73% of the cases. Once solved the SUC problem, we will consider different study cases. For that cases, we consider a real value for the demand estimation error that we denote by ω_t. Consequently, $\omega_t \in [\mu_t - 3\,\sigma_t, \mu_t + 3\,\sigma_t]$ in most of the cases.

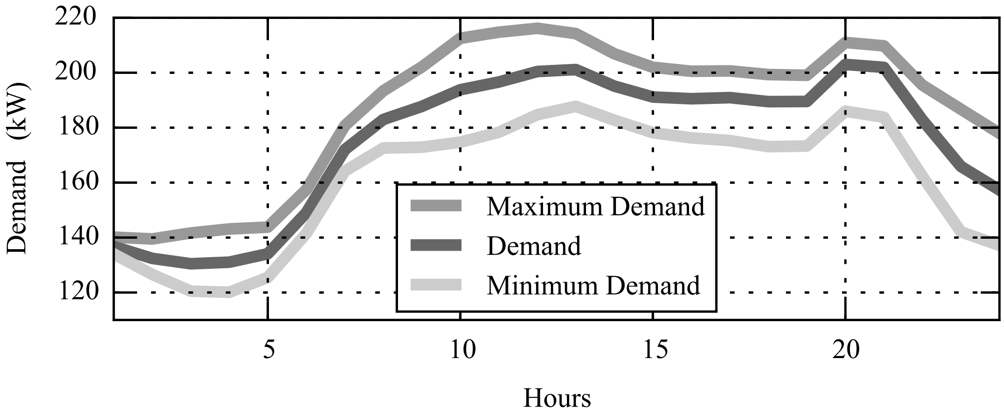

Figure 1: Demand of the microgrid, with confidence intervals according to criterion $3\,\sigma$.

The results of the simulations are shown in Figure 1, where a 24-hour case is depicted, together with the maximum and the minimum value for the demand forecast obtained after applying the $3\,\sigma$ criteria.

Note that a similar procedure can be used to estimate the error associated with uncertainty in renewable generation, including it in the problem of optimal programming of the microgrid resources and reserves. However, this paper focuses on the error associated with the demand, so that the renewable generation in the next 24 hours, both wind and PV, is considered exactly known.

3. Scheduling Problem

In this section we formally define the 24-hour-ahead scheduling problem. As it was introduced in Section 1, the problem is divided in several stages. The first stage was tackled in Section 2 where a model to obtain a demand forecast was introduced. In this Section we define stages two and three, where the SUC problem and a study case are presented.

Figure 2 shows a schematic diagram of the scheduling problem. Based on the historical data and the prediction model developed in Section 2, a prediction of the load for every time t is obtained, $\hat{P}_t^d$, together with the associate error distribution, $\mathcal{N}(\mu_t, \sigma_t)$. After that, by using the demand forecast and the error distribution, the SUC problem is solved, obtaining a robust solution that is valid for most of the cases. Finally, some scenarios are simulated, testing the behavior of the microgrid for different values of the error made in the demand estimation, ω_t.

[1]Four days data was used to estimate the fifth day. This test was repeated 96 times to obtain the parameters of the statistical distribution.

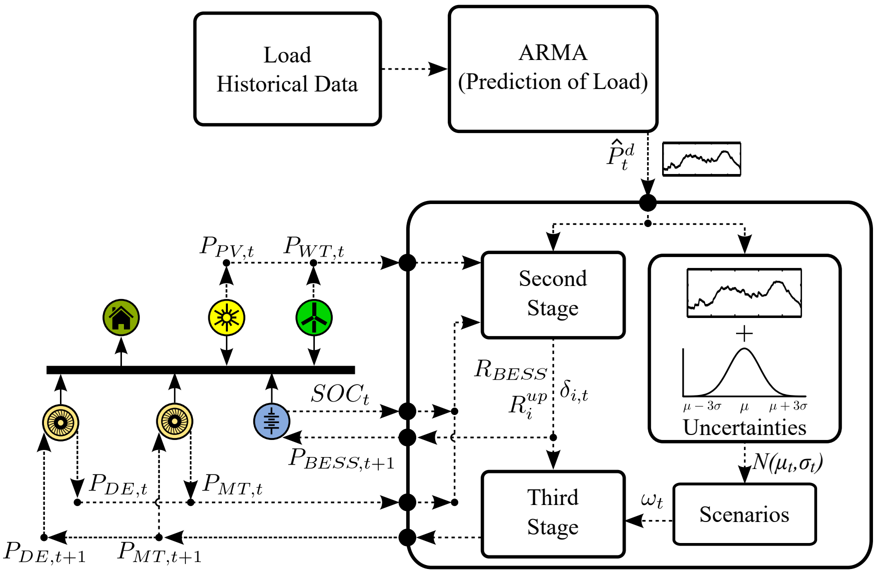

Figure 2: Flowchart of the problem.

111 *3.1. Microgrid Structure*

112 The structure of the simulated microgrid is shown in Figure 3 [23]. It is composed by a wind turbine (WT), a
113 photovoltaic plant (PV), a diesel engine (DE), a microturbine (MT) and a Battery Energy Storage System (BESS).
114 The power limits of the different generators are shown in the figure.

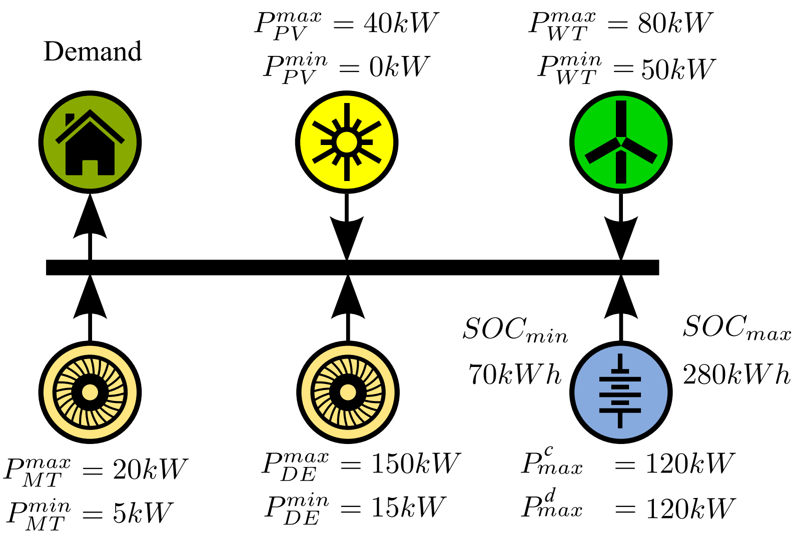

Figure 3: Structure of the microgrid considered in the problem.

115 For our study, we will consider that the powers generated by renewable resources (PV and WT) are known in
116 advance. Nevertheless, the power generated by the dispatchable units (DE and MT) are variables of our problem
117 as well as the management of BESS. Thus, the SUC problem is reduced to obtain which dispatchables unit will be
118 connected to the microgrid at each time t.

3.2. Stochastic Unit Commitment

Stochastic Unit Commitment (SUC) has been introduced as a promising tool to deal with the problem of power generation planning involving uncertainties [14]. Conceptually, the problem of stochastic optimization is formulated as a two-stage linear problem [15]. In this optimization problem, the state of the different dispatchable units at every time t is obtained. Let $\delta_{i,t}$ be a boolean parameter that specifies the status of the generator i at time t ($\delta_{i,t}$ takes 1 if the generator is on and 0 otherwise). Analogously, let $P_{i,t}$ be the power generated by generator i at time t.

Based on the demand forecast and the statistical distribution of the estimation error, the solution of the SUC problem must provide the state of all the dispatchable units involved in the microgrid. For this purpose, we propose a robust method: as the estimation error lay in a band defined by $[\mu_t - 3\,\sigma_t, \mu_t + 3\,\sigma_t]$ in the 99.73% of the cases, the SUC problem is solved in order to guarantee the reliability in the real-time operation under this hypothesis.

Next, the objective function and the different constraints involved in the problem are introduced.

1. Objective function.

   The objective function minimizes the overall production cost subject to the constraints (4)-(15). In this cost function two main components are considered: the energy and the reserve cost of the dispatchable units.

   On the one hand, the energy cost considers the start-up cost of the generators as well as the fuel cost used by the dispatchable units. On the other hand, the reserve cost reflects the effect of generating less power than the available by the generator. Reserve costs are typically much lower than energy costs [24], [25].

   Considering all the parameters aforementioned, we can define the sequel cost function:

$$\min \sum_{t=1}^{24} \Big[a_{DE}\delta_{DE,t} + b_{DE}P_{DE,t} + c_{DE}P_{DE,t}^2 + r_{DE}^{up}R_{DE}^{up} \qquad (3)$$
$$a_{MT}\delta_{MT,t} + b_{MT}P_{MT,t} + c_{MT}P_{MT,t}^2 + r_{MT}^{up}R_{MT}^{up} \Big],$$

   where a_i, b_i and c_i are the fuel cost coefficients associated to each dispatchable unit and R_i^{up} and r_i^{up} are, respectively, the spinning reserve of dispatchable unit i and its corresponding cost. It is worth pointing out that the costs associated with the dispatchable units are the same that the ones considered in [26], [27].

2. Constraints

   - Power balance
     The total power generated by all the generators (MT, DE, WT, PV) and the power generated or consumed by the BESS must equal the estimated power demanded by the microgrid at every time t,

$$\hat{P}_t^d = P_{MT,t} + P_{DE,t} + P_{WT,t} + P_{PV,t} + P_{BESS,t} \quad \forall t. \qquad (4)$$

   - Generation limits
     The power generated by the devices is physically limited. That is, the generation of each unit must be within the limits

$$P_{min_{DE}}\,\delta_{DE,t} \leq P_{DE,t} \leq P_{max_{DE}}\,\delta_{DE,t}, \qquad (5)$$

$$P_{min_{MT}}\,\delta_{MT,t} \leq P_{MT,t} \leq P_{max_{MT}}\,\delta_{MT,t}, \qquad (6)$$

     where P_{min_i} and P_{max_i} define the minimum and maximum power that the generator i can produce, respectively.

     Note that this constraint has been modified in order to consider the status on-off of the generator. Thus, if the generator is not active, $\delta_{i,t} = 0$, $P_{i,t}$ must be zero.

   - Storage constraints
     In the case of the BESS, the power $P_{BESS,t}$ can be both positive and negative. Positive values indicate that the battery is delivering power, acting as an additional generator. When the values are negative it means that the battery is charging, acting as a load in the microgrid.

The BESS management has several associated restrictions. First, the power given or received by the BESS is physically limited as it happens with the rest of dispatchable units. Therefore:

$$-P^c_{max}\,\delta_{BESS,t} \leq P_{BESS,t} \leq P^d_{max}\,\delta_{BESS,t}, \tag{7}$$

where P^c_{max} defines the maximum charging power admissible by the battery and P^d_{max} is the maximum discharging power.

Second, let us define SOC_t as the state of charge of the battery. This parameter evolves dynamically with time. Due to physical limitations in the battery storage capability, the SOC_t must lay in a band with the following limits:

$$SOC_{min} \leq SOC_t \leq SOC_{max}, \qquad \forall t, \tag{8}$$

where SOC_{min} and SOC_{max} are the minimum and maximum values for the state of charge of the battery, respectively.

Finally, the charging and discharging procedures of the battery have an efficiency associated that must be taken into consideration. Thus:

$$SOC_t = \begin{cases} SOC_{t-1} - \frac{\Delta t P_{BESS,t}}{\eta_d} & if \quad P_{BESS,t} \geq 0, \\ SOC_{t-1} - \Delta t P_{BESS,t}\,\eta_c & if \quad P_{BESS,t} < 0, \end{cases} \tag{9}$$

- Spinning reserve

  The spinning reserve defines the amount of power available in the generator for a given operating point. That is, if the generator is providing $P_{i,t}$, the spinning reserve, $R^{up}_{i,t}$, is defined as:

$$R^{up}_{i,t} = P_{max_i} - P_{i,t} \geq 0, \tag{10}$$

where i denotes the corresponding generation unit. Note that only the dispatchable units and the battery bank provide spinning reserve.

The sum of the spinning reserves for the three aforementioned generators is the total spinning reserve of the microgrid at time t, R^{up}_t:

$$R^{up}_t = R^{up}_{DE,t} + R^{up}_{MT,t} + R^{up}_{BESS,t}, \quad \forall t, \tag{11}$$

Analogously, let $R^{down}_{i,t}$ be the difference between the power generated by unit i at time t and the minimum power that the generator can produce:

$$R^{down}_{i,t} = P_{i,t} - P_{min_i} \geq 0, \tag{12}$$

$$R^{down}_t = R^{down}_{DE,t} + R^{down}_{MT,t} + R^{down}_{BESS,t} \quad \forall t, \tag{13}$$

In order to satisfy the three-sigma criteria, we impose that the spinning reserve must cover the demand estimation error in the 99.73% of the cases:

$$R^{up}_t \geq 3\,\sigma_t \quad \forall t, \tag{14}$$

$$R^{down}_t \geq 3\,\sigma_t \quad \forall t, \tag{15}$$

3.3. Economic Dispatch

In the second optimization problem, namely the Economic Dispatch [28], it is considered that the binary variables $\delta_{i,t}$ remain constant and the real demand differs from the predicted:

$$P^d_t = \hat{P}^d_t + \omega_t,$$

where $\hat{P}^d_t$ and P^d_t are, respectively, the estimated and the real power demanded by the microgrid, and ω_t is the error in the estimation for a real scenario. This means that the spinning reserve that was determined in the first stage (R^{up}_t y R^{down}_t) is affected by the variations in the demand, which causes an adjustment of the reserve of the dispatchable units and the battery bank.

Thus, the problem in this stage is to find the variations of the power supplied by the generators, $\Delta P_{i,t}$, such that the cost is minimized. To do that, let us formulate a second optimization problem.

1. Objective function

The following objective function minimizes the overall production cost subject to the constraints in (17)-(21). The cost function is defined as:

$$min \sum_{t=1}^{24} \Big[a_{DE}\, \delta_{DE,t} + b_{DE}\, (P_{DE,t} + \Delta P_{DE,t}) + c_{DE}\, (P_{DE,t} + \Delta P_{DE,t})^2 \qquad (16)$$

$$+\ a_{MT}\, \delta_{MT,t} + b_{MT}\, (P_{MT,t} + \Delta P_{MT,t}) + c_{MT}\, (P_{MT,t} + \Delta P_{MT,t})^2 \Big].$$

2 Constraints

- Power balance: The variation in the demand must be satisfied by the generators,

$$\omega_t = \Delta P_{MT,t} + \Delta P_{DE,t} + \Delta P_{BESS,t} \qquad \forall t, \tag{17}$$

- Generation limits: The power generated must lay in a band due to physical limitations:

$$P_{min_{DE}}\, \delta_{DE,t} \leq P_{DE,t} + \Delta P_{DE,t} \leq P_{max_{DE}}\, \delta_{DE,t} \quad \forall t, \tag{18}$$

$$P_{min_{MT}}\, \delta_{MT,t} \leq P_{MT,t} + \Delta P_{MT,t} \leq P_{max_{MT}}\, \delta_{MT,t} \quad \forall t, \tag{19}$$

- Storage constraints: The State of Charge of the battery must fulfill the constraints imposed in (7)-(9). Thus, that constraints can be reformulated as:

$$SOC_t = \begin{cases} SOC_{t-1} - \frac{\tilde{P}_{BESS,t}}{\eta_d} & if \quad \tilde{P}_{BESS,t} \geq 0, \\ SOC_{t-1} - \Delta t \tilde{P}_{BESS,t}\, \eta_c & if \quad \tilde{P}_{BESS,t} \leq 0, \end{cases} \tag{20}$$

$$-P^c_{max}\, \delta_{BESS,t} \leq \tilde{P}_{BESS,t} \leq P^d_{max}\, \delta_{BESS,t}, \tag{21}$$

where for simplicity in the notation we have denoted $\tilde{P}_{BESS,t} = P_{BESS,t} + \Delta P_{BESS,t}$.

4. Simulation Results

This section presents simulation results of the two-stage optimization problem presented in the previous section. It is worth pointing out that, although the problem is a Mixed Integer Non-Linear Programming (MINLP) problem, the only non-linear term is the quadratic one defined in the cost functions (3) and (16). Thus, it is possible to obtain the solution of the problem by solving subsequents MILP problems (see for instance [29]).

4.1. Microgrid data

Let us consider the power parameters of the generation units exposed in Table 1. Table 2 shows the cost coefficients considered for the simulation.

Table 1: Technical data of generator units [17]

Sourses	P_{min} (kW)	P_{max} (kW)	SOC_{min} (kWh)	SOC_{max} (kWh)	η_c	η_d	P^c_{max} (kW)	P^d_{max} (kW)
Microturbine	5	20	-	-	-	-	-	-
Diesel	15	150	-	-	-	-	-	-
PW	50	80	-	-	-	-	-	-
PV	0	40	-		-	-	-	-
BESS	-	-	70	280	0,9	0,9	120	120

Table 2: Costs of generator units [17]

DDG	Cost coefficients		
	a ($)	b ($/kW)	c ($/kW^2)
Microturbine	2,62	0,15	0,15
Diesel	0,6	0,05	0,02

Finally, Figures 4 and 1 show, respectively, the power profiles of the renewable energy generators and the actual and predicted demand for 24 hours onwards, respectively.

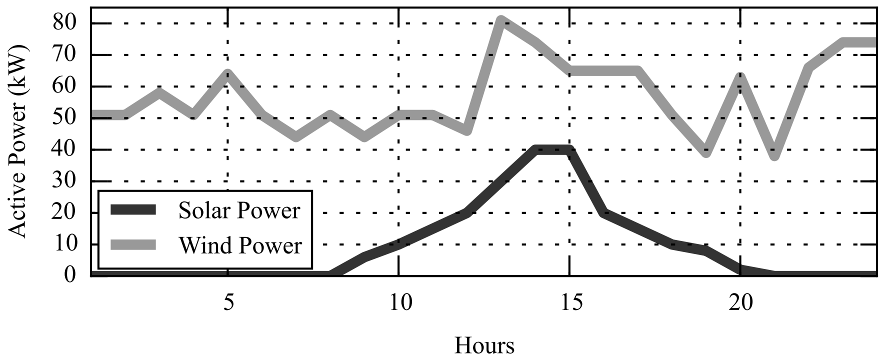

Figure 4: Output of solar and wind power unit for 24 hours.

4.2. Simulation Results

4.2.1. Base Case

First, Table 3 presents the solution of the Stochastic Unit Commitment problem (1: on; 0: off). As can be noticed, the dispatchable units are mostly connected due to the robust criteria followed in the SUC resolution, i.e., both dispatchable units are requiered to cover the necessary demand and the reserve due to uncertainty in demand. Note that this criteria can be relaxed for a less robust solution.

Table 3: Unit Commitment of the dispatchable units. Base case.

Unit	Hours (1-24)																							
MT	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
DE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0

Figure 5 shows the value of the power supplied by each generating unit at each time step as a result of the economic dispatch (stage three). In the case of the battery, the negative value of the power indicates that it is charging and the positive values indicate the power supplied by the battery to contribute to the coverage of the demand curve. According to Figure 5 the battery is charged during low demand hours, from 1 to 3 hours, and between 15 and 17 hours when demand begins to decrease after peak hours, 13 and 14 hours, and 23 and 24 hours. The battery is discharged from 8, when the demand starts to increase, to the peak demand at 14, and also from 19 to 20 hours.

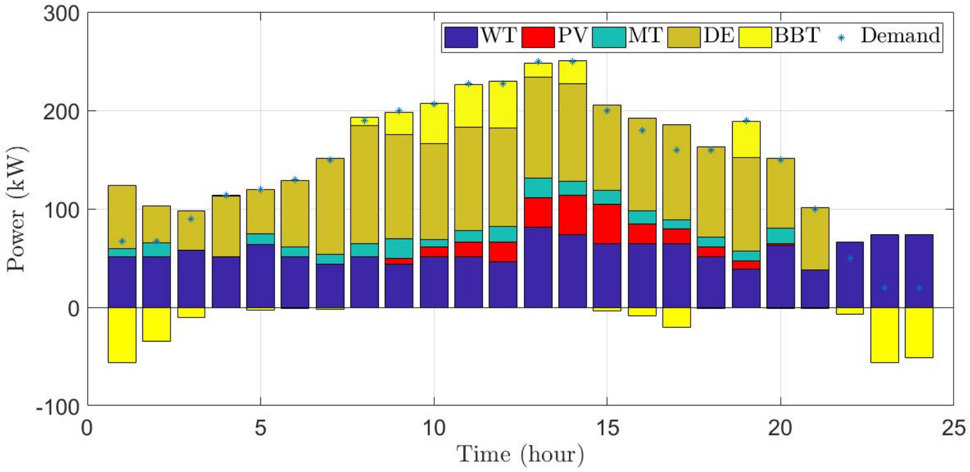

Figure 5: Demand coverage curve. Base case

188 Figure 6 shows the evolution of the SOC and the power supplied by the battery. Note that, consistent with Figure 189 5, the BESS discharges from 8 h to 14 h, the period of greatest consumption, providing power ranging from 10 to 50 190 kW, and it is significantly discharged in the interval from 19 h to 20 h, with a contribution of 40 kW.

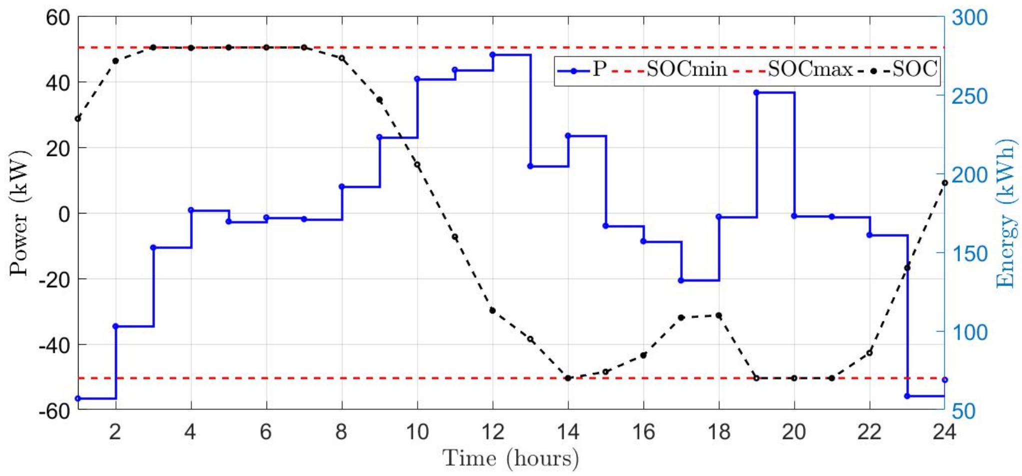

Figure 6: Process of charge and discharge of the battery. Base case.

191 Table 4 presents the changes in power generations given by eq. (17), i.e., the variation of the scheduled power for 192 each of the dispatchable generators (MT and DE) and the BESS, with respect to the power that is actually delivered 193 at each hour, (ΔP).

Table 4: Values of $\Delta P_{i,t}$ y ω_t.

Hour	$\Delta P_{i,t}$ (kW)			ω_t (kW)
	MT	DE	BESS	
1	-0.818	-3.632	4.050	-0.399
2	-0.318	-2.382	3.524	0.824
3	0	-2.382	-1.687	-4.069
4	0	-2.382	-4.886	-7.268
5	-0.318	-2.382	-1.002	-3.702
6	0.037	0.275	0	0.311
7	0.126	0.946	-0.708	0.364
8	0.126	0.946	-0.229	0.844
9	0	0.946	-1.152	-0.207
10	0.126	0.946	-0.392	0.679
11	0.126	0.946	-2.501	-1.430
12	0.126	0.946	1.181	2.253
13	0	0.946	-3.863	-2.917
14	0.126	0.946	0.030	1.102
15	0.126	0.946	-2.264	-1.192
16	0.126	0.946	-0.667	0.405
17	0.126	0.946	1.702	2.774
18	0.126	0.946	3.054	4.126
19	0.126	0.946	-1.835	-0.763
20	0.126	0.946	3.747	4.819
21	0	0.946	3.021	3.967
22	0	0	1.933	1.933
23	0	0	0.030	0.030
24	0	0	-1.086	-1.086

Figure 7 depicts variables $\Delta P_{i,t}$, that is, the difference between the power given by the generators as a result of the SUC problem and the real power given in the ED study-case. Thus, if ω_t is above the zero line, it means that there is a planed power excess.

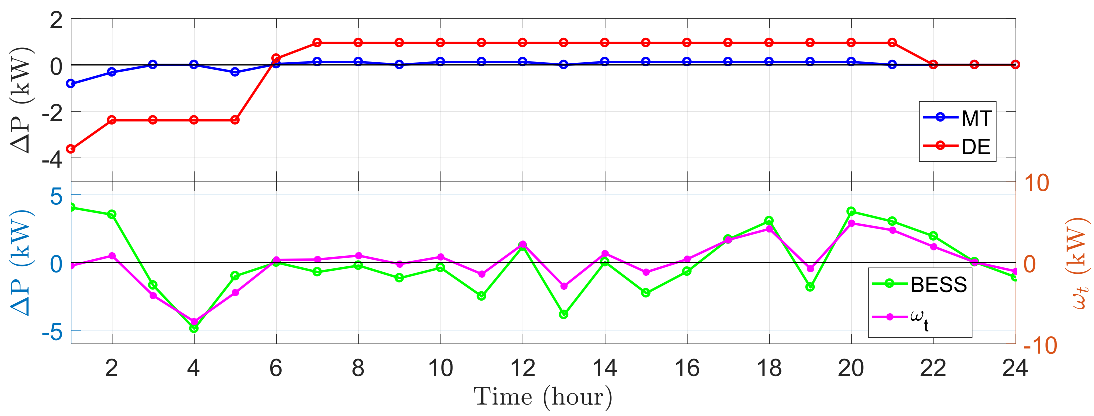

Figure 7: Estimation error ω_t and differences in power generation, $\Delta P_{i,t}$.

It is easy to see that the bigger variations in the power generated by the dispatchable units take place in the DE, meanwhile in the MT the variations are significantly lower. This fact is the result of the costs functions (3), (16) whose cost parameters are shown in Table 2.

4.2.2. Influence of BESS parameters on the problem

In this section, several cases are studied in order to show the effect of the BESS in the solution of the problem. Table 5 lists the values of the BESS parameters that were used to find the most economical variant. As a result of the simulations, it is observed that Case 4 is the one that provides the greatest savings in fuel cost, an improvement of 8.55%.

Table 5: Scenarios for BESS parameters.

Case	P^c_{max} (kW)	P^d_{max} (kW)	SOCmin (kWh)	SOCmax (kWh)	Cost ($)	Savings (%)
1	120	120	70	280	3.154,62	0,00
2	80	80	70	280	3.159,38	-0,15
3	120	120	70	250	3.230,73	-2,41
4	120	120	0	280	2.884,77	8,55
5	120	120	0	250	2.950,52	6,48

In Case 2, the value of the maximum charging and discharging power of the energy storage system is reduced in a 33%. The result obtained increase the operation cost in a 0.15% which is negligible. Case 3 proposes a reduction of the maximum SOC in a 10.7%, that is, the capacity of the battery is reduced. As a result, the operation costs are increased in a 2.41%. In case 5, the minimum SOC of the battery is reduced, which allows to use some extra 70 kWh with respect to base case, and the maximum energy that can be stored (SOCmax) is reduced by 10,7%. This variant will reduce the costs in the installation by 6,48%.

For Case 4, Table 6 shows the result of the Unit Commitment. Note that the DE unit generates power for 22 hours continuously, 1 hour more than in the base case. The MT has delivered power for 17 hours irregularly, 4 hours less than in the base case, and the BESS provides power for 19 hours irregularly (Figure 8), 1 hour less than in the base case.

Table 6: Unit Commitment of the dispatchable generators (BESS Case 4).

Unit	Hours (1-24)																							
MT	1	0	1	0	1	0	1	1	0	1	1	1	1	0	0	1	1	1	1	0	1	1	1	1
DE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0

It is noteworthy that the BESS discharge power reached with this alternative (Figure 8) are much higher in comparison to the values obtained in the base case (Figure 5), particularly between 9 to 14 h, that are the time with the highest consumption.

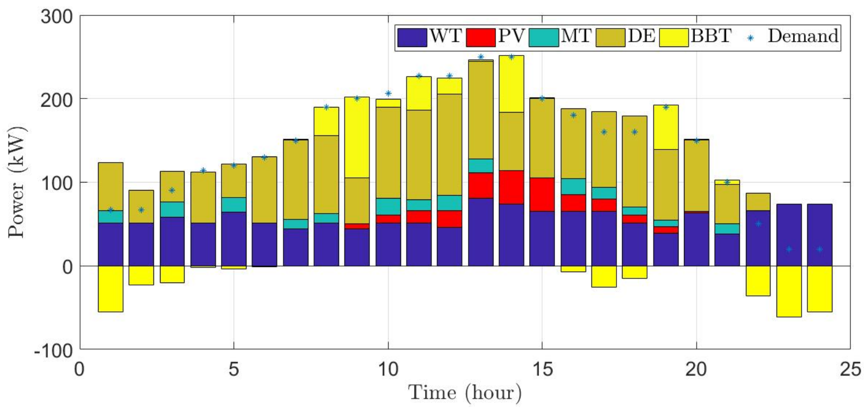

Figure 8: Demand coverage curve. BESS Case 4.

The analysis of Figures 8 and 9 shows that a trade off between the power given by the battery and the power supplied by the dispatchable units exists. In that way, the battery supplies more power during the peak hours of the day, reducing the power produced by the dispatchable units, and, therefore, reducing the operation cost of the microgrid.

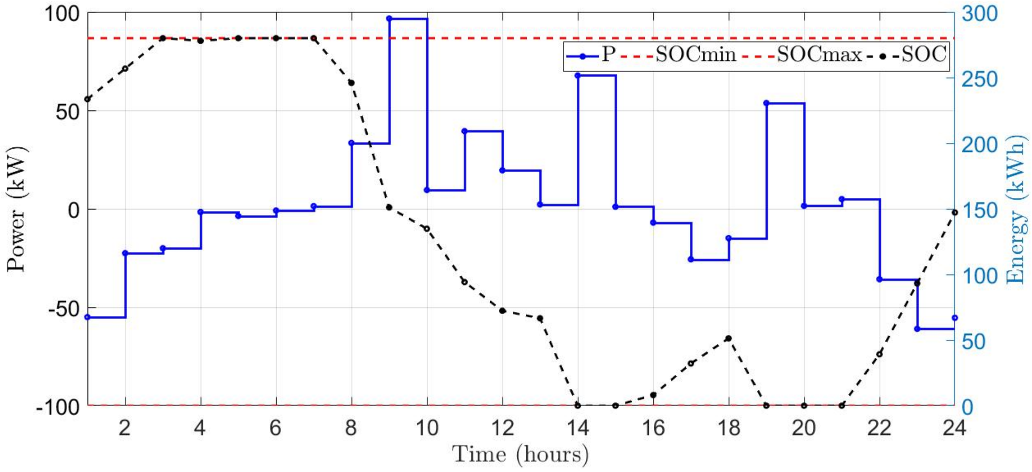

Figure 9: Process of charge and discharge of the battery. BESS Case 4.

5. Conclusions

In this work, a Stochastic Programming Unit Commitment model has been proposed for the scheduling problem of an hybrid generation microgrid in isolated mode of operation. The problem has been divided in three stages. Firstly, an ARMA technique is applied to the demand historical data to obtain a demand forecast model, including an estimation of the error. Secondly, based on this model, a Stochastic Unit Commitment Problem is solved, considering a spinning reserve of the dispatchable units able to cover the uncertainties in the demand estimation to provide a robust operation scheduling. Finally, a study case is stated, where the demand estimation error is numerically simulated. In this last stage, an optimization problem is solved in order to determine the power supplied by each generator and the management of the battery. This optimization problem minimizes the total cost operation of the microgrid. Some simulation examples have been included in order to show the effectiveness of the algorithm. In addition, the influence of the BESS parameters in the problem has been studied.

The consideration of the uncertainties in the renewable resource is an interesting topic that will be tackled as a further work. However, an immediate extension of the problem can be established if Gaussian perturbations are conside just adding this uncertainty to the one introduced by the demand forecasting.

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