Economic Model Predictive Control for energy management in a microgrid

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***Abstract*—This article proposes a design strategy for energy flow controllers in microgrids with renewable generation within the framework of Economic Model Predictive Control (EMPC). The model used is made up of a storage system and a generation source, considering the possibility of exchanging energy with the main network, thus allowing to the microgrid, through the proposed control strategy, the possibility of acting and participating within the electrical market. The proposed functional for the controller considers costs of use for the microgrid systems, as well the benefit from sale of energy to the main electrical network. The operation of the system is checked by simulating it in different scenarios.**

***Index Terms*—Microgrid, Energy Management, Distributed Energy Resources, Predictive Control**

I. Introduction

Microgrids appear as a structural solution to facilitate the correct and effective implementation of Distributed Energy Resources (DER) or distributed generation, while allowing efficient and safe inclusion for renewable energy sources. In this context, in the concept of microgrid introduced by [1], which can operate in isolated mode or connected to the electrical network, the control strategy to be used is a vital component for the safe, effective and sustainable realization.

The control objectives to be achieved by the implemented strategy can be summarized by what is presented in [2], [3] and [4], as:

- Voltage and frequency control in both modes of operation.
- Satisfy demand, by coordinating the different Distributed Energy Resources (DER) available in the microgrid, together with the main network.
- Connection and synchronization of the microgrid with the main network.
- Control of power flows between the microgrid and the network.
- Optimization of operation and maintenance costs.

Since these objectives have very different characteristics and time scales, they are addressed through a hierarchical control structure, where each objective is tackled at an established hierarchical level [2], [4]. This structure generally consists of three levels: primary, secondary and tertiary.

At the primary level, the goal is to control the voltage and frequency of the microgrid, and the circulation currents between the different DERs has to be mitigated, since it can cause serious inconveniences in the protection system.

At the secondary level, any steady-state voltage and frequency deviation caused by the primary level is eliminated, and also connection and synchronization with the main network can be regulated here.

The third and last level is in charge of managing the power flows between the microgrid and main network, optimizing the operating costs associated with the microgrid.

For the first two levels, the technique called *Droop Control* [2], [4] is usually applied, while for the third, one, some heuristic [5] or fuzzy logic algorithms [6], among others, can be used.

In this article, we propose a strategy for the last level, consisting in the application of a Model Predictive Control (MPC) approach [7]. As advantages of the method and focusing on the type of system to be controlled, the direct formulation for multi-variable systems can be highlighted, being able to consider the operational constraints, both in the states and in the control variables, directly in the design of controller, and taking into account external predictions of non-manipulated inputs, such as in this case, the generation profiles for renewable energy sources and consumption.

In addition, within the possible formulations of the MPC, we mainly consider the Economic Model Predictive Control (EMPC) [8] [9] [10], where the MPC stage cost is directly a functional related to economic parameters and variables. Therefore, the controller directly optimizes in real time, the dynamically economic performance defined in this function. This approach is very attractive for the system under discussion, since in this framework, it can be able to consider, for instance, operation and maintenance costs for the components of microgrid, as well as optimizing the exchange of energy with the main network.

The note is organized as follows: In section II the architecture and prediction model for the residential microgrid is presented, then in Section III the optimization problem to be solved is formulated, and in Section IV simulations are carried out to evaluate the behavior of the proposed controller, ending with the conclusions drawn in Section V.

II. Microgrid Model

The model of residential microgrid taken into account in this work is shown in Figure 1. It can be identified: a renewable energy source, consisting of an array of solar panels, the battery bank, which constitutes the storage system, the hybrid inverter, which performs the necessary transformations and acts as a node or DC bus of the microgrid, and a defined consumption for a domestic residence.

In [11], this model is described in detail. In this work only, a brief description is provided for its subsequent use.

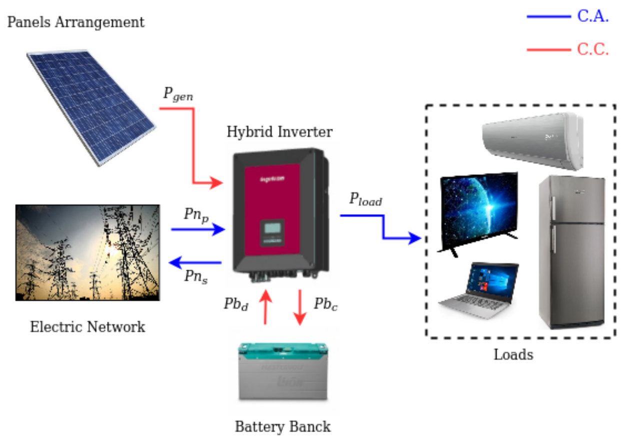

Figure 1. Microgrid architecture

The arrangement of solar panels is made up of 12 panels Poly-crystalline Panel TSM-330PD14. These are connected in a mixed way, 6 in series and these in turn in parallel, obtaining a nominal power of 3960 W. The battery bank consists of 4 batteries MLI Ultra 12/5500 connected in series. The Table I lists the characteristics technical of the solar panel, batteries and hybrid inverter used.

Table I
Technical specifications of the microgrid components

Dates	Description
Panel Poly-crystalline Panel TSM-330PD14	
Nominal power, P_{max}	330 W
Voltage at maximum power point, V_{mpp}	$37,4$ V
Maximum current, I_{mpp}	$8,83$ A
Battery-MLI Ultra 12/5500	
Nominal voltage, V_{bat}	12 V
Nominal capacity, C_{bat}	400 Ah
Useful life (cycles), N_c	3500
Inverter Ingecon Sun Storage 1 Play 3TL	
Maximum power of the photovoltaic field, P_{pv}	6.5 kW
Voltage range of the photovoltaic field, V_{pv}	$200 - 350$ V
Maximum current of the photovoltaic field, I_{pv}	20 A
Nominal battery voltage, V_b	$48 - 330$ V
Maximum charge / discharge current of the batteries, I_b	50 A
Inverter efficiency, η_{inv}	95.5%

The linear discrete-time state space model, discretized by the Tustin method and with a sampling period of $T_s = 3600$ s, is:

$$x(k+1) = x(k) + \begin{bmatrix} -7,11e^{-3} & 6,48e^{-3} & 0 & 0 \end{bmatrix} u(k) \quad (1)$$

$$\begin{bmatrix} 1 & -1 & 1 & -1 \end{bmatrix} u(k) + \begin{bmatrix} 1 & -1 \end{bmatrix} d(k) = 0 \quad (2)$$

In this model, $x(k) = SOC$ is the state of charge of the battery bank, $u(k) = \begin{bmatrix} Pb_d & Pb_c & Pn_p & Pn_s \end{bmatrix}^T$ are the manipulated input variables and $d(k) = \begin{bmatrix} P_{gen} & P_{load} \end{bmatrix}^T$ correspond to non-manipulated input variables or disturbances.

In the vector of manipulated inputs, Pb_d/Pb_c are the discharge/charge powers of the battery bank, while Pn_p/Pn_s represent the power purchase/sale to the main grid. On the non-manipulated inputs, P_{gen} is the power generated by solar panels and P_{load} corresponds to the demand of loads.

Equation (1) describes the dynamics of the state of charge of the storage system, while (2) represents the energy balance at the node of the microgrid. In this, the efficiency of the inverters is considered ideal.

III. Controller Formulation

The proposed controller is formulated using the Economic Model Predictive Control (EMPC) approach [8] [9] [10], which is a formualtion that ensures the convergence and stability of the closed loop.

The functional to be optimized considers economic criteria associated with the performance of system to be controlled. In this way, a mathematical expression is proposed, called the *EMPC Cost Function*, to capture the objectives to be optimized by the controller.

A. EMPC Cost Function

The EMPC functional will be made up of two terms. The first of these, called *"Economic Cost"*, considers the costs associated with the action of manipulated variables, that is, it will take into account the cost of discharge/charge the battery bank, as well as cost referred to the purchase of energy from the main grid and the profit due to the sale of this.

The other term, to be introduced in Section III-A2, *"Smoothness in control actions"*, penalizes sudden changes in the manipulated variables. The objective of this term is to preserve and maximize the useful life of the components, especially that of the power inverters. Furthermore, this condition boosts the effective fulfillment of the energy balance at the microgrid node.

1) Economic Cost: The objectives pursued by this cost will be:

- To minimize the degradation of battery bank and therefore, to maximize the lifespan of these.
- To minimize the purchase of energy from the main electricity grid.
- To maximize the sale of energy by the microgrid.

These are expressed mathematically, by the following function:

$$J_{eco}(k) = c(k) \cdot u(k) \tag{3}$$

The vector $c(k)$ considers the cost associated to the control actions, being:

$$c(k) = \begin{bmatrix} cb_d & cb_c & cn_p(k) & cn_s(k) \end{bmatrix} \tag{4}$$

where cb_d y cb_c are the costs of discharge and charge of the battery bank. These values are considered fixed throughout the prediction horizon, being:

$$cb_d = \frac{C_{ibat}}{Nc \cdot \eta_{inv}} \tag{5}$$

$$cb_c = \frac{C_{ibat} \cdot \eta_{inv}}{Nc} \tag{6}$$

where C_{ibat} represents the investment cost of the battery bank, N_c is the number of life cycles and η_{inv} is the inverter's upload/download performance. The reason for considering η_{inv} in the denominator for discharge and in the numerator for charge, is because the observation point is the node of microgrid. The investment cost considered for the acquisition of the battery bank is $C_{ibat} = \$1800000$.

Also in (4), $cn_p(k)$ y $cn_s(k)$ represent the costs of buying and selling energy to the main grid. They are considered variables during the prediction horizon, being represented by the following expressions:

$$cn_p(k) = p(k) \cdot t_s \tag{7}$$

$$cn_s(k) = -p(k) \cdot t_s \tag{8}$$

where $p(k)$ is the price of energy expressed in \$/kWh and t_s is the sampling period in h. The same price is considered for both purchase and sale, but they are variable during the day as indicated in Figure 2. This scenario is hypothetical, since for the residential type consumption level, there are not price variations with respect to the time of the day in the current regulations in Argentina. This price configuration does exist for large consumers (for example, industrial type), and it is divided into three areas called *peak, valley and rest*, where the *peak* hours goes from $18:00$ to $23:00$ h, the *valley* goes from $23:00$ until $05:00$ h and the *rest* from $05:00$ to $18:00$ h.

The negative sign in (8) is due to the fact that the sale of energy is not a cost, but rather a benefit for the management of microgrid.

2) Smoothness in control actions: To minimize sudden variations in control actions, the following quadratic term is used:

$$J_{\Delta u}(k) = \Delta u(k)^T \Delta u(k) \tag{9}$$

where $\Delta u(k) = u(k) - u(k-1)$, is the rate of change of the control variables.

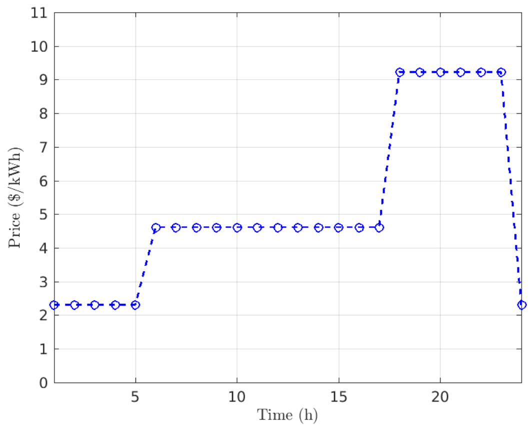

Figure 2. Energy price

The functional of the EMPC will be the sum of both terms presented above, multiplying each of them by a coefficient λ_i, $i = 1, 2$, that materializes the weight of prioritization within the functional. Also, $N \in \mathbb{N}$ indicates the prediction horizon of the controller. Therefore, we have that the functional to be minimized in each sampling period is:

$$J(k) = \sum_{k=1}^{N} \lambda_1 \cdot J_{eco}(k) + \lambda_2 \cdot J_{\Delta u}(k) \tag{10}$$

B. EMPC optimization problem

Once the EMPC functional has been defined, the optimization problem to be solved in each sampling period by the controller is presented:

$$\begin{aligned} \min_{\mathbf{u}} \quad & J(k) \\ \text{s.t.} \quad & x(0) = x \\ & x(k+1) = Ax(k) + Bu(k) + Cd(k) \\ & E_u u(k) + E_d d(k) = 0 \\ & x(k) \in \mathbb{X} \\ & u(k) \in \mathbb{U} \\ & x(N) = x_s \end{aligned} \tag{11}$$

Where the matrices, according to the model determined by (1) and (2) are:

- $A = \begin{bmatrix} 1 \end{bmatrix}$
- $B = \begin{bmatrix} -7.11e^{-3} & 6.48e^{-3} & 0 & 0 \end{bmatrix}$
- $C = \begin{bmatrix} 0 & 0 \end{bmatrix}$
- $E_u = \begin{bmatrix} 1 & -1 & 1 & -1 \end{bmatrix}$
- $E_d = \begin{bmatrix} 1 & -1 \end{bmatrix}$

The decision or optimization variable of the mathematical problem is the vector of manipulated variables $\mathbf{u}$, having to minimize the functional $J(k)$, subject to the constraints indicated in (11).

The first constraint indicates the initial charge status of the battery bank; then the two following expressions represent the model of microgrid, and therefore its dynamics; then there are the constraints on state and the manipulated input variables; the last one is a terminal equality constraint, imposing that the state at end of prediction horizon must reach the optimum steady state that minimizes the *economic cost*. This last condition guarantees stability in the control loop, as indicated in [8].

The optimization problem (11) is solved each sampling period, that is, in each instant the sequence of optimal actions is obtained $\mathbf{u}^*$ for the entire prediction horizon N, but due to the receding horizon strategy, only the first element of the obtained sequence is applied to the system $u^*(k|k)$, discarding the rest and re-solving the optimization problem, after having measured the new state of the system. This gives feedback to the open-loop problem-based formulation, giving it a certain degree of robustness. Therefore, the EMPC control law is implicitly given by:

$$u_k = K(x_k) = u^*(k|k) \tag{12}$$

To define the set of values for the state and input constraints, the limits and recommendations provided by the manufacturers of equipment involved are considered.

In the model considered in this work, there is only one state, which corresponds to the charge of the battery bank. With the premise of maximizing the lifespan of it, the manufacturer recommends, in order to reach 3500 life cycles, that it should work with a depth of discharge of 80% $(DOD = 80\%)$, indicating with this, that the state of charge must be kept between:

$$20\% \leq SOC \leq 80\% \tag{13}$$

The vector $u(k) = \begin{bmatrix} Pb_d & Pb_c & Pn_p & Pn_s \end{bmatrix}^T$ represents the manipulated input variables, therefore, to define the set of constraints, each particular input is analyzed.

The first two variables correspond to the discharge and charge of the battery bank. The manufacturer recommends that their currents should not be greater than 120 A, but the selected inverter, admits for their connection, a nominal current of 50 A; therefore, considering that the nominal voltage of the bank is 48 V, it is necessary that the powers for discharge and charging must not exceed 2400 W. For more detail, see [11].

Concerning the constraints for the purchase of energy from the main grid Pn_p, the nominal value of the AC power of the inverter is adopted, i.e. 3000 W, which is greater than the consumption peaks of the predicted demand profile. These circumstances will be discussed in the simulations carried out in section V.

Finally, regarding the sale of energy to the main electrical network by the microgrid Pn_s, as there are no regulations regarding their participation in the electricity market, it is considered that only a maximum 50% of Pn_p can be sold, considering this a primary and possible scenario in the future to come.

In summary, the set of constraints for the manipulated variables are:

$$\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \leq \begin{bmatrix} Pb_d \\ Pb_c \\ Pn_p \\ Pn_s \end{bmatrix} \leq \begin{bmatrix} 2400 \\ 2400 \\ 3000 \\ 1500 \end{bmatrix} \tag{14}$$

IV. Simulation

In order to evaluate the behavior of the proposed controller, a series of simulations are carried out in three different generation scenarios.

They were carried out in **Matlab 2016b**, where the optimization problem was solved using the open source tool for nonlinear optimization and logarithmic differentiation **CasADi** [12].

For the first simulation scenario, a prediction horizon $N =$ 24 h is used. The cell irradiance and temperature, are obtained from [13], to achieve the power profile generated by the arrangement of solar panels on a sunny January (summer) day for the city of Avellaneda, Santa Fe - Argentina. The other parameters of the simulation are those indicated in Table II.

Table II
Parameters for simulation I

Parameter	Value
Sampling period, t_s	1 h
Prediction horizon, N	24 h
Economic cost weight, λ_1	20
Weight of smoothness in control actions, λ_2	5
Initial condition, $x(0)$	40%

The results of this first simulation can be seen in the Figures 3 y 4.

In Figure 3, the evolution of manipulated variables is shown, both the power of battery bank P_{bat} as well as the one exchanged with the network P_{net}. Positives values of P_{bat} and P_{net} correspond to bank discharge Pb_d and the energy bought from the main network Pn_p, while the negatives values corresponds to the load of bank Pb_c and the energy sold by the microgrid Pn_s. Also, they are shown the profile of generated power, P_{gen}, and the consumption of the residence P_{load}.

It can be seen how the EMPC decides in real time, which is the optimal option, from the point of view of the proposed functional. In other words, the objective embodied with the cost of EMPC should minimize the purchase of energy from the main network, maximize the sale and avoid successive charges/discharges of the battery bank, in order to prevent its premature degradation. These objectives must be achieved satisfying at all times the imposed constraints.

It can be seen in Figure 3, how the desired objectives are achieved: in the hours of greatest generation, the controller decides to sell power to the grid and charge the battery bank at certain times, that is, maximize the sale and avoid successive charges/discharges by the storage system. Also, in the time zone with the highest energy cost, coinciding with the highest consumption, the EMPC decides to use the storage system together with the network, to meet the required consumption, minimizing the purchase of energy from the grid.

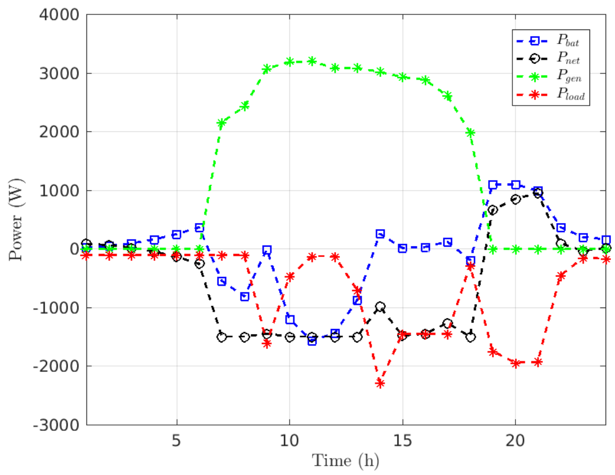

Figure 3. Power profiles with $N = 24$ h, for a sunny January day

In Figure 4, the evolution of state of charge for the battery bank is presented, complying at all times with the constraints defined in the optimization problem.

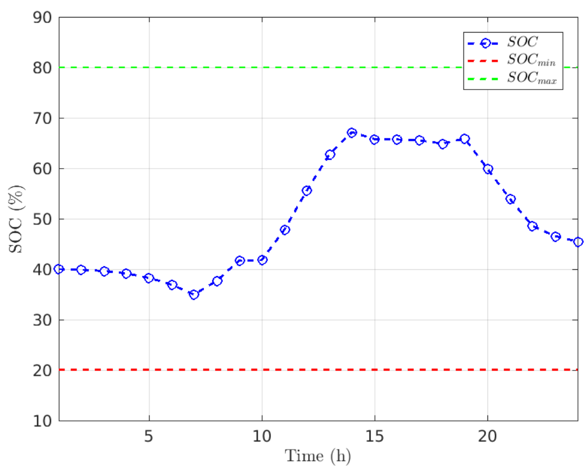

Figure 4. Battery bank charge status with $N = 24$ h for a sunny January day

For the second simulation, irradiance and cell temperature values are considered on a cloudy July (winter) day in the same city. The simulation parameters are indicated in the Table III.

The results obtained with these new conditions are observed in Figures 5 and 6. It can be seen that, given the small power generated by the panels, the demand is practically satisfied by the main network, and in the short period of time where there is solar radiation, the controller decides at first to charge the batteries, to then give higher priority to the sale of energy to the main grid, meeting the desired objectives.

Table III
PARAMETERS FOR SIMULATION II

Parameter	Value
Sampling period, t_s	1 h
Prediction horizon, N	24 h
Economic cost weight, λ_1	20
Weight of smoothness in control actions, λ_2	5
Initial condition, $x(0)$	35%

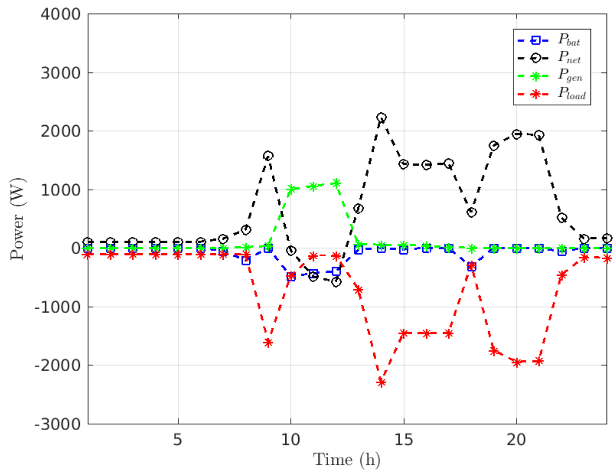

Figure 5. Power profiles with $N = 24$ h for a cloudy July day

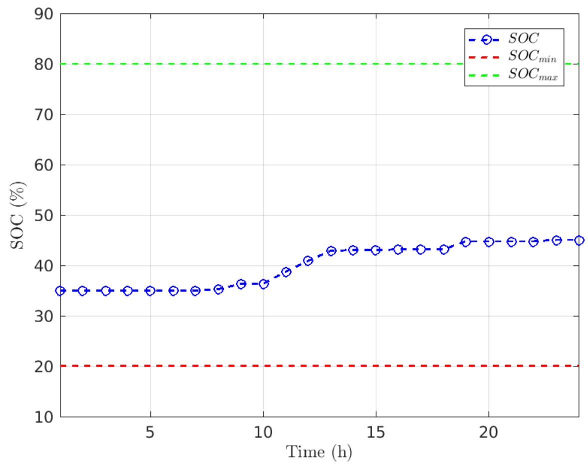

Figure 6. Battery bank charge status with $N = 24$ h for a cloudy July day

For the last simulation scenario, a higher prediction horizon was considered of 3 days. In this scenario, different seasons and climatic conditions were considered: the first day, corresponds to a sunny January, the second, one, to a partially cloudy October, while the third and last ones, to a cloudy July.

The values of parameters used in the simulation are shown in the Table IV.

The results are found in the Figures 7 and 8. They show

Table IV
PARAMETERS FOR SIMULATION III

Parameter	Value
Sampling period, t_s	1 h
Prediction horizon, N	72 h
Economic cost weight, λ_1	20
Weight of smoothness in control actions, λ_2	5
Initial condition, $x(0)$	40%

the correct behavior of the controlled system. It can be seen how the controller decides to load the storage system with great emphasis in the first hours, where it has the most solar radiation; to then use this stored energy at different times, highlighting, as in the hours of greatest consumption, coinciding with the highest price of energy, how the controller decides to satisfy demand, through the joint use of the stored energy and the electrical network.

Throughout the prediction horizon, the microgrid met the constraints imposed on the controller formulation.

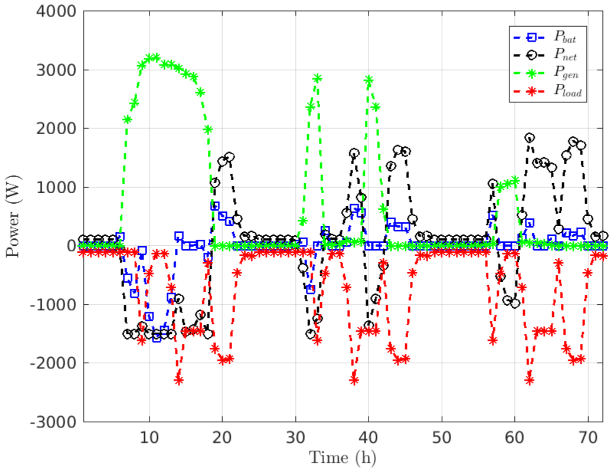

Figure 7. Power profiles for $N = 72$ h

V. CONCLUSIONS

In this work, an Economic Model Predictive Control (EMPC) based control strategy was proposed for the management of power flows in a residential microgrid. The operating conditions considered the possibility to work connected to the electrical network, so the energy exchanged with it is a decision variable in the optimization problem of the EMPC. This allows the microgrid to participate in the daily electricity market.

A correct operation of the system can be observed in the different simulated scenarios, achieving the objectives, always staying within the constraints, while complying with the energy demand requested by the loads.

For future work, it is intended to apply this strategy in microgrids with greater complexity, other types of consumption profile, with more storage systems and other renewable

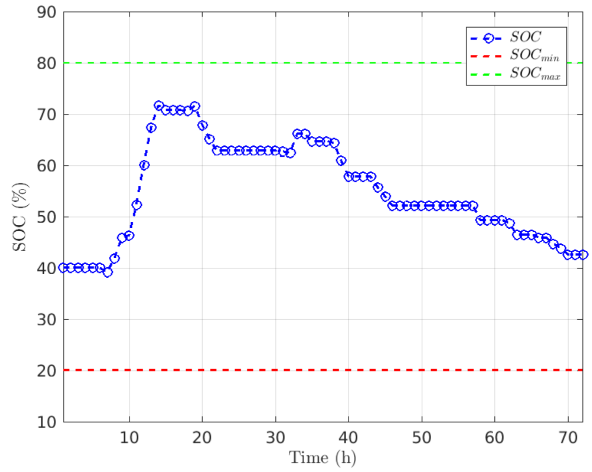

Figure 8. Battery bank charge status for $N = 72$ h

generation sources, where the controller has more options when making the decision, considering it, a better scenario for taking advantage of the virtues of the proposed control system.

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