Economic Energy Management of a Microgrid Including Electric Vehicles

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***Resumo*—This paper presents a predictive control algorithm for economic optimization of a microgrid. The proposed microgrid has a connection with the external electrical network and also with a charging station for electric cars. System modeling was carried out by the Energy Hubs methodology. The proposed algorithm has the task of performing the management of electricity purchase and sale to the power grid, maximizing the use of renewable energy sources, managing the use of energy storages and performing the charge of parked vehicles. Simulation results are presented to illustrate the satisfactory operation of the proposed system.**

I. Introduction

The transition from the current energy system based on fossil fuels to a new system with renewable energy and electric transport systems requires the development of new control algorithms. The use of storage systems enables the opportunity to decide the microgrid optimal operating point both in islanded mode as connected to grid and being possible to manage the ideal time to exchange energy with the external network. There are several energy storage technologies and is of great interest the design of hybrid systems considering these different technologies [1], [2]. Specifically, the hydrogen storage united to electric batteries and supercapacitors seems to be a suitable solution for renewable generation [3]. The use of hydrogen for storing electrical energy from renewable sources is based on the possibility of producing hydrogen by electrolysis, store and subsequently use it again to generate electricity through fuel cells.

In general, microgrids management is carried out by heuristic algorithms [4], although there are applications that use model predictive control (MPC) strategies, such as those presented in [5]. In the case of hybrid storage systems the MPC appears to be a good solution as shown in [6].

On the other hand, V2G systems (Vehicle-to-grid) consist of the use of electric car batteries, during periods when they are not used, as energy storages for an electrical network. Taking into account the current size of the fleet and the expectation of a gradual increase in the number of electric vehicles, it is expected that the energy storage capacity that can be provided in a more or less near future will be sufficient to balance the supply and demand on an electricity grid or microgrid, and hence, improve the performance and stability of the network.

It is estimated that a vehicle is in motion only 4% of time, so the rest of the time could be available as a electrical energy storage unit [7]. Furthermore, in normal use, cars batteries are recharged overnight (which is the period of low electricity demand) and are parked in the workplace during periods of high electrical demand, so the avaliable power could be used to meet peak demand. This storage capacity is especially useful with renewable energy sources, as its fluctuating nature makes it harder to adjust production and demand.

In addition, the use of V2G systems creates new business models with new actors, such as Load Managers, that would be responsible for recharging infrastructure, providing service to vehicles, buying or selling electrical energy and building relationships with the network managers. In the last years control algorithms for charging electric vehicles in intelligent networks have appeared. These controllers try to achieve the better charging service respecting driver preferences and also to ensure a given power profile on the network; considering the constraints imposed by vehicles, the station charging and the network. In [8] and [9] the problem is solved by real-time optimization algorithms, in [10] is presented an MPC based algorithm and in [11], [12], [13] some solutions based on hierarchical distributed algorithms are analyzed.

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In most of these algorithms very simplified models of power systems, vehicle motion and load characteristics. Particularly, the modeling framework called Energy hubs [14] allows the integration of different forms of production and storage of a microgrid, V2G system [15] and the interconnection of different microgrids or a microgrid connected to a electric network.

The objective of this paper is to present a MPC algorithm for optimizing a microgrid coupled to a V2G system consisting of four charge stations of electric vehicles. The proposed algorithm performs the management of the use of renewable energy sources, storage, vehicles charge and the purchase and sale of electric power to the external network. The operation of the system was modeled using the concept of Energy hubs. The rest of the paper is organized as follows. Section II and III are devoted the modeling aspects while section IV presents the optimization algorithm. The results an conclusions are given in sections V and VI respectively.

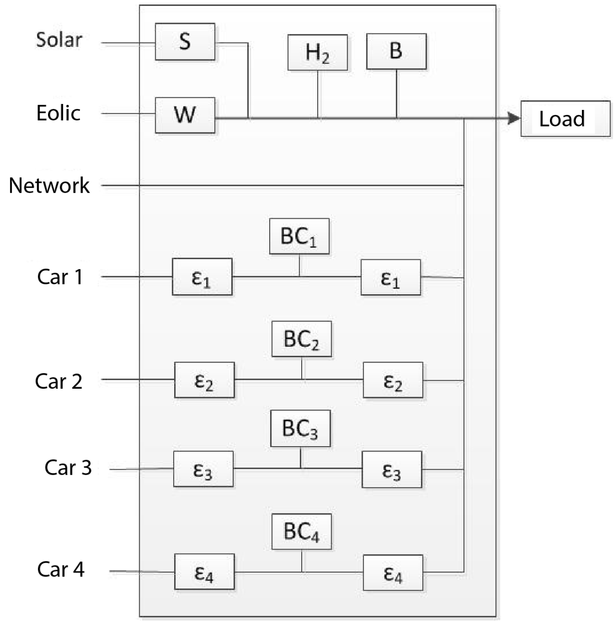

Figura 1. *Microgrid*

II. Modeling Framework

The system studied in this paper and shown in figure 1 is composed of a microgrid that has a solar power generating unit (S), a wind power generating unit (W) and a hybrid storage system comprises a hydrogen storage (H_2) and a battery bank (B) and an interconnection with the power grid which allows the purchase and sale of energy. The microgrid caters to a variable demand and has a connection to an electric vehicles charging station ($BC_{1,2,3,4}$).

A energy hub is defined as the interface between energy production, consumer and the transmission line. From the standpoint of the system an energy hub can be identified as a unit that provides the following features: (1) Input and output power; (2) energy conversion; (3) energy storage.

A converter unit converts, in every time instant k, a generic input flow $u_r^L(k)$ of a generic hub in a generic output flow $y_p(k)$. The input-output conversion is defined through coupling factors $\gamma_{p,r}^L$, which correspond to steady state conversion efficiency of the converter between the input and output flows:

$$y_p(k) \quad = \quad \gamma_{p,r}^L u_r^L(k) \tag{1}$$

The storage devices are composed of an interface and an internal storage. The interface can be seen as a flow converter, which modulates a generic storage interface input flow $u_s^E(k)$ into another generic storage interface output flow $\breve{u}_s^E(k)$. The converted energy is then stored in an ideal internal stage. Mathematically, the storage interface is modeled analogously to a converter device, where the steady-state input-output flow values is described by the relation:

$$\breve{u}_s^E(k) = e_s(k) u_s^E(k) \tag{2}$$

where $e_s(k)$ is the efficiency of the charge/discharge interface s of the Hub, which describes how much of the flow exchanged with the system affects the storage. This factor depends on the direction of the exchanged flow, that is, if the storage is being charged or discharged:

$$e_s(k) = \begin{cases} e_s^+ & \text{if} \quad u_s^E(k) \geq 0 \qquad (charging) \\ 1/e_s^- & \qquad \text{else} \qquad\qquad (discharging) \end{cases} \tag{3}$$

where e_s^+ and e_s^- are respectively the charging and discharging efficiencies. For the sake of simplicity, storage performance is assumed to be constant.

From a discrete-time point of view, internal storage state x_s at sampling time $k+1$ depends on the state at previous sample k and on the total exchanged flow $\breve{u}_s^E(k)$ during the period ΔT ranging from k to $k+1$, assuming $\breve{u}_s^E(k)$ to remain constant during ΔT:

$$x_s(k+1) = A x_s(k) + \breve{u}_s^E(k) \Delta T \tag{4}$$

The electric cars batteries are modeled in the same way that the storage but a binary variable ϵ is added, which has direct relation with the car's physical connection to the charging station. If the vehicle is connected we have $\epsilon = 1$ and the battery is enabled in the model, otherwise $\epsilon = 0$ and the battery is disabled. The final state equation regarding the battery of electric cars is

$$x(k+1) = \epsilon A x(k) + \epsilon \Lambda(k) u(k) \tag{5}$$

Considering previous models, a hub can be represented by the following state space equations:

$$\begin{aligned} x(k+1) &= Ax(k) + \Lambda^E(k) u^E(k) \\ y(k) &= \Gamma^L u^L(k) + \Gamma^E u^E(k) \end{aligned} \tag{6}$$

The state space representation of equation 6 is not linear as it includes bilinear terms related to equation 2. In order to avoid these terms, the state space representation can be transformed in a Mixed Logical Dynamic system (MLD) [16], where logic, dynamics and constraints are integrated according to:

$$x(k+1) = Ax(k) + B_1 u(k) + B_2 \delta(k) + B_3 z(k) \tag{7}$$

$$y(k) = Cx(k) + D_1 u(k) + D_2 \delta(k) + D_3 z(k) \tag{8}$$

$$E_2 \delta(k) + E_3 z(k) \leq E_1 u(k) + E_4 x(k) + E_5 \tag{9}$$

where $x(k) = \begin{bmatrix} x_c(k) \\ x_l(k) \end{bmatrix}$ is the state vector with $x_c(k) \in \Re^{n_c}$ and $x_l \in \{0,1\}^{n_l}$, $y(k) = \begin{bmatrix} y_c(k) \\ y_l(k) \end{bmatrix}$ is the output vector with $y_c(k) \in \Re^{p_c}$ and $y_l(k) \in \{0,1\}^{p_l}$, $u(k) = \begin{bmatrix} u_c(k) \\ u_l(k) \end{bmatrix}$ is the input vector with $u_c(k) \in \Re^{m_c}$ and $u_l(k) \in \{0,1\}^{m_l}$. $z(k) \in \Re^{r_c}$ are the continuous auxiliary variables, $\delta(k) \in \{0,1\}^{r_l}$ are the binary auxiliary variables, A, B_1, B_2, B_3, C, D_1, D_2, D_3, E_1, E_2, E_3 and E_4 are constant real matrices, E_5 is a real vector, $n_c > 0$ and $p_c, m_c, r_c, n_l, p_l, m_l, r_l > 0$.

In order to convert the bilinear equation 2 in the MLD form and taking into account the concepts of propositional calculus and integer linear programming, the following steps are performed:

1) The condition $u_s^E(k) \geq 0$ is associated with the binary variable $\delta_s(k)$ so that

$$[\delta_s(k) = 1] \leftrightarrow \left[u_s^E(k) \geq 0\right] \tag{10}$$

Equation 10 is represented by inequalities

$$\begin{aligned} -m_s \delta_s(k) &\leq u_s^E(k) - m_s \\ -(M_s + \epsilon)\delta_s(k) &\leq -u_s^E(k) - \epsilon \end{aligned}$$

where ϵ is a positive scalar and

$$\begin{aligned} m_s &\triangleq \underbrace{\min}_{k \in \Re, s \in N_s} u_s^E(k) \\ M_s &\triangleq \underbrace{\max}_{k \in \Re, s \in N_s} u_s^E(k) \end{aligned}$$

2) A new variable is defined $z_s(k) = u_s^E(k)\delta_s(k)$ which can be represented as

$$\begin{aligned} z_s(k) &\leq M_s \delta_s(k) \\ z_s(k) &\geq m_s \delta_s(k) \\ z_s(k) &\leq u_s^E(k) - m_s(1 - \delta_s(k)) \\ z_s(k) &\geq u_s^E(k) - M_s(1 - \delta_s(k)) \end{aligned}$$

3) The system model 6, can be described by the following linear relationships:

$$\mathbf{x}(k+1) = A\mathbf{x}(k) + \Lambda^{E-}\mathbf{u}^E(k) + \left(\Lambda^{E+} - \Lambda^{E-}\right)\mathbf{z}(k)$$

$$\underbrace{\begin{bmatrix} -M \\ m \\ -m \\ M \\ -m \\ -(M+\epsilon(\cdot)) \end{bmatrix}}_{E_\delta} \underbrace{\begin{bmatrix} \delta_1(k) \\ \vdots \\ \delta_{n_s}(k) \end{bmatrix}}_{\delta} + \underbrace{\begin{bmatrix} \mathbf{1}(\cdot) \\ -\mathbf{1}(\cdot) \\ \mathbf{1}(\cdot) \\ -\mathbf{1}(\cdot) \\ \mathbf{0}(\cdot) \\ \mathbf{0}(\cdot) \end{bmatrix}}_{E_z} \underbrace{\begin{bmatrix} z_1(k) \\ \vdots \\ z_{n_s}(k) \end{bmatrix}}_{z(k)}$$

$$\leq \underbrace{\begin{bmatrix} \mathbf{0}(\cdot) \\ \mathbf{0}(\cdot) \\ \mathbf{1}(\cdot) \\ -\mathbf{1}(\cdot) \\ \mathbf{1}(\cdot) \\ -\mathbf{1}(\cdot) \end{bmatrix}}_{E_u^E} \underbrace{\begin{bmatrix} u_1^E(k) \\ \vdots \\ u_{n_s}^E(k) \end{bmatrix}}_{u^E(k)} + \underbrace{\begin{bmatrix} \mathbf{0}(\cdot)_f \\ \mathbf{0}(\cdot)_f \\ -m_f \\ M_f \\ -m_f \\ -\epsilon(\cdot)_f \end{bmatrix}}_{E_0}$$

where,

$$\begin{aligned} M &= \begin{bmatrix} M_1 & & \\ & \ddots & \\ & & Mn_s \end{bmatrix}, M_f = \begin{bmatrix} M_1 \\ \cdots \\ Mn_s \end{bmatrix}, \\ m &= \begin{bmatrix} m_1 & & \\ & \ddots & \\ & & mn_s \end{bmatrix}, m_f = \begin{bmatrix} m_1 \\ \cdots \\ mn_s \end{bmatrix}, \\ \mathbf{a}(\cdot) &= \begin{bmatrix} a & & \\ & \ddots & \\ & & a \end{bmatrix}, \mathbf{a}(\cdot)_f = \begin{bmatrix} a \\ \cdots \\ a \end{bmatrix} \end{aligned}$$

Finally system model 6 can be written using the following MLD formulation:

$$\begin{aligned}\mathbf{x}(k+1)&=A\mathbf{x}(k)+\Lambda^{E-}\mathbf{u}^{E}(k)+\left(\Lambda^{E+}-\Lambda^{E-}\right)\mathbf{z}(k)\\ \mathbf{y}(k)&=\Gamma^{L}\mathbf{u}^{L}(k)+\Gamma^{E}\mathbf{u}^{E}(k)\\ E_{\delta}\delta+E_{z}\mathbf{z}(k)&\leq E_{u}^{E}\mathbf{u}^{E}(k)+E_{0}\end{aligned} \tag{11}$$

III. System Modeling

The methodology presented in section II will be now applied to the microgrid modeling and electric vehicles charging station. The entire system will be modeled as a single Hub as shown in figure 1. To model the hydrogen storage in a MLD form is necessary to define the variable $z_{H2}(k)=P_{H2}(k)\delta_{H2}(k)$. Subsequently is defined the Hub input vector according to:

$$\mathbf{u}=\begin{bmatrix}\mathbf{u}^{L}\\ \mathbf{u}^{E}\\ \delta\\ \mathbf{z}\end{bmatrix}=\begin{bmatrix}P_{Solar}\\ P_{Wind}\\ P_{Network}\\ \hline P_{B}\\ P_{H2}\\ P_{BC1}\\ P_{BC2}\\ P_{BC3}\\ P_{BC4}\\ \hline \delta_{H2}\\ \hline z_{H2}\end{bmatrix} \tag{12}$$

The model in equation 11 can be rewritten in a condensed form as:

$$\begin{aligned}\mathbf{x}(k+1)&=A\mathbf{x}(k)+\Lambda\mathbf{u}(k)\\ \mathbf{y}(k)&=\Gamma\mathbf{u}(k)\end{aligned} \tag{13}$$

where

$$A=\begin{bmatrix}1&0&0&0&0&0\\0&1&0&0&0&0\\0&0&\epsilon_1&0&0&0\\0&0&0&\epsilon_2&0&0\\0&0&0&0&\epsilon_3&0\\0&0&0&0&0&\epsilon_4\end{bmatrix}$$

$$\Lambda=\left[\begin{array}{cc|cccccc|c|c}0&0&\lambda_1&0&0&0&0&0&0&0\\0&0&0&\lambda_2&0&0&0&0&0&\lambda_3\\0&0&0&0&\lambda_4&0&0&0&0&0\\0&0&0&0&0&\lambda_5&0&0&0&0\\0&0&0&0&0&0&\lambda_6&0&0&0\\0&0&0&0&0&0&0&\lambda_7&0&0\end{array}\right]$$

$$\begin{aligned}\lambda_1&=\eta_B\\ \lambda_2&=\eta_{H_2,e}^{FC}\\ \lambda_3&=\eta_{e,H_2}^{E}-\eta_{H_2,e}^{FC}\\ \lambda_4&=\epsilon_1\eta_{BC1}\\ \lambda_5&=\epsilon_2\eta_{BC2}\\ \lambda_6&=\epsilon_3\eta_{BC3}\\ \lambda_7&=\epsilon_4\eta_{BC4}\end{aligned}$$

$$\Gamma=\left[\begin{array}{cc|cccccc|c|c}\eta_{rad,e}^{S}&1&-1&-1&-1&-1&-1&-1&0&0\end{array}\right]$$

where η is the storage and conversion efficiencies, P_{Solar} is the generated solar power, P_{Wind} is the generated wind power, $P_{Network}$ is the power of the external network, P_B is the power of the battery bank, P_{H2} is the power of the hydrogen storage and P_{BC1}, P_{BC2}, P_{BC3} and P_{BC4} are the powers of vehicle batteries.

IV. Optimization Algorithm

The proposed MPC algorithm uses the following objective function:

$$\begin{aligned}J=&\textstyle\sum_{l=0}^{N_p-1}\tilde{\mathbf{u}}(k+l)^{T}\mathbf{Q}\tilde{\mathbf{u}}(k+l)+\mathbf{f}^{T}\tilde{\mathbf{u}}(k+l)+\\ &\textstyle\sum_{l=0}^{N_p-1}(\tilde{\mathbf{u}}(k+l)-\tilde{\mathbf{u}}_{ref}(k+l))^{T}\mathbf{Qe}(\tilde{\mathbf{u}}(k+l)-\tilde{\mathbf{u}}_{ref}(k+l))+\\ &\textstyle\sum_{l=0}^{N_p-1}(\tilde{\mathbf{x}}(k+l)-\tilde{\mathbf{x}}_{ref}(k+l))^{T}\mathbf{Qx}(\tilde{\mathbf{x}}(k+l)-\tilde{\mathbf{x}}_{ref}(k+l))+\\ &(\tilde{\mathbf{x}}(k+N_p)-\tilde{\mathbf{x}}_{ref}(k+N_p))^{T}\mathbf{Q}_{N_p}(\tilde{\mathbf{x}}(k+N_p)-\tilde{\mathbf{x}}_{ref}(k+N_p))\end{aligned} \tag{14}$$

subject to local dynamics 13 and the following constraints:

$$\underline{\mathbf{x}}_i \leq \tilde{\mathbf{x}}_i(k+l+1)\leq\overline{\mathbf{x}}_i \tag{15}$$

$$\underline{\mathbf{u}}_i \leq \tilde{\mathbf{u}}_i(k+l)\leq\overline{\mathbf{u}}_i \tag{16}$$

$$\tilde{\mathbf{y}}_i(k+l) = \mathbf{y}_{dem}(k) \tag{17}$$

$$\mathbf{x}_i(k) = \check{\mathbf{x}}_i(k) \tag{18}$$

for $l = 0, \ldots, N_p - 1$, where $\mathbf{Q}$, $\mathbf{Qe}$, $\mathbf{Qx}$ and $\mathbf{Q}_{N_p}$ are positive definite weighting matrices, $\mathbf{f}$ is a vector and N_p is the prediction horizon. In these equations, tilde ("$\sim$") over variables is used to denote variables over the prediction horizon, $\underline{\mathbf{a}}_i$ and $\bar{\mathbf{a}}_i$ denote minimum and maximum allowed values respectively, and $\breve{\mathbf{a}}_i$ refers to variables which values are supposed to be known, for example, initial conditions. In this work we have assumed a bidirectional energy flow between the hub and the network so that the negative threshold is used.

The first term of the objective function is used for the management of renewable energy sources and purchasing power for the network. The weights $\mathbf{Q}$ and $\mathbf{f}$ are tuned according to the price of each energy source. The second term is responsible for ensuring the maximum use of renewable energy sources in order to minimize the error between the amount of power available and the amount of energy used. The third term is responsible for maintaining the load of storage around 50% of the total load, allowing deviations from this value when there is need to store more energy or use the stored energy. This term is also used to charge the batteries of electric vehicles according to the charging type, as will be explained below. Finally, the fourth term relative to the final state weights is introduced to ensure that the vehicle batteries will be fully charged at the end of the charging time.

To manage the purchase and sale of energy to the external network a different weights for sale and purchase were used. To make this possible a new variable $z_{Network}(k)= P_{Network}(k)\delta_{Network}(k)$ was defined and MLD constraints were introduced. The new input vector is defined in Equation 19.

$$\mathbf{u} = \left[\begin{array}{c} P_{Solar} \\ P_{Wind} \\ P_{Network} \\ \hline P_B \\ P_{H2} \\ P_{BC1} \\ P_{BC2} \\ P_{BC3} \\ P_{BC4} \\ \hline \delta_{H2} \\ \hline z_{H2}\delta_{Network} \\ \hline z_{Network} \end{array}\right] \tag{19}$$

Analysing only the part of the objective function in equation relating to the flow energy exchanged with the network are:

$$J=\sum_{l=0}^{N_p-1} \widetilde{P_{Network}}(k+l)^T Q_{sale} \widetilde{P_{Network}}(k+l)+ \tag{20}$$

$$\widetilde{z_{Network}}(k+l)^T (Q_{purchase}-Q_{sale}) \widetilde{z_{Network}}(k+l)+$$

$$f_{sale} \widetilde{P_{Network}}(k+l)+(f_{purchase}-f_{sale})\widetilde{z_{Network}}(k+l)$$

When power $P_{Network} > 0$ we have $\delta_{Network}=1$ and $z_{Network}(k)=P_{Network}(k)$, which means that energy is purchased in the network and therefore the purchase weight is used. Otherwise $P_{Network} < 0$ implies $\delta_{Network}=0$ and $z_{Network}(k)=0$ and sale weight is used. This makes it possible to use different weights for the same variable. The values of the weights were adjusted according to the price of energy.

To use the battery of electric vehicles over the network was designed a supervisory algorithm that determines the charging type and the charging time. At the time of vehicle connection to the charge station, the user must inform the charging type (slow or fast) and the time the vehicle will be parked. If slow charge is chosen, the battery charges over the parking time using low-power charge. In the case of fast charge the battery is charged with maximum power in half an hour just before the end of the pre-set parking time, and in the rest of the time the battery is available for use as a storage for microgrid. During charge periods, slow or fast charge weights $\mathbf{Qx}$ and $\mathbf{Q}_{N_p}$ are tuned to positive values in order to ensure that the load is charged on time. When the battery is used as a storage these weights assume null values.

V. Results

The proposed control system was applied to the microgrid model. A simulation with a period of 24 hours was performed. The control objective is to maximize the use of renewable energy sources, making the purchase and sale management of electricity to the external network, using the storage to minimize the oscillations between the production and demand, performing the charging of electric vehicles and ensuring the load demand at all periods of time. All quantities are expressed as per power unit (p.u.). The maximum load of the microgrid storages is $40p.u.$ and the car batteries is $5p.u.$.

In the first graph of figure 2 are shown the amount of solar and wind energy available, as well as the amount of energy used and the energy flow between the microgrid and the power grid. It's possible to check that virtually all renewable energy available is used and most of the day the excess energy is sold to the grid. In the second graph it s possible to see that the demand constraint is satisfied.

In the first two graphs of figure 3 is possible to check the operation of the microgrid storages. The algorithm tends to maintain the amount of stored energy in $20p.u.$ allowing fluctuations at times where there is no renewable energy enough to attend the demand. In the last graph is displayed the vehicles batteries management. Cars 1 and 3 use fast charge so that part of the time that they are connected to the network they function as storage elements and only in the last 30 minutes the batteries are actually charged. Cars 2 and 4 use slow charge so that take longer to perform the charge.

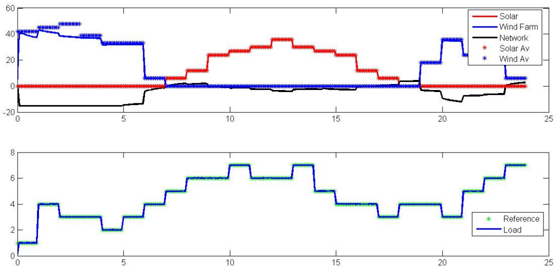

Figura 2. Energy sources and demand

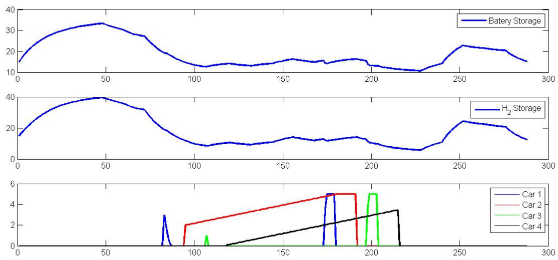

Figura 3. Storage and car batteries state of charge

VI. Conclusion

The controller presented satisfactory results, managing properly the purchase and sale of energy to the external network, making the charge of the electric cars batteries and ensuring the load demand.

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Referências

[1] G. Ferrari-Trecate, E. Gallestey, P. Letizia, M. Spedicato, M. Morari, and M. Antoine, "Modeling and control of co-generation power plants: a hybrid system approach," *IEEE Trans. of control systems technology*, vol. 12, pp. 694–705, 2004.

[2] W. Greenwell and A. Vahidi, "Predictive control of voltage and current in a fuel cell-ultracapacitor hybrid," *IEEE Trans. on Industrial Electronics*, vol. 57, pp. 1954–1963, 2010.

[3] H.Jiayi, J.Chuanwen, and X. Rongi, "A review on distributed energy resources and microgrid," *Renewable Sustainable Energy*, vol. 12, p. 2472–2483, 2008.

[4] W. Gu, Z. Wu, and X. Yuan, "Microgrid economic optimal operation of the combined heat and power system with renewable energy," *Power and Energy Society General Meeting*, 2012.

[5] L. Valverde, C. Bordons, and F. Rosa, "Power management using model predictive control in a hydrogen-based microgrid," *Annual Conference on IEEE Industrial Electronics Society*, 2012.

[6] A. D. Real, A. Arce, and C. Bordons, "Hybrid model predictive control of a two-generator power plant integrating photovoltaic panels and fuel cell," *IEEE CDC*, 2007.

[7] M. Gautschi, O. Scheuss, and C. S. C., "Simulation of an agent based vehicle-to-grid (v2g) implementation," *Documento interno EEH Power Systems Laboratory, ETH Zurich*, 2009.

[8] S. Deilami, A. S. Masoum, P. S. Moses, and M. Masoum, "Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile," *IEEE Trans. on Smart Grid*, vol. 2, 2011.

[9] P. Richardson, D. Flynn, and A. Keane, "Optimal charging of electric vehicles in low-voltage distribution systems," *IEEE Trans. on Power Systems*, vol. 27, pp. 268–279, 2012.

[10] A. D. Giorgio, F. Liberati, and S. Canale, "Electric vehicle charging control in smartgrids," *Mediterranean Conference on Control and Automation*, vol. 21, pp. 268–279, 2013.

[11] S. Bashash and H. Fathy, "Robust demand-side plug-in electric vehicle load control for renewable energy management," *Proc. ACC*, pp. 929–934, 2011.

[12] Z. Fan, "A distributed demand response algorithm and its application to phev charging in smart grids," *IEEE Trans. on Smart Grid*, vol. 3, pp. 1280–1290, 2011.

[13] M. D. Galus and G. A. S. Art, "A hierarchical, distributed pev charging control in low voltage distribution grids to ensure network security," *IEEE Power and Energy Society General Meeting*, 2012.

[14] A. J. del Real, M. D. Galus, C. Bordons, and G. Andersson, "Optimal power dispatch of energy networks including external power exchange," *ECC 09*, 2009.

[15] M. D. Galus, R. L. Fauci, and G. Andersson, "Investigating phev wind balancing capabilities using heuristics and model predictive control," *IEEE Power and Energy Society General Meeting*, 2010.

[16] A. Bemporad and M. Morari, "Control of systems integrating logic, dynamics and constraints," *Automatica*, vol. 35, pp. 407 – 427, 1999.