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Application of Periodic Economic MPC to a Grid-Connected Micro-Grid ⋆

M. Pereira, D. Limon, T. Alamo, L. Valverde

Departamento de Ingeniería de Sistemas y Automática, Escuela Superior de Ingenieros, Universidad de Sevilla. Sevilla, Spain. (e-mail: {dlm,mpereiram,talamo,vdi}@us.es)

Abstract: This paper presents the application of economic predictive control to minimize the cost of operating a non-isolated micro-grid connected to an electric utility subject to a periodic internal demand. A function that describes the economic cost of operating the plant taking into account aspects such as electric market costs, degradation of the micro-grid and amortization costs is proposed. Based on this cost and considering the periodic nature of the plant, an economic predictive controller capable of adapting to sudden changes on the cost function while guaranteeing stability and recursive feasibility has been successfully tested using the LTI model of an experimental configurable test-bed located at the laboratories of the University of Seville.

Keywords: Model predictive control, renewable energy, economic control, periodic control.

1. INTRODUCTION

The control of micro-grids has received a lot of attention over the last years and nowadays there exist several commercial solutions, however there are still open issues for research, see [Arefifar et al., 2015, Wang et al., 2015]. In [Miland and Ulleberg, 2012] an experimental small-scaled stand-alone power system based on hydrogen is presented. Model predictive control (MPC) has also been applied to this class of systems, see for example [Choi and Lee, 2015, Parisio et al., 2014b,a, Valverde et al., 2012]. In [Salazar et al., 2013] MPC techniques were applied to supervise a hybrid model of a micro-grid with hydrogen storage system. In [Touretzky and Baldea, 2014] a strategy for the optimal economic control of building heating, ventilation and air conditioning systems with chilled water thermal energy storage was proposed.

One issue that micro-grid control systems must take into account is the time varying operation conditions that result from the varying power generation of renewable energy systems, the periodic character of distributed loads and the fluctuations of the prices of the electric market. In this case, the optimal operation of a micro-grid from an economic point of view is not to remain at a certain steady state but to follow a non-steady trajectory, often periodic Huang et al. [2011]. Several model predictive control schemes that deal with this problem have been recently proposed, see for example [Gondhalekar et al., 2013]

This issue has been traditionally solved by means of a hierarchical control system where the economically optimal trajectory is calculated and provided to the advanced control system as target trajectory.More recently, model predictive control laws that take the economic costs into account have been proposed, the so-called economic MPC, see Angeli et al. [2012] for a discussion on the properties of this class of controllers. These control laws could be used for the efficient control of a micro-grid assuming that a cost function that measures the efficiency of the operation is available. However, this economic cost function depends on exogenous parameters, such as unitary prices of the electric market or the agreed power with the supplier, that may change throughout the operation of the micro-grid. When these parameters are changed, the optimal trajectory must be recalculated and the predictive controllers must be adjusted to this new scenario by adapting the constraints and/or the cost function appropriately. The subsequent variation of the constraints of the optimization problem could lead to feasibility loss Limon et al. [2012], Ferramosca et al. [2010].

Motivated by these issues, in this paper we present the application of a novel economic MPC for periodic systems [Limon et al., 2014] capable to deal with changing economic cost functions to minimize the cost of operating a non-isolated micro-grid connected to a electric utility made of a set of photovoltaic panels and a hybrid battery/hydrogen storage system. We consider a scenario in which the micro-grid has signed a contract with the electric utility in which it has to provide a predefined amount of energy in a given period of time each day. Out of this interval of time the energy the energy cannot be sold and is wasted, although the micro-grid can still purchase energy.

2. CONTROL OF A NON-ISOLATED MICRO-GRID

In this work we consider the control of a non-insolated micro-grid such as the one shown in Figure 1. This micro-grid is made of a photovoltaic (PV) energy source, an energy consumer, a cluster of batteries, an energy storage system based on hydrogen and a connection to an electric utility (EU) to which the micro-grid can buy/sell energy from/to. The micro-grid must try to sell an agreed power

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to the EU only during an certain interval of time. This power and interval of time are agreed with the EU.

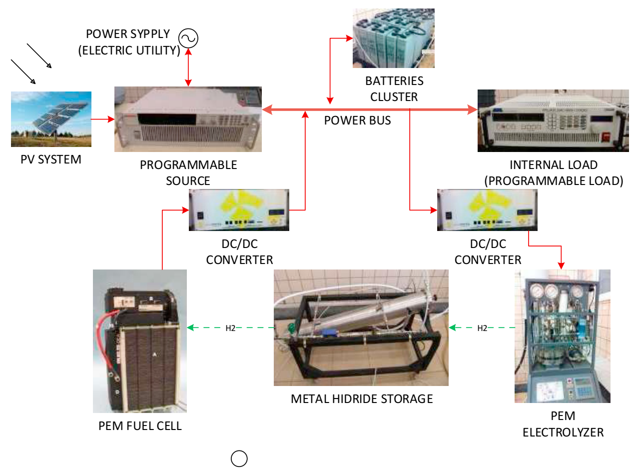

Fig. 1. Micro-grid scheme simulated in the test-bed located in the University of Seville.

The micro-grid has two storage systems: a batteries cluster and a hydrogen based storage system. The hydrogen storage system is composed by a proton exchange membrane fuel cell that provides energy consuming hydrogen, and a polymer electrolyte membrane electrolyzer that produces hydrogen consuming energy. The hydrogen is stored in a metal hydride deposit. The batteries cluster included is used to support the short transitory power peaks due to its fast dynamic and the hydrogen storage system was installed in order to support the long power peaks due to its high investment cost.

The manipulable inputs are the power reference of electrolyzer and fuel cell(P_{H_2}) and the power associated to the buying and selling of electric energy (P_{grid}). The power generation of the PV system (P_{PV}) and the internal demand of the micro-grid (P_{load}) are considered as known disturbances. The outputs of the plant are the stored energy rate in both storage systems: the stage of charge of the batteries (SOC) and the level of stored hydrogen in the metal hydride deposit (MHL). The dynamics of the batteries are assumed to be very fast so the power of the battery (P_{bat}) is obtained from the power balance in the power bus which can be expressed as $P_{bat} + P_{H2} + P_{grid} + P_{PV} + P_{load} = 0$.

We consider the difference between the power produced by the PV system and the power consumed by the inner load as an exogenous disturbance of the system and is defined as $P_{net} = P_{PV} - P_{load}$.

The objective of this kind of micro-grid is not only to satisfy the internal demand and the energy contract with the EU, which we assume to be periodic, while maintaining the operational limits of the plant, but also to keep the equipment at their maximum efficiency points while minimizing the economic cost taking into account the electricity market costs. The main control objectives can be described as follows: Maximize the profit of the energy exchange between the micro-grid and the EU taking into account the prices of the intraday electricity market and the contract constraints;fulfill a known periodic internal demand; try to extend the life time of the equipments of the micro-grid; and fulfill the operational constraint in order to prevent damage the equipments.

The proposed controller is based on the assumption that the internal demand is known which implies the use of a forecasting tool. The profile of large scale distribution grids presents periodicity and some predictability, however unpredictability is much more intense in small scale micro-grids with few loads. Nevertheless, we consider that the use of a prediction of the demand is one of the main advantages of using a model based approach, and can improve the overall performance even in the presence of deviations from the nominal predictions thanks to the receding horizon scheme and the possibility of adapting to possible changes in these predictions.

2.1 Controller design model and Simulation model

In order to implement the control law proposed in [Limon et al., 2014] a discrete time linear model is needed. After analyzing the response of the system, the micro-grid was modeled as two integrators with weighted inputs. A series of simulations were carried out using the nonlinear model to identify the slope of the step response to each input. For each input, over 300 simulations of 30 minutes with different initial states and step amplitudes were done. The parameters of the system were obtained as the mean value of these slopes. The following discrete time linear model used to design the controller was obtained using a Tustin method and a sampling time of 1800 second (30 minutes):

$$x(k+1) = x(k) + \begin{bmatrix} 8.1360 & 5.9568 \\ -15.2886 & 0 \end{bmatrix} u(k) + \begin{bmatrix} 5.9568 \\ 0 \end{bmatrix} w(k)$$

with $x = [SOC\ MHL]^T$, $u = [P_{H_2}\ P_{grid}]^T$ and $w = P_{net}$. The sampling time chosen is satisfactory for a long-term analysis assuming smooth irradiation profiles. The structure of the micro-grid considered includes a set of batteries to compensate the effects of intermittence by PVs. At any given time, the batteries provide the power needed to balance the energy in the micro-grid. This implies that short intermittence by PVs may affect the level of the batteries between sampling times, but in general the batteries have enough energy needed to provide the energy that the PV did not generate. In the next sampling time, the controller takes into account this disturbance in the SOC.

In this paper we use this linear model of non-isolated micro-grid presented in [Valverde et al., 2013] to carry out the simulations.There are technological constraints on the hydrogen systems (production, storage and consumption) that limit the values of power for this manipulated input in order to avoid possible damages of the equipments. Power P_{grid} is limited between -2.5 kW and 2 kW. Power P_{H_2} is limited between -0.9 kW and 0.9 kW. In addition, the batteries need to maintain a certain level in the SOC in order to maintain the voltage at appropriate values in the power bus of micro-grid and in the hydrogen storage system is necessary to maintain the hydrogen levels between a minimum and maximum to avoid damage to the equipment. To this end the proposed controller will be designed to maintain the SOC and MHL between 40% and 90% when possible, including these constraints as soft constraints in the MPC optimization problem.

3. ECONOMIC COST FUNCTION

We present next an economic cost function that takes into account the calculation of the power exchanged in the electricity market as well as technological issues and equipment operational costs. The cost of the battery bank, hydrogen storage, fuel cell and electrolyzer have been defined to reduce the intensive use these equipments might be subject to during normal operation.

The economic cost function h_{eco} is evaluated for a trajectory of the plant outputs and inputs along an operation period T, that is, $\mathbf{y} = (y(0), y(1), \cdots, y(T-1))$, $\mathbf{u} = (u(0), u(1), \cdots, u(T-1))$.The economic function depends on a set of time varying parameters, such as the price of power in the electricity hourly spot market C_{poolh} measured on $e.u./hour$, the price of buying power to the EU C_{buy} and the power agreed with the EU P_{of}. The predictions of these parameters are included in a vector denoted as $c = [C_{poolh}\ C_{buy}\ P_{of}]^T$. These parameters may change along the operation of the plant and they are assumed to be periodic. The trajectory of these parameters along an operation period is denoted as $\mathbf{c} = (c(0), c(1), \cdots, c(T-1))$ and it is such that C_{poolh} and C_{buy} remain constant along the period while P_{of} may vary.

The economic cost function is denoted by $h_{eco}(\mathbf{c}; \mathbf{y}, \mathbf{u})$. This function is defined as the sum of a number of costs that measures different economic aspects of the plant:

$$\begin{aligned} h_{eco}(\mathbf{c}; \mathbf{y}, \mathbf{u}) = &\beta_1 \big(h_{mg}(\mathbf{c}; \mathbf{y}, \mathbf{u}) + h_{sp}(\mathbf{c}; \mathbf{y}, \mathbf{u})\big) \\ &\beta_2 \big(h_b(\mathbf{y}, \mathbf{u}) + h_{fc}(\mathbf{y}, \mathbf{u}) + h_{ez}(\mathbf{y}, \mathbf{u}) \\ &+ h_{mh}(\mathbf{y}, \mathbf{u}) + h_{op}(\mathbf{y}, \mathbf{u})\big) \end{aligned}$$

where h_{mg} is the economic cost of the power exchanged with the EU and includes the benefits of electricity sold and the penalty for possible deviations from the agreed energy bid, h_{sp} includes the cost to purchase energy from the EU, h_b,h_{fc},h_{ez} and h_{mh} are costs related with the degradation of the micro-grid equipment, and h_{op} is a cost related with operational constraints of the micro-grid. All these costs are described in detail in the following sections. The parameters β_1 and β_2 are fixed by the designer to weight the term of the economic profit versus the term of the operation cost.

The economic costs considered in this work have terms that depend on the sign of a given value. The sign function is a non-differentiable function. In order to use gradient base techniques to solve the optimization problems that define the model predictive controller, the following functions will be used instead of the sign function: $\delta_1(x) = (0.5 + (0.5/\pi) \cdot \arctan(a \cdot x))$ and $\delta_2(x) = (0.5 - (0.5/\pi) \cdot \arctan(a \cdot x))$. Function $\delta_1(x)$ is 0 when $x < f(a)$, is 1 when $x > f(a)$ and $f(a) \to 0$ when $a \to \infty$. Function $\delta_2(x)$ is 1 when $x < f(a)$, is 0 when $x > f(a)$ and $f(a) \to 0$ when $a \to \infty$.

3.1 Sold energy cost h_{mg}

The term h_{mg} models the average benefit of selling energy to the PV and the penalty of a deviation between the energy bought or sold the the PV and the agreed value of the contract, often call the energy bid.

$$h_{mg}(\mathbf{c}; \mathbf{y}, \mathbf{u}) = \frac{1}{T} \sum_{j=0}^{T-1} f_{mg}(j)$$

where $f_{mg}(j) = f_{mg}(c(j), y(j), u(j))$ is the economic stage cost of the energy sold at sampling time j.

The term f_{mg} models the benefit of selling energy to the PV and the penalty of the energy bid, that is, the deviation between the energy bought or sold to the PV, P_{grid}, and the agreed value of the contract, P_{of}. The penalty for not fulfilling the contract is in general a complex function that depends on the deviation. In this work we consider two different linear costs depending on whether the deviation is negative (energy deficit) or positive (surplus of energy). $P^{up}_{enalc}(\%)$ is the penalization percentage due to a positive deviation and $P^{lw}_{enalc}(\%)$ is the penalization percentage due to a negative deviation. Using δ_1 and δ_2 in order to approximate these costs we obtain the following expression $f_{mg}(j) = f^{up}_{mg}(j) + f^{lw}_{mg}(j) - C_{poolh} \cdot P_{grid}(j)$ where

$$\begin{aligned} \Delta P_j &= P_{of}(j) - P_{grid}(j) \\ f^{up}_{mg}(j) &= -\delta_1(\Delta P_j) \cdot P^{up}_{enalc}(\%) \cdot C_{poolh} \cdot \Delta P_j \\ f^{lw}_{mg}(j) &= -\delta_2(\Delta P_j) \cdot P^{lw}_{enalc}(\%) \cdot C_{poolh} \cdot \Delta P_j \end{aligned}$$

3.2 Purchased or wasted energy h_{sp}

The term h_{sp} models the average cost of energy supplied by the SP as follows $h_{sp}(\mathbf{c}; \mathbf{y}, \mathbf{u}) = \frac{1}{T} \sum_{j=0}^{T-1} f_{sp}(j)$ where $f_{sp}(j) = f_{sp}(c(j), y(j), u(j))$ is the economic stage cost of the energy sold at sampling time j.

The energy provided by the EU is purchased in order to provide a power supply when the cost of use the stored energy are high. Positive values of P_{grid} imply returning or selling energy and negative values imply purchasing energy. The cost that represent the waste of energy (when $P_{of} = 0$, i.e. there are not power agreed with the EU) is a quadratic term and the purchase of energy ($P_{of} > 0$) is a linear term. This cost is expressed as follows

$$\begin{aligned} f_{sp}(j) = &\delta_2(P_{grid}) \cdot C_{buy} \cdot \|P_{grid}(j)\| \\ &+ (1 - \delta_1(P_{of})) \cdot \delta_1(P_{grid}) \cdot 10 \cdot \|P_{grid}(j)\|^2 \end{aligned}$$

where the weight of the quadratic term is a technological-economic weight chosen to avoid that the micro-grid throws away energy instead of storing it.

3.3 Degradation cost of equipments

Battery cost h_b The degradation cost of the lead acid batteries can be posed as follows

$$h_b(\mathbf{y}, \mathbf{u}) = \frac{C_{ibat} \cdot \frac{1}{3600}}{CN \cdot V_{dc} \cdot N_{cycles} \cdot \eta_{bat}} \cdot \frac{1}{T} \sum_{j=0}^{T-1} \|P_{bat}(j)\|$$

where C_{ibat} is the investment cost of the batteries and it has a value of 2548 e.u., CN is the nominal capacity of the batteries and has a value of 333 Ah. V_{dc} is the voltage of the batteries and has a value of 48 V, N_{cycles} is the numbers of equivalent cycles and it has a value of 96. Finally η_{bat} models the performances of the batteries and has a value of 0.8.

Hydrogen cost h_{fc},h_{ez},h_{mh} Each charging and discharging cycle of the metal hydride tank has a cost because of the limited number of cycles that the alloy can stand and the gradual loss of capacity. The cost of the electrolyzer and the fuel cell it is composed by two terms: a cost associated to the time that both systems stay on in a period T and a cost associated to the number of ignitions of any of these systems in a period T. Thus, $h_{fc}(\mathbf{y},\mathbf{u}) = J^{fc}_{TON} + J^{fc}_{NON}$ and $h_{ez}(\mathbf{y},\mathbf{u}) = J^{ez}_{TON} + J^{ez}_{NON}$ where J_{TON} penalizes the time that the equipment (the fuel cell or the electrolyzer) is switched on and J_{NON} penalizes the number of times that the equipment is switched on. These are described as follows:

$$J^{fc}_{TON} = \frac{C_{ifc}}{N^{fc}_{TH}} \cdot Tm \cdot \frac{1}{T}\sum_{j=0}^{T-1} \delta_1(P_{H2}(j))$$

$$J^{fc}_{NON} = \frac{C_{ifc}}{N^{fc}_{TH}} \cdot \frac{1}{T}\sum_{j=1}^{T-1} \Big(\delta_1(P_{H2}(j)) - \delta_1(P_{H2}(j-1))\Big)$$

$$J^{ez}_{TON} = N^{ez}_{TH} \cdot Tm \cdot \frac{1}{T}\sum_{j=0}^{T-1} \Big(\delta_2(P_{H2}(j)) \cdot (5 \cdot \|P_{H2}(j)\| + 1.5)\Big)$$

$$J^{ez}_{NON} = \frac{C_{iez}}{N^{ez}_{TH}} \cdot \frac{1}{T}\sum_{j=1}^{T-1} \Big(\delta_2(P_{H2}(j)) - \delta_2(P_{H2}(j-1))\Big)$$

where C_{ifc} is the investment cost of the fuel cell ($7000 e.u./Kw$), N^{fc}_{TH} is the total number of the life time hours of the fuel cell ($30000 hours$), N^{ez}_{TH} is the total number of the life time hours of the electrolyzer ($55000 hours$) and C_{iez} is the investment cost of the electrolyzer ($7000 e.u./Kw$).

Metal hydride tank h_{mh}: This cost penalizes the usage of the hydrogen based storage system. If this term is penalized then the batteries are prioritized as storage system. This cost is calculated as the average cost of the deviation of the metal hydride level from its initial value. This cost can be expressed as follows

$$h_{mh}(\mathbf{y},\mathbf{u}) = \frac{V_{H2}}{100 \cdot N_{TC}} \cdot \frac{1}{T}\sum_{j=0}^{T-1} \|MHL(j) - MHL(0)\|$$

where V_{H2} is the total volume of the deposit, N_{TC} is the total number of estimated cycles of life time of the metal hydride deposit ($30600 \quad cycles$), and $MHL(k)$ is the level of stored hydrogen of the metal hydride deposit at time k.

4. PROPOSED ECONOMIC CONTROL SYSTEM

The control system must be designed to operate the plant ensuring a safe and stable behavior while optimizing the economic costs. The cost function defined in the previous section will be used as the measure of the performance of the controller. The controller will be designed based on the linear control model derived in a previous section.

For a given set of predicted trajectories of the parameters that define the cost function, the optimal periodic trajectory of the linear system $(\mathbf{y}^\star(\mathbf{c}), \mathbf{u}^\star(\mathbf{c}))$ can be obtained solving a finite dimension optimization problem in which the initial state is a free variable. Thus, in general a control law $u(k) = \kappa(x(k), \mathbf{c})$ must be designed to ensure that the closed-loop system

$$\begin{aligned} x(k+1) &= Ax(k) + B\kappa(x(k), \mathbf{c}) + B_d w(k) \\ y(k) &= Cx(k) \end{aligned}$$

satisfies the constraints along its evolution, is stable and converges to the optimal trajectory $(\mathbf{y}^\star(\mathbf{c}), \mathbf{u}^\star(\mathbf{c}))$.

Notice that each time that the parameters $\mathbf{c}$ is changed, the optimal trajectory where the plant should be operated $(\mathbf{y}^\star(\mathbf{c}), \mathbf{u}^\star(\mathbf{c}))$ is also changed and the controller should be capable to steer the plant to this new optimal trajectory. This may lead to a possible loss of feasibility of the predictive controller.

In [Limon et al., 2014] an economic MPC for periodic systems that ensures stability and convergence to the optimal trajectory under changes in the parameters $\mathbf{c}$ has been proposed. In this paper, this control technique has been used to develop the control system of the micro-grid.

The main idea of this controller is the addition of an artificial reachable trajectory $(\mathbf{y}^r, \mathbf{u}^r)$ as decision variable of the optimization problem. Then two cost functions of the predictive controller are defined:

$$\begin{aligned} V_t(y; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N) &= \sum_{i=0}^{N-1} \|y(i) - y^r(i)\|^2_Q + \|u(i) - u^r(i)\|^2_R \\ V_p(\mathbf{c}; \mathbf{y}^r, \mathbf{u}^r) &= h_{eco}(\mathbf{c}; \mathbf{y}^r, \mathbf{u}^r) \end{aligned}$$

where it is assumed that $N \le T$. The term V_p is the economic cost function of the reachable trajectory while V_t is the tracking cost of the predicted trajectory w.r.t. the reachable trajectory. The total cost function of the optimization problem is defined as follows

$$V_N(y, \mathbf{c}; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N) = V_t(y; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N) + V_p(\mathbf{c}; \mathbf{y}^r, \mathbf{u}^r)$$

And the control law of the controller is derived from the solution of the following optimization problem $P_N(y, \mathbf{c})$

$$(\mathbf{y}^{r*}, \mathbf{u}^{r*}, \mathbf{u}^*_N) = \min_{\mathbf{u}, \mathbf{y}^r, \mathbf{u}^r} V_N(y, \mathbf{c}; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N)$$

$$\begin{aligned} s.t.\ & x(i+1) = Ax(i) + Bu(i) + B_d w(i) && \text{(1a)} \\ & y(i) = Cx(i) && \text{(1b)} \\ & x(0) = x && \text{(1c)} \\ & u(i) \in \mathcal{U} && \text{(1d)} \\ & x^r(i+1) = Ax^r(i) + Bu^r(i) + B_d w(i) && \text{(1e)} \\ & y^r(i) = Cx^r(i) && \text{(1f)} \\ & u^r(i) \in \mathcal{U} && \text{(1g)} \\ & x^r(0) = x^r(T) && \text{(1h)} \\ & x(N) = x^r(N) && \text{(1i)} \end{aligned}$$

The optimal solution to this optimization problem is assumed to be unique. The constraints force the system dynamics and constraints in the artificial reachable trajectory $(\mathbf{y}^r, \mathbf{u}^r)$ and in the predicted trajectories. In addition, two terminal constraints have been added for stability reasons. Constraint (1h) is added to guarantee that the reachable trajectory is periodic, while constraint (1i) guarantees that the terminal state of the predicted trajectory of the plant reaches the reachable trajectory.The control law is given by $u(k) = \kappa_N(x(k), \mathbf{c}) = u^*(0)$.

The proposed controller ensures that the controlled system is admissibly stabilized to the optimal economically reachable periodic trajectory $(\mathbf{y}^\star(\mathbf{c}), \mathbf{u}^\star(\mathbf{c}))$. Furthermore, the addition of the auxiliary reachable periodic trajectories in the MPC formulation leads to an enlargement of the domain of attraction of the predictive controller and to the guarantee of recursive feasibility when the set of parameters $\mathbf{c}$ is changed and convergence to the new economically optimal trajectory [Limon et al., 2014]. Since the control law is continuous, the closed loop system results to be robust to slow variations on the forecasted energy production or demand as well as small model mismatches.

5. SIMULATION RESULTS

In this section two main scenarios are proposed. In the first scenario, the convergence of the controlled system to the optimal operation trajectory is demonstrated. In the second scenario, the capability of the controller to operate the plant in presence of abrupt changes in the cost parameters is shown. All the simulations have been carried out using the high order nonlinear model presented in [Valverde et al., 2013].

The simulations were made in *Matlab 2013a* in a computer with i7-4700 processor and 16 GB of RAM. The optimization problem $P_N(y, \mathbf{c})$ is solved using a sequential quadratic programming algorithm implemented in the function *fmincon* provided by Matlab. The solver used was *fmincon* with the *sqp* algorithm. The period of the problem was $T = 48$ and the prediction horizon was $N = 24$. Thus the number of decision variables needed to solve the optimization problem was $4T + 4N = 288$. The average time needed to solve the optimization problem was about 190-240 seconds, which is lower than the sampling time of 1800 seconds.

The renewable generation power of PV system has been obtained using a sunny day profile shown in figure 2. The internal demand of the micro-grid is shown in figure 2. This demand profile correspond to the standard demand of a house in a 24h. period. The known and periodic disturbances are obtained subtracting the demand profile to the generation profile and it is shown in figure 2. These profiles are assumed to be periodic with a period of 24h.

The prices of intraday market used in this paper are taken from the OMI-Polo Español S.A. (OMIE) web page (www.omel.es). These data correspond to June 24, 2014. The power agreed with the EU are shown in figure 2. The weighting terms of the economic cost function have been taken as $\beta_1 = 10$ and $\beta_2 = 0.2$ to balance the unitary cost of operating the plant with the unitary cost of the energy dispatch.

5.1 First scenario: convergence.

In this scenario, the micro-grid is only allowed to sell power to the EU using the prices of the figure 2 between 07:00 and 16:00. The price to buy energy is 0.12 e.u.

Figure 3(a) shows the evolution of the batteries and metal hidride levels SOC and MHL. Figure 3(b) shows the power profiles P_{grid}, P_{H2} and P_{bat}. As shown in these 3, the controller tries to buy only the energy needed to maintain

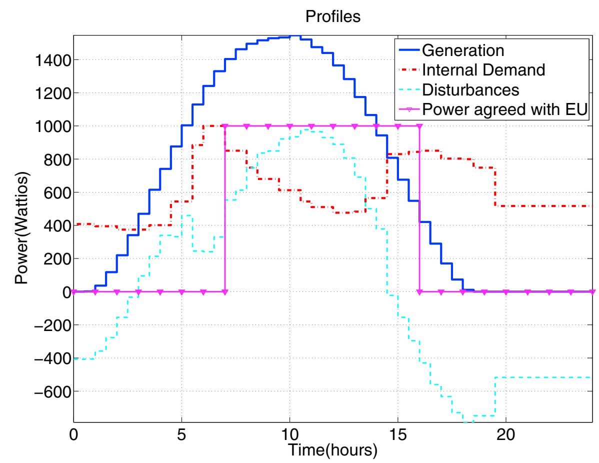

Fig. 2. Power profiles:(continuous) generation profile, (dash-dot) demand profile, (discontinues) disturbances obtained from generation and demand profile (generation minus demand) and (market continuous) power agreed with the EU

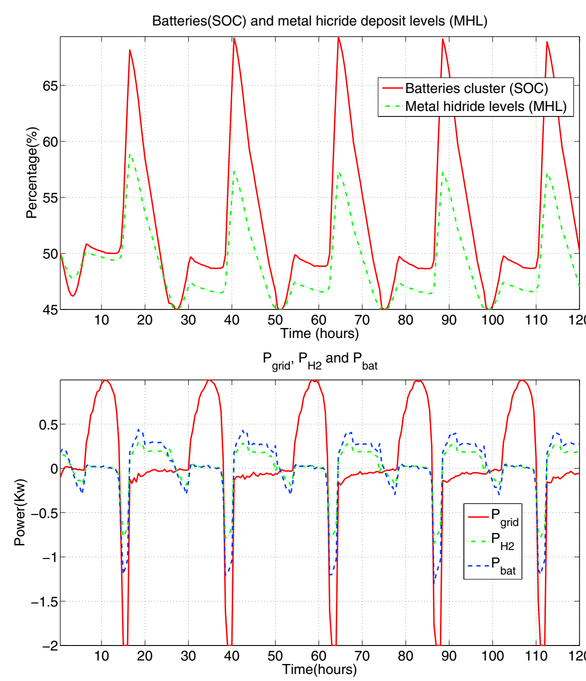

Fig. 3. (a) Batteries and metal hidride levels, (b) power profiles P_{grid}, P_{H2} and P_{bat} for scenario 1.

the SOC and MHL minimum levels. Between 07:00 and 16:00, the controller sells all the energy generated by the PV to the SP. Note that the controller buys energy when the selling price is lower. The evolution of the SOC is stabilized following a periodic trajectory near to its lower limit because during the transient, the energy extracted from the storage systems in a period of 24 hours is greater than the energy injected.

Figure 4 shows the accumulated cost of the economic function. These figures show that the economic cost decreases when the micro-grid sells energy to the EU and that it converges to a periodic trajectory which is optimal from an economic point of view.

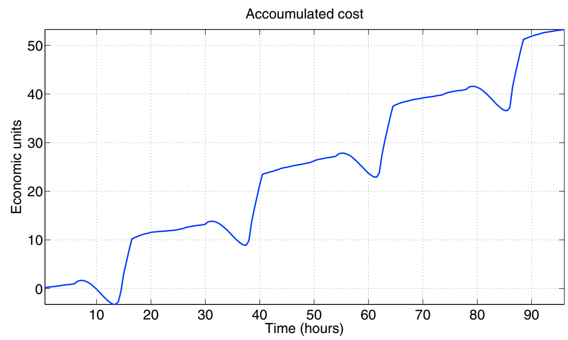

Fig. 4. Accumulated cost for scenario 1.

5.2 Second scenario: changing the economic cost

In the second scenario, after 48 hours the variable P_{of} becomes zero and the micro-grid can't sell energy. This implies a sudden change in the economic objective function, which modifies the optimal periodic trajectory. In two stage controllers, this sudden change may lead to a loss of feasibility. In the controller used however, the constraints of the MPC problem do not depend on the economic cost function, and hence recursive feasibility is guaranteed by design.

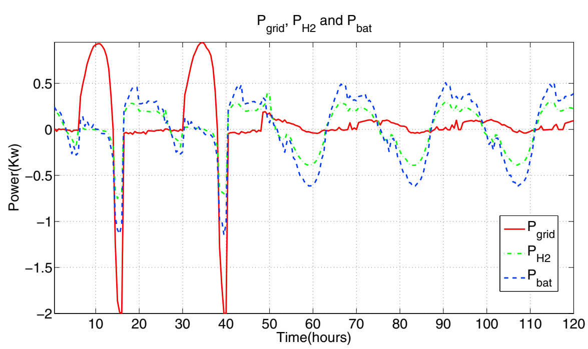

Fig. 5. Power profiles P_{grid}, P_{H2} and P_{bat} for scenario 2.

Figure 5 shows the power profiles P_{grid}, P_{H2} and P_{bat}. This figure show the change in the behavior of the storage systems after the cost function changes and how the controller maintains recursively feasibility.

6. CONCLUSIONS

In this paper we have presented an economic cost function that penalizes the deviation respect to the agreed power with the service provider and the degradation of the system associated with the micro-grid is proposed.The simulation results obtained using a model of a micro-grid demonstrate that periodic economic MPC is an appropriate approach to control this class of systems to guarantee optimal performance from an economic point of view in the presence of sudden changes on the economic criterion.

REFERENCES

David Angeli, Rishi Amrit, and James B. Rawlings. On average performance and stability of economic model predictive control. *IEEE Trans. Automat. Contr.*, 57: 1615–1626, 2012.

S.A. Arefifar, Y.A.-R.I. Mohamed, and T. El-Fouly. Optimized multiple microgrid-based clustering of active distribution systems considering communication and control requirements. *IEEE Trans. Ind. Electron.*, 62(2):711–723, Feb 2015. ISSN 0278-0046. doi: 10.1109/TIE.2014.2352212.

Dae-Keun Choi and Kyo-Beum Lee. Dynamic performance improvement of ac/dc converter using model predictive direct power control with finite control set. *IEEE Trans. Ind. Electron.*, 62(2):757–767, Feb 2015. ISSN 0278-0046. doi: 10.1109/TIE.2014.2352214.

A. Ferramosca, J. B. Rawlings, D. Limon, and E. F. Camacho. Economic MPC for a changing economic criterion. In *Proceedings of 49th IEEE Conference on Decision and Control, CDC 2010*, 2010.

Ravi Gondhalekar, Frauke Oldewurtel, and Colin N. Jones. Least-restrictive robust periodic model predictive control applied to room temperature regulation. *Automatica*, 49, 2013.

R. Huang, E. Harinath, and L. T. Biegler. Lyapunov stability of economically oriented NMPC for cyclic processes. *J. Process Control*, 2011. Article in press.

D. Limon, T. Alamo, D. Muñoz de la Peña, M. N. Zeilinger, C. N. Jones, and M. Pereira. Mpc for tracking periodic reference signals. *NMPC'12*, 2012.

D. Limon, M. Pereira, D. Muñoz de la Peña, T. Alamo, and J.M. Grosso. Single-layer economic model predictive control for periodic operation. *J. Process Control*, 2014.

Harald Miland and Øystein Ulleberg. Testing of a small-scale stand-alone power system based on solar energy and hydrogen. *Solar Energy*, 86:666–680, 2012.

Alessandra Parisio, Evangelos Rikos, and Luigi Glielmo. A model predictive control approach to microgrid operation optimization. *IEEE Trans. Contr. Syst. Techn., vol. 22 (2014),1813-1827*, 2014a.

Alessandra Parisio, Evangelos Rikos, George Tzamalis, and Luigi Glielmo. Use of model predictive control for experimental microgrid optimization. *Applied Energy*, 115:37–46, 2014b.

J. Salazar, F. Tadeo, and L. Valverde. Predictive control of a renewable energy microgrid with operational cost optimization. *IEEE 39th Annual Conference - IECON 2013 ,Industrial Electronics Society*, pages 7950 – 7955, 2013.

Cara R. Touretzky and Michael Baldea. Integrating scheduling and control for economic mpc of buildings with energy storage. *J. Process Control*, 24:1292–1300, 2014.

L. Valverde, C. Bordons, and F. Rosa. Power management using model predictive control in a hydrogen-based microgrid. *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society*, pages 5669–5676, 2012.

L. Valverde, F. Rosa, A.J. Del Real, A. Arce, and C. Bordons. Modeling, simulation and experimental set-up of a renewable hydrogen-based domestic microgrid. *Int. J. Hydrogen Energy*, 38:11672–11684, 2013.

Peng Wang, Chi Jin, Dexuan Zhu, Yi Tang, Poh Chiang Loh, and Fook Hoong Choo. Distributed control for autonomous operation of a three-port ac/dc/ds hybrid microgrid. *IEEE Trans. Ind. Electron.*, 62 (2):1279–1290, Feb 2015. ISSN 0278-0046. doi: 10.1109/TIE.2014.2347913.