Periodic Economic Control of a Nonisolated Microgrid

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Periodic Economic Control of a Nonisolated Microgrid

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***Abstract*—This paper presents the application of economic predictive control to minimize the cost of operating a nonisolated microgrid connected to an electric utility (EU) subject to a periodic internal demand. The microgrid considered is composed of a set of photovoltaic panels and two storage systems and it can buy and sell energy to an EU. The first storage system is composed of a cluster of batteries of lead acid, and the second storage system is based on hydrogen storage. A function that describes the economic cost of operating the plant taking into account aspects such as electric market costs, degradation of the microgrid, 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 on a realistic nonlinear model of an experimental configurable testbed located in the laboratories of the University of Seville.**

***Index Terms*—Economic control, model predictive control (MPC), periodic control, renewable energy.**

I. Introduction

MODERN countries must face the energy problem caused by an increasing demand with limited fossil fuel sources and environmental restrictions. Among the actions that have been taken to deal with this problem are the support to the use of renewable energy sources and the improvement of the efficiency of the equipment and energy systems. These actions have led to a change in the energy management policies allowing for more flexible scenarios that take into account the uncertain nature of the renewable energy sources and the consumers' demand. In these scenarios, microgrids, that is, a group of interconnected loads and distributed energy resources with clearly defined electrical boundaries that act as a single controllable entity with respect to the grid, have a relevant role. These systems can operate in both grid-connected and island modes and, in general, they try to satisfy their internal demand and, if possible, sell the excess of produced energy to the grid. To this end, microgrids rely on energy storage systems such as batteries or hydrogen-based storage systems.

The control of microgrids 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 [1] and [2]). In (3), an experimental small-scale standalone power system based on hydrogen is presented. Model predictive control (MPC) has also been applied to this class of systems (see, for example, [4]–[7]). In [8]–[10], nonlinear MPC techniques were applied to supervise a microgrid with wind-solar energy generation systems and water-system-based load. In [11], a Lyapunov-based economic controller for nonlinear systems was proposed and applied to a microgrid with renewable generation. In [12]–[14], MPC techniques were applied to supervise a hybrid model of a microgrid with a hydrogen storage system. In [15], 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 microgrid 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 microgrid from an economic point of view is not to remain at a certain steady state but to follow a nonsteady trajectory, often periodic [16], [17]. Several MPC schemes that deal with this problem have been recently proposed (see, for example, [18] and [19]).

In addition, efficient operation of microgrids can be enhanced if economic costs are taken into account in the control system design. For example, changing weather conditions and passing cloud cover produce varying power generation from solar systems such as photovoltaic (PV). This may cause large rapid power fluctuations. The exposition of the fuel cell and the electrolyzer to such short-term and highly variable power conditions may lead to degradation of performance and lifetime of these hydrogen-based power systems. In order to make these systems economically competitive, the cost associated with performance and lifetime degradation should be reduced. Using better power management strategies to operate these storage systems under the most favorable operating regimes has great potential for improving their lifetime.

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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 the target trajectory [20], [21]. More recently, MPC laws that take economic costs into account have been proposed, i.e., the so-called economic MPC (see [22]–[24] for a discussion on the properties of this class of controllers). These control laws could be used for the efficient control of a microgrid 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, which may change throughout the operation of the microgrid. 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 [25], [26].

Motivated by these issues, in this paper, we present the application of a novel economic MPC for periodic systems [27] capable of dealing with changing economic cost functions to minimize the cost of operating a nonisolated microgrid connected to a electric utility (EU) composed by a set of PV panels and a hybrid battery/hydrogen storage system. We consider a scenario in which the microgrid has signed a contract with the EU 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 cannot be sold and is wasted, although the microgrid can still purchase energy. To this end, we propose a cost function that takes into account the economic profit of the operation of the microgrid in the energy market as well as the economic cost of the operation of the plant in a realistic setting; in particular, the proposed cost function takes into account the benefit of selling energy from the microgrid, a nonlinear penalty for deviating from an energy bid, and the degradation of the batteries and the hydrogen storage systems. Assuming that precise predictions on the PV generation, internal demands, and energy bid contract are available, the efficient management of the facility is posed as an economic control problem of a periodic system. The proposed controller guarantees that the operation limits of the plant are satisfied and that the economically optimal operation trajectory of the microgrid is reached even in the presence of sudden changes in the parameters of the cost function. This control system has been validated through simulation on a nonlinear realistic model of a real microgrid [28], [29] located at the University of Seville. This testbed has been operative since 2011 and was designed to implement and study different modes of operation and control strategies to optimize hydrogen smart-grid operation.

II. Control of a Nonisolated Microgrid

In this paper, we consider the control of a noninsolated microgrid such as that shown in Fig. 1. This microgrid is made of a PV energy source, an energy consumer, a cluster of batteries, an energy storage system based on hydrogen, and a connection to an EU to which the microgrid can buy/sell energy from/to. The microgrid must try to sell an agreed power to the EU only during a certain interval of time. This power and interval of time are agreed with the EU.

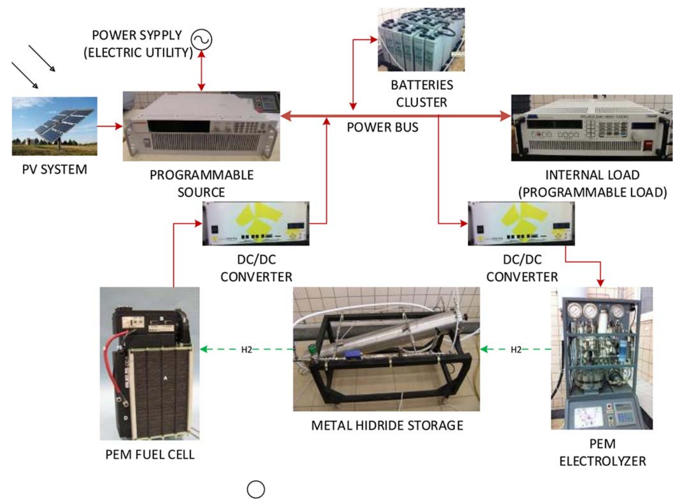

Fig. 1. Microgrid scheme simulated in the testbed located at the University of Seville.

The microgrid has two storage systems: a battery cluster and a hydrogen-based storage system. The hydrogen storage system is composed of a proton exchange membrane (PEM) 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 battery cluster included is used to support the short transitory power peaks due to its fast dynamics, 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 the 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 microgrid (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 such that the power of the battery (P_{bat}) is obtained from the power balance in the power bus, which can be expressed as

$$P_{\mathrm{bat}} + P_{H2} + P_{\mathrm{grid}} + P_{\mathrm{PV}} + P_{\mathrm{load}} = 0.$$

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

$$P_{\mathrm{net}} = P_{\mathrm{PV}} - P_{\mathrm{load}}.$$

The objective of this kind of microgrid 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.

(i) Maximize the profit of the energy exchange between the microgrid and the EU taking into account the prices of the intraday electricity market and the contract constraints.
(ii) Fulfill a known periodic internal demand.
(iii) Try to extend the lifetime of the equipment of the microgrid.
(iv) Fulfill the operational constraint in order to prevent damage to the equipment.

Remark 1: 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 microgrids 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 due to the receding-horizon scheme and the possibility of adapting to possible changes in these predictions.

A. Simulation Model

In this paper, we use the nonlinear high-order model of the nonisolated microgrid presented in previous work [28] to carry out the simulations. In this paper, a model based on first principles was developed and validated on the experimental configurable testbed located in the laboratories of the University of Seville. This testbed has been operative since 2011 and was designed to implement and study different modes of operation and control strategies to optimize hydrogen smart-grid operation. The testbed has the following equipment: a 6-kW programmable electronic source to emulate the renewable energy sources, a 1-kW PEM electrolyzer for the production of hydrogen, a 7-Nm3 hydrogen storage tank based on metal hydride alloy, a 367-Ah lead–acid battery bank, a 1.5-kW PEM fuel cell, and finally, a 2.5-kW programmable electronic load to emulate different demand profiles. The programmable electronic source was programmed to emulate the behavior of a PV generation system, as shown in Fig. 1. The testbed has a programmable control system that allows implementing advanced control strategies based on the MATLAB/Simulink environment, which communicates using OPC with a PLC that controls the low-level inputs.

In [28], the nonlinear and complex nature of the dynamics of the plant is described by a set of nonlinear algebraic and differential equations. The reader can refer to this work for a detailed description of the model. These equations were implemented in a Simulink, and a set of suitable parameters were identified and validated on the testbed. The equations of the simulation model and its validation can be found in [28] and [29]. The main parameters of the models that compose the storage systems are shown in Tables I–IV.

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 to the equipment. Power P_{grid} is limited between -2.5 and 2 kW. Power P_{H_2} is limited between -0.9 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 a microgrid, and in the hydrogen storage system, it is necessary to maintain the hydrogen levels between

TABLE I
PEM ELECTROLYZER MODEL PARAMETERS

PEM electrolyzer model parameters	
Comments	Values
Stack area	$212.5cm^2$
H_2 Partial pressure	$6.9bar$
O_2 Partial pressure	$1.3bar$
Anode current density	$1.0631^{-6}A/cm^2$
Cathode current density	$1^{-3}A/cm^2$
Membrane thickness	$178\mu m$
Membrane conductivity	$0.14S/cm$
Membrane water content	$21molH_2/molSO_3$
Thermal capacity	$402400J/K$

TABLE II
PEM FUEL CELL MODEL PARAMETERS

PEM fuel cell model parameters	
Comments	Values
Fuel cell stack mass	$5kg$
Fuel cell heat capacity	$1100Jkg^{-1}K^{-1}$
Fuel cell emissivity	0.9
Radiation exchange area	$0.1410m^2$
Fuel cell natural exchange area	$0.0720m^2$
Fuel cell forced exchange area	$1.2696m^2$
Natural heat transfer coefficient	$14WK^{-1}m^{-2}$
Forced heat transfer coefficient	$19.65WK^{-1}m^{-2}$

TABLE III
METAL HYDRIDE MODEL PARAMETERS

Metal hydride tank model parameters	
Comments	Values
MH powder porosity	0.55
MH density	$3240kg/m^3$
Max. absorbed/desorbed H2 weight frac.	$1.2174\%w/w$
MH specific heat at constant volume	$419J/(molK)$
Heat transfer area	$1.1453m2$
MH volume ratio	1
Absorbed radiation	$21.18KJ/nik$
Activation energy	$59.1871/s$
Desorption heat transfer coefficient	$966.1980W/(m^2K)$
Absorption heat transfer coefficient	$833.144W/(m^2K)$

TABLE IV
BATTERY MODEL PARAMETERS

Battery model parameters	
Comments	Values
Maximum battery capacity	$367Ah$
Battery voltage	$48V$
Charge/discharge polarization constant	$0.006215V$
Exponential zone amplitude	$11.053V$
Exponential zone inverse time constant	$2.452Ah^{-1}$

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.

B. Controller Design Model

In order to implement the control law proposed in [27], a discrete-time linear model is needed. After analyzing the response of the system, the microgrid was modeled as two integrators with weighted inputs. A series of simulations was 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 min with different initial states and step amplitudes were done. The parameters of the system were obtained as the mean value of these slopes. The resulting continuous-time linear model was

$$\dot{x} = \begin{bmatrix} 0.2712 & 0.1986 \\ -0.5096 & 0 \end{bmatrix} u(t) + \begin{bmatrix} 0.1986 \\ 0 \end{bmatrix} w(t)$$

with $x = [SOC\ MHL]^T$, $u = [P_{H_2}\ P_{\mathrm{grid}}]^T$, and $w = P_{\mathrm{net}}$. The following discrete-time linear model used to design the controller was obtained using a Tustin method and a sampling time of 1800 s (30 min), i.e.,

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

The sampling time chosen is satisfactory for a long-term analysis assuming smooth irradiation profiles. The structure of the microgrid 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 microgrid. 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.

III. 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 equipment devices might be subjected 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,

$$\begin{aligned} \mathbf{y} &= (y(0), y(1), \ldots, y(T-1)) \\ \mathbf{u} &= (u(0), u(1), \ldots, u(T-1)). \end{aligned}$$

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 $c = [C_{\mathrm{poolh}}\ C_{\mathrm{buy}}\ P_{\mathrm{of}}]^T$. 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

$$\mathbf{c} = (c(0), c(1), \ldots, c(T-1))$$

and it is such that C_{poolh} and C_{buy} remain constant along the period, whereas P_{of} may vary.

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

$$\begin{aligned} h_{\mathrm{eco}}(\mathbf{c}; \mathbf{y}, \mathbf{u}) = \beta_1 \left(h_{mg}(\mathbf{c}; \mathbf{y}, \mathbf{u}) + h_{sp}(\mathbf{c}; \mathbf{y}, \mathbf{u})\right) \\ \times \beta_2 \left(h_b(\mathbf{y}, \mathbf{u}) + h_{fc}(\mathbf{y}, \mathbf{u}) + h_{ez}(\mathbf{y}, \mathbf{u}) \right. \\ \left. + h_{mh}(\mathbf{y}, \mathbf{u}) + h_{op}(\mathbf{y}, \mathbf{u})\right) \end{aligned} \tag{1}$$

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 microgrid equipment; and h_{op} is a cost related with operational constraints of the microgrid. 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 nondifferentiable function. In order to use gradient-based techniques to solve the optimization problems that define the model predictive controller, the following functions will be used instead of the sign function:

$$\begin{aligned} \delta_1(x) &= (0.5 + (0.5/\pi) \cdot \arctan(a \cdot x)) \\ \delta_2(x) &= (0.5 - (0.5/\pi) \cdot \arctan(a \cdot x)). \end{aligned}$$

Function $\delta_1(x)$ is 0 when $x < f(a)$, 1 when $x > f(a)$, and $f(a) \to 0$ when $a \to \infty$. Function $\delta_2(x)$ is 1 when $x < f(a)$, 0 when $x > f(a)$, and $f(a) \to 0$ when $a \to \infty$.

Remark 2: If mixed-integer linear inequalities are used to model the sign cost function, the resulting optimization problem would be a nonlinear mixed integer, for which general-purpose solvers are not available, making implementation a much harder issue. We propose to use a nonlinear smooth approximation to simplify the implementation and inherit the closed-loop properties of the economic model predictive control scheme applied. In the simulations done, the resulting controller is not sensible to this approximation; however, the resulting optimization problem can be badly conditioned if this parameter is not appropriately chosen.

A. 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 energy bought or sold to the PV and the agreed value of the contract, which is often called the energy bid, i.e.,

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

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 energy bought or sold to the PV, i.e., P_{grid}, and the agreed value of the contract, i.e., P_{of}. The penalty for not fulfilling the contract is, in general, a complex function that depends on the deviation. In this paper, 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:

$$f_{mg}(j) = f^{up}_{mg}(j) + f^{lw}_{mg}(j) - C_{\text{poolh}} \cdot P_{\text{grid}}(j) \quad (2)$$

where

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

B. 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 of the stored energy is high. Positive values of P_{grid} imply returning or selling energy, and negative values imply purchasing energy. The cost that represents waste of energy (when $P_{\text{of}} = 0$, i.e., there is no power agreed with the EU) is a quadratic term, and that which represents purchase of energy ($P_{\text{of}} > 0$) is a linear term. This cost is expressed as follows:

$$\begin{aligned} f_{sp}(j) = &\,\delta_2(P_{\text{grid}}) \cdot C_{\text{buy}} \cdot \|P_{\text{grid}}(j)\| \\ &+ (1 - \delta_1(P_{\text{of}})) \cdot \delta_1(P_{\text{grid}}) \cdot 10 \cdot \|P_{\text{grid}}(j)\|^2 \quad (3) \end{aligned}$$

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

C. Degradation Cost of Equipment

1) Battery Cost h_b: The degradation cost of the lead–acid batteries can be posed as follows:

$$h_b(\mathbf{y},\mathbf{u}) = \frac{C_{ibat} \cdot \frac{1}{3600}}{CN \cdot V_{\text{dc}} \cdot N_{\text{cycles}} \cdot \eta_{\text{bat}}} \cdot \frac{1}{T}\sum_{j=0}^{T-1} \|P_{\text{bat}}(j)\| \quad (4)$$

where C_{ibat} is the investment cost of the batteries and has a value of 2548 e.u., and 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, and N_{cycles} is the number of equivalent cycles and has a value of 96. Finally, η_{bat} models the performances of the batteries and has a value of 0.8.

2) 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 is composed of two terms: a cost associated to the time that both systems stay on in period T and a cost associated to the number of ignitions of any of these systems in period T, i.e.,

$$h_{fc}(\mathbf{y},\mathbf{u}) = J^{fc}_{\text{TON}} + J^{fc}_{\text{NON}} \quad (5)$$

$$h_{ez}(\mathbf{y},\mathbf{u}) = J^{ez}_{\text{TON}} + J^{ez}_{\text{NON}} \quad (6)$$

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:

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

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

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

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

where C_{ifc} is the investment cost of the fuel cell (7000 e.u./Kw), N^{fc}_{TH} is the total number of the lifetime hours of the fuel cell (30 000 h), N^{ez}_{TH} is the total number of the lifetime hours of the electrolyzer (55 000 h), and C_{iez} is the investment cost of the electrolyzer (7000 e.u./Kw).

3) 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 a 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 the lifetime of the metal hydride deposit (30 600 cycles), and $MHL(k)$ is the level of stored hydrogen of the metal hydride deposit at time k.

D. Operation Costs f_{op}

This cost takes into account three different aspects of the operation of the plant: The cost J_{SM} penalizes sequence of control actions that are aggressive and is formulated as follows:

$$J_{SM} = \frac{1}{T}\sum_{j=0}^{T-1} \|\Delta u(j)\|. \tag{7}$$

The cost J_{DZ} penalizes values of P_{H2} in the zone of (−0.1, 0.1) as it is recommended by the vendor. This is given by

$$J_{DZ} = \frac{1}{T}\sum_{j=0}^{T-1} \delta_1\left(\|P_{H2}(j) - 0.1\|\right) \cdot \|P_{H2}(j)\|^2. \tag{8}$$

The cost J_{RB} penalizes those trajectories of SOC and MHL that are close to their operation limits, acting as a soft constraint on the limits on the outputs. Thus,

$$\begin{aligned} J_{RB} = \frac{1}{T}\sum_{j=0}^{T-1}\Big(&\delta_1\left(\|SOC(j)-48\|\right) \cdot \|SOC(j)-48\|^4 \cdot k_1 \\ &+ \delta_2\left(\|SOC(j)-75\|\right) \cdot \|SOC(j)-75\|^4 \cdot k_2 \\ &+ \delta_1\left(\|MHL(j)-48\|\right) \cdot \|MHL(j)-48\|^4 \cdot k_3 \\ &+ \delta_2\left(\|MHL(j)-75\|\right) \cdot \|MHL(j)-75\|^4 \cdot k_4\Big) \end{aligned}$$

where $k_i = 0.0001$ are weights that penalize the proximity of the output constraints.

The total operation cost is a weighted sum of these three cost, i.e.,

$$h_{op}(\mathbf{y}, \mathbf{u}) = \lambda_1 J_{SM} + \lambda_2 J_{DZ} + \lambda_3 J_{RB} \tag{9}$$

where λ_i are technologic-economic weights that designate the influence of each operational cost in the global economic function.

IV. 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 by solving the following finite-dimension optimization problem in which the initial state is a free variable:

$$\begin{aligned} \min_{\mathbf{y},\mathbf{u}} \quad & h_{\text{eco}}(\mathbf{c}; \mathbf{y}, \mathbf{u}) && \text{(10a)} \\ \text{s.t.} \quad & x(j+1) = Ax(j) + Bu(j) + B_d w(j) && \text{(10b)} \\ & y(j) = Cx(j) && \text{(10c)} \\ & u(j) \in U && \text{(10d)} \\ & y(T) = y(0) && \text{(10e)} \\ & j = \{0, 1, \ldots, T-1\} && \text{(10f)} \end{aligned}$$

where the set $\mathcal{U} = \{u : -0.9 \le u(0) \le 0.9, -2.5 \le u(1) \le 2\}$ is the set of limits in the control actions. Note that the limits on the outputs are considered as soft constraints in the economic cost function.

Thus, in general, a control law $u(k) = \kappa(x(k), \mathbf{c})$ must be designed to ensure that the closed-loop system

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

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 parameter $\mathbf{c}$ 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 of steering the plant to this new optimal trajectory. This may lead to a possible loss of feasibility of the predictive controller.

In [27], an economic MPC for periodic systems that ensures stability and convergence to the optimal trajectory under changes in parameter $\mathbf{c}$ has been proposed. In this paper, this control technique has been used to develop the control system of the microgrid.

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

$$V_t(y; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N) = \sum_{i=0}^{N-1} \|y(i) - y^r(i)\|_Q^2 + \sum_{i=0}^{N-1} \|u(i) - u^r(i)\|_R^2 \tag{11}$$

$$V_p(\mathbf{c}; \mathbf{y}^r, \mathbf{u}^r) = h_{\text{eco}}(\mathbf{c}; \mathbf{y}^r, \mathbf{u}^r) \tag{12}$$

where it is assumed that $N \le T$. The term V_p is the economic cost function of the reachable trajectory, whereas 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:

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

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

$$\begin{aligned} (\mathbf{y}^{r*}, \mathbf{u}^{r*}, \mathbf{u}_N^*) = \min_{\mathbf{u}, \mathbf{y}^r, \mathbf{u}^r} \; & V_N(y, \mathbf{c}; \mathbf{y}^r, \mathbf{u}^r, \mathbf{u}_N) \\ \text{s.t.} \quad & x(i+1) = Ax(i) + Bu(i) + B_d w(i) && \text{(13a)} \\ & y(i) = Cx(i) && \text{(13b)} \\ & x(0) = x && \text{(13c)} \\ & u(i) \in \mathcal{U} && \text{(13d)} \\ & x^r(i+1) = Ax^r(i) + Bu^r(i) + B_d w(i) && \text{(13e)} \\ & y^r(i) = Cx^r(i) && \text{(13f)} \\ & u^r(i) \in \mathcal{U} && \text{(13g)} \\ & x^r(0) = x^r(T) && \text{(13h)} \\ & x(N) = x^r(N). && \text{(13i)} \end{aligned}$$

The optimal solution to this optimization problem $(\mathbf{y}^{r*}, \mathbf{u}^{r*}, \mathbf{u}_N^*)$ 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 (13h) is added to guarantee that the reachable trajectory is periodic, whereas constraint (13i) guarantees that the terminal state of the predicted trajectory of the plant reaches the reachable trajectory.

The control law is given by

$$u(k) = \kappa_N\left(x(k), \mathbf{c}\right) = u^*(0).$$

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 [27]. Since the control law is continuous, the closed-loop system results in being robust to slow variations on the forecasted energy production or demand as well as small model mismatches. These are very interesting properties for the control of microgrids with periodic demand and generation and changing energy market. The following sections demonstrate the properties of the proposed control law on a validated simulation model of the microgrid considered.

Remark 3: The optimization problem solved is nonlinear, even if the model of the system is linear. However, the complexity of the optimization problems would be much higher if a nonlinear model was used for the system. This difference is more important in the case of periodic operation because the prediction horizon (at least for the artificial trajectory) must be equal to the period and, hence, leads to optimization problems with a large number of optimization variables.

V. Simulation Results

Here, 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 the 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 [28].

The simulations were made in *MATLAB 2013a* in a computer with a 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 s, which is lower than the sampling time of 1800 s.

The renewable generation power of the PV system has been obtained using a sunny-day profile shown in Fig. 2(a). The internal demand of the microgrid is shown in Fig. 2(b). This demand profile corresponds to the standard demand of a house in a 24-h period. The known and periodic disturbances are obtained by subtracting the demand profile from the generation profile, and it is shown in Fig. 2(c). These profiles are assumed to be periodic with a period of 24 h.

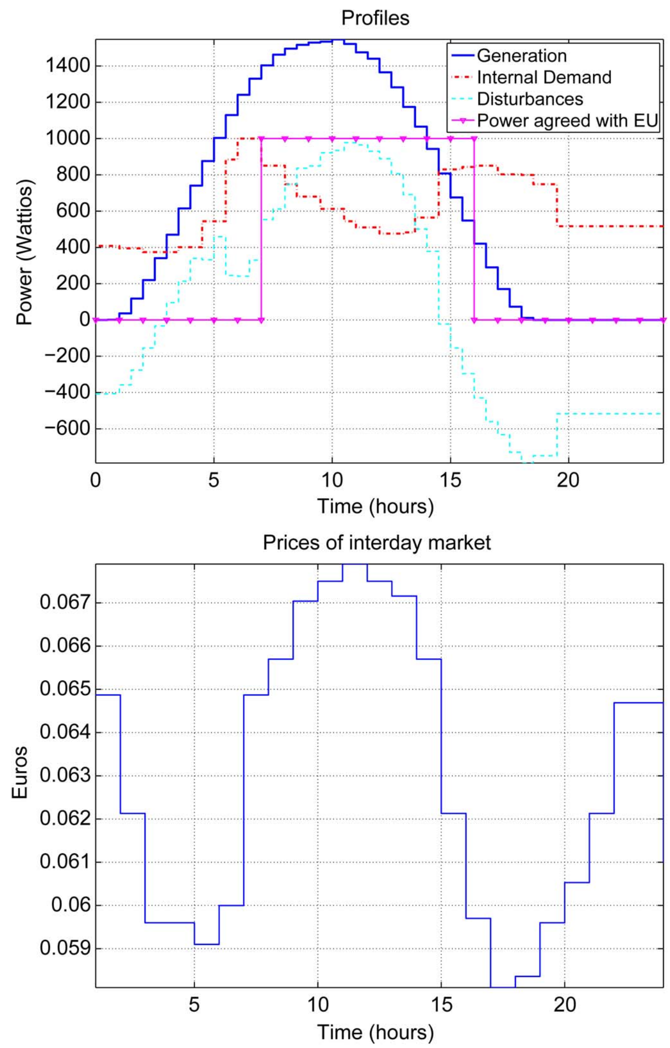

Fig. 2. (a) Power profiles: (continuous) generation profile, (dash-dot) demand profile, (discontinues) disturbances obtained from generation and demand profile (generation minus demand), and (market continuous) power agreed with the EU. (b) Prices profile: prices of intraday market.

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 price curve and the power agreed with the EU are shown in Fig. 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.

Remark 4: This approach can be applied to other microgrids with, for example, distributed generators or shiftable loads, taking into account appropriate changes in the cost function, particularly in the degradation cost of equipment. The generation power and internal loads are assumed to be known and are considered in the controller as disturbances of the system. A change in the generation systems or in the

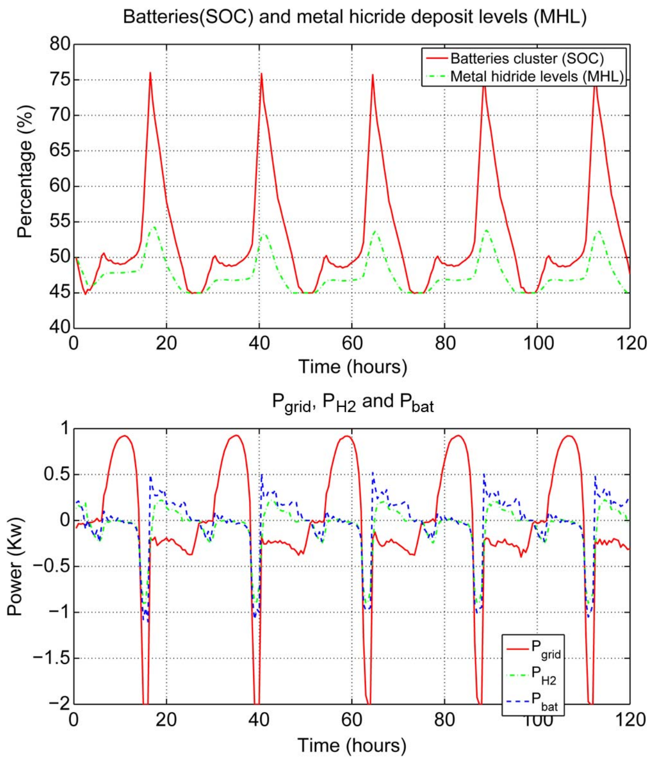

Fig. 3. (a) Batteries and metal hydride levels. (b) Power profiles P_{grid}, P_{H2}, and P_{bat} for scenario 1.

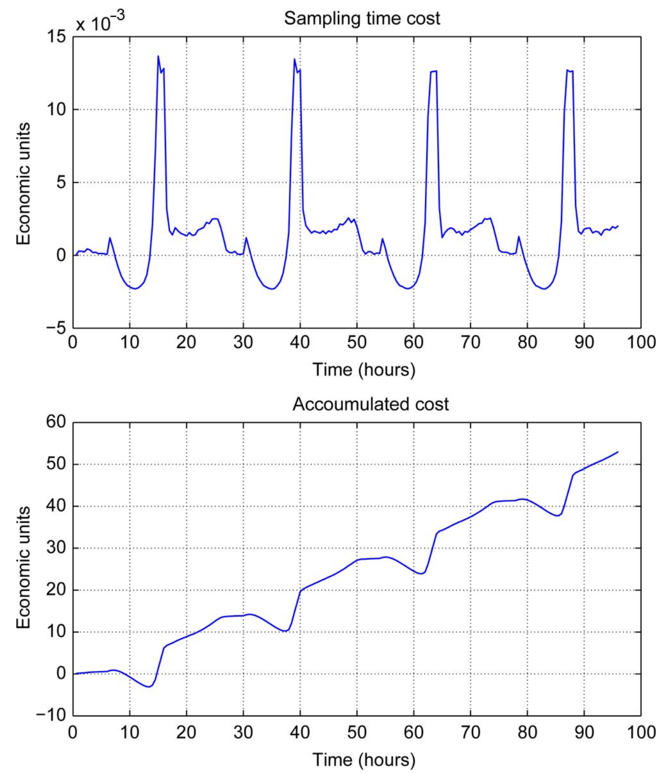

Fig. 4. Sampling time cost and accumulated cost for scenario 1.

loads is traduced as a change in the disturbances. The proposed controller has a certain degree of robustness (inherited from the receding-horizon scheme) to disturbance changes.

A. First Scenario: Convergence

In this scenario, the microgrid is only allowed to sell power to the EU using the prices in Fig. 2 between 07:00 and 16:00. The price to buy energy is 0.12 e.u.

Fig. 3(a) shows the evolution of the batteries and metal hydride levels SOC and MHL. Fig. 3(b) shows the power profiles P_{grid}, P_{H2}, and P_{bat}. As shown in these three, the controller tries to buy only the energy needed to maintain 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 its lower limit because during transient, the energy extracted from the storage systems in a period of 24 h is greater than the energy injected.

Fig. 4(a) shows the sampling time cost of the economic function. Fig. 4(b) shows the accumulated cost of the economic function. These figures show that the economic cost decreases when the microgrid sells energy to the EU and that it converges to a periodic trajectory that is optimal from an economic point of view.

B. Second Scenario: Changing the Economic Cost

In the second scenario, after 48 h, variable P_{of} becomes zero, and the microgrid cannot 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(a) shows the evolution of the batteries and metal hydride levels SOC and MHL. Fig. 5(b) shows the power profiles P_{grid}, P_{H2}, and P_{bat}. These figures show the change in the behavior of the storage systems after the cost function changes and how the controller recursively maintains feasibility. In this scenario, the storage systems reach its steady state near the upper constraint because it cannot sell the excess energy.

VI. Conclusion

In this paper, we have presented the application of a novel economic predictive control to minimize the cost of operating a nonisolated microgrid connected to an EU subject to a periodic internal demand. An economic cost function that penalizes the deviation with respect to the agreed power with the service provider and the degradation of the system associated with the microgrid was also proposed. One of the most interesting properties of the controller applied is that it provides a large domain of attraction and that the controller ensures closed-loop stability and convergence to the periodic trajectory that provides the optimal operation of the plant. In addition, if the unitary costs are changed, this controller remains feasible and converges to the new periodic optimal trajectory. The simulation results obtained using a high-order model of a microgrid demonstrate that periodic economic MPC is an appropriate

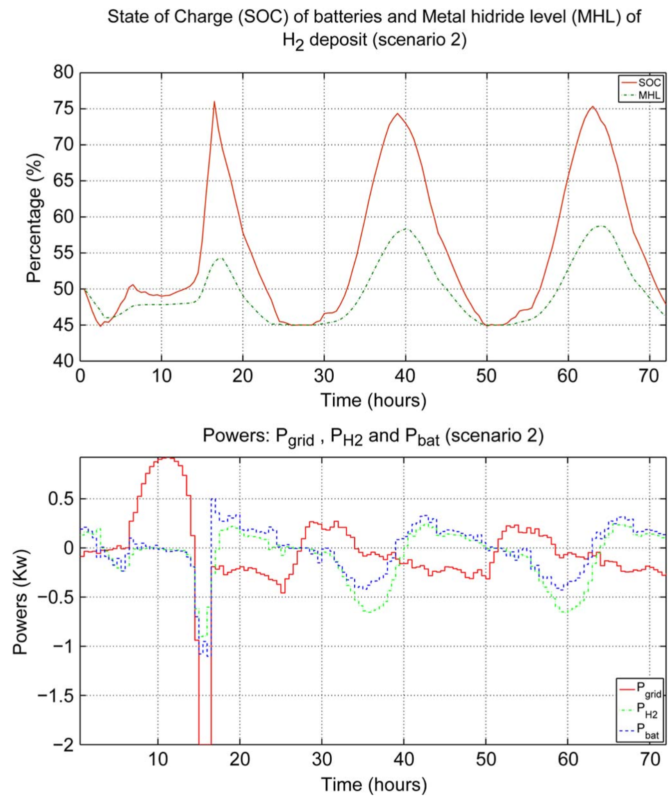

Fig. 5. (a) Batteries and metal hydride levels. (b) Power profiles $P_{\rm grid}$, P_{H2}, and $P_{\rm bat}$ for scenario 2.

approach to control this class of systems to guarantee optimal performance from an economic point of view in the presence of sudden changes in the economic criterion.

References

[1] S. Arefifar, Y.-R. Mohamed, and T. El-Fouly, "Optimized multiple microgrid-based clustering of active distribution systems considering communication and control requirements," *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 711–723, Feb. 2015.

[2] P. Wang *et al.*, "Distributed control for autonomous operation of a three-port ac/dc/ds hybrid microgrid," *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 1279–1290, Feb. 2015.

[3] H. Miland and O. Ulleberg, "Testing of a small-scale stand-alone power system based on solar energy and hydrogen," *Solar Energy*, vol. 86, no. 1, pp. 666–680, Jan. 2012.

[4] D.-K. Choi and K.-B. Lee, "Dynamic performance improvement of ac/dc converter using model predictive direct power control with finite control set," *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 757–767, Feb. 2015.

[5] A. Parisio, E. Rikos, G. Tzamalis, and L. Glielmo, "Use of model predictive control for experimental microgrid optimization," *Appl. Energy*, vol. 115, pp. 37–46, Feb. 2014.

[6] A. Parisio, E. Rikos, and L. Glielmo, "A model predictive control approach to microgrid operation optimization," *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 5, pp. 1813–1827, Sep. 2014.

[7] L. Valverde, C. Bordons, and F. Rosa, "Power management using model predictive control in a hydrogen-based microgrid," in *Proc. 38th IEEE IECON*, 2012, pp. 5669–5676.

[8] W. Qi, J. Liu, and P. D. Christofides, "Supervisory predictive control for long-term scheduling of an integrated wind/solar energy generation and water desalination system," *IEEE Trans. Control Syst. Technol.*, vol. 20, no. 2, pp. 504–512, Mar. 2012.

[9] W. Qi, J. Liu, X. Chen, and P. D. Christofides, "Supervisory predictive control of stand-alone wind–solar energy generation systems," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 1, pp. 199–207, Jan. 2011.

[10] W. Qi, J. Liu, and P. D. Christofides, "A distributed control framework for smart grid development: Energy/water system optimal operation and electric grid integration," *J. Process. Control*, vol. 21, no. 10, pp. 1504–1516, Dec. 2011.

[11] M. Heidarinejad, J. Liu, and P. D. Christofides, "Economic model predictive control of nonlinear process systems using Lyapunov techniques," *AIChE J.*, vol. 58, no. 3, pp. 855–870, Mar. 2012.

[12] F. Garcia and C. Bordons, "Regulation service for the short-term management of renewable energy microgrids with hybrid storage using model predictive control," in *Proc. 39th IEEE IECON*, 2013, pp. 7962–7967.

[13] J. Salazar, F. Tadeo, and L. Valverde, "Predictive control of a renewable energy microgrid with operational cost optimization," in *Proc. 39th IEEE IECON*, 2013, pp. 7950–7955.

[14] F. Garcia and C. Bordons, "Optimal economic dispatch for renewable energy microgrids with hybrid storage using model predictive control," in *Proc. 39th IEEE IECON*, 2013, pp. 7932–7937.

[15] C. R. Touretzky and M. Baldea, "Integrating scheduling and control for economic MPC of buildings with energy storage," *J. Process. Control*, vol. 24, no. 8, pp. 1292–1300, Aug. 2014.

[16] J. Lee, S. Natarajan, and K. Lee, "A model-based predictive control approach to repetitive continuous processes with periodic operations," *J. Process. Control*, vol. 11, no. 2, pp. 195–207, Apr. 2001.

[17] R. Huang, E. Harinath, and L. T. Biegler, "Lyapunov stability of economically oriented NMPC for cyclic processes," *J. Process. Control*, vol. 21, no. 4, pp. 501–509, Apr. 2011.

[18] R. Gondhalekar, F. Oldewurtel, and C. N. Jones, "Least-restrictive robust periodic model predictive control applied to room temperature regulation," *Automatica*, vol. 49, no. 9, pp. 2760–2766, Sep. 2013.

[19] J. V. Pinheiro, J. M. Lemos, and S. Vinga, "Nonlinear MPC of HIV-1 infection with periodic inputs," in *Proc. 50th IEEE CDC-ECC*, 2011, pp. 65–70.

[20] L. Würth, R. Hannemann, and W. Marquardt, "A two-layer architecture for economically optimal process control and operation," *J. Process. Control*, vol. 21, no. 3, pp. 311–321, Mar. 2011.

[21] S. Engell, "Feedback control for optimal process operation," *J. Process. Control*, vol. 17, no. 3, pp. 203–219, Mar. 2007.

[22] J. B. Rawlings, D. Angeli, and C. Bates, "Fundamentals of economic model predictive control," in *Proc. IEEE CDC*, 2012, pp. 3851–3861.

[23] A. C. Zanin, M. T. de Gouvea, and D. Odloak, "Integrating real time optimization into the model predictive controller of the FCC system," *Control Eng. Pract.*, vol. 10, no. 8, pp. 819–831, Aug. 2002.

[24] D. Angeli, R. Amrit, and J. B. Rawlings, "On average performance and stability of economic model predictive control," *IEEE Trans. Autom. Control*, vol. 57, no. 7, pp. 1615–1626, Jul. 2012.

[25] D. Limon *et al.*, "MPC for tracking periodic reference signals," in *Proc. NMPC*, 2012, pp. 1–6.

[26] A. Ferramosca, J. B. Rawlings, D. Limon, and E. F. Camacho, "Economic MPC for a changing economic criterion," in *Proc. 49th IEEE CDC*, 2010, pp. 6131–6136.

[27] D. Limon, M. Pereira, D. Muñoz de la Peña, T. Alamo, and J. Grosso, "Single-layer economic model predictive control for periodic operation," *J. Process. Control*, vol. 24, no. 8, pp. 1207–1224, Aug. 2014.

[28] L. Valverde, F. Rosa, A. Del Real, A. Arce, and C. Bordons, "Modeling, simulation and experimental set-up of a renewable hydrogen-based domestic microgrid," *Int. J. Hydrogen Energy*, vol. 38, no. 27, pp. 11 672–11 684, Sep. 2013.

[29] L. Valverde, F. Rosa, and C. Bordons, "Design, planning and management of a hydrogen-based microgrid," *IEEE Trans. Ind. Informat.*, vol. 9, no. 3, pp. 1398–1404, Aug. 2013.

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