Energy efficiency improvement through MPC-based peripherals management for an industrial process test-bench

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Abstract: High energy costs evince the growing need for energy efficiency in industrial companies. This paper presents a solution at the industrial machine level to obtain efficient energy consumption. Therefore, a controller inspired by the well-known model predictive control (MPC) strategy was developed for the management of peripheral devices. The validation of the control requires a test-bench to emulate the energy consumption of a manufacturing machine. The test-bench has four devices, two used to emulate the periodic and fixed energy consumption of the manufacturing process and two as peripherals, subject to rules associated with the process. Consequently, a subspace identification (SI) was employed to identify energy models to simulate the behavior of the device. As a final step, a performance comparison between a rule-based control (RBC) and the proposed predictive-like controller revealed the remarkable energy savings. The MPC results show an energy saving of around 3% with respect to RBC as well as an instant maximum energy consumption reduction of 8%, approximately.

Keywords: Industrial production systems, energy management systems, efficiency enhancement, predictive control

1. INTRODUCTION

Energy efficiency in industrial companies has been highly relevant due to the rising energy prices, the environmental legal restrictions and the regulatory incentives (Schulze et al. (2016)). In Germany between 2000 and 2015, electricity prices increased by more than 80% for industrial consumers (German Federal Statistical Office (2018)). However, this problem is not new. In the 1970s, after several reports, the depletion of the world's energy resources was alerted, which caused an increase in the price of energy (Abdelaziz et al. (2011)). This led to the creation of energy management strategies, which satisfy the demand for energy . Therefore, it is feasible to reduce energy cost/waste, without sacrificing production or quality, simultaneously reducing environmental effects (Abdelaziz et al. (2011)).

There are different strategies of energy efficiency in scheduling management used in industrial machines (European Commission on Information on Society and Media (2009); Bähre et al. (2012)). One of those approaches proposes the design of a controller to shut down and restart the machine when requested. Such approach is suitable if there are long waiting times for the arrival of the raw material in the machines. The results with that strategy suggested that, depending on the waiting time, the energy savings oscillate between 10% and 25% (Mouzon et al. (2007)). Nevertheless, it does not apply to all cases. Another approach is to optimize the activation sequence of process devices to maximize energy efficiency. This procedure must be computed before incorporating a machine into an industrial process line (Bähre et al. (2012)). Furthermore, the energy efficiency of the devices plays a key role in the design of machines. This is another path to achieve energy efficiency. Consequently, there are control methodologies specialized in reducing the energy of devices instead of the complete process (Zhou et al. (2016)).

One of the great challenges is the validation of solutions in real industrial machine scenarios, since it involves a high cost and risk. Therefore, a reliable test-bench was developed, which allows modifying the energy consumption by mimicking the shape of the industrial machine, with lower power consumption. The test-bench includes devices of different nature, a robust acquisition system, programmable actuators and a software platform to support integration with several programming languages and platforms, e.g., MATLAB®, C, C++, and python.

Thus, this paper proposes a control law to manage peripheral devices, considering both the periodic and fixed activation/deactivation sequences for industrial process devices. The control strategy is based on energy consumption models for each device of the machine. Therefore, a data-based system identification method allows to determine each model, offering a general framework to apply to the test-bench, as well as other types of plants. An optimization-based control (OBC) is proposed to establish the optimal activation sequence for the peripherals devices, along a defined prediction horizon H_p, at each time instant. The optimization problem considers an estimate of future consumption for all devices. Furthermore, it is subject to the activation/deactivation rules related to the machine process. The energy efficiency will depend on the defined objective function.

The main contribution of this paper is focused on the management of peripheral devices online, which to achieve energy efficiency without affecting the industrial process requirements. While other approaches perform the optimization of the activation sequence of peripheral devices offline (Zhou et al. (2016)). Therefore, the proposed solution provides robustness against disturbances that affect the efficiency of energy consumption.

This paper is organized as follows: in Section 2, the statement of the problem and the considerations are presented. Section 3 contains the general description of the proposed solution. Section 4 defines the validation problem to support the feasibility of the proposed solution. In Section 5, the experimental results of the test-bench and their respective analyzes are shown. Finally, the main conclusions and lines of further research are drawn in Section 6.

2. PROBLEM STATEMENT

The most frequent energy consumption waste in an industrial machine occurs due to incorrect configuration of peripheral devices (Zhou et al. (2016)). However, the process defines the constraints regarding allocation and set-up of the devices. Thereby, the smart management of the devices generates an optimal energy consumption. The machines used in the industrial process are constituted by synchronous and asynchronous devices. The process establishes a periodical scheduling of the activation/deactivation sequence for synchronous devices, whereas the activation/deactivation of asynchronous devices depends on the events associated with the sensors or timers. Therefore, asynchronous devices are not governed during the scheduling period, defined as T_{mp}. Often asynchronous devices are called peripheral devices.

The inputs of the devices are often defined by a binary signal, 1 when a device is on or 0 when it is off. However, certain devices allow the input to be modulated in a range of discrete values. Therefore, the energy consumption of the device depends on how high is established the input value. Then, the set of device input values is defined by

$$\mathbb{U} \triangleq \{u \mid \ u \in \{0 \wedge [\underline{u}, \overline{u}],\ \{\underline{u}, \overline{u}\} \in \mathbb{Z}_{\geq 1}\}\}, \tag{1}$$

where $\underline{u}$ and $\overline{u}$ are the lower bound and upper bound respectively for a specific input.

Furthermore, the peripherals devices must satisfy conditions associated with the process. Thus, the conditions indicate when a peripherals device will be activated or deactivated, e.g., each T_{mp} the compressor uses air, the asynchronous device will detect how the compressor pressure is decreasing, when the pressure is near the lower bound, the device must be turned on. This paper refers to those conditions as q-relations and could be of dynamic nature. The q-relations are expressed as

$$q(k+1) = g(q(k), \mathbf{U'_a}(k), \nu(k)), \tag{2a}$$

$$y_q(k) = w(q(k)), \tag{2b}$$

being g a function defined in discrete-time, which describes the dynamic evolution of the current state $q(k) \in \mathbb{Q} \triangleq \{\underline{q} \leq q(k) \leq \overline{q}] \mid \{\underline{q}, \overline{q}\} \in \mathbb{R}\}$ to the next state $q(k+1)$, $\mathbf{U'_a} \subseteq \mathbf{U_a}$ is a subset of the set of the asynchronous device inputs $\mathbf{U_a} \triangleq \{u_{a_1}, u_{a_2}, \ldots, u_{a_N} \mid u_{a_i} \in \mathbb{U}_{a_i}\}$, $\nu(k) = v(\mathbf{U_s}(k)) \in \mathbb{R}$ is an input which depends on the synchronous device inputs $\mathbf{U_s} \triangleq \{u_{s_1}, u_{s_2}, \ldots, u_{s_M} \mid u_{s_j} \in \mathbb{U}_{s_j}\}$, $y_q \in \mathbb{R}$ is the output perceived by the sensors associated with the process.

The problem considered that for the purpose of energy management, the machine only has one energy sensor, which will be installed before supplying power to the devices. Moreover, the apparent power signal will be used as the output of the system. Because the behaviors presented in reactive power and active power will be reflected in apparent power. Thereby, the consumption of the devices could be modeled as

$$x(k+1) = f(x(k), u(k)), \tag{3a}$$

$$y_{\hat{S}}(k+1) = h(x(k)), \tag{3b}$$

where $x \in \mathbb{R}^n$ represents the $n \in \mathbb{Z}_{\geq 1}$ internal states of the device dynamics respect to apparent power, f is the discrete function to relate the current state $x(k)$ and the current input $u(k) \in \mathbb{U}$ to generate the new state $x(k+1)$, h is a function to convert the states to apparent power $y_{\hat{S}} \in \mathbb{R}^3$ of a three-phase line supply.

Consequently, the problem is to determine the proper input sequence for a set of N asynchronous devices to obtain an energy efficiency in the total power consumption, subject to the periodic power consumption of a set of M synchronous devices and the q-relations established by the process.

3. PROPOSED SOLUTION

Based on a finite-horizon optimization approach to anticipate the future states of some devices and avoid high energy consumption, the general control system is proposed to achieve energy efficiency. However, the energy consumption models of the devices are required. Therefore, this section is divided into two parts: the models identification and the definition of the optimization problem.

3.1 Identification of energy consumption models

The subspace identification (SI) method is a suitable strategy in this case due to the great diversity of device types in industrial machines. Moreover, the SI method is useful to identify the linear time-invariant models in a state-space form the input and output data, which is adequate to design a linear MPC controller. Identification procedures must be performed for each device separately, i.e., take measurements only when a device is on and identify a model for this device. There are several SI algorithms reported in the literature (De Moor et al. (1999)). For the development of this paper, the Numerical algorithms For Subspace IDentification (N4SID) (Van Overschee and De Moor (1994)) was chosen, due to the use of robust numerical tools such as QR decomposition and singular value decomposition (SVD), the incorporation of implicit model order reduction. The N4SID algorithm requires the model order $n_s \in \mathbb{Z}_{\geq 1}$, according to the $n_u \in \mathbb{Z}_{\geq 1}$ inputs and the $n_y \in \mathbb{Z}_{\geq 1}$ outputs measured. The algorithm arranges input-output data into Hankel signal matrices. The states sequence are estimated with the geometrical projections and numerical linear algebra. Finally, the system matrices are determined according to the estimated state sequence, i.e.,

$$x(k+1) = Ax(k) + Bu(k), \tag{4a}$$
$$y(k) = Cx(k) + Du(k), \tag{4b}$$

with $x \in \mathbb{R}^{n_s}, u \in \mathbb{R}^{n_u}$ and $y \in \mathbb{R}^{n_y}$ the state, input and output vectors, respectively and the systems matrices are $A \in \mathbb{R}^{n_s \times n_s}$, $B \in \mathbb{R}^{n_s \times n_u}$, $C \in \mathbb{R}^{n_y \times n_s}$, and $D \in \mathbb{R}^{n_y \times n_u}$.

3.2 Model predictive control (MPC)

Considering the sequence $\mathbf{U_s}$ is known along the H_p and with the models previously identified, it is possible to compute the future power consumption for synchronous devices, i.e.,

$$\hat{x}_{s_j}(k|k) = \hat{x}^0_{s_j}(k), \tag{5a}$$
$$\begin{aligned}\hat{x}_{s_j}(k+k_h+1|k) = \; & A_{s_j}\hat{x}_{s_j}(k+k_h|k) \\ & + B_{s_j}u_{s_j}(k+k_h|k),\end{aligned} \tag{5b}$$
$$\begin{aligned}\hat{S}_s(k+k_h|k) = & \sum_{j=1}^{M} C_{s_j}\hat{x}_{s_j}(k+k_h|k) \\ & + D_{s_j}u_{s_j}(k+k_h|k),\end{aligned} \tag{5c}$$
$$\begin{aligned}\hat{\mathbf{S}}_s(k) = \{ & \hat{S}_s(k|k), \hat{S}_s(k+1|k), \\ & \ldots, \hat{S}_s(k+H_p|k)\},\end{aligned} \tag{5d}$$

for $k_h \in \{0, 1, \ldots, H_p - 1\}$ and an initial condition $\hat{x}^0_{s_j}$ of each j-th synchronous device, the dynamic models allow predicting the future evolution of the model states and total power consumption of the synchronous device. Thus, $\hat{\mathbf{S}}_s(k)$ is a set of the total energy consumption estimations from the instant k to $k + H_p$.

Owing to the need for extending the useful life of the devices, safety constraints are considered. Accordingly, the minimum on/off time required was included in the problem. It is posed using binary variables $u_{b_i} \in \{0, 1\}$ for each i-th asynchronous device along H_p. Then for the case, when the device will turn on, it must satisfy the following conditions:

$$\begin{aligned}\begin{bmatrix} u_{b_i}(k+k_h|k) \\ \vdots \\ u_{b_i}(k+k_h+\tau'_{up_i}(k_h)|k) \end{bmatrix} \geq \; & u_{b_i}(k+k_h|k) \\ & - u_{b_i}(k+k_h-1|k),\end{aligned} \tag{6a}$$
$$\tau'_{up_i}(k_h) = \min(H_p, k_h + \tau_{up_i} - 1), \tag{6b}$$

where $\tau_{up_i} \in \mathbb{Z}_{\geq 1}$ is the minimum time required to keep the device active after turning it on. When $u_{b_i}(k+k_h|k) - u_{b_i}(k+k_h-1|k)$ is 1, it means that the device is switched on at time $k + k_h$ and the inputs from $k + k_h + 1$ to $k+k_h+\tau'_{up_i}(k_h)$ will be activated; otherwise, it is 0 or -1, then the inputs might be activated or deactivated. And when the device will turn off, the constraint is similar but applies the property of complement. Moreover, the $\mathbb{U}_{a_i}$ domain is defined as:

$$u_{r_i}(k+k_h|k) \geq \underline{u_{a_i}}, \tag{7a}$$
$$u_{r_i}(k+k_h|k) \leq \overline{u_{a_i}}, \tag{7b}$$
$$u_{a_i}(k+k_h|k) \leq \overline{u_{a_i}}, \tag{7c}$$
$$u_{a_i}(k+k_h|k) \leq \overline{u_{a_i}}u_{b_i}, \tag{7d}$$
$$u_{a_i}(k+k_h|k) \geq u_{r_i} - (1-u_{b_i})\overline{u_{a_i}}, \tag{7e}$$
$$u_{a_i}(k+k_h|k) \geq 0, \tag{7f}$$

being $\underline{u_{a_i}}$ the upper bound, $\overline{u_{a_i}}$ the lower bound and $u_{r_i} \in \mathbb{Z}_{\geq 1}$ an auxiliary variable, which combining u_{r_i} with the binary variable u_{b_i} is established the device input u_{a_i}.

The design of the proposed predictive controller is based on the following finite-time optimization problem:

$$\min_{\mathbf{\Gamma(k)}} \mathbf{J}(\hat{\mathbf{S}}_a(k), \hat{\mathbf{S}}_s(k)) = \sum_{k_h=0}^{H_p} \hat{S}_a(k+k_h|k)\hat{S}_s(k+k_h|k) \tag{8a}$$

subject to

$$\hat{x}_{a_i}(k|k) = \hat{x}^0_{a_i}(k), \tag{8b}$$
$$\begin{aligned}\hat{x}_{a_i}(k+k_h|k) = \; & A_{a_i}\hat{x}_{a_i}(k+k_h|k) \\ & + B_{a_i}u_{a_i}(k+k_h|k),\end{aligned} \tag{8c}$$
$$\begin{aligned}\hat{S}_a(k+k_h+1|k) = & \sum_{i=1}^{N} C_{a_i}\hat{x}_{a_i}(k+k_h|k) \\ & + D_{a_i}u_{a_i}(k+k_h|k),\end{aligned} \tag{8d}$$
$$\begin{aligned}\hat{\mathbf{S}}_a(k) = \{ & \hat{S}_a(k|k), \hat{S}_a(k+1|k), \\ & \ldots, \hat{S}_a(k+H_p|k)\},\end{aligned} \tag{8e}$$
$$\begin{aligned}q_r(k+k_h+1|k) = g_r(& q_r(k+k_h|k), \\ & \mathbf{U'_{a_r}}(k+k_h|k), \\ & \nu_r(k+k_h|k)),\end{aligned} \tag{8f}$$
$$y_{q_r}(k+k_h|k) = w_r(q_r(k+k_h|k)), \tag{8g}$$
$$u_{a_i}(k+k_h|k) \in \mathbb{U}_{a_i}, \tag{8h}$$
$$q_r(k+k_h|k) \in \mathbb{Q}_r, \tag{8i}$$

for $r \in \{1, 2, .., Q\}$, being Q the number of q-relations defined and $\mathbf{\Gamma(k)}$ a set of $\mathbf{U_a}$ for each instant along H_p, i.e.,

$$\mathbf{\Gamma}(k) \triangleq \{\mathbf{U_a}(k|k), \ldots, \mathbf{U_a}(k+H_p|k)\}. \tag{9}$$

The use of the objective function (8a) is one of the contributions of this paper, since it is linear and the estimated consumption $\hat{S}_s$ performs as weights to penalize the activations at the instants of high power consumption. Then, the activation time of the devices will be deemed in the optimization. On the other hand, different approaches, such as the integral of instantaneous energy consumption, would yield in different results in case the activation of the device is delayed or not, fact given by the commutative property. Furthermore, the (8a) showed a proper performance in preliminary results compared to other objective functions such as the integral of energy consumption or maximum energy consumption.

The implementation of the controller executes the optimization problem (8) at each sampling time, hence (8) requires the initial states that are the current states of the devices, the future activation sequence and the estimated energy consumption $\hat{\mathbf{S}}_s(k)$ of the synchronous devices. Thereby, for the optimal sequence $\mathbf{\Gamma}^*(k)$ found, only $\mathbf{U_a}^*(k|k)$ will be applied to the devices and the rest of the sequence is discarded . Note that each sampling

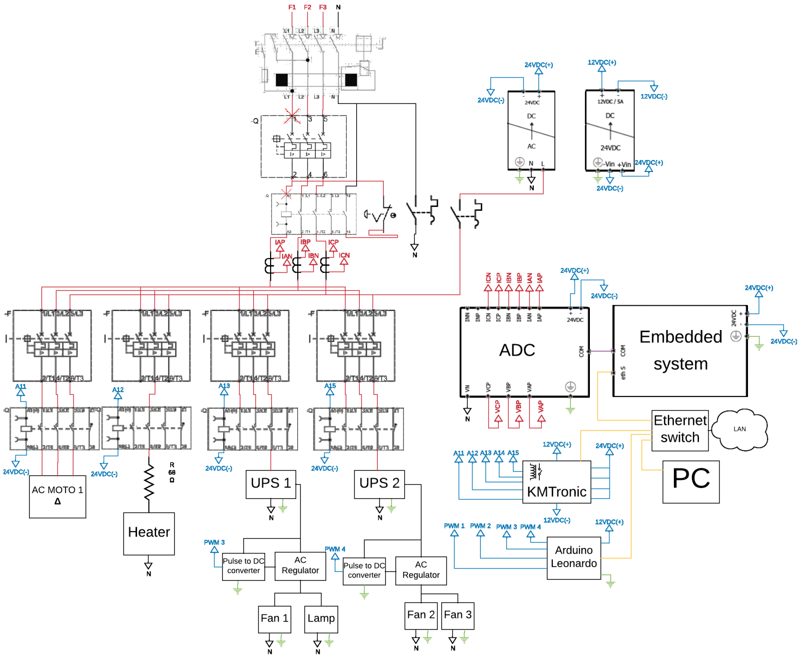

Fig. 1. The electrical diagram of the test-bench to simulate an industrial process.

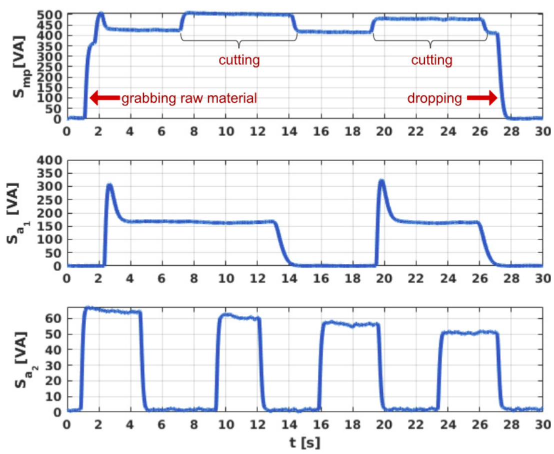

Fig. 2. Power consumption profile for manufacturing process and two peripherals.

time is necessary to know the current states of the devices according to the identified models, whereby an observer is required. This paper proposes to generate a new devices model with the union of all models and compute a Kalman filter.

4. CASE STUDY

For validating the proposed control strategy, a test-bench has been built to emulate the energy consumption of an industrial process. This section is divided into three parts: an explanation of the test-bench, the description of the industrial process to be emulated, and the implementation considerations of the controller.

4.1 The test-bench

For providing the versatility of the test-bench to emulate the power consumption for the great variety of industrial processes, devices of different types of nature were considered: a three-phase motor, a heater and two uninterruptible power supplies (UPS). The electrical diagram of the test-bench is shown in Figure 1. Note that each UPS supplies energy to two loads, one UPS has one fan and one lamp, and the other has two fans. The power consumption of the UPS is controlled by an Alternating Current (AC) regulator via a Pulse-Width Modulation (PWM) signal. Arduino Leonardo board generates the PWM signal. Furthermore, the activation/deactivation of the motor and the heater are controlled by the relays and a WEB LAN IP Ethernet relay controller (WLIE-RC).

A protocol was established to control each device through the User Datagram Protocol (UDP), where the WLIE-RC would receive a command that indicates which devices will turn on or off. The Arduino Leonardo expects the command with load identification and an integer between $0-255$ to establish the duty cicle of the PWM. Moreover, a power data acquisition module is configured to have a sampling rate of 250 μs. The measurements are sent by multicast to the Embedded system (ES) where the controller is running and to a computer for the measurements visualization. Since the test-bench has some single-phase devices, all single-phase devices are connected to the phase B. Therefore, the tests are focused only on the phase B. However, the proposed solution could be extended to more phases.

4.2 Description of the industrial process and q-relations

A manufacturing process was chosen to simulate the power consumption. The case considered is when a machine receives raw material and should cut it. Combining the heater (D_{s_1}) and one UPS (D_{s_2}) emulate the periodic power consumption of the raw material cut (see Figure 2). Furthermore, an air-supply pump and a coolant-supply pump are necessary during the process, which are emulated by the three-phase motor (D_{a_1}) and one UPS (D_{a_2}) respectively (see Figure 2). Thereby, the q-relations are defined next.

Air-supply pump: The pump provides an airstream with enough energy to grip the raw material during cutting, then, the pressure conditions must be met. The dynamics of the pump was modeled as follows:

$$q_1(k+1) = q_1(k) + \begin{bmatrix} M_{in_{air}} & -M_{out_{air}} \end{bmatrix} \begin{bmatrix} u_{a_1}(k) \\ \nu_1(k) \end{bmatrix}, \tag{10a}$$

$$\nu_1(k) = u_{s_1}(k), \tag{10b}$$

$$y_{q_1}(k) = q_1(k) \frac{R\,T}{V_T\,W_M} + P_{atm}, \tag{10c}$$

$$\underline{y_{q_1}} \leq y_{q_1} \leq \overline{y_{q_1}}, \tag{10d}$$

being $q_1 \in \mathbb{R}$ the mass and $y_{q_1} \in \mathbb{R}$ the pressure inside the pump tank with a range of operation $\underline{y_{q_1}} = 500000$ Pa and $\overline{y_{q_1}} = 750000$ Pa. The inputs $u_{a_1}(k) \in \{0,1\}$ and $u_{s_1}(k) \in \{0,1\}$ belong to D_{a_1} and D_{s_1} respectively. The model constants are defined as $M_{out_{air}} = 1.5 \times 10^{-3}$ m^3/s the air discharge coefficient while clamping the raw material, $M_{in_{air}} = 2.5 \times 10^{-3}$ m^3/s the coefficient of recharging air, $R = 8.314472$ Jk^{-1}mol^{-1} the gas constant, $T_{mp} = 298$ K the temperature, $V_T = 5 \times 10^{-3}$ m^3 the tank volume, $W_M = 28.966 \times 10^{-3}$ kg/mol the molecular weight and $P_{atm} = 101325$ Pa the value of an atmosphere.

Coolant-supply pump: a coolant system is required to avoid breaking the tool and deforming the raw material. The coolant-supply system was modeled as a recirculation system with a dirty tank and a clean tank, where the dirty coolant is filtered and reused. It is modeled as,

$$\begin{bmatrix} q_{2,1}(k+1) \\ q_{2,2}(k+1) \end{bmatrix} = \begin{bmatrix} q_{2,1}(k) \\ q_{2,2}(k) \end{bmatrix} + \begin{bmatrix} z_1 & \frac{-M_{tp1}}{A_c\ \rho_c} \\ -z_1 & \frac{M_{tp2}}{A_d\ \rho_c} \end{bmatrix} \begin{bmatrix} u_{a_2}(k) \\ \nu_2(k) \end{bmatrix}, \tag{11a}$$

$$z_1 = \frac{\eta}{(A_d\ \rho_c)(H_{t1\to t2}\ \rho_c + \Delta P_{filter})}, \tag{11b}$$

$$\nu_2(k) = u_{s_2}(k), \tag{11c}$$

$$\begin{bmatrix} y_{q_{2,1}}(k) \\ y_{q_{2,2}}(k) \end{bmatrix} = \begin{bmatrix} q_{2,1}(k) \\ q_{2,2}(k) \end{bmatrix}, \tag{11d}$$

$$\underline{q_{2,1}} \leq q_{2,1} \leq \overline{q_{2,1}}, \tag{11e}$$

$$\underline{q_{2,2}} \leq q_{2,2} \leq \overline{q_{2,2}}, \tag{11f}$$

with $q_{2,1} \in \mathbb{R}$ and $q_{2,2} \in \mathbb{R}$ the level in the clean tank and dirty tank respectively, the bounds are $\underline{q_{2,1}} = 0.3$ m, $\underline{q_{2,2}} = 0.6$ m, $\overline{q_{2,1}} = 0.5$ m and $\overline{q_{2,2}} = 0.8$ m. The inputs $u_{a_2}(k) \in \{0,1\}$ and $u_{s_2}(k) \in \{0 \wedge [100, 140]\}$ belong to D_{a_2} and D_{s_2} respectively. The model constants are defined as $A_c = 0.0314$ m^2 the clean tank area, $A_d = 0.0314$ m^2 the dirty tank area, $\rho_c = 1042.48$ kg/m^3 the coolant density, $\eta = 0.85$ the efficiency of pump, $H_{t1\to t2} = 0.6$ the energy losses by friction, $\Delta P_{filter} = 1000$ Pa the filtering coefficient and, $M_{tp1} = 11 \times 10^{-3}$ and $M_{tp2} = 9.1 \times 10^{-3}$ are constants associated with the coolant flow required.

4.3 Implementation

Due to the high sampling frequency of the acquisition system, an analysis of the apparent power of all devices through the Fast Fourier Transform (FFT) was required to determine the proper sampling frequency. The Nyquist-Shannon sampling theorem was considered to avoid the loss of information. Then, the suitable sampling frequency is 100 Hz. Therefore, a filter was designed after the acquisition system to re-sample at that sampling frequency. For developing the control system, the first step was executed several experiments for each device in order to get a relevant measures for the models identification. Through the N4SID algorithm, the energy models were found with an order of $n_s = 3$. Thus, the input sequence of the manufacturing process was defined with a period of $T_{mp} = 29$ s. Furthermore, a Kalman filter was designed combining all the energy models in a larger one.

A first implementation of the control strategy was carried out in MATLAB® with the YALMIP toolbox (Lofberg (2004)), due to the optimization problem (8) is of mixed linear programming nature then the solver engine used was IBM ILOG CPLEX Optimization Studio (ILOG (2013)). The stimulation phase evidenced the suitable H_p is equal to T_{mp} since the use of larger values implies no significant

Table 1. Performance indicator for MCP and RBC tests.

Indicators	MPC	RBC	Efficiency(%)
Power consumption	1.4943 MVA	1.4548 MVA	2.7%
Maximum consumption	899.0 VA	830.4 VA	7.7%s
Variance	30948 VA	16466 VA	46.8%
Load factor	66.66%	70.25%	5.5%

changes in energy consumption. Furthermore, a Rule-Based Control (RBC) was implemented to compare the efficient energy with the MPC. Since the RBC is often used in an industrial process. The RBC evaluates the value of the q-relations at each sampling time, when the constraints are violated, the corresponding device will be turned on. The device remains on until the maximum allowed value is reached, then the device will turn off.

The implementation of the controllers and the observer in real time was achieved using C++ language in the embedded system. Through the Basic Linear Algebra Subprograms (BLAS) (Blackford et al. (2002)) and Linear Algebra Packet (LAPACK) (Anderson et al. (1990)) libraries to compute linear algebra operations, and the ILOG CPLEX C++ API (ILOG (2013) to describe and solve the optimization problem (8).

5. RESULTS

The tests were performed for 41 minutes corresponding to 86 machine cycle times. To evaluate the energy efficiency obtained with respect to the RBC, it calculated four performance indicators: accumulated energy consumption, the maximum measured value, the variance of the measurements and the load factor [1].

Table 1 displays the performance indicators value and efficiency of MPC with respect to RBC. The energy saving is close to 3% and the MPC managed to produce 46.8% less variation than the RBC. That means the optimal use of resources, avoiding high power peaks and trying to convert it into a constant consumption. The maximum power consumption of the MPC is lower compared to RBC. Therefore, this reduction in real industrial machines can mean significant savings, and might reduce the costs associated with the contracted power supply capacity. Finally, the appropriate value for the percentage of load factor must be greater than 50%, because it represents which the energy consumed is relatively constant. In both cases, the MPC and the RBC have values greater than 50%. Nonetheless, the MPC managed to improve the percentage of the RBC. The convergence of performance indicators efficiency is shown in Figure 3, being $N_{T_{mp}}$ the number of T_{mp} executed. The variance efficiency has a high value higher than 40% throughout the test, while with the maximum power consumed remains almost constant.

[1] The typical indicator used to assess whether the contracted supply capacity is adequate. It is a relation between the power consumed and the power to the maximum demand contracted during a defined period (e.g., one hour, one day, weeks or months). The load factor is then defined as follows:

$$f_{load} = \frac{1}{N_{\mathbf{S}}\ S_{max}} \sum_{i=0}^{N_{\mathbf{S}}} S(i), \tag{12}$$

being ($N_{\mathbf{S}}$ S_{max}) the energy consumption at maximum demand contracted (S_{max}) in a period of $N_{\mathbf{S}}$ samples.

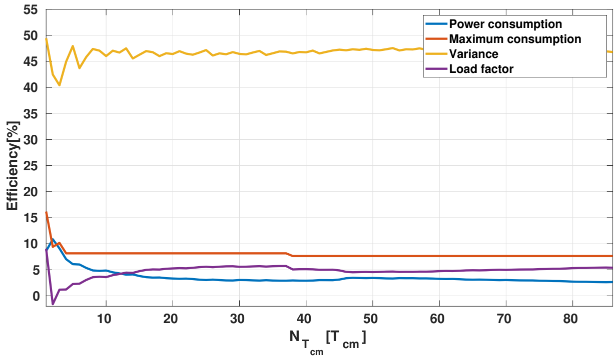

Fig. 3. Evolution of the performance indicators.

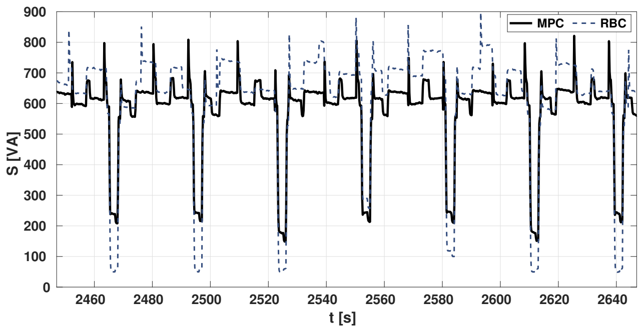

Fig. 4. The apparent power for RBC and MPC.

Moreover, the interesting behavior of the load factor when it decreases at the beginning, came to have a negative value. However, it increases to converge to a positive value, and a similar situation happens with energy consumption, it begins to increase, but then the decrease to converges to a positive value. Demonstrates that the energy efficiency of the MPC will be maintained over time with respect to the RBC. Figure 4 displays the power consumption of MPC and RBC. It is remarkable the poor management of RBC with respect to energy consumption. Because RBC is designed to satisfy the conditions without taking into account the power consumption of other devices, while the MPC tried to take advantage of the low power consumption of some instants to activate the peripherals.

6. CONCLUSIONS

Preliminary results with a test-bench, for a specific manufacturing process, demonstrate the remarkable performance and reduction of energy costs by the proposed MPC with respect to the RBC. Being RBC a traditional technique and popular in the industry, because it is only necessary to define the logical rules to works well without complex mathematical procedures. While the MPC implying a little more complexity. However, it is possible to create methodologies to transform these logical conditions into restrictions and migrate from a RBC to MPC.

The meaningful results obtained, it is encouraged to add more complexity to the problem. With more frequent problems in the industry and updating the test-bench to make emulations more realistic. Additionally, the solution must be proved in a small process of a company. Thus, increase the complexity of the problem to give more robustness and realism of the solution proposed. Furthermore, considering the disturbances or failures associated with the deterioration and wear of the devices. The model identification procedure must be automated and explore other techniques to obtain an adaptive solution online.

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