Preprints of the 21st IFAC World Congress (Virtual)
Berlin, Germany, July 12-17, 2020

Optimal production planning for flexible manufacturing systems: an energy-based approach

Jenny L. Diaz C. and Carlos Ocampo-Martinez

Automatic Control Department, Universitat Politècnica de Catalunya, Institut de Robòtica i Informàtica Industrial (CSIC-UPC), Llorens i Artigas 4-6, 08028 Barcelona, Spain (e-mail: {jenny.lorena.diaz, carlos.ocampo}@upc.edu).

Abstract:
Production programming in a manufacturing industry is usually performed based on off-line optimisations of the processing times or plant productivity. However, most of these approaches do not consider the energy market and its fluctuations. Therefore, it is not possible to take advantage of these fluctuations to also minimise the energy costs and to increase the plant profit. In this regard, a control strategy based on the Economic Model Predictive Control approach is proposed to reduce energy costs during the operation of a manufacturing plant. The proposed controller determines the instants in which the production programs should be executed to satisfy the daily demand while minimising the energy costs through regular updates of the energy prices according to the current energy market. Besides, by implementing a control strategy in real time, changes in the demand of parts according to the customer requirements could also be considered, adding more flexibility to the plant operation. The proposed control strategy has been tested in simulation, and the obtained results show that energy costs can be reduced without affecting the plant productivity.

Keywords: Economic model predictive control, Energy costs, Economic production programming, Mixed-integer linear programming

1. INTRODUCTION

Currently, the manufacturing industry is suffering a paradigm shift towards smart factories to achieve higher flexibility and sustainability to manufacturing systems. The leading promoter of this transformation has been the Industry 4.0, from which several proposals have been developed. Most of these works have focused on improving the modelling of manufacturing processes, the process planning and scheduling, and the process design and control to improve both the plant productivity and the quality of produced pieces (Li et al., 2017).

A manufacturing plant can be understood as an integrated system that comprises three partial systems: the production system itself, the technical Building Services (TBS) and the building (Herrmann and Thiede, 2009). The former refers to the interlinked machines and the personnel controlled through production management. On the other hand, TBS ensure the necessary production conditions of temperature, moisture, and purity through cooling/heating and conditioning of the air, besides of supplying energy, compressed air, steam or cooling water required for production systems (Fahad et al., 2017). Thus, at the plant level, all devices involved in both value and non-value tasks in a factory are included.

At the plant level, most of the researches have focussed on the design of production programs and process scheduling to minimise the processing time or, in other words, to maximise the production of the parts. The latter, since the incomes for a manufacturing plant, are mainly a result of the sale of parts. However, strategies that confer more flexibility to manufacturing systems and allow improving their energy efficiency are required. A suitable way to add more flexibility to manufacturing systems is through the design of modular process and proper control strategies to respond to changes in the product demand or design. The last fact to achieve a higher level of customisation according to customer requirements. Although many works reported in the literature focus on strategies for flexible manufacturing at the plant level, the energy consumption has been usually considered as an initial optimisation to minimise operational costs for a fixed demand (Lu et al., 2017). Based on these strategies, an optimal production program is determined at the beginning for specific operational conditions and, therefore, they cannot respond to the temporal variation of processes, demand, and working environment during the plant operation.

On the other hand, into the transformation towards Smart Manufacturing (SM), improvements in sensing technology, connectivity, and computer science have also promoted, addressing manufacturing systems as Cyber-Physical Systems (CPS). These latter refer to systems that incorporate physical processes and embedded computing elements (e.g., smart sensors and actuators) allowing a real-time interaction. Those interactions ease the exchange of information for tasks such as monitoring, control, and management of such systems (Jakovljevic et al., 2017). Nonetheless, in spite of all the recent advances and the new generation of Cyber-Physical Manufacturing Systems (CPMS), only a few strategies have taken to the energy market and its fluctuations for minimising energy costs and improving the energy efficiency of a manufacturing plant (Diaz and Ocampo-Martinez, 2019).

In this regard, the main contribution of this work is the design of an optimisation-based control strategy to minimise, in real-time, the energy costs related to the operation of a manufacturing plant taking advantage of energy-price fluctuations and without decrease the plant productivity. Due to the nature of the objective to be minimised, the proposed controller is designed according to the Economic Model Predictive Control (EMPC) approach that directly optimises an economical cost function. The main idea is to predict the instants of time in which the production program should be executed considering the product demand, the energy prices, and the operational constraints of the plant. Thus, the control strategy is based on the assumption that production programs have already been designed and optimised to minimise processing time and their energy consumption. Thereby, the proposed controller can be implemented as a complementary strategy to the optimal production programming to improve the plant productivity and its profitability. It is worth noting that although this work is proposed based on a manufacturing plant for producing automotive parts, both the problem statement and the proposed approach can be extended to other manufacturing industries without losing generality.

The remainder of the paper is organised as follows. In Section 2, the problem statement is presented in a general way. Next, the design of the proposed controller is introduced in Section 3. Afterwards, in Section 4, the case study to test the proposed control strategy is explained. Finally, the simulation results are presented in Section 5, while the conclusions based on the obtained results are drawn in Section 6.

2. PROBLEM STATEMENT

A manufacturing plant consists of arrangements of process lines and auxiliary devices that guarantee the operating conditions of each process line and its working environment. The energy costs in a manufacturing plant are related to the energy consumption of the productive and non-productive processes in addition to the surcharges produced by surpassing the nominal power purchased. Hence, the energy consumption profile of both the productive and non-productive systems in a manufacturing plant should be considered to determine the production programming of a plant. A scheme of a manufacturing plant considering the TBS and process lines is shown in Figure 1.

In addition to energy spent by the TBS and the process lines in a manufacturing plant, the energy consumed in the offices by the company workers should also be considered. Thus, according to the workday of each company, the energy consumption profile from offices could change along the day, and even, it could have small differences from one day to other. In the same way, the energy consumption profile of the TBS will depend on the production programs currently executed in the process lines since the requirements of resources can change from one production program to others. In this regard, the energy consumption from the offices could be considered as fixed while the energy expenditure related to both the production processes and TBS are regarded as a variable one since it will depend on time-varying product demand.

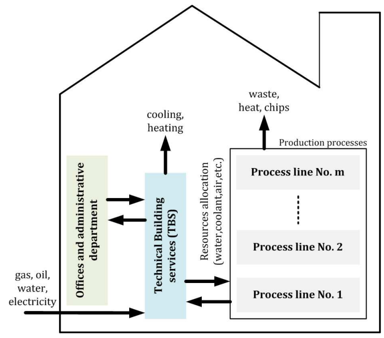


Fig. 1. Representation of a manufacturing plant and its constitutive elements. Based on Duflou et al. (2012).

Consider a manufacturing plant (e.g., an automotive parts manufacturing plant) with a fixed number of process lines, i.e., m, as shown in Figure 1. Assuming that each process line i (with $i = 1, 2, \dots, m$) involves a fixed number of machines n_i that perform different processes according to a pre-defined configuration, different parts could be processed in the same process line. The sequence of processes required to process a piece corresponds to the production program PP of the piece l. Thus, assuming that each machine in the process line performs only one machining operation (e.g., cutting, milling, turning, etc.), the production program for the piece l in the process line i, $PP_{i,l}$, involves the operation of n_i machines in the process line according to the machining processes required. Besides, since each machine j (with $j = 1, 2, \dots n_i$) in the i-th process line has its own processing time $T_{i,j}$, the time spent to produce a finished part by $PP_{i,l}$ is computed based on the machine with the longest processing time, i.e., $T_{PP_{i,l}} = \mathtt{max}\,(T_{i,j})$. That means, in the continuous operation of $PP_{i,l}$, the number of pieces produced in a fixed period is calculated according to $T_{PP_{i,l}}$, which is usually referred as the productivity of the process line.

Although the processing times of the machines are minimised offline, a real-time production programming that maximises the plant profit is required to face the new challenges imposed by SM. In this regard, the production program of a manufacturing plant should consider the energy consumption and its associated costs, the changes in the product demand, and customisation requirements from customers. This latter fact rises to improve both the energy efficiency of the plant and its flexibility by mean of constant updates of product demand and the temporal variations of energy prices. Thus, the plant profit should be optimised, taking into account the energy consumption of both value and non-value tasks in the plant, the changing energy market and marketplace demand, besides, the processing times. The last fact takes into account that a reduction in processing times and, therefore, the energy consumption of a manufacturing plant does not guarantee that energy costs are also be reduced. Thus, reductions in energy costs can be achieved if the energy price profile is considered. Thereby, to determine the economic-optimal operation of a manufacturing plant along an operation period of T, the following control objectives are proposed:

Revenues for sale of parts: According to the type of piece processed, the number of finished parts and their commercial value, the incomes for the sale of parts are defined as follows:

$$N_{i,l}(k) = \frac{T}{T_{PP_{i,l}}} u_{i,l}(k), \tag{1}$$

being $k \in \mathbb{Z}_{\geq 0}$ the discrete-time index, $N_{i,l} \in \mathbb{Z}_{\geq 0}$ the total number of pieces of type l processed in the i-th process line along a period T, and $u_{i,l} \in \{0, 1\}$ the activation/deactivation signal of the production program PP_l. Then, the total revenues are computed according to

$$\phi_1(k) = \sum_{i=1}^{m} \left[\sum_{l=1}^{p_i} \left[\gamma_{p,l} \; N_{i,l}(k) \right] \right], \tag{2}$$

being p_i the number of production programs that can be executed in the i-th process line, and $\gamma_{p,l} \in \mathbb{R}_{\geq 0}$ the selling price for the piece l. It is worth noting that each process line can only run one production program at a time, but a production program can be executed at the same time in different process lines.

Energy costs of manufacturing processes: The energy costs related to the value-added tasks are defined as follows:

$$\phi_2(k) = \sum_{i=1}^{m} \left[\gamma_e(k) S_{L_i}(k) \right], \tag{3}$$

being γ_e the energy price in the current market, and S_{L_i} the instantaneous power consumption in the i-th process line given by

$$S_{L_i}(k) = u_{i,1} \; S_{PP_{i,1}}(k) + \cdots + u_{i,p_i} \; S_{PP_{i,p_i}}(k), \tag{4}$$

with $S_{PP_{i,l}}$ as the power consumption of the l-th production program , and $\sum_{l=1}^{p_i} u_{i,l}(k) \leq 1$. Thus, S_{L_i} will depend on the production program that it is being executed.

Energy costs for non-value added task: In this item are included the costs related to the energy consumption of the TBS and the offices in the manufacturing plant, which are given by

$$\phi_3(k) = \gamma_e(k) \; \left(S_{TBS}(k) + S_{off}(k) \right), \tag{5}$$

with $S_{TBS} \in \mathbb{R}$ and $S_{off} \in \mathbb{R}$ the instantaneous power consumption from the TBS and offices.

According to (2), (3) and (5), to determine the optimal production program that maximizes the plant profit, the following economic cost function is proposed:

$$J(k) = \left(\phi_1(k) - \phi_2(k) - \phi_3(k) \right), \tag{6}$$

being $J \in \mathbb{R}$ the total profit of the plant. Therefore, to maximise (6), the control problem consists of determining the optimal activation/deactivation sequences $u_{i,l}$ of production programs at each process line, taking into account the demand of pieces, the energy market and its fluctuations, as well as the operational constraints in the manufacturing plant. Among the latter constraints can be included the work shifts, the maximum execution time for the production programs, and the incompatibility to run some production programs at the same time (even in different process lines). Besides, regarding the scenarios of flexible manufacturing, the time instants in which the changes in the production programs will be allowed can also be included as constraints.

3. PROPOSED APPROACH

To determine in real time the optimal production programming of a manufacturing plant from an economic point of view, a controller based on the EMPC approach is designed. Thus, the proposed controller is focussed on maximising the revenue for the sale of produced parts while minimising the operational costs along a prediction horizon H_p. In this regard, both the energy market and the changes in the marketplace demand should be considered in the controller design to minimise energy costs and to satisfy the requirements of flexible manufacturing.

The main idea underlying the use of optimisation-based control techniques is that the control problem can be transformed into an optimisation problem. Thereby, control objectives can be regarded as the cost function, while the process dynamics and operational limitations are defined as the set of constraint into the optimisation problem. Thus, due to the economic nature of the control objectives to be treated, the use of EMPC has been preferred concerning other approaches, such as the conventional MPC, since it directly optimises the economic performance of the process (Ellis et al., 2014) and it is also implemented in a receding horizon strategy (Maciejowski, 2002). Several works related to the design of EMPC controllers, the theoretical background and stability analysis of EMPC have been proposed in the literature. A detailed explanation of the EMPC strategy can be found in (Rawlings et al., 2012; Angeli et al., 2016).

The general idea is to predict which production program PP_l should be executed at each process line along H_p, such that the plant profit can be maximised taking into account the product demand, the operating constraints and the time-varying price profiles. Thus, the decision to activate/deactivate the l-th production program in the i-th process line, i.e., $u_{i,l}$, depends on the current value of the demand of pieces of type l and the energy price in the market. Then, if in each process line only a fix number p_i of production programs can be executed, the activation signals for each process line can be expressed as

$$\boldsymbol{v_i}(k) \triangleq \{u_{i,1}(k), u_{i,2}(k), \ldots, u_{i,p_i}(k)\}, \; i = 1, 2, \ldots, m, \tag{7}$$

with $u_{i,1} \in \{0, 1\}$ indicating that PP_l is being executed in the i-th process line if $u_{i,1} = 1$, or that it is deactivated when $u_{i,1} = 0$. Then, according to the defined control objectives in (6), the sequences [1] for J and $\boldsymbol{v_i}$ along H_p are defined as

$$\mathbf{J}(k) \triangleq \{J(k|k), \ldots J(k + H_p - 1|k)\}, \tag{8a}$$

$$\mathbf{U_i}(k) \triangleq \{\boldsymbol{v_i}(k|k), \ldots, \boldsymbol{v_i}(k + H_p - 1|k)\}, \tag{8b}$$

[1] Here, $z(k + i|k)$ denotes the prediction over H_p of the variable z at time instant $k + i$ performed at k.

with $\mathbf{J} \in \mathbb{R}^{H_p}$ and $\mathbf{U_i} \in \{0,1\}^{H_p}$. Thereby, the economic predictive-like controller is based on the following open-loop optimization problem:

$$\max_{\mathbf{U_i}(k)\ \forall\ i=1,2,\ldots,m} \quad \mathbf{J}(k) \tag{9a}$$

subject to

$$S_{PP_{i,l}}(k+r+1|k) = f_l\left(S_{PP_{i,l}}(k+r|k), u_{i,l}(k+r|k)\right), \tag{9b}$$
$$g_i(\mathbf{U_i}(k+r|k)) \leq 0, \tag{9c}$$
$$N_{i,l}(k+r|k) \geq \alpha_l, \tag{9d}$$
$$u_{i,l}(k+r|k) \in \{0,1\},\ l = 1,2,\ldots,p_i, \tag{9e}$$

for $\forall r \in [1, H_p - 1]$, and being $f_l : \mathbb{R} \times \{0,1\}^{p_i} \to \mathbb{R}$ the linear map for the energy consumption of PP_l, $g_i(\cdot) : \{0,1\}^{p_i} \to \mathbb{R}$ the linear maps that express the logical and operational constraints among the production programs allowed in any process line, and $\alpha_l \in \mathbb{Z}$ the demand for the piece l. Besides, safety times for the minimum execution time of a production program in a certain process line can be considered imposing constraints on $\Delta u_{i,l}$. In this regard, every time that $\Delta u_{i,l} = |u_{i,l}(k) - u_{i,l}(k-1)|$ will be different to zero, the current state of PP_j should be kept along for a period equal to the safety time t_{sw}.

Assuming that the optimization problem in (9) is feasible, i.e., $\mathbf{U_i}(k) \neq \emptyset$, the optimal sequence $\mathbf{U_i}^*(k)$ exists and, according to receding horizon approach (Maciejowski, 2002), the first component $\boldsymbol{v_i}^*(k|k), \forall\ i = 1,2,\ldots,m$ is sent to the process lines. Then, this procedure is repeated for the next instant once measurements of input signals and estimation of the required information about the plant are updated. Then, taking into account the nature of variables to be optimised, the optimisation problem in (9) is a mixed-integer linear programming (MILP) problem, for which suitable solvers should be chosen to solve the problem with a low computational burden.

It should be noted that since the proposed approach focusses on programming the plant productivity to minimise the operating costs according to the current demand, it is assumed that the production programs are previously designed and optimised offline regarding the processing time. Thus, the controller should decide the programs to execute in each process line to minimise energy costs, maximise revenues, and satisfy the daily product demand. Besides, according to (9), suitable energy consumption models for each production program are required.

4. CASE STUDY

According to Figure 1, a manufacturing plant with three process lines will be analysed. The manufacturing process lines are detailed in Figure 2, in which every line is drawn with its respective machines. The first and the second process lines have the same configuration for the machines and are able to process the same parts. That means, the production programs are the same in these process lines. Besides, machines in these process lines have the same processing time, i.e $T_{1,j} = 28$s, $\ j = 1,2,\ldots,n_1$ and $T_{2,j} = 28$s, $j = 1,2,\ldots,n_2$. The latter fact implies that in both process lines the same number of pieces can be processed during a fixed period. On the other hand, the third process line is formed by five machines, most of them with a different processing time. Thereby,

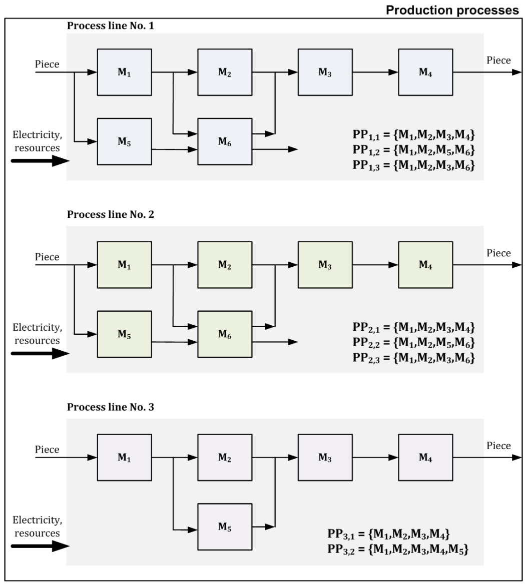


Fig. 2. Process lines in a manufacturing plant.

$T_{3,1} = 28$s, $\mathrm{T}_{3,2}, \mathrm{T}_{3,5} = 44$s, $\mathrm{T}_{3,4} = 22$s and $T_{3,6} = 36$s. In this case, the productivity of the line is computed based on the machines with the longer processing time, i.e., $T_{3,2}$ or $T_{3,5}$. In addition to energy consumption from value-added tasks and TBS, in this case, it is assumed that the offices has a known energy consumption profile along the day, which is repeated over the time with small variations.

Since the production programs have already been designed, using the real data from the energy consumption of each machine involved, energy consumption models can be obtained based on Subspace Identification (SI) methods (Qin, 2006). A detailed explanation of this procedure is presented in (Verhaegen and Hansson, 2016), and an application to identify energy consumption models of machine tools is introduced in (Diaz et al., 2019). Thus, by summing the instantaneous energy consumption of the machines involved in each $PP_{i,l}$, its energy consumption profile ($S_{PP_{i,l}}(k)$) can be obtained. Then, based on such profile, correlations to compute the cumulated energy consumption while $PP_{i,l}$ is on, can be defined as follows:

$$\tilde{S}_{PP_{i,l}}(u_{i,l}, k_{i,l}) = \theta_{i,l}\ k_{on_{i,l}}(k) + \delta_{i,l}\ u_{i,l}(k), \tag{10}$$

with $\tilde{S}_{PP_{i,l}} \in \mathbb{R}$ the accumulation of power consumed for $PP_{i,l}$, $k_{on_{i,l}}$ the accumulate operation time for $PP_{i,l}$, and $\theta_{i,l}$ and $\delta_{i,l}$ the increment coefficients for each $PP_{i,l}$. Thus, assuming a sampling time τ_s equal 10 minutes, along 30 minutes of operation of $PP_{i,l}$, it should be satisfied $\tilde{S}_{PP_{i,l}}(u_{i,l}, 10) \leq \tilde{S}_{PP_{i,l}}(u_{i,l}, 20) \leq \tilde{S}_{PP_{i,l}}(u_{i,l}, 30)$. Then, since $k_{on_{i,l}}$ is a cumulation of processing time for $PP_{i,l}$ while $PP_{i,l}$ is kept on, it should be updated as

$$k_{on_{i,l}}(k) = \left(k_{on_{i,l}}(k - \tau_s) + \tau_s\right) u_{i,l}(k). \tag{11}$$

It is worth noting that (11) is multiplied by $u_{i,l}(k)$ since if $PP_{i,l}$ is switched off, $k_{on_{i,l}}$ should be reinitialised to zero when it will be activated again. Besides, according to (10) and (11), the energy consumed at every τ_s can be computed as the different between the current value of $\tilde{S}_{PP_{i,l}}(\cdot)$ and the previous one. As an example, the energy consumption profile for $PP_{1,1}$, its cumulated energy con-

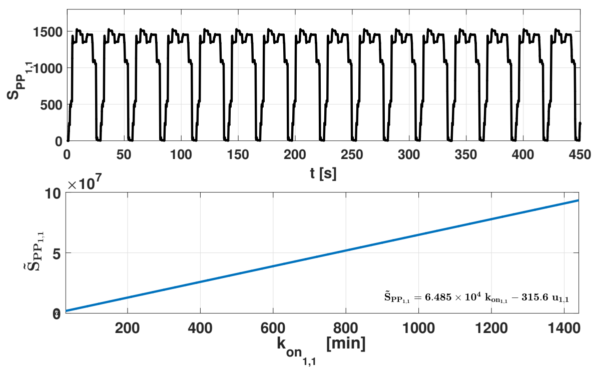


Fig. 3. Energy consumption profile and correlation for $PP_{1,1}$.

sumption, and the corresponding curve fitting parameters are presented in Figure 3.

Regarding the consumption from the offices, it is assumed that the energy consumption follows a daily pattern with small variations between days, which are added as white noise. Moreover, since the TBS provide the required resources to the machines in the process lines, the energy consumption from TBS is defined as a function of the production programs that are being executed and a constant portion related to the environment conditions of the plant. Thus, the energy consumption of TBS is given by

$$S_{TBS}(k) = S_{off}(k) + \sum_{i=1}^{m} \left(\sum_{l=1}^{p_i} \beta_{i,l}\ u_{i,l}(k) \right), \tag{12}$$

being S_{off} the constant consumption related to the environment conditions of the plant and $\beta_{i,l}$ the correlation coefficients for the l-th program in the i-th process line.
In addition to the energy consumption models, some logical constraints for the operation of the process lines should be considered as follows:

- Every time that a program is activated, it should be kept on for at least four hours.
- The program $PP_{i,2}$ cannot be executed at the same time in both process lines 1 and 2. It is given since this program has the highest energy consumption among the allowed programs in lines 1 and 2.
- Changes in the production program for the next day are allowed until four hours prior the next day. The last fact since the TBS should also be prepared to provide the required resources to the process lines.
- The daily energy-price profile will be updated every 30 minutes to include the price fluctuations.
- The program $PP_{3,2}$ in the third line cannot be executed at the same time that the program $PP_{1,1}$ in the first line. This scenario considers the case in which some programs cannot operate at the same time because it is not possible to provide all the resources required by both programs.
- The production of pieces per day can be only 10% higher than the daily demand.

Based on the previous system description, and taking into account the operational constraints of the process lines, the instants in which each production program would be executed to minimise energy costs and maximise productivity should be determined. Besides, it is necessary to guarantee that the pieces demand is satisfied every day considering its corresponding fluctuations. The simulation parameters are presented in Table 1, in which the economic costs are presented in economic units (e.u.).

Table 1. Simulation parameters.

Parameter	Value	Parameter	Value
t_{sw}	4 h	$\gamma_{p1,1}$	2.5 e.u.
$\gamma_{p1,2}$	3.0 e.u.	$\gamma_{p1,3}$	2.8 e.u.
$\gamma_{p2,1}$	2.5 e.u.	$\gamma_{p2,2}$	3.0 e.u.
$\gamma_{p2,3}$	2.8 e.u.	$\gamma_{p3,1}$	2.0 e.u.
$\gamma_{p3,2}$	2.8 e.u.	$\theta_{1,1}$	6.485×10^4
$\delta_{1,1}$	-315.6	$\theta_{1,2}$	8.005×10^4
$\delta_{1,2}$	-1063	$\theta_{1,3}$	6.463×10^4
$\delta_{1,3}$	-898.3	$\theta_{3,1}$	6.238×10^4
$\delta_{3,1}$	-171.2	$\theta_{3,2}$	7.903×10^4
$\delta_{3,2}$	-115.6	τ_s	30 minutes

5. SIMULATION RESULTS

According to the case study presented in Section 4 and the proposed control strategy (denoted as EMPC), some simulations were performed to test the effectiveness of the proposed controller. The results presented below were obtained considering a total simulation time $T_s = 7$ days with a execution time for the controller equal to $\tau_s =$ 30 minutes. Besides, a prediction horizon of $H_p = 24$ hours was considered, which means the controller makes decision 48 times along H_p. Thereby, the total number of decision variables corresponds to $|\mathbf{U_i}(k)| = 48$ per each process line i. The obtained results using EMPC were compared with another EMPC (denoted as EMPC$_2$), in which the fluctuations of the energy-price profile are not considered. Thus, for the last case, a constant energy price of $\gamma_e = 0.04$ e.u./kW was considered, while the energy-price profile for the first case is shown in the bottom plot of Figure 5a.

To determine the optimal production programming of the plant, at each sampling time, the predictions for the energy consumption from offices, the demand of pieces, and the current energy-price profile are updated when the proposed EMPC is implemented. Since the controller is executed every 30 minutes using a prediction horizon of one day ahead, the marketplace demand for the next day will begin to be considered into the optimisation problem in (9) just four hours before the current day finishes. Therefore, according to the receding horizon implementation strategy, the constraints to satisfy the daily demand of parts should be suitably adjusted to constrain the demand for the current day and the next one, when the latter starts to appear in the prediction horizon. Then, taking into account the constraints discussed in Section 4, the following expressions should be added to the optimisation problem in (9):

$$\sum_{l=1}^{p_i} u_{i,l}(k) \leq 1, \forall\ i = 1, 2, 3 \tag{13a}$$
$$u_{1,2}(k) + u_{2,2}(k) \leq 1, \tag{13b}$$
$$u_{3,2}(k) + u_{1,1}(k) \leq 1, \tag{13c}$$
$$M_{L1} \leq N_{1,l}(k) \leq 1.1\ M_{L1}, \tag{13d}$$
$$M_{L2} \leq N_{2,l}(k) \leq 1.1\ M_{L2}, \tag{13e}$$
$$M_{L3} \leq N_{3,l}(k) \leq 1.1\ M_{L3}, \tag{13f}$$

with M_{L1}, M_{L2} and M_{L3} the demand matrices of pieces for each process line, given by

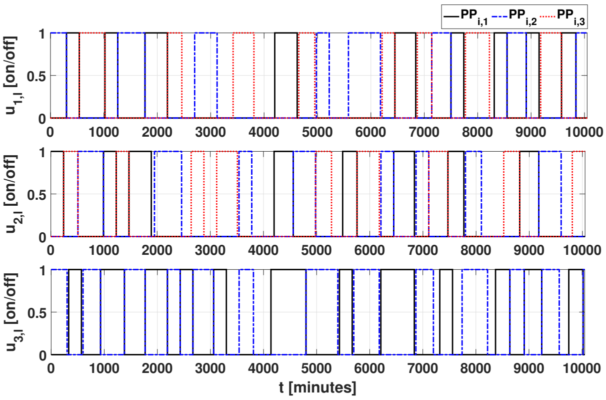


Fig. 4. Optimal activation sequences for $u_{i,l}$ by using EMPC.

$$M_{L1} = \begin{bmatrix} 1024 & 850 & 250 & \mathbf{1000} & 800 & 960 & 1000 \\ 1024 & 1000 & 500 & 850 & 950 & 800 & \mathbf{650} \\ 1024 & 550 & 800 & 600 & 1024 & 900 & 780 \end{bmatrix}, \quad (14)$$

$$M_{L2} = \begin{bmatrix} 1024 & 850 & 250 & 1000 & 800 & 580 & 700 \\ 1024 & 1000 & 500 & 850 & 950 & 600 & 860 \\ 1024 & 550 & 800 & 600 & 1024 & 780 & 900 \end{bmatrix}, \quad (15)$$

$$M_{L3} = \begin{bmatrix} 880 & 850 & \mathbf{250} & 900 & 800 & 650 & 760 \\ 880 & 1000 & 580 & 850 & 950 & 600 & 820 \end{bmatrix}, \quad (16)$$

with rows corresponding to the program and the columns referring to the day. The values in bold correspond to the changes that will be introduced in the product demand during the simulations. Thus, these values will be modified at suitable time instants to 600, 1000, and 550 pieces, respectively. Besides, expressions in (10), (11) and (12) for energy consumption of both productive and non-productive areas should also be added as constraints into the optimisation problem in (9). Afterwards, given the MILP nature of the optimization problem in (13), simulations were developed in Matlab® using the solver IBM ILOG CPLEX Optimization Studio (ILOG, 2013) and YALMIP toolbox (Löfberg, 2004) for stating the optimization problem in the specific format of the solver. Besides, simulations were performed using an Intel® Core™ i7-5500U CPU 2.40GHz and RAM of 8.0 GB.

In Figure 4, the optimal activation sequences obtained when the proposed controller (EMPC) is implemented are shown. Based on these sequences and the logical constraints included into the optimization problem, it is possible to see that the second program in both process lines 1 and 2 was never turned on at the same time. In the same way, the programs $PP_{1,1}$ and $PP_{3,2}$ were always turned on at different moment along the day with the aim to guarantee that the TBS were able to provide the required resources to both process lines 1 and 3. Then, according to these activation sequences, a comparison of the resulting energy consumption profile using both strategies, as well as the energy price profile along the whole simulation are shown in Figure 5a. Besides, in Figure 5b, the total energy consumption of the plant is discriminated in offices, TBS, and process lines based on the optimal production programming for the plant. Thus, according to these results, it can be observed that the proposed EMPC tries to switch off the productions programs at the moments of higher energy prices or to switch to programs of lower energy consumption. In contrast, the EMPC$_2$ without including the energy prices only decides to switch on/off the productions programs once the demand of pieces has been completed. This behaviour is also appreciated when an increment in the energy prices happen during six hours (highlighted with a red square), which was added to test the effectiveness of the proposed control strategy under uncertain scenarios. In concordance, during this event, the proposed controller tries to switch to the production programs with lower energy consumption, and only after the energy prices returned to their typical values, the second program in each process line was again executed.

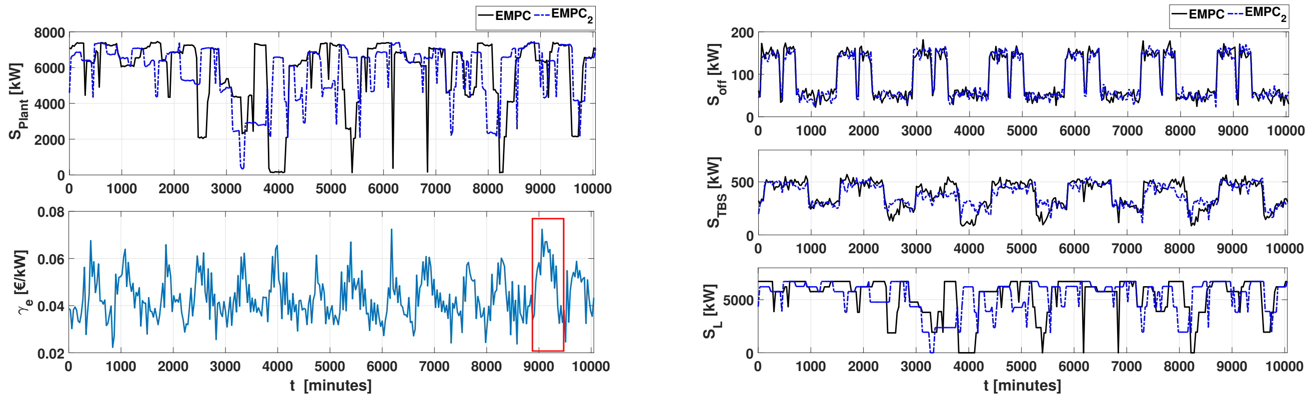
Then, according to the production of pieces and the energy consumed, the difference between the two tested approaches (EMPC and EMPC$_2$) concerning the total revenues, energy costs, and profit per day are presented in Figure 6. Based on these results, it is possible to see that, by including the energy-price fluctuations into the optimisation problem, energy costs can be reduced, achieving reductions up to 3% per day. Besides, based on the production programming, the revenues for the sale of parts and the total energy costs, plant profit can be increased in 2% per day, approximately. However, since both controllers try to maximise the part production, the incomes were quite similar using both strategies and the main differences concern to the reduction in the energy costs. Besides, although both controllers decide to maximise the revenues for the sale of parts to mitigate the energy costs, according to the constraints for the maximum production of pieces, the excess in the production never surpasses 10% of the real demand. Finally, a comparison of the computational time spent by iteration using both EMPC and EMPC$_2$ approaches is presented in Figure 7. Based on the sampling time and the maximum value of t_c, it is possible to conclude that the proposed control strategy is suitable to be implemented in real time.

6. CONCLUSION

In this work, an optimisation-based control strategy has been proposed to determine the optimal economic production programming of a manufacturing plant. Based on the marketplace demand and the energy-price fluctuations, the proposed controller finds the suitable instants in which the production programs must be executed to maximise the plant profit without affecting the system productivity since the production programs are not modified. Based on the obtained results, energy costs can be minimised and help maximising the plant profit taking advantage of time-varying energy prices. Thus, using the proposed approach, the decision makers should only determine the demand to be satisfied per day, and the controller will decide how to manage production processes. Then, to improve the proposed approach, costs with fixed prices like such related to the activation/deactivation of production programs and the resources used by machines could be added into the cost function.

REFERENCES

Angeli, D., Casavola, A., and Tedesco, F. (2016). Theoretical advances on economic model predictive control



(a) Energy consumption profile of the plant and energy price profile. (b) Energy consumption of productive and non-productive areas.

Fig. 5. Simulation results using the proposed EMPC and EMPC$_2$.

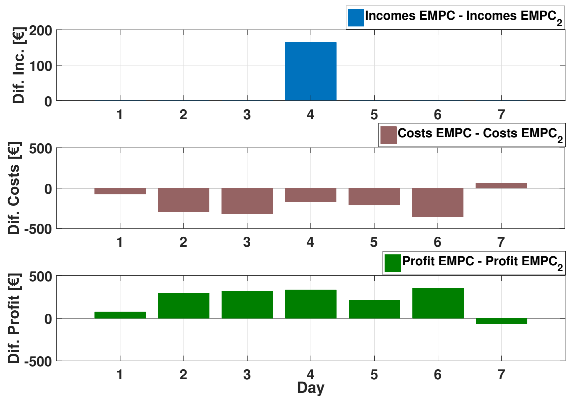


Fig. 6. Plant profit per day according to the total energy costs and incomes for the sale of parts.

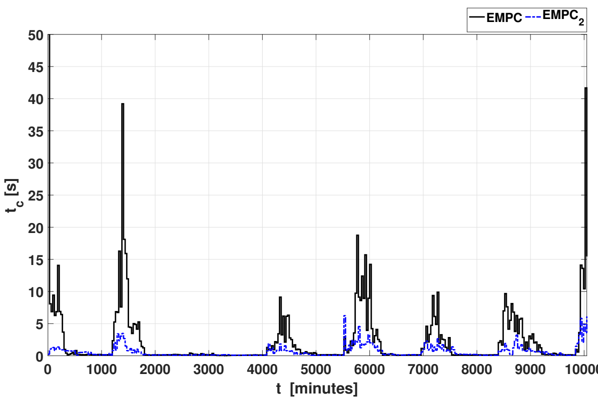


Fig. 7. Comparison of the computational burden along the whole simulation.

with time-varying costs. *Annual Reviews in Control*, 41, 218–224.
Diaz, J., Bermeo, M., Diaz-Rozo, J., and Ocampo-Martinez, C. (2019). An optimization-based control strategy for energy efficiency of discrete manufacturing systems. *ISA Transactions*, 93, 399–409.
Diaz, J. and Ocampo-Martinez, C. (2019). Energy efficiency in discrete-manufacturing systems: Insights, trends, and control strategies. *Journal of Manufacturing Systems*, 52, 131 – 145.
Duflou, J.R., Sutherland, J.W., Dornfeld, D., Herrmann, C., Jeswiet, J., Kara, S., Hauschild, M., and Kellens, K. (2012). Towards energy and resource efficient manufacturing: A processes and systems approach. *CIRP Annals*, 61(2), 587 – 609.
Ellis, M., Durand, H., and Christofides, P. (2014). A tutorial review of economic model predictive control methods. *Journal of Process Control*, 24(8), 1156–1178.
Fahad, M., Naqvi, S., Atir, M., Zubair, M., and Shehzad, M.M. (2017). Energy management in a manufacturing industry through layout design. *Procedia Manufacturing*, 8, 168–174.
Herrmann, C. and Thiede, S. (2009). Process chain simulation to foster energy efficiency in manufacturing. *CIRP Journal of Manufacturing Science and Technology*, 1(4), 221–229.
ILOG, I. (2013). IBM ILOG CPLEX optimization studio, v 12.5.
Jakovljevic, Z., Majstorovic, V., Stojadinovic, S., Zivkovic, S., Gligorijevic, N., and Pajic, M. (2017). Cyber-physical manufacturing systems (CPMS). In *Proceedings of 5th International Conference on Advanced Manufacturing Engineering and Technologies*, 199–214. Springer International Publishing, Cham.
Li, L., Li, C., Tang, Y., and Li, L. (2017). An integrated approach of process planning and cutting parameter optimization for energy-aware CNC machining. *Journal of Cleaner Production*, 162, 458–473.
Löfberg, J. (2004). Yalmip : A toolbox for modeling and optimization in Matlab. In *In Proceedings of the CACSD Conference*. Taipei, Taiwan.
Lu, C., Gao, L., Li, X., Pan, Q., and Wang, Q. (2017). Energy-efficient permutation flow shop scheduling problem using a hybrid multi-objective backtracking search algorithm. *Journal of Cleaner Production*, 144, 228–238.
Maciejowski, J. (2002). *Predictive control with constraints*. Prentice Hall, Harlow, England.
Qin, S.J. (2006). An overview of subspace identification. *Computers & Chemical Engineering*, 30(10), 1502–1513.
Rawlings, J.B., Angeli, D., and Bates, C.N. (2012). Fundamentals of economic model predictive control. In *51st IEEE Conference on Decision and Control (CDC)*, 3851–3861.
Verhaegen, M. and Hansson, A. (2016). N2sid: Nuclear norm subspace identification of innovation models. *Automatica*, 72, 57–63.