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Dual Mode Control Strategy for Complex and Flexible Manufacturing Systems

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Abstract

The manufacturing industry is shifting towards smart manufacturing, in which both energy efficiency and flexibility are some of the main objectives of this transformation. In this regard, the control strategies for manufacturing systems should be able to support the requirements of this transformation with a low computational burden towards their implementation in real time. To this end, in this paper, a dual-mode control strategy based on two control approaches is proposed to minimize the energy consumption of manufacturing systems without affecting their productivity, even when scenarios of flexible manufacturing are considered. The first control model is based on Model Predictive Control to determine the optimal and constrained behaviour of the system. Then, the second mode starts from the assumption that the system exhibits a periodic behaviour to switch to an autonomous control mode that not solve an optimisation problem online. The proposed control strategy is tested in a manufacturing process line in which changes in the production programs are considered with the aim to test the performance in flexible manufacturing scenarios. The obtained results show that the computational burden could be significantly reduced while reducing global energy consumption without affecting the system productivity.

Keywords: Dual control strategy, Model predictive control, Mixed-integer linear programming, Smart manufacturing systems, Flexible manufacturing

1. Introduction

Manufacturing refers to the industrial production processes through which the raw materials are transformed into finished products to be sold in the market. Thus, manufacturing systems can be considered as a set of processes for transforming resources and energy into industrial products and goods for consumers [5, 17]. Since manufacturing systems consume most of the electricity produced in the world, the minimisation of the energy consumption of such systems does not only allow reducing the energy costs of a manufacturing plant but also contributes to minimising the global electricity demand. Thus, due to the depletion of fossil energy sources, rising energy prices, and governmental regulation restrictions, the current manufacturing industry is shifting towards more efficient and sustainable systems. This fact has promoted the identification of energy-saving opportunities and the design of strategies oriented to improve the energy efficiency of such systems [18]. Besides, into the new era of manufacturing systems and their transformation towards smart manufacturing, these systems should be able to respond to changes in the production programs to processing pieces with different design specifications, allowing a higher level of customizability for the final users [3].

In this regard, manufacturing systems refers to a collection of machines and devices organised in a proper configuration for producing a finished piece, commonly named as process line. Complex structures are found in a process line, which corresponds to the aggregation of machines, peripheral devices, and

buffer devices for producing a piece. At this aggregation level, machines are organised logically according to the required operations to process a piece entirely. Besides, since the machines in a process line could have different operating cycles, buffers might be required in order to maximise the production and avoid the simultaneous input of two or more pieces to one machine. In these systems, peripheral devices refer to those devices that are not directly related to machining operations but are necessary to guarantee the correct operation of machines and the suitable supply of resources to machines in the process line. Some resources required by machines are, for instance, water for washing operations, the coolant to be used during machining operations, air or hydraulic fluids to clamp/unclamp of pieces according to the design of the machine, among others.

According to the processes performed on each machine and its connections, process lines present different configurations, such as serial and parallel structures. Based on the configurations in a process line, different energy and material flows, which represent either the interactions or relations between the machines and peripheral devices in the process line, could exist. These relationships add complexity to understand and modelling the energy consumption as well as designing control/management strategies at this level. Therefore, factors as the diversity of components in a process line, their energy consumption behaviour, their interactions, and the intrinsic characteristics of each component should be considered to analyse and propose energy efficiency improvements at the process-line

Nomenclature

Physics Constants

ρ_c	Density of coolant
R	The gas constant
T	Temperature of air in T_1
W_{air}	The molecular weight of air

Number Sets

\mathbb{R}	Real number set
$\mathbb{R}_{>0}$	Set of positive real number
\mathbb{V}_2	Discrete domain of $P_{G,2}$
\mathbb{Z}	Integer number set
$\mathbb{Z}_{\geq 0}$	Set of positive integer number

Acronyms

LTI	Linear time-invariant
MC	Markov chains
MPC	Model predictive control
PN	Petri nets
SI	Subspace identification

Symbols

α_{v_1}	Constant energy consumption of valve v_1 100% open
α_{v_3}	Constant energy consumption of valve v_3 100% open
β_i	Integral of the Energy consumption of M_i along T_{M_i}
η	Pump efficiency
γ_{P_j}	State vector of the energy consumption model of P_j
Γ	Sequence of Λ_p along H_p
Λ_p	The activation sequence of peripheral devices in the process line
Λ_{M_i}	The activation sequence of devices of the i -th machine
Λ_p^*	Optimal activation sequence of peripheral devices
Λ_v^*	Optimal activation sequence of valve aperture
D_{pk}	Distance vector among the first lag and the rest of the lags in \mathbf{l}_c
\mathbf{l}_c	Vector of lags among the peaks of \mathbf{u}_x
\mathbf{pk}	Peaks of in vector \mathbf{u}_x
\mathbf{u}_x	Vector of autocorrelation coefficients of signal u_j
\bar{q}_{G_1}	Upper bound for process dynamics related to P_{G_1}
\bar{q}_{G_2}	Upper bound for process dynamics related to P_{G_2}
\bar{q}_{L_1}	Upper bound for process dynamics related to P_{L_1}
\bar{u}_x	Maximum autocorrelation coefficient of signal u_j
τ_s	Sampling time
\underline{q}_{G_1}	Lower bound for process dynamics related to P_{G_1}
\underline{q}_{G_2}	Lower bound for process dynamics related to P_{G_2}
\underline{q}_{L_1}	Lower bound for process dynamics related to P_{L_1}
ε_{M_1}	Maximum flow required by M_1
A_{T_2}	Transverse area of T_2
A_{T_3}	Transverse area of T_3
Ap_{v_1}	Aperture of valve v_1
Ap_{v_3}	Aperture of valve v_3

b	Number of machines in the process line
H_p	Prediction horizon
$h_{f_1 \rightarrow 2}$	Energy losses by friction
$H_{p,c}$	Prediction horizon in the commutation protocol
J	Integral of the energy consumption signal
k	Discrete-time index
L_2	Level of clean coolant in T_2
L_3	Level of dirty coolant in T_3
m	Number of manufacturing devices in each machine
m_c	Flow of dirty coolant pumped by $P_{G,2}$
M_{T_1}	Mass of air in the tank 1
M_{T_4}	Mass of air in the tank 4
m_{ccl,M_i}	Flow of clean coolant required by M_i
m_{dcl,M_i}	Flow of dirty coolant recovered from M_i
N	Model order
n	Number of peripheral devices in the process line
N_u	Time to start running periodicity detection
p	Dimension of the state vector γ_{P_j}
P_{G_1}	Global peripheral device 1
P_{G_2}	Global peripheral device 2
P_{in}	Input pressure in the pipe system
P_{L_1}	Local peripheral device 1
P_{out}	Output pressure in the pipe system
P_{T_1}	Pressure of air inside the tank 1
P_{T_4}	Pressure of air inside the tank 4
q_{P_j}	States for the dynamics of P_j
r	Dimension of the state vector $\xi_{M_i,l}$
S	Total energy consumption of the process line
S_{M_i}	Power consumption of the i -th machine
S_{P_j}	Power consumption of the j -th peripheral device
S_{v_1}	Energy consumption of valve v_1
S_{v_3}	Energy consumption of valve v_3
T_2	Tank with clean coolant
T_3	Tank with dirty coolant
T_{M_i}	Cycle time of the i -th machine
T_{u_j}	Period of the peripheral device j
$u_{M_i,l}$	Activation/deactivation signal of the l -th device of the i -th machine
u_{P_j}	Activation/deactivation signal of the j -th peripheral device
V_{T_1}	Volume of T_1
V_{T_4}	Volume of T_4
\mathbf{J}	Sequence for control objective J along H_p
ω	Specific work per time unit
M_i	The i -th machine
m_{air,M_i}	Consumption of air from machine M_i
m_{in}	Air flow pumped by P_{G_1}
$m_{G,1,M_1}$	Flow of air provide by P_{G_1} to machine 1
$m_{L,1,M_1}$	Flow of air provide by P_{L_1} to machine 1

level [4]. However, to reduce the energy consumption of manufacturing systems, the improvements for single machine or device in the process line are not enough and, instead of this, the whole process line should be optimised to reduce its total energy consumption [14]. According to this fact, most of the strategies and technologies identified from literature are focused on capturing and tracking energy and material flows in a multi-machine ecosystem, and the offline processes planning and scheduling of machines.

Process planning and scheduling are essential and complementary factors regarding energy consumption and flexibility of manufacturing systems. The currently implemented strategies in manufacturing systems have only focused on the development of adaptable and sustainable processes plans, which

can be flexible regarding the market requirements. In [2], an approach of integration between the Energy-Aware Scheduling (EAS) methodology and a reference schedule generated by an Advanced Planning and Scheduling (APS) system that does not consider energy saving is proposed. This approach is employed together with a process model to control the power peaks in the shop floor for a given detailed schedule. Similarly, in [8], the energy-efficient Permutation Flow-shop Scheduling Problem with Controllable Time (PFSPCT) is studied to analyse the scheduling problem but including both transportation and processing times. A different approach that incorporates power models for a single machine and cutting-parameters optimisation into the scheduling problems is developed by [16]. In this work, the scheduling problem is solved by using a multi-level

optimisation approach considering both machine and line levels.

In the same way, the control of peak power demand has been another research focus to improve the energy efficiency of manufacturing systems at the process line level. In this sense, most of the strategies currently implemented regarding the peak power control consist of delaying the switching-on of some machines taking into account a threshold value. Usually, this latter value corresponds to the contracted nominal power, which produces economic penalties if it is exceeded. Although many works consider strategies for flexible manufacturing at the plant level, energy consumption is usually considered as an initial optimisation regarding the production planning of the existing devices in the plant. That is, these strategies determine an optimal sequence from the beginning, and therefore they cannot respond to the temporal variation of processes and working environment factors during the operation of the plant [3].

Given the complexity of manufacturing systems due to the processes performed, the strong relationships between the peripheral and machining devices, the time-varying constraints such as tool wear, the efficiency of each device and the changing-working environment, the most used control techniques in manufacturing systems are those based on optimisation. This fact is given since the control objectives, operating constraints of either devices or machines involved, their operating ranges, dynamic expressions for the relationships between machines and their environment, and any additional constraints that condition the performance of the system to be controlled can be included into an optimisation problem. However, although few control applications in manufacturing systems consider energy objectives, most of them have been limited to analyse the individual system and not consider interactions with both other devices and machines. Besides, most of these applications consist of designing closed-loop control schemes that minimise the difference between the real energy consumption and a reference behaviour, which is usually determined offline and without considering the temporal variations of its surroundings. Thus, in most of the case studies, disturbances or changes in the working environment are not considered. Therefore, and taking into account the current context of manufacturing industry, strategies able to respond in real time to any changes in the system or its environment, besides to consider flexibility in the processes plan and schedule should be developed [1].

Thus, in this paper, a dual-mode control strategy based on two control approaches is proposed to minimise the energy consumption of manufacturing systems without affecting their productivity. The main idea behind the design of the dual control strategy is to reduce the computational burden by switching from a control mode based on on-line optimisation to an autonomous mode without continually optimising. The latter, to design a control strategy that can be implemented in real time, considering both flexible manufacturing scenarios and disturbances management, but without sacrificing the performance of the controller in closed loop. To this end, the first control mode or the predictive one is designed based on Model Predictive Control (MPC) to determine the optimal system behaviour taking into account the current state of the process line (machines

and peripheral devices), the production program currently executed, and the operational and physical constraints of both machines and peripheral devices into the process line. Then, the second mode starts from the assumption that the system could exhibit periodic behaviour, inherited from the periodic behaviour of the machines. Therefore, when the system periodicity is detected the control system switches to an autonomous control mode. In this latter mode, the optimal and periodic behaviour achieved in the first control mode is repeated over time. However, to avoid undesirable behaviour of the process line, a prediction and a commutation protocol in which it is verified that the system remains into its feasible domain are performed while the autonomous mode is running. The proposed approach is tested to minimise the global energy consumption of a serial process line with three machines and three peripheral devices, taking into account disturbances in the operation of peripheral devices and flexibility scenarios such as changes in the production programs.

The remainder of the paper is organised as follows. In Section 2, the problem statement considered in this paper is presented. Next, Section 3 introduces the case study and presents the way to model both energy consumption and process dynamics of peripheral devices and machines in a process line. In Section 4, the proposed control strategy and the two control modes are presented and described. Besides, in Sections 4.1 and 4.2, the algorithm for detecting periodicity and the commutation protocol are explained, respectively. Afterwards, obtained results from the implementation of the proposed control strategy and an analysis of its effectiveness in disturbance scenarios are reported and discussed in Section 5. Finally, in Section 6, conclusions and future works based on the obtained results are drawn.

2. Problem Statement

The main units in a manufacturing system are the machine tools, which can be understood as a set of different devices that work in a sequential way to process a piece during a fixed period of time. Most of these machines are organized in a logical and sequential way to process a piece completely, which shapes a process line. In the current context of flexible manufacturing, process lines should be able to produce different finished parts, in which the line has the flexibility to react to changes in the product being manufactured, both in type and quantity. In this regard, a process line is a complex (and large-scale) system including several machines and peripheral devices that work synchronously and logically up to getting a finished part. Machines in a process line (M_i) correspond to a set of devices that are directly related to machining processes (e.g., milling, cutting, turning, grinding, drilling), while the peripheral devices are those devices that provide the resources required to machines for their proper operation.

The machines in a process line are characterized by a periodic behaviour according to the total time required for manufacturing a piece, which corresponds to a *operation cycle* denoted here by T_{M_i} . Therefore, the energy consumption of devices straight related to manufacturing operations in each ma-

chine, such as manufacturing processes, transport, and handle of pieces, shows also a periodic behaviour. However, due to the nature of the operations performed by machine devices (e.g., rotational motions, axial motions, cutting, milling), there exist stages of both high and low energy consumption along T_{M_i} .

On the other hand, since peripheral devices supply resources to machines in the process line, there exist several functional relationships between machines and peripheral devices that determine the productivity of the process line. When the machines in a process line have different values of T_{M_i} , the throughput of the process line level is determined based on the machine with the longest cycle time $\max(T_{M_i})$. Thereby, process lines are designed with the aim of processing a complete piece up to achieve the desired physical properties (e.g., shape, weight, volume, surface, among other) in the shortest possible time. However, peripheral devices might or might not show a periodic behaviour, which may match with T_{M_i} , as a consequence of the design of peripheral devices in the process line as well as the way they are managed. Therefore, to improve the energy efficiency of a process line, peripheral devices must be correctly managed such that their activation time does not match with the time instants/slots of higher consumption while satisfying the operating constraints of machines.

At the process line level, the functional relationships between machines and peripheral devices could be quite complex since some peripheral devices can be shared between two or more machines, provide the same resource to all the machines in the line, or even supply the same resource provided by another global peripheral device to a particular machine. Besides, peripheral devices in the process line should be able to adapt their operation to the changes in the production program and the new functional relationships imposed by these programs. In these cases, a consensus based on the management objectives (e.g., energy consumption, energy costs, productivity) should be established to guarantee the satisfaction of the operating constraints among machines and peripheral devices as well as the proposed control objectives. In Figure 1, a serial process line is shown, which consists of three machines and three peripheral devices. It should be noted that when a peripheral device is shared among two or more machines of the process line, it is called *Global* peripheral device, and when the device works only for the i -th machine in the line is known as *Local* peripheral device of the machine i .

According to the stages of higher and lower energy consumptions along T_{M_i} , the activation instants of each peripheral device should be selected taking into account both its operating constraints and its dependency on the activation sequence of machines Λ_{M_i} . Thus, considering a fixed number of both machines and peripheral devices in a process line, their activation sequences can be defined as

$$\Lambda_{M_i}(k) = \{u_{M_{i,1}}(k), u_{M_{i,2}}(k), \dots, u_{M_{i,m}}(k)\}, \quad (1a)$$

$$\Lambda_P(k) = \{u_{P_1}(k), u_{P_2}(k), \dots, u_{P_n}(k)\}, \quad (1b)$$

being $k \in \mathbb{Z}_{\geq 0}$ the discrete-time index and, $m = |\Lambda_{M_i}|$ and $n = |\Lambda_P|$ the number of manufacturing devices of the i -th machine and the number of peripheral devices in the process line, respectively. Usually, the activation signals of both machine devices and peripheral devices are constrained to $u_{M_{i,l}}(k) \in \{0, 1\}$, $l \in \mathcal{L} \triangleq \{1, 2, \dots, m\}$, and $u_{P_j}(k) \in \{0, 1\}$, $j \in \mathcal{J} \triangleq \{1, 2, \dots, n\}$. However, for the cases in which the activation load of devices can be modulated, the activation signal will be constrained to $u_{M_{i,l}}, u_{P_j} \in \mathbb{Z}_{\geq 0}$.

Since the activation instant of the machine devices $u_{M_{i,l}}$ and their execution time are given by the manufacturing process and are known a priori from the process planning and scheduling designed for each piece, both the machining sequences of each machine Λ_{M_i} and its associated power consumption S_{M_i} can be considered as fixed and periodic over the time. Otherwise, the power consumption of peripheral devices S_{P_j} depends on the operational relationships between them and machines in the process line since they must guarantee resources required for the manufacturing processes. Thus, in order to select the suitable activation instants of the peripheral devices that allow minimizing the global energy consumption S of the process line, the dynamics of both energy consumption and the process performed by the peripheral devices, and operating constraints between them and machines should be taken into account for the design of control strategies. In this regard, the control problem consists of determining the optimal Λ_P that minimizes the global S along a fixed period T . Indeed, the control objective can be defined as the minimization of the integral of the energy consumption signal, i.e.,

$$J = \sum_{k=1}^{k=T} \left[\sum_{i=1}^{i=b} S_{M_i}(k) + \sum_{j=1}^{j=n} S_{P_j}(k) \right]. \quad (2)$$

being b the total number of machines in the process line. Then, to compute the global apparent power consumption $S(k) = \sum_{j=1}^{j=n} S_{P_j}(k) + \sum_{i=1}^{i=b} S_{M_i}(k)$, power consumption models for each machine

$$\begin{aligned} \xi_{M_{i,l}}(k+1) &= h_1(\xi_{M_{i,l}}(k), u_{M_{i,l}}(k)), \\ S_{M_{i,l}}(k) &= h_2(\xi_{M_{i,l}}(k)), \end{aligned}$$

and each peripheral device are required, i.e.,

$$\begin{aligned} \gamma_{P_j}(k+1) &= f_1(\gamma_{P_j}(k), u_{P_j}(k)), \\ S_{P_j}(k) &= f_2(\gamma_{P_j}(k)), \end{aligned}$$

being $\gamma_{P_j}(k)$ and $\xi_{M_{i,l}}(k)$ the system states of the energy consumption model related to P_j and $M_{i,l}$, respectively. Besides, $f_1 : \mathbb{R}^p \times \{0, 1\}^l \mapsto \mathbb{R}^p$ and $f_2 : \mathbb{R}^p \mapsto \mathbb{R}_{\geq 0}$ are linear maps in function of both the current state and the activation signal of P_j , while $h_1 : \mathbb{R}^r \times \{0, 1\}^m \mapsto \mathbb{R}^r$ and $h_2 : \mathbb{R}^r \mapsto \mathbb{R}_{\geq 0}$ are the maps for $M_{i,l}$. Moreover, mathematical expressions for the dynamics of processes performed by peripheral devices, i.e.,

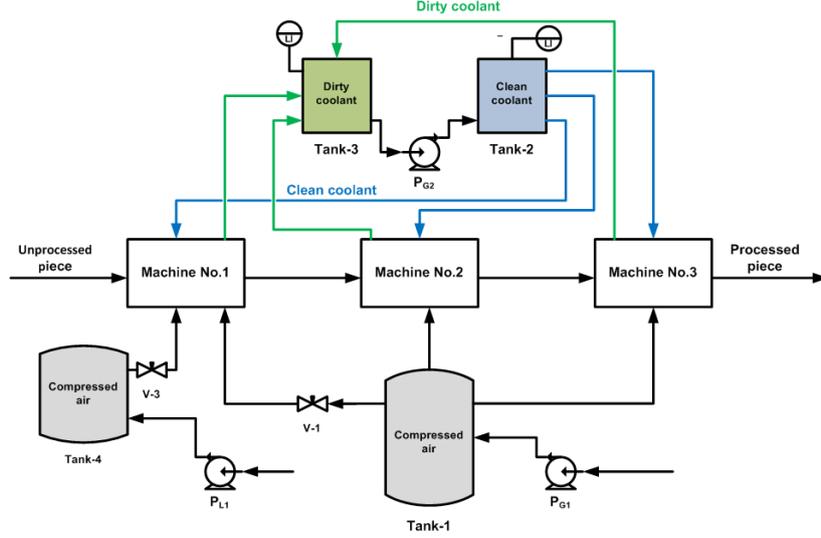


Figure 1: Three-stage serial process line with its corresponding peripheral systems.

$$q_{P_j}(k+1) = g_{P_j}(u_{P_j}(k), \mathbf{\Lambda}_{M_i}), \quad (5)$$

are also required to express the operational relationships between machines and peripheral devices. In (5), $q_{P_j}(k)$ corresponds to states related to the dynamics of peripheral devices P_j with $g_{P_j} : \{0, 1\} \times \mathbb{R} \mapsto \mathbb{R}_{\geq 0}$ the maps that consider the relationships between machines and peripheral devices.

3. A Benchmark System

According to Figure 1, a process line with three machines and three peripheral devices will be studied to test the performance of the control strategy to be proposed. In order to analyse a scenario of flexible manufacturing, two production programs in which the resource consumption of the machine M_1 in program 1 is duplicated for the second program are considered. In this case, it is assumed that all machines in the process line have the same cycle time, i.e., $T_{M_i} = 28 \text{ s } \forall i = 1, 2, 3$ and their machine sequences¹ $\mathbf{\Lambda}_{M_i}$ are fixed and periodic over the time. Besides, the peripheral devices P_{G_1} and P_{G_2} are considered as global peripheral devices since they are shared among the three machines in the process line, while P_{L_1} is a local device that only provides resource to machine 1. Thus, for the first production program, the global devices P_{G_1} and P_{G_2} are able to supply the resources demand of machines. However, when the second production program is executed, an extra peripheral device P_{L_1} is required since the device P_{G_1} is not able to supply the new demand of compressed air required by machines in the second program.

Both P_{G_1} and P_{L_1} are associated to the supply system of compressed air, which will be used for clamping pieces during the whole machining sequence. Besides, it is assumed that both

P_{G_1} and P_{L_1} have a nominal energy consumption whenever the device is turned on. It should be noted that the local peripheral device P_{L_1} works only for M_1 and its operation depends on the production program executed in the process line. Thus, in order to consider a flexible manufacturing scenario, it is assumed that P_{L_1} will be inactivated during the first production program, and will be activated when the second production program is executed since the resource consumption of M_1 during the second program is significantly higher than its consumption in the previous production program. For the case in which the second production program will be executed because a different part should be processed in the process line, new decision variables to determine the optimal flow to be taken from each device are required. Thus, according to Figure 1 the aperture of the valves v_1 and v_3 should also be optimized according to the new sequences of resources consumption of machines for the new production program.

On the other hand, P_{G_2} is related to a coolant supply system for the machining operations at each machine, and its activation could be modulated to different energy consumption levels. According to this, both the activation instant and the activation level for P_{G_2} should be optimised taking into account the resources consumption from machines. It is worth noting that the consumption of resources from machines depends on $\mathbf{\Lambda}_{M_i}$ and the production program, and although in this paper the machining sequences are not presented in detail since they are assumed to be fixed and constant over the time, in Figure 2, the consumption profile of compressed air and coolant from machines is presented. Based on Figure 2, it is possible to observe that the unique difference between the production programs regards the machine M_1 , in which the resource consumption is duplicated, as shown in this figure with a red line.

¹It corresponds to the sequence of processes performed by the machining devices of a machine to produce a piece.

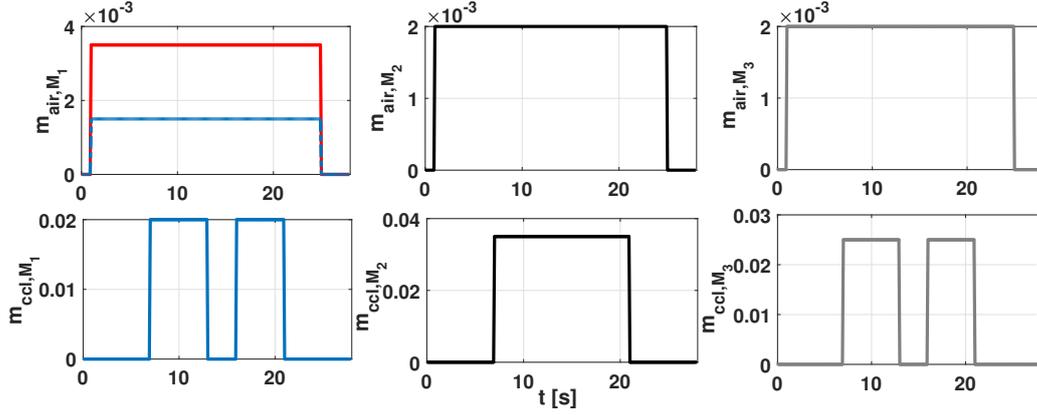


Figure 2: Sequences for resource consumption from machines in the process line along T_{M_i} .

3.1. Air-supply system

One of the functions of pneumatic systems is to supply air of pre-defined conditions of pressure to clamp/unclamp pieces during manufacturing operations. Considering the supply system shown in Figure 1, a pump provides to an air stream the energy enough to achieve the desired conditions of pressure, and then, this stream is transported towards the devices that required it. Based on this fact, the dynamics associated to P_{G_1} (and P_{L_1}) correspond to the dynamics for the total change of mass M_{T_1} (M_{T_4}) and pressure P_{T_1} (and P_{T_4}) inside a storage tank T_1 (and T_4), which are expressed in the discrete-time version as follows:

$$M_{T_1}(k+1) = M_{T_1}(k) + \tau_s \sigma(k), \quad (6a)$$

$$\sigma(k) = m_{in} u_{G_1}(k) - m_{G,1M_1} - \sum_{i=2}^b m_{air, M_i}(k) \quad (6b)$$

$$P_{T_1}(k) = \frac{M_{T_1}(k) R T}{V_{T_1} W_{gass}}, \quad (6c)$$

being τ_s the sampling time, m_{air, M_i} the air consumption from machine M_i , m_{in} the air flow pumped by P_{G_1} (and P_{L_1}) towards the tank T_1 (and T_4), and, R, T, V_{T_1} and W_{air} the gas constant, air temperature, volume of T_1 (and T_4), and the molecular weight, respectively. In addition, the pressure P_{T_1} (and P_{T_4}) must satisfy $\underline{P}_{T_1} \leq P_{T_1}(k) \leq \bar{P}_{T_1}$ (and $\underline{P}_{T_4} \leq P_{T_4}(k) \leq \bar{P}_{T_4}$), with \underline{P}_{T_1} and $\leq \bar{P}_{T_1}$ the lower and upper bounds for P_1 , respectively.

It should be noted that for the case in which both P_{L_1} and P_{G_1} provide compressed air to M_1 at the same time, the sum of $m_{G,1M_1}$ and $m_{L,1M_1}$ should be equal the flow required by M_1 at each instant k , namely $m_{air, M_1}(k)$. In this regard, two valves with modulated aperture are considered into the process scheme to determine how much flow of compressed air could be provided from P_{G_1} and P_{L_1} . The domain for variables v_1 and v_3 should be defined taking into account the maximum flow that can supply each device when the valves are 100% open as well as the admissible values into its domain to guarantee a feasible solution. Then, the energy consumption concerning valves is computed according to:

$$S_{v_1}(k) = \alpha_{v_1} A p_{v_1}(k), \quad (7a)$$

$$S_{v_3}(k) = \alpha_{v_3} A p_{v_3}(k), \quad (7b)$$

being α_{v_1} and α_{v_3} the constant energy consumption of valves v_1 and v_3 , respectively. Besides, the flows of compressed air provided by P_{G_1} and P_{L_1} , according to the values of both $A p_{v_1}$ and $A p_{v_3}$, can be compute according to the following equations:

$$m_{G,1M_1}(k) = \varepsilon_{M_1} A p_{v_1}(k), \quad (8a)$$

$$m_{L,1M_1}(k) = \varepsilon_{M_3} A p_{v_3}(k), \quad (8b)$$

with ε_{M_1} and ε_{M_3} the maximum flows provided by devices P_{G_1} and P_{L_1} , respectively.

3.2. Coolant-supply system

The supply of coolant is a critical task for manufacturing processes because if the coolant is not supplied in either sufficient quantity or at suitable time instants, manufacturing processes will not correctly work and the desired properties of the piece will not be reached. In many cases, coolant-supply systems are designed with re-circulation, filtering and re-use of coolant, as shown in Figure 1. According to this figure, a constant flow of coolant m_c is pumped from T_3 towards a clean-coolant tank T_2 passing through a filter in which the fine particles are separated. Next, the coolant flows required by the machines are pumped from T_2 . After manufacturing processes in the machine, the dirty coolant is collected and delivered to a dirty tank T_3 where gross chip particles are separated by gravity, and the process is repeated. In this case, the pump $P_{G,2}$ corresponds to the peripheral device of interest, and both the activation instant and the suitable flow of coolant to satisfy the operating constraints must be selected. Therefore, $u_{G_2} \in \mathbb{V}_2 \subset \mathbb{Z}$ such that $\mathbb{V}_2 \triangleq \{0, 100, 120, 140\}$. The dynamics for level changes in both tanks are the following:

Table 1: Physical dimensions and parameters for the supply systems of compressed air and coolant.

Parameter	Value	Parameter	Value
V_{T_1}	0.015m^3	V_{T_4}	0.01m^3
A_{T_2}	0.015m^2	A_{T_3}	0.015m^2
T_{air}	25°C	R	$8.1314\frac{\text{J}}{\text{kmol}}$
W_{air}	$28.966\frac{\text{g}}{\text{mol}}$	ΔP_{filter}	10000Pa
P_{atm}	101325Pa	η	0.95
ρ_c	$1042.5\frac{\text{kg}}{\text{m}^3}$	$h_{1\rightarrow 2}$	$0.12\frac{\text{m}^2}{\text{s}^2}$
$m_{in,1}$	$0.006\frac{\text{m}^3}{\text{s}}$	$m_{in,3}$	$0.004\frac{\text{m}^3}{\text{s}}$
α_{v_1}	2.5VA	α_{v_3}	2.5VA
ε_{M_1}	1.5×10^{-5}	ε_{M_3}	3.0×10^{-5}
\bar{P}_{T_1}	300kPa	\bar{P}_{T_1}	750kPa
\bar{P}_{T_4}	300kPa	\bar{P}_{T_4}	750kPa
\bar{L}_{T_2}	0.3m	\bar{L}_{T_2}	0.6m
\bar{L}_{T_3}	0.4m	\bar{L}_{T_3}	0.7m

$$L_2(k+1) = L_2(k) + \tau_s \gamma(k) \left(\frac{1}{\rho_c A_{T_2}} \right), \quad (9a)$$

$$\gamma(k) = m_c(k) - \sum_{i=1}^b m_{ccl, M_i}(k), \quad (9b)$$

$$L_3(k+1) = L_3(k) + \tau_s \theta(k) \left(\frac{1}{\rho_c A_{T_3}} \right), \quad (9c)$$

$$\theta(k) = \sum_{i=1}^b m_{dcl, M_i}(k) - m_c(k), \quad (9d)$$

$$P_{out}(k) = P_{in}(k) + \rho_c h_{f_{1\rightarrow 2}}(k) - \eta \frac{W(k)}{m_c(k)}, \quad (9e)$$

with m_{ccl, M_i} the coolant flow required by the i -th machine, and m_{dcl, M_i} the flow of the dirty coolant recovered. In addition, P_{in} and P_{out} correspond to the input and output pressure in the pipe system that transport the coolant from T_3 towards T_2 , while, ρ_c, η, ω and $h_{f_{1\rightarrow 2}}$ are the coolant density, efficiency of the pump, specific work per time unit and the energy losses by friction, respectively. In Table 1, the physical dimensions of the coolant system and the two air supply systems are presented.

3.3. Energy consumption models

Different approaches have been addressed for modelling and designing control strategies in manufacturing systems. Among others, the Markov chains (MC) and Petri Nets (PN) can be highlighted given their great application at both process line and plant levels [11]. Despite the great application of both MC and PN in the manufacturing systems, they have been focused on modelling the production states of the machine rather than to model the energy consumption behaviour of such systems. Thus, since the complexity to establish the different machine states, transitions between them, and their connections, data-driven models, such as those obtained from the Subspace Identification (SI) methods, have gained attention into the manufacturing industry to model its energy consumption.

Table 2: Model order and fitting percentage for the energy consumption models identified by SI methods.

Component	N	% fitting
M_1	5	94.83
M_2	5	95.11
M_3	5	94.83
$P_{G,1}$	3	74.96
$P_{L,1}$	4	60.27
$P_{G,2}$	2	90.37

Thereby, for determining the power consumption models of both manufacturing and peripheral devices, SI methods are addressed in this section. The SI methods allow identifying the matrices of a state-space realization of linear time-invariant (LTI) systems based on input-output data. These algorithms are useful since state-space realizations are convenient for estimation, control and prediction tasks. These methods start from the idea that a set of measurements of b input signals ($b \geq 1$) and p output signals ($p \geq 1$) satisfy an N -order state-space (unknown) realization as follows:

$$\mathbf{x}(k+1) = A \mathbf{x}(k) + B \mathbf{u}(k) + \mathbf{w}(k), \quad (10a)$$

$$\mathbf{y}(k) = C \mathbf{x}(k) + D \mathbf{u}(k) + \mathbf{v}(k), \quad (10b)$$

with $\mathbf{x} \in \mathbb{R}^\ell$, $\mathbf{u} \in \mathbb{R}^b$, and $\mathbf{y} \in \mathbb{R}^f$ are the state, input and output vectors, while $\mathbf{w} \in \mathbb{R}^\ell$ and $\mathbf{v} \in \mathbb{R}^p$ are the state noise and output measurement noise, respectively. In a deterministic case, in which \mathbf{w} and \mathbf{v} are neglected, the SI problem consists of estimating the system order N and the system matrices $A \in \mathbb{R}^{\ell \times \ell}$, $B \in \mathbb{R}^{\ell \times b}$, $C \in \mathbb{R}^{p \times \ell}$, and $D \in \mathbb{R}^{p \times b}$ [10].

In order to obtain a state-space representation of energy consumption models as shown in (4), this paper focuses on the Numerical algorithms For Subspace IDentification (N4SID) [15] because of their great application and implementation in software. The N4SID algorithms first estimate the state $\hat{\mathbf{x}}$ from the projection of input-output data, and then, systems matrices are determined based on the estimated state sequence. A detailed review about the different SI algorithms and their implementation can be found in [12, 15]. Thereby, to get suitable data sets for the modelling process, different activation sequences for both Λ_{M_i} and Λ_P should be tested to get information about their resulting energy consumption.

In this regard, different sequences of Λ_P and Λ_{M_i} were tested in a test bench that emulate the energy consumption of machine tools and their peripheral devices with the aim to obtain the corresponding outputs S_{P_j} and S_{M_i} . Afterwards, the energy consumption models for the three machines and the three peripheral devices in the process line were identified by using the `n4sid` routine of the System Identification ToolboxTM provided by Matlab®. Different values of N were tested to identify the suitable matrices A, B, C , and D , which allow the highest fitting degree between the real and modelled outputs. In Table 2, the model order and the fitting percentages between the model and real outputs are presented for each one of the machines and

peripheral devices. It should be noted that the models of machines correspond to the energy consumption profile along T_{M_i} and according to Λ_{M_i} . The obtained matrices for the energy consumption models of peripheral devices are presented below:

$$A_{G,1} = \begin{bmatrix} 0.4498 & 0.03599 & 0.00118 \\ -0.8389 & 0.3033 & -0.05152 \\ -0.1222 & 0.1909 & 0.7697 \end{bmatrix},$$

$$B_{G,1} = \begin{bmatrix} 0.06329 & -0.04165 \\ -0.05235 & 0.0655 \\ -1.536 & 1.183 \end{bmatrix},$$

$$C_{G,1} = [1650 \quad -478.3 \quad -75.28],$$

$$A_{L,1} = \begin{bmatrix} 0.269 & 0.118 & 0.1127 & 0.0137 \\ -0.3314 & 0.5097 & 0.1162 & -0.0414 \\ -0.8701 & -0.0211 & 0.5067 & 0.04843 \\ 0.1377 & -0.2754 & 1.287 & -0.4221 \end{bmatrix},$$

$$B_{L,1} = \begin{bmatrix} -0.1227 & 0.1363 \\ 0.1775 & -0.07527 \\ -0.1427 & 0.117 \\ 0.2009 & 0.2937 \end{bmatrix},$$

$$C_{L,1} = [-779.7 \quad 988.1 \quad 289.8 \quad -32.09],$$

$$A_{G,2} = \begin{bmatrix} 0.6217 & 0.07028 \\ 0.08679 & 0.9798 \end{bmatrix},$$

$$B_{G,2} = 10^{-4} [3.368 \quad -0.771]^T,$$

$$C_{G,2} = [529.8 \quad -31.4],$$

and $D_{G,1} = 0$, $D_{L,1} = 0$ and $D_{G,2} = 0$.

4. Control Mode Switching Strategy Based on MPC

Based on the stages of both higher and lower energy consumption, peripheral devices must be correctly managed in order to minimize the total energy consumption and to avoid also (if possible) the simultaneous activation of peripheral devices. Thus, to design a control strategy such that it does not affect the productivity of the process line, the machining sequences Λ_{M_i} of each machine for each production program will be considered as fixed and periodic over the time, assuming they are already optimized regarding energy consumption. This latter fact implies that the time T_{M_i} to process a piece at each M_i remains the same and, therefore, the process line can handle the same number of pieces as when the control/supervision strategy is not implemented. Besides, since Λ_{M_i} is considered fixed and periodic, its associated energy consumption $\beta_i = \sum_{k=0}^{T_{M_i}} S_{M_i}(k)$ along T_{M_i} will also be constant over any interval T_{M_i} and periodic over time.

In this regard, an optimization-based control strategy that allows minimizing the global energy consumption of a process line is proposed taking into account its dynamics, the global energy consumption S and, the operational relationships between machines and peripheral devices in the process line. Besides, the control strategy should be able to respond to changes in production programs and to adapt its operation according to the

new operating constraints and relationships among the process-line components. Therefore, the proposed control strategy is designed considering two different control modes. The former is based on the design of a predictive-like controller according to the Model Predictive Control (MPC) approach to determine the optimal activation sequence of peripheral devices in the process line $\Lambda_{\mathbf{P}}^*$ at the current production program. For the case of the second production program, the optimal sequences for the aperture of valves $\Lambda_{\mathbf{V}}^*$ should also be determined. The second control mode will be implemented only if the peripheral devices exhibit a periodic behaviour after a time period of running the former or predictive control mode. Then, if some peripheral device has a periodic behaviour, its periodicity should be detected and the activation sequence previously optimized in the first control mode will be sent to the system. That means, every time the energy response of a peripheral device is detected as periodic, it will be removed from the optimization problem behind the controller design in the former control mode with the aim to minimize the computational burden.

The predictive control mode is based on the design of a predictive-like controller considering both energy consumption models and operating constraints of peripheral devices into an optimization problem behind the design of such a controller. The general idea of this mode is to anticipate either activation or deactivation of peripheral devices that allow minimizing the global energy consumption of the process line taking into account their dynamics, the global energy consumption S and the operational relationships with the machines in the process line. Then, considering a prediction horizon $H_p = T$ (with $T = \max(T_{M_i})$), the decision of switching on or off a device j depends on the current value of the energy consumption of machines $S_{M_i}(k)$, i.e., although the manufacturing sequences for machines in the process line are already given and hence its energy consumption, its consumption values discriminated along the time are important for making decisions regarding peripheral devices management.

According to the control objective defined in (2), the sequences² for J , $\Lambda_{\mathbf{P}}$ and $\Lambda_{\mathbf{V}}$ along H_p are defined as

$$\mathbf{J}(k) \triangleq \{J(k|k), \dots, J(k+H_p-1|k)\}, \quad (11a)$$

$$\mathbf{\Gamma}(k) \triangleq \{\Lambda_{\mathbf{P}}(k|k), \dots, \Lambda_{\mathbf{P}}(k+H_p-1|k)\}, \quad (11b)$$

$$\mathbf{\Pi}(k) \triangleq \{\Lambda_{\mathbf{V}}(k|k), \dots, \Lambda_{\mathbf{V}}(k+H_p-1|k)\}, \quad (11c)$$

with $\Lambda_{\mathbf{V}}(k) = \{v_1(k), v_3(k)\}$, $\mathbf{J}(k) \in \mathbb{R}^{H_p}$, $\mathbf{\Gamma}(k) \in \{0, 1\} \times \mathbb{V}_2^{nH_p}$, and $\mathbf{\Pi}(k) \in \{0, 100\}^{nH_p}$.

Afterwards, the design of the proposed predictive-like controller is based on the following finite-time open-loop optimization problem:

$$\min_{\mathbf{\Gamma}(k), \mathbf{\Pi}(k)} \mathbf{J}(k) \quad (12a)$$

²Here, $z(k+i|k)$ denotes the prediction over H_p of the variable z at time instant $k+i$ performed at k .

subject to

$$\gamma_{G_1}(k+1) = f_1(\gamma_{G_1}(k), u_{G_1}(k)), \quad (12b)$$

$$S_{G_1}(k) = f_2(\gamma_{G_1}(k)), \quad (12c)$$

$$\gamma_{G_2}(k+1) = f_3(\gamma_{G_2}(k), u_{G_2}(k)), \quad (12d)$$

$$S_{G_2}(k) = f_4(\gamma_{G_2}(k)), \quad (12e)$$

$$\gamma_{L_1}(k+1) = f_5(\gamma_{L_1}(k), u_{L_1}(k)), \quad (12f)$$

$$S_{L_1}(k) = f_6(\gamma_{L_1}(k)), \quad (12g)$$

$$q_{G_1}(k+1) = g_{G_1}(q_{G_1}(k), u_{G_1}(k), \mathbf{\Lambda}_{M_i}), \quad (12h)$$

$$q_{G_2}(k+1) = g_{G_2}(q_{G_2}(k), u_{G_2}(k), \mathbf{\Lambda}_{M_i}), \quad (12i)$$

$$q_{L_1}(k+1) = g_{L_1}(q_{L_1}(k), u_{L_1}(k), \mathbf{\Lambda}_{M_i}), \quad (12j)$$

$$u_{G_1}(k) \in \{0, 1\}, \quad (12k)$$

$$u_{G_2}(k) \in \mathbb{V}_2, \quad (12l)$$

$$u_{L_1}(k) \in \{0, 1\}, \quad (12m)$$

$$v_1(k) \in \{0, 100\}, \quad (12n)$$

$$v_3(k) \in \{0, 100\}, \quad (12o)$$

$$q_{G_1}(k) \in \left[\bar{q}_{G_1}, \underline{q}_{G_1} \right], \quad (12p)$$

$$q_{G_2}(k) \in \left[\bar{q}_{G_2}, \underline{q}_{G_2} \right], \quad (12q)$$

$$q_{L_1}(k) \in \left[\bar{q}_{L_1}, \underline{q}_{L_1} \right], \quad (12r)$$

and the following logical constraints to avoid the high switching frequency of system actuators:

$$\Delta u_j(k) \neq 0 \iff u_j(k : k+4) = u_j(k), \quad (12s)$$

for $i \in \{0, 1, 2, \dots, H_p - 1\}$, and being γ_{G_1} , γ_{G_2} and γ_{L_1} the states of energy consumption models for P_{G_1} , P_{G_2} and P_{L_1} , respectively, q_{G_1} , q_{G_2} and q_{L_1} the model dynamics of peripheral devices, and $\Delta u_j(k) = |u_j(k) - u_j(k-1)|$ the activation/deactivation indicator of the j -th peripheral device. The q_j -dynamics in (12) correspond to the process dynamics for the compressed air supply system and the coolant supply system previously explained in Section 2 for the peripheral devices in the process line, i.e., P_{G_1} , P_{L_1} and P_{G_2} . It should be noted that when the first production program is running, the device P_{L_1} is deactivated, and therefore, its activation sequence is restricted to be null along the time.

If it is assumed that the problem (12) is feasible, i.e., $\mathbf{\Gamma}(k) \neq \emptyset$, $\mathbf{\Pi}(k) \neq \emptyset$, there will be an optimal solution for the activation sequence of peripheral devices defined by

$$\mathbf{\Gamma}^*(k) \triangleq \{\mathbf{\Lambda}_{\mathbf{P}}^*(k|k), \dots, \mathbf{\Lambda}_{\mathbf{P}}^*(k+H_p-1|k)\},$$

$$\mathbf{\Pi}^*(k) \triangleq \{\mathbf{\Lambda}_{\mathbf{V}}^*(k|k), \dots, \mathbf{\Lambda}_{\mathbf{V}}^*(k+H_p-1|k)\},$$

and then, according to the receding horizon philosophy [9, 13], $\mathbf{\Lambda}_{\mathbf{P}}^*(k|k)$ and $\mathbf{\Lambda}_{\mathbf{V}}^*(k|k)$ are sent to the process line discarding the rest of the optimal sequences from $(k+1)|k$ to $(k+H_p-1)|k$, while the whole process is repeated for the next instant $k \in \mathbb{Z}_{\geq 0}$ after measuring/estimating the proper information from the plant to update the current state of both the energy consumption models and process dynamics considered in (12). According

to Section 3.3, data-driven models have been selected to represent the energy consumption models of peripheral devices since the physical-based models require the full knowledge of several physical dynamics and parameters, which are often hard to represent, compute or estimate. Thus, linear state-space representations based on the real input-output data sets were obtained by using SI algorithms.

On the other hand, the second control mode or the autonomous mode will be executed when a periodic behaviour in the optimal activation/deactivation signal of each peripheral device is identified. Thus, the periodicity condition is checked for each peripheral device according to the dynamics of their associated processes. Next, once the periodicity of one peripheral device is detected, such device will be removed of the optimization problem (12) to reduce both the number of decision variables and the computational burden. Besides, the periodic sequence previously detected is sent to the plant at each time instant k , while the optimization for the other peripheral devices keeps taking also into account the energy consumption resulting from the devices that now have periodic behaviour. Finally, if the periodicity is detected for all peripheral devices in the process line, the control commutes to an autonomous mode in which there is no optimization in real time, and the optimal and periodic sequences for the activation/deactivation of peripheral devices are fixed and then sent to the plant.

When the system is on autonomous mode, the computational burden is reduced since no more online optimization is required. However, in this mode it is not possible to manage any disturbance or change that might affect the operation of the peripheral devices and the machines in the process line. Therefore, a protocol for commuting from the autonomous mode to the predictive/optimization mode is required. Since in the autonomous mode per se is not able to predict and find the activation/deactivation sequence of peripheral devices, a switching protocol is implemented while the autonomous mode is running, in which a prediction of the process is performed considering both the current measurements of the plant and the optimal sequences. Thus, this protocol aims to verify that the system constraints will be satisfied in the future according to the current state of the system. In this regard, any change or disturbance appreciated in the measurements from the plant could produce an abnormal behaviour in the future if the same activation sequence is kept and sent to the plant. If it happens, the commutation protocol should detect these abnormalities and should indicate that, at the current system conditions, the system state will be out of its feasible domain and, therefore the optimal sequence should be recomputed. Next, when abnormalities are detected the controller should be commuted to the predictive (or first control) mode with the aim to determine the new optimal activation/deactivation signals of peripheral devices at the current state of the process line.

To clarify the proposed dual control strategy, the control scheme proposed for the implementation of the control strategy in real time is shown in Figure 3. Besides, in the next sections, both the strategy for the detection of the periodicity of peripheral devices and the commutation protocol will be explained in detail.

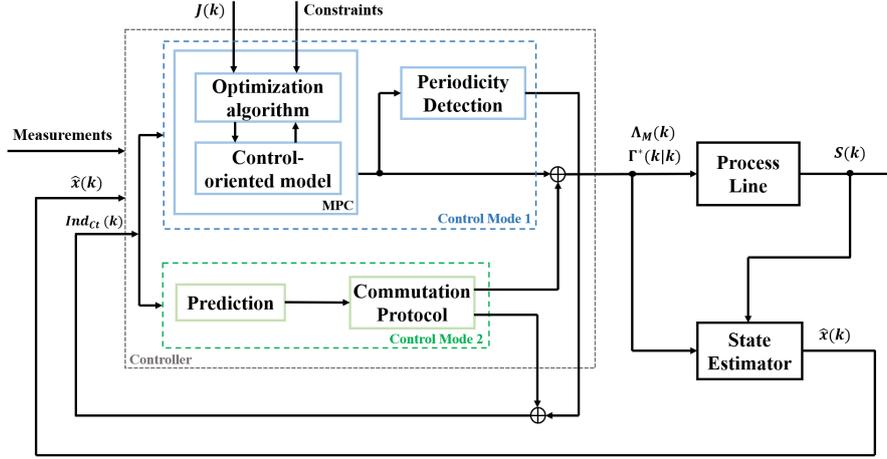


Figure 3: Real-time implementation scheme for the dual control strategy.

4.1. Periodicity Detection

To determine the periodicity for the operation of peripheral devices and to commute to the autonomous mode, Algorithm 1 is proposed based on signal processing tools such as autocorrelation. Thus, after a period time N_u of being running the first control mode, the optimal activation/deactivation sequence u_P of each peripheral device is used to determine its periodicity. At time instant $k \geq N_u$, a pre-processing of the activation/deactivation signal u_j is performed to remove its mean value and capture the more relevant changes of the signal. It should be noted that this procedure is more important for those peripheral devices in which the activation load could be modulated since their periodicity should be detected taking into account both the activation instant and the level of activation. Thus, removing the mean value, the small changes associated to load modulation gain relevance and could be easier to capture when the autocorrelation is computed. Autocorrelation is a mathematical tool that allows identifying repetitive patterns in a signal, such as its periodicity. Thus, autocorrelation is defined as the correlation between a signal and with a delayed version of the same signal to measure the similarity between them as a function of the lag. Therefore, correlation coefficients are calculated considering different values of signal delays with respect to itself. In this regard, high values of correlation coefficients correspond to lag values in which the signal is more similar.

Afterwards, using the `xcorr` routine of Matlab, the autocorrelation \mathbf{ux}_j of the pre-processed signal of u_j is computed and the vectors of both correlation coefficients and lags are determined. Since the nature of the activation/deactivation signal, in which shorter periods could be contained into the real and longer period of the signal, the periodicity condition should be verified for the different lags obtained from autocorrelation. In this regard, the maximum value of $\overline{ux}_j = \mathbf{ux}_j$ is determined, and then, only the peaks \mathbf{pk} in \mathbf{ux}_j with a height higher than μ percentage of \overline{ux}_j are considered to check the periodicity constraint, i.e.,

Algorithm 1 Periodicity detection of system actuator dynamics

```

1: procedure PERIODICITY DETECTION( $\hat{\mathbf{u}}_j$ )
2:   Define  $N_u$ 
3:   while  $T_{u_j} = 0$  do
4:     Define  $\hat{\mathbf{u}}_j(\cdot) = \mathbf{u}_j(k - N_u : k)$ 
5:     Remove mean value of  $\hat{\mathbf{u}}_j(\cdot)$ 
6:     Compute  $\mathbf{ux}_j = \text{xcorr}(\hat{\mathbf{u}}_j, \hat{\mathbf{u}}_j)$ 
7:     Compute  $\overline{ux}_j = \max(\mathbf{ux}_j)$ 
8:     Fix  $\mu$ 
9:     Define  $\xi = \mu \overline{ux}_j$ 
10:    [ $\mathbf{pk}, \mathbf{lc}$ ] = findpeaks( $\mathbf{ux}_j$ , 'MinPeakheight',  $\xi$ )
11:     $\mathbf{D}_{\mathbf{pk}} = |\mathbf{lc}(1) - \mathbf{lc}(2:\text{end})|$   $\triangleright$  distance among peaks
12:    Set  $h = 1$ 
13:    while  $h \leq \text{length}(\mathbf{D}_{\mathbf{pk}})$  do
14:       $T_h = \mathbf{D}_{\mathbf{pk}}(h)$ 
15:      if  $\mathbf{q}_j(k - T_{u_j}) = \mathbf{q}_j(k)$  then
16:         $T_{u_j} = T_h$   $\triangleright$  periodicity device  $j$ 
17:        Display  $T_{u_j}$ 
18:      else
19:         $h = h + 1$ 
20:         $k = k + 1$ 
21:      end
22:    end
23:  end
24: return  $T_{u_j}$ 

```

$$x(k) = x(k + pT_x),$$

$\forall p \in \mathbb{Z}$, and being T_x the period of the signal.

According to peaks \mathbf{pk} and the corresponding values of lags \mathbf{lc} , the distance between the first lag and the rest of the lags in \mathbf{lc} is calculated. Then, the periodicity condition is verified for all distance previously computed, which represent the different alternatives to be chosen as the period of the signal. To this end, one of the signals for the dynamics of the processes associated

to the operation of the peripheral device is considered. Thus, the period of the peripheral device T_{u_j} will be defined equal to the distance in \mathbf{D}_{pk} for which the periodicity condition is satisfied. Afterwards, this device is removed from the optimisation problem considered in the first control mode. Finally, if the periodicity is found for all devices in the process line, then, the control system can commute to the autonomous control mode. It should be noted that if more than one value in \mathbf{D}_{pk} satisfies the periodicity condition, T_{u_j} will be defined equal to the longer distance.

4.2. Commutation Protocol

Once the period for all devices is detected, a commutation protocol should start to run with the aim to anticipate when the control should come back to the first control mode. During the autonomous control mode the optimal sequences previously determined are sent to the process and, the operational constraints are verified for the current instants to guarantee that the system keeps in its feasible region. However, if there is some change in the system or any disturbance takes place, then the system could reach a state of higher energy consumption or even an infeasible state. In the worse case, if there is some abnormal behaviour of the system and the activation/deactivation sequence of peripheral devices is not updated at the suitable time instant, the system state might getaway of its feasible region. If this fact occurs, it will not possible to come back to the first control mode, such as the optimization problem behind the controller design will be infeasible for the current state of the process line. Therefore, even in the autonomous mode, a prediction of the system behaviour should be performed in order to anticipate these undesirable behaviours based on the current state of the process line and the optimal sequences found in the first control mode.

In this regard, always that the autonomous mode is running, a prediction of the behaviour of the process line is performed taking into account the models for both machines and peripheral devices and the current measurements from the available sensors. In this case, the prediction horizon has the same length as for the predictive control mode, i.e., $H_{p,c} = 28s$. Based on the system prediction, it is verified that the process variables q_j remain inside its boundaries \bar{q}_j and \underline{q}_j , and that the the energy consumption for the current prediction does not exceed the optimal energy consumption found in the first control mode. Then, if for some time instants along the prediction horizon the variables q_j are out of their boundaries or the energy consumption along the prediction horizon surpasses a percentage η of the optimal energy consumption, the commutation indicators will be activated at the current instant k for switching to the first control mode at the instant $k + 1$. Thus, the commutation protocol from the autonomous mode to the predictive control mode is based on a prediction of the behaviour of the process plant to guarantee that the dynamics of peripheral devices remain inside their feasible region and the energy consumption is not increasing. It should be noted that the commutation indicators are flag variables designed based on the results obtained from the first control mode, which correspond to the optimal values used for

the comparison in the autonomous mode. These indicators are defined as

$$\text{If } q_j \notin [\bar{q}_j, \underline{q}_j] \text{ then } \gamma_{q_j} = 1, \quad (13)$$

$$\text{If } \tilde{S} \geq \eta S^* \text{ then } \gamma_S = 1, \quad (14)$$

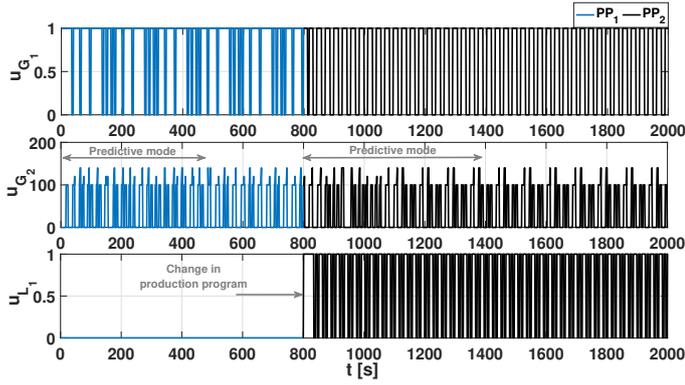
with \tilde{S} the energy consumption along the prediction horizon, S^* the optimal energy consumption, and γ_{q_j} and γ_S the commutation indicators.

5. Simulation results

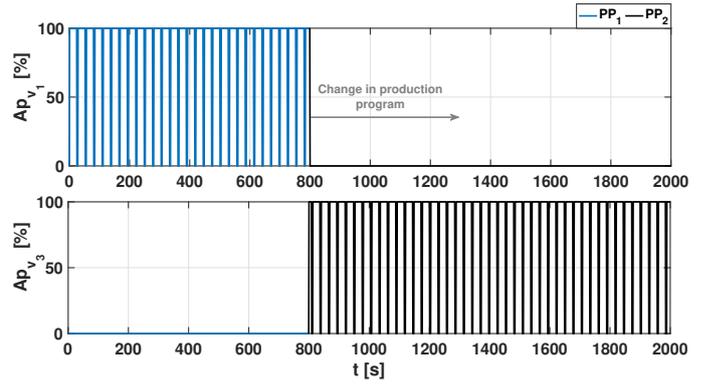
In order to test the performance of the proposed control strategy to improve the energy efficiency of manufacturing systems in flexible scenarios, the following production programs are considered:

- *Production program 1 (PP₁)*: In this program only the two global peripheral devices are required since the installed capacity is enough to supply the resources consumption of machines in the process line. It means that during the execution of *PP₁*, the sequences $u_{L_1}\{1 : H_p\}$ and $A_{p_1}\{1 : H_p\}$ should be null, and added to the optimization problem in (12) into the set of constraints. Besides, the energy consumption model and the process dynamics related to the device L_1 will not be considered into the set of constraints since this device remains inactive during the execution of *PP₁*. This production program will be executed during 800 s, and then, it is assumed that a change in the production program occurs since a new piece will be processed. The resources consumption of both compressed air and coolant of machines along Λ_{M_i} during this program is shown in Figure 2.
- *Production program 2 (PP₂)*: During this program, the consumption of compressed air from M_1 is increased from $0.0015 \frac{m^3}{s}$ to $0.003 \frac{m^3}{s}$ while keeping the same for the other two machines in the process line. Since the maximum capacity of the global peripheral device G_1 when is turned on is $0.006 \frac{m^3}{s}$, it is not able to provided the air stream required by all the machines in the process line, and therefore the local device L_1 should be activated to help supplying the air stream required by the first machine. The pipe system that connects L_1 to M_1 to allow a maximum flow of $0.003 \frac{m^3}{s}$, while the maximum flow thorough the connection between G_1 and M_1 remains equal to $0.0015 \frac{m^3}{s}$ as for the first program. In addition, when *PP₂* is running, the dynamics for the device L_1 and its energy consumption model should be considered into the set of constraints of the optimization problem in (12). It should be noted that the resource consumption for the rest of machines in the process line keep the same as for *PP₁* as shown in Figure 2.

Based on the previous description of production programs, *PP₁* was executed during the first 800 s of simulation, and then,



(a) Optimal activation sequences of peripheral devices in the process line.



(b) Optimal sequences of valve aperture for v_1 and v_3 .

Figure 4: Optimal activation sequences of peripheral devices by using the proposed control strategy.

the production program was commuted to PP_2 . In this case, simulations along 2000 s were performed using a execution time of the controller equals 1 s. This latter fact means that the controller makes decision every second along the prediction horizon, and the required information for the controller is also updated every second before to run the controller again. All simulations were performed using an Intel Core i7-5500U 2.4 GHz processor with 8G RAM and considering a sampling time $\tau_s = 0.1$ s. The simulation results were obtained in Matlab by using the software IBM ILOG CPLEX Optimization Studio [6] integrated to YALMIP toolbox [7].

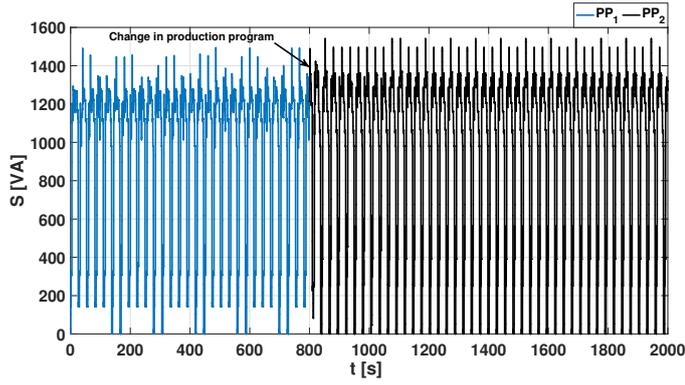
The obtained optimal activation sequences for both peripheral devices and the percentage of aperture valve for v_1 and v_3 are shown in Figures 4a and 4b, respectively. According to these results, the device L_1 is activated only when PP_2 is executed, and the periodic behaviour of all devices in the process line is appreciated. In Figure 4a, the time slots in which the predictive control mode is running are marked, while for the rest of the time the controller is on the autonomous mode. When the controller is in the autonomous mode, the periodicity of each device has been already determined during the predictive mode, and therefore, the periodic behaviour in the activation sequence is also appreciated in the final part of the predictive control mode. It should be noted that, only during the predictive control mode the controller solves the optimization problem in (12), and in the autonomous mode, the periodic sequences are sent to the plant and only it is verified that the system remains inside the feasible domain found in the optimization-based mode. The latter procedure corresponds to the communication protocol.

Besides, concerning the change in the production program, from Figure 4b, it can observe that since the energy consumption of G_1 is higher than the energy consumption of L_1 , the controller decides supplying all the compressed air required by M_1 from L_1 reducing the demand for G_1 , and allowing this latter device remains turned on for less time to minimize the global energy consumption. In this regard, L_1 is responsible for providing all the demand of M_1 , while v_1 is totally closed and G_1 supplies only to machines M_2 and M_3 . Next, according to the obtained activation sequences, in Figures 5a and 5b, the resulting energy consumption of the process line and the particular

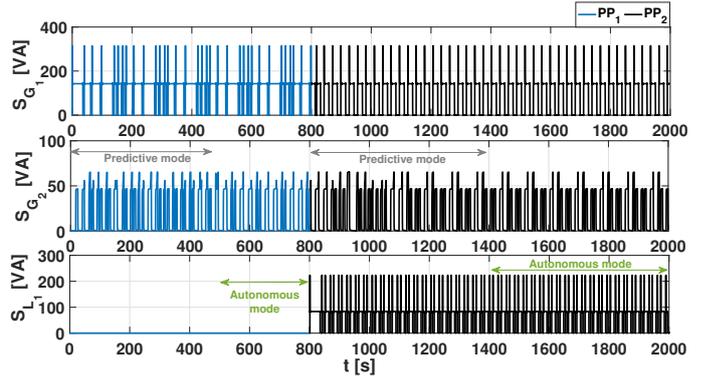
energy consumption of each device obtained when the proposed control strategy is implement are presented, respectively. From these results, it is also possible to see that the peripheral device L_1 starts to consume energy only when the second production program is activated, and therefore, the global energy consumption of the process line increases after this moment.

In the same way, in Figures 6a and 6b, the dynamics for the supply systems of compressed air and coolant associated to peripheral devices in the process line are presented. Based on these results, it can be seen that both the pressure and level dynamics remain inside their upper and lower bounds while either of the production programs is executed. Besides, the periodic behaviour can also be detected from these dynamics (for each production program) after the predictive control mode is run. Thus, due to the nature of these dynamics, both pressure and level dynamics were employed to check the periodicity condition as shown in Algorithm 1. The last fact is because when using the activation sequences of peripheral devices, which are usually constrained to $\{0, 1\}$, the periodicity condition could be verified for values of T_{u_j} that are not the real period for the devices. Then, based on the obtained results for the optimal sequences of u_j and process dynamics q_j , the values of $T_{u_{G_1}}$ and $T_{u_{G_2}}$ detected while PP_1 was ran were equal to 140 and 84 s, respectively. For the case in which PP_2 was executed, the periods identified for G_1 , G_2 and L_1 were 28, 84 and 28 s, respectively.

Next, to verify the computational burden and the suitability to implement the proposed control strategy in real time, the computational time spent by iteration is presented in Figure 7. Based on these results, it can be seen that even when the predictive control mode is on, the maximum time spent is lower than one second. Besides, it should be noted that when the autonomous mode is on, the computational time significantly decreases since, in this mode, it should not solve an optimisation problem. Thus, the time spent in the autonomous mode refers to the time required for the commutation protocol to predict the system behaviour and to verify that the system remains into its feasible domain for the whole prediction. Then, according to these results, it is possible to conclude that the proposed control strategy is suitable to be implemented in real time.

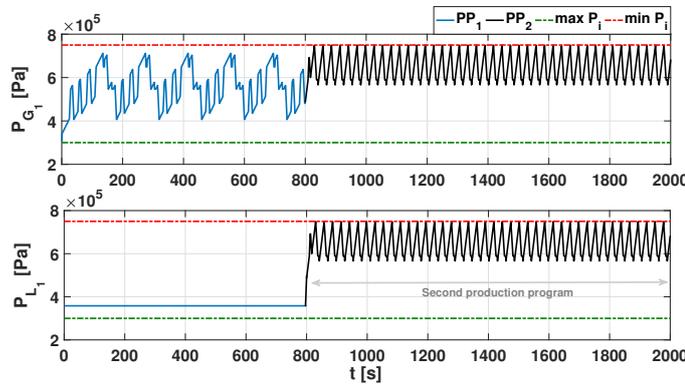


(a) Profile of the total energy consumption of the process line.

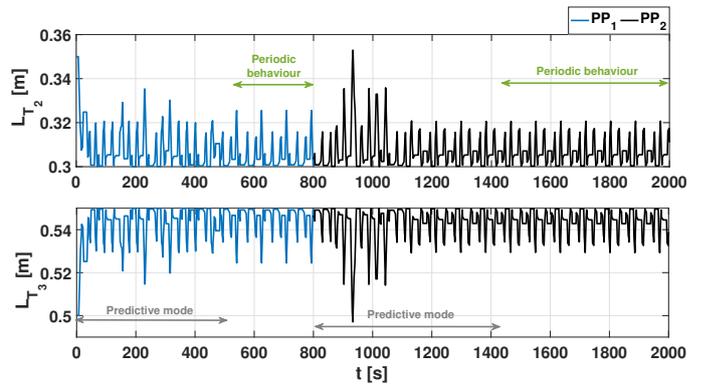


(b) Energy consumption profile of devices G_1 , G_2 and L_1 , respectively.

Figure 5: Energy consumption profiles by using the proposed control strategy.



(a) Pressure dynamics for both L_1 and G_1 .



(b) Level dynamics for both clean and dirty coolant tanks.

Figure 6: Process dynamics related to the operation of peripheral devices.

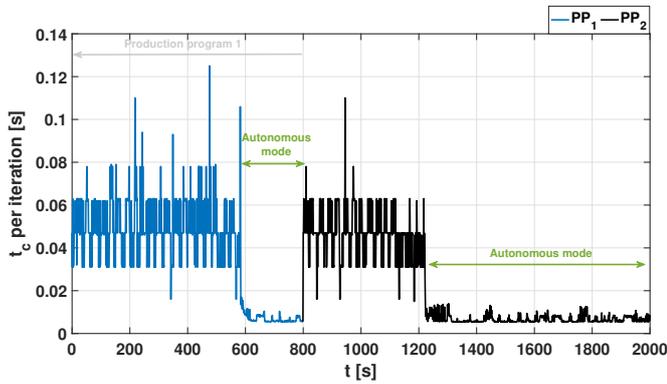


Figure 7: Real-time implementation scheme for the dual control strategy.

Table 3: Performance degradation with respect to a conventional MPC.

Controller	Energy consumption	Simulation time
MPC	3299596.872 VA	169.470 s
Dual control	3299578.348 VA	60.681 s

tivation sequences of peripheral devices when the optimization problem is solved during the whole simulation. The MPC controller was tested at the same operational conditions as for the dual control mode strategy and considering the same flexibility scenario presented in the previous section.

The obtained results for energy consumption profile are presented in Figure 8a and summarized in Table 3. From these results, it is possible to observe that the main differences in the activation sequences of peripheral devices are related to the device G_2 , for which the activation load can be modulated. These small variations in the modulation of u_{G_2} could be a consequence of the termination criteria defined by default for the solver `cplex` and the current state of the system. That means, depending on the current state of the system, i.e., the current state of energy consumption models and process dynamics of peripheral devices, the termination criteria might be achieved at different values of the feasible domain for the decision vari-

5.1. Performance degradation

In this section, the proposed control strategy based on two different control modes is compared with a conventional MPC controller with the aim to evaluate the performance degradation when a periodic behaviour is detected and the autonomous mode is switched on. In this regard, a predictive-like controller based on the MPC approach and the same optimization problem in (12) was designed and used to determine the optimal ac-

ables. Thus, regarding the performance of control strategies in closed-loop, the degradation of the performance when the proposed dual control strategy is implemented with respect to a control strategy that is constantly optimizing online is almost none, with differences near 8.7×10^{-4} . However, regarding the computational burden, when the system exhibits a periodic behaviour and it is used to commute to autonomous mode, the time spent is significantly lower and the possibilities to implement the strategy in real time increases. Besides, by implementing the commutation protocol during the autonomous mode to check that the system remains inside its feasible domain, the computational burden is reduced without affecting significantly the effectiveness of the control strategy.

5.2. Comparative assessment and disturbances management

In this section, the performance of the proposed dual control mode strategy is compared with an MPC controller that is constantly optimizing for the whole simulation when disturbances take place and affect the operation of the process line. The underlying idea of this comparative study is to understand how conservative the dual control strategy should be before to commute to the predictive control mode when some disturbance happens. As explained in Section 4.2, a prediction of $H_{p,c} = 28$ s is made at each iteration while the autonomous control mode is running, and, if it detects that the system reaches out of its feasible domain (determined from the predictive control mode) in any moment along the prediction horizon, the system should commute to the predictive control mode. That means if, at the current instant, the prediction shows that at the instant $t = 28$ s, the systems surpasses some of its boundaries, the control commutes. However, this is the most conservative possible scenario, since for the case in which the disturbance remains, for instance along 3 seconds from the current instant and then disappears, the control mode switching would be unnecessary, and the computational burden increases. In this regard, the proposed control strategy is tested considering scenarios with disturbances and different values of $H_{p,c}$ to evaluate its effectiveness regarding the conventional MPC. Then, based on the obtained results, the suitable length of $H_{p,c}$ can be determined, from which a proper performance can be achieved without increasing the computational burden.

Two different disturbances were considered and three different lengths of $H_{p,c}$ were tested in order to compare the performance and computational burden of the proposed control strategy with respect to the conventional MPC. For the former, a fault in the device G_2 is assumed, considering a reduction of its efficiency from 95% to 75% along 25 s. Thus, the real flow of coolant pumps from T_3 to T_2 will be lower than the flow considered into the control-oriented model (in the controller design). The second disturbance is applied to modify the operation of G_1 and emulates a fault of its operation. Thus, an air leak equal $0.0023 \frac{\text{m}^3}{\text{s}}$ was added during 25s. Based on the previous description of the considered disturbances, different simulations using the proposed dual control mode switching strategy were performed modifying the value of $H_{p,c}$ to compare both the resulting energy consumption and the time spent in the simula-

Table 4: Comparative assessment for different values of $H_{p,c}$.

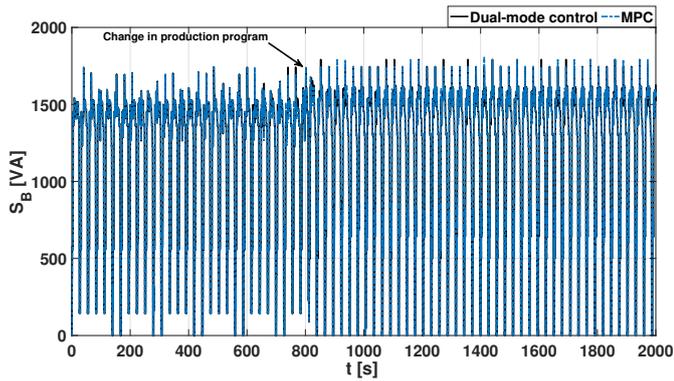
$H_{p,c}$	Controller	Energy consumption	Simulation time
Disturbance 1			
-	MPC	1363532.825 VA	77.139 s
28s	Dual control	1363447.325 VA	84.265 s
14s	Dual control	1363447.325 VA	74.062 s
7s	Dual control	Infeasible	-
Disturbance 2			
-	MPC	1364306.771 VA	83.680 s
28s	Dual control	1363872.542 VA	50.975 s
14s	Dual control	1364225.510 VA	50.530 s
7s	Dual control	1364325.510 VA	51.643 s

tions with respect to the control strategy that is constantly optimizing. The obtained results for the total energy consumption along 1400 s and the total simulation time are presented in Table 4.

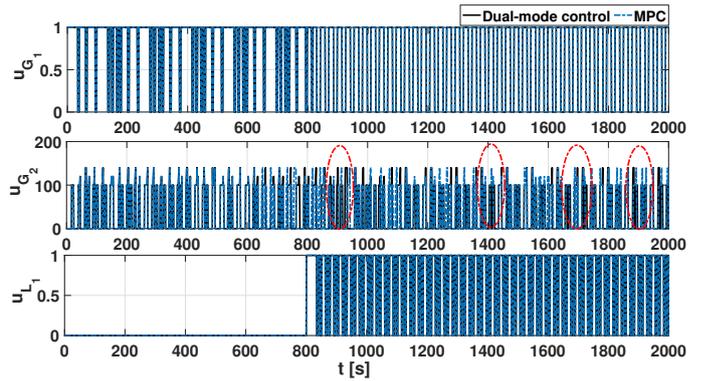
Based on the obtained results, it is possible to conclude that for choosing the length of $H_{p,c}$ both the nature of the disturbances applied as well as its duration should be considered. However, to analyse most of the possible situations, in magnitude and duration, is a hard and exhausting task. For the case of disturbance 1, the first time that the commutation protocol detects that the system will be outside of its feasible domain corresponds to the instant 13 s in the prediction horizon. Thus, for lengths of $H_{p,c}$ shorter than nine seconds the commutation protocol was not able to detect that the system will get out its feasible domain well in advance. Therefore, the optimisation problem in the second mode was infeasible at the time in which the commutation protocol decided to switch to the first control mode. Regarding the second disturbance, its effects on the operation of peripheral devices were only observed after the disturbance disappears. Thus, when the controller switched to the predictive control mode, the system is at the normal operational conditions again, and the MPC can reach faster the periodic behaviour. Therefore, in contrast to the scenario of the first disturbance, in this case, the length of $H_{p,c}$ was not critic since when the disturbance was detected, there were not unexpected behaviours that try to move the system outside of its feasible domain. In this regard, when selecting $H_{p,c}$ in the commutation protocol equals to H_p for the first control mode, it is possible to avoid the system to reach infeasible domains while the autonomous mode is running even when disturbances take place. Besides, according to the results in Table 4, the performance of the proposed control strategy is not significantly improved if the length of $H_{p,c}$ is shorter.

6. Conclusion

In this paper, a dual control mode switching strategy is proposed to improve the energy efficiency of complex manufacturing systems without affecting their productivity. In this regard, machines in the process line and their corresponding energy consumption were assumed constant over the time to process the same number of pieces as when the control strategy is not



(a) Profile of the total energy consumption.



(b) Optimal activation sequences of devices G_1 , G_2 and L_1 .

Figure 8: Simulation results of the comparison between the dual control mode strategy and the conventional MPC.

implemented. Thus, the strategy was designed based on two control modes. In the former, a predictive-like controller is executed up to a periodic behaviour of the optimized system is detected (if it occurs). Then, once the periodicity is detected, the system commutes to an autonomous control mode to reduce the computational burden. Due to the nature of system actuators, the predictive-like controller is designed based on a mixed-integer linear programming problem, in which both energy consumption models and the process dynamics performed by peripheral devices are included in the constraints set.

According to the obtained results, the proposed control strategy allows managing the peripheral devices to reduce the global energy consumption and reducing the computational burden without decreasing the productivity of the process line, even when flexible-manufacturing scenarios are considered. Thus, given the reduction in computational load, the proposed control strategy is suitable to be implemented in real time even when the number of decision variables increases, such as in the case of complex, large-scale, and flexible manufacturing systems. Besides, the proposed strategy is able to manage disturbances in the operation of peripheral devices, even when the autonomous mode is running, if the commutation protocol is suitably designed to switch fast enough to the predictive control mode and to avoid that the system reaches infeasible states.

Acknowledgments

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