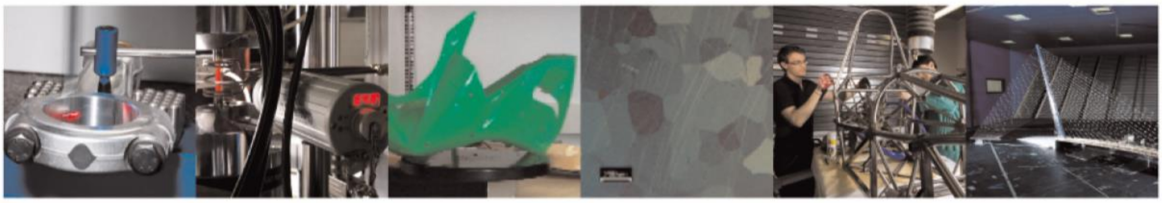


Simultaneous control of multiple machines for energy efficiency: a simulation-based approach

Nicla Frigerio, Barış Tan and Andrea Matta

This is an Accepted Manuscript of an article published by Taylor & Francis in International Journal of Production Research on 15 Feb 2023, available online:
https://doi.org/10.1080/00207543.2023.2175175

DIPARTIMENTO DI MECCANICA ■ POLITECNICO DI MILANO
via G. La Masa, 1 ■ 20156 Milano ■ EMAIL (PEC): pecmecc@cert.polimi.it
http://www.mecc.polimi.it
Rev. 0

Simultaneous control of multiple machines for energy efficiency: a simulation-based approach

N. Frigerio[a] and Barış Tan[b] and Andrea Matta[a]

[a]Department of Mechanical Engineering, Politecnico di Milano, Milano, Italy;
[b]College of Administrative Sciences and Economics, College of Engineering, Koç University, Istanbul, Turkey

ARTICLE HISTORY
Compiled February 16, 2023

ABSTRACT
Energy efficiency is crucial in contemporary industry and controlling the resource power state by switching off/on commands is a promising measure. The control problem of deciding when to switch off/on the machines depending on the state of the system at a given time is not trivial due to the effect the control might have on system production rate. Threshold-based policies using buffer occupancy information to control the machines can be effectively used to reduce energy consumption. Nevertheless, highly complex control policies are difficult to be applied and costly to be managed in the practice. Buffer-based threshold policies to control multiple machines simultaneously in a serial production line for energy efficiency purposes are analyzed in this work. The optimal control minimizes the energy consumption while assuring a certain target production rate for the system. The effects of controlling different combination of machines simultaneously with different number of thresholds have been investigated through numerical experiments with discrete event simulation. Insights regarding the trade-off between complexity of the control and the performance gains are provided. The proposed policy works effectively and the effect of a proper selection of the controlled machines or thresholds is significant.

KEYWORDS
Sustainable manufacturing; Energy efficient control; threshold-based control; Discrete event simulation.

CONTACT Nicla Frigerio. Email: nicla.frigerio@polimi.it

Abbreviation	Description
AO	Always On (policy)
DS	Downstream (policy)
EEC	Energy Efficient Control
EXH	Exhaustive (policy)
UD	Upstream-DownStream (policy)
US	Upstream (policy)
M_i	i-th machine in a serial line
B_i	i-th buffer in a serial line
H_i	capacity of buffer B_i
h_i	buffer occupancy (number of parts) in buffer B_i
$t_{\text{su},i}$	duration of the startup procedure of machine M_i
$s \in \mathbb{S}$	machine state s according to set $\mathbb{S}$ of machine states
$w_{s,i}$	power request of machine M_i in state s
$w_{h,i}$	holding power to keep a part in buffer B_i
P	production rate
E	energy per part produced
T	makespan
$\mathbf{x}$	vector of control parameters
$N^i_{\text{off},i}, N^i_{\text{on},i}$	off/on thresholds for machine M_i control based on buffer B_i
$N^i_{\text{off},i-1}, N^i_{\text{on},i-1}$	off/on thresholds for machine M_i control based on buffer B_{i-1}
n_m	number of controlled machines in the system
n_t	number of thresholds used in the control

Table 1. Notation table

1. Introduction

Green transition is crucial for contemporary manufacturing systems and increasing attention is devoted to operational measures that can improve sustainability of production systems. The topic of energy efficiency in manufacturing has gained an increasing prominence within the scientific community. As one of the most promising measure for machine tools, a proper control of machines standby can be applied to improve energy efficiency as highlighted by recent surveys, (Zhou et al. 2016; Yoon et al. 2015; Renna and Materi 2021; Sihag and Sangwan 2020). An energy efficient control policy determines when to switch off and on a resource depending on the state of the system at a given time. The energy efficient control (EEC) of resource state exploits start/stop features of manufacturing resources to reduce resource energy consumption. The EEC of machine state aims at reducing the non-processing energy consumed when the part flow is interrupted toward a better use of machine auxiliary equipment. The problem is not trivial since a startup procedure is commonly required to resume the operational readiness of a machine tool. Therefore, several EEC strategies have been defined and studied.

Indeed, nowadays machine tools have power saving (standby) modes to be used when the part flow is interrupted; nevertheless, very frequently, the standby mode is not exploited and machine tool users do not exploit the available standby modes. When machine standby is used, the control parameters are selected manually according to simple experience-based analyses. In practice, parameters are equal on all machines (even if machines have different loads) and are not updated when production changes resulting in a lack of effectiveness or efficiency.

Analyzing the performance of production systems controlled with EEC policies at machines is challenging and the control problem of deciding when to switch off/on machines is not trivial due to the high number of control parameters and the effect they might have on system production rate. Threshold-based policies using buffer occupancy information to control the machines can be effectively used to reduce energy consumption as discussed in Section 1.1. Nevertheless, these control rules do not consider the whole system state and can be far from the real optimum. On the other hand, a critical barrier for a practical implementation of EEC is related to the real-time observation of system state, which might be costly to be achieved and managed. The resulting control policy might also be very complex as for the optimization problem itself.

In this work, buffer-based threshold policies that are used to control multiple machines simultaneously in a serial production line for energy saving purposes are analyzed. We consider serial production lines where a subset of machines can be controlled with an energy efficient control policy that switches off/on each machine depending on the state of the system at a given time and we investigate the effect of selecting the subset of controlled machines and the number of thresholds used on the system performance.

The remaining of the paper is as follows. Section 1.1 discusses related literature and Section 1.2 states the contribution of the paper. The addressed system is described in Section 2 and Section 3 focuses on the control problem. Section 4 describes experiments and Section 5 discusses numerical results. Section 6 gives the conclusions.

1.1. *Review on Energy Efficient Control of Machine State*

A key towards cleaner manufacturing is improving production energy efficiency by applying effective measures. Due to the wide range of manufacturing activities, technologies and industries, strategic measures may be applied at different levels and may affect different manufacturing layers. Systematic overviews have been proposed by Zhou et al. (2016); Yoon et al. (2015); Renna and Materi (2021). Production planning and control can be enhanced with energy management so that improvements can be achieved in terms of energy efficiency of both brownfield and greenfield applications. Indeed, production equipment consumes energy both executing the manufacturing process and working and keeping the resource idle (Dahmus and Gutowski 2004). Process re-design and optimization aims at reduce the energy required to work on parts, whilst the control of machine state (EEC) aims at a better use of machine auxiliary equipment while the machine is idle. In addition, EEC differs from Energy Efficient Scheduling (EES) because it refers to a different level in the production planning and control hierarchy. EES plans jobs schedule and off/on modes to machines over a specific period of time before production starts.

The EEC of machine states provides policies to switch off/on machines depending on the state of the system at a given time. According to certain rules, the EEC aims at reducing the energy consumed by machines while not processing parts. Indeed, machine auxiliary equipment can easily require more energy than necessary because they keep requiring power during non-productive machine states (Dahmus and Gutowski 2004; Gutowski et al. 2009). The EEC of machine state assumes there exists a low-power request state, i.e., a *standby* state, where the machine is partially deactivated while the machine is starved or blocked. The effect of such policies is not trivial. Indeed, to restore machine availability after a sojourn in the standby state, the machine requires a compulsory *startup* procedure such that working condition is properly restored (e.g., thermal and pressure levels). Sometimes, another compulsory *closedown* (or shutdown) procedure might be required to enter in standby. These procedures cannot be interrupted nor avoided affecting machine production rate. In addition, according to the control parameters, the effectiveness of the policy in terms of energy saving varies. Nevertheless, the energy consumed in startup/closedown states might be higher than that saved during the standby. Differences in energy consumption in different states yield the trade-off in the decision problem.

Threshold-based EEC policies have been proposed and analyzed in the literature. A first group of works focuses on time thresholds to find a switching policy (Mouzon et al. 2007; Frigerio et al. 2021). Problem formulation has been recently extended to include multiple standby (i.e., sleeping or hybernation) states (Frigerio and Matta 2021), to model time-dependent startup duration (Frigerio and Matta 2021), and to learn from online collection of data (Frigerio et al. 2021). These works focus on station-level control problems and do not consider the state of the buffers and other stations in the system. A second group of works uses thresholds on the buffer levels from the buffers adjacent the controlled machine. Station-level (i.e., single machine with input/output buffers) is addressed in Frigerio and Matta (2016); Zhang et al. (2019); Tan et al. (2022). Systems composed by two or more production stages are considered in Su et al. (2016); Jia et al. (2016); Frigerio and Matta (2019); Wang et al. (2017, 2019); Renna and Materi (2020). This group also includes approximate analytical models to estimate energy opportunity windows (EOW) for controlling machines in serial lines (Sun and Li 2013; Chang et al. 2013; Li et al. 2016; Brundage et al. 2014). EOW are actually estimated assuming to know the system state, including buffer levels (Sun and Li 2013) so that switch off/on actions are applied during the estimated windows. Similarly, Zhang et al. (2019) estimate machine idle time according to the system state using Neural Networks and use machine hibernation states to save energy during such idle periods. An approximate analytical method is proposed by Jia et al. (2016) to evaluate the performance of a serial line with Bernoulli machines where a subset of non-adjacent machines is controlled with an EEC policy that uses buffer levels. Simulation-optimization is used to address the EEC problem for a serial line in Su et al. (2016) and Frigerio and Matta (2019) where energy is minimized under a specific throughput constraint. Su et al. (2016) compared three buffer-based policies controlling all machines composing the line and highlighted which policy is more advantageous. Similarly, Frigerio and Matta (2019) evaluated time and buffer-based policies as applied to all machine composing the line and evaluated how optimizing the control of a single machine locally affects system performance. Wang et al. (2017, 2019) propose a fuzzy controller to switch off/on machines of a serial line using buffer information. Renna and Materi (2020) propose a design model for production lines and, in a second phase, evaluate some buffer-based control policies to reduce system energy consumption.

This paper differs from the studies given in the literature in several ways. As opposed to the studies that consider the control of a single station (Frigerio and Matta 2016; Zhang et al. 2019; Tan et al. 2022), we consider the control of multiple stations. Although there are a limited number of studies that consider the control of multiple stations simultaneously (Su et al. 2016; Jia et al. 2016; Frigerio and Matta 2019; Wang et al. 2017, 2019; Renna and Materi 2020; Sun and Li 2013; Chang et al. 2013; Li et al. 2016; Brundage et al. 2014), this paper does not impose strict assumptions used in EOW-related works (Sun and Li 2013; Chang et al. 2013; Li et al. 2016; Brundage et al. 2014), that do not consider any startup time to resume the service, and the approach used by Jia et al. (2016), that does not deal with the control of adjacent machines. In addition, we present an optimization problem subject to a throughput constraint while the optimization problem is not addressed in Jia et al. (2016), whilst it is addressed without a constraint in Wang et al. (2017, 2019); Zhang et al. (2019). While we consider the control of different subset of machines in a given line, all machines are controlled (Wang et al. 2017, 2019; Zhang et al. 2019; Frigerio and Matta 2019; Renna and Materi 2020; Su et al. 2016). Our model does not impose the complete knowledge of system state as the model of Zhang et al. (2019) that assumes complete knowledge of system state to estimate idle times. We do not impose the restrictions such as controlling the machine only in isolation (Frigerio and Matta 2019) or controlling the machines with equal thresholds (Renna and Materi 2020). Our optimization approach uses exhaustive search so the optimal solutions are determined for each case while Su et al. (2016) use a commercial software to solve the problem in a few selected scenarios.

1.2. *Contribution*

This paper contributes to the literature by addressing the energy-efficient control (EEC) of *multiple machines simultaneously* in serial production lines using various *buffer-based threshold policies* and evaluating the control under multiple *production rate targets*.

The main problem is to find the energy states in which all the machines in the system should operate at a given time. Thus, the resulting control problem aims at minimizing the expected energy consumed per produced part while assuring a certain target production rate by switching off/on the machines depending on the state of the system at a given time. The performance of the optimal control is investigated based on the selection of the subset of machines to be controlled and the subset of control thresholds. Discrete Event Simulation is used to evaluate a set of scenarios and optimal solutions are obtained by exhaustive search.

The focus of this study is presenting an analysis of the effect of controlling different combination of machines simultaneously with different number of thresholds. Despite the presence of seminal works for EEC of serial lines in literature, the problem of selecting the machines to control and determining thresholds that are more significant for serial lines has not been studied in literature and this is the first study that addresses this problem.

2. System description and machine model

The production system under study is a serial flow line of m stages composed by m machines $M_i, i = 1, ...m$ and $m-1$ intermediate buffers $B_i, i = 1, ...m-1$. Machines can be controlled for energy saving purposes using the real-time information about the system state. Details follow.

i) Buffer capacity and power consumption model:
   - Buffers have a finite capacity $H_i, i = 1, \ldots, m-1$. The buffer level at time t is $h_i, 0 \leq h_i \leq H_i$.
   - Holding power $w_{h,i}$ is required to hold each part in buffer B_i. This allows to model a wider variety of systems, for example, the food or chemical industry where work-in-progress parts might need to be maintained at a certain temperature.

ii) Machine reliability model and assumptions:
   - M_1 is never starved of raw parts and M_m is never blocked.
   - Part processing times at machine i are random and follow a Weibull distribution with mean $t_{p,i}$.
   - Machines are perfectly reliable such that failures are modeled as variations onto a nominal value of the cycle time.
   - Blocking After Service (BAS) rule is assumed to control the production, thus machine M_i is blocked when buffer B_i is full and the part loaded on M_i needs to be released.

iii) Machine power consumption model:
   - Machine behavior is represented in Figure 1. The energy state of the machine at time t is $s \in \mathbb{S} = \{busy, id, bl, sb, su\}$. The machine is *Busy* ($s = busy$) while working on parts, *Idle* ($s = id$) while waiting for a new part to be loaded, *Blocked* ($s = bl$) while waiting for a buffer space to release the part. In addition, the machine is controlled with an EEC policy such that switching commands interrupt and resume machine service. When a part is released and before the beginning of a new cycle, a switch-off command might trigger the machine in the *Standby* state ($s = sb$). To resume the service, a switch-on command triggers the machine in the *Startup* state ($s = su$) so that the machine executes a procedure to establish the proper working conditions. Startup procedure cannot be interrupted and a new process begins after the procedure ends. Thus, the startup implies a deterministic delay $t_{su,i}$ in resuming the service. A blocked machine cannot be controlled.

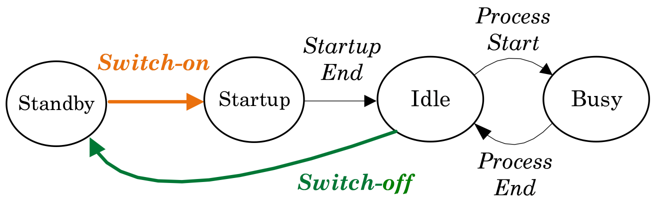


Figure 1. State model of controlled machine M_i.

- Machine M_i requires electrical power $w_{s,i}$ to operate in state s. We assume that power $w_{s,i}$ represents the average power request of machine M_i according to the functioning of machine components in state $s \in \mathbb{S}$.
- We assume the following condition hold: $w_{id,i} > w_{sb,i}$. Auxiliary systems activates whenever the machine condition deviates from the desired ones. Thus, the Idle power w_{id} is assumed to be greater than the Standby power w_{sb} ($w_{id} > w_{sb}$) since machine components are switched off (or partially switched off) in the latter state.
- We assume the following condition hold: $w_{su,i} > w_{id,i}$. During the Startup, machine auxiliary systems are functioning to resume machine conditions to work requiring power w_{su} which is trivially greater than the mean Idle power ($w_{su} > w_{id}$) where auxiliary are active periodically.

Regarding the machine power consumption model, similar assumptions are commonly used in literature as supported by real-case measurements, as examples (Frigerio and Matta 2015; Weinert et al. 2011). Trivially, the higher the power gap $w_{id} - w_{sb}$ and the lower the power gap ($w_{su} - w_{id}$), the higher the EEC potential.

For the sake of simplicity, we consider homogeneous stages in terms of buffer capacity $H_i = H$, machine power request $w_{s,i} = w_s$ and startup time $t_{su,i} = t_{su}$, and holding power $w_{h,i} = w_h$. Nevertheless, the approach proposed is valid also for systems with non-homogeneous stages and an example of application is provided as numerical case (Scenario S7 as in Section 4).

3. The energy-efficient control problem

The general EEC problem aims at increasing system energy efficiency by controlling the energy states of a subset of system resources simultaneously depending on the state of the system at a given time while meeting the production targets.

Problem formulation is provided in Section 3.1. We present in Section 3.2 a general buffer-based threshold policy as an approximate policy for this problem. As a benchmark, we present a policy, referred as the *Always On* policy, that controls the system without any energy-related considerations in Section 3.3.

3.1. *Problem formulation*

The control problem aims at minimizing the average energy consumed per produced part, denoted as E, that includes the energy consumption of machines and the energy eventually required to hold work-in-progress inventories. As a common practice in EEC, the system production rate P should meet a target value P^t so that the control does not jeopardize the production of parts. In addition, the total number of controlled machines n_m is bounded by setting a maximum level $N_{\max} < m$.

The EEC results in switching rules for the energy modes of machines that determine when to switch off/on a machine depending on the system state. A switch off command triggers the machine in the standby state and interrupts the production. Machine power request is reduced while parts might accumulate in buffers until the switch on command triggers the machine in the startup state so that production will be resumed as the startup procedure ends. The startup energy is not negligible in general making the EEC problem not trivial.

Let us assume that a certain control policy π is applied to control a subset $\mathbb{M} \subseteq \{M_i, i = 1, \ldots, m\}$ of machines simultaneously. Also, denote $\mathbf{x}$ the vector of control parameters representing the control policy π. The optimal control policy π^* maps switch off/on commands to system state to obtain the minimal energy per part while addressing the production rate target. The optimal set of control parameters $\mathbf{x}^*$ is found as follows:

$$\mathbf{x}^* = \operatorname{argmin}\{E(\mathbf{x}) \mid P(\mathbf{x}) \geq PR^t; n_m \leq N_{\max}\} \tag{1}$$

where $E(\mathbf{x})$ is the average energy consumed and $P(\mathbf{x})$ is the production rate when the control policy with parameter set $\mathbf{x}$ is used. The EEC control problem is actually two-fold: (i) to select the subset $\mathbb{M}$ of resources to be controlled, and (ii) to select the control parameter values.

Let us consider a benchmark control policy using parameter set $\mathbf{x}$. By definition, the optimal control $\mathbf{x}^*$ obtains $E(\mathbf{x}^*) \leq E(\mathbf{x})$ and $P(\mathbf{x}^*) \geq P^t$. If $P(\mathbf{x}^*) \geq P(\mathbf{x})$, the benchmark policy is dominated; otherwise we face the trade-off among energy and production rate. Nevertheless, the difference in production rate might be compensated by enlarging the production period of the system of a certain overtime. Therefore, the system makespan to produce a certain number of part N_p should be included in the discussion. Given a benchmark makespan $T(\mathbf{x})$ and $P(\mathbf{x}^*) < P(\mathbf{x})$, we obtain $T(\mathbf{x}^*) > T(\mathbf{x})$ at a reduced energy cost so that EEC might be of a high competitive advantage despite the decrease in production rate.

Significant results might be obtained by controlling only a few critical machines whilst, vice versa, the control of many machines might have a small impact on savings. Fixing a limit $N_{\max}$ to the controlled machines is related to the practical implementation of the control. Despite the majority of resources of new generation include green modes to save energy, to implement and to manage the EEC in brownfield systems might be costly. Thus, $N_{\max}$ might be related to the budget allocated for EEC.

The optimal policy for the general problem is not known and it might be very complex to be decoded. The control problem at hand, as in equation (1), gets more complicated as the number of simultaneously controlled machines enlarges and as the set of control parameters enlarges. As a consequence, the cost of implementing the control and of managing the control in the practice might be not advantageous. Approximate control policies are proposed assuming that significant results might be obtained also with few control parameters. In addition, the knowledge of system state might be limited. System state might be only partially observable or the information is costly to be acquired. Further, technological constraints might limit the information available at machine level.

According to observable state variables and to the set of control parameters to be optimized, approximate control policies might be formalized. As examples from the literature, time-based policies use time-based local thresholds to control machine tool

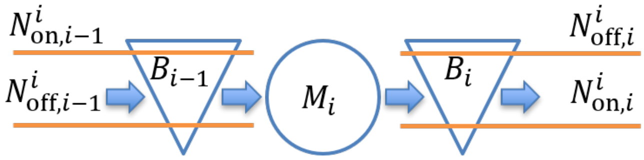


Figure 2. Threshold representation for controlled machine M_i

state in Frigerio et al. (2021), and buffer-based policies use the buffer levels of the two buffers adjacent the controlled machine in Jia et al. (2016).

3.2. *Buffer-based threshold policies for EEC*

Buffer-based threshold policies are considered such that a machine M_i can be controlled according to the occupancy of buffers as partial representation of system state. Buffer-based control rules are suggested from the recent literature and these policies usually use a subset of buffer information to control machine M_i, i.e., its upstream buffer B_{i-1} and its downstream buffer B_i. Specifically, given machine M_i and buffer levels h_i and h_{i-1} of buffers B_i and B_{i-1} respectively, the *Upstream-Downstream (UD) policy* triggers the following commands as given in Su et al. (2016):

- Switch-off: if the machine is in *Idle* state ($s_i = id$) and buffer level h_{i-1} equals threshold $N^i_{\text{off},i-1}$;
- Switch-off: if the machine is in *Idle* state ($s_i = id$) and buffer level h_i equals threshold $N^i_{\text{off},i}$ (with threshold $N^i_{\text{off},i} = H_i$ the machine is switched off instead of being blocked);
- Switch-on: if the machine is in *Standby* state ($s_i = sb$), buffer level h_{i-1} is above threshold $N^i_{\text{on},i-1}$ and buffer level h_i is below threshold $N^i_{\text{on},i}$.

Given a certain machine M_i, control thresholds are represented in Figure 2. Four thresholds are defined for each machine $M_i, i = 2, ..m-1$, and two thresholds are defined for M_1 and M_m; thus the vector $\mathbf{x}$ includes $|\mathbf{x}| = 4 \cdot (m-1)$ control thresholds if all the machines are controlled.

At machine level, the following conditions logically assure that the controlled machine M_i can resume the service after a switch off command:

$$N^i_{\text{off},i} > N^i_{\text{on},i} \quad \text{for } i = 1, \ldots, m-1 \tag{2}$$

$$N^i_{\text{on},i-1} > N^i_{\text{off},i-1} \quad \text{for } i = 2, \ldots, m. \tag{3}$$

Condition (2) assures that the machine can resume the service because the downstream buffer level decreases freeing space for produced parts. Similarly condition (3) assures the switch on when parts accumulates in the upstream buffer.

At system level, the necessary conditions to resume the service must be also feasible considering interactions among adjacent machines. Herewith, we define conditions on the control parameters to avoid deadlocks. Given two adjacent and controlled machines M_i and M_{i+1} with intermediate buffer B_i, the following condition must be satisfied for each buffer $i = 1, \ldots, m-1$:

$$N^i_{\text{off},i} > N^i_{\text{on},i} \geq N^{i+1}_{\text{on},i} > N^{i+1}_{\text{off},i}. \tag{4}$$

Conditions (4) assures that the control on machine M_{i+1} does not imply a deadlock for machine M_i and vice versa.

For the first and the last machines, simplified versions of the UD policy are used. Machine M_1 can be controlled using at most two thresholds based on the level of the downstream buffer B_1 (i.e., *Downstream* (DS) policy); vice-versa machine M_m is controlled using at most two thresholds based on the level of the upstream buffer B_{m-1} (i.e., *Upstream* (US) policy).

3.3. *The Always On policy*

The *Always On* (AO) policy is used as a benchmark production control policy where the system might be controlled with a certain production rule but it is operating without any consideration to save energy.

The common behavior of machines is to alternate the *Idle, Busy,* and the *Blocked* states according to part arrivals and their releases to stages. Machines turn *Busy* when a part is loaded and return *Idle* when the part is released and waiting for a new part to load. The blocking condition appears when part release cannot be executed because machine downstream buffer is full (BAS rule in this work). This machine dynamics is standard when manufacturing systems do not apply EEC and do not switch off/on any resource.

The buffer capacity controls the production and, therefore, AO policy can be considered as a pure production control policy. Also, assuming that the production rule does not change, the AO policy maximizes system throughput and it should be considered as benchmark for EEC policy comparison in this work. Solution $\mathbf{x}_0$ identifies the AO policy.

4. Design of experiments

This section describes the experiments included and discussed in Section 5. Several scenarios are designed to analyze how the control impacts the system performance. All experiments are created such that $N_{\max} = 3$ limits the EEC control to at most three machines simultaneously. Note that when there are m stations in a line, there will be $\binom{m}{3}$ different selections of the machines to be controlled simultaneously. Problem solutions are obtained by exhaustive search and, given a target P^t, the solution minimizing the energy is selected. Discrete Event Simulation is used as estimation method considering a total of $N_p = 5000$ parts to be produced. Sample-path optimization is performed (Fu 2015). The solutions obtained are then evaluated in terms of mean performance estimated by 100 independent random replications.

The processing times are generated as random variates distributed accordingly to a Weibull distribution with mean $t_p = \frac{1}{\mu_i} = 100$ seconds and shape parameter k. Buffer capacity is $H = 5$. Startup times and power values are obtained from real measurements on CNC machining centers used in automotive industry: $\{w_{sb}, w_{id}, w_{busy}, w_{su}\} = \{0.5, 5.3, 0, 6\}$ expressed in kW and $t_{\text{su}} = 20$ seconds (Frigerio et al. 2021). The power request while working on parts is not considered ($w_{busy} = 0$) because it does not affect the control problem.

4.1. *Scenarios for analyzing the effect of controlling multiple machines simultaneously*

A total of 19 main scenarios have designed. In the first set ($S1 - S7$ in Table 2), production lines with $m = 3$ stages are considered and 7 scenarios are created to represent a variety of systems. Scenarios S1-S4 are created by varying machine mean processing time $t_{p,i}$ so that we obtain three unbalanced cases (S1, S2, S3) where machine M_j has a higher mean processing time with respect to other machines (i.e., $t_{p,j} > t_{p,i}, \forall i = 1, ...m; i \neq j$) and a balanced scenario (S4) with equal mean processing times $t_{p,i} = t_p, \forall i = 1, ...m$. Machine M_j is defined as line bottleneck machine and it is respectively $M_j, j = 1, 2, 3$ for S1, S2, and S3. In scenarios S1-S4, processing times are assumed to be distributed according to a Weibull with shape parameter $k = 1$ resulting in a coefficient of variation for the processing times $cv = 1$, i.e., processing times are exponentially distributed as a special case of the Weibull. Scenario S4 is additionally evaluated by varying the holding cost w_h and by including a highly consuming machine in the middle stage so that three additional scenarios are designed. Starting from the balanced configuration of S4, the holding power is varied in S5 and S6 so that S5 represents a case where holding parts has no impact on the energy (i.e., $w_h = 0$). S6 a case with high holding power $w_h = 0.5$ kW/part. S7 replicates S4 but machine M_2 uses twice the power of other machines and its startup requires 60 s.

The second set of 6 scenarios (S8 and S9) in Table 2 represents production lines with $m = 9$ stages and with holding cost $w_h = 0.1$ kW/part. S8 represents a balanced configuration where $\mu_i = \mu, \forall i = 1, ...m$, whilst S9 represents unbalanced configurations where the bottleneck machine is $M_j = 3$ with $\mu_b = 0.008\bar{3}$. As for S1-S7, the processing times are distributed according to a Weibull with shape $k = 1$ ($cv = 1$). We consider 9-machine scenarios where the EEC is applied to machines M_1, M_9, and to a third machine M_i that can be selected along the line: M_2 (S8/2 and S9/2), M_8 (S8/8 and S9/8) and M_5 (S8/5 and S9/5). Other machines are controlled with a pure production control policy (i.e., the AO).

The third set ($S4+$ in Table 2) of 3 scenarios is created to perform a sensitivity analysis on the total buffer capacity of the line. Specifically, variants of scenarios S4 are created increasing the buffer capacity $B = 10$ and varying the holding cost w_h.

The last set ($S2+$ in Table 2) of 3 scenarios is created to perform a sensitivity analysis on system variability. Variants of scenario S2 are created by varying processing time distribution parameters. The shape parameter k changes to obtain different cv with constant mean. Respectively, $k = [1.5, 2, 3]$ generates scenarios with $cv = [0.68, 0.52, 0.36]$.

4.2. *Scenarios for analyzing the effect of the control parameters*

Variants of scenarios S1-S7 are created by varying the control policy applied. In details, the maximum number of controlled machines $N_{\max}$ is reduced and the subset of buffer threshold used to control the machines is also changed. Variants are denoted as *Si/N_{max}M/Acronym* where Si indicates the scenario, $N_{\max}$ indicates the controlled machines, and *Acronym* identifies the control policy (Table 3). In details, for S$i, i = 1, \ldots, 7$:

- Scenarios Si/3M/UD use the UD policy controlling M_1, M_2, and M_3 (i.e., $N_{\max} = 3$);
- Scenarios Si/2M/UD use the UD policy with $N_{\max} = 2$: either M_1 and M_2, M_2

ID	m	Bottleneck	cv	w_h [kW/part]	Machine power ($w_{s,i}, s \in \mathbb{S}$)	Controlled machine set
S1	3	M_1	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S2	3	M_2	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S3	3	M_3	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S4	3	bal	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S5	3	bal	1	0	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S6	3	bal	1	0.5	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S7	3	bal	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m, i \neq 2$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S8/2	9	bal	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_9\}$
S8/5	9	bal	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_5, M_9\}$
S8/8	9	bal	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_8, M_9\}$
S9/2	9	M_3	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_9\}$
S9/5	9	M_3	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_5, M_9\}$
S9/8	9	M_3	1	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_8, M_9\}$
S4+0.2	3	bal	1	0.2	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S4+0.3	3	bal	1	0.3	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S4+0.5	3	bal	1	0.5	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S2+0.68	3	M_2	0.68	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S2+0.52	3	M_2	0.52	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$
S2+0.36	3	M_2	0.36	0.1	$w_{s,i} = w_s, i = 1, \ldots, m$	$\mathbb{M} = \{M_1, M_2, M_3\}$

Table 2. Design of experiment summary (total 19 scenarios). *bal* identifies balanced lines.

ID	$N_{\max}$	Policy	Decision variables / Thresholds
Si/3M/UD	3	UD	$\{N^1_{\text{off},1}; N^1_{\text{on},1}; N^2_{\text{off},1}; N^2_{\text{on},1}; N^2_{\text{off},2}; N^2_{\text{on},2}; N^3_{\text{off},2}; N^3_{\text{on},2}\}$
Si/2M/UD	2	UD	$\{N^1_{\text{off},1}; N^1_{\text{on},1}; N^2_{\text{off},1}; N^2_{\text{on},1}; N^2_{\text{off},2}; N^2_{\text{on},2}; N^3_{\text{off},2}; N^3_{\text{on},2}\}$
Si/1M/UD	1	UD	$\{N^1_{\text{off},1}; N^1_{\text{on},1}; N^2_{\text{off},1}; N^2_{\text{on},1}; N^2_{\text{off},2}; N^2_{\text{on},2}; N^3_{\text{off},2}; N^3_{\text{on},2}\}$
Si/3M/EHX	3	EXH	$\{N^1_{\text{off},1}; N^1_{\text{on},1}; N^2_{\text{off},1}; 0; N^2_{\text{off},2}; N^2_{\text{on},2}; N^3_{\text{off},2}; 0\}$
Si/2M/DS	2	DS	$\{N^1_{\text{off},1}; N^1_{\text{on},1}; N^2_{\text{off},2}; N^2_{\text{on},2}\}$
Si/2M/US	2	US	$\{N^2_{\text{off},1}; N^2_{\text{on},1}; N^3_{\text{off},2}; N^3_{\text{on},2}\}$

Table 3. Scenario variants according to the policy applied (Scenario Si refers to Table 2).

and M_3, or M_1 and M_3);

- Scenarios Si/1M/UD use the UD policy with $N_{\max} = 1$: either M_1, M_2, or M_3;
- Scenarios Si/3M/EXH use an Exhaustive UD policy controlling $N_{\max} = 3$ where this policy is defined as the policy fixing two thresholds $N^i_{\text{off},i-1} = 0, i = 2, 3$ so that a machine produces until its upstream buffer is empty;
- Scenarios Si/3M/DS use the Downstream policy where machines M_1 and M_2 are controlled using downstream buffer information and machine M_3 is not controlled, thus $N_{\max} = 2$ and four thresholds are used: $N^i_{\text{off},i}; N^i_{\text{on},i}, i = 1, 2$.
- Scenarios Si/3M/US use the Upstream policy where machines M_2 and M_3 are controlled using upstream buffer information and machine M_1 is not controlled, thus $N_{\max} = 2$ and four thresholds are used: $N^i_{\text{off},i-1}; N^i_{\text{on},i-1}, i = 2, 3$.

Table 2 summarizes the created scenarios.

5. Numerical results

The scenarios described in Section 4 are analyzed and discussed. We define energy savings ΔE as relative percentage difference of $E(\mathbf{x})$ and that obtained with the AO policy in the same scenario:

$$\Delta E = \frac{E(\mathbf{x}) - E(\mathbf{x}_0)}{E(\mathbf{x}_0)} \cdot 100\% \tag{5}$$

where $\mathbf{x}_0$ is the set of control parameters representing the AO policy. Similarly, we define the throughput loss ΔP comparing the production rate $P(\mathbf{x})$ and $P(\mathbf{x}_0)$, and the makespan increase ΔT comparing the makespan $T(\mathbf{x})$ and $T(\mathbf{x}_0)$.

5.1. *Effect of controlling multiple machines simultaneously*

The goal of this analysis is to analyze the effects of controlling simultaneously more than one machine in a system. Scenarios S1-S9 are included in this analysis. Firstly, we discuss scenarios S1-S7 where all machines of the system are controlled. Then, the effect of controlling a subset of machines is addressed in scenarios S8-S9.

5.1.1. Controlling all machines simultaneously

Finding 1: Our results show that energy savings ΔE are up to 60-75% for all evaluated scenarios and indicate that high energy savings can be reached also with high production rate targets. Similarly, it is shown that the overtime required to complete the production

Scenario	Policy	P^t [part/h]	$E(\mathbf{x})$ [kJ/part]	$T(\mathbf{x})$ [h]
S1	AO	27.54 ± 0.06	427.93 ± 2.42	181.57 ± 0.38
S1	UD	25.60 ± 0.05	145.24 ± 0.45	195.34 ± 0.41
S2	AO	27.25 ± 0.06	469.67 ± 2.56	183.53 ± 0.38
S2	UD	25.21 ± 0.05	154.73 ± 0.49	198.38 ± 0.41
S3	AO	27.55 ± 0.06	463.67 ± 2.81	181.49 ± 0.38
S3	UD	25.57 ± 0.05	157.73 ± 0.48	195.59 ± 0.40
S4	AO	29.87 ± 0.06	385.16 ± 2.39	167.41 ± 0.32
S4	UD	27.11 ± 0.05	142.63 ± 0.44	184.42 ± 0.35
S5	AO	29.87 ± 0.06	324.68 ± 2.27	167.41 ± 0.32
S5	UD	27.11 ± 0.05	89.46 ± 0.34	184.45 ± 0.34
S6	AO	29.87 ± 0.06	627.09 ± 3.30	167.41 ± 0.32
S6	UD	25.80 ± 0.04	295.97 ± 0.77	193.79 ± 0.33
S7	AO	29.87 ± 0.06	493.16 ± 2.98	167.41 ± 0.32
S7	UD	26.70 ± 0.05	226.16 ± 0.67	187.28 ± 0.34

Table 4. Energy per part $E(\mathbf{x})$ and makespan $T(\mathbf{x})$ varying production rate target P^t so that two policies per scenario are reported: the AO policy and the UD solution minimizing the energy. Mean and 95%CI of 100 replications are reported.

of N parts has a limited increase ($\Delta T = 16\%$ in the worst case).

System performance of S1-S7 is given in Table 4. The impact of the holding energy is visible comparing scenarios S4, S5 and S6 where work-in-progress impacts respectively for the 15%, 0% and 46% of the total energy consumption. In scenario S7, the energy consumption is mostly related to M_2 (44%). Results are obtained by controlling all machines of the line so that two thresholds are used for M_1 as controlled with the Downstream policy, four thresholds for M_2 as controlled with the UD policy, and two thresholds for M_3 as controlled with the Upstream policy.

Figure 3 and Figure 4 represent the results obtained for the designed scenarios while varying the target production rate $P^t \leq P(\mathbf{x}_0)$. Results show that energy savings ΔE are up to 60-75% for all evaluated scenarios and indicate that high energy savings can be reached without a large production loss (maximum $\Delta P = -9.5\%$). In the left panels, the frontiers start from the single-objective solution maximizing P that is actually the AO case, i.e., $P(\mathbf{x}_0)$. Then, moving along the frontiers, from right to left, energy decreases while the production rate $P(\mathbf{x})$ decreases so that the last point of the frontier represents the single-objective solution minimizing $E(\mathbf{x})$ (single-objective solution results are reported in Table 4). In the right panels, the symmetric effect is observed so that $T(\mathbf{x})$ increases. Relative differences are similar for scenarios S1, S2, S3 and S4 despite the unbalanced scenario obtains higher savings and throughput in terms of absolute values. Scenarios S4, S5 and S6 differ significantly, showing that as the holding power increases, potential savings are smaller. Scenario S7 obtains less saving because machine M_2 is critical for energy consumption but also requires a long startup, reducing saving potential. Higher savings are obtained for unbalanced scenarios (S1,S2,S3) since the EEC exploits the idle periods of non-bottleneck machines; also, throughput loss ΔP are also higher because switching off/on control on the bottleneck is limited by the policy.

5.1.2. Controlling a subset of machines

Finding 2: The energy consumed by machines kept in idle state increases because of

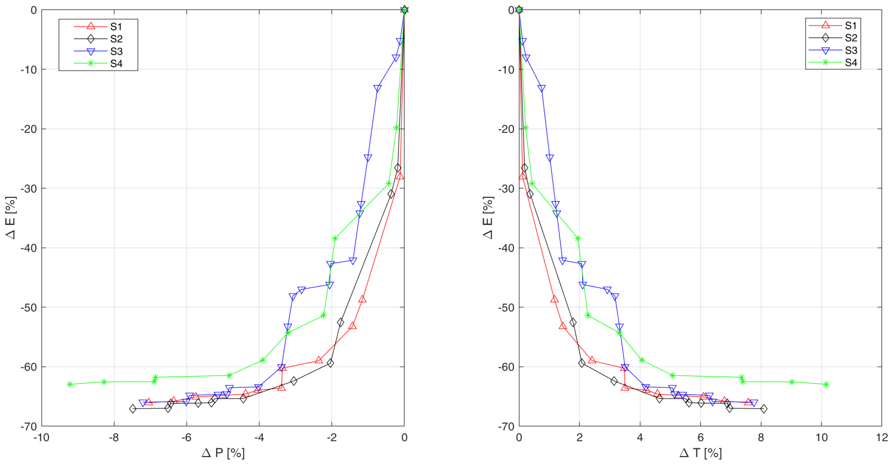


Figure 3. Throughput loss ΔP (left panel) and makespan increase ΔT (right panel) according to achieved energy saving ΔE as obtained in scenarios S1, S2, S3 and S4. Solutions at graph origin (0,0) represent the AO policy as benchmark. The mean of 100 replications is reported.

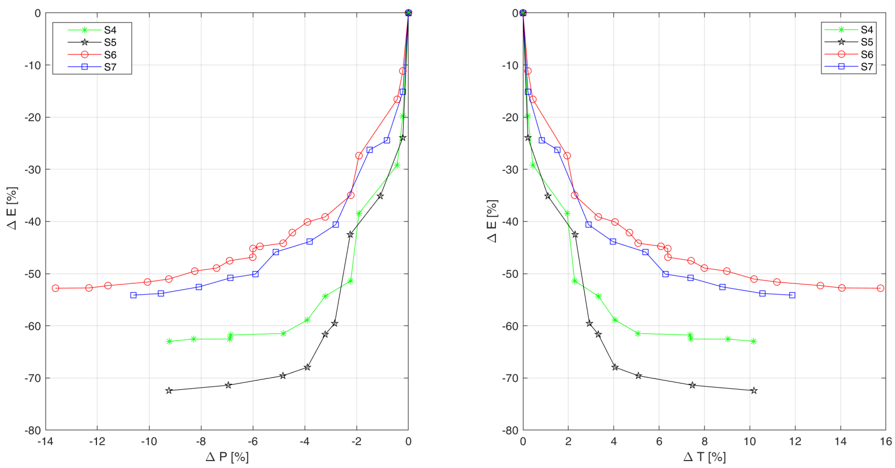


Figure 4. Throughput loss ΔP (left panel) and makespan increase ΔT (right panel) according to achieved energy saving ΔE as obtained in scenarios S4, S5, S6 and S7. Solutions at graph origin (0,0) represent the AO policy as benchmark. Mean of 100 replications is reported.

Scenario	Policy	P^t [part/h]	E [kJ/part]	T [h]
S8	AO	27.52 ± 0.04	1719.47 ± 7.61	181.67 ± 0.25
S8/2	UD	27.07 ± 0.04	1386.67 ± 5.63	184.71 ± 0.26
S8/5	UD	27.10 ± 0.04	1393.36 ± 5.55	184.48 ± 0.26
S8/8	UD	27.38 ± 0.04	1396.24 ± 5.50	182.62 ± 0.25
S9	AO	26.32 ± 0.04	1879.88 ± 7.57	189.99 ± 0.29
S9/2	UD	25.76 ± 0.04	1491.87 ± 5.90	194.12 ± 0.31
S9/5	UD	25.98 ± 0.04	1464.17 ± 5.25	192.45 ± 0.29
S9/8	UD	26.08 ± 0.04	1455.53 ± 5.32	191.73 ± 0.29
S9/last	UD	26.16 ± 0.04	1481.98 ± 5.78	191.17 ± 0.28

Table 5. Results of the AO policy and of UD solution minimizing the energy (i.e., relaxed production rate constraint) for 9-machine scenarios S8-S9 (mean and 95%CI of 100 replications).

the propagation of starvation and blocking phenomena from the controlled machines. Controlling a subset of machines might have large benefits. Further, it is shown that controlling M_1 reduces the work-in-progress along the line and enables higher savings.

In more details, results obtained in S8-S9 are reported in Table 5 and Figure 5. In the balanced scenarios S8, the mean energy savings are up to around 19% independently from the controlled machine set; whereas the mean energy savings vary up to 22.6% in unbalanced scenarios and it increases controlling machines far from the bottleneck (S9/5 and S9/8). Nevertheless, given the same throughput target, higher savings can be achieved by controlling last machines of the line.

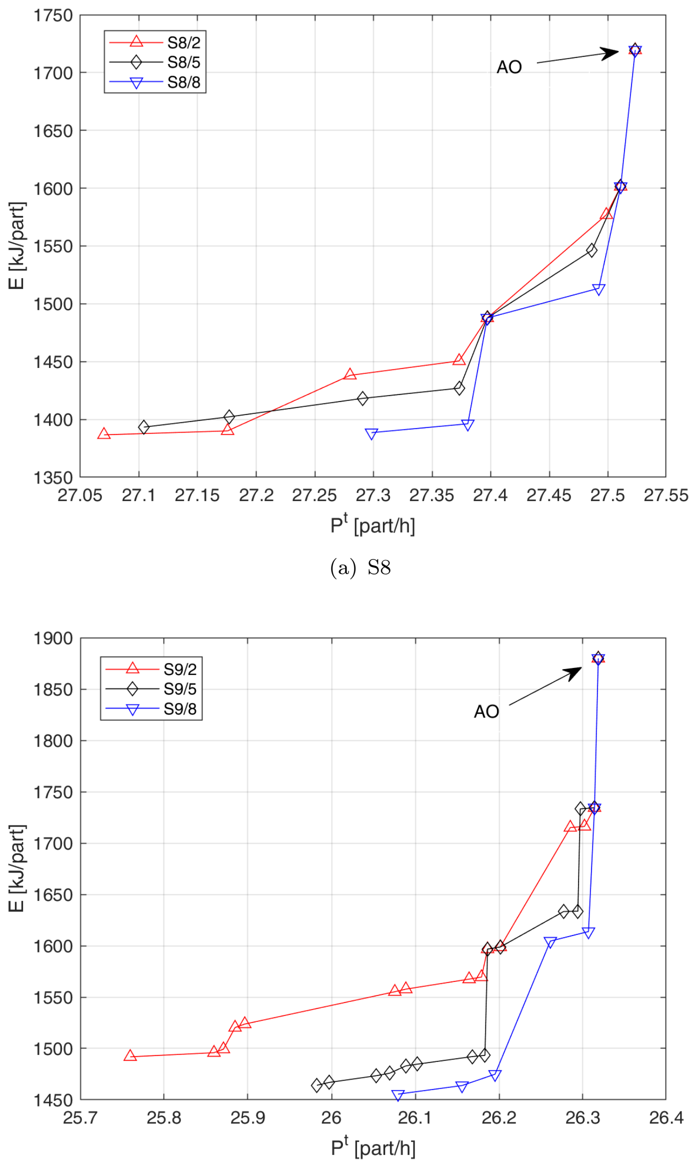
It is noteworthy that the energy consumption of the controlled machine decreases significantly. Figure 6 reports as example the savings achieved per machine in scenarios S9 and bars are ordered for increasing throughput target. Despite the savings can be up to 80% of the machine energy for the controlled machines, the energy consumed by machines without the EEC increases because of the propagation of starvation and blocking phenomena from the controlled machines. In S9/2, the energy increase of the bottleneck is due to M_3 starvation eventually caused by M_1 and M_2 being in startup or standby states. The effect is smaller in S9/5 and S9/8 because of the larger distance between the controlled machines and the bottleneck M_3. Similar results are obtained for S8.

Since the results seem to suggest that the control of three sequential machines at the end of the line might be more advantageous, we include S9 with controlled set $\{M_7, M_8, M_9\}$ in the analysis (i.e., S9/last in Table 5). Actually, the energy consumption related to this latter control set is higher than S9/8: since the holding cost is not negligible in S9, controlling M_1 reduces the work-in-progress along the line and enables higher savings.

5.2. *Effect of the number of thresholds used in EEC*

The goal of this analysis is to analyze the effectiveness of EEC policies depending on the number of thresholds used to control the system or the number of controlled machines.

Finding 3: The Exhaustive policy (EXH) is shown to be the most efficient in all evaluated scenarios obtaining the same results as the full UD policy with two control thresholds less. Further, it is noteworthy that controlling a single machine (i.e., Si/1M/UD) has significant savings (up to 28%, the maximum is obtained in S1). Also, having more control thresholds does not always reflect in higher savings.



(a) S8

(b) S9

Figure 5. Energy per part E as target production rate P^t increases in scenarios S8 and S9 for different subset of controlled machines. AO solution is indicated on the graph as benchmark. Mean of 100 replications is reported.

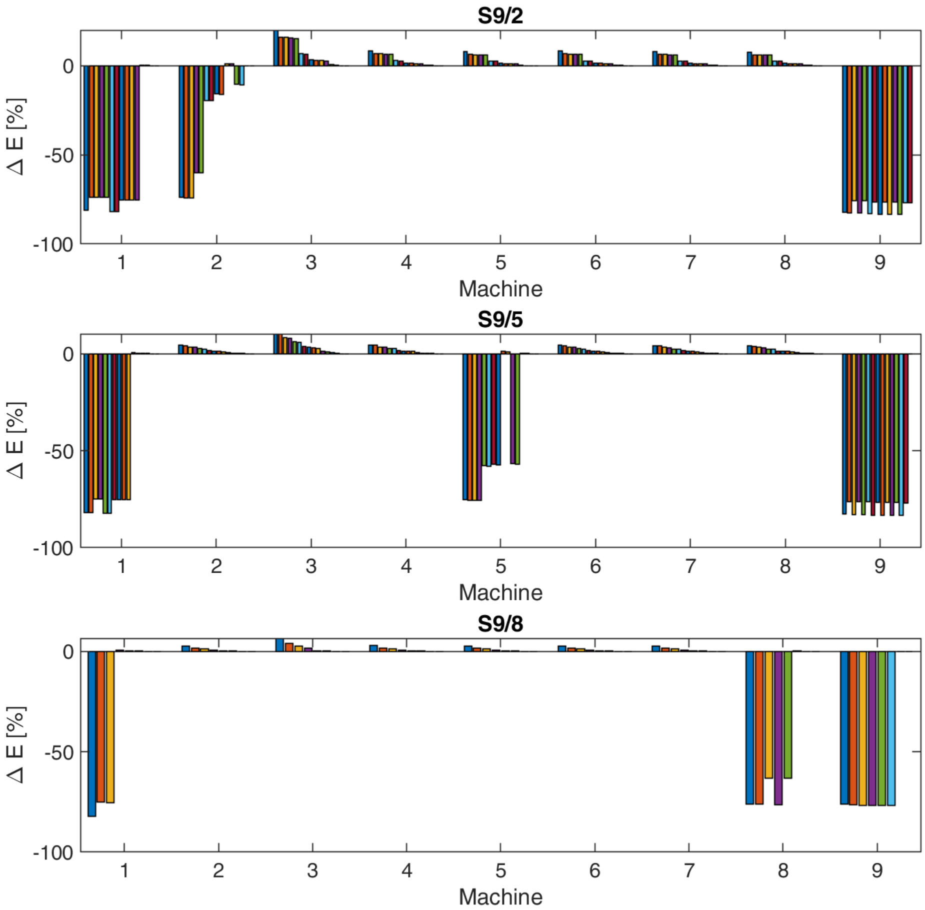


Figure 6. Energy savings ΔE at machine level as obtained varying the subset of controlled machines (S9/2, S9/5, and S9/8). Bars are ordered for increasing target production rate P^t. The mean of 100 replications is reported.

The results obtained for S1-S7 in terms of energy E given a target P^t are represented in Figure 7 varying the policy applied. Policies 3M/EXH and 3M/UD provide same results: to leave parts in the queue is not favorable for all criteria and it might require a tie-breaking rule, pushing production, to complete the batch. This insight is the first evidence that each threshold impacts differently on policy potential and that a careful selection of which threshold to use is significant.

Comparing policies 3M/UD, 2M/UD, and 1M/UD, the impact of EEC improves in terms of reduced energy consumption as the number of controlled machine increases. This insight holds for all scenarios. The control policies 2M/US and 2M/DS use a limited set of thresholds and their impact vary according to the scenario of application. In more details:

- The 2M/US policy performs better than 2M/DS policy except for S3. Since 2M/US uses the upstream buffer level to control M_2 and M_3, it is not effective in S3 where the bottleneck causes the system to be congested by part. Scenario S2, with a bottleneck in M_2, is an exception where 2M/US and 2M/DS performs similarly.
- For balanced scenarios, 2M/US and 2M/DS where expected to perform similarly due to line symmetry. Nevertheless, the holding cost matters and 2M/US performs better.
- Policy 1M/UD often outperforms 2M/DS (S1, S2, S5) or performs similarly (S4, S6, S7). Compared to 2M/US, its results are similar in S2, S4 and S5. This happens because the careful selection of which machine to control might be more efficient than controlling a larger machine subset with partial information.

An in-depth analysis of results obtained in Si/3M/UD enable the discussion of the actual machine control as the production rate target P^t increases. The UD policy with $N_{\max} = 3$ includes eight control thresholds to be optimized. However, the number of actually controlled machines n_m varies and it decreases for higher target P^t (Figure 8). Similarly, the number of actively used thresholds n_t decreases for high target P^t (Figure 8).

Solution performance as obtained in Figure 7 show that significant results can be obtained controlling only a subset of machines and using a subset of thresholds. As example, for high target P^t, the control of a single machine (1M/UD) performs equally to the 3M/UD since only a single machine is actually controlled.

5.3. *The effect of buffer capacity*

The effect of buffer capacity on the system energy consumption is investigated making use of Scenario S4+ results.

Finding 4: EEC thresholds $N^i_{\text{off},i}, i = 1, 2$ *limit the queue level resulting in a reduced buffer capacity for the controlled line. Thus the total buffer capacity of the controlled line decreases as the holding cost increases and as the target production rate decreases. This insight is of particular interest for companies where work-in-progress must be maintained in certain condition, e.g., the food, pharmaceutical or semiconductor industry.*

Buffer B_i is limited by the threshold $N^i_{\text{off},i}$ (see Section 3.2). For $N^i_{\text{off},i} = K_i$ the system uses the all available buffer capacity and the control switches off M_i when B_i is full. Solutions of scenarios S1-S7 always use the full buffer capacity of the line yielding to $N^i_{\text{off},i} = K_i$. Scenario S6 is indeed an exception where threshold $N^1_{\text{off},1} < K_1$

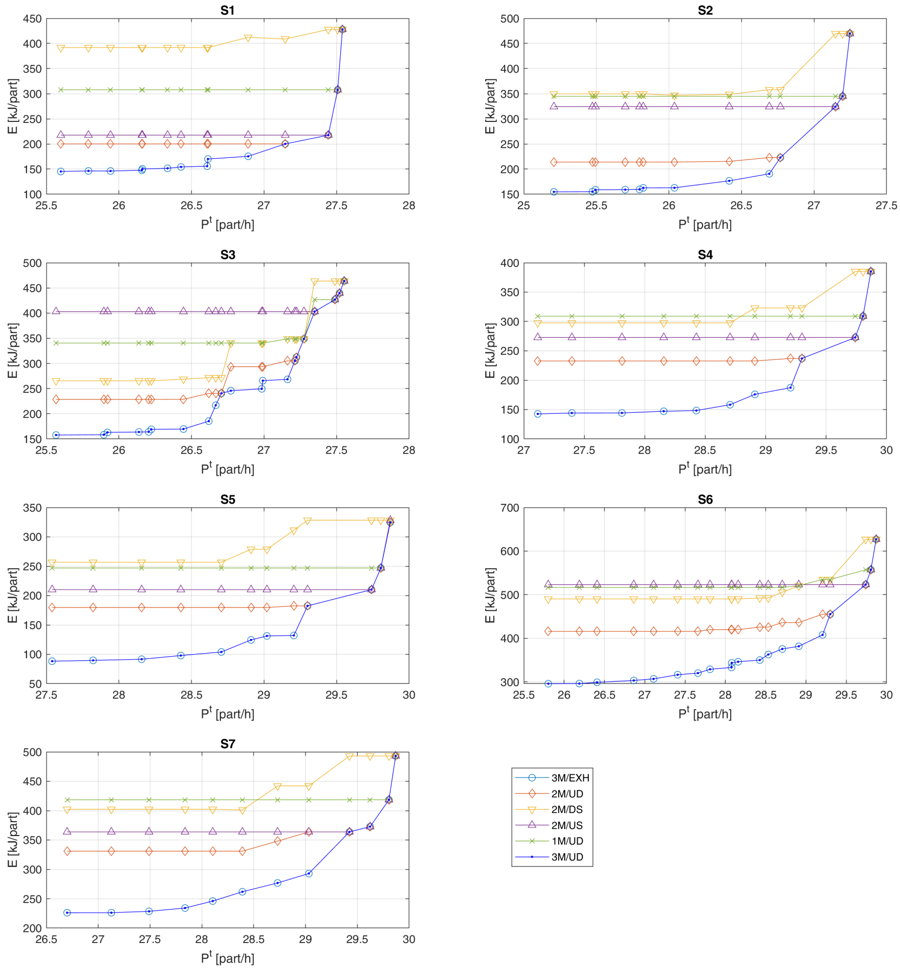


Figure 7. Comparison on policies in terms of energy per part E as target production rate P^t increases. Each frontier is obtained with a certain set of thresholds used to control the machines. The mean of 100 replications is reported.

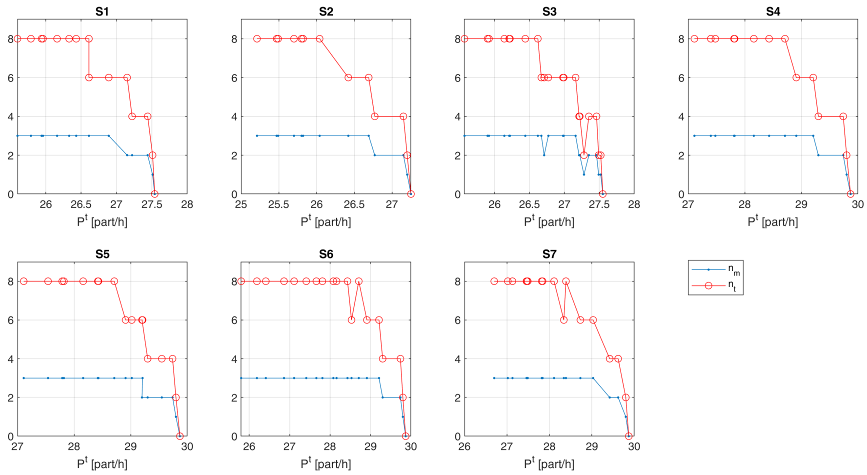


Figure 8. Number of actually controlled machines n_m and actually used thresholds for the 3-machine scenarios according to target P^t. $n_m = n_t = 0$ indicates the AO policy reaching the highest target P^t for the scenario.

varies among obtained solutions. Figure 9 shows the total buffer capacity actually used in the controlled lines of Scenario S4+. The EEC exploits the control thresholds to reduce the energy consumed by reducing the work-in-progress held in buffers. As a consequence, the total buffer capacity $K_{tot} = N^1_{\text{off},1} + N^2_{\text{off},2}$ is reduced to decrease the energy E (Figure 9 top panel).

5.4. *The effect of system variability*

The effect of system variability is assessed using Scenarios S2+.

Finding 5: Production target P^t is set to have limited ΔP and the obtained savings ΔE are up to 70% with higher values when system variability is low (i.e., small cv).

Results are included in Table 6 to show the increasing potential of EEC as the target production rate P^t increases. As example, for a maximum $\Delta P = -1\%$, savings ΔE are 30.96%, 52.72%, 62.10% and 69.39% respectively for $cv = 1, 0.66, 0.52, 0.38$.

As processing time variability decreases, the achievable P is higher and the E is lower so that the amount of energy saved is the highest for $cv = 1$ (up to 247 kJ/part saved compared to the AO policy).

6. Conclusions

This paper shows the effect of controlling selected multiple machines simultaneously by using buffer-based thresholds with varying number of control parameters. The proposed approach is useful to evaluate the potential energy cost reduction for a given serial line with the application of the EEC. In addition, the trade-off among energy saving, production rate and overtime is discussed for a set of scenarios. Guidelines for the practical application of the EEC are supported by numerical evidence.

Table 7 reports the mean performance obtained in the analyzed scenarios showing a significant energy saving (on average 37%) with a limited makespan increase. Energy savings are larger for unbalanced lines (up to 67% in S3) and for scenarios without

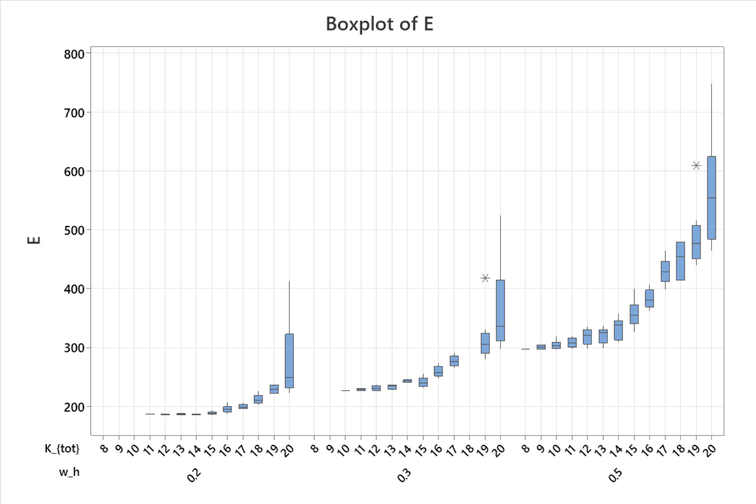


Figure 9. Boxplot of energy consumption E as the total buffer capacity of the system decreases. Results refer to Scenario S4+ as w_h varies.

Scenario	cv	P^t [part/h]	ΔP [%]	EN [kJ/part]	ΔE [%]	T [h]
S2+	1	26.70	-2%	222.90	-52.53%	186.81
S2+	1	26.97	-1%	324.23	-30.96%	184.20
S2+	1	27.25	–	469.67	0.00%	183.53
S2+	0.68	28.62	-2%	128.33	-60.40%	174.31
S2+	0.68	28.91	-1%	153.19	-52.72%	172.78
S2+	0.68	29.21	–	324.14	0.00%	171.21
S2+	0.52	29.20	-2%	97.49	-65.69%	170.65
S2+	0.52	29.50	-1%	107.66	-62.10%	169.33
S2+	0.52	29.79	–	284.25	0.00%	167.83
S2+	0.38	29.38	-2%	81.33	-70.09%	168.95
S2+	0.38	29.68	-1%	83.25	-69.39%	168.02
S2+	0.38	29.98	–	272.05	0.00%	166.78

Table 6. System performance in Scenarios S2+ varying target production rate P^t. Mean of 100 replications is reported.

Scenario	Policy	ΔE	ΔP	ΔT
S1	UD	-55.2%	-3.5%	3.7%
S2	UD	-53.5%	-3.7%	3.9%
S3	UD	-42.0%	-2.8%	2.9%
S4	UD	-49.1%	-4.4%	4.7%
S5	UD	-54.7%	-3.8%	4.0%
S6	UD	-39.9%	-5.9%	6.5%
S7	UD	-42.2%	-5.4%	5.9%
S4+ 0.2	UD	-48.9%	-7.1%	7.9%
S4+ 0.3	UD	-46.3%	-6.9%	7.7%
S4+ 0.5	UD	-48.7%	-9.2%	10.5%
S2+ 1	UD	-53.5%	-3.7%	3.9%
S2+ 0.68	UD	-48.1%	-1.5%	1.6%
S2+ 0.52	UD	-48.6%	-0.9%	0.9%
S2+ 0.38	UD	-51.6%	-0.3%	0.3%
S8/2	UD	-12.4%	-0.6%	0.6%
S8/5	UD	-12.8%	-0.6%	0.6%
S8/8	UD	-11.7%	-0.3%	0.3%
S9/2	UD	-14.8%	-0.9%	0.9%
S9/5	UD	-16.2%	-0.6%	0.6%
S9/8	UD	-14.7%	-0.3%	0.3%
S9/9	UD	-14.9%	-0.2%	0.2%

Table 7. Mean performance obtained in the evaluated scenarios

holding cost (up to 72% in S5). Further, the following insights are remarked:

- Energy consumption can be minimized admitting a limited increase of overtime (on average 3.2%) and a limited production rate decrease (on average -3%) showing the competitive advantage of EEC;
- Significant savings can be achieved while meeting a high target throughput (on average -31.8% is achieved with $\Delta P \leq -1\%$) ;
- The subset of controlled machines is significant and the subset selection should be carefully addressed;
- When the maximum number of controlled machines is limited, controlling machines at the end/beginning of the line is suggested;
- Exhaustive policies are dominating other policies and policies using only upstream or downstream information can be profitably used for machines near the bottleneck;
- Reducing the work-in-progress is significant for energy saving when holding cost is included so the control of the first machines is suggested.

The practical application of EEC policies requires the fitting of machine processing times, the estimation of machines power requests in three states (standby, startup and idle) and the estimation of machine startup time. The estimation of the holding energy should be considered according to the field of application. Also, the practical effort required to implement the EEC policies requires the buffer level information to be available at machines so that local controller can switch off/on machines. The controller implementation effort should be evaluated on the basis of the expected impact the EEC has on the line so that policies with a limited number of thresholds and/or a limited number of controlled machines are preferable.

Future effort will be devoted to develop optimization algorithms addressing the EEC problem for long lines and including the optimal selection of machines to be controlled. Analytical methods and surrogate models for performance evaluation might be used to guide the search. In addition, as system complexity increases, more information should be included to obtain effective control policies. New methods to select which information is more effective to be used for EEC are needed to enhance practical implementation and to reduce industrial barriers. Thus, future research will be focused on the value of information to jointly address production control and energy efficiency control problems. EEC policies might be based on aggregated information such that the dimension of the control problem is reduced. As significant model extension, multiple hibernation states can be included in the control problem thus the optimal state is also selected. As model complexity increases, proper solving approaches must be developed to cope with problem dimension. Further, the approach can be extended to include hybrid flow line with parallel machine workstations.

In conclusion, energy efficiency in a production line can be improved significantly by controlling the power modes of optimally selected machines with optimally selected thresholds while meeting the production target of the line.

Acknowledgment

This work was supported by TUBITAK (grant number 221M393) and European Union's Horizon 2020 Research and Innovation Programme [IN4ACT project under grant agreement No. 810318].

Disclosure statement

The authors report there are no competing interests to declare.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, N.F., upon reasonable request.

References

Brundage, M., Chang, Q., Li, Y., Xiao, G., Arinez, J., 2014. Energy efficiency management of an integrated serial production line and hvac system. Automation Science and Engineering, IEEE Transactions on 11, 789–797.

Chang, Q., Xiao, G., Biller, S., Li, L., 2013. Energy saving opportunity analysis of automotive serial production systems (march 2012). Automation Science and Engineering, IEEE Transactions on 10, 334–342.

Dahmus, J.B., Gutowski, T., 2004. An environmental analysis of machining, in: Manufacturing Engineering and Materials Handling Engineering ASME, pp. 643–652.

Frigerio, N., Cornaggia, C., Matta, A., 2021. An adaptive policy for on-line energy-efficient control of machine tools under throughput constraint n frigerio et al. Journal of Cleaner Production 287. doi:.

Frigerio, N., Matta, A., 2015. Energy-efficient control strategies for machine tools with stochastic arrivals. Automation Science and Engineering, IEEE Transactions on 12, 50–61.

Frigerio, N., Matta, A., 2016. Analysis on energy efficient switching of machine tool with stochastic arrivals and buffer information. Automation Science and Engineering, IEEE Transactions on 13, 238–246.

Frigerio, N., Matta, A., 2019. Analysis of Production Lines with Switch-Off/On Controlled Machines. Springer International Publishing, Cham; ISBN: 978-3-319-93730-4. URL: https://doi.org/10.1007/978-3-319-93730-4_8, doi:.

Frigerio, N., Matta, A., 2021. Modelling the startup of machine tools for energy efficient multi-sleep control policies. Journal of Manufacturing Systems 60, 337–349. doi:.

Fu, M.C., 2015. Handbook of Simulation Optimization. Springer-Verlag, Ed. New York, NY, USA; ISBN: 9781493913831.

Gutowski, T., Branham, M., Dahmus, J., Jones, A., Thiriez, A., Sekulic, D., 2009. Thermodynamic analysis of resources used in manufacturing processes. Environmental Science and technology 43, 1584–1590.

Jia, Z., Zhang, L., Arinez, J., Xiao, G., 2016. Performance analysis for serial production lines with bernoulli machines and real-time wip-based machine switch-on/off control. International Journal of Production Research 54, 6285–6301. URL: https://doi.org/10.1080/00207543.2016.1197438, doi:.

Li, Y., Chang, Q., Ni, J., Brundage, M.P., 2016. Event-based supervisory control for energy efficient manufacturing systems. IEEE Transactions on Automation Science and Engineering 15, 92–103.

Mouzon, G., Yiildirim, M., Twomey, J., 2007. Operational methods for minimization of energy consumption of manufacturing equipment. International Journal of Production Research 45, 18–19.

Renna, P., Materi, S., 2020. Design model of flow lines to include switch-off policies reducing energy consumption. Applied Sciences (Switzerland) 10. doi:.

Renna, P., Materi, S., 2021. A literature review of energy efficiency and sustainability in manufacturing systems 11. doi:.

Sihag, N., Sangwan, K.S., 2020. A systematic literature review on machine tool energy consumption. Journal of Cleaner Production , 123125doi:.

Su, H., Frigerio, N., Matta, A., 2016. Energy saving opportunities and value of information: A trade-off in a production line. Procedia CIRP 48, 301–306. doi:.

Sun, Z., Li, L., 2013. Opportunity estimation for real-time energy control of sustainable manufacturing systems. Automation Science and Engineering, IEEE Transactions on 10, 38–44.

Tan, B., Karabağ, O., Khayyati, S., 2022. Production and energy mode control of a production-inventory system. European Journal of Operational Research doi:.

Wang, J., Fei, Z., Chang, Q., Li, S., Fu, Y., 2019. Multi-state decision of unreliable machines for energy-efficient production considering work-in-process inventory. The International Journal of Advanced Manufacturing Technology 102, 1009–1021.

Wang, J., Xue, J., Duque, E.T., Li, S., Chang, Q., 2017. Fuzzy decision of machine switch on-off for energy efficient operation of manufacturing system, in: 2017 13th IEEE Conference on Automation Science and Engineering (CASE), IEEE. pp. 1158–1162.

Weinert, N., Chiotellis, S., Seliger, G., 2011. Methodology for planning and operating energy-efficient production systems. CIRP Annals 60, 41–44. doi:.

Yoon, H., Kim, E., Kim, M., Lee, J., Lee, G., Ahn, S., 2015. Towards greener machine tools – a review on energy saving strategies and technologies. Renewable and Sustainable Energy Reviews 48, 870 – 891. URL: http://www.sciencedirect.com/science/article/pii/S1364032115002609.

Zhang, Y., Sun, Z., Qin, R., Xiong, H., 2019. Idle duration prediction for manufacturing system using a gaussian mixture model integrated neural network for energy efficiency improvement. IEEE Transactions on Automation Science and Engineering .

Zhou, L., Li, J., Li, F., Meng, Q., Li, J., Xu, X., 2016. Energy consumption model and energy efficiency of machine tools: a comprehensive literature review. Journal of Cleaner Production 112, 3721–3734. doi:.

List of Table captions

Table 1 caption: Notation table.

Table 2 caption: Design of experiment summary. *bal* identifies balanced lines.

Table 3 caption: Scenario variants according to the policy applied (Scenario Si refers to Table 2).

Table 4 caption: Energy per part $E(\mathbf{x})$ and makespan $T(\mathbf{x})$ varying production rate target P^t so that two policies per scenario are reported: the AO policy and the UD solution minimizing the energy. Mean and 95%CI of 100 replications are reported.

Table 5 caption: Results of the AO policy and of UD solution minimizing the energy (i.e., relaxed production rate constraint) for 9-machine scenarios S8-S9 (mean and 95%CI of 100 replications).

Table 6 caption: System performance in Scenarios S2+ varying target production rate P^t. Mean of 100 replications is reported.

Table 7 caption: Mean performance obtained in the evaluated scenarios.

List of Figure captions and Alt text

Figure 1 caption: State model of controlled machine M_i.
Figure 1 Alt Text: Node-edge representation of the behavior of a controlled machine M_i. Nodes represent states and edges represent events. Starting from the standby state, the machine enters in startup state with the switch on event. From the startup state, the machine enters in idle state with the startup end event. From the idle state, the machine can either enter in standby with a switch off event or in busy state with the process end state. From the busy state, the machine enters in idle state with the process end event.

Figure 2 caption: Threshold representation for controlled machine M_i.
Figure 2 Alt Text: A production stage schematic representation. Part flow is represented from left to right through the input buffer, the server and the output buffer. Control thresholds are represented as levels on the buffers.

Figure 3 caption: Throughput loss ΔP (left panel) and makespan increase ΔT (right panel) according to achieved energy saving ΔE as obtained in scenarios S1, S2, S3 and S4. Solutions at graph origin (0,0) represent the AO policy as benchmark. The mean of 100 replications is reported.
Figure 3 Alt Text: Graph is composed by two panels. Left panel shows energy saving on vertical axis and throughput loss on horizontal axis. Right panel shows energy saving on vertical axis and makespan increase on horizontal axis. Four lines are reported in each panel, one for each scenario from S1 to S4. All lines show an increase of energy as throughput increases and makespan decreases.

Figure 4 caption: Throughput loss ΔP (left panel) and makespan increase ΔT (right panel) according to achieved energy saving ΔE as obtained in scenarios S4, S5, S6 and S7. Solutions at graph origin (0,0) represent the AO policy as benchmark. Mean of 100 replications is reported.
Figure 4 Alt Text: Graph is composed by two panels. Left panel shows energy saving on vertical axis and throughput loss on horizontal axis. Right panel shows energy saving on vertical axis and makespan increase on horizontal axis. Four lines are reported in

each panel, one for each scenario from S4 to S7. All lines show an increase of energy as throughput increases and makespan decreases.

Figure 5 caption: Energy per part E as target production rate P^t increases in scenarios S8 and S9 for different subset of controlled machines. AO solution is indicated on the graph as benchmark. Mean of 100 replications is reported.
Figure 5 Alt Text: Graph shows energy on vertical axis and target throughput on horizontal axis. Graph is composed by two subfigures: (a) shows results of S8, (b) shows results of S9. Three lines are reported in each panel, one for each subset of controlled machines. All lines show an increase of energy as throughput target increases.

Figure 6 caption: Energy savings ΔE at machine level as obtained varying the subset of controlled machines (S9/2, S9/5, and S9/8). Bars are ordered for increasing target production rate P^t. The mean of 100 replications is reported.
Figure 6 Alt text: Graph is composed by three panels, one for each subset of controlled machines in scenario S9. Each panel shows a bar-diagram representing the energy saving obtained by each machine from M1 to M9. Controlled machines have a negative ΔE, whilst not controlled machines have a positive ΔE; negative bars are significantly higher than positive bars.

Figure 7 caption: Comparison on policies in terms of energy per part E as target production rate P^t increases. Each frontier is obtained with a certain set of thresholds used to control the machines. The mean of 100 replications is reported.
Figure 7 Alt text: Graph is composed by seven panels, one for each scenario from S1 to S7. Each panel shows energy on the vertical axis and target throughput on the horizontal axis. Each panel shows six lines, one for each set of threshold used to control the machines (i.e., control policy). Lines are non-decreasing in target throughput and converge to the AO results. EXH policy obtains the best results in all panels.

Figure 8 caption: Number of actually controlled machines n_m and actually used thresholds for the 3-machine scenarios according to target P^t. $n_m = n_t = 0$ indicates the AO policy reaching the highest target P^t for the scenario.
Figure 8 Alt text: Graph is composed by seven panels, one for each scenario from S1 to S7. Each panel shows the number of actually controlled machines and the number of actually used thresholds on the vertical axis and target throughput on horizontal axis. Lines are non-increasing in target throughput and decrease to zero.

Figure 9 caption: Boxplot of energy consumption E as the total buffer capacity of the system decreases. Results refer to Scenario S4+ as w_h varies.
Figure 9 Alt text: Boxplots are clustered in two groups: according to w_h and to total buffer capacity K_{tot}. On the average, the energy E decreases as the total buffer capacity decreases and w_h decreases.