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Modelling the startup of machine tools for energy efficient multi-sleep control policies

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Abstract

Energy efficient control strategies have been of recent interest in literature as promising measures to reduce the energy consumed by production equipment during interruptions of part flow. A general time-based control policy is analyzed. Machine idle times are assumed stochastic and the expected value of the energy consumed per produced part is reduced while assuring a certain target of expected production rate. The startup time required to resume the service depends on the time period the machine stays in a low power consumption state. Since the startup is often related to one or more machine components, the optimal policy might be to partially switch the machine. Therefore, a policy acting at component level is also analyzed where the duration of the startup depends on the set of machine components that are switched off. The policy is compared to state-of-the-art policies and discussed for a set of simulated numerical cases representing several production environments.

Keywords: Machine Tools; Energy Efficient Control; Multiple Sleeping States; Time-dependent startup.

Abbreviation list

EE Energy Efficient; AO Always On; SP Single-sleep Switching Policy; MSP Multi-sleep Switching Policy; DES Discrete Event Simulation; CNC Computer Numeric Control; pdf probability density function; IHR Increasing Hazard Rate; DHR Decreasing Hazard Rate; CI Confidence Interval; GA Genetic Algorithm.

Nomenclature table

Machine control model (constant startup duration)	
t_p	processing time
X	machine idle times with pdf $f(x)$ and mean t_a
$\phi(x)^{AO}$	machine energy consumed in a cycle under AO policy
$h(x)^{AO}$	cycle duration under AO policy
$\mathbb{C}$	set of machine components
$\mathbb{I}$	set of machine controllable components
$\mathbb{J}$	set of machine states
w_j	machine power request in state $j = \{r, s, \text{su}\}$
w_q	holding power request
t_{su}	machine startup duration
$\tau = \{\tau_{\text{off}}, \tau_{\text{on}}\}$	vector of machine control parameters
$\phi(x, \tau)$	energy consumed in a cycle
$\phi_{\text{mach}}(x, \tau)$	machine energy consumed in a cycle
$h(x, \tau)$	cycle duration
$\theta(x, \tau)$	machine production rate
θ_{target}	target production rate
ε	maximum admissible reduction of production rate
$z(\tau)$	objective function
Machine control model (time-dependent startup)	
t_0, t_h	minimum (t_0) and maximum (t_h) duration of machine startup time
y	time spent by the machine in the sleeping state during a certain cycle
$t_{\text{su}}(y)$	time-dependent duration of the startup
β	time range of the startup duration
δ	instant at which the startup duration reaches its maximum
Component control model (time-dependent startup)	
$\tau^{MSP} = \{\tau_{\text{off,i}}, \tau_{\text{on,i}}\}$	vector of components' control parameters with $i \in \mathbb{I}$
w_0	power request of not controllable components
$w_{r,i}$	power request in state *enabled* of component i
$w_{s,i}$	power request in state *off* of component i
$w_{\text{su},i}$	power request in state *startup* of component i

1. Introduction

According to the U.S. Energy Information Administration (2019), the amount of energy absorbed by the industrial sector in 2018 accounts for more than 50% of the world energy consumption. Energy intensive manufacturing (food, pulp and paper, basic chemicals, refining, iron and steel, non-ferrous metals and non-metallic minerals) is the largest component in the sector (52%) but non-energy-intensive manufacturing (metal-based durables, other chemicals and other manufacturing) follows with a share of 35%.

Manufacturing plants are facing increasing pressure to reduce their carbon footprint, driven by concerns related to energy costs and climate change, and the Energy Efficient (EE) management of assets is key for industries competitiveness. In addition, the topic of energy efficiency in manufacturing has gained an increasing prominence within the scientific community. Several strategic measures can improve energy efficiency and, due to the variety of manufacturing activities and technologies, these measures cover different levels and may affect different manufacturing layers (Yoon et al., 2015, Zhou et al., 2016, Sihag and Sangwan, 2020). Systematic overviews have been proposed in recent literature where developing energy-aware models of manufacturing systems (e.g., Mawson and Hughes (2019)) and proper energy control strategies are frequent topic of discussion, e.g., Duflou et al. (2012), Devoldere et al. (2007), Zhou et al. (2016), Yoon et al. (2015), Sihag and Sangwan (2020), Shin et al. (2017), Esmaeilian et al. (2016), Diaz C. and Ocampo-Martinez (2019).

With a particular focus at machine level, four main areas can be identified as in Figure 1: the reuse of energy (including kinetic energy recovery and thermal management), the green-design of machine components (e.g., friction reduction, weight minimization), the re-design and control of processes (e.g., Rajemi et al. (2010), Albertelli et al. (2016), Bikas et al. (2016), Xiao et al. (2021)), and the control of machine state. In this work, we deal with the control of machine state that aims at reducing the *non processing energy* consumed to keep the machine ready-for-process while the part flow is interrupted. Indeed, machine tools consume energy while working on parts, i.e., *process-related energy*, but also while the machine is idle (Dahmus and Gutowski, 2004, Yoon et al., 2014). Figure 2 qualitatively illustrates the power profile of a machine during production: between the two working states, i.e., from t_1 to t_2, the machine is in idle state requiring a high amount of power. EE control provides policy for switching off/on the machine during operations and works at control level of the production planning and control hierarchy, differently from EE scheduling which works at planning level and plans jobs schedule and off/modes to machines over a specific period of time before production starts (Gahm et al., 2016).

The *non processing energy* is related to some machine components that keep executing their functions although the machine is not producing. For example, auxiliaries (e.g., chiller unit, hydraulic unit) allow to keep the machine in a ready-for-process state enabling machine tool cooling/heating, waste handling, and other machine conditions such that, whenever a part arrives, the part program can immediately start. Nowadays machine tools have power saving (*sleeping*) states to be used when the part flow is interrupted. The potential benefit of using a sleeping state relies in the reduction of the base load power request that is independent by machine load. Such EE control of machine tool state does not affect the manufacturing process and, if a proper startup procedure is executed after service interruptions, the quality of produced parts is guaranteed.

A recent EU report (Chan et al. (2015)) describes a total of 91 energy saving opportunities and, among them, integrated control systems account for the 14% of the total sector technical potential to obtain high efficiency equipment. Also, the increased uptake of energy management

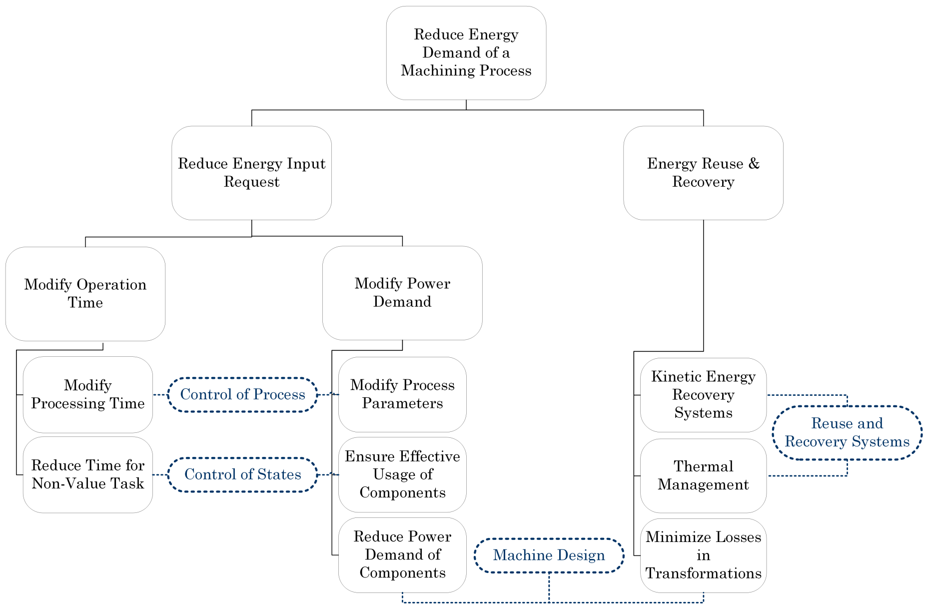


Figure 1: Classification of energy efficient measures at machine level.

systems accounts for an additional 4%. EE state control policies that switch off/on production equipment in manufacturing environments have been recently proposed in the literature and they are part of the aforementioned share. A switching off command triggers the machine in a sleeping state, where a subset of machine components are disabled. Then, a switching on command begins a startup procedure to reach the proper physical and thermal condition for working. All machine components are active at procedure completion and the machine is ready-for-process a new part. Referring to Figure 2, the machine could be switched off at t_1 reducing the power request and switched on in order to be ready before t_2.

Although state control strategies are promising, in several realistic cases the control is not advantageous because of significant startup energy or too long startup duration. For this reason, machine tool that have green functionalities (i.e., that enable switch off/on controls) are rarely working in "green mode" and control parameters are commonly selected either upon operator experience or using simplistic models. Indeed, a constant machine startup duration is commonly assumed. Nevertheless, during the startup, it might happen that one component ends its own procedure earlier than another. For example, the hydraulic unit might establish the proper pressure in the oil circuit before the chiller unit has stabilized the temperature. Therefore, each component has its own startup duration. Furthermore, such startup duration is often dependent on the amount of time the component has been switched off because pressure and temperature tend to reach environmental equilibrium.

This paper generalizes a time-based EE state control policy including a time-dependent startup time, depending on the length of the sleeping window, and multiple sleeping states, obtained by controlling separately machine components. A proper selection of switched-off components and a proper sequence of switching on commands can allow a synchronized startup completion improving machine energy efficiency. The approach can be applied to non-saturated

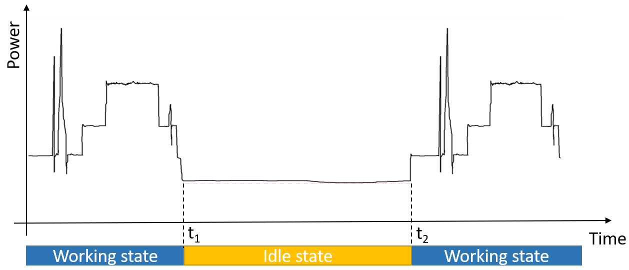


Figure 2: Qualitative representation of machine power profile: the idle state (from t_1 to t_2) appears between two working states of a not controlled machine.

machines working in complex production systems where disruption events in the system cause starvation on the controlled machine (e.g., failures of upstream processes, interruption of the flow, order delays).

1.1. Time-based control policies in the literature

In the common practice, when a machine tool starts executing the process on a certain part, it passes from the *idle* state to the *busy* state. At the completion of the process, the machine returns idle until the next cycle starts. These transitions represent the common behavior of a non-controlled machine tool, i.e., in an *Always On (AO)* policy.

Several works from the literature focus on EE control of machine state: the machine is assumed to be controllable such that it can be triggered in a sleeping state with low-power demand where the service is interrupted. The switching off command triggers the machine in a *standby* or *sleeping* state, and the service is interrupted. With the switching on command, the service can be resumed. The machine tool might need to visit a *startup* state before the service is resumed to reach the proper physical and thermal condition for working such that the quality of processed parts is guaranteed.

EE policies are defined by the control rule triggering the switching off/on commands. Although in literature the buffer-based policies are most commonly used as system complexity increases, for example in Brundage et al. (2016), Jia et al. (2016), Frigerio and Matta (2019), Zou et al. (2019), Wójcicki et al. (2021), they require several information and should be applied at system level. Time-based policies use a lower amount of information and can easily be applied at machine level in various production environments (from stand alone machines to production lines). Herewith we focus on the latter family of policies.

Time-based policies control the machine during starvation periods, i.e., interruptions of the part flow, which are affected by randomness. Control thresholds τ_{off} and τ_{on} are defined to respectively interrupt and resume the service according to the amount of time the machine waits for parts. The optimization problem incorporates an energy efficiency criterion in the objective function and a minimum production rate target as second objective or as a constraint. A list of literature works on time-based EE control policy in manufacturing follows: Mouzon et al. (2007), Li et al. (2011), Prabhu et al. (2012), Frigerio and Matta (2014, 2015) and Squeo et al. (2019).

Except for Prabhu et al. (2012) that did not consider any startup procedure, the body of literature models both constant and random duration of the startup procedure. Mouzon et al. (2007), Frigerio and Matta (2015) and Squeo et al. (2019) considered a constant duration assuming that such duration is conservatively chosen to assure that the startup procedure is completed. Other examples as Guo et al. (2012) and Maccio and Down (2013) modelled random duration of the startup procedure. In this case, the models did not consider any dependency between the startup duration and other stochastic processes involved and the parameters of the stochastic process should conservatively represent the behaviour of the machine. As an exception, Frigerio and Matta (2014) modelled a startup procedure as dependent on the time period the machine stays in the sleeping state which is closer to the physical behaviour of machine components. The authors focus on a time-based *Switch-Off* policy where the switch-on command was not optimized. Also, the optimization problem minimizes the expected energy consumed per part produced with no constraint on the expected production rate of machine. Hence, the considered problem is single-objective and unconstrained.

1.2. Multiple sleeping states in the literature

According to the literature, only one machine sleeping state is considered. As exceptions, multiple sleeping states are defined in Mashaei and Lennartson (2013), Li and Sun (2013) and Squeo et al. (2019). In Mashaei and Lennartson (2013), a scheduling problem is addressed and machines are assumed to have two sleeping states: *Hot Idle* and *Cold Idle*. However, only the Cold Idle requires a startup and the problem degenerates into a single-sleeping state problem. Li and Sun (2013) assumed that machines might have n sleeping states ($H_i | i = 1 \dots n$) where a startup is required to resume the service from state H_i. Given a certain production scenario, the control problem chooses the most advantageous state H_i to use whenever the machine in a production line is idle or blocked according to the estimated starvation/blocking periods. The addressed policy is a *Switch-off* policy where the switch-on command is not optimized and triggered by part arrival. Squeo et al. (2019) discussed the technological feasibility of multi-sleeping state control for CNC (Computer Numeric Control) machining centers. The authors addressed the problem of controlling machine tool components using time information, hence generating several sleeping states. The optimization problem minimizes the expected energy consumed per part produced with no constraint on the expected production rate of machine. Hence, the considered problem is single-objective and unconstrained.

1.3. Contribution and paper outline

Most of literature on EE state control policy provides over-conservative models for the evaluation of the startup time. This is consistent with the common practice where machine tool users run a part-program (e.g., a sequence of air cutting movements) with a fixed length as startup procedure, and eventually repeat such procedure a certain number of times according to environmental conditions (i.e., location of the plant and season). For example, machine temperature must be in a certain operative range to process and the time needed by the chiller unit depends on ambient temperature and increases as the machine actual temperature deviates from the desired interval. Energy can be reduced by properly reducing the startup length when not necessary, and this can be achieved by both considering that the startup duration is time-dependent and by controlling only a subset of components. This paper provides a model to better describe the startup phenomena and to evaluate the potential benefit of an EE state control policy under these assumptions.

This work develops and analyzes a general EE time-based control policy for machine tools including energy and production criteria. The proposed approach models a single resource with generally distributed arrivals; thus, it can be applied also to non-bottleneck machines included in more complex production systems. The contribution with respect to the literature is twofold. First, the standard *Single-sleep Switching Policy* (SP) is extended by modelling the machine startup time as dependent on the amount of time the machine has passed in the sleeping state. As a second contribution, the control is applied at component level toward the generalization of the *Multi-sleep Switching Policy* (MSP). Control variables represent the time to switch off/on the machine or machine components resulting in an optimal sequence of transitions between sleeping states. The startup transitory required to resume the readiness varies according to the control such that the selection of which component to switch is not trivial.

Further, the optimality of the proposed policies is discussed. A simulation-optimization algorithm is used: Discrete Event Simulation (DES) is used to evaluate machine performance in terms of energy consumption and machine production rate of a certain candidate solution while a searching method finds promising candidate solutions. The analysis is based on realistic CNC machining centers and numerical results are obtained by computer-based simulations. Results are compared with that of state-of-the-art policies.

The paper is divided into six sections. After the introduction and the state of the art (Section 1), Section 2 is dedicated to the description of EE control policies applied at machine level and assuming a constant startup duration. Section 3 focuses on the startup model and introduces time-dependent function in the SP. The control policy is moved at component level in Section 4. Numerical results follow in Section 5: the first part (5.1) is dedicated to the machine level, the second part (5.2) is dedicated to the component level. Section 6 concludes the work.

2. Policies at Machine Level with Constant Startup

This section is dedicated to state-of-the-art policies modelling a constant startup duration.

2.1. System Description and Assumptions

A single machine working a single part type is considered as the portion of system to be controlled.. We assume that the machine might be starving of raw parts and is never blocked. Also, the machine cannot fail while part processing time t_p is assumed to be constant. We assume that the part process is not affected by the control; therefore, without loss of generality, we consider a *cycle* as the time interval starting from the departure of a part and the beginning of the process for the next one. Therefore, the process is not included in the cycle. The cycle starts at $t = 0$ with the machine waiting for the part arrival and the duration of a cycle is stochastic.

It is assumed that an upstream mechanism manages the arrival process at machine and it is affected by failures such that machine starvation times X are distributed accordingly to a probability density function (pdf) $f(x)$ with mean t_a. Denote x the realization of X and, as a consequence, x is also the arrival time realization in a cycle. Also, it is assumed that the control is not affecting distribution $f(x)$. The results obtained in this paper are approximate whenever model assumptions are not verified.

We assume the machine can visit a set of states $j \in \mathbb{J}$ characterized by a constant power request w_j. The machine can be kept ready-for-process or it can be controlled for energy saving. A startup procedure is required to resume machine service and the duration of such procedure t_{su} is assumed constant.

2.2. Always On policy

As common practice, the machine is always kept *idle* (ready-for-process) while waiting for new parts and it becomes busy during part processing. Denote this policy as *Always On* (AO) policy. In this case, all machine components are enabled to maintain machine readiness and the machine requires w_r. The energy consumed by the machine is a cycle is a linear function of x: $\phi(x)^{AO} = w_r \cdot x$. Similarly for the cycle duration: $h(x)^{AO} = x$.

2.3. Switching policies

Given the set of machine components $\mathbb{C}$, assume that a sub-set of components $\mathbb{I} \subset \mathbb{C}$ can be controlled. A switch-off command trigger simultaneously components $i \in \mathbb{I}$ into an *off* state, and a switch-on command simultaneously wakes up components so as machine *startup* begins. Define the following *Single-sleep Switching* (SP) policy using two time-based thresholds τ_{off} and τ_{on} to control the state of the machine:

- Switch-off simultaneously components $i \in \mathbb{I}$ when τ_{off} has elapsed from the last departure;
- Switch-on simultaneously components $i \in \mathbb{I}$ when τ_{on} ($\tau_{\text{on}} > \tau_{\text{off}}$) has elapsed from the last departure or when next part arrives, whichever event happens first.

When components $i \in \mathbb{I}$ are *off*, the machine enters in a *sleeping* state requiring w_s. For the whole startup duration t_{su}, the machine require w_{su}. We also assume that $w_{\text{su}} > w_r > w_s \geq 0$ to realistically represent manufacturing equipment that commonly require high power while executing the startup. When the part waits for machine readiness, an additional power request w_q is considered.

Denote the vector of control parameters $\boldsymbol{\tau} = \{\tau_{\text{off}}, \tau_{\text{on}}\}$. The cycle duration $h(x, \boldsymbol{\tau})$ is:

$$h(x,\boldsymbol{\tau}) = \begin{cases} x & \text{for } x \leq \tau_{\text{off}} \\ x + t_{\text{su}} & \text{for } \tau_{\text{off}} < x \leq \tau_{\text{on}} \\ t_{\text{su}} + \tau_{\text{on}} & \text{for } \tau_{\text{on}} < x \leq \tau_{\text{on}} + t_{\text{su}} \\ x & \text{for } x > \tau_{\text{on}} + t_{\text{su}} \end{cases} \tag{1}$$

The energy consumed in a cycle $\phi(x, \boldsymbol{\tau})$ is:

$$\phi(x,\boldsymbol{\tau}) = \phi_{\text{mach}}(x,\boldsymbol{\tau}) + w_q \cdot \max\{0, h(x,\boldsymbol{\tau}) - x\} \tag{2}$$

where the second term is the part-holding energy required to hold the part waiting for machine readiness, and the first term is the energy consumed by the machine. In details:

$$\phi_{\text{mach}}(x,\boldsymbol{\tau}) = \begin{cases} w_r \cdot x & \text{for } x \leq \tau_{\text{off}} \\ w_r \cdot \tau_{\text{off}} + w_{\text{su}} \cdot t_{\text{su}} + w_s \cdot (x - \tau_{\text{off}}) & \text{for } \tau_{\text{off}} < x \leq \tau_{\text{on}} \\ w_r \cdot \tau_{\text{off}} + w_{\text{su}} \cdot t_{\text{su}} + w_s \cdot (\tau_{\text{on}} - \tau_{\text{off}}) & \text{for } \tau_{\text{on}} < x \leq \tau_{\text{on}} + t_{\text{su}} \\ w_r \cdot (\tau_{\text{off}} + x - \tau_{\text{on}}) + w_{\text{su}} \cdot t_{\text{su}} + w_s \cdot (\tau_{\text{on}} - \tau_{\text{off}}) & \text{for } x \geq \tau_{\text{on}} + t_{\text{su}} \end{cases} \tag{3}$$

An illustrative example is represented in Figure 3. SP increases the cycle duration when $x \in (10; 80)$ s resulting in a throughput reduction of the machine (i.e., whenever the arrival happens after the switch-off and before the completion of startup procedure). Nevertheless, the energy consumed with SP increases when the arrival happens right after the switch-off control; while the advantage appears for large arrivals ($x > 60$ s). Clearly, the control parameters should properly selected to obtain savings.

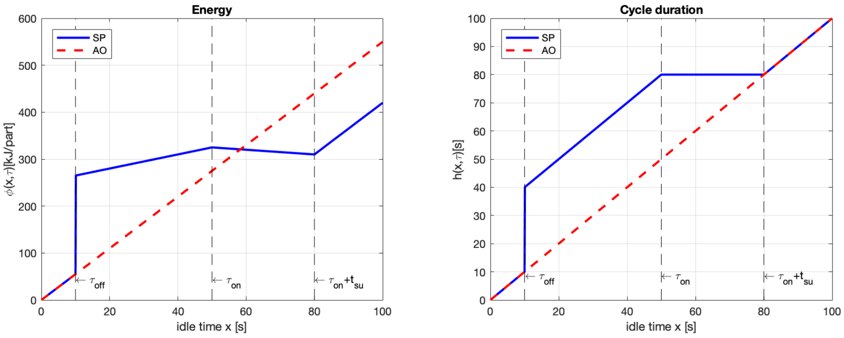


Figure 3: Energy consumed per cycle $\phi(x, \boldsymbol{\tau})$ and cycle duration $h(x, \boldsymbol{\tau})$ under AO and SP with $\tau_{\text{off}} = 10$ s and $\tau_{\text{on}} = 50$ s. Machine data are: $w_r = 5.5$ kW, $w_s = 1.5$ kW, $w_{\text{su}} = 6.5$ kW, $t_{\text{su}} = 30$ s, and $w_q = 0.5$ kW.

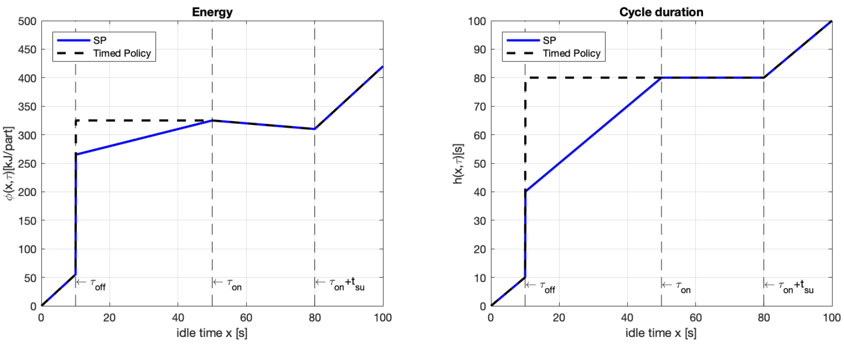


Figure 4: Comparison of SP and Timed policy in terms of energy consumed per cycle $\phi(x, \boldsymbol{\tau})$ and cycle duration $h(x, \boldsymbol{\tau})$ ($w_r = 5.5$ kW, $w_s = 1.5$ kW, $w_{\text{su}} = 6.5$ kW, $t_{\text{su}} = 30$ s, $w_q = 0.5$ kW, $\tau_{\text{off}} = 10$ s, and $\tau_{\text{on}} = 50$ s).

The machine is never switched off when $\tau_{\text{off}} = \infty$, and it is switched only upon part arrival when $\tau_{\text{on}} = \infty$. Trivially, when $\tau_{\text{off}} = \infty$ and $\tau_{\text{on}} = \infty$, the SP behaves as the AO policy. Simpler policies can be defined:

- *Switch-Off policy*: the switch-on transition is triggered only at part arrival, i.e., $\tau_{\text{on}} = \infty$;
- *Switch-On policy*: the switch-off transition is triggered at $\tau_{\text{off}} = 0$;
- *Timed policy*: the switch-on transition is triggered only at τ_{on} and not when the part arrives.

As demonstrated in Frigerio and Matta (2015), Switch-Off and Switch-On policies are optimal when the starvation time distribution $f(x)$ is, respectively, with Decreasing Hazard Rate (DHR) and Increasing Hazard Rate (IHR). The arrival probability decreases in time for DHRs, whilst it increases while approaching the mode of the distribution for IHRs. In addition, we herewith prove that the *Timed policy* is always dominated by the SP. The proof is graphical as in Figure 4. Indeed, the energy function of SP is always lower or equal to that of a Timed policy, as well as the cycle duration.

2.4. Optimization Problem

Solution τ^* solves the following optimization problem:

$$\min_{\boldsymbol{\tau}} \quad z(\boldsymbol{\tau}) = \mathbb{E}_X[\phi(x,\boldsymbol{\tau})] + \alpha \cdot \max\{0, \theta_{\text{target}} - \mathbb{E}_X[\theta(x,\boldsymbol{\tau})]\} \tag{4}$$

$$\text{Subject to:} \quad \tau_{\text{on}} > \tau_{\text{off}} \tag{5}$$

$$\tau_{\text{off}}, \tau_{\text{on}} \in \mathbb{R}_0^+ \tag{6}$$

Constraint (6) defines the domain of decision variables and constraint (5) represents feasibility constraint existing among control parameters such that each switch-on command must happen after the switch-off command. Problem objective in equation (4) is the minimization of two terms. The first term $\mathbb{E}_X[\phi(x,\boldsymbol{\tau})]$ represents the expected energy consumed per part produced. The second term represents a penalty term whenever the expected production rate $\mathbb{E}_X[\theta(x,\boldsymbol{\tau})]$ does not meet a certain minimum target θ_{target}. The weight $\alpha \in \mathbb{R}_0^+$ penalizes solutions where $\mathbb{E}_X[\theta(x,\boldsymbol{\tau})] < \theta_{\text{target}}$ such that as α increases, the second term becomes more important. On the contrary, when α decreases, the first term becomes more important and the energy is minimized while accepting machine production rate to be below the target. The extreme case where $\alpha = 0$ represents a problem without any throughput constraint.

The expected value of energy $\mathbb{E}_X[\phi(x,\boldsymbol{\tau})]$ is obtained as follows:

$$\mathbb{E}_X[\phi(x,\boldsymbol{\tau})] = \int_0^\infty \phi(x,\boldsymbol{\tau}) \cdot f(x)\, dx \tag{7}$$

Since the processing time is deterministic, the expected production rate $\mathbb{E}_X[\theta(x,\boldsymbol{\tau})]$ is obtained as follows:

$$\mathbb{E}_X[\theta(x,\boldsymbol{\tau})] = \frac{1}{t_p + \mathbb{E}_X[h(x,\boldsymbol{\tau})]} \tag{8}$$

where $\mathbb{E}_X[h(x,\boldsymbol{\tau})] = \int_0^\infty h(x,\boldsymbol{\tau}) \cdot f(x)\, dx$ is the expected value of the cycle duration. The target θ_{target} cannot be higher than that obtained with an AO policy: $\theta_{\text{target}} = (1-\varepsilon)(t_p + t_a)^{-1}$ so that $\varepsilon \in [0; 1]$ is the maximum expected throughput loss.

3. Policies at Machine Level with Time-dependent Startup

After a service interruption, it is possible that a machine tool can directly handle an operation without demanding a startup procedure, or that an amount of time is needed to properly prepare the machine. In the latter case, machine startup typically concerns time-dependent physical phenomena. For instance, machine chiller maintains the temperature within a certain range $[T_\ell, T_h]$ to maintain the machine ready-for-process. Assuming that in the sleeping state the chiller is not working, the temperature deviates from the desired range and tends to reach the equilibrium with ambient temperature $T_a \notin [T_\ell, T_h]$. Machine startup will be completed when the temperature is in the range and the amount of time required varies. If the switch off/on commands are distant in time, the startup will be longer and vice-versa.

In manufacturing, it is reasonable to assume that a sequence of activities is performed to resume the service after a stop. This includes, for example, the PLC restart, some security tests, the switch on of lights and displays, and the availability check of the machine sub-systems. Thus, the machine startup duration should be bounded between a minimum time t_0, to perform such tasks, and a maximum time t_h. The maximum duration t_h will be needed to complete machine startup when the machine is in equilibrium with the environmental conditions (i.e., after a long stop). Also, the startup duration can reasonably be assumed to be monotonically increasing over the time spent in the sleeping state.

We model the startup duration $t_{\text{su}} = t_{\text{su}}(y)$ as a continuous, bounded, and monotonically increasing function of y, where y is the time spent in the sleeping state during a certain cycle:

$$y = \max\{0, \min\{x - \tau_{\text{off}}, \tau_{\text{on}} - \tau_{\text{off}}\}\} \tag{9}$$

The optimization problem as in equations (4)–(6) increases complexity since the search of the optimal control τ^*_{off} is not independent from control τ_{on}, and vice-versa.

In order to represent several situations, some alternative functions are proposed to model the startup – linear (10), quadratic (11), cubic (12) – and they are expressed in their general forms:

$$t_{\text{su}}(y) = \min\left\{t_0 + \frac{\beta}{\delta}y, t_h\right\} \tag{10}$$

$$t_{\text{su}}(y) = \min\left\{t_0 + \frac{\beta}{\delta^2}y^2, t_h\right\} \tag{11}$$

$$t_{\text{su}}(y) = \min\left\{t_0 + \frac{\beta}{\delta^3}(y - \delta)^3, t_h\right\} \tag{12}$$

where β is the time range of the possible startup duration ($\beta = t_h - t_0$) and δ is the instant at which the startup duration reaches the maximum value. A high values of t_h refers to big-size machine tools that need time to reach thermal stability; large δ values mean that the transition from a fast startup (t_0) and a long startup (t_h) requires a long time, e.g., the thermal inertia is high. A small value of β represents machine tools with an almost constant startup; large β values mean that the startup duration varies significantly in time, probably due to machine size or process requirements, e.g. high quality. High β values are often related to high t_h as well. Several other continuous functions can be used with no particular changes to the developed analysis (examples are in Frigerio and Matta (2014)).

An illustrative example is in Figure 5 where different functions of $t_{\text{su}}(\cdot)$ are used to model the startup time. Trivially, the model with constant startup duration $t_{\text{su}} = 50$ s is more consuming and its cycle duration is longer. The comparison shows how the different functions $t_{\text{su}}(\cdot)$ affect the problem depending on how fast the startup reaches its maximum duration t_h, which happens at $x = \tau_{\text{off}} + \delta$. It is noteworthy that, whenever $\tau_{\text{on}} - \tau_{\text{off}} < \delta$, the startup duration never reaches its maximum.

4. Multisleep control policy

The second main contribution of this paper moves the control policy at component level assuming that machine components can independently be switched off/on instead of controlling the whole machine. Therefore, we assume that the sub-set $\mathbb{I}$ contains components that can be controlled with individual commands.

Define *enabled* the state of a component that is able to perform its functions and *off* the energy-saving state of the component. A dedicated switch-off command might trigger component i into its *off* state and a switch on command might start the *startup* procedure of component i before it can reach the *enabled* state. Figure 6 represents an illustrative case where the startups of machine components require a different amount of time. As a consequence, components $i = 1$

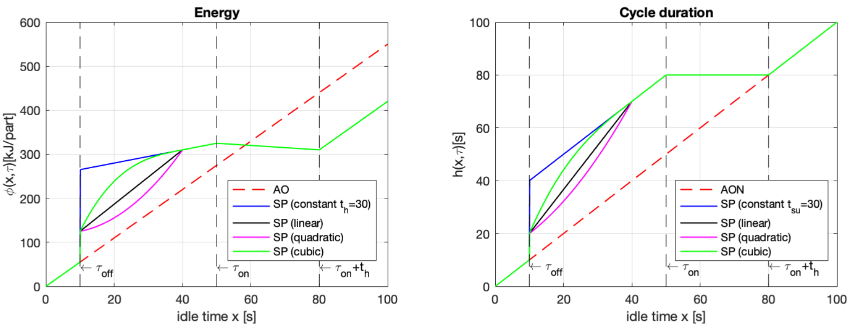


Figure 5: Effect of different functions $t_{su}(\cdot)$ on the energy consumed per cycle $\phi(x, \boldsymbol{\tau})$ and the cycle duration $h(x, \boldsymbol{\tau})$ (w_r = 5.5 kW, w_s = 1.5 kW, w_{su} = 6.5 kW, w_q = 0.5 kW, τ_{off} = 10 s, τ_{on} = 50 s, t_h = 30 s, t_0 = 10 s and δ = 30 s).

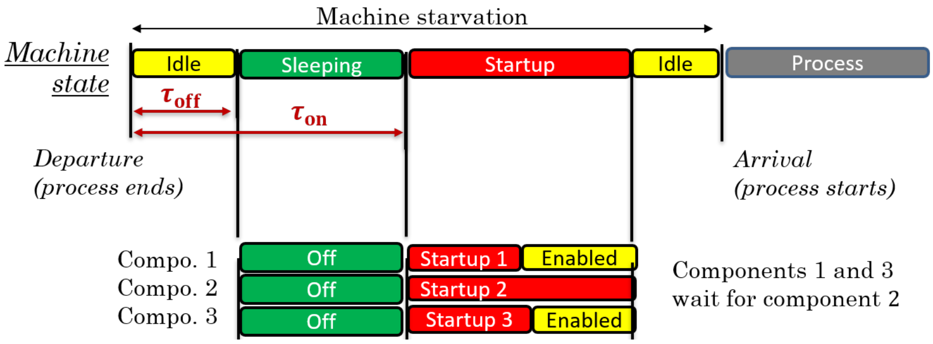


Figure 6: Illustrative example of a machine composed by three components that is controlled with the SP. The state of components are highlighted.

and $i = 3$ must wait for the startup completion of component $i = 2$. Trivially, the machine returns idle only when all components are *enabled*.

A time-based control policy acting at component level has been proposed in Squeo et al. (2019) as *Multi-sleep Switching Policy* (MSP). Thresholds $\tau_{off,i}$ and $\tau_{on,i}$ are used to control the state of each component $i \in \mathbb{I}$. Denote the vector of control parameters $\boldsymbol{\tau}^{MSP} = \{\tau_{off,i}, \tau_{on,i} | i \in \mathbb{I}\}$. The SP can be seen as a particular case of MSP where $\tau_{off,i} = \tau_{off}$ and $\tau_{on,i} = \tau_{on}$ for each component $i \in \mathbb{I}$. When components are controlled, their startup can be synchronized in completion so as energy is saved. Furthermore, components with long and highly demanding startup procedure can be kept enabled, i.e., $\tau_{off,i} = \infty$. As a result, the machine can visit a sequence of different sleeping states according to the combination of component states. This policy is promising for situations where the throughput target is high.

Given that more than one component can be controlled, it might happen that component i must wait for another component readiness. Machine components might have their own startup procedure, i.e., startup duration function. Clearly, machine readiness is achieved when all components has completed their own startup procedure and *enabled* components will consume additional energy while waiting for those is *startup*.

The total cycle duration is obtained as:

$$h(x, \boldsymbol{\tau})^{\mathrm{MSP}} = \max_{i \in \mathbb{I}} h_i(x, \tau_{\mathrm{off},i}, \tau_{\mathrm{on},i}) \tag{13}$$

where $h_i(x, \tau_{\mathrm{off},i}, \tau_{\mathrm{on},i})$ is the cycle duration assuming that only component i is controlled, i.e., $\tau_{\mathrm{off},j} = \infty | \forall j \neq i$. The energy function becomes:

$$\phi(x, \boldsymbol{\tau})^{\mathrm{MSP}} = \phi_{\mathrm{mach}}(x, \boldsymbol{\tau})^{\mathrm{MSP}} + \phi_{\mathrm{holding}}(x, \boldsymbol{\tau})^{\mathrm{MSP}}. \tag{14}$$

In details, the energy consumed to hold the part while waiting for machine readiness becomes:

$$\phi_{\mathrm{holding}}(x, \boldsymbol{\tau})^{\mathrm{MSP}} = w_q \cdot \max\{0, h(x, \boldsymbol{\tau})^{\mathrm{MSP}} - x\}. \tag{15}$$

Machine energy demand $\phi_{\mathrm{mach}}(x, \boldsymbol{\tau})^{\mathrm{MSP}}$ is:

$$\begin{aligned} \phi_{\mathrm{mach}}(x, \tau_{\mathrm{off},i}, \tau_{\mathrm{on},i}) \quad = \quad & w_0 \cdot h(x, \boldsymbol{\tau})^{\mathrm{MSP}} \\ & + \sum_{i \in \mathbb{I}} \{\phi_i(x, \tau_{\mathrm{off},i}, \tau_{\mathrm{on},i}) + \phi_{i,\mathrm{wait}}(x, \boldsymbol{\tau})\} \end{aligned} \tag{16}$$

where the first term is the energy request of all machine components that are not included in set $\mathbb{I}$ because not controllable, i.e., $j \in (\overline{\mathbb{C} \cap \mathbb{I}})$. The second term is the sum of component $i \in \mathbb{I}$ energy demands. Given the power $w_{r,i}$, $w_{s,i}$, and $w_{\mathrm{su},i}$ consumed by component i in state *enabled, off* and *startup*, respectively, the component consumes $\phi_i(\cdot)$ as in equation (3) (applied to a single component i), and an additional energy $\phi_{i,\mathrm{wait}}(\cdot)$ when the component waits for machine readiness. The latter is:

$$\phi_{i,\mathrm{wait}}(x, \boldsymbol{\tau}) = w_{r,i} \cdot [h(x, \boldsymbol{\tau})^{\mathrm{MSP}} - h_i(x, \tau_{\mathrm{off},i}, \tau_{\mathrm{on},i})]. \tag{17}$$

Figure 7 illustrates a case where two components are controlled. The two components are switched off respectively at 5 and 10 s increasing the energy required by MSP and cycle duration which increases in x because of the increase of startup duration. At 30 s, component $i = 2$ is switched on but component $i = 1$ stays in standby until its switch on at 70 s. Energy and cycle duration functions increase complexity as the number of components increases.

5. Numerical analysis

The numerical analysis is divided in two parts where several simulated scenarios are investigated varying the controlled machine, the arrival distribution and problem constraints: the first part (Section 5.1) is focused on machine policies with time-dependent startup, the second part (Section 5.2) is devoted to policies applied at component level. Section 5.3 collects summarizing remarks.

5.1. Part 1: Machine level and SP with time-dependent startup

The scope of this numerical analysis is to analyze how the objective function changes when a time-dependent startup is included and to analyze the solution of the problem. The optimization problem is solved in Matlab® with *Multistart* solver: a gradient based method with multiple starting points such that the risk of stopping in a local minimum is reduced. The number of starting points is set equal to 10. Also, experiments are replicated to verify the robustness of the solver.

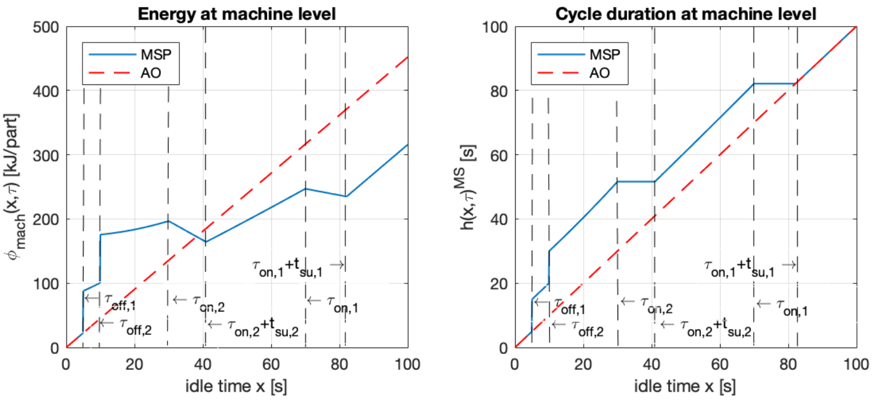


Figure 7: Energy consumed per cycle $\phi_{\text{mach}}(x, \boldsymbol{\tau})$ and holding time $h(x, \boldsymbol{\tau})^{\text{MSP}}$ assuming two controllable components with quadratic startup duration. ($w_r = [2, 2]$ kW, $w_s = [0, 0]$ kW, $w_{\text{su}} = [3, 3]$ kW, $w_q = 1$ kW, $w_0 = 0.52$ kW, $\tau_{\text{off}} = [5, 10]$ s, $\tau_{\text{on}} = [70, 30]$ s, $t_h = [30, 60]$ s, $t_0 = [10, 20]$ s and $\delta = [200, 100]$ s)

5.1.1. Experiment description

We consider the same machining center as in Frigerio and Matta (2014) with $w_r = 5.35$ kW, $w_s = 0.52$ kW, $w_{\text{su}} = 6$ kW and $w_q = 1$ kW, and $t_0 = 10$ s. The machine is a CNC machining center with 700mmX700mmX800mm of working cube, five linear axes, horizontal spindle, and a local chiller cooling both spindle and axes. The machine commonly executes machining operations (milling, drilling, finishing) for automotive purpose. Data are obtained by the use of a power meter that elaborates the three-phase voltages and the linked current, measured through LEM sensors. The problem is solved without throughput constraint ($\alpha = 0$). Four experiments are simulated varying the starvation time distribution and the startup duration function (i.e., constant, linear (equation 10), quadratic (equation 11), and cubic (equation 12) functions are used):

1. Experiment 1 (Exp1) considers a Weibull distribution with DHR (shape $k = 0.6$) and mean $t_a = 49$ s, and machine maximum startup duration $t_h = 50$ s is reached after 5 minutes ($\delta = 300$ s).
2. Experiment 2 (Exp2): same as Exp1 except that the startup duration increases faster, i.e., $\delta = 60$ s.
3. Experiment 3 (Exp3): same as Exp1 except that the maximum duration is higher, i.e., $t_h = 150$ s.
4. Experiment 4 (Exp4): same as Exp1 except for the Weibull distribution that has IHR (shape $k = 5$) and mean $t_a = 30$ s.

Experiments 1, 2, 3 and 4 have been replicated adding the request of a target expected throughput to be satisfied by the chosen policy. We have analyzed the cases where the target throughput is the 95%, the 98% and the 99% of that obtained with the AO policy (i.e., $\varepsilon = \{0.05; 0.02; 0.01\}$ respectively). A high weight α is chosen ($\alpha = 3.6 \cdot 10^8$) such that the target is met.

5.1.2. Experiment results

For the DHR distribution of Exp1, Exp2, and Exp3, the AO policy obtains an expected energy of 262.2 kJ/part and an expected throughput of 16.59 part/h. For the IHR distribution of Exp4,

Exp	δ [s]	t_h [s]	$t_{su}(\cdot)$	$\boldsymbol{\tau}^*$ [s]	$E_X[\phi(x, \boldsymbol{\tau})]$	$E_X[\theta(x, \boldsymbol{\tau})]$
Exp1	300	50	constant (t_h)	$\{67.1; \infty\}$	234.8 kJ/part	15.81 part/h
Exp1	300	50	linear	$\{2; \infty\}$	133.7 kJ/part	15.58 part/h
Exp1	300	50	quadratic	$\{1.4; \infty\}$	112.5 kJ/part	15.76 part/h
Exp1	300	50	cubic	$\{4.6; \infty\}$	169.1 kJ/part	15.34 part/h
Exp2	60	50	constant (t_h)	$\{67; \infty\}$	234.8 kJ/part	15.81 part/h
Exp2	60	50	linear	$\{13.8; \infty\}$	201.9 kJ/part	15.29 part/h
Exp2	60	50	quadratic	$\{5.2; \infty\}$	184.0 kJ/part	15.22 part/h
Exp2	60	50	cubic	$\{34.7; \infty\}$	220.7 kJ/part	15.53 part/h
Exp3	300	150	constant (t_h)	$\{\infty; \infty\}$	262.7 kJ/part	16.59 part/h
Exp3	300	150	linear	$\{14.1; 146.2\}$	227.4 kJ/part	15.56 part/h
Exp3	300	150	quadratic	$\{2.0; 194.9\}$	159.1 kJ/part	15.69 part/h
Exp3	300	150	cubic	$\{\infty; \infty\}$	262.2 kJ/part	16.59 part/h
Exp4	300	50	constant (t_h)	$\{\infty; \infty\}$	160.8 kJ/part	18.18 part/h
Exp4	300	50	linear	$\{0; 21\}$	98.2 kJ/part	17.77 part/h
Exp4	300	50	quadratic	$\{0; 25.9\}$	83.2 kJ/part	17.69 part/h
Exp4	300	50	cubic	$\{0; 15.3\}$	117.8 kJ/part	17.89 part/h

Table 1: Results of Part 1 – Optimal control parameters τ^*, expected energy $E_X[\phi(x, \tau)]$, and expected production rate $E_X[\theta(x, \tau)]$ of experiments 1, 2, 3 and 4. The mean of 5 replications is reported, whilst 95% Confidence Interval (CI) is not reported since smaller than 1%.

the AO policy obtains 160.8 kJ/part and 18.18 part/h. Other results are reported in Table 1.

In Exp1, Exp2, when a constant startup $t_{su} = t_h = 50$ is modelled, the SP is applied and obtains 10% of energy saving compared to the AO policy. The optimal parameters of SP are $\boldsymbol{\tau}^* = \{67; \infty\}$ so as the machine is switched off 67 s after departure and switched on when next arrival occurs. In Exp 3 and Exp4, the SP modelling a constant startup is not advantageous compared to the AO policy. The choice of modelling a time-dependent startup is significant and allows higher savings. Indeed, to model a constant startup is over-conservative.

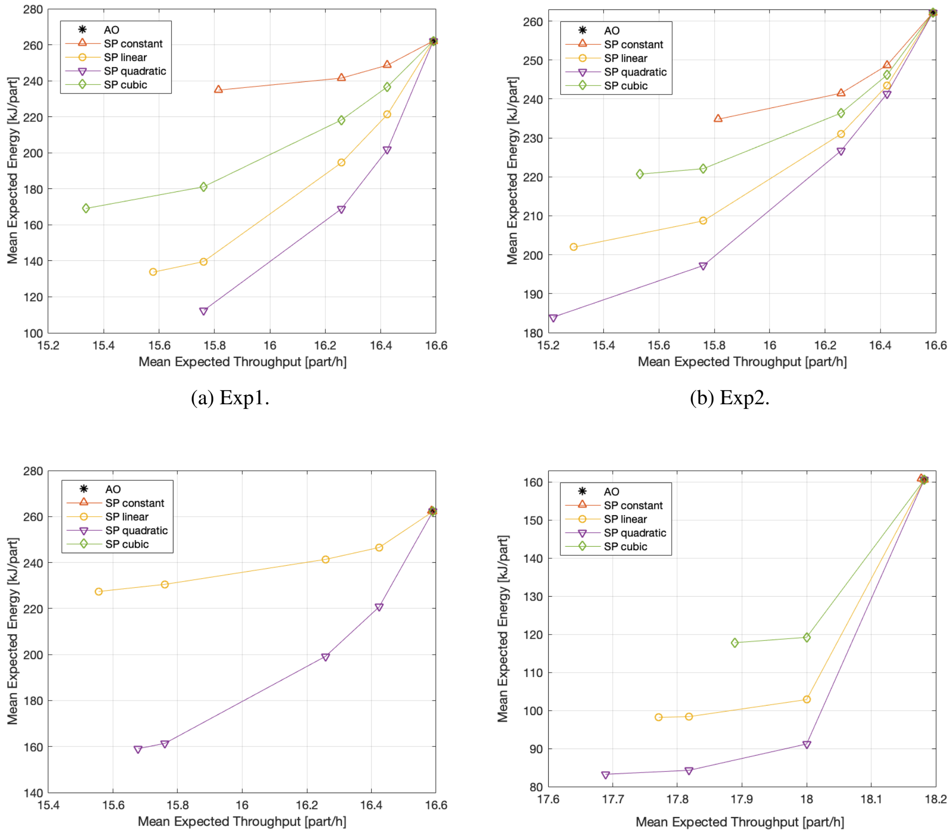
In Exp 3 and Exp4, the control parameters are set such that the startup duration is limited by a proper choice of τ^*_{on}. For example in Exp 4, the optimal parameters for the SP with a linear modelling of the startup duration are to switch off the machine immediately ($\tau^*_{off} = 0$) and to switch on after 21 s so that the startup duration is at most 19.8 s.

5.1.3. Constrained optimization

When a certain target throughput is required, the SP becomes more conservative. Referring to Figure 8a and Figure 8b, the optimized control obtains less energy saving in order to satisfy the throughput target and slowly converges to the AO policy.

As for Exp1 and Exp2, the optimal control parameter τ^*_{off} increases as the throughput target increases postponing the switch-off control. The optimal controls are reported in Table 2. For example, the SP with linear startup switches off the machine after 2 s when the problem is not constrained (Table 1); τ^*_{off} increases up to 92.1 s when $\varepsilon = 0.01$ (Table 2). A similar effect appears in Exp4 where the switch-on control parameter τ^*_{on} decreases to anticipate machine readiness (Figure 8d). For example, the startup command of "SP linear" decreases to 16.3 s from 21 s of the unconstrained case.

Results of Exp3 are more variable in terms of control parameters (see Table 2) but stable in terms of objective function (see Figure 8c) indicating that the objective function is very flat in this case.



(a) Exp1.

(b) Exp2.

(c) Exp3.

(d) Exp4.

Figure 8: Results of Part 1: Mean expected energy and throughput obtained in constrained problems (5 replications, CI95% is not reported because smaller than 1%).

5.2. Part 2: Component level and MSP with time-dependent startup

The scope of this numerical analysis is to analyze the control at component level when a time-dependent startup is included. The objective function in equation (4) is estimated with discrete event simulation so as machine energy demand $\phi(x,\tau)^{\mathrm{MSP}}$ and cycle duration $h(x,\tau)^{\mathrm{MSP}}$ are computed for a certain number of observations x and then combined to obtain the expected values of energy per part and production rate. Each estimation includes N produced parts and R independent replications. Common random number are used to evaluate candidate solutions (Law (2015)). Parameters N and R are chosen to assure a confidence interval of around 1% on the estimated performance.

Exp	$t_{\text{su}}(\cdot)$	$\varepsilon = 0.05$	$\varepsilon = 0.02$	$\varepsilon = 0.01$
Exp1	constant (t_h)	$\{67.1; \infty\}$	$\{141.5; \infty\}$	$\{215.5; \infty\}$
Exp1	linear	$\{9.1; \infty\}$	$\{54.5; \infty\}$	$\{92.1; \infty\}$
Exp1	quadratic	$\{1.4; \infty\}$	$\{37.5; \infty\}$	$\{66.9; \infty\}$
Exp1	cubic	$\{26.0; \infty\}$	$\{99.0; \infty\}$	$\{170.4; \infty\}$
Exp2	constant (t_h)	$\{67.1; \infty\}$	$\{141.5; \infty\}$	$\{215.5; \infty\}$
Exp2	linear	$\{41.8; \infty\}$	$\{119.9; \infty\}$	$\{193.3; \infty\}$
Exp2	quadratic	$\{34.7; \infty\}$	$\{112.3; \infty\}$	$\{185.7; \infty\}$
Exp2	cubic	$\{51.4; \infty\}$	$\{130.6; \infty\}$	$\{203.8; \infty\}$
Exp3	constant (t_h)	$\{\infty; \infty\}$	$\{\infty; \infty\}$	$\{\infty; \infty\}$
Exp3	linear	$\{33.5 \pm 0.3; 291.6 \pm 4.9\}$	$\{80.5 \pm 0.6; 205.1 \pm 1.8\}$	$\{81.8 \pm 0.5; 136.9 \pm 0.8\}$
Exp3	quadratic	$\{4.9 \pm 0.1; 196.8 \pm 0.5\}$	$\{29.7 \pm 0.3; 139.7 \pm 1.3\}$	$\{79.0 \pm 0.4; 202.5 \pm 1.2\}$
Exp3	cubic	$\{\infty; \infty\}$	$\{\infty; \infty\}$	$\{\infty; \infty\}$
Exp4	constant (t_h)	$\{\infty; \infty\}$	$\{\infty; \infty\}$	$\{\infty; \infty\}$
Exp4	linear	$\{0; 21\}$	$\{0; 20.2\}$	$\{0; 16.3\}$
Exp4	quadratic	$\{0; 25.9\}$	$\{0; 23.1\}$	$\{0; 18.5\}$
Exp4	cubic	$\{0; 15.3\}$	$\{0; 15.3\}$	$\{0; 13.3\}$

Table 2: Results of Part 1 – Optimal control parameters τ^* [s] of experiments 1, 2, 3 and 4 under throughput constraint. The mean of 5 replications is reported. CI95% is reported when larger than 1%.

The optimization problem is solved in Matlab® with a *Genetic Algorithm (GA)*. The solution provided with the GA is improved with a local search using *fmincon*, a gradient-based function of Matlab®. Parameters of the GA have been calibrated[1] using experiments in Section 5.1 such that the solution obtained with simulation and GA are not significantly different from those obtained with the analytical function.

5.2.1. Experiment description

We consider a fictitious machine composed by four controllable and independent components with equal power requests: $w_{r,i} = 2$ kW, $w_{\text{su},i} = 2.4$ kW, and $w_{s,i} = 0$ kW. Machine processing time is $t_p = 100$ s, no holding cost is included ($w_q = 0$) and all machine components can be controlled ($w_0 = 0$). In the first experiment (Exp5), component startup duration is modelled as constant but it varies among components such that $t_{\text{su},1} = 0$ s, $t_{\text{su},2} = 5$ s, $t_{\text{su},3} = 10$ s, and $t_{\text{su},4} = 30$ s. For instance, component $i = 1$ represents motor axis, lights and displays that do not have a significant startup transitory; whilst component $i = 4$ represents the chiller unit that requires a significant time to reach the proper temperature, or the exhaust gas extractor that requires time to ensure a proper air flow. A Weibull distribution with shape $k = 10$ and mean t_a is considered for machine starvation times such that the stochastic process has IHR. In order to represent cases with different theoretical machine utilization $u = t_p/(t_p + t_a)$, seven scenarios are created by varying t_a. Each problem is solved using $R = 5$ and $N = 2500$ for simulation, and relaxing the target throughput ($\varepsilon = 1$). Experiment 6 (Exp6) is as Exp5, but the startup duration

[1]The GA selects candidates using a fitness scaling function based on candidate ranking, a certain elite is guaranteed to survive in next generations, and the Arithmetic crossover function and the Adaptive Feasible mutation function are used to generate new candidates. Other parameters are: population size of 50 candidates, elite fraction of 0.05, crossover fraction of 0.5, and fitness tolerance of 10^{-6}. The computational budget is fixed at 1000 candidate evaluations for SP and 4000 for MSP.

Component i (or group of)	Startup $w_{su,i}$	Enabled $w_{r,i}$	Off $w_{s,i}$
Motor chiller unit $i = 1$	2 kW	0.6 kW	0
Hydraulic unit $i = 2$	0.75 kW	0.225 kW	0
Coolant extraction pump $i = 3$	0.24 kW	0.072 kW	0
Chip conveyor and coolant pumps $i = 4$	–	2.08 kW	0
	Startup function		
Motor chiller unit $i = 1$	Quadratic: $t_0 = 3$ s;	$t_h = 30$ s;	$\delta = 100$ s
Hydraulic unit $i = 2$	Constant: $t_h = 5$ s		
Coolant extraction pump $i = 3$	Linear: $t_0 = 0$ s;	$t_h = 10$ s;	$\delta = 30$ s

Table 3: Part 2 – Machine characterization for experiment 7. Not controllable components consumes $w_0 = 0.6$ kW.

of each component is modelled as linear (see equation (10)): $t_{0,i} = 0$ s and $\delta_i = 100$ s. Exp5 enables the comparison among SP and MSP, whilst Exp6 extends Exp5 modelling the startup duration as time dependent.

For experiment 7 (Exp7), we consider a CNC machining center machining center with 5-axis, vertical spindle, 30 kW of installed power and 600mmX450mmX450mm working cube. Nominal power requests are used to obtain power requests of components. Startup could not be characterized experimentally, but according to operator experience, it is assumed that a significant startup belongs to chiller unit, hydraulic unit, and extraction pump. Machine components are characterized as in Table 3 and the problem is solved with a throughput constraint ($\alpha = 3.6 \cdot 10^8$ and $\varepsilon = 0.01$). Within the simulation, the machine is assumed to be fed by a previous production stage such that a new part arrives in $t_a = 5$ s. When the upstream process suffers of a disruptive event, the arrival becomes stochastic and the starvation time increases of a stochastic quantity. We assume that starvation time X increases in 20% of occurrences and that the increase follows a Weibull distribution with mean 80 s and shape $k = 15$ (due to upstream failures) such that machine utilization with AO policy is around 0.86. Holding energy is $w_q = 0.5$ kW and processing time is $t_p = 100$ s.

5.2.2. *Result comparison for experiments 5 and 6*

Energy and production rate obtained for Exp5 and Exp6 are represented in Figure 9 and the optimal controls τ^* are in Table 4. The AO policy is considered as reference for the evaluated scenarios. As in Figure 9, the expected energy consumed per part decreases as machine utilization increases since the mean starvation time t_a decreases so as the idle time.

The SP with constant startup is the state-of-the-art policy. The machine is switched off immediately ($\tau^*_{\text{off}} = 0$) and switched on at arrival ($\tau^*_{\text{on}} = \infty$) in scenarios $u \in [0.6; 0.75]$. When the machine is highly saturated ($u \in [0.8; 0.9]$, it is kept always on ($\boldsymbol{\tau}^* = (\infty; \infty)$). In Exp5, with constant startup, the SP is dominated by MSP both in terms of energy and production rate (”SP (constant)” and ”MSP (constant)” in Figure 9). Better results are obtained because the MSP allows to control only a subset of components. For example, for $u \in [0.75; 0.9]$ component $i = 4$ is kept idle. Focusing on scenario $u = 0.75$, component $i = 3$ starts its startup as first at $t = 25.5$ s, then $i = 2$ at $t = 30.5$ s. Component $i = 1$ is switched on at arrival because it does not have any startup. In this case, all components are ready at $t = 35.5$ s.

Exp6 includes a linear startup duration and results are in Figure 9 and Table 4. The potential of SP increases but the MSP is more effective (”SP (linear)” and ”MSP (linear)” in Figure 9). The switch-on commands are modulated such that too long startups are avoided and that components

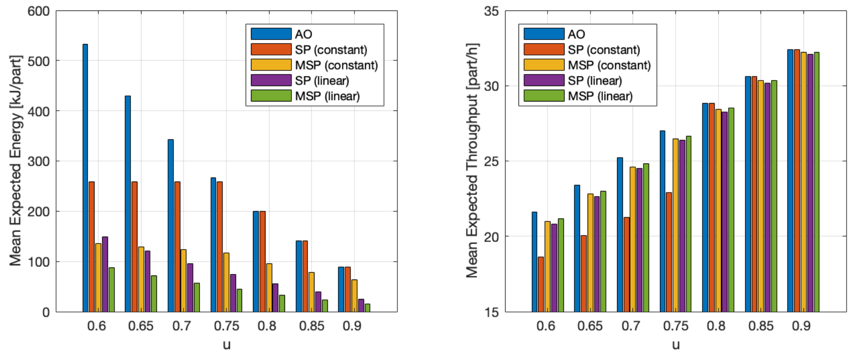


Figure 9: Results of Part 2 – Comparison on experiments 5 and 6 among AO, SP and MSP (5 replications,CI95% is not reported because smaller than 1%).

terminate their startup procedure simultaneously: component $i = 4$ starts its startup as first, then $i = 3$ and $i = 2$. Component $i = 1$ is always controlled with $\{\tau^*_{\text{off},1}, \tau^*_{\text{on},1}\} = \{0, \infty\}$ because it does not have any startup.

Exp	u	SP		MSP							
		τ^*_{off}	τ^*_{on}	$\tau^*_{\text{off},1}$	$\tau^*_{\text{on},1}$	$\tau^*_{\text{off},2}$	$\tau^*_{\text{on},2}$	$\tau^*_{\text{off},3}$	$\tau^*_{\text{on},3}$	$\tau^*_{\text{off},4}$	$\tau^*_{\text{on},4}$
Exp5	6	0	∞	0	∞	0	64.6	0	59.6	0	39.6
Exp5	0.65	0	∞	0	∞	0	51.5	0	46.5	0	26.5
Exp5	0.7	0	∞	0	∞	0	40.3	0	35.3	0	15.3
Exp5	0.75	0	∞	0	∞	0	30.5	0	25.5	∞	∞
Exp5	0.8	∞	∞	0	∞	0	21.0	0	16.0	∞	∞
Exp5	0.85	∞	∞	0	∞	0	13.0	0	8.0	∞	∞
Exp5	0.9	∞	∞	0	∞	0	5.9	∞	∞	∞	∞
Exp6	0.6	0	56.1	0	∞	0	65.7	0	62.7	0	51.4
Exp6	0.65	0	45.3	0	∞	0	53.1	0	50.7	0	41.5
Exp6	0.7	0	36.0	0	∞	0	42.2	0	40.3	0	33.0
Exp6	0.75	0	28.0	0	∞	0	32.8	0	31.3	0	25.7
Exp6	0.8	0	21.0	0	∞	0	24.6	0	23.5	0	19.2
Exp6	0.85	0	14.8	0	∞	0	17.4	0	16.6	0	13.6
Exp6	0.9	0	9.3	0	∞	0	10.9	0	10.4	0	8.5

Table 4: Results of Part 2 – Comparison of control parameters τ^* (in s) on experiments 5 and 6 among AO, SP and MSP. Mean of 5 replications is reported (CI95% is not reported because smaller than 1%).

5.2.3. Result comparison for experiment 7

Assuming the SP, the function describing machine startup duration is in Figure 10a. Machine startup duration varies according to the sojourn time in machine standby. Function in Figure 10a does not change while varying the control because components are controlled simultaneously. Differently, assuming the MSP, the machine enters in different sleeping states according to component's control. An example is Figure 10b where $\tau_{\text{off},1} = 30$ s, $\tau_{\text{off},2} = 15$ s, $\tau_{\text{off},3} = 0$ s and

Policy	ε	Energy [kJ/part]	Throughput [part/h]	Control [s]
AO	–	76.7	29.64	$\{\infty; \infty\}$
SP	0.01	43.8 (-43%)	29.50 (-0.47%)	$\{5; 70.9\}$
MSP	0.01	25.8 (-66%)	29.60 (-0.13%)	$\{5; 65.3; 5; 70.8; 5; 66.0; 0; \infty\}$

Table 5: Part 2 – Results of experiment 7.

$\tau_{\text{on},i} = \infty$ s. Thus, the complexity of the optimization problem increases significantly.

The optimized policy is as in Table 5 where SP and MSP are compared. SP obtains around 43% of energy reduction while the production rate is decreased less than 1%. The machine is switched off after the first peak of arrivals (5 s) and switched on after around 71 s so that machine startup terminates before the second arrival peak. The MSP improves the control to 66% of savings by switching off component $i = 4$ immediately after departure and on only at arrival (i.e., $\{\tau_{\text{off},4}; \tau_{\text{on},4}\} = \{0, \infty\}$), and by modulating the switch-on of components $i = 1, 2, 3$ such that they concludes the startup simultaneously. Indeed, components $i = 1, 2, 3$ are switched on respectively at 65.3 s, 70.8 s and 66.0 s so that the machine is ready at $t = 76$ s.

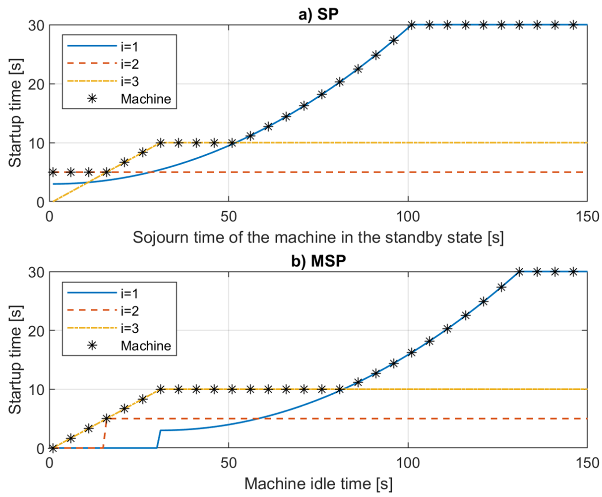


Figure 10: Part 2 – Startup duration at machine level according to machine sojourn time in standby (Exp7).

5.3. Remarks

According to the experiments simulated and the results obtained, the shape of the startup function $t_{\text{su}}(\cdot)$ might affect significantly the optimal control and to model the startup as constant is over-conservative. Table 6 collects the energy saving obtained with experiments Exp1-4. The effect appears more clearly when the state-of-the-art SP, i.e., with constant startup, is not advantageous (Exp 3 and Exp 4). Also it is possible to remark that:

- If the startup reaches the maximum value in a short time (δ small), the energy consumed is similar to the constant case associated with t_h, vice versa for high δ with t_0.

Unconstrained	SP constant	SP linear	SP quadratic	SP cubic
Exp1	11 %	49 %	57%	36%
Exp2	11 %	23 %	30%	16%
Exp3	–	13 %	39%	–
Exp4	–	39 %	48%	27%
$\varepsilon = 0.05$	SP constant	SP linear	SP quadratic	SP cubic
Exp1	11 %	47 %	57%	31%
Exp2	11 %	21 %	30%	16%
Exp3	–	12 %	39%	–
Exp4	–	39 %	48%	27%
$\varepsilon = 0.02$	SP constant	SP linear	SP quadratic	SP cubic
Exp1	8 %	26 %	36%	17%
Exp2	8 %	12 %	14%	10%
Exp3	–	8 %	24%	–
Exp4	–	39 %	48%	27%
$\varepsilon = 0.01$	SP constant	SP linear	SP quadratic	SP cubic
Exp1	5 %	16 %	23%	10%
Exp2	5 %	7 %	8%	6%
Exp3	–	6 %	16%	–
Exp4	–	36 %	43%	26%

Table 6: Summary of percentage energy saving with respect to the AO policy for Exp 1-4 (mean of 5 replications).

Exp	Policy	Energy saving [%]	Throughput loss [%]
Exp5	SP	[52; 40; 25; 3; 0; 0; 0]	[14; 14; 16; 15; 0; 0; 0]
Exp5	MSP	[74; 70; 63; 55; 51; 44; 28]	[2.8; 2.5; 2.3; 2; 1.3; 0.8; 0.6]
Exp6	SP	[72; 72; 72; 72; 72; 72; 72]	[3.7; 3.3; 2.8; 2.4; 1.9; 1.4; 1]
Exp6	MSP	[83; 83; 83; 83; 83; 83; 83]	[2.1; 1.9; 1.6; 1.3; 11; 0.8; 0.5]

Table 7: Percentage energy saving and throughput loss compared to AO policy (mean of 5 replications). Results of Exp5 and Exp6 for scenarios $u = [0.6; 0.65; 0.7; 0.75; 0.8; 0.85; 0.9]$ are listed.

- Trivially, if the startup duration changes within a narrow time range (β is small), there is no difference in modelling time-dependent or constant startup time.

The sensitivity analysis of Exp5 and Exp6 is summarized in terms of percentage energy saving and throughput loss obtained against AO policy as in Table 7. Both modelling choices (i.e., component level and linear startup) enable higher energy saving compared to the state-of-the-art SP with constant startup. The throughput loss is also reduced by a proper selection of control parameters such that too long startups are avoided. With a policy that controls the whole machine (SP), it is important to model a variable startup duration: despite all components are simultaneously controlled, long startups are avoided by increasing τ_{off} or decreasing τ_{on}. With a policy at component level, a similar effect is obtained by controlling each component separately.

6. Conclusion an future developments

Energy-efficient control policies to switch off/on machine tools and their components have been studied in this paper including a time-dependent startup duration. The solution of the optimization problem is found under throughput constraints. To model the startup as time-dependent affects significantly the optimal control τ^*, whilst considering the startup as constant might be over-conservative. In addition, individual control at component level is applied resulting in multiple sleeping states for the machine tool. Despite the energy saving potential of EE control policies is smaller for highly utilized machines, the potential benefit of controlling each component individually is clear also when machine idling time is small. Energy efficiency is improved thanks to the selection of which component to switch. As a consequence, machine startup duration becomes a combination of components startup duration functions.

In terms of practical applicability, machine tools can be more efficiently switched off/on and their startup procedure can be optimized to avoid frequent and too long startups while assuring the proper working condition. In addition, peak load reduction can be pursued by adding constraints or a second objective to the problem. Peak load will be more important at system level, when more resources are controlled simultaneously.

Critical barriers for practical implementation are the presence of some critical component that cannot be switched off and other barriers related to the knowledge of starvation time distribution and of the startup procedure. Components that are particularly critical for reliability reasons, for their impact on part quality (e.g., they are related to machine thermal behavior), or with high startup-power request ($w_{s,i}$) can be kept idle adding proper constraints to the problem. Automated learning methods can be included both in starvation time distribution and startup function fitting such that the applicability of the proposed policy for practitioners is increased. Nevertheless, simple startup functions can be easily adapted to many industrial cases, within discrete production, and would provide a benefit in terms of machine controllability. In addition, machine that are not equipped with automatic switch-off mode can be equipped with external devices that enable the control at machine level

The approach requires the fitting of the distribution modeling the part arrival times at the buffer, the estimation of average processing time, the fitting of startup time functions of machine components and the estimation of the average power adsorbed by components. The approach is flexible and it can be applied also to other machine tool types that require a significant startup.

Future effort will be devoted to the practical application of the model and to analyze the effect of the proposed policies at system level, for example for long production lines where more than one machine are controlled simultaneously (e.g., serial-parallel production lines). Also, the effect of the policy on component reliability will be topic of future investigations as well as the analysis of specific startup sequences.

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