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Impact reduction potential by usage anticipation under comfort trade-off conditions

Joost R. Duflou (1)[a,*], Andres Auquilla[a,b], Yannick De Bock[a], Ann Nowé[c], Karel Kellens[a]

[a] KU Leuven, Department of Mechanical Engineering, Celestijnenlaan 300A, B-3001 Heverlee, Belgium
[b] University of Cuenca, Department of Compute Science, Av. 12 de Abril, Cuenca, Ecuador
[c] Vrije Universiteit Brussel, Artificial Intelligence Lab, Pleinlaan 2, 1050 Brussels, Belgium

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ABSTRACT

Well-optimized intelligent control of products and systems with a substantial energy and/or consumables demand can allow to reduce the use phase impact of these devices and systems significantly. However, depending on the usage patterns and their variability, the system efficiency and tardiness, as well as comfort-impact avoidance trade-off considerations, the effectiveness of such strategies can greatly differ. This contribution describes models for and analyses the sensitivity of the achievable impact reduction with respect to these factors, thus facilitating use phase oriented eco-design decision making. The observations are illustrated by means of a zone heating and a laser cutting machine case study.

1. Introduction

The emergenceof a range of intelligent control systems that aim to accurately predict the usage of devices could be observed in recent years [1,2]. Basically such controllers have as objective to reduce energy and resource consumption while assuring the functional output for which the system is intended. The copier machine dilemma is a typical example: how to offer a readily available copy service while minimising the total energy consumption? Using historic usage pattern information, intelligent control systems anticipate the expected usage to determine optimal standby mode strategies. Applications range from smart thermostats to industrial controllers capable of autonomously selecting between ‘ready for operation’, ‘standby’ or ‘off’ modes for manufacturing systems. A trade-off between comfort and availability on one hand, and cost and impact minimisation on the other, typically has to be made. Recent review articles provide testimony of a growing capability for accurate system usage prediction for such controllers [3,4].

Depending on the application, facilitating intelligent control requires the availability of appropriate sensors, actuators and the actual control unit. Both from economic and environmental perspective the benefits of such intelligent control systems are not always obvious and the factors determining the return on investment are not well documented. While substantial attention has been spent to analysing the performance of intelligent control systems in terms of predicting future usage [3,5–7], the sensitivity of the potential environmental impact reduction for the system characteristics has not been investigated in depth. This contribution aims to expose the influence of different system and usage features on the impact reduction potential and to provide guidelines for evaluation of the anticipated effectiveness of intelligent control systems.

* Corresponding author.
E-mail address: Joost.Duflou@mech.kuleuven.be (J.R. Duflou).

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2. Influencing system features: definitions

In this contribution abstraction is made of the prediction capabilities of intelligent control systems: it is assumed that highly repetitive usage needs can be correctly predicted. The variability in historic usage records thus reflects the only uncertainty on the exactness of repetitive patterns. In order to assess this variability, statistical usage patterns are recorded. These records are clustered in order to distinguish the different usage patterns. The results are a number of probability distributions in function of time, typically for 24-h intervals (see orange coloured distribution example in Fig. 1). These cluster distributions can be directly used for the predictive models applied for usage anticipation: details for the use of cluster data for usage prediction can, for example, be found in reference [8].

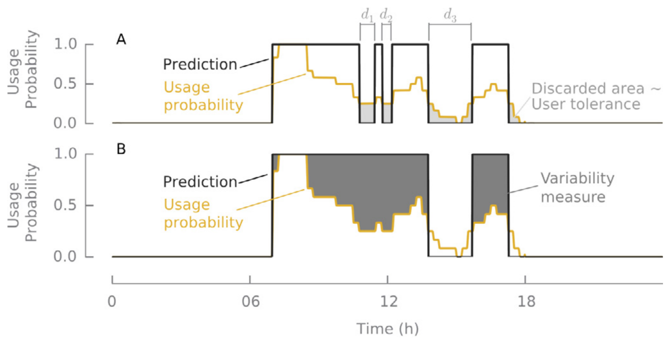

Fig. 1. Usage pattern: usage probability distribution (orange) and user tolerance based usage prediction (A) and tardiness based adjusted usage prediction (B) (see Section 2).

2.1. System specific characteristics

System specific characteristics are determined by the physical nature of the composing system components. They include the different consumption rates (Fig. 2):

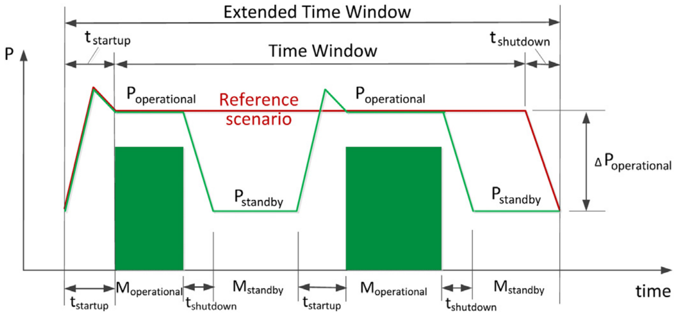

Fig. 2. Reference scenario (red) with transient regimes and indication of consumption levels in different modes (M) and transient periods for a usage example with Fractionality = 2 (green).

$P_{operational}$: average resource consumption level in ready for operation mode (as defined in [9]): e.g. power level, consumables consumption rate.
$P_{standby}$: average consumption level of the standby mode
$P_{startup}$: average consumption level during the transition from standby to ready for operation mode
$P_{shutdown}$: average consumption level during the transition from ready for operation to standby mode

Derived system characteristics are:

$$\Delta P_{operational} = P_{operational} - P_{standby} \tag{1}$$

$$\Delta P_{startup} = P_{startup} - P_{standby} \tag{2}$$

$$\Delta P_{shutdown} = P_{shutdown} - P_{\text{standby}} \tag{3}$$

Also the *Tardiness* (*T*) or inertia of a system is inherent to its design. It is defined as the duration of the transition between different system modes.

In this article the *Total Tardiness* (T_{total}) [minutes] is used as a condensed representation for this system feature:

$$T_{total} = t_{startup} + t_{shutdown} \tag{4}$$

where $t_{startup}$: transition time from standby to ready for operation mode $t_{shutdown}$: transition time from ready for operation to standby mode.

2.2. User specific characteristics

Besides the nature of the usage, as reflected by the number of distinguishable pattern clusters and the probability distributions of these clusters (cf. Fig. 1), also the tolerance of the user(s) towards system availability, as defined hereafter, is an important user specific factor:

User tolerance (*UT*): time percentage of non-availability of the product or system functionality a user (group) is willing to accept, relative to the total registered statistical usage period [%].

While in principle the full value range could be considered, in practice users are only willing to accept limited non-availability. Depending on the nature of the system functionality, this value will typically range between 0 and a few percent of tolerance.

For a given *UT* level, the corresponding required availability can be derived from usage probability distributions by determining the fraction of the probability distribution surface corresponding to the specified tolerance level: see Fig. 1A.

As a factor influencing the potential impact reduction through usage prediction, the variability of the usage can then be quantified as follows:

$$Variability\ (V) = \frac{(t_{operational} - t_{required})}{t_{operational}} \tag{5}$$

where $t_{required}$: total statistically required ready for operation time [minutes]; corresponds to the total area below the distribution of the predicted operational mode periods (after the user tolerance level has been applied: see Fig. 1). $t_{operational}$: total provided ready for operation time [minutes]; corresponds to the total area below the block diagram (probability = 1) of the predicted operational mode intervals (Fig. 1).

The Variability ranges between 0 and 1, with a value equal to 0 corresponding to completely deterministic usage.

The usage prediction (see Fig. 1) for a given distribution and *UT* level determines a number of periods during which the ready for operation mode of the system should be guaranteed. Depending on the duration of the time gaps between the operational periods (cf d_1, d_2, d_3 in Fig. 1), a transition to standby mode can be considered. For $d < T_{\text{total}}$ this is not feasible and such intervals are eliminated from the usage prediction scheme (see Fig. 1B).

The resulting number of periods in ready for operation mode in the predicted 24 h usage profile is referred to as the *Fractionality* (*F*). Fractionality values can range from 0 (no usage anticipated) till higher integer numbers.

2.3. Policy related characteristics

An extremely low variability ($V \approx 0$) is typical for operations under strict policy conditions, resulting in predetermined usage patterns. Examples are production environments with strict working hours and full machine occupancy. Such scenarios allow straight-forward control and eliminate potential impact reduction through usage anticipation. The more general case is the situation where operations are expected only part of the time during a predefined *Time Window* (*TW*). The flexibility offered by the size of the TW is a policy decision, but, once decided, the TW becomes an important characteristic of the system to be assessed.

When using a straight-forward control strategy, start-up to the operation ready mode and shutdown to the standby mode are performed just before and after the TW and determine the *Extended Time Window (ETW)* (see Fig. 2).

The *Time Fraction* (*TF*) is defined as a derived parameter and represents the maximum potential fraction of time (for tardiness = 0) during which the standby mode can be applied within the specified *TW*:

$$TF = \frac{(TW - t_{operational})}{TW} \tag{6}$$

3. Modelling the impact saving potential

Based on the system and user characteristics specified above, the impact reduction potential of intelligent predictive control methods can now be quantified.

3.1. Reference scenario

As reference scenario, the ready for operation mode (often also referred to as production ready mode in the case of machine tools [9]) is assumed active during the full time window (Fig. 2). Availability and comfort are thus guaranteed during the full TW period. This is a realistic assumption for systems where the users take little responsibility for the system control. In situations where only interactive control by the user is applied for switching between standby and operational mode, as is, for example, often the case for zone heating applications in private dwellings, anticipative switching on of systems is impossible. In such a context assuring availability/comfort upon arrival is not feasible, which excludes this scenario as a functionally equivalent alternative reference.

3.2. Impact reduction potential

For given consumption levels, the savings potential is determined by the total period ($t_{savings}$) during which the system can be allowed to reside in standby mode during the ETW period.