CIRP Annals - Manufacturing Technology 65 (2016) 33–36

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: http://ees.elsevier.com/cirp/default.asp

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

ARTICLE INFO

Keywords:
Pattern recognition
Energy efficiency
Usage patterns

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).

http://dx.doi.org/10.1016/j.cirp.2016.04.087
0007-8506/© 2016

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].

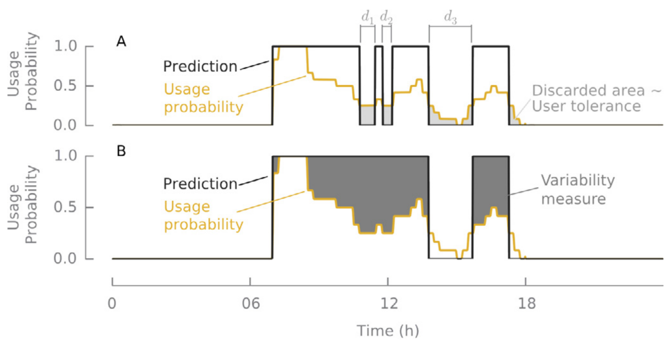

Fig. 1. Usage pattern: usage probability distribution (orange) and user tolerance based usage prediction (A) and tardiness based adjusted usage prediction (B) (see Section 2).

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):

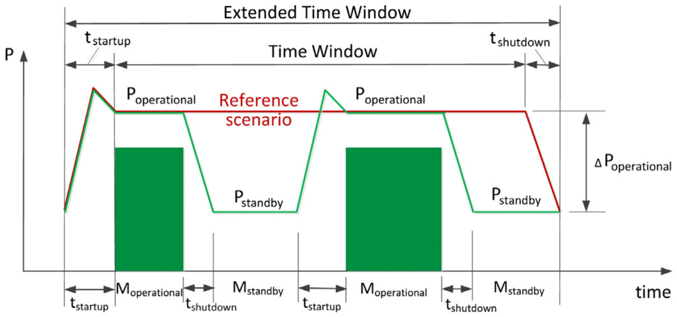

Fig. 2. Reference scenario (red) with transient regimes and indication of consumption levels in different modes (M) and transient periods for a usage example with Fractionality = 2 (green).

$P_{operational}$: 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:

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

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

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

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 $d < T_{\mathrm{total}}$ 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.

For known system characteristics and user characterisation data, $t_{savings}$ can be calculated as follows (Fig. 2):

$$\begin{aligned} t_{savings} &= TW + t_{startup} + t_{shutdown} - t_{operational} - [F * (t_{startup} + t_{shutdown})] \\ t_{savings} &= TW - t_{operational} + [(1-F) * (t_{startup} + t_{shutdown})] \\ t_{savings} &= TF * TW + [(1-F) * t_{total}] \end{aligned} \tag{7}$$

The *Consumption Reduction Potential* (*CRP*) can then be determined as:

$$CRP = [(TW - t_{operational}) * \Delta P_{operational}] + (1-F) * [(\Delta P_{startup} * t_{startup}) + (\Delta P_{shutdown} * t_{shutdown})] \tag{8}$$

or

$$CRP = TF * TW * \Delta P_{operational} + (1-F) * [(\Delta P_{startup} * t_{startup}) + (\Delta P_{shutdown} * t_{shutdown})] \tag{9}$$

For a given environmental impact per unit resource consumption (EI), the *Impact Reduction Potential (IRP)* can then be obtained:

$$IRP = CRP * EI \tag{10}$$

4. Sensitivity analysis

While the consumption levels in different modes are highly case specific and obstruct a systematic sensitivity analysis of the CRP, the expression for the Time Saving Potential $t_{savings}$ (Eq. (7)) is a function of generic system and user features only. For the special case that $\Delta P_{startup}$, $\Delta P_{operational}$ and $\Delta P_{shutdown}$ are identical, CRP and $t_{savings}$ are actually proportional to each other.

Fig. 3 shows the potential time in savings mode $t_{savings}$ (standby rather than ready for operations mode) as a function of the Time Fraction, the Total Tardiness and the Fractionality.

This graphical representation demonstrates the relevance of a sufficiently high Time Fraction in standby mode, or, in other words, a Time Window that is substantially larger than the expected time in operation ready mode ($t_{operational}$).

Higher values for the Total Tardiness of the system can eliminate a substantial part of the Time Saving potential if a higher Fractionality has to be taken into account. This is the case when the time in ready for operation mode is divided over a number of shorter usage sessions. For low Fractionality values (e.g. 1 or 2) the influence of the Tardiness is however less relevant and the Time Savings potential is largely defined by the Time Fraction. This can be obtained by a high Time Window value and by a short total usage period and/or a low Variability, which result in a minimal $t_{operational}$.

5. Case studies

While the variables chosen as input parameters for the graph in Fig. 3 allow to demonstrate the sensitivity of the CRP for different system and user features, these variables are not readily known in most practical cases. The following case studies illustrate the procedure to determine these variables and provide representative values for a number of typical applications of intelligent control systems.

5.1. Personalised zone heating in an office environment

The usage data summarised in the cluster probability curves depicted in Fig. 4 were collected by observing the presence of an individual office occupant in an academic environment during a period of 11 months [8]. The clusters were obtained applying a Dirichlet process mixture clustering algorithm to a dataset of 238 24 h profiles.

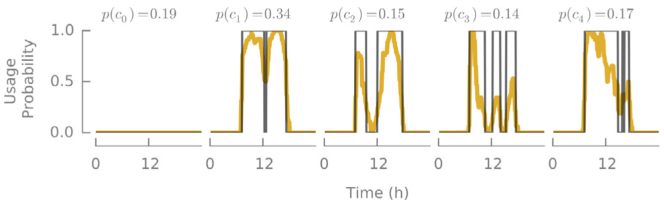

Fig. 4. Five office presence cluster distributions (orange), their probability of occurrence and derived operational periods for *UT* = 5%.

Table 1 contains the system characteristics as well as the policy information for the concerned building. Since the transient behaviour is different at the beginning of the day (heating up) than during the day (maintaining comfort temperature), there are two values for $t_{startup}$. The heating period at the beginning of the day can only be saved when no usage is expected and hence $F = 0$ (cluster c_0 in Fig. 4).

Table 1
Office building characteristics (average values as measured during the monitoring period) and heating policy information.

$P_{standby}$	$P_{operational}$	$\Delta P_{operational}$	$P_{startup}$		$\Delta P_{startup}$
0.00 kW	0.67 kW	0.67 kW	2.50 kW		2.50 kW
$P_{shutdown}$	$\Delta P_{shutdown}$	$t_{shutdown}$	$t_{startup}$		TW
0.00 kW	0.00 kW	0′	Initial: 72′	Restart: 16′	720′

Depending on the applied User Tolerance, different $t_{savings}$ (minutes) and *CRP* values are obtained as shown in Fig. 5.

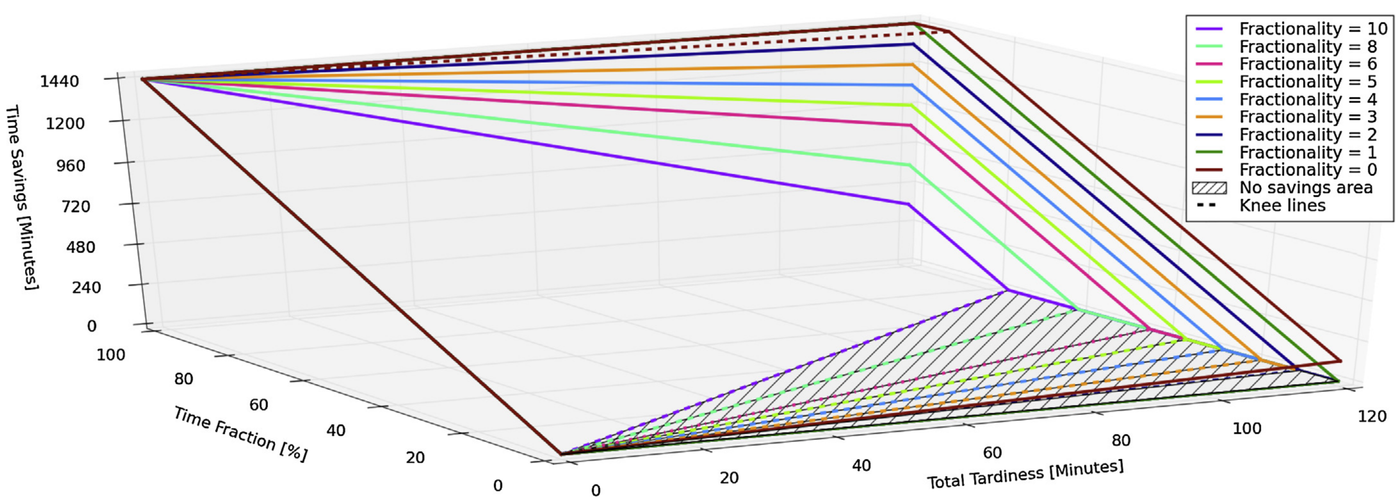

Fig. 3. Time savings potential ($t_{savings}$) as a function of the Total Tardiness and the Time Fraction for different fractionality values.

Using the system property values of Table 1 in Eq. (9), a *CRP* value can be calculated for every *UT* level (Fig. 5).

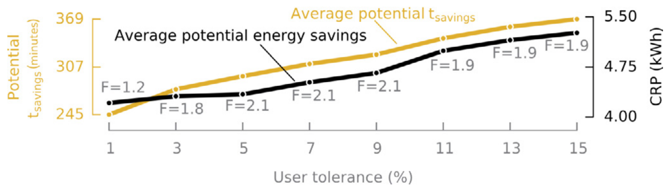

Fig. 5. Average daily time savings potential and average Consumption Reduction Potential (energy savings) as a function of *UT* for the office zone heating case, with indication of the fractionality (*F*) value averaged over the usage clusters taking into account the probability of occurrence.

As can be observed in Fig. 5, the higher average Fractionality resulting from a higher User Tolerance level can negatively affect the energy savings potential, even for gradually increasing $t_{savings}$ values. The relatively high $P_{startup}$ levels, compared to the $P_{operational}$ value, require a substantial additional time $t_{savings}$ in standby mode to compensate for the consumption during a restart period.

Taking into account the nature of the heating system and the corresponding unit flow impact values, the Impact Reduction Potential can now be determined as summarised in Fig. 6. While all used datasets were selected from the EcoInvent3 LCI database, the environmental impacts were quantified using the Europe ReCiPe H/A LCIA method. The resulting scores are expressed in ecopoints (Pts), 1000 Pts corresponding to the yearly impact of the average European citizen.

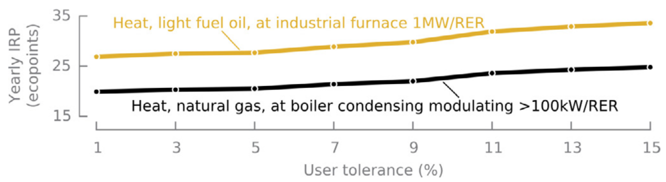

Fig. 6. Yearly IRP of intelligent zone heating control for the office occupancy case study.

5.2. Standby mode optimisation for a laser cutting machine

Detailed analysis of the machine control mode status for an industrial 5 kW CO_2 laser cutting machine [10] for a period of 252 working days provided the usage clusters depicted in Fig. 7. Usage is spread over a period of 18 h and covers one (C1, C2) or two (C0) working shifts. The third cluster (C3) represents weekends and holidays.

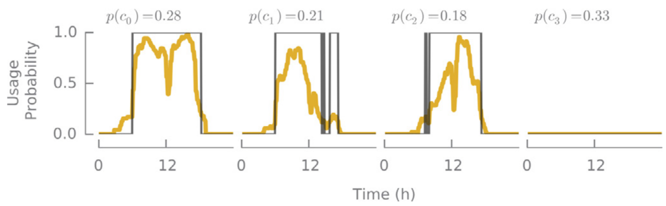

Fig. 7. Laser cutting machine usage cluster distributions, their probability of occurrence and derived operational periods for *UT* = 5%.

In this case, two TW policies were tested: 18 h as derived from historical data and 24 h to represent a non-stop scenario. The $t_{startup}$ and $t_{shutdown}$ values were observed to be 18 min and 4 min respectively; $P_{standby}$ = 2.07 kW, $P_{operational}$ = 27.15 kW, $P_{startup}$ = 22.98 kW, $P_{shutdown}$ = 10.5 kW [10].

Using Eqs. (7) and (8) the expected average daily $t_{savings}$ and CRP values were obtained for the *UT* = 5% usage predictions: for the *TW* of 18 h 623 min and 269.3 kWh; and for the *TW* of 24 h 923 min and 401.0 kWh respectively.

For an environmental impact score of 52.9 mPts per kWh (EcoInvent 3.0 Electricity, low voltage, production RER, at grid/RER), Eq. (10) allows to estimate the average daily impact reduction potential. On a yearly basis (225 working days) this results in potential impact reductions of 3206 and 4773 Pts for a TW policy of 18 and 24 h respectively.

6. Conclusions

For systems with documented usage patterns and known system characteristics, the usage analysis procedure and mode shift model described in this paper allow to assess the impact reduction potential that intelligent predictive control systems can offer. The following generic conclusions can be drawn from analysing the obtained model:

For well-designed systems with low ΔP consumption levels, the Impact Reduction Potential in absolute measures is by definition low. However, for systems for which an energy/resource intensive operational mode cannot be avoided (e.g. heating systems in poorly isolated buildings), intelligent control can make a difference if a number of conditions are fulfilled.

The variability in the historic usage patterns needs to be sufficiently low in order to assure good predictability: highly variable usage patterns will result in usage distributions characterised by high Variability values and thus relatively high $t_{operational}$ values for a given User Tolerance level.

Where the variability cannot be avoided, sufficiently high User Tolerance levels, corresponding to prioritisation of impact reduction in the trade-off comparison with comfort/availability considerations, are required to keep the time in operation ready mode relatively low. Awareness of the system users by transparently documenting the system performance can possibly help to achieve this.

Longer, continuous blocks of operation and absence periods (low Fractionality) are preferred to relatively short usage periods, especially for systems with a high tardiness.

It should be noted that, compared to a scenario in which users interactively control the activation of the system, the Impact Reduction Potential of intelligent control systems will always be less and possibly negative. However, this comparison should be corrected for the non-availability/discomfort periods linked to the system start-up, which is especially valid for systems characterised by a higher start-up tardiness.

References

[1] Oldewurtel F, Sturzenegger D, Morari M (2013) Importance of Occupancy Information for Building Climate Control. *Applied Energy* 101:521–532.
[2] Truong NC, McInerney J, Tran-Thanh L, Costanza E, Ramchurn SD (2013) Forecasting Multi-Appliance Usage for Smart Home Energy Management. *Proceedings of the 23rd International Joint Conference on Artificial Intelligence*, 2908–2914.
[3] Kleiminger W, Mattern F, Santini S (2013) Predicting Household Occupancy for Smart Heating Control: A Comparative Performance Analysis of State-of-the-Art Approaches. *Energy and Buildings* 85:493–505.
[4] Nguyen TA, Aiello M (2013) Energy Intelligent Buildings Based on User Activity: A Survey. *Energy and Buildings* 56:244–257.
[5] Oldewurtel F, Parisio A, Jones CN, Gyalistras D, Gwerder M, Stauch V, Lehmann B, Morari M (2012) Use of Model Predictive Control and Weather Forecasts for Energy Efficient Building Climate Control. *Energy and Buildings* 45:15–27.
[6] Mohanraj M, Jayaraj S, Muraleedharan C (2012) Applications of Artificial Neural Networks for Refrigeration, Air-Conditioning and Heat Pump Systems – A Review. *Renewable and Sustainable Energy Reviews* 16(2):1340–1358.
[7] Palau A, Velo E, Puigjaner L (1999) Use of Neural Networks and Expert Systems to Control a Gas/Solid Sorption Chilling Machine. *International Journal of Refrigeration* 22(1):59–66.
[8] De Bock Y, Auquilla A, Kellens K, Nowé A, Duflou JR (2015) User Adapting System Design for Improved Energy Efficiency During the Use Phase of Products: Case Study of an Occupancy-Driven, Self-Learning Thermostat. *Proceedings of EcoDesign 2015*978-981-10-0471-1.
[9] ISO14955-1 (2014) *Machine Tools – Environmental Evaluation of Machine Tools – Part 1: Design Methodology for Energy-Efficient Machine Tools.*
[10] Kellens K, Dewulf W, Overcash M, Hauschild MZ, Duflou JR (2012) Methodology for Systematic Analysis and Improvement of Manufacturing Unit Process Life Cycle Inventory. Part 2: Case studies. *International Journal of Life Cycle Assessment* 17(2):242–251.