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An Expert System-Based Approach For Improving Energy Efficiency Of Chamber Cleaning Machines

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Abstract

Increased transparency and domain expertise are often prerequisites for identifying energy savings potentials and improving energy efficiency in manufacturing systems. Small and medium-sized enterprises pursuing a reduction in CO_2 emissions are especially faced with challenges from the complexity of process data and limited domain expertise. Against this background, this paper presents an expert system for preliminary energy diagnostics using automated energy analysis of production machines and providing measures for improving energy efficiency. Due to their significant energy consumption and increasing importance along various process chains, the use case is developed for chamber cleaning machines. A knowledge base is combined with artificial intelligence techniques for data processing to reveal efficiency potentials based on machine load profiles. The knowledge base created by experts assigns domain-specific information to the automatically processed input data. Key performance indicators are then utilized for internal and external benchmarking and quantification of energy potential, narrowing down promising energy efficiency measures. The suitability of the proposed approach is demonstrated by applying the expert system to two different chamber cleaning machines.

Keywords

sustainable manufacturing; artificial intelligence; energy analysis; parts cleaning; knowledge management

1. Introduction

With rising energy costs and increasing pressure towards production sites to reduce carbon dioxide emissions, the industry sector is faced with the challenge of introducing measures for a more sustainable production, while keeping up with consumer demand and maintaining process quality [1]. Combined with a lack of knowledge surrounding process factors influencing the resource efficiency of production processes, operators often struggle with allocating and exploiting efficiency potentials [2]. Against the backdrop of German industrial energy consumption, where process heat represented around two thirds of final energy consumption in 2020 [3], process heat applications such as industrial cleaning machines harbor a variety of energy and resource savings potentials [4].

Meanwhile, the metal-working industry has been seeing a steady rise in the importance of parts cleaning along various process chains. Specifically, this process is often crucial for downstream processes, such as coating or joining, as well as lifetime and performance of the treated parts [5]. Hence, rising quality requirements – especially within the automobile industry – push manufacturers and users towards optimizing the parts cleaning process [6]. This is reflected in the acknowledgement of parts cleaning processes as elementary processes in their respective value chains [7].

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To contribute to tackling the mentioned challenges while focusing on energy consumption, we present an expert system-based approach for detecting energy saving potentials in the operation of industrial chamber cleaning machines. The approach aims to increase transparency by employing machine learning (ML) algorithms in identifying machine processes based on the machine's load profile and deducting suitable energy efficiency measures to present to the user.

The following work starts with an introduction to chamber cleaning machines and expert systems including the structure of the developed approach in section 2. Section 3 focuses on the implementation of the expert system and its individual components, while the specific use case and the corresponding expert system performance are subsequently presented and discussed in section 4. Finally, a conclusion is drawn and the outlook is considered in section 5.

2. Background

The following section provides an introduction to the fundamentals of chamber cleaning machines in subsection 2.1 and expert systems in subsection 2.2.

2.1 Chamber cleaning machines

According to DIN 8592, parts cleaning is described as the process of removing unwanted substances, i.e., soils, from the surface of parts up to a certain degree. The cleaning task can be carried out by a variety of cleaning techniques. [8]

Based on a survey conducted in 2020, aqueous parts cleaning processes are by far the most common in the German industry. Aqueous parts cleaning is most often performed in chamber cleaning machines, making them the most significant type of parts cleaning machine in terms of representativity and total energy savings potential in German industry. [7] Hence, the examined use case focuses on single chamber cleaning machines for spray cleaning. The corresponding process steps and most important machine components are presented in the following subsections.

2.1.1 Process steps

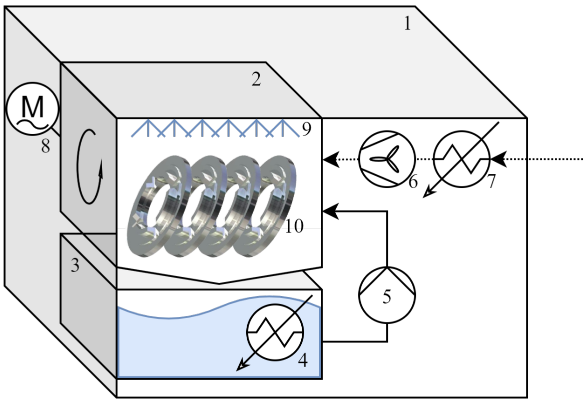
The parts cleaning process comprises of three main process steps: cleaning, rinsing (optional) and drying. Depending on the cleaning task, these steps may vary in length and repetition or include further intermediate steps, such as dripping or process pauses. [5]

The cleaning step aims to separate the soils from the surface of the parts. In aqueous cleaning, this task is conducted by a cleaning liquid containing an aqueous cleaning agent at a certain concentration. The type and concentration of the cleaning agent are manually chosen based on the cleaning task. The cleaning agent requires a certain temperature range to be effective in soil-removal. Furthermore, in the case of spray cleaning, the cleaning liquid is ejected at an elevated pressure through spray nozzles onto the part's surface to mechanically remove the soil. Additional movement of the cleaning basket or nozzle frame (e. g. rotation) further supports soil removal through mechanical action. The rinsing step is sometimes required to flush the parts from the soil-saturated cleaning liquid to ensure this does not subsequently cause unwanted residue on the part's surface. Rinsing usually operates at a similar temperature as cleaning and only varies in the soil-saturation and cleaning agent concentration of the liquid. Finally, the drying step is required to remove the cleaning or rinsing liquid from the parts surface to avoid corrosion of the metal part or enable following critical production processes. Drying can be performed evaporatively or non-evaporatively and is most often based on convection through blow-down with pressurized air or hot air. [5]

The following use case focuses on single-tank cleaning machines, which rely on just the cleaning and drying steps, eliminating the rinsing step. Furthermore, since chamber cleaning machines operate batch-wise, they must be loaded with soiled parts before the cleaning process and unloaded afterwards, adding one more process step to the machine process.

2.1.2 Components

Based on the considered use cases, we present the most important components of chamber cleaning machines as illustrated in Figure 1. As the name suggests, single-tank chamber machines (1) are mainly comprised of a treatment chamber (2) and one media tank (3). The treatment chamber carries the cleaning basket, which is loaded with soiled parts (10) before the cleaning process. To improve mechanical action supporting soil removal during the cleaning process, the cleaning basket is fitted with an electric motor (8) to effect relative movement between the parts and the spray nozzles (9). During the cleaning step, the spray nozzle system is supplied with cleaning liquid from the media tank with the help of an electrically driven spray pump (5). An electric tank heater (4) is installed in the media tank to maintain the temperature range required by the cleaning task. After the cleaning step, the parts are dried convectively via hot air supplied by the electrically driven drying fan (6), which passes ambient air through the electrical drying air heater (7) and into the treatment chamber.



1 Chamber cleaning machine
2 Treatment chamber
3 Media tank
4 Tank heater
5 Spray pump
6 Drying fan
7 Drying air heater
8 Basket motor
9 Spray nozzles
10 Parts

Figure 1: Chamber cleaning machine schematic with most important components

2.2 Expert system

Expert systems are a subfield of artificial intelligence with the objective of solving complex problems and providing the decision-making ability of a human expert in a particular domain [9]. The basic idea of an expert system is to represent the knowledge of experts in a computer system, aggregate it and make it available to support other users in their tasks and reduce their workload [10].

Figure 2 presents the overall architecture of the developed expert system. Electrical load profiles and the human expert provide the expert system with input information. The electrical load profiles are acquired for each analyzed machine by measuring the active power consumption at the main power supply, whereas the knowledge base must be defined only initially by the human expert and is applicable to all considered machines. The knowledge base contains all information and facts that makes an expert abundantly knowledgeable in their fields. The inference engine combines the problem-related expert knowledge with the measurement data of the analyzed entity and generates conclusions. [11] The explanation component presents the conclusions to the user via an interface and explains how or why the expert system arrived at a particular solution [10].

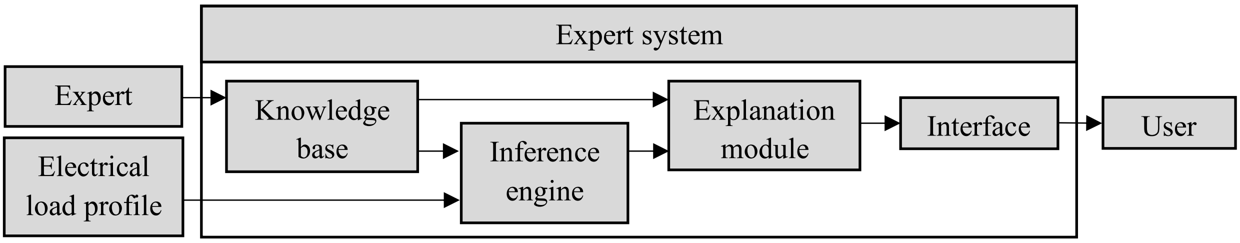


Figure 2: Expert system architecture

3. Implementation

Various methods exist for implementing the architectural features of an expert system. Since the interface is of minor importance for the proof of concept, it is implemented as a text-based output with a graph. The following section describes the other features in more detail that are implemented in Python.

3.1 Knowledge base

The knowledge base defined by the expert contains expertise as machine-readable data structures and is divided into two segments. Both segments are implemented as lookup tables. The first segment shown in Table 1 provides facts about the production process, for which the load profile is shown in Figure 3. As explained in section 2.1, parts cleaning consists of several consecutive steps. The cleaning machines investigated in the following use case operate with one media tank for the cleaning liquid, omitting the rinsing step. This leaves the processes with cleaning, drying and loading steps. The process steps are listed together with their respective identification numbers (ID) in Table 1. Other unspecified events, such as pauses between the steps, are expressed as other.

Table 1: Knowledge base for the production process of chamber cleaning machines

Process ID	Designation	Description
0	Clean	Remove soil from parts' surface (spray cleaning)
1	Dry	Remove cleaning liquid from parts' surface (hot air)
2	Load	Load/Unload parts in treatment chamber
3	Other	Unspecified events

The second segment, shown in Table 2, presents a knowledge base for improving energy efficiency by mapping energy efficiency measures to machine-readable rules. These are based on the duration $t_{i,j}$ of each identified iteration $j = 0, \ldots, k_i$ of each process step i (see Figure 3). The knowledge base relates to time-based measures, as these have promising savings potential and can be easily identified and implemented.

Table 2: Knowledge base for improving energy efficiency of chamber cleaning machines

Energy efficiency measure	KPI	Rules
Minimize clean time	$t_{0,j}$	IF $t_{0,j} > \min\{t_{0,0}, .., t_{0,k_i}\}$ THEN reduce $t_{0,j}$
Minimize dry time	$t_{1,j}$	IF $t_{1,j} > \min\{t_{1,0}, .., t_{1,k_i}\}$ THEN reduce $t_{1,j}$
Minimize load time	$t_{2,j}$	IF $t_{2,j} > \min\{t_{2,0}, .., t_{2,k_i}\}$ THEN reduce $t_{2,j}$
Minimize other time	$t_{3,j}$	IF $t_{3,j} > \min\{t_{3,0}, .., t_{3,k_i}\}$ THEN reduce $t_{3,j}$

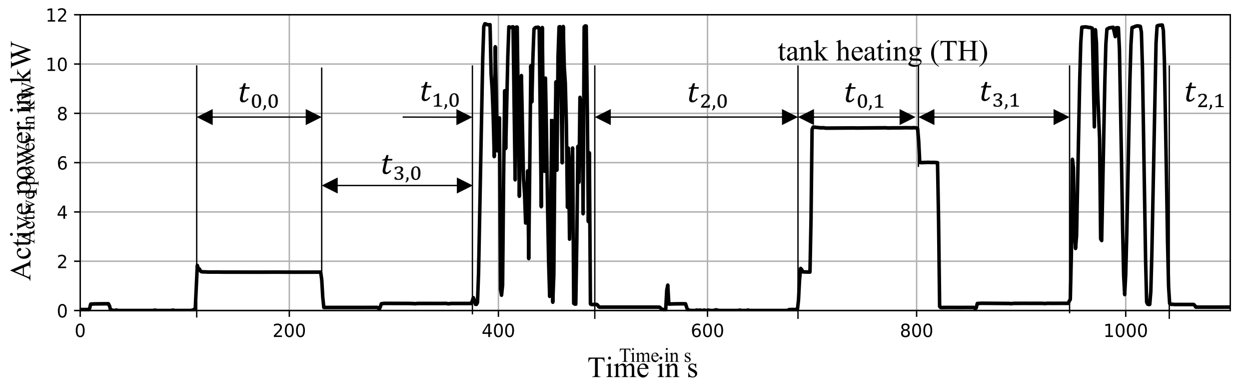


Figure 3: Visualization of a load profile with different machine processes

3.2 Inference engine

The inference engine derives promising energy efficiency measures based on electrical load profiles and knowledge. This corresponds to a typical forward chaining reasoning paradigm, as shown in Figure 4. Forward chaining from data to conclusions starts with a collection of knowledge and draws allowable conclusions [12]. In this instance, the input information is used to identify the production processes defined in Table 1. The identification of the production processes is achieved automatically by a trained ML model.

The development of the ML application for the identification of machine processes follows the Cross-Industry Standard Process for ML (CRISP-ML). CRISP-ML consists of six phases, starting from business and data understanding, which is also essential for the knowledge base and concluding with the long-term deployment of the ML model. [13] This paper focuses on the first four phases, with section 3.1 covering already the first phase, business and data understanding. The initial phase is followed by data preparation. In this phase, in accordance with [14], a supervised learning approach was pursued, using features based on a fixed window size. In the subsequent modeling several supervised algorithms, which are also considered in [14], are compared and the hyperparameters are optimized using grid search [15]. Being balanced datasets, where no machine process is vastly over- or under-represented, the results of the ML models are evaluated in the fourth phase based on the average accuracy using a 5-fold cross validation [16,17]. The Random Forest Classifier from the Python library scikit-learn [18] achieves the best results with 92.63 % for the identifiaction of unknown data of the same cleaning machine and with 90.79 % for the identifiaction of unknown data of a different cleaning machine.

Once the processes have been identified, the measurement data for each individual process is grouped into the corresponding timeslot $t_{i,j}$, as seen in Figure 3. Outliers are then processed by applying a median filter if the duration and energy demand of one timeslot deviates significantly compared to the majority of the residual timeslots of the same process. This also allows subsequent filtering of overlapping state-controlled processes, such as TH. Subsequently, energy key performance indicators (KPI) are calculated, enabling the derivation of promising energy efficiency measures on the one hand and the quantification of energy efficiency potentials and comprehensibility for the user on the other. The energy efficiency measures are mapped to the energy KPI in accordance with Table 2. The expert system prioritizes the energy efficiency measures based on the absolute energy savings potential.

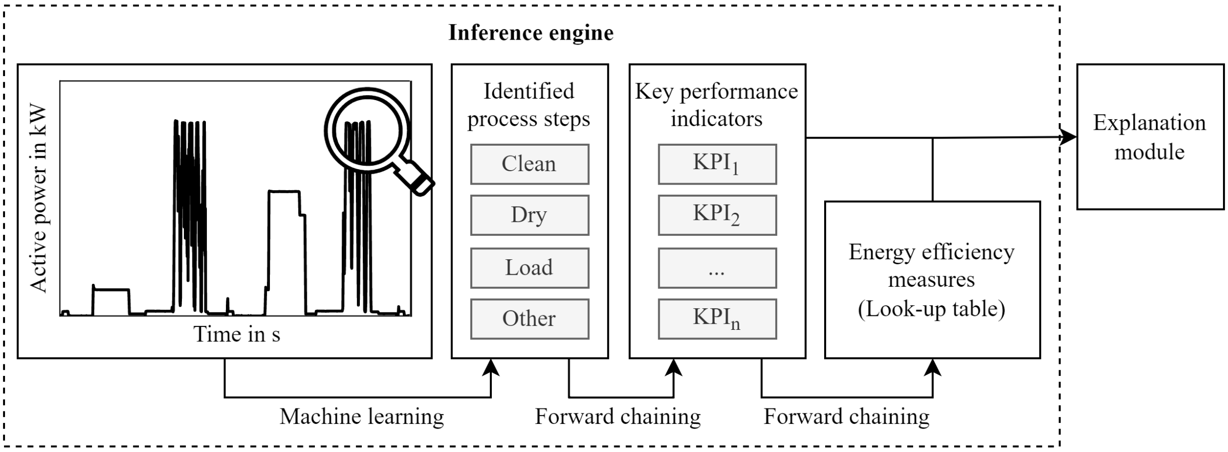


Figure 4: Inference engine architecture

3.3 Explanation module

To provide the user with an explainable presentation of concluded energy efficiency potentials and energy efficiency measures, energy KPI directly determined and calculated from the measurement data are used. For the implementation of the expert system basic KPI are first defined in Table 3, from which other energy KPI can be derived. The basic KPI include the sum of all durations $t_{i,total}$ for each process i, as well as the corresponding total energy consumption $E_{i,total}$. To later calculate the potential savings, the number of iterations k_i is also given for each process.

Table 3: KPI for the explanation module

KPI	Description	Unit
Cleaning time $t_{0,total}$	Total duration for cleaning	Second (s)
Drying time $t_{1,total}$	Total duration for drying	Second (s)
Loading time $t_{2,total}$	Total duration for (un-)loading the machine	Second (s)
Other time $t_{3,total}$	Total duration of other activities	Second (s)
Cleaning iterations k_0	Total iterations of cleaning steps	-
Drying iterations k_1	Total iterations of drying steps	-
Loading iterations k_2	Total iterations of loading steps	-
Other iterations k_3	Total iterations of other activities	-
Cleaning energy $E_{0,total}$	Total energy consumed while cleaning	Watt-hour (Wh)
Drying energy $E_{1,total}$	Total energy consumed while drying	Watt-hour (Wh)
Loading energy $E_{2,total}$	Total energy consumed while (un-)loading the machine	Watt-hour (Wh)
Other energy $E_{3,total}$	Total energy consumed during other activities	Watt-hour (Wh)

Further energy KPI are the potential relative time savings τ_i and the potential relative energy savings ε_i for each process i. These reflect the potential savings, when only the minimum time duration $t_{i,min}$ is applied to all iterations k_i of each process i, instead of the identified durations which result in the total duration. Potential time savings are the main driver of potential energy savings, since the efficiency measures recommended by the expert system are based on time. The potential relative savings, τ_i and ε_i, are calculated following equations (1) and (2):

$$\tau_i = \frac{t_{i,total} - k_i \cdot t_{i,min}}{t_{i,total}} \cdot 100\% \qquad \text{with } t_{i,min} = min\{t_{i,0}, .., t_{i,k_i}\} \tag{1}$$

$$\varepsilon_i = \frac{E_{i,total} - k_i \cdot E_{i,min}}{E_{i,total}} \cdot 100\% \qquad \text{with } E_{i,min} = min\{E_{i,0}, .., E_{i,k_i}\} \tag{2}$$

4. Use Case

The following subsections describe the experimental setup used for demonstration of the expert system and discuss the achieved results.

4.1 Experimental setup

To investigate the suitability of the approach, the expert system is applied to two batch cleaning machines at the ETA research factory at Technical University of Darmstadt, shown in Figure 5. For consideration of transferability of the expert system, machines of different manufacturers with varying constructive design were selected for the use case. The active power was measured for 3.5 hours at the main power supply of each cleaning machine, covering a number of at least 10 processing cycles. Wherein a process cycle includes a loading, cleaning, drying and unloading process. This ensures that the data set for training the ML model covers all processes in Table 1, even those that were not explicitly defined and may overlap with other processes, such as the TH. The electrical measurements were conducted as presented in [19] without interrupting the circuit.

(a) **(b)**

Figure 5: (a) BvL OceanRC 750 and (b) MAFAC KEA at the ETA Research Factory

4.2 Results

The measurement data of the BvL OceanRC 750 used for developing and training the ML model are shown in Figure 6 (a) and the classification results of the expert system implemented on the measurement data of MAFAC KEA are shown in Figure 6 (b). The graphical representation of the classification of the machine processes is also part of the explanation module and provides a basis for the comprehension of further results.

In addition to the graphical classification of the machine processes, the user is provided with the calculated energy KPI shown in Table 4. Furthermore, the expert system returns the corresponding energy efficiency measures in the same order as in Table 2.

Table 4: Results of the expert system for MAFAC KEA

KPI	value	KPI	value
$t_{0,total}$	8170 s	$E_{0,total}$	4.67 kWh
$t_{1,total}$	1260 s	$E_{1,total}$	1.18 kWh
$t_{2,total}$	2780 s	$E_{2,total}$	0.11 kWh
$t_{3,total}$	320 s	$E_{3,total}$	0.05 kWh
τ_0	6.36 %	ε_0	10.63 %
τ_1	7.14 %	ε_1	6.38 %
τ_2	82.73 %	ε_2	68.65 %
τ_3	6.25 %	ε_3	30.21 %

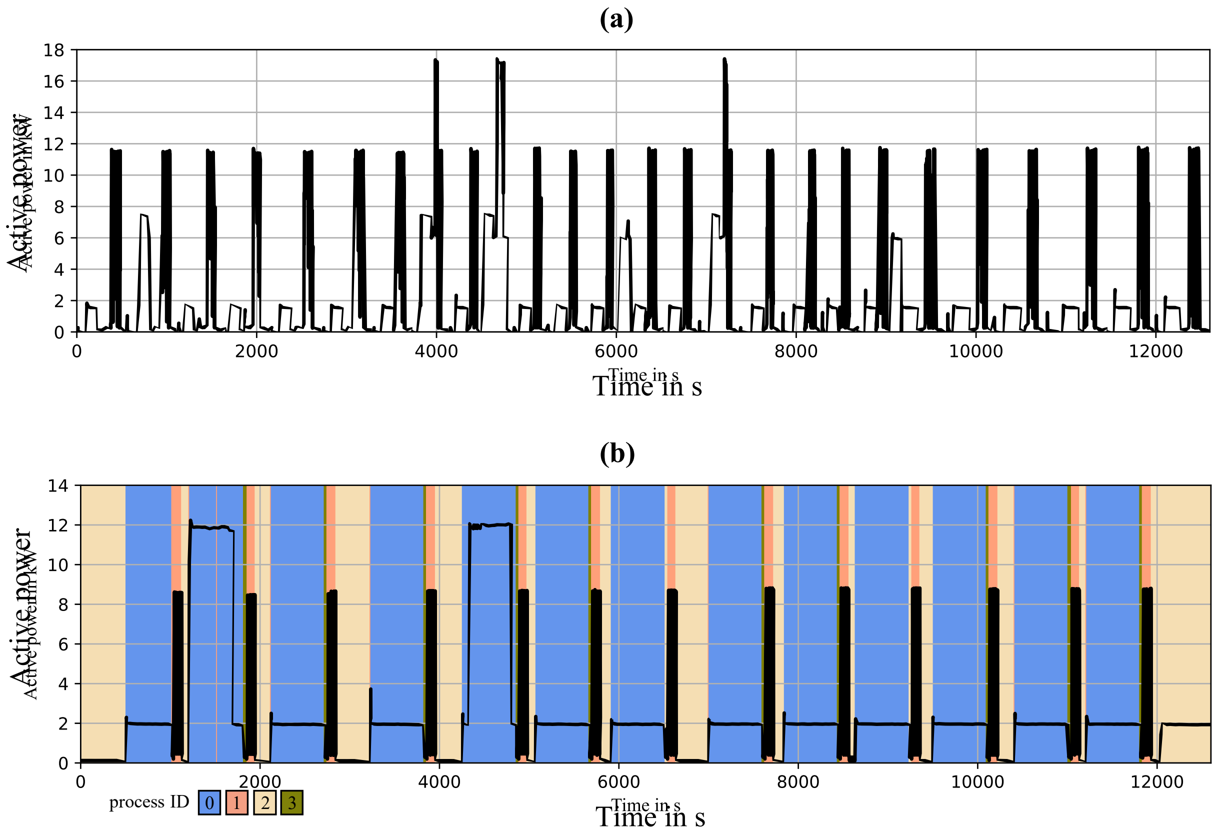


Figure 6: (a) Measurement data of BvL OceanRC 750 for training the ML model and (b) application of the expert system to measurement data of MAFAC KEA

4.3 Discussion

The expert system identifies energy saving potentials for each process and provides promising energy efficiency measures. For the presented use case, Table 4 shows that the cleaning process takes considerably longer, requires the most amount of energy and yields the highest potential absolute energy savings with 0,50 kWh. Therefore, the expert system first prioritizes to minimize the cleaning time. Significant energy savings potential is also found in the drying process with 0.08 kWh. Furthermore, due to the high potential relative time savings, the loading process shows potential energy savings of 0.08 kWh. In total, 11.02 % of energy could potentially be saved for the observation period and the production process could be shortened by 23.38 %.

The results shown in Table 4 support in determining an internal benchmark. However, energy KPI calculated by the expert system are archived, so that external benchmarks from other cleaning machines can also be applied. It should be taken into account that the maximum optimization potential relates to known processes, so it may be underestimated. Furthermore, the recommended energy efficiency measures only refer to the cleaning of parts with similar contamination and geometry. In case of deviations of the parts, batch size or strongly varying degrees of contamination, the required processes duration must be examined. The minimization of the loading time, however, is an exception where this does not have to be considered, as long as the number of parts or jigs remains the same.

5. Conclusion and outlook

This paper presents an expert system for improving the energy efficiency of chamber cleaning machines. For this purpose, a knowledge base consisting of process and energy efficiency knowledge was combined with an inference engine and an explanation module. The implementation of the expert system carried out with a BvL OceanRC 750 cleaning machine was applied to a MAFAC KEA cleaning machine. Thus, demonstrating the transferability of the expert system and the automated energy analysis with suggested energy efficiency measures. For the presented use case, the expert system identified potential energy savings of 11.02% and potential time savings of 23.38% that could be achieved by implementing time-based energy efficiency measures.

However, the expert system has its limitations in the knowledge base, the accuracy of the ML model and the defined energy KPI. Therefore, future developments will cover an extension of the knowledge base to include information regarding parts geometry, contamination, production-specific requirements and non-time-based energy efficiency measures. Furthermore, additional KPI for evaluating energy requirements and process performance can be defined. Lastly, improvements in the performance of the ML model can be achieved and the transferability of the expert system increased by extending it to other production machines.

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Biography

Borys Ioshchikhes (*1995) has been a research associate at the research group Energy Technologies and Applications in Production (ETA) at the Institute of Production Management, Technology and Machine Tools (PTW) at Technical University of Darmstadt since 2021. In his research, he focuses on machine learning-based energy analysis to increase energy efficiency in production.

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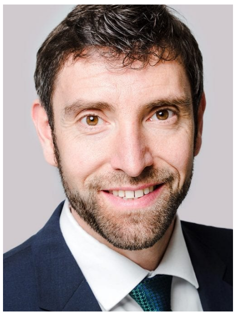

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