Machining Cycle Detection Based Expert System for Improving Energy Efficiency in Manufacturing

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Abstract. The transformation of manufacturing companies towards a carbon-neutral economy requires energy transparency, energy analyses and the implementation of energy efficiency measures. Given the continuing skills shortage, the need for automated analysis methods to gain insights from measurement data is increasing. Expert systems that combine the knowledge of multiple experts, analyze load profiles, and derive energy efficiency measures are one approach to tackle this challenge. This paper presents an expert system that quantifies energy efficiency potentials based on the detection of machining cycles and derives promising measures. For this purpose, a new algorithm for the detection of machining cycles is introduced, which shows an accuracy between 76.7 % and 94.3 % on a representative production day for electrical load profiles of different types of production machines. Since the detected machining cycles are in a form impractical for further processing, information is extracted as energy performance indicators. The expert system utilizes this aggregated information to identify energetic hotspots and derive appropriate energy efficiency measures. The machining cycle detection based expert system is demonstrated on a typical production chain for the metalworking industry within the ETA research factory at the Technical University of Darmstadt.

Keywords: Pattern Recognition, Energy Analysis, Sustainable Manufacturing

1 Introduction

As manufacturing companies increasingly face the challenges of transitioning to a carbon-neutral economy, rising energy costs and a shortage of skilled workers, the need for innovative solutions is becoming pressing [1]. One promising approach to solve these challenges by improving energy efficiency in manufacturing are expert systems, which are artificial intelligence applications that are designed to emulate the decision-making ability of a human expert in a specific domain. Expert systems can help manufacturers reduce energy costs and increase productivity through the analysis of large amounts of data and recommendations for energy optimization of production machines. Moreover, expert systems can contribute to solving the issue of skills shortages in manufacturing by providing a way to leverage the knowledge and expertise of skilled workers, even as they retire. [2]

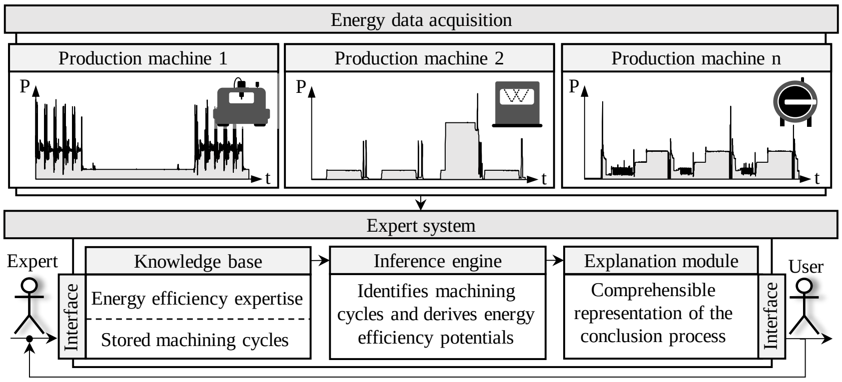

Fig. 1. Methodological approach.

Previous expert system approaches have focused on energy optimization of individual machines, possibly overlooking energy hotspots of other machines in the same production system [3, 4]. By extending the system boundary to multiple production machines, a cross-machine prioritization of energy efficiency potentials can be realized, with machining cycles which are serving as the comparison baseline.
Following the introduction, section 2 outlines the overall methodology, which is composed of the energy data acquisition and the expert system itself. In this context, the main elements of the expert system - the knowledge base, the inference engine and the explanation module - are covered. Section 3 describes the implementation of the underlying algorithm for detecting machining cycles. Subsequently, in section 4, the proposed approach is evaluated using a real production chain. Finally, section 5 provides a summary and a conclusion for future research.

2 Methodology

The general methodological approach shown in Fig. 1 aims to increase the energy efficiency of production machines within a production system. This approach involves the automatic identification and quantification of energy hotspots and inefficiencies, followed by proposals for prioritized measures to unlock potential improvements. The approach can be divided into two major parts: The energy data acquisition and the expert system. The energy data acquisition in this paper focuses on electrical energy, due to its high share in the industrial final energy consumption and the relatively low metering effort compared to non-electric energy flows [5, 6]. The prerequisite of the presented approach is the measurement at the main power supply of the considered production machines, which can be accomplished by stationary, temporary or virtual metering [6]. Important characteristic features of the expert system are the knowledge base, inference engine and the explanation module [7]. The knowledge base contains expertise related to the problem domain [7]. In this approach, the knowledge base includes stored machining cycles as well as facts and rules to increase the energy efficiency of production machines. Experts and users of the expert system can expand the knowledge base, e.g., when machining cycles for new production machines need to be defined. The inference engine analyzes the electrical load profile, identifies machining cycles and uses the stored knowledge to derive conclusions. The explanation module explains how the system comes to certain conclusions or recommendations, which helps the user understand the system's decision-making process [7]. Both the knowledge base and the explanation component provide a user interface, which serves as the communication channel between the expert and the expert system, and the expert system and the user.

2.1 Machining cycle detection

Dehning et al. describe the two value-based consumer states *unproductive* and *productive* [8]. The unproductive state covers the states off, standby, operational and powering up/down according to VDMA 34179 [9]. No value is created during this state. The productive state refers to a value-adding process and corresponds to the state working according to VDMA 34179 [9]. The productive state is typically characterized by cyclically recurring manufacturing operations and has the highest average power and energy demand [10]. For the presented expert system, we focus on the automated identification of machining cycles during the productive state.
In general, there are many approaches for pattern recognition in time series based on machine learning [11] and motif methods [12, 13]. However, these approaches are not robust to the effects of a dynamic production environment, varying setup times and other process anomalies [10]. To take these effects into account, Seevers et al. presented their own method, which, however, is based on the assumption that typical machining cycle times for machine tools have a time range from minimum 20 seconds to a maximum of 120 seconds [10]. Since this is not a valid assumption for all machine tools and other machine types, the algorithm developed in this paper does not follow this premise.

2.2 Energy efficient manufacturing

Given the necessity to minimize the energy demand of machine tools in the use phase, measures have been collected [14] and classified [15]. We propose that these measures are mostly applicable to other types of electric actuated production machines. Fig. 2 shows the classification into the three main levels of energy recovery, energy input reduction and energy reuse. Energy recovery is generally approached by thermal management, while energy reuse aims to operate motors as generators during deceleration processes. [15] Energy input reduction can further be devided into machine-related and process-related measures [16]. Machine-related measures are all measures that require a technical change, while process-related measures require organizational intervention. For the expert system, two measures are considered as examples. Demand-oriented-control aims at (partially) switching off or adjusting components when they are not required, while energy-oriented planning targets minimizing the energy demand of machining cycles, e.g., by reducing process times.

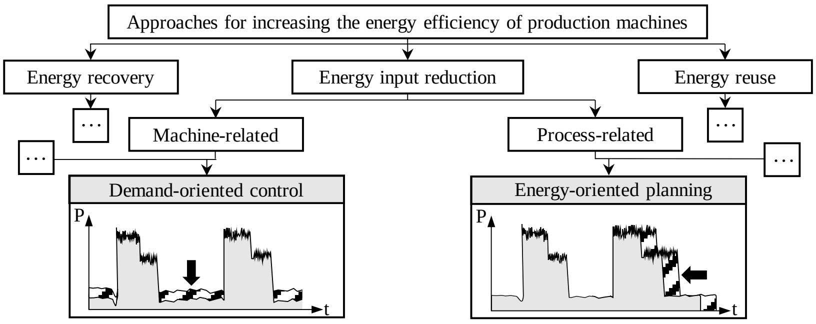

Fig. 2. Approaches to increase the energy efficiency of production machines bases on [15].

To identify the first measure, the unproductive energy factor ($UPEF$) is considered according to equation (1). It is defined as the ratio of the energy demand in unproductive times E_{np} and the total energy demand E_{total}. [8] For the second measure, the potential energy savings during the productive state ($PESP$) is calculated following equation (2). The $PESP$ reflects the potential energy savings during the productive state if the cycle with minimum energy demand $E_{cycle,min}$ would correspond to all identified cycles k instead of the measured energy demand E_p.

$$UPEF = \frac{E_{np}}{E_{total}} \cdot 100\ \% \tag{1}$$

$$PESP = \frac{E_p - k \cdot E_{cycle,min}}{E_p} \cdot 100\ \% \tag{2}$$

3 Machining cycle detection algorithm

Expert knowledge is needed to identify a representative machining cycle, hereafter referred to as a sample cycle, within each machine's load profile. These sample cycles are stored within the knowledge base. Subsequently, the expert system leverages this selected sample cycle to detect additional machining cycles using our algorithm.

The first step of the algorithm is to calculate the z-normalized Euclidean distance between the sample cycle and the load profile to generate a matrix profile using the Python library STUMPY [17]. The matrix profile contains the start indices of all identified putative patterns and the computed values of the z-normalized Euclidean distance. However, relying solely on STUMPY to detect machining cycles has two major drawbacks: Firstly, not every identified start index found by STUMPY corresponds to the actual beginning of a machining cycle. Secondly, STUMPY provides only the start indices, but not the end indices of the detected cycles. Our algorithm not only identifies incorrect start indices but also accounts for varying cycle lengths. To identify start indices that do not correspond to the actual beginning of machining cycles, we compare the identified cycles with the sample cycle based on additional statistical properties such as mean and standard deviation. If the deviation of these metric values surpasses a predetermined relative threshold, our algorithm labels the start index identified by STUMPY as one that does not correspond to a true machining cycle. Consequently, this index is removed from the matrix profile. To determine the lengths of the cycles, the length of each identified cycle is first calculated as the difference between two consecutive start indices. Subsequently, a comparison of the statistical properties and a condition check is conducted. If the discrepancies between the mean and standard deviation values are below the predetermined threshold, our algorithm designates the start index associated with the newly calculated length as a true machining cycle. In such cases, the algorithm continues with the next iteration and repeats this process for the subsequent start index. However, if the statistical properties differ significantly, the length of the identified cycles is adjusted by adding or subtracting a small percentage of the length of the sample cycle. The differences between these metrics are then recalculated. This process is repeated until the algorithm classifies the cycle as a true machining cycle, or until a predefined number of iterations is reached. If the specified number of iterations is reached without a true machining cycle classification, the cycle is identified as a false machining cycle, and the corresponding start index is removed from the matrix profile. The algorithm then continues with the next iteration, repeating the entire process for the next start index in the matrix profile. Finally, our algorithm returns the start indices of the classified true machining cycles, along with a list of their corresponding lengths. It's important to note that the specific percentage of length adjustment and the predetermined number of iterations are hyperparameters in this algorithm. These hyperparameters provide the flexibility to tailor and fine-tune the algorithm to suit specific data and analysis requirements, ensuring more accurate identification of machining cycles.

4 Use case

To ensure the practical applicability of the developed expert system, the approach is evaluated on a representative production chain for the metalworking industry in the ETA research factory at the Technical University of Darmstadt. The production chain manufactures parts for axial piston pumps and begins with lathing raw pieces on the machine tool EMAG VLC-100Y (EMAG Y), followed by the first cleaning process on the cleaning machine MAFAC JAVA. Subsequently, a tempering process is conducted on the gas nitriding furnace IVA RH65. Next, a grinding process is performed on the EMAG VLC-100 GT (EMAG GT), which is followed by the second cleaning process on the machine MAFAC KEA. [18]

4.1 Application

Fig. 3 shows a section of the identified machining cycles after the expert system was applied to measurement data of a representative production day. The highest accuracy of the machining cycle detection algorithm is achieved at EMAG Y with 94.3 % and the lowest accuracy at MAFAC KEA with 76.7 %. The accuracy corresponds to the ratio of correctly identified to total cycles. The lower accuracy on MAFAC KEA can be explained by the acyclic pulsing of a decentralized tank heating which occurs irregularly.

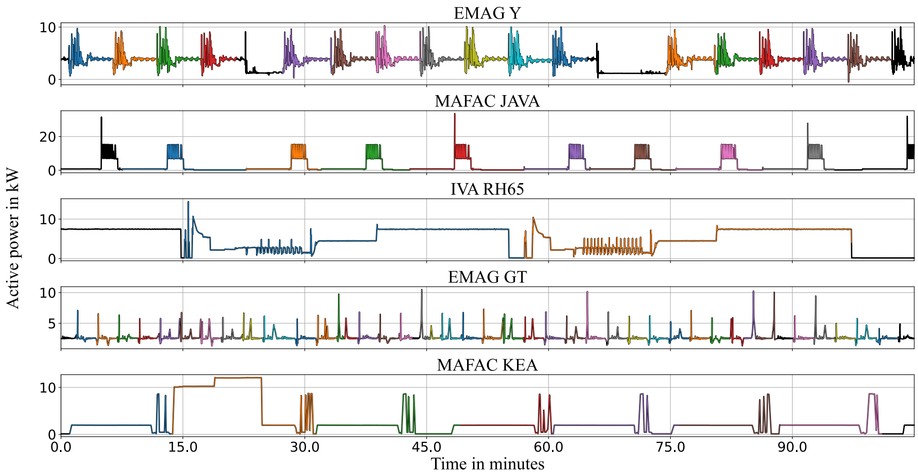

Fig. 3. Identified machining cycles.

The expert system extracts further information using the detected machining cycles, some of which can be found in Table 1. According to the results in Table 1, the lathing process at the machine EMAG Y is identified as an energetic hotspot for the produced part. Thus, this machine could have a significant impact on reducing energy consumption. In addition, with a $UPEF$ of 16.7 %, the same machine has the greatest potential for energy savings in the unproductive state. Consequently, the measure of demand-oriented control is prioritized here highly by the expert system. Furthermore, with a $PESP$ of 9.5 %, the measure of energy-oriented planning is given considerable priority at the EMAG Y. The cleaning machines MAFAC JAVA and MAFAC KEA show significantly higher $PESP$ values, which are caused by larger deviations in the cycle times, but also offer a lower energy savings potential due to the lower average energy demand per part.

Table 1. Results of the expert system.

Machine	Average parts per cycle	Average energy demand per cycle in kWh	Average energy demand per part in kWh	$UPEF$ in %	$PESP$ in %
EMAG Y	1	13849.6	**13849.6**	16.7	9.5
MAFAC JAVA	42	8883.1	211.5	2.8	29.7
IVA RH65	42	17653.8	420.3	1.7	2.2
EMAG GT	1	9655.7	9655.7	2.9	9.5
MAFAC KEA	42	9875.6	235.1	1.3	29.1

4.2 Evaluation

The use case reveals that the accuracy of the developed cycle detection algorithm can vary considerably with different machines. Especially for machines like MAFAC KEA, with a load profile strongly characterized by acyclic events, the algorithm performs inferior. As with all expert systems, it should be noted that the output is significantly determined based on the knowledge stored by the experts. Accordingly, the pattern cycles must be correctly defined for a useful utilization of the system. Furthermore, only one cycle pattern per machine, i.e., the production of identical parts, was considered in the use case. In industrial practice, multiple different parts could also be produced on one machine. Consequently, a sample cycle would have to be defined not only for one machine, but also for each part that is produced on a machine.

5 Summary and conclusion

The developed expert system enables automated data analysis with the aim of improving energy efficiency in manufacturing. In our use case, machining cycles within a production chain were identified, energy hotspots revealed, and exemplary energy efficiency measures derived. The algorithm for the detection of machining cycles takes into account two factors: Firstly, the possibility that there may be a pause between cycles, i.e., that cycles do not have to follow each other directly. Secondly, that cycles detected by STUMPY do not have to be true machining cycles. The algorithm achieves up to 94.3 % accuracy for similar machining cycles, while performing inferiorly for machines with acyclic events. Future research activities are expected to include further energy efficiency measures and deeper refinement of the developed algorithm. This optimization might involve comparing potential machine cycles with the sample cycle based on additional statistical properties, to increase the accuracy of the algorithm. Moreover, the algorithm can be utilized for semi-automated data labeling for machine learning applications. Some of the product's individual carbon footprint could also be calculated automatically by linking the current electricity mix with the identified cycles. By integrating forecasts of renewable energies, the expert system could also be extended to include energy flexibility measures.

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