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Automatic Time Series Segmentation as the Basis for Unsupervised, Non-Intrusive Load Monitoring of Machine Tools

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Abstract

Detailed energy monitoring and benchmarking at the individual component level is necessary to increase energy efficiency in complex production systems. Non-intrusive load monitoring (NILM) provides an economical solution for operational state detection and load disaggregation without the need for large-scale use of fine-grained energy meters. Existing supervised NILM approaches require detailed training data including control information about individual devices. Unsupervised approaches, on the other hand, often require high measurement resolution and are faced with the problem of detecting continuous states. This paper proposes a simple step-by-step, completely unsupervised NILM approach that distinguishes between almost constant and non-constant segments with flexible segment lengths. Taking into account various electrical parameters and their statistical moments, hierarchical density-based spatial clustering of applications with noise (HDBScan) is applied to constant segments. The analysis of non-constant segments is based on agglomerative hierarchical clustering and dynamic time warping. Based on real energy monitoring from a gear manufacturing system we show the applicability of our methodology and discuss how it can be combined with existing NILM techniques.

Keywords: energy management; sustainable manufacturing; intelligent sensor; load profile analysis; operational state identification; unsupervised learning

1. Introduction

While energy efficiency has played a minor role in the production and operation of machine tools in the past, it has become increasingly important in recent years due to rising energy prices and stricter political guidelines [1]. Large companies in particular are increasingly integrating energy and media demand queries into their specifications, and component suppliers are adding more efficient functional modules to their portfolio [2]. Since the energy saving potential is fundamentally dependent on the operational state and a large part of the energy demand is accounted for by auxiliary machine units in particular, the current research focus is on corresponding energy efficiency measures (e.g. [3–5]).

Nomenclature

maxVar	maximum allowable variance within a segment
SQ_{seg}	sum of the squared deviation of segment seg with segment length n_{seg}
SQ_{seg+1}	sum of the squared deviation of segment seg with segment length $n_{seg}+1$
maxSQDiff	maximum increase of the sum of the squared deviation
minSeg	minimum segment length

Flick et al. (2018) suggest various ways of determining the energy demand of individual plants or components by means of measurements or physical calculations in the event of incomplete information [6].

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Since the energy demand of a machine tool in operation sometimes deviates significantly from calculated or design values, detailed information on the energetic behavior of individual machine components based on real measured values is required for the systematic implementation of energy efficiency measures [7]. In order to obtain the most comprehensive possible picture of the condition of a machine tool, monitoring in practice should take a range of parameters into account [8]. An energy monitoring approach that is easier to implement in practice concentrates on the electrical power demand curve. While with Intrusive Load Monitoring (ILM) each component is equipped with a sensor, with NILM only one central measuring device is required for the aggregated total power consumption P(t), from which the power consumption of n devices pi(t) is extracted. [9]. For this purpose, supervised NILM techniques use, among other information, available control signals or information about the process steps of the machine tool [10], or extensive experimental algorithm training is carried out [11]. If this additional information and extensive training data are not available, either cost-intensive additional measurement sensors have to be installed or fully unsupervised NILM procedures are used.

Bernard & Marx (2016) present an approach with a household case study in which, in addition to active power, other electrical parameters such as reactive and apparent power, the total power transient and the phase angle of the first harmonics are used [12]. Using the algorithm, completely unknown device clusters can be detected on the basis of the measured parameters and assigned a unique ID, which is stored in an initially empty database. An event detector continuously checks whether a switching event occurs. If this is the case, the device features are analyzed before and after the event, compared with the device feature database and either assigned to the best device signature fit or newly stored. However, on the one hand no continuous loads are considered and on the other hand very high sampling rates (about 500kHz) are necessary for good results. Likewise, the algorithm of [13] has problems with the numerous variable loads and the relatively high complexity and number of machine tool components.

The novelty of this study is to reduce this complexity through automated operational state detection and to simplify further analysis with a robust process. It can be assumed that a machine tool has the same or a very similar component configuration at different times in its recorded operational state [14]. In order to filter out typical operational states of existing machines in industrial practice, we have developed a time series segmentation algorithm, which first divides the total power factor curve of the three-phase power supply of a machine tool into approximately constant and non-constant phases and then clusters the detected segments. A constant interval implies that there are no serious changes in the operating behavior of the machine tool - for example, in the form of switching components on or off. This case distinction is therefore particularly important against the background of NILM.

Chapter 2 deals with previous approaches for the detection of operational states from energy data of machine tools with an intermediate sampling rate (around 1HZ), followed in Chapter 3 by the methodology of this paper. Chapter 4 contains a case study with real energy monitoring data of two exemplary machine tools (milling and grinding). Finally, chapter 5 summarizes the results, discusses further fields of application and points out the need for further research.

2. Operational state detection in electric load profiles

In [15] a supervised learning procedure is developed and in [16] applied to a milling machine tool in a revised form, in which the algorithm is learned with training data of individual components so that operational states and component activities can be detected from the total power curve by means of an event detector similar to the one in [12].

Also according to the methodology of [17] numerous process-specific boundary conditions and threshold values must be specified in order to recognize the operational states. In [18] operational states are detected from energy data using information about planned process times. However, the algorithm only works with constantly different power demands between different operational states. A hydraulic storage tank loading in operational readiness, for example, or a power drop due to brake force recovery of the spindle drive in machining lead to incorrect results unless machine-specific mathematical boundary conditions are specified. A more general approach is taken by Oette et al. (2015), which divides any performance curve into fixed time segments and assigns them to different segment clusters using Bayesian classifiers. Apart from the fact that a threshold value must also be specified here, the division with a fixed length has the disadvantage, however, that significant patterns occur especially in different segment lengths and may be unfavorably separated by the intersection points [19]. For this reason, some approaches are presented in [20] that perform a suitable segmentation dynamically and flexibly. A well-known method, the Fisher's Natural Breaks Classification, divides the time series into a given optimal number of segments with a flexible segment length in which the values fluctuate as little as possible around the mean value. A drawback is the need to specify the number of segments in advance, which is difficult and time-consuming to predict or purely intuitive [21].

In the following, we therefore present a methodology for time series segmentation and clustering of machine tools in which neither process-specific threshold values and boundary conditions nor segment length and number of segments have to be specified in advance.

3. Methodology

The methodology for identifying and characterizing machine tool operational states consists of several steps that build on each other. These are illustrated in Fig. 1. The main focus of this work consists of the steps segmentation and clustering, which are explained in detail below.

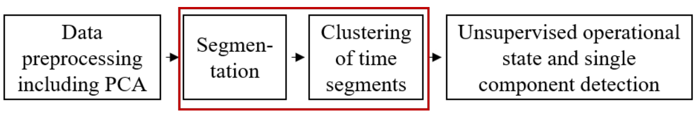

Fig. 1. Unsupervised state detection based on time series segmentation and clustering.

3.1. Identification of nearly constant segments

When dividing the power factor curve into approximately constant and non-constant segments, it is important that approximately constant segments contain varying values, but these may neither exceed a certain variance nor exhibit a rising or falling trend. An explicit specification of the number of segments is not necessary, but is based on the successive extension of the detected segments by one data point in compliance with the following three criteria:

1. maximum allowable variance within a segment (maxVar)
2. maximum increase of the sum of the squared deviation (maxSQDiff)
3. minimum segment length (minSeg)

The maximum allowable segment variance specifies the extent to which varying values are still regarded as approximately constant. It defines which segment is regarded as constant and declared as such by the algorithm.

$$maxVar \geq \frac{1}{n_{Seg}-1} \sum_{i=1}^{n_{Seg}} (x_i - \bar{x}_{Seg})^2 \tag{1}$$

In addition to the first criterion, a gradient criterion is introduced. This avoids that relatively weakly rising and falling tendencies, which are not recognized by the maxVar criterion due to the growing segment length, are mistakenly identified as constant segments. This problem is illustrated by the exemplary schematic progression in Fig. 2. The variances of the individual segments A, B, C and C' are below the given maxVar and are thus considered to be approximately constant, although segment C is obviously not a constant segment.

For segments A and B this declaration would be acceptable. Segment C, however, obviously includes a large peak and must not be filtered out as a constant segment. For this reason, a maximum allowable increase of the sum of the squared deviation (SQ) between segment seg and the one-data point extended segment seg+1 is introduced. This second criterion reacts more sensitively than maxVar criterion to a slight increase or decrease in the curve. With the help of the sum of the squared deviation, only the core area of the constant segments is filtered out, as is the case with segment C'.

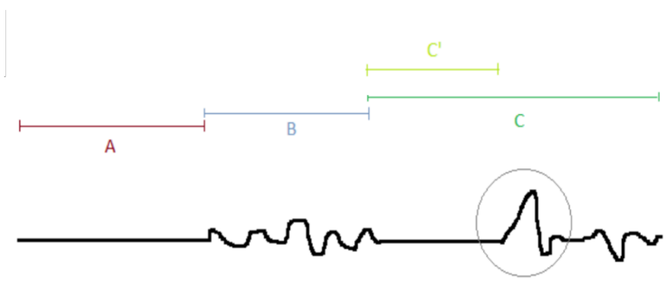

Fig. 2. Influence of the second criterion on segmentation quality.

For the second criterion, therefore, the two partial formulas result:

$$SQ_{seg} = \sum_{i=1}^{n_{Seg}} (x_i - \bar{x}_{Seg})^2 \tag{2a}$$

$$maxSQDiff \geq SQ_{seg+1} - SQ_{seg} \tag{2b}$$

The definition of a minimum segment length as a third criterion prevents a too detailed subdivision of the overall power factor curve. Without this criterion, even very small segments would be filtered out as constant and thus characteristic structures would possibly be overlooked that indicate certain machine activities.

$$minSeg \leq n_{Seg} \tag{3}$$

3.2. Feature extraction of nearly constant segments

For the suitability of the cluster analysis, the statistical parameters mean value, standard deviation, kurtosis and skewness derived from the available electrical parameters are examined, whereby the features kurtosis and skewness have always led to worse results in our calculations and are therefore ignored in the following. The segment length is not used as a feature, since in particular the constant operational states can vary strongly in their duration (e.g. standby phases of different lengths). This could result in similar operational phases being divided into different clusters due to their different lengths.

With the help of the segmentation algorithm it is possible to first extract long approximately constant operational states in two successive steps by temporarily increasing the criteria and then to carry out a fine segmentation of the rest of the total power factor curve.

3.3. Clustering of nearly constant segments

Before clustering, the number of principal components containing 95% of the variance is taken from the features using the PCA.

The clustering of the principal components takes place with the density-based method HDBScan. This has the following advantages over other clustering methods such as K-Means++ and agglomerative hierarchical clustering:

- no need to specify the number of clusters k
- detection of outliers
- is suitable for large amounts of data
- is suitable for the determination of complex cluster forms

In order to determine the best parameter settings, the silhouette coefficient is used, since it does not require ground truth. The silhouette coefficient is a measure of the quality of clustering that is independent of the number of clusters and has a real value range of -1 to +1.

3.4. Feature extraction and clustering of non-constant segments

The non-constant segments, which are obtained by filtering out the constant segments, are clustered using merely a distance measure between the different segments. Since the Dynamic Time Warping (DTW) method can also be used for time series of different lengths, it has the advantage over the Euclidean distance measure that the data points are not compared rigidly in time, but flexibly. Cluster analysis based on DTW can be performed either within segment groups of similar length or on the overall data. The agglomerative hierarchical method has proven to be the most suitable cluster method for the non-constant segments.

4. Case Study

The methodology described is explained using two typical machine tools in vehicle construction - a vertical grinding machine from the manufacturer *Buderus Schleifmaschinentechnik GmbH* and a milling machine from *Gleason-Pfauer Maschinenfabrik GmbH*. A selection of electrical parameters was collected over a period of one day in which the typical machine operational states "in machining", "operational readiness" or "warm-keeping mode" as well as standby operation are mapped. The different operational states have different characteristics with regard to the courses of the electrical parameters. The operating mode "in machining" as well as the "warm-keeping mode" typical for the grinding machine are characterized by varying values, while in particular the "operational readiness" of the milling machine as well as the standby phase show approximately constant values.

The universal parameters listed in Table 1 have been defined for all incoming load profiles with seconds measurement data resolution.

Table 1. Parameter settings of case study.

Extraction type	maxVar	maxSQDiff	minSeg
Long nearly constant segments	0,000008	0,000008	180
Any other nearly constant segments	0,0000002	0,0000002	10

4.1. Constant segments

In the first step, the long nearly constant phase of the milling machine's operational readiness is extracted (see the red break points in Fig. 3, which delimit the long constant segment).

After the preceding extraction of long, nearly constant phases, the finer subdivision takes place in the remaining part. With the milling machine, the long and short operational readiness times (2) between the machining cycles (1) are thus detected without any problems, as an approximately constant power factor curve is present in these operational readiness phases. The detected non-constant segments thus include the machining cycles, acceleration and deceleration times, set-up times, etc.

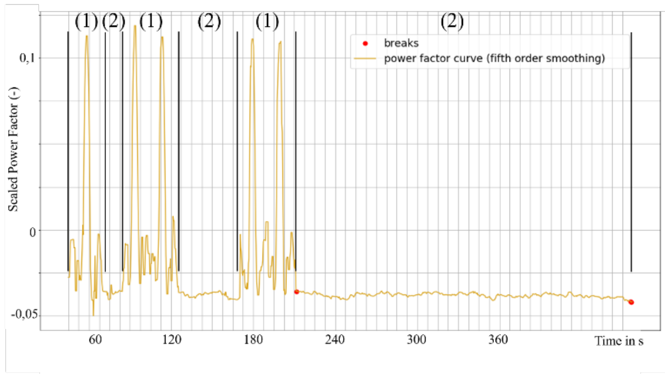

Fig. 3. Scaled Power factor curve of milling machine with break points marking of constant segments and two operational states: machining (1), and operational readiness (2).

The grinding machine differs significantly from the milling machine in its operating behavior. Fig. 4 shows that no approximately constant segments are detected during operational readiness times (1). However, constant segments are detected within the machining cycles (5). Although the "machining phase" of the grinding machine is characterized by strongly varying values of the electrical parameters, short constant phases are also present here. Shorter standby periods are also detected.

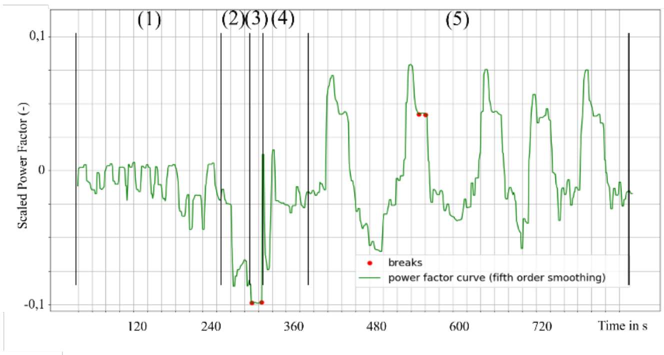

Fig. 4. Scaled Power factor curve of grinding machine with break point marking of a long constant segment and five operational states: operational readiness (1), power down (2), stand by (3), power up (4) and machining (5).

The necessity of smoothing the measured data series depends on the measured resolution and on whether the power meter transmits an instantaneous value or an average value calculated from 1000 values per second to the monitoring system. The machines examined by us in the monitoring system have instantaneous values per second. The results of the analysis of the unsmoothed and the smoothed are similar in this case, which is why the smoothed profiles are shown in Fig.3 & 4 and the unsmoothed profile in Fig. 5.

Within the resulting segment groups "nearly constant" and "non-constant", a separate cluster analysis is performed. Table 2 shows an example of the results of clustering the constant segments on the basis of different data from the grinding and milling machine. It is shown that a good SC can also be achieved with only the power factor characteristic.

Table 2. Clustering of constant segments with evaluation figure silhouette coefficient (SC).

Data specification	SC
grinding machine	0.573
Cluster analysis based on mean and standard deviation of the following electrical parameters:	
apparent power, active power, total power factor, current unbalance, current, first/second/third phase current	
grinding machine	0.646
Cluster analysis based on mean and standard deviation of the total power factor	
milling machine	0.563
Cluster analysis based on mean and standard deviation of the following electrical parameters:	
apparent power, active power, total power factor, first/second/third phase power factor	
milling machine	0.357
Cluster analysis based on mean and standard deviation of the total power factor	

Fig. 5 shows in detail clustered constant and non-constant segments in the power curve of the grinding machine. The constant phase within the machining cycle, which can also be found in Fig. 4, is represented by cluster c1.

Between each machining cycle there is usually also a constant segment with the cluster ID c2 or c3. Between the segment clusters c2 and c3 there is a power difference of about 1-2 kW. Energy measurement on single component level revealed that this is caused by a two-point controlled cooling unit. Thus a typical processing cycle is symbolized by the cluster sequence "nc1-c1-nc2-c2" or "nc1-c1-nc2-c3".

However, due to process fluctuations or measurement deviations, this constant phase within the machining cycle is not always recognized as a constant segment. This is the reason for a third cluster of non-constant segments (cluster nc3).

4.2. Non-constant segments

The seemingly arbitrary segmentation illustrated in Fig. 5 leads to an obviously more complicated clustering procedure for the non-constant segments. In Fig. 5 only three different clusters of non-constant segments are identified. If there are frequently machining cycles without a constant phase within the machining cycle (identified as c1), and if in some cases there is no constant phase between two cycles (identified as c2 or c3), any number of non-constant segment clusters could be found. These detected and clustered non-constant segments have a wide range of segment lengths. In Fig. 4, for example, only two constant segments are detected. As a result, there are relatively long non-constant segments between these captured constant segments. Initial analyses have shown that a pre-division of the segments according to time lengths is advantageous in terms of accuracy and interpretability for clustering over DTW distance measures.

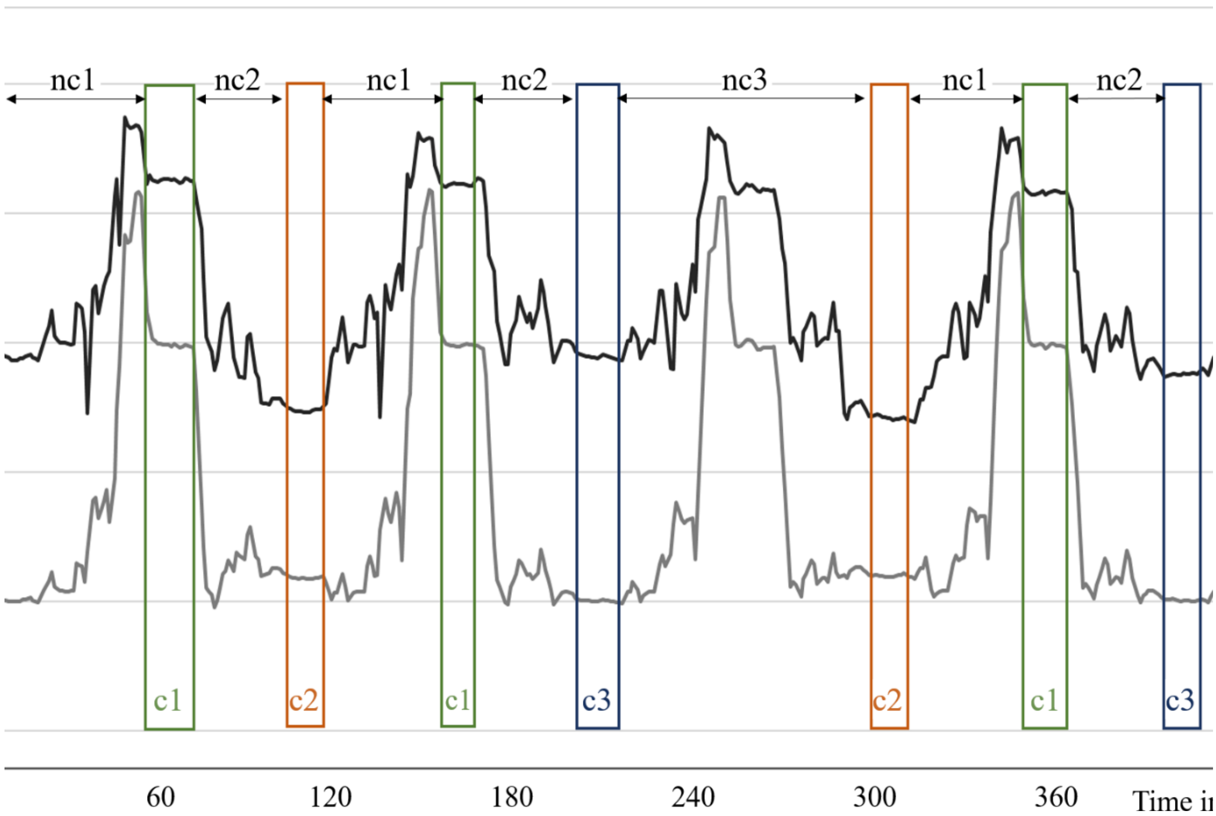

Fig. 5. Active power and power factor curve of grinding machine with clustered constant segments (c1-c3) and clustered non-constant segments (nc1-nc3).

5. Conclusion and Outlook

To achieve the overall goal of an improved unsupervised NILM at machine tool component level, existing approaches must be optimized to handle variable loads and an intermediate sampling rate (<1S/s). The most accurate unsupervised NILM approaches use state-based event detection methods and hidden Markov models [11, 12]. The segmentation of the power factor profile into constant and non-constant phases and the subsequent extraction of typical operational states can therefore serve as preparation for possible automatic device number recognition and load disaggregation at machine level in industrial applications.

Our algorithm for time series segmentation can be automated in practice without time-consuming manual adjustments on all machine tools and their time series. A determination of concrete universal values for very different machine tool types was shown in the case study of this paper.

Long constant phases as well as shorter constant segments can be clearly assigned to repeating operational states. Hence, on the one hand, operational state-based and self-adaptive condition monitoring is possible. On the other hand, the detected operational states provide information about the energy demand and the duration of value-adding and non-value-adding states of the machine tool. This helps to evaluate energy saving potentials like component dimensioning, standby control or efficient energy supply by heat pump storage systems that link heat sources and sinks in manufacturing systems [22].

In certain operational states, such as those of the grinding machine, the power factor profiles fluctuate relatively strongly. In this case, the determination of the non-constant segments depends somewhat arbitrarily on the extraction of the constant segments. Therefore, part of future research will consist of grouping the non-constant segment clusters according to segment length. The group(s) of the relatively short non-constant segment clusters then function as sub-patterns. In the longer non-constant segments with strongly varying segment lengths, these sub-patterns are to be searched for by means of a sliding window and Euclidean distance. In this way, the load curve can be further broken down systematically. To investigate the most frequent non-constant patterns, the implementation of MOTIF detection methods with variable lengths is also part of further research [23, 24].

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