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Signal based non-intrusive load decomposition

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Abstract

Driven by both regulatory and monetary interests the development of energy monitoring systems has been accelerated in recent years. Thus, a large amount of data is collected and stored in huge databases. This is a decisive step towards sustainable production systems since you can't improve what you don't know. This paper aims to use the datasets currently available and to combine databases to gather additional information on production systems, in particular energy flows. Therefore, an algorithm has been developed that combines energy consumption data from production lines with production information to estimate the consumption of connected subsystems. This paper analyzes the algorithm with case studies from companies with their specific databases and will show a deviation of less than 5 % of accumulated energy. Hence, the algorithm is able to create a more detailed analysis of production systems without additional sensor installations by combining existing databases.

Keywords: energy; energy efficiency; NILM, non-intrusive load monitoring; sustainable production; load decomposition

1. Introduction

The past years show a significant increase in the amount of stored data and thus a development in digital businesses. While companies like Google develop new business cases, the potential of collected data, especially energy data, in industrial plants is barely exploited. Simultaneously, the industrial sector is accountable for 25 % of the final energy consumption in Europe and thus every potential should be considered [1]. Furthermore, several governmental regulations have pushed the energy data aggregation in European countries by forcing companies to track their consumption more strictly. Thus, this paper analyses a simple algorithm that gathers additional information about the energy flows in plants and systems by combining existing databases. Basically, it needs one power meter's data, information about the structure of its sub-components and a database which provides information about machine states in any kind. By combining this information the power meter's load can be decomposed and assigned to the connected subcomponents. The algorithm was evaluated on three model cases. The cases differ in the temporal resolution of the energy data, the detail level the information and the composition and control concepts of the system's components. Consecutively the

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case's datasets require different preprocessing steps before being decomposed by the algorithm. This approach will extend monitoring systems with additional virtual meters by a simple algorithm. It replaces the need of an own sensor for each machine to monitor it's power demand. This opens possibilities to monitor machines which are not yet - and may never be - equipped with sensors. Hence, it is a different approach to a more resoluted energy monitoring system than the equipping of each component with a single meter (Internet of Things, IoT). Providing a more detailed energetic analysis of a production line's consumption is crucial for the identification of energy-intensive processes and thus finding measures to delevop a more sustainable production.

2. Load decomposition's state of the art

Trough the rapid expansion of load sensors and smart meters the analysis of various loads continuously gains more attention. For example, there is a great interest in decomposing an electrical grid's load since grid operators need to estimate the demand but usually has no information about his consumer's behaviors. Paisios proposes a method to decompose and profile the load for demand side management [2]. This has recently lead to the development of algorithms for non-intrusive load monitoring (NILM) techniques, which aim to assign a meter's load to the components connected to the meter. NILM often focuses on household meters to detect loads of various common household equipment [3]. The initial approach for NILM was proposed by Hart in 1992 and gained attention through the increasing digitalization over the last years ([3], [4], [5]). These algorithms aim to detect component states by analyzing the load profile. Often not just the load but also additional characteristics like harmonics are used like Srinivasan's analysis of loads with neural networks [6]. Like stated by Saitoh NILM can identify several component's states by analyzing the load [7]. Usually NILM requires the installation of smart meters that provide detailed measurements of the load, so these concepts aim for the design phase of electrical systems [8]. However, previous mentioned research focuses on analyzing load to allocate the load to the components or identify states via unsupervised learning methods. On industrial levels there is often no need to identify states of components since they are already recorded for other purposes like production planning and controlling. Energy monitoring systems also usually record just the power demand and no additional load information. An approach to decompose energy data in an industrial scale using NILM was proposed in by Holmegaard along with an analysis of the challenges, however not combining energy data with other production information [9]. Abele presents an analysis of a milling machine whose load is allocated to its components using PLC signals [10]. Eberspächer presents a similar approach but uses PLC signals as an input for a Model to determine the load via simulations [11] and Gebbe presents a decomposition approach using machine states and processing this data through a linear regression model [12]. The database of Gebbe's evaluation is quite similar to case study 2 in this paper, with different levels of state details though.
However, most analyses are carried out on a laboratory scale and hence have predictable boundary conditions. Analyses of load measurements of real production systems bring along more extensive requirements to handle factors like human behavior, sensor failures, transmission or conversion errors. Hence, this paper analyzed three load measurements of different systems in real plant operation. The algorithm is kept simple since it is considered to be implemented as an addition to monitoring software. The simplicity of the linear solving approach however lacks in decomposing nonlinear correlations. The implementation of expert knowledge into the algorithm, which is shown in case study 3 of this paper, will tackle this problem, however if expert knowledge is not available or relations not obvious, neural networks, like shown by Kelly, are able to handle non-linear correlations [13].

3. Methodology

The following method describes an algorithm which gains additional information about subsystems connected to a common load meter. It provides information about the individual load of the connected components in their specific states, which may vary depending on the underlying databases. Therefore, three case studies have been analyzed, each with different production information systems and complexity levels. These differences affect the data preprocessing and preparation, the base algorithm however remains the same. The basis for each evaluation is a matrix providing state changes for each machine with the corresponding timestamp and the mean power demand of all machines during the time interval. Table 1 is showing an excerpt of an example dataset.

Table 1. Example dataset for five machines with binary states.

Timestamp	M1	M2	M3	M4	M5	P [kW]
⋮	⋮	⋮	⋮	⋮	⋮	⋮
06-Oct-2017 06:09:28	1	1	0	0	1	71.16
06-Oct-2017 06:09:55	1	1	0	0	1	66.30
06-Oct-2017 06:11:00	1	1	0	0	1	64.97
06-Oct-2017 06:12:33	1	1	0	1	1	71.51
06-Oct-2017 06:13:53	1	1	0	1	1	73.95
⋮	⋮	⋮	⋮	⋮	⋮	⋮

The algorithm assumes that the common power demand of all machines in a time period can be derived from the sum off all states (s) multiplied with their specific power demand:

$$P_{t1} = \sum_{Mi=1}^{M} (s = 1) * P_{on,Mi} + (s = 0) * P_{off,Mi} \tag{1}$$

Table 1 therefore represents a linear equation system. Since there may also be a power demand when all machines are offline (i.e. the baseload), the matrix must be extended by binary offline states. The extension with offline states will lead to a doubling of the unknown variables without adding additional information and thus not enhancing the rank of the matrix. This will consequently lead to a higher deviation when solving the equation. To work around this problem the baseload (P_b) is identified by searching for the rows that contain just offline statuses and shared equally on all machines (n):

$$\begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 0 & 1 \end{bmatrix} * \begin{bmatrix} P_{on,M1} \\ P_{on,M2} \end{bmatrix} = \begin{bmatrix} P_{t1} \\ P_{t2} \\ P_{t3} \end{bmatrix} - \begin{bmatrix} 0 & 1 \\ 0 & 0 \\ 1 & 0 \end{bmatrix} * \begin{bmatrix} \frac{P_{b,M1}}{n} \\ \frac{P_{b,M2}}{n} \end{bmatrix} \tag{2}$$

Anyway, in most cases there is still not enough information available to exactly solve the system. Additionally, the data source is based on real measurements which inherently contain deviations and a classic solver for linear equation systems may output unrealistic machine power demands as the best solution. Hence, a solver for nonnegative linear least-squares problems is used:

$$\min_{P_M} \|S * P_{on,M} - P_t^*\|, \quad where \quad P_M >= 0. \tag{3}$$

where S contains the states of each machine in each timespan, P_M the machine's power in each state and P_t^* the baseload-adjusted aggregated power per timespan.

4. Case studies

The production information's level of detail varies between the three case studies depending on the available databases, so they require different preprocessing algorithms. Input data may furthermore just take binary ("on" and "off") or continuous states and may correlate in different ways with the power demand. Case study 1 examines machines with just two different states, case study 2 uses four states while case study 3 examines five machines with binary states as well as four machines with continuous states.

4.1. Case study 1: Automotive production line

The first case study analyzes a production line of an automotive plant with consecutive processing steps consisting of four grinding machines and a washing machine. However, there are storage possibilities between the machines so there is no temporal relation between the output of one machine to the input of another. There are process completion signals available for each machine, but all machines have one common power meter.

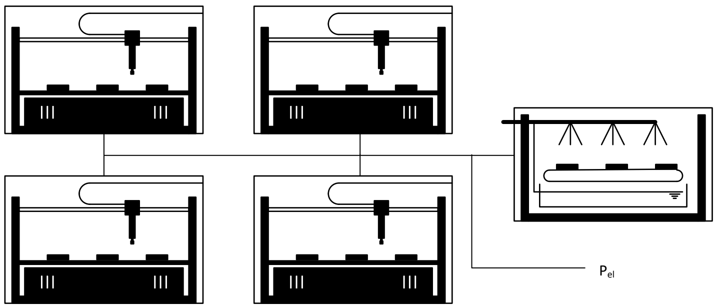

Fig. 1. Scheme of the automotive production line.

The first step is to process the signals to achieve Information about the runtime of each machine. Therefore the time difference between each signal is evaluated and tested for outliers as suggested by Grubbs [14]. Hence, very large time differences are not considered as production time and thus identified as outliers. Remaining time differences are assumed to be the actual cycle time of the processes. Based on this information the matrix representing the production status of each machine (see table 1) is built. If neccessary, the power consumption is adjusted to the matrix's timestamps.

4.2. Case Study 2: Plastic fabrication

The second case study analyzes a plastic fabricator's set of six injection molding machines connected to one power rail. Similar to the first case there is no temporal dependency between the machine's production cycles. There is however a more detailed production information system compared to the first case study. This system is logging detailed machine states like automatic operation, faults or offline states. This provides a more detailed resolution of the process, especially in non-producing times. However, previous analyses showed that it is recommended to concentrate the information to four states: automatic operation, manual operation, machine faults and offline. Furthermore, each injection molding machine can be equipped with different tools, whose power demands may significantly differ. Hence every tool is treated like a separate machine and is thus expanding the matrix's column size.

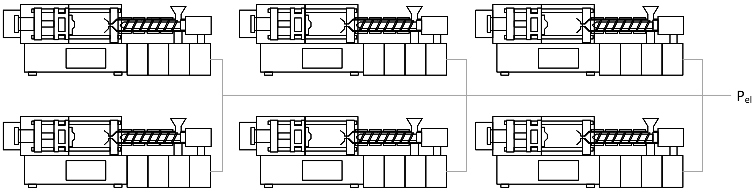

Fig. 2. Scheme of the plastic fabrication.

Since there are four states instead of two and there are several tools a more extensive dataset is required to solve the linear equation system. The sharper definition of machine states improves accuracy, though.

4.3. Case study 3: Cooling tower System

The last case study shows a cooling tower system with one circuit pump, four fans and their four corresponding pumps each connected to a heat transfer unit. The secondary cooling circuit connected to the heat transfer units however is not a part of this analysis.

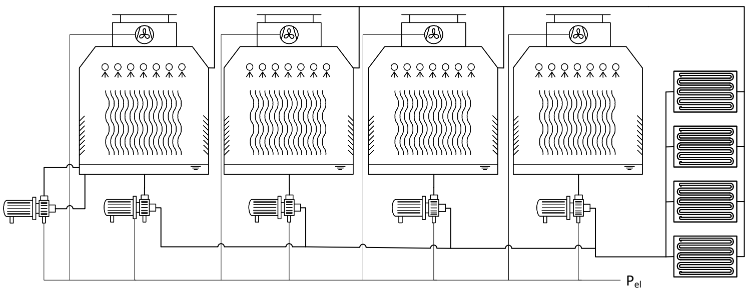

Fig. 3. Scheme of the cooling tower system.

This system differs from the other cases since there is a physical dependency between the pumps. They are connected through a hydraulic system and the status of one pump will affect the other. Consequently, the pumps are not treated separately but have to be interpreted as different combinations of states. There is no production system providing the state information, since there is no direct product relation, but PLC signals are used to decompose the power consumption instead. The pumps' states can have two values (on and off) while the fans are frequency controlled and can take partial loads between 50 % and 100 %. Since there is a cubic correlation between rotation speed (and thus partial load) of the fans and their power consumption and a linear equation system is used to decompose the power demand a direct evaluation of these partial loads would not represent the power consumption of the fans precisely. The results may be improved by defining discrete intervals of partial loads and summarize the corresponding continuous values in these classes. Smaller classes will increase accuracy. Since you know the basic cubic dependency between partial load and power demand you can use this information to enhance the performance. Hence the corresponding PLC values of the fans are raised to the power of 3 and afterwards solved linear. Figure 4 shows the difference between different approaches.

The best performance is clearly carried out by (d), while (c) is performing slightly worse. Obvious deviations show (a) and (b) while the last may be improved by a more sophisticated class distribution. Anyway, if there is information about the physical dependencies between the database and the power demand the result can be significantly improved by adapting the algorithm. If, however, there is no knowledge about the relationships, the performance for continuous datasets may be improved by classification.

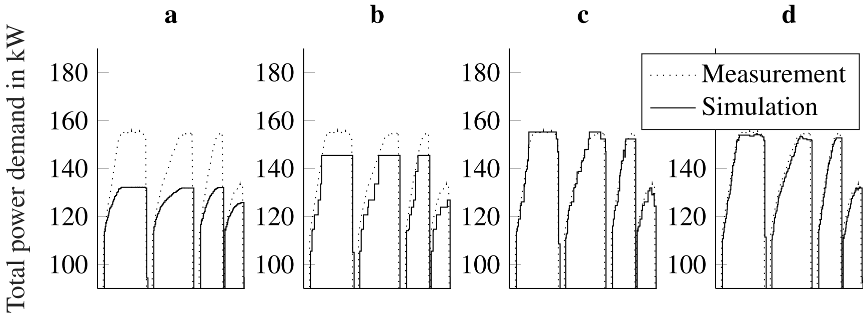

Fig. 4. Comparison of the (a) linear, (b) discrete-linear with 10 %-classes, (c) discrete-linear with 1 %-classes and (d) cubic approach.

5. Results

The algorithm provides the mean power demand for each machine with each tool in each state. Hence, based on the production plan, the common power meter's demand can be simulated. The simulation will output a discrete function and the averaging effect will lead to deviations when the actual power is peaking. However, this approach is not aiming to simulate the power demand at every point but rather to the mean power demand. Hence the quality of the results should be derived by the difference between the accumulated energy consumption. Figure 5 compares the discrete simulation with the measured values.

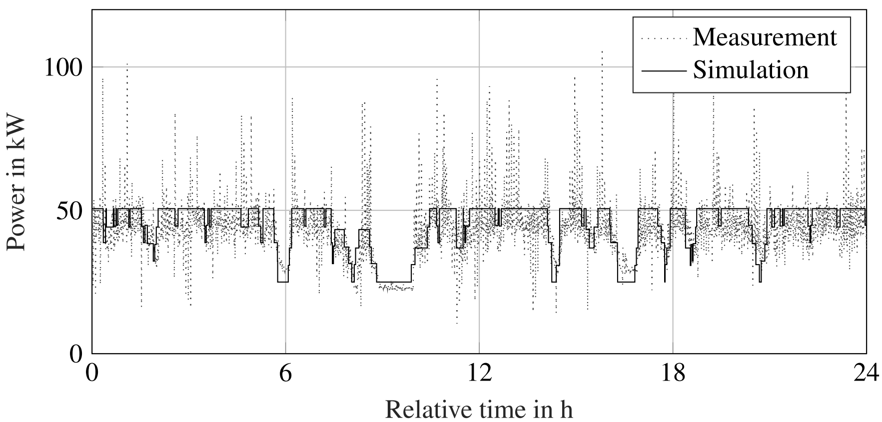

Fig. 5. Simulation of the power meter's consumption of the grinding machines compared to measurements (40-day-database).

Figure 5 compares the simulated to the measured power and shows severe short-time deviations. The power demand over time highly depends on the depth of cut and thus varies a lot during a grinding machine's duty cycle. Due to the constant power assumption during a duty cycle there are high short-time deviations between the measured and the simulated power. Although there are these short-time deviations in power the accumulated energy demand differs just by less than 5 %. Hence, the mean power demand over a long time period can be simulated quite accurately while a short-time simulation is not suitable. Further differentiation between offline- and standby-states could additionally improve the results.
The second case study provides more detailed information about different states with total energy consumption deviations with up to 3 %.

However, changes in machine or user behavior will result in wrong forecasts. Figure 6 shows how a machine remains in standby mode over a weekend while the power demand is near zero and depicts offline states. Since these factors may not be obvious and may change just slowly over time, the machine power demand database should be

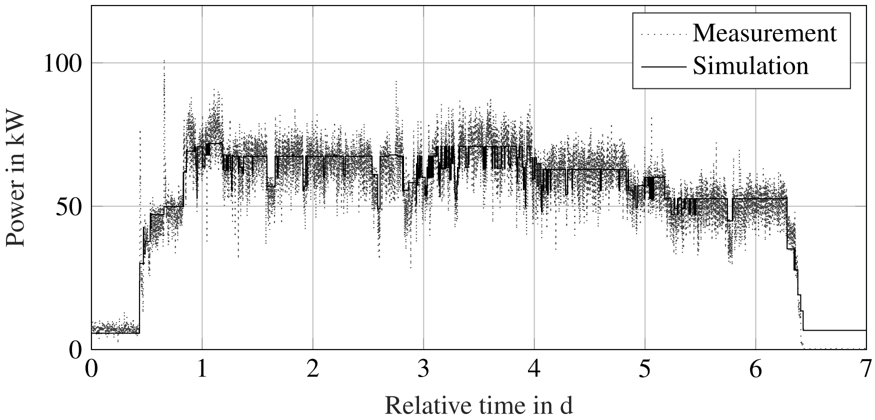

Fig. 6. Simulation of the injection molding machines power meter's consumption compared to measurements.

continuously updated.
The usage of expert knowledge to define base relationships between the parameters and the power consumption significantly improves the results. Especially components in partial load operation often have nonlinear relations.

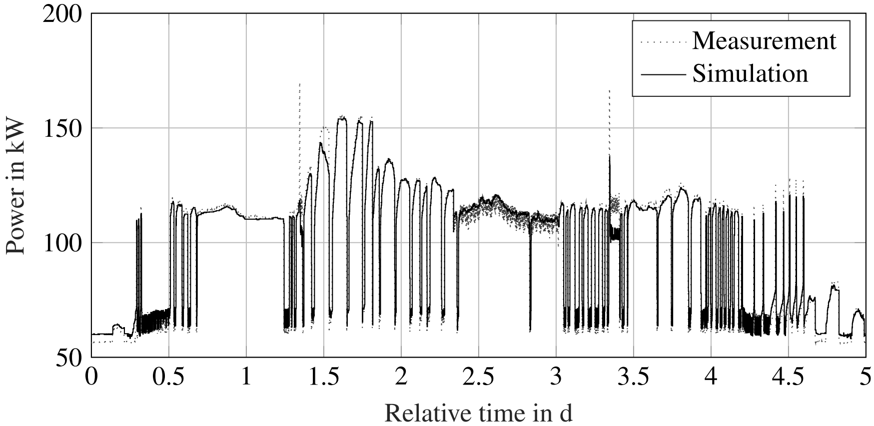

Fig. 7. Simulation of the cooling tower power meter's consumption compared to measurements.

The last case shown in figure 3 uses expert knowledge, considers physical relations between subsystems and thus performs very accurate at deviations lower than 1 %.

6. Conclusions

The algorithm presented in this paper decomposes a system meter's load and assignes it to the subsystems's components by combining information of common databases in an industrial plant. It depends on the power consumption of a power meter and production information of all its subcomponents. The production information system's raw data may be production signals, machine states or PLC signals while more detailed signals will naturally perform better. The algorithm outputs consumption information about each component with each tool in each state by solving a linear equation system. The algorithm however can not solve short-time power demands accurately, especially if the power demands varies a lot during a duty cycle. Hence, temporal peak power demands can not be estimated, which may be an important issue especially when analyzing large consumers.

To solve it nonnegative constraints should be set for the component's power vector, since there may be mathematically better results for negative loads. Also, the component's interdependencies have to be considered to get valid information. If there is continuous raw data it is recommended to use expert knowledge to define the base dependencies between load and raw data, if they are not linear. This will significantly improve the algorithm's performance. If, however, the dependencies are not clear a classification of discrete data will improve accuracy but simultaneously increase the computational effort.
As stated above there is a lot of research concerning load decomposition methods and NILM. This paper proposes a simple algorithm which is capable of running on machine level without requiring additional hardware. While it is a robust and fast algorithm for solving linear correlations. The use of expert knowledge improves the accuracy of nonlinear correlations, however unclear correlations may require more sophisticated algorithms. Further development of this algorithm will focus on the differentiation between baseload and offline states, if they are not provided by the system. Also, the use of neuronal networks is a promising advantage to the decomposition algorithm (see [13]). Advanced NILM algorithms however need to be trained with data while expert knowledge is directly available.
Disaggregating energy data is an additional step for understanding the basic energy distribution in production systems. The implementation of virtual load meters through energy data decomposition gains the actual energy demand without installing additional sensors or equipment. Implemented on factory level the algorithm can be continuously updated, adapted to changing circumstances and detect changes in the energy demand. Furthermore, using PLC signals a machine' power consumption can be assigned to the machine's components to gain an even more detailed energy analysis. These information opens new possibilities in detecting optimization measures or monitoring the component's quality leading to a more sustainable production.

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