Energy Load Profile Analysis and Application for Production Simulation and Scheduling using Energy Load Disaggregation

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Abstract: Rising energy prices and an increasing share of volatile energy supply from renewable energy are leading to greater interest in detailed modeling of energy consumption in manufacturing. Nevertheless, energy measurements and energy load profiling at the machine level as well as the application of energy-related data for production scheduling is challenging. To provide detailed information for applications like scheduling models, degrees of freedom to adapt to energy consumption must be considered even at the component level. Since metering hardware and energy load profiles are often not available for machine components, the methodical application of energy load disaggregation can contribute to these topics. The paper introduces a concept for incorporating event-based load disaggregation to create energy load profiles for production machines. It also explores and discusses potential applications for simulation and scheduling in manufacturing environments.

Keywords: Energy Load Profiles, Load Disaggregation, Load Profile Analysis, Production Modules

1 Introduction

Nowadays, there is an increasing demand for resource efficiency, where especially energy efficiency and the usage of renewable energy becomes more important in the manufacturing domain. The significance of these topics for future developments is also stated in the concept of the European Green Deal [Co19]. On the other side, current developments in the manufacturing domain can contribute to these challenges. Industry 4.0 offers possibilities

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to consider topics of resource efficiency like the integration of energy consumption in production facilities, especially for planning and operation purposes [KWH13].

Transparency about energy consumption and energy load-related patterns in modular production environments to build energy load profiles requires above all a flexible metering concept. The metering is more often provided in an aggregated way and not in detail, for example for the components level [Mo21]. Energy load profiles at machine level are important, although the interpretation of energy data is challenging at this level due to a wide range of measurement data which must be considered for further processing in a methodical way [Te18]. Cyber-Physical Production Systems can contribute to realizing energy-flexible operation of production machines, using simulation models, controllers for energy-flexible operation and automation data models [Gr22].

This paper focuses on the analysis and interpretation of already metered energy data of production machines, which are often based on several components to be activated and controlled to fulfill the purpose of the production steps of the machine. While those components have their own individual energy profiles, the metering and analysis of energy data on this detailed level of granularity is difficult, since related metering hardware must be provided. Energy load disaggregation can help to determine the appliances in operation and their individual energy consumption, as has already been demonstrated in the household sector in early contributions [Ha85]. Nevertheless, the application of energy load disaggregation on real-world production machines and data classification of the energy load patterns for further usage, for example to set up or improve scheduling models, can be individual to a certain degree.

The proposed concept of this contribution shows how a methodical usage of energy load disaggregation can be used for classification of load profiles at the component level of machines, which could then be integrated and used for further applications, for example simulation and scheduling components. Therefore, the method of an applied energy load disaggregation is shown, considering the data of component-related load profiles of an industrial machine. The load profiles are used to classify the flexibility of energy consumers for integration into a digital twin at the machine level. The possibilities of this classification in combination with load profile simulations for individual parametrization and model design, as well as model detailing of scheduler components are discussed.

This paper is structured as follows: The current state of the art of modular production systems and the importance of energy measurements and energy load profiling on the machine level is shown in Section 2. In Section 3, the concept for the integration of energy data is presented, focusing on the load disaggregation method and a subsequent simulation setup for scheduling application. Section 4 presents the results of the application of the concept to a real-world cleaning machine use case and provides a discussion on how the results of the load disaggregation can be used for further research and development. Section 5 summarizes the presented topics of the contribution.

2 State of the Art

2.1 Energy Load Profiles in Production Environments

The optimization of energy load demands of machines is of importance, especially considering the objectives of load minimization, load flexibilization and load smoothing [ASM16]. Metering data for energy consumption are mainly used with the aim of reducing energy costs or to improve the environmental impact, but the interpretation of this data is difficult on the level of production machines due to the mass of metering data which is not considered in a methodical and dedicated way [Te18]. Due to modularization and decentralization, continuous metering for data acquisition and situational monitoring of energy consumption as well as corresponding modeling for forecasting and scheduling purposes is challenging. Energy related knowledge is often not considered in centralized production systems, for example electrical energy consumption in relation with different operation modes or detailed process parameters [IA17].

Modular and flexible production environments are an important basis for the realization of manufacturing in decentralized manufacturing structures, in which machines can furthermore encapsulate their production capabilities and implement them with the skill-based approach [Be22]. Standardized interfaces at the machine level play an important role in modular structured production environments, since they can encapsulate the related functionality [Ko18]. Based on such modular and skill-based manufacturing environments, in which production modules encapsulate their manufacturing capabilities, the measurement of energy consumption can be realized on a more detailed level using the corresponding interfaces in combination with related metering hardware for production machines [Mo21]. Data acquisition, for example especially for energy consumption, is thus possible and realizable for production machines, where the skill-based approach offers potential to consider the individual components and processes of a machine and to provide transparency over energy consumption even at this level of granularity.

In this paper, the importance of energy measurements and detailed modeled energy load profiles are considered and placed in the context of modular production environments.

2.2 Energy Data Analysis using Load Disaggregation

In their recent publication, Leherbauer et al. argue that viewing the energy consumption of a machine as a single sensed entity misses the ability to extrapolate the energy profile in the face of changing machine parameters and is only suitable for batch manufacturing with recurring products [LH23]. The approach neglects the system's composition of multiple consumers (e.g. motors, heaters, etc.) whose aggregated individual load profiles form the machine's measured load. Disaggregating the machine's load profile into the subsystems' profiles allows reliable and explainable inference of the aggregated load while the process is re-parametrized.

Load disaggregation, often synonymously used with Nonintrusive load monitoring (NILM) as originally characterized by Hart describes the problem of deducing which appliances in a household are running as well as their individual energy consumption [Ha85]. It was introduced to avoid monitoring the consumption of the appliances individually. Since then, it has developed into a field with growing research activities [LWM24] at least in part due to the rise of smart grids and smart homes. The majority of publications still study the application of NILM on residential data [TMJ23]. Due to the increasing legislative pressure for increased energy efficiency, like the European Green Deal [Co19], and rising energy prices, there is a growing interest to apply these techniques in the manufacturing sector for granular energy monitoring as well [Go15].

With a growing number of approaches, algorithms and datasets from 40 years of research in NILM, it is imperative to specify the investigated problem as well as possible to find a suitable approach. Kaselimi et al. give an indication by differentiating between classification (determine the state of the appliances, e.g. on or off) and regression problems (determine the appliance's load profile) [Ka22]. They also distinguish between supervised and unsupervised approaches, while [LWM24] also recognize semi-supervised approaches, depending on the availability of labeled data in single- or multi-target model building. Liu et al. also distinguish further between state-based and event-based NILM approaches, where the former try to focus on identifying the consumers' state and the latter on transitions between states [LWM24]. Nevertheless, their reviews do not feature a generalized approach to NILM.

Complementary, Schirmer et al. present a generalized data-driven architecture for NILM consisting of the 6 steps of smart metering of the aggregated signal, pre-processing, framing, feature extraction, disaggregation, and post-processing [SM22]. Depending on the availability and quality of data, the steps of pre-processing and framing can be skipped. They also propose a classification of NILM approaches in machine learning, pattern matching and source separation approaches and give an overview of the performance of different algorithms of each class.

This work does not primarily add to this list of algorithms, although it presents its own approach. It assumes that information about machine state in an industrial setting exists, but is not available in the common definition of the load disaggregation problem. It rather focuses on continuing the efforts of Leherbauer et al. [LH23]. They identified that further research is necessary to describe methods to automatically parametrize the discrete event simulations with real data for flexible load scheduling. This paper recognizes the state of the art in NILM approaches and algorithms and leverages a simple, novel probabilistic, unsupervised, event-based classification approach to disaggregate a machine's loads. This, in combination with the machine's task execution schedule, can be used to recognize the relationship between the machine's profile and its process parameters. Thus, our work fills the gap identified by Leherbauer et al. [LH23].

3 Concept for Energy Load Analysis using Load Disaggregation and Application for Simulation and Scheduling

In this section, the concept for energy load analysis using load disaggregation for production machines is presented and described from a methodical perspective. Additionally, possible applications of the load analysis for simulation and scheduling are shown. The individual components of the architecture are explained in more detail in the subsequent sections.

3.1 Concept and Components

Figure 1 illustrates how energy load data can be used in a digital representation of a real factory, which provides data management for energy load profiles and services for simulation and scheduling. The utilization of these components follows the approach of [Mo20], where energy consumption data is the basis for a combined usage of energy load forecasts and production planning. One possible application is using the energy load profiles for various simulation models to mimic real energy consumption as closely as possible. The aim of this model is to optimize the energy consumption of the real factory through multi-criteria production scheduling.

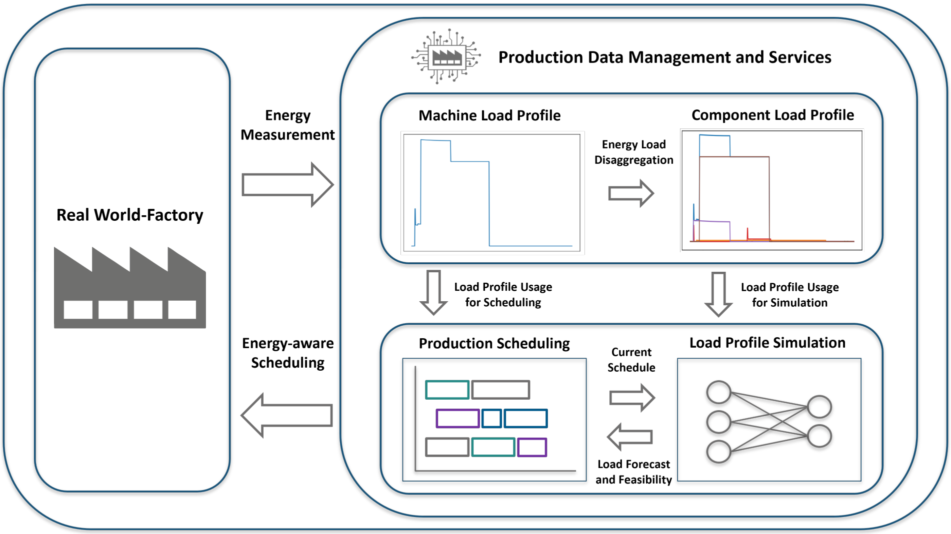


Fig. 1: Concept for Energy Load Analysis and Application based on the Load Disaggregation method

Based on measured energy data, energy load profiles can be updated and combined with the energy load disaggregation at the component level of a machine. This means that changes of machine behavior, for example based on different component parametrization or changed hardware components due to maintenance and repairs, can be considered and updated in the related simulation and scheduling components.

In the proposed concept, energy measurement data is collected and used for parametrization of the simulation and scheduling models. In this process, the load disaggregation employs a decomposition method to determine the consumption of individual components. The load profiles on machine and component level is then used in combination with the scheduler component, to predict energy consumption for a given schedule. A machine learning model could be used for these predictions. This model thus calculates the power consumption in combination with the scheduling model, realizing energy-aware scheduling for the real-world factory. This energy consumption serves as a constraint to exclude solutions that would overload the power grid, and the model also sets target values for production scheduling. The production schedule determined by the scheduler component is then executed by the real factory.

3.2 Method for Applied Load Disaggregation

Disaggregating the total energy consumption of a production plant enables a transparent allocation of the consumed energy per individual subsystem at every timestep of a process. In the initial context of NILM in residential energy monitoring, this association is typically achieved by recognizing complex patterns and profiles of distinguishable consumers (e.g. washing machine, dishwasher, etc.). In this setting, the observable data is usually limited to the aggregated load measured through a smart meter.

In industrial settings, access to the machine's control is usually possible. This is helpful when breaking down the profile of an industrial machine composed of multiple consuming subsystems: It enables access to more detailed information about machine states and the times of state transitions. With this key information, discontinuities in the load profile can in most cases be assigned simply due to their temporal correspondence with events in the machine control. For these discontinuities, the term *event* will be used in the following in accordance to its use in [Ha92].

The approach presented in this paper relies on the existence of rudimentary state information from the machine control (e.g., is a consumer turned on or off), thus following the assumption from [Go15], and additionally makes the following assumptions:

1. The number of consumers is known. This is implicitly covered by the information provided through the machine control.
2. The states between events can be approximated by steady (polynomial) functions.
3. The height of load jump during an event correlates to the following course of the load profile and is presumed to lie close in time to a state transition. This assumption is of a probabilistic nature and supported by the observations of [ABB21] and [Go15] on controlled loads and start-up peaks. These are especially related to electromechanical consumers (e.g. electrical motors) which have to overcome initial friction and inertia when set in motion.

Utilizing these assumptions, the approach presented is structured into the following three steps:

1. **Event detection:** The total load profile is analyzed and all transitions between steady states are registered.
2. **Event classification:** The detected events are correlated to the different consumers, either via the information about on and off states from the machine control or based on the probabilistic assumptions described above.
3. **Steady state regression:** The classified events are connected via steady functions. The regression problem is hereby formulated as a multi-objective optimization problem to minimize the difference between the reconstructed and the ground truth aggregated load profile.

3.3 Energy Load Profile Simulation and Scheduling Application

The following section explains how a parameterized event simulation can be used to avoid voltage peaks. Leherbauer et al. show a hybrid approach in which energy-aware scheduling is proposed, based on a discrete event-simulation which is then optimized by a hybrid optimizer [LH23]. In their approach, the discrete event simulation has to be carried out in each step of the optimization to determine whether a solution is permissible or not. In the current contribution, load disaggregation is additionally used for the classification of the flexibility of machine components or processes. Since load disaggregation can contribute to the transparency of energy load patterns, it provides a detailed analysis on which components are static or flexible.

Considering the flexibility of machine components, the aspects of parameter-flexible or time-flexible processes are of interest for a scheduling component model. Load patterns which are parameter-flexible vary depending on the parameters used and can have a higher or lower load for the execution of a production step. Time-flexible processes can, for example, be started with a time delay or paused during their execution. How a scheduling model can consider such degrees of freedom are shown as Mixed-Integer Programming (MIP) in the contribution of [Yf22]. To exclude solutions where the power consumption exceeds a certain threshold, machine learning models can be used and combined, for example with a discrete event simulation. The discrete event simulation can thus be used to provide an energy load forecast, to identify load peaks which are caused by single component parametrization, or to generate further training data.

Two types of training data would be possible for this. One approach would be to obtain the total load profile for a production schedule. Another would be to only obtain the statement whether the threshold value has been exceeded. This data is then used to train a model that can predict either the total profile or only whether the threshold value has been exceeded because of overlapping load peaks. The main aim is to provide a detailed energy model of the energy consumption behavior of production machines and their degrees of freedom in relation to their energy consumption with their corresponding load patterns. This energy model could then be integrated into scheduling models, which are for example formalized as MILP. An example of such a MILP model is presented in [Yf22], in which the flexibility of a production machine is modelled with four intensities, where each results in a different energy consumption and production time. Although the aim of these models is to come as close as possible to reality, there is usually still a degree of incompleteness, which is often not updated and tracked on the model side. The energy consumption of various machines has already been predicted using various machine learning models [Di20], [BKY23]:

1. neural networks
2. gaussian process regression
3. support vector machines
4. search trees

These models have already shown that load profiles can be reliably predicted. These models can also be integrated into MIP models. This has already been successfully demonstrated by [Tj20] and [An20].

4 Results and Discussion

In this section, the presented concept is applied to a real-world cleaning machine use case. The results of the load disaggregation method are presented. A discussion is provided on how transparency of energy load profiles can be used for further applications. Additionally, identified potential for further developments and research is described.

4.1 Cleaning Machine Use Case

A validation of the described concept is conducted using the BvL Ocean RC 750[7] rotating chamber cleaning and degreasing machine (see Fig. 2). The machine is equipped with a Siemens Simatic control SIMATIC S7-1500 and possesses several different process parameters including required and optional processing steps and is therefore an ideal research subject for the validation of the concept.

The parts cleaning process involves three primary steps: cleaning, rinsing (which may be optional), and drying. The duration and repetition of these steps can vary depending on the specific cleaning requirements. Additional intermediate steps, such as dripping or pauses in the process, may also be incorporated based on the particular needs of the cleaning task [Du06].

[7] BVL Cleaning, https://www.bvl-cleaning.com/en/cleaning-systems/ocean/oceanrc, 07.22.2024

Fig. 2: BvL Ocean RC 750 [IEW23]

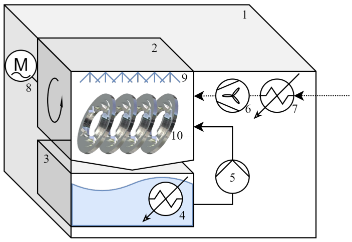
The objective of the cleaning is to remove soils from parts' surfaces [De03]. The cleaning is accomplished by a cleaning fluid containing an aqueous cleaning agent in a specific concentration. To be effective in removing soils, the cleaning agent requires a certain temperature range. During spray cleaning, the cleaning fluid is sprayed at high pressure through spray nozzles onto the surface of the part to remove the soil mechanically. Additional movement of the cleaning basket or the nozzle frame (e.g. rotation) further supports the cleaning process by mechanical action. Rinsing is sometimes necessary to rinse the parts from the cleaning fluid saturated with soil so that it does not leave excess residue on the surface of the part. Finally, a drying step is required to remove the cleaning or rinsing liquid from the surface of the part to prevent corrosion or to enable subsequent critical production processes [IEW23]. This paper focuses on single-tank cleaning machines, where only the cleaning and drying steps are carried out, and the rinsing step is omitted. Since chamber cleaning machines work in batches, they have to be loaded with soiled parts before the cleaning process and then unloaded, which adds another process step to the machine process [IEW23].

The consecutive process steps are summarized in Table 1. Other unspecified events, such as pauses between the process steps, are classified as Other. This results in a cyclical load profile corresponding to the process steps. One exception is the tank heating, which reacts independently of the process step.

Process step	**Description**
Clean	Remove soil from the surface of the parts (spray cleaning)
Dry	Remove cleaning fluid from the surface of the parts (hot air)
Load	Loading/unloading parts in the treatment chamber
Other	Unspecified events

Tab. 1: Process steps of the chamber cleaning machines [IEW23]

The main components of a chamber cleaning machine are shown in Figure 3. Single-tank chamber machines (1) possess a treatment chamber (2) and a media tank (3). The treatment chamber holds the cleaning basket, which is loaded with soiled parts (10) before the cleaning process. To improve the mechanical cleaning, the cleaning basket is equipped with an electric motor (8), which causes a relative movement between the parts and the spray nozzles (9). The spray nozzle system is supplied with cleaning fluid from the media tank during the cleaning process by an electrically driven spray pump (5). An electric tank heater (4) is installed in the media tank, which maintains the temperature range required for cleaning. After cleaning, the parts are dried with convective heat using hot air blown in by the electrically driven drying fan (6), which feeds ambient air through the electric drying air heater (7) into the treatment chamber [IEW23].



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

Fig. 3: Schematic of the chamber cleaning machine [IEW23]

For the sake of completeness: The exhaust fan draws the moist air out of the chamber after the washing process so that it does not end up in the production hall.

Table 2 shows the controllable parameters and their respective ranges.

Consumer	**Parameters**	**Range**
Tank heater	Cleaning fluid temperature T_{fluid}	40 - 60 °C
Spray pump	Washing time t_{washing}	60 - 240 s
Hot-air dryer	Drying air temperature T_{drying}	100 - 400 °C
Hot-air dryer	Drying time t_{drying}	60 - 270 s

Tab. 2: Controllable parameters of the BvL OceanRC 750 cleaning machine.

The machine has the following electrical consumers:

- Tank heater
- Hot-air dryer (Drying air heater and drying fan)
- Washing pump
- Exhaust fan
- Rotational drive

4.2 Load Disaggregation Results

The following sections detail the steps of load disaggregation, as briefly described in Section 3.2. The approach is demonstrated on the cleaning machine described in Section 4.1.

4.2.1 Event Detection

The main objective of the event detection is to localize occurrences of changing states (turn on/off, or a different mode). It is thereby assumed that such a state transition influences the course of the power consumption noticeably. As such, transition events are noticed as discontinuities that separate the steady states. This paper uses the algorithm described by Hart [Ha85] as implemented in the nilmtk software package[8], which relies on edge detection approaches developed in image processing. But as Hart already noticed, numerous signal processing approaches like filtering, differentiating and peak detection could be used to detect events [Ha92]. More advanced methods emphasize the robustness of detection methods, e.g. in the detection of near simultaneous events [Ya23]. Figure 4 shows the results of the detection algorithm applied on the cleaning machine's load profile, which reliably detected all events in the profile. The power value of the event is the mean of the following steady state.

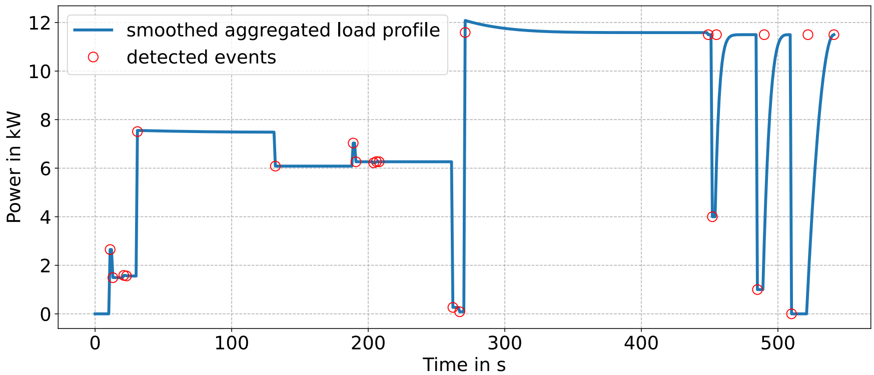


Fig. 4: Detected events using Hart's algorithm [Ha92] on smoothed aggregated load profile of cleaning machine.

4.2.2 Event Classification

Allocating the events to the different consumers is a difficult challenge, as it most likely involves some form of heuristic and is therefore mostly built on assumptions and likelihoods

[8] Github, https://github.com/nilmtk/nilmtk, 07.22.2024

about the energy consumption patterns. As such, the availability of additional information on the transition of consumers' states automatically introduces a higher grade of certainty, improving the event classification.

Blind approaches that estimate the events' allocation without this additional information typically utilize clustering methods like k-nearest neighbors (knn) or other heuristic algorithms, like Hidden Markov Models in modified versions [TMJ23]. In our approach, the state transitions are directly read from the PLC code and can be allocated to the contemporaneous events they cause in the load profile in an event pairing step.

Nevertheless, heuristics need to be applied in the case where events occur simultaneously (e.g. in the case consumers are synchronized) or the load profile is not constant during a state (e.g. with start-up peaks). In this case, we utilize a knn approach due to its effective simplicity. It relies on the 3rd assumption from Section 3.2. For that, the mean load of the individual consumer between the state switch $\bar{P}$ is interpolated linearly and compared relative to the absolute of the events' height $P_{\text{diff}}(t_e)$. The power dimension $d_P(t_e)$ of the classifier is calculated with the following equation:

$$d_P(t_e) = \left| 1 - \frac{\bar{P}}{P_{\text{diff}}(t_e)} \right| \tag{1}$$

In the time dimension $d_T(t_e)$, the distance between the event and the switch-on event T_{on} is put in relative to the difference between the switch-off time T_{off} and the switch-on time:

$$d_T(t_e) = \frac{t_e - T_{\text{on}}}{T_{\text{off}} - T_{\text{on}}} \tag{2}$$

The distance to the neighbors d_{knn} is calculated in a weighted space, as in the considered example it becomes evident that the power dimension has a stronger correlation to the target:

$$d_{\text{knn}} = w_T d_T + w_P d_T \tag{3}$$

For the presented cleaning machine use-case, the weights are chosen to be 0.1 for w_T and 1 for w_P.

These calculations are derived purely empirically, and future research needs to be conducted to systematically back up the underlying assumption and the classificator parameters based on it.

4.2.3 Steady State Regression

When all events have been classified as belonging to one of the machine's subsystems, the load line can be reconstructed according to the 2nd assumption from Section 3.2. For the sections in between neighboring events of the same consumer the term steady state is used according to [Ha92]. The reconstruction is formulated as an optimization problem to minimize the mean squared error (MSE) between the estimated $\hat{p}(t)$ and the measured total aggregated load profile $p(t)$ over the total process time T.

The construction of the load line itself is formulated as a 1D interpolation problem and approximated via a quadratic Lagrange polynomial. The start and end events of a steady state represent two of the support points. The third one is chosen as the middle between the two events, and its height is determined numerically during the optimization process to minimize the MSE of the total load. As such, the reconstruction problem is a hybrid between regression and interpolation.

$$\min \sum_{t=0}^{T} (p(t) - \hat{p}(t))^2 \tag{4}$$

$\hat{p}(t)$ is hereby the sum of a set of active consumers N:

$$\hat{p}(t) = \sum_{n \in N} \hat{p}_n(t) \tag{5}$$

$\hat{p}_n(t)$ is the piecewise function with a set of M steady states in between two events $T_{\mathrm{m,on}}$ and $T_{\mathrm{m,off}}$ described by Lagrange polynoms $L_m(t)$:

$$\hat{p}_n(t) = \begin{cases} L_m(t) & \text{if } t \in [T_{m,\mathrm{on}}, T_{m,\mathrm{off}}] \\ 0 & \text{else} \end{cases} \tag{6}$$

The Lagrange polynomial consists of a set of base polynomials $l_j(t)$ for all the nodes j

$$L_m(t) = \sum_{j=0}^{2} \hat{p}_{n,j}(t) l_j(t) \tag{7}$$

$\hat{p}_{n,j=1}$ is the missing support point and determined numerically in the optimization process. For the optimization process regarding this use-case $\hat{p}_{n,j=1}$ can additionally be constrained to lie between $\hat{p}_{n,j=0}$ and $\hat{p}_{n,j=2}$. This assumption, which is valid for this use-case, cannot be generalized for all machinery, and could be evaluated against future systematic research in generalized load patterns.

The presented load disaggregation approach is in theory scalable to any more complex machinery, since the approach relies on the deterministic mapping of events and states through the machine code. Problematic for this approach is the analysis of very noisy data, as typically associated with small consumers. This is due to the rigid boundaries of the event detection algorithm, which complicate the distinction between an event and random noise. This could also impact the performance of the approach as each steady state needs to be fitted. More robust approaches like [Ya23] tackle this issue but increasing the complexity of the event detection algorithm.

Further tests also need to be conducted on different machines and strongly differing load profiles. Especially, clocked processes with highly variable consumer profiles and more simultaneous events could be challenging to the approach due to the heavy reliance on the probabilistic event classification approach.

4.3 Discussion for Further Integration for Simulation and Scheduling

The methodical application of the load disaggregation on the cleaning machine example shows how metering data can be analyzed, considering several machine processes with regard to their components. The event detection and classification is important for the load processing procedure, but is also usable for further applications like scheduling. The results of the event detection can be used furthermore for the aggregated machine load profiles, providing a classification of load flexible components and processes. Figure 5 shows the disaggregation of the cleaning machine's load profile into the subsystems' consumption, including their associated events.

The disaggregation additionally allows to classify the consumers automatically as constant, controlled constant or variable and, more importantly, as process dependent or non-dependent according to [Go15]. This is done by running the process with the same parameters repeatedly and comparing the timestamps and the height of the individual events. If these vary, the subsystem can be labeled as non-dependent. The classification of constant, controlled constant or variable can be achieved by following the definition by [Go15]. For usage in a scheduler component, especially the aspects of process dependability and flexibility are of importance and are therefore considered in the classification.

The classification of the cleaning machine's subsystems as a result is shown in Table 3.

Considering the aspects of a skill-based manufacturing approach as shown in the Capabilities, Skills and Services Model (CSS-Model), as presented in [Di22], there is potential for further usage of manufacturing skills to consider the load patterns of the subprocesses of the machine. A subprocess of the cleaning machine could then be encapsulated as a skill,

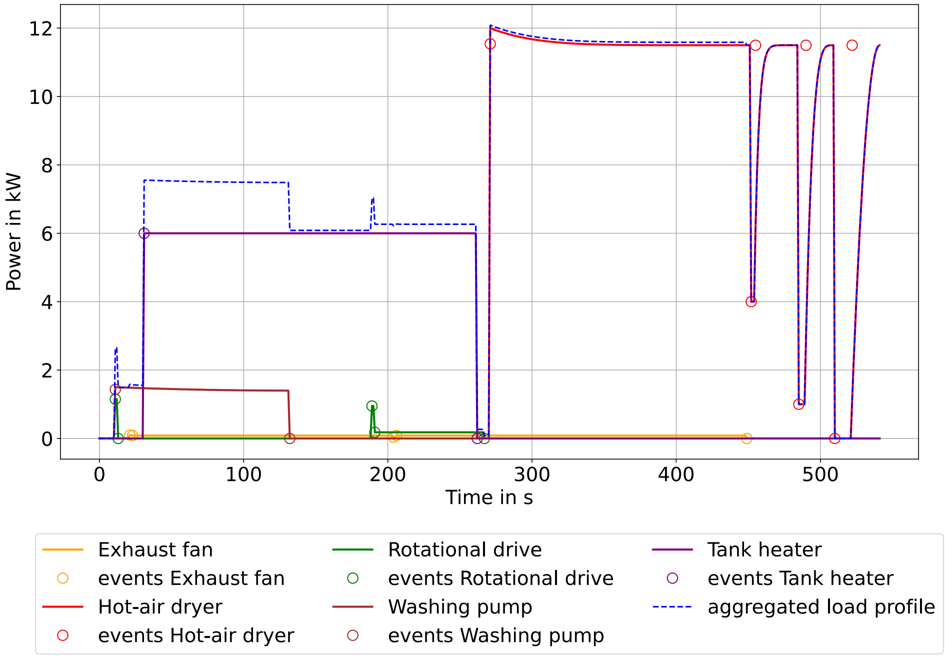


Fig. 5: Disaggregation of typical cleaning machine load profile

subsystem	**process dependence**	**class**
Tank heater	non-dependent	constant
Hot-air dryer (Drying air heater and drying fan)	dependent	variable
Washing pump	dependent	controlled constant
Exhaust fan	non-dependent	controlled constant
Rotational drive	non-dependent	controlled constant

Tab. 3: Classification of the cleaning machine's subsystems according to [Go15]

which follows the principle of subsidiarity as presented in [Be22]. The consideration of the concept of the skill-interface furthermore allows the connection to an interconnected factory control architecture, as suggested in [Be22]. This furthermore allows the integration into a planning framework for automatic flexible scheduling and energy-aware decision-making for rescheduling purposes, as presented in [MWR24]. The usage of skills could then follow the concept of standardized interfaces at the machine level as stated in [Ko18].

In general, further development can focus on the integration of detailed load profiles into skills, representing the subprocesses of machines. A focus could be on the integration and usage of such load profiles in combination with the principle of a feasibility check as part of implemented skills, as shown in [Vo21]. In this context, the integration of the energy behavior for machine parameter-dependent simulations could be used, for example to check the feasibility of a parameter configuration for a planned skill execution, if limits in energy consumption must be considered or possible load peaks should be identified in advance. This principle could furthermore be considered in combination with scheduling models, in which the expected load patterns for a given machine parametrization can be simulated in advance and then considered in an aggregated way at the machine level during the scheduling process.

Future research possibilities could be identified in the combination of the load disaggregation method with the possibilities of energy measurement. Flexible infrastructure in manufacturing enables the usage of metering hardware and services for analysis and monitoring on a modular level, as presented in [Mo21]. If metering can be provided at the machine level, the load disaggregation method of this contribution can be applied to identify load patterns, which are of interest for simulation and integration of scheduling models. Since the effects of parametrization for machines are difficult to predict on the level of multiple components, future developments can focus on a continuous model validation with a combined approach of a discrete event simulation to create data for load forecasts and measured energy data from several machine parametrizations.

Further research potential lies in the modular configuration of the production environment using skills, since the decentralized structure can be combined with an agent-based control concept as shown in [Ru20]. Energy agents, which are responsible for energy-related metering hardware, could provide a higher degree of automated data acquisition and processing to create and use energy load profiles, as it is presented in [Mo23]. The integration of the load disaggregation method into energy agents, which are responsible for energy load profiling on the level of production skills, could then contribute to the concept of a continuous update and validation of load profiles for further usage, like scheduling.

Since the Asset Administration Shell (AAS) [Ba22] is increasingly developing into the de facto standard for the interoperable communication in I4.0, the standardized description of energy data in an AAS conform is a relevant topic for standardization. The load disaggregation analysis could be integrated into such an interface, considering the standardized description of the utilized machinery for further automated data processing.

The connection to dataspaces furthermore enables the utilization of services as the disaggregation analysis within the company or even beyond company boundaries in a service ecosystem [Be24]. A uniform description of the energy data and the machine components using the AAS supports the interoperability and the seamless sharing of data here as well.

5 Conclusion

This contribution presented an approach for energy profile analysis for production machines using load disaggregation for further applications. The concept considers the integration of the load profile analysis into standardized machine interfaces. Thus, the result of the analysis can be used for scheduling and component-related load profiles for simulation in production orchestration and optimization. The application of energy load profiles which are provided on a detailed level using load disaggregation was shown. It can contribute to metering concepts in which the metering hardware is provided mainly on the level of production modules. The results of an applied load disaggregation on a real-world production machine were presented, and further development possibilities and potential for further research were presented and discussed.

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