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Autonomous Load Profile Recognition in Industrial DC Links Using an Audio Search Algorithm

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Abstract

Industrial manufacturing plants, including machine tools, robots, and elevators, perform dynamic acceleration and braking processes. Recuperative braking results in an increased voltage in the machines' direct current (DC) links. In the case of a diode rectifier, a braking resistor turns the surplus of energy into lost heat. In contrast, active rectifiers can feed the braking energy back to the AC grid, though they are more expensive than diode rectifiers. DC link-coupled energy storage systems are one possible solution to downsize the supply infrastructure by peak shaving and to harvest braking energy. However, their control heavily depends on the applied load profiles that are not known in advance. Especially for retrofitted energy storage systems without connection to the machine's control unit, load profile recognition imposes a major challenge. A self-tuning framework represents a suitable solution by covering system identification, proof of stability, control design, load profile recognition, and forecasting at the same time. This paper introduces autonomous load profile recognition in industrial DC links using an audio search algorithm. The method generates fingerprints for each measured load profile and saves them in a database. The control of the energy storage system then has to be adapted within a critical time range according to the identified load profile and constraints given by the energy storage system. Three different load profiles in four case studies validate the methodology.

Keywords

Load profile recognition; DC link; Audio search algorithm; Self-tuning control; Energy storage system

1. Introduction

Industrial applications, e.g., robots [1], machine tools, and lifts [2], perform dynamic movements. Braking processes lead to an increased DC link voltage within the machine's frequency converters [1]. A braking resistor usually wastes this surplus of energy in case there is no active rectifier for feeding the current back to the AC grid [3]. Energy storage systems represent one way to avoid the dissipation of braking energy and increase manufacturing systems' energy efficiency. Here, mechanical, electrical, electrochemical, hydraulic, and hydroelectric storages come into consideration [4]. In literature, the use of flywheel energy storage systems [1,5] as well as supercapacitors [6–8] with limited capacity is widespread. As stated in [8] and [2], a plug-and-play feature is crucial for retrofitting industrial DC links with energy storage systems. Proprietary communication units of manufacturing machines endanger this requirement [2]. Therefore, avoiding communication between the machine's and the energy storage system's control unit is a desirable feature [2]. Moreover, load profiles may vary during operation depending on the specific energy demands of manufactured products [9]. According to the product, there can be cyclically recurring load profile sequences.

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This paper deals with autonomous load profile recognition in industrial DC links to facilitate self-tuning control of retrofitted energy storage systems. A well-established audio search algorithm [10] provides a feasible solution for autonomous load profile recognition as the problem statement is similar to identifying pieces of music. Furthermore, this paper addresses measurement uncertainty. Noise amplitudes are usually smaller than a tenth of their sensors' accuracy. As a multiplication of the current and voltage signal takes place before receiving the actual load profile, their two single uncertainties add up to the total uncertainty [11]. Band-limited white noise expresses itself as a zero-mean statistical fluctuation [12]. As proposed in [11], a normally distributed random number generator provides the added white noise in this paper. Adding noise enlarges the amount of training data [11].

The rest of this paper is structured as follows. Chapter 2 illustrates the state of the art for industrial DC links as well as load profile recognition and forecasting. Chapter 3 presents the audio search algorithm and translates it according to the problem statement of this paper. Then, chapter 4 proves the validity of the algorithm using three different load profiles of a machine tool under the influence of noise. Chapter 5 concludes this paper and motivates future research work.

2. State of the art

This chapter introduces industrial DC links and distinguishes them from DC microgrids. In addition, it explains several variants of adaptive and self-tuning control. At last, this chapter discusses scientific approaches for load profile recognition and forecasting.

2.1 Industrial DC links

Figure 1 distinguishes variants of industrial DC grids connecting the AC grid to drive systems using power electronic converters. An intermediate circuit transfers energy from a rectifier to an inverter. DC links consist of at least two intermediate circuits and are usually based on one proprietary system manufacturer, e.g., for robots with more than one axis [13]. DC microgrids further extend DC links by integrating multiple drive systems, renewable energy sources, and energy storage systems [14].

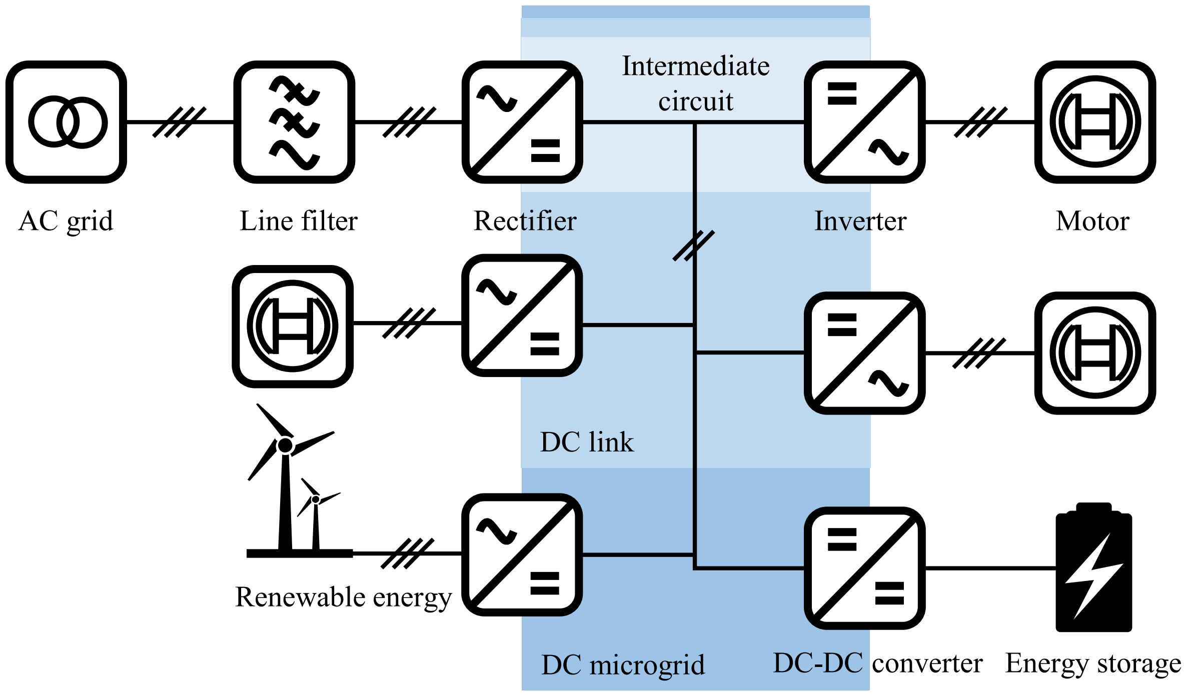

Figure 1: Topological distinction between industrial DC grids.

2.2 Adaptive and self-tuning control

There are three variants of adaptive control. The first is *gain scheduling*, often referred to as look-up table [15]. This approach is applied to energy storage systems in [16], and especially useful if the system performance and disturbances are known in advance [15]. The second variant is *model reference adaptive control* (MRAC) relying on a pre-developed model [17]. *Model identification adaptive control* (MIAC) marks the third variant. MIAC identify the process model during operation making them suitable for systems with high uncertainty [17]. MIAC and *self-tuning control* are used interchangeably [18]. Furthermore, *iterative learning control* (ILC) also belongs to self-tuning techniques [19]. *Iterative learning control* modifies the control loop's set point depending on error information of past cycles. Moreover, the quite similar *repetitive control* is appropriate for continuous processes, while *iterative learning control* returns to its initial conditions after each iteration [20].

2.3 Load profile recognition and forecasting

Forecasts are a sub-group of predictions. Both approaches rely on historical data to project future events. Forecasting represents a prediction based on time series data, whereas a prediction does not necessarily have to use time-based data [21]. This paper interprets recognition as a prediction of a load profile identifier. As soon as the applied algorithm correctly recognizes the load profile due to the knowledge of previous cycles, forecasting the future power demand seems rather trivial for deterministic processes.

This section provides the results of a literature review for load profile recognition and forecasting. Dietmair and Verl develop a generic energy consumption model for a milling machine [22]. They link system states to their specific energy consumption and simulate the G-code in advance [22]. Mühlbauer et al. forecast the energy intake of a milling machine using information from the G-code (e.g., rotational speeds, coordinates, tools, etc.). The authors compare several regression models, including linear, Gaussian process, polynomial, and random forest regression [23]. Brillinger et al. examine how decision trees and random forests can be applied when forecasting the energy use of CNC machines [24]. In order to recognize load profiles in an industrial DC microgrid and to enable adaptive control for energy storage systems, Männel et al. propose cross-correlation analysis [25]. Reger et al. combine hidden Markov models with cross-correlation analysis. Furthermore, the authors apply short-term Fourier analysis and wavelet transformation to generate features in the frequency domain [26]. K-means clustering is the basis for load profile recognition of a machining center and forecasting of an industrial robot in [9]. In addition, Barreto et al. use fuzzy c-means clustering to define typical load profiles of three industrial machines in the textile industry [27]. In [28], support vector machines for load profile forecasting are compared to neural networks and linear regression. Dietrich et al. analyze deep learning approaches, including long short-term memory networks (LSTM) and convolutional neural networks (CNN), to use demand response on the machine and factory level [29]. Efimov et al. investigate an adaptive neuro-fuzzy inference system (ANFIS) for load profile forecasting in an industrial robot [30].

Most of the described approaches rely on information provided by the machines' G-code, i.e., a widespread computer numerical control programming language. Interpreting G-code is a time-consuming challenge due to different software standards and numerous control system manufacturers. Therefore, this paper proposes a novel solution path. The authors apply a well-known audio search algorithm to measured load profiles of a DC link. A voltage, a current, and a trigger signal suffice to recognize several electrical load profiles without the need to access and analyze the machines' G-code. The proposed algorithm recognizes the load profiles within only a few seconds, is robust against noise and easily transferable onto other machines. Eventually, this allows for self-tuning energy storage control.

3. Modified audio search algorithm

This chapter introduces the adapted audio search algorithm, including its most crucial functions and calculation steps. In 2003, Wang [10] proposed a robust audio search algorithm to recognize music segments using hashed time-frequency constellations. Based on these generated fingerprints, the algorithm can identify tracks within a database containing millions of songs [10]. Multiple MATLAB implementations of the algorithm are available online. This paper uses a customized MATLAB version of [31]. The original methodology is adapted to the electrical load profile data of a machine tool. Figure 2 illustrates the adapted methodology of the load profile recognition in this paper.

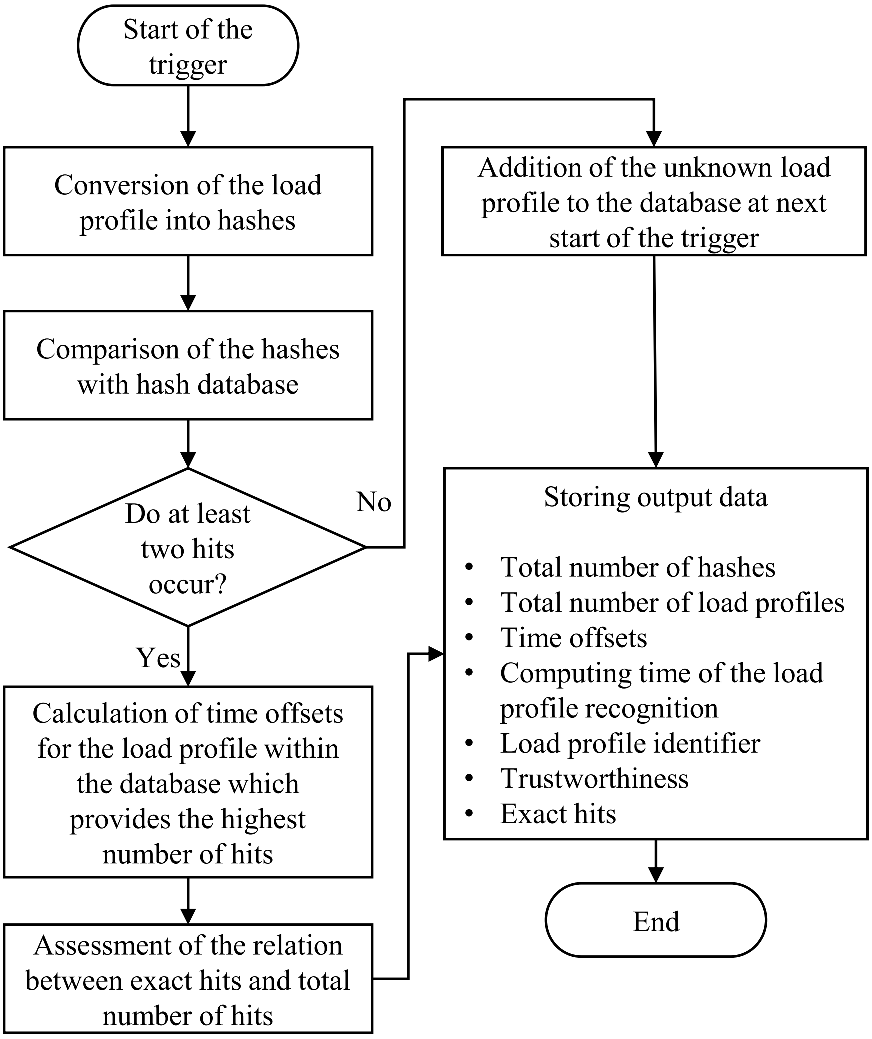

Figure 2: Simplified methodology of the load profile recognition.

First, the algorithm receives a trigger signal from the machine tool's control unit. This induces the manufacturing process as well as the DC current and DC voltage measurement located right behind the rectifier for the load profile recognition. The trigger signal solely marks the load profile's start and end. After five seconds, the algorithm starts generating so-called hashes from the load profile as well as the time vector and adds them to a table. As part of the hash generation, a filter has to smooth the load profile to eliminate irrelevant extrema and reduce disturbances. After applying the filter, the algorithm identifies the power extrema, i.e., relevant minimum and maximum power values. The hashes have a length of ten digits and are composed of four parts as described in (1):

1. Sign of the anchor point ($s_i = 0$ for negative power, $s_i = 1$ for positive power)
2. Absolute power value p_i of the anchor point rounded to one decimal place
3. Absolute power value p_{i+1} of the consecutive point rounded to one decimal place
4. Difference between the time stamp of the anchor point t_i and the consecutive point t_{i+1}

$$hash = s_i \cdot 10^9 + p_i \cdot 10^7 + p_{i+1} \cdot 10^4 + (t_{i+1} - t_i) \cdot 10^1 \quad (1)$$

Each extremum once serves as an anchor point within a loop. This logic is suitable for loads that are smaller than 100 kW and bigger than -100 kW. A higher number of digits is appropriate if the power values exceed the said limits. The number of digits also depends on the required accuracy and hash composition. Even an overflow caused by increased values would presumably not infringe on the uniqueness of a hash. To make the recognition more robust, one can easily generate additional hashes using a second consecutive extremum, as shown in Figure 3.

If at least one load profile has been measured before, another function calculates whether there are common hits between the recently generated hash table and already stored hash tables in the hash database. If a minimum of two hits is reported, the algorithm publishes the identifier of the matching load profile within the self-tuning control framework.

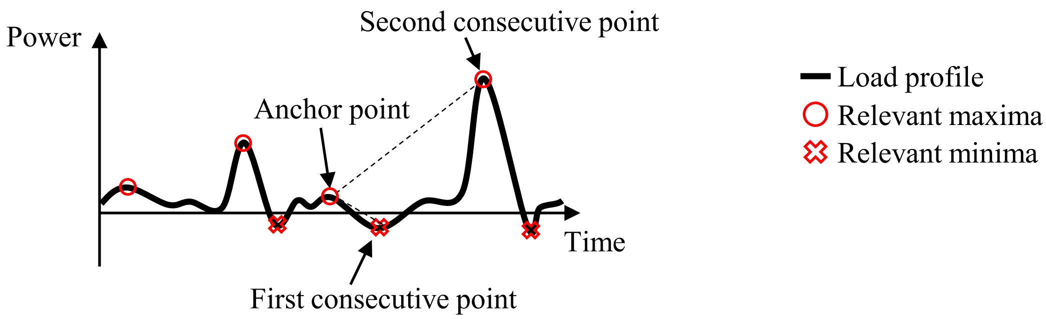

Figure 3: The load profile extrema lead to unique hashes.

Moreover, the time vectors of the currently sampled load profile and historical load profiles in the database can be put in a scatter plot to visualize hits (see Figure 4). In this example of an ideal recognition, the hits lie on a line with a slope of 1.

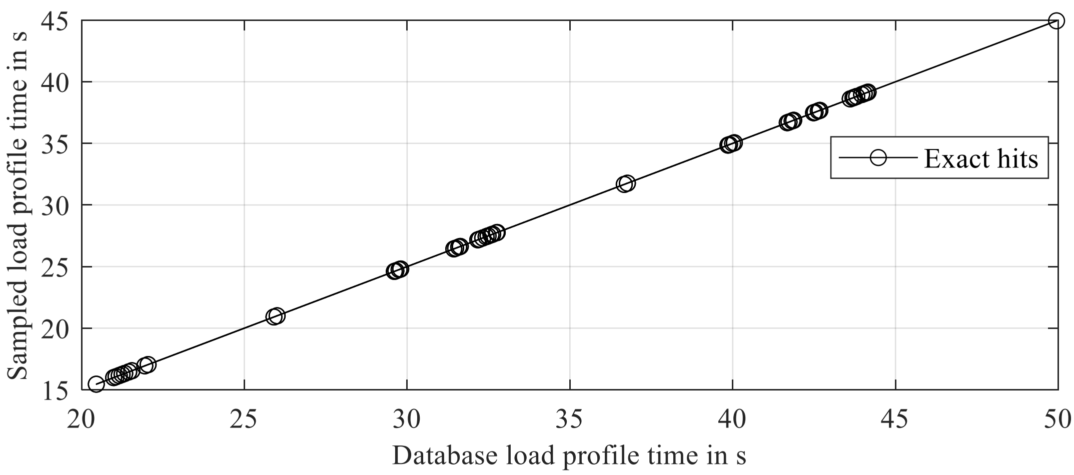

Figure 4: Exact hits in the second cycle of load profile 1 without added noise.

Eventually, the algorithm checks its trustworthiness by looking at the relation between exact hits and the total number of found hashes in (2).

$$Trustworthiness = \frac{Exact\ hits}{Total\ number\ of\ found\ hashes} \geq 50\ \% \quad (2)$$

Subsequently, either the load profile identifier is sent to the control design function or it supplies already designed trajectories for the energy storage system's state of charge and exchange power. In case the recognition of a load profile is not successful, it becomes a new part of the hash database with its own new identifier. Finally, a database stores the results.

4. Case study

The following case study validates the adapted audio search algorithm. First, the chapter focuses on the experimental design. Afterward, this chapter presents and discusses the results.

4.1 Experimental design

Three load profiles from the same machine tool are the inputs to the MATLAB simulation containing the recognition algorithm and a trigger signal that initiates the machine tool's manufacturing cycles. In the beginning, the algorithm has not yet witnessed any of the three load profiles. Therefore, the first cycle of each load profile will not lead to a recognition. Table 1 provides the chosen sequence of ten load profile cycles that all have a length of 50 s with a waiting time of 5 s at the beginning of the simulation to see the first trigger.

Table 1: Simulated sequence of load profiles.

Periods	Load profile identifiers	Number of cycles
5 s ≤ t ≤ 155 s	1	3
155 s < t ≤ 255 s	2	2
255 s < t ≤ 355 s	3	2
355 s < t ≤ 405 s	1	1
405 s < t ≤ 455 s	2	1
455 s < t ≤ 505 s	3	1

In this paper, a Savitzky-Golay filter of 15^{th} order over 501 samples serves to smooth the load profile before the generation of characteristic extrema and hashes. Furthermore, the extrema have to possess a time difference of at least 100 ms and a power difference of more than 2 kW. Moreover, white noise is added to the load profiles to check on the algorithm's robustness. The white noise accounts for measurement inaccuracies. This results in four case studies with noise amplitudes of 0.0 %, ± 0.1 %, ± 0.2 % and ± 0.5 % of the load profile's maximum power.

4.2 Results

Figure 5a depicts the load profile sequence of Table 1. The actual computing times for the recognition in Figure 5b are always less than two seconds. This computing time marks the period between the buffering of the first relevant extrema and the publishing of the load profile identifier.

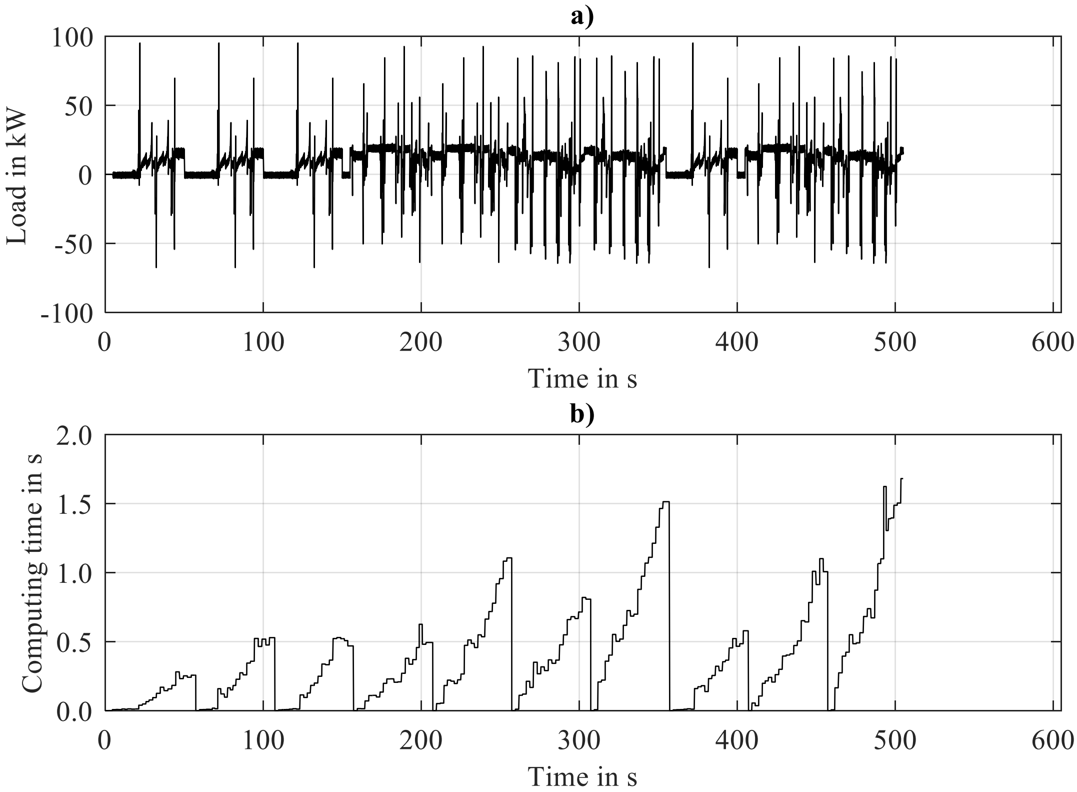

Figure 5: a) Load profile sequence, b) Computing times of the load profile recognition.

To challenge the algorithm's robustness, the authors add three noise amplitudes to the original load signal. The authors assume that ordinary sensors possess an accuracy of ± 1 %. The noise amplitudes should not exceed a tenth of this value for one sensor and, respectively a fifth of the accuracy for two sensors, i.e., 0.2 % in this specific case. Figure 6a shows the actual sequence of load profile identifiers according to Figure 5a. Figure 6b to Figure 6e depict the case study of different noise amplitudes. Figure 6f reveals the trustworthiness of each case. For a noise amplitude (NA) of 0 %, the algorithm provides almost ideal results as expected. A noise amplitude of 0.1 % also achieves good trustworthiness of over 70 %. The demanded robustness at a noise amplitude of 0.2 % is mostly achieved, but in the eighth cycle (355 s < t ≤ 405 s), the algorithm publishes the load profile identifier quite late, and the trustworthiness is sometimes lower than 50 % during the load cycle. This occurs due to the sparse number of extrema during the first 20 s of load profile 1. However, the algorithm can recognize load profiles 2 and 3 with levels of trustworthiness around 60 %. These two load profiles procure more hash information. A noise amplitude of 0.5 % pushes the algorithm beyond its limits, and the trustworthiness falls below the threshold of 50 % for most of the simulation time.

5. Conclusion

This paper has introduced the application of a well-established audio search algorithm for autonomous load profile recognition in industrial DC links to enable self-tuning control of energy storage systems. The present publication distinguishes DC links from DC microgrids, defines several variants of self-tuning control, and provides the state of the art for load profile recognition and forecasting. The methodology of the audio search algorithm is visualized, and its implementation in a case study leads to promising results. Increased added noise negatively influences the algorithm's trustworthiness.

Future research should focus on further reducing the computing time and storage space requirements. The authors have to increase the algorithm's robustness to cover applications with lower measurement accuracy. At least half of the found hashes should be exact hits to safely recognize the load profile.

Here, the filter design plays an important role. In addition, other signal features for hash generation might be suitable, e.g., in the frequency domain.

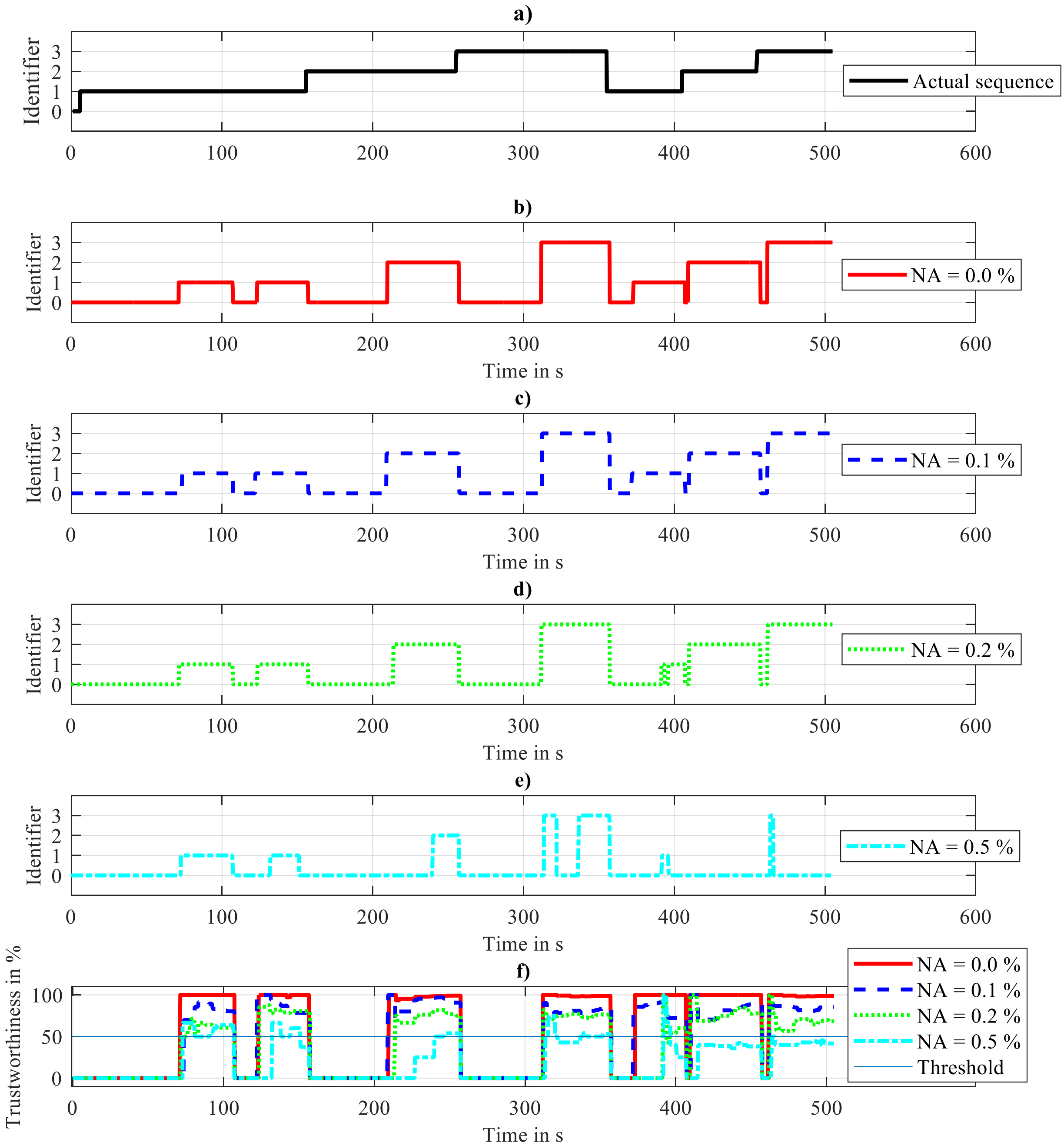

Figure 6: a) Actual sequence of the load profile identifiers and recognized load profile identifiers for noise amplitudes (NA) of b) 0.0 %, c) 0.1 %, d) 0.2 %, e) 0.5 % of the maximum occurring power, and f) trustworthiness and recognition threshold for the presented cases.

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Biography

Raoul Laribi (*1992) studied sustainable electrical energy supply and received his master’s degree from the University of Stuttgart in 2017. Since then, he has been working as scientific associate at the university’s Institute for Energy Efficiency in Production (EEP). His PhD work focuses on self-tuning control of energy storage systems in industrial DC grids.

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