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Review article

Advances in non-intrusive load monitoring for the industrial domain: Challenges, insights, and path forward

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ABSTRACT

Non-intrusive load monitoring has emerged as an important tool for disaggregating the energy consumption of individual appliances within a facility, relying solely on data from a centralized smart meter. Smart meters have become increasingly predominant in industrial facilities for many reasons, such as regulatory mandates, economic incentives, environmental considerations, and operational advantages. However, the implementation and research of non-intrusive load monitoring specifically for the industrial environment, which is notably complex, are still in their early stages.

This study provides a comprehensive overview of the current landscape of non-intrusive load monitoring in the industrial domain, reviews current approaches, identifies existing theoretical and practical challenges unique to the industrial setting, discusses key considerations for non-intrusive load monitoring industrial application development, and highlights the importance of data preprocessing in industrial applications. Additionally, it offers a forward-looking perspective, charting potential avenues for research and innovation. Ultimately, the study aims to provide a holistic view of the subject matter, equipping the reader with a well-rounded perspective that is vital for forming a robust base for subsequent research endeavors.

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Abbreviations

NILM	Non-Intrusive Load Monitoring
FHMM	Factorial Hidden Markov Model
AMI	Advanced Metering Infrastructure
EMS	Energy Management System
VFD	Variable Frequency Drives
IoT	Internet of Things
IIoT	Industrial Internet of Things

1. Introduction

Non-intrusive load monitoring (NILM) techniques have gained traction for their ability to disaggregate individual appliance energy usage, thereby fostering efficient energy management and potential cost savings. Their application has predominantly centered on domestic environments, largely due to the ready accessibility of household appliance records and the availability of numerous public datasets. Despite the successes witnessed in domestic arenas, applying NILM methods to industrial settings presents formidable challenges. These challenges arise from a combination of limited access to confidential industrial data and the fundamental disparities that exist between domestic and industrial facilities [1]. The inherent complexities that characterize industrial environments challenge the direct applicability of existing NILM algorithms. Nonetheless, the potential advantages of deploying NILM in industrial scenarios are immense, both economically and environmentally. Many industrial facilities have annual electricity expenditures ranging from seven to eight figures ($\$1,000,000 - \$10,000,000+$) and in many countries asked to reduce their energy footprint by regulation [2]. Beyond just the monetary aspect, industries account for a significant portion of global energy consumption. Hence, even marginal improvements in energy efficiency, driven by the insights from NILM, can lead to substantial reductions in carbon emissions, further emphasizing the role of industries in sustainable development and environmental conservation. The behavior of industrial machines and appliances differs considerably from domestic ones. In manufacturing environments, there is a diverse selection of devices, whereas in households, appliances generally fall into a few standardized categories, like ovens, toasters, and air conditioners. Moreover, the functioning of some industrial devices can be intricately complex, a stark contrast to the relatively straightforward operation of most household appliances. Furthermore, the industrial environment is much noisier than the domestic one [3].

The operational schedules might differ significantly. Most households exhibit a predictable electricity consumption pattern trend by time of day, weekends, seasons and holidays. In contrast, industrial entities typically operate based on distinct shift schedules, which necessitate collaboration with shift managers to gain insights into these timetables per facility [1]. The premise of industrial setups also diverges from domestic scenarios. For instance, the 'one-at-a-time' assumption [4], a staple in domestic NILM applications, is not suitable for industrial facilities. The sheer number of devices, coupled with the nature of electricity demand in these settings, suggests a high likelihood of concurrent appliance operations [5].

This study addresses a significant gap in the literature: the lack of a comprehensive, focused overview specifically dedicated to NILM for industrial use cases. While several review papers on NILM have been published, they predominantly focus on residential applications, and industrial approaches have often been either briefly mentioned or grouped together with residential ones [1]. Systematic reviews that focus exclusively on industrial NILM have been scarce. A dedicated review spotlighting industrial NILM only emerged as recently as September 2024 [6]. While that review focuses primarily on collecting and categorizing existing works, this study leverages both the review process and the authors' practical experience to extract insights and assemble key considerations and principles for advancing industrial NILM development. The limited number of review papers dedicated specifically to industrial NILM likely stems from the relative scarcity of research papers in this area. The limited number of publications on NILM implementations for industrial settings- up to ten per year over the past few years- illustrates the early stage of exploration in this domain. However, the growing number of publications reflects an increasing recognition of NILM's importance for the industrial sector. Industrial NILM holds significant potential for widespread adoption, driven by regulatory plans and economic viability. Furthermore, NILM for industrial facilities offers larger impacts compared to residential applications due to the high energy consumption typical of industrial operations. Given the key role that the industrial sector plays in global energy savings and emissions reduction, the development of effective NILM solutions tailored for industrial use is both timely and critical [7]. Current research highlights a critical need for studies that offer in-depth insights and a comprehensive mapping of the existing challenges, which is essential for pushing forward state-of-the-art research, especially in emerging fields like industrial NILM. This work addresses that gap by providing a practical, consolidated resource that pinpoints key insights into a single, comprehensive study. By doing so, it serves as a foundational knowledge source that the research community can build upon in future efforts. This study uniquely integrates a thorough literature review with real-world, industry-based perspectives, offering not only an overview of the state of research but also actionable insights that can directly inform both academic research and practical applications. The merging of theoretical and practical insights into one focused study strengthens its relevance and utility for advancing the field.

2. Literature review

2.1. Approaches

While there have been significant works in developing NILM methodologies for domestic environments, the adaptation to complex industrial landscapes remains an unresolved research challenge. Existing works tend to be restricted to specific case studies with a limited scope of electrical features. These works predominantly use-case demonstrations, lacking in robust methodologies that can be generalized across varied industrial settings. The evident gap and the lack of broad-based solutions underscore the need for deeper exploration and need for more comprehensive research.

A disaggregation method based on material production and energy consumption-manpower links, designed for industrial cases that have installed only simple energy measuring equipment for billing purposes, is presented in [8].

Factorial hidden markov model (FHMM) is a popular model applied for load disaggregation, and in particular in the industrial case [3,9]-[7], as well as for comparison purposes [10]. Five industrial equipment in one factory in China have been disaggregated using FHMM in [3]. The research is based on both active and reactive power measurements at a sampling rate of 1 Hz. The work introduces the first attempt of using FHMM with both active and reactive powers as outputs for modeling industrial load NILM. The learning was supervised, training the FHMM using labeled data because of the complex industrial load behaviors as well as the limited data of only 12 days. Unsupervised training led to poor performance, and is noted as an open research direction to explore. The complexity of the load behavior also manifested through poor identification results of one of the tested appliances of 52.36% F-measure, due to it having operational power consumption that is closely resembling the fluctuating power of other devices. Another work based on HMM approach [9] has been implemented on the publicly available HIPE and IMDELD datasets as elaborated in Section 2.2, showing that using reactive power and state duration features improve the results, underscoring the importance of comprehensive datasets with multiple features, rather than a single feature or a pair of current and voltage features.

Another work that explores challenges faced by NILM algorithms in industrial settings as well as the potential benefits of different levels of sub-metering is [7]. Based on electricity consumption data from a cold store located in the Danish city of Vejle, including compressors, industrial fans, evaporators, a comparison of combinatorial optimization, FHMM and FHMM with day specific training was conducted. Both algorithms attain similar performance overall. Using only the main meter, F1-score of 0.4 was reached, compare to 0.6 for a minimal set of four sub-meters related to logical sections in the cold store. Those are fair results but not accurate enough for real-world applications.

An event-detection method based on composite-window analysis for industrial NILM is presented in [11], on data collected from five kinds of industrial consumers in China: including cement manufacturing plants, metal foundries and food processing plants. The dataset includes 24–48 h of bus-side three-phase current and voltage signals, and 5–10 complete signals from open to closed for seven equipment with sampling frequency of 10 k/s. The method's results have an average F1-score of 82.9%.

A states based method incorporated with improved grey wolf algorithm is presented in [12], and simulated on the HIPE dataset [13]. The proposed method faces key limitations, including neglecting noise and sudden power changes and struggling with identical power consumption across different loads or loads that have notable fluctuations in their operation.

An unsupervised machine learning event-based clustering approach and feature fusion of low, mid and high frequency features was performed on data from two industrial facilities of a mushroom farm and a clinic kitchen [14], showing that high frequency features improve performance on both domestic and industrial facilities. Also demonstrating, once again, energy estimation performance deterioration on industrial settings. Another event-based approach of functional data clustering of transient state patterns, was implemented on industrial test-bed including a heater, two uninterruptible power supplies, and two three-phase motors, as well as conveyor belts of a baggage handling system at an airport [15]. Other AI implementation includes physics-informed time-aware neural networks [16] applied to the HIPE dataset, conditional variational autoencoder [17] applied to the brazilian industrial dataset [10], as well as deep learning generative model that is based on WaveNet [18], originally created for audio waveform generation. A unique neural network was trained on the active power demand feature for each appliance, attaining superior results in comparison to FHMM in most metrics for all the appliances. Still, there is a concern that the models overfit to the appliances data in the training-set. Additionally, the performance of the model for different machines with similar features remains to be assessed.

Another AI implementation based on physics-informed time-aware neural networks is presented in [16], applied on the HIPE dataset, that is limited to only ten appliances from a small-scale electronics factory. A temporal convolutional network-conditional random field deep learning model was used to disaggregate the consumption of air compressor and a hot water boiler circulation pump in [19], which also published the dataset and implemented code. The model achieves high accuracy for the mentioned multistate industrial loads, and does not successfully generalize for type I (see Section 3.3) loads as publicly available at the REDD dataset (see Section 2.2), highlighting the dedicated specific efforts that are required for industrial vs. residential use cases. Another deep learning model [20] incorporated with Pearson correlation coefficient between each load feature and the operational state of electrical devices was implemented on private dataset of seven enterprise-level devices. A UNet model was used to predict 16 individual controllable compressed air actuators [21] based on image analysis of the 2D signal representation. However, the model was tested on ideal test conditions and should be further validated on multiple production machines in a real production setting. CNN-LSTM neural network enhanced by attention mechanism and genetic algorithm was implemented on a private Brazilian feed factory composed of three devices [22]. Another attention mechanism application [23] and sequence-to-sequence network [24] were implemented on 12 gas station appliances, achieving an accuracy of 90.5% and 87.6% respectively, which falls on the lower end of the common accuracy spectrum. Another use-case of disaggregating gas station equipment based on gradient boosting algorithm [25] shows that the accuracy of high demand devices and type II devices (see Section 3.3) is high (up to 95%), while for low and complex demand pattern devices the performance significantly deteriorate to below 75%.

A study that shows the performance gap of seven prominent load disaggregation algorithms and models, namely combinatorial optimization, FHMM, recurrent neural network (RNN), denoising autoencoder, Seq2Point and WindowGRU when applied on industrial data vs. household data is presented in [26], showing a performance gap on individual appliances. The collected data is from an electronics production site in Germany with ten machines of types I-III. The work also contribute to further research in the field by publishing their data-set converter making the measurements directly usable with NILMTK [27], which is an open source toolkit for NILM, designed to enable the comparison of energy disaggregation algorithms in a reproducible manner.

NILM approaches can be categorized into two main types:

1. State (correlation) based – focused on the measured electric parameters of the consumption, where the operation of each appliance is represented as a finite state machine. The disaggregation is performed based on the state transition model that is learned during training. Such implementation would be HMM and its variants [3,7,28].
2. Event (differential) based – focused on the changes of the measured electric parameters of the consumption, and are based on detecting an on/off event of a single appliance. These methods usually consist of three steps: (1) event detection: detecting changes in time-series aggregate signal due to one or more appliances changing their state [28]; (2) feature extraction of the measured electrical features per event; (3) classification and pattern matching, used to classify the events using extracted features according to a-priory information of appliance-features pairs. Multi-state appliances are usually treated as multiple single-state appliances, where each state is considered as a single appliance and afterwards the contribution of all the states are summed to obtain an estimate of the total appliance consumption. Such classification methods include support vector machines [29], artificial neural networks [30], k-means [31], decision trees [32,33], and Graph Signal Processing [34].

Both approaches necessitates a-priori knowledge about the consumption levels for successful identification. Neural network strategies can be broadly divided into supervised and unsupervised methods. The supervised techniques necessitate a training phase, where data from devices and their corresponding labels are fed to the model, training it to recognize specific patterns. On the other hand, unsupervised methods work by naturally detecting patterns or clusters in the data, without the need for pre-labeled instances. While these unsupervised techniques are flexible and can adapt to diverse data, they may not always achieve pinpoint accuracy in every context. Moreover, even with unsupervised methods, labeling the identified clusters still requires a foundational understanding of the consumption characteristics of different scenarios. Beyond standard neural networks, deep learning frameworks incorporate methods like transfer learning and computer vision techniques:

- **Transfer learning**: Two main categories of transfer learning are often employed: appliance transfer learning (ATL) [35] and cross-domain transfer learning (CTL) [11]. The transfer learning approach is particularly valuable because it mitigates the need

Table 1
Categorization of selected NILM studies based on approach, public/private dataset availability, and tested equipment.

Study	Approach	Type	Dataset	Devices
Holmegaard et al. (2016)	Comparison of combinatorial optimization and FHMM	Private	Cold store in Denmark	Compressors, industrial fans, evaporators
Bernard et al. (2018)	Unsupervised clustering + feature fusion	Private	Mushroom farm + Clinic kitchen	Industrial kitchen appliances
Martins et al. (2018)	Conditional variational autoencoder	Public	Brazilian industrial dataset	Horizontal motors
Yi et al. (2019)	Event detection composite-window	Private	Industrial plants in China	Cement plants, metal foundries, food processing machines
Yang et al. (2021)	FHMM	Private	Factory in China	Five industrial machines
Kalinke et al. (2021)	CO, FHMM, RNN, WindowGRU, Seq2Point, Autoencoder	Public	Electronics production site in Germany	Electronics production machines of type I-III
Huang et al. (2022)	Physics-informed neural networks	Public	HIPE dataset	Electronics production, ten machines
Zhang et al. (2022)	Deep learning (TCN-CRF)	Public	test-bed	Air compressor, hot water boiler circulation pump
Wei et al. (2022)	Sequence-to-sequence	Private	Gas station appliances	12 gas station appliances
Li et al. (2022)	Gradient boosting	Private	Gas station appliances	Various high-power and low-power gas station devices
Luan, Wenpeng, et al. (2022)	HMM	Public	HIPE dataset	Electronics production machines
Bermeo et al. (2023)	Event-based clustering	Private	Airport baggage system	Heaters, uninterruptible power supplies, conveyor belts
Wang et al. (2023)	States-based Grey Wolf algorithm	Public	HIPE dataset	Electronics production machines
Xiong et al. (2023)	CNN-LSTM + Pearson correlation	Private	Private dataset (enterprise devices)	Seven enterprise-level devices
Wei et al. (2023)	Attention mechanism	Private	Gas station appliances	12 gas station appliances
Li Chuyi et al. (2023)	Mixed integer programming, DL model and FHMM	Public	HIPE, IMDELD dataset	Electronics production and pelletizers, double-pole contactors, exhaust fans (VFDs) and milling machines
Angelis, Georgios F. et al. (2023)	Transformer model	Public	IMDELD dataset	Eight machines including pelletizers, double-pole contactors, exhaust fans (VFDs) and milling machines
Gowrienanthan, Balarupan. et al. (2023)	Deep learning model	Public	IMDELD dataset	Eight machines including pelletizers, double-pole contactors, exhaust fans (VFDs) and milling machines
Faustine, Anthony, and Lucas Pereira et al. (2023)	Convolutional neural network on image data	Public	LILACD dataset	Six types of industrial appliances including permanent magnet motor, and squirrel motors
Pelger, Philipp et al. (2024)	Unet model	Private	Compressed air demonstrator	16 individually controllable compressed air actuators.
Chen, Fengxiang, et al. (2024)	ResNeSt model	Public	IAID dataset	Appliances from six industries including steel, metal, chemical, plastic, glass, and textile.
Li, Ce, et al. (2024)	Autoencoder transformer	Private	Gas station data	12 appliances including freezer, oil-submerged pump, convenience store socket, UPS and lounge socket

for large volumes of training data, which are typically required for deep learning models. By leveraging pre-trained models, this approach reduces the associated high computational burden of training from scratch and enhances the models' generalization ability, which is often limited in NILM tasks, particularly in industrial use-cases.

- **Computer vision techniques**: These approaches convert time-series records of power quality features into two-dimensional images, which are then analyzed using deep learning models like convolutional neural networks (CNNs) [36–38]. This method effectively applies image analysis techniques to NILM by treating the transformed time-series data as visual patterns, which CNNs can efficiently process.

Several solutions can be applied across both state-based and event-based approaches, either simultaneously or independently. For example, optimization-based techniques, such as mixed-integer programming (MIP), can be used on state data [39] or event data [40]. Additionally, some methods utilize both event and state data to improve disaggregation performance [41]. More comprehensive approaches, which combine various angles to address the problem, have greater potential for industrial use cases due to the high complexity typically involved in these environments.

Table 1 summarizes selected studies, categorizing them based on the NILM approach, dataset used, and the specific equipment disaggregated. This table covers the range of methodologies and datasets employed in industrial NILM. By mapping the equipment disaggregated in the various studies, it presents a clear and comprehensive view of the devices examined in existing literature.

2.2. Public datasets

While there are many available datasets of domestic settings [42], such as REDD [43,44], BLUED [45], COOLL [46], and SustDataED [47], AMPds [48] and more, for industrial setting this is not the case, with only known three publicly available industrial datasets, IMDELD [49], HIPE [13] and a heavy-machinery data of horizontal motors from the brazilian industrial sector [10] as well as a small testbed dataset, LILACD [50]. The laboratory-measured Industrial Load of Appliance Characteristics dataset LILACD contains aggregated and sub-metered current and voltage measurements for six industrial appliance types and was measured in a testbed rather than an actual industrial setting. IMDELD is collected in a poultry feed factory in Brazil, including two pelletizers, two double-pole contactors, two exhaust fans, and two milling machines, and is limited only to type-I appliances. HIPE (high-resolution industrial production energy) dataset contains smart meter readings of ten machines and the main terminal of an electronics production plant in Germany, over three months, including various electrical features such as active and reactive power, voltage, frequency, harmonic distortion, with a resolution of 5 s. Note that for both datasets, the aggregated data also includes unknown equipment, such as lighting. The industrial appliance identification dataset

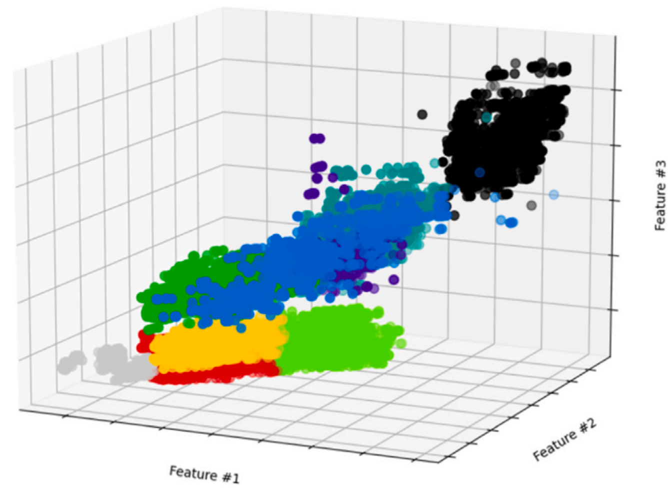

Fig. 1. A visualization of operational scenarios clustering within an industrial assembly line using distinct features.

(IAID), includes data of equipment from six industries: steel, metal, chemical, plastic, glass, and textile, sampled at 1 Hz from June 1, 2019 to June 30, 2019. The steel factory appliances include crusher, electric arc furnace, and filter. The metal factory appliances include tilting press, electric heat treatment furnace, and filter. The chemical factory appliances include a reaction tank and a filter. The plastic factory appliances include shredder, injection molding machine, and filter. The glass factory appliances include crusher, electric furnace, and filter. The textile mill factory appliances include spinning machine, weaving machine, knitting machine, dyeing machine, and decorating machine [51].

Publicly available datasets collected over short periods, such as 1.5 h [50], 30 days [52], and one week [53], are also available, all at 1 Hz resolution. While [50] covers 110 light industrial loads across three locations (Germany, Austria, and Indonesia), it includes only current and voltage measurements, lacking additional power quality features that are essential for advanced NILM capabilities. The one-month dataset [52], collected at a textile mill in China, contains only a single feature: the active power. Several works have been implemented on these public industrial NILM datasets, such as [54–56] using IMDELD, [9,54] using HIPE and [57] using LILACD. However, the effectiveness of all mentioned works is demonstrated on very limited data characteristics, whereas industry appliances are generally extremely diverse and particularly are not properly represented by such limited data sources.

3. Considerations for NILM industrial application development

For NILM applications, few aspects impact the analysis and therefore are needed to be taken into account during the development process.

3.1. Sampling rate

Sampling rates in NILM can be generally categorized into low and high. Low sampling rates range up to a few hundred hertz, often yielding one sample per second, whereas High sampling rates start at 1 kHz. Most standard smart meters, both in domestic and industrial settings, typically function at a low sampling rate.

For industrial facilities, a low sampling rate presents a double-edged sword. On one hand, it eases data storage and processing demands due to the vast and continuous nature of industrial data streams. On the other, its limited granularity may fail to capture rapid changes inherent to many industrial machines, thus compromising the depth of NILM analysis.

High sampling rates, on the other hand, offer a richer data set. They permit the capture of granular features like high-order harmonics, facilitating more detailed NILM analyses [58]. This can be invaluable in industrial facilities where nuanced distinctions between machine operations might be critical. However, the increased data volume demands more storage and computational power, potentially escalating costs. Moreover, high-frequency data might necessitate advanced algorithms to handle the complexity, which could be computationally intensive.

3.2. Features selection

Leveraging a diverse set of electrical features can significantly enhance NILM analysis. Features like current harmonics and current angle are particularly useful due to their unique signatures across different appliances [59]. This becomes crucial when multiple appliances exhibit similar behavior in one specific electrical aspect, necessitating the use of additional parameters for differentiation. A common household example can be seen with microwaves and heaters or computers and light bulbs. While they might have comparable active power consumption, their current profiles (and other electrical characteristics) differ markedly.

The input features provided to the NILM algorithm significantly influence its accuracy. Essentially, these features should be chosen based on their capability to distinguish effectively between different operational scenarios. Broadly, there are two methodologies for feature selection. The first is based on using the raw electrical features. This approach leverages the electrical parameters as recorded by the smart meters. It is particularly relevant for industrial settings equipped with advanced smart meters capable of logging a variety of electrical attributes such as current amplitude and angles, power components, total harmonic distortion, power factor etc.. By directly using these features, the algorithm can differentiate based on real-world electrical patterns. The second methodology includes feature transformation, where instead of using the raw data, this method applies certain transformations to the measured features, such as principal component analysis [60]. The primary motivation behind this approach is the assumption that transforming the data can amplify distinctions between varying scenarios. Such transformations might better highlight the unique electrical signatures of different equipment or processes, making it easier for the NILM algorithm to disaggregate consumption. Fig. 1 depicts the clustering of various scenarios in an industrial setting, specifically from an assembly line in a factory. The clusters are derived from three distinct features of the recorded raw data. The shape and separability of these clusters are influenced by the chosen features. By selecting other features, the differentiation between the clusters might

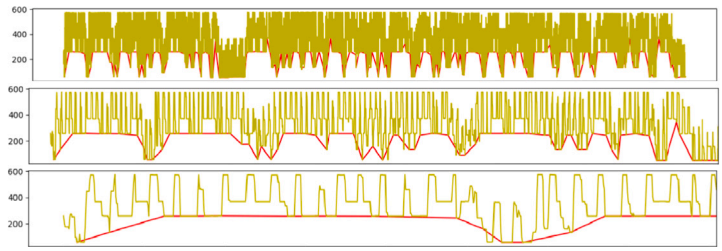

Fig. 2. Illustration of the effect of the resolution on the observed behavior.

change, either becoming more distinct or possibly more overlapped. The presented three-dimensional visualization underscores how the chosen parameters can influence the discernibility between clusters. Opting for different features might adjust the clarity between clusters. While integrating more features could potentially refine cluster separation, the representation here is confined to three dimensions due to visualization limitation associated with representing multi-dimensional data in a comprehensible manner. Another important factor that is disregarded in this visualization is the time dependency. As many industrial processes follow specific schedules over time, understanding these temporal patterns is essential to distinguish between the operational sequences.

3.3. Load type

Generally, loads are divided into four main types according to their common behaviors [61]:

1. **Type I (Binary state devices):** These are appliances with only two operational states: ON and OFF. Examples include simple pumps, fans and conveyor belts.
2. **Type II (Finite state machines):** These are appliances with a limited set of distinct operational states. They exhibit recognizable switching patterns. Such machine for example would be computer numerical control machine. Within this category, there are two subtypes:
   - Oscillating devices: Appliances that frequently switch between states. This includes constant oscillators, such as cyclic pumps and compressors where power fluctuates at a consistent amplitude, and variable oscillators like treadmills or adjustable-speed fans with changing power levels.
   - Non-oscillating devices: Appliances like industrial ovens and refrigerators that have distinct, but non-repetitive, states.
3. **Type III (Continuously variable devices):** Appliances in this category experience continuous power variations, resulting in an infinite range of operational states. Traditional steady-state identification approaches may not detect them effectively. Industrial motors with a soft starter is one example for type III load.
4. **Type IV (Permanently active devices):** These are appliances that consume power at a consistent rate over extended periods, often without switching off. They can be recognized by an initial activation and then prolonged activity without any evident deactivation, such as cooling towers.

3.4. Post-processing analysis and real-time analysis

The mode of analysis, whether it is conducted in post-processing or in real-time, significantly influences the approach and efficacy of NILM techniques. Each mode comes with its own set of advantages, challenges, and applications.

1. Post-processing analysis: Post-processing analysis involves collecting consumption data over a specified duration, storing it, and then analyzing the data after the fact. It does not offer immediate insights or feedback but can provide a detailed review once the data set is complete. This approach provides a thorough and detailed examination of the data without computational time performance constraints. Moreover, certain NILM algorithms as well as data pre-processing methods such as data correction and anomalies detection requires the analysis of chunk of data [62,63] that is not possible to attain in real-time processing. Nonetheless, the offline method might be ill-suited for situations that demand immediate responses or actions based on real-time demand.

2. Real-time analysis: Real-time analysis offers immediate insights as data is generated or captured, usually with a few seconds delay. It is ideal for applications requiring prompt feedback or actions based on the analyzed data. However, it could requires robust computing capabilities to analyze data on-the-fly, optimized for speed, potentially sacrificing depth or detail in analysis.

In industrial facilities, the need for both real-time analysis and post-processing is evident. When overseeing critical industrial processes, real-time analysis becomes indispensable. However, the implementation of such real-time systems introduces added complexities, both in terms of the underlying algorithm and the overarching system design. This can affect the algorithm's practicality and deployment. On the other hand, for routine activities such as energy audits, post-processing is favored because it avoids the intricate complexities inherent to real-time systems.

4. Data acquisition in industrial settings

Data acquisition in industrial facilities plays a pivotal role due to the intricacy and scale of operations. For decision-making, process optimization, and preventive measures, accurate and timely data is crucial. This section examines the methods for querying energy consumption data in industrial scenarios.

4.1. Methods for data query in industrial environments

- **Direct connection to the smart meter**: Industrial settings often demand a direct connection to smart meters to ensure real-time access to crucial consumption data. This contrasts with many domestic settings, which may rely on periodic updates.
- **Wireless connectivity**: The vast electronic equipment present in industrial zones can introduce potential interference, highlighting the necessity for stable wireless connections. Residential areas typically encounter fewer interference sources.
- **Remote data access via internet**: The expansive IT infrastructure in industries often facilitates secure remote data access. This is essential given the vast data volumes they process. In contrast, homeowners might access data through simpler, utility-provided portals.

4.2. Challenges in industrial data acquisition

- **Scalability**: With potential expansions or diversification in operations, the data acquisition systems in industries must exhibit seamless scalability.
- **Energy consumption of data acquisition systems**: In large industrial settings, data acquisition systems themselves can become significant energy consumers, especially when hundreds or thousands of sensors and large data processing units are involved.
- **Data storage**: In industrial settings, the sheer volume of data generated necessitates robust and expansive storage solutions. While cloud storage offers flexibility and accessibility, it can become prohibitively expensive for large-scale operations. On-site storage solutions, meanwhile, come with their own set of challenges, from maintenance to security concerns.
- **Real-time data acquisition**: Industrial operations may require real-time monitoring and control, with very low latency in data acquisition and processing.
- **Integration**: Amalgamating diverse data streams from varied machinery and systems can pose challenges, yet it is essential for a unified industrial view.
- **Redundancy**: To avert data inaccuracies or losses, industries must ensure redundancy, eliminating single points of failure in data acquisition.
- **Security**: The sensitive nature of industrial data necessitates robust security measures. In industrial settings, this concern is amplified due to the critical nature of the operations involved. Unauthorized access or breaches could lead to significant operational disruptions, financial losses, or even safety risks. Implementing secure data transmission protocols and multi-layered access control systems is crucial to safeguarding sensitive industrial data and ensuring uninterrupted operations.
- **Regulatory and compliance constraints**: In industrial facilities, there are often stringent regulations regarding data management, energy reporting, and safety standards. This adds another layer of complexity to data acquisition systems, as they must ensure compliance with relevant industrial standards and laws.

5. Importance of data pre-processing in industrial NILM

Data preprocessing is a foundational phase in the implementation of NILM algorithms within industrial environments. The uniqueness and complicated nature of energy data in these settings poses several challenges. Firstly, the intricate nature of industrial processes, characterized by numerous equipment and stages, results in data that is complex and intertwined. Preprocessing becomes essential in sifting through this data to extract meaningful and usable information. In addition, the large scale of operations in industries produces a considerable amount of data. Preprocessing assists in managing this volume, breaking it down into more meaningful units. Through preprocessing, raw data is transformed into a more analyzable format, enhancing the efficiency of subsequent analysis and pattern recognition. Key components of data pre-processing include:

- **Outlier removal**: Outliers are unusual data points that deviate considerably from the typical proper behavior of the data. The existence of outliers pose significant challenges in industrial environments. Their presence can distort results, potentially leading to misinterpretations, especially in applications like energy consumption monitoring. Recognizing and addressing these outliers is vital for various reasons:
  1. Operational efficiency can be compromised by erroneous data, which paints a misleading picture of machine or process performance. By addressing these anomalies, industries can gain a clearer, more accurate understanding of their operations, ensuring resources and energy are used most effectively.
  2. From a safety perspective, sudden spikes or drops in energy consumption can hint at malfunctioning components or other potential hazards. Detecting these anomalies is essential to safeguard both machinery and personnel.
  3. From a financial standpoint, undetected outliers can result in incorrect billing or misallocation of energy resources, potentially leading to significant costs.
  4. For predictive maintenance, outliers might serve as early warning signs of machine wear and tear. Recognizing these deviations allows industries to preemptively schedule maintenance, extending equipment life and sidestepping expensive malfunctions.
- **Noise filtering**: Noise, inherent in industrial operations, can overshadow genuine device signatures. Applying filtering techniques refines the data.
- **Normalization**: Given the variance in device sizes and consumption patterns, normalization ensures equal importance across all devices, specifically when high power and low power devices are present in the same facility.
- **Feature engineering**: Certain metrics or signature elements, when extracted from raw data, can significantly aid NILM algorithms in pattern discernment.
- **Data segmentation and resolution**: Breaking a large chunk of data into smaller segments can simplify pattern isolation and make data more manageable. Moreover, an important factor is determining the resolution of data inspection and processing. The granularity of segmentation needs to be chosen based on the objective of the analysis. For instance, in an industrial facilities operations span through a vast spectrum, from large equipment running for extended periods to transient activities of short-lived devices phenomena. Selecting an appropriate resolution can be the difference between capturing critical energy signatures and missing out on them. Too fine a resolution might clutter the analysis with noise, while too coarse might gloss over important events. This careful balance ensures that specific energy events or anomalies are accurately captured and acted upon.

  An illustration of the effect of the resolution's choice as recorded from an industrial facility in Israel is shown in Fig. 2. The graphs show in yellow the current readings. In all three sub-figures, the x-axis denotes time in seconds and the y-axis illustrates current in amperes. In red appears a lower envelope of the signal amplitude for reference. The top sub-figure shows a 4 h long recording, and the other sub figures are zooming in up to 800 (13.3 min) seconds duration. It can be clearly observed that analyzing different resolutions can provide different insights into the facility's operation.
- **Handling missing data**: Addressing gaps in data collection, be it through imputation, interpolation, or omission, is a critical preprocessing action.

6. State of monitoring in industrial settings

With the increasing importance of sustainable and efficient energy utilization, monitoring in industrial settings has undergone significant advancements. Some of the general trends observed globally include:

- **Advanced metering infrastructure (AMI):** Modern industries are moving beyond traditional meters, adopting AMI which provides real-time data and two-way communication between the meter and central system [64].
- **Energy management systems (EMS):** These are becoming increasingly sophisticated, offering features like predictive analysis, which allows industries to forecast their energy requirements and adjust accordingly [65,66].

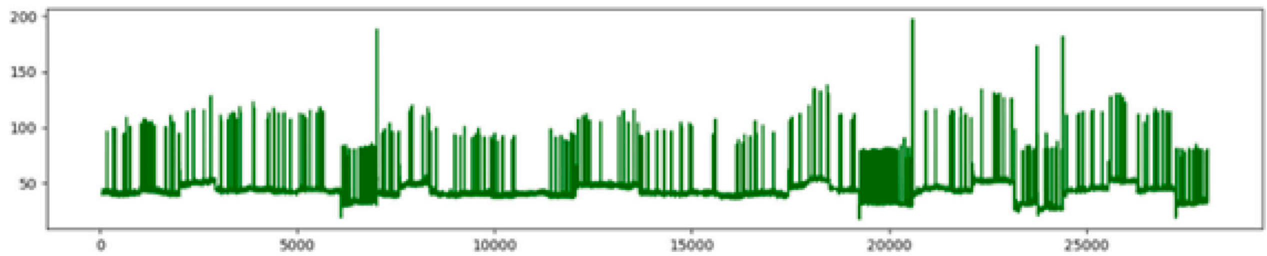

Fig. 3. Erratic activation of a compressor (current [A] over time samples [s]), observed in an industrial facility in Israel.

- **IoT integration:** The internet of things (IoT) has found its way into energy monitoring, enabling remote monitoring and control of various energy parameters in industrial environment [67].
- **Demand-side management:** Industries are actively participating in demand-side management programs, which involve adjusting their energy consumption in real-time based on grid requirements [68].
- **Cost efficiency:** As technology becomes more accessible, the cost of implementing advanced energy monitoring solutions has decreased.
- **Regulations and incentives:** Governments worldwide are offering incentives for industries that adopt energy-efficient practices, further driving the adoption of advanced monitoring solutions [2].

7. Unique challenges for NILM in industrial settings

Industrial settings pose distinct challenges on NILM algorithms, due to the complexity and high variability of machinery, dynamic and challenging environment with constantly changing operating conditions as well as the immense scope of energy consumption data to be accumulated and analyzed. The following points provide some recognized challenges in NILM algorithms development in the industrial setting.

- **Complexity of equipment and processes**: Industrial setups encompass intricate machinery and multi-stage operations. Each machine might have multiple states and operations, complicating the disaggregation process. Apart from distinct operational modes such as low-speed, high-speed, idle, etc. these machines may also ramp up or down in a smooth, gradual manner rather than exhibiting clear, stepwise changes in power consumption, making it harder for NILM algorithms to detect and differentiate between them. The distinction between different machines and their respective states becomes challenging due to their overlapping electrical signatures [69]. In particular, large-scale operations such as manufacturing plants or refineries have diverse machinery with interdependent functions, making it even more challenging to isolate and identify energy consumption patterns.
- **Continuous operations**: Many industrial processes are designed to run 24/7. The lack of distinct "off" periods or quiescent states means that the NILM algorithm cannot rely on clear transitions or patterns, complicating energy disaggregation [70]. The absence of these clear transitions makes it difficult for NILM to isolate specific load signatures. Continuous operations lead to more complex and overlapping energy patterns where multiple machines or systems are consuming power simultaneously without distinct pauses. Moreover, continuous operations increase the volume of data that should be collected and analyzed, requiring to store, manage and analyze high volumes of data.
- **Multiple concurrent processes**: Multiple machines operating simultaneously can produce intertwined energy consumption patterns. NILM algorithms need to disentangle such overlapping signatures to accurately attribute consumption to individual devices, a task that becomes more complex in the presence of numerous concurrent operations [5]. Moreover, high-power devices, prevalent at industrial facilities, that operate concurrently may mask the smaller loads, further complicating disaggregation. Thus, NILM applications for industrial facilities must adapt to both high-load and low-load appliances in parallel.
- **False startups**: Machines like compressors in industrial settings may have false startups, where they briefly turn on and then shut off. These events can appear as outliers in the data. The challenge lies in distinguishing these from genuine anomalies that might indicate a problem. An example of this phenomenon as recorded from an industrial facility in Israel is shown in Fig. 3. During an 8-h operation, the x-axis denotes time in seconds and the y-axis illustrates current in amperes. Noticeable many short spikes indicate the compressor's improper operation within the factory.
- **Variable frequency drives (VFDs)**: VFDs, prevalent in industrial settings, cause devices to operate at variable speeds, resulting in dynamic energy profiles [54]. This adds another layer of complexity for NILM algorithms, which now must account for continuously varying energy signatures. Unlike residential appliances with relatively steady power draws, industrial devices with VFDs have dynamic signatures that constantly shift depending on operational loads. This variability requires NILM algorithms to continuously adapt to the fluctuating consumption patterns in real time, which is more complex than handling fixed-load appliances.
- **Vital operations and high stakes**: Industrial operations are often mission-critical. Misclassifications or inaccuracies by NILM can have significant repercussions, from energy wastage to operational inefficiencies or safety risks. For example, failing to detect an issue in a critical piece of equipment may lead to catastrophic failures. Therefore, the accuracy and reliability of NILM in industrial settings are not just about energy savings but also about maintaining operational safety and preventing costly disruptions. Industrial NILM systems need to be fine-tuned for higher stakes and mission-critical applications.
- **Noise from external factors**: The susceptibility of industrial operations to external disturbances (e.g., voltage fluctuations, other industrial activities, or ambient conditions) can introduce noisy data patterns. For NILM algorithms, this means added difficulty in distinguishing genuine device signatures from transient disturbances.
- **Scalability**: Industrial settings can encompass hundreds or even thousands of devices, from small sensors to massive machines. Ensuring the NILM algorithm scales to handle such a wide range of devices, each with its consumption pattern, is crucial.

8. Future of NILM in industrial settings

A review on applications of NILM in measurement, diagnostic and automation systems in both industrial and residential facilities is elaborated in [71]. The anticipated developments mentioned there are: (1) smart grids management of the monitored distribution systems' loads and prediction of consumption peaks, (2) extension of NILM systems to the substation level to improve the efficiency of demand-side control, (3) prevention of dangerous failures of devices by detection of anomalies and malfunctions, and (4) monitoring the activities of daily living in order to serve ambient assisted living systems. Some additional developments and further research of relevant applications would be:

1. **Advanced predictive maintenance:** Industrial machinery often operates in critical, high-stakes environments where unexpected failures can lead to costly downtime or safety risks. NILM can be used to monitor subtle changes in energy consumption patterns, which may indicate early signs of equipment degradation or malfunction. In industrial settings, integrating NILM into predictive maintenance programs could allow for real-time detection of anomalies, enabling operators to schedule maintenance before a complete failure occurs. This early detection is especially valuable in industries where equipment failure can halt production or cause hazardous conditions.
2. **Integration with industrial IoT (IIoT):** IIoT can support NILM algorithms by filling gaps in facilities where older equipment lacks connectivity, while its signals provide valuable inputs to enhance the disaggregation process. Moreover, the integration of IIoT will ease the collection of labeled datasets, which remains one of the key challenges in scaling NILM solutions. The advancement of IIoT for industrial equipment has the potential to become a widespread standard, surpassing its adoption in residential and commercial sectors. As more industrial machines are equipped with built-in sensors and connected to the internet, IIoT will significantly boost NILM technologies, particularly in industrial environments.
3. **Enhanced demand response:** Industrial facilities are major energy consumers, and participating in demand response programs can lead to significant cost savings and energy efficiency improvements. Future NILM systems will enable industries to better participate in demand response programs by providing granular insights into energy consumption patterns at the machine or process level. In industrial applications, NILM can help identify flexible loads that can be curtailed or shifted during peak demand periods without disrupting critical operations, improving the facility's responsiveness to demand response signals.
4. **Machine learning and AI integration:** The complexity of industrial operations requires sophisticated algorithms for energy disaggregation. Future NILM systems in industrial settings will increasingly rely on AI to handle the vast data monitored from an industrial facility. AI-powered NILM can not only perform snapshot disaggregation but also adapt to the dynamic nature of industrial processes, uncovering trends over time. Moreover, it is capable of learning from vast amounts of historical data to improve predictions, making them more accurate over time and better suited for complex environments such the industrial use-case, positioning them as a leading candidate for future NILM industrial applications.
5. **Eco-friendly operations:** As industries face increasing pressure to meet environmental standards and reduce their carbon footprint, NILM will play a pivotal role in monitoring and managing energy consumption to ensure compliance with regulations. By offering detailed insights into energy usage, NILM systems can help industrial facilities identify inefficiencies and optimize processes to reduce energy consumption and greenhouse gas emissions.
6. **Customized reporting:** Future NILM systems in industrial settings will provide customized, actionable reports tailored to the specific needs of industrial operators. These reports will highlight areas where energy can be saved, identify underperforming equipment, and suggest operational adjustments to optimize energy efficiency. In the industrial domain, such reports will focus on large-scale energy-saving opportunities, such as optimizing machinery schedules, identifying energy-intensive processes, and reducing idle times, which are critical in high-consumption environments.
7. **Enhanced integration with PLCs:** In industrial settings, real-time control of machinery is often managed by programmable logic controllers (PLCs). Integrating NILM systems with PLCs would allow real-time adjustments based on snapshot and patterns of the disaggregated energy consumption. For example, if NILM detects inefficiencies or anomalies in a machine's operation, the PLC could automatically adjust the machine's parameters to improve efficiency or prevent malfunctions. This type of integration will enable dynamic control over energy-intensive processes and enhance automation capabilities in industrial plants.
8. **Cost-saving on infrastructure:** The non-intrusive energy disaggregation approach eliminates the need for installing individual meters on each machine. In large industrial facilities, where the cost of installing and maintaining extensive metering infrastructure can be prohibitive, NILM offers a scalable and cost-effective alternative. By leveraging NILM for energy monitoring, industries can reduce the need for extensive hardware installations while still gaining detailed insights into energy consumption.
9. **Decentralized energy management:** In large industrial complexes, different departments or divisions may have varying energy needs and priorities. Future NILM systems will allow for more decentralized energy management, where individual departments can monitor and manage their own energy consumption. This decentralized approach will empower specific teams to optimize their energy use independently, while still contributing to overall facility-wide energy efficiency goals.

9. Discussion

When considering NILM for industrial end users, the worthwhileness and profitability of the technology indeed raises legitimate concerns. Industrial environments differ significantly from residential settings in ways that present unique challenges to NILM implementation, particularly when factoring in the limited availability of ground truth data and the complexities of generalizing across varied industrial settings. Industrial settings typically involve a diverse range of machines with unique energy signatures that differ widely not only by industry type but also within individual facilities. Unlike residential NILM, where device patterns are more standardized and predictable, industrial processes operate under vastly different conditions, often with proprietary equipment that lacks standardized operational patterns. This diversity complicates the generalizability of NILM solutions. Developing a model that can accurately monitor and interpret energy consumption for a given industrial facility often requires a tailored approach, making it difficult to deploy "out-of-the-box" solutions with consistent accuracy.

Furthermore, the lack of readily available ground truth data in industrial settings limits the initial training and validation needed for effective NILM model development. Ground truth data, typically derived from sub-metering, is essential for training models to accurately disaggregate the energy loads of specific machines or processes. However, in many industrial settings, installing numerous sub-meters to generate this data is not only costly but may also disrupt ongoing operations. Given the typically high-energy demands of industrial environments, the ability to acquire precise, reliable data without excessive intrusiveness is crucial, yet often impractical, further questioning NILM's worthwhileness. As a result, many NILM applications in industry either default to using a limited number of sub-meters at critical points or turn to hybrid approaches. These approaches may include strategically placed meters on key processes, combined with NILM algorithms that can enhance load disaggregation accuracy for less critical equipment. This balance allows industries to maintain oversight of major energy consumers while minimizing the infrastructure and operational interruptions associated with full-scale sub-metering. From a strategic standpoint, NILM in industrial settings is key for advancing global energy efficiency goals and can contribute to grid stability. Studies [72] indicate that industrial energy consumption often exceeds optimal levels, revealing significant potential for energy savings within this sector. Given that industrial activities contribute directly and indirectly to a substantial share of global greenhouse gas emissions, effective NILM solutions that enhance monitoring can play a pivotal role in reducing excess energy use, yielding both economic and environmental benefits. Furthermore, improved operational awareness in industrial facilities can greatly impact the grid, given the sector's high consumption levels. Thus, optimizing energy efficiency in industry not only drives internal cost savings but also enhances the resilience and sustainability of the broader power system. In summary, the challenges posed by industrial settings for NILM technologies necessitate a careful evaluation of its applicability. While NILM solutions for non-residential end users may need to be adapted to each unique setting, their potential to contribute to energy savings and grid stability offers a compelling argument for investment, particularly through hybrid approaches that balance accuracy with practicality.

10. Conclusions and further research

Exploring NILM in industrial environments has revealed notable challenges and performance issues, especially when compared with its use in household settings. The complexity and ongoing operations of industrial machinery present unique challenges that current NILM methods struggle to handle effectively.

A strategy towards gaining substantial economic and environmental gains in industrial NILM involves making full use of the detailed knowledge available about machine operations in industrial facilities. A potential pathway might focus on developing adaptive algorithms that not only rely on electrical consumption data but also integrate explicit information about machine operation cycles and behaviors. Considering the complexity and volume of operations in an industrial setting, the NILM algorithms could be enhanced by embedding machine learning models that are trained and tuned with a hybrid of electrical usage data and metadata describing the machine's operational characteristics. By integrating this detailed information into the NILM process, algorithms can potentially achieve higher accuracy, even amidst the complex, overlapping energy use patterns that are common in industrial settings.

Further research and development should also focus on creating algorithms specifically designed for the intricate energy use patterns and overlapping operational states of industrial machinery. This involves developing methods capable of accurately identifying overlapping and simultaneous load events and ensuring they can manage the large amounts of data typical in industrial environments. Exploring different machine learning approaches, such as unsupervised and semi-supervised learning, may also provide useful methods for managing the challenge of labeling large amounts of industrial data.

Another crucial focus should be enhancing the capacity for real-time or near-real-time processing NILM applications in industrial settings, that would enable timely decision-making which is pivotal in an industrial setting. Here, the intersectionality of sustainable practices and operational efficiency becomes crucial. An algorithm that can swiftly and accurately disaggregate load, identifying not just the operational state of a machine but also highlighting anomalies or deviations from expected power consumption patterns, can aid in preemptive maintenance, reducing downtimes and potentially avoiding catastrophic failures. This might be achieved by developing algorithms that require less computational power or using edge computing to reduce latency and decrease the load on central processing systems. Ensuring such algorithms are scalable and computationally efficient would further enhance their practicality, providing industries with a tool that supports sustainability without imposing undue operational burdens. By reducing the computational demands, these algorithms also align with green computing principles, ensuring that the processing of NILM data does not in itself become a significant energy burden.

Additionally, developing a comprehensive database of industrial NILM scenarios, covering various machinery types and operational states, as well as developing data-converter tools such as the shared tool developed by [26] for standardization, will be critical for testing and validating algorithms in a realistic and diverse scenarios.

In conclusion, advancing NILM applications in industrial facilities is certainly challenging but holds significant potential for improving energy efficiency and operational practices. By combining detailed domain knowledge, developing specialized algorithms, creating robust databases and expanding initial standardization efforts, it is possible to move closer to realizing more sustainable and efficient industrial operations.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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