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Review article

Non-Intrusive Load Monitoring in industrial settings: A systematic review

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ABSTRACT

Addressing climate change and promoting sustainable energy practices is a pressing issue in our era and requires a comprehensive transformation of our energy production, transportation, and consumption methods. This is particularly relevant for industries and residential buildings, which together represent 70% of the total electricity demand. The Smart Grid, with its real-time data collection and renewable energy management capabilities, promotes energy awareness and intelligent energy transactions. Recent studies have highlighted the untapped potential for energy reduction in industrial settings. However, the effective deployment of advanced methodologies to enhance energy efficiency in these settings necessitates a detailed understanding of consumption patterns Non-Intrusive Load Monitoring (NILM), a technique that disaggregates consumption at the device level, has been identified as a key strategy in this context. Although NILM has been widely applied in residential settings, the need for its application in industrial settings is increasingly acknowledged, given the complexities associated with installing electrical sensors in such environments. Notably, the last review dedicated to NILM for industrial settings was published in 2015. In light of the growing body of research, this work aims, for the first time, to systematically collect, organize, and analyze the literature published to date. This is crucial for the ongoing research in this field and to highlight open challenges and limitations.

Contents

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1. Introduction

The increasing evidence for climate change and global warming underscores the urgent need for intelligent and effective solutions to reduce emissions and promote sustainable energy practices in all sectors [1]. According to the "Net Zero Emissions by 2050" [2], a complete overhaul of our energy production, transportation, and consumption methods is essential to achieve the goal of limiting the average global temperature increase to 1.5 ° C. The residential and industrial sectors deserve particular attention in this regard, as they are the main consumers of electricity, accounting for almost 70% of the global use of electricity [3]. Therefore, it is crucial to improve energy efficiency and sustainability, particularly in these sectors. These goals can be achieved by developing and promoting technologies that minimize waste, optimize energy use, and harness the potential of renewable energy sources.

In this context, the Smart Grid emerges as a pivotal technology. The Smart Grid is an advanced electricity network that uses digital communication technology to monitor, control, and optimize electricity production and distribution [4]. It enables a two-way flow of electricity and information and can react to changes in power demand, supply, and costs in real-time. This leads to improved energy efficiency, reliability, and sustainability [5]. The Smart Grid is also equipped with the necessary features for recording real-time electricity data via smart meters and the Advanced Metering Infrastructure. These data, when processed with advanced algorithms, can promote energy awareness, observability, forecasting, and intelligent energy use scheduling [6]. These are vital for reliability and energy savings, especially given the increasing penetration of electric vehicles [7].

In particular, by leveraging information on consumers' habits, energy utilities can offer opportunities for energy savings and efficiency through Demand-Side Management (DSM) strategies. Energy Management System (EMS) can ensure energy efficiency in residential buildings and industries by identifying the most effective solutions to optimize energy consumption and save money [8,9]. Both EMS and DSM are typically developed based on detailed knowledge of energy consumption within a building, allowing for the initial analysis and accurate management of appliance usage [10,11].

The potential for improvement in the industrial sector is particularly high. In fact, studies have shown that industries use about 50% more energy than they theoretically need [12]. Other studies have highlighted the substantial untapped potential for improving industrial energy efficiency [13] and the key role of the industry in energy savings [14]. Moreover, as reported in [15], studies have shown that the stress of the Smart Grid could be alleviated if industrial activities are planned and synchronized according to the constraints of power generation and the needs of other customers.

For improving efficiency, it is crucial to measure energy usage in a detailed and real-time manner, which helps in understanding energy consumption patterns [17]. Following the pioneering work of Hart [18], NILM has been extensively researched and proposed as an effective method of monitoring the consumption of multiple loads within a building. The primary advantage of NILM is its non-intrusive nature, as it allows one to estimate the power consumption of individual loads using only the aggregate measurements from the main meter. Fig. 1 illustrates the NILM approach with an example in an industrial setting. Numerous articles [19–22] and reviews [23–26] published on this topic in recent decades underscore the importance and effectiveness of NILM in the residential sector. This body of research demonstrates the growing recognition of NILM as a valuable tool for energy management.

In the industrial sector, this issue is of even greater importance due to the high energy requirements of the plants and the difficulty of installing a large number of meters to monitor each load [14,27]. The importance of NILM in this sector is also highlighted by the significant increase in the volume of recent research published, with the number of papers published in 2023 triple that of 2019 (11 vs. 2). This is further supported by the promising outcomes achieved in the residential sector for which the number of published papers is much higher. However, there is a noticeable gap in the literature for a review that systematically organizes the research efforts on this topic to date. Although several reviews appeared in the literature for residential NILM [25,28–30], it was only in 2015 that industrial approaches were briefly reviewed together with residential ones, and some aspects of the industrial context were discussed in [31]. Thus, it is strictly necessary to systematically review the innovative material published during these years, producing an up-to-date analysis and discussion.

To fill this gap, in this paper, we present a comprehensive review of NILM applied to industrial settings (hereafter called "Industrial NILM"). The key contributions of this study can be summarized as follows:

- We present the first systematic review of the literature about Industrial NILM, with a focus on the most important aspects and peculiarities of the methods proposed for industrial settings.
- We introduce a taxonomy for features and methodologies, categorizing them based on their core technical categories.
- We provide the first in-depth analysis of all publicly available datasets collected in industrial settings and their applications.
- We examine and discuss the characteristics of the loads present across various industries, based on power profiles, type, and usage patterns
- We compare and discuss the performance of the approaches that adopted public datasets, posing attention to the comparability and effectiveness of the current literature.

The outline of the paper is as follows: Section 2 provides background on NILM, outlining the general NILM problem and the peculiarities of NILM in industrial contexts. Section 3 details the characteristics of Industrial NILM based on the load profiles and industrial scenarios. In Section 4 the review methodology employed is described followed by the general NILM framework adopted by the selected approaches. Section 5.2 is dedicated to the description of publicly accessible datasets for Industrial NILM. Section 6 examines the characteristics of power

Abbreviations

AC	Alternating Current
ACC	Accuracy
ADC	Analog-to-Digital Converter
AE	Auto-Encoder
AM	Attention Mechanism
AMI	Advanced Metering Infrastructure
AMPds	Almanac of Minutely Power Dataset
BRNN	Bidirectional Recurrent Neural Network
CHP	Combined Heat and Power Machine
CNN	Convolutional Neural Network
CO	Combinatorial Optimization
CRF	Conditional Random Field
CUSUM	Cumulative Sum
CVD	Continuously Variable Devices
DBT	Decision Bagging Tree
DE	Disaggregation Error
DER	Distributed Energy Resources
DevMat	Device Matching
DNN	Deep Neural Networks
DSM	Demand-Side Management
DWT	Discrete Wavelet Transform
EMI	Electromagnetic Interference Signals
EMS	Energy Management System
FHMM	Factorial Hidden Markov Model
FHSMM	Factorial Hidden Semi-Markov Model
FN	False Negative
FP	False Positive
FSM	Finite State Machine
FT	Fourier Transform
GMM	Gaussian Mixture Model
HIPE	High-resolution Industrial Production Energy
I	Current
IGWO	Improved Grey Wolf Optimization
IMDELD	Industrial Machines Dataset for Electrical Load Disaggregation
knn	K-Nearest Neighbor
L	Power Factor
LILACD	Laboratory-measured Industrial Load of Appliance Characteristics
LSTM	Long-Short Term Memory
LVQ	Learning Vector Quantization
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MIP	Mixed Integer Programming
ML	Machine Learning
MLP	Multi-Layer Perceptron
MNE	Mean Normalized Error
MR	Match Rate
NDE	Normalized Disaggregation Error
NILM	Non-intrusive Load Monitoring
NMF	Non-negative Matrix Factorization
P	Active Power
PR	Precision
PSO	Particle Swarm Optimization
Q	Reactive Power
RBF	Radial basis function
RE	Recall
RF	Random Forest
RMS	Root Mean Square
RP	Recurrence Plot
S	Apparent Power
TCN	Temporal Convolutional Network
TECA	Total Energy Correctly Assigned
TMLD	Textile Mill Load Dataset
TN	True Negative
TP	True Positive
V	Voltage
W	Watt
WHITED	Worldwide Household and Industry Transient Energy Data Set
WRG	Weighted Recurrence Graph

signals found in industrial environments and investigates the commonly used features in the literature for Industrial NILM. Industrial NILM approaches are described in detail in Section 7, while the performance of approaches that employed public datasets are analyzed and compared in Section 8. Challenges, limitations, and future directions are discussed in Section 9. Finally, Section 10 concludes the paper.

2. Background

2.1. Problem statement

NILM aims to track the energy consumption of individual loads within a building, without needing to install additional sensors beyond the existing main meter. This approach is not only cost-effective but also addresses practical challenges such as the need to install smart plugs for each device under monitoring.

The total (or *aggregate*) active power consumption of a building measured by the main meter is the sum of the active power of each load within the building, expressed in Watt (W). This relationship can be expressed as follows:

$$p(t) = \sum_{k=1}^{K} p_k(t) + n(t), \tag{1}$$

where $p(t)$ is the aggregate active power, $p_k(t)$ the active power of load k, K is the total number of loads, and $n(t)$ is the measurement noise.

Generally, the number of loads of interest is less than the total number of devices within the building. The power consumed by the remaining appliances can be considered as noise. This can be represented as:

$$p(t) = \sum_{k=1}^{M} p_k(t) + v(t), \tag{2}$$

where $M \leq K$ is the number of loads of interest, and $v(t)$ is the sum of the power consumed by the remaining appliances and any measurement noise, represented as $v(t) = \sum_{k=M+1}^{K-M} p_k(t) + n(t)$.

NILM can be framed as a classification or regression problem. In a classification setting, the goal is to determine which loads are active at a specific time based on the aggregate measurements, as schematically depicted in Fig. 2. Throughout the paper, we also refer to this task as *load identification*. Mathematically, this means finding the state $s_k(t)$ for each load k, where $s_k(t) \in \{0, 1\}$. Here, 0 indicates that the load is off, and 1 indicates that it is on. The state of a load is typically determined using a threshold value θ_k, that is,

$$s_k(t) = \begin{cases} 0, & \text{if } p_k(t) < \theta_k, \\ 1, & \text{if } p_k(t) \geq \theta_k. \end{cases} \tag{3}$$

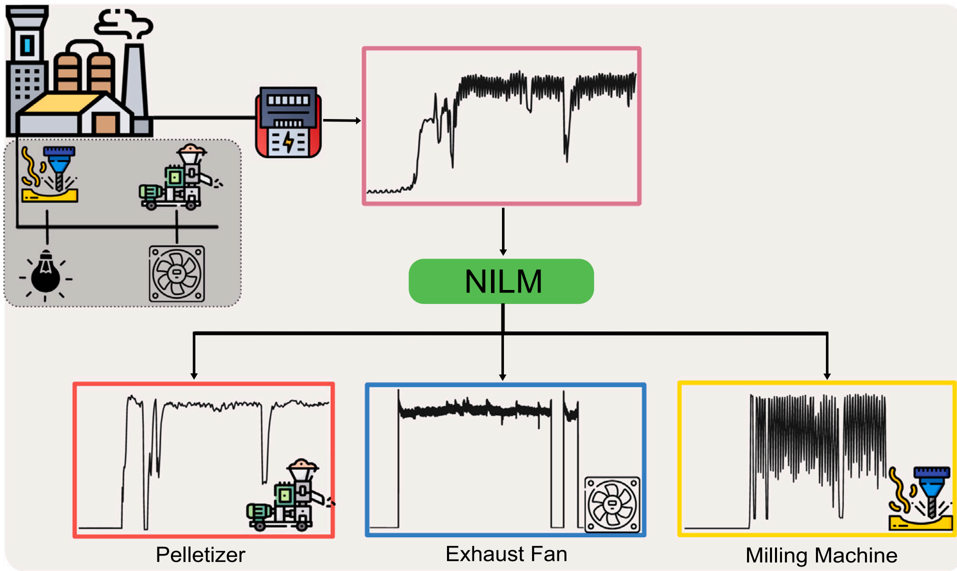

Fig. 1. Non-intrusive load monitoring. The machinery, the lighting system, and all the other electrical loads account for the total energy consumption of the plant, recorded by the main meter. The NILM block uses aggregate measurements to estimate the power profile of each individual load.
Source: Power signals are taken from IMDELD [16].

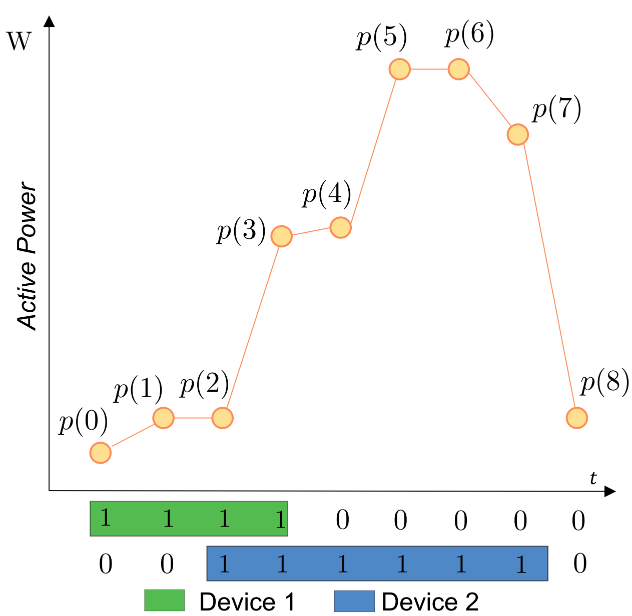

Fig. 2. Example of multi-label appliance classification. For one window of aggregate power signal the aim is to detect which device is active and when. $p(t)$ is the total power consumption recorded at the main meter. "1" means that the device is active for those samples, respectively for two different appliances (blue and green rectangles). "0" means that the device is inactive.

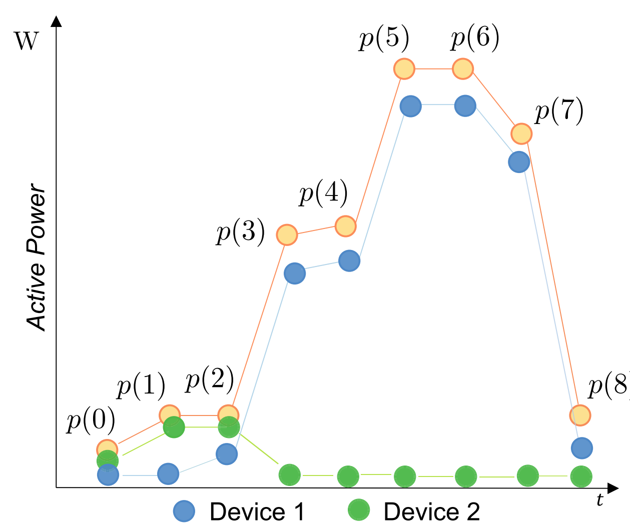

Fig. 3. Example of power profile reconstruction. For one window of aggregate power signal the aim is to estimate the power profiles of each appliance of interest. $p(t)$ is the total power consumption recorded at the main meter. Blue and green signals refer to active power profiles for two different devices.

It is worth to highlighting that in some classification works, especially the ones that use high-frequency signals, the task is not predicting the state of the device at a sample level resolution but identifying the presence or absence of an activation in a certain time segment.

In a regression setting, aggregate measurements are used to estimate the active power $p_k(t)$ of each individual load, as schematically depicted in Fig. 3. Throughout the paper, we also refer to this task as *load disaggregation*. These aggregate measurements can be represented solely by the active power $p(t)$, or can include other quantities such as the reactive power. This aspect will be discussed further in Section 6.

2.2. Types of device

Each load has a specific power signature that identifies its specific power consumption pattern. Hart [18] proposed to classify loads into three categories based on their activation states and consumption patterns:

- Type I: Single-state ON/OFF.
- Type II: Finite State Machine (FSM) or Multi-state.
- Type III: Continuously Variable Devices (CVD).

Type I devices are boolean switching devices that can only have one activation status at a time, such as bulb lamps, toasters, kettles, etc. Type II, or FSM, allows for a set of discrete states and state transitions. This category includes appliances such as washing machines, washer dryers, dishwashers, and heat pumps, which are characterized by repeatable patterns. Type III, or CVD, includes appliances that do not have a finite number of activation states and lack repeatability in their power profiles, making them more challenging to identify compared to FSM devices [18].

In addition to these classes, Zeifman et al. [23] proposed a fourth class for consumer devices that are active for long periods (e.g., days, weeks). This category comprises loads such as television receivers, smoke detectors, and telephone sets.

3. Characteristics of industrial NILM

Differently from NILM applied in residential settings, Industrial NILM has unique characteristics that have steered research in a different direction. In this section, we will explore aspects such as the power signature and industrial load patterns, the temporal correlation among consumption patterns, and other characteristics specific to Industrial NILM.

3.1. Characteristics of industrial loads profiles

Monitoring power consumption profiles in industrial settings poses unique challenges compared to residential buildings. This is primarily because industrial load power profiles are often continuous and do not exhibit clear state changes, as highlighted in a study by Wichakool et al. [32]. According to the classification presented in Section 2.2, industrial loads are predominantly Type III [14,33,34]. This is confirmed by the HIPE dataset [35], where most devices are Type III, although some Type I and II loads are also present. On the contrary, the public data set IMDELD [16] contains only Type II devices. In this dataset, each load can be modeled as a three-state machine (off, no load on, full load on) [36]. Evidently, there are limited publicly available datasets, and they only partially capture the diversity of industrial loads.

Considering the operational patterns of different loads in industrial settings, their active period is concentrated mainly during working hours [35] or within a predetermined period during the day, as illustrated in Figs. 4 and 5. Moreover, power profiles of industrial loads often exhibit cyclic patterns that repeat every work period. This is evident in the exhaust fan and the milling machine, as shown in Fig. 5 from the IMDELD dataset. Differently, the aggregate power signal varies across working days due to different power fluctuations (see the first and second rows of Fig. 4). This behavior is probably influenced by non-monitored machinery or appliances that depend on other factors, such as industrial building management (lighting, heating) or other industrial production processes. It is important to note that in this case, non-monitored loads account for 27% of total consumption. Other differences depend on weekend days or holidays, as shown on the third, fourth, and fifth rows of Fig. 4 where consumption patterns are similar (third and fourth) but shifted in time or the power profile is significantly different (fifth row). Additionally, small-batch production leads to frequent and irregular shifts in production schedules, coupled with changes in machine programs that consequently alter the load curves. Furthermore, most industrial equipment is managed by variable speed drives, making it difficult to learn a pattern [31]. This variability is present in a few residential appliances, while others maintain a stable load signature.

Another aspect worth considering is the variability of aggregate and load power profiles with location, even if they belong to the same scenario (e.g., dairy farms) [35,37]. This suggests that local factors, including climate and weather conditions, availability and cost of renewable energy sources, and the operational and maintenance practices of site owners, can influence load profiles. In general, there could be even more different behaviors in energy consumption when moving from one country to another.

The significant temporal correlation among consumption patterns of different loads, as noted in [33], is a noteworthy aspect in the industrial

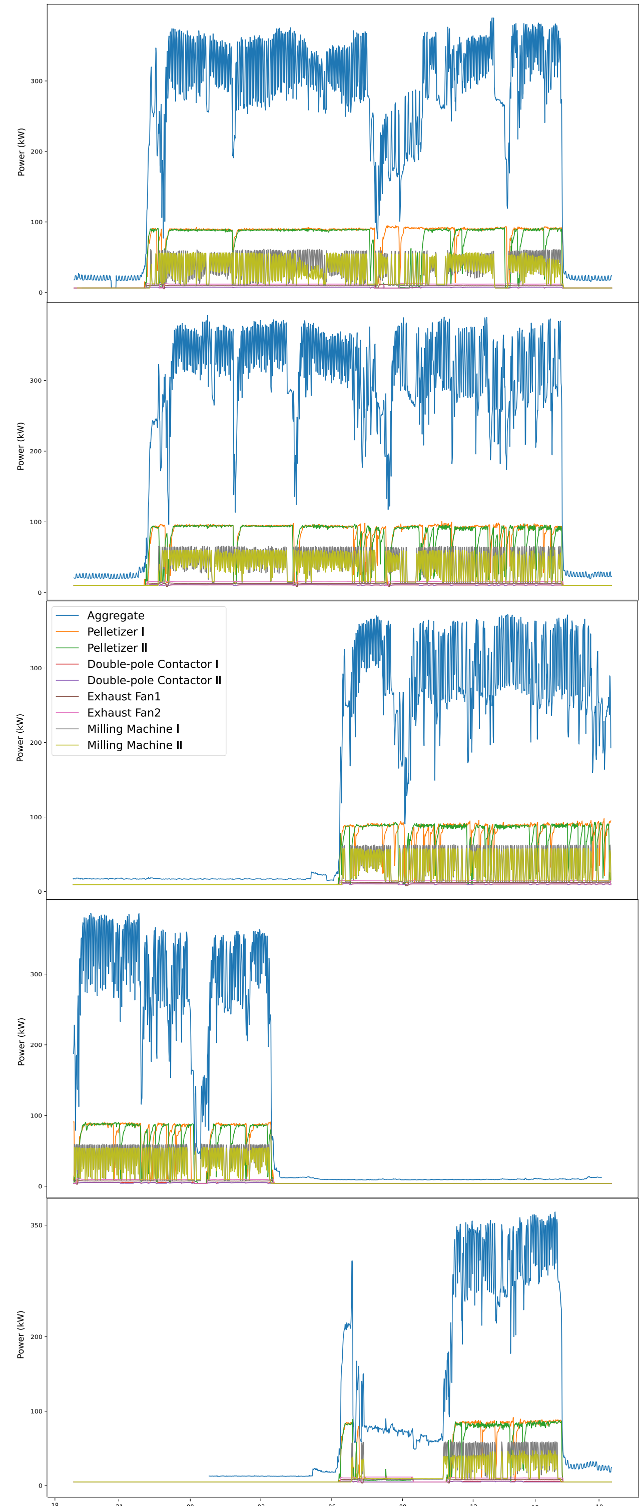

Fig. 4. Power consumption of different loads extracted from IMDELD. During the working period, all the monitored loads are active. Selected days are '2018-03-26', '2018-03-27', '2018-03-30', '2018-03-31', '2018-04-01', and '2018-04-02', from 19:00.

setting. Specifically, the HIPE dataset [35] reveals that machine usage is strongly correlated due to the logic of production processes (e.g., the operation of primary and secondary vacuum pumps or soldering devices and over-screen printers tends to be synchronized). Furthermore, depending on the specific manufacturing process, multiple devices can

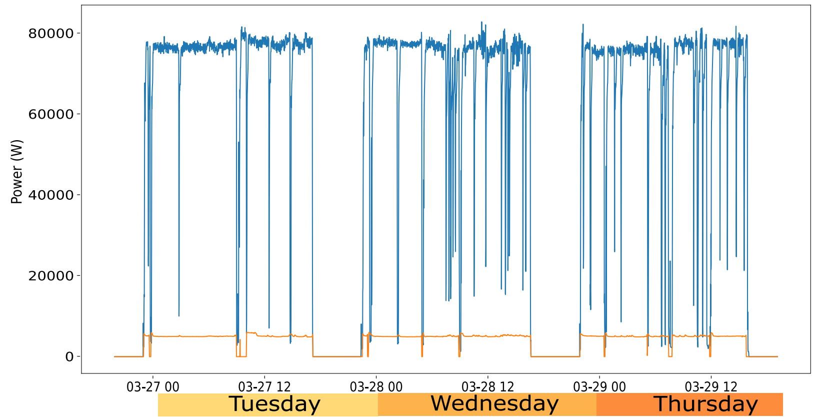

Fig. 5. Active consumption patterns for the Pelletizer I (blue) and Exhaust Fan II (orange) from the IMDELD dataset over a 3-days period (from 2018-03-26 19:00 to 2018-03-29 20:00).

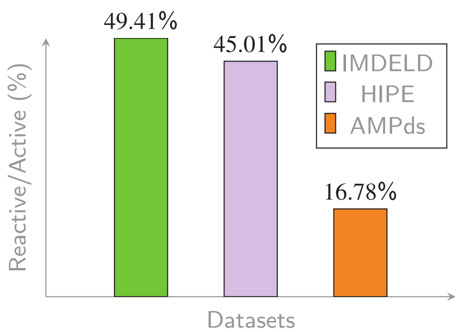

Fig. 6. Comparison between industrial (HIPE, IMDELD) and residential (AMPds) energy consumption datasets, based on the reactive energy contribution over the active energy one estimated for the entire datasets.

consume power at the same time, further complicating the disaggregation task [35,38]. In Fig. 4, it is notable that all the monitored devices in IMDELD are active at the same time, highlighting the difficulty of distinguishing between them. This behavior has also been observed for loads collected in HIPE [35] and Textile Mill Load Dataset (TMLD) [39]. For the sake of conciseness, we do not report other examples from the cited datasets.

Regarding power signals, due to the nature of industrial loads, the contribution of reactive power is generally greater than the contribution related to household appliances. This aspect is illustrated in Fig. 7 related to the IMDELD dataset, which clearly shows that most industrial devices have a significant reactive power contribution. Fig. 6 presents the ratio of reactive to active energy for two industrial datasets compared to AMPds [40], a residential dataset that also contains reactive power measurement. For both the HIPE and IMDELD datasets, this ratio is three times that of the AMPds dataset [40]. This characteristic of industrial loads has been utilized as an additional measure to reduce misidentification [41]. In fact, due to greater fluctuations in the active power signal, the reactive power can aid in reducing false positives. This has been shown in the monitoring of high temperature ovens [42] and devices in a brick factory [43].

The dynamic nature of industrial loads, along with the activity patterns and temporal inter-dependencies arising from industrial processes, has motivated the development of specialized approaches for the industrial setting. The study [33] experimentally demonstrated that common methods developed for monitoring household appliances are not suitable for industrial settings.

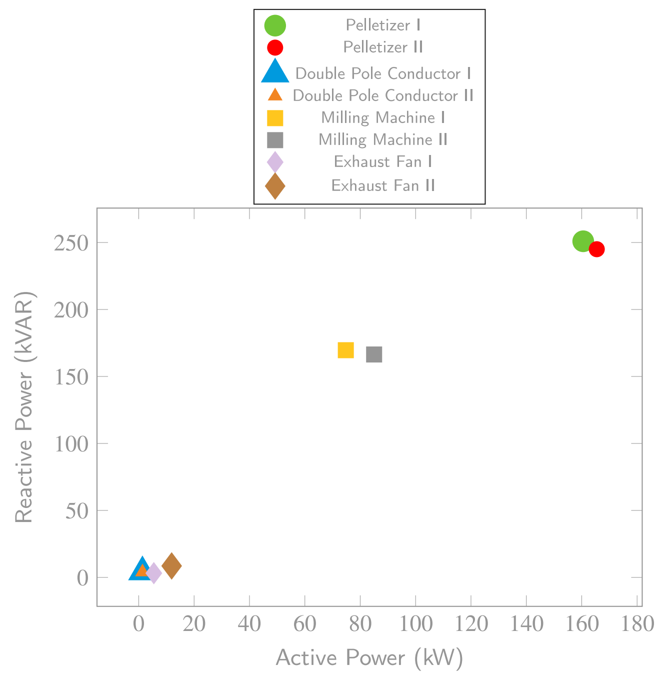

Fig. 7. IMDELD loads in the Active-Reactive Power plane. Values for every device are the maximum estimated on 1 day activation from '2018-02-21 21:00' to '2018-02-22 21:00'. All devices have a reactive contribution.

3.2. Industrial scenarios

In 2023, the U.S. Energy Information Administration (EIA) published a report on energy consumption in various industrial sectors [44] . Manufacturing, which involves transforming materials into products, accounted for the largest share of energy consumption at 76%. This was followed by mining (12%), construction (7%), and agriculture (4%), which includes farming, fishing, and forestry.

The research community has extensively investigated the food scenario, including poultry feed [33,36,45–47], mushroom farms and clinic kitchens [48], and dairy farms [37,49].

Regarding the manufacturing sector, with the availability of the HIPE dataset [35], research has also expanded to the power electronics production scenario. Industries related to materials, such as brick production [42,43], textile [39], electrical products manufacturing [50], cement plants, metal foundries, and steel mills [51], have also been explored.

Table 1
Industrial scenarios and the related equipment considered in this review.

Main scenario	Specific application	Equipment
Food	Poultry feed	Pelletizer, milling machine, exhaust fan, double-pole conductor
	Mushroom farms	Compost ground, washing machine, boilers, exhaust heat pumps, steam boilers,refrigeration cells, vacant space
	Clinic kitchens	Combination streamers, food distribution, coffee machine
	Dairy farms	Vacuum pump, compressor, milking robot, cleaning, water treatment, pipe cooler pump, water pump, dunging milking robot, milk cooling
Manufacturing	Power electronics	Vacuum pump, screen printer, chip press, washing machine, pick and place unit, high temperature oven, chip saw, soldering oven, vacuum oven
	Cement	Submersible pump, cement mixer, electrostatic precipitators, electric arc furnaces
	Textile	Machine tool, sewing machine
Energy and mining	Gas station	Submersible pump, central air conditioning, integrated office socket, canopy lights strip, uninterrupted power supply, kitchen socket, lounge socket, outdoor advertising signage counter socket, counter socket, convenience store socket, freezer
Others	Cold store	Compressors, light, industrial fans, condensers, evaporators, heat pumps

Other scenarios presented in the literature include chiller plants [52], cold storage facilities [14], while for the energy and mining sector includes energy and gas stations [50,53–56], and sewage treatment plants [51].

Electrical industrial loads and the machinery can be very different. Table 1 collects most of the scenarios discussed in this section and the related equipment for a better understanding of the various industrial loads treated in this review. Specific applications are clustered based on classification reported in [57]. Few of industrial fields cited above have been excluded due to missing details about equipment in the original works. As it is possible to see from Table 1, only the vacuum pump, the washing machine and heat pumps are in common among the various scenarios. The complexity and variety of industrial scenarios, compared to residential settings, highlight the need for tailored approaches to monitor energy usage of industrial loads.

The sectors considered by the research community for applying NILM can be evaluated based on the potential energy savings that NILM services can offer to various industries. The total energy consumption of the building can highlight the necessity for a more detailed investigation into energy usage. Based on the works collected in this review, the industries under investigation have been selected due to their high energy consumption and the variety of the processes within the building [14]. Specifically, food and agriculture sectors have been considered since their amount of energy consumption. As noted in [36], a large portion of the electricity consumption in Brazil's food industry is attributed to electric motors. The study conducted by Yadav et al. [49] highlighted the high energy consumption of dairy farms. Thus, monitoring can help identify potential energy savings and facilitate the implementation of demand-side management strategies. Similarly, Todic et al. [37] focused on dairy farms, emphasizing that as demand increases, measuring energy consumption becomes a valuable tool for decision-making and planning in the agricultural sector [37].

4. Overview of industrial NILM methods

4.1. Review methodology

In this study, we conduct a systematic review process to collect, organize and discuss pertinent research that aligns with the research question we have posed. Our discussion will primarily focus on the methodologies used in Industrial NILM and their contributions. This will allow us to highlight existing research gaps and challenges, laying the foundation for future studies. The discussion will largely include the methodologies for Industrial NILM and their contributions to clearly highlight current research limitations and challenges and pose the basis for future research.

Systematic reviews typically rely on search strategies, predefined search strings, and specific criteria for inclusion and exclusion. The fundamental steps followed in this research for the selection process are listed below:

1. Definition of the aim that motivates this review.
2. Selection of Scopus, IEEEXplore, and Google Scholar as databases for identifying eligible works.
3. Collection of studies published in peer-reviewed journals and conferences.
4. Check of the title and abstract to exclude papers on residential and commercial NILM.
5. Collected papers organization and taxonomy definition.
6. Analysis, report and critical discussion of the review findings.

Publications from the time of Hart's seminal work on residential NILM in 1992 [18] to the present day have been considered. Below are reported the entries used at point (3) to search papers titles, keywords and abstracts for Scopus:

> TITLE-ABS-KEY (industrial AND non-intrusive AND load AND disaggregation OR industrial AND non-intrusive AND load AND monitoring OR industrial AND non-intrusive AND load AND identification OR industrial AND non-intrusive AND load AND classification).

The same entries have been used for IEEEXplore and Google Scholar in the appropriate form.

4.2. General NILM framework

Since the first study on industrial load monitoring was introduced in 2007, there has been a significant increase in the number of published research papers, especially after 2020, as shown in Table 3. Although various approaches have been adopted by researchers over the years, the framework illustrated in Fig. 8 provides a general scheme for NILM methods.

The process begins with the "Acquisition" of electrical signals (see Section 6 for details). Electrical load measurements generally are conducted by installing energy meters at the site meter and on the selected devices or sub-circuits collecting more than one device. Then, "Preprocessing" step may involve re-sampling, missing values filling, or normalization. The "Event Detection" phase then identifies specific

Table 2
Public industrial NILM datasets characteristics. Labels refer to the activation state of the appliances sample by sample.

Dataset	Country	Scenario	Length	Nr. of loads	Resolution	Signals	Ground-Truth
IMDELD (2020) [16]	Brazil	Poultry feed	111 days	8	1 s	P, Q, S, RMS-V, RMS-I	P, Q, S RMS-V, RMS-I
HIPE (2018) [35]	Germany	Electronics	3 months	10	5 s	P, Q, S, V, I, THD, F, L	P, Q, S, V, I, THD, F, L
LILACD (2018) [60]	Germany	Laboratory[a]	–	16	50 kHz	P, V, I	P
WHITED (2015) [61]	Germany, Austria, Indonesia	Light industry	1.5 h	110	44.1 kHz	I, V	I, V
TMLD (2021) [39]	China	Textile mill	30 days	5	1 s	P	Appliance states
Zhang et al. (2023) [62]	–	Manufacturing	1 week	–	1 s	P, Q, V, I, phase angle	P
	–	Energy station	2 months	–	1 s	P, Q, V, I, phase angle	P

[a] Laboratory means that the signals have been simulated in a laboratory with industrial loads and acquired under specific predefined conditions. Missing information depend on lack of information in the original sources.

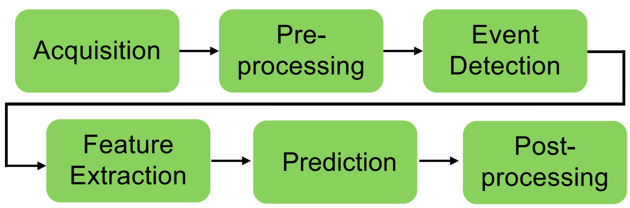

Fig. 8. Typical NILM framework.

events when a device is switched ON or OFF for feature extraction (refer to Section 6.2) or for signal windowing. A simple example of event detection is represented in Fig. 9. When there is a change in the aggregate power consumption signal, based on the power difference between adjacent samples, it can be associated with an event related to one or more devices. The "Feature Extraction" stage extracts significant parameters from the acquired signals. This stage can also be absent, as some approaches directly process raw data. The core part of the NILM framework, "Prediction", regards the algorithm to perform the inference and produce the output. The type of algorithm follows and depends on the task to be performed, i.e., classification, regression, or both tasks. In the residential sector, some recent approaches perform both tasks simultaneously [58,59]. However, in the industrial context, the approaches proposed in the literature generally comprise two consecutive steps: First, an initial estimate of the load state is performed, and then this information is used to estimate the power consumption [47,53]. The last step of the framework consists in the "Post-processing" as de-normalization, smoothing for treating spurious activations, and quantization. Then, the quality of the prediction can be evaluated by comparing it with the desired output.

Table 3 provides a detailed analysis of the main aspects of the industrial NILM literature, which will be discussed in depth in the following sections. The methodologies are described based on dataset, scenario, and the input signals used for the monitoring, the features extracted, the characteristics of the signals in terms of resolution, the type of approach, and the addressed task. The last column reports the best performance achieved in each study.

5. Data acquisition and datasets

Referring to the general NILM framework in Fig. 8, the acquisition of the data is the first step for building NILM algorithms. Thus, the hardware for acquiring energy data in industrial buildings will be presented and then, available public datasets will be described in details.

5.1. Smart energy metering

Advancements in measurement and communication technologies have brought the opportunity of collecting real-time data from users through Advanced Metering Infrastructure (AMI) [63]. Consumption data are typically acquired by smart meters, which are electronic devices that measure the power consumption of a building's electrical system. Smart meters locally record various electricity parameters and provide near real-time feedback on energy consumption. They allow for a bidirectional communication with the grid, receiving information from the utility, such as energy prices or control signals. Additionally, smart meters enable consumers to actively participate in energy communities [64]. The internal sampling rate of smart meters is typically between 1 Hz and 1 MHz [65]. However, meters owned by the utilities transmit low-resolution data, typically at intervals of 15 or 30 min, or even 1 h [66]. It is worth to underscore that, if a higher resolution is necessary for more accurate measurements, an additional meter should be installed at the main panel to transmit data with higher frequency. Other components are the Analog-to-Digital Converter (ADC) and a back-up section is placed for battery-supply for the entire meter. Monitoring is performed by using direct or indirect measurement of current and voltage values. Indirect measurements are based on Ampere's and Faraday's laws and voltage, utilizing the voltage induced on coils. Other measurements are the phase difference between voltage and current, frequency, etc. These values are calculated by the embedded signal processor located after the ADC. A general block scheme is shown in Fig. 11. These measurements are transmitted to suppliers or service providers via communication networks. The two most popular communication systems for advanced metering infrastructures are the Power Line Communications - PLC (wired option) and the Radio Frequency Mesh - RF Mesh (wireless option) [67].

5.2. Datasets

In contrast to the residential sector, there are fewer publicly accessible datasets for Industrial NILM. Fig. 10 shows the percentage of research papers that have used a public dataset or a custom dataset. It is evident that most studies have used a custom dataset, which aligns with the diverse range of devices found in industrial settings due to the existence of various application scenarios. Each specific work needed its specific set of data related to the particular machinery used in a certain production process. This is a stark contrast to the residential sector, where most of the research has used public datasets, justified by the similarity of appliances in different households. For detailed information on residential NILM datasets, please refer to [68].

Table 2 shows the characteristics of all public datasets used in research to date, including the length of the recordings, the number of recorder loads and resolution. All signals collected in each dataset

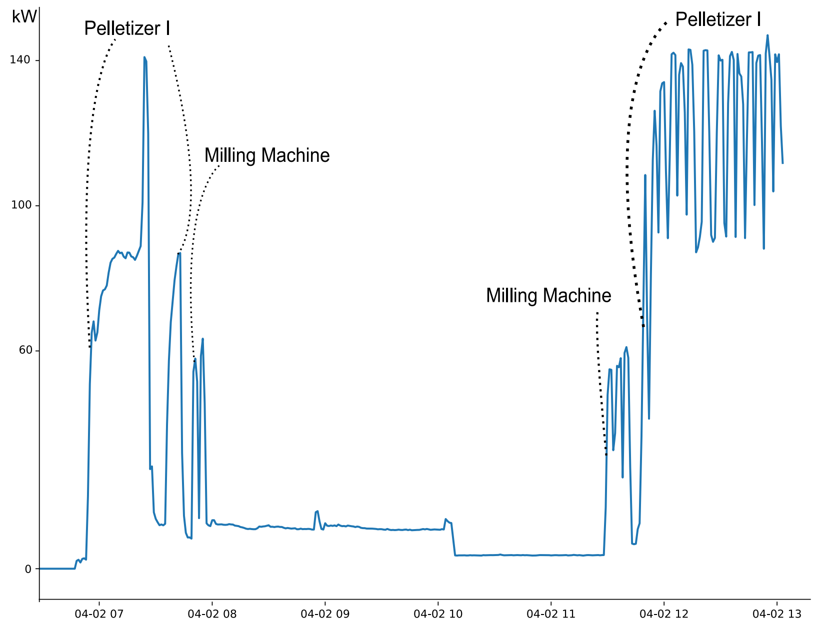

Fig. 9. "Event Detection" example. When a device is switched ON, an event occurs that significantly changes the aggregate consumption shape occurs.

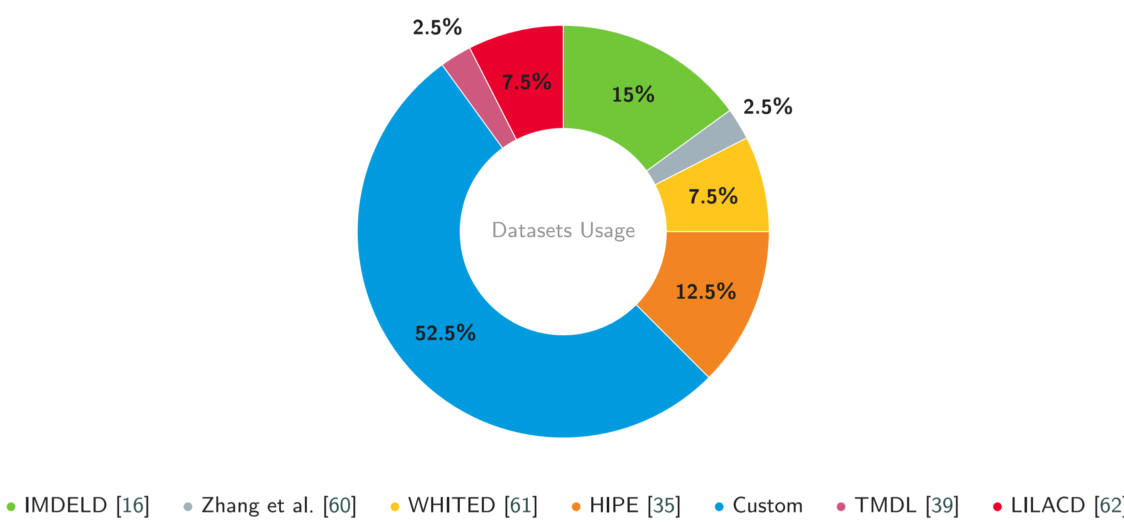

Fig. 10. Usage of industrial datasets in literature: over 50% of the studies acquired their own data.

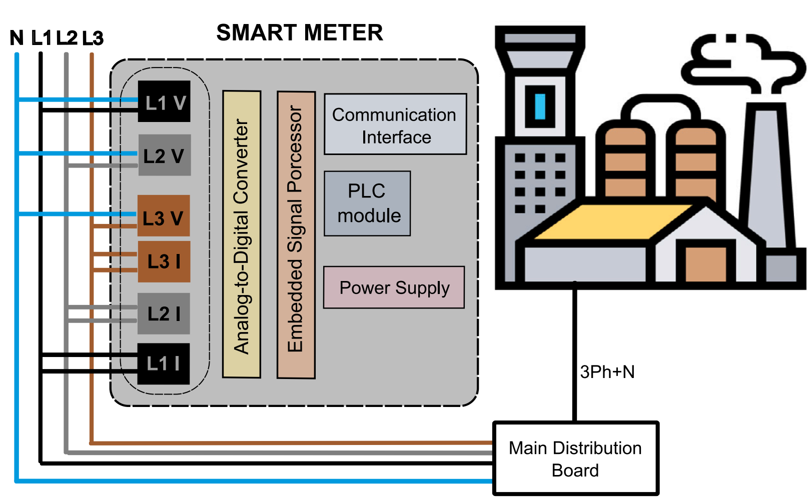

Fig. 11. Smart energy meter.

are explicitly stated, as well as the availability and type of ground-truth signals. Additionally, the country and scenario are reported where available in the original paper, as the industrial context encompasses a wide variety of sectors.

Among the publicly available industrial datasets, IMDELD [16] is one of the most frequently used for research. It contains electrical data from heavy machinery used in a poultry feed factory in Brazil, which produces pellets of poultry rations from corn or soybeans. The factory primarily operates during the hours of lowest energy cost, from 10 pm to 5 pm, Monday to Friday. Data were collected over a period of approximately 111 days, from December 2017 to April 2018, with a resolution of 1 s. The monitored loads are two pelletizers, two double-pole conductors, two milling machines, and two exhaust fans. For all machines, electrical signals such as Active Power (P), Reactive Power (Q), and Apparent Power (S), Current (I), and Voltage (V) were measured. The dataset also includes sub-circuit measurements related to the main medium voltage/low voltage transformer, the pelletizers sub-circuit, and the milling machine sub-circuit.

The HIPE [35] is another popular public dataset for research. This dataset, collected in 2018, includes data from 10 machines used in a German industry that manufactures electronic systems for particle physics, battery systems, and medical applications in small batches. The data collection period spans from October 2017 to December 2017, with a resolution of 5 s. The authors of the dataset provided an example of a production process to illustrate the temporal dependencies that can be observed among the load activation patterns within the data. However, it is important to note that power consumption can vary significantly due to the variability of the final products, especially when production is related to small batches of products. The monitored machinery includes a chip-press and a chip-saw machine, a high temperature oven, a pick-and-place unit machine, a screen printer, a soldering, a vacuum oven, two vacuum pumps, and a washing machine.

LILACD [60] contains three-phase aggregated current and voltage measurements. Measurements are sampled at 50 kHz for 16 different loads spanning both industrial and domestic scenarios. Most appliances were recorded in various states to encompass a wide range of electrical profiles. For example, hair dryers were measured at different heating temperatures, resistors at different resistances, and motors at different power usage levels. The dataset was collected in a controlled laboratory environment in Germany. The dataset comprises 381 single appliance measurements, 864 double appliance measurements, and 56 triple appliance measurements. Each combination of appliances within these groups has unique switching-on times.

The TMLD [39] includes 30 days of aggregate active power measurements. It also provides on-/off-state data, which serves as the ground truth for five loads, including four machine tools and one sewing machine. However, it does not include power measurements at the individual load level.

The WHITED [61] is a hybrid dataset that contains electrical signals from residential and small industrial settings in different regions of the world. The primary objective of the goal of the dataset is to capture a wide range of appliance types worldwide. To accomplish this, the dataset recorded the electrical signals 100 ms before and 5 s after the start-ups of each of the 110 appliances, capturing the transient event that characterizes each appliance. For each appliance, the user manually triggered 10 start-ups and measured the related current and voltage. As a result, the dataset comprises a total of 1100 different records.

"Non-Intrusive Load Monitoring Datasets for two Industrial Scenarios" [62] includes data from two industrial cases. Measurement devices were installed at the medium voltage bus entrance and at the target load to be identified. The types of data measured include three-phase V, I, P, Q, as well as the amplitude and phase angle of each harmonic. The first industrial scenario refers to a manufacturing industry for electrical systems, whereas the second refers to an energy station.

All other datasets used for Industrial NILM research to date are custom and are not publicly available. The only exception is [69], as the authors have stated that the data can be made available on request.

6. Signals and features

Before discussing the various types of electrical signals used in Industrial NILM, it is important to provide information on the acquisition sampling frequency. In fact, one of the major distinctions made for the NILM approaches is low-frequency and high-frequency. Based on [23], low-frequency methods employ data with a resolution equal or lower to 1 Hz and the rest are considered high-frequency. In [70], a slightly different definition is given, with low-frequency approaches defined based on rates lower than the Alternating Current (AC) current base frequency.

6.1. Signals

In the majority of studies, NILM has been carried out using only the active power signal, without any additional input signals. This is a common characteristic with residential NILM, where generally only active power information from the site meter is used for monitoring. However, a different approach is employed in [47], where the authors used power signals from each separate phase as input. Tavakoli et al. [41] suggested using details of production processes to improve disaggregation, while only using P as an electrical parameter. This is due to the wide variety of industrial loads and the possibility of some loads overlapping in the plane ΔP-ΔQ, where Δ indicates the difference of active and reactive power for detected events that characterize the various loads. Furthermore, in Castellani et al. [71], data on ambient and water temperature were linked to the P signal to disaggregate the production of a combined heat and power machine.Up to the authors knowledge, it is the only work that focused on the monitoring of energy production.

Several studies have incorporated Q alongside P to better distinguish the contributions of individual appliances. For instance, Wang et al. [43] found that using both P and Q improved load monitoring within a brick factory, as the P characteristics of the loads were quite similar, unlike the reactive signals. Similarly, Luan et al. [42] utilized both P and Q contributions to disaggregate loads, as multi-observation models reduced false positives by leveraging Q. The same study found that the reactive signal was particularly useful in monitoring machines in a brick factory, as it provided a clearer distinction between similar appliances. In [72] both aP and Q, expressed with each phase, are used as six columns matrix input for their particle swarm approach for disaggregation. Huang et al. [34] based their method on a physics-informed approach considering active, reactive, and apparent power signals. In a recent study [73], reactive and active power were used to cluster industrial appliances. Zhang et al. [50] utilized Q to extract features along with I, P, and transient events. In [54], I, P, V, Power Factor (L) signals and temporal information are used together as input to detect the status of appliances. In [74], P and Q are combined with I and V signals. The study demonstrated that the approach was more effective when additional information was included, such as the turning on transient energy signature. Afterwards, Chang et al. [75] used power signature information from P and Q, and/or turn-on transient energy as inputs for an electrical service entrance. In this case, the turn-on transient energy feature was used to distinguish different loads with the same steady-state P and Q. In another study by Rahimpour et al. [76], both power and current signals were considered as inputs, with a greater emphasis on current due to the lower hardware and installation costs of current transducers compared to those for other measurements. In [77] the aggregate I consumption is the only signal used to extract frequency information and recognize loads also to monitor the condition.

In [51], I and V signals were used to map trajectories as input for their proposed approach, in order to recognize transient events. Lai et al. [78] analyzed the variation characteristics of AC harmonics generated by switching each electric equipment, the mean square value of AC, and the P and Q to monitor two heating, ventilation and air

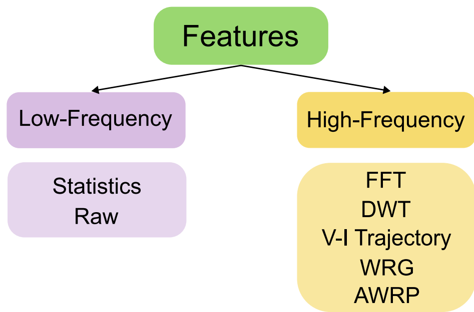

Fig. 12. Taxonomy of features used in industrial NILM methods.

conditioning systems. Faustine et al. [79] focused solely on current and voltage signals as input for their approach to achieve greater accuracy in the feature extraction process. The approach proposed in [80] used voltage and current to calculate the difference before and after start–stop events to extract features for load classification. In another study by Faustine et al. [81], the unbalanced three-phase I waveform was extracted from three-phase aggregate P measurements and transformed into an image-like representation.

6.2. Features

In recent years, NILM research in the residential sector has taken the direction of using raw active power signals as input for the proposed techniques. These approaches typically use low-frequency data that do not allow for the extraction of specific high-frequency features that require higher resolution. This includes transient-on events (which are related to very short time periods such as hundreds of milliseconds), time-frequency decomposition, or Electromagnetic Interference Signals (EMI). The same holds for Industrial NILM, where all the considered studies that use raw signals are based on low-frequency data. The only exception is [52], which extracted features from low-frequency signals such as mean, maximum, minimum, variance, delay, kurtosis, and skewness from the active power signal sampled at 1-minute period and are features that do not require high-resolution data. However, all studies that used high-frequency signals proposed methods based on features extracted from the available electrical data.

In studies that use high-frequency signals, the approach proposed in [82] focused on the v-sections, the core part of the transient event, to better distinguish between loads. Turn-on transient events were extracted in the study by Yang et al. [74]. The Discrete Wavelet Transform (DWT) was used in [75] to detect and localize various types of turn-on transient events. Lai et al. [78] incorporated minimum and average current values along with reactive and active power.

The study in [83] utilized transient features of a rotating electrical machine. They considered features such as the average power of one cycle after the instantaneous maximum power and the last cycle waveform. Additionally, they considered the quadratic polynomial coefficient, the exponential decay time coefficient, and the offset time of the attenuation component of the instantaneous power curves to identify different motors.

Faustine et al. [79,84] proposed an adaptive weighted recurrence graph-based approach, which demonstrated superior performance compared to V-I image features approaches. More recently, the same author applied the Fortesque Transform to balance unbalanced 3-phase current waveforms, thereby improving the quality of the V-I trajectories [81]. In [85] a data fusion strategy was developed using the outputs of four time-domain descriptors. These descriptors include root mean square, mean absolute deviation, integrated absolute magnitude, waveform length, zero-crossing, slope sign change feature, and auto-regressive feature. Tavakoli et al. [41] used the information from the production process associated with active power signals as a feature to improve the performance of their proposed approach. Shi et al. [80] utilized adaptive scaling Recurrence Plot (RP) due to their rich and evenly distributed information, which surpasses that of V-I trajectories or the continuous wavelet transform. Zhang et al. [50] employed features such as the minimum or average of apparent power and current signals, along with harmonics. Ayerbe et al. [77] used the Fourier Transform (FT) to extract the frequency spectra and identify loads within the aggregate current signals. A similar approach was adopted in [48] to analyze current signal harmonics, along with reactive and active power signals.

All the feature extraction approaches discussed above are summarized in Fig. 12.

7. Approaches

We have categorized the methods proposed in the recent literature into two main groups: data-driven and non-data-driven. The first group contains most of the research published to date, comprising Machine Learning (ML) and optimization approaches. Machine Learning refers to approaches that use algorithms that learn from data examples to adjust internal parameters in order to meet a specific objective or criterion. Optimization approaches refer to computational methods that optimize a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. The taxonomy of Industrial NILM methodologies is shown in Fig. 13.

7.1. Data-driven methods

Data-driven approaches rely on the knowledge of a set of examples employed to learn the values of a set of parameters to obtain satisfactory performance from the approach.

7.1.1. Machine learning

A significant number of solutions proposed in the Industrial NILM setting have centered on ML techniques. In [48], an unsupervised clustering method was introduced to assign individual switching events to an appliance. The authors used a modified K-Nearest Neighbor (knn) classifier, a hierarchical clustering approach, and a custom build Device Matching (DevMat) procedure, which proved to be the most effective in identifying industrial loads. Subsequently, a Decision Bagging Tree (DBT) classifier was adopted in [85], which achieved a high classification performance by combining various weak classifiers with a classifier for each appliance. Similarly, Li et al. [53] proposed a gradient boosting algorithm, showing superior performance compared to other machine learning techniques such as support vector machines, Gaussian Mixture Model (GMM), and Random Forest (RF). Recently, the same authors have proposed a Auto-Encoder (AE)-Transformer architecture to classify multiple states of appliances using the same datasets. Holmegaard et al. [14] applied Factorial Hidden Markov Model (FHMM)s and Combinatorial Optimization (CO), both implemented in the NILM-toolkit [86], in the industrial sector. Recently, Toledo-Orozco et al. [69] proposed and evaluated a FHMM approach, which proved to be superior to CO. To address the limitations of FHMM related to the state occupancy duration (which depends on the geometric distribution), Luan et al. [42] proposed an extension named Factorial Hidden Semi-Markov Model (FHSMM).

In [77], an unsupervised approach was proposed that clusters portions of the aggregate signal according to their temporal shape. Each cluster can then be associated with a specific load and its working state, based on a distance-based criterion.

Many strategies proposed for Industrial NILM are based on deep learning techniques This holds also in the residential sector, where deep learning represents the current state-of-the-art. Notably, all the deep neural network-based works discussed in the following paragraphs are based on supervised training.

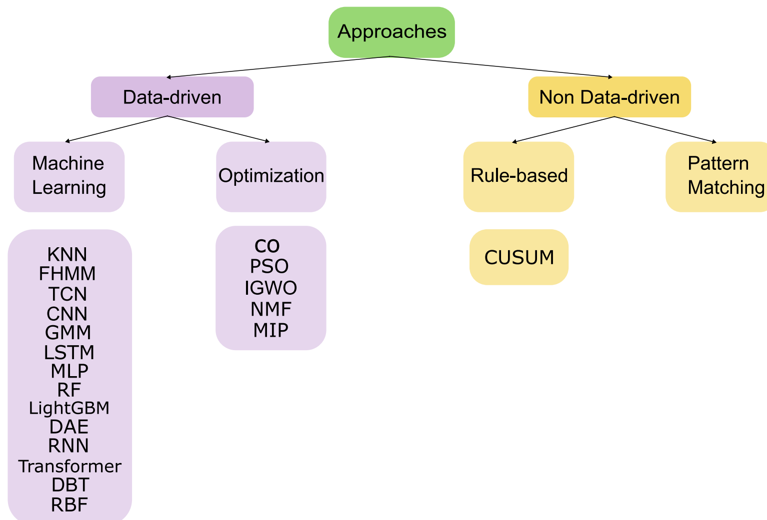

Fig. 13. Taxonomy of industrial NILM approaches.

The first work based on Deep Neural Networks (DNN) was proposed by Yang et al. [74], where they compared a neural classifier, trained with back-propagation, to the Learning Vector Quantization (LVQ) approach. A Multi-Layer Perceptron (MLP) was proposed in [75], with only a single hidden layer for classification. In Yuan et al. [52], a 4-layer back-propagation MLP was used to map the non-linear relationship between the input features and the disaggregated output power level. Recently, Xiong and colleagues [87] proposed an MLP with three hidden layers and the last dense layer producing the classification output. A 3-layer Radial basis function (RBF) network was employed in [83] to learn from mechanical transient features.

Martins et al. [36] utilized WaveNILM, originally developed for residential NILM [88], to disaggregate load power using one network per appliance. This approach was also applied by Todic et al. [37] to monitor milk machines at a dairy farm plant. Conversely, Gowrienanthan et al. [47] developed a 2-stage sequence-to-sequence Convolutional Neural Network (CNN) based on Wavenet, which takes single- and three-phase electrical power signals as input. The overall approach is an ensemble learning technique that eliminates the need to train multiple neural network models.

Yadav et al. [49] applied a sequence-to-sequence strategy using the multi-layer One-Directional Convolution Layer-Bidirectional Recurrent Neural Network (BRNN) (1DConv-BRNN) and a deep neural network based on long short-term memory (Long-Short Term Memory (LSTM)). The 1DConv-BRNN model demonstrated superior performance in the disaggregation of dairy farm machinery. Wei et al. [54] proposed an LSTM-based sequence-to-sequence approach to identify the working status of 12 industrial loads in a gas station scenario. They also used a k-means algorithm to cluster the active and reactive power of appliances, thereby obtaining representative electrical characteristics for each class that cover all possible operational statuses. In a subsequent work [55], the authors incorporated the attention mechanism to enhance performance, effectively integrating external features alongside total electricity consumption in the grid data. Also, recently the work of Zhu et al. [89] incorporated Attention Mechanism (AM) to improve the learning of CNN-LSTM network, proving its efficacy over two benchmark methods.

Wang et al. [43] proposed two functional neural networks, one for background filtering and one neural network for power estimation. Both networks adopt the extended input neural network structure based on AlexNet. Shi et al. [80] proposed the Swin-Transformer approach for industrial NILM, an advanced computer vision transformer suitable for visual-based features. Another transformer-based approach was developed in [46], called Energformer. This method aims to capture complex patterns in long sequences of data and employs 1D spatial convolutions in self-attention.

In [79], a convolutional deep learning approach with Weighted Recurrence Graph (WRG) was proposed. Subsequently, the method was extended by making the recurrence plots adaptive [84]. In a recent work [81], the convolutional network was trained with visual features obtained from a symmetric component transformation of the V-I trajectories. Similarly, Castellani et al. in [71] used a convolutional structure to estimate the power output starting from a time series input. In [34], a physics-informed neural network approach was proposed, which primarily included a time-aware feature enhancement module, a baseline deep learning module (composed of convolutional blocks) and a physics-informed training loss module.

A Temporal Convolutional Network (TCN) with an attention mechanism was implemented in [39] to classify the load activation states in a textile mill industry. This architecture is capable of capturing temporal dependencies of the industrial load data through the attention mechanism. Similarly, Zhang et al. [50] adopted the TCN but added a Conditional Random Field (CRF) layer to model the transfer probability between multiple states.

In the study by Kalinke et al. [33], the performance of all the approaches implemented in NILM-TK was explored. The test included two recurrent networks, a denoising AE, two convolutional networks, as well as CO and FHMM. The results clearly showed how the DNN-based approaches outperformed the others.

7.1.2. Optimization methods

Among the optimization methods, CO is the most commonly used approach [14,33,69]. Brucke et al. [72] proposed a Particle Swarm Optimization (PSO) strategy to disaggregate industrial loads. They applied four adaption methods to the final task to improve the disaggregation results, increase the optimizer robustness against local optima, and reduce the computation time. Recently, in [73], an optimization strategy called Improved Grey Wolf Optimization (IGWO) has been adopted, where improvement is the adoption of a genetic algorithm. Sum-to-k Constrained Non-negative Matrix Factorization (NMF) has been adopted in [76]. The task has been treated as a source separation problem, where the aggregated signal is expressed as a linear combination of basis vectors within a matrix factorization framework. Recently, a novel Mixed Integer Programming (MIP) model was proposed [45]. This model separately handles loads with variable frequency features and loads with steady-state features, making it more suitable for industrial scenarios involving various equipment.

7.2. Non data-driven methods

While most of the literature proposed data-driven methods, a few studies have suggested non-data-driven approaches. Lai and colleagues [78] proposed a rule-based strategy to detect and classify events for air-conditioner monitoring and fault detection. Yi et al. [51] proposed an algorithm based on Cumulative Sum (CUSUM) using a composite window for the Root Mean Square (RMS) current value event detection. The composite window consists of a ground state window for steady-state detection, a detection window for transient event detection, and a state window to verify the validity of the transient event detection. In [82], a pattern-matching strategy is used to compute a distance metric that locates a particular input vector in a region of a state space of known transient templates. The prototype event detector is a transversal or matched filter. A recent work published by Ayerbe et al. [77] proposed a rule-based approach to identify transient-state events, which are then clustered online based on a distance criterion.

8. Performance

The recent surge in studies focusing on non-intrusive load monitoring in industrial settings necessitates a performance analysis to assess their advancements and potential. Depending on the formulation of the problem described in Section 2.1, load monitoring can be addressed as a load state identification task or power profile disaggregation task. Initially, most of the research was concentrated on the identification task (Table 3). At the same time, recent trends show a shift towards disaggregation, likely due to the availability of public data where the appliance power signal can be accessed. Consequently, at the time of writing this research, the number of studies proposing identification methodologies is nearly equal to those focusing on disaggregation. Interestingly, some methods have been evaluated from both perspectives.

The following sections will describe the common metrics used to evaluate these methods, followed by a discussion on the performance trend. To ensure a fair comparison of the different approaches, we will limit our discussion to studies that have used the same public dataset and evaluation metrics.

8.1. Performance metrics

Just as we classified the approaches in Table 3 based on the task, we apply the same principle to the performance metrics. Classification methods are assessed on the ability to correctly detect whether a load is operating during a specific time period or on an instant-by-instant basis.

We define True Positive (TP) as samples where the load is correctly identified as active, and True Negative (TN) as samples where the appliance is correctly identified as inactive. False Positive (FP) refer to samples where the load is incorrectly identified as active, while False Negative (FN) are samples where the load is incorrectly identified as inactive. The most commonly used classification metrics include Accuracy (ACC), which is formulated as:

$$\mathrm{ACC} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FN}+\mathrm{FP}+\mathrm{TN}}. \tag{4}$$

This represents the ratio of all the correct predictions to all predictions (both correct and incorrect). Other widely used metrics are the Precision (PR) and Recall (RE), respectively defined as:

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}, \tag{5}$$

and

$$\mathrm{RE} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}. \tag{6}$$

Precision represents the ratio of correct predictions to total predicted positive samples, while Recall represents the ratio of correct predictions to total actual positive samples. From them, a more common used metric is generally used, that is the F_1-score defined as the harmonic mean of PR and RE:

$$F_1 = \frac{2\cdot\mathrm{PR}\cdot\mathrm{RE}}{\mathrm{PR}+\mathrm{RE}}. \tag{7}$$

As shown in Table 3, the F_1-score is generally included as an evaluation metric also in studies that reconstruct the load power profile. This is done to assess whether the activation state is accurately identified, regardless of the assigned power value.

When evaluating the performance of power profile reconstruction, two metrics are typically used: the Mean Absolute Error (MAE) and the Mean Absolute Percentage Error (MAPE). MAE is used to estimate the error in terms of absolute power, and is defined as:

$$\mathrm{MAE} = \frac{1}{T}\sum_{t=0}^{T}|p_k(t)-\hat{p}_k(t)|, \tag{8}$$

where $p_k(t)$ is the active power at time t and $\hat{p}_k(t)$ its estimate. On the other hand, MAPE is defined as:

$$\mathrm{MAPE} = \frac{1}{T}\sum_{t=0}^{T}\frac{|p_k(t)-\hat{p}_k(t)|}{p_k(t)}\times 100. \tag{9}$$

This metric provides a measure of the estimation error relative to the actual power. Similarly to MAE, the Disaggregation Error (DE) provides a global comparison between the estimated signal and the ground-truth and is calculated as:

$$\mathrm{DE} = \sum_{k=1}^{K}\frac{1}{2}\left\|p_k(t)-\hat{p}_k(t)\right\|_2^2. \tag{10}$$

One of the most popular metric is the NDE, defined as:

$$\mathrm{NDE} = \frac{\sum_{t=0}^{T}(p_k(t)-\hat{p}_k(t))^2}{\sum_{t=0}^{T}p_k^2(t)}. \tag{11}$$

NDE evaluates the disaggregation performance based on the total consumption of the load. Similarly to NDE, some studies assessed the performance using the Mean Normalized Error (MNE) or Energy Error (EE) [48], defined as:

$$\mathrm{MNE} = \frac{\sum_{t=0}^{T}|p_k(t)-\hat{p}_k(t)|}{\sum_{t=0}^{T}p_k(t)}. \tag{12}$$

Match Rate (MR), as proposed in [90] and used by Bernard et al. [37, 48], is calculated as follows:

$$\mathrm{MR} = \frac{\sum_{t=0}^{T}\min\left\{p_k(t),\hat{p}_k(t)\right\}}{\sum_{t=0}^{T}\max\left\{p_k(t),\hat{p}_k(t)\right\}}, \tag{13}$$

MR assesses performance based on the overlap between actual and estimated energy consumption. Lastly, the Total Energy Correctly Assigned (TECA), defined in [91], is expressed as:

$$\mathrm{TECA} = 1-\frac{\sum_{t=0}^{T}|p_k(t)-\hat{p}_k(t)|}{2\cdot\sum_{t=0}^{T}|p_k(t)|}, \tag{14}$$

TECA represents the proportion of total power consumption that has been correctly estimated.

8.2. Performance comparison of load identification methods

The studies addressing the load identification task often relied on custom datasets, making it challenging to compare them directly. As previously anticipated, the discussion will focus on works that adopted the same data and the same evaluation metric. In this case, works that employed WHITED and LILACD have been considered. The approaches from these studies are reported in Fig. 14, along with the corresponding F_1-score, as this is the commonly used evaluation metric. A brief discussion about the only work that used another public dataset (TMLD) has been included for completeness, covering all works that used publicly available datasets.

Table 3
The approaches proposed in literature for Industrial NILM are collected in the present table.

Reference	Dataset	Application	Signals	Features	Resolution	Approach	Task	Performance
Yang et al. (2007) [74]	Custom	Induction motors	I, V, P, Q	Transient-on event	High	ANN, LVQ	Identification	ACC: 100%
Chang et al. (2012) [75]	Custom	Induction motors	P, Q, harmonic distortion	DWT	High	ANN	Identification	ACC: 100%
Holmegaard et al. (2016) [14]	Custom	Cold store	P	Raw	Low	CO, FHMM	Disaggregation	F1: 60%, MNE: 0.3
Rahimpour et al. (2017) [76]	Custom	HVAC system	P, I	Raw	Low	NMF	Disaggregation	DE: 0.795
Bernard et al. (2018) [48]	Custom	Mushroom farm Clinic kitchen	P, Q, harmonics	FFT	High	kNN, HAC, DevMat	Identification	F1: 98% MR: 62%
Martins et al. (2018) [36]	IMDELD	Poultry feed	P	Raw	Low	WaveNet	Disaggregation	F1: 95.89%, NDE: 0.07
Yuan et al. (2019) [52]	Custom	Chiller plant	P	Raw	Low	MLP	Disaggregation	MAPE: 2.965
Yi et al. (2019) [51]	Custom	Cement manufacturing	V, I	Raw	High	CUSUM	Identification	F1: 82.9%
Himeur et al. (2020) [85]	WHITED	Laboratory	P	Time descriptors	High	DBT	Identification	ACC, F1: 100%
Brucke et al. (2020) [72]	Custom	–	P, Q	Raw	Low	PSO	Disaggregation	MAPE: 6.04%
Yadav et al. (2020) [49]	Custom	Dairy farm	P	Raw	Low	1DConv-BRNN	Identification	F1: 85%
Faustine et al. (2020) [79]	WHITED	Laboratory	I, V	WRG	High	CNN	Identification	F1: 97%
Wang et al. (2021) [43]	Custom	Brick factory	P, Q	Raw	Low	AlexNet	Identification	F1: 92%
Faustine et al. (2021) [84]	LILACD	Laboratory	–	AWRPs	High	CNN	Identification	F1: 98.33%
Castellani et al. (2021) [71]	Custom	CHP machine	P	Raw	Low	CNN	Identification	F1: 96%
Liang et al. (2021) [83]	Custom	Induction motor	I, P, pf	Mechanical	High	RBF	Identification	ACC: 94%
Kalinke et al. (2021) [33]	IMDELD HIPE	Poultry feed Electronics	P	Raw	Low	DNN, FHMM, CO	Disaggregation	NDE: 0.16 NDE: 0.58
Liu et al. (2021) [39]	TMLD	Textile mill	P	Raw	Low	TCN	Identification	ACC: 92%
Todic et al. (2022) [37]	Custom	Dairy farm	P	Raw	Low	WaveNet	Disaggregation	MAE: 1.28 W, MR: 98.42%
Li et al. (2022) [53]	Custom	Gas station	P, Q, I, pf	Raw	Low	LightGBM	Both	ACC: 71%, MAE: 21.38W
Wei et al. (2022) [54]	Custom	Gas station	P, I, V, pf	Raw	Low	k-means, LSTM	Disaggregation	ACC: 87.6%, MAE: 17.14 W
Shi et al. (2022) [80]	LILACD WHITED	Laboratory	I, V	ARPs	High	Swin Transformer	Identification	F1: 98.46%
Zhang et al. (2022) [50]	Zhang et al.	Electrical manufacturing	I, P, Q	Statistics	Low	TCN-CRF	Identification	ACC: 97.41%
Luan et al. (2022) [42]	HIPE Custom	Electronics Brick plant	P, Q	Raw	Low	FSHMM	Identification	F1: 76.7%, MAE: 340 W
Faustine et al. (2023) [81]	LILACD	Laboratory	I, V	V-I trajectories	High	CNN	Identification	F1: 96.43%
Gowrienanthan et al. (2023) [47]	IMDELD	Poultry feed	P	Raw	Low	2-stages WaveNet	Both	MSEloss: 0.0117
Angelis et al. (2023) [46]	IMDELD	Poultry feed	P	Raw	Low	Transformer	Disaggregation	TECA: 92.63%, NDE: 0.06
Li et al. (2023) [45]	IMDELD HIPE	Poultry feed Electronics	P	Raw	Low	MIP	Disaggregation	NDE: 0.076 NDE: 0.056
Toledo-Orozco et al. (2023) [69]	Custom	–	P	Raw	Low	FHMM, CO	Disaggregation	F1: 97.56%
Wei et al. (2023) [55]	Custom	Gas station	P	Raw	Low	AM-LSTM	Disaggregation	ACC: 90.5%, MAE: 16.15 W

(continued on next page)

Table 3 (*continued*).

Ayerbe et al. (2023) [77]	Custom	Testbed	P	FFT	High	Clustering	Identification	F1: 99.87%
Huang et al. (2023) [34]	HIPE	Electronics	P, Q, S, time	Raw	Low	2D-CNN	Disaggregation	NDE: 0.81
Wang et al. (2023) [73]	HIPE	Electronics	P, Q	Raw	Low	IGWO	Disaggregation	NDE: 0.023
Zhu et al. (2023) [89]	IMDELD	Poultry feed	P	Raw	Low	CNN-LSTM-AM	Disaggregation	NDE: 0.01
Xiong et al. (2023) [87]	Custom	Environmental monitoring company	P, Q, V, I, L	Raw	Low	MLP	Identification	ACC: 95.5%
Li et al. (2024) [56]	Custom	Gas Station	P	Raw	Low	AE- Transformer	Identification	ACC: 90.2%

The high performance (over 90%) reported in the initial work of Himeur et al. in 2020 [85] is largely due to the composition and sampling frequency of the public dataset WHITED. However, subsequent studies have shown slightly lower performance, which seems somewhat inconsistent given the effectiveness of the method of [85]. This inconsistency may be due to the experimental setup used in this study. In [85], the authors stated that out of over 47 load categories, only 11 were included in the experiments. It is not specified which categories and loads have been selected, thus making a fair comparison with other works unfeasible. The same holds for [79,80], for which it is not clear if all loads or a subset were monitored.

Additionally to the experimental setup, a critical discussion on the composition of these datasets is necessary to understand the high performance achieved in load identification. For example, WHITED is a high-frequency dataset consisting of several-second segments of light industry equipment. Similarly, LILACD was collected in a laboratory, that is, in a simulated light industrial environment. Moreover, both WHITED and LILACD are not continuous because they consist of several pre-segmented windows acquired separately. Inside these windows only three appliances can be active at the same time. The composition of the datasets favors high performance, as can be seen in Fig. 14.

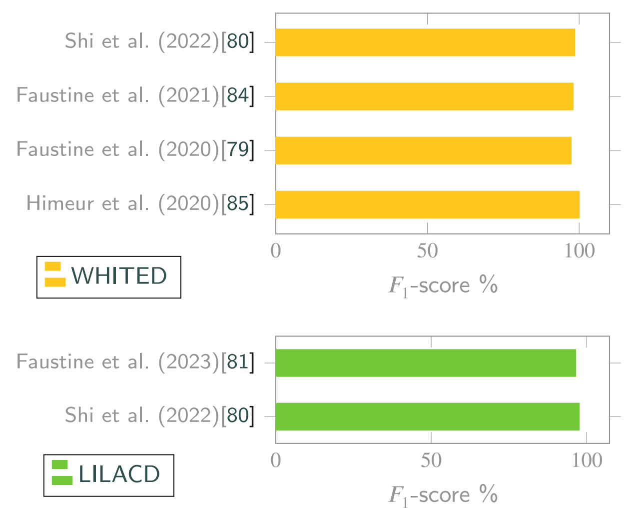

Fig. 14. Performance in terms of F_1-score for identification approaches that used the WHITED and LILACD datasets.

The characteristics of these datasets complicate the comparison of these approaches with other studies that used public datasets but with different attributes, such as those acquired at a different sampling frequency. For instance, Liu et al. [39] utilized the TMLD dataset, which was acquired in an industrial plant at a lower sampling frequency over a continuous one-month period. However, this study reported only the accuracy (ACC: 92%) thus it is hard to make a comparison with the other approaches. While the performance of identification methods using high-frequency public datasets shows promise, further exploration in more realistic scenarios is necessary.

8.3. Performance comparison of load disaggregation methods

Most studies that used publicly available low-frequency datasets addressed the disaggregation task. The choice of NDE as an evaluation metric in the industrial context can be justified by the significant differences in consumption among devices, necessitating the normalization of error.

Methodologies assessed over the IMDELD dataset, starting with the work of Martins et al. [36] (NDE:7%), have shown a consistent trend until Zhu et al. [89] (NDE: 0.9%), with the exception of [33] (NDE: 16%). It is important to note that in Kalinke et al. [33], the algorithms developed for residential NILM were adopted for the industrial setting, which could explain the lower performance. In [47], authors performed experiments on IMDELD but reported MAE for household appliances and the loss value without clearly specifying the test set.

A similar trend can be observed in experiments using the HIPE dataset, where the results of Kalinke et al. [33] are lower than others, except for Huang et al. [34] in which a state-of-the-art architecture for residential NILM [92] was considered and trained with industrial consumption data. As with the study by Kalinke et al. [33], this could explain the resulting performance. Moreover, it is important to remind that the experimental setup is not specified, thus performance inconsistency can be caused by substantial differences in data selection. In [42] the authors used MAE, making a comparison unfeasible, but the scores are reported here for completeness (MAE: 340 W).

Li et al. [45] proposed a disaggregation approach starting from an artificial aggregated signal, consisting only of the devices in interest. Thus, in particular for HIPE, the disaggregation error is smaller than other approaches.

Overall, it appears that the error on IMDELD is lower than HIPE, as illustrated in Fig. 15. This could be attributed to the types of loads contained in each dataset. In fact, the HIPE dataset contains more Type II and III loads.

8.4. Performance comparison on industrial loads

Due to the large variety of industries, it is reasonable to evaluate which sector can be more promising for NILM. Indeed, a specific method might be more appropriate for a particular situation, depending on the characteristics of the aggregate load and the types of loads (I, II and III). Performance on IMDELD (poultry feed industry consumption dataset) reported a smaller error on average (IMDELD: 6.9 vs HIPE: 36.7) than HIPE (electronics industry consumption dataset). Nonetheless, the approach [45] that used both sets produced a slight better disaggregation performance on HIPE than IMDELD. On the other hand, in the work proposed by Kalinke et al. [33] that applied all the algorithms implemented in NILMTK on IMDELD and HIPE showed very different results. The average NDE computed over all the tested approaches is 152.65 on HIPE while is 2.66 on IMDELD. These outcomes could suggest that the approach of Li et al. [45] works better in the electronics industry case study while the approaches tested by [33] work better with consumption of a poultry feed production industry.

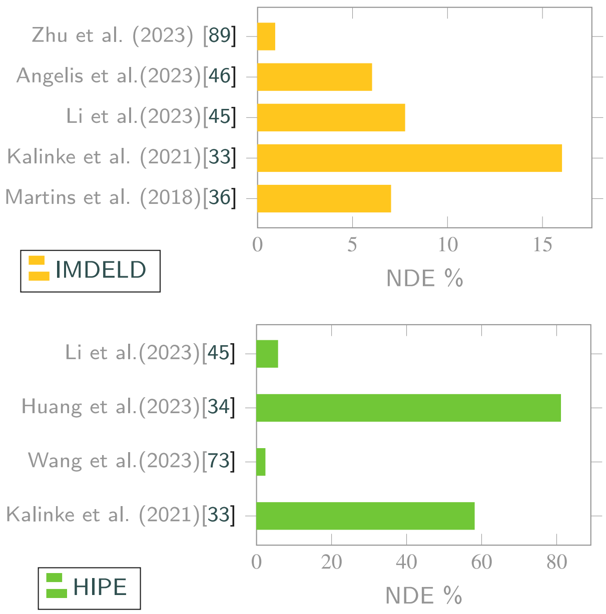

Fig. 15. Performance in terms of NDE for disaggregation approaches that used IMDELD and HIPE datasets.

9. Discussion

The preceding sections have outlined the key features of the Industrial NILM literature. In the following, we discuss its limitations and open challenges.

9.1. Comparability

While initial studies collected their own data from various industries, recent years witnessed a shift towards the use of public datasets. However, since 2023, 5 out of 12 published works still utilized datasets that were acquired by the authors. This leads to a significant challenge for Industrial NILM: the comparability of different approaches.

The data domain issue, for example, complicates the possibility of a fair comparison among different approaches, particularly if data acquisition is customized. In the residential sector, despite the limited and common types of appliances in households, significant differences arise when transitioning from a data domain to another [93–95]. This critical aspect of NILM is even more pronounced in the industry sector, where each industry has unique production processes and machinery. Additionally, there can be considerable differences even among industries that manufacture the same end products, which can adversely impact performance. Consequently, it is not feasible to compare results from the same industrial field if the experiments were conducted on different datasets.

Considerations regarding data domain and the results of Section 8.4 highlight a future direction for the research. For a better understanding of performance among various industrial loads, it is necessary for the approaches to use more than one dataset, as done in [33,45]. This way, performance depends on the consumption data characteristics rather than intrinsic characteristics of the approach. With the current Industrial NILM experimental setup, it is challenging to identify the factors have the most significant impact on performance. Investigating more scenarios can be very significant, potentially highlighting some industrial sectors where a particular approach may perform more effectively.

Another crucial factor related to comparability is the experimental setup. Recently, with the surge in research publications in the residential sector, a few standard public residential datasets have become widely used for developing innovative methods and demonstrating advancements over previous research. Hence, there is an urgent need to standardize the evaluation of methodologies in Industrial NILM, in terms of both datasets and evaluation metrics. In [36] the portion of the data used for training, validation, and test set are specified as percentages. However, in [47] the training portion is not specified, and the validation set coincides with the test set. Moreover, the discussion in Sections 8.2 and 8.3 highlighted the importance of the experimental setup to prevent inconsistencies among methods performance and difficulties in evaluating the trend of performance improvement over time. Therefore, using the same dataset is not sufficient to achieve a high level of comparability, and a standardized experimental setup should be defined. The same holds for the evaluation metrics, as evidenced in Section 8, where some approaches are excluded because they used different evaluation metrics.

9.2. Data availability

A wide variety of scenarios and appliances characterize the Industrial NILM research field. Industrial processes typically involve a diverse array of machinery and equipment, each exhibiting unique energy consumption patterns. This diversity can pose a challenge in developing a universal NILM approach that performs well in various industrial environments. Therefore, having more public datasets covering various industry contexts would be beneficial for research. Detailed information about the production processes and specific machinery used would aid researchers in leveraging public datasets to promote learning strategies such as transfer learning [96,97], which is widely used in many other fields. In this way, a public dataset could be used to train an initial model, and a small amount of local data could be used to fine-tune the model to a specific environment. However, as suggested in [31,98] due to privacy concerns related to energy demand patterns and strategic production processes, in the industrial sector, obtaining a wide variety of public datasets is more challenging. Compared to residential datasets, current public industrial datasets have a shorter duration since they typically contain less than 4 months of data. This is relatively short compared to datasets such as UK-DALE [99] or REFIT [100], which contain data spanning up to 2 years. This aspect is crucial at this stage of research, especially since most published studies focus on ML and specifically DNN-based methods, which require large amounts of data. Additionally, due to production requirements, the energy consumption of an industry can vary without a set periodicity [101], thus it is required to monitor extended time periods to capture the variability in power signals. This can be compared to the necessity to monitor at least an entire year of a house, in order to cover the seasons variability. The scarcity of public data from industries can also be attributed to industrial confidentiality [31], as industries might be reluctant to share information about their processes and equipment to avoid giving away competitive advantages.

To mitigate the issue of limited data availability, data augmentation techniques [102,103] can be tailored for the industrial sector to expand training data. Moreover, given the challenges of installing sensors or manually annotating data in the industrial sector due to the multitude of loads [27,31], weakly supervised strategies [19,104,105] can be utilized to leverage unlabeled data. This approach would allow one to enlarge the training dataset without the need for additional annotations.

Finally, considering that the penetration Distributed Energy Resources (DER) is constantly increasing [106], it would be significant to include them into the non-intrusive load monitoring problem. Up to the authors' knowledge, the only work that addressed this is [71], where the authors disaggregated the electrical power output of a Combined Heat and Power Machine (CHP).

9.3. Data granularity

The performance of NILM services is largely influenced by the quality of input data, which is directly related to data granularity. However, in real-world scenarios, acquiring and processing high-frequency signals is not always straightforward. Generally, consumption datasets have a low resolution (1 Hz), and it is important to note that smart meters typically have even lower resolution (15 min, 30 min, etc.) [66]. The granularity influence has been explored in the residential sector, such as in [107–109]. The study by [107] found that the ability to recognize different appliances varies with the sampling frequency. When it is above 60 Hz, it becomes possible to identify even those appliances that are always-on such as fridge, stand-by, alarm systems etc., which account for 15% of home energy consumption. However, this task becomes challenging at lower frequencies. The research by [108] in residential settings revealed that there is a threshold period value where performance remains relatively stable before it starts to decline. Furthermore, changes in sampling frequency can have different impacts on the approaches, depending on their architecture. For instance, denoising auto-encoders are more sensitive to frequency variations, while convolutional and recurrent networks may see some improvements when frequency decreases [108]. Another important factor is the nature of the phenomena being monitored. It has been confirmed that appliances with long-duration activations in residential buildings benefit from a reduction in sampling frequency [108]. In the study by [109], the proposed approach was tested using different non-uniform sampling strategies. The results showed that for some devices, the sampling frequency does not significantly influence performance. This holds for the dishwasher, that has large power variations for each activation and generally one cycle takes more than one hour. For other appliances, like the washing machine, performance drops drastically. Most of the industrial loads have large power variations and even longer working cycles and experimental results obtained for residential loads can be similar for industrial loads. Thus, specific studies are required. These considerations confirm the importance of evaluating NILM methods under different data resolution conditions, particularly those with low resolutions. Smart meters collect low-resolution data, and obtaining higher resolutions would require the installation of additional sensors. It is also worth to underscore that the approaches we reviewed are specifically designed for certain sampling frequencies. Methodologies that rely on extracted features need high-frequency signals and cannot be applied if only low-resolution signals are available. Only one work by Liu et al. [39] evaluated the proposed method and benchmarks for different sampling periods, demonstrating the stability of their methodology on load identification. Nonetheless, the results are presented on average, without details about the effect of different sampling periods on the single device performance. For these reasons, in the Industrial NILM literature there is a gap regarding this significant investigation, which would lead to a better understanding of the applicability of the methods already proposed in the literature.

9.4. Industrial energy scalability

In the industrial scenario, the energy consumed during a workday is typically greater than in residential buildings. This is due to the number of loads installed within the industrial building and the types of machinery used. For this reason, monitoring industrial loads can be more challenging, as there may be a significant number of non-monitored loads contributing to the total consumption, or a higher number of machines operating simultaneously. In contrast, in the residential sector, fewer appliances are active at the same time [99,100], and nonetheless the impact of non-monitored loads is significant [110]. This effect becomes more pronounced as the number of loads and energy consumption increase. It is also worth noting that, in published studies, the average number of monitored appliances is 5, whereas in the industrial sector, more than 5 appliances are typically monitored (e.g., works that employed IMDELD generally monitored 8 devices).

Despite the challenges of scalability, the use of NILM in industry is a promising option, mainly due to sensors cost, installation issues and the rapid advancements of monitoring algorithms seen in the residential sector. NILM service does not necessitate to install measurement devices on each machine and it is suitable also for monitoring devices where installing electrical sensors is not possible (such as HVAC systems [76], lighting etc.). Nonetheless, the introduction of semi-intrusive monitoring approaches could serve to pave the way for integrating NILM into industrial settings, with the ultimate goal of transitioning towards a completely non-intrusive architecture. Nowadays, most of the commercial monitoring solutions in industries are intrusive. This is directly associated with the difficulty of developing of a general approach that is effective across various scenarios or different industries belonging to the same scenario. This can be demanding without specific information from the target environment, as demonstrated for residential applications even though fewer loads are simultaneously on and the installed devices in homes are quite similar. This aspect represents one of the biggest challenges that Industrial NILM must address.

Another important factor to consider is the nature of the industrial loads (high or low power variations, long or short activation etc.) that are monitored. Performance in IMDELD and HIPE, as presented in Section 8.3, clearly shows how the nature of the devices influences monitoring accuracy. Therefore, it would be beneficial to acquire signals from more complex industrial loads (Type III), which are generally characteristic of the industrial scenario. This would allow for a better evaluation of the effectiveness of the proposed approaches in real-world applications and potential performance improvements. In general, acquiring a wide variety of industrial load data will facilitate more in-depth studies on load power profiles, considering both active and reactive powers.

9.5. Computational complexity

This section is focused on the computational complexity and real-time behavior of the algorithms discussed in this review. Limited attention has been given to these aspects and only qualitative evaluations of computational complexity and real-time behavior are presented in the existing literature. The only exception is the work of Angelis et al. [46] where inference time and a new metric that combines the predictive accuracy of the disaggregation models with computational performance has been introduced. For the rest of the literature, the main focus has been on the effectiveness of the approaches, which still requires significant attention and further study. Edge computing is emerging as a viable solution to maintain privacy and mitigate latency and bandwidth issues associated with cloud-based services [111] and in industrial scenarios can enhance connectivity, real-time control, and data optimization. It also supports intelligent applications, ensures robust security, and safeguards privacy [112]. This is particularly important given the proliferation of deep learning methods. The privacy and confidentiality of industrial processes have not favored the widespread sharing of energy data, as demonstrated by few public industrial consumption datasets. Similarly, it can be assumed that companies are reluctant to move their data to the cloud in order to avoid revealing sensitive information about production, production rates, and applied methodologies. For this reason, it is important to start considering strategies that can be applied at the edge level, in order to prevent data migration and avoid privacy issues. Monitoring machine status, including electricity consumption, is crucial for detecting anomalies promptly, making a real-time service essential. Rapid intervention becomes especially necessary in cases of serious damage. Focusing on real-world Industrial NILM applications is a vital direction for the future.

Table 4
Applications of industrial NILM.

Application	Functionality	Advantages
Awareness	Real-time power information Daily, weekly, monthly and yearly statistics Energy-aware production processes	Active participation in reducing waste, improving energy efficiency, reducing costs, and minimizing environmental impacts from production processes
Management	Load shifting, Peak shaving, Demand response, Self-consumption maximization	Support for achieving sustainability towards Industry 5.0, Integration and management of production with consumption information and self-consumption maximization
Maintenance	Production processes monitoring, Identification of missing cycles, Machinery state monitoring to anticipate or identify faults	State monitoring of machinery and processes to avoid waste derived from faults, preventing severe machine damages and guaranteeing a safe workplace.

9.6. Applications

In this review, NILM applications are divided into three main categories, as shown in Table 4. The first category, *Awareness*, includes all the applications directly related to the knowledge of energy consumption at the device level. NILM acts as a sensor to measure power consumption without installing sensors on each device. This directly promotes energy awareness and provides consumption details that may be unknown for non-skilled users, which is the first step towards supporting sustainable behaviors and energy efficiency for industrial users. As stated in [17], to achieve the desired efficiency improvements, energy use should be measured in more detail and in real-time, to achieve awareness of the energy use patterns of every part of the manufacturing system. Monitoring results can be used for computing statistics, highlighting normal or anomalous behavior in energy consumption, and even compare the consumption of a plant with similar industries. Knowing the energy consumed in a specific production line allows for estimating production costs associated with energy consumption and emissions. To ensure green manufacturing, the energy consumption of production processes should be transparent and minimized [113].

Additional functionalities can be built upon the knowledge of device-level consumption. The second category, *Management*, includes energy saving and self-consumption maximization, for instance.

Detailed knowledge of energy consumption can aid industrial users in minimizing electrical energy waste. Systems, such as EMS, can enhance energy efficiency, particularly when detailed information about machinery consumption and production processes is available. As highlighted in [114], there is substantial untapped potential for energy efficiency in the industry, with EMS being identified as one of the most promising methods for reducing energy consumption. The development of such management strategies should include continuous monitoring of energy usage in processes and plants, the establishment of energy performance indicators for these processes and plants, and an energy information system, as discussed in [115]. The significance of energy management in the industry, especially for energy-intensive industries, has been highlighted in other studies as well [13,116–118]. The above discussion can be framed within the context of Industry 5.0 [119,120]. In fact, one of the requirements of this future industrial scenario is the development of production systems based on renewable energy, sustainability and reduced energy waste, facilitated by the EMS. Additionally, depending on the flexibility of their loads and production cycles, some industries may be eligible for Demand-Response programs. This information can be obtained from NILM outputs.

The third category is *Maintenance*, which pertains specifically to applications on industrial production processes. In fact, the aim is a functional monitoring through the power consumption of the device itself. Analyzing the consumption patterns of industrial machines involved in specific production processes can help monitor the correct process flow and identifying missing cycles or malfunctions. Moreover, relating the load signature consumption and specific working parameters of the equipment (e.g., heating or cooling temperature of the machine), models to obtain parameter information from consumption patterns can be built. Then, these models can be used to indirectly monitor the correct functioning of the equipment itself. This can be useful to act promptly on the machine in presence of dangerous behavior. Also, this can ensure a better security in working environment for the employees [121]. Fault detection has been previously investigated by Lai et al. [78], and in [77] a ball bearing was driven to failure, allowing the acquisition of various phenomenological signals. Other applications identified in the literature include the detection of low-efficiency appliances. Fahad et al. [122] demonstrated this in a small manufacturing plant, where they identified old and low-efficiency equipment that could be replaced to improve the overall efficiency.

10. Conclusion

NILM has emerged as a significant area of interest, particularly for its potential to save energy, reduce emissions, and cut costs. Following widespread adoption and promising results in the residential sector, recent years have seen an increase in publications proposing methodologies for NILM in the industrial sector. Given the high number of devices installed in industrial settings, hardware installation for monitoring is more challenging than in residential environments, making a non-intrusive approach more viable.

This work presented a systematic review of the recently published literature on industrial load monitoring with non-intrusive methods. This effort was motivated by the recent growth of approaches for the industrial sector and the presence of a limited and outdated review that lacks a significant collection and discussion of methods, datasets, and scenarios. Our analysis covered signals, features, and approaches, highlighting the extensive use of raw input aggregate power signals and the adoption of deep learning-based strategies for load identification or disaggregation. A detailed analysis of algorithms' performance has been conducted to clearly assess the knowledge of the current state-of-the-art.

Similarly to the residential sector, a key direction for Industrial NILM is its application in EMS, given the importance of managing energy consumption to minimize its waste. Several challenges need to be addressed, especially concerning the acquisition of longer public datasets from various scenarios, complete with details on equipment and processes. The standardization of the experimental setup should be defined to properly evaluate the improvements achieved by new approaches.

CRediT authorship contribution statement

Giulia Tanoni: Conceptualization, Methodology, Investigation, Resources, Writing – original draft, Visualization. **Emanuele Principi:** Investigation, Resources, Writing – original draft, Writing – review & editing, Supervision. **Stefano Squartini:** Writing – review & editing, Supervision.

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.

Data availability

The data used in this research were not created or collected by the authors. All data refer to publicly available datasets.

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