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NILM in high frequency domain: A critical review on recent trends and practical challenges

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ABSTRACT

The benefits of monitoring aggregated electric load consumption and distinguishing it into its components are numerous and are mainly related to more efficient household energy management. Non-intrusive load monitoring (NILM) as a key method to accomplish this task has attracted the interest of the research community. The basis of this method is the acquisition process of the aggregated electrical signal, which can be performed at different sampling frequencies depending on the specifications of the disaggregation model. Nevertheless, the use of higher sampling frequencies can improve the performance of the disaggregation process. The development of different disaggregation models should be based on their applicability under practical conditions. This means that during their development, these models should include all parameters that will be met in real application. In this way, they will have a higher chance of effectively applying the load disaggregation in practice. Although there are several published review papers about NILM, there is a lack of a systematic review focusing on both the high-frequency domain and the practical aspects that need to be considered during model development. To this end, this study systematically reviews 40 recent papers in the high-frequency domain published between 2019 and 2022. Then, the practical issues derived from them are discussed and referred to the different steps of NILM development. Finally, 30 of them are evaluated in terms of their disaggregation performance and whether their development is focused on practical applications, according to several criteria.

Nomenclature

Abbreviations	
ARTMAP	Adaptive resonance theory mapping
BDT	Bagging decision tree
CNN	Convolutional neural network
COA	Combined operation of appliances
COA-EBTL	Combined operation of appliances with event based true labels
COA-LFTL	Combined operation of appliances with low frequency true labels
CUSUM-MLP	Cumulative summation-multilayer perceptron
DBSCAN	Density based spatial clustering of applications with noise
DR	Demand response
DSWC	Dual sliding window-based cumulative sum
DT	Decision tree
HD	Harmonic distortion
KNN	K-nearest neighbor
LSTM	Long short-term memory
MILP	Mixed integer linear programming
NILM	Non-intrusive load monitoring
RF	Random forest
RMS	Root mean square
FFT	Fast Fourier transform
SOA	Single operation of appliances
SoC	System on chip
SVM	Support vector machine
TSDM	Time shift downsampling matching
VIIF	Voting improved isolated forest
Units	
Time	second (sec), minute (min)
Frequency	Hertz (Hz)

1. Introduction

NILM is not a new concept. It was first introduced by Hart in 1992 to determine the electrical energy consumption of individual appliances based on the aggregated electrical power measurements at the main feeding panel of an electrical installation [1]. Since then, several researches have been performed in this area and many benefits have been

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identified, suggesting that NILM could offer much to the electrical energy sector.

The reduction of greenhouse gas emissions and the reduction of electricity consumption are more than ever a necessity due to the greenhouse effect and the recent energy price crisis. Recent studies have shown that if consumers of electrical energy are aware of their electricity consumption, they can significantly reduce it. When real-time feedback is provided and at appliance level, consumers can reduce their electricity consumption by more than 12 % [2]. Therefore, NILM could be a game changer in attempts to improve electrical energy efficiency and minimize greenhouse gas emissions.

Another aspect of using NILM in a more sustainable energy future is its applications in demand response (DR) activities. The decomposition of electrical energy into its component parts offers electric utilities and grid operators the opportunity to understand the consumption patterns at individual device level. In this way, DR strategies could be developed based on specific habits of electricity consumers, making specific suggestions for the use of appliances, or control certain appliances without disturbing the comfort of consumers [3].

Up to this point, the potential contribution of NILM to a more sustainable energy system was clearly related to consumer electricity consumption flow. Nowadays, however, renewable energy sources, such as photovoltaic (PV) systems, are increasingly being integrated into household electrical installations shifting the traditional consumer to act as prosumer [4]. This current state of affairs has revealed an important new potential contribution of NILM in the context of prosumers' electricity generation flow, bringing benefits to both prosumers and consumers. The literature has shown that NILM can be used to determine the electricity production of residential photovoltaic systems [5–7]. In this way, DR strategies could be further developed based on consumers'/prosumers' electricity consumption and prosumers' generation patterns and mitigate the potential negative impacts that could be hidden behind decentralized energy sources in a more sustainable way [5]. Power inverters coupled with PV systems or battery energy storage systems inject traceable harmonic distortion to the point of common coupling, thus NILM could also contribute in supervising the operation of these systems in order to ensure that the harmonic distortion does not exceed the permissible threshold set by the regulations. Also, in saturated distribution networks (DN) new regulations define that additional PV systems should cap their power injection in the DN to avoid congestion and power quality issues; with NILM it is possible to verify the compliance of the PV power output to the permissible set points defined by the system operator.

One of the main characteristics of the NILM framework is whether the disaggregation scheme is based on event detection. In the case that an event detection algorithm is integrated in the NILM process, the disaggregation is taking place only after an event occurrence [8]. An event could be considered as an appliance transition from one steady state to another [9].

Another important point for grouping NILM techniques is whether they use true labels during development. If this is the case, the technique is supervised; if not, it is unsupervised. Supervised NILM techniques use true labeled datasets to be trained in the training phase, in order to link the data with the available true labels and achieve accurate predictions when unknown data are fed into the already trained NILM model. On the other hand, unsupervised NILM implementations are developed without the inclusion of true labels. In this case, data are grouped during model development and execution, without any guidance [10]. In recent years, due to practical needs for NILM applications, another category has emerged for grouping NILM techniques. This is the semi-supervised category, which can be considered a compromise between the supervised and unsupervised techniques. In the latter distinction, a small set of true labeled data is used along with a much larger unlabeled dataset [10,11].

Feature extraction is an essential component of any NILM system. It is a central part of the NILM implementation, whether the model is considered event-driven or not, and whether it is supervised, semi-supervised, unsupervised, or any other type of categorization. As part of the feature extraction process, the NILM device located at the main distribution board takes measurements of instantaneous values of current and/or voltage at a specified sampling rate [12]. From these measurements, it is possible to calculate different types of features that can be employed by the disaggregation model. The type of calculated features is strongly dependent on the utilized sampling rate [13]. The literature review suggests that high sampling signals for feature extraction are those sampled at a frequency equal to, or higher than the fundamental frequency [14–16]. For example, the authors of [17] used instantaneous current measurements sampled at 10 kHz to apply short-time Fourier transform and extract current spectrograms. In Ref. [18], the amplitude and phase of the odd harmonic currents up to 5th order were used as a result of applying fast Fourier transform (FFT) to the instantaneous current using zero-crossing detection of instantaneous voltage. Both instantaneous current and voltage measurements were sampled at 50 kHz.

The higher the sampling rate, the more information is included in the extracted signals, since more instantaneous values of current and voltage are extracted. Therefore, there is a higher probability of capturing the characteristics of appliances' signatures, especially during transients or nonlinear behavior [19]. In addition, the advent of smart devices in modern homes, which are mainly power electronic loads, has led to the injection of harmonics into power lines. Hence, calculated features after harmonic analysis of an extracted signal could play an important role in a more robust description of the electrical signatures of such devices [20]. Consequently, a high sampling rate for the extraction of current and voltage signals could increase the robustness of the calculated features, leading to higher overall performance for the NILM task [21].

In recent years, the development of NILM has made great progress, especially involving high sampling rate signals. However, there is still a lack of practical applicability under real-world conditions. These conditions are described by the need for a relatively cheap, plug-in, and easy-to-use NILM device with high sampling capabilities that would be responsible for extracting high sampling rate signals and computing features [15]. In this way, the acceptance by users would be significantly increased, leading to full exploitation of all the benefits that NILM can provide for better electrical energy management. Under real-operating conditions, it is almost unrealistic to develop disaggregation models able to handle any possible appliance brand. Thus, there is a need to develop NILM architectures characterized by universal models that can be used in any electrical installation [22]. To this end, further analysis of the key aspects of high sampling rate NILM frameworks and of how practical challenges can be incorporated into the development of a more accurate NILM system, should be conducted.

Recent reviews of NILM have already been presented in Refs. [2,15,23]. In Ref. [15], the authors compared different NILM research works in terms of the features, algorithms, and datasets used, as well as the target applications of the developed frameworks. However, the literature compared use both low and high frequency, and its applicability in practice is compared and evaluated only within the narrow constraints of whether it incorporates publicly available benchmark datasets. Similarly, in Ref. [2], the authors review several recent NILM methods and features using any type of input signal sampling rate. As for the evaluation of the practicality of the compared works, it was limited to the general discussion of the difficulties of using NILM with supervised models due to the high labeling cost. Finally, in Ref. [23], the authors presented a multi-criteria comparison of different NILM implementations in terms of the datasets, models, and features used, as well as the associated extracted performance evaluation metrics without their values. Again, this work compared models belonging to both the low and high frequency domains. Furthermore, the comparison and evaluation of the literature in terms of practical challenges is limited to the computational costs related to the different NILM architectures.

Consequently, to the best of the authors' knowledge, an analytical review of recent developments in high sampling rate NILM and a detailed analysis of the practical challenges that should be considered at each stage of NILM development have not yet been thoroughly examined.

To address the identified research gap, this review work systematically examines the recently developed NILM frameworks that use high sampling rate input signals, discusses the parameters that should be considered with respect to practical NILM application, and critically evaluates most of the frameworks with respect to their performance and their applicability. In this sense, this work has the following contributions:

- Presentation, analysis, and comparison of all publicly available high-frequency NILM datasets and their critical evaluation in terms of how valuable they are in enabling the research community to benchmark their work towards the practical application of NILM.
- Present and analyze different data processing approaches in terms of training, validation, and testing, and how best to use them to develop NILM in practice.
- Summarize different types of features extracted from high-frequency input signals and present the features that could make the difference in the performance of NILM application, considering real practical challenges.
- Presentation, analysis, and comparison of different NILM architectures for the developed NILM frameworks and critical evaluation of these architectures in terms of their contributions and limitations in case of a practical NILM application.
- Detailed analysis and comparison of different current high sampling rate NILM implementations with an assessment of their performance and provision of their key metrics, while in parallel they are critically evaluated regarding all the above parameters that need to be considered in terms of their practicality. Providing the key metrics also gives the NILM research community the opportunity for benchmarking comparison, keeping in mind the practical challenges.
- Presentation of various other practical challenges that may arise in NILM development and the proposed solutions with concrete examples.

2. Data

2.1. High sampling NILM datasets

Datasets are an essential part of NILM development. They contain various electrical power measurements including aggregate and individual measurement points, along with the required true labels [24]. Over the past decade, a significant amount of publicly available NILM datasets have emerged, which is an important prerequisite for the development of NILM methodologies, i.e. the existence of a benchmark evaluation step. This step involves applying known evaluation metrics to various proposed NILM algorithms using measurements from these datasets [25].

In this review, a comprehensive analysis of the most recent publicly available versions of high sampling NILM datasets has shown that they can be divided into 3 categories. The categorization is firstly derived from whether the high sampling rate signals concern single or combined operation of appliances. Secondly, from whether the true labels of the signals for the combined operation of appliances are derived from time-stamped low-frequency measurements or are derived directly from time-stamped events of appliances.

1) Single operation of appliances (SOA): The basic goal of the disaggregation scheme is to decompose the extracted signal into its components. However, in this category there are only high sampling rate signals related to the single operation of appliances, which is far from the usual practical conditions and far from the goal of NILM [26]. Here, there are 4 high sampling NILM datasets.
   - WHITED [27].
   - COOLL [28].
   - HFED [29].
   - MORED [30].
2) Combined operation of appliances with low frequency true labels (COA-LFTL): These datasets provide publicly available electricity consumption data on the combined operation of appliances. However, they do not contain sufficiently reliable true labels due to the low frequency of them [26]. For example, the true operation of appliances is implied from power consumption data given every few seconds. Here, there are 4 high sampling NILM datasets.
   - REDD [31].
   - UK-DALE [32].
   - NILM-UY [33].
   - SustDataED2 [34].
3) Combined operation of appliances with event based true labels (COA-EBTL): This category of publicly available high-frequency NILM datasets fits perfectly with the requirements of real-world NILM development. Here, more than one appliance is operating simultaneously and true labels about appliance operation are derived directly and reliably from appliance events, facilitating accurate training and performance evaluation [26]. In this last category there are 6 high sampling NILM datasets.
   - PLAID3 [35].
   - BLOND [36].
   - HELD2 [26,37].
   - LIT [38].
   - BLUED [38,39].
   - LILAC [40].

The main features of the above high sampling NILM datasets under the scope of this study are shown in Table 1. In summary, the most useful datasets for the development of real-world high sampling rate NILM are those that allow researchers to apply their disaggregation algorithms to multiple instances that involve the simultaneous operation of appliances. The availability of highly reliable true labels through appliance events is of paramount importance for the development of accurate disaggregation methods. When this is not the case, biased errors occur during both training and evaluation, making benchmarking of the methods difficult.

2.2. Processing of NILM datasets

The use of datasets is a necessary step in the implementation of NILM. The way available data are processed during the development of the NILM framework strongly affects the generalizability that the disaggregation scheme gains over real-world data [41].

One of the main aspects of datasets' processing relates to the approach used to divide the data into training, validation, and test datasets for supervised and unsupervised techniques, or some other compromise thereof [42]. Several approaches to data partitioning are known in the literature. The most common of these for high sample rate NILM implementations are presented in the following analysis, along with a critical evaluation of the limitations and contributions to the potential application of the developed load disaggregation models in unseen data from real implementations.

A common method for splitting is to randomly split the dataset into only 2 subsets. The first is called the training set, in which the NILM algorithm is trained, and the second is called the test set, where the algorithm is evaluated. The percentage split of the total available data determines the size of the 2 sets. A common percentage split is 80 %/20 %, where 80 % of the total available data is considered the training set and the remaining 20 % is considered the test set [17,43]. Within this category of random data splitting, there are also some other percentage splitting values, for example, the 70 %/30 % [44] or the 50 %/50 % [45]. Despite the simplicity of this approach, it lacks good generalization

Table 1
High sampling NILM datasets.

Dataset	Sampling Frequency of Aggregate Signal	Class	True Labels' Availability	Predominant Appliance Types	Download Link
WHITED	44.1 kHz	SOA	–	Residential	WHITED
COOLL	100 kHz	SOA	–	Electrical Tools	COOLL
HFED	10 kHz–5 MHz	SOA	–	Residential	HFED
MORED	50 kHz	SOA	–	Residential/Electrical Tools	MORED
REDD	15 kHz (cut-off frequency of the current sensors at 300 Hz [39])	COA-LFTL	1/3 Hz	Residential	REDD
UK-DALE	44.1 kHz (down-sampled to 16 kHz for storage [32])	COA-LFTL	1/6 Hz	Residential	UK-DALE
NILM-UY	14 kHz	COA-LFTL	1/60 Hz	Residential	After request to the authors
SustDataED2	12.8 kHz	COA-LFTL	1/2 Hz	Residential	SustDataED2
PLAID3	30 kHz (cut-off frequency of the current sensors at 10 kHz [35])	COA-EBTL	Event Based	Residential	PLAID3
BLOND	250 kHz 50 kHz	COA-EBTL	Event Based	Office Equipment	BLOND
HELD2	4 kHz (low pass filter at 1.3 kHz was applied before sampling stage [26])	COA-EBTL	Event Based	Residential	HELD2
LIT	15.36 kHz	COA-EBTL	Event Based	Residential	LIT
BLUED	12 kHz (cut-off frequency of the current sensors at 300 Hz [39])	COA-EBTL	Event Based	Residential	BLUED
LILAC	50 kHz	COA-EBTL	Event Based	Industrial/Residential	LILAC

ability. This is because this random partitioning of data results in some data classes being trained with many examples and others with fewer examples, which means poor performance on the available test data [46].

In the same context, but with a different approach for dividing the dataset into training and testing subsets, there is the time-based data splitting. In this case, a certain percentage of the first entries of the dataset is considered as the training set, while the rest of the data collected in time form the test set. Again, the percentage partitioning varies. For example, in Ref. [47], the authors study the identification of a coil gun. For their work, they created a private dataset by extracting instantaneous current measurements from a single operation of a coil gun with a sampling frequency of 10 kHz. The first 70 % of the 140 monitored seconds of coil gun operation constituted the training set, while the remaining 30 % represented the test set. In the same way, the authors in Ref. [48] created a private dataset containing example sets of 10 features involving the percent harmonic distortion of odd total harmonic currents. All features were extracted from a commercial smart electricity meter with high sampling capabilities (62.5 kHz) and stored with a recording frequency of 1/60 Hz with respect to 4 different clusters for a total data collection of 6 months. This dataset was divided into training and test sets, with the first 70 % of the data assigned to the training set and the remaining 30 % to the test set. Other percentage apportionment approaches are the 90 %/10 % [49] or the 6 days/1 day [19] for training and test sets respectively. As with the random-based division of the dataset into training and test sets, the time-based approach lacks generalizability for the same reasons. However, this approach tests the NILM framework one step closer to reality by providing a clear time division in training and then applying the trained electrical energy disaggregation scheme to unseen data in practice [50].

To bring the character of practical real-world conditions into the developed model, the authors in Ref. [51] developed a private dataset with training and testing parts. The training set consisted of 7 subsets of 200 s of extracted instantaneous current measurements per appliance and aggregated instantaneous voltage measurements, including all 15 different appliance combinations from 4 different appliances with different starting conditions per subset. During the training phase a 7-fold cross validation approach was used. Finally, the test set included 6 subsets of instantaneous measurements, just like the training set, but this time with significantly more load variation.

The inclusion of a validation set along with the different types of measurements in all parts of a utilized dataset improves the generalization capability and evaluates the NILM model under unseen practical operating conditions [52]. However, not only different patterns in appliance operation, but also measurements coming from different brands of the same appliance type could be considered as an even greater practical challenge in real case NILM implementations [53]. In this direction, the authors in Ref. [54] used samples from an older version of the dataset PLAID and divided it into training, validation, and test sets. For the formation of the training set, samples from the appliances of 42 randomly selected houses were used, which are among the 60 available houses in the dataset. For the formation of the validation set, samples from the appliances of 6 of the remaining houses were used, and for the formation of the test set, samples from the appliances of the last 12 houses were used. In this way, generalizability under practical conditions and evaluation in real unseen scenarios are taken into account by using a validation set and a test set containing appliances of the same type but different in terms of brand, even if different from the training set. In this way, once a model has been developed and generalized to different data distributions, it is tested as an application-ready solution in different electrical installations [55].

As can be seen from the above analysis, the training, validation, and testing subsets are important for the development of real-world applicable disaggregation models. The availability of true labels is of great importance in all subsets and incurs significant costs in terms of time and money [56]. When applying a NILM model in practice, cost should be considered in all aspects. Therefore, reducing the cost of labeling while maintaining disaggregation performance is a current research goal. The main method that meets these requirements is active learning. In this approach, true labels are assigned only to those examples that contain the most valuable information. Thus, the development of the disaggregation algorithm is based only on high value features; the size of dataset used is reduced and that corresponds to a reduction in the labeling cost [57]. For example, in Ref. [56], the most valuable labeling samples were selected and the features were learned with an active deep learning model using a convolutional neural network (CNN) classifier, resulting in a significant reduction in the required samples while maintaining the same classification performance.

In summary, the nature of the data and the way they are processed during the development of the NILM model determines the scalability of the disaggregation scheme in real-world scenarios. In practice, it is more than likely that the NILM will have to be applied under different conditions for appliances of different brands and operating patterns, compared to those for which it was developed. Thus, the greater the generalizability that a model acquires, the greater the possibility of successfully applying it to completely unknown measurements. This possibility should be tested and the results should be presented regarding the performance of a proposed NILM framework on real-world scenarios. In this case, the NILM research community has the opportunity to evaluate the applicability of the proposed algorithms in terms of sufficient disaggregation performance on real implementations. In addition, NILM application should consider cost, even at this early stage of model development in terms of the data processing part. All of these desirable data processing aspects for a NILM that can be applied in practice are summarized in Fig. 1.

2.3. High sampling features

The datasets to be used for high-frequency NILM development, like those mentioned above, include high sampling rate feature extraction signals, or recorded features extracted from high sampling rate signals [48]. Either way, high sampling rate signals are an essential part of the necessary feature extraction in a high sampling rate disaggregation process. The contribution of using high sampling features has been highlighted in several works [33,58] and several high sampling features have been extracted in different implementations utilizing signals with high sampling rate of instantaneous current and/or voltage [59].

A common approach to create features is to directly use the high sampling rate signals of instantaneous current and voltage. The authors in Ref. [60] used instantaneous current and voltage measurements for extracting one electrical cycle at a time through the proposed method to form the recurrence plots for current and voltage cycles. These were then introduced in the proposed spatial pyramid pooling CNN architecture for appliance classification.

Another type of feature extraction is to process the high sampling rate current and voltage measurements and create features from the results of the processing. A common processing step prior to the feature creation phase is the application of frequency domain analysis. In this context, in Ref. [19], the instantaneous current and voltage measurements were preprocessed and converted into 1-sec frames with 16,000 samples per electrical feature to form the instantaneous power matrix per frame for the application of the double Fourier integral analysis and the extraction of the magnitude and phase matrices. These matrices were then used by the proposed CNN regression model per appliance to determine the power consumption of the appliances. The robustness of these features is based on the additional information of the sideband harmonics they contain. The sideband harmonics are ensembles of sums and differences of current and voltage waveforms that fully reproduce the spectral content of the appliance model, especially under the sign of even-order harmonics.

Another possible result of the frequency domain analysis is the amplitude and phase extraction of the current harmonics. In Ref. [61], the FFT for the instantaneous current was performed using the zero-crossing detection of the instantaneous voltage, both sampled at 50 kHz. Then, the amplitudes and phases of the odd harmonic currents up to the 5th order (1st, 3rd, and 5th) were extracted for 10 different appliances, taking a total of about 4–5 min per appliance for data collection. Here, the combined extraction of amplitudes and phases facilitates the formulation of the vectors of current harmonics, resulting in improved disaggregation performance. Similarly, in Ref. [48], the extracted amplitudes of odd harmonic currents up to the 7th order were used to calculate the % harmonic distortion of the 3rd, 5th, and 7th current harmonics provided by a smart electricity meter along with other general electrical characteristics. Finally, in the same context of

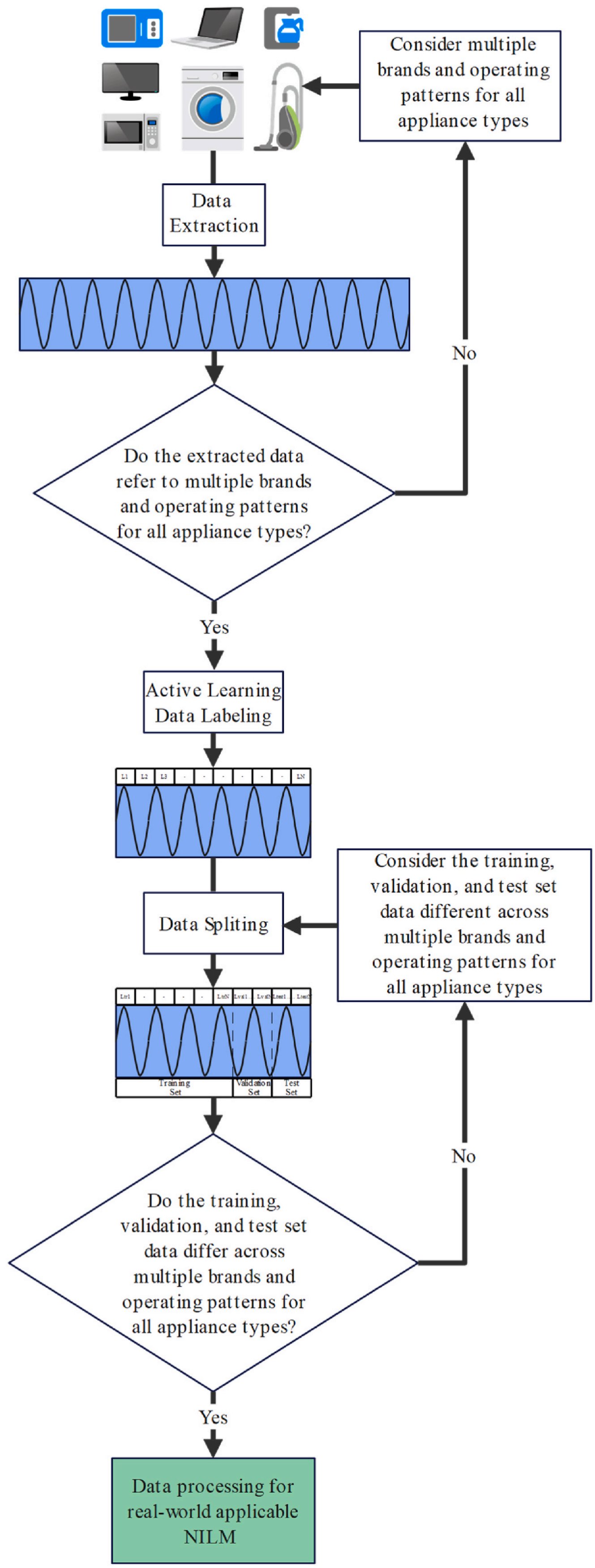

Fig. 1. Data processing steps for real-world applicable NILM development.

processing the instantaneous values prior to feature generation, the authors in Ref. [62] contributed to appliance classification by presenting a set of novel features describing the transient current shape of the harmonics of certain orders extracted by applying the Stockwell transform to the transient instantaneous current measurements. In Ref. [63], three proposed transient features were calculated from the application of the Hilbert transform to the extracted transient instantaneous current. These were the instantaneous amplitude, phase and frequency. The employment of them resulted in better appliance classification due to better description of time and shape of the transients.

The main objective of feature extraction based on instantaneous values of current and voltage with high sampling rate is to significantly improve the uniqueness of the created features. In this way, better disaggregation performance is anticipated for the NILM model. However, the robustness of the extracted features should be oriented to be preserved under real practical disaggregation conditions. For example, the high percentage of similarity that resistive appliances have in a real household makes appliance classification not an easy task without appropriate measures [40]. In this context, the authors in Ref. [64] proposed a reconstruction method for typical V-I images to make these features more unique and improve the identification performance among similar appliances, especially the resistive ones. Similarly, in Ref. [65], magnitude and phase of the lower odd harmonics were extracted by FFT processing of the instantaneous current signal to enable better classification performance for appliances with similar power consumption, which is common in the real household electrical installations.

3. High sampling NILM frameworks

3.1. Analysis

In general, after a common pre-processing phase, the analysis of which is beyond the scope of this study, the features extracted from high sampling rate signals are introduced into a NILM architecture that performs the necessary tasks to classify the appliances and/or determine the power consumption of the appliances [23,66].

In the pre-processing phase, some potential practical issues related to the data can be addressed to mitigate the negative impact on the subsequent feature extraction process. When using time series, missing values are not an unlikely scenario. Although there is no universal solution for this case in the literature, the variants of interpolation are commonly used [23]. Simple interpolation techniques, such as linear interpolation, have the advantage that they are easy to implement. However, for highly fluctuating time series, they may not be sufficient to accurately fill in the missing values. The main reason for this is that these methods do not consider the entire data series [67]. An improved method proposed in Ref. [67], called noisy interpolation, uses a cubic interpolation in which white Gaussian noise is added to fill in the missing values in a correlated but also stochastic way in a limited range. Another data-related aspect that could be solved in the pre-processing phase is the existence of outliers. A widely used solution for the presence of outliers is filtering. Median filters or other filter combinations applied to the input data aim to smooth it out, resulting in improved disaggregation performance [68,69]. The presence of outliers can also have a negative impact in certain NILM-related processes such as dimension reduction through principal component analysis (PCA) [70]. In Ref. [70], the negative effects of outliers are mitigated by the proposed robust PCA method, which leads to more reliable PCA features.

The number of different NILM architectures in the literature is huge and could be divided into several groups. However, given the high sampling rate nature studied in this review and the evaluation of the NILM frameworks under real-world applicability, the number of different disaggregation models is limited, and the main categorization perspective followed here depends on whether the disaggregation scheme follows a time-driven or an event-driven approach.

In a disaggregation model, a time-driven approach is assumed to be followed when the NILM algorithm is invoked to perform appliance classification continuously per each set of features extracted per each time window of the signal or signals. On the other hand, a disaggregation scheme is considered event-driven if it is invoked to apply the appliance classification for sets of features that come from time windows in which an appliance event occurs [9]. In particular, in the high frequency domain, this categorization is closely related to whether or not the NILM frameworks can be used efficiently in a real practical scenario. This conclusion stems firstly from the nature of NILM in the high-frequency domain, where the data resolution of the processed signals is high, and secondly from the frequency at which the total load disaggregation processing is invoked. Clearly, both of these issues significantly affect the computational complexity required in a NILM algorithm, especially in a real-time application [9]. The event-driven approaches have higher practical applicability in actual operating conditions since the total times in which the algorithm is invoked to apply high frequency load disaggregation are significantly lower.

1) Time-Driven High Sampling NILM Frameworks: The main point that characterizes all the different NILM frameworks in this category is that there is no event detection algorithm in the different implementations to detect state changes of the appliances and trigger load classification. There are 2 types of high sampling NILM frameworks in this category.

a) Time-Driven Appliance Event Type Classification High Sampling NILM Frameworks: In this type, the goal of the NILM framework is to use the extracted set of features continuously for each time window of the input signal to match it with an *on* or *off* event of a particular appliance, as implemented in Ref. [71].
b) Time-Driven Appliance Classification High Sampling NILM Frameworks: This type is different from the above in terms of the final output result. Here, the NILM framework tries to assign each extracted set of features to the corresponding cluster related to the operation of a particular load, as in Ref. [51].

2) Event-Driven High Sampling NILM Frameworks: In this category, the key process, which is also a fundamental difference in terms of how a time-driven NILM framework works, is event detection. The task of the event detection algorithm is to detect any change in the operational status of the appliances and trigger load classification. In this category, there are 3 types of high sampling NILM frameworks.

a) Event-Driven Event Matching and Appliance Classification High Sampling NILM Frameworks: The objective of this type is to extract sets of features related to the time windows of the input signal where events occur in order to match the *on* with the *off* events. This is followed by a classification process to associate the extracted features of the time window of the time frame between the *on* and *off* events to the operation of a particular load, as [72] performed. This approach to a high-sampling NILM framework is more applicable than the time-driven approaches under real practical conditions due to its event-driven nature, but it still has room for improvement in post-event detection processing. The processes of event detection, event matching, and load classification could be shortened to obtain the total load disaggregation in the same type of output.
b) Event-Driven Appliance Classification High Sampling NILM Frameworks: In this approach, there is no event matching within the load disaggregation task. More specifically, for the needs of event detection the model uses the input signal to detect if there is a change in the operating mode of the appliances. When an event is detected, the framework again uses the input signal to extract a set of features that describe the time window of the event. Then, usually, these features are introduced into the load classification algorithm to determine the appliances that participate in the total power consumption, as in Ref. [63]. This method, where there is no event matching step, leads

to the same load disaggregation result but with less complicated processing after event detection. When an event is detected, load classification determines the appliances in operation, taking into account that they will remain in operation until a new event is detected. Then the load classification determines again which appliances are in operation. From this new result, it can be concluded which appliance has changed its state, bypassing event matching.

c) Event-Driven Appliance Event Type Classification High Sampling NILM Frameworks: The above type of event-driven high-sampling NILM framework appears to involve dual processing within the overall implementation of load disaggregation [17]. This can be easily deduced by focusing on the completely separate processes of event detection in the first stage, which uses the input signal, and load classification in the second stage, which in turn uses the input signal of the measurements. On the other hand, in the event-driven appliance event type classification high sampling NILM framework, which is analyzed as a potential application in this section, event detection and classification of the detected event as *on* or *off* event of a particular appliance are implemented sequentially as one process. Thus, the classifier does not need to use the input signal again to extract a set of features describing the detected event and classify it. In this way, the processing time is reduced, which facilitates the development of a NILM framework that can be used in practice for high sampling rate measurements. For a general analysis of the framework, it could be noted that the event detection algorithm in the first phase could use the input signal to compute a feature that is used to detect the occurrence of an appliance event. After an event is detected, the feature related to the time window of the event could usually be introduced into the event classification part and assigned to a on or off of a particular appliance.

The summary representation of the different categories in relation to the high sampling NILM frameworks is shown in Fig. 2.

3.2. Literature evaluation

The crux of this section is the comparative presentation of 30 research studies. These studies were the result of a systematic search for NILM works published from 2019 to 2022, under the consideration that: (a) they should have used high sampling rate signals, (b) they can be evaluated in terms of disaggregation performance, and (c) they can be evaluated in terms of contribution to the development of NILM in the real world regarding the aspects that have been discussed. Specifically, the NILM papers published in the above-mentioned period were first evaluated according to whether or not they used high sampling rate signals as input for the corresponding disaggregation task. Obviously, only the papers that processed high sampling rate signals as input were selected for further evaluation. In the next step, the NILM works were evaluated as to whether or not they contained the required disaggregation performance evaluation of their proposed method. Only if this was the case, they could in turn be compared with the rest of the literature. The NILM papers that met conditions (a) and (b) were assessed for final selection according to whether or not they could be evaluated in terms of practical NILM development. Specifically, for the final selection related to the practical development of NILM according to the aspects discussed, the works were evaluated according to whether or not they contain the necessary information about the single or combined operation of appliances, the dataset(s) used, the type of framework and the utilized features. For example, if a paper used a high sampling rate input signal and presented its evaluation of disaggregation performance, but did not mention the type of operation of the appliances for which the evaluation metric was extracted, it could not be part of the literature review presented here. The same exclusion would apply in the case that not all necessary specifications were included to facilitate categorization under the NILM frameworks mentioned above.

Table 2 is a more general comparison table of the performance of the NILM frameworks presented. In Table 3, the reader will find a comparison that elaborates on the applicability of the included works in the real world. In Table 2, for each reference, some main aspects of the respective NILM framework are presented, starting with the year of publication, the frequency of the input signal used, and the general information of the framework. Furthermore, the main performance metric is listed. Indeed, the overwhelming majority of the compared works have included more than one performance metrics in their implementations. However, for the presentation in Table 2, the evaluation metric chosen was the one that was closer to evaluating the application of each proposed NILM method in real-world scenarios. In addition, the performance metric chosen was the one that more rigorously assessed the developed framework. For example, if a work was evaluated using both the FScore and the accuracy metric for the single and combined operation of appliances, the FScore for the combined operation of appliances was chosen as the final metric. In this way, the work is evaluated more rigorously by the comparatively more reliable FScore metric on the one hand, and under conditions closer to practical application, such as combined operation of appliances versus single operation of appliances, on the other. The type and number of instances used to extract each metric are presented subsequently. For example, in Ref. [45], the metric presented was extracted using 6 different appliances, 2 of which had 2 discrete modes of operation. Therefore, the total number of distinct groups for which the proposed disaggregation algorithm was applied was 8. In Ref. [73], the number of distinct appliances involved was 20, but the evaluation was the average result of a 10-fold

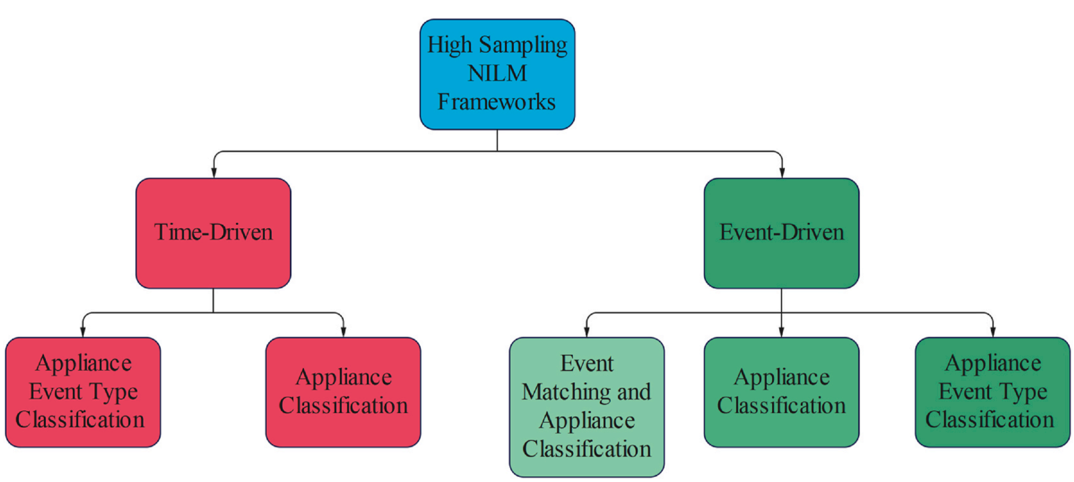

Fig. 2. Categories of high sampling NILM frameworks.

Table 2
Evaluation of high sampling NILM frameworks in terms of performance.

Ref.	Year of Publication	Frequency of Input Signal	General Description of Framework (core algorithm)	Critical Metric (Examined on Highlight Data Processing)				Competent Comparison with Literature
				Value	Number of Examined			
					Appl.	Combos.	Groups	
[45]	2021	6.25 kHz	Supervised Learning Machine Learning (KNN)	Multi-Class Macro- Averaged Accuracy **100 %**	6	–	8	X
[60]	2022	2.4 kHz	Supervised Learning Deep Learning (CNN)	Multi-Class Macro-Averaged FScore **89.42 %**	–	–	55	✓
[49]	2021	6.4 kHz	Supervised Learning Deep Learning (CUSUM-MLP)	Multi-Class Micro- Averaged Accuracy **99.10 %**	30	–	30	X
[58]	2021	16 kHz	Reinforcement Learning Machine Learning (KNN)	Multi-Label Micro- Averaged Accuracy **98.91 %**	21	–	21	X
[77]	2020	250 kHz	Supervised Learning Deep Learning (LSTM)	Multi-Label Macro-Averaged FScore **21.00 %**	–	–	4	X
[78]	2020	1.6 kHz	Unsupervised Learning Machine Learning (MILP)	Multi-Class FScore presented in graphs	19	–	–	X
[54]	2020	30 kHz	Supervised Learning Deep Learning (CNN)	Multi-Class Micro-Averaged FScore **78.96 %**	–	–	8	✓
[56]	2020	20 kHz	Active Learning Deep Learning (CNN)	Multi-Class Macro-Averaged FScore **88.00 %**	389	–	10	✓ For Labeling
[73]	2020	15.36 kHz	Supervised Learning Machine Learning (Prony's method)	Multi-Label Macro- Averaged Accuracy **97.00 %**	20	–	10	X
[47]	2020	10 kHz	Supervised Learning Deep Learning (LSTM)	Multi-Class Micro- Averaged Accuracy **99.94 %** (Coil gun)/**93.90 %** (Permanent magnet synchronous model)	1	–	4	X
[64]	2021	30 kHz	Supervised Learning Deep Learning (CNN)	Multi-Class Macro- Averaged FScore **97.36 %**	–	–	11	✓ For Private Dataset
[79]	2022	12 kHz	Supervised Learning Probabilistic and Expert Heuristic (VIIF-TSDM)	Micro-Averaged FScore **99.22 %**	–	–	3	✓
[21]	2022	15.36 kHz	Supervised Learning Deep Learning (CNN)	Multi-Label Macro-Averaged FScore **96.80 %**	–	–	3	X
[71]	2022	250 kHz	Supervised Learning Machine Learning (Dictionary method)	Multi-Label Micro- Averaged Accuracy **99.02 %** (Ons)/**98.90 %** (Offs)	14	–	14	X
[72]	2019	12 kHz	Supervised Learning Machine Learning (ARTMAP)	Δ ratio **+2.75 %**	6	–	6	X
[63]	2021	2 kHz	Supervised Learning Deep Learning (LSTM)	Multi-Class Macro- Averaged FScore **94.47 %**	5	4	9	✓ For BLUED & PLAID Datasets
[17]	2021	12 kHz	Supervised Learning Deep Learning (CNN)	Multi-Label Micro- Averaged FScore **99.80 %**	34	–	69	✓
[22]	2021	3.2 kHz	Transfer Learning Deep Learning (convolutional architecture)	Multi-Label Macro- Averaged FScore **93.80 %**	3	–	12	X
[20]	2021	2 kHz	Supervised Learning Machine Learning (fuzzy technique)	Multi-Class FScore **99.33 %** COA	5	1	1	✓
				Multi-Class Macro-Averaged FScore **99.03 %** Multi-State	2	–	8	
[74]	2020	3 kHz	Supervised Learning Machine Learning (KNN)	Multi-Label Micro- Averaged FScore **96.00 %**	5	1	5	X
[80]	2020	15 kHz	Supervised Learning Deep Learning (CNN)	Multi-Class Macro-Averaged Accuracy **92.40 %**	7	10	10	✓ For another testing within 5 houses
[51]	2020	200 kHz	Supervised Learning Machine Learning (RF)	Multi-Class Macro-Averaged FScore **99.45 %**	4	15	10	X
[65]	2020	15 kHz	Supervised Learning Machine Learning (BDT)	Multi-Class Macro-Averaged FScore **93.14 %**	5	4	9	✓ For PLAID Dataset

(*continued on next page*)

Table 2 (*continued*)

Ref.	Year of Publication	Frequency of Input Signal	General Description of Framework (core algorithm)	Critical Metric (Examined on Highlight Data Processing)				Competent Comparison with Literature
				Value	Number of Examined			
					Appl.	Combos.	Groups	
[81]	2019	1.6 kHz	Unsupervised Learning Machine Learning (DBSCAN)	Multi-Label Macro-Averaged FScore **94.70 %**	3	–	3	X
[18]	2019	50 kHz	Supervised Learning Machine Learning (DT)	Multi-Label Macro-Averaged FScore **86.62 %**	5	6	6	X
[61]	2019	50 kHz	Supervised Learning Machine Learning (Load signature)	Multi-Label Macro-Averaged FScore **88.43 %**	8	3	3	X
[82]	2021	50 kHz	Unsupervised Learning Machine Learning (K-means)	Multi-Label Macro-Averaged FScore **81.47 %**	6	22	23	X
[48]	2022	62.5 kHz	Supervised Learning Machine Learning (SVM)	Multi-Label Macro-Averaged FScore **86.11 %**	3	2	4	X
[19]	2021	16 kHz	Supervised Learning Deep Learning (CNN)	Multi-Label Macro-Averaged FScore **98.00 %**	5	–	5	✓

replicate. Therefore, the number in the Groups section is 10. Another example is [63] where the proposed disaggregation method concerned 5 different appliances and 4 different combinations of them, so the total number of different groups is 9. In Refs. [20,74], there was 1 combination of 5 different appliances. However, in the first study, the appliance classification was evaluated under a multi-class consideration, meaning that the identification aimed at the whole combination of appliances involved, so the number of groups was 1 [48]. On the other hand, in Ref. [74], despite the fact that the combination of appliances was 1, the identification of the 5 different appliances within the combination was evaluated under a multi-label consideration, resulting in a total number of 5 different groups. In the multi-label assessment, the identification of each appliance within the combination was assessed separately from the others [48]. As a result, the performance metric was extracted between 5 different groups. A more general explanation of the multi-label nature in the presented evaluation metrics is that in the corresponding implementations, the identification performance was focused on specific appliances while other appliances were in operation. Another concept that needs to be clarified is the macro/micro-averaged calculation of the presented metrics. The macro-averaged calculation refers to the well-known and easy-to-calculate arithmetic averaging which adds the separately extracted metrics for all participating groups and then divides the sum by the total number of all different groups [64]. The micro-average, on the other hand, is calculated considering the number of examples evaluated per group [75]. Table 2 concludes with the information about the inclusion of a competent comparison of the presented implementations with other literature methods regarding the listed performance metrics. A comparison is considered competent only if it was applied to the same type of data in terms of the dataset used, the appliances studied, etc. If there was another important comparison, this is indicated with the appropriate comment.

Table 3 compares the main aspects of each study that could facilitate the evaluation of each proposed method in terms of whether or not it was developed with real-world scenarios in mind. The first criterion for this type of evaluation is the dataset used and the processing of the data in the development of each proposed NILM disaggregation algorithm based on the analysis presented in Sections 2.1 and 2.2 respectively. In detail, for each work, all the examined datasets are presented with a further explanation of the dataset used to extract the highlight metric. The fifth and sixth columns of Table 3 provide the type of each developed NILM framework, in the context of the analysis presented in Section 3.1, as well as the features used, extracted from the high sampling rate signals and introduced in each proposed NILM architecture.

Finally, the last three columns of Table 3 contain the rest of the assessment of the applicability of the compared studies in real world applications. In particular, the seventh column indicates whether or not the proposed NILM schemes have evaluated the disaggregation algorithms on the combined operation of appliances, which is more than expected in a real scenario. It is not uncommon to see research works in the field of NILM that evaluate their developed models on single appliance operation. In other words, they evaluate the identification performance of the algorithms while a single appliance is operating at a time. The eighth column of Table 3 indicates whether or not the compared studies explored disaggregation of appliances into multiple states for the extraction of highlight metrics. This type of disaggregation is a criterion for evaluating applicability in the real case, since in real life a non-negligible number of appliances operate in different modes. Thus, if a disaggregation model could recognize the different modes of operation, then it could be useful for application to a complicated disaggregation task that corresponds to reality and provides a more detailed understanding of the electrical energy consumption [76]. The last column of Table 3 lists the information about the appliances with the lowest active power consumption that participated in the disaggregation task. The identification of appliances with low power consumption is a proof of the robustness of the proposed NILM models, which can even classify appliances whose consumption is comparable to noise [77].

4. Other practical challenges

4.1. Noise effects

The presence of noise is inevitable in measurements related to NILM and is associated with performance degradation in terms of load disaggregation accuracy [84]. Therefore, various approaches have been used to try to reduce the noise effects in different parts of the NILM pipeline.

For example, in Ref. [72], the authors converted the classical cumulative sum control chart algorithm into a DSWC control chart algorithm for transient event detection. This was achieved by applying variable point identification in a composite dual sliding window method. In DSWC, small variables in composite sliding windows are more sensitive and the effects of data noise are reduced. As a result, the true load event can be extracted from the raw data and isolated from the power fluctuations.

Aiming to reduce the effects of noise in load disaggregation, the authors in Ref. [79] developed a novel method for event detection combining probabilistic and expert heuristic models. This method is overall more powerful than other implementations, especially when the events are characterized as small current events (when the difference in

Table 3
Evaluation of high sampling NILM frameworks in terms of applicability on real conditions.

Ref.	Utilized Datasets	Highlight Data Processing for NILM Development		Type of Time/ Event Driven Framework	Utilized Features	Kind of Appliances' Operation	Multi-State Disaggregation of Appliances	Involved Appliance with the Minimum Nominal Active Power Consumption
		Dataset	Brief Description					
[45]	Private	Private	Load Signature	Event-Driven Appliance Classification	V-I trajectory Amplitudes of current harmonics (1st, 3rd, 5th and 7th) Active power overshoot multiple	SOA	Display screen and Microwave oven	LED lights (5 W)
[60]	PLAID COOLL WHITED	PLAID	Leave One Group Out	Time-Driven Appliance Classification	Unthreshold recurrence plots for current and voltage cycles	SOA	X	–
[49]	Private	Private	Time-Based Split into Training (90 %)/Test (10 %) Sets	Event-Driven Appliance Classification	Active power Reactive power Apparent power Power factor RMS current value of odd harmonics from 1st to 21st order	SOA	X	–
[58]	REDD	REDD	Load Signature	Event-Driven Appliance Classification	Current waveform difference before and after an event detection	COA	X	–
[77]	BLOND	BLOND	Unspecified Split into Training/Validation/Test Sets	Time-Driven Appliance Classification	Not clearly specified voltage and current features	COA	X	Computer monitor and fan (5 W)
[78]	Private	Private	3 Sets of Private Data Used in an Unsupervised Implementation	Event-Driven Event Matching and Appliance Classification	Active power Reactive power RMS value of the 3rd order current harmonic	SOA	X	–
[54]	COOLL PLAID UK-DALE	PLAID	Samples of the appliances of: •42 randomly selected but different from the validation and test houses used for Training Set development •6 randomly selected but different from the training and test houses used for Validation Set development •12 randomly selected but different from the training and validation houses used for Test Set development	Time-Driven Appliance Classification	Features extracted by the proposed CNN architecture	SOA	X	–
[56]	Private	Private	The Private Dataset that was developed based on PLAID, COOLL and WHITED datasets randomly split into training (80 %) and test (20 %) parts for each cluster to form the Training and Test Sets. This split was repeated 10 times for average evaluation.	Event-Driven Appliance Classification	RMS features extracted by the proposed methodology	SOA	X	–
[73]	COOLL LIT	LIT	Random Split into training and test parts for each cluster to form the Training (80 %) and Test (20 %) Sets. This split was repeated 10 times for average evaluation.	Event-Driven Appliance Classification	Exponential damping Frequency Phase Amplitude	COA	Microwave Drill Oil heater Hair dryer	Microwave-standby (4.5 W)
[47]	Private	Private	Time-Based Split into Training (70 %)/Test (30 %) Sets	Time-Driven Appliance Classification	Time and frequency features extracted by the proposed methodology	SOA	Coil gun and Permanent magnet synchronous model	–
[64]	PLAID Private	PLAID	Unspecified Split into Training (80 %)/Test (20 %) Sets. In the training set there was followed a 10-fold cross validation approach.	Time-Driven Appliance Classification	Reconstructed V-I images	SOA	X	–
[79]	BLUED PLAID Private	BLUED	Unspecified Split into Training/Test Sets	Event-Driven (Event Detection only)	RMS current Fundamental frequency purity up to the 5th order	COA	X	–
[21]	LIT	LIT	Unspecified Split into Training/Test Sets	Time-Driven Appliance Event Type Classification	Features extracted by the proposed CNN architecture	COA	X	Microwave-standby (4.5 W)

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Table 3 (*continued*)

Ref.	Utilized Datasets	Highlight Data Processing for NILM Development		Type of Time/ Event Driven Framework	Utilized Features	Kind of Appliances' Operation	Multi-State Disaggregation of Appliances	Involved Appliance with the Minimum Nominal Active Power Consumption
		Dataset	Brief Description					
[71]	Private	Private	Load Signature	Time-Driven Appliance Event Type Classification	Current waveform difference between specific cycles	COA	X	4x LED (5 W)
[72]	BLUED Private	BLUED	Unspecified Split into Training/Test Sets	Event-Driven Event Matching and Appliance Classification	Active power Reactive power 1st, 3rd and 5th order current harmonics	COA	X	Lights (60 W)
[63]	BLUED PLAID Private	Private	Unspecified Split into Training/Test Sets	Event-Driven Appliance Classification	Instantaneous current amplitude Instantaneous current phase Instantaneous current frequency	COA	X	–
[17]	BLUED Private	BLUED	Random Split into Training (80 %)/Test (20 %) Sets	Time-Driven Appliance Event Type Classification	Instantaneous current spectrograms	COA	Hairdryer (added on [83])	–
[22]	COOLL WHITED	COOLL WHITED	The COOLL dataset was split into Training (60 %)/Validation (20 %)/Test (20 %) Sets to develop the NILM model that was fine-tuned on the Transfer (50 %) part and tested on the Test (50 %) part of the WHITED dataset. The Transfer (50 %)/Test (50 %) split of the WHITED dataset was done 4 times to develop 4 different scenarios. In each scenario different appliance brands for the used appliance types of the background load were employed. The 3 target appliances were also different in brand between the COOLL and WHITED datasets.	Time-Driven Appliance Event Type Classification	Current images	COA	X	–
[20]	PLAID Private	Private	Unspecified Split into Training (50 %)/Test (50 %) Sets	Time-Driven Appliance Classification	Ratio of 3rd harmonic current component to fundamental current Ratio of 5th harmonic current component to fundamental current Ratio of 7th harmonic current component to fundamental current Ratio of 5th harmonic current component to 7th harmonic current component Fundamental current phase angle	COA	Dimming bulb and Ceiling fan	–
[74]	Private	Private	Random Split into Training (70 %)/Test (30 %) Sets and extra 120 examples for Validation Set formation	Time-Driven Appliance Classification	Instantaneous current	COA	X	Phone (8 W)
[80]	UK-DALE REDD	Not clearly specified		Event-Driven Appliance Classification	Current gray scale images	COA	X	–
[51]	Private	Private	Split into Training (55 % or 7 independent subsets)/Test (45 % or 6 independent subsets) Sets containing data that differ from each other in terms of appliances' operation patterns. During the training phase a 7-fold cross validation approach was followed. The testing was repeated 10 times for average evaluation.	Time-Driven Appliance Classification	Magnitudes of the Fourier series coefficients at the fundamental, 3rd, 5th, 7th, 9th, 11th, and 13th current harmonics Normalized magnitudes of the Fourier series coefficients at the 3rd and 5th current harmonics Coefficients #12–23 for a total of 12 out of the 25 total discrete wavelet	COA	X	–

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Table 3 (*continued*)

Ref.	Utilized Datasets	Highlight Data Processing for NILM Development		Type of Time/ Event Driven Framework	Utilized Features	Kind of Appliances' Operation	Multi-State Disaggregation of Appliances	Involved Appliance with the Minimum Nominal Active Power Consumption
		Dataset	Brief Description					
					transform coefficients derived from an 8-level 1-D discrete wavelet transform 3 wave shape features analytically explained in the study			
[65]	PLAID Private	Private	Unspecified Split into Training/Test Sets	Event-Driven Appliance Classification	Magnitude and Phase of 1st, 3rd, 5th and 7th odd order current harmonics	COA	X	Monitor (private dataset), compact fluorescent lamp and fridge (PLAID dataset) (23 W)
[81]	Private	Private	3 Sets of Private Data Used in an Unsupervised Implementation	Event-Driven Event Matching and Appliance Classification	Active power Reactive power	COA	Washing machine	–
[18]	Private	Private	2 Sets of Private Measurements extracted form 2 Houses and used for Training (7525 s of measurements from House 1)/ Test (5375 s of measurements from House 2) Sets. The appliances between the 2 houses differed in brands.	Time-Driven Appliance Classification	Amplitude and phase of odd harmonic currents up to the 5th order (1st, 3rd and 5th)	COA	X	–
[61]	Private	Private	Load Signature	Time-Driven Appliance Classification	Amplitude and phase of odd harmonic currents up to the 5th order (1st, 3rd and 5th)	COA	X	–
[82]	Private	Private	Random Split into Training (70 %)/Test (30 %) Sets	Time-Driven Appliance Classification	Amplitude of odd harmonic currents up to the 5th order (1st, 3rd and 5th)	COA	Hair dryer	–
[48]	Private	Private	Time-Based Split into Training (70 %)/Test (30 %) Sets	Time-Driven Appliance Classification	RMS current Power factor Reactive power Active power % Harmonic distortion (HD) of 3rd, 5th and 7th harmonic currents Previous minute % HD of 3rd and 5th harmonic currents	COA	X	–
[19]	UK-DALE	UK-DALE	Time-Based Split into Training (6 days of measurements)/ Test (1 day of measurements) Sets	Time-Driven Appliance Classification	Magnitude and phase matrices of power matrix	COA	X	–

high-frequency current amplitude of the current transition from one steady state to another is less than 1 A), with a lower signal-to-noise ratio and a larger fundamental current.

4.2. Execution time

A crucial parameter for NILM implementation in real-time applications concerns the execution time of the disaggregation scheme [85].

In this review work, we highlight some attempts aimed at reducing the time required for the load disaggregation process. In Ref. [49], a multi-threaded architecture for real-time load identification was proposed that significantly reduces the time required to implement parallel NILM tasks. A comparison showed that the single-threaded cumulative summation-multilayer perceptron (CUSUM-MLP) NILM framework required 45 ms to identify a single example, while the multi-threaded CUSUM-MLP NILM framework required 7 ms to identify the same example.

In another example from the literature, the authors in Ref. [80] suggest that translating the instantaneous current waveform into grayscale images can reduce the time required to identify loads. More specifically, in their implementation, the process of capturing the event instantaneous current is applied with the use of the sliding window algorithm. Each sliding window (containing periods of instantaneous current waveform) is converted into a 320x320 grayscale image. All 320x320 extracted grayscale images are compared with the grayscale images (under the same resolution) extracted during the training phase and stored in the database. The comparison is achieved by the proposed CNN-based architecture, which uses the extracted 320x320 grayscale images and leads to the identification of the load. The extended results by determining the start-stop time and state change of the load facilitate the determination of the power consumption of the load.

4.3. Equipment

As NILM evolves in practical applications, the existence of devices that can perform measurements at a high sampling rate and function properly the NILM tasks at an affordable cost is a goal that some researchers have already investigated. In Ref. [86], the authors propose a device for measuring instantaneous current and voltage and provide a design analysis of the hardware architecture for the current and voltage conditioning stages along with the software implementation in an Arduino MKR Zero microcontroller that mainly uses an interrupt routine for real-time data acquisition and storage on a micro-SD card. The proposed system implementation enables a high sampling rate (6.25 kHz), resulting in a duration of about 37 ms for storing 204 current and voltage values on the used SD card. Moreover, the whole data acquisition process could be applied for 25.4 days. The proposed system is low-cost and low-power, requires its own power supply, and is easy to install. Some other specifications of the proposed measurement system are the maximum active power monitoring of about 6 kW with granularity of 11.3 W. Therefore, this device could be used for monitoring the electrical power of a main feeding panel for the needs of practical application of NILM.

In this sense, in Refs. [87,88], the authors have proposed a system on chip (SoC) architecture based on a field programmable gate array device targeted to real-time applications of NILM. More specifically, the architecture is associated with an ADE9153A circuit that extracts the instantaneous current and voltage measurements with a sampling frequency of 4 kHz. In addition, a low-level peripheral integrated into the SoC architecture is responsible for real-time filtering and event detection of the extracted signals. The event detection algorithm examines the amplitude value of the difference between 2 consecutive samples of the mean square current. An event is considered as such if the amplitude value is greater than a threshold and at the same time the maximum of the amplitude values of a given window of amplitude value samples. Finally, an ARM processor controls the entire system and could be used by a NILM load identification model. This type of architecture facilitates real-time, high-sampling-rate event-driven load disaggregation at the input point of an electrical system. Also, enables real-time, high--sampling-rate event data transmission to the cloud side of an end-cloud NILM framework for load disaggregation without bandwidth congestion. In this way, the overall implementation cost remains low despite the high sampling rate of the device.

5. Conclusion and study outputs

Research on the development of NILM has been at the forefront for more than three decades. Its contribution to the energy sector has been highlighted in various research papers in different ways and improving its performance has been a goal of researchers. Technological development in measurement systems has enabled higher sampling rates, which allowed the investigation of the contribution of higher sampling rate to improve the performance of the NILM application. The results suggest that a deeper analysis of the electrical signal in terms of acquiring a higher number of samples for a given time window could significantly improve the performance of load disaggregation and distinguish the fingerprints of the different types of electrical loads represented on the aggregated electrical signal. However, NILM is a framework developed with the perspective of applying it in practice to fully exploit its benefits. To this end, several parameters should be considered in the different steps of NILM development. This review study shows that:

- The type of a public high sampling NILM dataset is of paramount importance for the NILM research community to benchmark its work against practical conditions of combined operation of appliances. Thus, such a dataset should contain instances of combined operation of appliances along with high reliability of true labels' availability.
- Processing the available data in terms of training, validation, and testing of the developed NILM models should be done considering different operating patterns and different brands of appliances participating in the training, validation, and test sets to ensure improved generalization capability of the developed models. In this sense, better disaggregation performance could be achieved in practice if completely unseen data are fed into the NILM model used.
- The development of high-frequency features should aim to represent inherent characteristics that could distinguish appliances with similar electrical behavior in terms of their operation, which is a common challenge in practice.
- The character of the developed high sampling rate NILM frameworks should be event-driven to reduce computational complexity and make the NILM systems applicable in a real-world scenario.
- The disaggregation capabilities should include the combined and multi-state operation of appliances, which correspond to reality. In addition, noise, computation time, and other practical challenges should also be considered.

In this way, the maturity of the NILM system could be significantly increased so that its application in the real world would be reliable and feasible.

Declaration of competing interest

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

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Data availability

Data will be made available on request.

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