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REVIEW

A Review of NILM Applications with Machine Learning Approaches

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ABSTRACT

In recent years, Non-Intrusive Load Monitoring (NILM) has become an emerging approach that provides affordable energy management solutions using aggregated load obtained from a single smart meter in the power grid. Furthermore, by integrating Machine Learning (ML), NILM can efficiently use electrical energy and offer less of a burden for the energy monitoring process. However, conducted research works have limitations for real-time implementation due to the practical issues. This paper aims to identify the contribution of ML approaches to developing a reliable Energy Management (EM) solution with NILM. Firstly, phases of the NILM are discussed, along with the research works that have been conducted in the domain. Secondly, the contribution of machine learning approaches in three aspects is discussed: Supervised learning, unsupervised learning, and hybrid modeling. It highlights the limitations in the applicability of ML approaches in the field. Then, the challenges in the real-time implementation are concerned with six use cases: Difficulty in recognizing multiple loads at a given time, cost of running the NILM system, lack of universal framework for appliance detection, anomaly detection and new appliance identification, and complexity of the electricity loads and real-time demand side management. Furthermore, options for selecting an approach for an efficient NILM framework are suggested. Finally, suggestions are provided for future research directions.

KEYWORDS

Non-intrusive load monitoring; transfer learning; machine learning; feature extraction

1 Introduction

Universal access to electricity is a crucial task which ensures sustainable economic growth in a country. According to [1], the number of people with access to electricity is very low in sub-Saharan Africa, which was 589.46 million in 2019. Furthermore, 77% of the population uses solid fuel for household work, leading to non-communicable diseases due to air pollution. The use of non-renewable sources increases global warming and climate change. On the other hand, the availability of renewable energy sources directly impacts the country's income. The study [2] shows that there is a relationship between energy production and Gross Domestic Product (GDP) and having steady electricity production directly affects economic growth. Because of the global population and economic and technological development, electricity usage has increased. To solve the energy crisis, the paper [3] suggested using control-optimized methods, passive design in transportation and buildings and green alternatives to save energy.

Microgrids (MGs) were developed by combining conventional and non-conventional energy sources with the integration of the Internet of Things (IoT) to address the electricity demand effectively. Conventional energy sources include non-renewable energy sources such as fossil fuels, while renewable energy options are composed of non-conventional energy sources, including wind, biogas, and hydropower [4]. Further, microgrids have been introduced to achieve the higher impact of renewable energy sources in the power grid. The energy storage system saves the excess energy generated in the microgrid to improve load consumption. However, the paper [5] highlights Microgrid (MG) configuration is limited in rural areas due to the unavailability of internet resources. On the other hand, load transition identification in the MG is difficult due to the non-linear behavior of loads [6]. Several models [7] and algorithms are proposed in the literature to identify the load variations [8]. Furthermore, studies [9] found that the accuracy of the forecasting results depends on the demand. However, the microgrid's demand side response can be improved by implementing policies, power flow constraints and energy monitoring.

Understanding energy consumption benefits consumers and suppliers in the power grid. From the consumers' point of view, they can identify the appliances that contribute to the electricity bill and take the initiative to reduce that. On the other hand, from the suppliers' point of view, they can identify the electricity demand of each consumer and expand the service accordingly. Related statistics published in the paper [10] shows that direct feedback from consumers can save energy wastage by more than 15%. However, energy monitoring is flexible by installing smart meters attached to the appliance. Overall, load monitoring can be classified into three approaches: Intrusive (ILM), Semi-Intrusive (Semi-ILM) and Non-Intrusive (NILM) based on the number of smart meters installed in the power grid. The complexity of the energy disaggregation in the NILM approaches is difficult because a single smart meter is used to collect the load. However, the cost of installation and configuration is lower in the NILM-based energy management solutions.

ML models have been presented in the literature to address the complexity of the NILM load disaggregation [11]. Such as Hidden Markov Models (HMMs) [12,13], Neural Networks [14,15] and Convolutional Neural Networks (CNNs) [16]. Approaches applied in the load disaggregation, such as supervised, semi-supervised and unsupervised, are labeled based on the learning process of the data. Supervised learning requires a large amount of data to learn the appliance. On the contrary, unsupervised learning does not require labeling before the training and is idle for identifying new appliances. However, studies [17] found that unsupervised learning is effective with small application areas since anomaly detection does not affect appliance recognition.

The smart grid compromises with different appliances that consume different loads at different frequencies. Therefore, the availability of public datasets such as REDD [18], PLAID [19], WHITED [20], UK-DALE [21], and COOLL [22] help to train the supervised model to learn the ground truth about appliances in the NILM research area. A summary of the available datasets in the NILM research area is available in Table 1.

Table 1: Summary of the publicly available datasets

Data set	Period	Features					Ref.
		Number of appliances	Sampling rates	Load type	Location	Challenges	
REDD	3 weeks	Six different homes with appliances	1 Hz	All	MIT Sustainable lab	Diverse appliance behavior. Varying sampling rates of appliances.	[18]
PLAID	One year	55 homes	30 kHz	All	US	No ground-truth labels for individual appliances.	[19]
WHITED	–	110 appliances	44 kHz	All	Germany	Only contain start-up transients.	[20]
UK-DALE	One year	Five different homes	6 s	All	UK	Variability in appliance usage patterns.	[21]
COOLL	One month	42 appliances	100 kHz	All	France	Variability in appliance signals is difficult to record.	[22]
LIT	–	Three subsets, including different numbers of appliances	15.3 kHz	I, II, III	Brazil		[23]
AMPds	Two years	One home with 21 sub meters	1 Hz	All	British Columbia	Real-time applicability	[24]
IAWE	73 days	One building	1 Hz	I, II, III	India	Real-time applicability	[25]
iAWE	16 bimonthly periods	9923 homes	1 Hz	I, II, III	Ireland	Multiple meters per house are available. Houses with less than six observations are dropped from the data collection.	[26]
ECO	Eight months	Six homes	1 Hz	All	Switzerland		[27]
BLUED	2–4 weeks	One home with 30 appliances	1 Hz	I, II, III	US	It is unsuitable to evaluate classification and energy estimation (EE) algorithms.	[28]
HFED	–	24 appliances	10 kHz	All	India	Only contain start-up transients [24].	[29]
BLOND	213 days	53 appliances	50 kHz	All	Germany	Only high-frequency data is available.	[30]
RBSA	–	101 houses	15 min	All	USA	Only low-frequency data is available.	[31]
IDEAL	22 months	255 houses	–	All	UK	Only low-frequency data is available.	[32]
HUE	Three years	22 houses	–	All	Canada	Only low-frequency data is available.	[33]

(Continued)

Table 1 (continued)

Data set	Period	Features					Ref.
		Number of appliances	Sampling rates	Load type	Location	Challenges	
ENERTALK	29–122 days	22 houses	15 Hz	All	Korea	Only low-frequency data is available.	[34]
SynD	180 days	21 appliances	5 Hz	All	Austria	Only low-frequency data is available.	[35]

In addition to the mentioned challenges in Table 1, preprocessing the dataset before applying the model is required because of the contradiction of data; missing and noisy data may affect the load identification in the NILM approach [36].

This paper provides an inclusive review of the NILM applications with ML approaches, and challenges are discussed for future research directions. The main contributions of this paper are as follows:

1. To identify different Supervised and Unsupervised Learning approaches used in Electricity Management with NILM

2. To highlight the current research challenges to find the feasibility of developing a reliable ML Approach in the NILM research field.

The remaining sections of this article are organized as follows: In Section 2, the NILM framework is explained with load identification using different ML approaches, and it discusses how demand-side management helps improve awareness. In Section 3, the different research works conducted with various ML approaches are discussed, and it further explains implemented hybrid frameworks. Section 4 outlines open challenges and issues in the conducted research and explains why the hybrid framework is feasible for real-time implementation. Finally, Section 5 concludes the article.

2 NILM Framework

Load Monitoring enables energy consumption monitoring by a smart meter attached to the electricity appliance. The concept of NILM was invented by Hart [37] in 1984 to extract the load consumption of devices using aggregated power load collected at the end of the power source. The initial approach is suitable to capture the ON/OFF state of the electrical appliances in the smart grid. After that, NILM implementation has become an emerging area for load monitoring in the home and commercial setting.

NILM contributes to identifying the energy consumption of appliances, leading consumers to reduce usage and lower electricity bills. Further, it helps to identify the appliance's health and then recognize the need for maintenance or replacement. As a result of demand-side management features provided in the NILM architecture, the operational times of each appliance can be recognized and controlled [38]. Overall, NILM works as a powerful and cost-effective tool to increase energy efficiency, minimize energy crises, and environmental impact.

The Typical NILM framework comprises five stages: Data acquisition and preprocessing, feature extraction, load identification through a learning process, and demand-side management. Since the NILM architecture depends on the aggregated data, computational work is high throughout the disaggregation process. This section discusses the framework of NILM with the methods and techniques used in each stage.

2.1 Data Acquisition

In general, different types of electrical appliances are available in the power grid. Based on the load behavior, devices can be classified into four categories: Type I (with ON/OFF states), Type II (with multi-states), Type III (continuously varies) and Type IV (constant power). And different sampling rates are used to collect aggregated data: Low sampling (less than 1 Hz) and high sampling rate (10 kHz). Conducted research works with low sampling rates are limited due to the feature loss [39,40]. Furthermore, the study [41] highlights that the results of the load disaggregation can be improved using the data collected on low sampling frequency. On the other hand, high-frequency applications are limited due to the high computational cost [42]. However, it supports feature analysis with ML to improve load identification [43]. However, the load identification performance depends on the input data quality in the disaggregation process.

In NILM, data preprocessing is crucial since the entire framework depends on the aggregated data collected at the end. It involves data cleaning, feature engineering, temporal alignment of data, resampling for a consistent time interval, and normalization and scaling for a similar interval. The paper [44] presented a hybrid statistical filtering method for outlier detection on the aggregated data collected with a high-frequency rate. However, Low-frequency outlier detection remains questionable for practical settings. The article [45] suggested the Transform NILM method to handle the data balancing. It replaces aggregated data with fake samples and creates masked aggregate data. Then, the Transform generator takes the masked aggregated signal as input and trains the data to predict the original values at the masked aggregate data positions.

2.2 Feature Extraction

In NILM, the feature extraction stage refers to deriving relevant information from the preprocessed aggregated load data. Features are characteristics of the aggregated load data, which can be identified from the time-series data of the electric signal. In overall, approaches used in the feature extraction can be divided into two use cases based on the changes in the electrical signal: Steady state (appliances with stable operation) and transient state (appliances with sudden changes). Steady-state approaches use changes in the load transitions, and the system only works with the finite forms of the load [46–48]. On the contrary, transient state approaches monitor the load transitions in real-time [49]. Therefore, transient state approaches are idle for real-time feature extraction.

2.3 Load Identification

The load identification stage uses aggregated load features to identify individual appliances by applying ML algorithms or signal processing techniques. ML models in this stage can be categorized into supervised and unsupervised learning. The model can be selected based on the requirements of the NILM solution, such as cost, accuracy and time. Studies show that supervised approaches such as Deep Neural Networks (DNN) [50–54], k-Nearest Neighbor (k-NN) [55–58], Support Vector Machine (SVM) [59–61], Decision Tree are commonly used for classification of aggregated load data. However, a supervised NILM approach for all appliances remains questionable due to the variability of the appliances in PowerGrid, and it requires prior training to detect appliances. For practical settings, unsupervised learning approaches have been recommended by various studies [62–66]. Neural Networks have significantly impacted the development of unsupervised NILM approaches [67]. CNNs

[68], Long Short-Term Memory Networks (LSTM) [69–71], Recurrent Neural Networks (RNN) [72], Encoders [73], Graph Signal Processing [74–75] are commonly used to develop a unsupervised NILM approaches. However, conducted research works are limited to the lab, and a solution for a large-scale environment is unexplored.

Several research works have been done as hybrid works to improve generalizability and efficiency.

2.4 Demand Side Management to Improve Awareness

Appliance level energy consumption monitoring motivates consumers to reduce electricity usage [76]. The article [77] reviewed the social impact of the NILM on financial savings, quality of life, security, time management and energy saving. The study [78] developed a real-time NILM solution that provides a web-based appliance-level consumption monitoring system. Further, the study [79] developed a mobile application to detect anomalies.

This section discussed the stages of the NILM framework with the models and technologies used in the domain. Furthermore, the work that has been conducted is concerned with drawbacks. The following section will highlight the ML approaches in the context of energy management.

3 Machine Learning in the Energy Management Context

ML plays a significant role in the NILM domain to optimize energy consumption, reduce energy bills, and improve the efficiency of the disaggregation process. This section will explore the different machine-learning approaches used in the NILM domain, mainly for appliance detection in residential and commercial buildings. Furthermore, it will describe the hybrid modeling approaches used in NILM to improve performance.

3.1 Supervised Learning Approaches in NILM

The model should be trained with aggregate and disaggregate loads in supervised learning. Different supervised approaches such as Naïve Bayes, Linear Regression, Logistic Regression, k-NN, SVM, Random Forest and DNN are used to identify electrical appliances in the NILM context. However, the supervised learning results lead to incomplete decisions because of the unlabeled data in the aggregated load. To address the incomplete supervision issue, the paper [80] presented a Multiple Instance Regression (MIR) approach, which estimates the appliance state of the unlabeled data. The UK-DALE dataset evaluated the model's performance with different training conditions. Furthermore, the results show that the suggested model significantly improves compared to the Convolutional Recurrent Neural Network and Sequence-to-point (Seq2Point) using annotated data with unlabeled data. However, research is conducted with Type I and Type II appliances, and the model should be trained with transfer learning techniques to make it work in real-time conditions. Furthermore, it is required to collect data with high frequencies to obtain accurate results in supervised learning. Therefore, solutions may not be applicable in real time because having a one-to-one training profile for each appliance is recommended. The study [81] presented a supervised learning approach based on SVM with a linear kernel for load identification. However, the research is limited to Type II appliance recognition. The study [82] compared different supervised NILM algorithms for load classification. Results show that Decision Tree (DT) performed better than k-NN, NN, Ensemble and SVM with high-frequency data for steady-state appliance recognition. The paper [83] compared the status prediction of home residential appliances with six supervised learning approaches: DT, Linear Discriminant, k-NN, Quadratic Discriminant, SVM, and Ensemble. Results show that k-NN and SVM predict the status of Type II appliances than other algorithms.

Supervised learning approaches are common in the NILM domain for load classification and appliance detection. The selection of a supervised learning approach depends on the objective of the research work. Furthermore, a rich aggregated load profile with a high computational environment is required in the training phase of supervised learning. However, the real-time implementation of supervised NILM is limited due to its cost.

3.2 Unsupervised Learning Approaches in NILM

Unsupervised learning does not require labelled data for the model's training. In NILM, K-means clustering, Principal Component Analysis (PCA) and Density-Based Spatial Clustering of Applications with Noise (DBSCAN) are typical to discover the hidden patterns, structures and clusters within the data. An unsupervised NILM approach using odd harmonic current amplitudes is presented in the paper [84], and it uses k-means clustering to group appliances with similar electrical patterns. The proposed approach explores the appliance based on the 3rd and 5th odd harmonics current. Therefore, the research is limited to Type I and II appliances. To address the generalizability and data shortage problem in the NILM domain, the study [85] introduced a self-supervised learning approach based on Seq2Point, Bidirectional Recurrent Gated Unit (Bi-GRU) and LSTM. However, data preprocessing should be addressed during the implementation.

Overall, unsupervised learning minimizes the training phase's computational time and cost. However, unexpected behavior of the appliance limits the general adoption of the model in the study [17].

3.3 Hybrid Modeling in NILM

In NILM, hybrid modeling combines multiple approaches, such as classification and regression models, to perform better in the training stage. Article [86] examined the feasibility of a multi-output model for appliance identification. The model is tested with high-consumption appliances, and generalizability is unexplored. The study [87] presented a scalable hybrid classification-regression method, which identifies the appliance load based on the state transition of the data.

Moreover, model selection can be different based on the objectives of the NILM research and the applicable domain. Unsupervised hybrid models are suitable for large domains such as commercial buildings. This section highlighted the standard ML approaches used in the NILM and their limitations. The following section will discover the open challenges of real-time implementation.

4 Open Challenges in Real-Time Implementation

This section will explain the open challenges in the real-time implementation of the NILM solution.

4.1 Difficulty in Recognizing Multiple Loads at a Given Time

The traditional smart grid consists of different types of appliances which perform different operating patterns. The study [88] presented that there is a shortcoming for a universal NILM framework. To improve the efficiency of multiple loads recognition, the study [16] proposed a CNN-based architecture based on signal analysis of real-time aggregated data. However, a large sample is required to train the model. Further, the presented framework cannot differentiate appliances with similar electrical loads. On the other hand, the suggested model is validated and tested with the LIT database and UK-DALE, PLAID and REDD datasets cannot be applicable because aggregated data is collected as the summation of watts. To overcome that issue, the paper [89] presented an optimization-based approach with mixed-integer formulation to detect the state transition of the appliance automatically. However, the research is limited to a low sampling load, but the work has not been investigated in a noisy environment. In addition, the paper [90] introduced a correlation-based feature extraction from the current waveforms to identify multiple electrical appliances in the grid. However, the research is conducted with fewer devices in the lab. In conclusion, Difficulties in multiple load recognition should be addressed to find a scalable solution in the NILM domain.

4.2 Cost of Running the NILM System

Studies show that consumers' awareness of the usage can reduce energy consumption. On the other hand, the cost of smart meters can be minimized with the NILM approach. However, a robust computational environment is required to implement NILM systems, which consumes energy to run the system. To address that, the paper [91] presented a cloud based NILM algorithm that provides real-time load disaggregation. The experiment is validated and tested with two servers, a dedicated server, and a virtual server, to evaluate the efficiency of cost modeling in two use cases. The suggested model combines HMM-based algorithms and sliding-window functions, providing accurate results for the large-scale aggregated data. Therefore, the processing time and noises in the network should be addressed in the implementation. However, a reliable network is expected to transmit vast amounts of data to the cloud, which would be expensive [92]. Therefore, a research gap exists for a cost-effective, low-sampling NILM solution.

4.3 Lack of a Universal Framework for Appliance Detection

Different types of appliances can be used in residential and commercial buildings and suggested NILM frameworks in the literature use different devices to validate results. They may not be applicable in another domain. To address that, relative research works have used transfer learning methods to learn the appliance with the existing dataset and manipulate the knowledge to another domain. The research [93] presented two transfer learning approaches based on seq2point learning. Appliance transfer learning: CNN layers are trained on the washing machine (Type III appliance) for other devices. However, the results have not been presented for Type IV appliances. Cross-Domain Transfer Learning (CTL): CNN layers re-trained on REFIT [94] and tested with UK-DALE and REDD. If the domains are not similar, fine-tuning should be done when applying the CTL. The study [95] proposed a transfer learning approach based on the Long Short-Term Probabilistic Neural Network (LSTM-PNN) algorithm but has not been tested with multistate appliances. However, research works [96] conducted with transfer learning predicted accurate results when the source and target domain have similar or less different types of devices. Furthermore, the paper [97] stated that the lack of a dataset with all kinds of appliances is the major issue when evaluating the performance of the transfer learning approaches in the NILM area.

On the contrary, the study [98] suggested a pre-trained model that can train with less data to identify the appliance. The proposed scheme quickly learns appliances and avoids negative learning. Further, the model was investigated using the same types of appliances.

A NILM framework that can identify completely unknown appliances using aggregated data remains challenging.

4.4 Anomaly Detection and New Appliance Identification

Overall, more research has been done assuming the collected aggregated data has fixed appliances. But in real-time, appliances may be replaced, and the appliances may work with faults. This abnormal behavior of the aggregated data may affect the efficiency of the appliance recognition. Submetering is widely used to overcome that. However, installing additional meters to the power grid costs extra money. As a solution, the study [99] presented work to detect anomalies based on the appliances' power distribution and participation index. Further, the consumer can obtain feedback about the devices in the grid using the mobile application. However, the detailed description of the anomalies is not addressed.

In practice, NILM approaches can identify unknown load features when training the model. These novel features can be faulty in an existing or new appliance. To address that, the paper [100] proposed adaptive NILM based on the Siamese network. It uses similarity information between training and testing V-I trajectories. It recognizes new appliances accurately with a smaller number of training samples. However, the Siamese network should be run simultaneously to match the features, and computational efficiency is low.

There should be appliance signatures to train the model for the abnormal operation. Therefore, such a dataset should be available for anomaly detection and new appliance recognition.

4.5 Complexity of the Electricity Loads

NILM research has generally been conducted using public datasets, including different residential building appliances. Then, it is extended to commercial buildings. However, the unavailability of a shared dataset in commercial buildings leads to addressing a NILM approach in commercial buildings. The study [101] highlighted the practical limitations of a NILM approach in Commercial buildings: The existence of small and similar electrical load appliances, difficulty in detecting small changes in load consumption, and availability of Type IV appliance readings. As a solution for those limitations, they suggested applying NILM through audits. However, adding a new appliance to the PowerGrid may be difficult since each appliance requires submetering to learn the ground truth about the device.

4.6 Real-Time Demand Side Energy Management

The integration of energy meters in modern electrical appliance has revolutionized how consumers interact with and manage their energy usage. These smart appliances allow consumers to track their energy usage patterns, identify higher load consumption devices, and make informed decisions to optimize energy efficiency. The convenience of accessing energy consumption data through smartphone apps has contributed to increased consumer awareness and engagement in energy conservation efforts. Therefore, the study [102] introduced cloud-based demand side EM platform that uses disaggregated loads in cloud and access via smart phone or web. Further, it supports to control the energy consumption via platform by changing the operating status of appliances. Furthermore, the paper [103] introduced WeChat applet to control the devices remotely. The study [104] accessed database through the Bluetooth to monitor the energy consumption of appliances using smart app. Further, the article [105] introduced a mobile app to view cost of the energy usage. In addition to that, the paper [106] added a feature to visualize the load behavior by changing the appliance status via app. But adding new appliances and anomaly detection are not supported in suggested platforms. On the other hand, load forecasting is developed in the paper [107] with appliance controlling options. but anomaly detection is remaining a challenge.

Furthermore, Challenges in the development lead to identifying criteria for selecting an approach for an efficient NILM framework. Table 2 highlights the available options for the selection.

Table 2: Selection measurements for the NILM implementation

Selection criteria	Options
Scope	Residential or commercial buildings.
Purpose of the energy disaggregation	Predict energy usage based on historical data or real-time data Understand the daily usage of energy Develop an intelligent health energy platform Minimize the cost of the implementation Increase the efficiency of the energy disaggregation
Fault diagnosis and anomaly detection	Early detection of faults Detection of the anomalies through the preprocessing Identification of faulty appliances [107]
Use of ML model	Chose a model or combine several models based on the sampling rate and appliance types
Representation of load data characterization	Graphical or numerical representation [108]

This section highlights open challenges in the real-time implementation of the NILM framework. Potential future research directions in NILM will be discussed in the next section.

5 Potential Future Research Directions in NILM

The initial version of the NILM framework focused only on identifying the status of the appliance through disaggregation. Later, it was developed with a vast scope and various applications. This section will discuss the future directions for a NILM framework based on the literature.

1. Update the load profile: Commercial and residential buildings have a vast diversity of appliance and aggregate loads. Some appliances in the grid may not perform well because their life span may be near the end. Therefore, filtering the health status of the appliance during the data collection would be effective for a reliable load profile. Furthermore, the load dataset can have faulty and unknown data because of the addition of new appliances and faults of the existing appliances. Therefore, effective implementation to update the load profile would offer productive solutions in the NILM domain.
2. Minimize the complexity of the aggregated dataset: NILM models require high-frequency load profiles to implement disaggregation techniques. However, training the model requires a more robust computational environment and consumes cost. As a solution, a cloud-based NILM system can be developed. However, having a higher data transmission rate is compulsory to maintain the communication between the server and the grid. Furthermore, a supervised NILM system takes a few days or weeks to disaggregate the load to provide results. On

the contrary, unsupervised NILM systems are highly computationally expensive. However, a preprocessed aggregated dataset would be helpful to minimize the issues mentioned above.

3. Develop a load profile for commercial buildings: There is a considerable diversity of appliances used in the retail sector. Moreover, it uses Type IV appliances. The available public dataset includes appliances used in residential buildings. In addition, commercial sector consumers expect a NILM solution with a software-based monitoring platform. Therefore, a commercial load profile is required to develop such a solution.
4. Recognition of similar load features: Developed NILM solutions have selected appliances with different load signatures in the training phase. Further, the NILM is a promising research area in energy management; however, developed solutions lack recognition of similar appliances.
5. Develop a Transfer Learning approach for a real-time solution: There is a research shortcoming in developing a universal solution for energy disaggregation. In supervised learning, similar load signatures are expected in the training and testing dataset. On the contrary, unsupervised approaches address only a few appliance types in the literature. In addition, transfer learning has been developed to expand the disaggregation for a real-time solution. However, the one-to-one profile is required in the testing phase. Therefore, the one-to-one appliance profile remains questionable in the energy management sector.
6. Develop a software-based monitoring platform: Integration of real-time energy metering in smart appliances offers unique opportunities for advancing NILM research. The availability of fine-tuned disaggregated loads using ML allows users to monitor and control the energy usage. In addition to that, adding new appliances, updating the load profile and detecting anomalies using existing profile can be included when implementing real-time smart app.

This section provided suggestions for future research in the NILM area, and the next section will conclude the paper.

6 Conclusion

NILM is an effective energy management solution that motivates energy usage control by monitoring appliance behavior. Compared to Intrusive Load Monitoring, the installation and configuration are less expensive, with a single meter attached to the power grid. Different public datasets are available and presented as an overview in this paper to study disaggregation. However, integrating ML models makes the load identification stage less effortless since the diversity and complexity of the available public datasets are enormous. This paper used the current literature to introduce the framework of NILM with comprehensive literature about the ML approaches used in the NILM sector. Accordingly, NILM based models provides benefits in the energy disaggregation domain due to its non-intrusive nature with cost-effectiveness deployment. Further, NILM Based models are inherently scalable and can be deployed across a wide range of residential and commercial environments without significant infrastructure modification. Further, it exposed various reasons for applying ML for energy disaggregation: Automated appliance disaggregation, scalability and efficiency, adaptability to new appliances, learning complex patterns, and handling noisy and missing data in the load profile. However, model selection can depend on the purpose of the NILM research. Then, this paper highlighted the challenges in the energy management sector in developing a real-time ML approach. Therefore, achieving robust performance across different households and appliance types remains a significant challenge for NILM-based models. Variations in appliance behavior, energy usage patterns, and household demographics pose obstacles to generalization, requiring tailored approaches and extensive training data to ensure reliable performance. Further, NILM algorithms face challenges in accurately disaggregating energy consumption data, especially in environments with multiple appliances operating simultaneously. The complex interplay between appliance signatures, noise, and variability in energy usage patterns can hinder the accuracy of NILM-based models, leading to misclassification errors and false positives. Further, different appliances exhibit unique power consumption patterns, which can be further complicated by variations in usage patterns and the addition of new devices over time. Consequently, accurately disaggregating these loads and identifying individual appliances from aggregate power readings becomes a challenging task, requiring sophisticated ML algorithms and data preprocessing techniques. Additionally, this paper discussed the challenges in real-time demand-side management. Finally, it provided options for selecting a ML criterion for the NILM research.

In the residential and commercial sectors, the appliance diversity is high in real-time. In addition, the appliance's operating status may not be as expected. Furthermore, new devices can be added to the power grid anytime. Therefore, a research gap exists to develop an approach to update the load profile accordingly. On the other hand, ML approaches require high computational conditions to train models. In addition, the complexity of the load profile contributes to the computational requirement for running the model. A few suggestions have been provided as future research directions to address issues in the current literature. Monitoring the appliance's health status helps identify faulty and missing data in the load profile. Therefore, the load profile should be updated to maintain error-free aggregated data. Furthermore, Implementing NILM techniques is expensive since it requires high computational power. However, a preprocessed aggregated dataset would minimize the complexity issue in the implementation. In addition, NILM research in the commercial sector has been limited due to the great diversity of the appliance load profile and the unavailability of a commercial load profile. Therefore, future research work can be expanded to design a detailed load profile for the commercial sector. Suggestions have been provided at the end as future research directions to address the issues in the NILM sector, such as the inability of similar load recognition and failure to learn new features.

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