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Review

Comparative Study on Load Monitoring Approaches

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Abstract: Without an appropriate monitoring system, the condition/state of electrical appliances/devices in operation in households cannot be fully assessed, resulting in uncontrolled expenses. The purpose of load monitoring techniques is to save electricity consumption. With proper controls, overconsumption of energy can be reduced and unwanted activity that can lead to unnecessary electricity consumption can be eliminated. To achieve this, two approaches are used. The first approach, which says that each device is monitored by means of individual meters or metering devices, is called intrusive load monitoring (ILM) and requires expensive deployment of metering devices for its use. In contrast to the first one, the second approach is non-intrusive load monitoring (NILM), which monitors electricity consumption without the need for any intrusion. In this configuration, the total energy consumed is disaggregated into the individual consumption of each load. With progress/advances in artificial intelligence, this approach is gaining interest with influences in other areas of research. Knowing that these developed techniques aim to encourage the occupants of dwellings to save energy by optimizing their electricity consumption, the paper presents a comparative study of these approaches, in order to highlight the strengths as well as the weaknesses of each of them. It is therefore a means of offering researchers the opportunity to make choices according to the orientations given to the research work.

Keywords: electricity consumption; intrusive load monitoring; non-intrusive load monitoring

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1. Introduction

The ever increasing demand for electricity in the residential sector is a global concern, the causes of which are known to some and remain unknown to others. In addition to climate change, the technological revolution had a strong and direct impact on improving the comfort of building occupants. This is observed in households through the proliferation of household appliances and connected devices, which contribute strongly to the increase in electricity bills. To address this concern, which is growing over the years in this sector, many levers have been identified, including the reduction of electricity consumption, so that it can be used to control the energy demand of this sector. In developed countries, residential loads represent 40% of the total electricity demand [1]. In the United States, residential electricity consumption accounted for about/approximately 21.09% in 2017 and 22.56% in 2018 of the total energy consumption [2]. In China, the average annual household electricity consumption increased from 481 to 10,058 (100 million kWh) between 1990 and 2018 [3]. In Africa, the electrical energy consumed in the residential sector was estimated at 56% [4].

Considering the current climate context and energy issues, as well as the significant amount of energy consumed in the sector and the increases recorded, the control of consumption flows by limiting overconsumption and waste seems appropriate. Among the solutions developed is load monitoring, where the aim is to control the electrical energy consumption of loads, providing consumers with information about the energy they consume [5]. In addition to the previous objective, load monitoring facilitates energy conservation by considering energy efficiency measures, such as using fewer energy consuming devices, eliminating unwanted activities, as well as setting an appropriate schedule for the use of electrical devices, among others. Previous studies have shown that a detailed consumption feedback on electrical loads can help consumers achieve energy savings of more than 12% [6,7]. Based on this finding, load monitoring is therefore a serious tool that can significantly contribute to both the reduction of energy waste and of electricity bills among consumers, as well as the improvement of energy efficiency in residential settings. Therefore, the implementation of load-following programs can be beneficial to both the environment and consumers' finances.

For consumers, monitoring and automating electrical energy in the home provides incentives to use electricity efficiently. This gives them a way to monitor and control their electricity consumption and, in turn, provides detailed knowledge and information about the rate of consumption through easy and quick access [8,9]. For electricity providers and utilities, it is important to improve the accuracy of load forecasts, which provide a useful basis for energy management strategies [10].

Depending on a country's level of industrialization, electricity consumed in residential settings can account for a very large percentage of the energy produced. Research has shown that up to one-third of electricity consumption in this context is wasted due to the unconscious use of various appliances and poor electricity management [11]. Therefore, in order to avoid crises related to uncontrolled management of energy needs, it has become essential to develop measures for effective monitoring and management of these needs [12,13].

Load monitoring is one of the ways to effectively manage electricity consumption in households, as it can result in significant energy savings. These energy savings, cumulated on a large scale, contribute significantly to the reduction of the energy deficit in many countries. In addition to being a tool with great potential for controlling household electricity consumption, load control also has a positive impact on the environment, in particular, by reducing greenhouse gas emissions and other pollutants. Therefore, the implementation of electricity control and automation measures in households can provide significant benefits to both consumers and energy providers.

This study compares intrusive and non-intrusive approaches to load monitoring by evaluating the respective capabilities and limitations of each approach in monitoring and analyzing electricity consumption in residential environments. By comparing the performance of ILM and NILM, researchers can better understand which approach is more suitable for specific applications, such as residential energy management.

The majority of studies that have addressed load monitoring issues address energy disaggregation, with appliances varying from household to household. Datasets have the ability to substitute for data collected in situ, and thus play a critical role in the development of NILM. However, the public accessibility of these datasets, despite their plurality (REDD, UK-DALE, PLAID) is not sufficiently representative of the diversity of appliances and devices that might be found in different types of households or buildings.

Furthermore, despite the growing interest in ILM and NILM, there are still weaknesses in the literature that need to be addressed. An example is the lack of standardized evaluation measures to compare the performance of ILM and NILM algorithms. This makes it difficult to compare the results of different studies and establish a baseline for the accuracy and reliability of these methods. Thus, further research is needed on the cost-effectiveness and practicality of implementing ILM and NILM in real-world settings, as these factors may affect the adoption and sustainability of these approaches. In addition, it is also critical to focus on the privacy and security issues that NILM may have on its users.

The contribution of this article is based on presenting in detail the different approaches to load monitoring, highlighting some aspects that other authors do not present when discussing the different approaches to load monitoring in their work. In this way, readers are given a range of information to form their own ideas about each of the approaches presented.

This document is organized into several sections. The first section highlights the causes of energy growth in the residential environment and presents the reasons for energy conservation. The second section presents the concept of load monitoring, as well as the different approaches that comprise it, and an overview of the concept of load monitoring, as well as the different variations that comprise it. Section three discusses the strengths and weaknesses of the approaches presented. Section four discusses the cybersecurity risks faced by the different approaches to load monitoring. Section five provides a summary of what was presented in Section three.

2. Load Monitoring

Load monitoring is the concept that refers to the process of identifying and acquiring the consumption measurement of the load in an electrical system [14]. It is essential for effective management and accurate control of the electrical energy consumed [15,16], as it provides detailed information to electricity end-users about their consumption patterns and power consumption habits. In households, load monitoring is assessed by directly monitoring each device or by breaking down the total power signal [14,17]. Through these actions, consumers can understand how each device works and contributes to daily power consumption.

Over time, many research works have contributed to the evolution of this concept, resulting in two distinct types of load monitoring approaches: intrusive and non-intrusive. In practice, the choice of approach for obtaining satisfactory results depends on several criteria that the researcher must first evaluate. In the literature, the non-intrusive approach to load monitoring is by far the most developed, probably due to the rise of artificial intelligence and machine learning.

When it comes to artificial intelligence, it has the merit of revolutionizing load monitoring by improving the accuracy of load predictions, detecting anomalies in energy consumption, and optimizing load management in real time. Here are some examples of AI techniques that have been applied to load monitoring:

Deep Neural Networks (DNNs): Deep neural networks have been used to predict short-term load demand with high accuracy. To this end, a study by [18] showed that a DNN architecture, in this case Recurrent Deep Neural Network (Deep-RNN) with a tanh activation function, performs better than other cases in terms of MAPE metric values.

Convolutional Neural Networks (CNNs): Convolutional neural networks have been used for feature extraction and classification of energy consumption data. A study by [19] showed that a combination of a convolutional neural network (CNN) and long-term memory (LSTM) could extract complex features from energy consumption. Exploiting this elaborate combination, it was possible to make a near perfect prediction of electricity consumption, which was once difficult. The results indicate that the CNN-LSTM model predicts residential electricity demand in an efficient and stable manner, and has the best performance compared to other existing methods, such as linear regression model (LR), random forest regression (RF), decision tree regression (DT), and multilayer perceptron (MLP).

2.1. *Intrusive Load Monitoring (ILM)*

Intrusive load monitoring (ILM) is a technique used to identify, locate, and monitor the power consumption of each device in a given system using wireless sensors or smart plugs [20,21]. Based on this definition, it can be deduced that the number of devices to be monitored is equivalent to the number of sensors to be installed. In energy management systems, ILM is often used to help identify energy usage patterns and thus improve energy efficiency. In addition, it can also be used in residential, commercial or industrial environments to track device power consumption, providing granular data that can help identify energy waste and optimize energy use. For ILM, the main objective remains the automatic identification of electrical appliances by means of pre-identified tags. In this way, ILM can provide accurate and satisfactory results on the consumption status of each device. As seen in Figure 1, the different stages of intrusive load monitoring are shown.

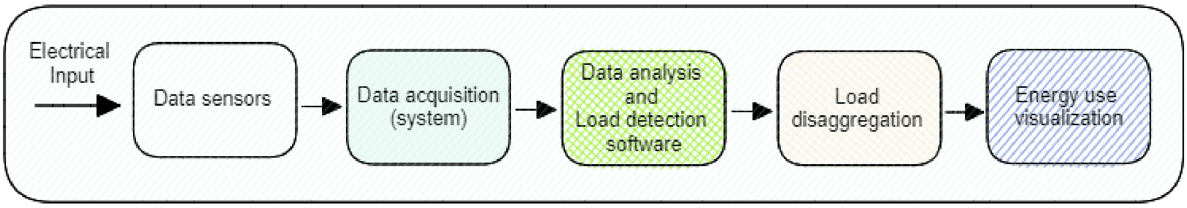

Figure 1. Steps of Intrusive Load Monioring (ILM).

Although the accuracy of the feedback of the consumed electrical energy remains the strong point of this approach, the implementation can be quite costly due to the high acquisition cost of the smart plugs or sensors required for the system [21]. In addition, ILM requires a sub-metering system, as the consumption measurements made on each device all converge to a main meter that centralizes the consumption information of each load. As a result, there is an interdependence in terms of functionality between the different sub-meters, which, in case of failure of one of these sub-meters, could hamper the communication of results, affecting the accuracy. Therefore, careful planning and management of the sub-metering system are essential to ensure that intrusive load monitoring works properly. Figure 2 illustrates the operating principle of intrusive load monitoring.

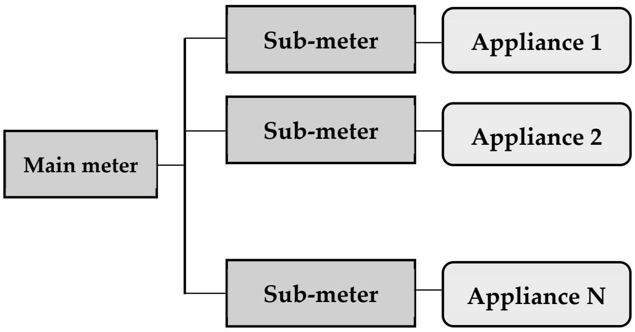

Figure 2. Intrusive Load Monitoring.

The intrusion level of monitoring meters can be determined by considering the number of loads to be connected to the measuring devices, Ridi et al. [22] in their work organized intrusive load monitoring into three (03) subdomains which are distinguished by their levels of intrusion. Indeed, the first subdomain called "ILM1" refers to submeters installed between the main meter of the electricity supplier and the main circuit breaker. This type of installation is generally used to monitor a part of the house. The second sub-domain, named "ILM2" refers to the metering devices installed at the outlets. In this case, the devices directly connected to the socket or power strip are monitored. The third sub-area, "ILM3", refers to the case where the monitoring device is integrated into the device or placed at the socket.

These applications are accessible because they are based on technologies that use data, signal processing, statistics, and machine learning. The collected data for the case of ILM labelled and a pattern matching through the signals of known and unknown loads is performed.

Given the complexity of implementing the intrusive load monitoring, the non-intrusive load monitoring approach is positioned as an alternative solution due to its ease of implementation. However, it remains an older technique than ILM. It was developed in the early 1980s by George William Hart, who, for reasons of energy saving, ventured into work that led to the birth of this concept.

Intrusive load monitoring relies, as much as the second approach, on data sets constituted either by labelling (supervised learning) or by not labelling (unsupervised learning). According to Nguyen et al. [5], existing ILM techniques depend on labels entered by end users and are usually subject to a supervised learning scheme. It turns out that in the real world, device labelling is laboriously done by the consumer, and thus training data are insufficient for supervised learning models. Load identification is an essential aspect, as much as consumption control. Ridi et al. [22] showed that in its implementation, ILM can be configured in two ways. That is, manually and automatically, depending on the identification to be done. Thus, we distinguish:

- Manually configured intrusive load monitoring: Refers to training the models on load data acquired in the learning environment. In this situation, manual user intervention is required to "in-place" label the data based on the load. The load recognition performance is good because the signals are emitted by the same load that was used for model learning. In this case, only temporal variability impacts model performance.
- Intrusive monitoring of the automatically configured load: It does not require "on the spot" labelling of the data, which will later constitute the database. The system is trained a priori and can receive signals from "untrained" devices. However, temporal variability, as well as intra-class variability, could have an impact on the recognition performance. Furthermore, the observed intra-class variability is caused by the differences in the make or model of the devices in the same class.

They add that, while manually configured, intrusive load monitoring requires more time than automatically configured intrusive load monitoring to implement and operate, it is still much more accurate than automatic configuration.

In summary, while ILM provides accurate and satisfactory results on the power status of each device, implementing it as part of an infrastructure deployment can be costly and complex. The use of smart outlets or sensors is essential, and a sub-metering system is required for its operation. In addition, careful planning and management of the sub-metering system is required to ensure proper operation of the ILM.

2.2. Non-Intrusive Load Monitoring (NILM)

Non-intrusive load monitoring is the process of recognizing and disaggregating the total aggregated energy of electrical appliances into individual electrical consumptions from a single measurement point located at the electrical meter [20,23]. In other words, non-intrusive load monitoring is still the disaggregation of the total energy consumed by a building into individual electrical load consumptions. In this way, it is possible to easily determine the contribution of each switched-off or switched-on load to the overall consumption of a dwelling or any other type of building, by analyzing in detail the overall electrical voltages and currents of the loads in the system obtained from a single measurement point [24]. Unlike intrusive monitoring, which requires the installation of several devices, making installation complex and maintenance difficult [24], the non-intrusive approach is relatively simpler in its deployment and implementation [14]. Indeed, it requires only one measuring device to monitor the electricity consumption of the whole household, thus reducing its acquisition cost. Moreover, the installation is done very close to the main meter in the absence of any intrusion and requires almost no maintenance. Figure 3 gives an overview of the operating principle of this approach.

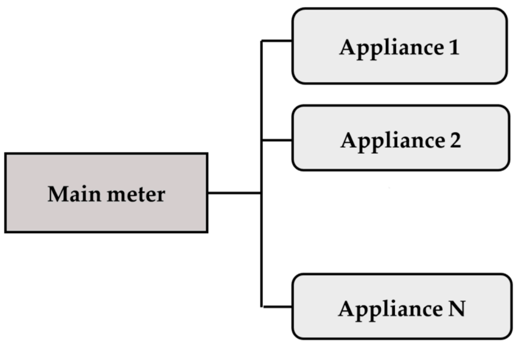

Figure 3. Non intrusive load monitoring.

Given the broader scope of NILM than ILM, users have more opportunities to monitor their devices both remotely and nearby [17]. Non-intrusive load monitoring (NILM) is an older research topic than intrusive load monitoring (ILM). The 1990s marked the beginning of the first scientific publications on the subject, notably with the work of G.W. Hart [25]. Due to the technological revolution caused by artificial intelligence, ILM has seen a resurgence of interest, manifested by research work that has led to the development of numerous machine learning methods, such as supervised learning, unsupervised learning, deep learning, and reinforcement learning, to name a few. For the scientific community, it is above all a question of finding solutions to the problem of energy disaggregation, which remains the main challenge. Figure 4 shows the number of publications on NILM over the last two decades.

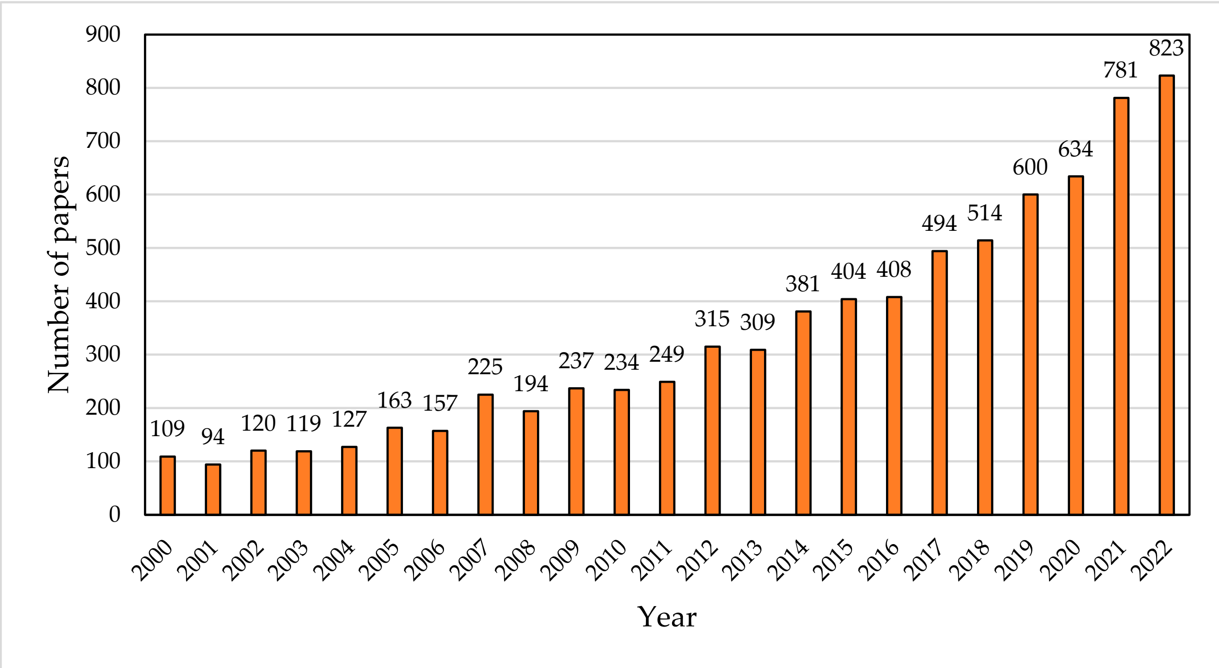

Figure 4. Number of publications on non-intrusive load (NILM) from SciencesDirect database.

As recalled by Faustine et al. [26], in their work, the best way to disaggregate the total energy of loads is to design an algorithm that can be generalized to any type of building and is capable of operating in real time. In general, the algorithms used in non-intrusive load monitoring (NILM) are composed of the essential steps of data acquisition; event detection (optional step); feature extraction; and load identification, which again refers to load inference and classification, as can be observed in Figure 5.

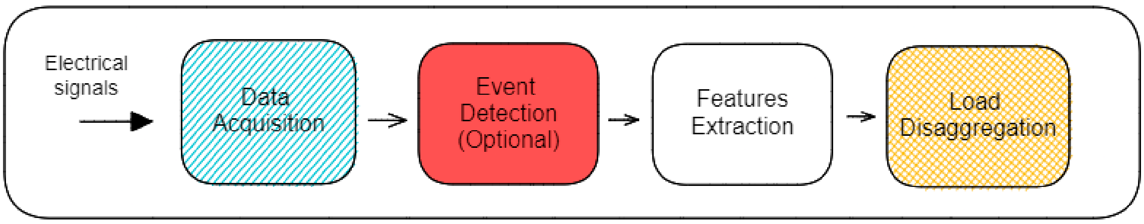

Figure 5. Steps of Non-Intrusive Load Monitoring (NILM).

Data acquisition or electrical signal measurement is the step in which data about a building's overall energy consumption are collected using sensors, smart meters, or other monitoring devices. This data are then used for further disaggregation. NILM relies on non-intrusive data acquisition techniques, which means that it does not require sensors to be installed on the monitored devices. Methods and techniques have been developed to facilitate data acquisition. These include voltage and current signal measurement; harmonic analysis; and reactive power measurement.

Voltage and Current Measurement: This method involves measuring voltage and current waveforms at the main electrical panel or other key points in the electrical circuit, using voltage transducers, current transformers (CTs), or Rogowski coils. The voltage and current waveforms are then processed to extract individual device loads [27–29].

Harmonic analysis: Harmonics are frequencies that are multiples of the basic electrical frequency (50 Hz in Europe). Electrical devices introduce harmonics into the electrical current, which can be measured and analyzed to identify individual device loads [30].

Reactive power measurement: Reactive power is the portion of power consumption that does not contribute to work production. Electrical devices have different energy consumption behaviors for active and reactive power. Therefore, reactive power analysis can be used to identify individual device loads [28].

Event detection remains an optional step that is not always considered in the energy disaggregation process. Thus, two approaches to NILM have been developed, one event-based and one non-event-based [9,31]. Once the stage has been considered in the energy disaggregation process, it contributes to the identification of events, such as on, off or any other change related to the operation of the devices. From the literature, [32] methods based on event detection can be grouped into three categories, i.e., based on expert heuristics; probabilistic models; and matched filters.

The first one aims at splitting the normalized powers into stable and transient periods. Thus, it is established that stable periods are sets of fixed and contiguous samples, in which the input data do not vary more than the fixed threshold. The on/off transients are detected using the "state change detection" rule, which analyzes the series of total power differences and compares the values obtained to the predefined ranges for the start and end power changes (on/off) associated with each device.

The second category, which refers to the probabilistic models, states that the identification of the precise time at which the event occurs is often referred to as change point detection. By introducing a generalized likelihood ratio, it calculates a "decision statistic, starting from the natural logarithm of a probability distribution ratio before and after a possible change in the mean".

The third category refers to the use of matched filters, linking a known signal called "mask" with an unknown signal. The aim is to detect the presence of the mask in the unknown signal. In this way, the mask is identified with the power signals containing the transients of start-up or shutdown of the various devices, while the unknown signal represents the total energy consumption.

However, let us add that [32,33] point out that the addition of the event detection also contributes to:

Increasing its accuracy: By identifying specific events related to the operation of appliances or devices, the energy disaggregation algorithm can more accurately attribute energy consumption to individual devices.

Better visibility: Event detection provides more detailed information about how devices are used, which can be useful in identifying opportunities to reduce energy consumption or optimize energy use.

Better understanding of device behavior: Event detection can provide information about how devices are used, which can be useful in identifying patterns and anomalies in device behavior.

Nevertheless, errors can occur, such as false events or missed events, which could affect the quality of the expected result and thus contribute to degrading the performance of the overall NILM process.

On the other hand, in the absence of event detection, the energy disaggregation process, as presented in Figure 5, ignores this step. As a result, the algorithms used, such as hidden Markov models and their variants [29,34], directly process each sample of the overall voltage and current signal. In addition, removing the event detection step also has advantages, such as simplifying the energy disaggregation process, which can make it easier to implement and maintain; and reducing computational costs, as event detection can be computationally expensive, so removing this step can reduce the computational resources needed for energy disaggregation.

Feature extraction involves extracting relevant features from the collected data, such as energy consumed, current, voltage, frequency, and other parameters that can be used to distinguish between different devices, such as harmonics. These features are used to feed the machine learning algorithms in the next step. In addition to the previously mentioned features, the statistical characteristics of the electrical energy can also be used to train machine learning algorithms, such as k-NN, decision trees, and neural networks, to predict the energy consumption of each device. Ghosh et al. [35] reported that the use of statistical features can help achieve a high performance in detecting electrical appliances, with accuracy rates up to 99% for some appliances.

Load disaggregation refers to the training of a machine learning algorithm using the extracted features and the data collected in the previous steps. There are three methods of machine learning: supervised learning, unsupervised learning, and deep learning [36,37].

In the supervised learning approach, the loads undergoing disaggregation of consumed energy are labeled. The electrical signals collected during the data acquisition phase are then used to train the device signatures. Regarding the supervised learning algorithms usually used in the NILM process, the literature provides more information about them. For example, k-Nearest Neighbor (kNN) [38,39], support vector machines (SVMs) [40,41], decision trees [42], genetic algorithms [43,44], artificial neural networks (ANNs) [45,46], hidden Markov models (HMMs) [29,34], Naïve Bayes classifier [47,48], and deep learning neural networks that are used in NILM as supervised learning algorithms.

In addition to the fact that these algorithms have demonstrated their ability to identify devices and allocate the total energy consumed, they nevertheless display limitations when implemented in real time. Because supervised learning algorithms cannot adapt to changes in the environment, updates to device signatures must be made based on a number of factors, such as aging of devices, decrease in device performance, replacement or addition of a device in the home or building, and power line disturbances.

Unsupervised learning algorithms do not require labeled data to disaggregate the total energy consumed. Of the most common algorithms in the literature dealing with NILM problems, we can cite hidden Markov models (HMMs), k-means clustering, and expectation maximization (EM) [37,49]. For HMMs, the identification of the device state (on/off) and energy consumption (active and reactive power) are respectively an assimilated concept of hidden events and observed events of hidden Markov models. As for the transitions of the device state, they are observed through the transition matrix. Although unsupervised learning algorithms compete with supervised learning algorithms, both still require strong features that can contribute to the performance of NILM systems. These features can be obtained by extracting device-independent characteristics through feature matching and transformation techniques. In recent times, deep learning algorithms have shown the ability to extract device-specific features from raw data without using any expertise.

Given the interest in deep learning algorithms, precisely in terms of their ability to solve complex problems in applications, such as speech recognition, computer vision, and asset condition monitoring, many researchers have, in the context of NILM, undertaken to improve the identification of devices, in order to make energy disaggregation algorithms more efficient. This is the case for algorithms, such as convolutional neural networks (CNN), recurrent neural networks (RNN), and autoencoder (AE) to automatically extract the eigenfeatures from the aggregated signal, in order to improve device classification and energy disaggregation [50,51]. Deep neural networks (DNNs) have been used as a multi-classifier to identify individual devices [52].

The reported results indicate that the model trained by the deep neural network from a washing machine can be used to detect other appliances, such as a kettle, microwave oven and refrigerator.

In sum, the NILM technique is a powerful tool for analyzing energy consumption and identifying energy saving opportunities. It can be used to improve energy efficiency, reduce energy waste, and provide more detailed information about the energy consumption of individual devices.

The performance evaluation of NILM requires data sets, without which energy disaggregation could not be done. Indeed, in its operation, NILM uses the energy consumption data of a house (electrical signatures of the different appliances found in a household) stored in a database called the dataset. To date, there are several open access datasets proposed by researchers; these include the PLAID [53], REDD [54], UK-DALE [55], AMPds [56], and BLUED [57] datasets. However, the use of datasets in NILM responds to the choice of inference type. In supervised learning, datasets are used both as training data to train the algorithm and as test data to ensure accuracy in matching trained and tested signatures. In semi-supervised learning, the consumption data of the datasets is partially used, i.e., it is only used when training the algorithm.

For non-intrusive load monitoring, datasets are valuable because they typically represent a means of evaluating the performance of algorithms used in NILM. A dataset is a collection of samples collected over time, in which we find voltage, current, active power, reactive power and to a lesser extent power factor and harmonics data [58]. These data collected through their respective signatures are the object of training to accustom the algorithm to the signatures and of testing, when it is a question of making correspondences to ensure the ability of the algorithm to correctly assign the signatures to the devices. All this is made possible by supervised, semi-supervised, or unsupervised learning algorithms, chosen according to the circumstances.

3. Advantages and Disadvantages of Intrusive and Non-Intrusive Load Monitoring

3.1. Advantages and Disadvantages of Intrusive Load Monitoring

3.1.1. Advantages

Some of the advantages of the intrusive approach to load monitoring include:

High accuracy: it is possible to accurately obtain information about the power consumption of different devices installed in the system [22]. Therefore, the details obtained from the analysis of the household or building power consumption could be exploited for modeling purposes.

Finer control: intrusive load monitoring gives consumers the ability to control their electricity consumption with more finesse, identifying appliances with high power consumption potential, and readjusting their operation.

Anomaly detection: With the intrusive approach to load monitoring, it is possible to detect anomalies in energy consumption due to faulty equipment, power leaks, or any other problems.

In addition to the above benefits, ILM has the ability to identify the power consumption of devices that are on standby, plugged in, and not in use, also known as "phantom loads". In this way, consumers can adopt measures that lead to the reduction in overall electricity consumption in their homes or buildings. In addition to this benefit, the data collection devices used in the ILM provide real-time information about electricity consumption. Seen in this way, it can help users track their energy consumption throughout the day and adapt their consumption patterns or habits for efficient energy optimization.

Thanks to the concept of intrusive load monitoring, several applications have been developed with the aim of improving the daily life of energy consumers. The applications developed aim to:

- Understand energy consumption in a localized way. That is, give households accurate information about the consumption status of a single appliance. Typically, the information made available to the household is accessible at the power outlet, a static display, or on a mobile device [21,22].

- Monitor appliances. With ILM, it is possible to identify abnormal consumption, or consumption deviations, as well as faulty appliances that may disrupt load monitoring [21,22].
- Evaluate non-intrusive load monitoring environments. In this case, ILM is used to evaluate the performance of non-intrusive load monitoring through the disaggregation of consumed energy. This involves comparing the data from the results obtained from the non-intrusive load monitoring disaggregation algorithm to the data that the ILM sensors provide [21,22].
- Daily recognition of human activities. With ILM it is possible to identify during their operations the devices that are involved in facilitating the daily life of the occupants of a household [21,22].
- Detecting occupied space. Intrusive monitoring devices can also detect intrusion into a space, through sensors that control the on/off state of an appliance, and thus save energy [21,22].

Overall, while ILM can be costly and complex to implement, it offers significant benefits in terms of identifying energy waste, optimizing energy use and improving overall energy efficiency.

3.1.2. Disadvantages

In its implementation, the intrusive approach to load monitoring is presented as expensive, complex to install, and difficult to maintain [59].

The High acquisition cost of installing an ILM system is justified by the need to install sensors or measuring devices on each device to be monitored.

Sub metering of the system makes it depend on the functionality of all submeters for accurate monitoring, that is, if one of the submeters is faulty, the accuracy of the monitoring system will be affected. An illustration of this situation can be seen in Figure 1.

Intrusion: The installation of sensors on electrical circuits can be considered an intrusion into the privacy of the occupants of a dwelling or any other type of building, which may be a concern for some people.

3.2. Advantages and Disadvantages of Non-Intrusive Load Monitoring

3.2.1. Advantages

Non-intrusive load monitoring (NILM) has some interesting advantages, including:

Lower acquisition cost: NILM does not require the installation of sensors on each electrical device. Therefore, the number of sensors is reduced to one, and the cost is significantly reduced compared to ILM.

Easy installation: Unlike ILM, where installation is complex and cumbersome, NILM is much easier to install because it does not require special electrical knowledge.

Absence of intrusion: For its start-up, the NILM does not integrate any intrusion into the consumer. Indeed, it does not imply the installation of sensors respectively on each electrical appliance as is done in the ILM. In this way, the building occupants are truly reassured of their privacy.

In addition, the non-intrusive approach is more scalable, as it can be used to monitor the energy consumption of many devices at once, without requiring physical changes to the building's electrical infrastructure. Another important point of this approach is that NILM systems have a wide communication bandwidth that allows them to cover a large number of loads, unlike intrusive systems, where the communication bandwidth limits the coverage of loads.

In addition, the accuracy with which NILM breaks down total energy into individual consumptions also informs the performance of the associated algorithms [60] and the presence of the utility at the customer's end, leading to changes in consumers' energy consumption patterns [61].

NILM does not have only advantages. As it is still a maturing technique, the limitations identified are mostly technical and are continuously being improved.

3.2.2. Disadvantages

Like ILM, non-intrusive load monitoring also observes limitations in its operation. Among the obstacles that contribute to its reduced performance are:

Lower accuracy: NILM tends to provide less accurate data than ILM because it is based on mathematical models that may not take into account all relevant variables, unlike the individual sensors placed on each load in the case of ILM. This lower accuracy in load classification increases the rate of undetected errors.

Limited detection: The ILM is unable to detect devices of a certain type. Continuously variable loads (HVAC), such as dimmers, electric drills, and split air conditioners, have electronic components that vary their power consumption over time, without a fixed number of states, which makes it difficult to allocate power consumption. In addition, it is difficult for the MILM to distinguish between units with identical electrical operations. However, to overcome this difficulty, it is possible to make use of harmonic current signatures to differentiate between devices that are confused.

Technical limitations: NILM may be limited by the technical capabilities of the load detection algorithms, which may limit the reliability and accuracy of the monitoring.

In summary, while the NILM approach has the advantage of being less expensive and less intrusive than ILM, it may be less accurate and have technical limitations.

4. Load Monitoring Approaches and Cybersecurity

The various load monitoring approaches (ILM and NILM) are energy monitoring techniques that can pose cybersecurity risks if the data is compromised or misused. These risks include data breaches, data tampering, identity theft, data hijacking, and denial-of-service attacks. To ensure the security of ILM and NILM data, it is important to implement security measures that can ensure data integrity and confidentiality, such as cryptography [62], access management, and data verification.

Here are some of the cybersecurity-related aspects of load monitoring that should be considered:

Data privacy: Load monitoring approaches rely on the collection and analysis of energy consumption data, which can potentially contain sensitive information about individuals and their daily habits. It is critical to ensure that this data is stored securely and that only authorized individuals have access to it.

Network Security: ILM and NILM systems often rely on a network of sensors and devices to collect and transmit data. These devices can be vulnerable to cyberattacks, making it important to implement appropriate security measures, such as firewalls, intrusion detection systems and encryption protocols, to protect the network.

Authentication and authorization: Access to the ILM and NILM system and data should be limited to authorized users only. Strong authentication and authorization controls are essential to prevent unauthorized access to the system.

Data Integrity: The accuracy and reliability of the data collected by ILM and NILM is critical to its effective use. Any tampering with the data can lead to incorrect conclusions and decisions. It is therefore important to ensure that data is not manipulated or altered in any way.

Physical Security: Sensors and devices used for NILM must be physically secured to prevent unauthorized access or tampering. Access to the equipment must be limited to authorized personnel.

5. Discussion

In the previous sections of the paper, the advantages and disadvantages of each of the different approaches to load monitoring were presented. Intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) are two approaches for which the purpose is to monitor and analyze household electricity consumption. While ILM provides much more accurate results than NILM, this accuracy is still dependent on users correctly labelling their appliances. Furthermore, this accuracy in results is also dependent on a significant amount of effort to install the measuring devices, as physical modifications to the building's electrical system are mandatory. The maintenance of such devices requires, among other things, expert hands in electricity, in order to avoid accidents that could occur, as well as the discomfort that this would produce for the occupants of the buildings. Table 1 provides a summary of the key points of each of the approaches presented.

Table 1. Elements of comparison between intrusive and non-intrusive approaches to load monitoring.

Aspect	ILM	NILM
Installation	Requires installation of individual sensors on each appliance, which can be time-consuming and expensive.	Does not require any additional hardware installation, as it collects data from existing power meters.
Accuracy	Provides high accuracy due to its ability to monitor energy consumption at the individual appliance level.	The accuracy of NILM can vary depending on the complexity of the load signature and the quality of the data collected.
Data Collection	Provides real-time data on the energy consumption of individual appliances, which can help identify energy-intensive appliances and opportunities for energy savings.	Provides aggregate data on overall energy consumption and does not offer detailed information on individual appliances.
Cost	Can be expensive due to the installation and maintenance costs associated with individual sensors.	Generally less expensive since it does not require any additional hardware installation.
Privacy	Requires access to individual appliances and usage data, which can raise privacy concerns for some users.	Collects data in a central location, so there are no privacy or confidentiality issues.
Scalability	Can be difficult to scale up to larger buildings or multiple units since it requires the installation of sensors on each individual appliance.	Scalable to larger buildings and multiple units since it collects data from existing power meters.

6. Conclusions

In summary, intrusive load monitoring (ILM) and non-intrusive load monitoring (NILM) are two different approaches, each with its own advantages and disadvantages, which should be exploited depending on the expectations one may have. ILM provides more detailed and accurate information, but is more expensive and invasive to implement. Another consideration that today justifies the choice of NILM rather than ILM is the confidentiality of the data collected. Indeed, by using ILM, it is possible that sensitive information is collected, such as usage habits or device activity. To this end, it would be more appropriate to implement appropriate data privacy measures such as data encryption and access controls, in order to protect the privacy of users. As for NILM, it remains a less expensive and more scalable technique. However, it is less accurate than ILM and more prone to error, as it is based on mathematical models that may not take into account all relevant variables and may have technical limitations that restrict its reliability and accuracy. From the points presented, it is clear that no one approach is entirely satisfactory, despite the evidence on both sides. Thus, the choice of one approach over the other depends on the specific objectives that the researcher wishes to achieve on the one hand, and on the other hand, the needs expressed by the users. If the user needs precise results, ILM seems to be the best option. On the other hand, if the user wants to monitor overall energy consumption patterns and identify potential energy savings, ILM seems to be the most appropriate. From the readings done, we have chosen to adopt NILM as the approach that should underpin our research work, because, in addition to gathering the advantages presented, its drawbacks are challenges to be met, in order to contribute to its growth and maturation, so that it constitutes a revolution for energy savings in the residential sector.

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