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Non-Intrusive Load Monitoring (NILM), Interests and Applications

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Abstract

In developing effective energy management mechanisms, new concepts have been developed to provide new approaches. Non-intrusive load monitoring (NILM) is an approach that was originally developed to allow the occupants of a room to identify the contribution of each appliance to the total electricity consumption of the room through a single point measurement device. The aim is to provide customers with information that will enable them to act as "consum'actors", i.e., people who undertake to change their electricity consumption habits for an objective cause. The progress of artificial intelligence in its various forms (machine learning, big data, internet of things) have greatly contributed to increase the interest of NILM among researchers in different fields. Indeed, some of them are adapting this concept to research areas such as water, transport, health, the environment and agriculture. In this context, applications in these fields have been developed to show the potential and benefits of using this approach. In addition to presenting non-intrusive load monitoring (NILM) in its general framework, this article presents the interests and applications of this approach in various fields.

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1. Introduction

The upheavals caused by climate change, the decline in fossil fuel resources and the increase in global energy demand are some of the reasons why we need to review the way we manage and consume electrical energy. To respond to these worrying challenges, solutions have been proposed, including demand-side management (DSM). According to the French Agency for the Environment and Energy Management (ADEME), DSM refers to the grouping of energy saving actions implemented for the end consumer and not for the energy producer. In many countries around the world, few energy saving actions are promoted. This creates an imbalance between supply and demand that needs to be addressed. Faced with this concern, which has major economic implications, technological solutions have been proposed to help reduce this imbalance and thus reduce CO_2 emissions. Previous studies have shown that when energy supply companies communicate information on their consumption patterns to end-users of electricity, either directly or indirectly, the impact is that energy savings of over 12% are observed [1]. However, capitalizing on technological advances

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such as artificial intelligence and machine learning is helping to extend this type of action. For many scientists, the context is the development and improvement of existing solutions that can address these concerns. One of the solutions being exploited is load monitoring and specifically non-intrusive load monitoring (NILM), which is being used to reduce electricity consumption in households and buildings of all kinds. From the beginning, the NILM concept was limited to the field of electricity. The results obtained as well as the improvements regularly proposed, have greatly contributed to the renewed interest that is currently observed. The applications developed have aroused the interest of researchers in other fields to adapt this concept to their different fields of research. For the latter, it is a question of presenting the great advantage that NILM offers, through its applications in fields such as water, the environment, transport (maritime and rail), health (teleconsultation and assistance to elderly people living alone) and agriculture. In the rest of the paper, we briefly present the context and the different approaches to load monitoring, the general framework for the implementation of NILM, the interests and applications of NILM in the fields where it has been exploited, and finally a conclusion.

2. Load monitoring, context and approaches

Real-time feedback on the electricity consumption of a house or other building to end consumers reflects the desire to influence consumption patterns, with the intention of improving them. The aim is to reduce energy demand by limiting over-consumption and waste. To achieve this, it is essential to have the load signatures (measurable electrical data) that can be detected by the installed measuring device(s). Basically, it is a matter of monitoring electricity consumption by appropriate technological means. In energy management, load monitoring refers to the process of identifying and acquiring measurements of electricity consumption of the loads of an electrical system [2–4]. Inspired by technological advances and particularly by machine learning methods, load monitoring is attracting a lot of interest [5]. Depending on the approach used and the results sought, it can be intrusive or non-intrusive.

2.1. Intrusive load monitoring

Intrusive load monitoring (ILM) is needed when it is necessary to go inside a house or other premise to install a measuring device for each appliance present. The measuring device can be a wireless sensor, a digital meter, or any other object that fulfils this role. This approach is laborious as it requires the installation. Depending on the level of intrusion, three types of intrusive load monitoring can be distinguished [6,3]:

Type 1: metering device are installed at the circuit breaker and only measure the consumption of one part of the house.

Type 2: the metering devices are placed at the outlets, so as to monitor one or more appliances at the same time.

Type 3: A measuring device is installed on each appliance.

Despite the accurate measurement results, this approach is not very cost-effective for the reasons mentioned above.

2.2. Non-intrusive load monitoring

In contrast to the intrusive approach, non-intrusive load monitoring (NILM) refers to the process by which the overall electricity consumption of a building is identified without intrusion from a single point of measurement, and then the detailed consumption of each device is provided [2,7,8]. The non-intrusive approach is more advantageous than the intrusive one, as it requires only one sensor to be installed, very low maintenance, in addition to being affordable, and non-intrusive to the user [9]. Moreover, it represents an interesting alternative to the intrusive approach, as stated by Verma *et al.* [4] in their work, in addition to encouraging many researchers to adapt it to various research domains to obtain new results. For G. W. Hart [10], who pioneered the concept of non-intrusive load monitoring, identifying the contribution of each appliance to the total electricity consumption of a house was the beginning of energy savings. The operation of the NILM integrates four (4) steps respectively: data acquisition, event detection, feature extraction and load identification. Based on machine learning (ML) and artificial intelligence (AI) techniques, the NILM system identifies variations in voltage and current signals, which can be compared to fingerprints or signatures of each device. This identification is only possible thanks to dedicated algorithms belonging to the supervised, semi-supervised and unsupervised learning algorithm families [11].

3. General framework and concept of non-intrusive load monitoring

In NILM, each step performs a specific task, so that the desired objective (energy disaggregation) is easily achieved. The success of the process of disaggregating the total energy consumed into individual load consumptions provides information on the level of accuracy and performance of the chosen feature extraction and learning methods. In the following, we present the contribution of each step in the NILM process.

3.1. Data acquisition

The energy consumed in an electrical installation is counted by an electrical meter and therefore represents a data that can be exploited in several ways. In the NILM concept, data acquisition or recording is essential, in that the sampling frequency determines the types of information [12]. For example, at low frequencies, the low sampling rate considerably limits the range of devices that can be detected, and the choice of scheme (steady state, transient or non-conventional) also has an influence. In some NILM systems, transient characteristics of loads or noise generated by devices may be required at high sampling rates to obtain accurate measurements [13]. The choice of electrical characteristics to be recorded depends on the frequency class ; high frequency when the sampling frequency is between 10 and 200 kHz, medium frequency when it is between 50 Hz and 10 kHz, and low frequency for frequencies between 1 and 50 Hz [14]. As a reminder, smart meters belong to the low frequency range and are suitable for low sampling rate collections [15].

3.2. Event detection

This step corresponds to the detection of switches (ON/OFF, steady state to transient state and vice versa) that occurs during the operation of the devices. These detected switches provide information on the variations in energy consumption during operation (source). In the literature, two approaches to non-intrusive load monitoring have been developed depending on the algorithm to be used. These are event-based non-intrusive load monitoring, which requires an event detection step during its implementation as discussed by some authors in their work [16,17], and non-event-based load monitoring [18]. In the case of the first approach, the performance of the algorithms to be used is crucial. During the feature extraction and classification (learning) phase, they allow to limit the number of false commutations likely to appear and affect the performance of the algorithm. In contrast to the previous approach, the non-event-based NILM does not include an event detection step. Here, Hidden Markov Models (HMM), as well as their variants that we present in section 3.4.3, are usually used as a learning algorithm. This algorithm has the advantage of processing each global signal sample (power, voltage, current, etc.), and in the end identifying each device [19–20].

It should be added that, for devices that obey ON/OFF, multi-state and continuous operation, respectively, it is easier to detect them. On the other hand, continuously variable device (CVD) devices are more complicated to detect, as their energy consumption is arbitrarily modified. In the literature, different types of devices commonly encountered in energy disaggregation are presented [1,13,17]. These include devices for:

Type I: These are appliances with only two operating states (ON/OFF) and consuming constant energy throughout their operation, such as an incandescent light bulb, electric kettle, toaster or microwave. These appliances are called resistive appliances because the reactive energy they give off is almost zero.

Type II: This category includes finite state machines (FSM) or multi-state machines, because they have a finite number of distinct states that can be repeated. In addition, the state transitions that take place during operation are identified using variations in energy consumption over a period of time. Appliances such as electric cookers, refrigerators with automatic defrosting, washing machines, variable speed fans are considered to belong to this family.

Type III: loads belonging to this group are called continuously variable Devices (CVD). They are characterized by electronic devices that vary their power consumption over time, without a fixed number of states. For these devices, it is difficult to easily allocate their energy consumption. Examples include dimmers, electric drills and split air conditioners. Figure 1 shows the operating states of the first three types of appliances.

Type IV: Appliances that can be operated at a constant rate throughout the day, such as TV receivers, smoke detectors and telephone sets, belong to this group.

The continuous nature of the operating state of devices belonging to the last group cannot be represented in Figure 1, but it can be done in a pictorial way.

In view of this non-exhaustive inventory, it should be recalled that the main challenge of NILM remains the disaggregation of the energy consumed by each of the loads belonging to these categories, both separately and simultaneously, at regular or different time intervals.

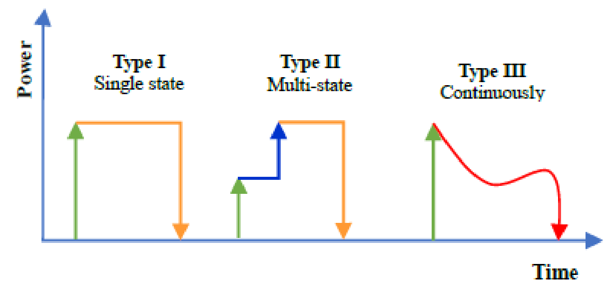

Figure 1. Illustration of the operating status of the devices in the various groups

3.3. Features extraction

Once the detection of the event is done, the essential features of the event are extracted for the identification of the device that caused it [21]. Feature extraction plays a crucial role in learning device signatures [1]. Furthermore, these features can be classified into three categories: steady state, transient and non-conventional.

3.3.1. Steady state

A steady state is said to exist when the characteristics of the load remain unchanged for a certain period of time. These are characteristics such as : real (P), reactive (Q), apparent (S) power, root mean square (RMS), power factor (PF), frequency (F) and time domain characteristics, voltage-current paths, voltage noise, which can be used for load identification [1,3]. In the steady state, the load signature represents the information found in the analysis between two consecutive operational steady states [22]. In steady state, the extraction of the characteristics is done at low frequency, as this favors the detection of small variations that occur continuously, due to the nature of the loads. Moreover, this is much easier than a momentary indication. It should be added that in the transient scheme, the steady state signatures are the set satisfying the zero-loop sum constraint, where the sum of power changes in any cycle of state transitions is zero. However, recall that some device signatures may overlap due to their similar characteristics, thus making load identification and disaggregation complex. To solve this difficulty, V-I trajectories are used, in order to distinguish device events [1]. Figure 2 shows the different schemes, depending on the features to be extracted and trained in the NILM algorithms.

3.3.2. Transient state

When a device is switched on, an event (transient state) occurs for a period of time before the stable state indicating the operation of the device. It can be observed in both (ON/OFF) and multi-state devices [23]. A transient is characterized by a

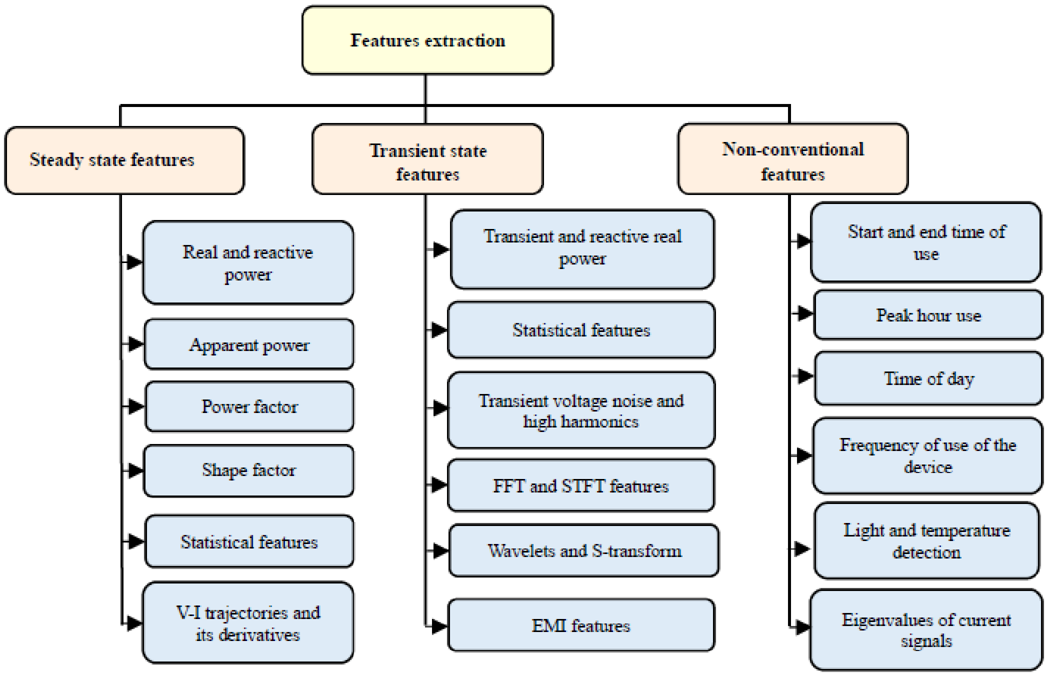

Figure 2. Categorization of NILM systems based on features extraction schemes

relaxation time, a damping rate or a quality factor. It usually occurs when there is a change in the system. In the steady state, when two or more loads are in similar power ranges, event detection becomes less and less accurate [1]. The use of transients can overcome this shortcoming, by accurately identifying the events that take place. To make this possible, sophisticated, high-cost, high-accuracy equipment adapted to the circumstances is recommended [24]. The features (transient power, inrush current, transient voltage noise, transient V-I paths and higher order harmonics) extracted for examination are highly sampled (from kHz to MHz) [1,3,25,26].

3.3.3. Non-conventional features

The non-conventional regime includes characteristics that do not belong to the steady state or the transient regime. This group includes a combination of conventional, contextual, behavioural or indicator features of electrical devices [24]. These include features such as start time, end time, peak time, time of day, frequency of appliance use, current signal eigenvalues, light detection and temperature, which are used to add additional information to the conventional features [1,3,23].

3.4. Load identification and inference

This is the next step after features extraction. During the load identification phase, the signatures extracted from the overall power signal of the loads are analyzed, with a view to labelling the loads [15,23]. Also, to learn the detected signatures, learning algorithms are used, while the deductions of the load states are performed using inference algorithms, following the observed aggregate power data [15]. The algorithms used in this stage of the NILM belong to either the supervised, semi-supervised or unsupervised families of learning algorithms. Indeed, supervised learning algorithms require large amounts of data (datasets or dataset) on the characteristics of the individual loads extracted, in order to train the algorithm to classify the loads in operation [3,27]. In addition, this data needs to be labeled, so that the algorithm correlates the input and output data perfectly during the training phase. For example, when the algorithm is trained to deduce whether the signal shape is that of a coffee maker, with supervised learning, it creates a label for each signal used in the training data, indicating whether the signal is that of a coffee maker in operation or not.

Semi-supervised learning algorithms use a set of labeled and unlabeled data. In order to learn successfully, they need to train small amounts of labeled data [3,23]. These algorithms fall between supervised ones using labeled data and unsupervised ones not using labelled data. It has been shown that the use of unlabeled data, in combination with labeled data, significantly improves the quality of learning. Furthermore, labelling data sometimes requires the intervention of a human user. However, when datasets become very large, this operation can be tedious. In this case, semi-supervised learning, which requires only a few labels, is of obvious practical interest. As an example, co-learning is an example of semi-supervised learning, where two classifiers learn a set of data, but each using a different, ideally independent, set of features. If the data are objects to be classified according to their nature, one might use size and the other shape for example.

With unsupervised learning, the algorithms are trained on unlabeled data. They scan the data sets for significant connections. In addition, in the context of non-intrusive load monitoring, pre-processing of unlabeled input data is not useful, thus favoring NILM applications operating in real time [15]. Furthermore, Klemenjack *et al.* [27] add that unsupervised algorithms must both perform load disaggregation and detection of connected devices in the circuit they monitor. However, there are discrepancies in the assessment of this form of learning. According to Tezde *et al.* [23], although unsupervised learning is suitable for NILM, it is more difficult to achieve satisfactory results than supervised learning. Moreover, it is up to the consumer to define (label) which device and state should belong to the clusters formed during learning. However, in the research that is being done, NILM is making remarkable progress, thanks to the construction of much more reliable and inexpensive unsupervised learning models, as reported in [5,28].

3.4.1. Supervised learning methods

In their implementation, supervised learning methods make use of labeled training data, and the detected signals are used to establish load signatures [1]. However, these methods can be classified into two approaches [3,23]:

Optimization approaches: learning problems are evaluated as optimization problems. That is, using the learning experience, they help to optimize the performance criteria by comparing the features extracted from loads to the stored features of loads in a database, in order to obtain the closest possible match. In their work, authors such as [29,30] have used genetic algorithms (GA) as learning methods. In the literature, Zoha *et al.* [5] point out that apart from pattern recognition approaches, optimization approaches are also suitable learning methods for load disaggregation.

Pattern recognition-based approaches: In this approach, patterns are recognized by machine learning algorithms. Pattern recognition is defined as the classification of the data extracted from patterns and/or their previously acquired representations. In sum, solving pattern recognition problems is solving classification problems. In the literature, there are many algorithms that have been used to achieve this. These include Support Vector Machine (SVM) algorithms [16,31–36], k-Nearest Neighbours (k-NN) for load classification based on power signals [37–41], Decision Trees [42–44], Bayes classifiers [45–46], Artificial Neural Networks [47–49], and Hidden Markov Methods [50,51] - which have been shown to be capable of introducing temporal and state change information. However, Hidden Markov Methods (HMM) can be used as a supervised or unsupervised approach, depending on the results sought.

3.4.2. Semi-supervised learning methods

These are methods that combine small amounts of labeled data with large amounts of unlabeled data during training [52,53]. It is a special case of weak supervision. In the literature, few authors have used these methods, although they present interesting performances, as demonstrated by Barsim *et al.* [52] in their work, where they use self-training as a learning tool to solve the energy disaggregation problem. They point out that semi-supervised learning tools have the ability to reduce the labelling effort required, by providing a learning disaggregation system whose performance gradually increases as it observes more unlabeled aggregate measures. According to Li *et al.* [53], semi-supervised learning algorithms are a good alternative to supervised learning algorithms that require the labelling of all the loads connected in the power system, in addition to the fluctuations of the main power supply that must be trained. Thus, using graph-based multi-label classification, they manage to obtain better results than the state of the art on some datasets such as REDD (Reference Energy Disaggregation Data Set), BLUED or AMPds.

3.4.3. Unsupervised learning methods

As mentioned earlier, unsupervised learning methods do not need labeled data to run their algorithms. This makes them suitable for NILM applications running in real time. Furthermore, the current trend is that due to their low operating cost and reliability, they are being further developed and improved [15]. These authors add that in the literature, unsupervised learning methods can be classified into three subgroups, namely: unsupervised approaches that use unlabeled data in training to build a database of devices; unsupervised approaches that use labeled data from known buildings to build load models that are then used to disaggregate the energy consumed in unknown buildings; and finally unsupervised approaches that do not require training prior to energy disaggregation.

There are authors in the literature who have used unsupervised learning methods for various reasons. For example, K-means algorithms have been used by Yang *et al.* [54] to analyze the clustering formed by matching after detection of events (ON/OFF) of appliances and by Buddhahai *et al.* [55] to perform partitioning of load data by clusters in number of power states, which helped to identify the power state of appliances such as water heater, air conditioner with accuracy and F-score values above 89%. Abubakar *et al.* [13] and Gopinath *et al.* [1] mention in their research that expectation maximization has been used as an unsupervised learning algorithm to detect unknown load states. To identify ON/OFF states of devices Gopinath *et al.*[1] adopt the concept of hidden events and for real and active power consumption the concept of observed events, which together with the transition matrix and initial states will give good accuracies. In order to improve the results previously obtained with Hidden Markov Models (HMM), different variants have been explored, such as Factorial HMM (FHMM), Conditional FHMM (CFHMM), Factorial Hidden Semi Markov Model (FHSMM), Conditional Factorial Hidden Semi Markov Model (CFHSMM) [1,23]. From the observation made, it appears that the CFHSMM performs better than the HMM variants for energy disaggregation and that the CFHMM is the second best in its performance. An explanation is given for these HMM variants, in order to better understand them:

1. FHMM: this is the extension of HMM where several hidden state variables are used instead of one hidden state variable.
2. CFHMM: This is a variant used to represent the state sequence. However, it requires the addition of features such as time and sensor measurements.

3. FHSMM: This is an extension of FHMM that uses an alternative probability density function for the occupation time of the devices.
4. CFHSMM: is the combination of FHSMM and CFHMM.

At the end of the load identification and learning process, the overall aggregate consumption of the loads is decomposed into individual consumptions of the loads installed in the power system. Thus, using detailed information obtained from each load, the consumer is informed of what each load represents in the total consumption.

3.5. *Non-intrusive load monitoring dataset*

Datasets are databases consisting of naturally or synthetically obtained energy consumption measurements (as they reduce costs, increase time savings by eliminating corrupted data and missing values [23]). They are the result of long measurement campaigns in households in various European and North American countries. In addition, these accessible datasets are also used to train the different algorithms of the learning methods mentioned above [27].

To be tested and improved, in order to prove their performance when called upon, the energy disaggregation algorithms need training data from the available energy consumption datasets. The datasets are intended to provide researchers with real-world energy consumption data, so that during the training phase, real-world energy consumption data achieves very good match rates and high levels of accuracy. The Reference Energy Disaggregation Data Set (REDD) is the first publicly available energy dataset released by the Massachusetts Institute of Technology (MIT) in 2011 [56]. This dataset aggregates consumption data from six (6) households in the United States obtained at low and high frequencies over relatively short time periods.

Following the development of REDD, a number of datasets have emerged, including the Plug-Level Appliance Identification Dataset (PLAID) that Gao *et al*. [57] presented in in their paper, which is a 30 kHz sampled and labeled dataset containing 1876 individually measured device from 17 different appliance types of 330 different makes and models, with 1314 simultaneous operating records from 13 appliance types (i.e. measurements obtained when several appliances were active simultaneously). United Kingdom recording Domestic Appliance-Level Electricity (UK-DALE) presented by Kelly *et al*. [58] is an open-access dataset for households with data recorded at high frequency (16 kHz) describing the overall and actual consumption situations of individual appliances. Other examples include BLUED, GREED, AMPds and AMPds2.

4. Interests and applications of NILM

NILM is a concept that was first developed by George William Hart of the Massachusetts Institute of Technology (MIT) in the early 1980s to monitor and evaluate the number and type of loads and their individual energy consumption. Despite the revolution that this technology heralded at the time of its inception, it was not a great success, due to its complexity (very large statistical data to be processed, limited computing power of computers). However, the rise of artificial intelligence, as well as improvements in computer performance, have greatly contributed to the renewed interest in NILM among researchers. Figure 3 shows the number of publications per year for the research topic *"non-intrusive load monitoring"* in the ScienceDirect database. Also, the continuous discoveries and improvements proposed over the years have led to adaptations of the concept to other research areas

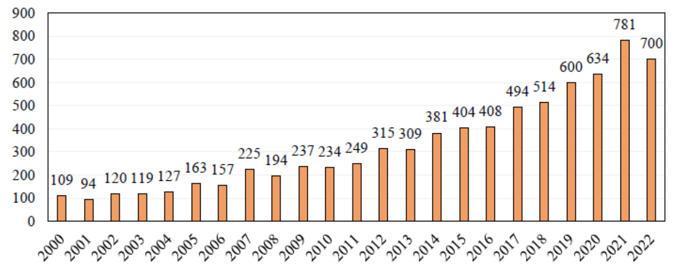

Figure 3. Number of publications on non-intrusive load monitoring from the *ScienceDirect* database

In addition to the characteristics of non-intrusive load monitoring (NILM) to provide information on the status of appliances, the amount of electricity consumed per appliance or information on the electricity consumption habits of the occupants, it also has potential in areas other than electricity. Its non-intrusive nature gives it an originality that adapts to the specificities of each field, where it can play an essential role in the search for expected solutions.

In electricity, NILM has seen a lot of progress in terms of improving the performance of learning algorithms. In practice, there are mobile applications that allow detailed monitoring of electricity consumption, so that electricity bills can be reduced. For the same authors, NILM has enabled some researchers to develop applications that detect illegally connected loads in households and buildings, as well as the presence or absence of people. The aim is to identify respectively the theft of electrical energy that may occur and cause overconsumption [3]. In another case, the development of the Internet of Things and smart homes has led to the creation of new applications aimed at enabling consumers to save energy [12,59]. NILM toolkits (NILMTK) have also been developed to monitor loads during operation [60].

The daily use of water in a household, a building, or an agglomeration varies according to factors such as age, income level, lifestyle or geography. Thus, to considerably reduce overconsumption and waste, communication actions aimed at informing customers about their consumption patterns and habits should be encouraged for common satisfaction. Real-time feedback is an action that many water supply companies need to adopt in order to limit water wastage. Inspired by the concept of non-intrusive load monitoring developed in electricity, Kim *et al*. [61] have adapted it to water consumption monitoring by proposing an easy-to-install calibration system. The system uses wireless vibration sensors installed in the pipes to inform users about the amount of water used, when and where it is used. In addition, its non-intrusive and self-contained nature requires no plumbing expertise for installation. In a similar vein, Schantz *et al*. [62] carried out similar work to the above. It was found that the designed system is accurate and its use by households on a large scale would contribute to its popularization and to the achievement of large water savings.

In the transport sector, the very high level of use of means of transport means that the prevention of failures, which can occur during multiple journeys, should be taken into account and integrated into maintenance systems. To this end, some researchers have deemed it relevant to integrate NILM into warships, freighters or cruise ships, in order to present its usefulness and the great interest it brings. Thus, Nation *et al*. [63] have in their work used NILM for the detection and isolation of faults in automated systems on board ships, showing that with NILM, as well as the event (ON/OFF) of the ship's grey water discharge pump. In the same vein, Lindahl *et al*. [64] have looked at the detection of faults on board ships through non-intrusive load monitoring. According to them, the use of NILM through its applications contributes to improving the health of ships by monitoring engine room equipment and providing early detection of faults that can cause irreversible damage and inestimable losses.

There are also some applications of non-intrusive load monitoring in rail transport. In this respect, Mariscotti [65] presented the interest of the efficiency of NILM in AC railways. Indeed, considering only the identification and extraction steps of the electrical characteristics (current, voltage and harmonics) of the NILM, the performances obtained through classification and clustering methods show that the NILM is not as relevant as in households, due to the fact that the rolling stock obeys regulations dictated by very strict standards.

In a completely different area, Batra *et al*. [66] used NILM to develop a technique that predicts household size, occupancy, income and age. In the health sector, a non-intrusive anomaly detection monitoring system has been developed for the elderly to report interference with daily activities [67]. The developed device is based on the concepts of NILM, as mentioned by these authors. The study was motivated by the authors' desire to provide facilities to improve their health care and well-being by making them more independent. Later, the same authors Alcalá *et al*. [68], then proposed a paper in which they examined the home care monitoring system through the data of smart meters installed in these elderly people. Later, Dai *et al*. [69] developed in the context of telehealth and for elderly people with reduced mobility and dementia, a model for recognizing patterns of activities of daily living (ADL) based on the NILM. For the specific case of NILM applied to ADL, the demand response is able to deliver real-time information to the involved parties. However, there is still a threat to the privacy of users. Indeed, the identification of user activities is based on user consumption profiles. There are still some flaws in this system, notably the exposure of private habits. On this aspect, Gong *et al*. [70] presented a succinct plan to preserve user privacy for demand in smart grids. The developed and proposed scheme allowed consumers to protect their identity by participating in the demand response program, but offered consumers the possibility to publish their identity under certain scenarios, such as legal disputes.

In agriculture, pest diseases are a huge obstacle to increasing crop yields. They result in lower harvests, leading to huge losses of income. The case of soybean cultivation is a clear example, where in some research centers it is difficult to identify the symptoms and types of pest diseases in soybean cultivation [71]. In order to provide suitable solutions, Simunjutak *et al*. [71] have developed an application that helps researchers to identify soybean pests by classification. Although the accuracy of the results depends on the amount of data trained, such applications should be improved and disseminated.

The search for effective solutions to climate change remains an ongoing challenge, and innovative solutions combining artificial intelligence and big data are now common. To this end, Kee *et al*. [72] conducted a study on the impact of non-intrusive load monitoring on CO_2 emissions in Malaysia. The results of the study revealed that by making use of energy efficiency practices in daily electricity consumption, overall CO_2 emissions would be reduced by 10.2% in the country. Furthermore, by incorporating energy efficiency practices into daily electricity consumption, overall CO_2 emissions would be reduced by 10.2% in the country. Furthermore, by integrating non-intrusive load monitoring into these consumption practices, the rate of CO_2 emission reduction would increase from 45% to just over 60% by 2030. In conclusion, the authors state that the application of energy efficiency practices based on NILM is a valuable benchmark for the development and adoption of energy efficiency policies to control CO_2 emissions.

In sum, the applications presented in this work reflect the interest that many fields of research and activities would have in integrating artificial intelligence, machine learning and big data for well-functioning solutions that incur reduced operational costs.

5. Conclusion

Given the energy and climate challenges, it is clear that more effort needs to be made to use solutions that meet the requirements of the established difficulties. Energy management is one such solution. Developing ways to drastically reduce the observed wastage would help to reduce the carbon footprint, the adverse effects of which the world feels on a daily basis. To this end, the concept of non-intrusive load monitoring (NILM) was first developed to allow household occupants to identify how much electricity each appliance consumed as part of the overall household consumption. Advances in artificial intelligence have led to major revolutions that have generated growing interest, so that the concept of non-intrusive load monitoring is no longer confined to the electricity sector alone, but also to other sectors such as transport, medicine, water management and environmental protection. The applications developed in this area show the great interest in extending it and proposing new ways of managing and controlling activities. In addition, progress is continually being made to improve the performance of learning algorithms dedicated to NILM, as well as all other essential points contributing to its performance. Despite the fact that it is considered as an alternative to be popularized on a large scale to encourage energy savings, and that it also has many advantages such as its affordable cost, its installation at a single measuring point, and the absence of intrusion into the household for its operation, it still remains for many researchers an immature technology that needs to be perfected.

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