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Review

NILM Techniques for Intelligent Home Energy Management and Ambient Assisted Living: A Review

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Received: 30 March 2019; Accepted: 6 June 2019; Published: 10 June 2019

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Abstract: The ongoing deployment of smart meters and different commercial devices has made electricity disaggregation feasible in buildings and households, based on a single measure of the current and, sometimes, of the voltage. Energy disaggregation is intended to separate the total power consumption into specific appliance loads, which can be achieved by applying Non-Intrusive Load Monitoring (NILM) techniques with a minimum invasion of privacy. NILM techniques are becoming more and more widespread in recent years, as a consequence of the interest companies and consumers have in efficient energy consumption and management. This work presents a detailed review of NILM methods, focusing particularly on recent proposals and their applications, particularly in the areas of Home Energy Management Systems (HEMS) and Ambient Assisted Living (AAL), where the ability to determine the on/off status of certain devices can provide key information for making further decisions. As well as complementing previous reviews on the NILM field and providing a discussion of the applications of NILM in HEMS and AAL, this paper provides guidelines for future research in these topics.

Keywords: non-intrusive load monitoring; home energy management systems; ambient assisted living; demand response; machine learning; internet of things; smart grids

1. Introduction

Non-Intrusive Load Monitoring (NILM) techniques have become one of the most relevant alternatives for energy disaggregation, since they provide a method to separate the individual consumption for certain appliances, respecting consumers' privacy and often using already-deployed smart meters. The rise of these NILM techniques has also been fostered by the recent importance of some emerging domains, such as Internet of Things (IoT), Smart Grids (SG) or Demand Response (DR) energy programs, where the information provided by NILM can be useful for deciding on further developments or services.

Most applications that use NILM techniques pursue energy efficiency, using itemised energy information to give feedback to tenants, who can consequently take actions to reduce their consumption through "energy awareness". One of the major advantages of the NILM approach is its non-intrusive nature; it is also easily deployed if smart meters are already installed.

On the other hand, with the increasing age of the population and medical advances, there is increasing demand for technology that supports the elderly with leading independent lives. Many digital solutions have been investigated to achieve personalized care, also taking into account other aspects such as acceptance and cost. Among them, NILM not only can provide information about activities within the home, but also has become an emerging alternative to be used in health and care applications. In this case, again, non-intrusiveness is the main and crucial advantage for NILM.

Consequently, as a new contribution and a complement to previous reviews in this field, this work will be focused on Home Energy Management Systems (HEMS) and Ambient Assisted Living (AAL), which are two domains where NILM has clearly contributed to the proposal of new solutions and services, with significant ongoing research, oriented to the achievement of a more efficient energy management, and to the enhancement of AAL systems in response to daily needs of an increasingly ageing population. The review has been conducted to include recent NILM proposals and work using NILM techniques, with a particular emphasis on the requirements that these two types of applications (HEMS and AAL) imply. The analysis includes aspects in the low-level processing (e.g., sampling rate and signal features) as well as in the high-level (e.g., algorithm considered for load identification). Additionally, it deals with the involved data sources and highlights the main contributions of each work.

The rest of the manuscript is organized as follows: NILM techniques are reviewed in detail in Section 2; Section 3 illustrates the application of NILM to Intelligent Home Energy Management; Section 4 deals with the use of NILM in the AAL domain; Section 5 points out current issues and presents guidelines for future research; and, finally, conclusions are drawn in Section 6. A summary of the most important characteristics of the works referenced in this review is presented in the Appendix.

2. NILM Review

A few reviews are already available in the literature about NILM techniques [1–4], which the reader is encouraged to read. This section briefly introduces NILM techniques and presents significant references, focusing on the most recent ones, not covered in previous reviews. For that purpose, the main stages in NILM are:

1. Data collection: electrical data, including current, voltage, and power data, are obtained from smart meters, acquisition boards or by using specific hardware;
2. Event detection: an event is any change in the state of an appliance over time. An event implies variations in power and current, which can be detected in the electrical data previously collected by means of thresholds;
3. Feature extraction: appliances provide load signature information or features that can be used to distinguish one from another;
4. Load identification: using the features previously identified, a classification procedure takes place to determine which appliances are operating at a specified time or period, and/or their states.

2.1. Data Collection

The first stage of energy monitoring system is dedicated to data acquisition or collection. This is an aspect frequently considered as less relevant, but it has major consequences in terms of the types of application that can later be tackled by NILM algorithms, as well as the performance, granularity, etc. This data acquisition is commonly related to a device or system, very close to the existing electrical facilities, where different approaches can be deployed in order to measure certain parameters, such as currents or voltages, in a certain household or building. Sometimes other parameters, actually coming from these voltage and current signals, can be determined, such as the real power, the apparent power, the power factor, or the I-V trajectory [5], and used as features. Not only these parameters, but also their variation over time, are clues to guide our approach to any further energy disaggregation and appliance identification. Taking these considerations into account, this section has basically considered two main criteria when analysing previous works: the sampling rate employed in the data collection and the type of hardware architecture implemented.

For simplicity's sake, maybe the most straightforward solution for data collecting is to think about available commercial plug-in devices. These provide off-the-shelf platforms, normally with the basic functionality ready to be used, but also with some significant drawbacks, especially in terms of sampling rates and flexibility. This trend was already stated in [6], where, after studying different commercially available smart meters and/or energy monitoring, it was concluded that these provide the required computational capacity to cope with advanced techniques, such as NILM. Neurio Technology Inc [7] and Smappee N.V. [8] provide similar energy monitoring solutions, both based on a current clamp, together with a set of utilities and applications intended to display and process the collected information as easily as possible. Furthermore, they provide different communication protocols to report data to other points; Ethernet or Wi-Fi links are the most popular, but this also includes other protocols such as ZigBee or RS-485. Other companies, such as ONZO Ltd. or Bidgely, Inc., propose similar approaches, most of them based on a smart meter/sensor and machine learning for energy disaggregation.

With regard to the drawbacks presented by the commercial solutions, it is worth noting that most of them are constrained to low sampling rates, 1 Hz maximum [9,10], thus limiting the achieved performance and the chance to use them in some demanding types of applications. Even worse, sometimes this sampling frequency is not consistent over time, thus adding a new challenge. In any case, it is widely accepted that systems providing higher sampling frequencies support deeper analysis of the measured features in order to achieve better energy disaggregation [11]. In some previous works, such as [12], the influence of the sampling frequency on the final performance was analysed, concluding that to implement more feasible and reliable appliance classifiers than those already proposed in the field, sampling frequencies should be higher than 4 kHz. As a counterpart, the use of high sampling frequencies is costly, both in terms of software and hardware complexity, and also requires larger communications bandwidth to transmit data to any monitoring or centralized station. Overcoming these difficulties is technically feasible nowadays, but the integration of these enhancements into commercial smart meters will definitely increase the final cost.

Although some smart meters are capable of acquiring signals in the range of kHz [13], their deployment is not actually so extended among electrical companies, likely due to their higher cost. This is the reason why those efforts focused on high sampling rates have been particularized in the design and development of ad-hoc acquisition systems, most of them based on a current clamp and a voltage sensor, together with fast enough analogue-digital converter. This trend is followed in [14,15], where an oscilloscope or a power analyser was used as the acquisition module. Furthermore, in order to employ less expensive and more specific and portable hardware, commercial or ad hoc dedicated data acquisition modules have been applied to measure voltages and currents [16–20]. A direct example of this approach is the BLUED database, acquired by a specific hardware design based on a commercial NI 16-bits acquisition board, which samples current and voltage [21]. Figure 1 gathers the different aforementioned alternatives for data collection in NILM applications, according to the sampling rate.

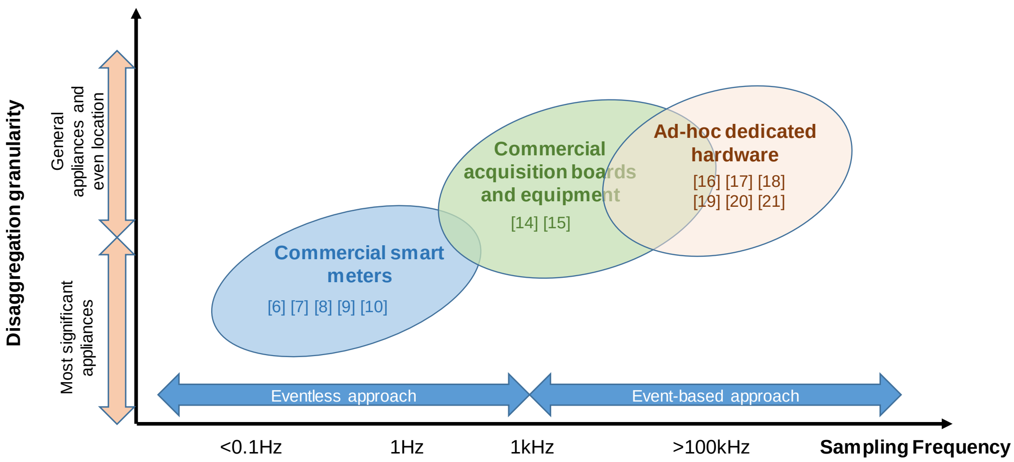

Figure 1. Data collection systems for NILM applications versus sampling frequency.

As has already been mentioned, the main drawbacks of the high sampling frequencies required by NILM algorithms to boost their disaggregation capabilities and identification performance are the increase in computational complexity and the real-time constraints associated with any implementation of these proposals, particularly when commercial smart meters or energy monitors are considered. For that purpose, different techniques have been proposed, aiming at reducing the algorithms' load. One of them is compressed sensing, which achieves a trade-off between the sampling frequency and the degree and accuracy in the disaggregation [22].

Figure 2 summarizes the above-stated aspects concerning data collection in systems oriented to NILM applications. It is also used to introduce the concept of locally and remotely computed tasks in the context of data collection for NILM applications.

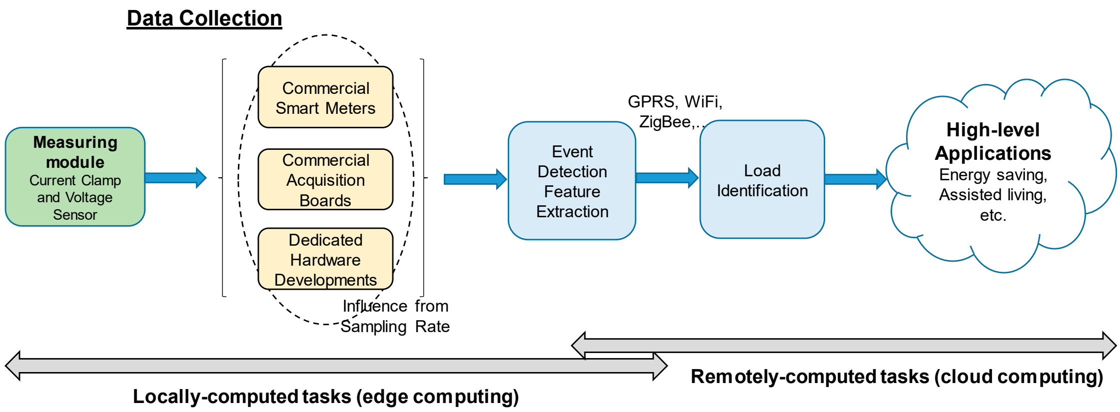

Figure 2. General view of the different aspects involved in the process of data collection for NILM applications.

After acquiring raw data, event detection (typically the on/off switching of electrical devices) should be tackled, as well as some parameters (often classified as steady-state features and transient ones) determined. These procedures, associated with data acquisition and first processing, can, depending on the computing capacity of local devices, be computed locally, thus reducing the amount of data to be transferred to a remote monitoring system. In this way, feature extraction tasks are sometimes implemented in local devices, especially when high sampling rates are available. In these cases, the hardware architecture should present a minimum computing capacity, and be designed keeping in mind that, as they will be finally installed in buildings and households, they should be portable, plug-in and easy to handle [23]. On the other hand, these features are often reported to remote centres where they are processed for further applications, such as load identification or even higher-level tasks, such as energy saving, assisted living, etc.

Keeping in mind the communication needs represented in Figure 2 between the local devices and the remote computing centres, a last relevant point must be considered: how to transmit event detection data as well as the features, locally determined. This data link can be tackled by means of a wide range of technologies and protocols, such as GPRS, PLC, Wi-Fi, Internet and so on, including in-home networks (ZigBee, Bluetooth, etc.) [24–26]. Another approach consists of subcontracting any telecommunication supplier or company, as shown in [27] with Orange. In [28] a gateway based on the OSGi framework is designed to collect information from sensors and smart meters via a ZigBee link.

It is also worth noting that many works in the literature avoid facing the issues that arise from practical and experimental implementations by verifying their proposals using existing databases composed of samples measured from real scenarios under different conditions [29]. Some of these popular databases are REDD [30], BLUED [21], PLAID [31], REFIT [32], TRACEBASE [33], WHITED [34], UK-DALE [35], DRED [36] or PECAN street (https://www.pecanstreet.org/). This approach allows researchers to deal in advance with the challenges and problems otherwise found in later stages, such as event detection or feature extraction, at the expense of limiting their results to the data collection system implemented during the creation of the database, with a particular key influence from the aforementioned sampling rate.

Summing up, the performance and type of hardware setup in the data collection determine the options available in later stages, enabling in some cases the detection of events in the signals of interest, and, specially, profiling a feature set that can be used for load identification. Both aspects are tackled in upcoming sections.

2.2. Event Detection

In NILM, any switch in a signal from a certain steady state to a new one is considered an event. It is often associated with high sampling rates, as this condition is necessary during the corresponding signal processing to achieve a suitable performance in the detection of events. Due to the fact that events are more clearly identified in current signals, compared to voltage ones, it is worth noting that most previous event detectors have dealt with this type of signal. Furthermore, event detectors typically use three different approaches, according to previous work [37]: expert heuristics, probabilistic models and matched filters.

Expert heuristics consist of the creation of a set of rules for each appliance. They commonly require the initialization of certain variables, such as the total power demand and power variation. Most previous works based on this approach were published in the 1990s and 2000s, focused on the detection of main appliances with significant power consumption. On the other hand, probabilistic models provide a probability, used to make a decision about the occurrence of events. For that purpose, they require a training process to fix certain variables and learn some statistical models for appliances and environments. A particularly well-known case is the Generalized Likelihood Ratio (GLR) method [37,38]. Finally, matched filters are characterized by extracting the signal waveforms and correlating them with known patterns. Although in this case no previous training or knowledge is needed about appliances or environments, this approach often implies high sampling rates. Techniques such as envelope extraction, advanced filtering, Kalman filter and Hilbert transform are usually involved here in a post-processing stage to achieve suitable event detection and even energy disaggregation [39–41]. Clustering and bucketing techniques have also been used in event detection [42].

Event detection is often evaluated in terms of certain metrics [37]. The most relevant ones are the true positive rate, the true positive percentage, the total power change and the average power change. The false positive rate and the false positive percentage are less frequently used metrics. In many cases, all the above metrics are combined into one, usually called a score function, where the different parameters can be weighted according to their desired influence on the final performance of the event detector.

In [43] a probabilistic method, based on a Goodness-of-Fit (GOF) methodology, is compared with an expert heuristic method on the REDD database; the authors found that the GOF event detection methodology achieves the smallest number of false positives. In [44] an event-based algorithm is proposed to identify load signatures, according to trajectories of real, reactive and distortion power. In [45] a simple and fast event detection algorithm is proposed for the variations of the current signal. Its main advantage is the higher determination accuracy of the beginning of the events. On the other hand, the detected events are used in [46] to drive a finite state machine based on fuzzy transitions that disaggregates different appliances on signal sampled at 2 Hz.

More recently, Decision Trees (DT) and Long Short-Time Memory (LSTM) models are used for event detection [47], obtaining 98.6% and 92.6% detection accuracy, respectively. Furthermore, [48] presents a very simple detection algorithm used in a low-complexity NILM proposal, achieving suitable performance in six houses from the REDD dataset.

Another novel approach is presented in [44], where, after pre-processing the voltage/current signals to enhance the event change detection, that event is classified into certain categories of appliances by applying principal component analysis (PCA) to the PQD (active, reactive, and distortion powers) trajectories captured during the event change. This approach follows the trend of considering event transients as an additional feature in later appliance identification [2].

In general terms, if event detection is applied, it leads to the determination and selection of the most representative features for a certain appliance, so they can be used in a later identification. These features are particularly significant around the change of state (event), thus justifying the importance of successful event detection when necessary. Figure 3 presents a general overview of blocks involving such event-based NILM algorithms. The next subsection is dedicated to introducing these sets of features and how they are employed in appliance identification.

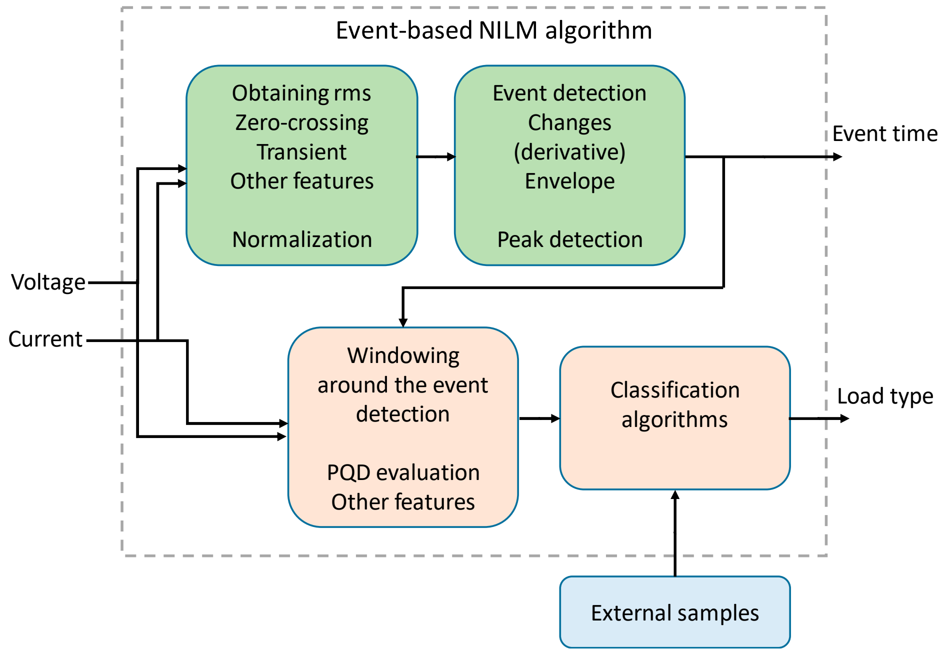

Figure 3. Block diagram of an event-based NILM algorithm to obtain event times and types of loads involved in each event.

2.3. Feature Sets

Energy disaggregation is achieved by identifying active appliances using a classification procedure. This way, a set of features must be available that should be closely related, on one hand, to the data collection and, on the other hand, to the methods that will be used for appliance identification. NILM features are highly dependent on the sampling rate used, which must be understood as the rate of the data output by the measurement device and that will be used for disaggregation, not the sampling rate of the current and voltage that constitute the device's input. A coarse division, using the threshold of 1 s for the sampling period, enables separating features between macroscopic or low-frequency and microscopic or high-frequency. A finer division proposed in [22] and used here divides the range of sampling rate into six classes: *very slow*, slower than 1 min; *slow*, between 1 min and 1 s; *medium*, faster than 1 Hz but slower than the fundamental frequency, *high*, from the fundamental frequency up to 2 kHz; *very high*, sampling frequency between 2 and 40 kHz; and *extremely high*, faster than 40 kHz. In this section we shall use this division, introducing the features used in representative NILM works and focusing on the most recent ones.

Most applications using very slow or slow sampling employ features obtained from the time series of power variables: voltage and current, apparent, active and or reactive power, power phase angle and power factor, etc. We shall assume in the following that the instantaneous values of the current voltage and power are denoted as i, v and p, respectively; their RMS values as I_{RMS} and V_{RMS}; the Active, Apparent and Reactive Powers as P, S and Q, respectively; the Total Harmonic Distortion as THD; and the Power Factor as PF.

The most employed feature is S, exclusively used in [26,49–51]; P and Q were employed in [52,53]. In a recent work [54] P and V_{RMS} measurements were used, sampled at 1 Hz, obtaining a high level of accuracy, even with varying supply voltages.

The various time series can be used in several ways. In a number of applications they are used directly, as it is the case of [55], where the P time series of the Individual Household Electric Power Consumption Dataset (IHEPCD) [56] is employed; in [57], where P and I_{RMS} are used, taken from the Almanac of Minutely Power dataset (AMPds); and [58], which employed the S and I_{RMS} series, from the AMPds and REED datasets. On the other hand, in [59] the power time series is segmented into sub-sequences that are used to compute the statistical moments of the load consumption, and in [60] the high-frequency current signal is subject to time-domain transformations.

Time-based features are typically used in eventless NILM algorithms, and the ones belonging to the low-sampling are typical steady-state ones. Within this sampling category, several other approaches have additionally been proposed. For instance, the authors of [61] split a power signal into "powerlets," which are the minimal group of short sequences (that represent the signal), obtained from Auto-Regressive models with eXogeneous inputs (ARX), characterizing each appliance. "Shapelets" [62] are similar, since every shapelet is a small subgroup of a time series.

Moving on to the next sampling category, the medium-rate range allows the characterization of transient electrical behaviour as appliances change state. While some transients may be visible from low-rate sampling, medium-rate sampling allows for much more detailed information on the transient shapes to be acquired. The authors of [63] proposed the use of seven features, extracted from the current waveform: number of spikes; number of semi-steady states (permanence in the state between 1 and 5 s); number of steady states (permanence longer than 5 s); total time in semi-steady states/length of the operating waveform; total time in steady states/length of the operating waveform; number of states per time window; and existence or nonexistence of repeating patterns.

As a time series often provides a high level of redundancy, increasing the model complexity and possibly leading to a low accuracy, it can be transformed into a frequency domain. This requires high sampling rates, however. Several features can be extracted from frequency information, such as harmonics [64] obtained with Fourier transform and multiple frequency bands using information entropy [65]. Due to its multi-resolution and time-frequency localization property, Discrete Wavelet Transform (DWT), is also employed [4,66]. Other transforms were also employed, such as the Stockwell Transform [67], and combinations of different techniques, such as DWT and harmonics [68], have also been proposed.

Very high rate data allows us to obtain much more detail about each appliance's waveform, either from the higher harmonics or from the shape of the raw current and voltage waveforms themselves. Two-dimensional voltage-current (V-I) trajectories, corresponding to the normalized steady-state voltage and current signals during one cycle, have already been considered as a likely method to identify load signatures in terms of features [69]. Generally speaking, the V-I trajectory presents unique characteristics for appliances with different working principles (resistive or inductive), which night be collected by wave-shape (WS) features, where it is possible to extract certain features, such as the looping direction, the enclosed area and the number of self-intersections. More recent applications [13] used additional features extracted from the V-I trajectory. Other features involving the shape of the waveforms [70] can be obtained from $p(t)$ and from the Instantaneous Admittance Waveform (IAW).

Higher-order harmonics can be obtained an using extremely high sampling rate, also enabling the capture of electric noise. In fact, the authors of [71] showed that the use of high frequency ElectroMagnetic Interference (EMI) signals enables the differentiation of similar switching mode power supplies in a home, which cannot be obtained with other techniques. Higher-order harmonics are employed in [18–20]. The first work is an extension of [65] for the simultaneous operation of various appliances, whereas the third one proposes to use, instead of the amplitudes of the current harmonics, the harmonic current phasors. The results show important improvements in performance when several combinations of appliances are considered. The second work uses the same type of features, although employing a different identification procedure. It achieves excellent performance for different combinations of small nonlinear loads. Unfortunately, as the data used are different and private, the performance of approaches [19,20] cannot be compared.

The features identified above can be computed from the main power feeder of the house. However, other information can be used. Variables such as time and duration of usage for a given event can be inferred just from the main power sensor [72]. In [73–75] the frequency of usage of an appliance, as well as the correlation of usage of multiple appliances, have been applied. This information can be extended with users' behaviour to express the uncertainty for each state of each appliance [76]. Occupancy, which can be measured or inferred in several ways, has been used to reduce the complexity of NILM algorithms [36]. For HVAC systems, external weather information has also been used [77].

It is not uncommon to use combinations of the features described above, leading in this way to hybrid approaches. For instance, [70,78] employ P, Q, IAW, p, eigenvalues and switching transient waveform, as features applied to a "Committee Decision Mechanism." More recently, feature selection algorithms have been employed to reduce an original dataset of 55 steady-state and 23 transient features to the 20 most relevant features [79].

2.4. Load Identification

Using the features described above, computed from the aggregate load, the objective here is to identify the appliances that are operating at a given time. This can be formulated as a not so simple optimization or classification problem, as four appliance models are usually considered:

- Type I—On/off devices: most appliances in households, such as bulbs and toasters;
- Type II—Finite-State-Machines (FSM): the appliances in this category present states, typically in a periodical fashion. Examples are washer/dryers, refrigerators, and so on;
- Type III—Continuously Varying Devices: the power of these appliances varies over time, but not in a periodic fashion. Examples are dimmers and tools.
- Type IV—Permanent Consumer Devices: these are devices with constant power but that operate 24 h, such as alarms and external power supplies.

This way, for the case of type II appliances, identification is not only translated into which appliances are active, but also their states. Additionally, some appliances can be replicated (for instance, two fridges might be available in a household), and it might be necessary to identify the operation/state of each replicated device using similar load signatures.

As a myriad of approaches has been proposed for this last step of NILM, the aim of this section is not to provide a deep review of the existing alternatives, but rather to point out important works on optimization and machine learning (supervised and unsupervised) algorithms used for load classification. Before introducing them, it should be noted that the performance of the different algorithms must be compared, using common datasets (please see Section 2.1) and similar performance criteria (please see [29,80] for a comprehensive list of performance metrics employed).

Optimization approaches use different methods to perform a combinatorial search. Examples are hybrid programming [81], genetic algorithm [82] and segmented integer quadratic constrained programming [83]. The main problem with this type of method, however, is their heavy computational burden. For this reason, most approaches belong to the so-called machine learning algorithms, involving both supervised and unsupervised methods.

Supervised techniques use offline training to achieve a database of information used to design the classifier (s). Some common supervised learning techniques that have been applied in NILM are (shallow) Artificial Neural Networks, mainly Multilayer Perceptron (MLP) [66,84], concatenated Convolutional Neural Networks (CNNs) [85], Deep Neural Networks [53,86–91], Support Vector Machines (SVM) [66,92], K-Nearest Neighbours (k-NN) [92–94], naïve Bayes classifiers [64,94,95] and, recently, linear-chain Conditional random fields (CRFs), which takes into account how previous states influence the current state and can deal with multi-state loads [96]. In [97] the performance of three classifiers, MLPs, Radial Basis Function (RBF) networks and SVM, with different kernels, is compared by employing odd harmonics (up to the 15th) from the current waveform, measured in a proprietary experimental setup. It has been concluded that all models provide excellent classification performance and correctly identified the existing devices, establishing the applicability of the proposed approach.

Unsupervised methods do not require any training prior to classification. This is an important advantage since, in this way, minimum effort is required from the user and the intrusiveness involved in building a database is reduced. Feature clustering, and the later labelling of each cluster with meaningful appliance names has been applied in [98,99]. A fusion of a supervised training process over available labelled datasets with an unsupervised training method over unlabelled aggregate data is proposed in [50].

The most recent unsupervised techniques applied to NILM belong to a family of methods that assume that the electrical signal is the output of a stochastic system, maintaining a representation of the whole system state, instead of dealing with individual events [100]. Examples are Hidden Markov Methods (HMM) and variants [14,26,83,100–105].

Another powerful option for solving data mining and signal processing problems is Graph Signal Processing (GSP). GSP applied to NILM [41,106,107] showed that this approach had remarkable performance related to the HMM approaches, offering additional advantages compared with conventional NILM methods, not requiring a training phase and obtaining good performance in low-sampling environments.

Tables A1 and A2, in the Appendix A, summarize the features employed, the load identification technique, the main contributions, the data source used, as well as the main application of the most important works referenced here. Notice that only two applications (HEMS and AAL) have been considered, identifying the context in which the referenced work was developed. All the other unlabelled references did not have a specific application in mind. No indication of performance was incorporated in the tables, as different data sources were used and, even in works using the same datasets, different houses/frequencies/number of appliances/performance criteria were involved, making a performance comparison not meaningful. For the sake of readability, references were ordered according to the sampling frequency employed and divided into two tables. The former considers approaches requiring data acquired up to medium sampling rates, and the latter proposals requiring higher sampling frequencies.

Having reviewed the steps comprising NILM methods and the most relevant and recent proposals in this topic, we will in the next two sections address their use in two important applications, HEMS and AAL.

3. Home Energy Management Systems

3.1. General Overview of HEMS

Buildings are actually the most demanding sector in terms of consumption, representing 40% of the total primary energy and accounting for 74% of the electricity sold in the USA [108]. For this reason, Home Energy Management Systems (HEMS) are becoming increasingly important to invert the continuously increasing trend in (electrical) energy consumption. Reviews on HEMS can be found in [109–114], as well as the works included in [115].

HEMS offer advantages to both residential occupants and electricity suppliers. For the former, HEMS are a means to reduce energy consumption in a household (or, perhaps more important, the electricity bill) while maintaining occupant's comfort. Notice that HEMS should not only perform real-time monitoring and scheduling of various home appliances, based on the user's preferences, but are also employed for the management of home renewable energy systems and energy storage systems, if available [115].

For the suppliers, the two-way communication enabled by smart grids allows much better management of the whole electricity network and the implementation of several mechanisms known as Demand Response. DR are those modifications in the electric usage of costumers, compared to other previous consumption patterns, as a consequence of the variations in the electricity cost over time, or incentives payments designed to ease a reduced electricity usage during those intervals with high prices, or suspected system reliability. Currently, DR are often grouped into two categories: price-driven and incentive or event-driven. The former can be sub-divided into several forms—time-of-use pricing, critical peak pricing, real-time pricing and peak-time pricing; while in the latter category we can find direct load control, emergency demand response programs, capacity market programs, interruptible/curtailable services, demand bidding/buyback programs and ancillary service market programs [112,116].

The first step of any HEMS is to monitor the electricity consumption of the several devices existing in a household. This can be achieved intrusively or using NILM techniques. In general terms, the non-intrusive approach is more popular both in academia and industry [3], mainly due to the fact that sub-metering installation is often expensive, difficult to upgrade, and involves certain privacy issues, thus avoiding any intrusive approach.

By reviewing previous literature [117], the availability of a disaggregated energy bill might be related to the reduction of domestic electricity consumption by 0.7–4.5% on average. This, as we know, is obtained with NILM techniques, by estimating the active appliances consumption. The availability of load disaggregation data via NILM can also enhance some other aspects, such as the load demand forecasting accuracy, and provide better criteria for companies to decide. For the grid operators, NILM additionally allows flexible resources management for demand response and tackling with uncertainty derived from renewable sources [118].

3.2. Use of NILM in HEMS

As mentioned before, a HEMS should schedule conveniently the electrical appliance's usage, as well as the electric energy flow, if renewable energy sources and/or storage are available at home. NILM techniques can also improve this overall goal, but some factors should be taken into consideration.

Firstly, it is important to classify appliances as non-deferrable (or non-schedulable) and deferrable (schedulable). The former comprises devices such as lighting, cooking or refrigerators, whose operation cannot be delayed. The latter includes washers and dryers, water pumps, and so on, whose period of operation can change according to the price of energy. Of special importance are HVAC systems, such as electric water heaters, and space heating/cooling systems, which sometimes are denoted as Thermostatically Controlled Loads (TCL). As NILM identifies the appliances that are active at any one time, it allows us to know in real time which schedulable and non-schedulable appliances are active.

Secondly, in previous sections we have essentially used NILM to identify appliances. For HEMS, electric consumption should also be estimated, and higher scheduling priority should be given to the appliances requiring high energy consumption. The level of consumption should also be estimated by the NILM module, and consumption can be predicted using forecasting methods. It is well known that HVAC systems actually are the largest part of energy consumption in buildings, and therefore correct HVAC control is important. Considering again the case of the USA [108], HVAC systems account for 35% of the primary energy and 45% of electricity consumed in buildings.

Thirdly, appliances' turn-on and turn-off times and time duration are important parameters for appliance scheduling. Note, however, that for Type II devices, these parameters should be available for all states of operation. The frequency of usage for each class of appliances can be obtained by means of these variables.

Finally, appliance flexibility is important for HEMS applications: This is a concept that is not universally accepted, with different forms proposed for its calculation. One definition, introduced in [119], is the possibility of the appliance getting involved in DR programs, taking into account not only the appliance characteristics but also the usage preferences from the user. Note that HVAC and power heaters are highly flexible loads, thanks to the inertia of an associated thermal storage and the need to fulfil some quality constraints [120].

The use of NILM techniques in HEMS has been increasing over the years. Perhaps the first proposal of using NILM in DR programs was in [121]. The authors analysed the requirements of DR and proposed a new NILM system with an enhanced load space and measurement approach.

Evolutionary multi-objective power scheduling using NILM techniques has been proposed for DR in [122]. Based on a real-home assessment of their proposal, the authors conclude that the automated mechanism is workable and feasible. They pointed out, however, that the power of each household appliance should be adaptively updated to improve the estimates of the daily power consumption. As their application did not include renewables, they proposed to include them, together with a forecasting mechanism for the electricity produced, in future work.

The same authors subsequently proposed a model of a residential consumer-centric Demand-Side Management [123], employing NILM, achieving, in simulations, a significant reduction (14%) of the Peak-to-Average Ratio (PAR). For future implementations, the authors proposed employing edge/IoT-based computing, in order to improve cloud computing technologies [124]. In a more recent work [125], the same group focused on the improvement of NILM classification, employing for that Particle-Swarm Optimization to the design of the ANN classifier.

Edge-computing is also advocated in [126]. The authors implemented a load-shifting mechanism, which allows non-time-constraint applications to be moved from rush hours to off-peak hours. This implies a reduction in the peak demand of the household, while maintaining the householders' comfort. Employing day-ahead pricing information, their system is composed of five modules: *energy production*, which consists of solar radiation and air temperature predictors, used to forecast the PhotoVoltaic (PV) energy generation; *solar energy management*, which manages the flow of energy between the grid, PV and battery storage; *NILM module*, which not only disaggregates the energy and estimates consumptions, but also computes usage patterns and features of each appliance; *classifier*, which labels the appliances as schedulable or not and, in the former case, passes this information, together with adjustable ranking, to the next module; and *appliances scheduling*, which, based on the information received from the previous module for deferrable appliances, proposes a dynamic algorithm to determine which state sequences in a certain appliance provide a lowest electricity cost over time. Using two test scenarios in a real testbed, they concluded that the use of the proposed HEMS achieves reductions of electricity consumption and cost of 73% and 82%, respectively. They pointed out that a better usage of solar energy could be obtained by merging solar energy forecast and appliances scheduling schemes.

The authors of [76] have addressed appliance-level dispatch with smart plugs for HEMS, employing in their application the D'hulst concept of appliance flexibility. Assuming that each appliance operation can be divided into states, these are estimated from the appliance power consumption using a combination of the minibatch k-means method [127] and the X-means technique [128], followed by an agglomerative clustering approach. User behaviour is characterized by different variables, such as state turn-on and off times, state on-duration, state energy consumption, state power value, etc.; to consider uncertainty, the features are often modelled as Gaussian distributions.

In operation, each state is assigned to an appliance type according to a k-nearest neighbours' classifier, where the likelihood is determined by means of the Hellinger distance. The appliance type is derived from weighted voting, where the weight is defined by the state's power consumption over a certain time T.

Appliance flexibility depends on the DR application and thus is a function of the start time, duration, controllability, user behaviour and power. Based on the desired DR event, the DR program is chosen. Then the HEMS searches for and selects suitable appliances. Finally, the flexibility of the selected appliances is calculated and inserted into a priority list and the appliances are dispatched according to that list. This approach has been evaluated on a REDD dataset, obtaining an excellent classification performance.

Finally, it is worth noting that new NILM methods have been proposed with application in HEMS in mind. This is the case, for instance, with [129], where, using only a single active power sample acquired at the general entry point with a rate of 1 Hz, it is feasible to distinguish turned ON appliances, their operating modes, as well as power consumption, together with the amount of solar power. In a more recent work [130], the authors extended their previous solution and were able to properly forecast the active power demand of a set of five households.

4. NILM in Ambient Assisted Living

4.1. AAL General Overview

Ambient assisted living (AAL) includes products and services for the physical independence of elderly people. In fact, the current increase of life expectancy has become a public health priority, mainly in developed countries, and most of the recent technological advances are used for constituting smart environments to assist the elderly. There are three important aspects or actuation levels to consider in AAL:

1. Using specific sensors (e.g., wearables, ambient sensors or even smart meters) to measure ambient (environmental) or physiological (person-related) parameters.
2. Monitoring a particular parameter of activity (e.g., physiological signals, movements or Activities of Daily Livings - ADL)
3. Taking appropriate decisions or recommendations (e.g., monitoring health deterioration in the long term or producing alerts for short-term intervention).

Figure 4 shows a general overview of current home monitoring systems in terms of accuracy and scalability. In general, accuracy is inversely proportional to scalability and to intrusiveness (and consequently to the grade of acceptance of the systems).

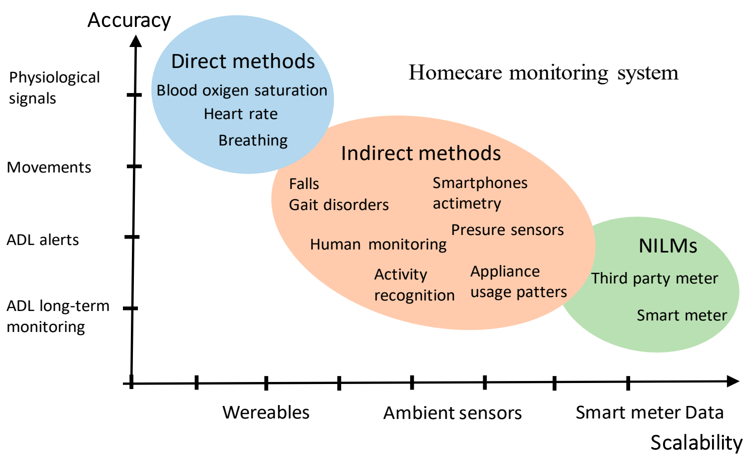

Figure 4. General overview of current homecare monitoring systems for AAL depending on accuracy and scalability (adapted from [131]).

As can be observed in Figure 3, four levels of accuracy have been considered depending on the outputs of the home monitoring system: ADL long-term monitoring, ADL alerts, movements and physiological signals. Scalability, strongly related to intrusiveness, depends on the kind of sensors needed (wearables, ambient sensors and smart meters). Direct methods may diagnose the health or monitor the activity directly by evaluating some physiological parameters; on the other hand, indirect ones can derive it from a parameter that may involve the health status or activity.

Physiological signals related to direct monitoring methods are often blood oxygen saturation, heart rate and breathing [132]. The acquisition of these signals is normally very accurate, but difficult to scale since the corresponding transducers required to be attached to the body. Accelerometers and gyroscopes in wearables and smartphones allow movement to be estimated, and can detect falls and gait disorders [133], but their acceptance is still reduced as users must carry them for proper operation.

Most of the approaches for AAL are based on ambient sensor on heterogeneous high-density sensor networks to perform Activity Recognition. These systems have to deal with overlapped activities; heterogeneous activity duration; the deployment of a complex and sometimes intrusive WSN; and with the need of a supervised training process for each individual household [134].

With a very low intrusiveness, a new approach to monitor ADLs by means of electrical signatures of appliances coming from plug-meters was proposed in [27]. Human activity can be inferred from the usage pattern of appliances, as they are strongly connected to daily activities. In this case, the activities monitored were food preparation and eating, hygiene and elimination. It should be noted that any labelling task, such as the weight of appliances on the activity and finding the activity duration, depends on the particular person monitored. Electrical events are mapped over daily activities using a k-means neighbours' classifier.

In a similar way, other works also proved the correlation between the appliance usage patterns with ADLs [135]. Here, the authors used the Latent Dirichlet Allocation (LDA) method to map appliance events with ADLs. The sensor density could be minimised, and the hardware cost and complexity reduced (of particular importance in large deployments). A major issue to be solved was again related to the overlapping of tasks and their heterogeneous duration.

The authors of [136] also proposed an approach to monitor the behaviour of the elderly based on detection of the usage of certain home appliances. In this case, the system is based on a smart meter that periodically acquires the global energy consumption in the house, associated with some smart plugs for punctually monitoring specific electrical devices. Although the system is simple and low-cost, it can detect unusual behaviour in the elderly.

All these methods are intended to measure health deterioration and are deployed for long-term monitoring. There are other methods that produce alerts during short-term monitoring of a particular health aspect. These only use the appliance usage pattern instead of inferring ADLs. For example, a relevant variable to detect changes in routines could be monitoring the kettle or the TV set [137]. Another example in [138] is the usage patterns of the kettle and fridge during the night to detect sleep disorders.

4.2. Use of NILM in AAL

There are several relevant health features that can be inferred from data obtained with smart meters or third-party devices installed as unique sensors at home (after applying energy disaggregation algorithms). These features can be inactivity, sleep disorders, memory issues, variations in activity patterns, low activity routines, occupancy and unhealthy living [139]. The main advantages of using smart meters are their flexibility, low cost, ubiquity and ability to generate data over time.

Figure 5 shows a general diagram that most systems follow when using NILM for AAL.

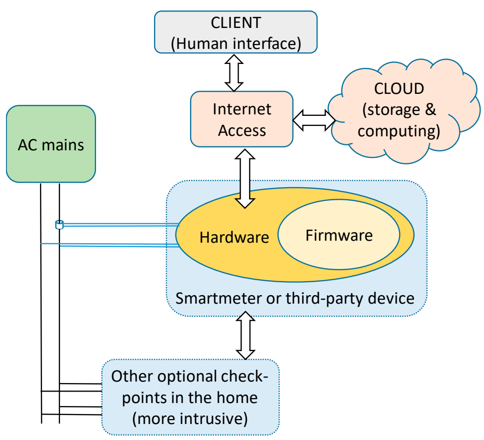

Figure 5. General diagram of systems that use NILM in AAL.

Applications can include launching alerts to caregivers or relatives whether unusual activity patterns are recognised [140], or even in a further extension, monitoring the progress of some treatments or living conditions (such as the use of specific devices). For instance, in [131] a unique power usage profile is derived for every appliance. The usage was categorized into usual and unusual patterns. Such appliance training methods are common in NILM, and the major challenge is to detect a wide range of devices with enough accuracy.

One of the first works on this topic, using only disaggregated data from a single home sensor, can be found in [141]. The system was developed with the main goal of determining load signatures of appliances to detect daily activities in a smart home. It was based on steady-state operations and signatures of appliances extracted with a single power analyser. Afterwards, in [101] the authors proposed the disaggregation of data coming from smart meters in order to monitor health. They employed an iterative time-dependent HMM to disaggregate appliances, according to a priori knowledge of the activities of people at home. After the disaggregation, every appliance was bounded to a certain monitored activity. Other studies, such as the one presented in [142], made use of a smart meter, which periodically measured the global energy consumption in the house, combined with some smart plugs for punctually monitoring specific electrical devices. The goal was also to track elderly behaviour by detecting the usage of home appliances.

Another work on this topic is [131], which also proposes the use of only smart meter data to develop sustainable models for healthcare in smart homes, with very low intrusiveness, massive deployment and reduced cost. The usage patterns of appliances are used to evaluate the behaviour of elderly people and to determine when a subject has modified their routine. The system provides a daily score of normality regarding the regular behaviour (obtained from previous statistical analysis, using Dempster-Shafer theory on the disaggregated consumption of several homes). When this score was lower than a predetermined threshold, an alert could be derived. The same authors, in [141], present an interesting study of NILM classification, depending on disaggregation accuracy and sampling frequency, and of homecare monitoring system classification according to accuracy and scalability (where the systems based on NILM are less intrusive and more scalable, but at the cost of accuracy).

Despite the intrusiveness of these systems being low, privacy can still be an important issue. The authors of [143] analysed the electricity consumption of more than 5000 households over a 18-month period and deployed several machine learning methods to forecast home occupancy in the short and long term. The results revealed that the present and future occupancy status of households can only be established with high confidence based on smart meter data. In this context, it is also significant to secure the communication and storage techniques and equipment related to smart meter data, as well as to fulfil the corresponding legislation about how to treat such data.

5. Guidelines for Future Research

Although NILM methods are becoming recognized tools for home energy management systems and for ambient assisted living applications, several aspects still deserve further research.

NILM has been an active topic of research, mainly due to advances in computational intelligence and sensing technology. Although NILM has been around for 30 years now, only recently has the technology made its way into public domain, due to high equipment cost, which hinders the scalability, and a lack of disaggregation accuracy [6]. Future research and development in this area should focus on the solutions to these problems.

Current NILM methods work well for two-state appliances, but it is still difficult to identify some multi-state appliances, and even more challenging with continuous-state appliances. Typically, supervised methods are able to generalize better to unseen scenarios, e.g., different houses, than unsupervised techniques. However, they require a huge database and an off-line training phase. The use of semi-supervised algorithms, requiring some labelled training examples, might be a mechanism to achieve "low-cost" generalization accuracy. Another aspect would be using special features, such as time of day, temperature, frequency of appliance usage, and so on, together with more classical features obtained from steady and transient signatures. Notice that some of these features are already employed in HEMS applications.

Finally, the different techniques should be compared using common datasets. Nowadays, there are several public datasets available; however, these only cover developed countries. Regarding the established performance criteria, they should also consider the complexity of the solution, both from the software and hardware points of view, as well as the level of load usage and their usage patterns.

Focusing now on the application of NILM in HEMS, several aspects are worth mentioning. First, the performance of NILM techniques should be considered according to the final impact and cost; e.g., a classification accuracy improvement in appliance identification from 85% to 87% can be translated, in HEMS operations, into a much smaller reduction in electricity consumption (or in the electricity bill), requiring, however, much more complex hardware and/or software solutions.

Research in HEMS should also consider the absolute improvement that the different types of apparatus might achieve in the final electricity consumption. A 5% improvement in lighting, for instance, has much less impact than the same reduction in HVAC equipment consumption. For this reason, HVAC equipment should not only be efficiently scheduled by the HEMS, but its real-time control during their periods of operation should be as efficient as possible. The authors of [142], in a study of a large appliance consumption database in Sydney, Australia, studied the real influence of air-conditioners on summer demand peaks. By clustering the load profiles and proposing load control strategies, they estimated that 9% of the total peak demand could be reduced. Model-Based Predictive Control (MBPC) is the control technique that has the largest potential of energy reduction for HVAC systems [144]. By employing MBPC approaches such as the one detailed in [145], allowing user-defined schedules and thus being suitable for HEMS, and allowing different levels of occupants (thermal) comfort to be considered, the potential for savings in home electricity consumption is large.

As reported before, the concept of appliance flexibility and its calculation deserve further research. Usage patterns should take into account the type of day, such as weekday, weekend or bank holiday; season and/or outside weather information (HVAC systems usage is strongly correlated with average outside air temperature and, therefore, with the season); associations of appliances (for instance, cookers and range hoods are typically used together); and, obviously, occupancy and occupants' preferences. Taking all these factors into consideration is not, however, an easy task.

The existence of disaggregated energy achieved by NILM allows us to obtain better forecasts of energy consumption, which, together with the better forecasts of electricity produced by renewables, allows for better appliance scheduling and flexibility for DR schemes. In this way, improvements in HEMS also require research on the forecasting methods applied to the variables at stake. As examples, as equipment usage depends on household occupation, the authors of [146] proposed a method based on dynamic genetic programming to detect, and forecast, the occupancy of residential buildings, starting with their smart meter data. Several techniques for short-term load forecasting can be found in [147] and in the works included in [148]. Short-term forecasts of the electricity produced by PVs require forecasts of solar radiation and atmospheric air temperature, the former being the most difficult due to the existence of clouds. In this time range, machine learning methods are the most used techniques [149]. There is already commercial instrumentation available that is capable of producing not only measurements, but also forecasts of weather variables [150].

Regarding AAL, better activity recognition needs to be achieved, requiring smart meters or third-party devices with higher sampling frequency. The regulations on the way smart meter data are stored and shared with third parties in health contexts must be adapted from the current situation. The level of fault tolerance in critical health uses is much lower than in those applications about standard energy metering, and, consequently, possible responsibility should be clearly defined in case of failure.

In addition, in AAL more advances and contributions are necessary in the field of linking patterns of energy use to health conditions. That implies the work of multidisciplinary teams, involving computing and engineering people with specialists and practitioners working in health and care (with new ethical issues). Novel use cases should be proposed and tested with a representative population. Finally, it is important to consider issues concerning user acceptance of smart meters applied to health domains and compared with other tele-healthcare approaches.

6. Conclusions

Although it was proposed nearly 30 years ago, NILM technology has only made its way to public domain in more recent years, mainly due to advances in computational intelligence, sensing technology and the Internet of Things, smart grids and demand response energy programs. Since then, the NILM field and its applications to home energy management systems and ambient assisted living have evolved rapidly.

We hope that this review, focusing on proposals that appeared recently in the literature and pointing out new research issues related to the techniques and their applications in HEMS and AAL, is able to foster further interest in this technology.

Finally, we should remark that NILM techniques have the potential to be used for other applications that are outside of the scope of this paper. Examples are, for instance, recommender systems for energy efficiency, whether for individuals [151], companies or governments, or fault diagnosis applications [146,152].

Author Contributions: All authors contributed equally to the review.

Funding: This research was funded by Programa Operacional Portugal 2020 and Programa Operacional Regional do Algarve (grant 01/SAICT/2018/39578); Fundação para a Ciência e Tecnologia grants SFRH/BSAB/142998/2018, SFRH/BSAB/142997/2018 and UID/EMS/50022/2019, through IDMEC, under LAETA; Junta de Comunidades de Castilla-La-Mancha, Spain grant SBPLY/17/180501/000392; and the Spanish Ministry of Economy, Industry and Competitiveness (SOC-PLC project, ref. TEC2015-64835-C3-2-R MINECO/FEDER).

Conflicts of Interest: The authors declare no conflict of interest.

Acronyms

AAL	Ambient Assisted Living	ILM	Intrusive Load Monitoring
ADL	Activities of Daily Livings	IoT	Internet of Things
ANN	Artificial Neural Networks	k-NN	K-Nearest Neighbours
ARX	Auto-Regressive models with eXogeneous inputs	LDA	Latent Dirichlet Allocation
CNN	Convolutional Neural Network	LSTM	Long Short-Time Memory
D	Distortion power	MLP	Multilayer Perception
DBSCAN	Density-based spatial clustering of applications with noise	NILM	Non-Intrusive Load Monitoring
DR	Demand Response	PAR	Peak-to-Average Ratio
DT	Decision Trees	PCA	Principal Component Analysis
DWT	Discrete Wavelet Transform	PSQ	Active, Apparent and Reactive Powers
EMI	ElectroMagnetic Interference	PF	Power Factor
FSM	Finite-State-Machines	PV	Photovoltaics
GLR	Generalised Likelihood Ratio	QDA	Quadratic Discriminate Analysis
GOP	Goodness-Of Fit	RBF	Radial Basis Function Network
		RF	Random Forest
GSP	Graph Signal Processing	RMS	Root Mean Square
HMM	Hidden Markov Model	SG	Smart Grids
HVAC	Heating, Ventilating and Air Conditioning	SVM	Support Vector Machines
HEMS	Home Energy Management Systems	TCL	Thermostatically-Controlled Loads
HMM	Hidden Markov Methods	THD	Total Harmonic Distortion
IAW	Instantaneous Admittance Waveform	WS	Wave-Shape

Appendix A

Table A1. Main characteristics of selected NILM techniques with very low, low and medium sampling rates.

Ref #	Sampling Rate	Features	Load Identification	Contribution	Data Source	Application
55	Very Low	P	Source Separation via Tensor and Matrix Factorization (STMF)	Analysis of the seasonal trend patterns using	IHEPCD	HEMS
57	Very Low	P and I_{RMS}	Maximum a Posteriori (MAP) probability	Usage of MAP in NILM	AMPds	
75	Very Low	Power consumption and appliance consumption patterns	Fuzzy c-Means Clustering and Dynamic Time-Warping	Iterative disaggregation approach based on appliance consumption pattern	AMPds	HEMS
87	Very Low	V-I trajectory	Deep Neural Networks	Learning based on multiple layers	REDD and Pecan Street	
88	Very Low	Power features	Neural networks (autoencoders)	Unsupervised anomaly detection of building operational data	Experimental data	HEMS
49	Very Low and Low	S	Discriminative Disaggregation Sparse Coding (DDSC) and Source Separation Via Tensor and Matrix Factorizations (SMTF)	NILM interpreted as a source separation problem	REDD	HEMS
83	Very Low and Low	Power features	HMM with Viterbi decoding	Consider the identification problem as a segmented integer quadratic program, together with constraint programming	REDD	
10	Low	Voltage, current, power	DBSCAN followed by QDA	Correlates occupancy events and power changes	Private data	HEMS
36	Low	Power consumption and occupancy information	Modified Combinatorial Optimization	A location-aware energy disaggregation framework (LocED) proposed to derive accurate appliance level data.	DRED, REDD	HEMS

Table A1. *Cont.*

Ref #	Sampling Rate	Features	Load Identification	Contribution	Data Source	Application
41	Low	P	GSP compared with several other methods	Mitigates the effect of measurement noise and unknown loads in	REDD and REFIT	
50	Low	S	HMM	Hybrid approach, combining supervised and unsupervised methods	TRACEBASE and REDD	HEMS
52	Low	P and Q	MLP	MLP parameters tuned by PSO	Laboratory data	
53	Low	P and Q	LSTM, denoising autoencoders, specific Deep NN architecture	Comparison of 2 Deep NN architectures against combinatorial optimization and Factorial HNN	UK-DALE	
53	Low	P and V_{RMS}	Karhunen-Loève Spectral Decomposition	Real-Time NILM working under severe voltage fluctuations	Private Data	
61	Low	Powerlets	Optimization with several priors	Collects power signatures (powerlets) in a dictionary, using optimization to solve	REDD	
85	Low	Power features and WS	HMM, Deep Neural networks.	Disaggregation based on Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) and advanced deep learning. Novel signature model based on multistate appliance case	UK-DALE and REDD	
99	Low	Power features	HMM	Adaptive approach for estimating devices based on HMM	REDD	
100	Low	Power features	Factorial Hidden Markov Models and Iterative Subsequence Dynamic Time Warping	Hybrid Signature-based Iterative Disaggregation (HSID)	AMPds	

Table A1. *Cont.*

Ref #	Sampling Rate	Features	Load Identification	Contribution	Data Source	Application
102	Low	Power features	Hierarchical HMM and particle filtering	Modelling of multi-mode appliances by HHMM	REDD	
104	Low	P	Graph signal processing Event detection	No training required for NILM	REDD and REFIT	
128	Low	P trace and usage pattern profiles	MAP criterion	Incorporates appliance usage patterns for load identification and forecasting	TRACEBASE and REDD	HEMS
15	Medium	Parameters of current transients	KNN applied to examples selected by Cross-Validation strategies	Identification considering the influence of voltage variations	Laboratory data	
24	Medium	Features obtained from the PSD of the power signal	Gaussian Process Classifier	Use of multiple models in a committee voting mechanism	Laboratory data	HEMS
59	Medium	Current Duty Cycle, Slope of On-State, Variance of On-State, Zero Crossing and combinations	K-NN and Naive Bayes, DT and Adaboost classifiers	Compares different features and different classifiers	Private Data	
63	Medium	7 features extracted from the I_{RMS} FSM representation	Several supervised classifiers	Efficient method to represent long-term raw current waveforms of electric loads by FSMs.	Public Database	

Table A2. Main characteristics of selected NILM techniques with high, very high and extremely high sampling rates.

Ref #	Sampling Rate	Features	Load Identification	Contribution	Data Source	Application
119	Low and High	I_{RMS}, Average Displacement power PF, Fundamental Phase angle Average THD, and the 3th and 5th current harmonics	Self-Organizing Mapping (SOM)	Integration of NILM into a DR system	Private data	HEMS
14	High	Real and Reactive Power and Current Harmonics	Variant of HMM, against Particle Swarm Optimization (PSO)	New HMM algorithm to detect appliances and their states, for DR applications	Laboratory data	HEMS
64	High	Steady-state current harmonics and the rate of change of the transient signal after an event	Rule-Based and Naïve Bayes Classifier	Method with small complexity	Laboratory Data	
65	High	Shannon and Renyi entropies and spectral band energy for specified frequency bands of the current spectrum	Linear search of a database	Simple method for the configuration of robust and distinct load signatures	Private data	
66	High	Wavelet Transform Coefficients (WTC)	MLP	Number of WTCs reduced using Parseval's theorem	Simulation and Laboratory Data	
67	High	Maximum magnitude of the first to eighth harmonics of current, obtained by Stockwell's Transform	Ant Colony Optimization	Delivers good results for Multiple Loads	Private Data	
123	High	P and D	ANN designed using PSO	Integration of NILM into a Demand-Side Management system	Private data	HEMS
5	High and Very High	V-I Trajectory Images	Siamese ANNs, followed by DBSCAN	Detects unidentified appliances	PLAID and WHITED	
139	High, Very High	P, Q, D trajectories	PQD-PCA	Excellent classifier performance, compared with other approaches.	PLAID and BLUED	AAL

Table A2. *Cont.*

Ref #	Sampling Rate	Features	Load Identification	Contribution	Data Source	Application
12	Very High	current *WS*, *P* and *Q*, harmonics, quantized waveforms, V-I binary image	K-NN, Gaussian Naive Bayes, logistic regression classifier, SVM, linear discriminant analysis/QDA, DT, RF,Adaptive Boosting	Compares the discriminative power of different features and the performance of different classifiers	PLAID	
13	Very High	V-I Trajectory	SVM	Introduces features based on the V-I trajectory	REDD and laboratory data	
42	Very High	Current Harmonics, V-I trajectory, and *PQD*	MLPs	Uses DBSCAN for Event Detection, followed by MLP classification	BLUED and laboratory data	
60	Very High	Current (*i*)	DWT and ensemble of DTs	Investigates the effect of DWT order and the DTs number in the ensemble	Simulated Data	
69	Very High	*WS* metrics	MLPs, SVM and AdaBoost	Applicable for challenging scenarios such as multiple near-identical appliances	REDD	
77	Very High	55 steady-state and 23 transient features	Random Forest	Proposes a feature selection algorithm	PLAID	
89	Very High, Extremely High	V-I trajectories	Convolutional neural networks	CNN applied to loads identification	PLAID and WHITED	
18	Extremely High	Current amplitudes of the fundamental frequency and the 3rd and 5th harmonics	Linear search of a database	Extension of [65] for simultaneous operation of various appliances	Private data	
19	Extremely High	Current vectors (phasors) of the fundamental frequency and the 3rd and 5th harmonics	Naïve Bayes Classifier	Able to identify simultaneous combinations of small nonlinear loads	Private data	
20	Extremely High	Current vectors (phasors) of the fundamental frequency and the 3rd and 5th harmonics	Linear search of a database	Extension of [18] considering Harmonics phasors, instead of amplitudes	Private data	
71	Extremely High	EMI signals	K-NN	Able to differentiate similar switching-mode power supplies	Private Data	

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