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State of art overview of Non-Intrusive Load Monitoring applications in smart grids

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ABSTRACT

Nowadays, non-intrusive load monitoring (NILM) systems represent an effective alternative to monitoring individual appliances' consumption, avoiding the costs and spatial constraints imposed by the installation of additional sensors. Modern artificial intelligence algorithms, such as machine learning algorithms, make it possible to split the aggregate power absorption profile of a user into the individual power absorption profiles of the main household appliances. However, there is still no full awareness of how these systems can be used effectively and in what situations they can provide consistent support.

This paper illustrates the most promising management, diagnostics, and automation activities that can be carried out with the help of an efficient NILM system, referring to the most significant works in literature. A discussion of challenges and future research directions is also provided.

1. Introduction

A non-intrusive load monitoring (NILM) system, also called energy disaggregation systems, allows to obtain information relating to the power absorption of individual appliances connected to a user, through the use of voltage and current transducers positioned at its connection point to the grid [1,2], starting from the measurement of aggregate power, or sometimes even from the current alone [3,4].

The first NILM system was proposed by Hart in 1985 [5], consisting of an algorithm based on the identification of events through edge detection and clustering.

Hart proposed a classification of appliances based on their operating states:

1) ON/OFF appliances, e.g. lamps, toaster, etc.;
2) Multi-state appliances, with a finite number of operational states, also called finite state machines (FSM);
3) Continuous variable appliances, i.e. appliances that absorb a variable amount of power without a fixed number of states, such as the drill;
4) Permanent consumer appliances, i.e. appliances that remain active for weeks or days absorbing power at a constant rate.

Clearly, his approach, although it was functional in certain situations, showed significant limitations since a multi-state appliance had to be managed as a set of distinct ON/OFF appliances, while the continuous variable appliances and the permanent consumer appliances could not be detected correctly. Since then, many researchers have tried to provide better solutions to Hart's one, both by measuring different quantities in addition to the active power and by using different algorithms [6–8].

The interest in this type of monitoring system has been favored, especially in recent years, from the introduction of the smart home and, at the same time, from the development of increasingly performing artificial intelligence algorithms. Traditional disaggregation methods are inferior to those based on artificial neural networks due to their poor accuracy, complex operational feasibility, and manual feature extraction requirements [9].

Over the years, the use of deep learning algorithms [9,10] has allowed to overcome many of the limits that have characterized previous methods, thus allowing measurement systems to adapt to homes never seen during the training phase. Furthermore, in terms of accuracy, systems based on convolutional neural networks [11] have overcome other state-of-the-art methods such as those based on Factorial Hidden Markov Models [12,13].

Current knowledge of NILM systems allows to create reliable monitoring systems that can be installed both inside electrical panels and remotely. The first case concerns an embedded microcontroller that acquires the signals and processes them locally. In the second case, the data is transmitted to a cloud by the smart meter; this data will be processed and then stored or displayed through a specific user interface [14].

When non-intrusive monitoring systems are required, the disaggregation accuracy and the possibility of installing the system without training on the specific user (for example houses never seen before) are two fundamental aspects. However, in some applications, the ability to recognize a broader range of appliances by accepting a (brief) training phase may be more critical [15]. In still others, real-time status detection of devices may be more critical than its absorbed power profile [16].

The results of a NILM system can be used in various applications, the purposes of which are not limited to information aimed at saving energy. They can be used to provide timely alarms that allow the user to avoid catastrophic failures on their appliances, predict consumption peaks in Smart Grids, monitor the normal activities of daily living (ADL) and older people's conditions [17]. In the remainder of the paper, several applications involving non-intrusive monitoring systems will be discussed, and the characteristics that these systems must have to perform these tasks in the best possible way will be highlighted.

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2. Energy management system for microgrid and smart home

An energy management system (EMS) is a technology platform consisting of hardware and software that allows the user to monitor the use and generation of energy and manually control and automate energy within a house. Consumers can use EMS to reduce electricity consumption and consequently reduce utility bills while maintaining a high comfort level.

The first step of any EMS is to monitor the electricity consumption of the different devices within a home. It can be achieved through intrusive monitoring or using NILM techniques. In general, the non-intrusive approach is more prevalent in academia and industry, mainly because the sub-metering facility is often expensive, difficult to upgrade, and involves some privacy concerns, therefore any intrusive approach. EMSs need to properly plan the use of household appliances and the flow of electricity when renewable energy sources and storage are available locally. NILM techniques can improve this overall goal, but appropriate considerations need to be made.

First of all, it is crucial to classify devices according to their schedulability or non-schedulability [18]. The former includes lights, kitchen appliances, or refrigerators, whose operation cannot be delayed. Schedulable household appliances include, for example, washing machines and dryers, water pumps, and so on, the operating range of which can be suitably shifted based on the price of energy. Since NILM identifies the devices active simultaneously, it allows us to know in real-time which devices, programmable or not, are active, especially in those apartments that are not born "Smart".

A NILM system must provide information on the electrical consumption of individual appliances, not just information on their status, to serve an EMS. It allows you to give higher programming priority to appliances that require high energy consumption. Obviously, in addition to consumption, essential parameters for device management will be the switch-on and switch-off times and the operating interval of the devices. These can also be deduced through the use of NILM systems. It is possible to obtain the frequency of use for each class of equipment, using these variables, In Refs. [18,19], the authors propose an EMS to minimize household electricity costs while meeting their needs (mainly in terms of comfort and meet safety requirements, for example).

3. Demand response in smart grids

Demand Response (DR) is the active management of energy demand, which is a product created to allow commercial and industrial consumers to modulate the energy demand, increasing or decreasing, as market conditions change. The DR revolution consists precisely of the possibility of generating revenues for consumers. In simple terms, therefore, one is rewarded for one's flexibility.

In [20] an algorithm was proposed for calculating the flexibility of the different household appliances for DR purposes. The network operator starts by signaling to the aggregator that a DR will be required in a given time window.

In the proposed system, the aggregator, considering the related incentive, evaluates the availability and the flexibility foreseen according to the data made available by the users, coming from a NILM system. With a response based on these evaluations, the aggregator proposes the offer to the network operator and waits for the activation order. At this point, the client is provided with the proposed planning and the related incentive.

Furthermore, in Ref. [21] a study was conducted to evaluate the potential of NILM techniques to support Smart Grids in the analysis of:

1) the possibility of deferred use of household appliance loads during the management of consumption peaks;
2) the ability to recommend discount offers or time-of-use pricing programs to incentivize customers to defer part of their electricity demand to periods of lower overall demand;
3) which customers show greater potential and should be targeted first.

4. Appliances anomaly detection

NILM systems represent a good solution for monitoring different appliances without the need to sub-monitor them. The ability of these systems to accurately detect anomalous behavior of the various monitored appliances has not yet been recognized. In order to fulfill this task, the NILM systems, in addition to producing an accurate estimate of the energy consumption of the appliance, must also be able to faithfully reproduce its power absorption profile, which other anomalies identification systems will then analyze.

In [22], a study about the ability of state-of-the-art NILM systems to identify the anomalous behavior of household appliances inside an apartment was presented, starting from the aggregate power measurement provided by the smart meter. The study focuses on air conditioners and refrigerators, as both are common household appliances, with high consumption and based on a compressor that determines their main energy consumption.

Therefore, any failure in the compressor itself or in any other part affecting it is reflected in the absorbed power profile. The anomalies were manually entered into the aggregate power profiles to verify if the NILM system could detect them correctly. These anomalies consisted of lengthening the duty cycle and increasing the frequency of the ON/OFF cycles, typical reflections of classic failures that can arise in air conditioners and refrigerators. Subsequently, an anomaly detection algorithm was proposed based on measuring the standard deviation of average energy consumption during an ON/OFF cycle within particular time bands.

The disaggregated power profiles obtained from the NILM system were subjected to the anomaly detection system. The performances were compared with the results obtained by subjecting the sub-measured profiles to the same algorithm. The authors concluded that to identify appliances anomalous behaviors correctly, a NILM system must guarantee a disaggregation error of less than 0.1 for the appliances considered.

5. Condition-based maintenance

Condition-based maintenance (CBM) conducts maintenance activities based on data collected from equipment condition monitoring, unlike traditional maintenance performed on a scheduled basis or in the event of a failure. The data is used to warn of failure so that equipment repair or replacement can be scheduled. CBM aims to detect minor failures before they turn into major failures. These defects, often invisible to observers, could be identified by analyzing electrical power measurements. A NILM system must necessarily detect and identify both the signatures of the load and its anomalous behaviors to be an effective CBM tool. Furthermore, the data should be presented as an intuitive decision aid for users.

In [23], a NILM system was built to monitor energy and failures in electromechanical systems aboard the United States Navy to minimize the number of sensors to monitor the loads in the on-board electrical system. Such a system monitors loads such as motor, pump, engine, and generators via the NILM dashboard [24]. These loads are all ON/OFF, except for a diesel oil purifier, which is an FSM, and each state is considered separately.

The NILM systems installed on these ships have two primary objectives: to identify the operational programs of the apparatuses to give a better awareness of the situation to the operator; to detect anomalies to improve system operation. An event-based NILM system was used to achieve these objectives: a first algorithm detects events, and an artificial neural network, trained to recognize signatures, identifies anomalous situations starting from the active and reactive powers measured on the three phases. It allows the NILM to detect load events, which occur when the equipment switches from on to off state, thus generating the operating schedules of the individual equipment. In this application, therefore, the NILM system is required to notify in the shortest possible time the change in status of the loads monitored from OFF to ON and vice versa.

6. Disaggregation of regional demand

An attempt was made to adapt the NILM technique for monitoring distributed energy resources (DER) connected to regional substations.

In [25], the NILM has been applied to the disaggregation of regional demand into its traditional load, flexible load, and distributed generation components. The power supplied by distributed generators, such as photovoltaics or small wind turbines, is considered a negative load. Therefore, the power obtained as the sum of the total load and the distributed generation allows multiple disaggregation solutions, consisting of different combinations of distributed loads and generators. Consequently, the use of NILM systems to separate the two contributions leads to non-unique solutions. To overcome this problem, the authors propose a three-step approach:

1) The first step involves the disaggregation of the traditional load from the aggregate output power from the substation through a NILM system;
2) In the second step, the contribution of the photovoltaic systems is determined through an estimate based on meteorological data;
3) Finally, in the third step, the residual power contribution, defined as flexible loads and represented by the recharges of electric vehicles, is further processed to obtain the number of electric vehicles and the different charging modes.

The method described, called Regional-NILM, provides a way to estimate the real-time status of DERs without costly monitoring and data privacy issues.

7. Ambient Assisted Living

Ambient Assisted Living (AAL) includes all those products and services designed to improve lives and promote the physical independence of older people. Knowledge of a person's ability to undertake normal ADL is an essential part of the overall assessment of their status and is critical in determining a diagnosis. Most approaches to AAL rely on high-density environmental sensor networks to perform activity recognition, which is often characterized by high intrusiveness.

Several relevant health features can be inferred from data obtained from NILM systems, such as inactivity, sleep disturbances, memory problems, changes in activity patterns, low activity routines, employment, and unhealthy living [26]. The main advantages of using NILM systems are non-intrusiveness, low cost, and ubiquity.

In [27], an NILM-based AAL system is proposed. The proposed system observes the switching on and off household appliances to infer the position and activities of people, detecting the space-time context and, therefore the ADL of the subject. In this way, every household appliance in the house is transformed into a sensor, without disturbing the private environment of the subject.

Similarly, in Ref. [28] a model was created to infer the activities performed by individuals starting from the absorption profiles of household appliances using a Latent Dirichlet Allocation (LDA) algorithm.

It is clear that to create efficient AAL systems based on NILM algorithms, the accuracy in estimating the consumption of household appliances is irrelevant, but the system must be able to determine the status of the household appliances monitored correctly.

8. Conclusions

NILM systems have always been conceived as a useful tool for saving energy and costs in the bill, however, to date, the applications in which these systems can work efficiently are many. Depending on the different applications, the system may be required to accurately estimate the consumption of appliances, a clear definition of their status, a timely response to events or the possibility of installation without direct training. This work aims to increase awareness of how NILM systems can be employed in automation, monitoring and diagnostic systems. After a brief definition of the state of the art of these systems, some applications, related to both industrial and residential environments, were discussed. For each application, the objectives have been defined, and the most significant works have been introduced, furthermore, it is specified which characteristics are required of the NILM system in the different situations.

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