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RECENT APPROACHES AND APPLICATIONS OF NON-INTRUSIVE LOAD MONITORING

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ABSTRACT
The Appliance Load Monitoring is vital in every energy consuming system be it commercial, residential or industrial in nature. Traditional load monitoring system, which used to be intrusive in nature require the installation of sensors to every load of interest which makes the system to be costly, time consuming and complex. Nonintrusive load monitoring (NILM) system uses the aggregated measurement at the utility service entry to identify and disaggregate the appliances connected in the building, which means only one set of sensors is required and it does not require entrance into the consumer premises. We presented a study in this paper providing a comprehensive review of the state of art of NILM, the different methods applied by researchers so far, before concluding with the future research direction, which include automatic home energy saving using NILM. The study also found that more efforts are needed from the researchers to apply NILM in appliance energy management, for example a Home Energy Management System (HEMS).

Keywords: nonintrusive load monitoring (NILM), energy management, appliance signature, home automation, artificial intelligence.

1. INTRODUCTION
The energy consumption pattern of a utility appliances can be accurately known through proper monitoring of the appliances' operation, in which the actual consumption and state of operation of the appliances is ascertained. In a traditional load monitoring system, a meter is installed on each load of interest in order to monitor the power consumption and other activities of the load. The load monitoring in which multiple sensors measure the power consumption of each appliance is known as the intrusive load monitoring. This process imposes costs and complex installations [1-3]. On the other hand non-intrusive load monitoring system do not require to intrude an appliance when measuring its power consumption, rather it is a process of disaggregating the overall electricity usage measured at the meter level into constituent appliances, which provides a simple and cost effective methodology of capturing the individual appliances' information [1, 4]. The main aim of the load monitoring is to create an awareness of the level of energy consumption among the consumers for appropriate action towards efficient energy usage[5]. With global increase of energy demand due to increasing population, urbanization and civilization it is mandatory for load management to be observed in electrical services. This therefore calls for a system that can actively monitor and manage the energy usage and also automatically prevent unnecessary loses. Studies in the NILM systems show that if the actual energy consumption of each load is made available to the consumers, it motivates them to conserve the energy and helps the government and the utility companies to device appropriate energy saving policies [6]. A very significant saving in terms of the cost of electricity and reduction in greenhouse gas emission can be achieved by energy audits through the equipment upgrade and altering the usage pattern of the appliances [7].

A considerable amount of electrical energy source, at global level is from oil and gas, these energy sources are non-renewable sources which are estimated to perish any moment from the middle of twenty first century. Hence the load monitoring with the view of management and optimization of the sources is essential in order to reduce the risk of energy crisis in the world, possibly by avoiding an unnecessary and illegal power usage observed [8, 9]. With the NILM system employed by the majority of the consumers, the appliance manufacturers will also compete in upgrading traditional household appliances to the intelligent ones which can also take into consideration the energy savings [10]. The recent advancement in communication, especially the wireless communication and also the advancement in sensor technology, give more opportunity for energy management and automation in which the appliances are interconnected with home area networks [11, 12] or other monitoring and management applications [13, 14]. In this paper an overview of the methods used in NILM system and its application are presented. Section 2 provides the NILM frame work while section 3 gives a detailed state of art of the appliance signature for the load disaggregation. Section 4 gives the NILM approaches based on steady state signatures while sections 5, 6 and 7 discussed the approaches based on transient, hybrid and non-traditional signatures respectively. Event based and non-event based detection methods are highlighted in section 8 and section 9 presents the artificial intelligence learning classification. Application of NILM are discussed in section 10, section 11 suggests some future research direction, before concluding in section 12.

2. GENERAL NILM FRAME WORK
The purpose of NILM is to disaggregate the whole-building's energy consumption into its major constituents that is both in terms of energy consumption and appliances' state of operation. The idea of NILM was pioneered by G. W. Hart [15] in 1982 from the Massachusetts Institute of Technology. After Hart's

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discovery of the possibility of using the aggregated measurement to know the energy consumption of the individual loads, it was realized that this method can be beneficial to the utilities [1]. In fact later works in the area of NILM showed that it is also beneficial to the consumers through its application in home monitoring and home energy management especially with smart meter becoming more available [16-19]. The method suggested by Hart used the steady state variations of real and reactive power to detect the status of loads in ΔP-ΔQ plane. The work focused on assumption that each load in the house consume a unique value of real power as well as a unique value of a reactive power, therefore if a change in the real and reactive power corresponding to a particular load is observed, then that determine the ON or OFF of that particular load, though in some cases more signatures are required to identify some kinds of loads [17, 20-29]. This is because of the overlapping clusters, as the result of the appliances with equal real power and equal reactive power consumption as shown in Figure-1 [30].

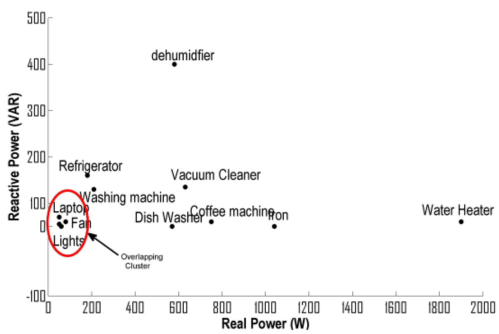

Figure-1. The loads on ΔP - ΔQ plane.

The load disaggregation also depends on the kind of appliances in a system. Basically there are four classification of appliances based on the nature of their operation, these classifications also determine the procedure for the load disaggregation [15, 30].

a) **Type I:** The appliances with only two states of operation (ON/OFF). Example Table lamp and Toasters.

b) **Type II:** The multi-state appliances with finite number of operating states also referred to as Finite State Machines (FSM). Consumer appliances belonging to this category includes washing machine, variable speed fan and stove burner.

c) **Type III:** The continuously variable devices (CVD) which are characterized by variable power draw with no fixed number of states. The dimmer lights and power drill are examples of loads in this category. The disaggregation of appliances in this group is very challenging.

d) **Type IV.** There are devices that remain active throughout the weeks or days at constant rate, they are referred to as "permanent consumer devices". Devices like TV receivers, telephone sets and hardware smoke detector are examples of loads in this category.

The NILM process basically involved three stages, these are the Data Acquisition, Feature Extraction and Appliance Classification [6, 30]. The stages depends on the type of appliances to be disaggregated and the appliance signature to be used in the disaggregation procedure [1, 4, 31, 32]. Figure-2 shows the stages of NILM process as will be described in the sessions that follow:

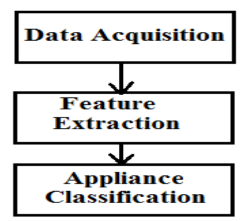

Figure-2. Stages of NILM process.

2.1 Data acquisition

The data acquisition is the measurement of the aggregated load consumption (Voltage and Current) sampled at appropriate rate for the purpose of appliance recognition. The sampling rate of the data depends on the appliance signature to be captured, for example for basic power metrics like, real power, reactive power, apparent power, root mean square currents and voltages and even power factor can be captured at low sampling rates. Within the steady state analysis in which there is the need for capturing higher harmonics the sampling rate must fulfil the Nyquist criteria. In some NILM systems the transient features of the loads or noise generated by the appliances may be required, in that case the sampling rate should be very high in order to acquire accurate measurement [30]. T. M. Chung and H. Daniyal [33] designed an accurate power meter using instantaneous power calculation method with the help of current sensor, voltage sensor and arduino microcontroller. The developed system is able to measure voltage, power, current and power factor, an indication that it can be used for real time load monitoring application. The data acquisition is not limited to electrical quantities, in an event the non-traditional signatures are used in the NILM system, getting their measurements is also part of the data acquisition.

2.2 Feature extraction

Feature extraction is the next step after the data acquisition; it is the collection or calculation of the appliance signature from the acquired data which is usually the measured voltage and current as the case may be. In some of the NILM works the signature extraction involved data optimization [10] and data processing [34].

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The extracted feature may be steady state or transient state depending on the NILM method. The steady state methods make use of the steady state load signatures, like change in steady state real or reactive power to identify whether the appliance is being ON or OFF. Whereas transient method makes use of the transient signatures like, shape, size and total transient energy to identify the loads. The steady state signatures are more traditional than the transient ones and the cost of using the steady state solution is cheaper.

2.3 Appliance classification

In the appliance classification, the signatures acquired are used to run a particular algorithm for the load classification. Most of the research works in NILM use the supervised methods in the load disaggregation, the method that require a labelled data for training the classifier. The supervised learning methods are mostly optimization or pattern recognition. Some researchers [35-37] adopt unsupervised method of disaggregation which does not require the training data.

3. APPLIANCE SIGNATURE

Appliance signature refers to a specific feature that characterizes the behavior of the load. Signatures can also be defined as the measurable parameters of the total load that gives information about the nature and operating status of the individual appliances [38-41]. An example of appliance signature can be the steady state current it consume or the reactive power it consume when it is turn on. There are two main classification of load signatures, the intrusive signatures, which require entrance or rather contact with the appliance before it can be taken and non-intrusive signatures which are measured by passive observations. As shown in Figure 3 the intrusive features can be measured using electrical quantities or if the need arise they can be taken physically from the appliances' physical properties.

In nonintrusive load monitoring application, an appliance signature can be a steady-state or transient in nature. Some research works use the steady state signatures, while some concentrated on the transient signatures and a few number of researches uses the combination of the two. The load disaggregation is sometimes complex, especially when there is overlapping signatures within different appliances. This makes some of the researchers to use the nontraditional signatures to identify the loads, mostly in combination with steady state or transient signatures.

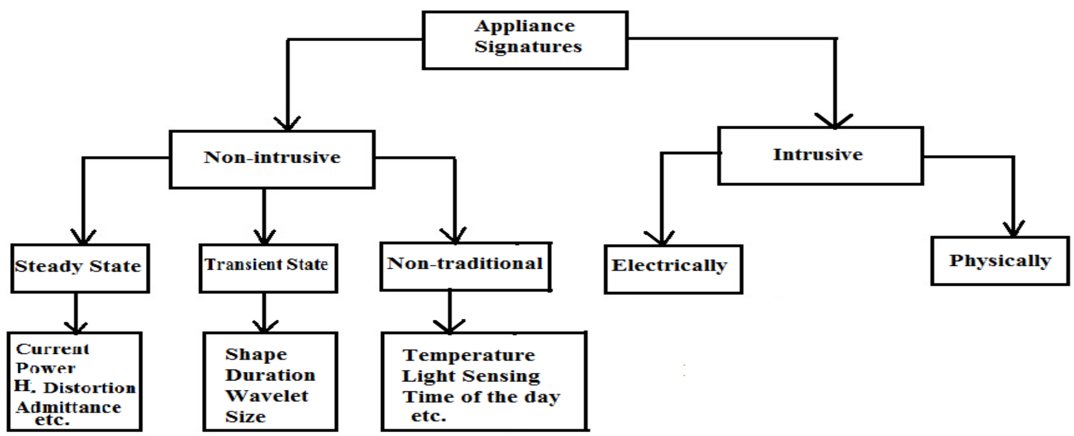

Figure-3. Appliance signatures.

4. APPROACHES BASED ON STEADY STATE SIGNATURES

The methods under the steady state make use of the load signatures when the load is in its steady state operation. These signatures include, Real power (P), Reactive power (Q), Root mean square current (I) and steady state harmonics signatures taken when the appliances is steadily in operation [42, 43]. The real and reactive power are the most common features used in the load disaggregation under steady state even though there are difficulties when it comes to identifying type II and type III loads or when there is an overlapping cluster.

In some research works [44, 45] the real power alone is used to disaggregate the appliances, where it is realized that the method can accurately disaggregate high power appliances like electric kettle and geyser. However it is easy to get an identification error when there are appliances with similar real power consumption.

Benyoucef *et al*. [16] carried out a research in NILM in order to demonstrate the usefulness of smart meter for customers by determining a way of reducing energy consumption. The method used a systematic collection and examination of appliances steady state signatures to form a data base containing different loads profile. The data base is intended to be analyzed then followed by an algorithm to identify and isolate the different appliances in the loads profiles. The steady state signatures alone are simple signatures that require minimal hardware for installation though incorporating them with some transient signatures in some cases yields better recognition efficiency [34].

In [46, 47] multiple signatures were used to overcome the limitations of using only the real and

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reactive power. H. H. Ming [46] uses real power, Reactive power, Apparent power, rms Current and power factor as a set of signatures for identifying some lighting loads in the laboratory. Using a constructed load profiles of 33 lightings (from 3 types of fluorescents) an accurate tracing of the loads combination was obtained within 2.63% error. The clustering profile was analyzed using Microsoft visual studio under certain tolerance, even though only lightings loads are used. In [48, 49] a novel method of using the V-I trajectory of the appliances has been used to categorize the appliances for identification. The V-I trajectory is the mutual locus of the steady state instantaneous voltage and current. Using the normalized values of I and V during one cycle, the plot gives different shapes depending on the load connected. [49] classify the V-I trajectory of appliances based on asymmetry, looping direction, area, curvature of mean line, self-intersection, slope of middle segment, area of left and right segments and peak of middle segment. Figure-4 is a V-I trajectory of a group of appliances [48].

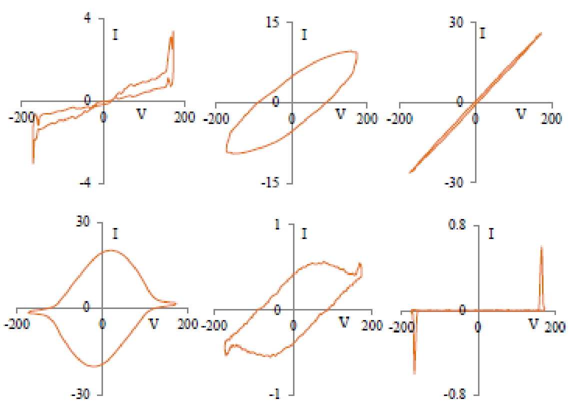

Figure-4. V-I Trajectory of a group of appliances.

Harmonic analysis on the other hand is also used to carryout load disaggregation. It is applied where there are non-linear loads, which as the result of reactive power consumption, they turn to consume a non-sinusoidal current. The non-sinusoidal current produces odd harmonics in the system because of its periodic nature. Several research works [50-52] have been carried out using the harmonics characteristics of the loads. C. Y. Feng et al [50] used the steady state harmonic current values to trace the combination of three set of load i.e. Personal Computer (PC), fluorescent lamp (T5 type) and compact fluorescent lamp (CFL). They used power quality meter to capture the signature of each kind of load based on the rms value of the total current and 3rd to 15th harmonic values of the current, and they developed a load profile of all possible combination of the appliances, which they used in tracing the loads. The method is capable of tracing the energy consumption of different combination of the appliances, though it will need the support of other methods when identifying linear loads, more especially those with equal energy consumption. When there are so many kinds of loads, getting the harmonic value of all possible combination of the loads may be unreliable.

5. APPROACHES BASED ON TRANSIENT SIGNATURES

The transient behavior of most electrical appliances is distinct, this therefore makes it suitable for load identification [30]. Whenever an appliance is switched ON there used to be a transient state at the beginning of the appliance turn-on, a momentary event preceding the steady state which comes as the result of a sudden change in the circuit [53, 54]. Transient features are utilized in numerous researches in NILM [3, 41, 55-58].

One of the works on transient signature was done by H. H. Chang [57]. The load identification was analyzed using transient response time and transient energy through discrete wavelet transformation (DWT) and short-time Fourier transformation (STFT). The method was used to compare the recognition efficiency of three major loads, which were disaggregated using steady state real power, reactive power and total harmonic voltage and current. The analysis shows that the transient features (transient response time and transient energy) are better than the steady state signatures in terms of recognition accuracy and computational requirement. The results of the analysis using STFT and DWT is excellent, though the identification accuracy will be less if the loads are linear that do not have distinct transient behavior.

In an effort to promote traditional NILM systems of using real power and reactive power as the loads signatures, C. Kun-Long *et al*. [58] proposed a method of extracting a power indices (PIs) of the loads using convolution and wavelet multi-resolution analysis (WMRA). The load identification was carried out using the inner product algorithm with a recognition efficiency of up to 86.66%. Not only did the method reduced the computation time but it also reduce the cost of database installation. However real life application of the NILM may require higher accuracy. In a later work C. Duarte *et al*. [55] proposed a method of filtering the transient power signal to get a clean transient for the analysis using "envelop trigger".

Even though the transient offers very rich information concerning the appliances, but one of the problems with it is that the turn-on transients are not similar with their turn-off counter parts. Also in the transient analysis high sampling rate is required in order to capture its accurate measurement because it die out within a very short time. With smart meters mostly having a sampling rate of 1 hertz, a more capable device need to be installed for transient analyses. In addition appliances with similar transient can also face challenges in recognition.

6. APPROACHES BASED ON HYBRID SIGNATURES

Hybrid approach means combining the steady state signatures with transient signatures for more accuracy. Electrical appliances, especially the ones commonly found in residential settings, come in many types. While some are better recognized using some kind of signatures, others are recognized using another kind of signatures. H. H. Chang *et al.* [34], [59] combine the steady-state real power (P), reactive power (Q) and total transient energy (U_T) to disaggregate different appliances with the same real and reactive power. The recognition accuracy of the combined signatures is far better than when only P and Q are used.

In a similar way an interesting work has been done by Lian *et al.* [60, 61]. They extracted a multiple of signatures from both steady-state and transient conditions of the loads to disaggregate the appliances separately and then combine the results through "committee decision mechanism" to produce best final estimation. The separate disaggregation took place with the following as the signatures: Current waveform (CW), Active and reactive power (PQ), Harmonics (HAR), Instantaneous admittance waveform(IAW), Instantaneous power wave (IPW), Eigenvalues (EIG) and Switching transient waveform (STW). The method is quite promising, though the evaluation of a single feature single algorithm followed by the committee decision may be computationally boring and not applicable in real world.

7. NON-TRADITIONAL SIGNATURES

Apart from the steady-state and transient analysis, there are other methods of using non-traditional features in identifying the appliances. Non-traditional features refer to features extracted from other appliance's condition, i.e. not necessarily from the measured electrical data. Time of the day, frequency of appliance usage, on and off duration distribution and the correlation between the usages of different appliances are some of the nontraditional features that add accuracy to the disaggregation procedures [30].

H. Kim *et al.* [37] integrated additional features related to when and how appliances are used in the home to disaggregate the loads using factorial hidden Markov model. With the additional feature the method outperform other unsupervised methods. A single nontraditional feature can make a barrier between two appliances with similar traditional features. The research works reported in [62] and [63] used modified versions of Viterbi algorithm and estimate the most likely sequence of states, which also shows the power of nontraditional events.

8. EVENT BASED AND NON-EVENT BASED DETECTION

The NILM methods can be categorized in to event-based or non-event-based methods. The event-based method uses the edge detection algorithm on the power consumption curve to detect the appliances when a change in the curve is detected. The edge features of the curve are classified according to a set of rule by machine learning methods. Several works have been done using event-based methods [42, 64-66]. Anderson et al. [65] discovered the importance of using power metric for selecting an event detection algorithm through the method. [42] uses edge symbol detector (ESD) and transient detection approach based on support vector machine to locate the loads events more precisely.

Non-event-based methods on the other hand doesn't rely on edge detection to do the classification, instead it takes every sample of the aggregated data for inference. The Hidden Markov Model in [37] and [67] are examples of non-event detection. J. z. Kolter and T. Jaakola [67] achieved a very good performance using Additional Factorial Approximate MAP (AFAMAP) inference. The method has achieved the goal of disaggregating virtually all the appliances in a home with un-supervision. Event-based methods are more computationally efficient than the non-event based methods.

9. ARTIFICIAL INTELLIGENCE LEARNING CLASSIFICATION

The learning techniques of NILM systems can be broadly classified into two groups; the supervised and unsupervised learning methods. Each of these methods estimates the associated appliances which contribute the aggregated loads as seen from the service entry.

9.1 Supervised learning

Supervised learning techniques require a data set for training the classifier so that it can recognizes the appliances from the aggregated data either by Optimization methods or by Pattern recognition methods. Optimization method compares the load signature with a data base and tries to minimize the error for closet possible matching. Whereas the pattern recognition use the pattern matching of the appliances. Some researchers [51], [52, 68-70] used Artificial Neural Network (ANN), while some [71, 72] used Support vector machine (SVM) and others [7, 73] used k-nearest neighbor (kNN).

9.2 Unsupervised learning

The training requirement of the supervised identification algorithm is expansive, time consuming and laborious. Thus researchers use the unsupervised learning, which does not require the training data and of course reduces the intrusiveness of the training steps. The researchers in [74] used Gaussian mixture model, Sequential Expectation-maximization and adaptive fine-tuning to detect unknown states of the loads. Other research works involving the unsupervised learning method can be seen in [32] and [35].

10. APPLICATIONS OF NILM.

NILM is one of the two major classifications of load monitoring (with ILM on the other hand). Of course, monitoring the connected loads for proper and efficient utilization is the main purpose of NILM; this is because it is difficult to know the operating condition of appliances without monitoring. Moreover, the NILM provides the appliances' disaggregation/identification non-intrusively, which means no need of entry into the building before giving account on the appliances, hence the NILM method takes into consideration the privacy of the building's owners.

The single point metering of the NILM method also makes it reliable and less complex in terms of circuitry when compared to ILM where the system has to communicate to every appliance. This type of metering also makes the NILM to be cost effective, as only one set of sensors is required for the whole system. The applicability of NILM in appliance energy management and automation is the major concern of researchers [75, 76]. S. Barker *et al* [75] recommended that the NILM research works should emphasize on the design of novel applications that use NILM rather than improvement in the accuracy for different problem variants. The research conducted by R. W. Cox [77] demonstrated that the NILM can be applicable in shipboard supervisory control systems, where they demonstrated that the NILM can potentially reduce overall sensor count if used in the supervisory control system.

The non-intrusive monitoring also has the blessing of other professions like fluid/water engineering in which the flow is observed non-intrusively using sensors [78, 79]. M. M. Campagna *et al* [79] use the linear relationship between the fluid flow in a pipe and the amplitude of its transversal vibration oscillation to device a way of measuring the flow rate of the fluid non-intrusively.

11. FUTURE RESEARCH DIRECTION

So many efforts have been put by the researchers in the area of NILM, especially in the trend of increased recognition/disaggregation efficiency. However, there are more efforts needed to step the NILM state of art to a more physical applications. Through this review we observed some of the issues to be tackled by the researchers as follows:

a) Though there are advancements in the recognition efficiency of NILM realized by so many researchers in the last decades, efforts are still needed to come out with NILM system with more recognition/disaggregation accuracy.

b) There are many research works where the loads to be monitored are few. Therefore more NILM systems that can recognize as many loads as possible are still in view. This is more especially in home appliances' monitoring where we can have so many category of loads.

c) The advent of smart meter with sampling capability and communication enable is a good opportunity for researchers. Hence NILM researches combining smart meters with some communication facilities will form good research works in energy management and automation [80].

d) A method need to be adopted for measuring the performance of NILM and more researches are needed to link the NILM with appliances' energy management systems and automation [81].

e) The use of non-traditional signatures in load disaggregation will also increase the NILM accuracy [63]. Therefore more efforts is needed from the researchers to explore more opportunities with nontraditional features.

12. CONCLUSIONS

The load monitoring researchers nowadays focused more on NILM methods because of the cost effectiveness and less complexity of the system. A review of NILM methodologies has been presented in this paper. Few works incorporated the non-traditional signatures of the load, but majority of the researches discussed used either the steady state or transient signatures, with some of them combining the two. The works discussed also concentrated on the supervised learning for the load identification with few of them using the unsupervised learning.

The paper generally presented a state of art of NILM with areas that need further works to improve the recognition accuracy. In our future research works we are going to focus on the application of the Nonintrusive Load Monitoring NILM in energy management system, in which we will focus more on the automation of the NILM system for significant energy savings, the savings that take into account the satisfactory energy supply as well as the greener environment.

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