Non-intrusive and Intrusive Energy Monitoring Methods Overview and Their Relation with Household Appliances State Sensors Devices

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Abstract This work deals with different types of residential energy monitoring methods, comparing their advantages and disadvantages. More specifically, this works focus on the relationship between these methods and the usage of state sensors devices. They are classified as: ILM (*Intrusive Load Monitoring*), where power information is acquired per household appliance and NILM (*Non-intrusive Load Monitoring*), where only one meter is used to get the total energy consumption information. Although, the first method is more effective for regular consumers to help saving energy, both of them provide good energy estimation values. We have shown that when comparing both methods, the state sensor devices can assist to reduce computational efforts for NILM disaggregation algorithms and to infer energy estimate with ILM techniques. Comparing with the commercial devices, the last method can be considered an important and low cost solution, with only 10% error rate.

Keywords NILM and ILM · State sensor devices · Energy efficiency

1 Introduction

The continuous feedback about the energy consumed can lead to significant energy savings. The annual costs reducing can achieve around 12% considering a real-time feedback energy consumption per appliance for end users [1]. This level is reduced when the information is gathered at no-real time or at the building-level. So, the behavior change effectiveness about electric power usage is directly associated with level information methods.

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Hart [2] has suggested two concepts to obtain the amount of energy consumption for residential loads. He introduced the ILM (*Intrusive Load Monitoring*) and NILM (*Non-Intrusive Monitoring*) concepts based on the energy meter intrusiveness in a house, and the electrical load signatures information.

This paper is organized as follows. Section 1.1, provides a brief explanation of NILM and ILM methods and their implementation forms. Section 2 presents some types of load and state sensors devices. Section 3, reports how these sensors devices and these methods can aid saving energy and costs.

1.1 NILM and ILM

The NILM method determines the energy consumption per appliance, it is based on the detailed analyses of current and voltage acquired by one meter installed on the distribution panel. Then, it is possible to obtain the active power per time, (as depicted Fig. 1), as long as the reactive power and power factor.

By using computational techniques, the individual load power can be obtained. This method is called Disaggregation and it is divided in three steps: Event Detection, Recognizing and Consumption Estimation [3].

From the total real power signal acquired, the first part is to determine the rising and falling edges in order to employ the events changes for the next step load operation. It will indicate if the load is turned on or off. According to literature, Hart presents an event detection method that uses arithmetic mean among real power samples. It is the oldest detection method and it is named derivation method.

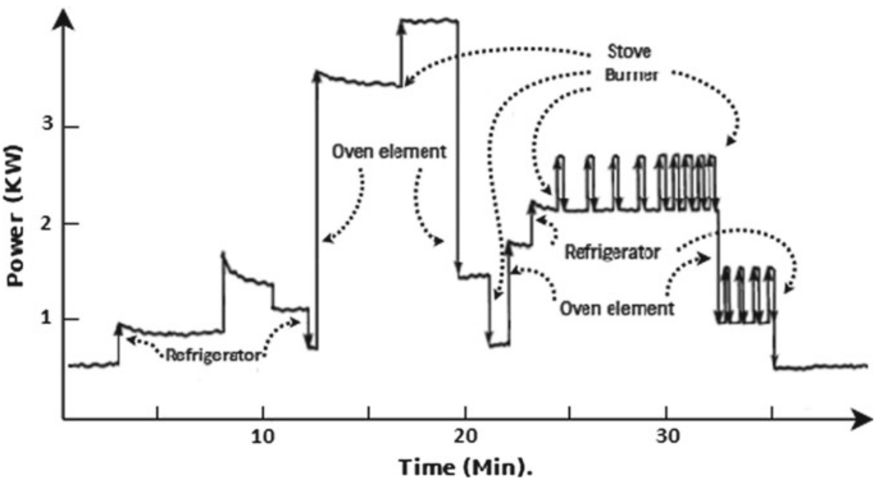

Fig. 1 Real power *versus* time—the aggregated measurement power of the total building [2]

This detection methodology was detailed by Dong [4]. Their approach determines noise limits and the samples below of its are wasted. Monzani [5] has suggested even more analyses for noisy situations by using moving average. New methods, as proposed by Azzini [6] considers two calculus windows to filter transient signals for shifted samples and dispersion measurements.

In addition, Sultanem [7] presents an event method that is appropriated for commercial and industrial environments. Usually, these places deploy electrical machines that presents large starting torque. He proposes an algorithm that identify several changes on real power signal to determine load turning on or off for motors.

The second part uses electrical load signatures to recognize load operation. It can be done by soft computation, supervised and no-supervised approaches [6]. The supervised approach needs a specific data set of the individual load signatures acquired earlier. This step is named as training data set.

The non-supervised approach does not consider the training data set since it uses similar data to determine each appliance. The soft computational methodologies explore tolerances using imprecision and uncertainties results to obtain treatable, robust and low cost solutions [8].

In the last procedure, the load signature (i.e. total energy consumption) is estimated by integrating the Real Power along the time curve, as presented in Eq. 1. Usually, the integration procedure estimation uses squares and trapeziums geometric shapes placed over the load signatures area curves [6].

$$Energy[W.h] = \int_{t_{On}}^{t_{Off}} P(t)dt \tag{1}$$

The NILM method implementation needs just one meter. It is a cheaper solution but the computational cost is higher and complex. Moreover, its installation is not feasible for regular consumers.

A second monitoring method is called ILM. This method consists installing power meters between the outlet and appliance, allowing them to obtain appliance-specific energy consumption. Then, the resulting sum of each meter produces the total energy estimation of a house. Commercially, this meter device is named smart plugs.

Although, to install these meter devices is required enter into the user house, turning it in an intrusive method, it has become increasingly easy to install for regular consumers, since it is a plug.

Nowadays, the management systems of NILM and ILM together have wireless communication facilities, allowing them to present the energy consumption results for end users in real time. Commonly, the smart plugs are linked with Apps that provides amount energy estimation per appliance, operation time duration and daily report linked with the current tariff so to estimate real time costs. Some devices can also actives loads to turn on or off. Some commercial brands of smart plugs are Wemo [9], TP-link [10] and Peanut [11].

2 State Sensor Devices

As described above, ILM monitoring method provides an energy estimation per appliance. The metering power is instantaneous and the data acquired provides the energy progress on load operation. By observing the power load behavior is possible to look for similarities to find systematic function shapes called load signature.

The load signatures can be defined as the variation of the power load with time. They are grouping in electrical and non-electrical signatures. The first, voltage and current load parameters vary in a specific according to the type of load. The non-electrical signatures, such as sound, magnetic field and light, are also used to infer appliances operation (see Fig. 2).

Metering electricity per load can be done directly and indirectly. In general, direct power devices need to be installed or coupled into appliance. They are used to acquire electrical signatures.

In the indirectly measurements the meter devices are installed near to appliances and gather no-electric characteristics (light, magnetic field or sound) to deduce the loads operation. They provide no-electric signatures.

Usually for both direct and indirectly measurement the signal presence (or not) can indicate the appliances state. However, associated works about indirect methods combines more than one load characteristic to determines the load operation. They look for redundancy check.

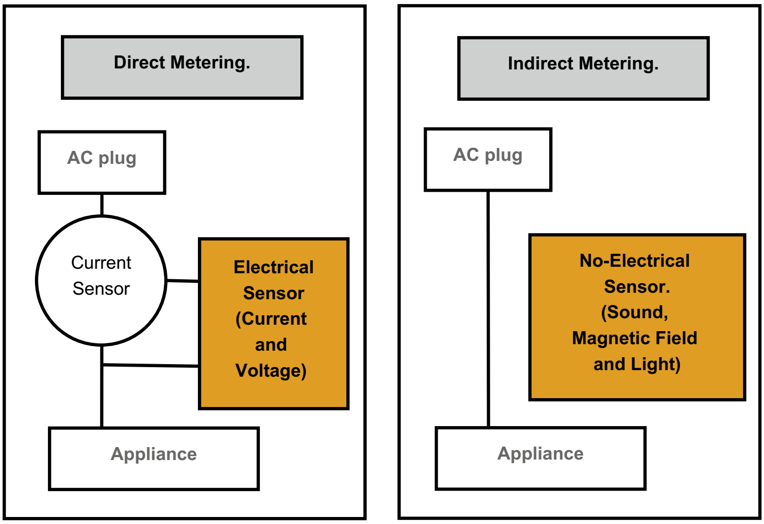

Fig. 2 Diagram of direct and indirect energy intrusive metering per appliance—illustration based on [12]

The device that senses several power changes level could indicate whether the appliances are turning on or off. These state sensor circuits is called state sensor devices (SSD) in this work.

Most of the circuits monitors line or neutral conductor to predict the state of one appliance. Then, the load sensing is based on electrical load signature. To appoint if the load is On/Off, these SSD uses transformer current (TCs) coupled to line to measure the current flowing on conductor. Other possibility is to measure the current flow based on differential voltage, using a shunt resistor in parallel to neutral [13].

Other specific load characteristics can be used to determine the appliances state. A refrigerator, for example, produces noise that indicates the compressor operation. So one can use acoustic signature to determine its state. One also can use RF signal to identify household appliances on/off states [14].

According to Srivastana, the magnetic field can change near to a computer and so it can infer whether the PC is activate or off, as presented in Fig. 3. In Srivastana's work magnetic field characteristics, aid electrical signatures to load identification through a system called *Viridi Scope* [12].

Associated works with no-electric signatures can achieve good energy consumption estimation around 10%. Some of them use the signatures to testify the true values and waste falses values to aid the electrical signatures, as in the *Viridi Scope* project [12], others works estimate energy directly with the same information, as present by *TinyEars* [15].

So, besides so many procedures to identify appliances consumption, one of the best approach per appliance is ILM technique since it is cheaper (depending the devices quantify), easy to install and is able to obtain the real time feedback per load helping end users to save energy to simple mode.

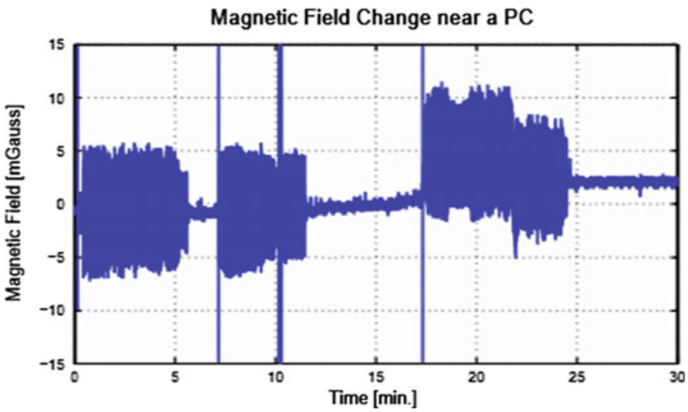

Fig. 3 The magnetic field near a PC. The noisy region indicates that PC is active—Ref. [12]

3 NILM and ILM Assisted by State Sensors Devices

Associated works have been revealed electrical and no-electrical SSDs information can be aid NILM and ILM monitoring methods. These states information can support cheap solutions, optimize and reduce computational costs.

As described above to measure the building energy amount NILM need to carries out Event Detection, Recognize and Consumption Estimation steps. The key of the first and second step is the load identification and activate/deactivate instants, because the total power signal draw acquired by the main meter is aggregated and laborious to select each load.

To diminish NILM computational efforts, these steps can be mitigated due the knowledge about states of appliances and a their identifiers (ID), [2]. It could be indicated how appliance is in operation eliminating the Event Detection.

If a load is detected and associated with an ID, the supervised and clustering non-supervised approaches from Recognize step is unnecessary. According to Azzini [6] the first approach needs labeled events set trained earlier. It could be eliminated due the load previously identified.

The non-supervised approach doesn't require previously training but needs anothers information as power factor (fp), real and reactive power as function time to define an appliance. These information are important to clustering data where the loads will be classified according the similar groups.

Moreover the supervised approach can be eliminated with SSDs and IDs information. Just real power draw signal is considered (fp and reactive power are unnecessary) to Recognize and Consumption Estimation steps.

Considering the whole NILM process, all adjustment made for Event Detection and Recognition steps provide lower storage data and more soft systems. Although it has numerous advantages as smaller computational efforts, the extras low costs sates sensor (per appliance) in addition the main meter could be an expensive solution and uncomfortable to regular consumers.

The ILM method monitoring can be aided by state sensors, supported by the electrical load signatures. The SSDs and IDs per appliance information are gathered on database and they are related with electrical load signature adjusting the time operation indicated by SSDs.

Then, the energy consumption per appliances are estimated and the sum of their energy values provide the amount of total energy consumption estimation of house. According to Azzini [6], this method is named ACE (Aggregated Consumption Estimation).

In addition, Azzini [6] formalized these new forms to gather energy amount by state sensors. Their work has presented ILM− and NILM+ monitoring methods devices. The first is the ACE presented techniques and the second, is SSDs usage supported to electrical load signatures to avoid sames steps NILM the disaggragation method as described above in this work (see Table 1).

It is necessary to take into account that the described ACE measurement method are applied to on/off load types. This loads doesn't work with several switching

Table 1 Brief taxonomic about energy monitoring concepts—according to Azzini [6]

Type of energy monitoring	Device installed per appliance	Device installed on distribution panel
NILM	No	Energy meter
ILM	Energy meter	No
NILM+	State sensors devices (SSDs)	Energy meter
ILM−	State sensors devices (SSDs)	No

states, hence switching states, hence the SSDs associated to signatures constant models can be infer the energy consumption estimation. In addition, most of the common household appliances are of this type.

According to Zeifmam and Roth [3], an house has four loads types: *Permanent Consumer Devices*, devices that remain active 24 h and with constant real and reactive power (as external power supplies), *Finite State Machines (FSM)*, includes devices that switching states on operation cycle (as washing machine), *Continuous Variable Consumer Devices*, that includes devices with variable and aperiodic power draw (dimmer lights) and, *On/Off Appliances* as described before (as toaster, light bulb etc.).

Comparing NILM and ILM methods aided by SSDs, both of them use the load signature with interesting purposes, more especially, the NILM to simplify computational effort and ILM to saving costs, because most of state sensors devices has cheaper project and materials.

Note that, NILM is not an intrusive method but NILM+ needs SSDs to aid detect and infer an load, then it needs to be also intrusiveness. Then, look at the intrusiveness concepts they have to turning inappropriated to classified a energy monitoring methods, but it has been the best term to associated works as yet.

In spite of these advantages, in general they are not an accurate energy estimation methods and also the exactly SSD depends depends on the communication network stability and speed. And in most of the cases, the communication can also be a limiting factor for energy estimation of a house.

4 Conclusion

There are many low cost ways to estimate energy consumption for a house. This work has highlighted the NILM and ILM monitoring concepts to validate them and also to have an overview of many associated works.

The key concept is the meters intrusiveness installation. If the meter device is installed on each outlet, the embraced monitoring method can define ILM (Intrusive Load Monitoring). Usually, this method for each appliance measurement is a feasible installation for end users.

If only one meter is installed on the distribution panel, the metering is called NILM (Non-Intrusive Load Monitoring). The total building energy is aggregated and one uses a computational method to load disaggregation.

As described above, devices have used NILM and ILM methods to reduce the computational data efforts. More especially, Azzini [6] summarized and formalized these concepts in: NILM, NILM+, ILM and ILM−.

Associated works indicates that SSDs have presented another household appliances characteristics beyond electrical signatures to indicate their states, as for example, TinyEars with acoustic signatures.

The SSDs are able to inform loads activation/deactivation patterns using a simple and low cost way, but they are not able to detect the appliances power stages operation, as washing machines for example. Then, SSDs should be employed only in solutions that considers On/Off load's type.

Although the assisted solutions by SSDs have good results in order to saving energy and money, each energy monitoring method has its disadvantages. Therefore, it is important to define how parameters are relevant for an specific usage and their technical installation intrusiveness limitations, so to mitigate computational efforts, to have good estimation values of energy consumption estimation per appliance and a suitable solution for each scenario.

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