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House energy management using non-intrusive load monitoring

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***Abstract*— Reducing the energy bill is nowadays one of the main priorities to both professionals and clients. However, the instability of the energy prices invites us to think about new solutions other than improving renewable energies, in order to deal with high energy losses in an electrical network. Lately, many works have dealt with intelligent electrical networks known as 'smart grids'. These particular networks are based on real time measurement of electrical parameters, allowing an efficient energy management and reducing the losses. On one hand, this work intends to discover the different techniques used to establish the measures and load profiles, and sort out the devices that have high consumptions. On the other hand, it presents possible future improvements allowing an advanced energy management.**

***Keywords*— Communication technologies; Electricity grids; Smart grid; Smart Metering; Non-Intrusive Load Monitoring; Load signatures.**

I. Introduction

As awareness of Energy saving and green energy raises, significant changes have been introduced to our grids. As a result, we have nowadays a wide range of options to produce energy, but, as consumption is still not managed, these options will not be as effective as they are meant to be.

In order to optimize energy consumption, and avoid high overloads during the pick hours, a consumer can schedule his consumption as not to use greedy devices during peak hours. However, real-time information about the power consumed by each device is needed to make a consumption schedule that meets to our expectations.

To get this information, smart meters are used to provide data about different electrical parameters (Active and reactive power, current, voltage, phase shifting, harmonics,). Unfortunately, these devices are expensive, and installing a smart meter at each point of the electrical circuit would not be affordable, especially in situations where many devices are used. This leads us to choose a Non-Intrusive Load Monitoring strategy.

As we obtain a global load profile, this diagram needs to be analyzed, based on a database of 'signatures' (electrical parameters that characterize each electrical device and make it 'recognizable') and broken down into many load profiles, where each one of them characterizes a device. Thus, in the first part of this paper, we present the previous works that have been established in Non-Intrusive Load Monitoring and Load signatures.

As this information, is analysed and the decisions about consumption schedules are made, the suggested system would be able to execute these schedules by switching off the unnecessary greedy devices during peak hours, change the performances of lighting, ventilation, or air conditioning for example. This requires system automation and a sort of communication between the different devices and the user. The state of art corresponding to energy management and electrical installation automation will be presented in the second part of this paper.

Finally, we present our perspective and the strategy that we intend to come up with, in order to improve electrical efficiency in our grids and avoid high energy losses.

II. Load Identification using signatures and Non-Intrusive Load Monitoring:

A. *Signature construction and identification:*

Load Identification is a process based on collecting data from the device, analyzing it, and finally using learning algorithms to identify the device. The concept of 'signatures' is based on the fact that each device has its own behavior, based on how his electrical parameters change during transition from one regime to another (ex: from transient state to permanent state). The study is based on active and reactive power measurements, the voltage and current variations, and sometimes, the phase shift variations.

In [1], the authors propose 2 approaches in order to identify a device:

1. Measure and represent the load characteristics.
2. Use signal processing and estimation algorithms to disaggregate the signal and identify the load.

Taking into account the current and the voltage measures, an algorithm is defined in order to obtain a database of loads signatures. This would constitute a reference to identify each electrical device. The diagram proposed by the authors

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to obtain a signature was presented by the authors as following:

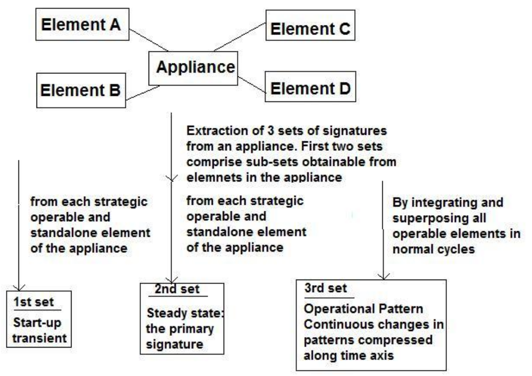

Fig. 1 Constitution of the load components' signatures [1]

The process that allows the load signature construction is presented in figure 2

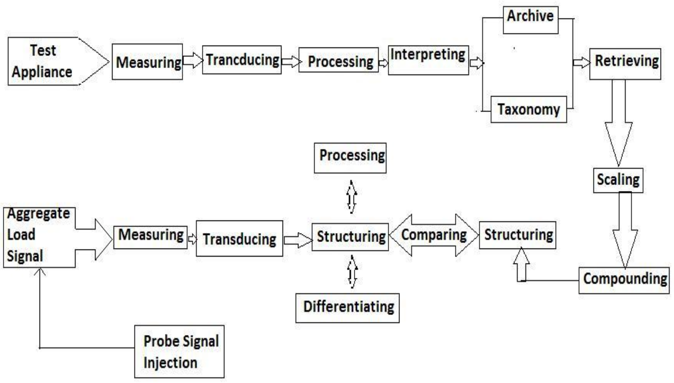

Fig. 2 Identification process of a load [1]

This research allowed obtaining load signatures for each one of the following devices:

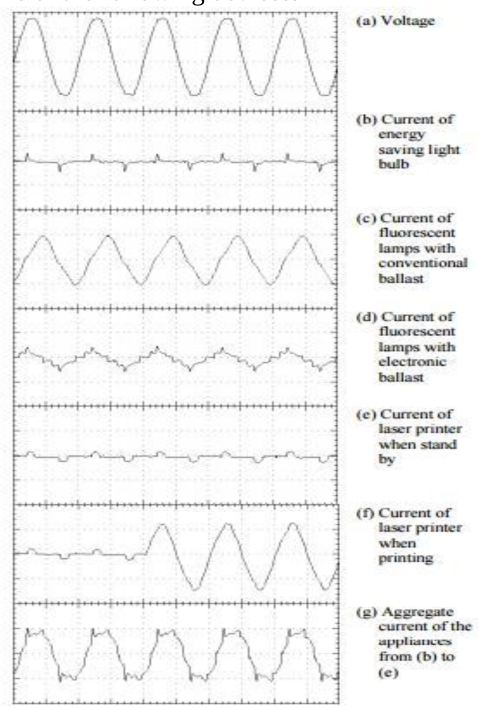

Fig. 3 Signatures of some electrical devices [1]

In [2] a method to identify electrical appliances in real time using intelligent algorithms is suggested. The identification process of the electrical appliance is initiated by collecting information on the energy consumption of the household electric appliances. A data acquisition system prototype has been implemented to extract parameters such as active power, reactive power, phase shift, the average voltage and current characterizing the connected devices. The analysis is performed using neural networks, machines Support vector, k-means, Mean-shift and classifiers silhouette. The aim is to choose the best algorithm that produces optimal results.

Data collection covered all operating modes of each device to obtain a full understanding of their behaviors during each operating mode.

In this work, the importance was given to the active power consumed. When two devices consume the same active power, this factor is not enough anymore. As a result, other features were considered to support the classification task such as: reactive power, phase shift, the medium voltage and current.

The author distinguishes between 2 types of learning: The Unsupervised Learning, and the supervised Learning

Supervised Learning

In this case, all the electrical parameters that may be used as inputs in the identification process (Active power, Reactive power, current…) are defined at the beginning of the algorithm, to avoid any difficulty during the process.

Unsupervised Learning

The only input to the algorithm is a training data set and it defined the data that will be used by itself.

TABLE I
RESULTS OF THE LEARNING ALGORITHM [2]

Active Power	Reactive Power	Vrms	Irms	Phase Shift	Device Name
59.13	63.00	232.60	0.27	0.94	Bulb
751.33	752.00	210.82	3.57	1.00	Toaster
63.66	64.60	228.71	0.28	0.99	Fan
211.02	237.00	225.77	1.05	0.89	Blender

TABLE II
ACCURACY AND EXECUTION TIME [2]

Type	Classifier	Accuracy (%)	Execution (s)
Supervised	SVM	97	0.010
Supervised	ANN	96	13.000
Unsupervised	Mean Shift	94	0.013
Unsupervised	Silhouette	98	0.012
Unsupervised	K-Means	98	0.15

B. Load disaggregation:

The figures that we obtain using one smart meter include all the load profiles of the loads that are functioning. Which

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requires algorithms to be able to disaggregate this load profile into individual load profiles.

In [3] M. Zeifman presents the conditions for a good load disaggregation which must meet the following conditions:
1) The sampling rate should be higher than 1Hz
2) Accuracy: the minimum acceptable precision of the disaggregation algorithm is 80% -90%; 3) No training algorithm for load identification is required
4) The algorithm must operate in real time;
5) Scalability: the algorithm must be scalable if the number of connected devices increases
6)The ability to operate in the presence of various types of devices: On-Off Devices, Appliances with multiple states, the continuous consumption devices,

However, another criterion is also important: The end customer feedback.

In [4] the different methods used in NILM are presented to identify the components connected to the network: one of the first approaches to NILM was established in 1980 by George Hart, but the first system using NILM appeared in 1990. The methods discussed in this article are presented as 2 types: steady state analysis and transient state analysis

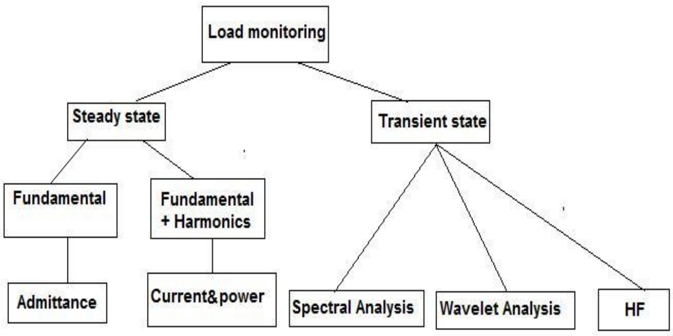

Fig. 9 Load Identification Methods [4]

Steady State Analysis:

❖ <u>Fundamental Analysis:</u>

This analysis is based on the detection of the moment when the electric power value changes considerably, which marks the device's activity duration. The load identification begins with the detection of the peak between steady state and transient state. The transient state will be eliminated in the steady state analysis. Many methods follow this approach as in [5], others have studied the variations of ΔP-ΔQ [6] [7] the variations of I [5], and Z [8].

However, this method does not deal with the following situations:

- Non-linear loads that overlap in the PQ plan.
- Linear loads that overlap in the PQ plan.
- Simultaneous activation of several loads, and fast sequences.
- Too long steady states for specific variable loads.

New types of residential appliances not listed in the database.

❖ <u>Harmonic analysis</u>

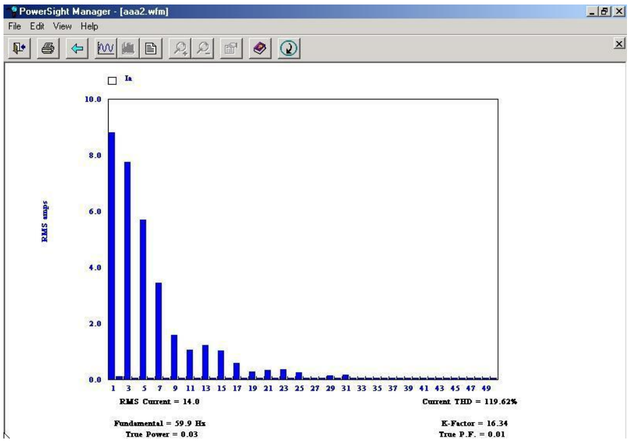

Fig. 10 Spectral Analysis showing the fundamental and the harmonics

The harmonic analysis can be used to complete the fundamental analysis in the case of ambiguous overlapping of loads in the P-Q plan; especially when the installation contains non-linear loads. Other authors would complete this information using the phase shift between the fundamental input current and the voltage.

❖ <u>Transient State Analysis:</u>

In this analysis, the transient behavior of a device is compared to a database of transients

However, the transient state analysis has many shortcomings such as:

• High sampling frequency is required
•The transient models need to be unique and reproducible
• Establishing the database is difficult and expensive especially when there are many devices connected

In [9] the author presents an algorithm of disaggregation that takes as inputs the indications on the electrical device (Power, Voltage, the device's type: on/off, multistate…)

The problems that can be encountered are:

Quality of inputs: the information entered may be incorrect. The difference between the measured power and the manufacturer indications

Operational Complexity: two or more devices change their functioning modes simultaneously.

The author distinguishes between 2 types of switching:

Contemporary switching (CS): two or more devices are switched simultaneously.

Simultaneous switching (SS): two or more devices change the state at the same time, some turn on, others turn off.

As it is sometimes complicated to disaggregate a signal, a feedback algorithm is required.

In [10] Two feedback actions are identified: forward feedback action and backward feedback action. Forward action is immediate and it comes from a counter or a display monitor, whereas in a backward feedback, information is presented in detailed electricity bills or specific advices to reduce electricity consumption. In this work, both approaches were considered. In real time, the results of the algorithm are presented NIALM but if there are differences between the actual condition of the equipment and the results, the user can interact with the system. The user can play a key role in the

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disaggregation, using a dedicated website that not only provides information on electricity consumption, but also the results of the disaggregation algorithm. In fact, it is assumed that the customer engagement may allow significant improvements in the effectiveness of the algorithm. Two types of feedback, can be defined:

- Check the condition: the user confirms the status of one or more devices taken from a list of equipment offered by the website. Using this information, the PQ - DA modifies the state apparatus to its output.

- Check the signature: the user is prompted to enable and / or disable a specific device, to revise the signature of the i-th load.

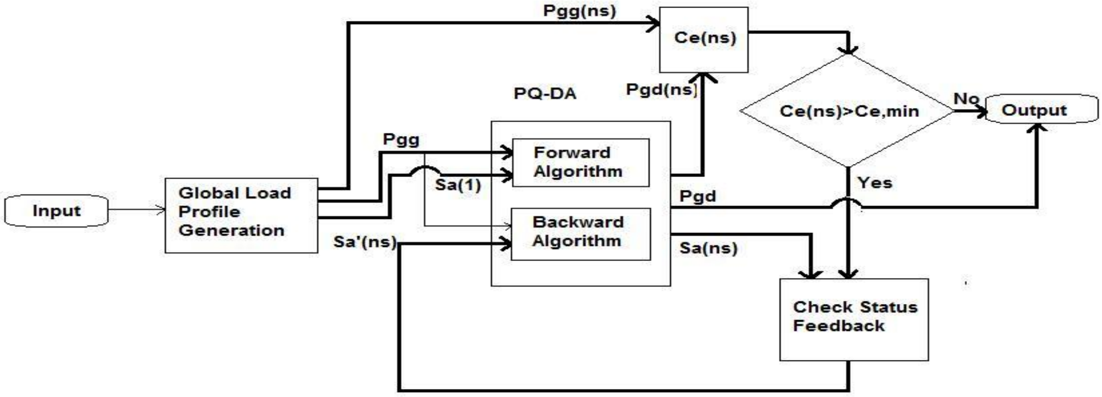

Fig. 11 Identification Algorithm with Feedback [10]

III. ENERGY MANAGEMENT:

Energy management will be the next step of our research work. As we have identified the different devices in our grid, and have a registry of all the changes in the states of these devices, it will be possible to decide which devices can keep functioning, and which one of them can produce an overload in our system and its functioning schedule should be moved to out-peak hours. Moreover, we may study the possibility of reducing the performances of a device (i.e. changing the lighting intensity of a bulb).

Many researches can be related to energy management, control, security and intelligence. In [11] the authors try to compare between different energy management systems that have been developed during the last few years. The results of this comparison are presented in the next table:

TABLE IIII
DIFFERENT ENERGY MANAGEMENT WORKS [11]

Evaluation Criteria	**Monitoring**	**Disaggregation**	**Availability & Accessibility**	**Information Integration**	**Affordability**	**Control**	**Security & Privacy**	**Intelligence**
PERSON (Yang & Li, 2010)	Yes	Yes	Monitor & Control centre available at user premise	integrates a wide range of variables	Low cost & low power consumption	Manual remote control	No.	Context aware intelligent algorithm
WattDepot (Brewer & Johnson, 2010)	Yes	Possible to implement	Web-based interface	Automatic Interpolation	Open source, freely available	No	Limited privacy model	No
ViridiScope (Kim et al., 2009	Yes	Yes	Not discussed	Aggregates magnetic, acoustic, & light info	Requires indirect sensors;	No	No	No
Mobile Feedback (Weiss, et al., 2009	Yes	Yes	Interactive	Integrates historical information	Through mobile app	No	No	No
DEHEMS (Sun-dramoorthy, et al., 2011)	Yes	Yes	Web-based UI, real-time display unit	Integrates info from sensors, electric supply	Requires sensors	No	No	Not yet (planned for 3rd phase)
EnergyWiz (Petkov, et al., 2011)	Yes	No	Mobile phone app	Integrates historical usage, and user info from peers, and EnergyWiz users	Requires mobile app installation	No	No	No
NOBEL (Karnouskos, 2011)	Yes	Yes	Mobile phone app	No	Requires mobile app installation	No	Yes	Limited (User behaviour analytics)
AUS (Bartram, et al., 2010)	Yes	No	Web, smartphones.	Integrates historical use	Less affordable	No	No	No

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In [12] a method named 'Deep Demand Response' is presented. The authors define a parameter called ‘slack’, which measures the possible delay of consumption. Taking a refrigerator as an example, they define the thresholds of temperature that are allowed and base their calculations on the constraint that temperature should never reach the threshold value.

The suggested system delays the functioning of a refrigerator until it reaches the threshold value. At this point, the system uses the stored energy in the batteries (produced by photovoltaic panels) to avoid the grid overload. In this system, Sensors and Actuators are used to dynamically match production to demand. The method uses a prediction model of electrical production as well.

As we’ve seen in the previous research, the authors had a refrigerator or an oven as an example, whose consumptions can be reduced or delayed using actuators. Nevertheless, this kind of control cannot be always as simple as that.

In fact, it is possible to reduce consumption using dimmers in lighting systems; which reduce the value of voltage and as a result, the power’s value would decrease. Or reduce the velocity of a motor using variable frequency drives, which would reduce our consumption as well. But all of these systems need manual control.

In [13], we have an example of this kind of control, where TV remote controls are used to control lights and fans not only by switching them on or off, but also by adjusting the different electrical features.

IV. Future PERSPECTIVES

The study of the different researches covering the loads identification and Load disaggregation, allows us to come up with optimizations in order to reduce the costs of a smart grid implementation. As a result, one smart meter would be sufficient to have an idea about the consumptions of the different devices.

This information will constitute an input to an algorithm that helps us make decisions as to reduce the performances of a device, or delay consumption to out-peak hours.

The future work would be the establishment of this algorithm, and the conception of an automated system that is based on this algorithm and that is able to make the necessary changes in the performances of a device automatically.

Another perspective would be to exploit these results in a larger context as to reduce the consumption of high level installations (an industrial unit, High Voltage clients…), and improve the distribution of electrical energy at each point of the electrical line.

V. Conclusions

This paper was an overview of different works that intends to allow a better understanding of an electrical consumption profile, which would be the first step in developing an energy management system.

Having the ability to control the consumption level of an installation through an automated control, would help us reduce consumptions, especially during peak hours. As a result, the overloads will be reduced and the load profile will show less peaks during a day, which would make the electrical losses due to Joule Effect less important; and the electrical grid energetically more efficient.

However, consumption reduce is not always possible, either because of the device’s configuration itself that doesn’t allow performance modification, or due to difficulty of automatic control.

The system that we intend to develop, even if it doesn’t include the use of many smart meters, which would make it too expensive, may require a massive use of sensors and communication devices. We intend to discuss these matters in our future work.

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