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Real-time monitoring system of the electricity consumption in a household using NILM techniques

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***Abstract* – Non-Intrusive Load Monitoring (NILM) allows providing appliance-level electricity consumption information and decomposing the overall power consumption by using simple hardware (one sensor) with a suitable software. This paper presents a NILM-based monitoring system suitable for a typical house. The proposed solution is a hybrid event-detection approach including an event-detection algorithm for devices with a finite number of states and an auxiliary algorithm for appliances characterized by complex patterns. First results show that the proposed approach works well in detecting and classifying what appliance is working and its consumption in complex household load dataset.**

I. INTRODUCTION

Knowing how electric appliances are used and how different appliances contribute to the aggregate total consumption could help users to have a better understanding on how the energy is consumed, thus leading possibly to a more efficient management of their loads. Non-Intrusive Load Monitoring (NILM) is an area of computational sustainability research, and it presently identifies a set of techniques that can disaggregate the power usage into the individual appliances that are functioning and identify the consumption of electricity for each of them [1].

In residential buildings, where it is impractical to monitor single appliances, or even groups of appliances, through specific meters, NILM techniques are a low-cost and not invasive option for electric consumption monitoring, considering a single monitoring point where a smart meter is installed.

Literature reports several papers that applied different methods throughout the years to solve this problem. A first classification of NILM techniques could be done in supervised and unsupervised methods [2]. Supervised methods require a database of information to train the model. Unsupervised methods are targeted to extract all information to operate directly from the measured aggregate data consumption profiles. Due to their better performance, most of the approaches are based on supervised algorithms and they require appliance data for model training to estimate the loads number, type and power by analyzing the aggregate consumption signal.

Solutions based on machine learning range from classic supervised machine-learning algorithms (e.g., Support Vector Machines, and Artificial Neural Networks) to supervised statistical learning methods (e.g., K-Nearest Neighbours and Bayes classifiers) and unsupervised method (e.g., Hidden-Markov Models and its variants). A review of these methods is reported in [2]. Recently, Deep Learning (DL) methods were also employed and seem promising for the most challenging problem posed by the consumption profiles of multi-state appliances [3-6].

The frequency of energy data monitoring drives the use of the analysis techniques and the specific tools. Although higher the frequency of energy data monitoring frequency higher could be the accuracy of the NILM disaggregation algorithms, commercial smart meters for homes supply low frequency sampling (less than 60 Hz) of the electric power quantities. In this field, the majority of the research efforts focused on event-based techniques that identify significant variations in the power signals as switching events of appliances. These events must be classified as a state transition related to a specific appliance. For this purpose, electric signal characteristics extracted from measurements in proximity of the events (i.e., signatures) are used as distinctive features, and then labeled with classification procedures.

In this paper, a monitoring system is proposed that, using a smart meter, is able to disaggregate and keep track of the power consumption of the devices existing in a typical house. The households should follow the proposed procedure to customize the system for their homes, choosing the appliances of interest and collecting the corresponding measurements. The

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disaggregation algorithm is an improvement of the one proposed in [7]: the load disaggregation is performed applying a hybrid approach to power data, i.e. event-based techniques and pattern recognition techniques for large household appliances.

II. THE HOME ENERGY MANAGEMENT SYSTEM

The Home Energy Management System (HEMS) is used to provide comfortable life for consumers as well as to save energy. This can be obtained using a home's smart meter to monitor the electricity consumption of the devices existing in a household applying NILM techniques. The HEMS should identify the appliances that are active at any time, disaggregate the energy and estimate consumptions of the single device. In this work, the chosen low-frequency smart meter is a sensor belonging to a pre-commercial prototype [7] which provides steady-state signatures, such as real and reactive power time series. It is important that the HEMS set-up is easy to understand and interact with. It should have features, like auto-configuration, which make the set-up process very easy. The non-intrusive technique, resorting to only one smart meter for the household, requires some effort in the first set-up phase, but it can be sometimes the only possible choice because installing a specific monitoring infrastructure, including new devices cables, may result in high implementation cost to the user.

The implemented acquisition system of the electricity consumption data consists of:

- one EASTRON SDM220 single-phase energy meter [8], for residential and industrial applications at a rated voltage of 230 V (range 176-276 V) and current of 10 A (range 0.5-100 A). The accuracy requirements of the meter are reported in Table 1;
- a PC on which the measurement software and the load disaggregation algorithm are implemented;
- a MODBUS/RS485 Serial interface, including a Serial Port Converter Adapter Cable USB-RS485, allowing the remote communication between the energy meter and the PC.

Table 1. Accuracy requirements of EASTRON SDM220

Parameter		Accuracy
Voltage		0.5% of range maximum
Current		0.5% of nominal
Power	Active Reactive Apparent	1% of range maximum
Energy	Active	Class 1 IEC 62053-21 Class B EN 50470-3
	Reactive	1% of range maximum

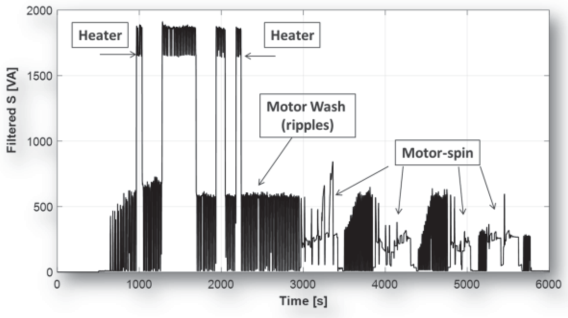

Fig. 1 Apparent power for a washing machine (hot water).

Several domestic consumption data have been acquired, by installing the energy meter between the investigated appliances and the domestic network.

The acquisition frequency is equal to 1 Hz. During the set-up phase, the user should select the devices of interest and collect the measurements from each of the plugs connected to those appliances when they are working alone, i.e. when the other electrical equipment in the house is switched off. A label should be supplied for each device. Then, the system automatically creates the home database of signatures that will be interviewed during the recall phase to identify the appliances from the aggregate power consumption.

In this work the appliances are categorized into four types based on their operation states [9]: 1) Type-I, appliance with ON/OFF states (binary states of power); 2) Type-II, finite state machines with a finite number of operation states (multiple states of power); 3) Type-III, continuously varying devices with variable power consumption, as a washing machine and a light dimmer (infinite middle states of power); 4) Type-IV, appliances that stay ON for days or weeks and with a constant power consumption level.

In case of Type-II, data for all the transitions between possible states should be acquired and labeled (manual set-up). In case of Type-III devices, data from each cycle are characterized by complex patterns. As an example, Fig. 1 shows the typical behavior of the apparent power for the washing machine. As can been noted, the power consumption fluctuates while heating/washing or rinsing/drying the laundry. The proposed technique facilitates the training process by pre-populating the training data set with signatures of some Type-III devices showing typical patterns (automatic set-up).

III. THE PROCEDURE

In the following, the implemented procedure is presented showing how the variations of apparent (S), real (P) and reactive powers (Q), the oscillation frequencies of the signals and the varying patterns of

Type-III appliances are used in the training phase for the creation of the signatures database, whereas during a recall phase the appliances are recognized inside an aggregated signal. In order to better understand the whole procedure, Fig. 2 shows its flow chart.

A. The training phase

The automatic procedure to create the database of signatures consists of the following steps. For each Type I and II device the user provides the label and the number of possible states. In fact, kitchen ovens, stoves, clothes dryers, etc., go through several states where heating elements and fans can be switched in various combinations. For instance, for an electric stove with three power levels (states), the system asks for twelve possible switching events, among OFF/ON states. From the plugs connected to each appliance, the user must collect several measurements for each switching event. This allows to increase data robustness to the noise, e.g., small fluctuations in appliance consumption, electronics constantly on, and appliances turning ON/OFF with consumption levels too small to be detected.

In this phase, for each device, an edge detector finds the switching events in the apparent power data when the absolute value of the difference ΔS between two consecutive values is larger than 20 VA. The sign of ΔS identifies the start up or the shutdown of the appliance. These data are normalized with respect to the constant voltage of 230 V in such a way that the voltage drops due to the load insertion do not influence the result. Then, the real ΔP and reactive ΔQ power variations in each edge must be determined and candidate as signature of the individual load. In order to evaluate these candidate signatures, a causal filtering is applied to apparent, real, and reactive power signals. In this way, possible spikes and outliers can be discarded or smoothed. With such a low sampling frequency, fast transients should be removed, since they could be sometimes recorded, and other times missed during the acquisition. Fig. 3 shows the changes in electricity consumption due to the switching ON and OFF of a fan before and after the filtering.

Within the time interval between two consecutive ON/OFF events there is an almost constant *power level* consumption. In order to find a candidate signature of the appliance-switching event, the difference between the mean values of the measurements before and after each edge of real and reactive power is evaluated. Among all the candidate signatures, the *k-medoids* clustering method [10] is applied to partition the set of switching events into a set of clusters whose number k depends on the possible states of the single appliance and must be set by the user. This clustering method is

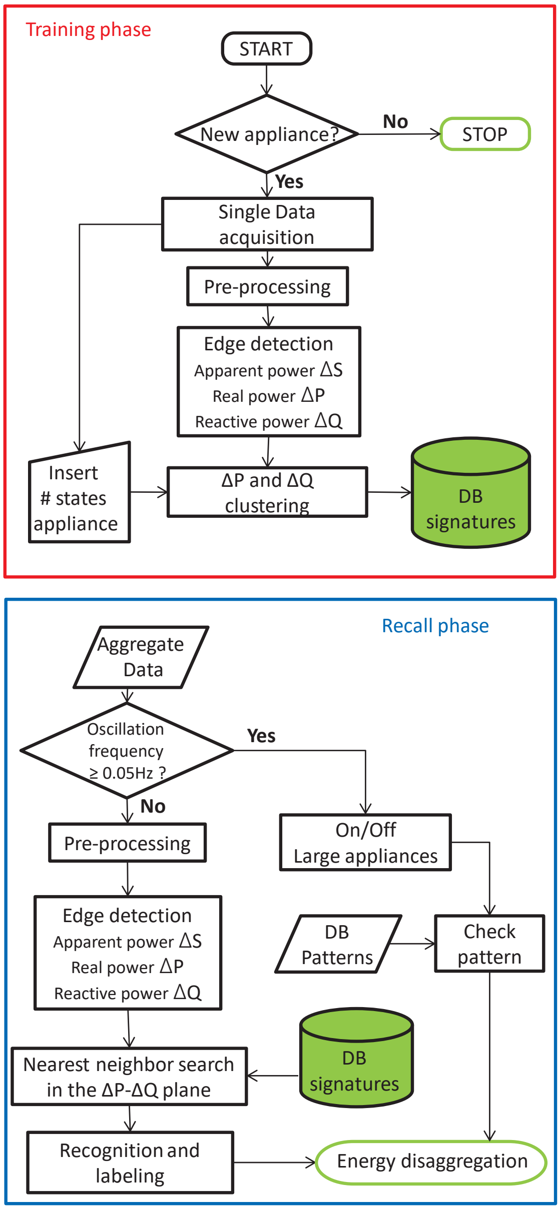

Fig. 2. Flow chart of the procedure.

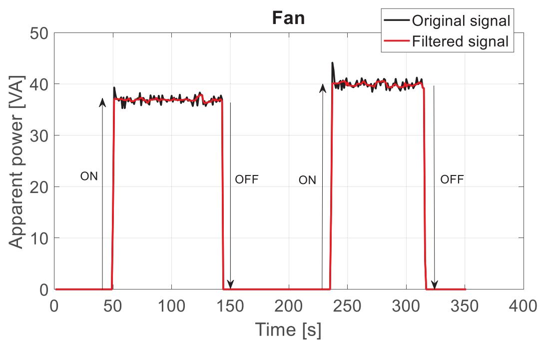

Fig. 3. Original and filtered fan power consumption.

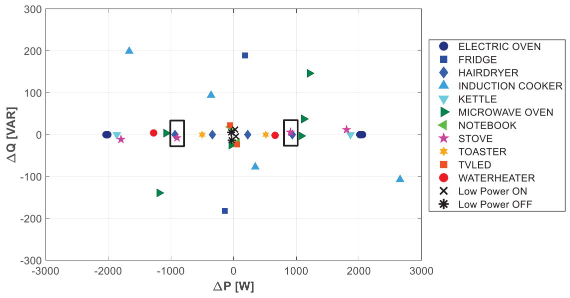

Fig. 4. Appliance signatures in $\Delta P - \Delta Q$ plane. The overlapping signatures of hairdryer and stove are highlighted with black rectangles [7].

robust to noise and outliers and it chooses data points as centers of the clusters. At the end of the clustering procedure, these centers will form the signatures associated with each appliance transition.

Note that, as appliances with small power consumptions are not interesting from the point of view of energy savings, and hardly distinguished, loads with $P < 20$ W are discarded and loads with $20\text{ W} < P < 50\text{ W}$ are associated to a unique "low consumption" cluster. For the same reason, switching events lasting less than 5 s are not taken into account. Note that, the threshold of 50 W is implemented by default, but it can be modified by the user, in case only consumptions greater than a predetermined power are of interest.

At the end of the training phase, all the collected data are given as input to the monitoring system; in case of errors in the classification, new common clusters are created for those devices characterized by close consumptions of real and reactive power. In Fig. 4, an example of database of signatures is shown in the ΔP-ΔQ plane [7].

B. The recall phase

During the recall phase, when an edge in the aggregated signal is detected, the corresponding point in the ΔP-ΔQ plane is evaluated. Then, a nearest neighbor search in the ΔP-ΔQ plane is performed, and the event is associated to the appliance with the nearest signature vector. Moreover, a check on the sign of Q is considered as further information, in addition to the cluster center distance, to identify the proper cluster. This allows increasing the discrimination capabilities; see as an example the signatures of the hairdryer and stove in Fig. 4, where the signatures are very close but the former, unlike the latter, is characterized by zero reactive power. If no association is performed, the event is labeled as unidentified.

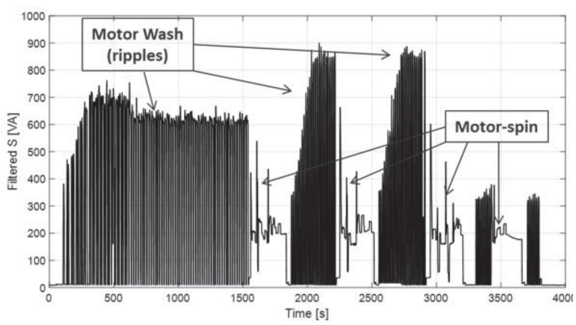

Fig. 5. Apparent power for a washing machine (cold water).

C. Large appliances

For large Type-III appliances, the events do not correspond to simple steps in the power consumption, but characteristic complex patterns appear in the power time series, as shown in Fig. 1 and Fig. 5, where the filtered apparent power consumption of different models of washing machines with different wash cycles are reported. As it can be noted, heating water accounts for about 90% of the energy needed to run a washer and in both figures the washing machine typically has electrical components which turn ON and OFF in sequence. A procedure has been implemented that permits to detect the start and the end of the washing machine operation and the motor-spin events. To this aim, the peak values of the oscillations that identify the heating and washing phases are detected. In order to avoid peaks due to noise or other events not characterizing this device, maximum relevance peak values are selected, i.e., those that drop at least 30 W on either side before the signal attains a higher value. A statistical analysis of the time distance of such peaks shows that the typical time distance between the peaks is close to 20 s. The switching ON (OFF) of the washing machine operation is then identified when the oscillations, characterized by a frequency greater than or equal to 0.05 Hz, start (end).

The detections of ON/OFF events during a washing machine cycle is quite challenging with such a low frequency and many false switching could be triggered applying the described procedure. Thus, in this case, the lower envelope of Q is extracted. Since the washing-machine Q lower envelope during the heating phases is equal to zero, the presence of the intervals of constant values greater than 100 var indicates the switching-on of an appliance.

Moreover, in order to avoid spurious detections, the presence of the motor spin pattern is monitored. The motor-spin pattern shown in Fig. 6 is identified in the individual appliance signals. The pattern identified in the individual appliance signals is already included in the database of the system. In the recall phase, using a similarity search algorithm, it is possible to identify, in

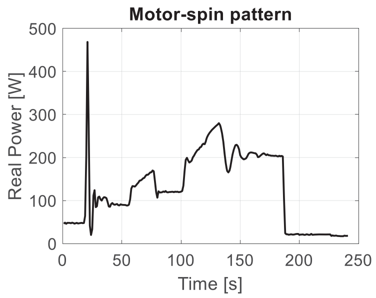

Fig. 6. Motor-spin pattern.

the aggregate signal, the operating phase that best matches with the reference associated to the spin motor functioning. This procedure could be applied for other devices with characteristic patterns, e.g. microwave ovens, to distinguish their operating conditions. The procedure described in section III.A is then applied to the remaining aggregate power consumption signals.

IV. RESULTS

The described procedure has been tested on aggregate signals composed of Type-I and Type-II appliances with and without the washing machine. Using the pattern shown in Fig. 6, the operation phases of the motor-spin are individuated even considering washing machines of different brands and with different washing programs. In Fig. 7 an example of the identification of the various appliances is shown. The ON and OFF events are shown as markers at the level of $+\Delta P$ and $-\Delta P$ respectively, whereas the motor spin functioning is indicated with red segments.

Fig. 8 shows an example of the results of the estimation of energy consumption.

In order to show the effectiveness of the improvements proposed in this paper, in Table 2 a comparison with the results presented in [7] is reported. The dataset was obtained acquiring multiple appliances simultaneously via a multi-socket. A synthetic dataset was obtained by combining the consumption data of the individual appliances, by summing the measurements of S, P and Q and

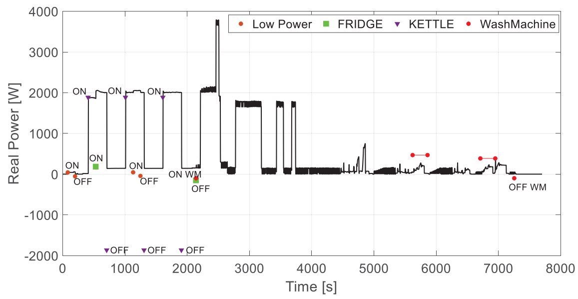

Fig. 7. Aggregate power and ON/OFF transitions during the recall phase.

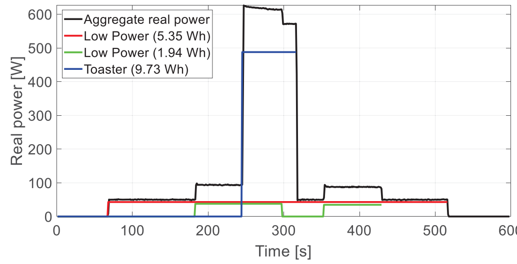

Fig. 8. Aggregate consumption power and estimated average consumption for the appliances examined.

averaging the values of V. The results have been evaluated using the metric F-score, which is defined as:

$$F\text{-}score = \frac{Precision \cdot Recall}{Precision + Recall}$$

Precision is the ratio between the number of correctly detected appliances (True Positive (TP)) and the total number of the detected ones (TP + False Positive (FP)), and it represents the fraction of correct detections. The Recall is the ratio between the number of correctly detected appliances (TP) and the total number of appliances in the dataset (TP + False negative (FN)) and it represents the fraction of the actual events that has been detected. As it can be noted, despite the performance index obtained in [7] for the synthetically generated aggregate signals was already very high, a slight improvement has been achieved. A more significant improvement in the performance index can be observed on the experimental data after the introduction of the described changes.

Table 2. Performance metrics for NILM Algorithm tested on synthetic and experimental dataset.

Test Set	# *Actual Events*	TP	FP	FN	Pr	Re	F-score
Synthetic Data [7]	140	133	7	1	0.95	0.99	0.97
Synthetic Data		136	4	1	0.97	0.99	0.98
Experimental Data [7]	137	121	16	2	0.88	0.98	0.93
Experimental Data		127	8	4	0.94	0.99	0.98

Figure 9 shows the power demand of a household over a 14-hour period, between 08:00 and 22:00. As it can be observed, the aggregate power demand is generated by the fridge, which shows a periodical power consumption behavior, and other appliances. The results are very satisfactory, especially regarding identification of the activation status of appliances that consume more energy, such as the washing machine. As an example, in Fig. 10 the events detection during a washing machine cycle, is shown. Flat-top intervals of the Q lower envelope identify the switching ON/OFF

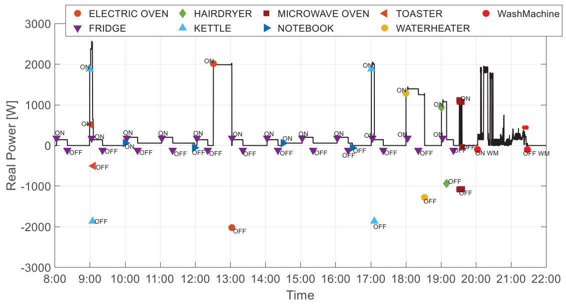

Fig. 9. Household power demand over a 14-hour period.

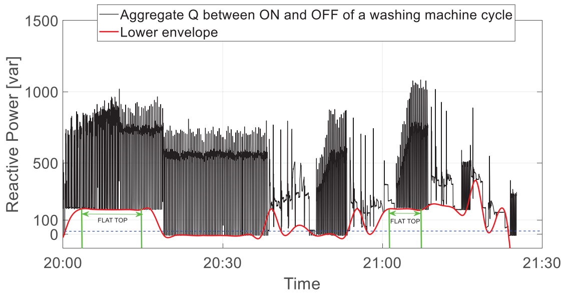

Fig. 10. Detections of ON/OFF events for the fridge during a washing machine cycle.

of the fridge. The pie charts in Fig. 11 compare the estimated decomposition results with ground truth of energy consumption. As can be observed, the proposed method is capable of disaggregating energy consumption of the appliances with good accuracy.

V. CONCLUSIONS

In this paper, a monitoring system has been proposed that is able to disaggregate and keep track of the power consumption of the devices existing in a typical house analyzing low frequency aggregate data.

By applying a hybrid approach to power data, i.e. event-based techniques and pattern recognition techniques for large household appliances, the load disaggregation is performed with good performance, even when complex type III devices, such as the washing machine, are working.

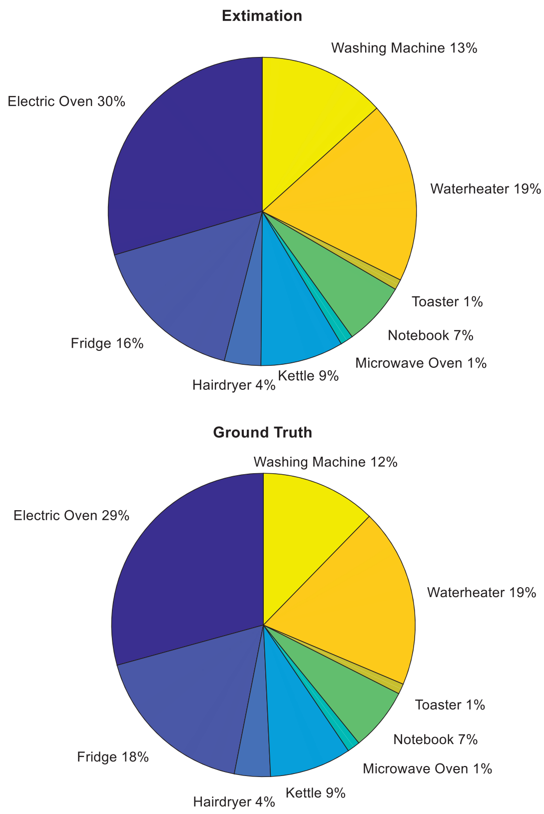

Fig. 11. Energy disaggregation results.

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