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Event Detection for Load Disaggregation in Smart Metering

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***Abstract*—The reduction of consumption is an objective of the Smart Grid paradigm. The pursuit of efficient solutions requires the knowledge that can be derived from each installation's energy consumption measurements through Smart Metering. This work presents an event detection methodology, aimed to help in the disaggregation of the total measured energy consumption in an installation to a number of partial curves corresponding to individual appliances. The work has been conducted within the scope of the EU funded FP7 project "CASSANDRA - A multivariate platform for assessing the impact of strategic decisions in electrical power systems".**

***Index Terms*—Event detection, smart metering, load disaggregation, non intrusive load monitoring (NILM).**

I. Introduction

Smart Home applications are based on the concept of online monitoring and control of the Low Voltage (LV) loads. In that sense, they require the knowledge of the operational status of each LV appliance within an installation. This information can be easily utilized in the context of demand side management programs towards energy savings and efficiency by the implementation of personalized incentives for consumed energy reduction or peak shaving [1]–[4].

The necessity for the knowledge of the operational status of the appliances has been traditionally addressed either by installing sensors on every appliance, or by using an intermediate monitoring system in order to record the appliance's operation [5]. However, this intrusive load monitoring method is considered inconvenient, due to its high cost for large scale implementations. A more simple methodology, namely the Non-Intrusive Load Monitoring (NILM), has been proposed at the early 90s [6], with the advantage of requiring only one single power meter installed at the main feeding panel, in order to monitor and identify the status of the plugged appliances. Although this approach leads to a lower implementation cost, its challenge so far has been the task of load identification from aggregated voltage and current signals. NILM algorithms rely on the utilization of the electrical and functional characteristics of the loads towards the formulation of distinct and robust data fingerprints, i.e. Load Signatures (LS). The higher the uniqueness of these load signatures, the easier the identification procedure. The latter led to a lot of research during the last decade [7]–[10], since the sufficiency of the LS constitutes the key role for successful load recognition.

Moreover, several approaches regarding the implementation of the NILM concept have been proposed. These approaches utilize several load features, [11]–[14], such as the active and reactive power, the harmonic distortion, the transient behavior, and even the voltage distortion in order to structure an appropriate data formation that describes the load's behavior in a unique and representative way.

Nevertheless, the proposed approaches in the literature are designed to take into account measuring sampling rates of at least several kHz. This produces a technological gap with respect to practices used today by electrical utilities, where measurements are typically taken per 15 minutes at best. Aiming to find a realistic common ground, the CASSANDRA platform [15] utilizes per minute measurements of active and reactive power in an installation. In this context, a new procedure had to be developed from scratch. Therefore, the goal of the CASSANDRA platform disaggregation methodology is to recognize the individual appliances within a given aggregated consumption curve and determine the duration of their operation, so as to produce an effective personalized model of each installation regarding its energy needs.

The available measurements per installation consist of per minute consumption of active and reactive power. Consequently, the data per installation can be regarded as two distinct data vectors $\mathbf{P}$ and $\mathbf{Q}$, respectively. Considering that the measurement data correspond to a N-minute time period, the aforementioned vectors are comprised of elements, where elements P_i and Q_i are the respective measured active and reactive power of the i^{th} minute.

The first step in a disaggregation methodology to be applied to these vectors, is to decompose the aggregated consumption curve to a number of partial curves corresponding to the consumption of unknown individual appliances. This procedure comprises an event detection algorithm, and it is the outcome of the methodology proposed here. Subsequently, an identification process has to take place, in order to assign the consumption of each partial curve to a particular type of appliance.

II. Methodology

The event detection methodology takes as input the aggregated consumption curve (one for the active and one for the reactive power) of an installation, and decomposes it in particular consumption event curves.

An aggregated active power consumption curve can be considered to consist of two specific states depending on

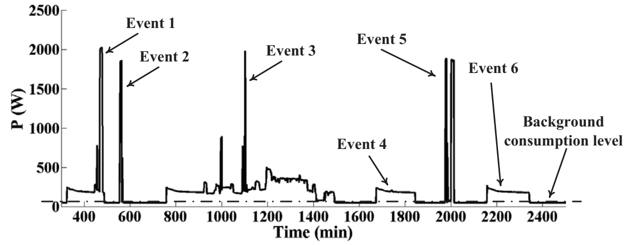

Fig. 1. Per minute measurement of active power consumption, and distinction between events and background consumption level.

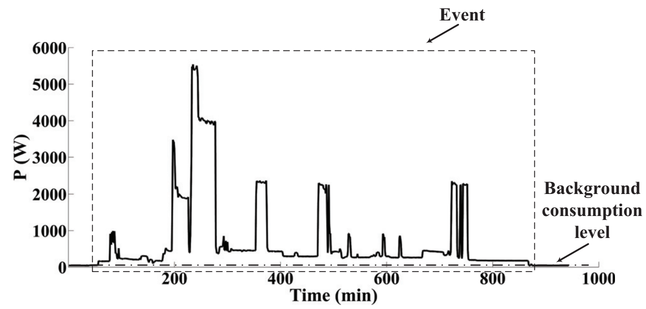

Fig. 2. Event detection and separation from the background consumption zone.

the respective electrical activity of the installed appliances. The first state corresponds to the background consumption that exists mainly due to the stand by mode consumption of the appliances operating in the installation. The main characteristic of this state is that it is permanently present, without significant alterations regarding its active and reactive power consumption. The second state corresponds to events in which the electrical activity exceeds the background consumption level. An example that illustrates this classification is shown in Fig. 1. In this figure, the active power consumption curve consists of a background consumption level close to 50 W, and six events where the consumption levels exceed the background level, denoting thus electrical activity.

The first step of the methodology is the analysis of the aggregated consumption curve. The analysis consists of two subroutines. The first one corresponds to the detection of the background consumption, and the second one to the analysis of the events taking place during the time period under study.

A. Background Consumption Analysis

The aim of the background consumption analysis is to identify the constant minimum value of the consumption in an installation (background consumption). The analysis determines a Background Consumption Zone (BCZ). Every consumption measurement P_i within this zone is omitted from the disaggregation calculations. The BCZ is defined as a set of active power values, and extends from zero to BCZ_{max}, which is a value that has to be determined. In order to do this, the minimum power value of the curve, $min(P)$, is calculated, and the value of BCZ_{max} is computed as shown in equation (1). The α factor added to the minimum power value of the curve in order to produce the BCZ_{max} value is an empirical factor related to the measurement accuracy and the overall resolution of the methodology. Having calculated that value, all the measurements that belong to the set BCZ, i.e. $P_i \in [0, BCZ_{max}]$, are neglected from the rest of the procedure.

$$BCZ_{max} = min(P) + \alpha \tag{1}$$

B. Event Detection

Every differentiation in the power consumption values outside of the BCZ is considered as an event.

In the beginning of the event analysis, an upper level event detection takes place. During this procedure, the values of the active/reactive power that are different from the background consumption zone are derived. One event starts when the value of the power consumption rises above the background zone and finishes when the power value returns to the BCZ. By implementing this approach all events can be considered as closed systems, in which it is ensured that all of the appliances that have been turned on during a specific event have also been turned off before its ending. Taking into account the causality principle that applies to each recognized event, all the time instants at which an active power reduction is recorded can be correlated to time instants of active power rise within the same event. An example of the described procedure is shown in Fig. 2, in which the activation of an appliance increases the measured power consumption above the defined BCZ. Furthermore, several more appliances are turned on and off during this event.

The next step in the analysis of the events is the comparison between the individual curves of each event, in order to detect repeated events during the period of the measurement. An example of repeated events is plotted in Fig. 3, in which the active power consumption of a refrigerator is presented. When similar curves are recognized, they form a group and further analysis is applied only to one of the group curves. The similarity criteria applied are:

- the average active and reactive power consumed in an event, and;
- its duration.

Considering two events X and Y respectively, the average active power values P_{av_X} and P_{av_Y}, and the average reactive power values Q_{av_X} and Q_{av_Y} have to be calculated and compared. The same applies for the durations t_X, t_Y of the corresponding events. If the two criteria described in the following equations (2)-(4) are met, where $T_{P_{min}}$, $T_{P_{max}}$, $T_{Q_{min}}$, $T_{Q_{max}}$, $T_{t_{min}}$ and $T_{t_{max}}$ are arbitrary threshold values, the two events are considered to be similar.

$$T_{P_{min}} < \frac{P_{av_X}}{P_{av_Y}} < T_{P_{max}} \tag{2}$$

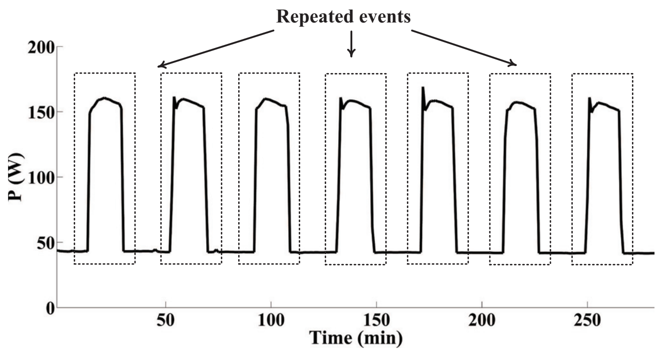

Fig. 3. Repeated events corresponding to refrigerator operation.

$$T_{Q_{min}} < \frac{Q_{av_X}}{Q_{av_Y}} < T_{Q_{max}} \tag{3}$$

$$T_{t_{min}} < \frac{t_X}{t_Y} < T_{t_{max}} \tag{4}$$

The aim of this procedure is to derive appliances used periodically within a day, e.g. a refrigerator, and to perform the respective identification procedure only once, thus reducing the necessary computational time.

C. Individual Event Analysis

After having detected all the events and separated repeated events, the analysis of each event follows. As aforementioned, the consumption of an event corresponds to at least one appliance. Hence, this consumption could be the aggregated curve of more than one appliances, or the curve of an individual appliance. Thus, the events can be divided into two categories. In the first category, only one appliance is used during the event, while in the second category more than one appliances are used, and their aggregated consumption can be decomposed into consumptions of individual appliances.

Considering an event *X*, which corresponds to the active and reactive power measurement vectors $\mathbf{P_X}$ and $\mathbf{Q_X}$ respectively, the following analysis has to be conducted in order to acquire the consumption patterns of the respective individual appliances.

Firstly, a Slope Percentage Vector, $\mathbf{SPV}$ is calculated using the active power measurements of the vector $\mathbf{P_X}$. The elements of vector $\mathbf{SPV}$ can be computed by the equation (5), as the percentage slopes between adjacent active power measurements $P_{X_{i+1}}$ and P_{X_i}, with respect to the latter. Significant changes observed between successive active power measurements indicate a Point Of Interest (POI) into the event consumption. To that purpose, a specific threshold has to be defined so that, once the criterion included in equation (6) is met, a POI is considered. Through this procedure a vector $\mathbf{POI}$ containing all points of interest can be formed. The value of the threshold T_{SPV} has to be larger than the uncertainty relative to the active power measurements exhibited by the measuring device. POIs correspond to event time instants at which an appliance has been turned on or off, depending on the sign of the respective element SPV_i.

$$SPV_i = \frac{P_{X_{i+1}} - P_{X_i}}{P_{X_i}} \cdot 100\% \tag{5}$$

$$|SPV_i| > T_{SPV} \tag{6}$$

For the i^{th} element of vector $\mathbf{POI}$, the deviation in active ΔP_i and reactive power ΔQ_i can be computed. When the value of the corresponding SPV_i is positive, this POI is considered to be a point in which a device has been turned on, denoted as a rising point, whereas when the value of the corresponding SPV_i is negative, it is assumed that a device has been turned off, with the respective POI denoted as a reduction point. Considering *n* rising points and *m* reduction points, the respective matrices $\mathbf{\Delta PQ_{up}}$ and $\mathbf{\Delta PQ_{down}}$ can be formed. Specifically, the $\mathbf{\Delta PQ_{up}}$ matrix contains all deviations ΔP_i and ΔQ_i corresponding to rising points, while the $\mathbf{\Delta PQ_{down}}$ matrix contains all deviations ΔP_i and ΔQ_i corresponding to reduction points, as shown in equations (7) and (8) respectively.

$$\mathbf{\Delta PQ_{up}} = \begin{bmatrix} \Delta P_{1_{up}} & \Delta Q_{1_{up}} \\ \Delta P_{2_{up}} & \Delta Q_{2_{up}} \\ \vdots & \vdots \\ \Delta P_{n_{up}} & \Delta Q_{n_{up}} \end{bmatrix} \tag{7}$$

$$\mathbf{\Delta PQ_{down}} = \begin{bmatrix} \Delta P_{1_{down}} & \Delta Q_{1_{down}} \\ \Delta P_{2_{down}} & \Delta Q_{2_{down}} \\ \vdots & \vdots \\ \Delta P_{m_{down}} & \Delta Q_{m_{down}} \end{bmatrix} \tag{8}$$

Due to the inaccuracy of the measuring devices and the time span between successive measurements that is equal to one minute, the dimensions of the aforementioned matrices can be in general different. For the same reason, the calculated variations in active and reactive power when an appliance is turned on will generally differ from the corresponding variations at the time instant that the appliance is turned off. Therefore the Euclidean distances between the rows of matrix $\mathbf{\Delta PQ_{up}}$ and those of matrix $\mathbf{\Delta PQ_{down}}$ have to be calculated as shown in equation (9), where element ED_{kl} yields the Euclidean distance between the row of matrix $\mathbf{\Delta PQ_{up}}$ that corresponds to POI *k* (elements $\Delta P_{k_{up}}$ and $\Delta Q_{k_{up}}$) and the row of matrix $\mathbf{\Delta PQ_{down}}$ corresponding to POI *l* (elements $\Delta P_{l_{down}}$ and $\Delta Q_{l_{down}}$). Furthermore, due to the fact that multiple appliances can be turned on or off during the time span of the same measurement, the distance between combinations of the calculated differences has to be taken into account. The only principle that limits the examined combinations is the causality criterion that has to be met, because in order for an appliance to stop it has to have been started at a previous time instant.

$$ED_{kl} = \sqrt{(\Delta P_{k_{up}} - \Delta P_{l_{down}})^2 + (\Delta Q_{k_{up}} - \Delta Q_{l_{down}})^2} \tag{9}$$

After having computed all possible distances between rows of matrices $\mathbf{\Delta PQ_{up}}$ and $\mathbf{\Delta PQ_{down}}$, and combinations of them in which the causality criterion applies, a vector $\mathbf{ED}$ is formed and a procedure has to be followed aiming to determine the combination of distances that includes all points of interest, and simultaneously minimizes the sum of the corresponding calculated distances. The mathematical formulation of this minimization problem is presented in equation (10), in which total N elements of $\mathbf{ED}$ are considered which have to correspond to all involved points of interest.

$$min \sum_{i=1}^{N} ED_i \tag{10}$$

III. Simulations

In order to apply the proposed method some certain variables have to be set to specific values. For that reason the α variable for the distinction among events and BCZ has been set to 30 W, $T_{P_{max}}$, $T_{Q_{max}}$ and $T_{P_{min}}$, $T_{Q_{min}}$ have been set equal to 1.01 and 0.99 respectively. Moreover, $T_{t_{max}}$ and $T_{t_{min}}$ were set equal to 1.5 and 0.5, respectively and T_{SPV} which has to be larger than the uncertainty introduced by the measuring device was set equal to 5%. All these values have been determined after a large set of tests for fine tuning. The proposed methodology has been rigorously tested and evaluated using measurements from 30 household installations for time periods of approximately 3 months. Due to lack of space, two indicative test cases have been chosen to be presented here, each of which corresponds to the daily measurements of a household installation located in one of the three pilot cases of CASSANDRA in Luleå, Sweden. Furthermore, for each of the daily consumption curves, one recognized individual event has been chosen to be decomposed into consumptions corresponding to individual appliances.

A. Test Case 1

The power consumption of one day for Test Case 1 is shown in Fig. 4. The proposed method for event detection, which separates the consumption into events and BCZ, is applied and the outcome is that there are 29 recognized events and a BCZ of 44 W. As a next step an investigation is conducted to detect repeated events, and it is deducted that 27 of the aforementioned events correspond to the same appliance, and thus can be grouped. For that reason only three distinct events are included in Table I with their respective start and end times. The repeated events correspond to event number 1, whereas in order to reduce the size of the Table only the first start and end times are included. Furthermore, the event number 3, as shown in Fig. 5 is selected to be decomposed into individual appliances' by applying the proposed methodology. The six appliances detected in this event as well as their respective operation start and end times, are included in Table II. The success of the proposed methodology can be easily deduced by comparing the outputs in the tables with the information provided by the respective figures.

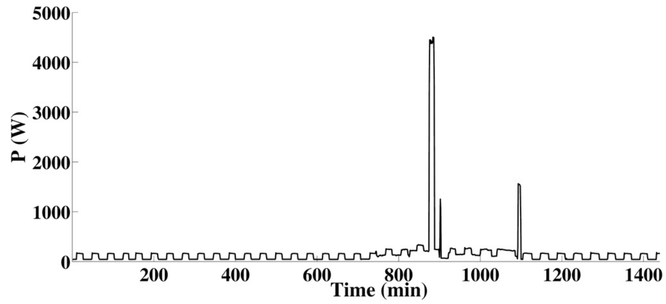

Fig. 4. Power consumption of one day for Test Case 1.

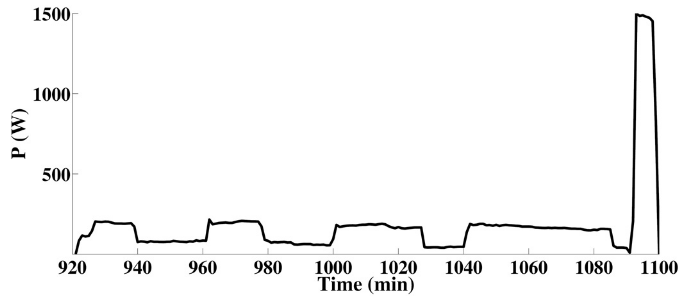

Fig. 5. Recognized individual event of Test Case 1.

TABLE I
Event Detection for Test Case 1

Distinct event number	Start time (min)	End time (min)
1	10	28
2	729	905
3	921	1101

TABLE II
Individual Event Decomposition Into Appliances for Test Case 1

Appliance ID	Start time (min)	End time (min)
1	921	939
2	925	1090
3	961	978
4	999	1027
5	1040	1086
6	1091	1099

B. Test Case 2

The second Test Case corresponds to the consumption of a different household for one day. The respective power consumption is shown in Fig. 6. After the application of the event detection method six events are identified with a BCZ of 46 W. The detected events with their respective operational start and end times are included in Table III, while no repeated events were detected. Furthermore, the first detect individual event, shown in Fig. 7, was selected to be decomposed into individual appliances. The six detected appliances as well as their respective operation start and end times are included in Table IV. Once more the success of the proposed methodology

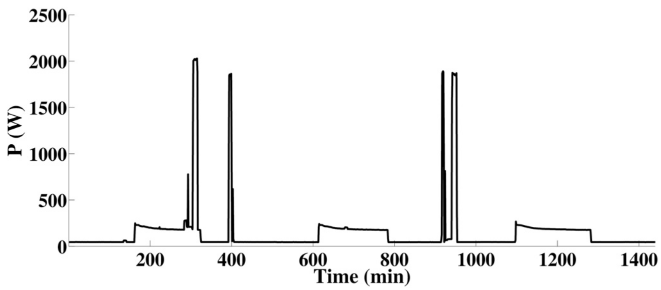

Fig. 6. Power consumption of one day for Test Case 2.

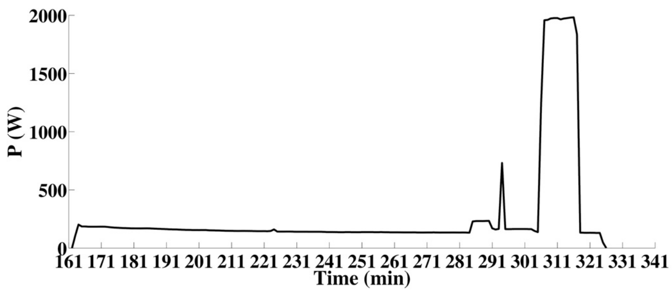

Fig. 7. Recognized individual event of Test Case 2.

TABLE III
EVENT DETECTION FOR TEST CASE 2

Event number	Start time (min)	End time (min)
1	161	326
2	392	406
3	613	786
4	914	926
5	930	955
6	1097	1284

TABLE IV
INDIVIDUAL EVENT DECOMPOSITION INTO APPLIANCES FOR TEST CASE 2

Appliance ID	Start time (min)	End time (min)
1	161	326
2	222	223
3	283	290
4	283	303
5	292	293
6	304	316

can be easily deduced by comparing the outputs in the tables with the information provided by the respective figures.

IV. CONCLUSION

This work presents a novel methodology which can be used to extract information regarding the energy consumption from smart metering data. The method separates the consumption to two distinct parts, i.e. the background consumption zone that is constant and the events, in which electrical activity is detected. The proposed formulation identifies points of interest in the consumption of each event, and solves an optimization problem regarding the combination of these and their respective changes in active and reactive power. Therefore, the consumption of each event can be decomposed into individual appliances of steady or variable consumption. The methodology, apart from the low sampling rate deriving limitations, has been tested and evaluated to per minute active and reactive power measurements from 30 households and two test cases are presented indicating its efficiency.

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