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Multi-feature Load Detection Algorithm

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Abstract. Each appliance determines a specific variation in power consumption when is switched from one state to another. Analysing the profile of this variation, a set of features can be extracted and further used to detect the consumer's transitions. Based on this principle, a multi-feature load detection algorithm is presented in this paper. The algorithm detects the transient profiles, extracts their features and by comparing them with the ones from a database it can detect which consumer generated that transient profile. Providing this information to the user, can offer him an overview of how energy is consumed and help him detect possibilities to reduce the consumption.

Introduction

Electricity plays an important role in our daily lives, as it's the source powering most devices used by humans. From complex systems used in satellites to simple devices found in a home, they all meet different functions that are designed to help peoples in their work. Thus, the electricity is found all around us, influencing to some extent every aspect of our lives. Therefore, it can be said that is an important factor that helps human evolution.

Since the beginning of the commercial use of electricity, a main concern was monitoring of the electricity consumption for billing purposes. Currently, consumption monitoring has become important and for other purposes, such as: obtaining estimates of electricity consumption, monitoring the power quality or finding opportunities to reduce the electricity consumption.

Information on electricity consumption usually is offered to home users in an abstract and unfamiliar form, representing the whole consumption of the entire house. Also, this information is brought to the user after a long period of time, usually one month, so they don't have the possibility to take decisions on changing their consumption behaviour. A more efficient way of providing information on consumption is in the form of real-time graphics of the entire consumption and also of each of the appliances found in that home. With this information, the user will be more aware about the way the electricity is used inside his home and will find possibilities to reduce it [1].

One way of detecting the appliances (electrical consumers) is by monitoring the voltage and current in order to identify certain characteristics determined by the consumers' transition from one state to another. These characteristics represent a consumer's electrical signature and are used in non intrusive load monitoring methods (NILM).

Initially, G. W. Hart noticed that he can interpret what is happening in people's homes, in terms of device use, by simply analyzing the changes in energy consumption [2]. The method proposed by Hart analyses active and reactive normalized power changes between two steady-states (ΔP_{norm}, ΔQ_{norm}) within a home, in order to detect the electrical consumers. Starting from Hart's idea, researchers analysed various features in order to detect electrical consumers.

Depending on the physical task to be accomplished, start-up transient signals can vary from one consumer to another. Consumers with similar levels of power consumption can determine start-up transient currents that can be used in the detection process [3-6]. Transient profiles are different depending on the generating mechanism and can be distinguished by analyzing their characteristic parameters: amplitude, duration, time constant, etc. Also, the profiles generally tend to retain their shape over time even for devices that use active waveshaping or power factor correction methods.

Harmonic analysis can also be used to characterize the consumers' electrical signature [7-12]. While linear loads draw currents of fundamental frequency, nonlinear loads also draw higher frequency currents. Analysing their amplitude along with the changes in active and reactive harmonic powers, certain correspondences can be determined between a consumer and its spectral components. Harmonic analysis can also be used to detect consumers with variable consumption. In this regard it was noted that there can be a correspondence between the fundamental and different harmonic components [9, 12]. Using this correspondence the consumption of the variable consumer can be estimated and extracted from the total load.

Current waveforms, instantaneous admittance, instantaneous power and eigenvalues can also be used to characterize the consumers' electrical signature [13-14]. Depending on their electrical components, the current waveform can vary from one consumer to another. Also, since different currents are drawn, the instantaneous admittance and power can offer information about the operating status of a consumer. The dynamic of variable loads can be observed through eigenvalues analysis of the temporal series of current's samples rearranged in a matrix form.

Analysing the noises that occur in the electrical network was also used to detect the presence of a consumer [15]. These noises can be present for a short period of time, when a consumer switches from one state to another, or for a longer period of time during the operating state of a consumer. The method consists in analysing the frequency spectrum of the noise generated by a consumer and comparing it with the ones recorded in a database in order to detect which consumer generated it.

In this paper a new consumer detection algorithm is presented which uses a complex of features in order to characterize the electrical signature. In a previously implemented algorithm, only active and reactive power changes were used to detect the consumers [16]. In the current paper the information about the transient signals along with the active power change are used in the detection process. The features used to characterize a consumer are: active power step changes (ΔP), duration of the transient signal (d), number of ascending slopes (N_a) and descending slopes (N_d) and sum of variations within a transient signal (S). Using a multi-feature electrical signature leads to an improvement in the accuracy of the detection and discrimination process of electrical consumers.

Algorithm description

In Fig. 1 the algorithm's block diagram is presented. To extract the features needed for electrical signature's characterisation, first the algorithm needs to separate the steady states from the transient one. Since the powers are mainly influenced by the variation in current consumption, a method which analyses the current consumption was implemented to separate the steady states from the transient ones. Considering the current's fundamental frequency is constant, the current will be divided into periods whose RMS values will be estimated. Acquired data will be divided into segments characterized by a constant RMS value, represented by the mean of all RMS values that belong to that segment. Each period (RMS_j) is compared with the one that characterize the previous segment (RMS_{ant}). If the variation (var_1) between them is smaller than 10%, then the corresponding period will be part of that respective segment; otherwise it will be part of a new distinctive segment. To avoid the situations when transient signals lead to detection of new segments, an additional verification is performed, with the next RMS value. If this variation (var_2) is also greater than 10%, then a new segment is detected and RMS_{ant} is updated with the current value.

Next, starting from these segments, the steady states will be separated from transient ones, which will allow determining the necessary features to characterize the electrical signature. First, the algorithm searches for significant power changes which could be caused by a consumer's transition from one state to another. Once a transient state is detected, its features will be calculated. In Fig. 2 a transient profile of a random consumer is presented and will be used as an example to determine the features which will be used to characterize the electrical signature. Within the current transient profile, 3 significant power changes are detected: P_1, P_2 and P_3 whose durations are d_1, d_2 and d_3.

Considering these, the parameters used for consumer detection will be calculated with:

$$\Delta P_i = P_i - P_a,\ S = \sum_{i=1}^{n} \Delta P_i \times d_i \text{ and } d = \sum_{i=1}^{n} d_i \tag{1}$$

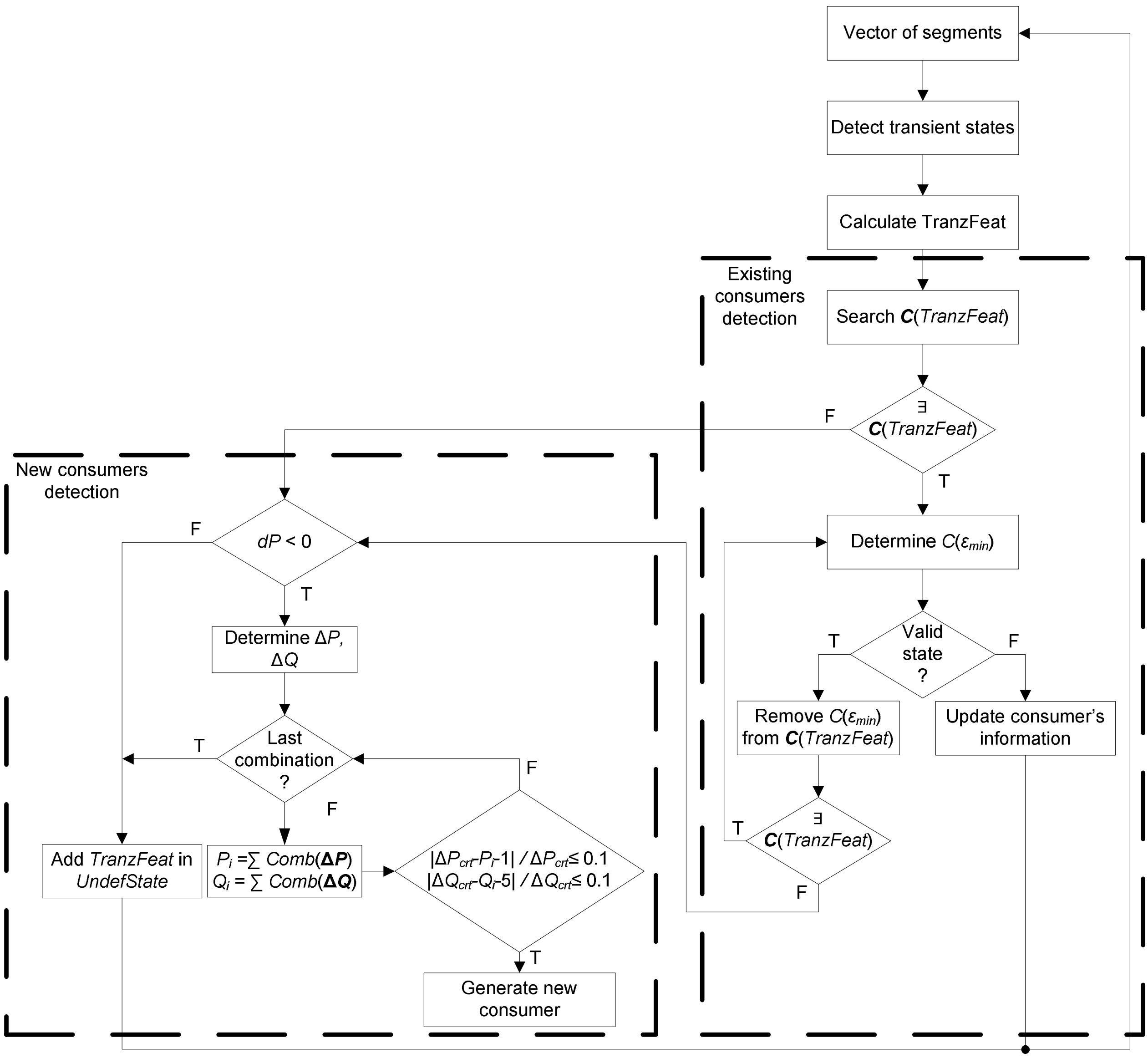

Fig. 1. Block diagram of multi-feature load detection algorithm

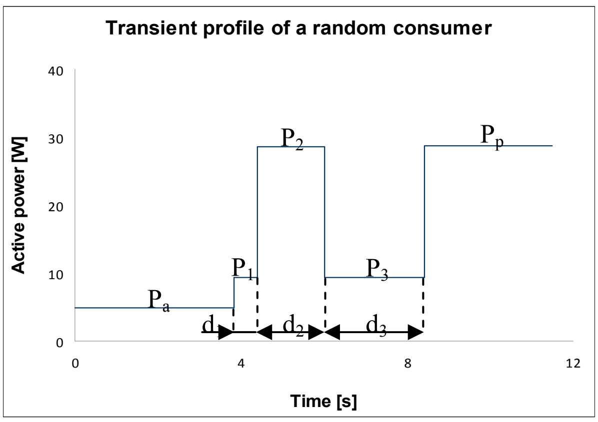

Fig. 2. Transient profile of a random consumer: P_a and P_p are the powers that characterize the steady states before and after the transient state, P_i (i = 1 ... 3) are the powers changes of the segments that compose the transient profile and d_i are the durations of each segment that compose the transient profile

When a transition is detected, its information is determined and will be used to compare it with each set recorded in the database. When all the features are validated, it is assumed that the two transient states were generated by the same consumer. For the two transitions a deviation coefficient

ε is calculated, which together with the detected consumer is added in a list of possible consumers. To determine the deviation coefficient ε, the deviations corresponding to the sum of variations (ε_s), duration (ε_d) and power changes (ε_p) are considered:

$$\varepsilon_s = \left\| S_{crt} - S_i \right| \div S_i \right|, \ \varepsilon_d = \left| d_{crt} - d_i \right| \div d_i \ \text{and} \ \varepsilon_p = \left| \Delta P_{crt} - \Delta P_i \right| \div \Delta P_i \,. \tag{2}$$

where S_{crt}, d_{crt} and ΔP_{crt} are the parameters of the current transient profile. The deviation coefficient of the current transient state is obtained by summing the terms ε_s, ε_d şi ε_p. If, for a certain transition, more than one consumer is detected, the one with the smallest deviation coefficient will be chosen.

For a transient state to be determined by a consumer, it must be valid in terms of operating status of the consumer. As a consumer switches from one transition to another, the power level determined by that consumer is updated with the ΔP power change corresponding to the transition. One transition will be invalid if it determines a decrease of the power level under a certain threshold, whose value was chosen to -5 W. A consumer is considered to be turned off, if after a transition, the power level is between -5 W and +5 W. In this case, to not propagate the errors, the power level will be made zero.

If, for a transient profile, no possible consumers are detected, the algorithm will proceed with the detection of new consumers. Detection of new consumers is made based on the principle that the sum of all power changes, during an on-off cycle, is zero. Each time no consumers are detected, for a certain transient profile, the parameters of the current transient profile are recorded in an undefined states file. Once a new transient profile is detected its power changes are compared with different combinations recorded in the undefined states file. If a correspondence is found, then the respective transient profiles will define a new consumer.

Experimental verification

In Fig. 3a a succession of transitions generated by two LCD monitors made by two different manufacturers is presented. Detection of the two consumers was previously made and their signatures are presented in Table 1. The information of the four detected transitions are also presented in Table 2. Each of these states will be analyzed to detect the consumers.

As example, the last detected state is discussed below. Since the power change is negative, the algorithm will only search the negative states from the database. After the search is performed, the algorithm finds that the second consumer satisfies the conditions imposed by the current state. As it is a negative state, the power level of the detected consumer is checked. According to the second transition, the power level has a value of 22.61 W and the current transition determined a power change of -22.5 W. After applying the power change generated by the current transient state, a level of 0.11 W will be obtained, higher than the limit of -5 W. This values falls between the limits -5 ... +5 W, so that the consumer will be considered as being turned off and the power level will be made zero. Consumer’s information will be updated according to the new values and the algorithm will continue analysing the following transient states which will be detected. Similarly the algorithm will analyse the other detected transitions. After processing all four transient profiles, the signatures of the two consumers are updated and are presented in Table 3. The new values were obtained by averaging the values of the detected transient profiles and the ones from the database.

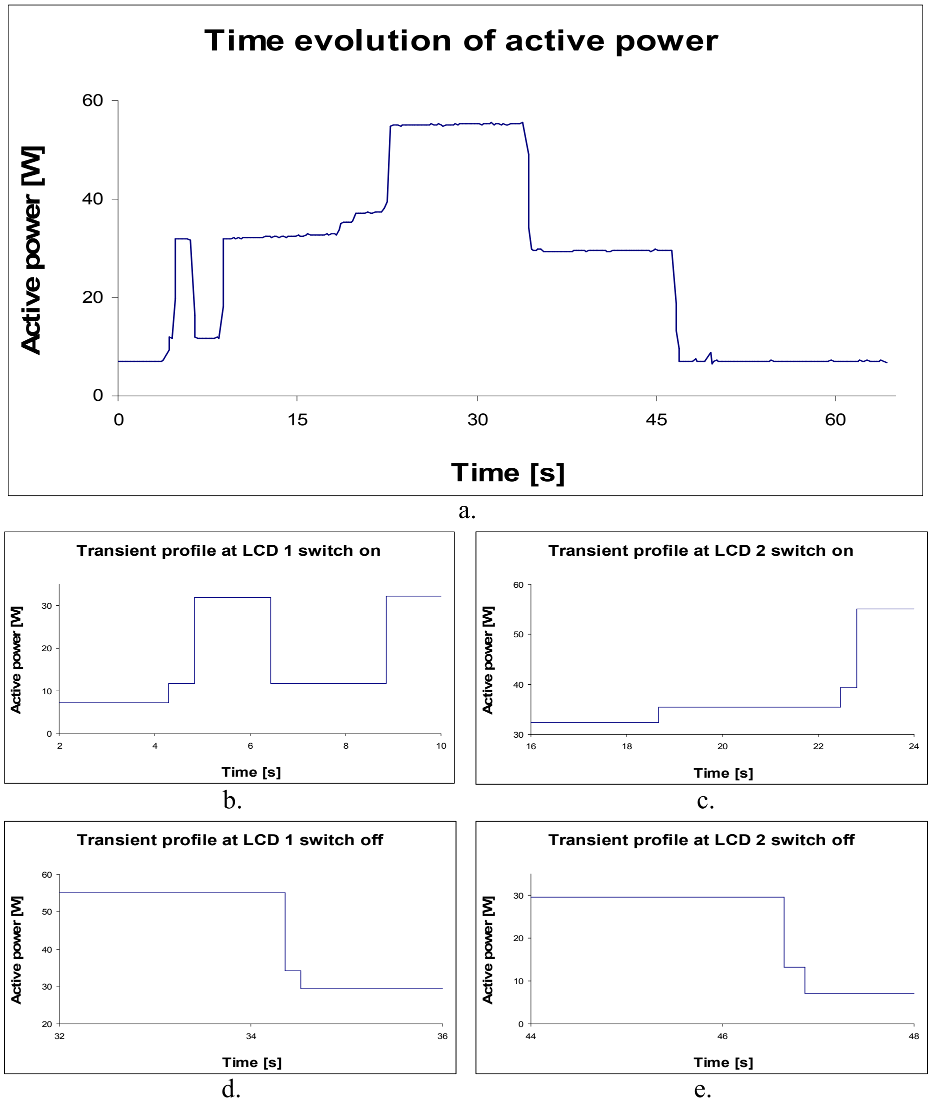

Fig. 3. Transient profiles generated by the transitions of two LCD monitors: a. evolution of the four transient profiles; b. transient profile generated by turning on the first type of monitor; c. transient profile generated by turning on the second type of monitor; d. transient profile by turning off the first type of monitor; e. transient profile by turning off the second type of monitor

Table 1. Electrical signatures of the two monitors

	***TranzFeat*₁**					***TranzFeat*₂**					***P***
Feature	*S* [W]	*D* [s]	N_a	N_d	Δ*P* [W]	*S* [W]	*d* [s]	N_a	N_d	Δ*Q* [W]	[W]
Monitor 1	52.07	4.56	3	1	24.3	-0.86	0.2	0	2	-25.2	0
Monitor 2	12.48	4.14	3	0	21.8	-1.44	0.22	0	3	-22.2	0

Table 2. Transient profiles of active power generated by transitions of two LCD monitors

Start of transition [s]	**End of transition [s]**	***S* [W]**	***d* [s]**	N_a	N_d	**Δ*P* [W]**
4.3	8.86	52.98	4.56	3	1	25.01
18.66	22.8	13.53	4.14	3	0	22.61
34.36	34.52	-1.04	0.16	0	2	-25.67
46.64	46.86	-1.35	0.22	0	2	-22.5

Table 3. Updated signatures of the two consumers

	***TranzFeat*₁**					***TranzFeat*₂**					***P***
Feature	*S* [W]	*d* [s]	N_a	N_d	Δ*P* [W]	*S* [W]	*d* [s]	N_a	N_d	Δ*Q* [W]	[W]
Monitor 1	52.53	4.56	3	1	24.65	-0.95	0.18	0	2	-25.44	0
Monitor 2	13.01	4.14	3	0	22.21	-1.4	0.22	0	2.5	-22.35	0

Conclusions

A consumer detection algorithm based on analysis of transient profiles was presented. When a consumer switches from one state to another transient profiles of the power evolution are distinct from one consumer to another. The analysis of these profiles can be used in consumer detection.

Most of the previously implemented algorithms are based on analysis of a single feature. The algorithm presented in this paper uses a set of features which improves the accuracy of the detection and discrimination process. Mistaking one consumer with another has slight changes to occur within multi-feature load detection algorithm, since each type of consumers determines a characteristic transient profile depending on the nature of the operation it must fulfil.

This algorithm can be used to disaggregate the energy consumption within homes and offer to the user a more detailed view of how the energy is consumed. Having at its disposal this information, the user can identify the large consumers within his house and can find solutions to improve the efficiency of energy use. For example, in the current situation, when increasingly more utility providers use tariffs differentiated on time frames, the user can switch a major consumer (such as washing machine) from a time frame when the energy price is high to one when the price is low.

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