Augustyn WÓJCIK, Wiesław WINIECKI

Institute of Radioelectronics and Multimedia Technology, Warsaw University of Technology

doi:10.15199/48.2016.11.22

The method of identification operating states of multi-state electrical devices with complex modes of operation

***Abstract**. This paper presents the method for detecting operating states of electrical appliances. Based on the sequence of transitions between the operating states the method allows to obtain information about the mode of operation of a particular device. The article describes the structure of the system applying the proposed method, discuss the stages of the system operation and presents the results.*

***Streszczenie.** Artykuł dotyczy opracowanej metody rozpoznawania stanów pracy odbiorników energii elektrycznej. Na podstawie sekwencji przejść między stanami metoda pozwala na uzyskanie informacji o programie pracy urządzenia. Przedstawiono strukturę systemu realizującego proponowaną metodę oraz opisano metodę działania jego części składowych, prezentując uzyskane wyniki. (**Metoda rozpoznawania stanów pracy odbiorników energii elektrycznej o złożonych programach pracy**).*

Keywords: NIALM, classification, multi-state devices (FSM), electric signal features.
Słowa kluczowe: NIALM, klasyfikacja, urządzenia wielostanowe (FSM), parametry sygnałów elektrycznych.

Introduction

Statistical data from the last years shows an increase in electricity consumption in households. Moreover, among the different groups of energy consumers, households have the lowest rate of progress in saving energy in Poland [1]. European trends in the field of energy saving indicate that providing information on actual energy consumption motivates end-users to conscious and rational use of electricity. Each household involves dozens of electrical appliances with different nominal power which in different ways affect on the total energy consumption. Obtaining information on the operation of different devices may allow users to manage energy more efficiently [2].

The use of electricity meters for each device is not efficient and troublesome when new monitored devices are attached into the energy network [3]. An alternative approach to the electricity usage monitoring is NIALM - Non-intrusive Appliance Load Monitoring [4] [5]. In such a system, on the basis of data from single meter arranged in a network node, operating appliances are identified and total energy consumption is disaggregated. It is crucial for the proper operation of the identify algorithm to determine a device pattern, which constitutes a set of features describing the current and voltage waveforms associated with the device [6].

Classification of electrical appliances

According to the number of operating states, electrical appliances can be classified into four groups [7]. The first group consists of devices working permanently, examples being surveillance cameras or heating control systems. The second group embraces two-state devices (on/off type), e. g. light bulb or hair dryer. Another category involves the multi-state devices (FSM - finite state machine), whose work cycles constitute a repetitive sequence of time intervals with a specific energy consumption, examples being washing machine, dishwasher or microwave oven. The last type are devices with smoothly variable, such as a drill.

Architecture of the developed method

The article describes a method which allows identifying an operation mode of multi-state devices (the settings made by the user), on the basis of currents and voltages waveforms measured during operation of the device. Fig. 1 presents a flowchart of the developed method. It was assumed that the measuring device samples the current and voltage waveforms with a frequency of at least 1.6 kHz. In our research we used sampling frequency of f_s = 2 kHz. Measured waveforms are divided into sampling windows, in which the pattern of the device pattern is determined. Next, event detection is performed. When an event occurs, it is classified with use of appliance models. The result of the state classification is input for the next classifier. The outcome of the system is determining the mode of operation (the user's settings) as well as the power consumption of the device. Further sections of this paper discuss the following elements of identification method: creation of the machine model and determining a pattern (because of the similarity between these stages, they are described together), event detection, state identification using the KNN rule, building a model of operation modes and mode of operation classifier.

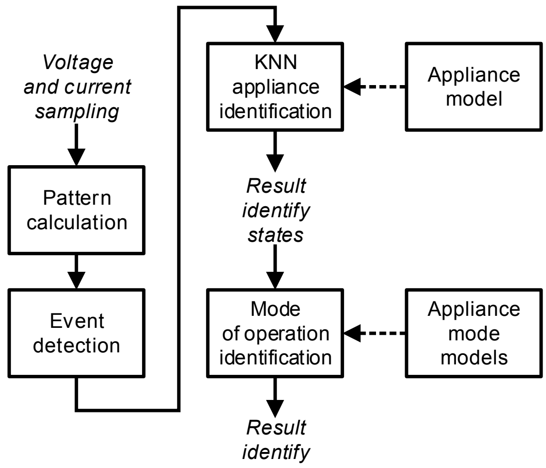

Fig.1. Block diagram the method of identification

Event detection

Event detection involves comparing signal in consecutive time windows with the window observed in the previous step being a reference for the next window [5] [8]. In the developed method, this is done by comparing the maximum value of the instantaneous current. A new event is noted, if the maximum value of instantaneous current in observed windows has changed by more than 60%. A threshold value was matched experimentally in order to meet two conditions. Firstly, all true events must be detected. Secondly, as little as possible false events are detected. A false event occurs when there is no device state change.

Device model

In order to ensure the proper operation, the method presented requires a supervised learning, during which on the basis of the current and voltage waveforms a label of a device is extracted. To be more precise, a vector magnitude is specified which enables to describe a device unambiguously. The features of the device model which were used in the described method are presented in Table 1. The ways/methods of setting the parameters are described in detail in [9–11] and [12].

Table 1. Features of device label

No.	Feature
1-16	Magnitude of current harmonics 1-16
17-32	Cosine of phase shifts of current harmonics 1-16
33	RMS value of the current
34	Mean value of the current
35	Maximum instantaneous current value
36	Magnitude of DC component of current
37	Mean power
38-53	Magnitude of real power harmonics 1-16
54-69	Magnitude of reactive power harmonics 1-16
70-85	Real part of complex spectrum of current harmonics 1-16
86-101	Imaginary part of complex spectrum of current harmonics 1-16
102-117	Magnitude of resistance harmonics 1-16
118-133	Magnitude of reactance harmonics 1-16
134-149	Magnitude of conductance harmonics 1-16
150-165	Magnitude of susceptance harmonics 1-16

In the case of multi-state devices, the parameter values may differ in terms of the device state, the reason being that the patterns should be set individually for each device state. The device work cycles were divided to states arbitrarily (Fig. 2). Thus, the full model of the microwave oven embraces three sets of patterns, each of them having 165 parameters. Each pattern set was determined one hundred times.

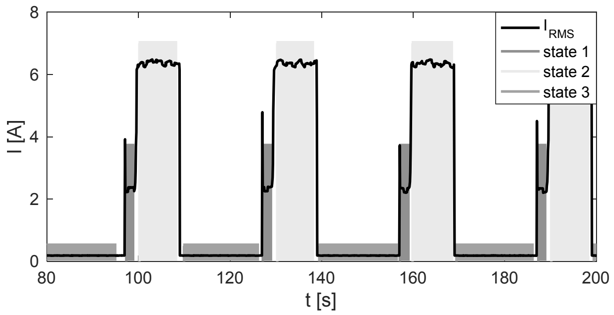

Fig.2. Division of microwave oven work cycle

Among the set pattern parameters it is necessary to select those that most accurately characterize observed appliance in each of the work state. In other words, parameter should be constant as a function of time. Due to the accuracy of identification, it is also important that the value of the parameter was varied in different operating states of the device [6]. It is necessary to determine the similarity of the objects or otherwise, the distance between the random variables, which are the pattern parameters. The parameter values are characterized by a different variation depending on the operating state. The measure used to determine the similarity between operating states should respect the variance of parameter. Because of the aforementioned requirements, the Mahalanobis distance was used. It is defined as follows:

$$d_n(i,j)=\sqrt{\left(\overline{x_i}-\overline{x_j}\right)\cdot \sigma_{i,j}^{-1}\cdot\left(\overline{x_i}-\overline{x_j}\right)^T} \quad (1)$$

$$\sigma_{i,j}=\sigma_i+\sigma_j \quad (2)$$

where: i, j – numbers of device operating states, d_n – operating states distance matrix, σ_i – variance, $\overline{x_i},\overline{x_j}$ – mean parameter values.

For each operating state pattern parameters were determined one hundred times. The parameters were normalized to range of values [0,1]. Then, the distance between the determined parameter values was calculated for each possible combination of the operating states. For the considered microwave oven, which work cycle is divided into four states, 6 unique values of Mahalanobis distance were calculated. To facilitate interpretation of the obtained Mahalanobis distances, for each parameter the minimum and maximum distance is selected and average distance is determined by the formula:

$$d_{AVG}(n)=\frac{\sum_{i=1}^{L}\sum_{j=1}^{L}d_{i,j}}{2L},\ i\neq j \quad (3)$$

where: d_{AVG} – mean Mahalanobis distance, L – number of operating states n – feature number

Mahalanobis distance for identical objects is 0. It is expected that the best for identify algorithm is parameter, for which values of all the designated distance are the greatest. Particularly important is that the parameters selected for identification were characterized by a maximum value of the minimum distance d_{MIN}. It specifies diversity of two most similar operating states. The resulting minimum values of Mahalanobis distance for microwave oven for all pattern parameters are shown in Fig. 3:

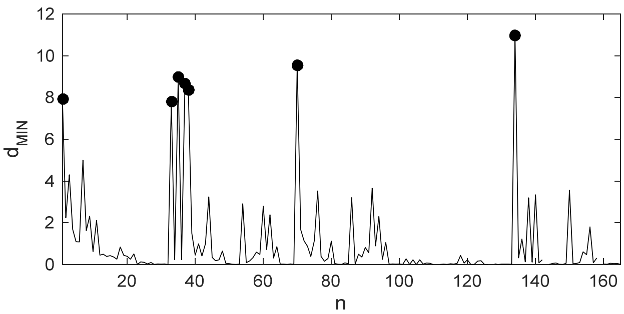

Fig.3. The minimum distance between the operating states of microwave oven for all pattern parameters

From all the 165 features of voltage and current waveform, best-conditioned parameters are: 1st current harmonic, RMS value of the current, the maximum value of instantaneous current, mean power, 1st real power harmonic, Real part of complex spectrum of 1st current harmonic and 1st conductance harmonic (Tab. 2).

Table 2. Mahalanobis distances for selected parameters

No.	Feature	d_{AVG}	d_{MIN}	d_{MAX}
1	I_1	32,7	7,9	85,2
33	I_{RMS}	30,7	7,8	76,9
35	I_{MAX}	33,3	9,0	83,7
37	P_{AVG}	26,1	8,7	59,9
38	P_1	25,8	8,4	59,6
70	$Re(C_1)$	41,6	9,6	110,4
134	G_1	89,3	11,0	285,5

Operating state identification

Event classification is based on comparison of the parameter value obtained based on the actual current and voltage waveforms with the values of this parameter for different states in which device may operate. At this stage, the system decides about which of the states occurred just after event detection. There are many object classifiers. In this method, KNN (k-Nearest Neighbor) classifier was used. KNN rule is based on assigning a label which appeared most frequently among nearest neighbors of considered object [6]. Neighbors of object are elements of patterns collected during creating the model. As a measure of the distance of objects Euclidean distance is used. Device model constitute two parameters: Real part of complex spectrum of 1st current harmonic and 1st conductance harmonic. Features have been normalized to the range of values from 0 to 1. The optimal number of neighbors for the test dataset was 1. Fig. 4 presents the result of the identification of states microwave oven set to *300 W* mode. *0* state occurs when the device is turned off. Red dots on the RMS value graph indicate event detection.

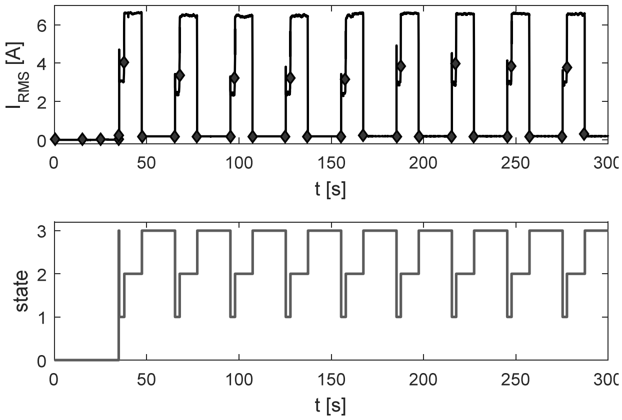

Fig.4. Classification of Microwave oven operating states

Classification result corresponds to arbitrarily assigned operating states. According to proposed in [13] measure of the accuracy of operation of the NIALM, the accuracy of detection events is $\eta_{DET} = 0.95$. However, the most important from the point of view of proper operation of the system is the accuracy of detection, which amount $\eta_{DIS} = 1.00$. This value mean that all detected events have been classified correctly.

Label of operation mode

The result of operating state identification are two vectors, one of which comprises a sequence present state of the device, and the second duration of the corresponding state (Tab. 3). Sets of vectors, or labels of individual operating modes allow to describe the work cycle of the device in the form of a graph of transitions between states [14] (Fig. 5). Identification of the microwave oven operating state was repeated for *180 W* mode. Thus prepared labels of modes determine a model for operating mode identification algorithm.

Table 3. Label of microwave oven in *300 W* mode

State	Duration
1	T_{12} = 5480 (2,7 s)
2	T_{23} = 19120 (9,6 s)
3	T_{31} = 35960 (18,0 s)
1	T_{12} = 4920 (2,5 s)
⋮	⋮

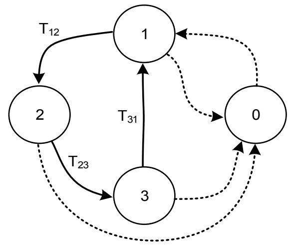

Fig.5. Cycle of microwave oven operation

Mode of operation identification

The basis of the mode identification algorithm is to describe a cycle of operation using a matrix of transitions between states. In the considered group of devices operating modes are distinguished because of individual states duration. In that case, it is important to obtain information about the maximum and minimum duration of each state employing prepared patterns (Tab. 3). Identification algorithm looks through the vector of operating states, selecting a specific length of state cycles. For presented microwave oven, state cycle is a sequence of length 3. If the sequence is detected, transitions matrix similar to the model of the device is created. Then, it is compared with minimum and maximum permitted duration of states. Conclusion of this is a decision whether the detected sequence of states is known mode of the appliance.

Fig. 6 shows the result of the algorithm for the microwave oven test data. Modes 180 W o 300 W differ the duration time of state 2 amounting respectively about 5.7 s and 9.6 s and the duration time of state 3 (about 21.9 s and 18.0 s). For the first 20 s of a sequence the microwave oven was turned off. At the time $t = 20$ s the oven was switched on. Just after turning on, the algorithm detected state 3 and then the known sequence of states 1-2-3-1 (see Fig. 4 and Tab. 4). On the basis of duration of states the sequence was classified as *300 W* mode. At time $t = 100$ s oven has been turned off (state *0*), so *microwave off* mode was indicated. About the time $t = 120$ s the sequence 1-2-3-1 was repeated, but the durations of each state were different than before. Mode *180 W* was activated. Fig. 7 shows a similar identification carried out for induction cooking. The results correspond to the settings entered by the user.

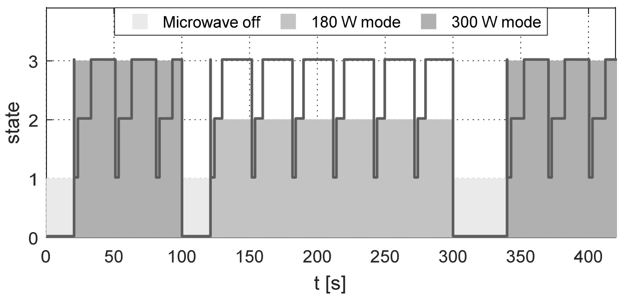

Fig. 6. Mode of operation identification - microwave oven

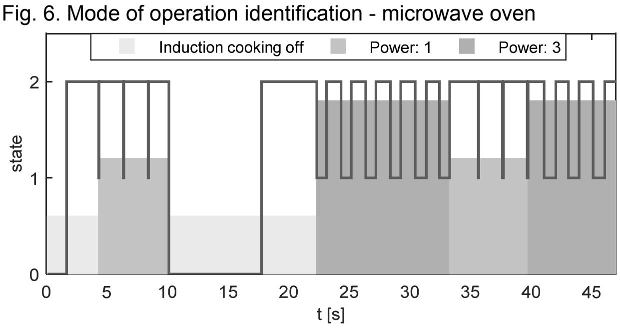

Fig.7. Mode of operation identification – induction cooking

There are also devices that are in the unique operating states occurring in particular mode of operation, or depending on the operating mode the sequence of states is different. In the case of such devices (e.g. washing machine, dishwasher), operating mode identification is based not only on the basis of the length of the individual states, as it did in the presented examples, but already at the stage of looking at sequence transitions between states of operation.

Conclusion

The proposed method is a part of the NIALM system which provides information on the energy consumption of individual appliances on the basis of measurements in a power grid node. Knowledge of the operating states of individual devices and determining the sequence of transitions between them in various operating modes provide support for building the NIALM system. While in the monitoring area many devices operate at the same time, the detection of a known sequence of states allows to increase the accuracy of algorithms performing disaggregation of the total energy between particular appliances. This is particularly important when operating devices constitute a similar load for power grid. The longer the sequence of the device states, the lower is the chance of identification inaccuracy.

The described method can also be used to inform the users on the manner in which the device settings influence the real energy consumption. The research also revealed that many devices operating states alter in a periodic sequence for a great deal of devices. The proposed solution can therefore be applied in the field of diagnostics to identify the failure of devices. The occurrence of the values with the current waveform which significantly differ from the expected ones or any abnormal sequence of operating states may indicate damage of the appliance [15]. Information about possibility of device failure presented by Nonintrusive Appliance Load Monitoring System increases the safety of the use of electrical equipment.

This work was supported by the Polish National Center of Research and Development, grant No. PBS2/A4/8/2013

***Authors**: M.Sc. Augustyn Wójcik, Prof. D.Sc. Ph.D. Wiesław Winiecki, Warsaw University of Technology, Institute of Radioelectronics and Multimedia Technology, Nowowiejska 15/19, 00-665 Warszawa, E-mail: A.Wojcik@ire.pw.edu.pl, W.Winiecki@ire.pw.edu.pl.*

REFERENCES

[1] Peryt Sz., Asztemborski B., Efektywność wykorzystania energii w latach 2003-2013, *Główny Urząd Statystyczny*, (2015)

[2] Kelly J., Knottenbelt W., Does disaggregated electricity feedback reduce domestic electricity consumption? A systematic review of the literature, *Proc. NILM2016 3rd International Workshop on Non-Intrusive Load Monitoring*, (2016), 5-7

[3] Liszewski K., Łukaszewski R., Kowalik R., Nogal Ł, Winiecki W., Different Appliance Identification Methods in Non-Intrusive Appliance Load Monitoring, in: V. Haasz, K. Madani (Eds.), Advanced Data Acquisition and Intelligent Data Processing, *River Publishers,* (2014), 31-59

[4] Winiecki W., Systemy inteligentnego pomiaru energii elektrycznej (Systems of Smart Measurement of Electrical Energy), in: A. Michalski (Ed.), Wybrane Aspekty Mobilnych Systemów Pomiarowych, *Wyd. Wojskowej Akademii Technicznej,* (2014), 91-122

[5] Khalid K., Mohamed A., Shareef, H., Sabeeh, M., Event-based S-transform approach for nonintrusive load monitoring, *Przegląd Elektrotechniczny*, 92 (2016), n.5, 194-198

[6] Duda R.O., Hart P.E., Stork D.G., Pattern Classification (2nd ed.), *Wiley Interscience*, (2001)

[7] Roth K., Zeifman M., Nonintrusive Appliance Load Monitoring: Review and Outlook, *IEEE Transactions on Consumer Electronics,* 57 (2011), n.1, 76-84

[8] Rababaah A. R., Tebekaemi E., Electric Load Monitoring of Residential Buildings using Goodness of Fit and Multi-Layer Perceptron Neural Networks, *Proc. IEEE International Conference on Computer Science and Automation Engineering* (CSAE), 2 (2012), 733-737

[9] Burkhardt D., Zaheer M., Steinmetz R., Reinhardt A., Electric Appliance Classification Based on Distributed Current Sensing, *Proc. 37th Conference on Local Computer Networks Workshops (LCN Workshops)*, (2012), 999-1005

[10] Wójcik A., Wzorce odbiorników energii elektrycznej w nieinwazyjnych metodach wyznaczania rozkładu zużycia energii elektrycznej, M. Sc. Thesis, *Politechnika Warszawska*, (2015)

[11] Wójcik A., Wzorce odbiorników energii elektrycznej w nieinwazyjnych metodach wyznaczania rozkładu zużycia energii elektrycznej, *Mat. XVI Seminarium z cyklu Radiokomunikacja i Techniki Multimedialne*, (2015), 51-58

[12] Bilski P., Winiecki W., Non-Intrusive Appliance Load Identification with the Ensemble of, *Proc. NILM2016 3rd International Workshop on Non-Intrusive Load Monitoring*, (2016), 5-9

[13] Liang J., Ng S. K. K., Kendall G., Cheng J. W. M., Load Signature Study-Part I: Basic Concept, Structure, and Methodology, *IEEE Transactions on Power Delivery*, 25 (2010), n.2, 551-560

[14] Liszewski K., Winiecki W., Łukaszewski R., Methods of electrical appliances identification in systems monitoring electrical energy consumption, *Proc. IEEE 7th International Conference on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS)*, 1 (2013), 10-14

[15] Chen K., Gupta S., Larson E., Patel S., DOSE: Detecting User-Driven Operating States of Electronic Devices from a Single Sensing Point, *Proc. IEEE International Conference on Pervasive Computing and Communications*, (2015), 46-54