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Methods of Electrical Appliances Identification in Systems Monitoring Electrical Energy Consumption

Robert Łukaszewski, Krzysztof Liszewski, Wiesław Winiecki
Warsaw University of Technology,
ul. Nowowiejska 15/19 00-665 Warszawa Poland,
rlukaszewski@ire.pw.edu.pl, krzysztof.liszewski1@gmail.com, W.Winiecki@ire.pw.edu.pl, http://www.pw.edu.pl

Abstract—**The aim of appliance identification methods is to get electrical energy consumption at appliance level based on aggregate measurements from a single energy meter. Disaggregation of measurements from a single meter allow to reduce the costs of the hardware part of the energy management systems. The article presents results of home appliances identification based on active power measurements. The Factorial Hidden Markov Model is applied to identify different appliances in the same time. Independent changes in active power of every appliance is described by each Markov chain. Having measurements of active power from single meter it is necessary to compute hidden variables defining states of appliance. The Additive Factorial Approximate MAP algorithm allows to designate states of each appliance. Moreover, an analysis of available solutions in terms of measurement frequency and appliance mathematical modeling is presented. We present the flowchart of the prototype appliance identification system with low measurement frequency energy meter. In the experimental part of the article, results of the selected home appliances identification are presented. Based on the results we conclude that probabilistic models of appliances allow to identify appliances working simultaneously.**

Keywords—electrical appliances identificationt; smart metering

I. INTRODUCTION

Growing prices of electrical energy increase the demand for development of systems monitoring and managing electrical energy consumption. European Union noticed the problem and included the need for smart metering and smart grid in its directive. Currently, plans for Advanced Metering Infrastructure (AMI) systems designed by energy suppliers do not include detailed analysis of energy consumption by consumers in households. Providing consumers with detailed statistics of electrical energy consumption could lead to a reduction in energy consumption, including increased consumer awareness. Thus, it becomes important to develop new methods for monitoring energy consumption by end-users. The solution of using a measuring energy consumption meter of each device is an inefficient. Whereas, the Non-Invasive Load Monitoring Systems (NIALMS) offer a possibility to monitor all appliances based on aggregated data from single meter. Main advantages of such systems are the relatively simple installation process, low cost of the installation and small requirements for modification in existing electrical installations. The main aim of the presented work was to investigate the possibility of identifying electrical appliances based on aggregate measurements from a single meter using NIALMS.

II. CLASSIFICATION OF ELECTRICAL APLIANCES

Electrical appliances can be divided into groups according to the number of operating states. The first group include appliances which are turned on permanently. This group of appliances require roughly constant active and reactive power 24 hours a day. The second group defines the most typical appliances in household called on-off type. The appliances can be identified with a state of constant power and off state. The third group of electrical appliances is a group of multi-state appliances, such as washing machine and dishwasher. Duty cycle of these devices can be described by a graph with different states. The identification of multi-state appliances is conducted based on appropriate operating modes sequence. The appliances with on, off and standby mode are 3-state appliances. To the last group belong appliances with continuously varying energy consumption. The identification of such devices is the most difficult because these appliances cannot be described by well-defined states.

III. ELECTRICAL ENERGY MONITORING SYSTEMS

Electrical energy consumption monitoring systems can be divided into invasive and non-invasive (Fig. 1). In the invasive systems it is required to introduce an additional meter associated witch each appliance. Whereas in the non-invasive systems the appliances identification algorithms are used based on the aggregate measurements from a single meter.

Invasive systems (IALMS – Intrusive Appliance Load Monitoring System) are the easiest way to monitor electrical energy consumption by each appliance. For example, in such systems individual meters for each appliance are used or an unique signal is transmitted indicating current state of the appliance. In invasive systems the use of appliances identification algorithms is not required and in these solutions it is possible to identify appliances with the same or similar signatures (including lighting in different rooms). On the other hand the invasive systems are inefficient in terms of installation costs as a large number of meters or modules transmitting information about appliance state is required. The introduction of a new appliance in such system requires a new meter and system reconfiguration.

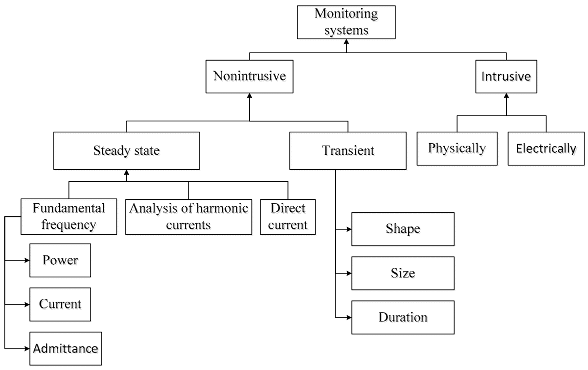

Figure 1. Classification of methods for monitoring electrical energy consumption [2]

The second group of systems monitoring energy consumption by separate appliances are NIALMS. In the NIALMS individual appliance energy consumption is based on aggregate measurements from a single main meter and electrical appliance signature for each appliances. The appliance signature is a set of parameters describing electrical nature of the appliance obtained from passive observation of these parameters during normal work cycle of the appliance. The signature may contain information about values of electrical parameters during steady and transient states. The information about transient states can specify shape and duration of changes in electrical parameter values. Whereas, in case of steady states, values of active power, current or admittance may be used to identify appliances.

The main advantage of NIALMS is that the system provide electrical energy consumption of each appliance based on the measurements from a single, central meter. In addition introduction in the home area a new appliance does not require a new measuring meter. The disadvantage of the NIALMS is the necessity of using advanced signal processing algorithms in order to identify appliances.

IV. METHODS OF APPLIANCE IDENTIFICATION

Methods of appliance identification depend on the measurement frequency of electrical parameters (Fig. 2). Having measurements of electrical parameters with measurement frequency greater than 100 Hz, it is possible to analyze variability of the parameters in time and frequency domain. The variability of electrical parameters may occur in steady and transient appliance states.

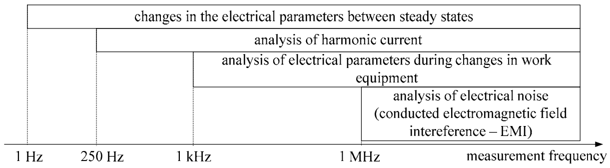

Figure 2. Classification of methods for monitoring electrical energy consumption based on measurement frequency criterion [3]

Appliance identification is also possible with the use of measurements with low measurement frequency [2]. Analysis of measurements with low measurement frequency enables only observation of macroscopic changes of electrical parameters. For example changes in active and reactive power can be analyzed by the algorithm proposed by G. Hart [2], that consists of the following steps:

- Identification of changes in active power during changes of appliance states;
- Clustering of the power changes in the ΔP, ΔQ plane;
- Grouping of clusters with opposite signs of change;
- Assign of ungrouped clusters to new appliances;
- Assign of the grouped clusters to appliances.

The algorithm may be applied in a large scale due to its ability to identify appliances with the use of measurements with low measurement frequency. However, the proposed algorithm is able to identify only on/off appliances and appliances, which duty cycles could be described as finite state graph. It is possible to extend the algorithm using other mathematical models. In the following paragraph the. possibility of using Hidden Markov Models as appliance probabilistic models is presented.

An extension of the Hart's algorithm was proposed by Ch. Laughman and co-workers [4]. The authors described a possibility of adding an amplitude of the third current harmonic to modify the original algorithm. In order to take into account values of amplitude current harmonics up to 11 – 13, the measurement frequency should be at least 1.2 -2 kHz. With higher measurement frequency the identification of appliances is based both on steady and transient states analysis. An example of appliance signature containing amplitude and phase values of current harmonics is shown (Fig. 3). The appliance identification is performed by the information comparison of current harmonics with the appliance signatures saved in appliances library (Fig. 4.). For appliances identification artificial neural networks may be applied as well [6]. The structure of the proposed artificial neural network uses the information about current harmonics as input dataset (Fig. 4.).

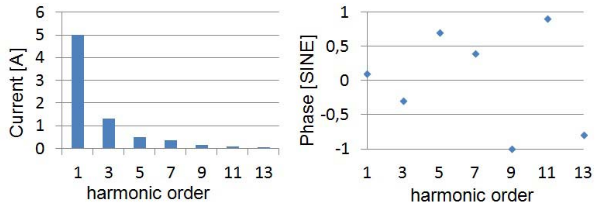

Figure 3. Appliance signature containing information about current harmonics [5]

Applying the artificial neural network from the output layer the classification of appliances is obtained. This method uses the artificial neural network, as a nonlinear classifier, to monitor information about current harmonics.

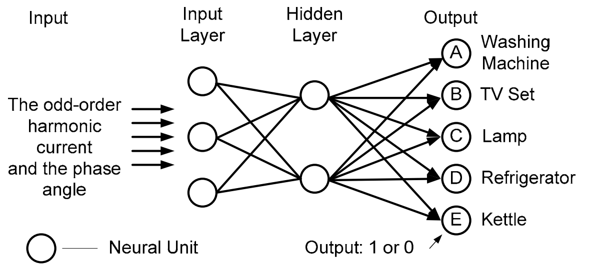

Figure 4. An example of applying artificial neural networks for appliance identification [6]

Artificial neural network parameters are obtained during learning process based on training dataset. The training dataset should include measurements of electrical parameters during normal operation of all appliances. For example, the data may consist of amplitude and phase of current harmonics in the moment when different appliances were turned-on. In neural network learning process the gradient and the Levenberg-Marquadt algorithms are the most common.

Moreover, appliance identification can be performed using the signature containing current and voltage values. In this solution, the signature in the form of the two-dimensional trajectory on the plane of normalized current and voltage is proposed. Based on the course and shape of the trajectory a set of parameters can be defined.

For example, parameters may describe the average shape line of the trajectory (Fig. 5. – dashed line). For linear appliances the average shape line should be a straight line with an appropriate angle. Whereas in case of non-linear appliances the trajectory is more complicated with intersection points.

Based on the number of trajectory intersections the dominant current harmonics can be determined. For example, in case of two intersections (Fig. 6.) in addition to fundamental current harmonic, the third harmonic can be also observed.

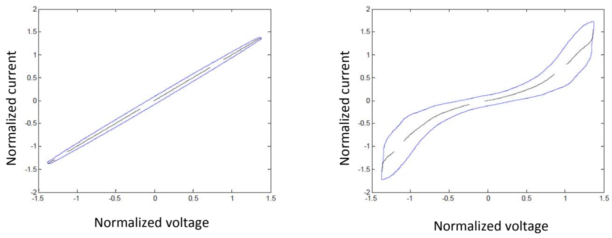

Figure 5. An appliance signature as a voltage – current trajectory

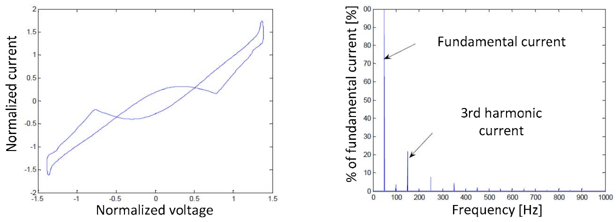

Figure 6. The relationship between the number of trajectory intersection points and the number of dominant current harmonics

It is possible to identify different appliances based on a set of parameters describing the course of the trajectory on normalized voltage and current plane. The first step in appliance identification is to extract parameters from trajectories. Then, the extracted parameters are compared to the parameters from appliances library. In such case the result of appliance identification is the appliance with the smallest mean square error between the input data and signatures in the appliances library.

Another appliance signature which may be used in NIALM systems is an identification based on electrical interference [7]. For example, appliances with power supplies Switched Mode Power Supply during operation generate a high-frequency electrical noise. These disturbances are specific for different appliances and can be used as an appliance signature. The NIALM system which uses electrical inference in appliances identification consists of Power Line Interface. The module provides adequate filtration and isolation between NIALM system and electrical system. The next module is the data acquisition (DAQ). Based on data from the DAQ module, the Fast Fourier Transform is calculated. Event detection module scans the signal for events when the noise level is greater than defined threshold value. In appliances library the interference is defined as Gaussian distribution for each appliance. The appliances are identified using k Nearest Neighbor algorithm.

V. Appliances Identification Using Hidden Markov Models

Hidden Markov Models (HMMs) are the most commonly used in speech recognition and in many other areas. HMMs may also be used to identify appliances based on measurements of electrical parameters. In this paper for further analysis of the appliance identification the HMMs were chosen. The choice was motivated by the possibility of using measurements with low measurement frequency.

In the active power waveform as a function of time the steady states are determined (Fig. 7.). The HMM (Fig. 7.) includes steady states (circles), the likelihood of state changes (arrows) and the likelihood of remaining in the same state (directed arcs).

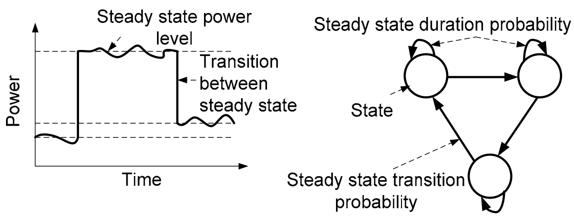

Figure 7. Appliance modeling using Hidden Markov Models

In disaggregation of the total electrical energy consumption for each appliance the probabilistic approach seems to be the most appropriate. Changes in active and reactive power are derived from aggregate time series and are assigned to different appliances. In addition, changes in appliances states are independent of each other. Changes in states of appliances are relatively rare and more likely remain in the same state. The total power consumption disaggregation may be directly reflected in Factorial HMMs. In the model there are independent chains of hidden variables, which describe the current status of each appliance. Changes in active and reactive power are expressed by observed variables. Active power changes are dependent on all hidden variables which determine current state of each appliance at a time. In Factorial HMMs the inference between observed variables and a number of hidden variables is a more complex problem. To solve this problem, the approximate Gibbs sampling algorithm is commonly applied [8]. In this study additive and differential Factorial HMMs [1] and approximate inference algorithm (AFAMAP – Additive Factorial Approximate MAP) [1] are used. The assumptions of the used AFAMAP algorithm are as follows:

- the analysis is based on the differences in active power;
- a parameter to make the model more robust in case of new appliances is introduced
- at a time only one appliance could change state.

In the first stage of the AFAMAP algorithm (Fig. 8.) the processing of raw measurements is performed. The purpose of the data processing is to eliminate changes in electrical parameters that are not related to changes in states of appliances. Then, the calculations are carried out iteratively for all appliances in library of appliances. For each appliance changes according to matrix with likelihood of transitions and Gaussian emission distributions are identified and assigned to different appliances. The appliances identification is based on measurements and models of appliances in the library. The identification is performed as minimization of the objective function. In this paper in order to optimize the objective function IBM ILOG Optimization Studio is used. After data processing and optimization stages the most probable sequences of all appliances states is obtained.

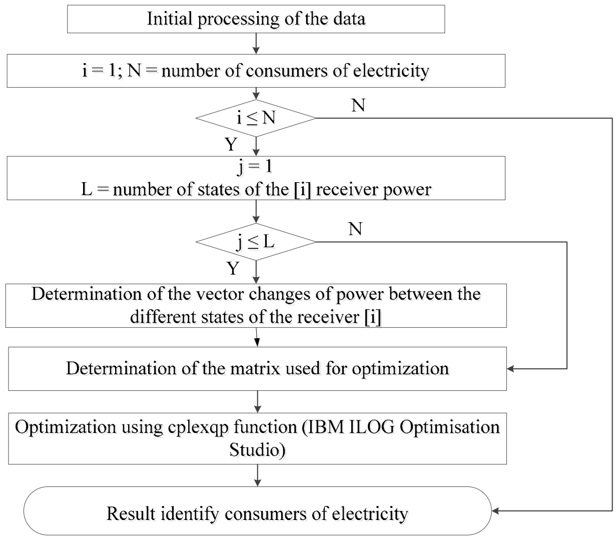

Figure 8. The flowchart of the AFAMAP algorithm

VI. Test and Verification of the Method

For the purpose of the method evaluation measurements obtained with Christ CLM 1000PP ELEKTRONIK power meter are used. The measurements were obtained during normal operation of selected home appliances, with the measurement frequency of 1 Hz. The scheme of NIALM system applied in this study is shown in Fig. 9.

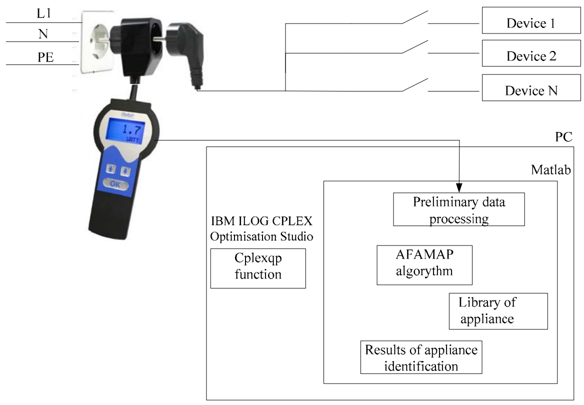

Figure 9. The schematic of the NIALM system used in the experimental part of the article

The method verification was performed as follows:

- in the first part measurements of electrical parameters of two appliances, not working at the same time, were analyzed;

- the second part concerns the identification of three appliances turned on and off at different moments, the appliances were not working at the same time;
- then the identification of three and two appliances turned on and off at different moments was performed, the appliances were working at the same time.

Results of appliance identification in case when three of them were working at the same time with different active power are presented in Fig. 11.

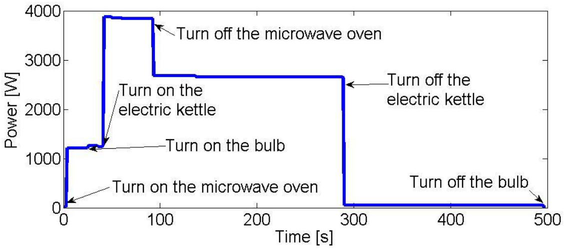

Figure 10. Active power value during simultaneously working of three appliances (electric kettle, 40 W bulb, microwave oven)

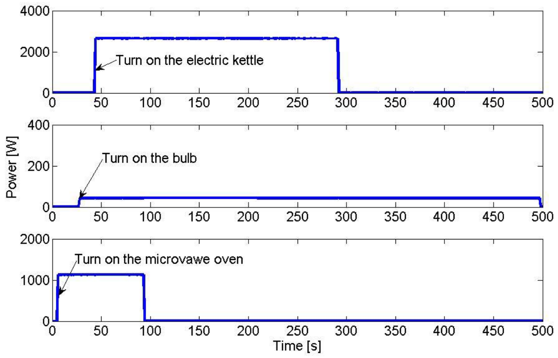

Figure 11. The results of appliance identification of three appliancesworking simultaneoulsy

The identification error values are based on obtained identification results (Table I). The identification error expressed in percentage is determined by dividing the identification mean square error and the turned on appliances overall active power. The identification error values are less than 0.01% in every considered case. Basing on the obtained results it can concluded that the chosen method of appliances identification allows to determine sufficiently accurate enough the electricity consumption by appliances individually.

TABLE I. THE SUMMARY OF THE OBTAINED APPLIANCE IDENTIFICATION ERROR

The number of turned on and off appliances	Identification error – mean square error [W]	Identification error [%]
1	43.15	0.006
2 (electric kettle, bulb)	20.01	0.008
2 (microwave oven, bulb)	73.42	0.003
3	41.39	0.005

The results consider the identification of on/off appliances. In case of multistate appliances the identification problem becomes much more difficult.

VII. SUMMARY

The NIALMS enable to monitor each appliance state based on aggregate measurement from a single meter. The main advantages of NIALMS are: the ease and low cost of installation and a small modification of the existing electrical system. The use of the NIALMS provide detailed information about electrical consumption on an appliance level. In the article a verification of appliance identification using HMMs is presented. The described method allow to monitor every appliance working independently. The verification of the selected appliance identification method was based on total active power measurements with frequency measurement equal to 1 Hz. Due to the possibility of using measurements with low frequency measurement, the introduction of the NIALMS for a large scale could be considered. The results obtained in the verification confirm proper identification regardless different appliances changing their operating states. It can be concluded based on the obtained verification results that the identification error value remains at a similar level during changes of operating states of different appliances. In addition, the identification error value compared to average appliances active power is acceptable. The obtained results confirm that using the selected appliance identification method operating states of different appliances can be determined

The primary and open research problem is verification or development of a new identification method for monitoring multistate appliances and appliances with continuously varying energy consumption.

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