Analysis of the artificial intelligence methods applicability to the non-intrusive load monitoring

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***Abstract*—The paper presents the comparative analysis of the data-driven intelligent methods used in the non-intrusive appliances identification. Because in the current research various measured characteristic features (symptoms) are combined with the selected classification approaches, the wider view of their application and advantages are required. The methods applied so far are categorized and their abilities compared. Also, approaches with potential benefit for the NIALM (Non-Intrusive Appliances Load Monitoring), but not yet applied are considered. The paper is concluded with future prospects and applications of selected methods.**

***Keywords*—artificial intelligence, load monitoring, classification methods**

I. INTRODUCTION

The non-intrusive approaches of the electrical appliances disaggregation rely mainly on the data gathered from the laboratory simulations, where each device is examined separately, delivering symptoms allowing for its further identification. The domain of signal analysis with selection of particular parameters acquired from the voltage and current measurements are the most important aspects of the identification process. Multiple approaches were made so far to increase the classification resolution by introducing various symptoms. The second important task for the NIALM designer is to select the optimal classification method, working with symptoms and identifying appliances with the highest accuracy. Although multiple methods were used in practice, their advantages and drawbacks were not compared. Usually only one of the methods is used with the particular set of symptoms. Comparative analysis was made so far for machine learning algorithms from WEKA library (including decision trees, Bayesian classifiers and rules induction) [1] and selected types of neural networks (including radial basis functions (RBF) networks and support vector machines SVM) [2]. However, it is not known, what is the efficiency of selected approaches compared to other popular methods, such as fuzzy logic and rough sets. Determining the optimal classifier for the particular set of symptoms is a time-consuming task, requiring numerous trials and multiple algorithms implemented.

The paper presents the overview and analysis of artificial intelligence (AI) methods usable in the NIALM framework. In section II the problem of collecting measurement data and creating data sets for the intelligent method is discussed. Section III introduces AI applications to the appliances identification: machine learning, expert system inference and method optimization. Here particular groups of algorithms are also presented, including examples of their applications to the particular tasks. In section IV the analysis of existing approaches usefulness and propositions of new methods are considered. Conclusions and future prospects are in section V.

II. DATA COLLECTION

The NIALM methodology assumes it is possible to correctly identify subsequent devices working in the residential premises based on the analysis of consumed power (measured in one location, external to their area of operation). Unfortunately, because of the vast number of various devices, distinguishing between them is difficult based only on their energy consumption in the steady state. Multiple approaches were proposed to acquire characteristic features from voltage and current signals (see section II.B). Data-driven intelligent methods aim at assigning the set of measured symptoms $\boldsymbol{e}_i$ (see (1)) to the particular device identifier. They first extract general knowledge about the relation between symptoms and the particular identifier using the learning data set $\boldsymbol{L}$ with examples of the appliances' behavior in various conditions. To verify the approach, testing ($\boldsymbol{T}$) sets are used. They are created during the laboratory simulations (the "off-line mode", where calculations are performed before using the method to the real object analysis). Next, the intelligent method is used (Fig. 1). The standard approach is to extract knowledge $f(\mathbf{e}_i)\rightarrow\boldsymbol{Z}$ based on $\boldsymbol{L}$ and then verify its usefulness using $\boldsymbol{T}$.

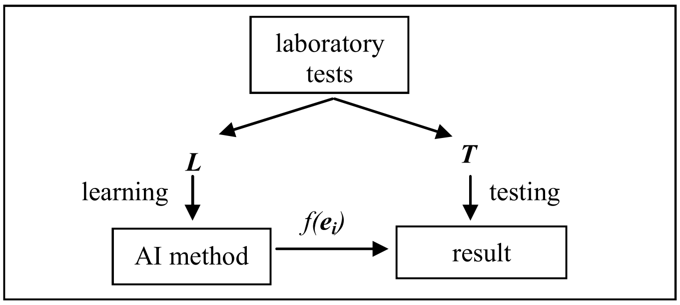

Fig. 1. Scheme of intelligent NIALM operation

A. Data sets structure

The general form of the data set used by the AI method is the table containing examples (results of simulations) in each row, being the ordered set of symptoms s_{ij}, supplemented by the discrete identifier of the analyzed device c_l.

$$\boldsymbol{T} = \boldsymbol{L} = \begin{bmatrix} \boldsymbol{e_1} \\ \vdots \\ \boldsymbol{e_n} \end{bmatrix} = \begin{bmatrix} s_{11} & \cdots & s_{1m} & c_1 \\ \vdots & \ddots & \vdots & \vdots \\ s_{n1} & \cdots & s_{nm} & c_k \end{bmatrix} \quad (1)$$

Each example is obtained by analyzing the single appliance in the particular state (depending on the type of the device). Because of the multitude of appliances it is impossible to distinguish between all of them with 100% accuracy, therefore the method should be trained for the specific configuration of the apartment or building.

The set $\boldsymbol{L}$ from (1) is used for the supervised training, where the information about the appliance responsible for the power consumption change represented by the set of symptoms in the example $\boldsymbol{e_i}$ is considered. Alternatively, the unsupervised learning may be used, disregarding the identifier c_l information in examples from (1). This way the data clustering may be performed, creating groups of similar examples, not necessarily representing the same device. They are difficult to detect.

The important extension of this scheme in NIALM is that from the practical reasons the data sets contain examples with information about only one device turned on at the same time. The actual situation in the residential area includes multiple appliances to identify. The set $\boldsymbol{T}$ is used for the verification of the applied method, assuming that each example is the new change in the repeatedly monitored power consumption. In the actual application ("on-line" mode) the classification algorithm must be executed each time the change in the power surge is detected, identifying the device responsible for the change. The following problems exist during the device classification:

- The inability to distinguish between different appliances based on measured symptoms. Sets of such devices form the ambiguity groups [3].
- The inability to detect the change in the power consumption (below 2W) [4].
- There is the possibility of turning on, off, or changing the state of multiple devices simultaneously. This is multiple category detection problem, difficult to solve using some methods (e.g. decision trees).

B. Categories of symptoms

So far the following domains of the power signals analysis were considered, requiring specific measurement conditions:

- active and reactive power with the resolution of 1Hz, applicable for capacitive or inductive devices [5]. Each appliance is represented by the point in two-dimensional plane.
- analysis in the time domain, where voltage parameters, such as amplitude, mean or RMS values, crest or form factors [6].
- analysis in the frequency domain, looking for the fundamental frequency and up to its 11 harmonics, measured with the frequency of 22kHz [7].
- analysis of transient components in the consumed power signals during the time-frequency analysis (using the short-time Fourier or wavelet transforms) [8].
- analysis of the electromagnetic interference, caused by the devices with impulse power sources [9].

Eventually, all parameters become symptoms s_{ij} in $\boldsymbol{L}$, $\boldsymbol{T}$ and $\boldsymbol{V}$. To acquire the described parameters, various devices are used, differing in the sampling frequency range and the measurement data processing algorithm. Considering all domains is costly, therefore in most cases only one measurement technology is used.

III. AI IN NIALM APPLICATIONS

Among all tasks assigned to AI approaches (classification, optimization, regression), the first two are used in NIALM. The classification (belonging to the supervised learning scheme) uses the function $f(\boldsymbol{e_i})$ constructed during the training (see Fig. 1) to identify the particular device. The unsupervised learning scheme can also be used for the classification of appliances easily distinguishable. The optimization is applied to find the classifier (such as the Bayesian network) parameters or the configuration of the residence model that suits best the measured symptoms. Because both applications are run in the "on-line" mode, their computational efficiency is a key factor. The taxonomy of AI approaches used in NIALM is in presented Fig. 2. Below the particular groups of methods are characterized and their applications provided. Presented approaches are used to identify binary appliances (working in the "on/off" state, e.g. TV) and finite state machines (working in the limited number of states, e.g. the washing machine).

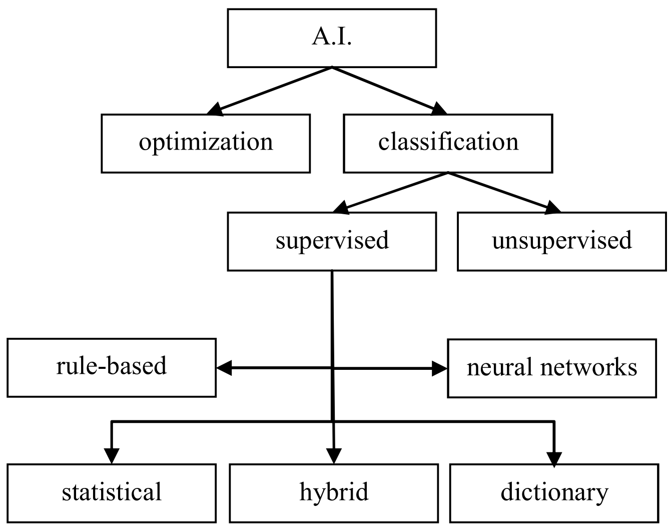

Fig. 2. Taxonomy of intelligent NIALM approaches

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A. *Supervised classification*

This is the most popular approach to the appliances identification, extracting knowledge from the complete set $\boldsymbol{L}$ (1). The following description discusses representatives of subsequent groups of algorithms, considering their ability to learn, identify the change of the state for multiple appliances at the same time and the form of stored knowledge.

1) Rule-based methods: The oldest form of storing knowledge is the set of "*if-then*" rules, readable by the human operator. During the identification, all rules are checked and the ones with fulfilled premises (all conditions met in the "*if*" part) are activated, pointing at the paricular device. The following approaches are:

- The set generated by the rules induction algorithm (such as JRip) [1]. All rules are activated simultaneously, therefore the method is useful for identifying changes in multiple appliances. It is possible to detect the unknown appliance (if no rule is activated). The stored knowledge is memory-efficient and the rules are able to work with both discrete and continuous data.
- Decision trees and forests are the alternative to the classical rules-based approach, working only with the continuous data [1]. They are memory efficient, but the trees (unlike forests) detect only one appliance at a time.
- Fuzzy logic is the extension of the classical rule-based approaches by considering the uncertainty conditions, which may be useful in distinguishing devices with similar values of symptoms [10]. The method is the typical expert system, able to detect multiple appliances simultaneously. Its main drawback is the absence of the machine learning method, requiring the input of the human expert or the external training algorithm.

2) Statistical approaches: These methods are based on the Bayes theorem, where the appliance identification is based on the conditional probabilities of observing the particular set of symptoms. The decision is made using the *apriori* (given beforehand) and *aposteriori* (extracted from learning data) probabilities. These include:

- Naïve Bayes Classifier (NBC) [1] is similar to rules-based approaches, as it requires calculating the probability of identifying each appliance based on the observed symptoms. The device, for which the probability of detection is the highest, is selected as the response of the identification system. The *apriori* probability is not required for comparison, which simplifies the procedure. NBC works mainly with discrete data, so its application requires the discretization of measured symptoms. It is also unable to detect multiple appliances.
- Bayesian networks store knowledge in the form of the graph, requiring *apriori* probabilities, which may be difficult to obtain. This method also works with the discrete data and is unable to detect multiple appliances.
- Hidden Markov Chains (HMC) are models of the devices' configuration in the residence, which deliver the information about the most probable changes in the appliances' states leading to the current values of symptoms. The parallel versions of HMC make them useful for identifying multiple devices at the same time [11]. Again, the problem is determining values of the *apriori* probabilities.

3) Artificial neural networks (ANN): They are used widely in most of scientific domains, proving usefulness in most classification tasks. Their efficiency highly depends on parameters, such as the number of neurons in hidden leayers or the type of activation functions. Classification is possible thanks to coding the appliance identifier by the binary output (each neuron produces one binary value). All configurations work with the continuous data and identify multiple devices:

- Multilayered perceptrons (MLP), i.e. the oldest type of network, consisting of hidden layers (usually less than three) with sigmoidal or linear activation functions and the output layer [7] with sigmoidal activation functions.
- Radial Basis Function (RBF) networks contain only one hidden layer with Gaussian activation functions and the output layer identical to. MLP [12].
- Support Vector Machines (SVM), being theoretically the optimal classifiers in the presence of noise. Their structure includes parameterized kernel functions (Gaussian, polynomial, etc.) [2].

4) Dictionary methods: This group contains currently one approach, i.e. kNN classifier. The inference mechanism is based on the distance calculation between the observed set of symptoms and the examples stored in the database. The identification is based on the voting of *k* examples closest to the analyzed set. Because of its simplicity it was used multiple times in NIALM applications [2].

5) Hybrid approaches: This group covers combinations of methods from other sections. The best established is the Fuzzy Neural Network (FNN), which binds the ANN ability to learn with the separation of objects in the uncertainty conditions provided by the fuzzy logic. The approach was used in [13], additionally exploiting the unsupervised learning to create rules. The FNN has advantages of both methods, working with continuous symptoms and being able to detect multiple appliances (thanks to rules executed in parallel).

B. *Unupervised classification*

This is the scheme usable in NIALM under two conditions. The first one assumes all devices in the analyzed residence are easily identified based on their symptoms and allows for extracting knowledge based only on symptoms' values. This is the new methodology, not yet fully explored in NIALM, although fuzzy c-means was used to design rules during the FNN training [13].

C. *Optimization*

The optimization methods are used as the auxiliary algorithms to find the configuration of the residential appliances models (including finite state machines), best fitting the current set of symptoms. For this task dynamic programming with extensions (Viterbi algorithm) and evolutionary approaches were used [14]. Also, the optimization scheme is useful during training the parametric classifiers, such as SVMs. These applications are not explored in NIALM, although some solutions (such as simulated annealing or particle swarm optimization) are known. Because the optimization is usually a calculation demanding task, its application in the on-line conditions imposes as effective algorithms as possible.

IV. Extensions of the Existing Scheme

Although the usage of AI approaches in NIALM is well established, the conducted analysis shows the following directions of further development:

- Apply the combination of learning algorithm (such as decision tree) with the fuzzy logic, which was done for other applications [15].
- Implement other classification approaches for NIALM, such as rough sets, which have similar abilities to fuzzy logic and SVM, as they work in the uncertainty conditions. They store knowledge in the form of rules and require discretization of symptoms.
- Apply other unsupervised learning schemes, such as graph clustering or Kohonen maps to find relations in data disregarding the appliance identifier in (1). This would be useful especially during finding the groups of similar appliances, difficult to distinguish from each other.
- Use other optimization methods to tune models of finite state machines, such as ant colony algorithm or tabu search. Both methods were successfully used in similar fields, such as technical diagnostics and could improve performance of NIALM as well.
- Thorough comparison between the classification and optimization approaches for the same set of symptoms and as many appliances as possible. This would result in the more detailed knowledge about advantages and drawbacks of presented approaches, which are in most cases applied separately (with minor exceptions [2,8,16]). The analysis also requires selecting the optimal set of symptoms maximizing the classification accuracy.

V. Conclusions

The overview provided in the paper proves multiple intelligent approaches are currently used in NIALM and their application has a great potential. Two aspects of the identification require researchers' attention. Firstly, the proper selection of symptoms (from all presented in section II.B) is required, as they influence the efficiency of algorithms. Secondly, the comparison between existing intelligent methods should be performed to determine their advantages and drawbacks. The discrete classifiers should be confronted against the continuous ones. Also, the methods working in the uncertainty conditions (SVM, FL, RS) must be compared with simpler and more traditional approaches (decision trees, kNN, NBC). Also, the fusion of classifiers can increase the identification efficiency, but the careful selection of approaches to the voting committee is needed.

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