# Supporting consumer decision-making by a softsensors with classifiers in an optimized feature space

***Jacek Bartman***
*University of Rzeszow, Institute of Computer Science,*
*Rzeszow, Poland* *jbartman@ur.edu.pl*

***Boguslaw Twarog***
*University of Rzeszow, Institute of Computer Science,*
*Rzeszow, Poland* *btwarog@ur.edu.pl*

***Bogdan Kwiatkowski***
*Rzeszow University of Technology, The Faculty of Electrical and Computer Engineering,*
*Rzeszow, Poland* *b.kwiatkowsk@prz.edu.pl*

***Tadeusz Kwater***
*The State University of Technology and Economics, Institute of Technical Engineering,*
*Jaroslaw, Poland* *tadeusz.kwater@pwste.edu.pl*

***Przemysław Hawro***
*The State University of Technology and Economics, Institute of Technical Engineering,*
*Jaroslaw, Poland* *przemyslaw.hawro@pwste.edu.pl*

**Abstract**

Non-intrusive monitoring of electrical loads (NILM) implemented by the state analysis method critically depends on the selection of appropriate features to identify devices. The commonly used expert selection is not optimal, and computational methods of feature selection require the establishment of an optimisation criterion that will ensure a satisfactory level of NILM system performance. An important element of the discussed method is the selection of the classifier and its matching with the selection method to construct a softsensor. In this work, four feature selection methods (Boruta, ReliefF, mRMR, the author's method) and four classifiers (decision trees, random forests, artificial neural networks and a hybrid classifier) were implemented and tested. Software was implemented for the softsensor architectures tested, enabling the verification of optimal configurations for NILM. The research confirmed that the selection of features using optimisation methods and the use of a softsensor allow for better support in the decision-making process.

**Keywords:** classification algorithms, softsensors, feature selection, machine learning.

## 1. Introduction

Artificial intelligence is an important component in solving problems in the field of broadly understood classification, supporting decision-making processes [3, 8, 23]. Various approaches have been proposed to implement Non-Intrusive Load Monitoring (NILM) in scientific works [8], [23], [9], [14], [27], [30], [34]. Their analysis emphasises the key relevance of selecting identification characteristics and identification methods [15], [19], [26], [29], [32, 33]. The most widely used classification methods in NILM include artificial neural networks, including deep learning networks [5], [16], [25], [31], [33, 34], statistical methods [31], [34], k-nearest neighbours [4], [33, 34], rule-based methods [24], [33, 34], genetic algorithms [8], optimisation methods [2], and hybrid methods [1]. The work uses intelligent classification methods, such as artificial neural networks, decision trees, and random forests, and proposes an original hybrid classifier. Additionally, analytical methods for selecting identification features were used instead of the most commonly used expert selection [29], [34], usually limited to basic features such as active power, reactive power, and effective current value. In this way, two sets of components were obtained, necessary to design and construct an optimal soft sensor dedicated to non-intrusive monitoring of electrical devices. The latest studies indicate that real-time monitoring of device operation, enabling detailed analysis of energy consumption, can lead to 15-20% of energy savings. This is possible due to the detection of devices that do not work and devices that cause anomalies in the network due of their faulty operation [8], [23].

### 1.1. Motivation and Contribution

A detailed list of features used in NILM can be found in [29], [32]. In the present study, 168 features obtained from high-frequency measurements (51.2 kHz) were used. A large number of potential identification features increase the likelihood of finding features relevant to the identification process but also increase the chances of processing features that carry no information or redundant information. This causes the need for a larger number of objects representing individual classes to determine the correct division of the test set in terms of device type identification. Meeting this condition is often impossible. To ensure the same classification accuracy as in the case of a lower-dimensional space, the number of samples must increase exponentially with increasing dimension of the feature space. Therefore, efforts have been made to reduce the dimensionality of the feature space [4, 5], [6, 7], [13], [15], [25],and limit it only to the essential features for identification. The available research results and their analyses show that redundancy and relevance of features can be assessed based, among other things, on mutual information entropy, neighbourhood analysis, and evaluation of the influence of individual features by randomly modifying them using selection methods [4], [6], [22], [28]. The process of identifying a set of features that enable effective identification of electrical devices for NILM purposes has been the subject of scientific research and has been especially intensive in recent years [4], [6], [15], [19], [29], [32].

The key contribution of the present work is as follows:

- the use of the precise and reliable class A energy quality analyser for empirical testing in a real environment. The analyser used for the measurements allowed for 1024 samples in the voltage period and 256 samples in the current period;
- the use of 168 steady-state descriptive characteristics, in particular reactive power harmonic characteristics and peak factor parameters as input variables, which fills a gap related to the use of these parameters for NILM;
- an innovative contribution of the work is the proposal and design of a softsensor as a component that integrates feature selection and identification in a single module built on the synergistic cooperation of both components. This solution aims to maximise the value of the identification quality index of device classes (rather than individual devices). Different combinations of selection and classification methods were tested, assessing the optimality of their interaction and proposing:
  - a hybrid classifier (HC) that uses the reliability of the subclassifiers determined at the testing stage for decision-making;
  - a feature selection method that combines the properties of the nearest-neighbour method with correlation analysis between features and features and score.

### 1.2. Review of the state-of-the-art

In [29], Sadeghianpourhamami implemented NILM using data from the PLAID repository. They examined 11 different types of devices using 55 steady state features and 23 transient state features collected from 56 households. To eliminate redundant features, they implemented a process in which features were first selected using the recursive feature elimination (RFE) method. In the second step, the random forest algorithm (RF) is iteratively trained using the selected features and the permutation relevance of each feature is calculated simultaneously to eliminate the less significant features. The highest classification accuracy, at approximately 91%, was achieved for signatures composed of a combination of 20 features.

Bao presented non-intrusive monitoring of 11 electrical devices in his work [19], achieving an Accuracy coefficient of 95.2%. They performed the optimal identification feature selection using information about entropy and the ReliefF algorithm, and the number of neighbours for the kNN algorithm was chosen by trial and error. They showed that the results obtained for the selected feature set are better than those for the original set. Both steady-state and transient-state parameters were used for the studies.

In the work [15] presented by Hoiudi and colleagues, research was conducted on two data sets: the author's data set that contains data on 24 types of devices, from which the authors extracted 61 classes, and the PLAID data set that describes 11 types, from which the authors extracted 70 classes. For the studies, 34 features that met additivity conditions were selected. The authors used the following feature selection methods: the NN-based sequential forward feature selection method, principal component analysis (PCA), linear discriminant analysis (LDA), mutual information (MI), and two proprietary methods: a method involving iterative addition of features and evaluation of the Accuracy indicator values and a method using a specially prepared deep neural network (DNN). Individual methods, as a result of selection, chose from 12 to 27 features for the author's data and from 12 to 33 features for the PLAID database. Classification was carried out with four methods: k nearest neighbours (kNN, k=7), LDA, DNN and RF methods for each selected subset of features. For both datasets, the authors achieved accuracies exceeding 99% for the author's dataset for MI selection and for the RF classifier and for the PLAID dataset for kNN-based sequential forward selection and the kNN classifier. When evaluating the results obtained, it is essential to remember that they are incomparable to the others, as each type of device was divided into several classes.

Souza [32] et al. used 38 features selected based on IEEE 1459-2010 and Conservative Power Theory (CPT). Using collinearity analysis of the features, they made a stepwise reduction in the number of features. They used three machine learning methods: k-NN, decision tree, and random forests, evaluating the results using a 10-fold cross-validation method to check whether the resul-ting set offered a good representation of the loads. The authors did not state what criteria they used to extract the initial 38 features from their complete set derived from IEEE and CPT power theory.

Isanbaev [19] use their own data acquired using a high-frequency method that involves measurements for 10 electrical devices. For each device, they select a set of 150 features (50 harmonics: current, active power, and a non-standard combination of these features) and statistical measures (min, max, mean, and standard deviation). They implement and compare eight data preprocessing techniques and six-dimensionality reduction methods for energy consumption data. The analytical results obtained vary according to the preprocessing and feature reduction methods used. The authors obtained them for individual devices rather than device classes, so they can be compared with the results obtained by Houidi [15] but cannot be related to the results of other works.

The authors of related research do not mention the factor that influences the ambiguity of signatures, which is the variability of the power supply conditions. Device signatures are then burdened with deviations that result not only from changes in the effective voltage, but also from the variable contribution of higher harmonics, which introduce distortions to the waveform [22]. Many of the defined device types exhibit several different operating states, sometimes an infinite number of operating states [12]. For the purposes of the research, electrical quantities were measured, ensuring very diverse power supply conditions by conducting the measurements at different locations.

## 2. Softsensor design methodology for steady-state analysis

Analysis of steady-state operation of electrical equipment for monitoring purposes allows a great deal of potential information features to be extracted. The main difficulty of this method is: the selection of features that have relevant information properties, selection of a classifier that will make the best possible identification on the basis of these features. These two steps form the basis for the construction of a sotftsensor that forms a coherent component based on the synergistic cooperation of the constituent components. In this paper, we present four feature selection methods that use different criteria to assess their identification properties and four different classifiers, which is the basis for the construction of 16 softsensors.

### 2.1. Data Acquisition

Eleven types of single-phase, two-state and multi-state electrical devices were used in the study, with finite and infinite numbers of states: kettles (1450÷1900 W), laptops (22÷49 W), soldering irons (10÷80W), hoover (450÷1100 W), mixers (20÷103W), microwave (210÷1360W), dryers (142÷1722W), grinders (37÷394W), TV (20÷206W), toasters (630÷887W), irons (1024÷1786W). It is worth analysing these devices in the context of electrical engineering because not only the number of identified devices, but also their type affects the quality of identification. The traditional division of devices into inductive, resistive, and capacitive devices is essential because of the similar nature of the characterisation of devices of one type. Consequently, it is much more challenging to find parameters that distinguish them if their power falls within overlapping ranges. This problem was deliberately addressed in the present research. To obtain identification data, electrical device operations were measured in 12 households in the Podkarpackie Voivodeship. Conducting measurements in multiple locations ensures that the data is obtained in various power supply systems, which, on the one hand, complicates the identification process and, on the other hand, allows for easier generalisation. Each type of device is described by 7 to 22 sets of samples obtained from different representatives of that type. Feature sets were obtained by measurements made using the Elspec BlackBox G4500 power quality analyser. The analyser used for the measurements was a Class A measuring instrument, allowing for the execution of 1024 samples in the voltage period and 256 samples in the current period. Following the recommendations of standards IEC 61000-4-7 [17] and IEEE 1459-2010 [18], along with expert knowledge in the field of the impact of energy consumers, 168 steady state features were selected for further analysis.

### 2.2. Selection of Identifying Features

The goal of feature selection is to reduce the dimensionality of the data set describing devices. The selection is based on an optimising criterion that aims to decrease the size of the data set without losing its identification properties. If we denote the set of device classes as $\boldsymbol{D} = \{d_1, \ldots, d_k\}$ and the set of identifying features that describe these classes as $\boldsymbol{A} = \{a_1, \ldots, a_n\}$, we can build a set $\boldsymbol{C}$ (1)

$$\boldsymbol{C} = \left\{\boldsymbol{c_i} : \boldsymbol{c} \in comb(\boldsymbol{A}), i = 1,2,\ldots,\binom{n}{1} + \binom{n}{2} + \binom{n}{n}\right\} \tag{1}$$

including all possible feature combinations. The selection leads to finding in this set the optimal feature combination according to the adopted criterion $\boldsymbol{C}^*$, such that [5]

$$(\forall \boldsymbol{d} \in \boldsymbol{D})(\exists \boldsymbol{c}^* \in \boldsymbol{C})(\forall \boldsymbol{c} \in \boldsymbol{C})(\boldsymbol{f} : \boldsymbol{A} \to \boldsymbol{D})((\boldsymbol{f}(\boldsymbol{c}^*) \geq \boldsymbol{f}(\boldsymbol{c})) \tag{2}$$

Four different feature selection methods were considered in the research, utilising various criteria for feature selection: the Boruta algorithm, the ReliefF method, the mRMR method (min. Redundancy – Max. Relevance), the author's method using feature surroundings, and the nNmRMR (nearest Neighbours – min. Redundancy – Max. Relevance) information measures.

#### *The Boruta algorithm*

The Boruta algorithm is a wrapper-type method that enlarges the set of features by adding variables that are permutations of the input parameters. These features are classified using the random forest method. The relevance of a feature is measured by the loss of classification accuracy caused by a random permutation of the values that describe the class. This is calculated separately for all trees in the forest that use a given feature for classification. Then, the average value and standard deviation of the loss of accuracy are calculated. An alternative measure of relevance is the Z-score, which is calculated by dividing the mean loss of accuracy by its standard deviation. Although the Z score is not directly related to the statistical relevance of the feature returned by the random forest algorithm, this indicator has been adopted as a measure of the relevance of the features in the Boruta algorithm [21]. Table 1 presents a set of features deemed significant by the Boruta algorithm.

**Table 1.** Feature comparison selected using the Boruta method.

| Feature of an electrical signal | Mean Relevance | Median Relevance | Min Relevance | Max Relevance | Norm Hits |
|---|---|---|---|---|---|
| **I** - current | 10.60 | 10.66 | 8.62 | 12.02 | 1.00 |
| **$U_h$** - higher harmonic voltage | 5.32 | 5.30 | 4.07 | 6.69 | 1.00 |
| **$I_h$** - higher harmonic currents | 7.43 | 7.39 | 6.47 | 9.02 | 1.00 |
| **$THD_i$** - total harmonic histortion of current | 7.54 | 7.50 | 6.63 | 8.64 | 1.00 |
| **$CF_i$** - current crest factor | 8.02 | 8.04 | 6.46 | 9.42 | 1.00 |
| **P** - active power | 9.82 | 9.86 | 8.41 | 11.43 | 1.00 |
| **$P_1$** - fundamental harmonic of active power | 9.75 | 9.72 | 8.22 | 11.11 | 1.00 |
| **$P_h$** - higher harmonics of active power | 7.28 | 7.28 | 5.19 | 8.99 | 1.00 |
| **Q** - reactive power | 11.16 | 11.22 | 9.46 | 12.81 | 1.00 |
| **$Q_1$** - fundamental harmonic of reactive power | 11.16 | 11.22 | 9.68 | 12.56 | 1.00 |
| **$Q_h$** - higher harmonics of reactive power | 7.14 | 7.14 | 5.79 | 9.00 | 1.00 |
| **S** - apparent power | 10.33 | 10.34 | 9.10 | 11.90 | 1.00 |
| **$S_1$** - fundamental harmonic of apparent power | 10.35 | 10.30 | 9.06 | 11.82 | 1.00 |
| **$S_h$** - higher harmonics of apparent power | 7.42 | 7.41 | 6.34 | 8.44 | 1.00 |
| **PF** - power factor | 10.31 | 10.33 | 9.14 | 11.39 | 1.00 |
| **$PF_1$** - power factor of fundamental harmonic | 10.26 | 10.23 | 8.83 | 11.66 | 1.00 |
| **$PF_h$** - power factor of higher harmonics | 6.79 | 6.83 | 5.36 | 8.21 | 1.00 |
| **$P_1$, $P_2$, $P_3$, $P_5$, $P_7$, $P_9$, $P_{11}$, $P_{13}$, $P_{15}$** - active power harmonics | 4.15÷5.52 | 4.36÷5.54 | 2.33÷4.25 | 5.62÷6.76 | 0.94÷1 |
| **$Q_1$, $Q_2$, $Q_3$, $Q_5$, $Q_7$, $Q_9$, $Q_{15}$, $Q_{17}$, $Q_{19}$** - reactive power harmonics | 3.31÷9.91 | 3.22÷8.90 | 1.27÷7.42 | 4.98÷10.31 | 0.72÷1 |
| **$I_1$ – $I_{50}$** - current harmonics | 3.44÷10.72 | 3.40÷10.72 | 1.02÷9.27 | 4.60÷12.20 | 0.78÷1 |

### *The ReliefF algorithm*

The ReliefF algorithm is based on the analysis of feature neighbourhoods. Its essence lies in promoting features whose neighbours belong to the same class and discriminating against those who describe other classes. This allows us to determine a measure of each feature's relevance for class description. The relevance measure $w_f$ for a feature in the ReliefF method is determined for observations collected in an $n$-element training set. For each element $x$ in this set, $k$ closet neighbours of the same class, called hits $h$, and $k$ nearest neighbours of other classes, called misses $m$. Then, for each feature, the weight increases by the distance from $x$ to m and decreases by the distance from $x$ to $h$ [20]:

$$w_f(m,k) = \frac{1}{nk}\sum_{i=1}^{n}\left(\sum_{j=1}^{k}\left|x_i, m_{ij}\right| - \sum_{j=1}^{k}\left|x_i, h_{ij}\right|\right) \quad (3)$$

It was decided that different devices would be described by a different number of features and the final training set would constitute the sum of feature sets that describe individual devices. For most devices, after the features are arranged according to their relevance, a sudden decrease in their values is observed. For each device type, of the min 8 highest relevance are included in the identification set. Fig. 1 shows the variability in the relevance of the features for selected devices. The navy blue bars denote the range of changes in the relevance of the feature depending on the number of considered neighbours, while the red dots indicate the median of these values.

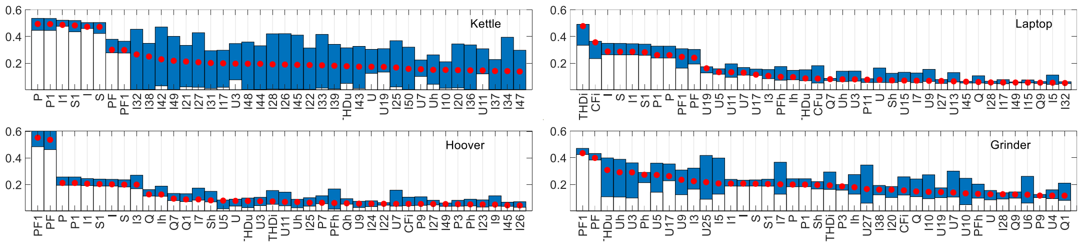



**Fig. 1.** Descendingly ordered values of the relevance coefficients for individual features of the examined devices.

The selected identification features for the monitored devices are the following: I, $I_1$, $I_h$, $I_3$, $I_5$, $THD_i$, $CF_i$, $PF_1$, PF, $PF_h$, P, $P_1$, $S_1$, S, Q, $Q_1$, $Q_7$, $U_h$, $U_3$, $U_5$, $U_{17}$

### *The mRMR algorithm*

The algorithm aims to select the most significant features that are as independent as possible. Therefore, features with high correlation with the class are chosen; these features are described by the relevance measure; and features with low correlation between themselves are described by the redundancy measure. Using the defined measures, the weights of each feature are determined for the class description [10]:

$$w = \max_{S}\left(\frac{1}{|S|}\sum_{s_i \in S} I(s_i, d) - \frac{1}{|S|^2}\sum_{f_i, f_j} I(s_i, s_j)\right) \tag{4}$$

where *S is* the set of features*, s* is the individual feature, and *d* is the class.

The research yielded significant values for the individual features shown in Fig. 2. The analysis of the figure indicates that most features are entirely insignificant according to the mRMR method, as their relevance coefficient values are close to 0.

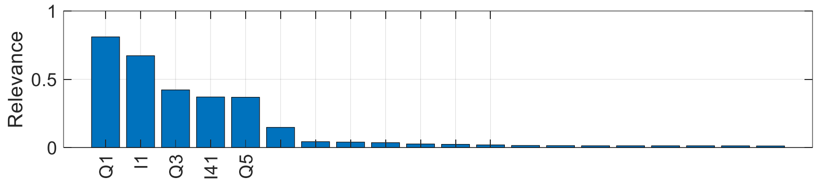



**Fig. 2.** Values of the relevance coefficient for parameters determined by the mRMR method (in descending order).

The following features were utilised for train and test a classifier used for the identification of electrical devices: the reactive power of the first harmonic $Q_1$, the effective current of the first harmonic $I_1$, the reactive power of the third harmonic $Q_3$, the effective value of the current of the forty-first harmonic $I_{29}$, the reactive power of the fifth harmonic $Q_5$.

### *The nNmRMR algorithm*

This paper proposed an original feature selection technology that takes into account information about the feature's environment and its informational value. Its implementation is described below:

1. The selected features according to the criterion of the nearest neighbourhood, following the principle that the feature belongs or does not belong to the device:
   a. the matrix containing features describing operating electrical devices along with device identifiers is defined:

$$A = \begin{bmatrix} A^1 \\ A^2 \\ \vdots \\ A^k \end{bmatrix}, \quad A^i = \begin{bmatrix} a^i_{1,1} & a^i_{1,2} & \dots & a^i_{1,p} & i \\ a^i_{2,1} & a^i_{2,2} & & a^i_{2,p} & i \\ \vdots & \vdots & & \vdots & i \\ a^i_{n,1} & a^i_{n,2} & \dots & a^i_{n,p} & i \end{bmatrix} \tag{5}$$

   where: $A$ – matrix of features and identifiers for all types of devices, $A^i$ – matrix of features and the value of the identifier of the device $i$-th, $a^i_{n,l}$ – $l$-th feature of the $n$-th instance of the device with the identifier $i$, $i$ – identifier of the $i$-th device, $k$ – number of device types, $p$ – number of parameters that describe devices;

   b. divide the data set repeatedly into two subsets according to the criterion of affiliation of electrical equipment. For this purpose, separate $k$ matrices, each dedicated to a different $i$-th device according to the scheme that the $i$-th device is described by a different identifier than the other devices:

$$C^i = \begin{bmatrix} A^i \\ B^i \end{bmatrix}, \quad B^i = \begin{bmatrix} a_{1,1}^{j\neq i} & a_{1,2}^{j\neq i} & \dots & a_{1,p}^{j\neq i} & j \\ a_{2,1}^{j\neq i} & a_{2,2}^{j\neq i} & & a_{2,p}^{j\neq i} & j \\ \vdots & \vdots & & \vdots & j \\ a_{m_j,1}^{j\neq i} & a_{m_j,2}^{j\neq i} & \dots & a_{m_j,p}^{j\neq i} & j \end{bmatrix} \tag{6}$$

where: $C^i$ – matrix of features of the $i$-th device with binary identifiers, $A^i$ – matrix of features and the identifier value of the $i$th device, $B^i$ – matrix of features and identifiers of devices different from the $i$th device, $i$ – identifier of the selected device, $j$ – identifier of the remaining devices, $m_j$ – number of instances of the $j$-th device;

c. the implement feature selection by independently determining, for each device, the relevance coefficients of the parameters based on the feature neighbourhood:

$$W^i = [w_1^i, w_2^i \dots w_p^i] \tag{7}$$

where: $W^i$– matrix of feature relevance describing the operation of the device with the identifier $i$, $w_l^i$ – relevance of the $l$th feature in identifying the device with the identifier $i$.

2. The eliminate redundant features by adjusting the relevance coefficients of correlated parameters. For each of the vectors $W^i$, calculate the coefficient values according to the relationship:

$$\forall(h = 1 \dots p)\left(\forall(l = 1 \dots p)\left(\forall(w_h^i < w_l^i), w_h^i = w_h^i(1 - \eta|r_{h,l}|)\right)\right) \tag{8}$$

where: $\eta$ is the correction coefficient, $r$ – correlation value between the $h$-th and $l$-th parameters.
From each vector $W^i$ containing features describing the $i$-th device, select the features with the highest values:

$$A_{max}^i = \left[a_1^i, a_2^i \dots a_q^i\right] \tag{9}$$

where: $q$ – selected number of parameters.

3. The set of features selected based on the information value of the feature (mRMR) is determined:

$$A_{mRMR} = mRMR(a_1, a_2 \dots a_k) \tag{10}$$

4. The addition to the obtained set of features is the selection of features based on their information value (mRMR):

$$V = \cup_{i=1}^{k} A_{max}^i + A_{mRMR} \tag{11}$$

The application of the method resulted in the extraction of the following features: Q, I, $PF_h$, $U_3$, $Q_7$, $PF_1$, $I_h$, $I_1$, $Q_1$, $Q_3$, $I_{29}$, and $Q_5$.

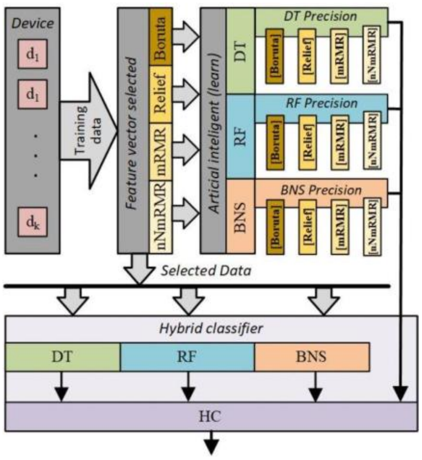
### 2.3. Classifiers Used for Identification

Four types of artificial intelligence-based classifiers were used to identify electrical devices: decision trees, random forests, neural classifiers, and custom hybrid classifiers.

Identification using trees (DT) was implemented using binary trees adapted for multiclass decisions. The CART algorithm was applied to build the tree, which uses the binary division of input elements for its operation. In each tree node, the data set was divided into two subsets and the data division was carried out using the Gini criterion, which divides the input set into as homogeneous a result set as possible. Other tree parameters were experimentally selected.

Random forests (RF) are a set of many individual decision trees. All decision trees that make up the forest use the same set of data, but they use differently selected variables to achieve the goal. This results in an improvement in classification quality. The applied forest algorithm used the AdaBoostM2 algorithm, which divides the input space, considering the distribution of the probability of drawing examples during learning and improving the final classification quality.

The binary neural selector (BNS) was built on the basis of artificial neural networks, serving as a preliminary classification module supported by a decision-making module. The preliminary classification module consists of 11 feedforward artificial neural networks, with the number of networks equal to the number of identified devices. Each network is used to identify one device, providing a type of response that indicates whether the given feature vector corresponds to a particular device. The networks have identical structures and consist of an input layer with a length corresponding to the length of the input vector, two hidden layers, and an 11-element output layer. Due to the lack of analytical methods that allow determination of the number of neurones in the hidden layers, this selection was made experimentally. The neurones in the hidden layers had a tangent transfer function, whereas the output neurones had a linear function. The Levenberg–Marquardt method was used for network training due to its efficiency and ability to learn quickly. The decision-making block determines the final response of the system. Its operation is based on the following principle: if only one network indicates the device, it is recognized, and such a response is provided at the system's output. If more than one network points to the recognition of the device, the decision-making module compares the response values. The device assigned to the network that provided the highest response value is indicated as the classifier's response.




```
Algorithm: Decision making by a hybrid classifier
Input:  DT, RF, BNS          //classifier decisions
DTPrec, RFPrec, BNSPrec     //classifiers precision
Output:                 HC    //hybrid   classifier
decision
    if DTPrec ≥ RFPrec &DTPrec ≥ BNSPrec
        HC ← DT
    elseif RFPrec ≥ DTPrec          &   RFPrec   ≥
    BNSPrec
        HC ← RF
    else
        HC ← BNS
    end
```

**Fig. 3.** Hybrid classifier scheme and algorithm decision making by a hybrid classifier.

The hybrid classifier (HC) consists of three subclassifiers: the BNS, DT, and RF, as shown in Fig. 3. The structure of the subclassifiers is identical to the structure described above. The operation of the hybrid classifier involves voting by the subclassifiers: if the decisions of the subclassifiers are consistent, the hybrid classifier accepts their decisions. When inconsistent responses occur among the subclassifiers, their decisions are weighted and the weight values are predicted based on the reliability assessment of the responses (as shown by arrow 4). The measure of reliability is the value of the Precision indicator obtained during the training and testing process of the subclassifiers. The hybrid classifier makes a decision consistent with the decision of the subclassifier that guarantees the highest predicted reliability value.

## 3. Identification of electrical devices by softsensors

Using the selection methods discussed in part 2.2, four sets of identification features were obtained, which together with the four classifiers presented in part 2.3, enabled the construction of 16 soft sensors. Softsensor tests were carried out using 10-fold cross-validation. The quality of device identification was determined using indicators: Precision, Recall, F1-score and Accuracy.

### 3.1. Analysis of device identification quality by softsensor

This section presents analyses on the quality of identification of individual devices. The tests assess the information stability of selected features, understood as insensitivity to changes in the classifier and the type of identified device. For each device, the average values of the coefficients used for its assessment were determined, depending on the applied feature selection method. The average was determined based on the individual indicator values obtained for the four classifiers discussed in part 2.3. The range of value changes resulting from identification by different classifiers is shown using scatter bars (Fig. 4). Fig. 4a shows the average values of the indicators (for all classifiers) depending on the feature selection method used. Fig. 4b shows the average values of the indicators (for all selection methods) depending on the classifier used. Analysis of the charts indicates that TV sets and laptops are the least well identified, followed by iron and electric kettles. Moreover, it is difficult to identify a feature selection method that allows for optimal identification results. In the case of some devices, the selection method clearly influences the identification results. Analysis of the obtained results revealed the following:

- the quality of identification of individual devices depends on the selected set of features,
- the informational value of the selected feature sets is not stable, showing sensitivity to changes in the classifier and the type of identified device.

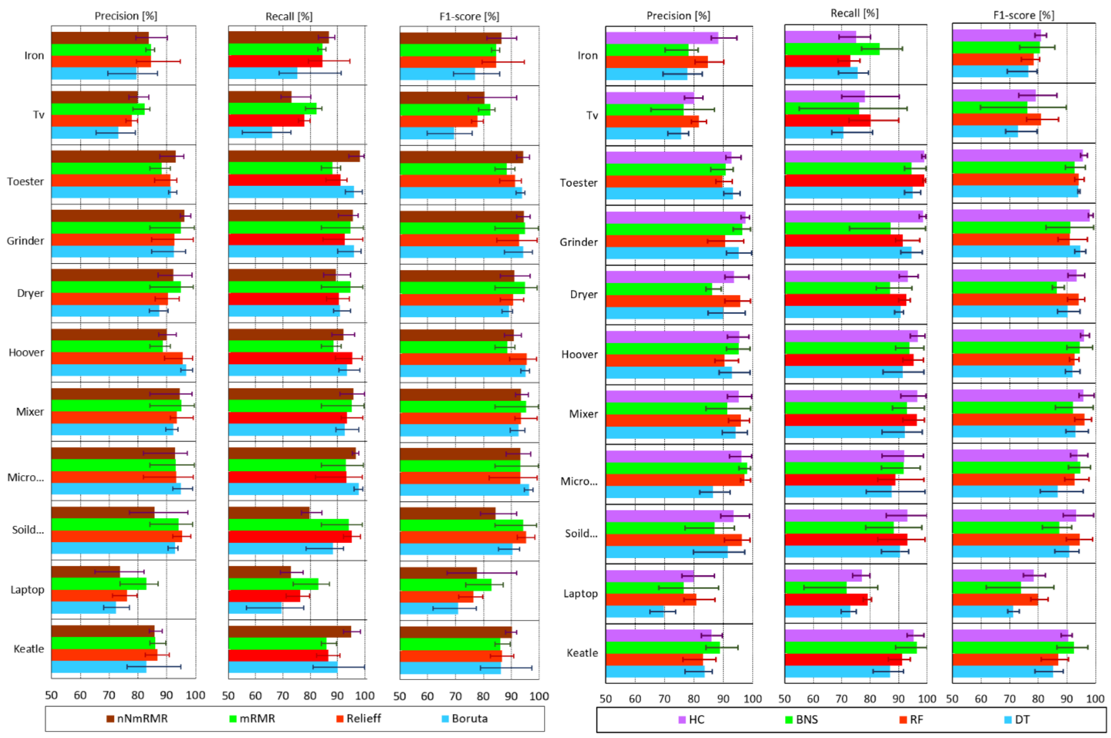



**Fig. 4.** a) Average values of identification quality indicators and the range of their changes depending on the applied feature selection method, b) average values of identification quality indicators and the range of their changes depending on the classifier used

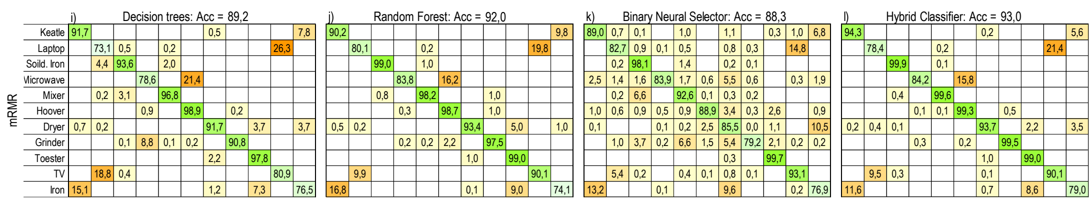



**Fig. 5.** Confusion matrices for the best feature selection methods and different classifiers.

The tests carried out allow for the construction of confusion matrices for different feature selection methods and different classifiers, demonstrating the quality of identification of individual devices (Fig. 5). The numbers on the diagonal of the matrix express the percentage of correct classifications. Analysis of the matrix revealed that some devices were confused due to similar work characteristics; this is shown in orange. The values of the indicators that reflect the quality of identification of other devices were satisfactory and fell within the range of 90-100% (Fig. 5).

### 3.2. Evaluation of classifiers and data selection to choose the optimal softsensor

The values of Recall indicator collected in Table 2a allow us to assess how the selection method affects the quality of identification. A detailed analysis of the collected data clearly showed that selecting universal signatures through direct use of data obtained from the examined feature selection methods was not possible. Globally, toasters are the most accurately identified devices (97.8%), and their identification depends to a small extent on the selection method used, indicating that many features associated with the operation of this device have informative properties. The opposite situation is observed for laptops and TV sets, which are often confused due to similar feature values and the resulting low identification value.

**Table 2.** Recall (a) and Precision (b) indicator values according to the selection and identification method

| Recall [%] | | Keatle | Laptop | Soild. Iron | Microwave | Mixer | Hoover | Dryer | Grinder | Toester | TV | Iron | **Avg** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Boruta | DT | 81,0 | 69,8 | 91,6 | 99,2 | 89,5 | 90,5 | 88,5 | 97,8 | 94,3 | 66,4 | 68,8 | **85,8** |
| | RF | 86,3 | 77,6 | 91,2 | 98,9 | 91,5 | 91,5 | 90,0 | 90,1 | 98,7 | 72,9 | 68,6 | **87,0** |
| | BNS | 100,0 | 56,7 | 78,4 | 96,0 | 92,0 | 98,2 | 94,7 | 97,5 | 92,8 | 55,1 | 91,3 | **86,6** |
| | HC | 92,9 | 73,9 | 92,2 | 97,5 | 97,8 | 94,1 | 90,3 | 98,7 | 99,1 | 69,9 | 72,2 | **89,0** |
| Relieff | DT | 93,7 | 69,0 | 78,1 | 95,4 | 91,0 | 92,0 | 88,6 | 97,4 | 94,2 | 72,1 | 88,9 | **87,3** |
| | RF | 92,2 | 77,4 | 76,8 | 96,6 | 93,3 | 88,0 | 94,8 | 90,4 | 99,5 | 69,2 | 87,4 | **87,8** |
| | BNS | 98,3 | 71,4 | 84,3 | 96,8 | 100,0 | 96,2 | 85,0 | 97,6 | 99,7 | 80,2 | 83,0 | **90,2** |
| | HC | 95,8 | 73,7 | 79,6 | 97,7 | 99,5 | 93,1 | 89,8 | 97,4 | 99,7 | 70,7 | 88,5 | **89,6** |
| mRMR | DT | 91,7 | 73,1 | 93,6 | 78,6 | 96,8 | 98,9 | 91,7 | 90,8 | 97,8 | 80,9 | 76,5 | **88,2** |
| | RF | 90,2 | 80,1 | 99,0 | 83,8 | 98,2 | 98,7 | 93,4 | 97,5 | 99,0 | 90,1 | 74,1 | **91,3** |
| | BNS | 89,0 | 82,7 | 98,1 | 83,9 | 92,6 | 88,9 | 85,5 | 79,2 | 99,7 | 93,1 | 76,9 | **88,1** |
| | HC | 94,3 | 78,4 | 99,9 | 84,2 | 99,6 | 99,3 | 93,7 | 99,5 | 99,0 | 90,1 | 79,0 | **92,5** |
| nNmRMR | DT | 89,3 | 75,2 | 92,8 | 79,5 | 84,2 | 91,8 | 90,9 | 90,9 | 92,1 | 68,1 | 79,5 | **84,9** |
| | RF | 94,2 | 80,4 | 99,3 | 82,8 | 96,6 | 98,2 | 93,1 | 89,0 | 98,5 | 85,4 | 72,6 | **90,0** |
| | BNS | 98,1 | 77,2 | 86,5 | 89,8 | 88,0 | 89,0 | 85,5 | 72,8 | 92,1 | 78,1 | 78,9 | **85,1** |
| | HC | 95,8 | 80,7 | 95,3 | 88,1 | 91,8 | 96,7 | 92,5 | 97,3 | 98,3 | 83,1 | 80,9 | **90,9** |
| Boruta avg. | | 90,1 | 69,5 | 88,4 | 97,9 | 92,7 | 93,6 | 90,9 | 96,0 | 96,2 | 66,1 | 75,2 | **87,0** |
| Relieff avg. | | 95,0 | 72,9 | 79,7 | 96,6 | 95,9 | 92,3 | 89,5 | 95,7 | 98,3 | 73,1 | 86,9 | **88,7** |
| mRMR avg | | 91,3 | 78,6 | 97,7 | 82,6 | 96,8 | 96,4 | 91,1 | 91,8 | 98,9 | 88,5 | 76,6 | **90,0** |
| nNmRMR avg | | 94,3 | 78,4 | 93,5 | 85,0 | 90,1 | 93,9 | 90,5 | 87,5 | 95,2 | 78,7 | 78,0 | **87,7** |
| **Avg** | | **92,1** | **73,6** | **88,6** | **92,4** | **95,1** | **94,1** | **90,5** | **94,5** | **97,8** | **75,9** | **79,6** | |

| Precision [%] | | Keatle | Laptop | Soild. Iron | Microwave | Mixer | Hoover | Dryer | Grinder | Toester | TV | Iron | **Avg** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Boruta | DT | 76,9 | 68,8 | 93,9 | 92,3 | 89,7 | 99,0 | 84,8 | 95,5 | 93,5 | 71,0 | 69,4 | **85,0** |
| | RF | 76,2 | 77,1 | 90,4 | 96,6 | 94,0 | 95,1 | 90,4 | 84,8 | 91,0 | 79,1 | 80,4 | **86,8** |
| | BNS | 94,9 | 68,0 | 93,8 | 99,0 | 93,4 | 94,9 | 84,0 | 93,4 | 90,6 | 65,4 | 81,0 | **87,1** |
| | HC | 83,6 | 75,9 | 93,8 | 92,0 | 92,0 | 98,2 | 90,5 | 96,4 | 90,8 | 76,8 | 86,8 | **88,8** |
| Relieff | DT | 95,0 | 73,7 | 91,0 | 90,0 | 89,9 | 97,0 | 87,6 | 84,8 | 92,5 | 73,7 | 83,4 | **87,2** |
| | RF | 96,6 | 73,6 | 89,2 | 84,8 | 89,4 | 93,1 | 93,0 | 88,2 | 96,2 | 78,2 | 83,4 | **87,8** |
| | BNS | 93,6 | 77,0 | 97,2 | 98,8 | 93,2 | 98,7 | 91,8 | 89,7 | 92,7 | 77,1 | 80,0 | **90,0** |
| | HC | 97,7 | 73,9 | 97,8 | 91,2 | 91,6 | 97,5 | 91,5 | 89,5 | 92,4 | 76,2 | 85,7 | **89,5** |
| mRMR | DT | 85,9 | 73,7 | 94,7 | 89,7 | 98,2 | 88,6 | 97,5 | 99,6 | 90,1 | 78,2 | 82,8 | **89,0** |
| | RF | 84,7 | 87,0 | 99,0 | 99,3 | 98,9 | 90,2 | 99,2 | 96,8 | 87,7 | 84,2 | 85,3 | **92,0** |
| | BNS | 84,1 | 88,4 | 84,3 | 98,4 | 88,6 | 96,0 | 84,1 | 97,2 | 93,2 | 86,9 | 70,3 | **88,3** |
| | HC | 89,5 | 87,0 | 98,9 | 99,5 | 99,6 | 91,3 | 98,8 | 98,9 | 91,2 | 83,1 | 85,8 | **93,1** |
| nNmRMR | DT | 85,4 | 65,0 | 79,8 | 81,9 | 97,4 | 88,8 | 91,2 | 94,8 | 95,6 | 76,9 | 79,3 | **85,1** |
| | RF | 83,9 | 82,1 | 97,4 | 97,0 | 98,8 | 87,1 | 98,8 | 95,8 | 87,5 | 83,7 | 90,2 | **91,1** |
| | BNS | 85,4 | 71,7 | 77,0 | 95,3 | 84,1 | 91,0 | 86,9 | 95,8 | 93,3 | 78,1 | 79,6 | **85,3** |
| | HC | 89,1 | 78,1 | 89,8 | 97,4 | 97,9 | 93,7 | 92,9 | 98,4 | 96,1 | 82,9 | 86,6 | **91,2** |
| Boruta avg. | | 82,9 | 72,5 | 93,0 | 95,0 | 92,3 | 96,8 | 87,5 | 92,5 | 91,5 | 73,1 | 79,4 | **86,9** |
| Relieff avg. | | 95,7 | 74,6 | 93,8 | 91,2 | 91,0 | 96,6 | 90,9 | 88,1 | 93,5 | 76,3 | 83,1 | **88,6** |
| mRMR avg | | 86,1 | 84,0 | 94,2 | 96,7 | 96,3 | 91,5 | 94,9 | 98,1 | 90,5 | 83,1 | 81,0 | **90,6** |
| nNmRMR avg | | 85,9 | 74,2 | 86,0 | 92,9 | 94,6 | 90,2 | 92,4 | 96,2 | 93,1 | 80,4 | 83,9 | **88,2** |
| **Avg** | | **88,2** | **77,0** | **93,7** | **94,3** | **93,2** | **95,0** | **91,1** | **92,9** | **91,8** | **77,5** | **81,2** | |

The results confirm that the quality of identification of individual devices depends on the selected feature selection method (signature selection) and the applied identification method. The set of features closest to optimal in terms of Recall indicator is obtained using the mRMR method.

The values collected in Table 2b for the Precision indicator provide information on the identification reliability of the devices and allow the assessment of whether the reliability of the identification features depends on the method of feature selection. Like for identification quality, it is not possible to establish an optimal vector of signatures in terms of identification reliability using only one selection method. The set of features closest to optimal in terms of Precision indicator is obtained using the mRMR method.

**Table 3.** Ranking of classifiers and feature selection methods based on Accuracy and F1 indicators.

| Ranking | Classifier | Selection method | Accuracy [%] | F1-score [%] |
|---|---|---|---|---|
| 1 | Hybrid classifier | mRMR | 93,0 | 92,6 |
| 2 | Random Forests | mRMR | 92,0 | 91,5 |
| 3 | Hybrid classifier | nNmMRM | 91,4 | 91,5 |
| 4 | Random Forests | nNmMRM | 90,8 | 90,3 |
| 5 | Binary Neural | Relieff | 90,5 | 90,0 |
| 6 | Hybrid classifier | Relieff | 90,0 | 89,4 |
| 7 | Hybrid classifier | Boruta | 89,4 | 88,7 |
| 8 | Decision tree | mRMR | 89,2 | 88,5 |
| 9 | Random Forests | Relieff | 88,5 | 87,6 |
| 10 | Binary Neural | mRMR | 88,3 | 88,0 |
| 11 | Decision tree | Relieff | 87,7 | 87,1 |
| 12 | Random Forests | Boruta | 87,7 | 86,8 |
| 13 | Binary Neural | Boruta | 87,7 | 86,6 |
| 14 | Decision tree | Boruta | 85,8 | 85,1 |
| 15 | Binary Neural | nNmMRM | 85,6 | 85,0 |
| 16 | Decision tree | nNmMRM | 84,9 | 85,5 |

Table 3 contains the classification of classifiers based on accuracy and F1 score. It is worth noting that, regardless of whether the criterion is Accuracy or F1-score, the order remains practically unchanged (except for positions 9-10 and 15-16). When classifiers are evaluated, the hybrid classifier and the mRMR selection method should be rated highest.

## 4. Conclusions

The presented research was carried out on the basis of data representing different power supply environments collected using the precise energy quality analyser. Due to the large number of high-frequency measurements, 168 potential information features were extracted, including current harmonics, active and reactive power, crest factor, and power factor, which were used to project a softsensor for the needs of NILM.

This study investigated the use of dedicated classifiers in an optimised feature space as a softsensor for non-intrusive device monitoring. Research focused on the selection of optimal features and classifiers to improve the accuracy and reliability of NILM systems.

The implementation of four feature selection methods Boruta, ReliefF, mRMR, and a hybrid selection method allowed for a comparative analysis of their efficiency in reducing dimensionality while preserving identification accuracy. Additionally, the study evaluated four classification algorithms: decision trees, random forests, artificial neural networks, and a hybrid classifier.

Experimental results demonstrated that feature selection methods have a notable impact on the quality of identification, with the mRMR method showing to be the most effective in balancing redundancy and relevancy. Furthermore, among the classifiers, the hybrid model that incorporating decision trees, random forests, and neural networks achieved the highest performance in terms of precision, recall, F1-score, and accuracy.

Key findings indicate that the selection of features using optimisation methods and integrating them with an appropriately chosen classifier significantly improve device identification performance.

In conclusion, the findings of this study reinforce the relevance of intelligent feature selection and its integration into NILM softsensors. The proposed methodology provides a solid foundation for future advancements in nonintrusive monitoring, potentially contributing to more efficient energy management and device monitoring solutions.

## References


1. Andrean V., Zhao X., Teshome D. F., Huang T., Lian K.: A Hybrid Method of Cascade-Filtering and Committee Decision Mechanism for Non-Intrusive Load Monitoring, IEEE Access, 6, 41212-41223, (2018)
2. Azizi E., Shotorbani A. M., Hamidi-Beheshti M. T., Mohammadi-Ivatloo B., Bolouki S.: Residential Household Non-Intrusive Load Monitoring via Smart Event-based Optimization, IEEE Transactions on Consumer Electronics, 66 (3), 233-241, (2020)
3. Baghbani A., Faradonbeh R.S., Lu Y., Soltani A., Kiany K., Baghbani H., Abuel-Naga H., Samui P.: Enhancing earth dam slope stability prediction with integrated AI and statistical models, Applied Soft Computing, 64, 111999, doi.org/10.1016/j.asoc.2024.111999, (2024)
4. Bao S. et al.: Feature Selection Method for Nonintrusive Load Monitoring With Balanced Redundancy and Relevancy, IEEE Trans. on Industry Applications, 58 (1), 163-172, (2022)
5. Bartman J., Kwater T.: Identification of Electrical Appliances Using Their Virtual Description and Data Selection for Non-Intrusive Load Monitoring, IEEE Transactions on Consumer Electronics, 67 (4), 393-401, doi: 10.1109/TCE.2021.3135423, (2021)
6. Bartman J., Kwater T., Kwiatkowski B., Mazur D.: Analysis of the coherence of parameters of electricity receivers in the context of nonintrusive device identification, Przegląd Elektrotechniczny, 2022 (11), 267-270, doi:10.15199/48.2022.11.54, (2022)
7. Bermeo-Ayerbe M., Ocampo-Martinez C., Diaz-Rozo J.: Non-intrusive condition monitoring based on event detection and functional data clustering, Eng. Appl. of AI, 124, 106625, (2023)
8. Chui K., Lytras M., Visvizi A.: Energy Sustainability in Smart Cities: Artificial Intelligence, Smart Monitoring, and Optimization of Energy Consumption, Energies, 11, 2869 (2018)
9. Çimen H., Çetinkaya N., Vasquez J., Guerrero J.: A microgrid energy management system based on nonintrusive load monitoring via multitask learning, IEEE T. Smart Grid, 12 (2), 977-987, (2021)

10. Ding C., Peng H. C.: Minimum redundancy feature selection from microarray gene expression data, *in* IEEE Computer Society Bioinformatics Conf 2003, 523–528, (2003)
11. Faustine A., Mvungi N. H., Kaijage S., Michael K.: A survey on nonintrusive load monitoring methodies and techniques for energy disaggregation problem, arxiv.org/abs/1703.00785
12. Figueiredo M., Almeida A., Ribeiro B.: Home electrical signal disaggregation for nonintrusive load monitoring (NILM) systems, Neurocomputing, 96, 66–73, (2012)
13. Gomolka Z., Twarog B., Zesławska E.: State Analysis of the Water Quality in Rivers in Consideration of Diffusion Phenomenon, Applied Sciences, 12 (3), 1549, (2022)
14. Herrero J. R., Murciego A. L., Barriuso A. L., de la Iglesia D. H., Gonzalez G. V., Rodriguez J. M. C., Carreira R.: Non Intrusive Load Monitoring (NILM): A State of the Art, Trends in Cyber-Physical Multi-Agent Systems. Adv. in Intell. Syst. and Comp., 619, (2018)
15. Houidi S., Fourer D., Auger F., Sethom H.:| Comparative Evaluation of Non-Intrusive Load Monitoring Methods Using Relevant Features and Transfer Learn, Energies, 14, 2726, (2021)
16. Huber P., Calatroni A., Rumsch A., Paice A.: Review on Deep Neural Networks Applied to Low-Frequency NILM, Energies, 14, 2390, (2021)
17. IEC 61000-4-7 Testing and measurement techniques - General guide for harmonics and interharmonic measurements and instrumentations for current supply systems.
18. IEEE Std 1459–2010. IEEE Standard Definitions for the Measurement of Electric Power Quantities under Sinusoidal, Nonsinusoidal, Balanced or Unbalanced Conditions.
19. Isanbaev V., Baños R., Arrabal-Campos F.M., Gil C., Montoya F.G., Alcayde A.: A comparative study on pretreatment methods and dimensionality reduction techniques for energy data disaggregation in home appliances, Adv. Eng. Inf., 54, 101805, (2022)
20. Kononenko I.: Estimating attributes: Analysis and extensions of RELIEF, Machine Learning: ECML-94. Lecture Notes in Computer Science, 784. Springer, Berlin, Heidelberg. 171–182.
21. Kursa M. B., Jankowski A., Rudnicki W. R.: Boruta - A System for Feature Selection, Fundamenta Informaticae, 101, 271-285, DOI 10.3233/FI-2010-288, (2010)
22. Kwiatkowski B., Bartman J.: The Influence of Measurement Methodology on the Accuracy of Electrical Waveform Distortion Analysis, Measurement Science Review, 18 (2), 72-78, (2018)
23. Lee D., Cheng C.: Energy savings by energy management systems: A review, Renew. Sustain. Energy Rev., 56, 760-777, (2016)
24. Lemes D., Cabral T., Fraidenraich G., Meloni L., De Lima E., Neto F. B.: Load Disaggregation Based on Time Window for HEMS Application, IEEE Access, 9, 70746-70757, (2021)
25. Lin L., Liu J., Huang N., Li S., Zhang Y.: Multiscale spatiotemporal feature fusion based non-intrusive appliance load monitoring for multiple industrial, Appl. Soft Comp., 167, 112445, (2024)
26. Mollel R.S., Stankovic L., Stankovic V., Explainability-Informed Feature Selection and Performance Prediction for Nonintrusive Load Monitoring. Sensors, 23(10), 4845, (2023)
27. Nutakki M., Mandava S., Review on optimization techniques and role of Artificial Intelligence in home energy management systems, Eng. Appl. of Artificial Intelligence, 119, 105721, (2023)
28. Ruano A., Hernandez A., Ureña J., Ruano M., Garcia J.: NILM Techniques for Intelligent Home Energy Management and Ambient Assisted Living: A Review, Energies, 12, 2203, (2019)
29. Sadeghianpourhamami N., Ruyssinck J., Deschrijver D., Dhaene T., Develder C.: Comprehensive Feature Selection for Appliance Classification in NILM, Energy Build., 151, 98–106, (2017)
30. Schirmer P. A., Mporas I.: Non-Intrusive Load Monitoring: A Review, IEEE Transactions on Smart Grid, 14 (1), 769-784, doi: 10.1109/TSG.2022.3189598, (2023)
31. Singh S., Majumdar A.: Non-Intrusive Load Monitoring via Multi-Label Sparse Representation-Based Classification, IEEE Trans. on Smart Grid, 11 (2), 1799-1801, (2020)
32. Souza W.A., Alonso A.M.S., Bosco T.B., Garcia F.D., Gonçalves F.A.S., Marafão F.P.: Selection of features from power theories to compose NILM datasets, Adv. Eng. Inf., 52, 101556, (2022)
33. Tabanelli E., Brunelli D., Acquaviva A., Benini L.: Trimming Feature Extraction and Inference for MCU-Based Edge NILM: A Systematic Approach, IEEE Trans. on Ind. Inf., 18, 943-952, doi: 10.1109/TII.2021.3078186, (2022)
34. Wójcik A., Łukaszewski R., Kowalik R., Winiecki W.: Nonintrusive Appliance Load Monitoring: An Overview, Laboratory Test Results and Research Directions, Sensors, 19, 3621, (2019)