Non-intrusive electrical appliances identification using Wavelet Transform analysis

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Abstract. The paper presents the application of the Wavelet Transform (WT) analysis to identify electrical appliances operating in the end-user household. The generic approach to the non-intrusive devices identification, i.e. using aggregated current and voltage signals is described. Next, the novel approach to extract features from the signals using WT coefficients is introduced. This allows for monitoring the appliance in the transient state, during the on-off event or while changing its mode (in the multi-state devices). This approach may replace or support the traditional steady-state analysis. Features extracted during switching the specific appliance in the laboratory conditions are then used to train the artificial intelligence-based classifier. It is further responsible for identifying the devices in the on-line mode. As the classifier, the random forest was applied. Its evaluation on the available data proves the usefulness of the proposed approach.

1. Introduction
The Non-Intrusive Load Monitoring (NILM) [1] is currently a fast developing technical domain. The need to provide energy-efficient solutions to not only industrial installations, but also households, requires sophisticated approaches to determine, which appliances are the most power-consuming in the longer term. To achieve this goal, every event of turning the device on, off or changing its state (directly related with the consumed energy) should be identified, based only on the analysis of aggregated voltage and current signals, measured at the single location, outside of the apartment. Because of the large number of appliances, distinguishing between them is difficult and multiple approaches are tried with varying efficiency. In most cases, the analysis is made in the steady state, after the specific event takes place and the device is already operating in the new work regime. Multiple research show deficiencies of such approaches, mainly difficulty in distinguishing between similar devices, detecting the change of state in power-efficient appliances (such as light bulbs) and the accurate identification of multi-state devices (such as washing machine or dishwasher). To overcome these drawbacks, we introduce the analysis of transient states, i.e. identification of the appliance during the change of state. During such an event, short high frequency components are observed in the measured signals. Methodology applied to extract useful information from them may improve the NIALM approaches accuracy.

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The aim of the paper is to present a novel NIALM methodology, based on the analysis of transient states in the aggregated current signal. To extract relevant features the Continuous Wavelet Transform (CWT) was used. The decision about the appliance identifier is made using the Random Forest (RF) classifier, which proved to be effective during previous works. The content of the paper is as follows. In Section 2 the proposed NILM system architecture is presented. Section 3 describes the approach to extract features allowing for the appliance identification in the transient state. In Section 4 the applied classifier is presented, while Section 5 presents experimental results. Section 6 contains the summary and future prospects of the approach.

2. NILM system architecture
The proposed NILM system uses transients to support identification methods based on the analysis of steady-state current-voltage parameters [2]. During the laboratory tests it was observed that the change of states in a group of appliances (such as lightbulbs) is associated with significant current amplitude surge. This allows for identifying the appliance based on features extracted from the signal during the event. Often used steady-state identification methods are not capable of detecting turning on of power-saving devices, especially in the presence of noise or when the power-consuming device (such as kettle or iron) is operating in the background. The proposed architecture (Figure 1) supplements the traditional approaches, detecting the change in the devices configuration based on the analysis of the current level.

The architecture exploits the data acquisition hardware near the energy meter. To thoroughly analyze transient state [3] and isolate sharp signal edges, the high sampling rate (like 20 MHz) must be applied. The hardware tool allows for acquiring the current signal during transient events. Collected waveforms are processed in the second main part of presented NILM architecture, which is software module. The following blocks have been implemented in this module:

- Event detection, that is checking if the analyzed waveform contains a transient state and determining the exact moment in which the transient occurs. The moment of switching the appliance on, the sharp current edge is located. This causes the power line becoming a transmission line, so the oscillations (which shape depends on the parameters of the local electricity network) appear. The transients detection facilitates the detection of an operating state changes [4].
- Determination of parameters characterizing the transient state using the Continuous Wavelet Transform (CWT). The vector of appliance parameters, further called pattern is the key element of the solution, because its content determines the ability to identify the device. The pattern ensuring discrimination between various appliances should contain repeatable values from many observations for the specific device, different from all other devices.
- Appliance identification, verifying quality of features prepared features. For that purpose, the AI-based classifier is used.

The difficulty in obtaining high accuracy in the NIALM methodology is that knowledge about each appliance is collected from the laboratory experiments, where each device is turned on and off individually. This way multiple patterns for each device form the training data set, used to train the classifier. It then operates in the on-line mode, when multiple appliances are turned on and off in
various moments. The problem is to correctly detect the change of the specific device with other candidates operating in the background.

3. Transient state analysis
The starting point for transient analysis was the observation of the current during events of switching on various devices. It was noticed that the transients have a different but repeatable shape for the specific device (Figure 2). Extraction of signal features was performed using CWT (Figure 3) [5]. It is more computationally demanding than the multiresolution analysis or discrete wavelet transform, but because of the lower scale factor step it allows to analyze the transient state in the selected range of the scale with high accuracy. To accelerate the analysis, the FFT algorithm was employed for calculating convolution of the tested signal with the mother's wavelet. An analytical bump wavelet defined in the frequency domain was selected arbitrarily as the mother wavelet.

![Figure 2](image1.png)  ![Figure 3](image2.png)

**Figure 2.** Switch on transient state of LED bulb. **Figure 3.** CWT coefficients of the LED bulb transient

Selection of scale factors is crucial to obtain distinctive CWT coefficients. The range of the scale was determined empirically on the basis of the frequency analysis of the quasi-periodic fragments of transients. An example of analysis for LED bulb transient is in Figures 2 and 3. Red diamonds in the waveform representation in the time domain mark fragment of transient represented on the scalogram as an increase in the magnitude of CWT coefficients. The result of the transient analysis is the pattern containing the following features:

- the scale factor of the dominant CWT coefficient (represented by the highest magnitude in Figure 3),
- width of the dominant scalogram component with cut-off levels of 50% and 90%,
- the scale factor for the beginning and the end of the dominant scalogram component with cut-off levels of 50% and 90%.

4. Applied classifier
The Artificial Intelligence-based classifier was used in the presented system to perform the appliance identification task. The RF is the ensemble of trees, which are trained on the same data set, but each has different structure of nodes, depending on the randomized selection method. The algorithm was used before, having the accuracy higher than other approaches, such as the decision tree or k Nearest Neighbours, at the cost if the higher computational demands. The main parameter of the method is the number of generated trees, which varied between 3 and 21, always being the odd number to avoid the tie between trees supporting different appliances.
The data set to train RF was created as follows. For each switch on event the CWT analysis was performed in three different ranges of the scale factor. Therefore, the single vector (representing the single transient during the switch-on event) consists of 21 features. For the experiments, forty vectors were collected for each appliance, which was enough to train the identification module. As eight appliances were selected for the tests, the data set consisted of 320 vectors. To make sure the method is resilient to the level of the background current, measurements were taken in various configurations (with all devices switched off or some of them operating constantly).

5. Experimental results
The laboratory test stand consisted in recording the sequence of turning the selected appliances on and off in the random order. Eight devices were selected for the test. As the method is promising mainly for power-saving ones, they form the majority of the set: LED and fluorescent bulbs (five appliances). The remaining ones were more power demanding and easier detectable by the traditional approach relying on the change in the current level: vacuum cleaner, juicer and mobile phone connected through the charger. Each device was turned on six times during the half-hour period. Table 1 presents the accuracy results for the applied methodology (only switch on events were counted). Most of power-saving bulbs are detected correctly, even when the power consuming device (such as the vacuum cleaner) operates in the background. Unfortunately, accuracy for some devices (like juicer) is lower, but they can be analysed using traditional identification methods.

| Appliance       | LED bulb | fluorescent bulb | vacuum cleaner | juicer | LED_Lexman | Sony Ericsson | LED_11W5 | LED_11W |
|-----------------|----------|-------------------|----------------|--------|------------|---------------|----------|---------|
| Acc [%]         | 83.33    | 100               | 66.66          | 50     | 66.66      | 33.33         | 83.33    | 83.33   |

More results (including the optimal configuration of RF) will be presented in the full paper.

6. Conclusions
The proposed approach focuses on the analysis of transient states, present when the appliance is turned on. This allows for distinguishing between some problematic power-saving appliances (such as lightbulbs), especially in the presence of the background noise. Usage of the RF classifier leads to the high identification accuracy in the uncertainty conditions. Disadvantages of the proposed approach include the high computational cost related with the high sampling frequency (leading to the large number of sample sin the processed vector). Also, to detect the turn-on event of the appliance, the calculation of transient-related features must be performed continuously. Future work should be aimed at decreasing computational requirements, allowing for the practical implementation of the approach.

References
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