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Detecting Consumer Devices by Applying Pattern Recognition to Smart Meter Signals

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Abstract

Future energy supply requires an intelligent load management for efficient distribution of the available energy, at national level, as well as on a regional scale. For this purpose, one necessary prerequisite is the immediate detection of the currently connected appliances (loads), for example white or brown goods. If the devices that are currently active at the time of a data point are known, it is possible to level the load curve by means of selectively connecting and disconnecting appliances, which results in an optimized usage of the available energy.

To realize the measurement of the energy consumption, we devised a low-investment system for centralized data acquisition and recorded and digitized characteristic load profiles. Afterwards, the application of different pattern matching algorithms allowed for recognizing and assigning individual loads from the measured sum signal. In the course of laboratory experiments, we could identify individual appliances and their combinations with this system.

Keywords

Pattern recognition, load monitoring, classification, nonintrusive low-investment, transient signal processing

1. Introduction

The term “smart metering” is a broad term and combines several meanings. In general, it is used to indicate (electricity-, gas-, water-, or heat-) meters with integrated “intelligent” electronics. Besides merely measuring the consumption, they offer extended functionalities, like load management via varying prices, i.e. to incite customers to refrain from connecting additional appliances through temporary rises in the price (at peak loads) and vice versa. In case of intelligent power meters, two approaches with different starting points are pursued:

One possibility is to equip all electrical devices, or outlets respectively, of a household with a communication interface that allows for in situ measurement and transmission of the wattage to the energy supplier (decentralized data collection). The disadvantage of this method lies in the high cost of materials for the conversion. Another possibility is to measure and analyze the power consumption of individual loads within a household at one central point (quasi-centralized)[4]. This method detects the total power consumption and computes the individual loads from the sum signal by means of pattern matching algorithms (disaggregation).

Within the scope of this contribution, we evaluated the technical feasibility of the second approach, due to the fact that, in general, the high investment cost makes the decentralized approach unacceptable for

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4 This method is denoted as “quasi-centralized” to rule out confusions with the centralized measurement (e.g. in the control room of the energy supplier).

private households. First, we used suitable hard- and software to perform a series of tests to gather the loads of selected electrical devices and to extract characteristics from them, inter alia, through discrete Fourier transformation. Afterwards, we utilized this reference data for the unambiguous reproducibility of the connected loads. Thereby, we compared the success rates of two methods with different strengths and weaknesses. On the one hand, we attempted to filter the individual loads from the aggregated signal by means of artificial neural networks (ANN). On the other hand, we analyzed whether or not a brute-force method – more precisely a nearest-neighbor (NN) classifier – would already suffice to deliver sufficiently accurate results in justifiable computing time.

2. State of the art

The market for intelligent meters in Germany developed rapidly, at the latest with the decision of the Federal Government to convert the operation of measuring stations to "smart metering" until 2014 (BMWI 2009). The detailed recording of the energy consumption for identifying energy saving possibilities is also applicable in industrial areas. For example, reference projects from the German Energy Agency (Deutsche Energieagentur GmbH) show potential savings of several 100,000 *kWh/a* for smaller manufacturing plants (DENA 2010). In combination with the transition to flexible rates on part of the energy suppliers, new horizons are opening for energy cost reduction. For such a load management, very accurate temporal and spatial resolution of the consumption of individual components is essential.

The smart meter technology that is available today usually consists of an intelligent central measuring point, where the energy consumption of several components is recorded. Hence, only the sum signal of the measured electrical line is available. Current research in the area of home automation shows that it is possible to identify individual devices from the sum signal, by means of their specific load profiles (Geller 2010). The used attributes like power factor, effective power, and peak voltage/current are provided via a smart meter unit and classified e.g. through an ANN (Ruzzelli 2010). This approach uses sampling rates in the minutes range and is only suitable for continuous loads. Patel et al (2007) take a step forward with the identification of transient signals: On the basis of short time frequency spectrums of the current signal, they identify short events. Besides individual devices, they were able to match mechanical switches' chatter signals through the individual noise spectrums. Therefore, frequency components of up to several *MHz* were analyzed. However, already at lower temporal resolutions, consumer types can be clearly distinguished.

After the recognition, a clear and intuitive visualization of the analysis results is necessary. Geller (2010) describes possibilities to deliver transparent and prompt feedback by using mobile devices like smartphones or tablets. Hereby, users are enabled to identify devices with high consumption values and thus adjust their usage, exchange old appliances for new energy-saving ones, or to detect malfunctions.

3. Centralized, low investment data acquisition

Commercial energy meters provide continuous information on the current instantaneous power, as well as the effective values of electric current and voltage. For that matter, usually sampling rates in the seconds range are common and reasonable. The goal of our contribution is to record and analyze the power signal with a high temporal resolution. Therefore, we based the developed smart meter upon the consumer energy meter KD 302 (Reichelt Electronics Co.) and used its analog and sampling units (Energy IC CS5460, Cirrus Logic Inc.) unaltered. We analyzed the communication (SPI interface) between the IC and the built in microcontroller and replaced the microcontroller with a communication module (ZigBit ATZB-24-A2, Atmel Co.). The hardware layout is depicted in figure 1.

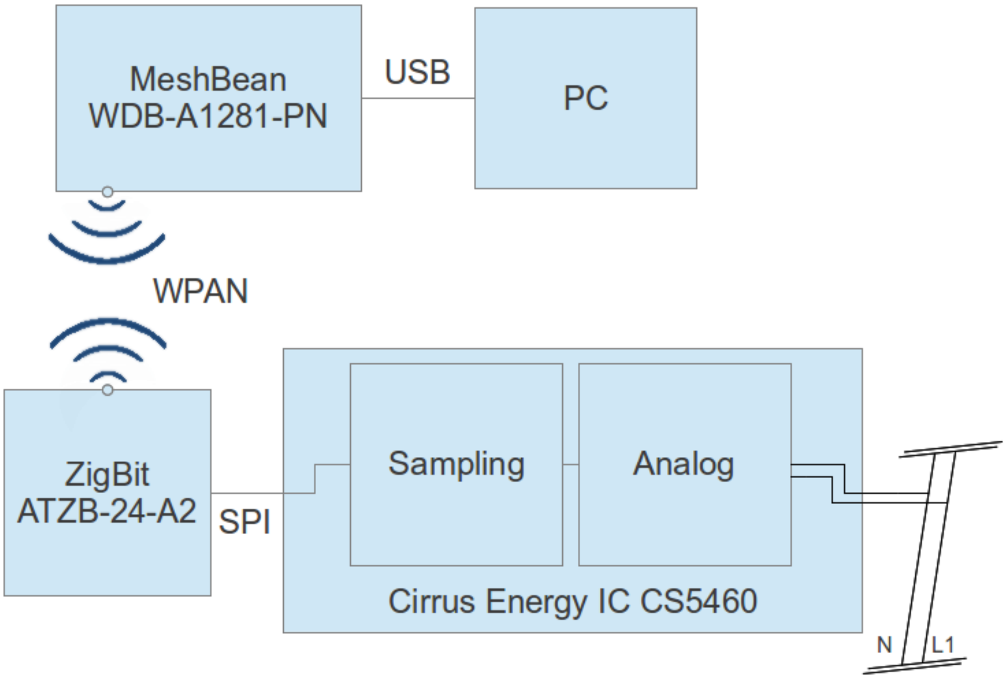

Figure 1
Hardware configuration for the smart meter

We then implemented a firmware that is capable of sampling the electric current and voltage trajectory in real time with a sampling rate of 4 *kHz*. The raw data gathered by this means is sent to a PC via WPAN communication as described in IEEE 802.15.4 (Callaway 2010). Afterwards, we analyzed and classified the incoming signals with the PC in a laboratory test (cf. figure 2). The used algorithms were realized as prototypes in MATLAB.

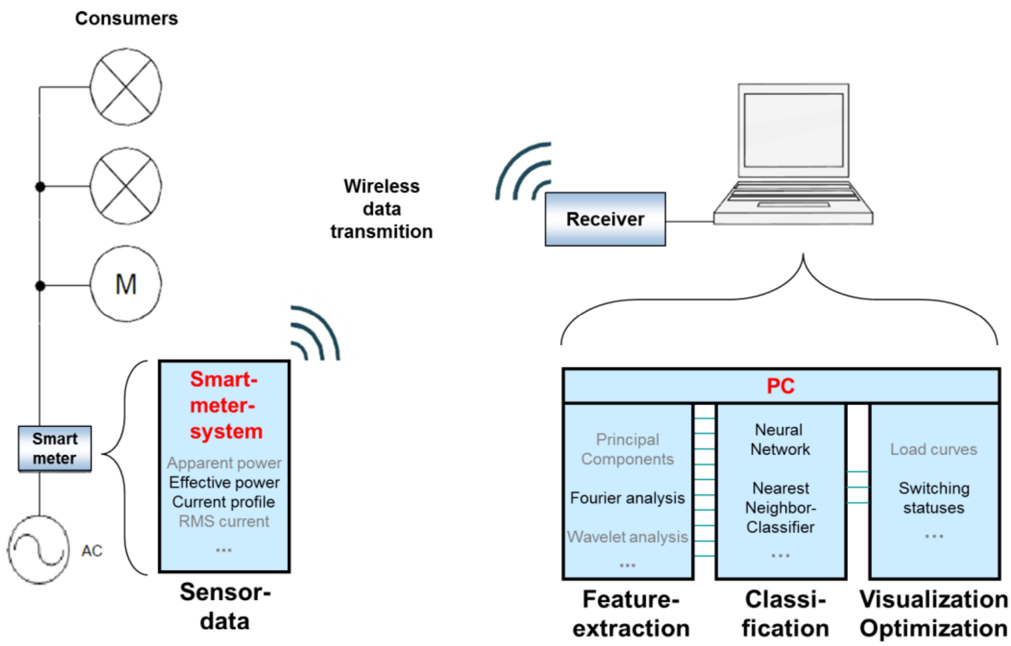

Figure 2
System for recording, feature extraction, pattern matching, and visualization

4. Signal processing in MATLAB

Via the wireless network, we measured time intervals of 0.25 seconds, i.e. 1,000 scan points of the current profile, as well as effective values of the current and voltage. In a first step, the system calculates 22 attributes from them that it subsequently evaluates in a classification step. Eventually, this allows for determining the currently active consumers. Due to the periodicity of the signals (cf. figure 3), e.g. the Fourier decomposition provides a simple method for generating significant values (in this case the values of the frequency spectrum), which then served as input for the used analysis methods for detecting the current consumers (cf. figure 4).

Besides the frequency spectrum, our experiments showed that the effective value of the current is also suitable as input for the pattern matching algorithms. This is due to the fact that it allows for the identification multiple homogeneous consumers that are active simultaneously.

As mentioned before, we used artificial neural networks, as well as nearest neighbor classifiers for pattern matching. As ANN, we used two layer perceptrons, which MATLAB's neural network toolbox contains for pattern matching tasks. They possess one output per recorded consumer and were trained in a way that when passed the characteristic values as input, the corresponding output assumes a value of [0,1], where 0 equals "consumer inactive" and 1 equals "consumer active".

In order to obtain reference data, in a laboratory experiment, we recorded the current signals of six partially homogeneous consumers (cf. table 1) and generated reference patterns from them. Subsequently, we used these data points as training and test data for the ANN and the NN classifier respectively.

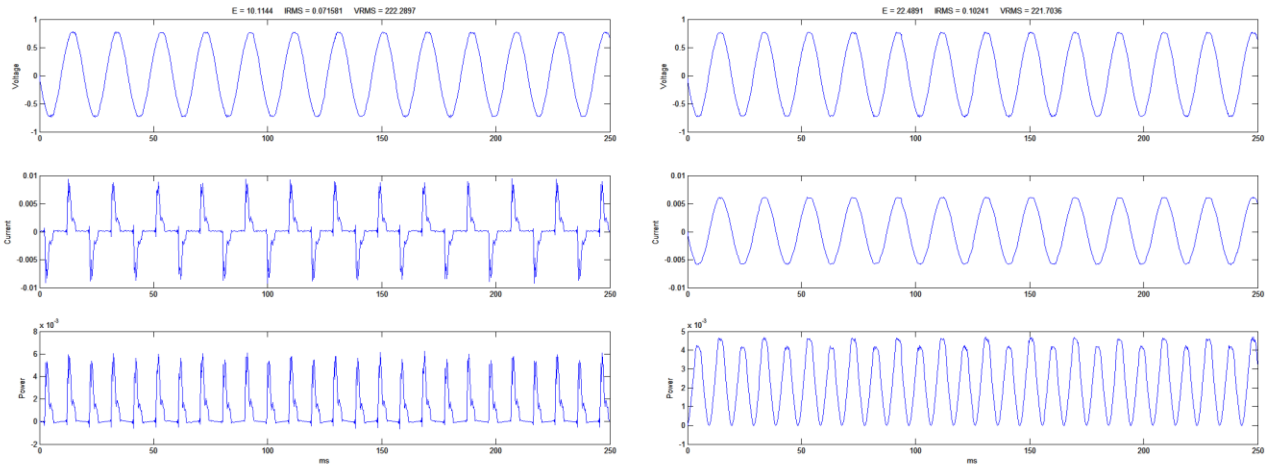

Figure 3
Normalized input signals of the voltage *U*, current *I*, and wattage *P*
for an energy saving bulb (left) compared to a filament light bulb (right)

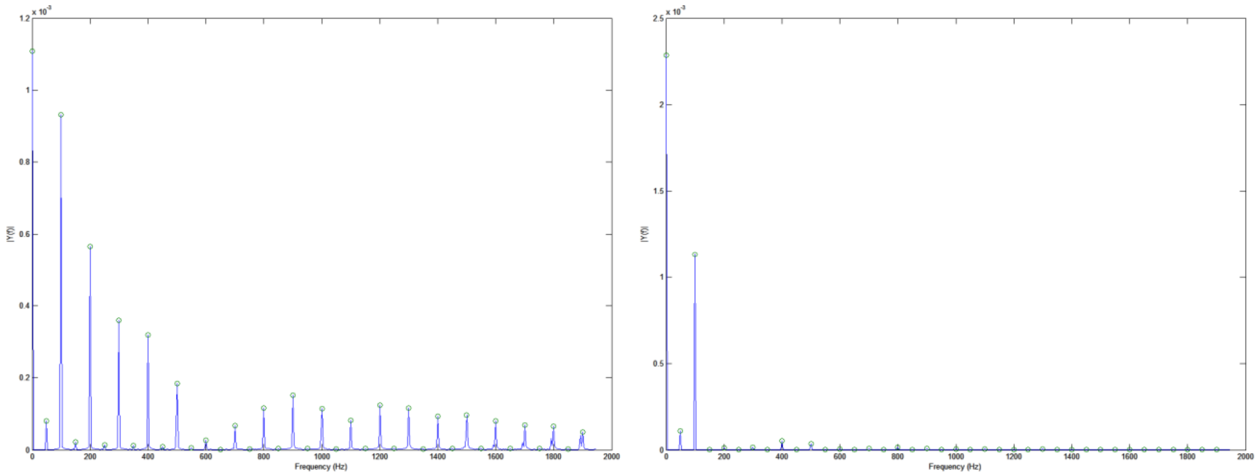

Figure 4
Fourier spectrum of the instantaneous power of
an energy saving bulb (left) compared to a filament light bulb (right)

Table 1
List of the consumers in the experiment

Label	Type	Wattage
C1	Energy saving bulb ES11L0602	11W
C2	Filament light bulb	25W
C3	Energy saving bulb N18319	11W
C4	Transformer 1 for electronic scale	5.8W
C5	Transformer 2 universal power supply VOLTCRAFT SNG 1500	25.5W
C6	Transformer 3 universal power supply VOLTCRAFT SNG 1500	25.5W

In the following recognition process, first we only activated one consumer, calculated the characteristic value and passed it to the pattern matching algorithms. In doing so, we found that the trained ANN, as well as the NN classifier are able to identify all consumers unambiguously. We were even able to distinguish individual energy-saving bulbs from different manufacturers, and power adapters of the same construction type respectively.

In a second step, we activated several consumers simultaneously. At this, the ANNs were even able to classify some simultaneously active consumers, however this approach is subject to current research. When utilizing NN classifiers, an artificial extension of the reference patterns is necessary. In the context of a brute-force approach, we generated all possible combinations of consumers from the collection of reference patterns. For each combination, we added a new reference to the classification process. This reference is calculated as the sum of the all the respective Fourier coefficients from each individual consumer of the current combination. This allows our system to identify all consumers in arbitrary combinations unambiguously and without errors.

5. Conclusion and outlook

In the course of the contribution, we examined the capacity of the approach by means of an experimental set-up with six different loads. Besides a light bulb as ohmic load, we included different wall plug transformers and energy saving bulbs in the scenario. The results showed that the considered methods allow for identifying individual consumers and combinations of consumers based upon the extracted characteristic values.

The laboratory experiment with six consumers (n=6) resulted in only $2^n = 64$ combinations of consumers. If we take a household with an assumed 70 electronic consumers, the number of combinations rises to $2^{70} \approx 1.18 \times 10^{21}$. If we now wanted to calculate the deviation between the calculated reference patterns and the currently incoming signal and assume a duration of 1 µs per comparison operation, we would end up with a computation time of approx. 37,440 millennia.

A workaround for this problem might be the analysis of the difference signal between two measurements. Therefore, we would only have to calculate simultaneous toggling of a limited number of combinations, which are calculated as the sum of the binomial coefficient $\sum_{k=0}^{m}\binom{n}{k}$, with m simultaneously activated consumers and n consumers total. The activation of a multiple socket outlet with m=5 consumers can be seen as an example. This results in 13,077,135 combinations which would yield 13 seconds of computation time. This is subject of further studies.

In the future, the experiment is to be extended and in the area of data logging, we want to append other consumer types. This could e.g. be implemented via a scenario in an office, an apartment, or a production facility. Additionally, we want to add further attributes to improve the pattern matching process. Besides the Fourier coefficient, especially the phasing of the signal is to be mentioned, in order to rule out misclassifications. Furthermore, the combination of several parameters (possibly with different weights) may improve the presented methods.

The used neural networks have proven to be an appropriate approach to the disaggregation of consumers. However, they too can be optimized. First, by means of adjusting the neuron count, additional network topologies, and variation of the input values the adequacy of individual nets can be increased and the nets can be compared. The automated creation and testing of networks with different initial settings is feasible as well. Finally, the visualization of the consumers should be improved and the users should be enabled to create a profile that allows for optimizing the energy consumption.

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