SMART METER

Artificial Neural Network for Disaggregation of Electrical Appliances

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Abstract: Goal of that paper is to show a possibility for the disaggregation of electrical appliances in the load curve of residential buildings. The advantage is that the measurement system is at a central point in the household. So the installation effort decrease. For the disaggregation of the appliances out of the load curve, an approach for the development of classification algorithms is presented. One method for the classification of appliances is to use Artificial Neural Network. This idea is the main part of that paper. It is shown a method, to classify one kind of appliances. At the end, the first relsults and the next steps are presented. The disaggregation of the appliances is part of a research project at the University of Furtwangen.

1 INTRODUCTION

The world wide energy demand has risen during the past years. As an example the consumption in the European Union (EU) has increased by 10.8 % from 1999 through 2004 (Bertoldi and Atanasiu, 2006). In contradiction to this development the amount of available resources is decreasing. This makes energy saving a necessity. One way to achieve this is to influence and change the behavior of the human population (Bertoldi and Atanasiu, 2006). To adapt the users' behavior to the new challenges of energy saving it is necessary to provide them with a transparent report of their energy usage. This can be achieved by installing so called smart meters. Therefore the introduction of smart meters becomes more interesting. The smart meters should allow for detailed information on the consumption of each of the appliance in a household. It is important that this information includes how much and when each appliance consumes energy. This information could be presented in a detailed energy bill at the end of each month. The comparison with other appliances of the same type could reveal the out-dated equipment consuming too much energy.

Another advantage is that smart meters are able to measure real and reactive power in one-second intervals. This information is crucial to electric supply companies for determination of grid load, grid faults and the power factor $\cos(\varphi)$ in a smart grid.

The new systems should be cost-effective. Therefore it is desirable to use only one measuring device at a central location in each house. The use of signal processing (disaggregation algorithms) should reveal information on active appliances. This approach is known as *Non-Intrusive Appliance Load Monitoring* (NALM) (Najmeddine et al., 2008).

2 STATE OF ART

The methods for disaggregating different appliances from the power consumption can be divided into two groups: the steady state analysis and the transient state analysis. An overview of the different methods is given in Fig. 1.

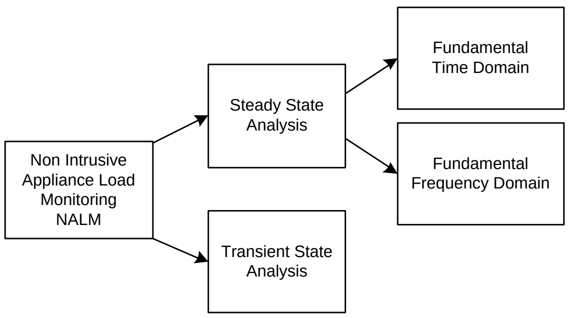

Figure 1: State of Art NALM.

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2.1 Steady State

The first NALM system was developed by George Hart at the Massachusetts Institute of Technology (MIT). In the 1980s, he wanted to analyze the load of residential buildings (Hart, 1992). His system recorded active and reactive power in intervals of one second. This system reaches its limits, when there are multiple switching edges of linear and non-linear loads at the same time. Also different appliances with similar or identical power consumption as well as loads with quick switching cycles cannot be disaggregated correctly. In 1998, Mr. Pihala built a system in Finland based on Hart's approach. This system worked with one-phased and three-phased load (Pihala, 1998). In 2000 and 2001, Murata et al. made an classification of loads (Murata and Onoda, 2000)(Murata and Onoda, 2002). This classification based on the steady state approach.

In 2006, a further system based on Hart's approach was developed by Mr. Baranski (Baranski, 2006) for German households at the University of Paderborn. All the systems described above, used a data base in which information on the appliances was stored. Obviously, this procedure demanded a great deal of measuring effort before using the system.

2.2 Transient State

Many disadvantages of the steady state analysis can be eliminated by analyzing the transients of the switching events. When turning on or off a device, characteristic oscillations in the voltage and current signal may occur. The shape of those oscillations is dependent on the inner structure and the operation mode of the appliance. The distorted reactive power, the product of the distorted voltage and the distorted current, are mainly caused by non-linear loads, for example, switching power supplies. In contrast, linear but non-real loads like motors consume reactive power.

Lee established that the sum of the currents at higher frequencies can reach up to 150% of the current in the fundamental wave of the power grid (Lee et al., 2003). Thus to determine the energy consumption of a device, it is crucial to regard the higher frequencies as well.

In 2000, Shaw investigated the transient state analysis in detail (Shaw, 2000). In 2003, Lee (Lee et al., 2003) and Laughman (Laughman et al., 2003) used the steady state analysis and the transient state analysis for disaggregating the real power of appliances. For the transient state analysis, they assumed that the voltage is ideally sinusoidal and that only the current is distorted.

All of these methods use databases of individual appliances. This has the disadvantage that all devices must be included in the database during the installation of the system. A solution is to include characteristics of classes of appliances in the database. Furthermore all listed algorithms are specialized on the detection of one group of appliances. A complete system that detects all possible appliances in the load curve of private homes and that tracks their energy consumption does not exist. At this point it should be recognized.

3 RESEARCH PROJECT

The research project "SmartMetering" is divided into four parts (Benyoucef et al., 2010b; Benyoucef et al., 2010c; Benyoucef et al., 2010a). The first part is to fill a data base with measurements of individual appliances. Currently there are 350 of those measurements available. These measurements are used for a qualitative analysis of the behavior of loads which means that characteristic features of the loads are to be extracted. The measurements are performed using a measuring system for the three phases of the line in a house. This system was developed in-house and it provides information on the distribution of the consumed power over the three phases.

In the second part modeling especially of the switching on behavior of appliances is done. These models are used for classification of load profiles.

The algorithms are verified using a test system which is the third part of the project.

The major part is the development of disaggregation algorithms. In a first stage all switching events (on and off) are detected. A suitable event detection algorithm was developed for this purpose. The event detection is followed the classification of the detected turn-on events. After the classification a tracking algorithms tracks the consumed power of all detected appliances and finds the appropriate turn-off event. The tracked power is used to compute the consumed energy. This detection strategy is sketched in Fig. 2.

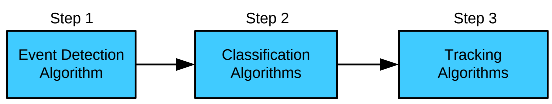

Figure 2: Structure for the disaggregation.

The topic of the following chapters is the detection of the switching on profile of appliances. Experience shows that it is necessary to include multiple methods for a successful classification of all possible load types. Therefore several algorithms, each one for the detection of some of all possible classes, are under development. The main focus is put on loads consuming most of the energy comprising refrigerators and freezers (EU, 2009; NRW, 2006). The proposal of this paper is based on the idea to detect groups of loads showing periodic switching behavior by employing an artificial neural network (ANN).

4 APPROACH

Electrical appliances can be classified into several groups by applying several criteria. One criterion is the number of possible operation states. One the one hand there are on-off-loads (electric kettles, refrigerators, ...) with two states and on the other hand there are complex appliances like e.g. dish washers.

Another criterion is to consider the switching behavior of loads. There are loads which are directly influenced by the user (manually controlled), like e.g. televisions (volume and contrast adjustment, program change). Another group is filled with autonomously controlled machines like refrigerators, freezers, etc. In this paper an approach for the disaggregation of the group containing autonomously controlled on-off appliances is described. The approach is described at the example of refrigerators and freezers.

Fig. 3 shows an exemplary measurement of the power profile of one phase of the grid in a house. It can be seen that, after subtracting the power drawn by stand-by appliances, only one machine is active in the nighttime. This is the profile of a refrigerator. At around 7.00 am additional loads were switched on by the house owner. The idea is to train the ANN with

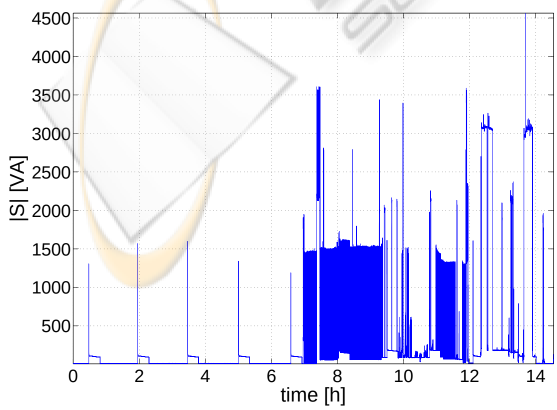

Figure 3: Power profile of one phase in a house.

the operating cycles of the refrigerator in the nighttime. In the daytime the signatures of all loads are classified. The ANN detects the match of a newly classified signature with the trained signature. Then this signature is assigned to the refrigerator.

Fig. 4 shows the apparent power profile of eight turn-on signatures of the refrigerator recorded at night. The signatures show little variation and they have a duration of about 1.5 s. The start signature of the signature consists of a transient of about 250 ms. The profile was normalized to the maximum of the signature. As said in the beginning several algorithms

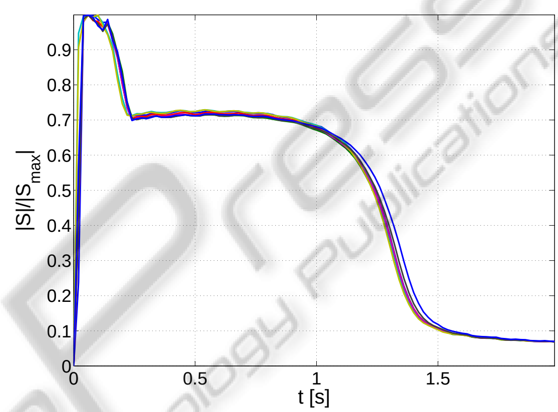

Figure 4: Switching on events of a refrigerator.

are required for detection of all equipment of a household. Especially for the periodically switching machines the ANN can be accompanied by the a priori information on the duration of the operating cycles. For the computation of these times the nighttime measurement can be used as well. During the day the results of the ANN can be enhanced by the cycle times to improve the detection accuracy, but for now only the ANN is examined.

5 ARTIFICIAL NEURAL NETWORKS

The basic structure of artificial neural networks is similar to nerve cells, so called neurons.

5.1 Neurons

A simplified model of the structure of an artificial neuron is shown in Fig. 5. On the right side the compact form of the neuron is shown. The inputs of the neurons are the values x_i which is a vector of length $L+1$. These values may come from other neurons or from sensors. The first value x_0 can be used to set

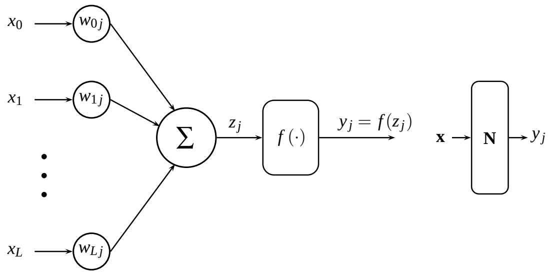

Figure 5: Model of an artificial neuron and its compact structure.

up the offset. The input values are weighted by the weights w_{ij} and afterwards added. The result z_j is mapped by a non-linear function f to the final result y_j. In the following the model is described in vector notation. The input vector is described by

$$\mathbf{x} = \begin{bmatrix} x_0 & x_1 & \cdots & x_L \end{bmatrix}^T. \tag{1}$$

Analogously the weight vector is given by

$$\mathbf{w}_j = \begin{bmatrix} w_{0j}, w_{1j}, \cdots, w_{Lj} \end{bmatrix}^T. \tag{2}$$

The final output is therefore given by

$$y_j = f(z_j) = f(\mathbf{x}^T \mathbf{w}_j). \tag{3}$$

Equation (3) applying the non-linear image function is known as the *transfer function*.

There are several types of artificial neural networks with various structures. The three basic types are separated into the feed forward structure, the feed back structure and the recurrent structure (Cichocki and Unbehauen, 1993).

If several layers d of neurons are stacked the resulting ANN is called a multilayer ANN. There are three distinct layers, namely the input layer, the hidden layers and the output layer. Furthermore it is possible to connect several neurons in parallel. This makes a multiple outputs y_k $k = 0, \cdots, N$ in the output layer possible. The d^{th} input layer always depends on the output layer $d-1$.

5.2 Learning Algorithms

The individual weights of the neurons can be determined in many different ways. The simplest learning algorithms are based on the method of least means squares (LMS) (Haykin, 2002). It is for an ANN consist of one neuron. The common principle of all known methods is to minimize the error e in order to determine the optimum weight vector $\mathbf{w}_{opt}$. The block diagram for the computation of the error is shown in Fig. 6. The first method used for the evaluation in this paper is the gradient descent method. The optimum is reached when the mean square error becomes

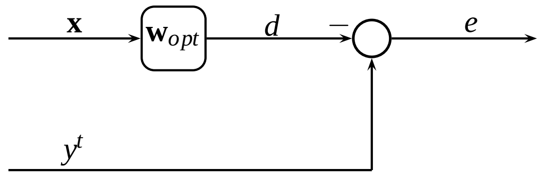

Figure 6: Block diagram for the error claculation.

minimal. For a weight vector of length two this error is given by (cf. Fig. 6)

$$e^2 = (y^t)^2 - 2y^t \mathbf{x}^T \mathbf{w} + \mathbf{w}^T \mathbf{x}\mathbf{x}^T \mathbf{w}. \tag{4}$$

Since the vectors $\mathbf{x}$ represent stochastic signals it is useful to use the expectation of the mean square error. The optimum weight vector is computed by finding the minimum of the derivative of equation (4). It is given by

$$\mathbf{w}_{opt} = \mathbf{R}^{-1}\mathbf{p}. \tag{5}$$

This equation is known as the *Wiener-Hopf Equation* with the autocorrelation matrix $\mathbf{R} = E\left\{\mathbf{x}\mathbf{x}^T\right\}$ of the input signal $\mathbf{x}$. $\mathbf{p}$ is the cross-correlation vector of the desired value $\mathbf{y}^t$ and the input signal $\mathbf{x}$. A detailed derivation of this principle is given in (Haykin, 2002).

Another approach would be an adaptive learning method. Then the data for the training process of the ANN could be the measured data during nighttime. With that the time-variant behavior of switching cycles of the refrigerator can be reacted.

6 RESULTS

The first simulation results were obtained by using an ANN with three layers. The learning method was the gradient descent method. The input vector $\mathbf{x}$ had a length of 80 values representing the first 80 values of the apparent power measured after a detected switching on event (cf. Fig. 4). All layers used the same activation function. This function is known as the simple limiter transfer function. The measured data for the simulation is shown in Fig. 7. This is a one day long measurement of one phase of the power line of a house. It commences at 0:00 am and it ends at 12:30 am. During the night the refrigerator showed seven operation cycles. At 6:30 pm additional appliances were turne on. The refrigerator went through another seven cycles during the rest of the measurement time which results in 14 operation cycles in total. The results of the classification achieved by the ANN are shown in Fig. 8. The output vector is the two-dimensional vector $\mathbf{y} = \begin{bmatrix} y_1 & y_2 \end{bmatrix}^T$ with the components shown on the axes of Fig. 8. All of the 14 operation cycles of the refrigerator are clearly separated

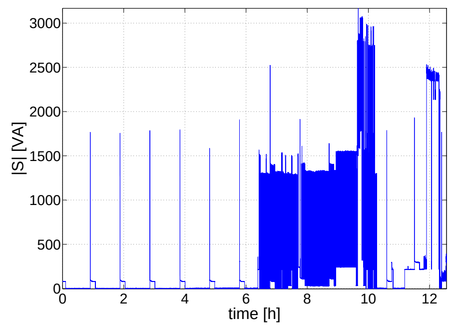

Figure 7: Measurement for the analysis of the ANN.

from the other events. Additional clusters show up, one of which representing the oven which was operated from 6:30 to 10:15. For our future work the ANN

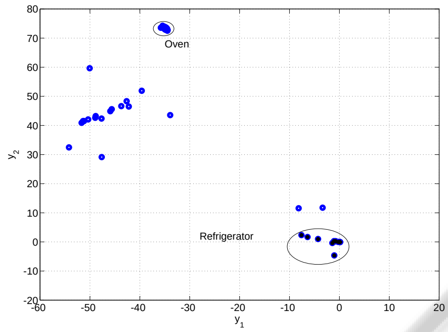

Figure 8: Outputs of the ANN.

is to be applied to additional measurements. This will show if the ANN method is suitable for the classification of other equipment. An option for increasing the classification accuracy and classification ability is to increase the dimension of the output vector y from currently two to higher values. In order to use the ANN method in time variant systems an adaptive learning algorithm might be used.

7 CONCLUSIONS

This paper provides an overview of the state of the art of the area of NALM. The research project with the goal to find methods for the identification of individual appliances in the load profile of private apartments and houses was presented. This project is divided into four parts, one of which is to develop disaggregation algorithms which was shown in more detail. A method for the detection of periodically switching appliances was discussed. This method is based on artificial neural networks. The description of the method was accompanied by first simulation results.

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