A Neuron Nets Based Procedure for Identifying Domestic Appliances Pattern-of-Use from Energy Recordings at Meter Panel.

A. Prudenzi, *Member, IEEE*

Abstract-- **The paper illustrates an artificial neural network (ANN) based procedure for the identification of pattern-of-use of some main domestic electric appliances from daily profiles of energy recordings taken at household's meter panel at 15 minute steps. The paper describes the architecture used which is structured into multiple subsequent stages based on ANNs. The application of the procedure to some real daily load diagrams as recorded at few household meters demonstrates the efficiency of the proposed approach. The utility of ANNs for extracting further useful information concerning energy usage from data bases typically available for electric companies is finally discussed.**

Index Terms-- **Load research, neuron nets, domestic appliance, pattern-of-use.**

I. Introduction

WITHIN a competitive market of electricity the importance of a deep knowledge of the customer needs and requirements could be a key issue for the electric companies. This task involves even significant economic efforts for implementing effective load research studies whose results, however, can provide a large support to DSM (Demand Side Management) strategies and to Marketing policies as well [1].

This task requires the individual household energy consumption be differentiated among the individual appliances of the household mix. Such a task is achieved when every individual appliance turning on and off is identified.

Electric companies typically monitor several (up to hundreds) of their residential customers. They typically use intrusive methods requiring placing of sensors on individual appliances.

Since the last decades, more sophisticated methods have been proposed which provide non intrusive load monitoring. Such methods provide identification of individual appliances turning on and off through even sophisticated analyses of current and voltage waveforms monitored for the aggregated total load. Such methods check for certain "signatures" in the total load of the customer that can provide information about duty cycle of certain appliances [2]-[6]. Such procedures involve typically simple hardware for monitoring electrical quantities at a single point (meter panel) but complex software for signal processing and analysis.

The monitoring activity of electric companies for load research development typically involves even energy measurements at individual customer's meter panel. Such an activity provides energy recordings typically taken at 10-15 minute time intervals. The recordings thus made available with this activity go to form a bulk of archival data that could be used for further analyses involving energy usage. In fact, recordings provide information that can be useful for identifying typical domestic appliances pattern-of-use and its evolution with time (lifestyle and technology evolution concerns).

This problem has been faced and the present paper illustrates a method for identifying the pattern-of-use of some more consuming appliances typically present in an Italian household mix from aggregated load shapes. The method implements a pattern recognition procedure applied to the daily demand diagrams as recorded at the meter level of the household.

The procedure provides three different ANNs sequentially processing the load shape. The identification task is assigned to two different ANNs (BPN1 and BPN2) trained with a back-propagation algorithm. A preliminary classification activity of the patterns to be processed by the two ANNs above mentioned is performed by an unsupervised net implementing the Self-Organizing Map (SOM) of Kohonen.

The data required for the training sets have been built with load profiles as obtained from several experimental measurements made in laboratory.

An available residential load simulator reproducing daily electric load shapes of domestic customers has been used for the test stages based on simulated daily load diagrams [7].

Finally, the procedure accuracy has been tested on some decines of real daily load shapes as recorded at the panel level of nine selected domestic customers.

A. Prudenzi is with Electrical Engineering Dept. of University of L'Aquila, 67040 Monteluco di Roio, L'Aquila, Italy (e-mail: prudenzi@ing.univaq.it).

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II. Domestic Appliances

A. Identification Task and Time Intervals

In comparison with the more known non intrusive methods, the proposed methodology, since it is based on the off-line processing of the daily energy recordings taken at the individual customer's at 15 minute time intervals, obviously, applies to a limited bulk of data. Therefore, since energy consumption values as recorded every 15 minutes are concerned, it is reasonable to try and detect only appliances with a major energetic impact on the daily load shape. They are, for instance, washing machines, dish washers, water heaters and (in principle) air-conditioners. In other terms the method proposed, that uses energy recordings made at such steps, is applicable to identification of the appliances whose average demand, even if calculated over the above mentioned intervals (15 minutes), still maintains a peculiar pattern.

However, due to the typical characteristics of residential energy usage in Italy, these latter appliances represent also the principal end-users in this segment.

B. Residential Energy Usage in Italy

The residential customer in Italy presents a number of peculiarities which distinguish it from that in most other countries of Europe and America: a) a contractual demand limit of 3 kW; b) an average consumption per customer less than 2600 kWh per year, that is among the lowest in industrialised countries. Moreover, at present, less than 2% of Italian household own an air-conditioning device and the National Energy Plan militates against the growing use of electricity for applications such as home and water heating. Finally, the 3 kW contractual limit adopted by more than 90% of domestic customers also ensures that the electric companies implicitly operate an effective control over the energy impact of this end-use segment.

Table I shows the appliances most commonly used the figures of the typical energy consumption per appliance type.

Table I
Domestic Appliances Main Features

Appliance	Breakdown of total consumption (%)	Penetration rate (%)
refrigerator	16.2	96.2
freezer	4.9	22.4
washing machine	*11.5*	*84.1*
TV set	9.5	91.2
dish washer	*3.3*	*16.2*
electric cooking	0.6	0.1
lighting	13.6	100.
iron	3.5	96.
air conditioning	0.3	1.9
electric water heater	*19.4*	*39.9*

C. Domestic Appliance Characteristics

The first step of any methodology aimed to the appliance pattern-of-use identification is the learning stage of the electric characteristics ("signature") of each appliance of interest. To this aim, it has been preliminary necessary to extrapolate, from the experimental measurements available for the various appliances, the typical average demand profile that should be associated to a certain appliance usage uniquely. All such typical profiles go to take part of the ANNs training set.

Several laboratory tests have been conducted on different appliance types and brands in order to carry out duty cycle of the appliance and their variations with different operating modes, different manufacturer and technology innovation as well as the typical periodicity of duty cycle.

Figures 1 a) and b), for instance illustrate the difference that can be found for a washing machine duty cycle.

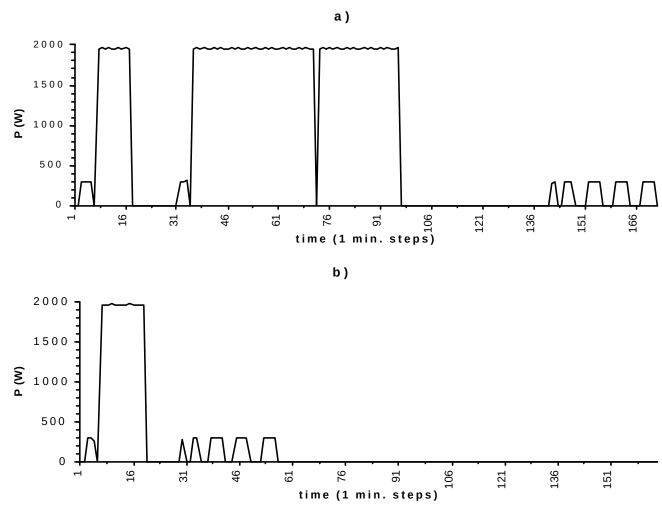

Fig. 1. Washing machine duty cycle for two different set up programs; a) complete working cycle with Tmax=90°C; b) reduced working cycle with Tmax=40°C.

The typical duty cycle of the investigated appliances has suggested to classify them into two different groups: washing machine and dish washer (group W), water heater (group H). The former group contains appliances typically used once a day (rarely more often), each usage being represented by a duty cycle of a fixed, although not uniquely determined duration, and very similar for the two appliance types. Instead, the latter group includes an appliance with a duty cycle extending over wider time intervals with repeated on/off states, the duration of which depends on the thermal characteristics of the environment and on the preferences (in terms of thermostats setting) of the household. In particular, in the duty-cycle of a water heater, continuously operated during the day, two different types of On states can be distinguished: the On state consequent to a large usage of warm water (bath, shower), the periodical On states driven by the thermostat and not consequent to a large warm water usage. The proposed procedure aims to identify only the first type of On states.

III. The Proposed Procedure

The main task of isolating an appliance contribution from the ones of other appliances simultaneously operating is provided by a combined procedure structured into three different ANNs that process data sequentially. Analogous combined procedures using ANNs have already demonstrated their utility for other tasks [8].

Some pre/post-processing activities had to be implemented in order to adapt the data available to the input/output characteristics of the neuron nets, as well as to make easier the identification task. Therefore, the proposed methodology has been structured as schematically illustrated in Fig. 2.

Each individual domestic customer’s daily load shape, as obtained from 15 minute steps energy recordings at meter panel level, represents the input of the proposed procedure.

A. Pre-Processing Stage

In this stage, the available data (96 values of household’s daily average demand profile) are firstly adapted to the optimal input dimensions for the neuron nets. In fact, some preliminary tests have shown the utility of dividing the daily load shape into multiple subsequent time segments, of up to eight hours each (for instance 32 steps of 15 minutes each) [9]. Furthermore, in order to avoid possible identification errors occurring with an appliance duty cycle falling into two subsequent segments, the following six different time bands have been considered: 0.00 a.m.-8.00 am; 4.00 a.m.- 12.00 a.m.; 8.00 a.m.-4.00 p.m.; 12.00 a.m.- 8.00 p.m.; 8.00 p.m.-4.00 a.m.-4.00 p.m.-24.00 p.m.

In order to limit the number of different segments to be processed in the identification stage, an unsupervised neuron net implementing the Kohonen’s SOM learning algorithm has been provided with the task of classifying the various segments into two cluster types:

- the first one, including all the segments of load shape for which the contribution of at least one appliance of either groups is probable (clusters P),

- the second one, including the remaining segments of the daily load shape (clusters A).

The classification activity is performed on patterns of some characteristic parameters of the segments, as illustrated further ahead. Only the segments classified in the P clusters are then processed in the identification stage.

B. Time-of-Use Identification Stage

The identification activity is provided by two supervised learning based ANNs sequentially applied to data.

The identification task requires that the average demand of the appliance of interest be isolated from the one of other appliances in the aggregated load of a daily load shape. This problem could be considered similar to that of identifying a typical pattern within a noisy contest. Washing machine, dish-washer and water heater duty cycles present both much higher instantaneous demand values and energy consumption values than any other appliance in the mix. Therefore, even in a 15 minute average demand profile, the identification of their pattern-of-use results possible.

The first supervised neuron net (BPN1) processes data coming from pre-processing stage and identifies the time-of-use of any appliance of the two groups (W and H).

The BPN1 is a two-layer perceptron trained with the back-propagation algorithm that processes one at a time the segments of the cluster P.

The BPN1 output consists in ones placed at each step within the time-segment where any appliance (water heater or washing machine or dish-washer) is identified in operation and zeros elsewhere. The BPN1 output relevant to each load shape segment is stored in a row of a table with 32 columns.

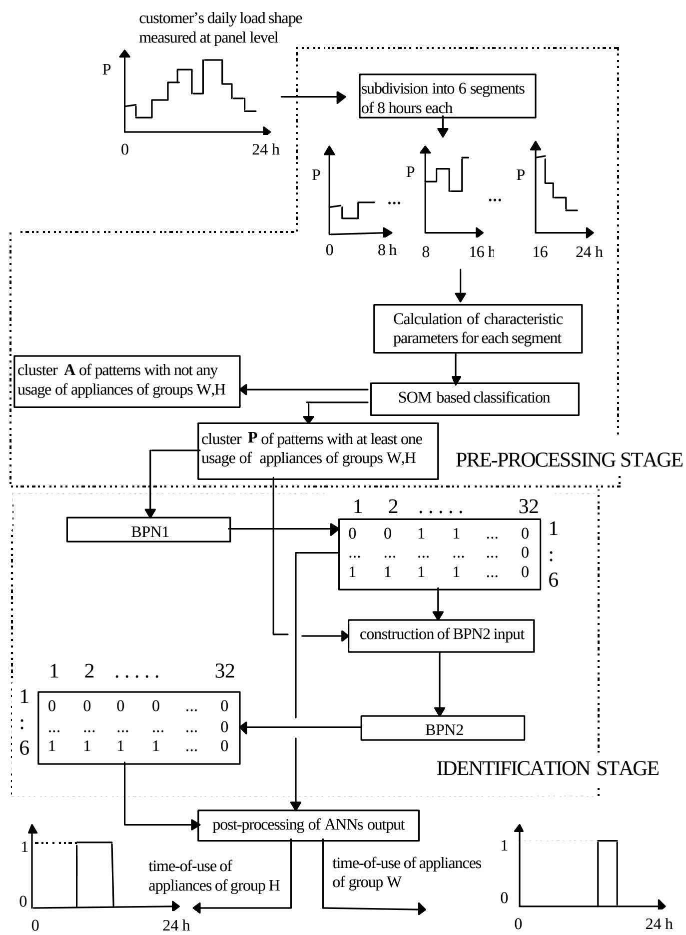

Fig. 2. Simplified schematic of the proposed procedure architecture.

The output relevant to each customer’s daily load shape gives origin to a table with 6x32 (one row for each segment of the daily load shape and one column for each 15 minute time step) elements with values in the range 0-1.

Since only patterns of cluster P are processed by BPN1 thus making possible to fill some rows (n) of the Table, the remaining rows (6-n), as relevant to the patterns classified in cluster A, are filled by default with all zero values. The rows of the Table are ordered by following the sequence of each segment of the day.

The patterns thus obtained are given in input to the BPN2 which has the task of discriminating the water heater pattern-of-use from washing machine and dish-washer ones (H from W patterns). Also BPN2 is a two-layer perceptron trained with the back-propagation algorithm having the same structure of BPN1.

The input patterns of BPN2 are built through the output table of BPN1. Each row of the BPN1 output table is multiplied for the values of the demand in each segment, so obtaining a filtered version of the original profile, with non zero values only in correspondence of the ones of the BPN1 output table. On the segments thus obtained a moving average with adequate characteristics is then calculated. The results obtained go to form a pattern of the BPN2 input.

The BPN2 output is a table with the same structure of the BPN1 one presenting non-zero values only in correspondence of electric water heater usage. The comparison between BPN1 and BPN2 output permits to identify the water heater usage from the ones of washing machine or dish washer (H from W).

C. Post-processing stage

The above mentioned output tables are post-processed in this stage in order to translate the information coded in the output tables into a physically meaningful concept (e.g.: the household has used dish-washer or washing machine from 9:00 to 10:15 a.m., the water heater from 3:00 p.m. to 5:15 p.m.). To this aim some simple rules have been implemented for associating the correct relevant appliance group to each duty cycle as identified, or for determining the correct pattern-of-use for any appliance usage partially identified in more than one segment.

IV. ANNs' Architecture

A. SOM Architecture

In the pre-processing stage a Kohonen's SOM is used for classifying the different daily load shape segments into separate clusters: clusters P, classifying segments in which the operation of any of either appliance groups is detectable; cluster A, classifying segments in which not any operation is evident.

The selected SOM architecture has been obtained through some parametric analyses aimed identifying few characteristic parameters whose value correctly summarizes the differences between patterns of either clusters. In particular, the following three parameters have been carried out:

- Pmax: maximum average demand value in each segment
- Pavg: average demand value calculated in each segment
- ΔPmax: maximum demand change in each segment, calculated as,

$$\Delta P_{\max} = \max\left|(P_{i+1} - P_i)\right|_{i=1,\ldots,n} \tag{1}$$

The three parameters value calculated for each segment form a single input pattern of the SOM.

Some parametric analyses have been also conducted both on each parameter of the algorithmic formulation (maximum neighborhood radius, learning rate value, conscience value) as well as on dimensions of the input vectors [10].

B. BPN1 and BPN2 Architecture

Both BPN1 and BPN2 have the same architecture that has been selected since it showed the best performance from the point of view of the necessary trade-off between training speed and identification results. The selected architecture provides a totally-connected two-layer network (input, hidden and output layers) with the following characteristics:

- 32 inputs
- 24 hidden neurons
- 32 outputs.

The BPN1 input vectors are formed by the average demand values relevant to the time intervals of each segment of the daily load shape, while the actual output vector components have values comprised in the range 0-1.

The BPN2 input vectors derive from the BPN1 input, adequately corrected, and the actual output vectors are values comprised in the range 0-1.

The dimensions of the hidden layer have been empirically determined through many preliminary tests. The dimensions thus obtained have been then assigned also to BPN2 [10].

C. BPN1 Training Stage

The BPN1 training sets have been built with several examples of typical appliance duty cycles. The duty cycles have been obtained both from laboratory tests and from manufacturers' data. The various examples of the training set have been selected in order to strengthen the BPN1 generalization capability. To this aim, the training sets have been built with the following patterns:

- patterns formed by single duty cycles presented in various positions of the time window,
- patterns formed by combining the duty cycle with a stochastic noise level extracted from a normal distribution with mean equal to zero and standard deviation varying in the range from 20% to 40% of the peak demand of the duty cycle.

The range of the noise amplitude is motivated by observations of measurement results of real domestic customer daily load shapes.

Figures 3 a) and b) illustrate an example of the artificial patterns used in the training set.

D. BPN2 Training Stage

The BPN2 training sets have been built starting from BPN1 input patterns. These patterns have been firstly adequately filtered through the target output vectors used for BPN1 training activity. On the patterns thus obtained a moving average has been calculated, according to the formula,

$$P_i = \frac{1}{2N}\sum_{k=1}^{N}\left(P_{i-k} + P_{i+k}\right) \tag{2}$$

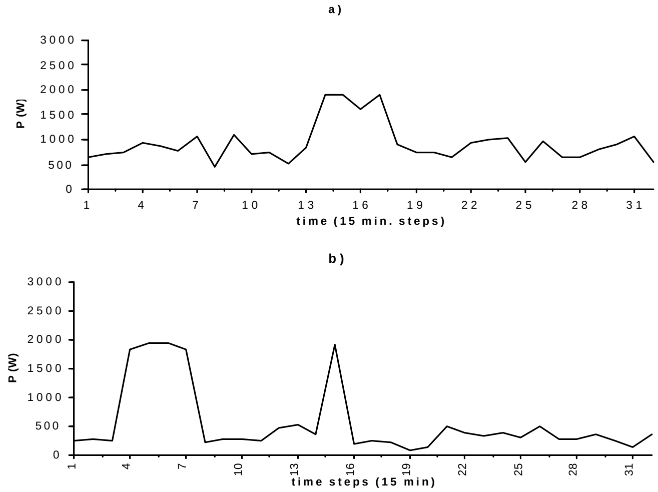

Fig. 3. Examples of artificial patterns used for BPN1 training set; a) washing machine duty-cycle (noise 40%); b) water heater duty cycle (noise 20%).

For better illustrating the training procedure used for BPN2, the Figs. 4-6 show the subsequent steps through which the input patterns of BPN2 are built starting from the input pattern of the procedure. For the sake of clarity the steps are illustrated on a recorded daily load shape with the appliances used as indicated. In particular, Fig. 4 shows the daily load shape of a customer (BPN1 input pattern) together with the BPN1 target output.

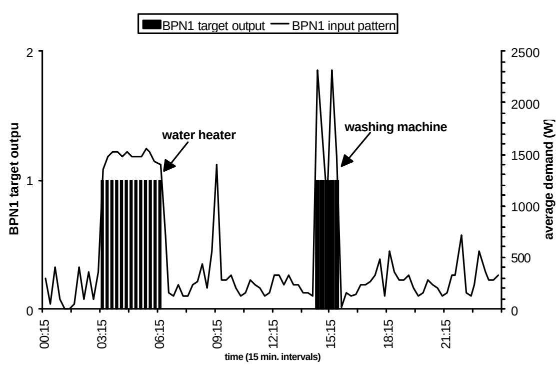

Fig. 4. BPN1 input and target output for a recorded load shape.

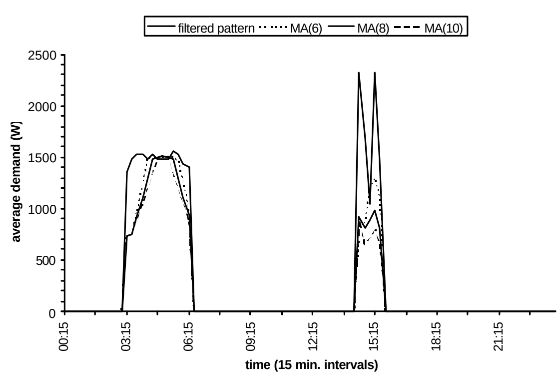

Fig. 5. BPN2 input patterns building activity for the recorded load shape.

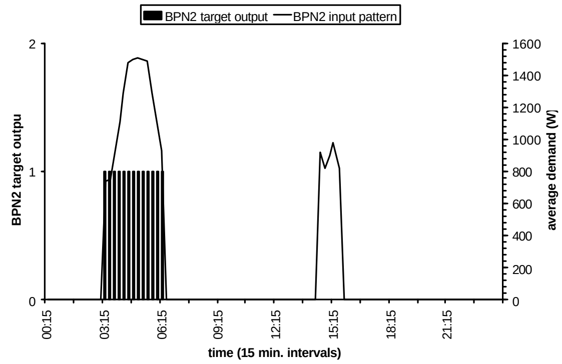

Fig. 6. BPN2 input and target output for the recorded load shape.

The original load shape is transformed as illustrated in Fig. 5. To this aim, first, the product between the BPN1 output and the original load shape is made, thus obtaining a filtered diagram of the original input. For the diagram obtained a moving average operation is applied thus obtaining the curves reported in Fig. 5 relevant to different values of N (N=6, 8 and 10) in (2).

The patterns obtained for N>6 show how useful is the moving average operation for the purpose of better evidencing the water heater duty cycle from washing machine or dish-washer ones.

In Fig. 6, for the case illustrated, both the input and the target output of BPN2 are illustrated.

For a better understanding, in the Figs. 4-6 the daily load shape segmentation used in the training sets has not been reported.

E. ANNs Testing Stage

The ANNs performance have been preliminarily tested on a wide set of individual households daily load profile as obtained from computer simulations via an available residential load simulator [5]. The simulator implements a psychological model of the Italian domestic customer that has permitted to reproduce a wide sample of household load shapes. In particular, the simulation of load conditions being particularly critical for the identification task, although possible in practical conditions, has permitted to perform a severe testing activity of the ANNs performance on simulation based case studies.

V. Procedure Accuracy Testing in Practical Cases

A. Testing Activity

In order to test in practical conditions the accuracy of each neuron net and of the overall procedure, an experimental activity has been performed by monitoring the demand of some domestic customers at 15 minute time intervals.

The monitoring activity has provided 125 patterns (of eight hours each) corresponding to about 1000 hours of recordings.

Nine different customers have been involved in the test.

Each customer has been provided with a questionnaire where indicating the time-of-use of each appliance operated during the investigated period.

The data thus obtained have permitted to test the procedure on real-life load conditions.

B. Overall Procedure Accuracy

The accuracy of the whole procedure has been determined by evaluating each individual stage of the architecture.

In the practical testing cases the accuracy found for both Kohonen's SOM and BPN2 has been greater than 96%.

For BPN1 the accuracy has been estimated by differentiating the various possible errors among the following:

a) the BPN1 finds a usage where it does not exist

b) the BPN1 does not find a usage where it exists

c) the BPN1 finds a usage where it exists but overestimates the On state duration

d) the BPN1 finds a usage where it exists but underestimates the On state duration

e) the BPN1 finds a usage where it exists but shifts the On state of at least one step.

The Table II reports the BPN1 accuracy results obtained for the 125 patterns available.

In the Table, for the errors of type c) and d) a complete detail of the over/underestimate involved is also provided.

According to the above mentioned considerations, the figures reported in the Table can be assumed for characterizing the overall procedure accuracy.

TABLE II
BPN1 ACCURACY OBTAINED FROM PRACTICAL TESTING

Error type	Occurrence
a)	6
b)	3
c) (1 step overest.)	7
c) (2 steps overest.)	3
c) (3 steps overest.)	2
d) (1 step under.)	5
d) (2 steps under.)	2
d) (3 steps under.)	2
e)	5

The results reported in the Table show that the procedure is generally able to identify the investigated appliances (washing machine, dish washer and water heater) usage in a day. In fact, by considering only a) and b) type errors, an accuracy higher than 90% can be attributed to the procedure.

For that concerns the remaining error types, certain load conditions, e.g. high level of simultaneous demand from different appliances (miscellanea), have been evidenced in the testing as possible causes of both the type c) and d) errors. Furthermore, nearly all the errors of type e) have been obtained for load conditions providing subsequent duty cycles not sufficiently spaced in time. In these cases the BPN1 can often confuse the starting time of the different duty cycles.

VI. CONCLUSIONS

The paper illustrates a novel procedure for pattern-of-use identification of some main appliances (water heater, washing machine and dish washer) from average demand daily profiles obtained from energy recordings available at residential customer's meter panel level.

The procedure is structured into three subsequent stages based on the pattern recognition capabilities provided by neuron nets.

The accuracy of the whole procedure has been tested on some real daily load shapes that have been obtained from field measurements performed at several households. The results obtained are interesting.

The procedure can be applied for automatically processing historical data bases of energy recordings taken at customers' meter, since such data are typically available to electric companies as a typical result of load research activities performed even from many years.

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VIII. BIOGRAPHIES

Alberto Prudenzi (M'92) received the degree and the Ph.D. degree in Electrical Engineering from the University of Rome "La Sapienza". From 1992 to 1998 he was Assistant Professor in Electrical Power Systems at the Dept. of Electrical Engineering of the University of Rome. Since 1998 he has been Associate Professor at the Dept. of Electrical Engineering of the University of L'Aquila. His main interests include power systems analysis, load research and power quality. Since 1999 he has been member of the Italian CIRED Committe. He is IEEE-PES and AEI (Italian Electrical Association) member.

E-mail address: prudenzi@ing.univaq.it