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HYBRID NEURAL NETWORK SYSTEM FOR ELECTRIC LOAD FORECASTING OF TELECOMUNICATION STATION

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Abstract − This paper describes a neural network system for power electric load forecasting of telecommunication station. Getting an accuracy useful for contractual purpose a separately daily forecast of both main load and its oscillation is proposed.

For the mean daily forecast we used a three layers multi-layer perceptron (MLP), while to the oscillation forecasting we realized a system composed by a MLP and a self organizing map (SOM): the typology information obtained by the SOM unsupervised algorithm has been utilized as binary code in MLP input.

The proposed system with hourly power load data of a big telecommunication operator has been tested.

The total forecast has been obtained combining the two components. The forecasting accuracy for a whole year test data is around 2%. Some problem exists in the forecasted load of summer time.

Keywords: Short Term Load forecasting, SOM, MLP.

1. INTRODUCTION

As well is know, the electric power energy can't be stored, so it is therefore necessary to know in advance how much energy is required by users to manage their production.

Historically, the problem of the electrical power load forecasting has been aimed exclusively at producers for the planning of production. The methods reported in literature, have been applied to the national load data.

In the Italian case, after the liberalization of the energy market, many companies can buy and sell energy. By this point of view, the Short Term Load Forecast (STLF) problem is also felt the users and wholesalers.

In the analysis of the electric power load of the single users the random unforeseeable components have more relevance than in the case of the national load; indeed the national load is the product of many user requests, and this produces a balanced in the random effects.

In recent years, the most of the recently approaches on the Short Term Load Forecast (STLF) are based on Artificial Neural Network (ANN) techniques.

This success is mostly due to the capacity of ANN of automatically identify the non-linear correlation within series of data. In STLF problems they have especially used architecture based on:

- Multi-Layer-Perceptron (MLP) supervised networks to forecast the load hour by hour [1] or all 24 hours simultaneously.
- Self-Organizing-Map (SOM), unsupervised networks to classified load typology [2] or to implement some forecasting methods based on the selection of similar days [3].

In cases of anomalous days, to improve the forecasting, a hybrid system is proposed based on a MLP that uses clusters information as input, obtained by a SOM [4].

In this paper we propose a system to forecast the daily load (24 hours) of a user.

The hourly load forecasting of a whole day is also divided in two parts:

- the forecast of the mean daily load;
- the forecast of 24 hourly values of depolarized (without the mean value) daily consumption (oscillation forecast).

The total forecast is obtained by adding to each of the 24 values of the load oscillation the value of average daily consumption.

For the mean load forecast is used a three layers MLP, while for the oscillation forecast is used an hybrid system where a part of MLP input is dynamically varied by the SOM output during the forecasting phase, after the learning.

The available data are three years length of hourly electric power load of a big Italian telecommunication operator.

2. OSCILLATION FORECAST

2.1. SOM training

The first network trained is the SOM; the information obtained by SOM will be used to training MLP later.

The dimensions of the Khoonen map trained is 9x9, with 81 neurons, that permits to isolate on specific neurons the anomalous power load vectors with adequate accuracy. The input layer is composed of 24 neurons, one for each hour of the day. The training set has composed of daily load vectors normalized to the maximum value of two years of data, and depolarized of the mean value. The SOM has been trained for 200 epochs by Khoonen algorithm learning rule.

To measure the vectors similarity has been used the Euclidean distance [3]. In a specific input the winning neuron is characterized by the lowest distance between the weight vector and the input.

During the training, once evaluated the winning neuron, its weight vector is updated. The weight vectors of the winning neuron neighborhood are updated at the same time.

The update is proportional to the product between the difference among the current input and the weight vector and the neuron distance on the map from the winning neuron:

$$\Delta w_{m,n}(t) = \eta \cdot exp\left(\frac{-|j-j^*|^2}{\sigma^2}\right) \cdot (X(t) - w_{m,n}(t)) \qquad (1)$$

Where η is the learning rate which determines the strength of weights update, m and n are the rows and columns indexes that identify a neuron on the map, X(t) is the input vector, $W_{m,n}(t)$ is the weight vector of neuron *m,n* at n^{th} epoch and σ is a parameter that decreases at each new presented vector during an epoch.

During the same epoch the exponential term decreases for each vector provided as input in random order while decreases when the distance from the winning neuron increases.

The load oscillation of available data can be divided in two category:

- working days: the power load trend between Monday and Friday is very similar and, as main feature, there is a peak in the central hours of day;
- week end days and midweek holidays: Saturday, Sunday and midweek festivity. During this days the power load is quite flat.

After the training, the SOM classifies daily vectors according to two criteria. In order to locate these criteria is useful to compare the neurons weight vectors in the map along the horizontal and vertical axis:

- in the horizontal axis the vectors are placed mainly according to the amplitude oscillation;
- in the vertical axis the SOM is sensible to power load peak position.

This allows to more finely classify the power load typology. The obtained information will be later used in MLP training.

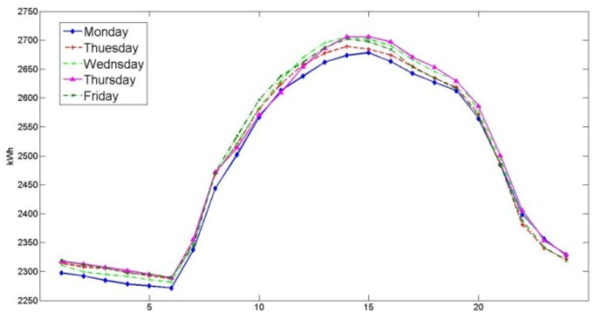

Fig. 1. Mean hourly power load of working days.

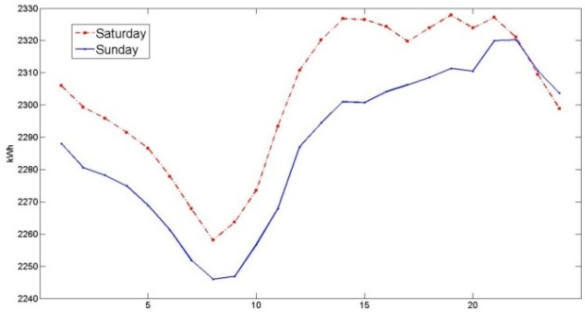

Fig. 2. Mean hourly power load of no working days.

In the figures 1 and 2 are respectively shown the hourly mean power load of the working and no working days of the week. The trained SOM is able to isolate no working days in a corner of the map.

2.2. MLP training

The MLP structure in the power load oscillation forecast is constituted by:

Input layer:

1) bit that point out if the day to forecast is a working one or not;
2) max power load of previous day;
3) hour of max power load;
4) min power load of previous day;
5) hour of min power load;

6-12) binary code of winning neuron of target vector (24 power load values of the next day), obtained by the SOM

Hidden layer: 25 neurons;

Output layer: 24 neurons.

The input variables have been chosen taking into account the classification criteria identified by the SOM. Due to the low variability of power load data to maximize the generalization ability of network the choice of 25 neurons on hidden layer provides the best results (least mean square error) compared to other tested structures. Moreover this network is very resistant to anomalous spikes and it always produces meaning output.

The MLP training set is composed both by the input vectors and by the target vectors. The first are obtained by daily power load data normalized to maximum value of two years of data, and depolarized of mean values and the second are composed by 24 values of power load oscillation of the day after the one used for input.

The network has been trained for 10000 epochs using the modified back-propagation algorithm with momentum and adaptive learning rate [1]. The choice of 10000 epochs assures the convergence of network independently from initial condition and network structure to obtain the necessary accuracy condition.

The weights were updated by the following formulae:

$$\Delta w_{ji}(n) = \eta\delta_j(n)y_j(n) + \alpha\Delta w_{ji}(n-1)$$

where n points out the epoch, is the learning rate and is the momentum (between 0 and 1).

During the training, the learning rate value is dynamically changed according to the global error of an epoch. It has increased or decreased in comparison with the global error of the previous epoch.

This system is necessary to avoid the training abruptly interruption caused by local minimum typical of error surface.

2.3. Forecasting

The MLP inputs have composed by a static part of information (neurons 1-5) and a dynamic part (neurons 6-12), constituted by binary code of the output winning neuron. In the forecast phase, the neuron code is unknown. To obtain the forecast, the code is dynamically changed in MLP input testing all 81 codes according to SOM neurons.

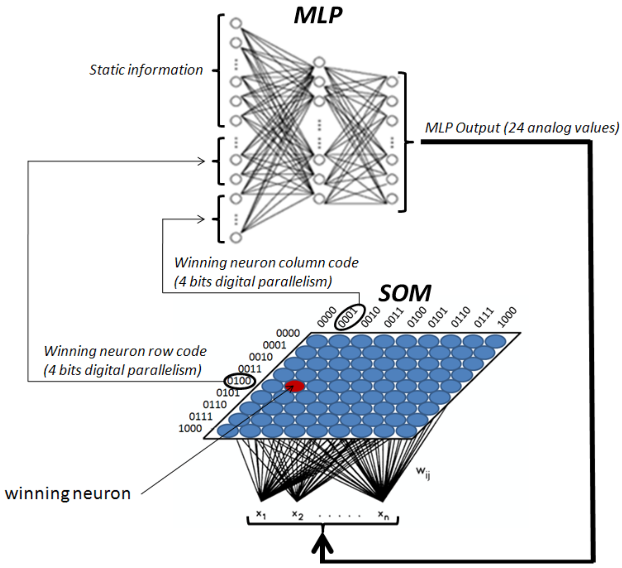

Fig. 3. Structure of the oscillation forecast system.

The algorithm steps to obtain the forecast are the following:

- For every code has obtained a MLP output;
- The MLP output vectors is used as SOM input;
- The program checks if the index of the winning neuron of every MLP output is equal to the index of the code used in MLP input; for example, if the MLP input current code is 23 the program has to verify if that the SOM winning neuron has index 23.
- The previous condition comes true several times during the 81 MLP inputs test; to obtain the oscillation hourly forecast, the program realizes the average hour by hour of the MLP outputs that satisfies this condition.

The forecast is obtained by MLP non linear model. This model combines the relationship between the calendar information and the previous day power load that are static information, with a day typology that is a dynamic information.

The used method allows to use the dynamic information of wining neuron to chose only the compatible ones with the structure of MLP training set.

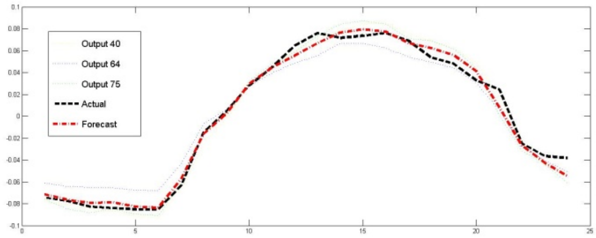

Fig. 4. Comparison for a normal working day. The forecast is obtained, in this case, by the mean of MLP output using the code 40, 64 and 75.

The dynamic part of input variables represents an historical bond. Indeed, if the condition is satisfied using a certain neuron, it means that an analogous case is present in the training set (past years power load data).

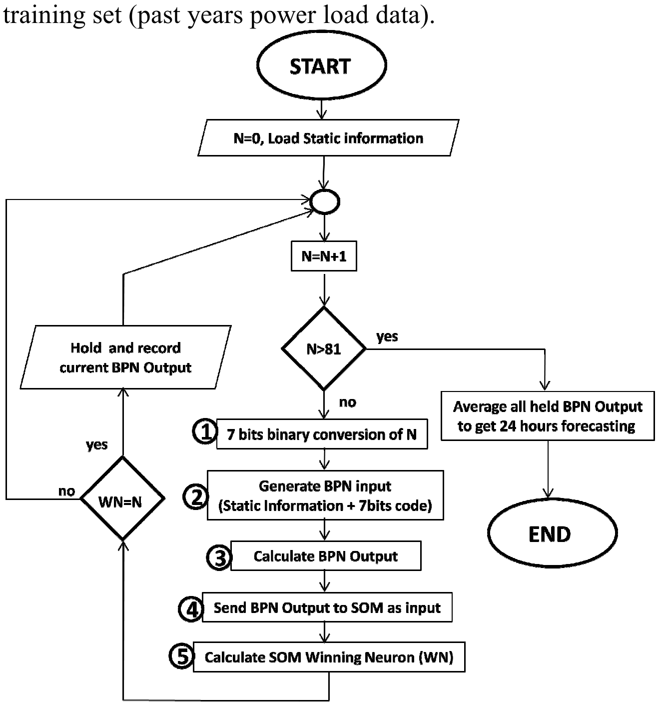

Fig. 4. Forecast system flow chart.

2.4. Mean Power load Forecast

The mean power load forecast uses three layers MLP network with the following structure:

Input layer:

1) mean power load of the previous day;

2-4) identifying binary codes of the week's day;

Hidden layer: 35 neurons;

Output layer: 1 neuron.

This structure has been selected by an heuristic attempts set, characterized by different input variables and different dimension of hidden layer. Also in this case the choice of 35 neurons on hidden layer warrants the highest sensibility towards the input data.

This configuration has been chosen because provides the least mean square error.

The network is trained for 10000 epochs with the same algorithm used for oscillation power load forecast.

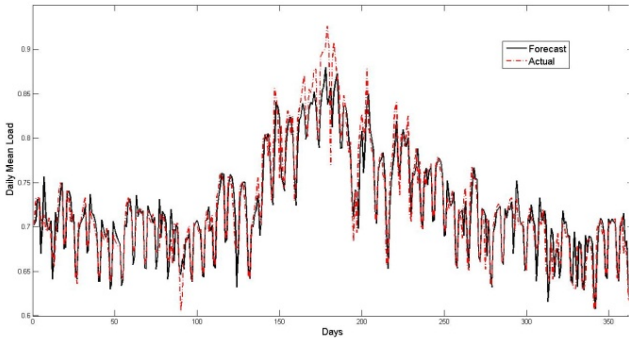

Fig. 5. Actual and forecast daily mean power load of whole test year, from 1st February 2006 to 31th January 2007.

In figure 5 is shown the actual daily mean power load compared with the forecasted one obtained by the MLP. In the summer time (central part of the curve) the forecast is less accurate than the rest of the year.

3. RESULTS

In order to obtain the total forecast, the mean daily power load forecast and the oscillation one have to be summed.

The figure 6 shows the comparison between actual and forecasted power load of a two weeks of the test year.

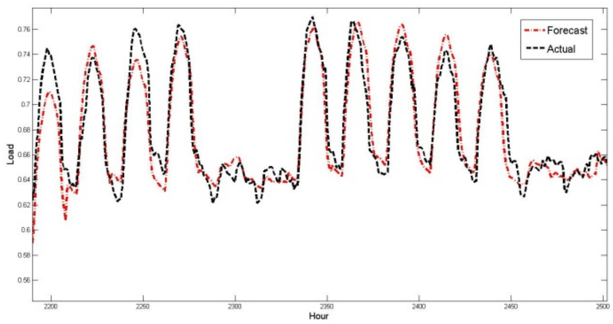

Fig. 6. Actual and forecast values for the period 2-14 May 2006.

The forecast accuracy of this system of one year data is evaluated by the mean absolute percentage error (MAPE), defined by:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|P_{Ai} - P_{Fi}|}{P_{Fi}}$$

where P_A is the actual power load data, P_F is the forecasted power load data and N is the number of data points.

The mean absolute percentage error amount on 2.75% for the whole test year. In the summer MAPE amount on 3.5%.

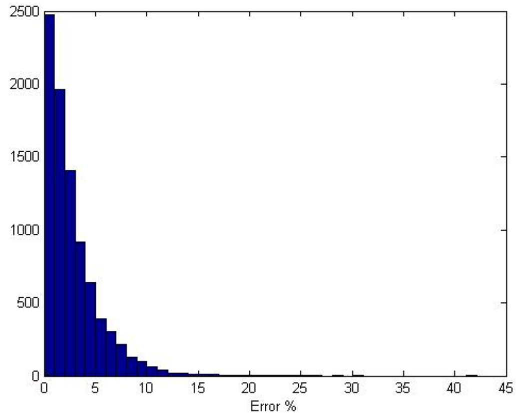

Fig. 7. Whole test year MAPE distribution.

In figure 7 has shown the MAPE distribution of whole test year. In the 85% of forecasted values, MAPE is less than 5%.

4. CONCLUSIONS

The results obtained by this system confirm the applicability of neural network techniques to the forecast of a big user electric power load.

The presented system, has the advantage of the adaptability to a different kind of power load data.

The main difficulty about the forecast in the summer suggests that the relations between the parameters are not the same during the year. An analogous problem exists for some week days. Training different networks accorded to the different seasons can improve the forecast. In this way, the networks would create specific models adapted to different periods.

On the other hand, a more specialized system could significantly increase the architecture complexity.

The use of KLT opens new perspectives in terms of reduction of computational power load and increase of forecasting accuracy.

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