A NEURAL NETWORK BASED TECHNIQUE FOR SHORT-TERM FORECASTING OF ANOMALOUS LOAD PERIODS

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Abstract - The paper illustrates a part of the research activity conducted by authors in the field of electric Short Term Load Forecasting (STLF) based on Artificial Neural Network (ANN) architectures.
Previous experiences with basic ANN architectures have shown that, even though these architectures provide results comparable with those obtained by human operators for most normal days, they evidence some accuracy deficiencies when applied to "anomalous" load conditions occurring during holidays and long weekends. For these periods a specific procedure based upon a combined (unsupervised/ supervised) approach has been proposed.
The unsupervised stage provides a preventive classification of the historical load data by means of a Kohonen's Self Organizing Map (SOM). The supervised stage, performing the proper forecasting activity, is obtained by using a multi-layer perceptron with a back-propagation learning algorithm similar to the ones above mentioned.
The unconventional use of information deriving from the classification stage permits the proposed procedure to obtain a relevant enhancement of the forecast accuracy for anomalous load situations.

Keywords: Self-Organizing Map, Artificial Neural Networks, Short-Term Load Forecasting.

Introduction

In recent years, an increasing number of researchers have applied ANN models to some power system problems such as static and dynamic security assessment, fault detection and diagnostic, dynamics modeling and stability analysis, identification and control, economic dispatch, load forecasting [1].
In particular, Short-Term Load Forecasting (STLF), namely limited to 24 hours ahead, is certainly a frequent application. Several authors in the field of ANN applications to STLF have already evidenced the main advantages of these architectures as an alternative to traditional methods [2,14]. Main reasons for this success are in the capacity of ANNs to automatically identify correlations within raw series of data with simplicity of synthesis, training and use.
Results obtained internationally confirmed good performances of the neural forecasters for every load pattern during common days, i.e. normal conditions [3].
Less care, on the contrary, has been internationally taken to the application of ANNs to the forecast of the anomalous load condition periods characterized by exceptional circumstances of a national nature, such as strikes, holidays and sports events. In fact, these events represent weak statistical samples for an adequate calibration activity of the traditional algorithms used for STLF as well as for human forecasters and, consequently, for forecasting tools (such as expert systems) built on their knowledge.

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The STLF for anomalous periods seems, therefore, an interesting field where investigating the potentialities of ANNs as a promising alternative to the traditional methods as well as an effective support to the human forecaster's knowledge.
This paper describes the research activity conducted in this field.
Some different forecasting models have been previously implemented by the authors using multi-layer perceptron ANN with appropriately modified back-propagation learning algorithms, obtaining analogous forecasting performances [4,5].
In particular, for a model, ANN 1, that adopts a static approach to make a load forecast for all the 24 hours of the day of concern, some example results of the performances obtained during normal days are reported for three weeks of 1993 in section III.
An extensive application of the different ANN architectures to historical load data has evidenced basic deficiencies of the models concerning the load forecast of critical periods such as Christmas and Easter holidays, August as well as some long weekends.
So, a new ANN based procedure (SOM+ANN1) has been implemented in order to enhance the forecasting accuracy in the above mentioned periods. The procedure provides a combined approach (unsupervised/ supervised) structured in three subsequent stages. The first stage provides some identification criteria of the characteristics of the days through the classification of historical hourly loads, thus to obtain clusters of similar load profiles. The classification is performed by means of a Kohonen's SOM. The second stage consists in an actualization process of the information deduced from the previous day type identification. This activity is performed by human operators who give a meaning of the load classes. The third stage, performing the proper forecasting task, is realized by means of a multilayer perceptron based on the back-propagation learning algorithm already used for the ANN 1 implementation.
The paper also compares the two different models respectively aimed to the STLF of normal days (ANN 1) and of anomalous days (SOM+ANN 1) for some Italian typically critical periods, such as December weeks, the Easter week, the Middle August period as well as for some individual anomalous day such as December 8 and May 1st.

I. STF of the Italian Electric Hourly Load

At present, the winter daily peak load in Italy reaches almost 40000 MW. Hence, short-term hourly load forecasts require a high accuracy due to the fact that even small errors have a big economic impact. The forecast made by ENEL personnel with the support of an elaborate adaptive bivariate Box & Jenkins model reduces the average daily error close to 1% on the peak load and, in any case, less than 2%, when normal days are involved. This can be considered a good performance, even by international standards. This result is attributable to the forecasters' experience and the substantial daily repetitiveness of the load diagram, due to the inertia associated with a sound industrial component.
The daily load data used for all the applications illustrated in the paper derive from ENEL's historical load database. The hourly load values given by ENEL are obtained from a preventive processing stage of the data available for each 15 minute step, which provides

also a filtering activity aimed to eliminate the rare inconsistent data found.

II. The ANN 1 Basic Model

II.1 Formulation of the learning algorithm used by ANN1

ANN 1 adopts a static approach to the STLF by performing a simultaneous estimate of the electric load for the 24 hours ahead [6]. To obtain an accuracy of one or two percentage points, requested by ENEL standards, appropriate corrections have been made to the general back-propagation algorithm [7,8]. The proposed model splits the learning process into two successive steps. In the first step a back-propagation algorithm with a "smoothing" technique, as described by equation (1), is used [9].

$$\Delta W_{ij}(n+1) = \eta \delta_{pj} i_{pi} + \beta(\Delta W_{ij}(n)) \tag{1}$$

where:

ΔW_{ij} is the increment of the weight of the i-th interconnection in the j-th output neuron;
η is the synaptic permeability;
i_{pj} is the i-th input to the j-th neuron for pattern p;
δ_{pj} is the error signal.
β is the momentum
n is the iteration number

During the second step weights are adapted by means of the exact calculation of the gradient.

$$W_{ij}(n+1) = W_{ij}(n) + \eta \sum_p \delta_{pj} i_{pi} \tag{2}$$

In order to increase the convergence rate of this approach, the parameter η is adaptively varied using the following criterion:

$$\eta(n+1) = \begin{cases} 1.2\,\eta(n) & E(n+1) < E(n) \\ 0.9 & E(n+1) \geq E(n) \end{cases} \tag{3}$$

Fig. 1 represents the objective function evolution for fifty training iterations between the 5000 th and the 5050 th. The abrupt reduction of parameter η in presence of peaks of increasing error, allows a fast recovery of the previous error value.

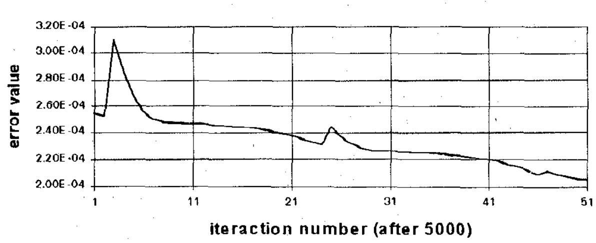

Fig.1 - Example of error evolution as obtained with few iterations of the adaptive algorithm. Error values are scaled by 0.02 for a better diagram reading.

II.2 ANN 1 architecture

The model implemented consists of a totally-connected two-layer network (input, hidden and output layers) having the following structural characteristics. Fifty-one inputs, namely:

- 24 hourly load values of the day preceding the forecast day ($y_{(i-1,tj)}$, j = 1,..,24);
- 24 hourly load values of the day preceding the foregoing (two days prior to the forecast day ($y_{(i-2,tj)}$, j=1,..,24);
- 3 binary codes flagging the two previous days and the day of the forecast (e.g. 001 Sunday and 111 Saturday).

The number of hidden neurons was parametrically optimized to 31.
The number of outputs was set at 24, comprising the simultaneous forecast of the load of the day concerned.
A simplified form of the proposed model can thus be summarized as follows:

$$y_i = F[W_i, y(i-1), y(i-2), bc] \tag{4}$$

where bc indicates the binary code of the day of the week.
The Figure 2 reports the schematic of the architecture of the ANN1, as implemented.

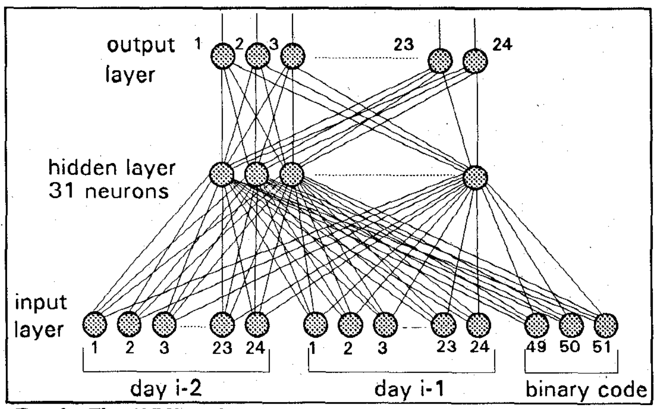

Fig. 2 - The ANN1 architecture.

The ANN1 is trained on training sets composed by the hourly daily load patterns of an entire month. Therefore 12 weight sets result from the training stage for the forecasting task of a complete year. No further specialization is required concerning the day type, since the binary code included in the patterns permits the network to achieve a sufficient accuracy for all the day types included in periods with normal load conditions.
The ANN1 is trained on the load data of the previous year. The test sets include the load data of the year to be forecasted. For instance, in order to forecast the daily load for January 4 1993, the weight set obtained from the ANN training stage relevant to January 1992 must be used. The input used in the forecasting activity will include the daily load data of Jan. 2 and 3 of the 1993.
The high accuracy levels required from the forecasts as well as the significant dimensions of the structure implemented, call for a long training activity of the ANN1. Generally 200 thousand iterations guarantee a well-trained network.
These large computational requirements have determined the implementation of the ANN1 on a parallel computation platform composed of a PC386 with two Transtech TMB08 boards complete with 11 transputers.
A basic ring-connection topology has been used for connecting the individual transputers to the data-processing network. The whole calculation load has been shared among different transputers by means of an equal allocation of the whole number of neurons used for the architecture. The platform permits to complete the training stage approximately within two hours.

III. Forecasts Obtained for Normal Days

Various tests have been carried out on data concerning the Italian hourly load supplied by ENEL in 1992 and 1993. As an instance of

the results obtained, the hourly load forecasts for the following weeks in 1993 (weeks of normal days), are reported:
- Fourth week of February;
- Second week of May;
- First week of October.

The hourly load recorded in the same months of 1992 provided the set of information needed to train the ANN forecasting models.

Table I

t(h)	IV week of February		II week of May		I week of October	
	ε (%)	PRE (%)	ε (%)	PRE (%)	ε (%)	PRE (%)
0	1.56	0.86	3.66	1.86	2.76	1.31
1	1.24	0.5	3.84	2.24	2.72	1.61
2	1.21	0.56	4.05	1.80	3.09	1.76
3	1.98	1.02	3.82	1.81	2.44	1.57
4	2.15	0.97	3.78	1.84	2.66	1.78
5	2.18	0.94	2.24	1.47	2.93	1.70
6	4.	2.57	1.12	0.62	3.	2.12
7	5.29	3.12	2.41	0.71	3.81	1.61
8	3.03	1.57	1.35	0.77	2.16	1.19
9	1.31	0.54	1.11	0.84	2.93	1.21
10	3.03	1.1	1.28	0.70	2.88	1.35
11	3.72	1.56	1.88	0.84	4.56	1.61
12	3.92	1.6	1.63	0.94	3.94	1.57
13	3.88	1.7	2.30	1.11	3.80	1.50
14	4.29	2.25	3.09	1.03	3.99	1.58
15	5.4	2.74	2.18	1.29	3.86	1.90
16	5.31	2.78	2.02	1.48	4.00	2.39
17	5.56	2.38	3.71	1.45	4.30	1.90
18	2.73	1.24	3.58	1.62	2.70	1.81
19	1.98	1.08	2.25	1.41	3.06	2.17
20	2.32	1.28	1.65	1.11	2.45	1.58
21	2.26	1.28	2.25	0.85	3.74	2.36
22	2.14	0.94	1.96	0.93	3.15	1.67
23	3.3	1.5	2.26	1.23	3.61	1.93

For each of these forecasting periods Table I reports the following information:
- maximum value, in the week considered, of the forecasting error of ANN 1 for each hour of the day, calculated by the formula,

$$\varepsilon\%(t_i) = 100 \cdot max\left|\frac{\hat{y}_j(t_i) - y_j(t_i)}{y_j(t_i)}\right|^{j=1..7} \tag{5}$$

- PRE (Percentage Relative Error) calculated, for each hour of the day, by the formula,

$$PRE\%(t_i) = \frac{1}{7}\sum_{j=1}^{7}\left(\varepsilon\%(t_i)\right) \tag{6}$$

In Figures 3 to 5 the hourly load forecast are compared with the actual data.

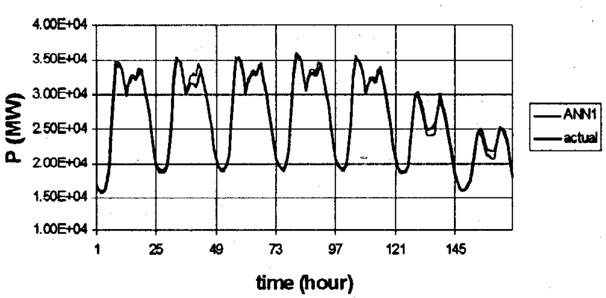

Fig. 3 - Actual and forecast values for 4th week of February 1993.

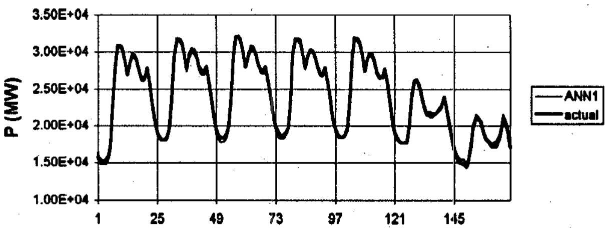

Fig. 4 - Actual and forecast values for the 2nd week of May 1993.

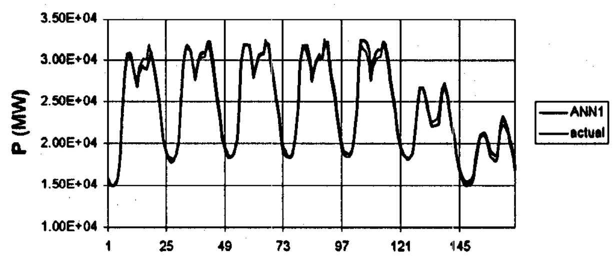

Fig. 5 - Actual and forecast values for the 1st week of October 1993.

At present the ANN1 does not take into account the weather influence.

It is well known that a correct understanding of the influence exerted on electric load by meteorological and climatic factors as temperature, cloud-cover, wind-speed, etc. would improve the forecasting results achieved through a neural architecture [3,6].

To this aim a wide research activity is in progress for determining an adequate meteorological model that could be used for integrating the training sets of the back-propagation based ANN used at present for the STLF tasks, thus achieving better forecasts for days with normal load conditions.

However, even though the influence of weather data on the hourly electric load is almost certain, this influence seems less important during the anomalous periods, when all the social aspects influencing the load profiles become predominant.

In these periods the maximum forecasting error (as shown further ahead) exceeds even 50% of the actual value, with a daily average up to 20%.

It seems therefore unlikely that representing correctly the weather influence could change significantly the forecasting performances.

Moreover, the limited occurrence of such anomalous periods makes it difficult to build a training set which reproduces correctly the weather influence on the load profile.

IV. Day-Type Classification by means of Unsupervised Learning

Vacation periods, holidays and long weekends are some of the most noticeable factors which can determine anomalous load conditions, with respect to typical load patterns. Most of the STLF models presently available show a sensitive decrease of accuracy during these periods. Thus, ENEL's experience suggested to develop a specific procedure only for anomalous load conditions.

This task has required a day-type classification aimed to identify similarities among patterns of load profiles.

Recent works have illustrated the effectiveness of an unsupervised learning approach for this task [10]. They are based on the assumption that load patterns already incorporate all the information concerning the external influences affecting the load.

This typical pattern recognition task can be adequately achieved by using a Kohonen's Self Organizing Map (SOM).

IV.1 Formulation of Kohonen's SOM

The Kohonen's SOM is composed of two layers, input and output. The output layer is a bidimensional matrix of processing elements individually fully connected to the input layer by means of a vector of weights. The implementation of the SOM requires the implementation of a discrimination criterion generally based on the calculation of the Euclidean distance between the input pattern and each output element. The calculated distances are used to select and activate the output element with the minimum value ("winner") and its neighbors through a well defined activation function. The weight vectors of the selected elements are adaptively updated using the following algorithm:

$$W_{i,j}^{new} = W_{i,j}^{old} + \eta(t)(X_i - W_{i,j}^{old}) \qquad (7)$$

where η, in this case, has been held fixed throughout the various procedure iterations.
The implemented algorithm also incorporates a "conscience" mechanism that causes each element of the output layer to win less frequently if it has won too much in the past, thus assuring that each output element win an approximately equal fraction of time in the long run. This mechanism tends to concentrate the output where the Probabilistic Distribution Functions of the input is lowest [11].

IV.2 Load data classification

An extensive classification of load profiles relevant to the years 1991-1993 has been performed through an 8x8 SOM classifier.
The input patterns were daily load vectors composed by 24 hourly values, such as:

$$\overline{P} = [P_1, \ldots, P_{24}] \qquad (8)$$

Parametric analyses have been conducted both on each parameter of the algorithmic formulation (maximum neighborhood radius, learning rate value, conscience value) as well as on different sizes of the training set (1, 3 and 12 months). Tests conducted on yearly data have provided results analogous to those reported in similar applications [12,13].
The algorithm tends to cluster the load profiles in the following principal day types: Sundays, Saturdays, Mondays and working days after a Holiday, working days from Tuesdays through Fridays, main Holidays such as Christmas, Easter days, Middle August day, etc.
The number of different clusters ranges between 11 and 15 for the years analyzed.

The following questionable classifications have been also evidenced:
- working days of August (generalized vacation period) have been classified together with the Sundays of late Fall;
- days between weekends and bank holidays are classified both as Saturdays and as Sundays.

A seasonal classification can be deduced among a spring-summer season comprising April, May, June, July and September, an intermediate season comprising March and October, and a winter season comprising January, February, November and December.

In Table II the main characteristics of the different daily load profiles within each cluster for the entire 1991 have been reported. The Table also reports the maximum value of the peak demand, the minimum value of the minimum demand, the average daily energy value of the various profiles in the cluster. The relevant standard deviation values are also indicated.

Table II

clust.	Pmax (MW)	STD (MW)	Pmin (MW)	STD (MW)	Energy (MWh)	STD (MWh)
0	23528	695	12660	857	441021	12856
1	23999	503	13597	493	464061	6390
2	27240	979	14604	533	496391	12092
3	28252	698	16022	856	525884	12284
4	29157	742	13165	1588	539755	12717
5	31656	901	17605	413	586767	16101
6	32154	806	16955	343	601264	11916
7	32492	698	12674	792	584613	15050
8	33729	537	16106	638	625677	8797
9	33797	453	18711	410	644056	9548
10	33872	763	14686	1530	617432	13730
11	36169	580	14567	1323	659632	11841
12	38246	680	15973	834	687094	4987
13	38166	253	19362	207	715047	4599
14	21336	673	11883	672	389865	18471

Table III

December 1991			*December 1992*			*December 1993*		
day type	*date*	*clus. n.*	*day type*	*date*	*clus. n.*	*day type*	*date*	*clus. n.*
Sa	07	45	Tu	15	40	Su	05	31
Sa	14	45	We	16	40	We	08	31
Sa	21	45	Th	17	40	Su	12	31
Mo	23	47	Fr	18	40	Su	19	31
Fr	27	50	Tu	01	41	Fr	24	31
Sa	28	50	We	02	41	Sa	25	31
Su	29	50	Th	03	41	Su	26	31
Mo	30	50	Fr	04	41	Mo	27	36
Tu	31	50	We	09	41	Tu	28	36
We	25	51	Th	10	41	We	29	36
Th	26	51	Fr	11	41	Th	30	36
Su	01	52	Mo	14	41	Fr	31	36
Su	08	52	Mo	21	41	Sa	04	37
Su	15	52	Tu	22	41	Sa	11	37
Su	22	52	We	23	43	Sa	18	37
Tu	24	52	Sa	05	45	Th	23	40
Tu	10	55	Sa	12	45	Mo	06	41
We	11	55	Sa	19	45	Th	09	41
Th	12	55	Mo	07	46	Mo	13	41
Fr	13	55	Su	06	47	Mo	20	41
Tu	17	55	Tu	08	47	We	01	43
We	18	55	Su	13	47	Th	02	43
Mo	02	57	Su	20	47	Fr	03	43
Tu	03	57	Th	24	47	Tu	07	43
We	04	57	Fr	25	47	Fr	10	43
Th	05	57	Sa	26	47	Tu	21	43
Fr	06	57	Su	27	47	We	22	43
Mo	09	57	Mo	28	47	Tu	14	44
Mo	16	57	Tu	29	47	We	15	44
Th	19	57	We	30	47	Th	16	44
Fr	20	57	Th	31	47	Fr	17	44

The size of the training set of a Kohonen's SOM (time horizon) can be considered as a convenient mean for calibrating the accuracy provided by the classification activity.
The detailed results of the classification stage conducted by reducing the training set to a monthly time horizon for the month of December of years 1991-1993 have been illustrated, in the Table III.
The accuracy thus obtained has been considered more satisfactory for a correct identification of anomalous daily load conditions.
For instance, the day December 8 is an Italian holyday and the 1992 calendar time represents a typical case of a long winter weekend. In the Table III, therefore, Tuesday Dec. 8 is included in a cluster used for classifying Sundays and Holidays. The day Monday Dec. 7 is

included in a contiguous cluster, thus indicating that its load shape is closer to a holiday's one rather than to a Monday's one being classified with other working days in a farer cluster.
In 1993 the Thursday Dec. 9 is included in a cluster containing two Mondays. The load pattern of this day type is in fact similar to a typical working Monday.

IV. 3 The proposed unsupervised/supervised approach

Several authors have already illustrated how a preventive classification of historical load data can enhance forecasting accuracy of the ANN models [10,12,13].
Various approaches using this technique share the basic concept that the unsupervised stage tries to map many not very dissimilar patterns to the same output, thus reducing the burden assigned to the supervised stage which is provided of the forecasting task. In fact, the supervised stage can perform its learning procedure on the clustered data rather that on the entire data set. Thus, the information provided to the supervised stage is alternatively composed:
- by all the load patterns grouped in the same cluster [13];
- by a representative feature of the various load patterns of the same cluster (cluster centre, average load pattern) [12].

In [10] authors have also proposed an interesting ANN architecture that allows the unsupervised/supervised stage to be carried out with the same network configuration. Previous tests have been performed on these architectures. The results obtained were not satisfactory, in consideration of the characteristics of the Italian load and of the high accuracies required.

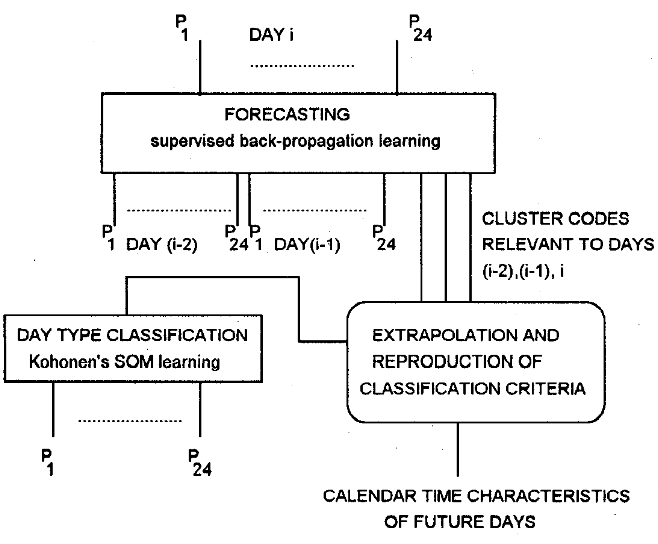

Fig. 6 - Unsupervised/supervised procedure adopted (SOM + ANN1).

The purpose of implementing a methodology well tailored to the good capabilities of the ANN 1 model, has suggested an unconventional use of the information deriving from the classification stage. Fig. 6 illustrates the structure implemented.
The Kohonen's SOM provides a cluster identification code for each input pattern. The daily load profiles and the binary codification of their cluster constitutes the new training set of the ANN1 previously illustrated. The cluster codification substitutes the original day type coding used for the ANN 1 model.
The application of the procedure illustrated requires a labeling procedure for each future day based only on its *a priori* characteristics such as calendar variables. This task, that aims to replicate the classification obtained by the unsupervised ANN is assigned to human operators. In a recent paper, a supervised multilayer perceptron has been suggested for this task [13]. This approach has not been followed here for still leaving the forecasters a decision role in their activity, according to ENEL recommendations.
The calibration activity of the Kohonen's SOM parameters for anomalous periods is performed through a feed-back process driven by an expert user who calibrates the parameters with the results of the forecasting stage activity. If the cluster codes obtained permit to achieve adequate forecasts for all these periods, the accuracy obtained by the classification stage can be considered suitable.

V. Case Studies

V.1 Description of the test activity

Extensive tests have been conducted on load data of the years 1991-1993.
In order to test the potentiality of the proposed procedure, some anomalous periods of the above mentioned years have been selected for comparing the results provided by the basic method (ANN1) and the combined (SOM+ANN1) method.
The month of December 1992 presented a typical anomalous load situation in correspondence of December 7 that takes part of a typical long winter weekend. Furthermore the day December 31 represents a typically critical day for load forecasting.
Figures 7 and 8 illustrate comparatively the forecast results for these days as obtained with both the illustrated procedures. Figures 9 and 10 comparatively illustrate the performances of the two procedures for the week December 5-11 as well as for the Christmas week (December 25-31). For these weeks an analytical comparison among the results, as based on the calculation of coefficients of (5) and (6) is also reported in Table IV.

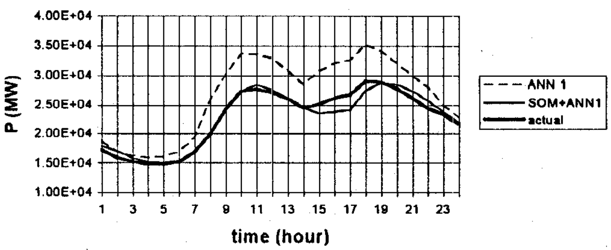

Fig. 7 - Comparison for the day December 7.

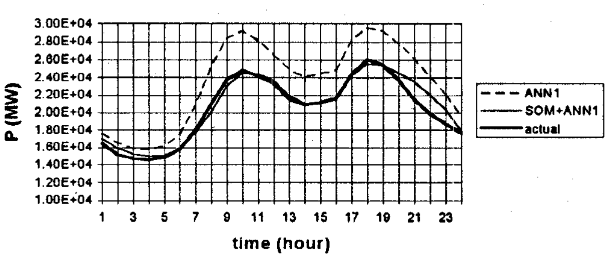

Fig. 8 - Comparison for the day December 31.

The combined procedure (SOM+ANN1) determines a noticeable increase of the forecast accuracy in all the anomalous load conditions analysed. The forecast results of the combined procedure have been obtained by using a day type classification such as that shown in Table II (monthly basis).
The Table IV reports the statistic of maximum and average hourly errors for the two weeks of December analysed in detail with the two methods.

Table IV

	December 5-11				December 25-31			
	ANN 1		SOM+ANN1		ANN 1		SOM+ANN1	
t(h)	ε(%)	PRE (%)	ε(%)	PRE (%)	ε(%)	PRE (%)	ε(%)	PRE (%)
0	8.84	6.18	6.47	3.48	20.36	8.78	5.45	2.54
1	9.98	6.11	6.28	3.29	21.90	9.79	5.95	2.78
2	11.09	6.70	6.49	2.74	25.24	10.18	8.69	2.92
3	11.97	7.07	6.38	2.59	27.42	12.33	10.44	2.90
4	13.96	7.87	3.25	2.20	29.03	13.19	11.19	3.06
5	20.66	10.27	4.53	1.31	30.37	15.54	10.55	4.14
6	34.67	18.37	10.99	4.80	41.27	22.09	9.76	6.09
7	44.37	24.45	17.23	6.07	52.58	26.6	17.26	9.57
8	41.94	21.45	17.83	6.28	49.98	24.02	16.18	9.78
9	37.25	17.95	13.69	5.97	44.34	20.90	14.39	8.15
10	35.12	17.83	10.73	5.23	41.20	18.79	14.37	7.47
11	32.13	16.53	6.71	4.38	37.47	16.96	14.62	7.59
12	32.64	15.84	7.98	4.90	37.82	17.72	14.35	7.72
13	38.67	20.95	9.20	6.11	45.14	20.99	18.08	10.20
14	40.61	23.82	8.44	6.35	46.60	21.23	20.29	10.98
15	41.88	24.53	8.03	6.49	48.62	21.44	20.64	11.60
16	39.29	21.20	12.94	6.24	45.97	20.91	17.12	10.06
17	35.51	17.23	14.88	6.00	41.09	18.86	13.64	8.96
18	32.13	14.23	12.58	5.99	37.22	17.94	14.25	7.45
19	29.25	12.15	8.60	6.29	33.51	17.06	14.00	6.32
20	26.50	11.18	9.78	6.26	29.49	16.92	14.32	6.42
21	23.64	10.01	10.24	3.68	25.39	14.19	12.24	6.89
22	22.79	9.41	8.79	3.68	26.06	14.35	10.10	5.24
23	23.13	9.04	8.18	3.80	25.98	13.88	7.52	2.99

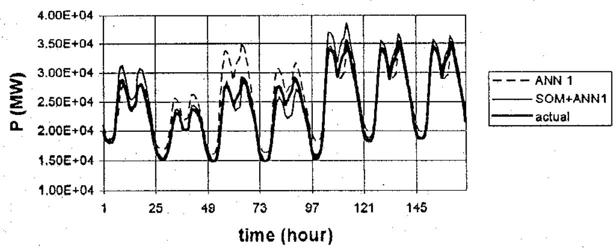

Fig. 9 - Comparison for the week December 5-11.

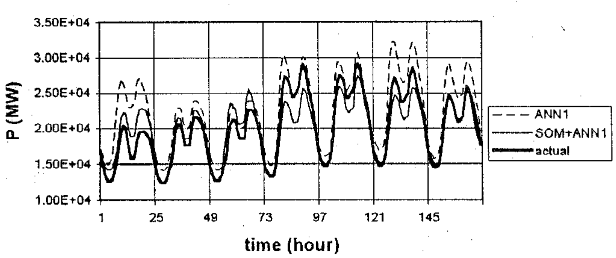

Fig. 10 - Comparison for the week December 25-31.

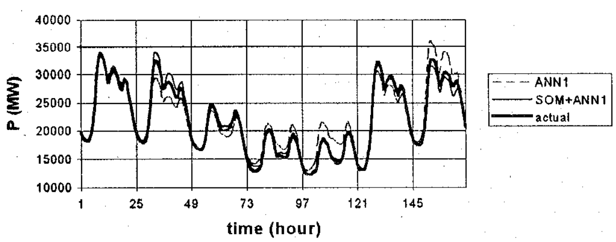

Fig. 11 - Comparison for the Easter week (April 8-14 1993).

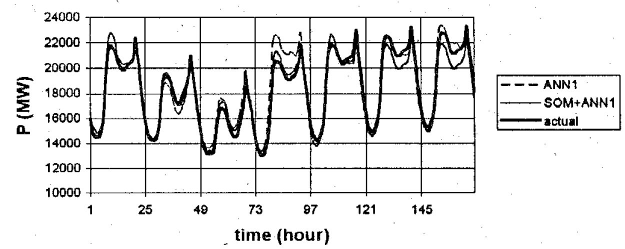

Fig. 12 - Comparison for the Middle August week (Aug.13-19,1993)

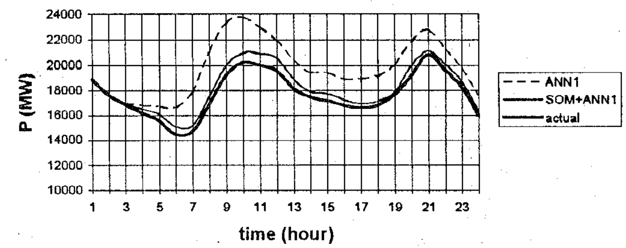

Fig. 13 - Comparison for the day May 1st 1993.

Analogous results have been obtained for different holidays periods of the years such as the Easter week, the Middle August week and some festive days such as May 1st. The figures 11, 12 and 13 report the comparison between the results obtained with the two methods and the actual load values.

V.2 Discussion of the results

Figures 7-13 clearly evidence that the combined procedure (SOM+ANN1) provides much better forecasts for anomalous load conditions.

For instance, in Fig. 9 the days December 6 and 7 constitute a segment of a long weekend for which the day type classification based only on calendar characteristics (such as for ANN 1) falls in defect. Instead, for normal days such as Dec. 9, 10 and 11, the ANN 1 model achieves better results.

Analogous results can be evidenced for the week Dec. 25-31. In particular, for that concerns the days Dec. 26 and 27, the small difference between the two forecasts is justified by the coincidence of these dates respectively with Saturday and Sunday. For normal days such as Dec. 28 and 29 the ANN1 forecasts are more accurate. Instead, higher accuracy provides the combined procedure for Dec. 30 and 31, real anomalous load conditions.

Analogous considerations can be extended to the periods illustrated in the figures 11-13.

The combined procedure (SOM+ANN1) gives much better results for all the days of the Easter week (April 8-14). The better performances are particularly obtained for days such as April 9, 12 and 14, which represent the periods before and after the Easter Day, where the load conditions present significant changes with respect the days of the same type during the same month. The same characteristic is also shown by the results obtained for the Middle August week. The coincidence of the day August 15, that is a typical generalized holiday in Italy, with Sunday makes the forecasts of the two models for this day very close. However the combined procedure achieves much better performances for the days August 14 and 16 for the same reasons above mentioned. For the normal days such as Aug. 17-19, where the load conditions come back to a stable behavior, the ANN1 gives better results than the combined procedure.

Finally, for May 1st, that is a typical international holiday (Workers' Day), the Figure 13 shows how the combined procedure gives much better results than ANN1.

From the above illustrated results the following fundamental considerations can be derived:

- the ANN 1 model shows better performances for all load patterns that reproduce the typical day type characteristics (normal days);
- for each anomalous load situation examined the combined approach gives generally better forecasts than those obtained through the ANN 1;
- an aprioristic identification of anomalous periods should include in this category, in addition to all the holidays, the long week-end days, and each day perturbed by special events, also all the days coincident typically with the days before and after these periods. In fact the holiday periods can generate an inertia effect on the social activities that can result in load conditions that are difficult to predict;
- an input data set of the day type classification activity as limited to a monthly time horizon has seemed the most effective both for the typical Italian load patterns and for the characteristics of Kohonen's SOM implemented.

The results obtained suggest the adoption of different specific procedures for STLF of anomalous and normal days. An ANN based forecasting tool can be, therefore, implemented by integrating the two different procedures. This tool should provide that the ANN1 be applied to forecast the normal load conditions periods, while the combined procedure be applied to each anomalous period that must have been identified through an accurate preventive classification activity conducted on various years of historical load data. The preventive classification permits to achieve the detailed knowledge relevant to the typical anomalous load conditions that is required from the end user of the integrated tool.
For the Italian case, the months of January, February, May, June, July, September, October and November can be considered almost entirely composed by normal periods, with only few anomalous load conditions. The application of the ANN1 model to these months results in the following accuracy statistic:

- maximum hourly error = 7.1%
- maximum average error = 2.6%
- maximum standard deviation value = 2.8%

The application of the proposed integrated procedure (ANN1 for normal periods and SOM+ANN1 for anomalous periods) has given for the months of December and April, typically the months including the largest occurrence of anomalous load conditions, the following results:
December:

- the maximum hourly error decreases from 52.5% to 14.9%
- the maximum average error decreases from 12.9% to 7.7%
- the maximum standard deviation decreases from 14% to 4.5%

April:

- the maximum hourly error decreases from 33.2% to 9.8%
- the maximum average error decreases from 6.9% to 2.7%
- the maximum standard deviation decreases from 6.1% to 2.1%

Conclusions

The present paper investigates the possibility to enhance Short-Term Load Forecasting for anomalous load conditions that still remains not satisfactorily covered by statistical and common Artificial Intelligence (AI) techniques. To face this problem an unconventional neural architecture, which uses the combined characteristics of an unsupervised and supervised neural network, has been proposed.
The benefits of this architecture (SOM+ANN 1) with respect to a basic multi-layer perceptron neural network (ANN 1) have been illustrated for some highly anomalous conditions of Italian load patterns.
The results obtained show that the proposed architecture can provide a considerable improvement of the forecast accuracy, can be assumed ranging up to a factor of three.
Therefore, an ANN tool obtained by the integration of two specific procedures, respectively, for normal and anomalous days, could be implemented as an effective support to the human forecasters' task.

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