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Electric load analysis using an artificial neural network

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SUMMARY

Load forecasting in the current, increasingly liberalized, electricity power market is of crucial importance as a means for producers to optimize and rationalize energy supply. A number of electric power companies are equipped to make forecasts with the aid of traditional statistical methods. This paper presents the use of an artificial neural net to an hourly based load forecasting application for a small electric grid on an Italian island (Lipari) not connected to the mainland. The aim was to examine the forecasting ability of a neural net in a situation where the electric load was subject to considerable seasonal variations over the year. The variations are affected by energy demand related to the tourism season as well as by climatic conditions, especially temperature. The network developed was a multi-layer perceptron type built on three layers trained with a back-propagation algorithm. The input layer receives all the most relevant information regarding: the class of day type, the hour in the daytime, the load and background temperature recorded at the indicated time for the months of March, August and October whilst the output layer provides the forecast value at the indicated time in December. The results obtained are encouraging; in the training phase the RMS error rate was around 2% and this rate settled at about 2.6% during testing. As both the margins of error recorded are acceptable, the use of a neural network for electric load forecasting applications can be considered an attractive option. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: neural network; electric load analysis; forecasting

1. INTRODUCTION

The liberalization of the electric supply system set the scene for energy production in a dynamic and competitive market. Electricity is, of course, a commodity that cannot be stored, therefore balancing supply and demand is crucial to strategy management. The performance and the efficiency of production plants are critical factors in meeting total demand for electrical energy. It is within this context that 'load forecasting' plays a key role in the various operations involved in energy production systems. Obtaining information on future patterns of demand assists the planning and purchasing (of fuel), the start-up or the shutdown of a power plant to avoid any problem arising from interruption of supply to customers, and also enables the excess of production to be effectively assessed. In general it is very important for energy companies,

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particularly in the electricity sector, to have forecasts of the short-term variations in electricity demand. Load forecasting can therefore be of great importance for the management and distribution of electric power.

2. FORECASTING ELECTRIC LOADS

In general terms, different types of users consume the load of the national electrical grid; although industry accounts for a substantial chunk, a large part is used for a wide range of domestic purposes: light, heat, food preparation, use of household electrical appliances, laundry, etc. The services offered by public sector enterprises (e.g. streetlighting, railways, etc.) also influence demand for power and thus affect the shape of the load curve. The level of demand from industry is generally fairly stable and it is possible to estimate its relationship to production levels. In contrast, the factors that impinge on domestic demand may vary depending on the consumption patterns of individual households. In addition many social factors, such as certain television programmes, sporting or religious occasions can produce unpredictable surges in demand. Even meteorological conditions can strongly affect the demand curve and the effects can be traced back to a greater or lesser use of electric air conditioning and/or heating devices. The main factors that should be considered regarding consumption of electricity can be classified as follows (Bao, 2002):

- *Temporal* (calendar) effects: seasonal load differences between summer and winter (increased hours of daylight, start or end of the school year), daily load differences (between night and day), weekly cycles (load is significantly lower at weekends compared to weekdays), times of year linked to festivals such as Christmas (20-12/31-12);
- *Economic* effects: economic trends (recession or expansion), new industrial sites, electricity price changes, demand side management;
- *Meteorological* effects: mean and maximum temperatures, humidity levels, rainfall and snow, cloud cover;
- *Random* events: sporting events, popular television shows, start-up or shutdown operations of industrial plants requiring a lot of power (iron and steelworks, etc.).

The type of load forecasting can vary depending on the end result desired; it may be *spatial* if it mainly relates to the study of future patterns in a specific region, country or state, otherwise it is *temporal* if concerned with forecasting on an hourly, daily, monthly or yearly basis (Bao, 2002). The temporal type load forecasting models cited in the literature are split into four main groups according to the time period under review as follows.

Where the forecasting period is a few minutes this is referred to as *very-short-term* (VSTLF), if the time spanned ranges from a few hours up to 1 week then this is covered by the most widely available models called *short-term* (STLF) used for daily unit allocation (Kermanshahi and Iwamiya, 2002), STLF calculates the load of every hour of the day and this estimate can be used to control the number of generators in use and the shutdown of some units when the load forecast is low or their start-up when high loads are foreseen. In the case in which the time period lasts from a few weeks up to 1 year then we are dealing with *mid-term* (MTLF). Lastly, if the activity forecast spans a period from a few years up to one or two decades then these are *long-term* (LTLF) and they are generally used to aid resource planning activities and to assess the need for restructuring or extension of production facilities.

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In the recent past, a variety of techniques were used to develop load forecasting models and some of the cases and applications reported in the literature are the following: exponential smoothing (Christiaanse, 1971), regression (Al-Garm *et al*., 1994; Papalexopoulos and Hesterberg, 1990), the Box and Jenkins method, stochastic time series models, autoregressive moving average (ARMA) and integrated autoregressive moving average (ARIMA). An overview of the most widely used load forecasting methods can be found in Murto (1998) together with the references therein. These methods have been applied fairly successfully to short-term load forecasting problems, however, in many cases, when put to work on real applications, accuracy has been only modest and the stability of results obtained has been low.

Another important family of models that should be mentioned are those concerning the application of expert systems based on *fuzzy-set* logic; these have produced extremely encouraging results (Ranaweera *et al*., 1996; Murto, 1998).

3. THE DEVELOPMENT AND SPREAD OF NEURAL NETWORKS

In the last decade (mid-1990s) a great deal of interest was dedicated to the development of load forecasting models based on neural networks and on expert systems. Neural net forecasting has recently enjoyed considerable success in pattern recognition and process prediction and has gained worldwide research interest. It has been widely used in various applications relating to energy systems in general. However, the most convincing results have been obtained in those applying to the field of load forecasting. One study (Sforna and Proverbio, 1995) indicates that around 20% of all neural network applications regarding energy systems do in fact concern load forecasting and that a back-propagation algorithm was employed in the learning phase in over 56% of neural net models developed. The realization of neural networks represents an attempt to reproduce the functions of the human brain artificially by mimicking learning mechanisms. Neural networks correct the parameters of a model on the basis of input and output data supplied in order to find relations between data.

The pioneering work in this area was conceived in the early 1940s by McCulloch, a neurophysiopathologist, and by W. Pitts, a mathematician. They reproduced a simple neural network by using linked electrical circuits thus demonstrating the ability of an artificial neuron model to form connections. Another milestone publication was that of D. Hebb in which the theory of connections was set out (the so-called Hebb's law) and constitutes the underlying theory of the learning mechanisms of neural networks. In 1958, Rosenblatt coined the term *perceptron* to describe the first model of a neural network assembled in hardware. The results of this research, however, were not to enjoy great success, as Minsky and Papert subsequently carried out a painstaking and in-depth study on perceptrons highlighting the limitations of the model and thus were critical of Rosenblatt's work and the advances it had brought to the sector.[‡] The publication of Minsky and Papert's work made a devastating impact as it initiated a long period when research activity in the neural networks came almost to a halt. Much later, in 1982, the results of Hopfield's research vigorously revitalized interest in neural networks. Indeed, it was thanks to his paper, setting out in advanced mathematical terms and adopting a meticulously scientific approach, examining how networks could work and what results they

[‡] In an interview Minsky stated: 'we do not have enough researchers and at the same time we see people throwing their lives away on perceptrons'.

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could achieve that they bounced back on the scene (Lawrence, 1994; Javeed Nizami and Al-Garni, 1995; Carrella, 1995). Hopfield deserves recognition for his contribution to the affirmation and spread of this new science.

Neural networks possess specific qualities that are particularly attractive for the analysis and treatment of data. When they are applied to studying historical series they show great adaptability in handling incomplete and uncertain data affected by noise, and manage to reconstruct the trend of a historical series in the training phase and thus enable forecasts to be made on the basis of past data (Marino, 2002). A variety of real-life applications are to be found in the literature and include, for example, the following areas: data classification, medical diagnosis, financial forecasting, image recognition, optimization and control of processes, weather forecasting and environmental pollution applications.

Neural networks are, by definition, nonlinear and make no hypothesis on the characteristics of the data unlike techniques such as nonlinear regression. The advantage of using them lies in the fact that when an analysis is carried out it is not necessary to develop a specific model, as it is the network itself, on the basis of training set, that will define its own model from which it will generate a plausible approximation. Furthermore, neural networks are capable of identifying interactions between variables themselves, whilst in regression these have to be spelt out. The analyst, although not restricted by the limited hypotheses that are typical of other models, must nonetheless define the architecture of the network to be used and the effectiveness of the network structure is therefore heavily dependent on the analyst's level of experience. The main disadvantage of neural networks lies mainly in the fact that it is difficult to provide an explanation accounting for the outcome of the pattern reproduced. Hence neural networks are useful for analysing objective variables in the presence of strong nonlinearities and interactions, but are of little help when the characteristics of the data must be explained in some way. It is for this reason that neural networks belong to the so-called *black-box* category of models.

3.1. How networks work: a summary

The wide-ranging applicability of neural networks is intrinsic to their skill in extrapolating the relations existing between the input and output variables within an environment that is dynamic and often extremely nonlinear; this is what occurs in the *training* phase 'learning from examples' of input–output. They are in essence a class of models inspired by biological nervous systems and the approach is based on computing systems able to learn through experience by recognizing patterns existing within a data set (Sudhakar and Truman, 1998). The models are composed of many computing elements called *neurons* connected by *synaptic weight* which are allowed to adapt through a *learning process* and exhibit some small similarity in their behaviour with a narrow range of human cognitive skills. They apply knowledge from past experience to similar problems and they can be utilized as adaptive machines that store knowledge through the learning process (Murto, 1998).

The most well-known and widely used type of neural network for short term forecast model (STFM) is the multi-layer perceptron (MLP) network. In a neural network each unit (neuron), grouped into layers, can be linked with any other unit. The neurons in the same layer are not connected with each other but only with the neurons outside that layer (see Figure 1). The network contains an *input unit* layer from which signals start, the state of activation of these units is determined from outside the network, then there is a second layer called *output units*

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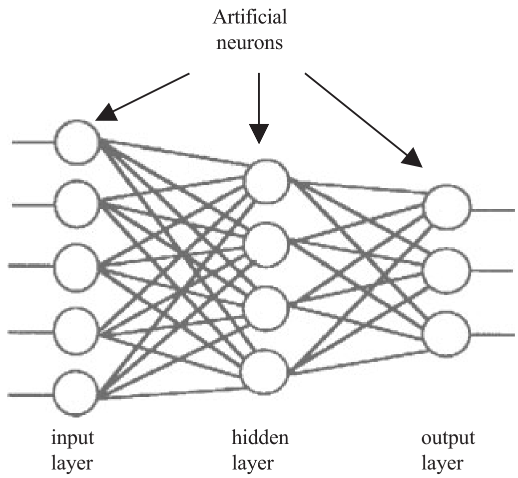

Figure 1. A simple three-layer neural network.

which only receive signals but send none out. Neural networks also normally have one or more *hidden-layers* between the input and output which have no direct contact with the outside.

The neurons process inputs and produce outputs and each neuron receives inputs from many other neurons. Just as there can be a number of inputs for a biological neuron there can be many inputs for an artificial neuron. In response to the incoming signals a node can be activated or not depending on whether or not its threshold value is exceeded (inhibitory or excitatory signals).

A specific relative weight is linked to every input which takes into account the impact generated by the input signal. The weight can be regarded as a measure of the strength of the connection. The inputs are multiplied by the weights associated with the corresponding connections that represent the lines of communication between the different neurons.

On the basis of the weighted sum of the inputs and on a threshold value, a nonlinear operator calculates the activation value and determines whether or not the neuron is to be switched on. Each neuron in the network produces an internal activity level, net_i defined by the following equation:

$$\mathrm{net}_i = f\left(\sum_{j=1}^{n} w_{ij}x_j - \theta_i\right) \tag{1}$$

where w_{ij} is the weight of the connection between neuron i and neuron j (the synapse), x_j is the activation level sent from neuron j which is linked in the previous layer (see Figure 2), and θ_i (bias) represents the threshold value which will be compared with the sum of the inputs coming from all the neurons connected with the current one. Thus the transfer function f is applied using a standard sigmoid function:

$$y = \frac{1}{1 + \mathrm{e}^{-x}} \tag{2}$$

or the sigmoid from -1 to 1 (see Figure 3):

$$y = -1 + \frac{1}{1 + \mathrm{e}^{-x}} \tag{3}$$

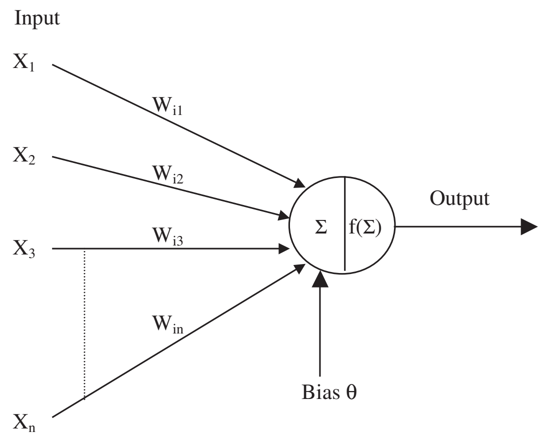

Figure 2. Neuron *i*.

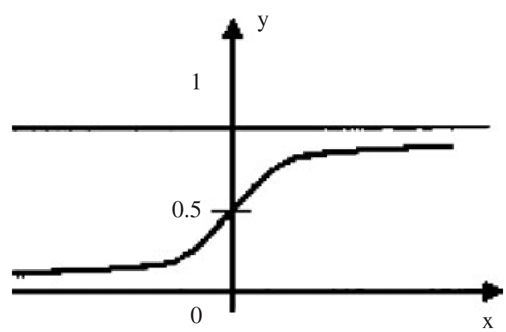

Figure 3. Sigmoidal transfer function.

The signals pass through the input layer and therefore cross the hidden layer to reach the output layer where the signal is finally produced. Neural networks have two distinctive features: the learning–training phase and the working application phase. In the first phase the network is able to a learn a correct pattern by processing a set of data selected by the analyst for training and by tuning the weights of connections. Subsequently, the same network can be supplied with different data from those used for training to produce forecasts. At the start the network will give random answers; however, by being repeatedly exposed to the training data it will progressively and autonomously modify its weights in order to generate the desired outcome. Neural networks do not have to be programmed but they learn to learn how to give a specific performance (Parisi, 1989). A network can be trained to learn the functional relations between its inputs and its output as follows: the network is supplied with a well-defined set of training data, (incoming signals) supplying for each input vector the vector that is expected to come out of the output layer i.e. the network is given a set of examples from which it must learn. Training continues by repeated data runs, even thousands, and the network processes this series of patterns until the average error between the desired output and the actual output from the network falls below a pre-determined threshold.

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The most widespread training method is the *back-propagation* algorithm. During training not only the pattern for activation (input) is presented but also the pattern expected from the network as output; at the start of the iterative process this will differ wildly from the desired pattern given the random weights of connections. Consequently, the network calculates the error for each unit of output, i.e. the difference between the state of output produced by the network and the output desired. This error calculation serves to modify the weights of the connections that reach the output units and is done in order to reduce the error. The aim of network training is to minimise the overall error which is calculated as the average of the squared errors of each output unit called sum squared error (SSE) expressed as follows (Grimaldi and Mariani, 1994):

$$\mathrm{SSE} = \sum_{p=1}^{n_v} \sum_{o=1}^{n_o} (t_{op} - x_{op})^2 \tag{4}$$

where $t_{op}-x_{op}$ is the difference between target experimental output and the network output, n_o is the number of neurons, and n_v is the size of the input and output vectors. Generally this size, being dependent on the number of vectors considered in the set, is referred to a mean error value thus the root mean square error can be drawn from the following:

$$\mathrm{RMS} = \sqrt{\frac{\mathrm{SSE}}{n_v n_o}} \tag{5}$$

where n_v is the number of vectors of the set and n_o is the number of output neurons.

The back-propagation algorithm uses the Windroff–Hoff rule for adjusting the weights, running data sets many times. Training terminates when the overall error is considered to be acceptable or in any case when no further reduction in error is achieved by doing further runs. At this point the network is trained, which means that it is capable of supplying output for every input. The great success, even in commercial terms, of neural networks in different fields of application lies in its ability to generalize and infer, i.e. it possesses the ability to go beyond what it has been taught (Parisi, 1989).

3.2. *Energy load forecasting using neural networks*

The literature abounds with examples of the applications of neural networks to load forecasting problems. This began in 1990 when the first researchers to put neural networks to work on STLF were Lee *et al.* (1990). Park *et al.* (1991) proposed a multi-layer network adopting a back-propagation algorithm with three layers: one input, one hidden and one output. By using historic data on grid loads and weather conditions their system was capable of forecasting movements in three different variables (peak load, total daily load and hourly load). An exhaustive description of neural networks applied to load forecasting containing the most important references to work in this area can be found in Metaxiotis *et al.* (2003). Other papers of great interest concerning neural networks applications containing a variety of network architecture or type of data used (Sforna and Proverbio, 1995; Mohamed *et al.*, 1998; Kiartzis *et al.*, 1995; Islam *et al.*, 1995).

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4. ANALYSING LOAD ON AN ISOLATED ELECTRIC GRID USING A NEURAL NETWORK

4.1. Electric grid location

The aim of this work is to build a neural network to study movements in loads on an electricity grid for a small island of the coast of Sicily (Italy) in order to investigate, on the basis of past movements, the evolution of future patterns also with respect to the influence of temperature (Figure 4).

Lipari is the biggest of the Aeolian islands (Italy) with a surface area of around 38 km^2. It also has the largest population, about 9000 people, the majority of whom live in the only large town on the island while other residents are scattered throughout the area. The island is rugged in its overall appearance with a coastline characterized by high cliffs. Its climate is arid, due to the scarcity of rainfall, the average annual temperature is approximately 18.2°C and average annual humidity is 71% (Figure 5).

The prevailing wind directions are north westerly (maestrale) and south easterly (seirocco). Up to the start of this century, the main economic activities in the Aeolian islands were

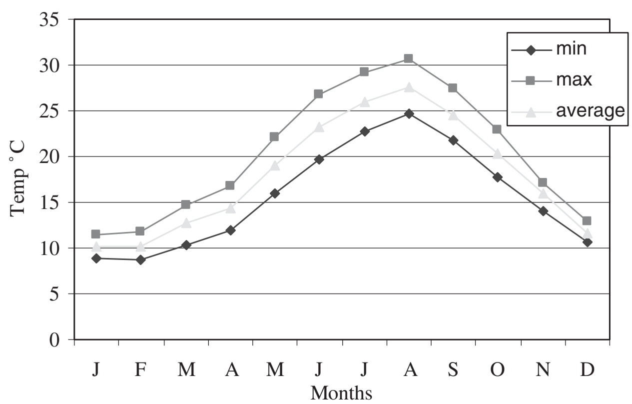

Figure 4. Monthly changes in temperature (minimum, maximum and average). Source: our elaboration (Cicala and Blanco, 1996).

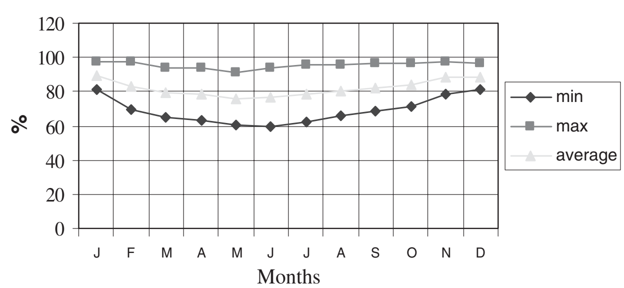

Figure 5. Monthly changes in humidity (minimum, maximum and average). Source: our elaboration (Cicala and Blanco, 1996).

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agriculture, fishing, and commercial activities related to the pumice quarrying industry on Lipari itself. In the past the quarrying and working of pumice constituted a secure source of income for the local population due to the favourable situation of the specific market for this resource. Subsequently, the development of the Aeolian microinsular economies have centred almost exclusively on tourism and all the activities related to this industry.

4.2. Characteristics of the local electric energy production system

Each of the Aeolian islands is equipped with an autonomous diesel power station for the production of electricity and therefore none of them are linked up to the mainland grid. These plants have a high industrial production cost (more than the national grid) mainly due to the cost of transporting fuel from the mainland and other factors relating to the infrastructure that affect the production efficiency of the plant. All of the energy generated is put into the small grid to which almost all commercial and domestic users are linked up. Electricity production and distribution on the island of Lipari is guaranteed by a local enterprise the 'Società Elettrica Liparese' (SEL). Currently the power station is fitted with 12 diesel generators and has a total installed power of 19 764 kW. Annual production in the year 2000 reached 29 900 MWh. The local grid has a 10 kV medium voltage line 36 km in length and a 0.4 kV low-voltage distribution grid of around 133 km with recorded dispersion in the range of 7.75%. As mentioned above, the local economy, apart from a small pumice quarry and works, relies mostly on tourism and all that this entails, therefore there are quite a few hotels, bars and restaurants. Consequently, there is a big difference in electricity consumption between the tourist season in summer and a typical winter day when only residents are living on the island.

Monthly changes in electricity consumption clearly shows two distinct periods in the year, the summer tourist season, from May to October, and the winter one from November until April (see Figure 6). Consumption levels remain almost constant within these two periods. Monthly consumption peaks in May and October (the first and last months of the season), when the tourist season is getting underway or closing down. Figure 7 shows the different hourly movements in maximum power for a typical summer day and for one in winter. In winter the peak occurs in the morning at around 9:00, whilst in summer the peak occurs in the evening at 21:00.

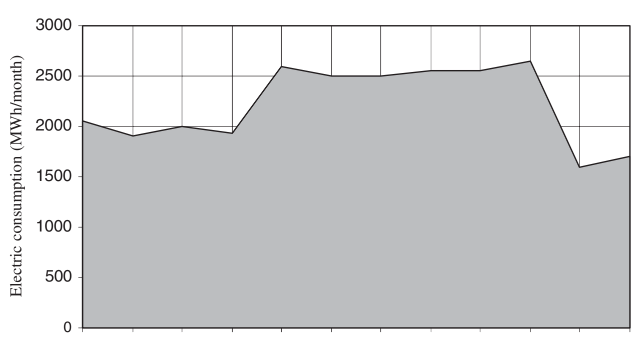

Figure 6. Changes in electricity consumption. Source: our elaboration—SEL (local power plant).

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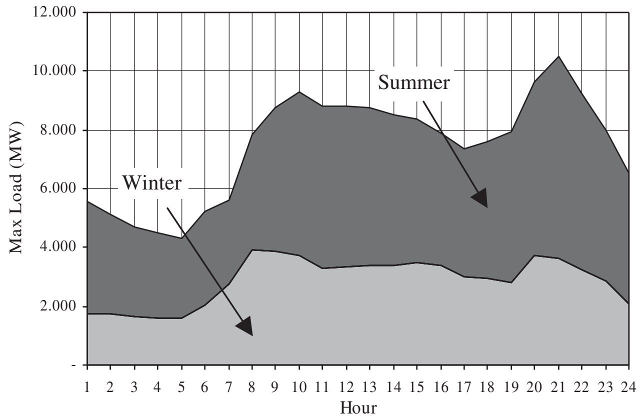

Figure 7. Electric load patterns in summer and winter.

4.3. *Data collection and analysis*

In order to demonstrate the effectiveness of neural network models for load forecasting on the grid, a net was developed as described below. The network used had three layers: into the first were supplied input data, in the last the output variables were recorded (electricity demand) and the intermediate layer handled the internal structuring of the network. The knowledge domain for training the network included a set of data relating to hourly demand over a 24-h period for a 14-day period taken from each of the months of March (1–15), August (1–15), October (15–30) and December (10–25) for a total of 56 days. Training data was taken from the entire year of distribution as it was considered opportune to provide sample data relating to the entire annual cycle given the marked fluctuation in energy demand between different seasons. This seasonal change was attributable for the most part to the tourist season but was also due to the climate to some extent. The structure of the network is illustrated below (see Figure 8):

- *8 input units*: [day class type] day of the week (D) from 1 = Monday to 7 = Sunday, [daytime class] time of day for which a forecast is desired (h) (1–24), energy demand at the time (h) of the month of March (l_{m}), the average temperature at that time in March (t_{m}), energy demand at the time (h) in the month of August (l_{a}), the average temperature at that time in August (t_{a}), energy demand at the time (h) in the month of October (l_{o}), the average temperature at that time in October (t_{o});
- *17 neurons in the intermediate layer*, the number of neurons in this part of the net is determined by trial and error until the best network performance is obtained;
- *1 output unit* represented by the forecast value for load on the grid in the month of December (l_{d*}) (* = load forecast) corresponding to the time to the day and the recorded temperature.

The training set is made up of 336 patterns (24 h for 14 days) i.e. the whole set of examples that the network has to learn. Each pattern contains the data of the eight variables selected for the input unit plus the one output variable, so that for each pattern is identified: the day of the week

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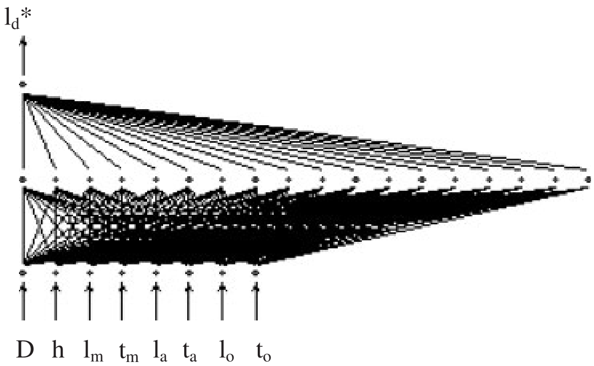

Figure 8. Network architecture.

(naturally there are differences in consumption levels between days during the week and those at weekends that will affect the load curve), the time, the demand and the temperature, at that date and time, in the months of March, October, August and the corresponding load on the grid on that day of the week and at the time recorded in the month of December.

It should be noted that by modifying both the number of hidden layers and the number of neurons in every single layer that the performance of the network can either improve or get worse. In theory there are no precise guidelines that indicate *a priori* the type of net architecture that is able to provide the best results. It is up to the researcher to experiment with different types of architecture to achieve the configuration best suited to the set of data and the objectives.

4.4. Suitability of the model and discussion of results

Numerous experiments were carefully performed in order to identify the pattern that gave the best results within a reasonable training period. The results of training are presented in Figure 9; on training sets of 336 pattern 14 days a maximum error rate of 5.8% was recorded for a load of 4420 MW power demand, in general however the RMS settled at just slightly over 2% (see Figure 10) and this was held to be a satisfactory enough result to indicate that the net was well-trained.

The pattern reproduced shows an excellent ability of the network to forecast, the error margin is greatest at the peak loads compared to the rest of the load movements (see Figure 9). As regards the testing phase, a period of 1 week (7 days) was used to assess network performance and in this case the pattern varies according to whether the day fell at the weekend or on a weekday.

Figure 12(a) shows performance tested on a weekday (Wednesday) whilst Figure 12(b) shows measures for a day at the weekend (Sunday); from the figures it can be seen that the weekend compared to weekdays showed a slightly lower error margin. Overall the RMS obtained settled at about 2.6% and this rate is satisfactory. Table I gives the figures obtained from the net (forecasts), the actual figures and the percentage error of the discrepancy between the two. The scatterplot in Figure 11 showing the comparison between the forecast series and the actual one further confirms the excellent correlation between the two series.

Figures 13(a) and 13(b) illustrate the error distributions related only to the variance between the forecast values and the actual values in percentage terms. The figure for Wednesdays shows

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a fairly uniform error rate in the hours between 8:00 and 17:00 (see Figure 13(a)) whilst for Sunday the changes in error rate are more erratic, which seems to indicate a random distribution. The way in which error rate is distributed over a 24 h period is not clear and shows

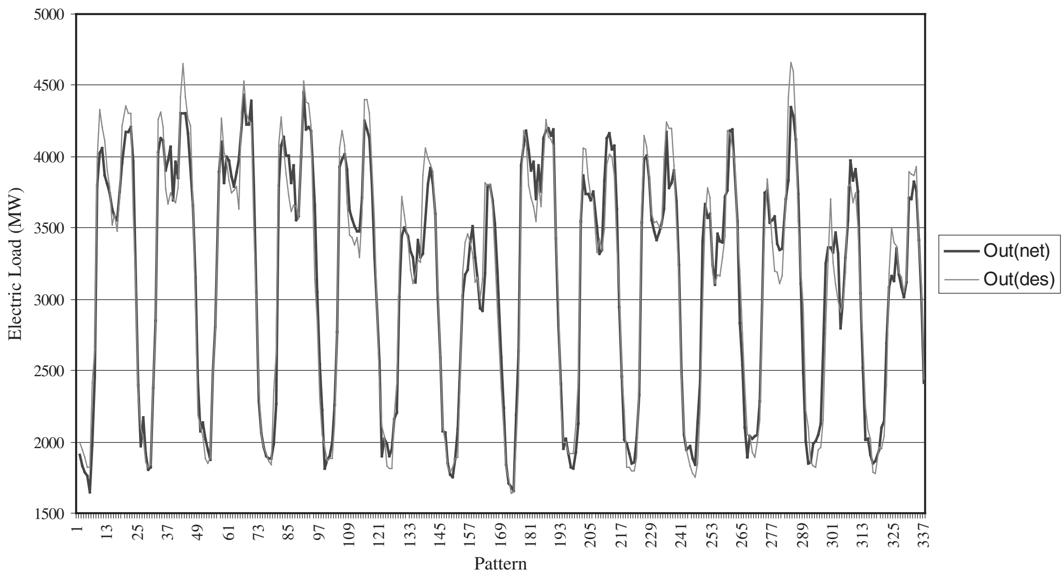

Figure 9. Forecasted and actual load electric profile.

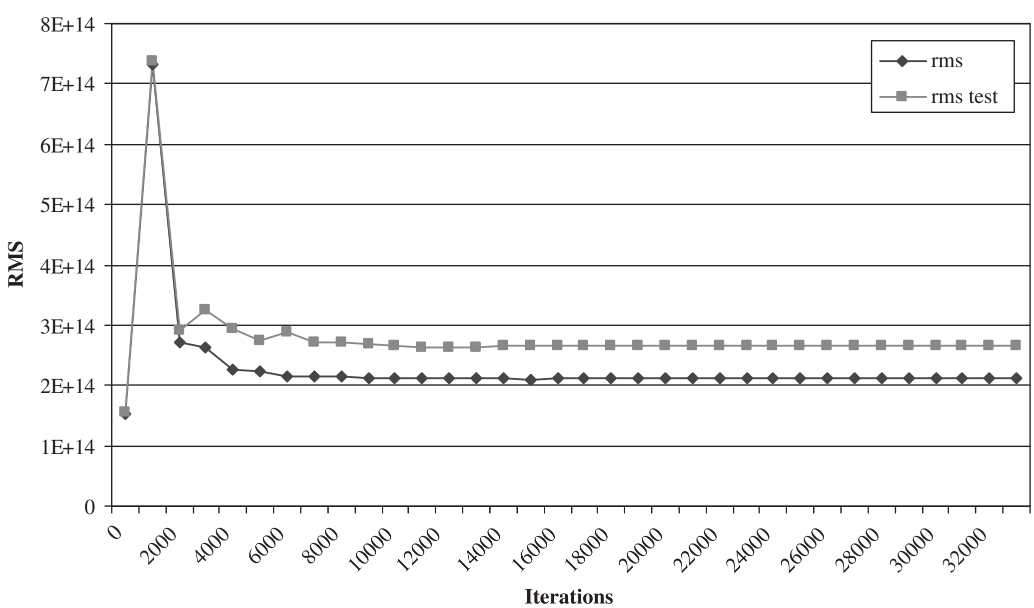

Figure 10. Changes in RMS during the training process.

Table I. Prediction error (%) for weekday and weekend.

	Weekday (Wednesday)			Weekend (Sunday)		
Time	Out (net)	Out (des)	NN Error	Out (net)	Out (des)	NN Error
1	1961.093	2380	4.19	2153.764	2180	−0.26
2	1994.735	2140	1.45	1801.967	2040	−2.38
3	1843.303	2040	1.97	1898.400	1920	−0.22
4	1759.131	2010	2.51	1810.513	1790	0.21
5	1759.175	2010	2.51	1816.450	1800	0.16
6	2201.256	2130	−0.71	1933.619	1923	0.11
7	2544.258	2550	0.06	2155.600	1920	2.36
8	3714.463	3360	−3.54	2365.534	2245	1.21
9	4089.500	3880	−2.10	2998.621	2795	2.04
10	4182.833	4050	−1.33	3225.776	3290	−0.64
11	4050.663	3860	−1.91	3270.094	3480	−2.10
12	3830.846	3570	−2.61	3253.842	3400	−1.46
13	3720.217	3410	−3.10	3238.400	3345	−1.07
14	3700.868	3310	−3.91	3331.596	3155	1.77
15	3810.191	3360	−4.50	3211.315	3150	0.61
16	3770.397	3380	−3.90	3073.289	3030	0.43
17	4000.409	3580	−4.20	3134.749	3140	−0.05
18	4147.628	4040	−1.08	3488.339	3855	−3.67
19	3990.092	4240	2.50	3767.143	3840	−0.73
20	4030.312	4230	2.00	3809.968	3840	−0.30
21	4343.509	4160	−1.84	3700.498	3790	−0.90
22	3665.799	3700	0.34	3409.565	3355	0.55
23	3194.652	3070	−1.25	3045.628	3005	0.41
24	2412.667	2770	3.57	2503.668	2410	0.94

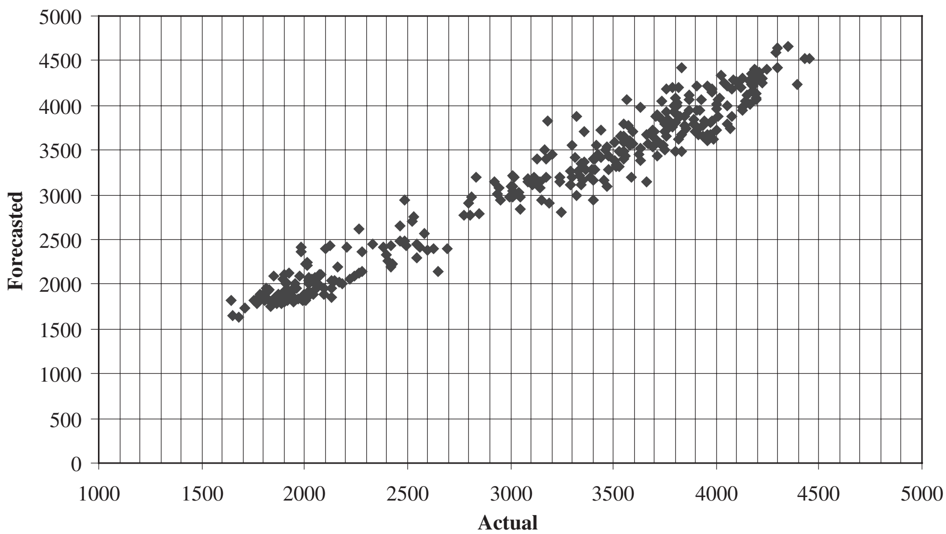

Figure 11. Comparison of actual data with forecasted data.

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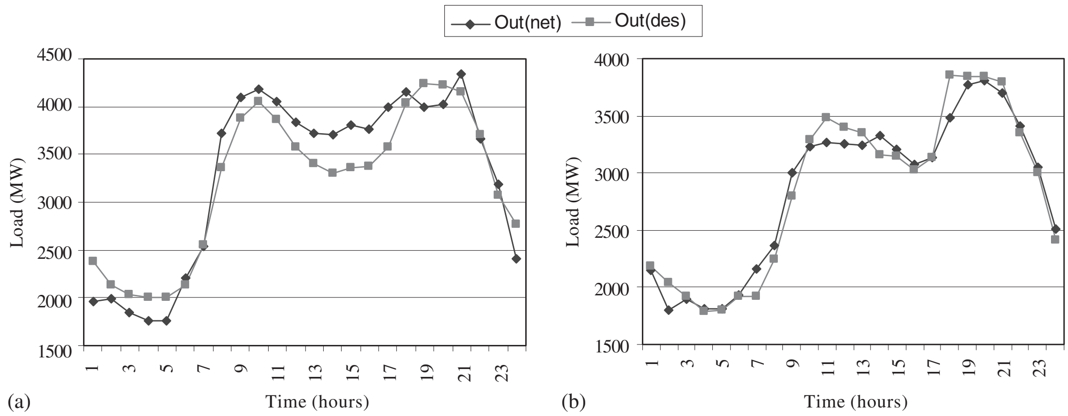

Figure 12. (a) Test on a non-working day (Sunday); and (b) test on a weekday (Wednesday).

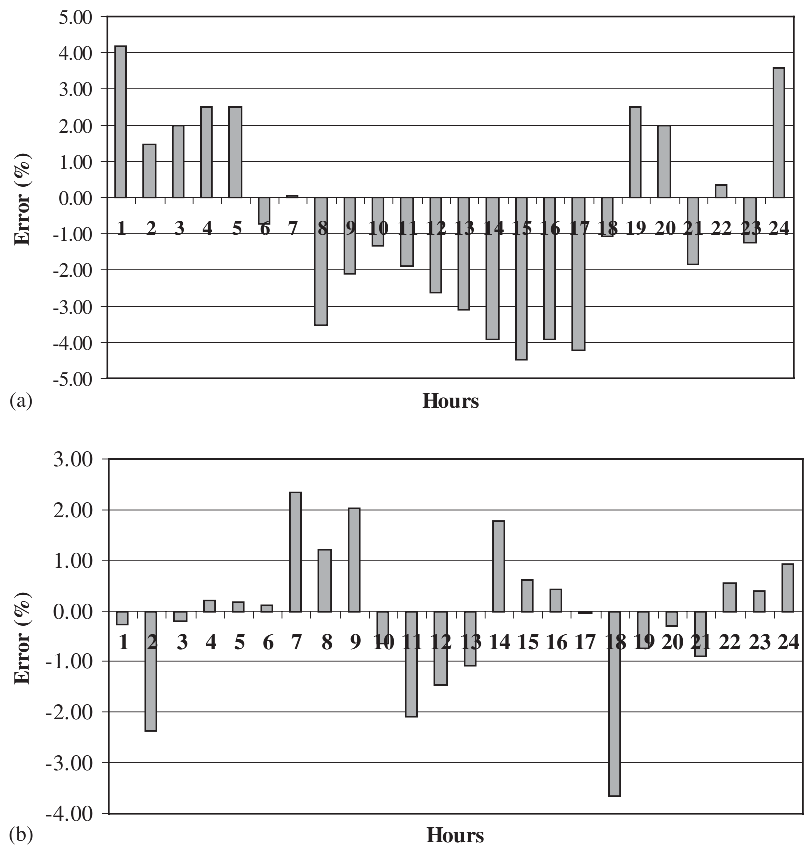

Figure 13. (a) Error distribution for a Wednesday; and (b) error distribution for a Sunday.

the above-mentioned limitation of neural network model in this respect being a black-box model and therefore one that does not give any explanation for a specific phenomenon.

5. CONCLUSIONS

Neural networks represent a very interesting and attractive way forward for STLF and this has been confirmed by the amount and quality of accounts presented in the literature. The results of this work also seem to confirm the dependability and effectiveness of these tools and their superiority, in terms of their better performance, over traditional statistical tools. Neural networks are therefore useful for analysing an objective variable in the presence of strong nonlinearity and uncertainty. Unfortunately however, they shed no light on the causal characteristics of the data. Nevertheless the level of accuracy of the results from using neural networks appears to be more stable than the one reported for classic statistical methods in the literature. In this analysis the training of a network designed on three layers using a back-propagation algorithm yielded encouraging results, the RMS error settled at 2% in the training phase and at around 2.6% during testing, therefore the result fully met expectations regarding the accuracy and ability to generalize.

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