Available online at www.sciencedirect.com
SCIENCE DIRECT®
ELSEVIER
Energy and Buildings 37 (2005) 595–601
ENERGY and BUILDINGS
www.elsevier.com/locate/enbuild

Prediction of hourly energy consumption in buildings based on a feedback artificial neural network

Pedro A. González, Jesús M. Zamarreño*

Department System Engineering and Automatic Control, Faculty of Science, University of Valladolid c/Prado de la Magdalena, s/n 47011 Valladolid, Spain

Received 12 January 2004; received in revised form 10 August 2004; accepted 15 September 2004

Abstract

In this paper a new approach for short-term load prediction in buildings is shown. The method is based on a special kind of artificial neural network (ANN), which feeds back a part of its outputs. This ANN is trained by means of a hybrid algorithm. The new system uses current and forecasted values of temperature, the current load and the hour and the day as inputs. The performance of this predictor was evaluated using real data and results from international contests. The achieved results demonstrate the high precision reached with this system.

Keywords: Intelligent buildings; Energy demands and consumption; Neural networks; Load forecasting; Optimization methods

1. Introduction

In [1], an intelligent building was defined as the one that maximizes the efficiency of the service with a minimum cost. This author enumerates a list of intelligent building components, placing in first place, the energy management system (EMS). This system controls the building energy consumption. For a good operation of EMS, accurate information of this consumption is needed in order to know how it behaves in a short-and medium-term. This ''short-term load forecasting'', STLF, can predict electric load of regions, countries and even in buildings or industries during a period of minutes, hours, days or weeks.

The reported literature in the last years about artificial neural networks (ANN) applications in the prediction of electric load demonstrates that this technique is one of the more successful in areas so dissimilar like countries or buildings. In these studies, the ANN have been applied in order to correlate climatic conditions, schedules, etc., with the variations of the load, in order to predict, either the picks of daily load, the total consumption, or the load at every hour. The advantage of ANN with respect to the other models is their ability of modeling a multivariable problem given by the complex relationships between the variables. Also, ANN can extract the implicit non-linear relationships among these variables by means of ''learning'' with training data. Many excellent results in real applications have been reached with ANN in STLF using a wide variety of ANN architectures. The works of [2–4] are a good example.

An issue that has been investigated in the last years in order to solve the problem of STLF with ANN has been the selection of the best structure to use. In a suggestive work, [5], several rules are given in order to build a quasi-optimal neural network for STLF. Those that plan to use a frequently re-trained recurrent network are very interesting.

The main objective of this paper is to present a new approach for load prediction with high precision using a feedback neural network trained by means of a hybrid algorithm. In order to validate the proposed method, data and final results from two contests of the ASHRAE has been utilized. The paper is divided in 10 sections. After Section 1, Sections 2 and 3 show the ANN architecture and the training method. Sections 4 and 5 illustrate the general configuration of the predictor. In Sections 6–9 the results are presented, and finally, Section 10 describes the conclusions of the paper.

* Corresponding author.
E-mail address: jm@autom.uva.es (J.M. Zamarreño).

0378-7788/$ – see front matter
doi:10.1016/j.enbuild.2004.09.006

Nomenclature

CV	coefficient of variation of the root-mean-square error
E	error of the Neural Network
G	specific parameter for change from MROM to BPM algorithm
MBE	mean bias error
MAPE	mean absolute percentage error
q^{-1}	a one-step delay
$u(k)$	system input
w^k	weights of the Neural Network at iteration k
$\hat{x}(k+1)$	prediction of the system state x
$\hat{y}(k+1)$	prediction of the system output
z	measured output
ε'	specific parameter for change from BPM to MROM algorithm

2. The used ANN and its training

In this paper, the key idea is to use as predictor a special kind of ANN with a feedback (FB) structure [6] that is shown in Fig. 1. This network operates as follows: the system input $u(k)$ and a presumable value of the initial state $\hat{x}(0)$ are passed through a multilayer neural network (with any topology) whose output, for the next sampling instant $k+1$, is the prediction $\hat{y}(k+1)$ of the true system output y, and the prediction $\hat{x}(k+1)$ of the system state x, which is fed back to the network via a one- step delay, q^{-1}. The prediction error $e(k+1) = z(k+1) - \hat{y}(k+1)$, with respect to the measured output z, is used to train the network. By "mapping" $\hat{x}(0)$ and $u(k)$ to $\hat{x}(k+1)$ and $\hat{y}(k+1)$, the FB structure can approximate, to any degree of accuracy, using a finite number of hidden nodes, any dynamic system for which a state-space description with functions g and h exists.

$$x(k+1) = h\{x(k), u(k)\}$$

$$y(k+1) = g\{x(k+1)\}$$

The algorithm for training this ANN, in the original paper, is a hybrid one formed by the well-known delta rule and a random search [6].

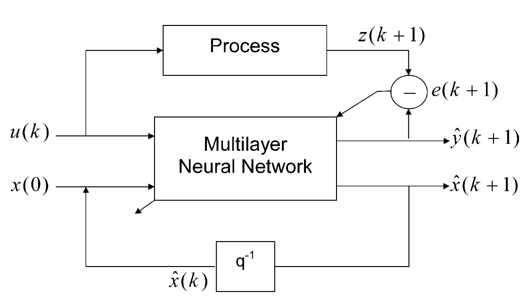

Fig. 1. General schema of the feedback neural network designed in [6].

3. Structure of the network and training

It is also explained in [6] that any multilayered topology of ANN can be used for supporting the FB structure. In our paper a Perceptron has been used, composed of one hidden layer and neurons with hyperbolic tangent transfer functions due to the reported results about the improvement, in terms of the required number of iterations during learning, of a neural network that uses the backpropagation method (BPM) algorithm [7]. In the configuration shown in Fig. 1 errors produced by the states are not analysed during training. However, if they are known, it is also possible to train using these errors and thus to get a greater precision. In fact, this is the proper way when a mapping $u(k)$ and $\hat{x}(0)$ to $\hat{y}(k+1)$ and $\hat{x}(k+1)$ is required.

The FB ANN has been trained using a similar strategy suggested by [8] (in our paper, it was decided to use the classical BPM with increments of the learning coefficient, in order to avoid long time execution when the BPM is running). That method works as follows: first, the training is carried out using a modified version of the BPM.

When the decreasing of the total error function is lower than a specified value ε', $|E(w^{k+1}) - E(w^k) < \varepsilon'$, the hybrid algorithm conjectures that the current point is near to a local minimum, so the random optimization MROM (modified random optimization method) [9] is activated. The BPM is executed again if the decreasing of the error function becomes bigger than max $(E(w^k)G,\varepsilon)$; $(0 < G < 1)$ [8]. This strategy was also improved by using the method proposed in [10] where the MROM was enhanced by means of some heuristic but effective ideas: to use the same Gaussian random vector of parameters in the next iteration if the total error function was decreasing, and to change the variance in dependence of this error decrease.

4. The general structure of the predictor

The general structure of the predictor is shown in Fig. 2. As it can be observed, it is a cascade of predictors. The first of them, the temperature predictor (any kind) provides the presumable value of the environmental temperature at the hour to predict the load. Important efforts have been developed to predict on line this temperature value [11–13].

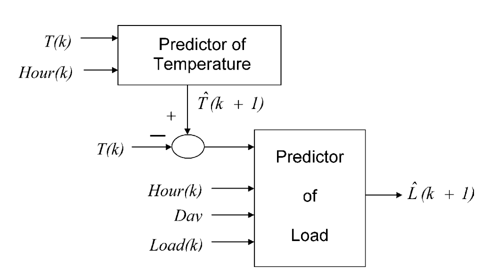

Fig. 2. General Structure of the load predictor.

The output of this predictor becomes one of the inputs to the second network: the load predictor.

Fig. 2 illustrates how the input temperature (the unique environmental variable) is utilized. Instead of using a forecasted value of this variable as an input for providing the most probable value that corresponds to the relationship load/ temperature, a small change in the consideration of this input has been introduced: to use the difference (1).

$$\Delta T = T_{k+1} - T_k \tag{1}$$

where T_{k+1} is the predicted temperature for the period k+1, and T_k is the value of temperature measured in the instant k. This signed difference ΔT, would indicate if an increment (or decrease) of the environmental temperature has occurred during the time period between the hour or instant of prediction and the following period, and therefore, a possible increment or decrease of the load.

The second element of this database is the time: the hour of the day and the day of the week. The hour is coded by means of its sine and cosine values as usual in reported literature [14,15]. In regard to the days, it is well known that during weekends and holidays, public and social buildings consume less amount of energy independently of the ambient temperature. This change is determined by the schedule of work. (In [16], for instance, a special emphasis was made on weekend and non-working days). This circumstance makes that, in spite of the fact the ambient temperature has a tremendous importance as an input variable in STLF on the normal days, the accuracy of the temperature prediction looses importance during weekends, because the operation of the building in these days requires a lower consumption. Given this condition during weekends or holiday days, one could simplify the predictor system analyzing only the normal days. However, a FB ANN has been chosen, so, it is not possible to interrupt the dynamic of the network every five days, so it was decided to include these types of days. That implies to add an index in the database that specifies to the ANN what type of day it is. This index is also formed by two vectors with the sine and the cosine of the days of the week (see Table 1). The third input is, perhaps, the most important one: the current load. Since this predictor is designed to predict the load at k+1, the used value for this input is the value of the load at the hour k, supplied by the energy consumption instrumentation. The information of this value has a supreme importance since it reflects how the energy consumption of the installation behaves. While other systems need, for example, data like the occupation level, values of the environmental variables (which sometimes include information on raining, for example), it could be said that, by introducing the actual value of the load to the network, one is introducing the effect produced by all these situations until the instant k, therefore, the task of the predictor is to predict the next value in dependence of the quality of the "acquired knowledge" during the previous training. This database is formed, then, by a "moving" window that contains a matrix of data $n \times m$, (see Table 1), where: n is equal to 6 inputs and m is equal to the number of days, that is, the size of the window in days multiplied by 24 h. In these simulations, a window of only 21 days has been used. The window is normalized between the values [−0.9,0.9] by means of (2). Specifically, in this paper, the difference (1) was normalized by adding ±10 °C to the maximum and minimum of this difference, while, for the current load input, ±50 kW were added to the maximum and minimum values of the consumption on the period formed by the moving window (Table 1).

$$X_n = 1.8\left[\frac{X - X_{\min}}{X_{\max} - X_{\min}}\right] - 0.9 \tag{2}$$

In Table 1, the nomenclature is as follows:

$(T^{d-n}_{h=1} - T^{d-n}_{h=0}), (T^{d-n}_{h=2} - T^{d-n}_{h=1}) \ldots (T^{d+1}_{h=0} - T^{d}_{h=23})$: set of differences between the temperatures at the hours $(h+1)$ and (h) from the day in which the window of data begins $(d-n$ days), until the difference between the temperature of the hour 00:00 of the day $(d+1)$ minus the temperature at hour 23:00 of the day (d) in which the training is carried out.
$\sin(\pi((h^{d-n}_0 \ldots h^{d}_{23})/12))$; $\cos(\pi((h^{d-n}_0 \ldots h^{d}_{23})/12))$: code of the hours. The hours go from 0 to 23.
$\sin(\pi((d^{d-n} \ldots d^{d})/3.5))$; $\cos(\pi((d^{d-n} \ldots d^{d})/3.5))$: code of the days. The days go from 1 to 7. Many authors define a specific number for each day, but this is not important. For convenience, it has been used 7 as Sunday.
$C^{d-n}_{h=0} \ldots C^{d}_{h=23}$: set of values of electric load from the hour (h) 00:00 of the day in which the data window starts $(d-n$ days) until the hour 23:00 of the day (d) in which the training is carried out.
$C^{d-n}_{h=1} \ldots C^{d+1}_{h=0}$: set of values of electric load from the hour (h) 01:00 of the day in which the data window starts $(d-n$ days) until the hour 00:00 of the day $(d+1)$.

After normalization, the sine and the cosine of the day and hour remain exactly between the limits [−0.9, 0.9]; however the current load and the difference of temperature remain normalized taking into account the kilowatt and Celsius degrees added, as it was explained before.

Table 1
Database used for load prediction

Variable	Data
Temperature	$(T^{d-n}_{h=1} - T^{d-n}_{h=0}), (T^{d-n}_{h=2} - T^{d-n}_{h=1}) \ldots (T^{d+1}_{h=0} - T^{d}_{h=23})$
Hour	$\sin(\pi((h^{d-n}_0 \ldots h^{d}_{23})/12)); \cos(\pi((h^{d-n}_0 \ldots h^{d}_{23})/12))$
Day	$\sin(\pi((d^{d-n} \ldots d^{d})/3.5)); \cos(\pi((d^{d-n} \ldots d^{d})/3.5))$
Input load	$C^{d-n}_{h=0} \ldots C^{d}_{h=23}$
Output load	$C^{d-n}_{h=1} \ldots C^{d+1}_{h=0}$

5. Parameterization of the ANN and the hybrid algorithm

In Table 2, the set of necessary parameters to configure the ANN and the training algorithm is shown. The function

Table 2
Parameters of the ANN and of the hybrid algorithm

Parameter	Value
Number of neurons	Five
Type of neurons	Hyperbolic tangent
Epochs	1000, first day 750, the rest of the days
Learning rate η	To start BPM: 0.001 increased by 1.1 in each iteration if $E(w^{k+1}) < E(w^k)$
Coefficient of momentum α	0.9
Switch from BPM to MROM (ε')	0.1
Switch from MROM to BPM (G)	0.05
Variance	[0.001, 0.05]

to optimize is considered in (3) where z and $\hat{y}$ are the real and predicted values of the output; y, the number of elements of the output training set; x and $\hat{x}$ the real and predicted values of the states and x, the number of elements of the state training set.

With the purpose of improving the benefits of the ANN, each datum from the set of training output states, was equalled to the load in $k+1$, so that the feedback of each state has the biggest precision during the training.

$$\mathrm{SSE} = \sum_{i=1}^{y}(z_i(k+1) - \hat{y}(k+1))^2 + \sum_{j=1}^{x}(x_j(k+1) - \hat{x}_j(k+1))^2 \tag{3}$$

6. Results of the application of the FB predictor with real data

In 1993 and 1996, ASHRAE developed two contests on predicting hourly building energy use. Parts of the data used in those competitions were used here (the whole-building electricity use, WBE). The first database is the benchmark PROBEN1.[1] The second database is The Great Building Energy Predictor Shootout 2 [17]. We have called DATA1 and DATA2 to these databases.

In order to evaluate the results obtained by this prediction system, several experiments were carried out using the coefficients demanded by the organizers of the competitions of ASHRAE [17]. These are: the coefficient of variation of the root-mean-square error (CV-RMSE) (4) used in order to decide the better results and the mean bias error (MBE) (5) used in case of a tie.

$$\mathrm{CV} = \frac{\sqrt{\sum_{i=1}^{n}(y_{\mathrm{pred},i} - y_{\mathrm{data},i})^2/n-p}}{\bar{y}_{\mathrm{data}}} \times 100 \tag{4}$$

[1] ftp://ftp.ira.uka.de/pub/neuron/, specifically, its entry: *building*.

$$\mathrm{MBE} = \frac{\sum_{i=1}^{n}(y_{\mathrm{pred},i} - y_{\mathrm{data},i})/n-p}{\bar{y}_{\mathrm{data}}} \times 100 \tag{5}$$

where $y_{\mathrm{data},i}$ is the data of the dependent variable corresponding to a particular group of the independent variables, $y_{\mathrm{pred},i}$ the dependent variable predicted for the same group of independent variables, $\bar{y}_{\mathrm{data}}$ the mean value of the dependent variable, n the number of data, and p the total number of model regression parameters (arbitrarily set to 1 by the event organizers [17]).

7. Using DATA2

As a first experiment, the data from the competition number 2 were used for a quantitative comparison, because the results of the winners reported in terms of the coefficients previously exposed were available. It should be emphasized that the winners had to predict energy consumption of periods intentionally emptied by the organizers. The models used by the winners (see Table 3, where E^* are the codes given to the winners) allow looking for any day or period, since the systems are trained with long periods of well-known data.

In Fig. 3, it can be seen the behavior of the predictor for a week after training with a window of only 21 previous days. This period begins with a weekend where it can be appreciated the difference of consumption between the normal days and the weekends (approximately 300 kW). If this figure is carefully observed, it could be noted that the bigger deviation occurs on a point where the consumption changes its tendency to decrease, with a slight increment, but all of this occurs after the hours of high consumption, where the highest precision of the predictor is required.

In Fig. 4, a week with a different pattern with respect to the normal weeks is presented. In fact, on Wednesday, it can be noted a decrease of the consumption that resembles a day of weekend. After consulting the database, it was seen that this day corresponds to July 4, 1990, the Independence Day in the United States. That is why, the work of the forecaster can be declared correct, because although the index that indicates the day is on Wednesday, which would correspond to a high consumption day, the deviation is not considerable. Probably, this is the better example of the importance of the input signal C_h^d: electric load at the hour h of the day d, because even though the index ''type of day'' is specifying a high consumption day, the ANN is able to solve this problem without an input that points out to these special days.

Finally, Fig. 5 shows two consecutive weeks presenting a marked difference between their daily consumption. In this case, this difference comes from a problem of work scheduling. This period corresponds, according to the database, to the days from August 18–31 of 1990. In the scheduling table of this building it is specified that, on

Table 3
The methods and values for CV and MBE achieved by the four winners of the competition [17] and those reached in this project

Authors	Method	CV	MBE
E4	Neural Network, 2 hidden layers, 25 neurons. Hyperbolic tangent. Choice of the input variables by means of the "Wald test"	2.9032	−0.0907
El	Perceptron trained by a non-lineal Bayesian regression method	3.1205	0.2722
E3	Statistical classification of the types of day in dependence of the climatic situation. Regression models per each hour	8.6475	−6.555
E2	Auto associative "feed-forward" neural network. Hyperbolic tangent	13.212	−1.805
González and Zamarreño	FB neural network. Hyperbolic tangent, hybrid training algorithm	1.4423	0.0033

Monday 27 of August, another period of classes began, but previously, the building occupants were possibly on vacations or summer courses, hence, from this date on, the consumption rises considerably. It is good to highlight that the prediction of energy of that week remained generally below of the actual value, probably because the ANN was trained with 21-day window, and maybe, it did not cover a period with a greater consumption. This demonstrates that the length of the data window is important and constitutes a design factor. In this paper, its optimal value has not been determined because it is considered case depending. Indeed, what it is offered as a result is the fact that it is not necessary to have an extensive database because the results obtained here using a small window are comparable to others reported in the literature.

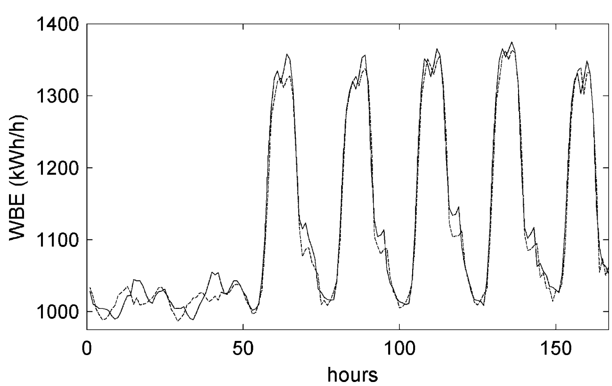

Fig. 3. A week of data. The solid line is the actual load.

8. Robustness of the design

With the objective of determining the influence of the temperature prediction error, the same experiment is repeated but a random component was added to the temperature database at $k+1$ (T_{k+1}, the predicted temperature). This component introduces an error of ± 0.5 °C. The results of this experiment indicate that this error has an insignificant transcendence on the predictor of energy, which confirms the robustness of this design in the case of this input could have a noisy component (supposing that the measurement of temperature in k, T_k, has a much minor error). The mean value of the registered CV was equal to 1.4979, while the value of MBE was 0.0123 (compare them with the values reported in Table 3).

9. Using DATA1

With the objective of continuing showing the benefits of the designed STLF system, the database DATA1 was used. In first place, this database is longer and secondly, it presents a bigger variation in the behavior of the variables. For this period, the values of CV and MBE were also calculated, obtaining 2.55 and 0.0123, respectively. However, it was

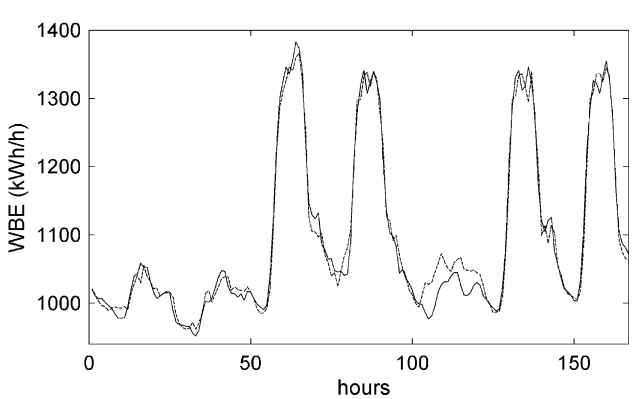

Fig. 4. A week that includes a holiday day. The solid line is the actual load.

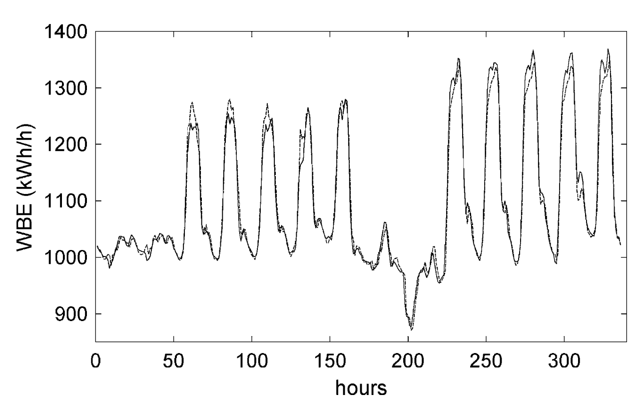

Fig. 5. Weeks with different consumption. The solid line is the actual load.

Table 4
Summary of several MAPE coefficients

Reference	Year	MAPE
[2]	1995	2.26
[18]	1996	1.75
[19]	1996	2.23
[20]	1996	2.88
[21]	1998	1.53
[4]	1998	2.12
[22]	1999	1.73

preferred to evaluate the behavior of the neural predictor by means of (6), the Mean Absolute Percentage Error (MAPE), which is considered a standard for examining the quality of the models of prediction of load as it repeatedly appears in the consulted literature [2,4,14–18].

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{|C_{\mathrm{r}}(i) - C_{\mathrm{p}}(i)|}{C_{\mathrm{r}}(i)}\times 100 \tag{6}$$

where N is the total number of samples, in this case, 24, because of the daily evaluation. $C_{\mathrm{r}}(i)$ is the actual value of load and $C_{\mathrm{p}}(i)$ the predicted value by the ANN for the instant of prediction i. In this case, it is not possible to carry out a quantitative comparison because the data sets used by other authors are different from the one considered here. Nevertheless, some of the values of MAPE that have been reported in the last years can be seen in Table 4. In this project, the average of MAPE for the analyzed period was equal to 1.945. As it can be appreciated, from a qualitative point of view, this value of MAPE is very good, taking into account that this value could be different if the data sets are different, but at least, the order of magnitude reached in this project is the same as others.

An example of this good value of MAPE is illustrated in Fig. 6. As it can be observed, the pattern of consumption is very well determined by the predictor in spite of an interesting situation: the behavior of Thursday and Friday is completely different to the other weeks, therefore it could be suspected that those days were declared like holidays ones. Indeed, the database tells us that the "Thanksgiving Day", one of the national parties in the United States, was on Thursday of this week. Also, the graph allows us to conjecture that the following day was declared as holiday too. Thus, the predictors has been confronted, first, with two days with consumption similar to a weekend, and afterwards, with two days in weekend.

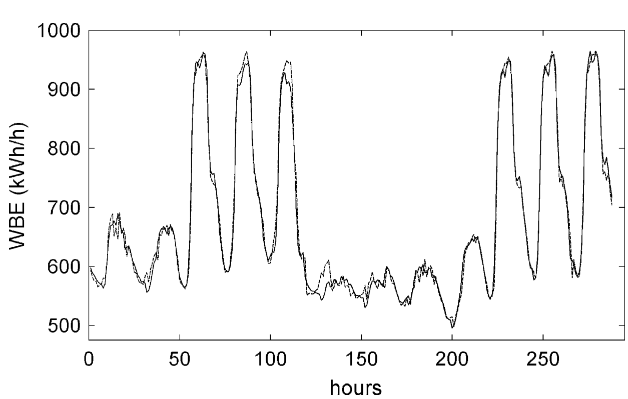

Fig. 6. A period with an abnormal pattern. The solid line is the actual load.

10. Conclusions

In this paper it has have been shown the excellent results of a method for electric load forecasting in buildings based on a feedback ANN. The new energy predictor presents a precision comparable to the better results reported in the literature. The main virtue of this system is its simplicity, which is based on the fact that the developed tool is very simple and the resources for its application are tiny and available at modern automation systems. In particular, in order to apply it to a STLF system, only simple methods for atmospheric temperature and electric power measurement are required.

The number of neurons that compose the hidden layer of the ANN, the optimal size of the data window and the parameters of the algorithm of training have not been deeply analyzed. The experimental works carried out suggest that these values should be carefully studied, but anyway, as it is expounded in [6], many neurons were not needed to get satisfactory results.

References

[1] B.M. Flax, Intelligent Buildings, IEEE Communications Magazine (1991), April.
[2] A. Khotanzad, R. Hwang, A. Abaye, D. Maratukulam, An adaptive modular artificial neural network hourly load forecaster and its implementation at electric utilities, IEEE Transactions on Power System 10 (3) (1995) 1716–1722, August.
[3] A. Khotanzad, R. Afhkhami-Rohani, T.L. Lu, A. Abaye, M. Davis, D. Maratukulam, ANNSTLF a neural network-based electric load forecasting system, IEEE Transactions on Neural Networks 8 (4) (1997) 835–845, July.
[4] A. Khotanzad, R. Afhkhami-Rohani, D. Maratukulam, ANNSTLF–artificial neural network short-term load forecaster–generation three, IEEE Transactions on Neural Networks 13 (4) (1998) 1413–1422, November.
[5] M.H. Choueiki, C. Mount-Campbell, S. Ahalt, Building a quasi optimal neural network to solve the short-term load forecasting problem, IEEE Transactions on Power Systems 11 (4) (1997) 1432–1439, November.
[6] G. Schenker, Prediction and Control Using Feedback Neural Networks and Partial Models. Ph.D. dissertation, Swiss Federal Institute of Technology, Zurich, 1996.
[7] S. Haykin, Neural Networks, a Comprehensive Foundation, Maxwell Macmillan, 1994, pp. 160–161.
[8] N. Baba, Y. Mogami, M. Kohzaki, Y. Shiraishi, Y. Yoshida, A hybrid algorithm for finding the global minimum of error function of neural networks and its applications, Neural Networks 17 (8) (1994) 1253–1265.
[9] F. Solis, R. Wets, Minimization by random search techniques, Mathematics of Operation Research 6 (1981) 19–30.

[10] J.M. Zamarreño, P. González, A hybrid method for training a feedback neural network, in: Proceedings of The First International NAISO Congress on NEURO FUZZY TECHNOLOGIES, January 2002, Havana, Cuba, ICSC-NAISO Academy Press, 2002.
[11] A. Khotanzad, M. Davis, A. Abaye, D. Maratukulam, An artificial neural network hourly temperature forecaster with applications in load forecasting, IEEE Transactions on Power System 11 (No. 2) (1996) 870–876.
[12] P. González, J.M. Zamarreño, A short-term temperature forecaster based on a novel radial basis functions neural network, International Journal of Neural Systems 11 (1) (2001) 71–77.
[13] P. González, J.M. Zamarreño, A short-term temperature forecaster based on a state space neural network, Engineering Applications of Artificial Intelligence 15 (2002) 459–464.
[14] M. Ohlsson, C. Peterson, H. Pi, T. Rognvaldsson ,B. Soderberg, Predicting System Loads with Artificial Neural Networks-Methods and Results from the Great Energy Predictor Shootout. Technical Report LU T 93-24, September 1993.
[15] R. Dodier, G. Henze. Statistical Analysis of Neural Network as applied to Building Energy Prediction. Energy Systems Laboratory. Technical Report ESL-PA-96/07.
[16] D. Srinivasan, C.S. Chang, A.C. Liew, Demand forecasting using fuzzy neural computation, with special on weekend and public holiday forecasting, IEEE Transaction on Power Systems 7 (4) (1996) 1897–1903, November.
[17] S. Haberl and S. Thamilseran The Great Energy Predictor Shootout II: Measuring Retrofits Savings-Overview and Discussion of Results. Energy Systems Laboratory. Technical Report ESL-PA-96/07-03(1).
[18] T.W.S. Chow, C.T. Leung, Neural network based short-term load forecasting using weather compensation, IEEE Transactions on Power Systems 11 (4) (1996) 1736–1742, November.
[19] R.C. Hwang, S.J. Huang, K.Y. Kou, W.Y. Tsai, Power signal prediction by nonfixed neural network model, in: Proceedings of the International Symposium on Multi-Technology Information Processing, National Tsing Hua University, Taiwan, R.O.C, 1996.
[20] R. C. Hwang, H. C. Huang, S. J. Huang, S. R. Huang, Y. J. Chen, Power Signal Prediction by Fuzzy-Neural Model with Considering Training Problems, Proceedings of the IEEE International Conference on Industrial Technology (1996) 687–691.
[21] M. Daneshdoost, M. Loftalian, G. Bumroonggit, J. Ngoy, Neural network with fuzzy set-based classification for short-term load forecasting, IEEE Transactions on Power Systems 13 (4) (1998) 1386–1391, November.
[22] H. Kassaei, A. Keyhani, T. Woung, M. Rahman, A hybrid fuzzy neural bus load modeling and predication, IEEE Transactions on Power Systems 14 (2) (1999) 718–724, May.