Daily Load Forecasting Using Quick Propagation Neural Network with a Special Holiday Encoding

I. Aquino, C. Perez, J.K. Chavez and S. Oporto

Abstract— **In the last decade, neural networks have been applied in Daily Load Forecasting. Nevertheless, two main problems are still present for using neural networks in this domain: first, poor load forecasting in holidays because complex load behavior, and second, the lack of a global model for both holidays and non-holidays. To solve these two problems, we propose a new special holiday encoding that considers holidays and its preceding and following days which are also affected by the holiday. This proposed encoding is used in conjunction with quick propagation neural network. In the experiments the proposed holiday encoding is compared with other encoding based on the forecasting error of quick propagation. To evaluate their performances, we used a Peruvian load data set. The results show that the proposed holiday encoding produce better forecasting results than the results produced by other holiday encoding. Finally, these same results are also better than those results obtained by using ARIMA model which is a statistical technique also used in practice.**

I. Introduction

Load forecasting is an important topic in Energy Markets for planning the operations of load producers. There are three types of load forecasting: short-term load forecasting which consist in forecasting the load demand curve from 1 hour, 24 hour to one week ahead, mid-term load forecasting which consist in forecasting the load demand curve from 1 week to 1 year, and long-term load forecasting which consist in forecasting the load demand from 1 year to 20 years ahead. For doing these tasks, artificial neural networks have been widely used in the last decade due to their power to recognize patterns even with noisy data [3], [5], [6], [9], [1], [2]. Nevertheless, there are still two problems for using neural networks in load forecasting: the first problem is the poor load forecasting in holidays due to the complex behavior of load in holidays and the lack of samples to train correctly the neural network. This problem forced researchers to build special models for load forecasting in holidays [14] and other special models for non-holidays [11], [9], [15]. This fact leads us to the second problem which is the lack of a global model that can perform acceptable forecasting for both holidays and non-holidays. To solve these two problems, we present a novel encoding that consider not only holidays and non-holidays, but also days preceding and following holidays. This consideration is because a holiday not only affects the load in this day, but also affect load in days located before and after holidays. Furthermore, this proposed encoding is used in combination with quick propagation neural network [10] which is a technique used successfully for the first time in this paper for load forecasting problems. This combination has three characteristics: first, it reduces the problem of poor load forecasting in holidays by encoding holidays and days located before and after holidays appropriately to train neural network, second, it can recognize both load pattern in holidays and load pattern in non-holidays because of their special encoding and their use of quick propagation neural network as learning technique, and third it is very simple to implement it.

For the experiments, a historical load data set from a Peruvian Electric Company has been used. The problem in this data set is to forecast daily load forecasting of one month ahead (mid-term load forecasting type). In the experiments the proposed holiday encoding is compared with other encodings. This comparative study is based on the forecasting error of quick propagation neural network in testing phase. For the testing phase, load data of July and August of 2005 has been chosen because they have two and one local (Peruvian) holidays respectively. The results show that the proposed holiday encoding produce better forecasting results in July and August than the results produced by the other holiday encoding for the same months. Furthermore, these results obtained using the proposed holiday encoding and quick propagation neural network are also compared with those results obtained by using Autoregressive Integrated Average Model (ARIMA) which is a statistical technique also used in practice [8]. These last comparative results show that the proposed holiday encoding with quick propagation neural network outperform ARIMA model in average in both months. Moreover, the proposed encoding with quick propagation neural network clearly outperform ARIMA model in forecasting holidays and its preceding and following days in the two months.

The rest of this paper is organized as follows: Section 2 presents data and problem description, Section 3 presents load data analysis in holidays, Section 4 presents quick propagation neural network, Section 5 presents the experiments and the results, and Section 5 presents conclusions and further works.

II. Problem and Data Description

The problem in the Peruvian Electric company is to forecast the daily load demand or energy demand of one month ahead, i.e. to forecast 30 or 31 (depend of the month) days. This forecasting task is very important because it allows the company to schedule maintenances of machines or to

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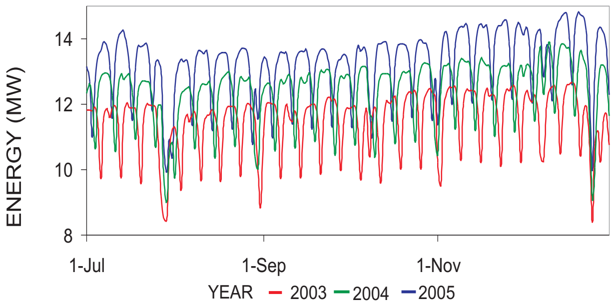

Fig. 1. Load curve demand of 2003, 2004 and 2005

doing other operations without affecting the load generation to satisfy the demand of clients through days of the next month. The evaluation of the forecasting accuracy is based on the Median Average Percentage Error (MAPE) which is computed as follows:

$$\text{MAPE} = 100\frac{\sum_{i=1}^{n}\frac{|L_i-\hat{L}_i|}{L_i}}{n}, \qquad n = 29, 30, 31 \qquad (1)$$

where L_i and $\hat{L}_i$ are the real and the forecasted value of load demand on the ith day of the month under forecasting, n is the number of days of the next month. The goal is to forecast the daily load of the next month with minimum MAPE, which means minimum error or better accuracy.

On the other hand, the data provided consist of daily energy demand of years 2003, 2004, 2005 and additional features such holiday mark is included. The data scheme is: $Data = \{Y, M, DoM, DoW, H, L\}$

where:

$Y(Year) = \{2003, 2004, 2005\}$
$M(Month) = \{1, 2.., 12\}$
$DoM(DayOnMonth) = \{1, 2.., 31\}$
$DoW(DayOnWeek) = \{1, 2, .., 7\}$
$H(Holiday) = \{0, 1\}$
$L(Load) \approx \{8MW, .., 15MW\}$

where $MW = Megawatts$

III. Data Analysis

A. Properties of Load Demand

Load demand data given contains records of load demand per day. In our study **Energy** and **Load** will treated as synonyms. Fig 1 gives a simple description of the load data from 2003 to 2005. By simple analysis, it is noticeable that there is a seasonal pattern in each year: a little high demand in summer (beginning in November) and low in winter(beginning in July until September). In addition, there is a increment of load from one year to the next year. This figure also shows the repetitive patterns in days of 2003, 2004 and 2005.

B. Holiday Effects in Load Curve

Holidays are special days that have a high influence in the load demand curve. In the data set it is observed that load

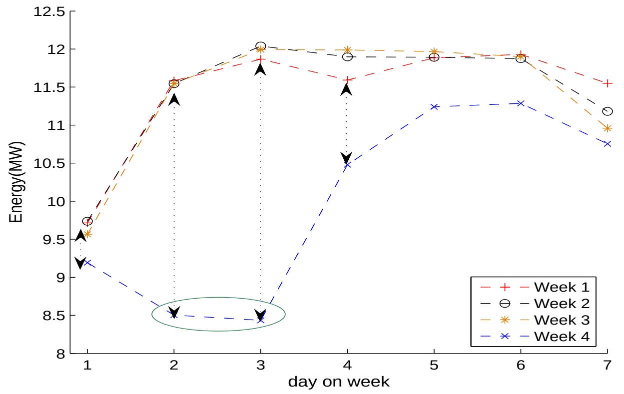

Fig. 2. Load curve of July 2003. Week 4 contains 2 holidays which are within the circle

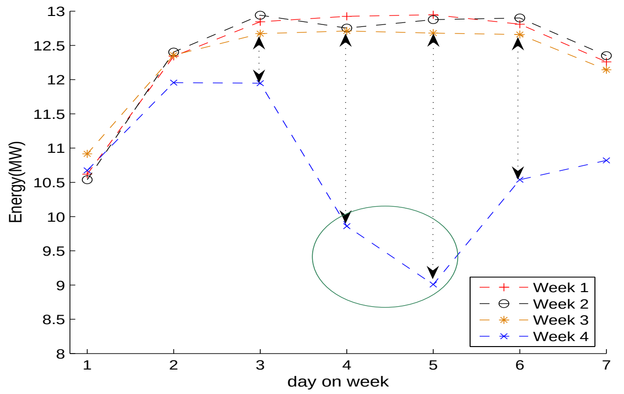

Fig. 3. Load curve of July 2004. Week 4 contains 2 holidays which are within the circle

demand is lower in holidays than in weekdays. Moreover, the load demand curve is not only affected in holidays, but also in days located before and after holidays as shown in figures 2,3,4,5. Figure 2 and 3 present load demand curve of July 2003 and 2004 respectively in which we can see that load curve on the week that contains two holidays (week 4) decrease in the holiday and days located before and after the holiday, i.e. load curve in this week present a different shape than its neighboring weeks. Similarly, figure 4 and 5 present load demand curve of August 2003 and 2004 respectively in which load demand curve on week 3 (week that contain one holiday) decrease in holidays and days located before and after holidays. For this reasons, it would be useful to make the neural network know this load curve behavior in a holiday and its neighboring days, so it can learn the real load curve behavior in these days. In this paper we present a holiday encoding that encode this behavior in a way that is suitable for the neural network.

IV. Quick Propagation Neural Network

Quick propagation is a heuristic modification of the standard back propagation algorithm [12]. It was introduced by Fahlman in 1988 [10]. This algorithm works as follows.

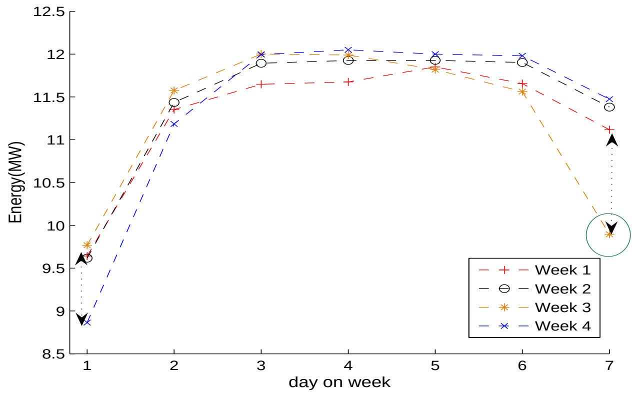

Fig. 4. Load curve of August 2004. Week 3 contains 1 holiday which is within the circle

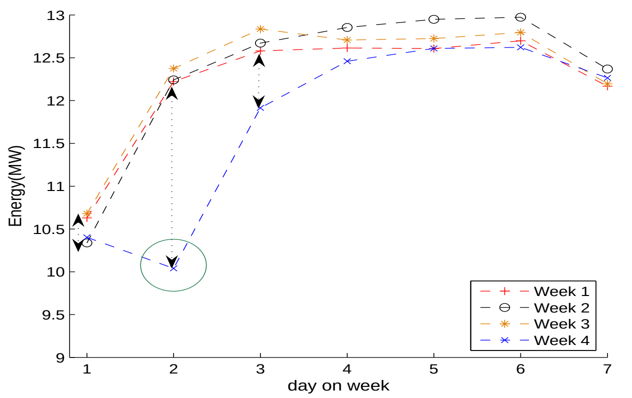

Fig. 5. Load curve of August 2004. Week 4 contains 1 holiday which is within the circle

Assume the three-layer neural network with N input neurons, K hidden neurons and M output neurons respectively. The output of the m-th output node due to the p-th input pattern is given by o_{pm}, whereas the output of the k-th hidden node for the p-th input pattern is given by $\bar{o}_{pk}$. Let ω_{km} be the weight between the m-th output neuron and the k-th hidden neuron, and $\bar{\omega}_{nk}$ be the weight between the k-th hidden neuron and the $n-th$ input neuron. The desired output for the m-th output neuron due to the p-th input pattern is given by d_{pm} . The input for the n-th input neuron due to the p-th input pattern is denoted by x_{pn} . Using this definition, the output of the k-th node in the hidden layer is given by:

$$\bar{o}_{pk} = f(\sum_{n=1}^{N} \bar{\omega}_{nk} x_{pn}) \tag{2}$$

where f is the activation (sigmoidal) function defined as

$$f(x) = 1/(1+e^{-x}) \tag{3}$$

Similarly, the output of the m-th node in the output layer is given by:

$$o_{pm} = f(\sum_{k=1}^{K} \bar{\omega}_{km} o_{pk}) \tag{4}$$

The error of the p-th input pattern is computed as

$$E_p = \sum_{m=1}^{M} (d_{pm} - o_{pm})^2 \tag{5}$$

Now, let the error curve slope with respect to a weight be

$$S_t = \frac{\partial E_p}{\partial \omega_t} \tag{6}$$

The quick propagation algorithm updates every weight as follows:

$temp = \frac{S_t}{S_{t-1}-S_t} . \Delta\omega_{t-1}$
$if(temp > \mu . \Delta\omega_{t-1})$
  $temp = \mu . \Delta\omega_{t-1}$
end
$if(S_{t-1} . S_t < 0)$
  $\Delta\omega_t = temp$
$else$
  $\Delta\omega_t = temp + \varepsilon S_t$
end
$\omega_{t+1} = \omega_t + \Delta\omega_t$

where t is the actual iteration, μ is the growing factor of the weight updating, ε is the learning rate and Δ means variation. The principal features of this technique are: faster learning than standard back propagation algorithm, and easy implementation. Further theory about how to compute equation 6 can be found in [12].

V. Forecasting Model

The forecasting model used in this paper involve: Input selection, Input Encoding, Input transformation, Parameters tuning, and Forecasting(see figure 6).

A. Input Selection

As we saw in Section III-B, the energy demand is higher in weekdays than in weekends. Also, there is a linear trend from one year to the next as shown in Section III-A. In addition, as we saw in Section III-B, the load demand is lower in holidays than in non holidays. Therefore, including this information: Year(Y), Month(M), Day in a month(DoM), Day in a week(DoW) and Holiday(H) in the model may be useful for having accurate forecasting results.

B. Input Encoding

The inputs Year(Y), Month(M), Day in a month(DoM)and Day in a week(DoW)will not be encoded, i.e. they will keep their initial values (e.g. $Y = \{1, 2, .., 12\}$). They will only be transformed using Min-Max method (it will be explained below). Holiday input will be encoded using four methods:

1) Method 1 (M1): The input Holiday encode a holiday with 1 and non holidays with 0. $(H)Holiday = \{0, 1\}$

2) Method 2 (M2): With this method, a holiday is considered as a weekend. So the input Holiday encode holidays and Sundays with 1 and the rest of days with 0. Hence $(H)Holiday = \{0, 1\}$

3) Method 3 (M3): This is our proposed method to encode holidays. In this method, the input Holiday encode holidays with 3 and days located just before and after holidays with 1 and 2 respectively. With this method, we attempts to consider the effect of holidays and their neighboring days in the load curve. Hence $(H)Holiday = \{1, 2, 3\}$

4) Method 4 (M4): With this method, the input holiday encode holidays and Sundays with 3, and days located just before and after these two days with 1 and 2 respectively. Hence $(H)Holiday = \{1, 2, 3\}$

C. Data Transformation

After encoding the input features, a transformation step is needed to put the inputs in the same scale. In this study, two ways to transform inputs is used:

1) Min-Max (T1): It encodes each value of an input as follows:

$$V_i = 2\frac{(V_i - V_{min})}{(V_{max} - V_{min})} - 1 \quad (7)$$

where V is the vector containing the values of one input. The combination of method 2 of encoding and this Min-Max transformation was used in [4], [13].

2) Binary (T2): It encodes each value of an input using a binary string. The length of the string is such that the string can represent all the possible values of the input, e.g. an input with 4 possible values can be represented with a binary string of length $2(2^2 = 4)$. The combination of method 1 of encoding and this binary transformation was used in [5]

D. Parameter tuning

In this step, the data for training will be the load demand of the twelve months before the validation month, e.g. months from July 2003 to June 2004 will be used as input data to forecast load demand in July 2004. The objective of this step is to find the optimal architecture and parameters of the quick propagation neural network (See Table I).

E. Forecasting

Once the optimal architecture and parameters have been found, to forecast July 2005 (Month for test), we first retrain the neural network using load data from July 2004 to June 2005 and July 2003 but keeping the architecture and parameters found. We add load data of July 2003 for giving the neural network more samples from month July. Similarly, to forecast August 2005 (Month for test), we retrain the neural network using load from August 2004 to July 2005 and from August 2003. We add load data of August 2003 for giving the neural network more capability to forecast load in August 2005. Table II presents the data used in retraining and testing. The quick propagation neural network consist of three layers with 5 neurons, h neurons and 1 neuron in the input, hidden and output layer respectively as shown in Figure 7. Input neurons for transformation T2 will be 6. In this paper July and August of 2005 are the target months. These months have 2 and 1 local holidays respectively.

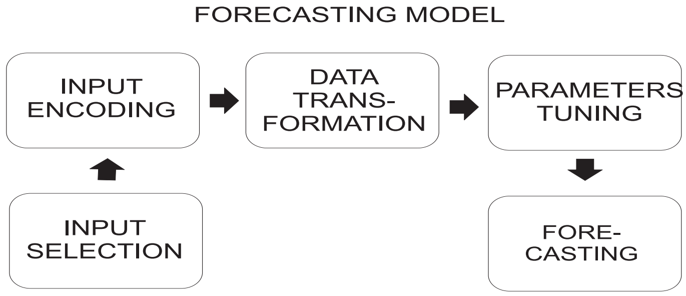

Fig. 6. Load forecasting model

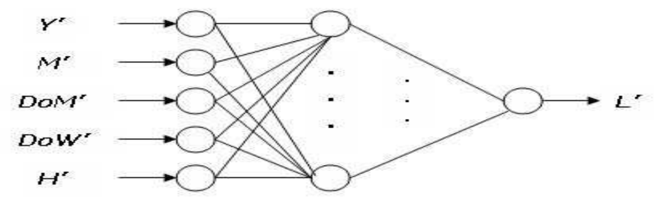

Fig. 7. Architecture of Quick Propagation Neural Network using transformation T1. Input neurons will be 6 when using transformation T2 in the forecasting process

VI. Experiments and Results

In the experiments, the target months under forecasting will be July and August of 2005. July and August have two and one local holidays respectively. Table I presents the data used for parameters tuning. Table III presents parameters values used in the experiment and the optimal values found after the experiments. These optimal values are $h = 10$, $iter$=300 $\varepsilon = 0.3$ and $\mu = 1.75$.

Then, these optimal neural network parameters will be used in the testing phase to forecast the load demand of July and August of 2005 (See Table II). A comparative study of the four methods to encode holidays with the two methods of transform it will be performed, i.e. eight possible alternatives $(4x2)$. Table IV presents the results, each value of the table is the MAPE obtained by using each combination with the quick propagation neural network for July and August 2005.

Figure 8 and 9 presents the same comparative results but only for the three best combinations based on MAPE for July and August of 2005 respectively. Also Table IV shows that M3-T1 is the combination that produce the minimum MAPE (the best forecasting) for both July and August of 2005.

Training	Validation
$July_{2003}...June_{2004}$	$July_{2004}$
$August_{2003}...July_{2004}$	$August_{2004}$

TABLE I

Data used for parameters tuning phase.

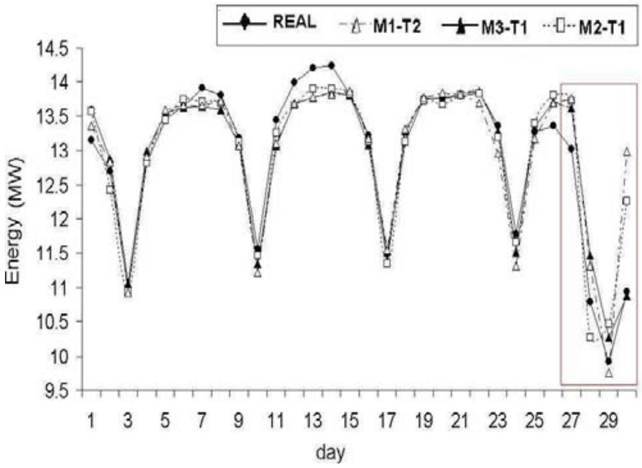

Fig. 8. Forecasting results of July 2005. Days 28 and 29 are holidays

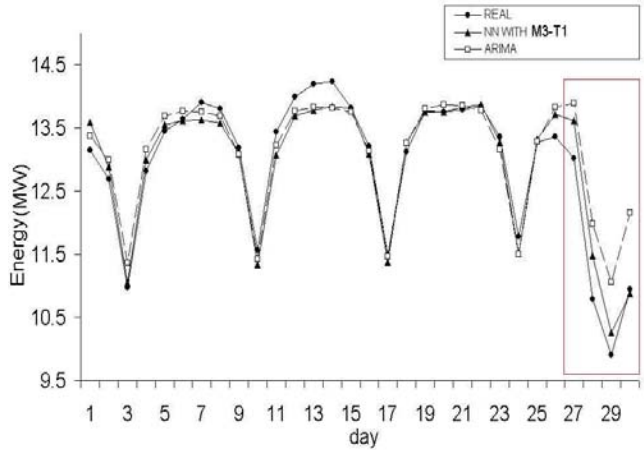

Fig. 10. Comparative results between neural networks with M3 and T1 and ARIMA model in July

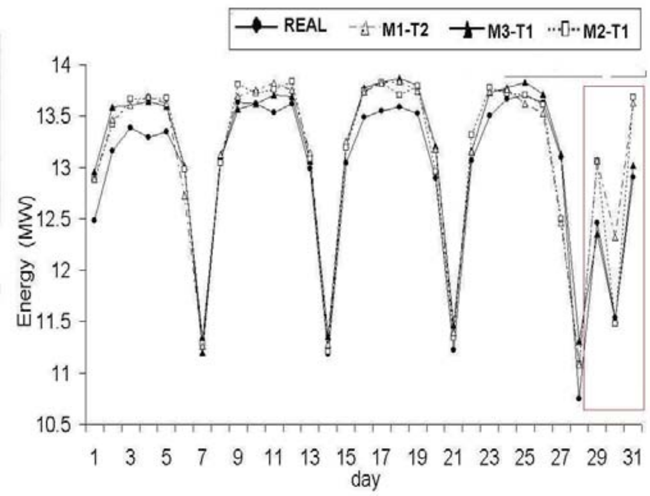

Fig. 9. Forecasting results of August 2005. Day 30 is holidays

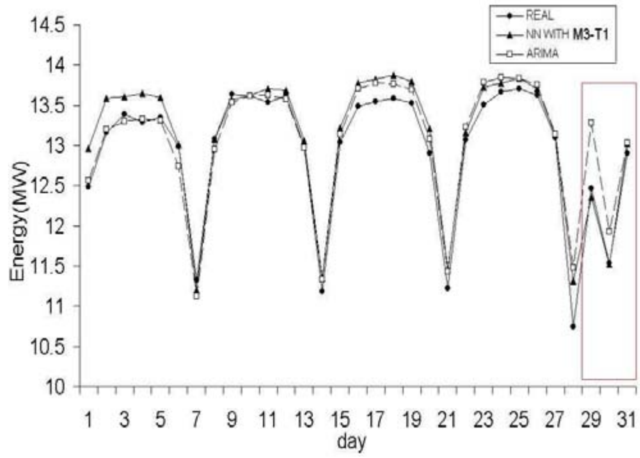

Fig. 11. Comparative results between neural networks with M3 and T1 and ARIMA model in August

Furthermore, the best combination M3-T1 using quick propagation neural network is compared with the Autoregressive Integrated Average Model (ARIMA) in July and August of 2005. Figures 10 and 11 present the results. Also, Table V presents the values of MAPE obtained by each technique. As we can see, M3-T1 using quick propagation outperforms ARIMA model with an average improvement of 24.32%. Moreover, Table VI presents the comparative results for holidays and days located just before and after holidays of July and August of 2005. As we can see M3-T1 using quick propagation neural network clearly outperforms ARIMA model with an average improvement of 66.98%.

VII. Conclusions and Further Work

A novel holiday encoding that considers not only holidays, but also days located before and after holidays have been presented. This holiday encoding has been used in conjunction with quick propagation neural networks. Besides, a suitable

Retraining	Test
$\text{July}_{2003}, \text{July}_{2004}...June_{2005}$	July_{2005}
$\text{August}_{2003}, \text{August}_{2004}...\text{July}_{2005}$	August_{2005}

TABLE II

Data used for Retraining and Testing. The months for test the neural network are July and August of 2005.

Parameters	Ranges	Optimal
h	{1,2,..., 20}	**10**
iter	{100, 200,..., 500}	**300**
ε	{0.1, 0.2,..., 0.7}	**0,3**
μ	{ 0.5, 0.75,..., 2.5}	**1,75**

TABLE III

Parameters Values used for the experiment

Target	M1		M2		M3		M4	
	T1	T2	T1	T2	T1	T2	T1	T2
J_{2005}	2.08	2.24	1.85	2.30	***1.64***	1.86	2.28	2.13
A_{2005}	1.75	1.77	1.69	1.55	***1.45***	1.60	1.65	1.89

TABLE IV

MAPE obtained by using the 8 possible combinations (4 holidays encoding and 2 transforming methods) in July and August 2005 using quick propagation neural network

Month	(M3-T1) with NN	ARIMA	Improvement (%)
July 2005	1,64	2,81	41,64
August 2005	0,93	1,00	7,00
Average	**1,29**	**1,91**	**24,32**

TABLE V

MAPE of July and August of 2005 obtained by using M3-T1 with quick propagation neural network (NN), and ARIMA

data structure based in taking the last twelve months and months equal to the target month of past years has been used. Then the forecasting results of the proposed holidays encoding have been compared with those obtained by using other holidays encoding used in some other papers. The comparative study has been made using the forecasting error of the quick propagation neural network as indicator. For the testing phase, load data of July and August of 2005 has been chosen because they have two and one local (Peruvian) holidays respectively. The results show that the proposed holiday encoding produce better forecasting results in July 1.64% and August 1.45% than the results produced by the other holidays encoding for the same months. Furthermore, these results obtained using the proposed holiday encoding and quick propagation neural network are also compared with those results obtained by using ARIMA model which is a statistical technique also used in practice. These last comparative results show that the proposed holidays encoding with quick propagation neural network outperform ARIMA model in both July and August with an average improvement of 24.32%. Moreover, the proposed holidays encoding with quick propagation neural network clearly outperform ARIMA model in forecasting holidays and days located just before and after holiday in the two months with an average improvement of 66.98%.

Further work includes developing an in-depth research in holiday encoding and other input encoding for neural network to the load forecasting problem. Also it would be interesting to structure further the data prior to be exploited by the neural network.

Day	(M3-T1) with NN	ARIMA	Improvement (%)
27 of July	4,58	6,71	31,74
28 of July	**6,37**	**11,10**	**42,61**
29 of July	**3,61**	**11,60**	**68,88**
30 of July	0,54	11,12	95,14
29 of August	0,85	6,53	86,98
30 of August	**0,13**	**3,45**	**96,23**
31 of August	0,93	1,00	7,00
Average	2,43	7,36	66,98

TABLE VI

MAPE of holidays and days located just before and after holidays using M3-T1 with quick propagation neural network (NN), and ARIMA

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