J. KingSaud Univ., Vol. 12, *Eng. Sci.* (2) *pp.* 269-284 (A.H. 1420/2000)

Medium to Long-term Peak Load Forecasting for Riyadh City Using Artificial Neural Networks

Fahd A. Alturki and Adel Ben Abdennour
Electrical Engineering Department, College of Engineering
King Saud University, Riyadh, Saudi Arabia
(Received 27 January 1999; accepted for publication 14 June 1999)

Abstract. Load forecasting plays a paramount role in the operation and management of power systems. Accurate estimation of future power demands for various lead times facilitates the task of generating power reliably and economically. The forecasting of future loads for a relatively large lead time (months to few years) is studied here with application to Riyadh city. Such a problem typically depends on a number of factors such as temperatures, number of customers, and past loads. However, considering other factors like special events and holidays improves the forecasting results, but makes the problem more difficult to solve with classical methods. In this paper, an Artificial Neural Network (ANN) approach to the medium/long-term load forecasting problem is presented. The results reveal that accurate estimates of future loads are achieved.
***Keywords*.** Neural networks, load forecasting.

Introduction

Accurate load forecasting leads to an economic, secure, and reliable power system planning and operation. Power demands need to be estimated ahead of time in order to plan the generation and distribution schedule. Estimation of future load demands is done for various lead times (forecasting intervals) ranging from few seconds to more than a year. Four basic types of load forecasting can be defined in terms of both the lead time and the purpose of the forecast.

1. *Very-short term*: The lead time for this type of forecasting is typically few seconds to several minutes.
2. *Short-term*: The lead time in this type is from half an hour to several hours. This forecasting is usually needed for the allocation of spinning reserve.
3. *Medium-term*: This forecasting is used in preparing to meet load requirements at the height of the winter or summer seasons. It is also needed for scheduling fuel supplies and maintenance operations which require a lead time of few days to several weeks.

4. *Long-term*: Forecasting of this type is mainly used to plan the growth of the generating capacity and the transmission expansion which requires a lead time ranging from few months to few years.

Various methods of load forecasting models have been used [1,2]. Most of the conventional methods fall into the class of time series or regression analysis. Precisely, standard methods include ARIMA modeling, regression modeling, and spectral decomposition. However, due to the importance of the forecasting problem, research has lead to alternative approaches dominated by intelligent methods. Among these intelligent systems successfully used for load forecasting is Fuzzy Logic [3], Artificial Neural Networks [4-7], and hybrid approach [8].

The overwhelming majority of load forecasting research has been on the short-term. In fact, very little published work can be found on the medium or long-term problem. Part of the reason is that the long-term forecasting requires years of economic and demographic data which may not be easy to gather or access. In contrast, the short-term problem can be successfully formulated in terms of temperature and load data over just several hours or weeks. Long-term forecasting (even when the data is accessible) is complex in the sense that it is affected by environmental, economical, political, and social factors. For instance, a change in the life style of a large part of the population can change the long term power consumption.

This paper discusses the medium-term to long-term load forecasting for the City of Riyadh. Forecasting of weekly peak loads for a lead time of one year is accomplished using a single-hidden-layer Feedforward Artificial Neural Network.

Overview of the Electrical Energy in Saudi Arabia

The generating capacity of electrical power in Saudi Arabia witnessed a major development in both quality and quantity within few years [9]. Concerning quantity, the actual generating capacities for all electric companies in the Kingdom reached the level of 19351 Mw by the end of 1996 which is approximately 17 times of what it was in 1975.

The peak load of the Kingdom during the year 1996/1997 reached 17995 Mw which is more than 21 times what it was in 1975. The generated energy in 1997 reached 81.1 million Mw which is 19 times of what it was in 1975. The total number of customers by the end of 1996 reached 3,151,198 which is around 9 times its value in 1975. Figure 1 summarizes this growth over the last quarter of the century.

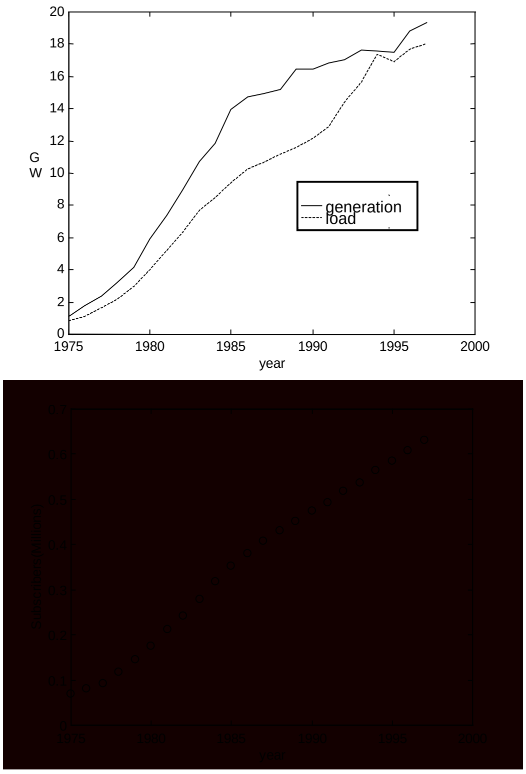

Fig. 1. Electrical energy growth.
(a) generating capacity and peak loads (for the Kingdom)
(b) subscribers (for Riyadh).

The Forecasting Problem for Riyadh City

The medium or long-term forecasting of peak loads for Riyadh is atypical and perplexing. There are at least three factors that participate to an extent in making the forecasting for Riyadh a challenge and unique in its nature:

1. The rapid economical, commercial, and residential growth of the city being the capital of the Kingdom,
2. The fluctuation of temperatures over the seasons, especially during the hot summers, and
3. The use of the Hijri calendar (based on the moon) which entails the movement of special holidays and school days to different weeks or even months of the year which weakens the correlation between load demands and seasonal cycles.

The forecasting of future loads depends, in addition to the load history, on the history of a number of variables. Some of the variables that could be considered are: total number of subscribers, maximum temperatures, minimum temperatures, and special holidays. The number of history years to be considered for each variable needs to be carefully determined because many of these variables follow a pattern that changes over the years.

Figure 2 shows the maximum load for the city of Riyadh for a selected number of years. It can be noted from the figure that the load exhibits more of a flat pattern during the early 1980's. The pattern started to change with the use of air conditioners, and the emergence of weather sensitive life style to produce peaks and valleys depending on the time of the year.

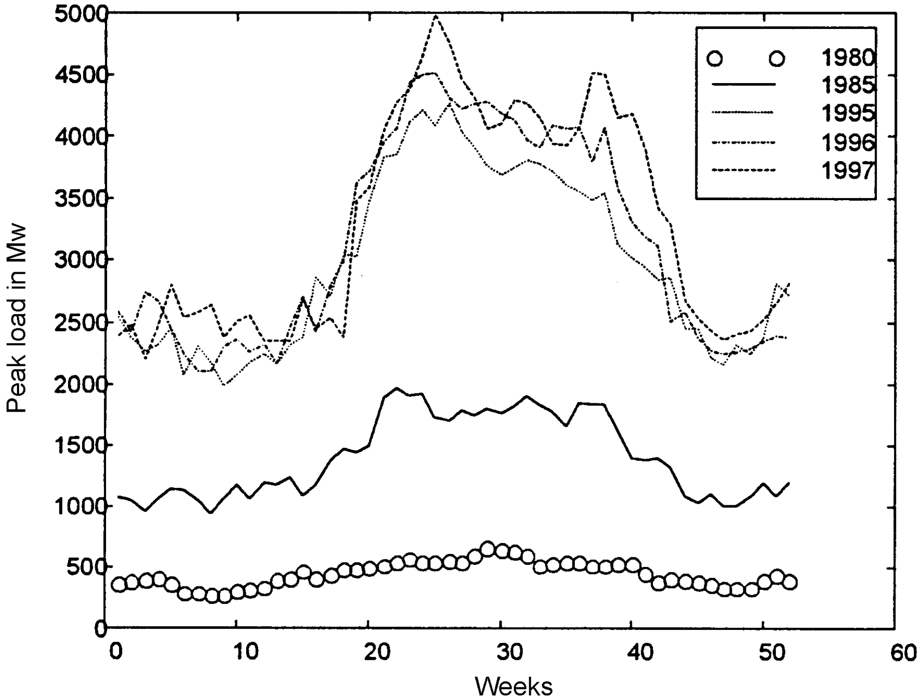

Fig. 2. Weekly peak load for Riyadh city.

The typical maximum and minimum temperatures are illustrated in Figs. 3 and 4. The figures reveal that the temperatures follow the same pattern over the years with some fluctuations around the mean.

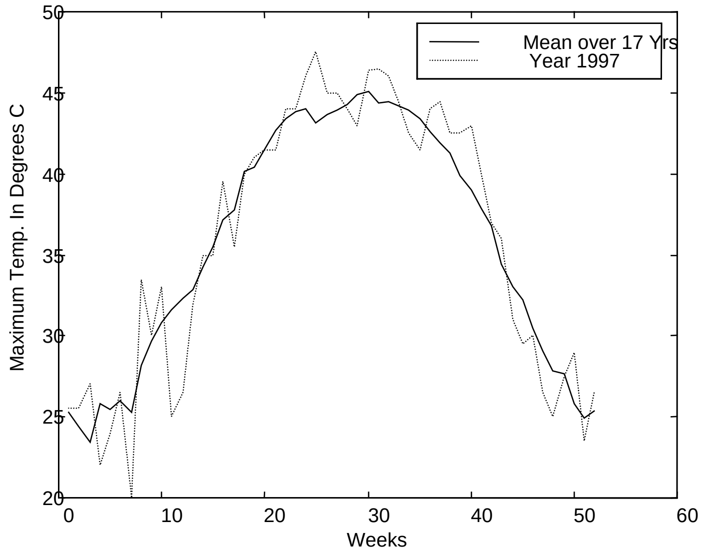

Fig. 3. Weekly maximum temperatures for Riyadh city.

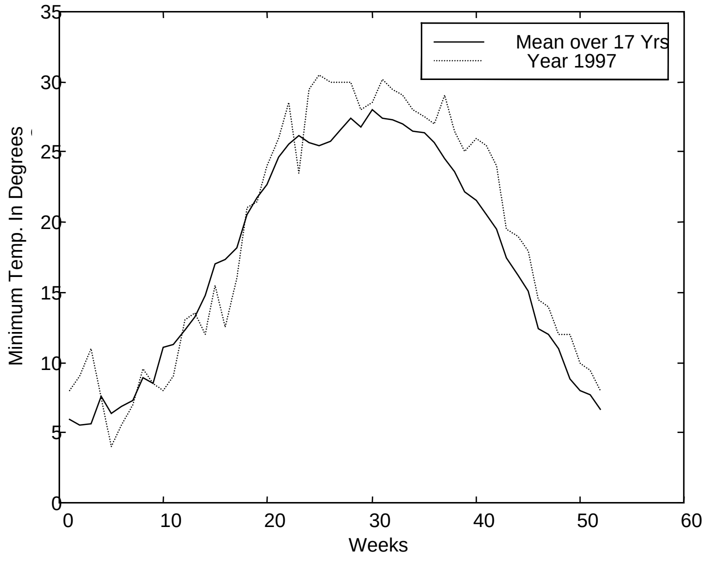

Fig. 4. Weekly minimum temperatures for Riyadh city.

The special holidays (Eid and school vacations) have also a big effect on the load. Over the course of one school year, four vacations are usually given: Eid Al-fitr, Eid-Al-adha, mid-year vacation, and the summer vacation. In some years, two vacations are combined in one. The beginnings of these vacations depend on the Hijri calendar. These vacations for the last six years are shown in Fig. 5. The figure illustrates that the holidays do not follow a clear pattern, which represents one of the most difficult points in the medium to long-term accurate load forecasting for Riyadh.

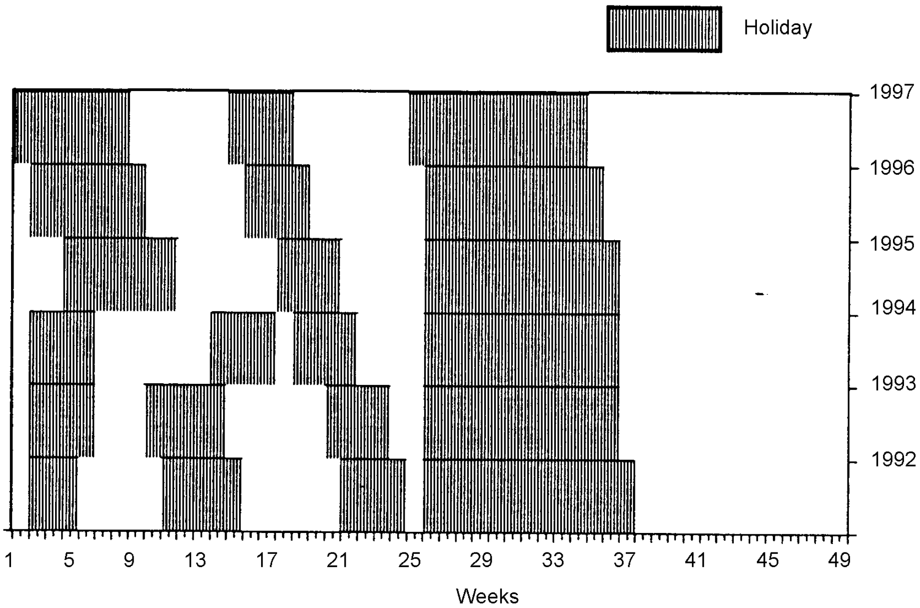

Fig. 5. Special holidays for the past 6 years.

Overview of Artificial Neural Networks (ANN)

Artificial Neural Networks (ANN) are networks that mimic the biological neural networks found in living organisms. They basically simulate how our brains work, and they help explain why our brains outperform computers in many decisions. The brain is believed to attain its power and flexibility from a highly interconnected multiprocessor architecture. It is on this very architecture that ANN is based.

In the generic ANN, there are three main components: the *neuron*, the network *topology*, and the *learning algorithm*. The neurons (also called processing elements) are the components where most, if not all, of the computation is done in most AN systems. As shown in Fig. 6, they receive signals from other neurons or from the input through the interconnections. These signals can be formulated as an input vector:

$$A = (a_1, \cdots, a_i, \cdots, a_n).$$

Associated with each connected pair of neurons is an adjustable value called *weight*. The weights connected to the j^{th} neuron can be expressed as a vector of the form:

$$W_j = (w_{1j}, \cdots, w_{ij}, \cdots, w_{nj})$$

where w_{ij} represents the connection strength from neuron a_i to neuron a_j .

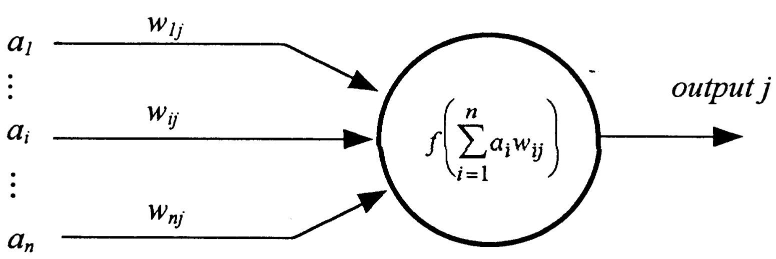

Fig. 6. General symbol of a j^{th} neuron.

The neuron contains an internal limit when it exceeds a threshold, it can propagate an action through its connections to other neurons. Many neurons can be active at the same time and thus neural networks can be considered to be parallel computational systems. The output value of the j^{th} neuron can be defined as:

$$\text{output}_j = f\left(\sum_{i=1}^{n} a_i w_{ij}\right)$$

There are many functions that could be used for *f*. Some of these functions are *linear*, *Gaussian*, and *sigmoid*. The most popular of these options is the sigmoid function described by:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The neurons of a neural network are connected together and the overall system behaviour is determined by the structure and weights of these connections. The neurons are arranged in groups or *layers*. Layers can be either input layers, output layers, or hidden layers. The hidden layers provide networks with the ability to perform complex nonlinear mappings. Signals between layers can propagate in one of the two ways: *Feedforward* (allowing information to flow along one direction) and *feedback* signals (allowing information to flow in either direction). A general structure of a feedforward artificial neural network is shown in Fig. 7.

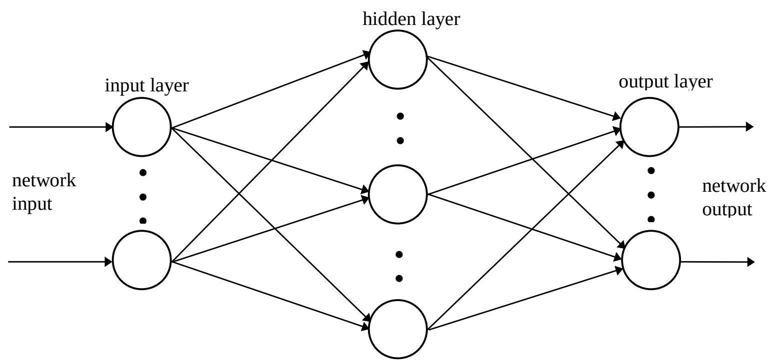

Fig. 7. General structure of a feedforward ANN.

The third aspect (arguably the most important of the three ANN components) is *learning*. Since the basic need for ANN is to try to imitate how the brain makes decisions, some way of "teaching" or "training" the ANN to perform a particular task is needed. The most common training style is *supervised learning*. The supervised learning depends on training data set that contains input vectors and corresponding output vectors. These vector pairs are used to determine the non-linear mappings that exist in the data set.

For the training task, the most general purpose and widely used paradigm is the *backpropagation* (BP) which achieves its generality because of the *gradient-decent* technique used to train the network. The gradient-decent is similar to error minimization which is an attempt to fit a closed-form solution to a set of data points such that the solution deviates from the exact value by a minimal amount.

The BP learns to generate a mapping from the input pattern space to the output pattern space by minimizing the error between the actual output produced by the network and the desired output across a set of pattern vector pairs. The learning process begins with the presentation of an input pattern to the BP. That input pattern is propagated through the entire network, until an output pattern is produced. The BP then makes use of what is called the *generalized delta rule* to determine the error for the current pattern contributed by every unit in the network. Finally, each unit modifies its input connection weights slightly in a direction that reduces its error signal, and the process is repeated for the next pattern. More details on ANN and its applications can be found in [10].

From this brief overview, it is apparent that the ANN due to its highly parallel architecture and its adaptive structure, is well suited for modelling. In fact it is in this very aspect that ANN found its strength among other intelligent methods. Once designed, the ANN can be retrained any time new data is available allowing for continuous improvement of the network if needed.

ANN Solution to the Load Forecast Problem

It is usually not very difficult to identify the different factors that affect peak loads. For example, the medium to long term forecasting is affected, one way or another, by at least variables like minimum and maximum temperatures, the number of subscribers, load history, and special holidays. The difficult task, however, is to determine how each of these variables influences the load demand. In other words, if we precisely know these variables, how can we accurately determine what the peak load will be in the future. The problem, therefore, is reduced to finding an accurate mapping between the influencing factors and the predicted outcome.

Artificial neural networks have been known to possess a powerful generalization capability making them good candidates for problems of this type. The data pertaining to the number of subscribers, temperatures, past loads, and holidays have been collected to train the ANN. It is worth noting that such data is intended for illustration and research purposes only and may not necessarily represent the local utility.

Two ANN solutions are suggested and compared. In the first, only one neural network is used to perform the forecasting task. In the second solution, the year is divided into three parts. For each of these parts, a neural network is designed resulting in three networks that perform the forecasting task.

General approach and optimization strategy

In solving the load forecasting problem using neural networks, two major set of issues need to be addressed separately. The first is with respect to the forecast problem itself, while the second is with respect to the ANN.

a) Issues related to the forecasting problem:

The variables that are likely to affect future medium to long term loads are maximum temperature, minimum temperature, past load history, number of subscribers, and special holidays. The first step is to identify which of these variables are actually influencing the peak loads for the case of Riyadh. Once these variables are identified, the needed number of history years is determined. As an example, if it was determined that past loads are needed to predict future loads, then we need to determine how many history years are necessary.

To resolve these issues, an ANN is built and supplied with a set of training data. A program is written to automate the selection of crucial influencing variables and the corresponding needed number of history years. The combination that yields the minimum error between the actual and predicted loads is used as input to the ANN.

b) Issues related to the ANN architecture:

It is well known that the neural network is sensitive to a number of factors among which are: normalization of the training set, initialization of the weights, number of neurons, and number of training epochs. The neural network results can vary considerably due to variations in these factors.

Here, also, a program is written to automate the selection of the neural network variables. This program loops through a number of normalization (scaling) factors, initial weights, number of neurons, and number of training epochs. The combination that induces the minimum error between the actual and predicted loads is chosen.

The one-network solution

In this approach, a one ANN is used to forecast future load demands. A block diagram of the solution strategy is shown in Figure 8. The optimization routine mentioned in the previous section lead to the following input variables: *P(k), P(k-1), P(k-2), sub(k),* $T_{max}(k)$, $T_{min}(k)$, $T_{min}(k-1)$, $T_{min}(k-2)$, and *hol(k),* where

k: current year
P: weekly peak load demand
sub: number of subscribers
T_{max}: weekly maximum temperature
T_{min}: weekly minimum temperature
hol: holidays (*hol=1* if the week in question is a holiday, hol=0 otherwise)

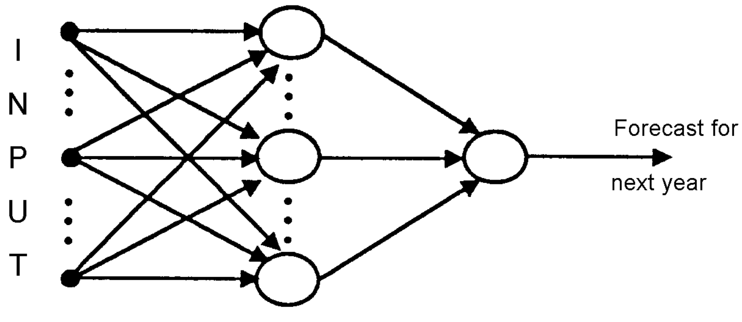

Fig. 8. The one-network solution.

This network uses 17 neurons and is trained for 3500 epochs. The training period covered all the weeks from 1992 to 1995. The training data collected over this period is enough as will be seen later.

The three-network solution

When examining the load patterns for recent years (as was presented in Fig. 2), three distinct intervals can be easily identified. The first interval covers weeks 1-18 (January-May) and it is characterized by low peak demands, low temperatures, and a number of school vacations. The second period covers weeks 19-42 (June-October) and it is characterized by very high temperatures, high load demands, and the summer vacation. The last period covers the remainder of the year (November-December) where temperatures are mild and there are generally no vacations.

As there are three apparently distinct periods of the load pattern, it may be tempting to use three distinct ANNs (one for each period) leading to a three-network solution to the problem as shown in Fig. 9. Here also, the optimization strategy described in the previous section is used to find the optimal input variables and the ANN parameters for each network. These results are summarized in Table 1.

Table 1. Summary of parameters for the three-network solution

	ANN1	**ANN2**	**ANN3**
Inputs	P(k)	P(k)	P(k)
	P(k-1)	P(k-1)	P(k-1)
	P(k-2)	P(k-2)	P(k-2)
	P(k-3)	P(k-3)	P(k-3)
	Sub(k)	sub(k)	sub(k+1)#
	sub(k+1)#	T_{max}(k)	sub(k)
	T_{max}(k)	T_{min}(k)	sub(k-1)
	T_{min}(k)	T_{min}(k-1)	sub(k-2)
	hol(k)	hol(k)	sub(k-3)
	hol(k-1)		T_{max}(k)
			T_{min}(k)
			T_{min}(k-1)
			T_{min}(k-2)
			hol(k)
Number of neurons	22	15	22
Number of epochs	3500	2000	3500

# indicates that future (expected) number of subscribers is used.

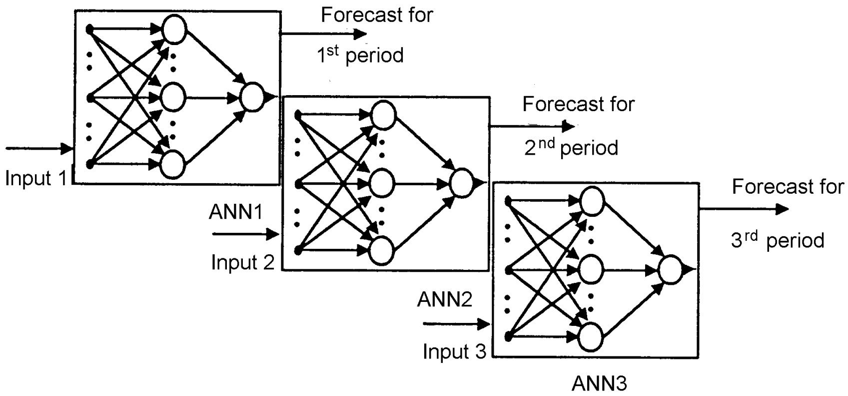

Fig. 9. The three-network solution.

Results

The two solutions (the one ANN and the three ANNs) are used to forecast the weekly peak loads for 1996 and 1997. A comparison between the two approaches and the actual data is shown in Figs. 10 and 11. Table 2 summarizes the Mean Square Error (MSE), Root Mean Square Error (RMSE), and Absolute Relative Error (ARE) for the one and three-network solutions.

$$MSE\% = \frac{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}{\sum_{i=1}^{N} y_i^2} \times 100$$

$$ARE\% = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{\hat{y}_i - y_i}{y_i} \right| \times 100$$

$$RMSE\% = \frac{\sqrt{\sum_{i=1}^{N} (\hat{y}_i - y_i)^2}}{\sum_{i=1}^{N} y_i} \times 100$$

where $\hat{y}$ and y are the forecasted and actual values respectively.

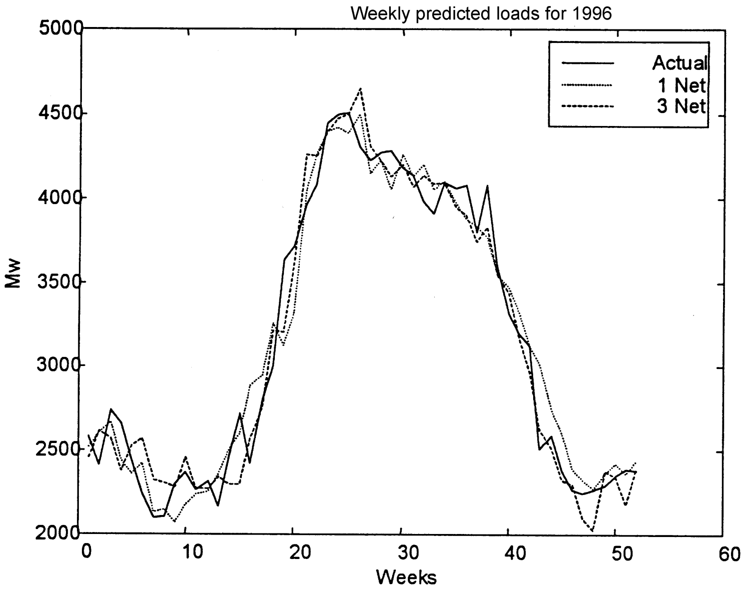

Fig. 10. Comparative results for forecasting 1996 weekly peak loads.

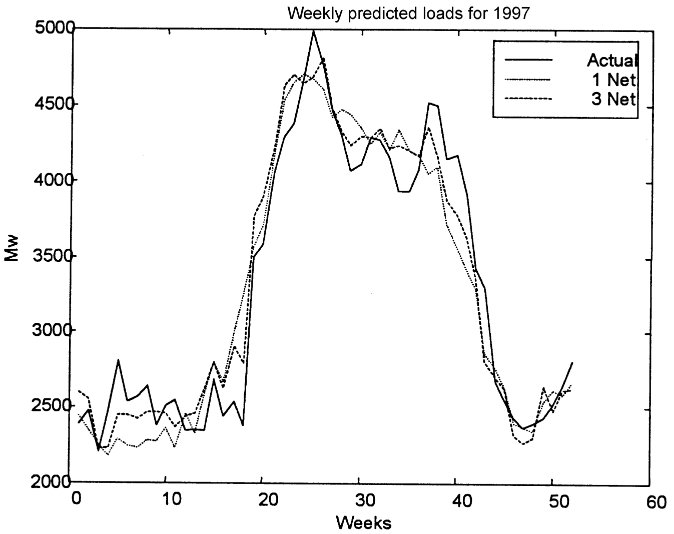

Fig. 11. Comparative results for forecasting 1997 weekly peak loads.

The figures reveal that both techniques predicted the weekly peak loads exceptionally well. However, by examining the quantified performance (Table 2), the three-network solution outperforms the single network. Nevertheless, its structure is more complex. Whether the slight improvement is worth the increased complexity is a matter of a judgement call.

Table 2. Forecasting errors for 1996 and 1997

Year	Method	MSE%	ARE%	RMSE%
1996	One-Net	0.5286	4.7629	0.8223
	Three-Net	0.2777	4.6526	0.7560
1997	One-Net	0.6997	6.9321	1.2005
	Three-Net	0.3937	5.5754	0.9005

Conclusions

Forecasting weekly peak loads for a one-year lead time using artificial neural networks was studied. Two ANN architectures (the one-network solution and the three-network solution) were investigated. Both structures were trained using data covering the period from 1992 to 1995. It was possible to use the history of power, minimum temperatures, maximum temperatures, number of subscribers, and special holidays, to accurately predict future Riyadh city peak loads for 1996 and 1997. In the worst possible case, the mean square error did not exceed 0.7% whereas it was as low as 0.28% in some cases. An added edge of the use of ANNs in the solution of such problems is its ease compared to the classical statistical and time series approaches. In addition, it can be retrained any time to improve its performance; a quality that is of a particular importance especially with the always changing load patterns.

Acknowledgment. The authors gratefully acknowledge the Research Center at the College of Engineering, King Saud University, Riyadh, Saudi Arabia for the financial support.

References

[1] IEEE Committee Report "Load Forecasting Bibliography Phase I". *IEEE Transactions on Power Apparatus and Systems*, PAS-99 (1988), 53-58.

[2] Gross, G. and Galiana, F.D. "Short-term Load Forecasting". *IEEE Proceedings*, 75, No. 12 (1987), 1558-1573.

[3] Lamber-Torres,G., Silva L.E., Valiquette, B., Greiss, H., Mukhedkar, D. "A Fuzzy Knowledge-based System for Bus Load Forecasting". *Fuzzy Logic Technology and Applications*, (Marks, R.J., Ed.), IEEE Technical Activities Board, (1994), 221-228.

[4] Peng, T.M., Hubele, N.F., Karady, G.G. "Advancement in the Application of Neural Networks for Short-Term Load Forecasting". *IEEE Transactions on Power Systems*, 7, No. 1 (1992), 250-257.

[5] Lee, K.Y. and Park, J.H. "Short-Term Load Forecasting Using an Artificial Neural Network". *IEEE Transactions on Power Systems*, 7, No. 1 (1992), 124-132.

[6] Ho, K.L., Hsu, Y.Y., Yang, C.C. "Short term Load Forecasting using a Multilayer Neural Network with an Adaptive Learning Algorithm". *IEEE Transactions on Power Systems*, 7, No. 1 (1992), 141-149.

[7] Heinrich, I., Tolke, P., Winkler, G. "Application of Neural Networks for Load Forecasting in a Regional Power Company". *IEE CIRED Conference*, Conference Publication No. 438 (1997), pp 4.12.1-4.12.6.

[8] Kim, K.H., Parl, J.K., Hwang, K.J., Kim, S. H. "Implementation of Hybrid Short-term Load Forecasting System Using Artificial Neural Networks and Fuzzy Expert Systems". *IEEE Transactions on Power Systems*, 10, No. 3 (1995), 1534-1539.

[9] Electricity Growth and Development in the Kingdom of Saudi Arabia up to the Year 1996/1997, *Report by Studies and Statistics Department*, Electrical Affairs Agency, Ministry of Industry and Electricity, Kingdom of Saudi Arabia, 1997.

[10]

توقع الأحمال الكهربائية متوسطة/طويلة المدى لمدينة الرياض باستخدام الشبكات العصبية الاصطناعية

فهد بن عبد الله التركي وعادل بن عبد النور

قسم الهندسة الكهربائية، كلية الهندسة، جامعة الملك سعود، ص.ب ٨٠٠،

الرياض ١١٤٢١، المملكة العربية السعودية

Skapura, D. M. *Building Neural Networks.* New York: ACM Press, 1995.

(استلم في ١٩٩٩/١/٢٧م؛ وقبل للنشر في ١٩٩٩/٦/١٤م)

ملخص البحث. يؤدي توقع الأحمال الكهربائية دورًا جوهريًا في تشغيل أنظمة الطاقة الكهربائية وإدارتها، حيث إن التوقع الدقيق للأحمال المستقبلية، لأوقات متفاوتة، يسهم في إنتاج الطاقة بشكل معتمد واقتصادي. تمت في هذا البحث دراسة توقع الأحمال الكهربائية لفترات طويلة نسبيًّا، (شهور- عدة سنوات)، وتطبيق تلك الدراسة على مدينة الريط. عادة، تتأثر أنظمة توقع الأحمال بدرجات الحرارة، عدد المشتركين وتاريخ الأحمال السابقة، إلا أن هناك عوامل أخرى ينبغي أخذها في الاعتبار، كالأحداث الخاصة، الأعياد والإجازات، وهو ما قد يُحسّن النتائج لكنه يزيد منصعوبة الحصول على الحل الأمثل باستخدام الطرق التقليدية، ومن ثم فإن هذا البحث يقترح استخدام الشبكات العصبية الاصطناعية، كإحدى طرق الذكاء الاصطناعى، لبناء نظام دقيق لتوقع الأحمال متوسطة/طويلة المدى في مدينة الريط.