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A Fuzzy Neural Approach for Forecasting Peak Power Demands

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Abstract. Accurate prediction of future electrical power demands greatly facilitates the task of power generation reliably and economically. In this paper, the new soft computing technologies, namely neuro-fuzzy techniques are adopted to improve precision of medium to long-term load forecasting. Performance of the proposed methodology is verified using simulations of some data pertaining to the Riyadh power system. This approach is compared with time series and neural networks design methods. It is demonstrated that the proposed methodology surpasses other methods by producing very accurate peak load forecasts.

Key-words: Fuzzy logic, Neural networks, Neuro-fuzzy, Load forecasting.

Introduction

Load forecast for electricity generation companies is important for scheduling of resources on an hourly basis or for the more long term planning activities. To meet daily load demands in a timely fashion, prediction of loads for lead times in the order of minutes or hours is necessary. However, for planning purposes or maintenance scheduling, lead times in the order of days, months or even years are commonly used.

The search for enhanced forecasting techniques has been reflected by a wealth of recent papers utilizing different techniques for load modeling [1-2]. Most of the conventional methods belong to the class of time series or regression analysis. Standard methods include ARIMA modeling, regression modeling, and spectral decomposition [3]. In appreciation to the importance of load forecast, research has been recently renewed and has led to alternative approaches dominated by intelligent methods. These methods include designs based on Artificial Neural Networks, Fuzzy Logic, and hybrid systems [4-9].

Most of load forecast research has been on the short-term problem and very few studies are on medium or long-term cases. The reason for this could be partly due to the fact that such cases require many years of socio-economic and demographic data, which are not always easy to obtain.

Load Forecast

The precise estimate of instantaneous and future loads is important for the economical and effective planning of power plant operation. To honor daily load demands reliably, prediction of loads is done for different lead times ranging from few seconds in the case of very short-term intervals to few years for very long-term planning strategies. Depending on the lead times, load forecast is usually characterized into several types that include:

1) Short-term: the lead time is typically half an hour to several hours. It is needed for the allocation of spinning reserve.

2) Medium-term: the lead time is a few days to several weeks. It is used for scheduling fuel supplies to meet load demands at the height of winter or summer seasons.

3) Long-term: This type is mainly used to plan the growth of the generating capacity or the transmission expansion which requires a lead time of few months to few years.

It is known that the load required by a region is largely affected by many factors that include general trends, time dependent factors such as season and holidays, weather conditions, special events, and economy growth related factors. Load forecast takes these factors into account and helps in the management of resources, such as planning sufficient generation, spinning reserve or standby reserve. When done accurately, it plays an important role in reducing cost of power generation.

Electrical Energy Consumption for Riyadh

As a fast developing country, Saudi Arabia and particularly Riyadh city, the capital, has witnessed probably unparalleled development in most sectors including social and economic life styles. This expansion has largely affected the trend of electric power generation and consumption [10]. As depicted in Fig. 1, the yearly minimum and maximum peak loads of the period from 1980 to 1997, show how the demand was rapidly increasing. This fact can be partly attributed to the monotonic increasing pattern of the number of customers over the same period, Fig. 2.

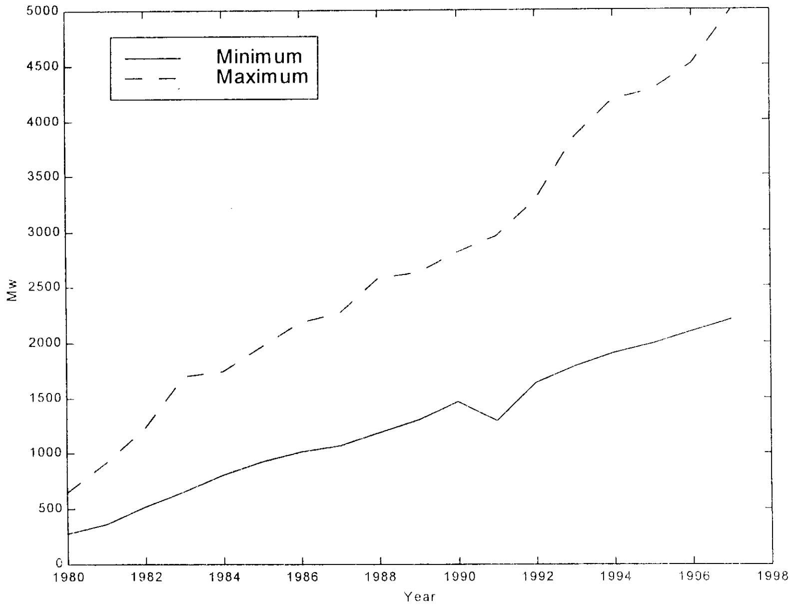

Fig. 1. Minimum and maximum peak loads (1980-1997).

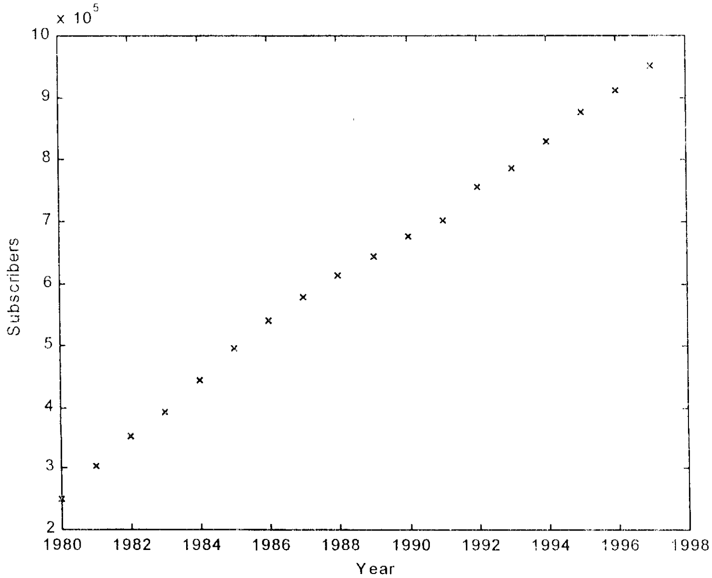

Fig. 2. Growth of the number of customers (1980-1997).

The problem of forecasting the peak load for Riyadh as an example of a fast developing city, is a typical and intricate which makes such a problem a challenge and perhaps unique in its nature. This stems from the fact that there are many complex factors that influence the amount of load needed each season and each year. Some of these factors are:

1. The rapid economical, commercial, and population growth of the city: the economy of Riyadh city depends mainly on oil prices which are very hard to predict.

2. The large diversity of minimum and maximum temperatures over seasons: typically, the high temperature period (July and August) is characterized by high ambient temperatures that may exceed 47° C and the minimum can drop to subzero degrees in winter (Fig.3).

3. The dependence of the special holidays and school days on the Hijri calendar which is a lunar calendar, constitutes a major factor that affects the peak load. The largest religious festivals in the country are: Ramadan (fasting month for Muslims), Eid Al-fitr that marks the end of Ramadan, and first part of the month of Dul-Hijjah in which Hajj pilgrimage to Makkah takes place. In these events, peak loads are subject to significant changes. For instance, during Ramadan the load is usually increased due to the increase in some residential and commercial activities. After each festival the load is substantially decreased since a large portion of the population leaves Riyadh for Hajj or for holidays in addition to the closure of most government establishments. School and religious holidays are cyclic and irregular in some sense, Fig. 4, with respect to seasons which normally change the system peak in both magnitude and the time of its occurrence. The formation of these factors makes the process of demand forecasting difficult and more difficult than those commonly published.

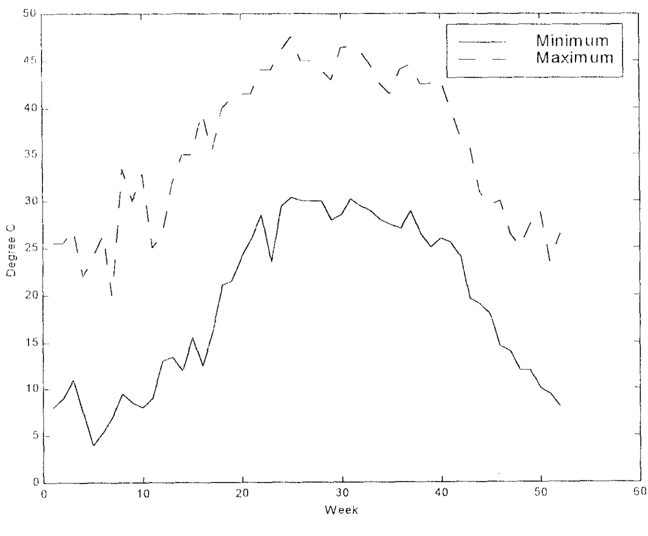

Fig. 3. Weekly minimum and maximum temperatures of Riyadh in 1997.

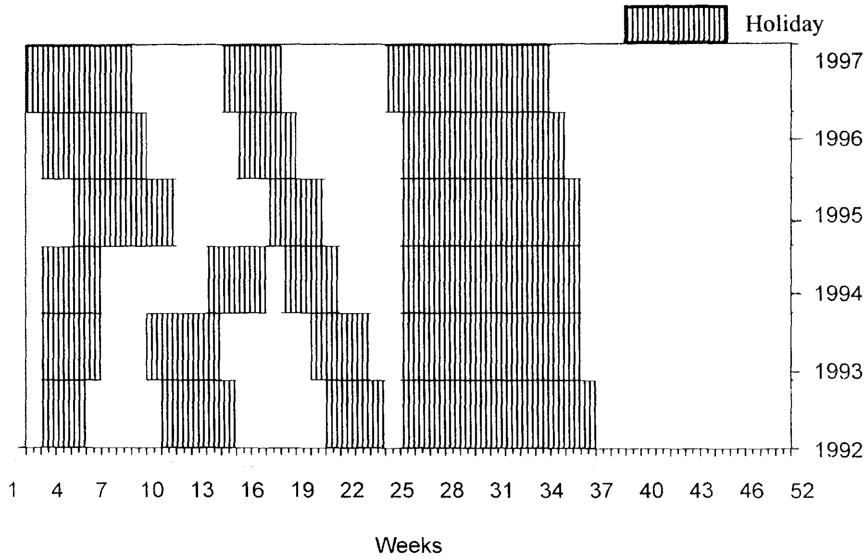

Fig. 4. Special holidays for the past 6 years.

Adaptive Neuro-fuzzy Systems

It is now realized that complex real-world problems require intelligent systems that combine knowledge, techniques and methodologies from various sources. These intelligent systems are supposed to possess human like expertise within a specific domain, adapt themselves and learn to do better in changing environments, and explain how to make decisions or take actions.

Neuro-fuzzy approach combines two powerful computing disciplines: adaptive neural networks and fuzzy set theory. Neural networks are well known for its ability to learn and adapt to unknown or changing environment to achieve better performance. Fuzzy set theory, on the other hand, can by its effectiveness in handling linguistic information, incorporate human knowledge, deal with imprecision and uncertainty, and clarify the relation between input and output variables.

Adaptive Network-based Fuzzy Inference Systems (ANFIS) are fuzzy Sugeno models put in the framework of adaptive systems to facilitate learning and adaptation [11]. Such framework makes such models systematic and less relying on expert knowledge. To describe the ANFIS architecture briefly, consider two fuzzy if-then rules based on a first order Sugeno model:

Rule 1: if (x is A_1) and (y is B_1) then ($f_1 = p_1 x + q_1 y + r_1$)
Rule 2: if (x is A_2) and (y is B_2) then ($f_2 = p_2 x + q_2 y + r_2$)

where x and y are inputs; A_i and B_i are appropriate fuzzy sets; p_1, q_1, and r_1 are certain parameters. f_1 and f_2 contribute to the output of the system.

Figure 5 shows one possible ANFIS architecture for implementing these two rules. In this five-layer architecture, a circle indicates a fixed node whereas a square indicates an adaptive node whose parameters are changed during adaptation or training.

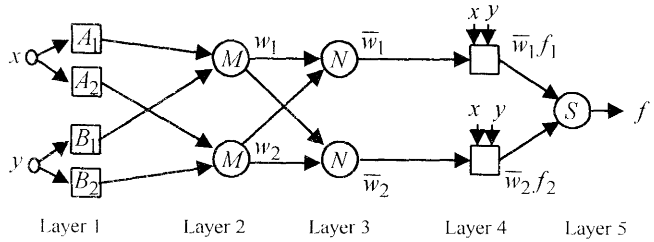

Fig. 5. Equivalent ANFIS architecture [11].

Clearly, the implementation of ANFIS is not unique. Some layers can be combined and still produce the same output. In this design of ANFIS, there are two adaptive layers (layers 1 and 4). Layer 1 has three modifiable parameters (a_i, b_i, and c_i) pertaining to the input fuzzy membership functions (MF). These parameters are called premise parameters (the if part of the rule). Layer 4 has also three modifiable parameters (p_i, q_i, and r_i) pertaining to the first order polynomial. These parameters are called consequent parameters (the then part of the rule).

The task of the training or learning algorithm for this architecture is to tune all the modifiable parameters to make the ANFIS output match the training data. Therefore, a hybrid learning algorithm using both least-squares method and backprobagation is used to identify the optimal values for the parameters p_i, q_i, and r_i. and for the parameters of the MF's if required. Detail of this algorithm is described in [11].

A Neuro-fuzzy solution to load forecasting for Riyadh

For Riyadh, unlike other cities, the seasonal effects are no longer the only major factor. For example a summer peak load can drastically change depending on when the vacation is scheduled. A decision system for load forecast requires detailed analysis of data and the rule base has to be fixed heuristically for each season. The rules fixed in this way do not always yield the best forecast. This necessitates the development of a robust forecasting technique to achieve a reliable forecast with improved overall accuracy.

The available data for Riyadh for the period (1980-1997) on a weekly basis are: actual power demands (*P)*, number of subscribers (*sub)*, minimum (*Tmin*) and maximum

($Tmax$) temperatures , and public holidays (*hol*). Religious events which are based on Hijri calendar are incorporated by an index, (*hindex*), that relates Hijri to Gregorian, and a binary code was used to flag a holiday or school day. All input and output data were re-scaled to lie in the range 0-1.

The number of MFs assigned to each input variable is chosen empirically, that is, by plotting the data sets and examining them visually, or simply by trial and error. For data sets with more than three inputs, visualization techniques are not very effective and most of the time the designer tends to rely on trial and error. This situation is similar to that of neural networks where there is just no simple way to determine in advance the minimal number of hidden units needed to achieve a desired performance level.

Input selection

To obtain accurate load forecasts, the most relevant factors should be determined and included in the model. By removing insignificant input variables, the resulting design is easier to interpret and implement. In addition, including unnecessary variables causes loss of resources and may lead to over-fitting.

In the literature, many techniques have been proposed for input selection. This includes CART [12], Automatic Relevance Detection (ARD) [13], and the δ -test [14] which determines dependencies within data in order to select relevant inputs. In this paper, a method that takes advantage of the ANFIS structure will be used. This method, which is described in [15], is based on the assumption that the ANFIS model with the smallest MSE after small number of epochs, has a greater potential of achieving a lower MSE when given more epochs of training. Hence, if there are ten candidate inputs and it is required to determine the three most influential three inputs, then we can construct ($C_3^{10} = 120$) ANFIS models and the model with the smallest Mean Square Error (MSE) is chosen.

Based on the result of [9] and to limit computational cost, seven candidate inputs were initially selected, namely: $P(k)$, $P(k-1)$, $sub(k)$, $T_{max}(k)$, $T_{min}(k)$, $hol(k)$, and $hindex(k)$, where k is the current year. The method of selection introduced for ANFIS in [15] is adopted here and repeated seven times. In each time, the MSE is calculated for all combinations of variables (for example: at the third time the combinations are $C_3^7 = 35$) and the minimum is recorded. The algorithm is run for one variable at a time then two variables at a time, until seven variables at a time. To investigate the effect of adding more inputs, one more variable ($P(k-2)$) is added. Figure 6 depicts the recorded values of the smallest MSE at each step. From Fig. 6 , one can conclude that a model with eight variables have very small improvement over a 7-input model. However, this slight increase in performance may not be favorable taking into account the large undesirable increase in complexity.

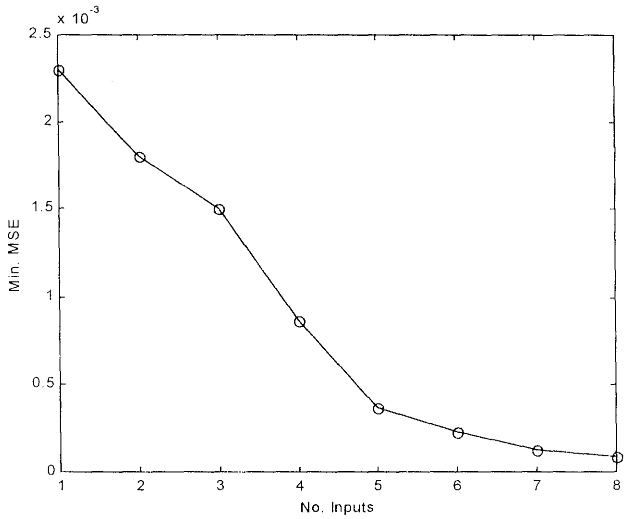

Fig. 6. Minima of MSEs for each number of inputs at a time for 1996.

The proposed structure is basically an ANFIS based neuro-fuzzy system that has seven inputs and one output as shown in Fig. 7. For a grid partition and using two MF's for each input, the number of rules becomes 128 rules. This fuzzy system forecasts the peak load at a particular week for one year lead. It can be re-tuned when any new information is available.

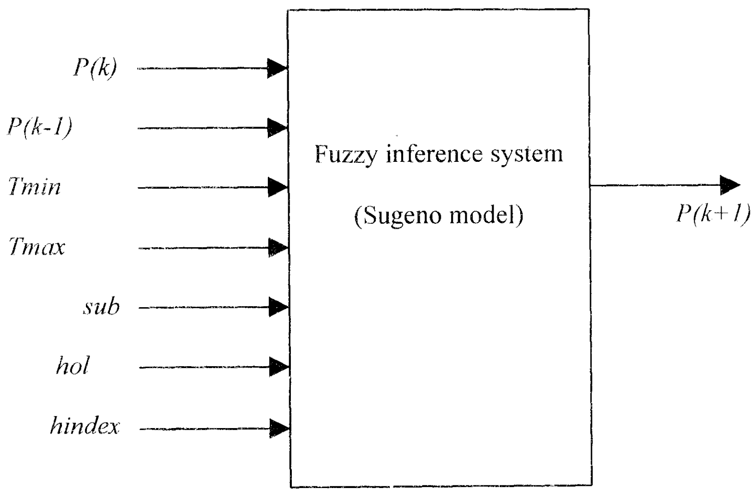

Fig. 7. A general structure of the fuzzy neural forecasting model.

Results

Using a seven input model described above with each input having two gaussian MF's, the ANFIS, which is readily available in neural net toolbox for Matlab® users, is trained with actual weekly peak loads for the period 1980-1995. The model is then tested for the years 1996 and 1997. Table 1 shows that using the suggested neuro-fuzzy approach resulted in a significant improvement in forecasting accuracy over traditional ARIMA(1,1,1) model and the results obtained from the neural networks based forecaster reported in [9]. A graphical comparison between the proposed approach, ARIMA model and the actual data for the years 1996 and 1997 is depicted in Figs. 8 and 9 respectively.

The Mean Square Error (MSE), Absolute Relative Error (ARE), and Root Mean Square Error (RMSE) reported in Table 1 are defined as follows:

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

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

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

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

Table 1. Forecasting errors for 1996 and 1997

Year	Method	MSE%	RAE%	RMSE%
	ARIMA	0.5609	6.6920	1.0744
1996	One-Net[9]	0.5286	4.7629	0.8223
	Three-Net[9]	0.2777	4.6526	0.7560
	Neuro-Fuzzy	0.0276	1.5183	0.2384
	ARIMA	0.7353	6.9352	1.2306
1997	One-Net[9]	0.6997	6.9321	1.2005
	Three-Net[9]	0.3937	5.5754	0.9005
	Neuro-Fuzzy	0.0869	2.6385	0.4230

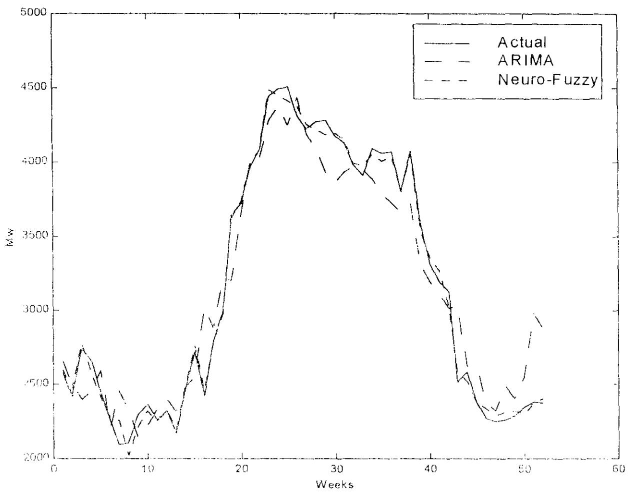

Fig. 8. Forecasting 1996 weekly peak loads for Riyadh.

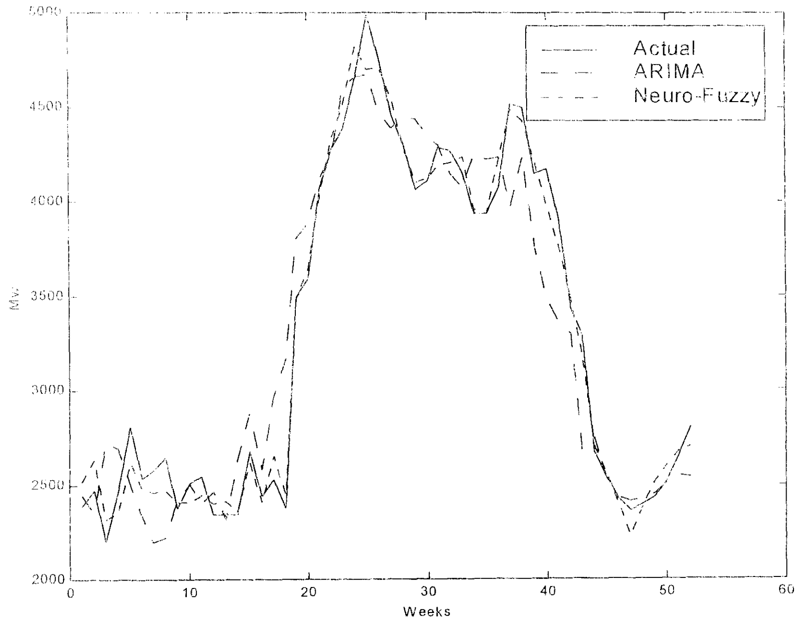

Fig. 9. Forecasting 1997 weekly peak loads for Riyadh.

Conclusion

A main concern in power distribution is the prediction of future electrical peak loads in order to plan the power generation optimally with minimum loss and cost. This paper introduces a neuro-fuzzy approach to predict peak loads for Riyadh city. Validity of this predictor is demonstrated by comparing the forecast obtained from this approach with corresponding ones produced by an established time series method, neural networks, and actual data. In such comparison, the prediction obtained by the proposed neuro-fuzzy methodology performs the best.

References

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

[2] Liu, K., Subbarayan, S., Shoults, R., Manry, M., Kwan, C., Lewis, F. and Naccarino, J. "Comparison of Very Short-term Load Forecasting Techniques." *IEEE Trans. on Power Systems*, vol. 100, pt.2 (1994), 1053-1062.

[3] Box, G and Jenkins, G. *Time Series Analysis Forecasting and Control*. San Francisco: Holden-day, 1976.

[4] 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.

[5] Peng, T.M., Hubele, N.F. and 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.

[6] Lamber-Torres,G., Silva L.E., Valiquette, B., Greiss, H. and 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.

[7] Kim K.H., Parl, J.K., Hwang, K.J. and 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.

[8] Dash, P.K., Liew, A. C. and Rahman, S. "Peak Load Forecasting Using a Fuzzy Neural Network." *Electric Power Systems Research*, 32 (1995) 19-23.

[9] Alturki, F. A. and Abdennour, A. "Medium to Long-term Peak Load Forecasting for Riyadh City Using Artificial Neural Networks." *Journal of King Saud University*, 12, {Engineering Sciences (No. 2)} (2000) 269-283.

[10] 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).

[11] Jang, J-S.R. and Sun, C-T. "Neuro-fuzzy Modeling and Control." *Proceedings of IEEE*, 83 (3) (1995) 378-406.

[12] Breiman, L., Friedman, J. H., Olshen, R. A. and Stone, C. J. *Classification and Regression Trees*. Belmont, California, U.S.A: Wadsworth, 1984.

[13] MacKay, D. J. C. "Bayesian Nonlinear Modeling for the Prediction Competition." *ASHRAE Trans.*, 100, pt. 2 (1994), 1053-1062.

[14] Ohlsson, M.B., Peterson, C.O., Pi, S., Rognvaldsson, T. and Soderbereg, B. P. "Predicting System Loads with Artificial Neural Networks", *ASHRAE Trans.*, 100, pt. 2 (1994) 1063-1074.

[15] Jang, J., Sun, C. and Mizutani, E. *Neuro-Fuzzy And Soft Computing: A Computational Approach to Learning and Machine Intelligence*. Prentice-Hall, 1997.

طريقة لتوقع الاحتياجات القصوى للطاقة الكهربائية باستخدام تقنية منطق الغموض و الشبكات العصبية

فهد بن عبدالله التركي

قسم الهندسة الكهربائية ، كلية الهندسة ، جامعة الملك سعود ، ص . ب [illegible]

الرياض ١١٤٢١ ، المملكة العربية السعودية

(قُدّم للنشر في ٢٠٠٠/٦/٣م، وقبل للنشر في ٢٠٠٠/١١/٧م)

ملخص البحث. إن التوقع الدقيق لاحتياجات الطاقة الكهربائية المستقبلية ييسّر بشكل كبير عملية إنتاج الطاقة الكهربائية وإدارتها على نحو اقتصادي و معتمد. تم في هذا البحث تبني تقنيات جديدة تتمثل في علمي منطق الغموض و الشبكات العصبية لتحسين دقة توقع الأحمال الكهربائية على المدى المتوسط/البعيد. جرت عملية التحقق من أداء الطريقة المقترحة باستخدام محاكاة لبعض البيانات الخاصة بنظام الطاقة الكهربائية بمدينة الرياض. تمت مقارنة هذه الطريقة بطرق المتسلسلات الزمنية و الشبكات العصبية. أظهرت نتائج هذا البحث تميز الطريقة المقترحة على الطرق الأخرى بإعطاء توقعات دقيقة جدًا للأحمال الكهربائية القصوى.