Comparison of Very Short-Term Load Forecasting Techniques

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Abstract -- **Three practical techniques -- Fuzzy Logic (FL), Neural Networks (NN), and Auto-regressive model (AR) -- for very short-term load forecasting have been proposed and discussed in this paper. Their performances are evaluated through a simulation study. The preliminary study shows that it is feasible to design a simple, satisfactory dynamic forecaster to predict the very short-term load trends on-line. FL and NN can be good candidates for this application.**

Keywords: AGC, load forecast, artificial intelligent

I. INTRODUCTION

The primary task of an area Automatic Generation Control (AGC) system in a multi-area interconnected power system is to (1) match area generation to area load, (2) regulate system frequency and area net interchange to their scheduled values, and (3) economically distribute area generation among available resources [4, 10, 14]. The primary response of generator governors to sudden load changes takes place within seconds following load upsets. This primary regulation satisfies the first objective but due to governor regulation factors (droop), the system frequency and net area interchange experience "quasi-steady-state" type errors. Thus, the Load Frequency Control (LFC) function in the Energy Management System (EMS) returns system frequency and area net interchange to their scheduled values within a few minutes, accomplishing the second objective. The third objective is accomplished by Economic Dispatch (ED).

LFC and ED methods presently in use are reactionary in their control response, *i.e.*, they respond only after load upsets occur or after actual frequency and/or area net interchange values drift significantly from their scheduled values. Present methods also require a high degree of tuning to operate satisfactory.

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Today's LFC is based on an instantaneous estimate of load demand via the so-called Area Control Error (ACE). However, due to the relatively fast area load demand fluctuations and the relatively slow area generation response rate, only the instantaneous estimate of load demand cannot provide us with the satisfactory performance. A look-ahead feature is needed if a more effective LFC is expected.

With the objective to improve current operating practices and reduce fuel costs, an advanced LFC project is currently under development that is a component of the EPRI sponsored Resource Scheduling and Generation Control (RSGC) project (RP3555-04). A key feature of this project is the development of a look-ahead capability for LFC and ED. This look-ahead feature requires very short-term load prediction on an ongoing basis. The idea is to predict the load 20 to 30 minutes ahead of real time (moving window) on intervals of 1 or 2 minutes. This load prediction will be dynamically dispatched to each available generator over the moving window of time. Thus, generation control will be accomplished based primarily on anticipated values rather than after-the-fact response.

Several researchers have been working on this topic for years. In [2] a linear extrapolation method using an auto-regressive model for load forecasting was suggested. In [1, 3, 5, 11-12] the short-term load forecasting using neural networks was proposed. All the researches mentioned above are concentrated on hourly system loads for next 24 hours. It is known that knowledge of load trends in the next 15-30 minutes can help in designing better LFC control strategies [2]. However, to our knowledge, no satisfactory technique has been reported for very short-term load forecasting thus far.

The balance of this paper contains a comparative study of three prediction techniques used to develop the very short-term load forecast. These three different techniques are based upon, respectively, (1) Fuzzy logic (FL), (2) Neural networks (NN), and (3) Auto-regressive model (AR).

II. LOAD FORECASTING VIA FL, NN, AND AR

The generation control process is fundamentally a tracking problem in which area generation must be controlled to match the time-varying area load and prearranged interchange transactions within an acceptable tolerance defined by system control performance criteria. Area load consists of two components: a slowly-varying component that has a fairly predictable pattern and a rapidly-varying random component of relatively small magnitude that can be ignored. In this section, several forecasting techniques, *i.e.*, fuzzy logic-based

(FL), neural network-based (NN), and auto-regressive model-based (AR) approaches, will be studied to predict the former underlying area load trends for each minute of a moving 30-minute forecast period resolution based on the previous 30 minutes metered data.

A. Load Forecasting via Fuzzy Logic

The possibility of using fuzzy logic approach in this research is based on the following observations:

(i) The very short-term load forecasting problem can be treated as a multiple-input-multiple-output unknown dynamic system. It is known that a fuzzy logic system with centroid defuzzification can identify and approximate any unknown nonlinear dynamic systems on the compact set to arbitrary accuracy [8, 16].

(ii) It is known that there is sort of periodic change in weekly load trends and there exist similarities in load trends between weekdays and weekdays, weekends and weekends, months and months, seasons and seasons, and so on. The fuzzy logic systems have been proved to have great capabilities in drawing similarities from a huge of data. Therefore, as long as enough historical input-output data pairs are available, the similarities exiting in load trends are able to be identified.

These observations provide the justification to use a fuzzy system as identifier and forecaster. However, how to implement this kind of forecaster, or in other words, how to identify the similarities or unknown dynamics, is still a question.

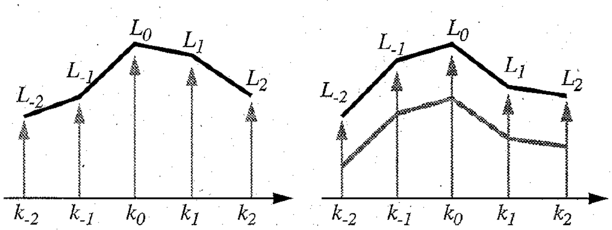

Figure 1: Load Patterns

The similarities can be identified by different patterns as shown in Figure 1. The input data (L_{-2} - L_0) for the left pattern and the right one have different first-order difference (V_k) and second-order difference (A_k), which are defined as

$$V_k = \frac{L_k - L_{k-1}}{T}, \quad A_k = \frac{V_k - V_{k-1}}{T} \tag{1}$$

respectively. They may generate different output data (L_1 - L_2) which possess different V_k and/or A_k. However, the two patterns on the right side of Figure 1 have the same V_k and A_k, they are expected to generate output data with the same V_k and A_k in the fuzzy sense. Therefore, totally $(m+n)$ V_i and $(m+n)$ A_i, i=k-(m-1), k-(m-2), ..., k-1, k, k+1, ..., k+(n-1), k+n, are used to define one load pattern as shown in Figure 2.

The proposed fuzzy logic-based forecaster works in two stages, that is, training and on-line forecasting. In training stage, the metered historical load data with a one-minute period resolution are first passed through a low-pass filter to

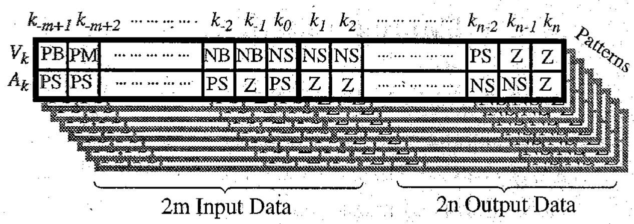

Figure 2: Structure of Pattern Database

filter out the rapidly-varying random component. The filtered data are then used to train a $2m$-input, $2n$-output fuzzy-logic-based forecaster to generate patterns database and a fuzzy rule base by using the first-order and second-order differences of the data. After enough training, it will be linked with a LFC controller to predict the load change on-line.

To generate the patterns database and the rules, appropriate fuzzy membership functions are first defined for input data and output data, respectively. Note the choice of different membership functions, *e.g.*, triangular, Gaussian, or trapezoidal, does not significantly affect the performance of the forecaster as long as they cover the whole work domain intervals. The number of regions in input domain and output domain is not necessarily identical. In this research, a simple triangular fuzzy membership functions are used [7, 17] and the number of regions in output data is selected as twice as the one in input domain.

As more and more input-output data pairs are put into the FL forecaster for training, more and more patterns will be recognized and stored into the database.

Once the patterns database has been built, it is ready to work. Each time when the input data (the previous $2m$ data, V_k and A_k, k=0, −1, ..., −(m-1), in crisp values) are put into the forecaster, they are first converted to fuzzy values via a fuzzifier, then compare with the patterns through the inference engine. If a most probably matching pattern with the highest possibility was found, then an output pattern will be generate through a centroid defuzzifier. Finally, the $2n$ output data, V_k and A_k, k=1, 2, ...,n, are used to predict the next n load data by

$$\hat{L}_{k+1} = \hat{L}_k + V_k T + \frac{1}{2} A_k T^2, \qquad k = 0, 1, \ldots, (n-1) \tag{2}$$

Figure 3 shows the structure of the proposed fuzzy logic-based forecaster.

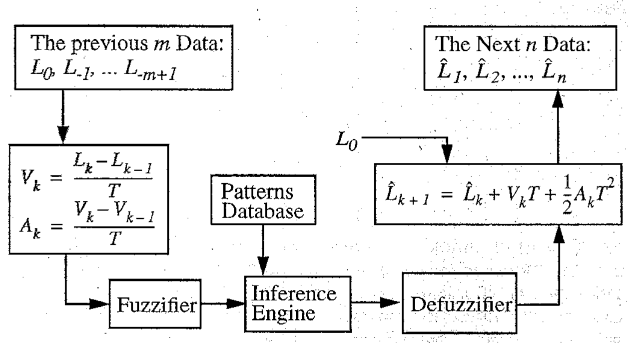

Figure 3: Structure of Fuzzy Logic-Based Forecaster

B. Load Forecasting via Neural Networks

The fuzzy-logic-based approach is not the only way to predict the very short-term load change, nor is it necessarily the best way for all purposes. A neural network-based very short-term load forecasting system was also developed in this research.

There are many types of neural networks (NN). For example, multilayer perceptron network, self-organizing network, Hopfield's recurrent network, and so on [6]. NN has been applied to time-series prediction and load forecasting for power systems [1, 3, 5, 11-12]. The previous work in this field used NN to predict the peak load of a day or the hourly load of a day. The performance of such applications is generally acceptable in terms of accuracy. However, there is no applications of NN to the very short-term load forecasting as we did in this research has been reported to our knowledge.

Neural network has many applications because of its capability to learn. The structure of a typical NN is shown in Figure 4. There are multiple hidden layers in the network. In each hidden layer there are many neurons. An individual artificial neuron, called a unit or perceptron, has the structure shown in Figure 4. Inputs come in from the left, are multiplied by weights ω_i, and are added to a threshold θ to form an inner product number called the net function. The net function, NET, is put through the activation function y, to produce the unit's final output, y(NET).

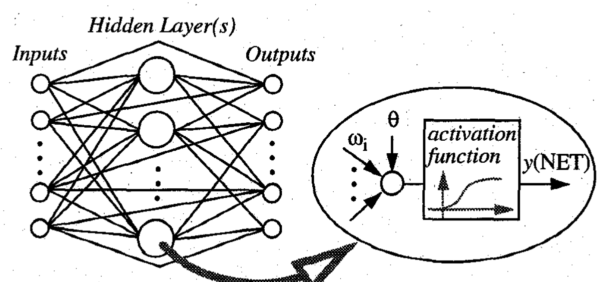

Figure 4: Structure of Multilayer Feedforward NN

The main advantage of NN approach is that no load model is required. The disadvantages of NN are that the training process is very time-consuming and there is no assurance of convergency.

In this research a fully-connected feed-forward type NN is used. In the multilayer perceptron, network outputs are linear functions of the weights which connect inputs and hidden units to output units. Therefore, linear equations can be solved for these output weights. In each iteration through the training data (epoch), the output weight optimization training method [9] uses conventional back-propagation to improve hidden unit weights (those feeding into hidden units) and then solves linear equations for the output weights. Because these equations are ill-conditioned, the conjugate gradient approach is used to solve them [13]. The inputs to the neural network at a given time, $t=kT$, are the past 30 minutes of load values (L_{k-29}, L_{k-28}, ..., L_{k-1}, L_k), along with four time components (τ_{1k}, τ_{2k}, τ_{3k}, τ_{4k}), and four load parameters (Net interchange deviation $NIDEV_k$, Frequency deviation $FREDEV_k$, Raw ACE $TACE_k$, and Filtered ACE $FACE_k$). The outputs of the neural network are 30 load values for the next 30 minutes ($\hat{L}_{k+1}$, $\hat{L}_{k+2}$, ..., $\hat{L}_{k+30}$).

The data was preprocessed for presentation to the network in such a manner so as to present the network with past history of load values and load parameters. The time component was presented by transforming the time values using sinusoidal transfer functions in order to avoid the nonlinearity when time changes from 24.00 hrs to 00.00hrs. The time components presented to the network are $\sin(2\pi kT/1440)$, $\cos(2\pi kT/1440)$, $[\sin(2\pi kT/1440)]^2$, and $[\cos(2\pi kT/1440)]^2$ where T=1 minute.

In order to reduce the data linearly dependence in training and to reduce the size of training data, the neural network output data ($\hat{L}_{k+1}$, $\hat{L}_{k+2}$, ..., $\hat{L}_{k+30}$) were first transformed to 16 output values ($L'(1)$, $L'(2)$, ..., $L'(16)$) using the discrete Karhunen-Loeve Transform (KLT) technique [15]. The transform coefficients were saved for re-transforming network's outputs to the actual loads ($\hat{L}_{k+1}$, $\hat{L}_{k+2}$, ..., $\hat{L}_{k+30}$) in MW.

C. Load Forecasting via Auto-regressive Model

If the present load is simply assumed to be a linear combination of the previous load, then an auto-regressive (AR) model of the form

$$\hat{L}_k = -\sum_{i=1}^{m} \alpha_{ik} L_{k-i} + \omega_k \tag{3}$$

can be used to model the load profile. In (3) $\hat{L}_k$ is the predicted system load at time k (in minutes), ω_k represents a random load disturbance, α_i, i = 1, ..., m are unknown coefficients. (3) is referred to as an AR model of order m.

The unknown coefficients in (3) can be tuned on-line using the well-known least mean square (LMS) algorithm. The advantages of this algorithm is that it is simple and easy to understand, no off-line training is necessary (no historical data base is needed), and easy to implement.

Assume the disturbance in (3) has zero mean, then the mean square prediction error can be expressed as

$$E\left[e_k^2\right] = \left(L_k + \sum_{i=1}^{m} \alpha_{ik} L_{k-i}\right)^2 \tag{4}$$

The objective of LMS algorithm is to minimize the mean square error (4). Define

$$\boldsymbol{a}_k = \left[\alpha_{1k}\ \alpha_{2k}\ \cdots\ \alpha_{mk}\right]^{\mathrm{T}} \text{ and } \boldsymbol{LM}_k = \left[L_{k-1}\ L_{k-2}\ \cdots\ L_{k-m}\right]^{\mathrm{T}}$$

it is not difficult to derive the update law for the unknown coefficient vector $\boldsymbol{a}_k$ [11]

$$\boldsymbol{a}_k = \boldsymbol{a}_{k-1} - 2\mu e_k \boldsymbol{LM}_{k-1} \tag{5}$$

where μ is a small positive constant.

It should be noted that the AR model can only predict one datum of the nearest future at a time. However, in the very short-term forecasting problem, one prediction makes no sense from practical point of view. To fulfill this need, the following strategy is adopted. Whenever a new prediction is generated, this datum is then treated as the most recent new actual load datum. Therefore the next prediction can be made using the previous (m-1) real data and the new-predicted-datum. This procedure will be repeated again and again until the next 30 data are finally generated.

One obvious problem with this method is that, due to the lack of actual load data, the prediction deteriorates when m>5. Another problem will occur when the real load data contain highly nonlinear components. Actually AR approach is a linear extrapolation technique, its success depends on the assumption that the present datum is a linear combination of the previous data. Since this assumption is invalid in most cases, a medium to large relative prediction error is expected by this approach.

III. SIMULATION STUDIES

To justify the discussions in Section II and compare the performances of different short-term load forecasting techniques, a simulation study has been carried out for a 24-hour area load trends forecasting. This study is done by using the metered data provided by TU Electric, Co. Historical data were first used to generate FL patterns database or to train NN. Then a typical 24-hour load change in Winter as shown in Figure 5 is compared with the forecasting outputs from FL and/or NN to evaluate their performances. The same data are also tested by using AR approach.

A. Fuzzy Logic Approach

From Figure 5 it can be seen that two crests of daily power trends occur at 7:00am-10:00am and 6:00pm-9:00pm, respectively, while two troughs occur around midnight and afternoon. The actual load trends are different day-by-day, but the "shape" of the daily load trends is similar to each other in the fuzzy sense. It is the similarity of the load "shape" that provides us with the possibility of predicting very short-term load changes using fuzzy logic approach.

Since there exist high-frequency noisy components in the metered load, a 24-hour historical data were first passed through a 20-minute-moving-window low-pass filter. Then the filtered data are put into the FL forecaster to automatically generate the patterns database and the rules. This procedure is referred to as training. After training, a set of previous 30 pre-filtered real data extracted from load profile as shown in Figure 5 were put into the fuzzy-logic-based forecaster as input data. These data generate a certain pattern which will be compared with the patterns already learned by the forecaster in the training procedure. If the forecaster found the most probably matching pattern with the highest possibility, an output pattern will generate 30 output data as a prediction of the next 30-minute period.

These procedures are repeated every minute to predict the area load trends for each minute of a moving 30-minute forecast period resolution. These forecasting data are stored and compared with the real load change (after filtering out the high-frequency noise) when the metered load data are available. Then the root of mean-square value (RMS) of the relative prediction errors are calculated to give the performance evaluation of the forecaster. A preliminary test lasting 1,000 minutes obtains a fairly good result as shown in Figure 6. Note that Figure 6 is obtained by calculating

$$\mathrm{RMS}_i = \sqrt{\frac{1}{30}\sum_{k=i}^{i+29}\left(\hat{L}_k - L_k\right)^2}, \quad i = 1, 2, \ldots, 1000 \qquad (6)$$

which represents the prediction error over each moving 30-minute forecast period. The RMS is remained within 1.0%. Figure 7(a) shows a sample of the actual pre-filtered load data and the predicted load data in the case of RMS≈0.1%.

B. Neural Network Approach

As in FL case, the historical load data for a 24 hour period were available for the neural network training. The data essentially consisted of the time, the load parameters ($NIDEV_k$, $FREDEV_k$, $TACE_k$, and $FACE_k$), and the actual load. The load data and load parameters were available for every 1 minute interval for a 24-hour period.

The NN used in this simulation study is a fully connected 4 layer network with 38 inputs (τ_{1k}, τ_{2k}, τ_{3k}, τ_{4k}, $NIDEV_k$, FRE-

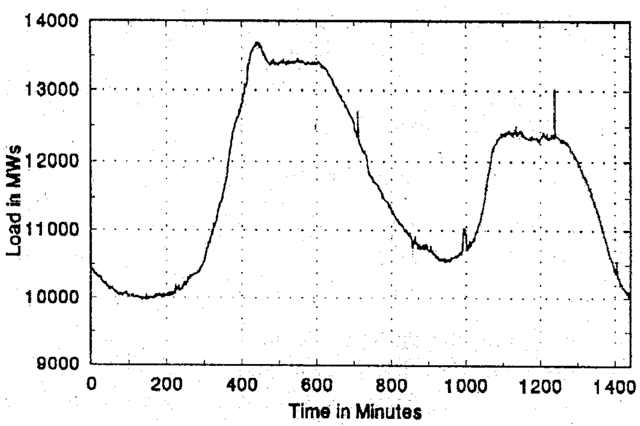

Figure 5: The Load Profile in 24 hours

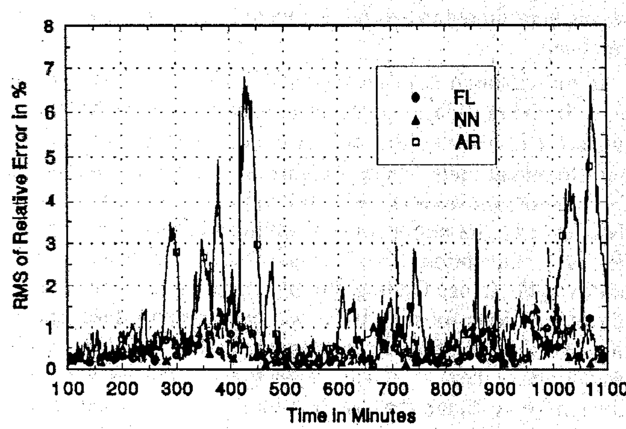

Figure 6: The RMS of Relative prediction Error

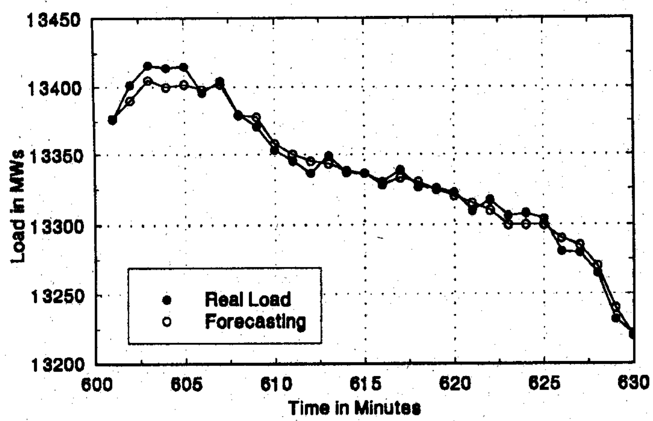

Figure 7(a): A Forecasting Sample via FL

DEV_k, $TACE_k$, and $FACE_k$, L_{k-29}, L_{k-28}, ..., L_{k-1}, L_k) and 16 outputs ($L'(1), L'(2), ..., L'(16)$). The 16 outputs are finally re-transformed using the KLT coefficients to 30 outputs (L_{k+1}, L_{k+2}, ..., L_{k+30}). The hidden layers had 30 and 25 units with sigmoidal activation functions.

The training parameters were set with initial learning rate of 0.001 and the training was stopped after 120 iterations with the RMS relative error around 1.5%. The averaged load data were used to generated 1379 patterns.

After the training, the NN-based forecaster is ready to predict the load change in the next 30 minutes using the previous 30-minute load data. Figure 6 shows the RMS and Figure 7(b) shows a forecasting sample in the case of RMS≈1.0%.

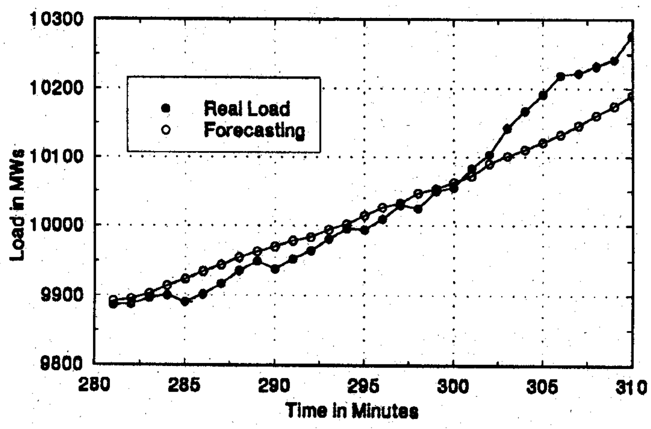

Figure 7(b): A Forecasting Sample via NN

Remarks:

(i) The low values for RMS errors from FL and NN are obtained based on the assumption that the metered load data are available in real time. In case that these data cannot be easily obtained, these errors may grow up to higher values. One possible strategy to deal with this problem is that repeating the predication very 5-10 minutes instead of very 1 minute if there is no enough metered data available.

(ii) The frequency of re-training process for FL and NN may depend on the performance of the forecaster. One possible strategy is that retraining FL or NN forecaster when the average RMS over 24-hour prediction period is higher than certain criterion, say 1%.

C. Auto-regressive Model Approach

Since AR approach does not require off-line training as in FL and NN cases, no historical data is needed in this method. This is probably the only advantage of AR over FL and NN. However, this advantage is gained at the cost of high prediction errors as shown in Figure 6. The RMS of relative error by user AR method is as high as 7%.

As discussed in Section II, AR approach is essentially a linear extrapolation technique. It cannot deal with highly nonlinear signals as in the area load trends case. Besides, the prediction errors are accumulated with the increasing of the number of prediction data. This point is clearly shown in Figure 7(c), in which the prediction via AR becomes seriously inaccurate after at most 5 minutes.

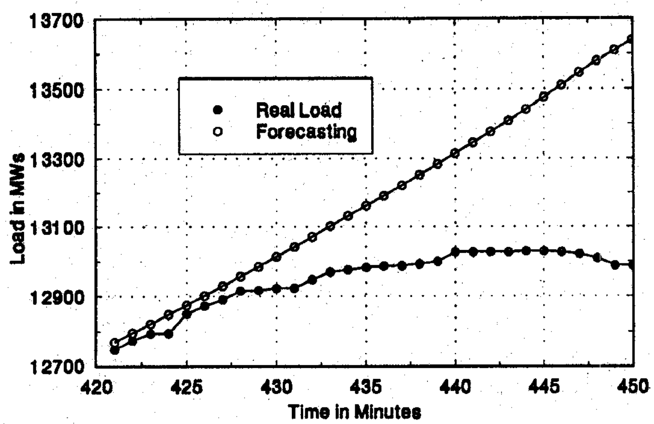

Figure 7(c): A Forecasting Sample via AR

IV. CONCLUSION

Three practical techniques for very short-term load forecasting have been proposed and discussed in this paper. Their performances are evaluated through a simulation study. The preliminary study shows that it is feasible to design a simple, satisfactory dynamic forecaster to predict the very short-term load trends on-line and FL and NN can be good candidates. The performances of FL-based and NN-based forecaster are much superior to the one of AR-based forecaster. In this research we only predict the next 30-minute data. Theoretically FL-based and NN-based forecasters can predict much longer than 30 data as long as enough historical data are available for training. On the other hand, AR-based forecaster does not require pre-training. However, its ability for forecasting only limits to a few data.

V. ACKNOWLEDGMENT

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VI. REFERENCES

[1] A. Asar and J.R. McDonald, "A Specification of Neural Network Applications in the Load Forecasting Problem," IEEE Trans. on Control Systems Technology, vol.2, no.2, 1994, pp.135-141.

[2] A.S.Debs, *Modern Power Systems Control and Operation*, Kluwer Academic Publishers, 1988.

[3] K.L. Ho, Y.Y. Hsu, and C.C. Yang, "Short Term Load Forecasting Using A Multilayer Neural Network with an Adaptive Learning Algorithm," IEEE Trans. on Power Systems, vol.7, no.1, 1992, pp.141-149.

[4] N. Jaleeli, L.S. VanSlyck, D.N. Ewart, H.F.Lester, and A.G. Hoffmann, "Understanding Automatic Generation Control," IEEE Transactions on Power Systems. 7(3), 1992, pp. 1106-1122.

[5] K.Y. Lee and J.H. Park, "Short-Term Load Forecasting Using An Artificial Neural Network," IEEE Trans. on Power Systems, vol.7, no.1, 1992, pp.124-132.

[6] F.L. Lewis, K.Liu, and A.Yesildirek, "Neural Net Robot Controller with Guaranteed Tracking Performance," IEEE Trans. on Neural Networks, vol.6, no.3, 1995, pp.703-715.

[7] K. Liu and F.L. Lewis, "Some Issues about Fuzzy Logic Control," Proc. 32nd IEEE Conference on Decision and Control, 1993, pp.1743-1748.

[8] K. Liu and I. H. Yu, "Adaptive Fuzzy Logic Approximation of Unknown Nonlinear Systems: State-Variable Feedback Tuning," Proc. 1994 American Control Conference, 1994, pp.190-194.

[9] M.T.Manry *et al.*,"Fast Training of Neural Networks for Remote Sensing," Remote Sensing Reviews, vol.9, 1994, pp. 77-96.

[10] NERC. 1992. *NERC Operating Guides, Guide I: Systems Control*. North American Electric Reliability Council.

[11] D.C. Park, M.A. El-Sharkawi, R.J. Marks II, L.E. Atlas, and M.J. Damborg, "Electric Load Forecasting Using An Artificial Neural Network," IEEE Trans. on Power Systems, vol. 6, no.2, 1991, pp. 442-449.

[12] T.M. Peng, N.F. Hubele, and G.G. Karady, "Advancement in the Application of Neural Networks for Short-Term Load Forecasting," IEEE Trans. on Power Systems, vol.7, no.1, 1992, pp. 250-257.

[13] W.H. Press *et al.*, *Numerical Recipes*, Cambridge University Press, New York, 1986.

[14] R.R. Shoults and J.A. Jativa, "Multi-Area Adaptive LFC Developed for a Comprehensive AGC Simulator," IEEE Transactions on Power Systems, vol.8, no.2, 1993.

[15] H.L.Van Trees, *Detection, Estimation, and Modulation Theory-Part I*, New York, NY: John Wiley and Sons, 1968.

[16] L.X. Wang, "Fuzzy Systems Are Universal Approximators," Proc. IEEE International Conf. on Fuzzy Systems, 1992, pp.1163-1170.

[17] H.J. Zimmerman, *Fuzzy Set Theory and its Applications*. Kluwer-Nijhoff Publishing, 1992.

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