ANNSTLF - Artificial Neural Network Short-Term Load Forecaster - Generation Three

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Abstract: This paper describes the third generation of an hourly short-term load forecasting system known as ANNSTLF (Artificial Neural Network Short-Term Load Forecaster). This forecaster has received wide acceptance by the electric utility industry and is being used by 35 utilities across the US and Canada. The third generation architecture is substantially changed from the previous generation. It includes only two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by adaptive combination of these two forecasts. The effect of humidity and wind speed are considered through a linear transformation of temperature. A novel weighted interpolation scheme is developed for forecasting of holiday loads, giving improved accuracy. The holiday peak load is first estimated and then the ANNSTLF forecast is re-shaped with the new peak forecast. The performance on data from ten different utilities is reported and compared to the previous generation.

Keywords: Load forecasting, artificial neural networks, adaptive neural networks, holiday forecasting.

I. INTRODUCTION

The quality of short term hourly load forecasts with lead times ranging from one hour to several days ahead has a significant impact on the efficiency of the operation of any electric utility since many potentially costly operational decisions such as economic scheduling of generating capacity, scheduling of fuel purchases, system security assessment, and planning for energy transactions are based on such forecasts. The importance of accurate load forecasts will increase in the future because of the dramatic changes occurring in the structure of the utility industry due to deregulation and competition. This environment compels the utilities to operate at the highest possible efficiency which, as indicated above, requires accurate load forecasts. Moreover, the advent of open access to transmission and distribution systems, calls for new actions such as posting the available transmission capacity (ATC) which will depend on the load forecasts.

In the deregulated environment, utilities are not the only entities that need load forecasts. Power marketers, load aggregators, and independent system operators (ISO) will all need to generate load forecasts as an integral part of their operation.

This paper describes the third generation of an artificial neural network (ANN) hourly load forecaster known as ANNSTLF (Artificial Neural Network Short-Term Load Forecaster). ANNSTLF, developed by Southern Methodist University and PRT, Inc. under the sponsorship of the Electric Power Research Institute (EPRI), has received wide acceptance by the electric utility industry and is presently being used by 35 utilities across the US and Canada. Such a large user base has provided a unique opportunity for this software to be tested and evaluated under a wide variety of operating conditions and scenarios. As a result, the forecasting engine has gone through three major changes based on analysis of performance and feedback from users. This paper describes the latest version (third generation) of the forecasting engine which has a new architecture and produces more accurate results.

The first implementation of ANNSTLF in an electric utility took place in 1992 at Texas Utilities Electric (TUE) Control Center in Dallas, Texas. Since then, the number of users has grown steadily and stands at 35 as of July 1997. Table 1 lists the names and locations of the present users. This implementation effort is supported by EPRI under a Tailored Collaboration project that enables the participants to obtain the software and receive maintenance and support.

The first generation forecasting engine remained in use until 1995, when it was replaced with the second generation. The process of installing the third generation engine at the users sites is presently in progress.

Application of the ANN technology to the load forecasting problem has received much attention in recent years [1], [2], [3], [4], [5], [7], [8], [9], [10], [11], [12], [13]. This is mainly due to the ability of ANNs to "learn" complex and non-linear relationships that are difficult to model with conventional techniques such as time series or regression analysis. This capability enables the

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TABLE I
ANNSTLF INSTALLATIONS AS OF JULY 1997

UTILITY	STATE
1. Alabama Electric Cooperative	Alabama
2. Allegheny Power System	Pennsylvania
3. BC Hydro	Canada
4. Bonneville Power Administration	Washington
5. Buckeye Power Inc.	Ohio
6. Central & Southwest Corp.	Texas
7. City Public Service of San Antonio	Texas
8. Detroit Edison	Michigan
9. Entergy	Louisiana
10. Houston Lighting and Power Company	Texas
11. Illinois Power Company	Illinois
12. Idaho Power	Idaho
13. Kansas City Power & Light	Kansas
14. Kentucky Utilities Company	Kentucky
15. Madison Gas & Electric	Wisconsin
16. Metropolitan Edison	Pennsylvania
17. Nevada Power Company	Nevada
18. New England Power Exchange	New England
19. North East Utilities	Connecticut
20. Northern Indiana Public Service Company	Indiana
21. Ottertail Power Company	Minnesota
22. PECO Energy	Pennsylvania
23. Pennsylvania Power & Light Company	Pennsylvania
24. Potomac Electric Power Company	Washington, DC
25. PJM Interconnection	Pennsylvania
26. Public Service Electric & Gas	New Jersey
27. Rochester Gas & Electric	New York
28. Salt River Project	Arizona
29. San Diego Gas & Electric	California
30. Southern California Edison	California
31. Southern Company Services	Alabama
32. Tennessee Valley Authority	Tennessee
33. Texas Utilities Electric	Texas
34. Western Area Power Administration	California
35. Wisconsin Power & Light	Wisconsin

ANN-based system to model the correlations between the load and such factors as climatic conditions, past usage pattern, the day of the week, and the time of the day, from historical load and weather data. Among the ANN-based load forecasters discussed in published literature, ANNSTLF is the only one that is implemented at several sites and thoroughly tested under various real-world conditions.

A multi-ANN strategy has been followed in development of all three generations of ANNSTLF. While the first and second generation engines used 38, and 24 ANNs, respectively, in the third generation the number of ANNs is reduced to just two with improved accuracy. Additionally in the generation three engine, a novel algorithm for holidays and special days is used. Another major change is in the approach to model the effect of the secondary, i.e. other than temperature, weather variables. In the first and second generation, only relative humidity could be considered whereas in the new model the impact of wind speed could also be taken into account.

A noteworthy aspect of ANNSTLF is that a single architecture with the same input-output structure is used for modeling hourly loads of various size utilities in different regions of the country. The only customization required is the determination of some parameters of the ANN models. No other aspects of the models need to be altered.

II. KEY FEATURES OF ANNSTLF

Before discussing technical details, several key features of ANNSTLF are listed below so that its overall function can be put in perspective.

- The package runs on an IBM compatible PC under the MS-DOS, MS-Windows 3.1, 95 and NT operating systems;
- ANNSTLF has an extensive Windows-based graphical user interface with several data management, performance analysis, and plotting tools;
- Two to three years of historical hourly load and weather data is required to train the package;
- On-line operation requires actual hourly load and weather data of the previous day and hourly weather forecasts for future days;
- If hourly weather forecasts are unavailable, they can be generated within the package using the predicted daily high and low values of weather parameters [6];
- Hourly load forecasts for up to 35 days ahead can be generated;
- Forecasts can be updated on an hourly basis with the most recent load and weather data;
- Forecasts can be modified and re-shaped by the user;
- Data quality is checked using data validation filters with user defined sensitivities;
- A wide range of performance tracking and error analysis routines enable the user to examine load and weather forecast accuracy on both daily and hourly basis, locate instances of maximum deviation, and compare forecasts with different lead times;
- ANNSTLF includes an automatic back-up feature that allows it to recover from the effects of inaccurate data input;
- Several regions within a service area can be defined with separate forecasters for each region;

Most of these features were developed based on feedback and suggestions provided by ANNSTLF users. These tools make the package quite user friendly, and easy to work with and maintain.

III. THE BUILDING BLOCK ANN

The workhorse of all generations of the ANNSTLF forecasting engine is the multi-layer feed-forward ANN also known as a multi-layer perceptron (MLP) network, shown in Fig. 1. An MLP consists of n input nodes, h hidden layer nodes, and m output nodes connected in a feed-forward fashion via multiplicative weights, W_{ij}. Inputs (X_i) are multiplied by the connection weights (W_{ij}) and passed on to the neurons in the hidden layer nodes. Neurons in the hidden and output layers have an S-shaped nonlinear transfer function known as the "sigmoid activation function," $f(z)=\frac{1}{1+e^{-z}}$. The weighted inputs received by a sigmoid node are summed and passed through this non-linear function to produce an output.

For hidden layer nodes, the output is:

$$H_j = \frac{1}{1+exp(-\sum_{i=1}^{n} W_{ij} X_i)} \tag{1}$$

where H_j is the output of the jth hidden layer node, $j = 1, \ldots, h$, and X_i represents the ith input connected to this hidden node via W_{ij} with $i = 1, \ldots, n$.

The output of the kth output node is given by

$$Y_k = \frac{1}{1+exp(-\sum_{j=1}^{h} W_{jk} H_j)} \tag{2}$$

where Y_k is the output of the kth output layer node with $k = h+1, \ldots, m$, and W_{jk} representing connection weights from hidden to output layer nodes.

Although the MLP is one of the most fundamental and by now a classic model, it has by far been the most favorite type of ANN architecture for practical applications. We have investigated the use of several other kinds of ANNs such as recurrent ANNs and radial basis function ANNs but did not discover any major advantage over the MLP topology for the load forecasting problem.

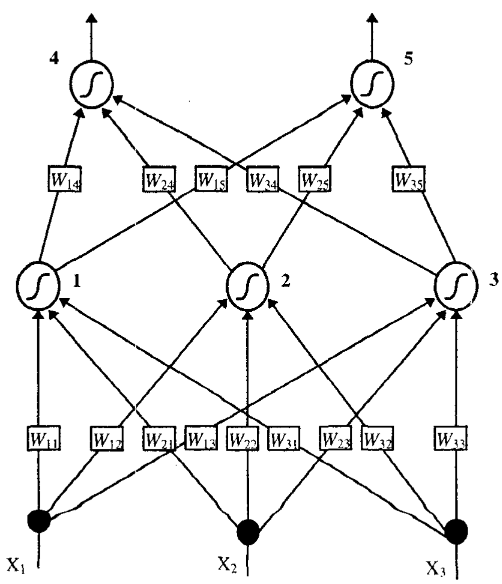

Fig. 1. An MLP with 3 input, 3 hidden and 2 output nodes

A. Error Back-Propagation Learning Rule

The MLP must be trained with historical data to find the appropriate values for W_{ij} and the number of required neurons in the hidden layer. The learning algorithm employed is the well-known error back-propagation (BP) rule [15]. In BP, learning takes place by adjusting W_{ij}. The output produced by the ANN in response to inputs are repeatedly compared with the correct answer. Each time the W_{ij} values are adjusted slightly in the direction of the correct answers by backpropagating the error at the output layer through the ANN according to a gradient descent algorithm.

To avoid over-training, the cross-validation method is used. The training set is divided into two sets. For instance, if three years of data is available, it is divided into a two-year and a one-year set. The first set is used to train the MLP and the second set is used to test the trained model after every few hundred passes over the training data. The error on the validation set is examined. Typically this error decreases as the number of passes over the training set is increased until the ANN is over-trained, as signified by a rise in this error. Therefore, the training is stopped when the error on the validation set starts to increase. This procedure yields the appropriate number of epochs over the training set. The entire three years of data is then used to re-train the MLP using this number of epochs.

The required number of hidden layer nodes is determined using a similar approach. By examining the error over a validation set for a varying number of hidden layer nodes, an architecture yielding the smallest error is selected. It has been our experience that this is not a critical parameter as long as the number of hidden layer nodes is in the 30 to 60 range.

B. Adaptive Update of the Weights During On-Line Forecasting

A unique aspect of the BP MLP use in ANNSTLF is the adaptive update of the weights during on-line operation. In a typical usage of an MLP, it is trained with the historical data and the weights of the trained MLP are then treated as fixed parameters. This is an acceptable procedure for many applications. However, since load is a non-stationary process and can go through rapid changes due to weather swings or seasonal changes, a tracking mechanism with sensitivity to the recent trends in the load can aid in producing better results. Another factor to be considered is the load growth. Typically, utilities experience annual load growths that increase their loads. A static training with historical data will have difficulty accounting for this gradual load growth.

To overcome these problems, we have developed an adaptive weight adjustment strategy that takes place during on-line operation. The ANN is initially trained using the BP algorithm; however, the trained weights are not treated as static parameters. During on-line operation, these weights are adaptively updated on a daily basis. The updating task relies on the availability of the actual hourly values of the load and weather parameters of the past few days. In most utilities this information is available from their energy management system (EMS). Before forecasting the next day's load, ANNSTLF is run again in a back-cast mode to re-generate load forecasts for the past few days using actual weather parameters. Based on these load forecasts and the knowledge of actual loads corresponding to them, a small scale error BP operation is performed involving only this small data set. This mini-training with the most recent data results in a slight adjustment of the weights and biases them toward the recent trend in data.

IV. ARCHITECTURE OF THE FIRST AND SECOND GENERATIONS

The ANNSTLF's first generation load forecasting engine consisted of 38 separate MLPs grouped into three weekly, daily, and hourly modules [7]. Each module was used to model the respective trend of the load data and generate its own load forecasts. In the next stage, these three load forecasts were adaptively combined to arrive at the final forecast. The block diagram of this system is shown in Fig. 2.

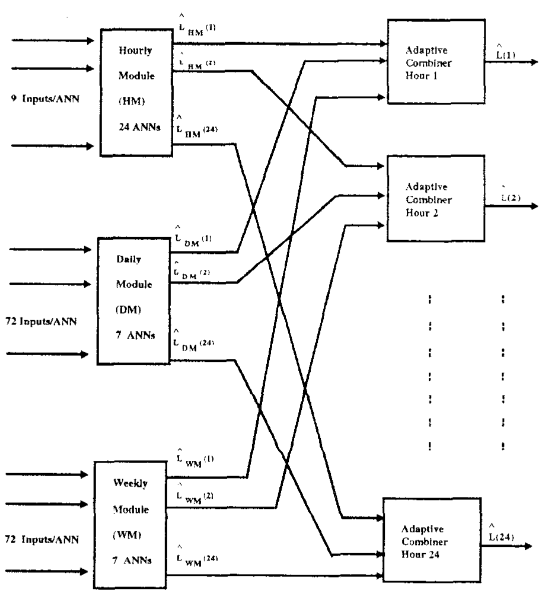

Fig. 2. The first generation load forecasting engine of ANNSTLF

This forecaster was implemented at over twenty utilities in a three year period form 1992 until 1995. Although the performance was superior to the other forecasting algorithms, analysis of results indicated that the performance of the engine can be improved by eliminating the redundancy that was present in inputs of the three utilized modules. This led to the development of the second generation engine [5] whose block diagram is shown in Fig. 3.

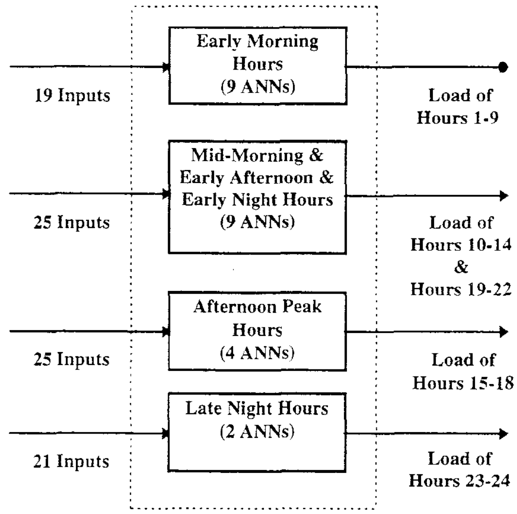

Fig. 3. The second generation load forecasting engine of ANNSTLF

In the second generation engine, the number of ANNs were reduced to 24, one for each hour of the day. The hours of the day were categorized into four groups as follows:

1. Early morning (hours one to nine)
2. Mid-morning, early afternoon, and early night (hours ten to fourteen and nineteen to twenty-two)
3. Afternoon peak (hours fifteen to eighteen)
4. Late night (hours twenty-three and twenty-four)

Different number of inputs consisting of past loads, past weather, and weather forecasts were used for the ANNs of each category resulting in 19,25,25, and 21 inputs for the ANNs of category one to four, respectively. Extensive analysis indicated that the second generation engine outperforms the first generation. Starting in 1995, ANNSTLF users were provided with this upgraded engine.

One of the drawbacks of the first and second generations engines was their slow response to rapid changes in the load caused by the warm or cold weather fronts. Although the adaptive mechanism of the models enables them to track load changes, it might take longer than desired before these models track a rapidly increasing load.

Another issue concerned holidays and special days with unusual load profiles. These days presented a problem to these models. Such days were treated as weekends by both generations, but the forecasts were not as accurate as the other days.

Lastly, the impracticability of re-training the models on site on a PC platform was a concern to the users. After a few years, the models need to be retrained for better accuracy, but the large number of ANNs used in the first two generations would make it difficult to carry out this task.

To address these issues, as well as to respond to the ever present desire to increase the accuracy, the third generation engine discussed in the next section was developed.

V. THIRD GENERATION ANNSTLF

The third generation ANNSTLF consists of three modules, two ANN load forecasters and an adaptive combiner. Both load forecasters receive the same set of inputs and produce a load forecast for the same day, but they utilize different strategies to do so. The function of the combiner module is to mix the two forecasts to generate the final forecast.

Both of the ANN load forecasters have the same topology consisting of 79 inputs and 24 outputs. These inputs are:

- 24 hourly loads of the previous day (previous day is denoted by k), $L_k(1)$, $L_k(2)$, …, $L_k(24)$
- 24 hourly weather parameters of the previous day (temperatures or effective temperatures as discussed later), $T\_eff_k(1)$, $T\_eff_k(2)$, …, $T\_eff_k(24)$
- 24 hourly weather parameters forecasts for the coming day, $\hat{T}\_eff_{k+1}(1)$, $\hat{T}\_eff_{k+1}(2)$, …, $\hat{T}\_eff_{k+1}(24)$
- 7 day type indicators for each day of the week

The difference between the two ANNs is in their outputs. The first forecaster is trained to predict the regular (base) load of the next day, i.e. the 24 outputs are the forecasts of the hourly loads of the next day. This ANN will be referred to as the "Base Load Forecaster (BLF)." On the other hand, the second ANN forecaster predicts the *change* in hourly load from yesterday to today. This forecaster is named "Change Load Forecaster (CLF)." Hence, the outputs of the two forecasters are:

- BLF: $\hat{L}^B_{k+1}(1)$, $\hat{L}^B_{k+1}(2)$, …, $\hat{L}^B_{k+1}(24)$

  (superscript B represents BLF, and ^ indicates forecast)

- CLF: $\Delta\hat{L}^C_{k+1}(1)$, $\Delta\hat{L}^C_{k+1}(2)$, …, $\Delta\hat{L}^C_{k+1}(24)$

  (superscript C represents the CLF module).

where $\Delta\hat{L}^C_{k+1}(i)$ is the change in the i-th hour load from day k to day $k+1$, i.e. from previous day to today.

To get the CLF load forecast, the outputs of the CLF module are added to the load of yesterday,

$$\hat{L}^C_{k+1}(i) = \Delta\hat{L}^C_{k+1}(i) + L_k(i) \qquad i = 1, \cdots, 24 \qquad (3)$$

The two ANN forecasters complement each other because the BLF emphasizes regular load patterns whereas the CLF puts stronger emphasis on yesterday's load. Combining these two separate forecasts results in improved accuracy. This is especially true for cases of sudden load change caused by weather fronts. The BLF has a tendency to respond slowly to rapid changes in load. On the other hand, since the CLF takes yesterday's load as the basis and predicts the changes in that load, it has a faster response to a changing situation. This point is illustrated in Fig. 4 for a five day period in August, 1995 when a strong heat wave hit the service area of a utility in the South, creating an all time peak demand. The BLF and CLF forecasts are superimposed on this graph. On the first day, both forecasters under-predict the load. However, from the second day on, the CLF forecasts catch up with the large load demand whereas the BLF model still under-predicts. When the heat wave starts to subside on the fifth day (8/17/95), the CLF module tends to over-forecast since it is basing its prediction on the high load of the previous day, but the BLF forecast is back on track for this day. This example is a good illustration of the complementary nature of these two forecasters.

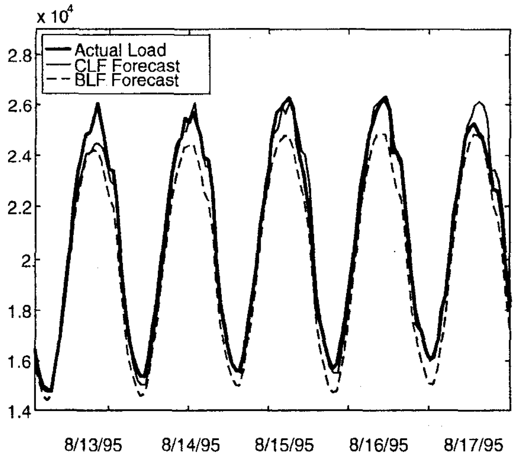

Fig. 4. An example of the performance of the BLF and CLF forecasters during an all-time peak demand.

To take advantage of the complimentary performance of the two modules, their forecasts are adaptively combined using the recursive least squares (RLS) algorithm [14]. The final forecast for each hour is obtained by a linear combination of the BLF and CLF forecasts as:

$$\hat{L}_{k+1}(i) = \alpha_B(i)\hat{L}^B_{k+1}(i) + \alpha_C(i)\hat{L}^C_{k+1}(i), \quad i = 1, \ldots, 24 \qquad (4)$$

The $\alpha_B(i)$ and $\alpha_C(i)$ coefficients are computed using the RLS algorithm. This algorithm produces coefficients that minimize the weighted sum of squared errors of the past forecasts denoted by J,

$$J = \sum_{k=1}^{N} \beta^{N-k} \left[L_k(i) - \hat{L}_k(i) \right]^2 \qquad (5)$$

where $L_k(i)$ is the actual load at hour i, N is the number of previous days for which load forecasts have been made, and β is a weighting factor in the range of $0 < \beta \leq 1$ whose effect is to de-emphasize (forget) old data.

The block diagram of the overall system is shown in Fig. 5.

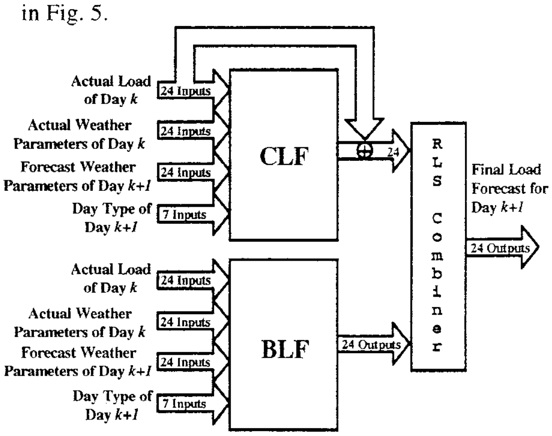

Fig. 5. Block diagram of the third generation ANNSTLF

VI. HUMIDITY AND WIND SPEED

Although temperature (T) is the primary weather variable affecting the load, other weather parameters such as relative humidity (H) and wind speed (W), also have a noticeable impact on the load. In the first and second generation ANNSTLF, impact of relative humidity was taken into account through direct input of this data into the ANN models. The effect of wind speed was not considered in the previous generations.

In the third generation model, the effect of both relative humidity and wind speed are taken into account indirectly through transforming the temperature value into an effective temperature, *T_eff*. We investigated the use of several non-linear combinations of these weather variables with temperature, e.g. *THI*, wind chill, etc. However, we found that the accuracy can only be slightly improved using such indices. On the other hand, a linear combination used here produce better results. Consequently, the following relationship is used to compute *T_eff*,

$$T\_eff = \begin{cases} T + \alpha * H & T > 75^\circ \\ T & 65^\circ \leq T \leq 75^\circ \\ T - \dfrac{W * (65^\circ - T)}{100} & T < 65^\circ \end{cases} \qquad (6)$$

Note that humidity is used for temperatures above 75° whereas windspeed influence is considered for temperatures below 65°.

VII. HOLIDAYS AND SPECIAL DAYS

Holidays and special days pose a challenge to any load forecasting program since the load of these days can be quite different from a regular workday. The difficulty is the small number of holidays in the historical data compared to the typical days. For instance, there would be three instances of the Christmas Day in a training set of three years. The unusual behavior of the load for these days cannot be learned adequately by the ANNs since they are not shown many instances of these days.

In the first and second generation ANNSTLF, holidays were treated as either a Saturday or a Sunday, depending on whether shopping centers are open or close on that day. The analysis of the results indicated that the error of holiday forecasts is considerably larger than regular days. Consequently, a new strategy was developed for the third generation. It was observed that in most cases, the profile of the load forecast generated by the ANNs using the concept of designating the holiday as a weekend day, does resemble the actual load. However, there usually is a significant error in predicting the peak load of the day. The ANNSTLF package includes a function that enables the user to re-shape the forecast of the entire day if the peak load forecast is changed by the user. Thus, the emphasis is placed on producing a better peak load forecast for holidays and re-shaping the entire day's forecast based on it.

The holiday peak forecasting algorithm uses a novel weighted interpolation scheme. This algorithm will be referred to as "Reza Algorithm" after the author who has developed it. The general idea behind the Reza algorithm is to first find the "close" holidays to the upcoming one in the historical data. The closeness criteria is the temperature at the peak-load hour. Then, the peak load of the upcoming holiday is computed by a novel weighted interpolation function described in the following.

The idea is best illustrated by an example. Let us assume that there are only three holidays in the historical data. The peak loads are first adjusted for any possible load growths. Let (t_i, p_i) designate the i-th peak-load hour temperature and peak load, respectively. Fig. 6 shows the plot of p_i vs. t_i for an example case.

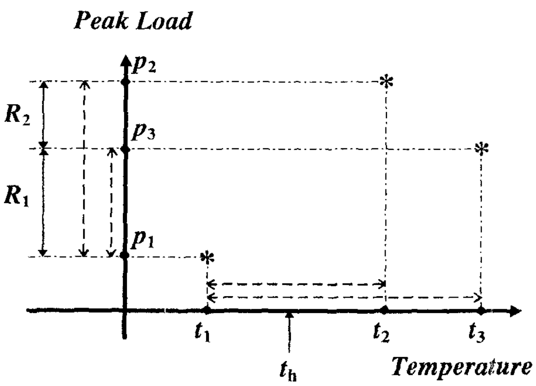

Fig. 6. Example of peak load vs. temperature at peak load for a three - holiday database.

Now assume that t_h represents the peak-load hour temperature of the upcoming holiday. t_h falls in between t_1 and t_2 with the implication that the corresponding peak load, p_h, would possibly lie in the range of $[p_1, p_2]=R_1+R_2$. But, at the same time, t_h is also between t_1 and t_3 implying that p_h would lie in $[p_1, p_3]=R_1$. Based on this logic, p_h can lie in either R_1 or R_1+R_2. However, note that R_1 is common in both ranges. The idea is to give twice as much weight to the R_1 range for estimating p_h since this range appears twice in pair-wise selection of the historical data points.

The next step is to estimate p_h for each non-overlapping interval, R_1 and R_2, on the y axis, i.e., $[p_1, p_3]$ and $[p_3, p_2]$.

For $R_1=[p_1, p_3]$ interval :

$$\hat{p}_{h1} = \frac{p_3 - p_1}{t_3 - t_1} * \left(t_h - t_1\right) + p_1 \qquad (7)$$

For $R_2=[p_3, p_2]$ interval:

$$\hat{p}_{h2} = \frac{p_2 - p_3}{t_2 - t_3} * \left(t_h - t_3\right) + p_3 \qquad (8)$$

If any of the above interpolation results in a value that falls outside the respective range, R_i, the closest p_i, i.e. maximum or minimum of the interval, is used instead.

The final estimate of p_h is a weighted average of $\hat{p}_{h1}$ and $\hat{p}_{h2}$ with the weights decided by the number of overlaps that each pair-wise selection of historical datapoints creates. In this case, since R_1 is visited twice, it receives a weighting of 2 whereas the interval R_2 only gets a weighting coefficient of one.

$$\hat{p}_h = \frac{w_1 * \hat{p}_{h1} + w_2 * \hat{p}_{h2}}{w_1 + w_2} = \frac{2 * \hat{p}_{h1} + 1 * \hat{p}_{h2}}{2+1} \qquad (9)$$

This algorithm can be generalized as follows:

Step 1: Select "close" historical points using $|t_h - t_i| < \varepsilon$ criterion, with ε being a small value selected by the user.

Step 2: Select all possible pairs of t_is such that $t_i < t_h < t_j$ and note the corresponding ranges $[p_i, p_j]$.

Step 3: Sort p_js from smallest to largest.

Step 4: Compute the number of times each subinterval $[p_j, p_{j+1}]$ is visited when all the pair-wise selections in step 2 are considered. p_j and p_{j+1} refer to two consecutive peak loads in the sorted list. Denote this number by w_j.

Step 5: Using linear interpolation, compute the estimated p_h for each sub-interval $[p_j, p_{j+1}]$, and denote it by $\hat{p}_{hj}$.

Step 6: if $\hat{p}_{hj} > \max(R_j)$ then $\hat{p}_{hj} = \max(R_j)$

if $\hat{p}_{hj} < \min(R_j)$ then $\hat{p}_{hj} = \min(R_j)$

Step 7: Final peak forecast, $\hat{p}_h$, is obtained by combining $\hat{p}_{hj}$s computed in step 5 using:

$$\hat{p}_h = \frac{\sum_j w_j * \hat{p}_{hj}}{\sum_j w_j} \qquad (10)$$

Before applying Reza algorithm, if there are more than one p_j associated with one t_j, their average is used as a single p_j instead.

The performance of this algorithm is tested on holiday data from five different utilities for a period of one year. The results are shown in Table 2 in terms of mean absolute percentage error (MAPE) defined as:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} \frac{|Actual(i) - Forecast(i)|}{Actual(i)} \qquad (11)$$

with N being the number of observations.

TABLE 2
MAPE OF HOLIDAY FORECASTS

		Utilities					
	Generation	**1**	**2**	**3**	**4**	**5**	**Avg.**
All Hours	**Three**	4.40	5.42	5.29	4.62	9.68	**5.88**
	Two	5.62	6.89	5.21	5.57	10.07	**6.67**
Peak Load	**Three**	6.33	5.59	6.27	7.75	9.17	**7.02**
	Two	8.85	10.18	6.84	9.50	10.15	**9.10**

It can be seen that using Reza algorithm results in significant improvement in holiday forecasting.

In Fig. 7, a pictorial example of the performance of the algorithm for one holiday is presented. Again note that using this algorithm, the third generation forecast is much closer to the actual load.

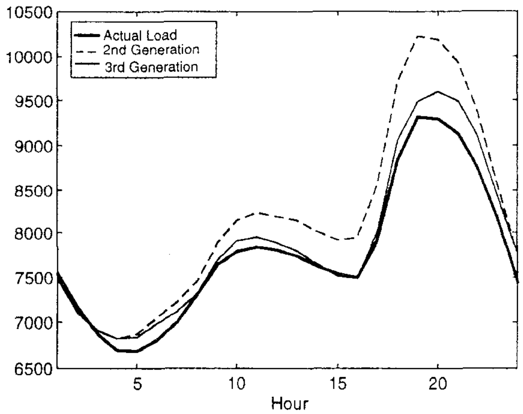

Fig. 7. An example of the holiday forecasting performance of the third generation ANNSTLF using Reza algorithm

VIII. PERFORMANCE

The performance of the third generation ANNSTLF is tested on real data from ten different utilities in various geographical regions. Information about the approximate location of these utilities and the length of the testing period are provided in Table 3.

TABLE 3
THIRD GENERATION ANNSTLF STUDY, UTILITY INFORMATION

Utility	No. Days in Testing Period	Weather Variable	Location
1	141	T	Canada
2	131	T	South
3	365	T,H,W	North East
4	365	T	East Coast
5	134	T	Mid West
6	365	T	West Coast
7	365	T,H	Southwest
8	365	T,H	South
9	174	T	North
10	275	T,W	Midwest

In all cases, three years of historical data is used to train ANNSTLF. Actual weather data is used so that the effect of weather forecast errors do not alter the modeling error. The testing is performed in a blind fashion meaning that the test data is completely independent from the training set and is not shown to the model during its training.

One-to-seven-day-ahead forecasts are generated for each test set. To extend the forecast horizon beyond one day ahead, the forecast load of the previous day is used in place of the actual load to obtain the next day's load forecast.

The forecasting results are presented in Tables 4 and 5, in terms of MAPE. The forecasting error for all hours of the day is considered in Table 4. The error in the daily peak load forecast is presented in Table 5. The results are also compared to the performance of the second generation ANNSTLF.

Note that the average MAPEs over ten utilities as reported in the next to last rows of Table 4 and 5 indicate that the third generation engine is quite accurate in forecasting both hourly and peak loads. In the case of hourly load, this average remains below 3 percent for entire forecast horizon of seven days ahead and for the peak load it reaches 3 percent on the seventh day. Also, the percentage of accuracy improvement over second generation reported in the

TABLE 4
COMPARISON OF SECOND AND THIRD GENERATION ANNSTLF FORECAST ERRORS, MAPE OF ALL HOURS

		Days-Ahead						
Utility	ANNSTLF Generation	1	2	3	4	5	6	7
1	Three	1.91	2.29	2.53	2.71	2.87	3.03	3.15
	Two	2.11	2.61	2.96	3.26	3.52	3.76	4.25
2	Three	2.72	3.44	3.63	3.77	3.79	3.83	3.80
	Two	2.94	3.57	3.78	3.89	3.99	4.07	4.33
3	Three	1.89	2.25	2.38	2.45	2.53	2.58	2.65
	Two	1.95	2.45	2.66	2.76	2.93	3.04	3.38
4	Three	2.02	2.37	2.51	2.58	2.61	2.65	2.69
	Two	2.86	3.76	4.10	4.32	4.46	4.59	4.94
5	Three	1.97	2.38	2.61	2.66	2.65	2.65	2.74
	Two	2.06	2.38	2.58	2.73	2.84	2.96	3.36
6	Three	1.57	1.86	1.99	2.08	2.14	2.17	2.18
	Two	2.04	2.57	2.79	2.97	3.10	3.23	3.61
7	Three	2.29	2.79	2.90	3.00	3.05	3.10	3.18
	Two	2.39	2.98	3.22	3.38	3.51	3.61	4.00
8	Three	2.22	2.91	3.15	3.28	3.39	3.45	3.50
	Two	2.04	2.57	2.79	2.97	3.10	3.23	3.61
9	Three	1.63	2.04	2.20	2.32	2.40	2.41	2.50
	Two	1.82	2.28	2.50	2.69	2.87	3.06	3.48
10	Three	2.32	2.97	3.25	3.38	3.44	3.52	3.56
	Two	2.40	3.09	3.38	3.60	3.77	3.92	4.25
AVERAGE	Three	**2.05**	**2.53**	**2.72**	**2.82**	**2.89**	**2.94**	**2.99**
	Two	**2.26**	**2.83**	**3.08**	**3.26**	**3.41**	**3.55**	**3.92**
Accuracy Improvement (%)		9	11	12	14	15	17	24

last rows of Tables 4 and 5 indicates that the third generation engine produces significantly better forecasts.

Fig. 8 is a plot of one-to-seven-day-ahead load forecasts for utility 2.

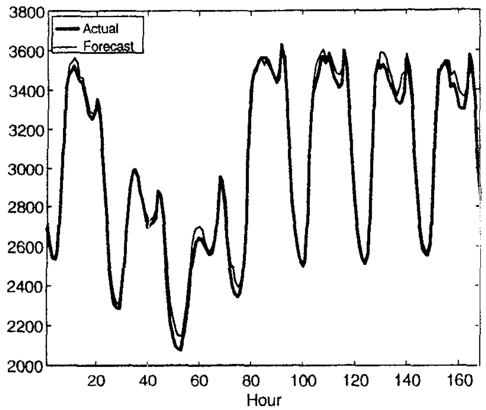

Fig. 8. An example of ANNSTLF generation three one-to-seven-day-ahead load forecast.

As pointed out earlier, all the weather variables (T or T_eff) used in these studies are the actual data. In on-line usage of the model, weather forecasts are used. The quality of these weather forecasts vary greatly from one site to another. In our experience, for most cases, the weather forecast errors introduce approximately 1 percent of additional error for one to two days out load forecasts. The increase in the error for longer range forecasts is more due to less accurate weather forecasts for three or more days out.

IX. CONCLUSIONS

The third generation of ANNSTLF (Artificial Neural Network Short-Term Load Forecaster), the most widely used ANN-based load forecasting algorithm with 35 utility users, is described. The architecture of this forecasting engine consists of only two ANN load forecasters and an adaptive combiner which mixes the forecasts of the ANN predictors. One ANN predicts the base load while the other one forecasts the change from the previous day's load. The effect of humidity and windspeed are accounted for by a linear transformation of temperature into an effective temperature. A novel algorithm for forecasting holiday loads is developed. The algorithm is based on a weighted interpolation scheme involving past holiday peak loads. It is shown that this algorithm significantly improves the accuracy of the holiday forecasts.

The performance of the system is tested on data from ten different utilities and compared to the second generation model. It is shown that the much smaller and simpler architecture of the third generation out-performs the previous model and produces more accurate results.

TABLE 5
COMPARISON OF SECOND AND THIRD GENERATION ANNSTLF FORECAST ERRORS, MAPE OF DAILY PEAK LOAD

		Days-Ahead						
Utility	**ANNSTLF Generation**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1	**Three**	1.70	2.11	2.39	2.62	2.73	2.94	3.10
	Two	1.96	2.26	2.50	2.75	2.91	3.07	3.18
2	**Three**	2.64	3.33	3.46	3.37	3.42	3.52	3.40
	Two	2.88	3.36	3.50	3.64	3.80	3.99	4.09
3	**Three**	1.96	2.26	2.41	2.49	2.60	2.69	2.82
	Two	1.87	2.26	2.43	2.51	2.68	2.72	2.79
4	**Three**	2.26	2.59	2.69	2.83	2.85	2.93	2.94
	Two	3.68	4.47	4.69	4.91	4.99	5.07	5.13
5	**Three**	2.03	2.36	2.49	2.37	2.49	2.51	2.55
	Two	2.04	2.00	2.13	2.26	2.34	2.39	2.53
6	**Three**	1.82	2.25	2.38	2.50	2.61	2.62	2.63
	Two	1.96	2.47	2.72	2.96	3.16	3.34	3.51
7	**Three**	2.42	2.78	2.90	2.98	3.07	3.17	3.28
	Two	2.49	3.21	3.62	3.9	4.13	4.29	4.46
8	**Three**	2.38	3.00	3.12	3.29	3.40	3.45	3.52
	Two	1.96	2.47	2.72	2.96	3.16	3.34	3.51
9	**Three**	1.83	2.25	2.36	2.51	2.54	2.64	2.78
	Two	2.08	2.59	2.86	3.10	3.34	3.56	3.76
10	**Three**	2.15	2.75	2.93	3.08	3.16	3.27	3.27
	Two	2.44	3.11	3.45	3.76	4.03	4.25	4.49
AVERAGE	**Three**	**2.12**	**2.57**	**2.71**	**2.80**	**2.89**	**2.97**	**3.03**
	Two	**2.34**	**2.82**	**3.06**	**3.28**	**3.45**	**3.60**	**3.75**
Accuracy Improvement (%)		**9**	**9**	**11**	**15**	**16**	**18**	**19**

X. ACKNOWLEDGEMENTS

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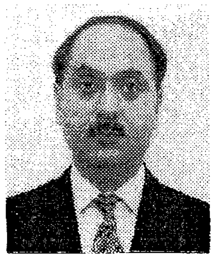
XII. BIOGRAPHIES



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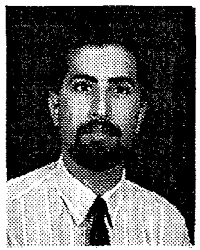

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