AN IMPLEMENTATION OF A NEURAL NETWORK BASED LOAD FORECASTING MODEL FOR THE EMS

Alex D. Papalexopoulos Shangyou Hao
Pacific Gas & Electric Company
San Francisco, California

Tie-Mao Peng
Consultant
San Francisco, California

Abstract - This paper presents the development and implementation of an Artificial Neural Network (ANN) based short-term system load forecasting model for the Energy Control Center of the Pacific Gas & Electric Company (PG&E). Insights gained during the development of the model regarding the choice of the input variables and their transformations, the design of the ANN structure, the selection of the training cases and the training process itself will be described in the paper. Attention was paid to model accurately special events, such as holidays, heat-waves, cold snaps and other conditions that disturb the normal pattern of the load. The significant impact of special events on the model's performance was established through testing of an existing load forecasting package that is currently in production use. The new model has been tested under a wide variety of conditions and it is shown in this paper to produce excellent results. Comparison results between the existing, regression based model and the ANN model are very encouraging. The ANN model consistently outperforms the existing model in terms of both, average errors over a long period of time and number of "large" errors. The ANN model has also been integrated with PG&Es Energy Management System (EMS). It is envisioned that the ANN model will eventually substitute the existing model to support the Company's real-time operations. In the interim both models will be available for production use.

Keywords: System Load Forecasting, Artificial Neural Network Technology, Training, Regression Analysis.

I. Introduction

An accurate System Load Forecasting (SLF) function, used to calculate short-term electric load forecasts, is an essential component of any Energy Management System (EMS). Forecasts of hourly loads for up to one week ahead are necessary for scheduling functions such as Hydro-Thermal Coordination and Transaction Evaluation and for network analysis functions such as Dispatcher Power Flow and Optimal Power Flow. Based on the load forecasts and depending on the operational security objectives of a specific utility, power operators would then •undertake the preventive or corrective actions needed to operate the power system securely and economically.

A wide variety of procedures for short-term load forecasting have been reported in the literature. These procedures typically make use of two basic models: peak load models and load shape models [1-3]. Peak load models are not widely used since they do not provide any information about the shape of the load curve. Load shape models describe the load as discrete time series over the forecasting interval and can be categorized into two groups: static models [4] and dynamic models. Dynamic load shape models incorporate in their predictions the cumulative effects of such factors as recent load behavior, weather, and random effects. They are of two basic types: autoregressive moving average (ARMA) models [5-7] and state space models [8]. ARMA models can be used to model stationary processes with finite variances. Non-stationary processes can be modeled by differencing the original process. The differencing operation produces an Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models can be converted into state space models (and vice versa [8]), in which the current and relevant past behavior is included in the current state of the system. Load and weather states are updated using Kalman filtering. With state space formulations it is possible to make new forecasts based on results from the previous hour, rather than recomputing the effect of the same past behavior in several previous hours.

In PG&E, a powerful linear regression model has been developed that utilizes nonlinear transformations, reverse-error-in-variables techniques and other statistical methodologies to effectively capture load variations due to special events, weather pattern deviations from normal and other random correlation effects [9]. After two years of production use in the EMS environment, an assessment of the model's adequacy strongly indicated that the performance of the algorithm is acceptable during normal operating conditions. However, improvements may be needed for accurate forecasts during rapidly changing weather conditions. The study also confirmed the theoretical limitations of most conventional statistical methods. These are: a) the nonlinear relationships of the input and output variables are difficult to capture; b) the collinearity problem of the exploratory input variables limits the number of these inputs that can be used in the model; and c) the models are not very flexible to rapid system load changes.

Recent progress [10-17] in the application of Artificial Neural Network (ANN) technology to power systems in the areas of forecasting, security assessment, and fault diagnosis among others, has made it possible to use this technology to overcome some of the limitations mentioned above in the short-term system load forecasting problem. We embarked on the development of an ANN based SLF model because we felt that neural network technology has been most useful in the area of data modeling. Our objective was not merely to develop an ANN based methodology for the SLF problem, but to a) implement a new SLF model that overcomes the limitations of the existing SLF package, b) test it in the field extensively in order to gain the operators confidence, c) integrate it with PG&E's EMS and d) put it in production use to support the real-time operations of the Company.

This paper presents the implementation of this new ANN based improved SLF model. Section II describes the basic neural network structure for the next days load forecasts. Section III describes the models that are suitable to a) handle special events, b) update the forecasts for the remaining hours of the current day and c) produce weekly forecasts. Section IV describes some implementation details and the integration with the EMS for full production use. It also presents the numerical results of the evaluation of model. Section V discusses some of the major findings reached during the development and testing of the model and some limitations of the

94 WM 209-7 PWRS A paper recommended and approved by the IEEE Power System Engineering Committee of the IEEE Power Engineering Society for presentation at the IEEE/PES 1994 Winter Meeting, New York, New York, January 30 - February 3, 1994. Manuscript submitted August 2, 1993; made available for printing November 29, 1993.

ANN technology. Section VI summarizes the major contributions of the paper.

II. BASIC NEURAL NETWORK STRUCTURE

In this development we used the widely known model called multi-layered feedforward ANN. Its structure, contrary to previously published work [10-15], has a relatively large number of neurons. It consists of 77 input neurons, 24 hidden neurons with the Sigmoid transfer function, and 24 output neurons representing next day's 24 hourly forecasted loads. Another somewhat different feature of this model, compared to others published in the literature, is that a large number of training data is used in the network learning process. The objective was to avoid updating the network weights and thresholds frequently. The same approach was followed and was proven successful with the existing SLF program that is currently on-line [9]. That program is based on a linear regression model whose coefficients are updated once or twice a year.

Alternative structures were also evaluated but were rejected because they produced, in the long run, suboptimal results. For example, a small ANN model was considered with few hidden nodes and training data sets that span a three week period. Training was updated once a week. The performance of this model was acceptable on specific instances but it was not satisfactory in the long run.

II.1. Neural Network Input Variables

The most important work in building an ANN load forecasting model is the selection of input variables. There is no general rule that can be followed in this process. It largely depends on engineering judgement and experience and is carried out almost entirely by trial and error. However, some statistical analysis can be very helpful in determining which variables have significant influence on the system load. In our model, three types of variables are used as inputs to the neural network: a) seasonal related inputs, b) weather related inputs, and c) historical loads. In the remaining of this section these input variables along with their nonlinear transformations are discussed in detail. Other input variables that were evaluated during the development, but not accepted in the final design for performance reasons, are also discussed.

1) Seasonal Input Variables

Seasonal load trend is the load component that is changing slowly from month to month. This component reflects seasonal load variations caused by cooling and heating load over one year period. We used the following trigonometric functions to capture this load component.

$$\sin(2n\pi \cdot i/365),\ \cos(2n\pi \cdot i/365),\ (n=1,2,3)$$

where i (i=l,2,…,365) is number of days in the year.

2) Temperature Input Variables

Temperature is the most important weather variable. In our model, these variables are divided into four groups a) direct temperature variables, b) indirect temperature variables, c) temperature change variables, and d) cooling/heating degree day variables.

Direct Temperature Variables

Due to non-uniform geography and climate in the PG&E's service area, temperatures in different areas have different impacts on the system load. Forecasted maximum temperatures for tomorrow and recorded maximum temperatures for today in six PG&E designated areas are selected as direct temperature inputs to the ANN model.

Indirect Temperature Variables

The above direct temperature variables provide weather information to the model on an area level. However, during numerical simulations, we realized that the performance of the model can be improved by using temperature inputs that represent operating conditions in a system level. For this purpose, average forecasted maximum temperatures for the six locations and the average maximum temperature of last week were added to our input list.

Temperature Change Variables

System load is very sensitive to temperature changes that occur at the high and low ends of the temperature range. To capture this sensitivity of the nonlinear influence of temperature change on load, the difference of the forecasted average maximum temperature and today's actual average maximum temperature and its quadratic term were used as network inputs. Similar terms using the minimum temperatures were also added as input variables. However extensive testing strongly indicated that the quadratic term for the minimum temperatures was not needed. This is probably attributed to the fact that the electric heating load in PG&E constitutes only a small portion of the total load. Consequently the effects of winter weather on load demand are less than those of summer weather in most of PG&E service area.

Cooling /Heating Degree Day Variables

Temperature effects at the high and low ends of the range are further modeled using cooling and heating degree day inputs which are based on physical considerations and on graphical analysis of the historical relationships between load and temperatures. The cooling degree function is zero until a threshold temperature is reached and then increases quadratically.

This function reflects a physical model with the following characteristics: a) below some lower threshold there is negligible cooling load, and b) as temperatures increase, more individuals and offices turn on air conditions, trying to keep temperatures at their own individual thresholds. Thus the air conditioning grows, and the rate of growth increases as well. The heating degree function has the same form, but increases as temperatures decrease. Cooling and heating degree day input variables have also been introduced in [9]. The thresholds were chosen based on graphical analysis of historical data and extensive testing of the model. The cooling threshold temperature was set to 78°F, while the heating threshold temperature was set to 65°F.

3) Historical Load Variables

Hourly loads for today and yesterday were used as historical load inputs. These historical hourly loads provide load shape and magnitude reference for the forecasted hourly loads. The average peak load of last week was also used as input. This variable attempts to capture the load trend over the recent past.

4) Other Tested Input variables

Other input variables were also tested but were not used in the final design for performance or other reasons. For example, humidity, and cloud cover were tested, and it was shown that they have a minimal effect on PG&E's system load. Because of the difficulty in producing accurate forecast values for these variables, it was decided not to use them in the final design. Another variable that was tested and finally rejected was the yearly growth rate; the system load of the company does not have a consistent growth in recent years. For example, the all-time system peak load was recorded in 1991. A model with the above input variable did not fare well during testing.

II. 2. Nonlinear Modeling Justification

The above list contains several nonlinear input variables to account for the influence of temperatures and seasonal trends on future loads. This modeling is different from the approach taken in previously published models [10-15]. In fact, the application of nonlinear functions to the ANN based system load forecasting modeling is one of the main contributions of the paper. The need to rely on nonlinear input variables is further explained below.

In neural network load forecasting models, when the output neurons are modeled with a linear transfer function, the forecasted load is represented as a linear combination of the outputs of the hidden neurons. Under this assumption, a load forecast is given by:

$$y(k) = a0 + a1 \bullet f1 + a2 \bullet f2 + ... + am \bullet fm \qquad \text{(II.1)}$$

where m is the number of the hidden neurons; fi (i=1,…,m) is the output of the ith hidden neuron; a0 is the threshold of the output neuron k; and ai (i=1,…,m) is the weight between the hidden neuron i and the output neuron k. Even when a Sigmoid transfer function is used to model the output neurons, the output is still close to that of the linear representation given by Eq. (II.1). This similarity is due to fact that the output neurons are usually designed to work in the linear interval of their transfer function by scaling their output range.

In Equation (II.1), the outputs of the hidden neurons can be grouped into three states: non-activated, linear and saturated. In both the non-activated and saturated states, hidden neurons are in a approximated off or on status and are not very sensitive to input changes. However, in the linear state, they will transfer most of the impact of input changes to the output.

In the linear state, the hidden neurons have an input/output relationship described by

$$fi = 1/[1+\exp(-\sum wij \bullet xj - \theta\, i)] \approx [1+(\sum wij \bullet xj + \theta\, i)/2]/2 \qquad \text{(II.2)}$$

where wij is the weight between the ith hidden neuron (whose output is *fi*) and the *j*th input neuron (with input xj), and θi is the threshold of the neuron i. From Equations (II.1) and (II.2) and the fact that most hidden neurons operate in the linear state, it can be concluded that when an input changes, the output will change at about the same order. This feature of neural networks requires that some nonlinear terms be included in the input set in order to effectively capture nonlinear effects. Experience from the development and extensive testing of the model has verified this claim.

The use of linear terms only, in the initial steps of the development, to model the temperature effect resulted in a neural network model whose performance was deteriorating at the two ends of the temperature range. The reason is, that under these conditions, load changes with temperature at a quadratic rate. However, the outputs of the neural network change with temperatures at an almost linear rate. The use of nonlinear functions of temperatures as network inputs (defined as cooling degree/heating degree day variables in Section II.1), resolved this problem. Furthermore, temperature changes from day to day at the two ends of the temperature range influence the load in a substantial way. Hence, another set of nonlinear input variables, the temperature change variables, were used in the model to take into account the influence of temperature changes that occur on a daily basis. Finally, a set of trigonometric functions were used to represent seasonal trends. Experience with the existing model 19] strongly indicated that this modeling was necessary to model the load behavior over a one year period.

III. CURRENT DAY, HOLIDAY & WEEKLY MODELING

According to standard practice, system operators adjust tomorrow's load forecasts the following day to take into account observed actual hourly loads and temperatures. Depending on actual conditions, the adjusted forecasts can differ drastically from the original load forecasts. The "current day forecasting" model provides this capability. Furthermore, system operators need load forecasts for the following seven days for generation scheduling and transaction evaluation purposes. The "weekly forecasting" model provides this capability. In all developed models, special attention was paid to accurately represent the effects of special events, such as holidays. Holiday loads are generally lower than other loads, and this effect spills into surrounding days as well. In this section, the current day and weekly forecasting models are presented. The holiday adjustments model is also described in this section.

Current Day Modeling

Let the hourly forecasts for the current day, made in the previous day, be represented as {y(i) | i=1,2,…,24} and the forecasting errors as {e(i) I i=l,2,…,K; k<24}, where K is the last hour of the current day with known hourly loads. The hourly load forecast errors for up to the Kth hour are given by:

$$e(i) = Y(i) - L(i);\ i = 1,2,...,K$$

where L(i) is the actual hourly load at the ith hour.

Let the correlation coefficients matrix between the hourly loads be represented as {Cor [i,j] | i=1,2,…,24; j=1,2,…,24). This matrix is estimated from historical load data and is updated once a year. The procedure of adjusting the current day's loads is given by:

$$Y(i) = y(i) + Cor[i,j] \bullet e(j);\ j = 1,...,K;\ i = K+1,...,24 \qquad \text{(III.1)}$$

where Y(i), i=K + l,…,24, are the adjusted current day's hourly loads.

Testing has indicated that the current day model, depending on actual conditions, may substantially improve the performance of the ANN algorithm. Based on a similar option available in the existing model, it is expected that this capability will he extensively used by the dispatchers.

Weekly Modeling

The weekly load forecasting model produces hourly loads up to 168 hours in the future. For that purpose the basic model is called iteratively to produce the multiple-day forecasts. When historical load data is not available, the forecasted load values are used as inputs. Multiple-day forecasting errors are compounded, to a certain extent, depending on the forecasting errors of the basic model. Substantial effort was made to eliminate any type of bias introduced in the basic daily forecasts, so that the compounded errors remain within acceptable bounds.

Holiday Modeling

As mentioned earlier, holiday loads are lower than other loads. To capture the holiday effect, an adjustment is calculated to modify a holiday's forecasted load that has been computed with the basic model (i.e., as if it were a normal load). Therefore, each holiday load forecast can be viewed as having two components: a) the normal day component and b) a holiday effect adjustment. Therefore, for a particular holiday:

$$\hat{L}_{holiday} = \hat{L}_{normal} - \Delta\hat{L}_{holiday} \qquad \text{(III.2)}$$

where L is a vector that contains 24 hourly forecast loads.

The normal load component is computed by the basic neural network model that has been trained using regular data that do not include holiday loads. The normal load is given by:

$$\hat{L}_{normal} = N(X) \qquad \text{(III.3)}$$

where X is the neural network input vector of temperatures and historical loads for a given holiday and N is the neural network input/output mapping, whose weights have been solved from a training session using normal day's data. The holiday effect adjustment for a particular holiday is computed using historical data of previous years for that holiday. The holiday loads in historical records containing m years of data are expressed as:

$$\{(X_1|L_1),(X_2|L_2),...,(X_m|L_m)\} \qquad \text{(III.4)}$$

where Xi and Li (i=l,...,m) are the associated inputs and the actual loads respectively of a given holiday for the ith previous year.

The normal loads corresponding to these holidays can be found by using the network defined in (111.3). Hence,

$$\hat{L}_{i,normal} = N(X_i),\ (i=1,2,...,m) \qquad \text{(III.5)}$$

Since actual holiday loads Li (i=1,...,m) are known, the holiday effect adjustments for that particular holiday in previous years are:

$$\Delta\hat{L}_{holiday} = \hat{L}_{i,normal} - L_i = N(X_i) - L_i,\ (1=1,2,...,m) \qquad \text{(III.6)}$$

An average load adjustment for that holiday is then given by:

$$\Delta\hat{L}_{holiday} = \Delta\hat{L}_{mean} = \sum_{i=1}^{m}\Delta\hat{L}_i /m \qquad \text{(III.7)}$$

The holiday load forecast for that holiday is given by:

$$\hat{L}_{holiday} = \hat{L}_{normal} - \Delta\hat{L}_{mean} = N(X) - \Delta\hat{L}_{mean} \qquad \text{(III.8)}$$

IV. IMPLEMENTATION AND RESULTS

In this section the on line implementation and the integration of the ANN model with PG&E's EMS will be presented. During the integration numerous practical problems were encountered and resolved. Most of the problem were related to data communications, man-machine interface, access to real time data in the EMS Cyber computer and downloading EMS data from the database to a workstation. The integration of the model with the EMS was a major milestone in our efforts to put the ANN model to full production use. It followed an extensive testing process during which the model consistently outperformed the existing SLF package. Sample results from the testing are also presented in this section.

IV.1. On Line Implementation

The developed ANN-based forecasting model consists of two parts: a) the off line neural network model that is used for learning and testing, and b) the on line model that is designed to be used by the system dispatchers in daily operations. The integrated package and its functional components are shown in Figure 1.

The off line model consists of the data organization programs, which organize the learning and testing data into the appropriate format, and the training model, which trains the network by a Backpropagation algorithm and produces the network weights and threshold values. The output of the off line model consists of seven neural network parameter files corresponding to the seven day-types from Monday to Sunday. Each file contains a set of network weights and threshold values that correspond to a given day-type. It also contains data used for I/O data scaling, such as maximum and minimum values of each input and output, and numerical ranges that are used to scale the initial data.

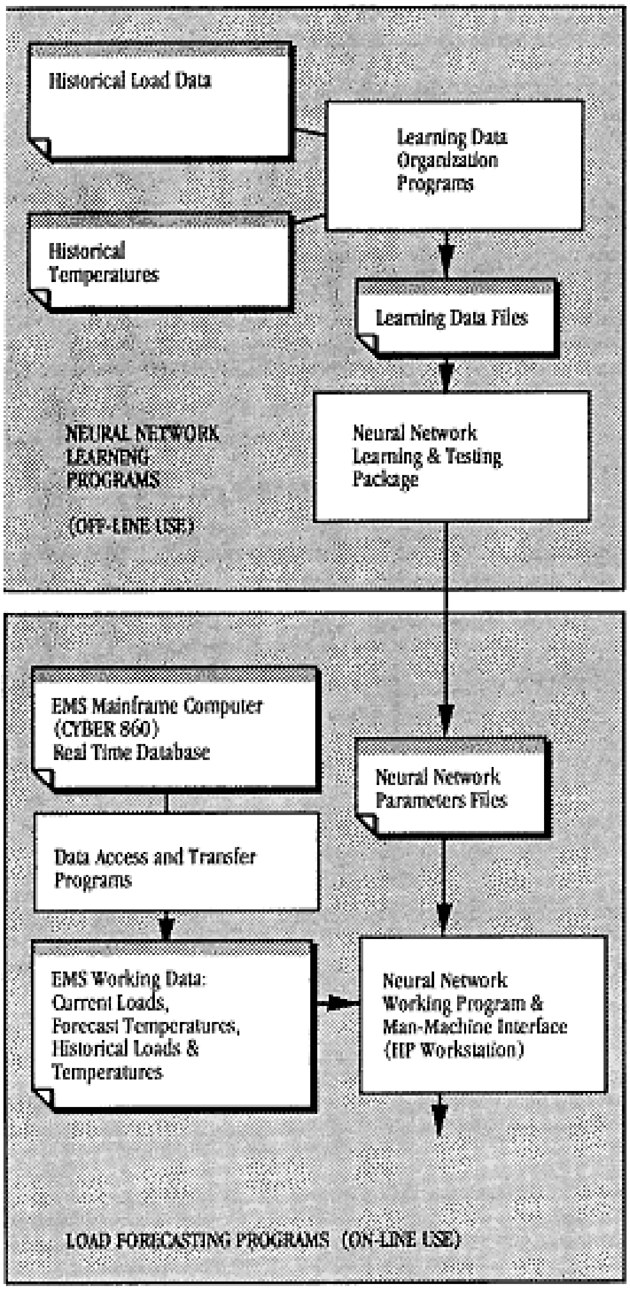
The on-line ANN forecasting model consists of two programs. The first transfers relevant real time data from the EMS database that resides on a CYBER 860 to an HP workstation that is used for load forecasting. The second program reads the EMS real-time data and the neural network parameter files and produces load forecasts for the current day, next day or next week.

IV.2. Simulation Results

This section presents some of the comparison results between the ANN based model and the existing regression based model that is currently in production use in PG&E's Energy Control Center. The results were obtained by backcasting system peak and hourly loads for 1991. Data from 1986 up to and including 1990 were used to train the ANN model. The same database was used to estimate the coefficients of the regression model. Table I contains the results produced by the two models broken down in the seven day-types starting from Monday. The first column for each model represents the average absolute peak load forecast error and the second column the number of large peak load forecast errors. From a practical point of view, it is the "large" errors that undermine a system operator's confidence in an SLF algorithm. PG&E's

operations personnel consider a 500 MW peak load forecast error to be the rule-of-thumb dividing line between accurate and inaccurate forecasts as errors exceeding this threshold may cause substantial problems in load dispatching, reserve allocation, security assessment, and scheduling of large steam-driven generating units.

Figure 1. Integrated ANN Forecasting Model



As can be seen from Table 1, performance was improved for all day-types. For the Friday day-type, for example, the average absolute peak load forecast error for the whole year of 1991 was reduced from 290 MW to 219 MW, which amounts to an improvement of 24.4 percent. At the same time, the number of large peak load forecast errors (>500MW) was reduced from 4 to 2, which amounts to an improvement of 50 percent. The average absolute peak error for all day-types was reduced from 253 MW to 211 MW (an improvement of 16.6 percent), while at the same time, the number of large errors (>500MW) was reduced from 23 to 18 (an improvement of 21.8 percent). These results, and numerous similar results obtained during the extensive testing of the model, strongly indicate that the ANN model consistently outperforms the existing model in terms of both, average errors over a long period of time and number of large errors. This outcome came as a welcome surprise to us given that a) the existing model employs sophisticated statistical techniques, b) it has been in production use for over two years and its performance is already acceptable for normal operations, and c) the development cycle (and consequently the development cost) of the ANN model was reduced to less than half compared to the development cycle (and cost) of the existing model. Based on our experience with similar developments we have come to realize that the short development cycle of models employing ANN technology is one of its biggest advantages compared to other statistical methods.

Table 1. 1991 Peak Load Forecast Comparison Results

DAY-TYPE	REGRESSION MODEL		ANN MODEL	
	|Error| (MW)	|Error|> 500	|Error| (MW)	|Error|> 500
Monday	261	4	209	2
Tuesday	247	4	205	4
Wednesday	322	6	258	4
Thursday	182	1	178	1
Friday	290	4	219	2
Saturday	216	1	188	2
Sunday	253	3	2211	3
Aver/Total	253	23	211	18

To illustrate the type of forecasts that are obtained using the new model, the absolute peak load forecast errors for the month of June of 1991 using both models are presented in Figure 2. This month was characterized by rapidly changing weather (especially for the days of June 11, 12, and 29). As can be seen, the existing model did not perform very well under these circumstances (five times the error was larger than 500 MW) but the ANN model’s forecasts followed the actual load pattern more accurately and reliably, on the average, throughout the forecasted period (only two times the error was larger than 500 MW). This high level of performance is due mainly to the more accurate temperature modeling, and the ability of the ANN model to respond rapidly to sudden changes. Rapid model response was one of main objectives of this development from its conception and it is certainly one of the main contributions of this work.

Similar accuracy improvements were achieved in the hourly forecasts as well. However, as expected, the hourly load forecasts are slightly less accurate than the peak load forecasts using the same model. Table 2 presents the peak and hourly load forecast errors for 1991 using the ANN model. The results are broken down in the seven day-types starting from Monday. As can be seen from Table 2, the hourly load forecast errors are slightly larger than the peak load forecast errors. The average absolute peak load forecast error for all day-types is 211 MW, while the average absolute hourly load forecast error is 216 MW, which amounts to an increase of 2.37 percent.

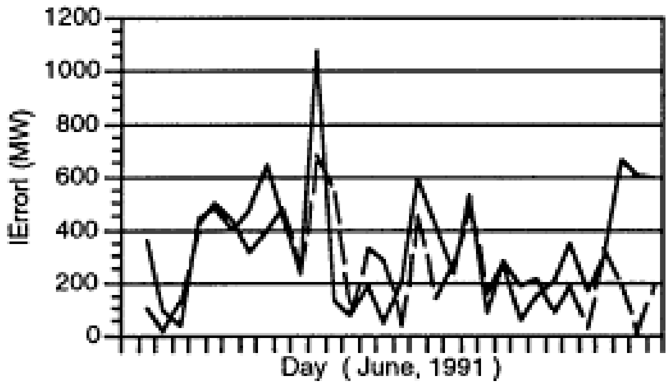


Figure 2. Peak Load Forecast Errors for June of 1991
(dark line: linear regression; dashed line: neural network)

Table 2. ANN Based Peak/Hourly Load Forecast Errors for 1991

	Peak Forecasts		Hourly Forecasts	
Day-Type	Absolute Error (MW)	Percent Error *(%)*	Absolute Error (MW)	Percent Error *(%)*
Monday	209	1.711	229	2.047
Tuesday	205	1.775	235	2.036
Wednesday	258	1.840	248	2.119
Thursday	178	1.636	208	1.826
Friday	219	1.838	210	1.842
Saturday	188	1.868	204	2.007
Sunday	221	1.815	179	1.838
Average	211	1.783	216	1.959

V. DICUSSION

The results presented above and similar results obtained during testing provide compelling evidence of the excellent performance of the new ANN based SLF model. The major advances in system load forecast modeling incorporated in PG&E's new ANN based SLF algorithm include the following:

- Robust forecasting. One of the major problems associated with traditional statistical modeling is the handling of outliers that can adversely impact the quality of forecasts. Compared to other statistical techniques, neural networks are particularly effective in handling outliers, although other methods can make, to some extent, the same claim [9]. If strong input signals are present, some hidden neurons will move from their linear to saturated range. Hence, the neural network output tends to increase by a smaller amount than that of its linear counterpart (say a linear regression model). On the other hand, if weak input signals are present, some hidden neurons will move from their linear to the non-activated range. This makes the decrease in the network output less than that of a linear model. In either case the impact of outliers is minimized.

- ANN input selection. Since at the present time systematic design procedures are not available, the input side of the ANN architecture of the model was built almost entirely by trial and error based on engineering judgement and previous experience. The results of the extensive testing strongly indicate, however, that the final selection of the ANN inputs was probably optimal or nearly optimal.

- Accurate temperature modeling. Temperature effects are incorporated in PG&E's new ANN based model using direct temperature variables and nonlinear transformations of these variables as inputs to the neural network. The inclusion of nonlinear input variables, such as temperature change and cooling/heating degree day variables is very important to capture nonlinearities, since the output of the developed network responds to input changes at a nearly linear or superlinear rate. Furthermore, special inputs were selected to always produce a load increase for both temperature increases and decreases at the high and low ends of the temperature range respectively. This is crucial for good performance, since the output of the hidden neurons is monotonicly increasing with respect to their inputs.

- Accurate modeling of special events, including holidays and holiday weekends. These effects are modeled using a simple, yet effective holiday model that is integrated into the ANN model structure.

The experience acquired from the development of the ANN based model strongly indicates that the ANN technology has matured enough to be applied successfully in many power system problems. However, its success will eventually depend on its ability to remove a major obstacle; at present, there is neither a firm theory nor even a set of heuristic guidelines or procedures to assist the developer to design neural networks. In general, it is viewed as an advantage of the neural networks that they are trained rather than programmed. However, from development point of view, this feature only shifts the main effort from one task to another. The very flexibility that makes the ANN technology so amenable to data modeling also creates a burden for the developer to select a "good" if not the "best" combination of topology, learning rules and parameters, activation functions, thresholds and input variables. At the present time there is no complete theoretical basis to relate the above parameters to known characteristics of the system that is being modeled. This lack of a complete set of systematic design procedures constitutes the main obstacle to the practical use of neural networks. Furthermore, even a completely trained network provides little insight into the nature of the problem being solved. In the short run, since there is no clear relation of a network's own structure and the parameters to the data is attempting to model, it is very important to choose application areas that experience and knowledge has already been acquired. In the long run, substantial more work is needed to improve the theoretical underpinnings of the technology whose theoretical foundation lags far behind the practice in neural networks, as it also does in other forms of data representation, compression and expansion. Any future work will only produce lasting results in this area if it also recognizes the fact that the ANN technology can hardly provide all the modeling capabilities needed in a real-life application. Consequently, any progress in ANN design should allow for integration of this technology with other modeling techniques from the statistical arena and especially with other technologies from the artificial intelligence area.

VI. CONCLUSION

The System Load Forecasting model is a critically important decision support tool for operating the electric power system securely and economically. Virtually all the scheduling and advanced application functions in the EMS, such as Hydro-Thermal Optimization and Optimal Power Flow, require system load forecasts. From our experience in developing the existing linear regression SLF model and the ANN based SLF model, it was found that the ANN model produces accurate load predictions under a wide variety of power system operating conditions. It is robust, adaptive to changing conditions, and capable of incorporating in its forecasts the cumulative effects of such factors as recent load behavior as well as weather and random effects.

The main contribution of this work is that an ANN based load forecasting model has been successfully implemented for on-line use at PG&E's Energy Control Center. The concepts used in developing the model fall into the following areas: a) selection of the appropriate ANN inputs, b) selection of nonlinear transformations of direct inputs as additional ANN input variables, c) accurate weather modeling, and d) the training process itself that has eliminated the need for on-line update of the neural network parameters.

ACKNOWLEDGEMENTS

The authors would like to thank Thomas Miller, Jim McIntosh, Felmir Singson and Lloyd Cibulka of PG&E for their comments and support of this project.

REFERENCES

[1] G. Gross, F. D. Galiana, "Short-Term Load Forecasting," *Proceedings of IEEE*, Dec. 1987.
[2] T.N. Goh, H.L. Long, and Y.O. Lee, "A New Approach to Statistical Forecasting of Daily Peak Power Demand," *Electric Power Systems Research*, Vol. 10, No.2, pp. 145-148, Mar. 1986.
[3] P.C. Gupta, "A Stochastic Approach to Peak Power Demand Forecasting in Electric Utility Systems," *IEEE Trans. on Power App. & Syst.*, Vol. PAS-90, Mar./Apr.1971.
[4] W.R. Christiaanse, "Short-Term Load Forecasting Using General Exponential Smoothing," *IEEE Trans. on Power App. & Syst.*, Vol. PAS-90, No. 2, pp. 900-911, Mar./Apr. 1971.
[5] G. E. P. Box and G. M. Jenkins, "Time Series Analysis Forecasting and Control," Revised Edition, Holden-Day, Oakland, 1976.
[6] S. Vemuri, B. Hoveida, and S. Mohebbi, "Short-Term Load Forecasting Based on Weather Load Models," *Proc. IFAC conf. on Power Systems and Power Plants Control*, Beijing, People's Republic of China, pp.565-570, Aug. 1986.
[7] S. Vemuri, W. L. Huang, and D. J. Nelson, "On-Line Algorithms for Forecasting Hourly Loads of an Electric Utility." *IEEE Trans. Power App. & Syst.*, Vol. PAS-l00, No. 8, pp. 3775-3784, Aug. 1981.
[8] L. Ljung and T. Soderstrom, "Theory and Practice of Recursive Identification," Cambridge, MA:MIT Press, 1983.
[9] A.D. Papalexopoulos, and T.C. Hesterberg, "A Regression-Based Approach to Short-Term System load Forecasting, *IEEE Trans. on Power Systems*, Vol. 5, No. 4, pp. 1535- 1547, Nov. 1990.
[10] D. Park, M. El-Sharkawi, R. Marks, A. Atlas, and M. Damborg, "Electric Load Forecasting Using an Artificial Neural Network" *IEEE Trans. on Power Systems*, Vol. 6, No. 2, pp. 442-449, 1991.
[11] K.Y. Lee, Y.T. Cha, and J.H. Pack "Short-term Load Forecasting Using an Artificial Neural Network," *IEEE Trans. on Power Systems*, Vol. 7, No.1, pp.125-132, Feb. 1992.
[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, pp.250-257, Feb. 1992.
[13] S. Chen, D. Yu, and A. Moghaddamjo, "Weather Sensitive Short-Term Load Forecasting Using Nonfully Connected Artificial Neural Network," *IEEE Trans. on Power Systems*, Vol. 7, No.3, pp.1098-1105, Aug 1992.
[14] T.M. Peng, N.F. Hubele, and G.G. Karady, "An Adaptive Neural Network Approach to One-Week Ahead Load Forecasting," Presented at the *IEEE Power Engineering Society Summer Meeting*, Seattle, July 12-16, 1992.
[15] C.N. Lu, H.T. Wu, and S. Vemuri, "Neural Network Based Short Term Load Forecasting," Presented at the *IEEE Power Engineering Society Winter Meeting*, New York, Jan. 26-30, 1992.
[16] D. Sobajic and Y. Pao, "Artificial Neural Net Based Dynamic Security Assessment for Electric Power Systems," *IEEE Trans. on Power Systems*, Vol. 4, No. 1, pp.220-228, Feb. 1989.
[17] E.H. Chan, "Application of Neural Network Computing in Intelligent Alarm Processing," *Proc. of PICA*, pp. 246-25 1, May, 1989.

BIOGRAPHIES

Alex D. Papalexopoulos received the Electrical and Mechanical Engineering Diploma from the National Technical University of Athens, Greece in 1980, the M.S. degree in Electrical Engineering in 1982 and the Ph.D degree in 1985, from the Georgia Institute of Technology, Atlanta, Georgia. Since October 1985, he has been with Pacific Gas and Electric Company working on the development of advanced applications for PG&E's new Energy Management System. Alex is also responsible for the development and implementation of advanced methodologies and models to support the Company's operations, planning and electric industry restructuring efforts. His primary research interests include applications of large-scale theory to the real-time control of power system, dynamic simulation of power systems and electromagnetic transient analysis. Dr. Papalexopoulos is a senior member of IEEE and a member of Sigma Xi and the Technical Chamber of Greece.

Shangyou Hao received the B.S. degree from Wuhan Institute of Hydraulic and Electrical Engineering, PRC, in 1982, MS. and Ph.D. degrees in Electrical Engineering at the Ohio State University in 1984 and 1988, respectively. He worked for PG&E as an independent consultant from 1988 to 1990. He has been a Systems Engineer with PG&E since 1990, working on the development of various analytical functions.

Tie-Mao Peng was born in Hebei, China. He received his B.S. in Electrical Engineering from the North China Institute of Electric Power (China) in 1982, and the M.S. and Ph.D degree in Electric Engineering from Arizona State University in 1988 and 1991 respectively. Since 1991, he has been working as a consultant with Pacific Gas & Electric Company.