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MAINTAIN, ENHANCE AND IMPROVE RELIABILITY OF CALIFORNIA'S ELECTRIC SYSTEM UNDER RESTRUCTURING

APPENDIX - X

Customization of the EPRI Artificial Neural Network Short-Term Load Forecaster (ANNSTLF) and User Support for the California Independent System Operator (CA-ISO)

PIER FINAL PROJECT REPORT

Prepared For:
California Energy Commission
Public Interest Energy Research Program

Prepared By:

Lawrence Berkeley National Laboratory

CERTS
CONSORTIUM FOR ELECTRIC RELIABILITY TECHNOLOGY SOLUTIONS

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Customization of the EPRI Artificial Neural Network Short-Term Load Forecaster (ANNSTLF) and User Support for the California Independent System Operator (CA-ISO)

1007506

Final Report, November 2002

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PRODUCT DESCRIPTION

Load forecasting is an important part of power system planning and operation. In the past, forecasting was achieved by extrapolating existing load data combined with other influencing factors. This method is no longer accurate enough. The Artificial Neural Network Short Term Load Forecaster (ANNSTLF) is a tool for the quick and accurate prediction of hourly loads that provides the level of accuracy required by today's complex and competitive power markets. This report describes all the deliverables for the continued support and enhancement of the EPRI-ANNSTLF as implemented at the California Independent System Operator (CA-ISO).

Results & Findings

EPRI-ANNSTLF—as implemented at the CA-ISO—is a viable forecaster capable of meeting all of the requirements of short-term load forecasting. The overall accuracy of 1.5% or less (Mean Absolute Percent Error (MAPE)) is below the CA-ISO goal of 2% and acceptable for daily system and market operations. The delivered CA-ISO ANNSTLF forecaster is easy to use and will update the hour and half-hour forecasts with minimal manual intervention. ANNSTLF has many user options for making the forecaster more adaptive, detecting input data problems, making manual adjustments for special days, and incorporating additional weather variables.

Challenges & Objectives

Accurate hourly forecasts are crucial to CA-ISO decision-making. EPRI improved the capabilities of ANNSTLF and optimized it for CA-ISO. The key objectives of CA-ISO customization included the following:

- Retraining of all CA-ISO regions to improve performance, including one final retraining with the modified PG&E region (with the SMUD area removed from the PG&E control area)
- Optimization of weather station weighting factors
- Implementation of half-hour forecaster

Applications, Values & Use

ANNSTLF has already shown considerable improvement in accuracy and ease of use over other short-term forecasting tools. The delivered CA-ISO ANNSTLF forecaster is easy to use and will update the hour and half-hour forecasts with minimal manual intervention.

EPRI Perspective

EPRI is continually enhancing the capability and functionality of ANNSTLF to address the emerging issues of the energy market, such as forward price forecasting, sensitivity of price to loads, and influence of real-time pricing on load demand. ANNSTLF is in use at more than 40 utilities worldwide. ANNSTLF is more accurate and less time-consuming than previous methods of load forecasting. The program is also user-friendly and has low maintenance requirements.

Approach

The California ISO consists of three individual regions: PG&E, SCE, and SDG&E. The total ISO load at any time instant is the sum of the loads of these regions. For each region, there are several weather stations and for each such weather station, the weather service company (Weatherbank) provides hourly updates on all weather variables, which also includes a 7-day forecast for all such variables. The requirements of CA-ISO can be stated as follows:

- Provision of 7 days of hourly forecasts of each region, together with the overall forecast of the entire ISO
- Provision of capabilities to calculate optimal weighting factors for the weather stations in each region to optimize the use of weather data in predicting the load
- Provision of capabilities to predict the load every half hour, instead of every hour
- Training of the CA-ISO staff to effectively use EPRI-ANNSTLF and all of its user options

In order to meet these requirements, the approach used by DSI consisted of the following:

- Development of a pre-filer software package (called, "CONVERTER") which would perform the following tasks:
  - Check the historical load and weather data provided by the customer for data problems and provide the user with means to fix such problems.
  - Create the corrected data files for the ANNSTLF training step
  - Integrate the three regions into a single CA-ISO region
  - Provide the data needed for the daily and hourly updating of the forecasts
- Actual "training" of ANNSTLF for a three-year period and the updating it daily.
- Development of a program that would optimize the weighting factors for the weather stations. Two methods were carefully tested, both using the Evolutionary Programming (or Genetic Algorithm) optimization method. Method 1 was based on maximizing the correlation between the historical load and the weighted temperatures. Method 2 attempted to maximize the "mutual information" performance index.
- Adapting the EPRI-ANNSTLF to perform half-hour forecasts. In this case, the same neural network was used for the mid-hour and top-of-the-hour data.
- Intensive training of the CA-ISO staff on the use of ANNSTLF. At least three separate training sessions were carried out at the CA-ISO with substantial daily and on-line support.

Keywords

Load forecasting
California ISO
Artificial neural networks
Load weather correlation
Energy management

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1
INTRODUCTION

This Final Report describes all the deliverables for the continued support and enhancement of the EPRI-ANNSTLF as implemented at the California ISO. The key developments that took place consisted of the following:

- Retraining of all CA-ISO regions to improve performance, including one final retraining with the modified PG&E region (with the SMUD area removed from the PG&E control area)
- Optimization of weather station weighting factors
- Implementation of half-hour forecaster
- Final training of CA-ISO staff on the use of the ANNSTLF on a regular basis

The report is organized as follows:

- Section 2 provides an overall summary of the delivered ANNSTLF
- Section 3 provides the details of weather station optimization
- Section 4 provides a set of recommendations for future actions
- Section 5 provides a summary of project deliverables
- Appendix A provides a technical paper describing the weather station optimization procedure.

2
THE DELIVERED ANNSTLF

2.1 General

The delivered ANNSTLF consists of two sets of regions as follows:

Set 1: For the middle of the hour forecasts

- Region 1: SDGE1
- Region 2: SCE1
- Region 3: PGE1
- Region 4: CAISO1

Set 2: For the top of the hour forecasts

- Region 6: SDGE2
- Region 7: SCE2
- Region 8: PGE2
- Region 9: CAISO2

The "System Settings" display below provides the actual specification of these regions. Note that the CAISO "regions" are not true ANNSTLF regions, but they have been created to provide the sum of the loads and forecasts for the three corresponding composite regions.

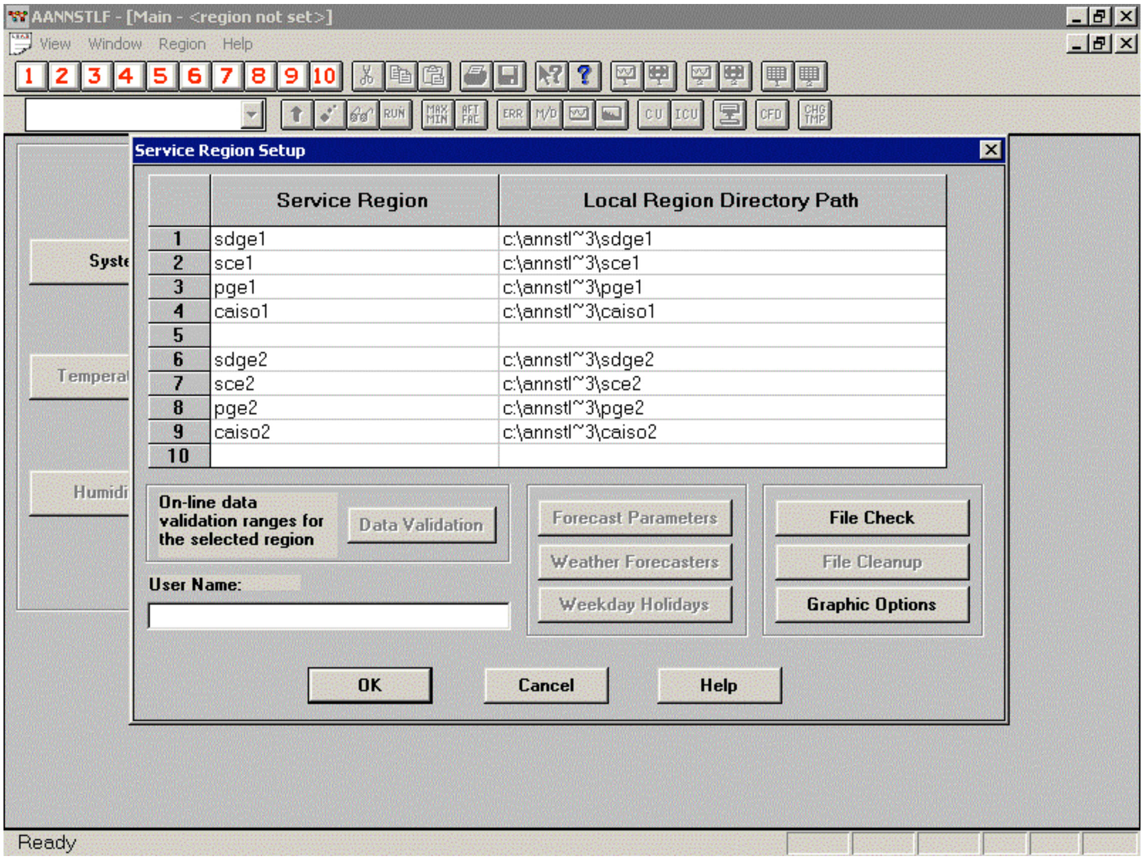

Figure 2-1
Designation of CA-ISO Regions in the System Settings Display

The two sets of regions for the half-hour and hourly forecasts can be updated simultaneously using the following 4 modes:

Hourly updates during the current day: This can be achieved by running the "CurrentDay.bat" program every time the load changes (i.e. every half hour) in the IO-Data folder. This requires first the updating of two text files during the day (Load1.txt and Load2.txt). The CurrentDay.bat program will download the latest actual weather and temperature data from WeatherBank and then move all the needed data to ANNSTLF. The user will have to "run" the individual regions (1-3 and 6-8) first and then run the ConvertOut.bat program to update the two CAISO regions.

Daily update at the end of a full day: The daily update is done in a similar manner, but requires the Load1.txt and Load2.txt files to be updated for the day before ending at midnight in the "Weather" for "today." The updating of the weather data is done by running the "ConvertInput.bat" program. Once done the ANNSTLF will have to be run for each region (1-3 and 6-8) and then following by running the ConvertOut.bat program.

Initial Catch-up (ICU): Should the user miss several days of updating, then he/she can run the ICU from the Data Analysis display. The load.hst and atemp.hst files will have to be populated manually prior to this action. CAISO staff have been trained on running the relevant "Converter" software to achieve this result.

Catch-up (CU): Should the user discover data errors in the last ten weeks, then he/she can correct the situation by correcting the errors in the load.hst and atemp.hst data files and then run CU from the Data Analysis display.

In all of the above cases, one may run the “Create_Caiso1_Forecast.bat” and “Create_Caiso2_Forecast.bat” to update the CAISO1 and CAISO2 region folders.

2.2 Performance Information

Using the copy-to-spreadsheet feature of ANNSTLF the half-hour forecasts were merged into one spreadsheet. The performance data for the months of July and August and September are given in the table below.

Table 2-1
Summary of CAISO Performance in the Last 3 Months

Period Considered	**Standard Deviation (MW)**	**MAPE (% Error)**
July ‘02	706	1.76
Aug ‘02	387	0.99
Sept ‘02	718	1.67
3 Months Average	616	1.45

The actual comparison charts for these three months for one-day-ahead forecasts are given below.

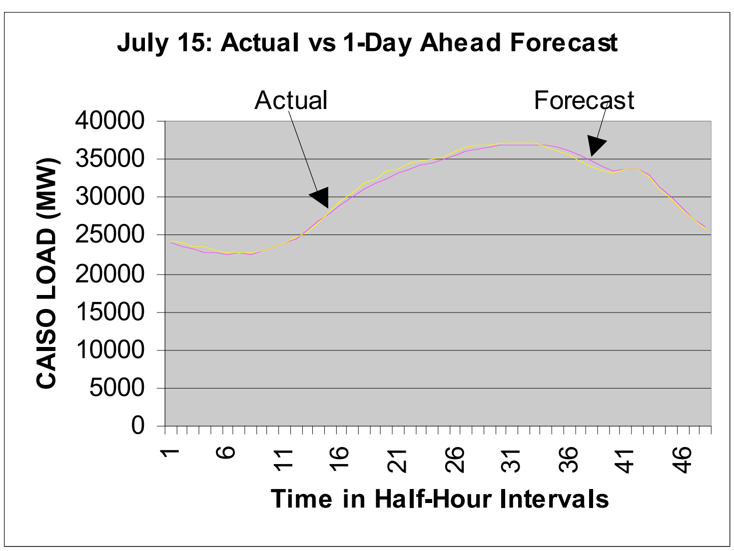

Figure 2-2
Comparison of Load and 1-Day Ahead Forecast for Half-Hour Intervals for July 15, 2002.

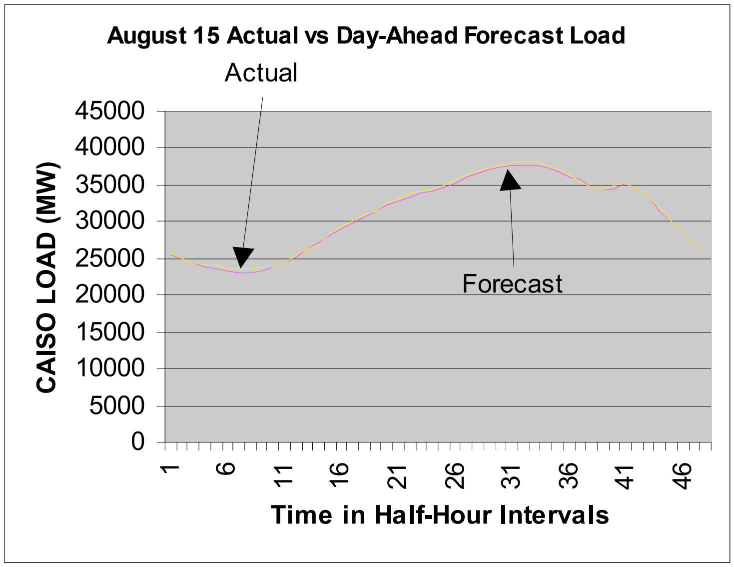

Figure 2-3
Comparison of Load and 1-Day-Ahead Forecast for Half-Hour Intervals for Aug. 15, 2002.

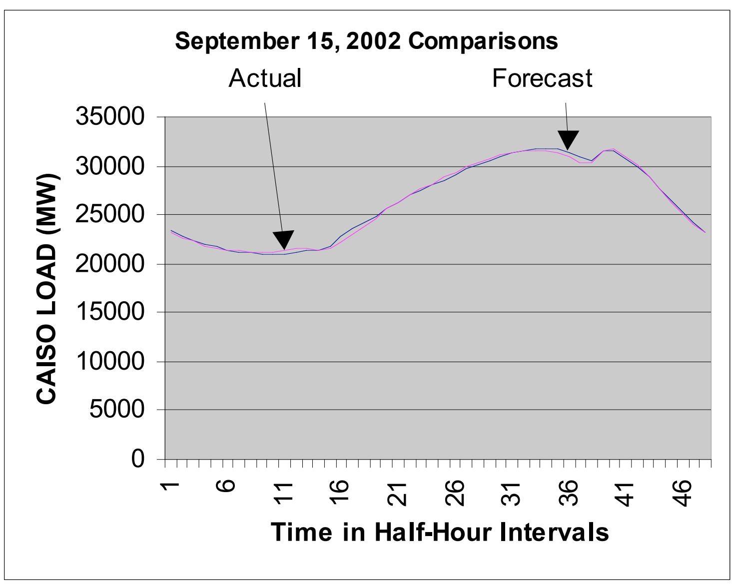

Figure 2-4
Comparison of Load and 1-Day-Ahead Forecast for Half-Hour Intervals for Sept. 15, 2002.

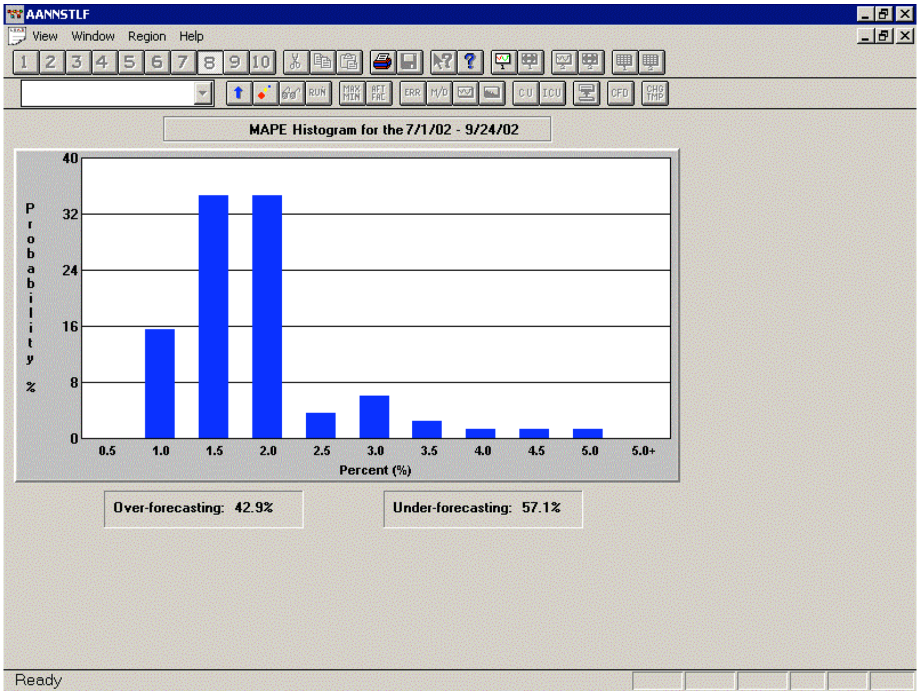

Figure 2-5
Error Histogram for 3 Months for Top-of-the-Hour Forecast

2.3 Holidays

ANNSTLF performance during holidays is shown in the figure below. The results are consistent with other regions and tests reported in the ANNSTLF literature.

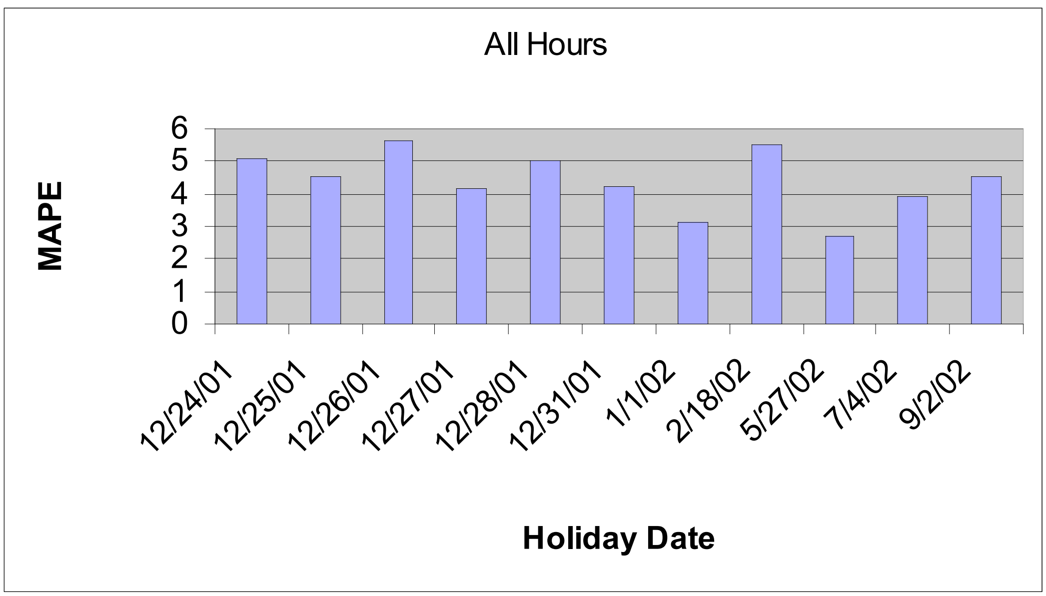

Figure 2-6
MAPE for All Hours for Holidays.

2.4 Performance Using Forecasted Weather

Data on weather forecasts in 2002 was made available in late September. Hence, there is limited information on system performance. In the figures below we provide data on forecaster performance using both actual (after-the-fact) and forecasted temperatures. The summary for this period is as follows:

Table 2-2
Error Comparisons Using Actual and Forecasted Weather Data

	After-the Fact	1-Day Ahead	2-Days Ahead
All Hours	1.04%	1.43%	2.32%
Peak Load	1.13%	1.75%	2.87%

Thus, the deterioration in performance due to weather forecast errors is as follows:

- For All Hours: 38%
- For Peak Hours: 55%

Clearly, forecaster performance with forecasted weather should be monitored on a regular basis to identify the extent of deterioration due to weather forecast errors and to come up with remedies to improve performance.

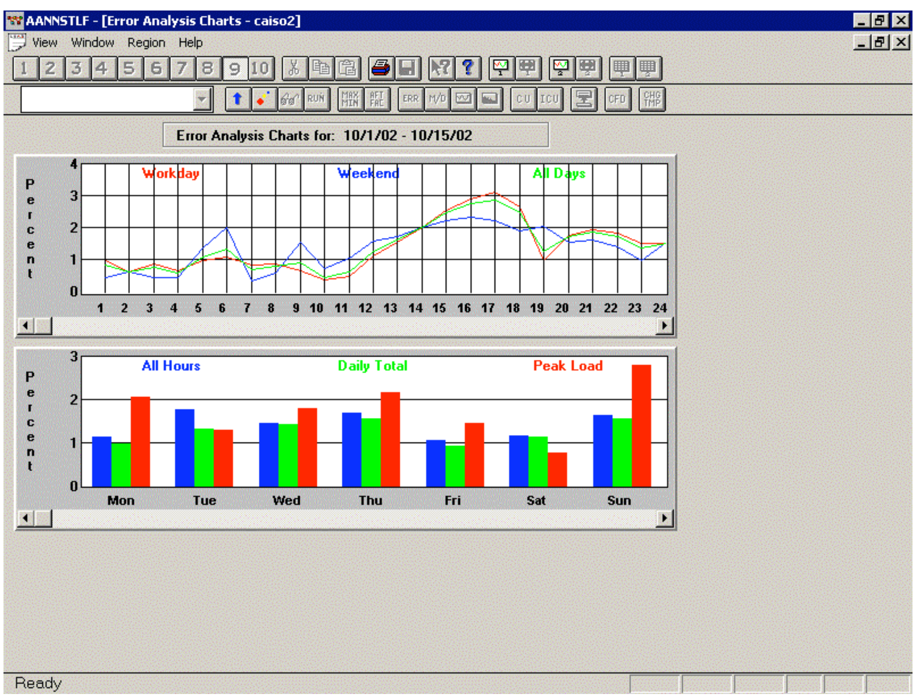

Figure 2-7
Error Charts for the First Two Weeks of October, 2002 Using Forecasting Weather (Day-Ahead Forecast)

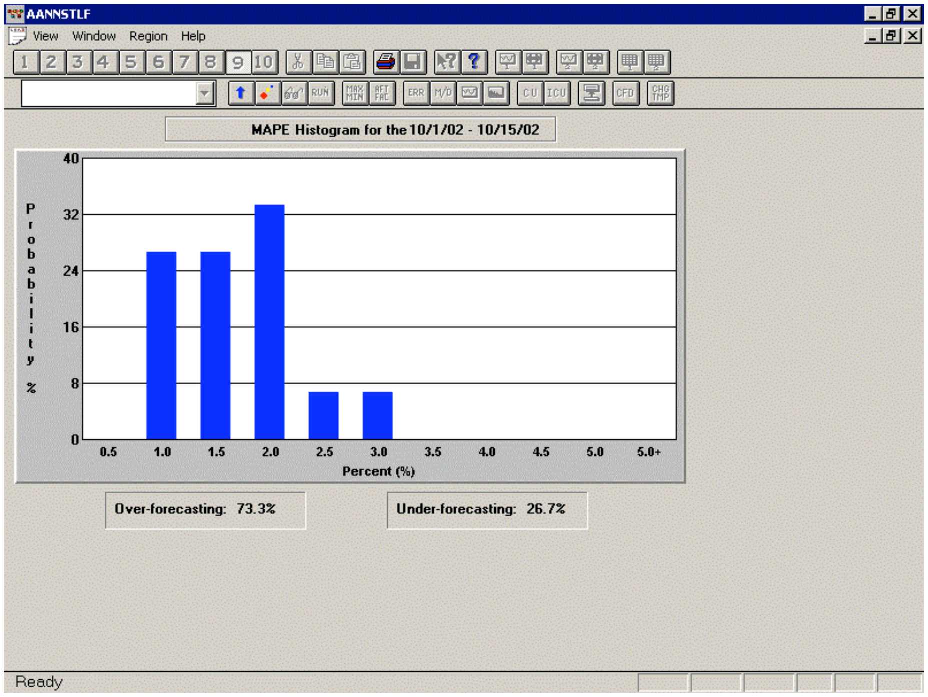

Figure 2-8
Error Histogram for Day Ahead Forecast Using Forecasted Weather

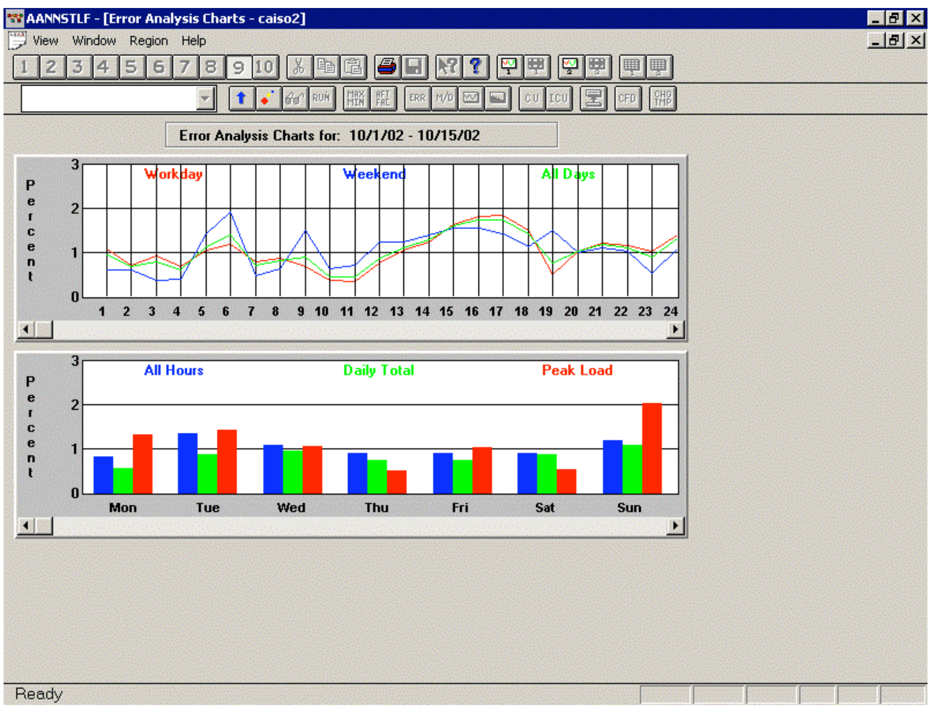

Figure 2-9
Error Charts Using Actual Weather (After-the-Fact)

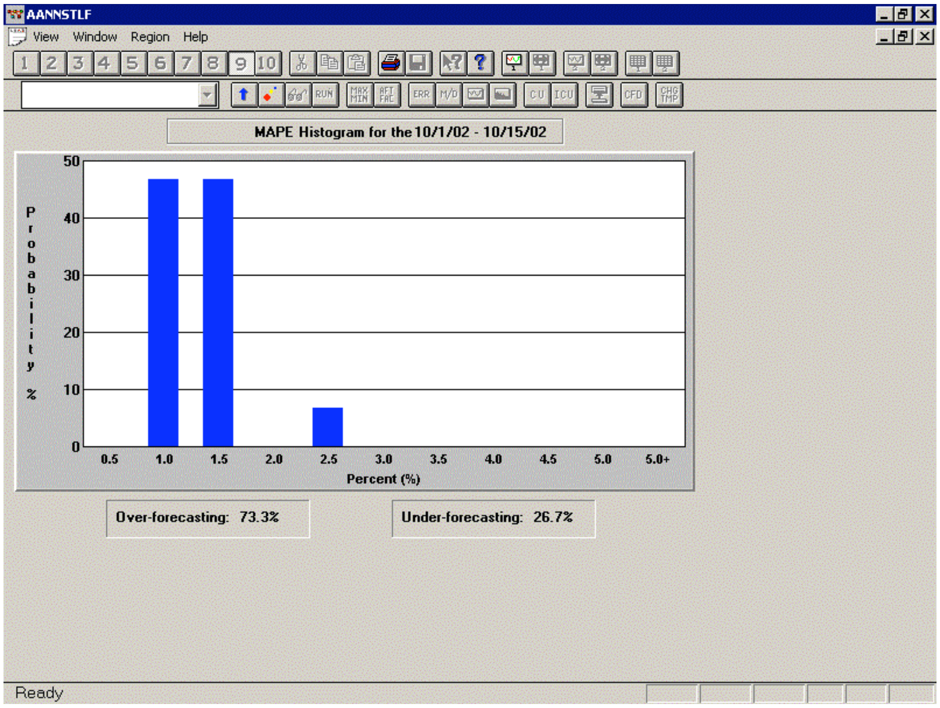

Figure 2-10
Error Histogram Using Actual Weather.

3

OPTIMIZATION OF WEATHER STATION WEIGHTS

Appendix A provides the technical details of optimizing the weather station weights for CAISO and other test regions also. It demonstrates the following improvements in overall accuracy of the forecasts as follows:

- PGE: Improvement of 5% over original weights (obtained heuristically)
- SCE: Improvement of 2%
- SDG&E: Improvement of 1%
- Overall CAISO: Improvement of 3%

The table below provides a comparison of the original vs the optimal weather station weights.

Considering the overall effort as reported in Appendix A, the following conclusions can be made:

- The optimization algorithm has yielded improvements over the heuristic weights. The improvement is most noticeable when the number of weather stations and variability of weather zones is large, e.g. PG&E vs SDG&E as shown above.
- The “optimal weights” themselves are quite different from the original heuristic ones. This demonstrates the fact that relying on heuristics may miss the point sometimes since the key issue is the relationship between various temperatures readings and the load itself.
- In studying the correlation between temperature and load time series, there is a strong argument for fine-tuning the weighting factors on a seasonal or even monthly basis. Thus further refinements of the optimization algorithm may be required.

Table 3-1
Comparison of Original and Optimal Weights for the Three CAISO Regions.

PGE Region	Original Weights	Optimal Weights
Bakersfield (BFL)	0.14	0.26
Fresno (FAT)	0.14	0.0
Santa Rosa (STS)	0.11	0.0
Stockton (SCK)	0.11	0.19
Redding (RDD)	0.11	0.11
Sacramento (SAC)	0.11	0.0
Concord (CCR)	0.08	0.21
San Francisco (SFO)	0.08	0.03
San Jose (SJC)	0.08	0.03
Arcata (ACV)	0.04	0.17

SCE Region	Original Weights	Optimal Weights
Los Angeles-Airport (LAX)	0.20	0.0
Riverside (RAL)	0.20	1.0
Ontario (ONT)	0.20	0.0
Santa Ana (SNA)	0.20	0.0
Los Angeles-Civic Center (CVC)	0.10	0.0
Long Beach (LGB)	0.10	0.0

SDG&E Region	Original Weights	Optimal Weights
San Diego (SAN)	0.40	0.0
El Cajon (ECJ)	Not Used	Not Used
Santee (SEE)	0.60	1.0

4
CONCLUSIONS AND RECOMMENDATIONS

Conclusions:

- EPRI-ANNSTLF as implemented at the CA-ISO is a viable forecaster capable of meeting ALL of the requirements of short-term load forecasting.
- The overall accuracy of 1.5% or less (MAPE Error) is acceptable for daily system and market operations,[1]
- Half-hour forecasting is achievable using the standard ANNSTLF. The delivered CAISO ANNSTLF forecaster is easy to use and will update the hour and half-hour forecasts with minimal manual intervention.
- Optimization of weather station weights will improve overall performance by a few percentage points. However, improvements can be attained by adjusting the weights monthly and/or seasonally.
- Staff training is crucial in improving forecaster accuracy. ANNSTLF has many user options for:
  - Detecting input data problems,
  - Manual adjustments for special days, controllable load variations, blackouts, etc,
  - Making the forecaster more, or less, adaptive
  - Incorporation of additional weather variables, if needed.
  - The main areas of further accuracy improvement are:
  - Holiday forecasting,
  - Sub-regional forecasting to yield a finer grain forecasts that more correlated to sub-regional weather data.

[1] CA-ISO staff have indicated that their goal was a forecast which is accurate at 2%.

Recommendations

- Full automation of ANNSTLF is recommended, by this we mean the automatic loading of weather and load data every half hour, the automatic running of ANNSTLF, and the display of the updated forecast,
- Data pre-filtering for the initial training effort should include an option for optimising the weather station weights. In this regard, these weights should be adjusted monthly and/or seasonally.
- In conjunction with the automation effort, all safeguards associated with manual user options (item (1-e) above) should either be partially automated to the extent of generating user messages and other information for quick user action.
- The 32-bit conversion effort should be carried out as soon as possible, as it is a key pre-requisite to any automation effort,
- ANNSTLF should be interfaced with the CIM database, and or, other databases used at the ISO.
- A procedure should be developed for the easy training of new regions, and their consequent integration with other regions in a hierarchical manner.

5
LIST OF DELIVERABLES

ANNSTLF system comprised of the following:

- ANNSTLF executable program and associated files
- Six (6) trained “regions,” 3 for the half hour and 3 for the top of the hour, plus two corresponding CAISO regions.
- Converter program for pre-filtering the initial data files for any region and placing the data in appropriate ANNSTLF text files. These text files can then be used for initial training or initial catch-up, once the training is completed,
- Converter program for integrating forecasted results into the corresponding CAISO folders
- A third converter program group for the daily and hourly downloading of weather data into appropriate text files and the movement of those files plus the user-entered load data updates into ANNSTLF.
- Procedure and results for the optimization of the weather station weights. The genetic algorithm used for this purpose was not delivered as it is a proprietary commercial package.
- At least two intensive CAISO staff training sessions to insure that they fully understand all of the ANNSTLF user options for improved forecaster performance.
- User and procedure manuals for all of the above.

A

INFLUENCE OF TEMPERATURE ON SHORT-TERM LOAD FORECASTING USING THE EPRI-ANNSTLF

The following technical paper details the theory and application of the optimization of weather station weights as developed for this project. The paper was accepted and presented at the Balkan Power Conference, Belgrade, Yugoslavia (June 2002).

Influence of Temperature on Short-Term Load Forecasting Using the EPRI-ANNSTLF

D. Paravan[2], A. Debs[3], C. Hansen[2], D. Becker[4], Peter Hirsch,[3] and R. Golob[1]

***Abstract* — Close tracking of system load by system generation at all times is the basic requirement in the operation of any power system. In the new environment, a Transmission System Operator (TSO) requires accurate short-term load forecasts to assure reliable system operation. One such forecasting tool is the EPRI artificial neural network short-term load forecaster (EPRI-ANNSTLF) which utilizes a single temperature variable for each "region" to be forecasted. If there are two or more weather stations in such a region then a weighted average temperature is substituted for the single temperature variable. This paper focuses on the development of a practical methodology for selecting such weather-station weighting factors. In the paper, two methods for calculating weather-station weighting factors for regions with multiple weather station data are presented. The influence of temperature on load is measured with correlation coefficient and by using mutual information theory. Weighting factors for each weather station are then calculated by maximizing these the two criteria, which is done by means of evolutionary optimization technique. The proposed methods are verified on five test regions with at least three years of data. Results show that application of proposed methods for calculating the substitutive temperature always increase the accuracy of the generic short term load-forecasting model.**

***Index Terms* — load forecasting, temperature, correlation coefficient, mutual information, neural networks.**

Introduction

LOAD forecasting has always been a very important issue in power system planning and operation. The need for accurate short-term forecasts increased even more with deregulation: independent system operator has to provide enough regulating power to assure system reliability, producers bidding strategies depend on electricity consumption, and retail electric providers have to buy exactly the required energy for their customers, since

scheduled deviations are penalized. As a result, the number of electric power utilities that require efficient short-term load forecasting is increasing.

Application of the artificial neural network (ANN) technology for forecasting in power systems has received much attention in recent years [1]. The main reason why ANN became so popular lies in its ability to learn complex and non-linear relationships that are difficult to model with conventional techniques [2]. Even for input samples quite different from learning samples neural network can give good results. That capability enables the ANN-based system to model the correlations between the electricity load and such factors as temperature and other climatic conditions, time and type of the day effect, season effect, etc. As a result, the artificial neural network technology is very suitable for building a generic short-term load forecasting model.

The advantage of a generic structure is easy implementation of the model in different conditions. However, a drawbackis that not all specifics of a given environment can be embraced. One such varying property is often the number of temperature variables, where measurements from multiple weather stations are available. Based on considerable research it was recommended that only one temperature be used for input into the ANN model [2,3,4], the temperature data have to be pre-processed and replaced with a a weighted average temperature.

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[3] Decision Systems International (DSI), Atlanta, Georgia, USA

[4] EPRI, Palo Alto, California

In this paper the influence of temperature on short-term load forecasting is investigated. Two methods for measuring relationship and dependency between input and output variable are used: (i) correlation coefficient and (ii) mutual information. As a result, two methods for calculating a substitutive temperature in the pre-processing phase are proposed by optimising the correlation coefficient and mutual information. As a result, a standard genetic algorithm was implemented to define "optimal" temperature weights in multiple weather station regions.

The proposed methods were tested on five real cases. For each region about three years of data were available, thus enabling a large out-of-sample period for the verification phase. Results presented in the paper illustrate that weights obtained with proposed methods increase the forecaster accuracy.

Measuring input-output Dependency

Two methods were selected for measuring relationship between temperature and load. For a given numerical data set (x_i, y_i) where $i \in \{1, 2, \ldots N\}$, a natural way in which to measure linear correlation is Pearson's Product Moment Correlation [5]. This method is widely used and is offend referred to as the simple correlation coefficient. Another way to estimate the relevance between two variables is by using Shannon's concept of mutual information [6]. The method is based on the entropy concept and is not limited to linear relationships.

Correlation coefficient

The correlation coefficient is used to determine whether two ranges of data move together — that is, whether large values of one set are associated with large values of the other (positive correlation), whether small values of one set are associated with large values of the other (negative correlation), or whether values in both sets are unrelated (correlation near zero). The linear correlation coefficient r is given by the following equation [5]:

$$r(x,y) = \frac{\operatorname{cov}(x,y)}{\sqrt{\operatorname{cov}(x,x)\operatorname{cov}(y,y)}}$$
$$r(x,y) = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sigma_x \sigma_y} \tag{1}$$

where $\bar{x}$ is mean and σ_x standard deviation for a given set of data.

Mutual information

The mutual information (MI) measures arbitrary dependencies between random variables and is suitable for assessing the information content of input variables in complex classification tasks. In the paper a method for calculating MI as proposed by Bonnlander was selected [7, 8, 9]. The method first determines the relationship between input and output variables using nonparametric density estimation and then measures the relevance of input variables using Shannon's concept of mutual information [6].

Mutual information measures the reduction in uncertainty of output variable Y due to knowledge of the input variable X. The uncertainty of output variable Y with probability $p(y)$ is defined using the entropy formula:

$$H(Y) = -\sum_{y \in Y} p(y) \log p(y) \tag{2}$$

while the average uncertainty after knowing input variable X is the conditional entropy:

$$H(Y|X) = -\sum_{x \in X}\sum_{y \in Y} p(y,x) \log_2 p(y|x) \tag{3}$$

where $p(y|x)$ is the conditional probability for variable Y given the input variable X. Mutual Information (MI) between measurement x drawn from a set X and measurement y drawn from a set Y is the amount learned from measurement of x about the measurement of y:

$$I(Y;X) = H(Y) - H(Y|X)$$
$$I(Y;X) = -\sum_{y \in Y} p(y) \log p(y) + \sum_{x \in X}\sum_{y \in Y} p(y,x) \log p(y|x) \tag{4}$$

The MI is therefore the amount by which the knowledge provided by the input variable decreases uncertainty about the output variable. Here, an unbiased estimator of mutual information is utilized [8].

Multi weather station weights calculation

Load forecasting for needs of a transmission system operator is ussualy done for the whole power system, which can cover a large and geographically diverse teritory. Weather parameters can differ a lot within this area and usually more than one temperature measurement is available. However, in the generic short-term load forecasting model only one temperature is used as imput. Thus, a logical consequence is to preprocess the temperature data and represent multiple weather stations (MWS) with a substitutive weather station, which would map all relevant information referring to the electricity load. Here, a linear combination of all weather stations' temperatures was used to calculate the substitutive temperature of the whole system:

$$\begin{aligned} T &= f(T_{WS1}, T_{WS1}, \ldots, T_{WSM}) \\ T &= w_1 T_{WS1} + w_2 T_{WS2} + \ldots + w_M T_{WSM} \end{aligned} \qquad (5)$$

T ... substitutive temperature of the whole system

T_{WSi} ... i-th weather station

w_i ... weight for the i-th weather station

M ... number of weather stations

For calculating weights w_i, three methods were implemen-ted:

Heuristics: number of inhabitants P_i living in the area coverd with a given weather station, divided by total population in the system P_{sys}:

$$w_{Hi} = \frac{P_i}{P_{sys}} \qquad (6)$$

Maximized correlation coeficient:

$$\begin{aligned} &\max[f(w_1, w_2, \ldots, w_M)] \\ &\max[\|r(w_1 T_{WS1} + w_2 T_{WS2} + \ldots + w_M T_{WSM}, L)\|] \\ &\Rightarrow w_{ri}^{\max} \end{aligned} \qquad (7)$$

Maximized mutual information:

$$\begin{aligned} &\max[I(L; w_1 T_{WS1} + w_2 T_{WS2} + \ldots + w_M T_{WSM})] \\ &\Rightarrow w_{MIi}^{\max} \end{aligned} \qquad (8)$$

For optimizing the correlation coefficient and mutual information between load and substitute temperature a standard genetic algorithm was implemented [10]. A genetic algorithm is an iterative procedure that simulates the natural evolution of a constant-size population of individuals, each one represented by a finite string of symbols, known as the *genome*, encoding a possible solution in a given problem space. This space, referred to as the *search space*, comprises all possible solutions to the problem at hand. The standard genetic algorithm proceeds as follows: an initial population of individuals is generated at random or heuristically. Every evolutionary step, known as a *generation*, the individuals in the current population are *decoded* and *evaluated* according to some predefined quality criterion, referred to as the *fitness*, or *fitness function*. To form a new population (the next generation), individuals are *selected* according to their fitness. Many selection procedures are currently in use, one of the simplest being *fitness-proportionate selection*, where individuals are selected with a probability proportional to their relative fitness. This ensures that the expected number of times an individual is chosen is approximately proportional to its relative performance in the population. Thus, high-fitness (*good*) individuals stand a better chance of *reproducing*, while low-fitness ones are more likely to disappear. Selection alone cannot introduce any new individuals into the population, i.e., it cannot find new points in the search space. These are generated by genetically inspired operators, of which the most well known are *crossover* and *mutation*. Crossover is performed with probability p_c (the *crossover probability* or *crossover rate*) between two selected individuals, called *parents*, by exchanging parts of their genomes (i.e., encodings) to form two new individuals, called *offspring*; in its simplest form, sub strings are exchanged after a randomly selected crossover point. This operator tends to enable the evolutionary process to move toward *promising* regions of the search space. The mutation operator is introduced to prevent premature convergence to local optima by randomly sampling new points in the search space. It is carried out by flipping bits at random, with some (small) probability p_m.

In our case, a real-value encoding scheme is applied. A chromosome consists of M real numbers varying between 0 and 1, which represent weights for each weather station temperature. The evaluation of a given individual is made in three steps: (i) first, encoded weights are weighted such that their sum equals to 1, (ii) a substitute temperature is calculated (equation 5), and (iii) the fitness of each individual is equal to the absolute value of the correlation coefficient between load and substitute temperature. GA operators for real encoding schemes are applied: real valued mutation, intermediate crossover, extended line crossover, and tournament selection. GA parameters are presented in table 1:

Table 1: GA parameters.

Parameter	*Value*
Number of individuals	**15**
Number of generations	**100**
Real valued mutation probability	**0.01**
Intermediate crossover probability	**0.40**
Extended line crossover probability	**0.40**
Tournament size for tournament selection	**3**

The computational time and convergence of the optimization algorithm are acceptable, since in almost each run same optimal value is reached. An example of evaluation process with 200 generations is show on figure 1.

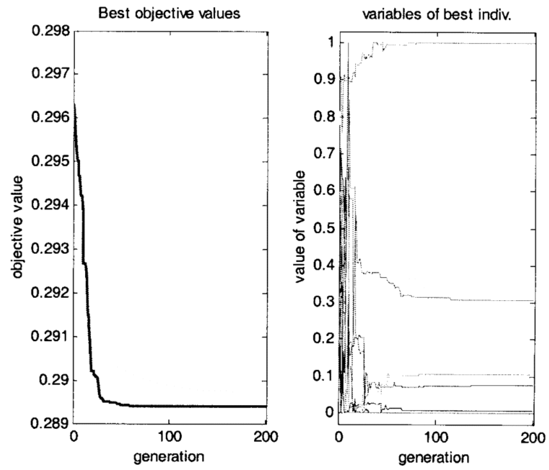

Figure 1: GA evolution of best objective value and weight values.

Artificial neural network short-term load forecaster

In the paper the EPRI's artificial neural network short-term load forecaster (ANNSTLF) was used for verification of proposed methods [3]. More than 40 utilities use the forecasting tool in their daily operation. The model allows only one variable for temperature per hour, thus it is suitable for testing the multiple weather station algorithm. The forecasting tool includes two ANN forecasters; one predicts the base load and the other the load change. At the end, the final forecast is computed by adaptive combination of both outputs. A unique feature of the model is the adaptive update of the neurons' weights during daily operation. This mini-training with the most recent data enables the ANNSTLF to adapt to rapid changes due to weather swings or seasonal changes, and to embrace the gradual load growth (seasonal effect and trend effect). Distinctive features of the ANNSTLF are also the build-in temperature forecaster and the powerful and user-friendly graphic interface.

Results

The influence of temperature on short-term load forecasting and the efficiency of methods and optimization algorithms for multi-weather stations' weights calculation were tested on 5 real cases. First three regions (PG&E, SCE, SDG&E) are part of the area covered by CA-ISO (California, USA), fourth is located in southeast Brazil (ONS SE) and fifth in Slovenia (ELES). Peak load, base load, load shape and seasonal effect differ a lot between the five regions, which can be observed in Table 2 and in figures 2, 3 and 4 (load demand time series for PG&E, ONS and ELES).

Table 2: Description of test regions.

	PG&E 1	SCE 2	SDG&E 3	ONS SE 4	ELES 5
Maximal load [MW]	21,747	18,183	3,195	34,929	1,838
Minimal load [MW]	8,051	7,519	1,384	16,364	0,674
Average load [MW]	12,676	11,208	2,108	25,846	1,263
Peak season [MW]	Summer	Summer	Summer	Winter[5]	Winter
Number of MWS	10	6	2	4	6
Available data [months]	46	46	46	36	30

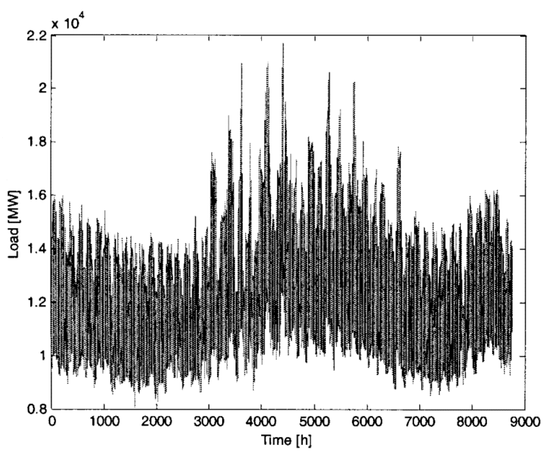

Figure 2: PGE load demand – 2001.

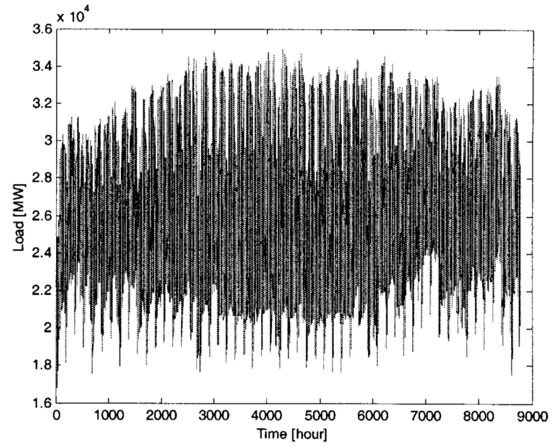

Figure 3: ONS SE load demand.

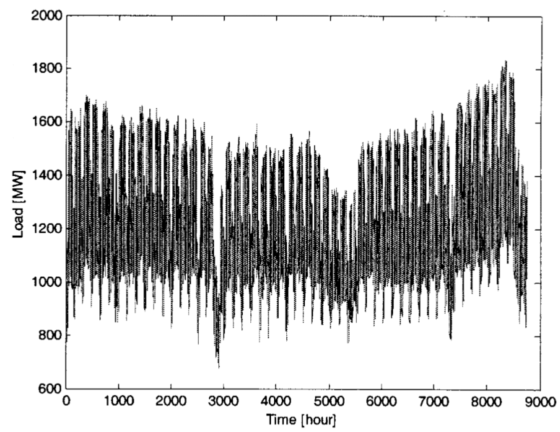

Figure 4: ELES load demand – 2001.

It can be seen, that regions from CA-ISO (PG&E) demonstrate high peaks in summer due to air conditioning, and high demand in winter, due to lower temperatures and daylight time length. ONS load demand is relatively constant with slight increase in winter, which is also the case of the Slovenian power system (December), due to short daylight time and cold temperatures. Figure 4 also shows a very low consumption in beginning of May (Labor holiday) and in August (vacation time). Consequently, the correlation coefficient was calculated for each of the three regions and for each month of the year separately (Figure 5). Since both

[5] Winter in Brazil is in June, July, August, September.

temperature and load are low during the night and high during the day (positive correlation), this can affect the total temperature-load correlation in winter, which is expected to be negative. To eliminate this hour-effect a daily mean temperatures and daily mean loads were used when calculating correlation coefficient.

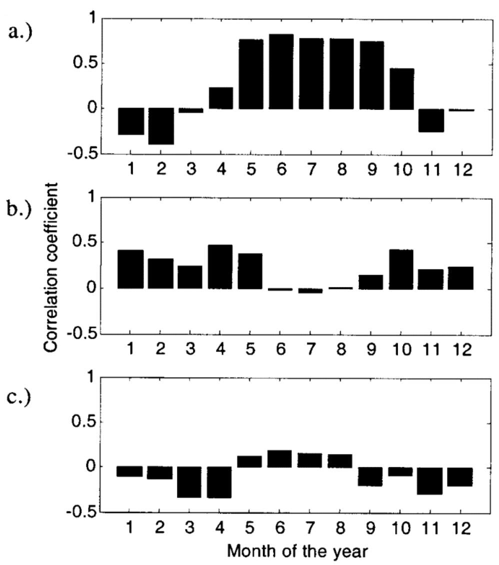

Figure 5: Monthly correlation coefficients for a.) PG&E, b.) ONS and c.) ELES region.

The results confirm high positive relationship between load and temperature during summer months in California, while negative correlation in winter months is present in all cases. As shown in figure 5c, the load-temperature correlation in Slovenian system is relatively week.

For a reliable verification of the proposed methods (multi-weather station weight calculation) a reference case has to be determined. For this purpose, the ANNSTLF model was trained without temperatures (*T=0*) – load and the day-type were the only two inputs into the model. Next, weather stations' weights were calculated for each region with all proposed methods. The appurtenant substitute temperatures were then used to train the artificial neural networks in the model. A total of 4 trainings per region were performed:

- M0: without temperatures (reference case),
- M1: heuristic weights,
- M2: weights by maximizing correlation coefficient,
- M3: weights by maximizing mutual information.

Six months of out-of-sample data were left for the verification phase. The accuracy of the models, and consequently the efficiency of proposed methods and optimization algorithm, was compared by mean average percentage error (MAPE).

As expected, the model using only loads as input variable (M0) produced the highest error. For clearance of presentation, the normalized MAPE was use (MAPE value for a given model was divided by MAPE of the model M0). Normalized MAPE values for models trained without temperatures, models trained using heuristics for determination of MWS weights and models with highest accuracy are presented on figure 6 for each region respectively. MWS weights producing highest ANNSTLF accuracy were in all cases calculated using method M2, only in case of PG&E region the method M3 gave better result.

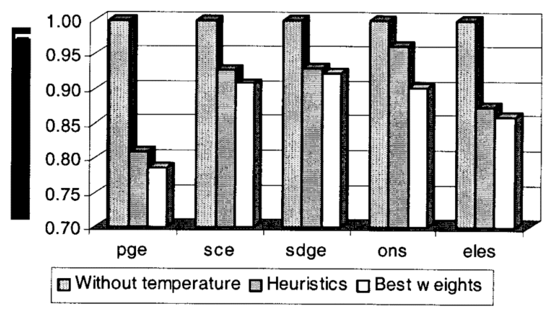

Figure 6: Comparison between models using different temperature as an input variable.

"Optimal" weights for each weather station of the five regions analyzed in this paper are illustrated in figure 7. It can be observed, that the optimization method eliminates irrelevant temperature data. For example, in Slovenian case (ELES) the weather station three is located in Ljubljana. The capital of Slovenia is the biggest city and is also

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geographically located in the center of the country. As a result, the weight 1 for this weather station is a logical decision. A sample day-ahead forecast for ELES region is illustrated in figure 8.

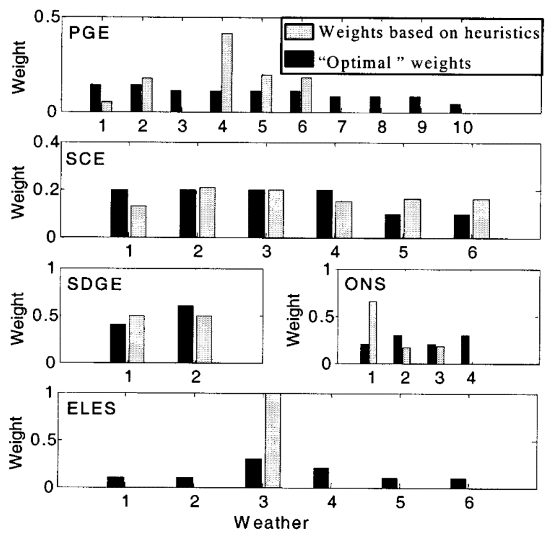

Figure 7: Weights base on heuristics and "optimal weights".

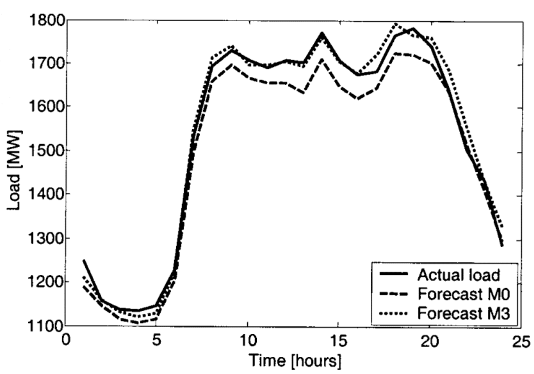

Figure 8: A sample day-ahead forecast for ELES region.

MAPE errors of models with "optimal" weights for multi weather stations are show on figure 9. Five completely different regions in terms of peak load, seasonal effect and geographical location were analyzed. Notwithstanding, the ANNSTLF computational tool produced in all cases accurate load forecasts with MAPE error varying between 1.5 % and 2 %, which makes ANNSTLF an efficient generic short-term load forecaster.

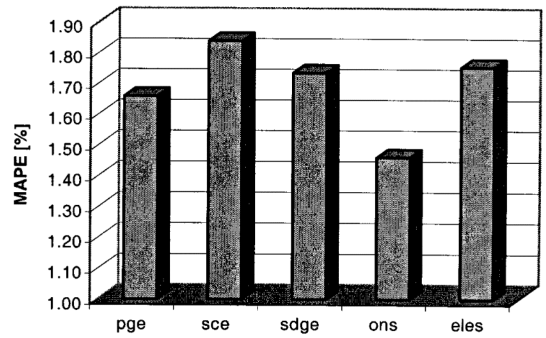

Figure 9: MAPE error for all regions.

Conclusions

In the paper, the problem of pre-processing temperature data from multiple weather station for short-term load forecasting is addressed. Generic forecasting models usually allow only one temperature as input variable, which is also the case of EPRI's efficient forecaster AANNSTLF. For this reason, two methods for optimising weights of multiple weather station data are tested. As a criterion, correlation factor and unbiased estimator of mutual information are optimised by means of genetic algorithms.

The proposed methods are tested on five systems with multiple weather stations. Systems are completely different on from each other in every respect, thus making the verification phase credible. Moreover, having a large database of historical data, at least six months of out-of-sample-data were employed. The obtained results show that for all regions the forecaster accuracy was increased, when proposed methods for calculating multiple weather stations' weights were implemented.

Although five completely different regions in terms of peak load, seasonal effect and geographical location were analyzed, the ANNSTLF forecasting model always gave accurate results, which confirms its generic structure and width range of implementation possibilities. This now allows utilities using the EPRI-ANNSTLF to obtain better accuracy by employing multiple weather stations per region.

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Biographies

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