

Methodologies for Load Forecasting

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Abstract— The ability to accurately forecast Load is vitally important for the electric industry in a deregulated economy. Load forecasting has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of methods have been developed for and applied to load forecasting. In this paper we examine various approaches to Load forecasting, highlighting the importance of Intelligent Systems and explore the possible future directions of forecasting research.

Index Terms— Artificial Intelligence, Load Forecasting, Power Systems, Statistical Analysis,

I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on purchasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour (increasingly shorter durations are now common) to one week, medium forecasts which are usually from a week to one year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company. The natures of these forecasts are different as well. For example, for a particular region, it may be possible to predict the next day load with an accuracy of approximately 1-3%. However, it may be impossible to predict the next year peak load with the similar accuracy since accurate long-term weather forecasts are unavailable. For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak

weather conditions for a given area. Weather normalized load is the load calculated for the so-called normal weather conditions which are the average of the weather

characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another. Most companies take the last 25-30 years of data.

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important. With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market.

In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects. Most forecasting methods use statistical techniques or artificial intelligence algorithms such as regression, neural networks, fuzzy logic, and expert systems. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, statistical learning algorithms, fuzzy logic, and expert systems, have been developed for short-term forecasting.

As we will show, a large variety of mathematical methods and ideas have been used for load forecasting. The development and improvements of appropriate mathematical tools will lead to the development of more accurate load forecasting techniques. The accuracy of load forecasting depends not only on the load forecasting techniques, but also on the accuracy of forecasted weather scenarios. Weather forecasting is an important topic which is outside of the scope of this paper. However, mention will be made of the significant progress in the development of computerized weather forecasting systems, including the Mesoscale Model MM5 developed and supported by a consortium of universities [1].

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II. IMPORTANT ISSUES IN FORECASTS

For short-term load forecasting several factors should be considered, such as time factors, weather data, and possible customers' classes. The medium- and long-term forecasts take into account the historical load and weather data, the number of customers in different categories, the appliances in the area and their characteristics including age, the economic and demographic data and their forecasts, the appliance sales data, and other factors.

The time factors include the time of the year, the day of the week, and the hour of the day. There are important differences in load between weekdays and weekends. The load on different weekdays also can behave differently. For example, Mondays and Fridays being adjacent to weekends, may have structurally different loads than Tuesday through Thursday. This is particularly true during the summer time. Holidays are more difficult to forecast than non-holidays because of their relative infrequent occurrence. Weather conditions influence the load. In fact, forecasted weather parameters are the most important factors in short-term load forecasts.

Various weather variables could be considered for load forecasting. Temperature and humidity are the most commonly used load predictors. An electric load prediction survey published in [2] indicated that of the 22 research reports considered, 13 made use of temperature only, 3 made use of temperature and humidity, 3 utilized additional weather parameters, and 3 used only load parameters. Among the weather variables listed above, two composite weather variable functions, the THI (temperature-humidity index) and WCI (wind chill index), are broadly used by utility companies. THI is a measure of summer heat discomfort and similarly WCI is cold stress in winter.

Most electric utilities serve customers of different types such as residential, commercial, and industrial. The electric usage pattern is different for customers that belong to different classes but is somewhat alike for customers within each class. Therefore, most utilities distinguish load behavior on a class-by-class basis [3].

III. FORECASTING METHODOLOGIES

Over the last few decades a number of forecasting methods have been developed. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, expert systems, fuzzy logic, and statistical learning algorithms, are used for short-term forecasting. The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of

factors. For example, Chen *et al.* [4] presented an additive model that takes the form of predicting load as the function of four components:

$$L = Ln + Lw + Ls + Lr \quad (1)$$

where L is the total load, Ln represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year, Lw represents the weather sensitive part of the load, Ls is a special event component that creates a substantial deviation from the usual load pattern, and Lr is a completely random term, the noise. Chen *et al.* [4] also suggested electricity pricing as an additional term that can be included in the model. Naturally, price decreases/increases affect electricity consumption. Large cost sensitive industrial and institutional loads can have a significant effect on loads. Chen *et al.* used Pennsylvania-New Jersey-Maryland (PJM) spot price data (as it related to Ontario Hydro load) as a neural network input. The authors report that accurate estimates were achieved more quickly with the inclusion of price data. A multiplicative model may be of the form

$$L = Ln \cdot Fw \cdot Fs \cdot Fr \quad (2)$$

where Ln is the normal (base) load and the correction factors Fw , Fs , and Fr are positive numbers that can increase or decrease the overall load. These corrections are based on current weather (Fw), special events (Fs), and random fluctuation (Fr). Factors such as electricity pricing (Fp) and load growth (Fg) can also be included. Rahman [5] presented a rule-based forecast using a multiplicative model. Weather variables and the base load associated with the weather measures were included in the model.

A. Medium/Long-term Load Forecasting Methods

The end-use modeling, econometric modeling, and their combinations are the most often used methods for medium- and long-term load forecasting. Descriptions of appliances used by customers, the sizes of the houses, the age of equipment, technology changes, customer behavior, and population dynamics are usually included in the statistical and simulation models based on the so-called end-use approach. In addition, economic factors such as per capita incomes, employment levels, and electricity prices are included in econometric models. These models are often used in combination with the end-use approach. Long-term forecasts include the forecasts on the population changes, economic development, industrial construction, and technology development.

1) End-use Models

The end-use approach directly estimates energy consumption by using extensive information on end use and end users, such as appliances, the customer use, their age, sizes of houses, and so on. Statistical information about customers along with dynamics of change is the basis for the forecast. End-use models focus on the various uses of electricity in the residential, commercial, and industrial sector. These models are based on the principle that electricity demand is derived from customer's demand for

light, cooling, heating, refrigeration, etc. Thus end-use models explain energy demand as a function of the number of appliances in the market [6]. Ideally this approach is very accurate. However, it is sensitive to the amount and quality of end-use data. For example, in this method the distribution of equipment age is important for particular types of appliances. End-use forecast requires less historical data but more information about customers and their equipment.

2) Econometric Models

The econometric approach combines economic theory and statistical techniques for forecasting electricity demand. The approach estimates the relationships between energy consumption (dependent variables) and factors influencing consumption. The relationships are estimated by the least-squares method or time series methods. One of the options in this framework is to aggregate the econometric approach, when consumption in different sectors (residential, commercial, industrial, etc.) is calculated as a function of weather, economic and other variables, and then estimates are assembled using recent historical data. Integration of the econometric approach into the end-use approach introduces behavioral components into the end-use equations.

3) Statistical Model-based Learning

The end-use and econometric methods require a large amount of information relevant to appliances, customers, economics, etc. Their application is complicated and requires human participation. In addition such information is often not available regarding particular customers and a utility keeps and supports a profile of an “average” customer or average customers for different type of customers. The problem arises if the utility wants to conduct next-year forecasts for sub-areas, which are often called load pockets. In this case, the amount of the work that should be performed increases proportionally with the number of load pockets. In addition, end-use profiles and econometric data for different load pockets are typically different. The characteristics for particular areas may be different from the average characteristics for the utility and may not be available. In order to simplify the medium-term forecasts, make them more accurate, and avoid the use of the unavailable information, Feinberg *et al.* [7], [8] developed a statistical model that learns the load model parameters from the historical data. Feinberg *et al.* studied load data sets provided by a utility company in Northeastern US. The focus of the study was the summer data. We compared several load models and came to the conclusion that the following multiplicative model is the most accurate

$$L(t) = F(d(t), h(t)) \cdot f(w(t)) + R(t) \quad (3)$$

where $L(t)$ is the actual load at time t , $d(t)$ is the day of the week, $h(t)$ is the hour of the day, $F(d, h)$ is the daily and hourly component, $w(t)$ is the weather data that include the temperature and humidity, $f(w)$ is the weather factor, and $R(t)$ is a random error. In fact, $w(t)$ is a vector that consists of the current and lagged weather variables. This reflects the fact that electric load depends not only on the current weather conditions but also on the weather during the previous hours and days. In particular, the well-known

effect of the so-called heat waves is that the use of air conditioners increases when the hot weather continues for several days.

To estimate the weather factor $f(w)$, we used the regression model

$$f(w) = \beta_0 + \sum \beta_j X_j \quad (4)$$

where X_j are explanatory variables which are nonlinear functions of current and past weather parameters and β_0, β_j are the regression coefficients. The parameters of the model can be calculated iteratively. We start with $F = 1$. Then we use the above regression model to estimate f . Then we estimate F , and so on.

The described algorithm demonstrated rapid convergence on historical hourly load and weather data. We have applied it to many areas with population between 50,000 and 250,000 customers. Figure 1. presents an example of a scatter plot that compares the model and real parameters. Figure 2 demonstrates the convergence of the correlation between the actual load and the model for the iteration process. Figure 3 demonstrates the convergence of the linear regression procedures in the algorithm.

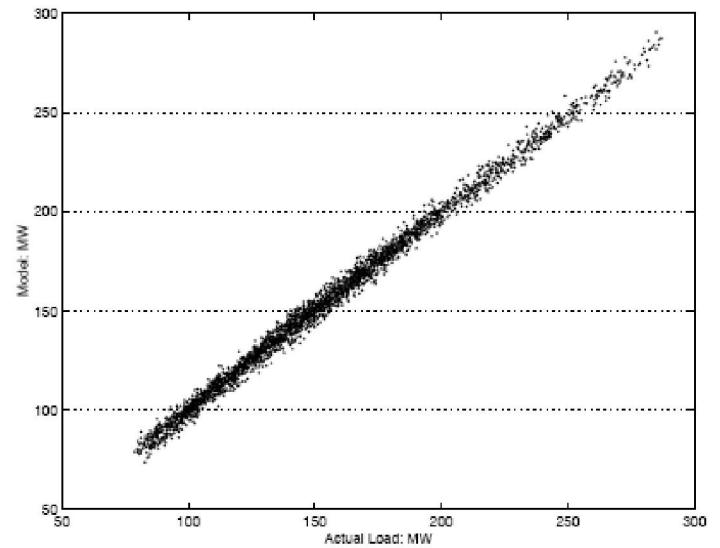


Fig. 1. Scatter plot of the actual load vs. the model.

The software [9], that uses the described method, learns the model parameters and makes next-year predictions based on the model loads for the last 25-30 years of data. Though historical loads may not available, the software applies the last year models to the historical weather data to estimate the next year's peak distribution.

The software generates several important characteristics. For example, for each load pocket and for the system, it calculates a weather normalization factor that is a ratio of the peak load to the load that would be observed under average peak conditions. It also produces probability distributions for the next year peaks. The described methods can be applied to both medium- and long-term forecasting. However, the long-term forecasts should incorporate economic and population dynamic forecasts as input parameters.

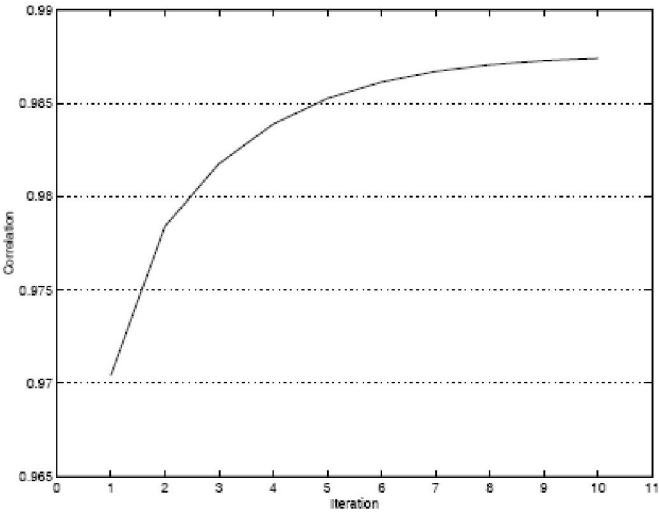


Fig. 2. Correlation between the actual load and the model.

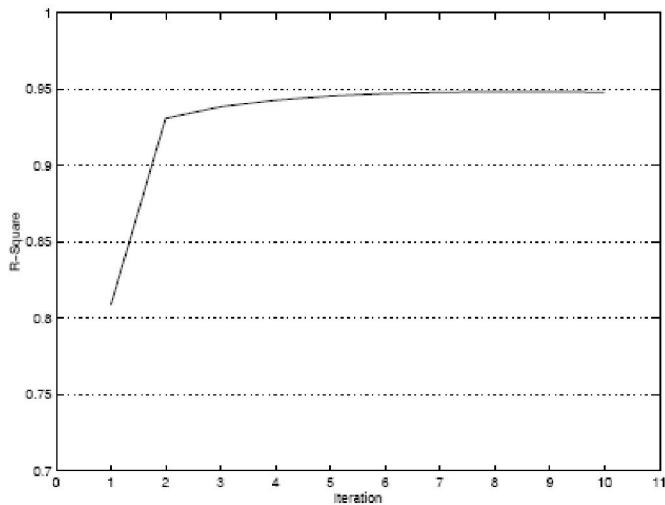


Fig. 3. Convergence of R^2 for the actual load vs. the model.

B. Short-term Load Forecasting Methods

A large variety of statistical and artificial intelligence techniques have been developed for short-term load forecasting.

1) Similar-day Approach.

This approach is based on searching historical data for days within one, two, or three years with similar characteristics to the forecast day. Similar characteristics include weather, day of the week, and the date. The load of a similar day is considered as a forecast. Instead of a single similar day load, the forecast can be a linear combination or regression procedure that can include several similar days. The trend coefficients can be used for similar days in the previous years.

2) Regression Methods

Regression is the one of most widely used statistical techniques. For electric load forecasting regression methods are usually used to model the relationship of load consumption and other factors such as weather, day type,

and customer class. Engle *et al.* [10] presented several regression models for the next day peak forecasting. Their models incorporate deterministic influences such as holidays, stochastic influences such as average loads, and exogenous influences such as weather. References [11]-[14] describe other applications of regression models to loads forecasting.

3) Time Series

Time series methods are based on the assumption that the data have an internal structure, such as autocorrelation, trend, or seasonal variation. Time series forecasting methods detect and explore such a structure. Time series have been used for decades in such fields as economics, digital signal processing, as well as electric load forecasting. In particular, ARMA (autoregressive moving average), ARIMA (autoregressive integrated moving average), ARMAX (autoregressive moving average with exogenous variables), and ARIMAX (autoregressive integrated moving average with exogenous variables) are the most often used classical time series methods. ARMA models are usually used for stationary processes while ARIMA is an extension of ARMA to non-stationary processes. ARMA and ARIMA use the time and load as the only input parameters. Since load generally depends on the weather and among the classical time series models. Fan and McDonald [15] and Cho *et al.* [16] describe implementations of ARIMAX models for load forecasting. Yang *et al.* [17] used evolutionary programming (EP) approach to identify the ARMAX model parameters for one day to one week ahead hourly load demand forecast. Evolutionary programming [18] is a method for simulating evolution and constitutes a stochastic optimization algorithm. Yang and Huang [19] proposed a fuzzy autoregressive moving average with exogenous input variables (FARMAX) for one day ahead hourly load forecasts.

4) Neural Networks

The use of artificial neural networks (ANN or simply NN) has been a widely studied electric load forecasting technique since 1990 [20]. Neural networks are essentially non-linear circuits that have the demonstrated capability to do non-linear curve fitting. The outputs of an artificial neural network are some linear or nonlinear mathematical function of its inputs. The inputs may be the outputs of other network elements as well as actual network inputs. In practice network elements are arranged in a relatively small number of connected layers of elements between network inputs and outputs. Feedback paths are sometimes used. In applying a neural network to electric load forecasting, one must select one of a number of architectures (e.g. Hopfield, back propagation, Boltzmann machine), the number and connectivity of layers and elements, use of bi-directional or uni-directional links, and the number format (e.g. binary or continuous) to be used by inputs and outputs, and internally. The most popular artificial neural network architecture for electric load forecasting is back propagation. Back propagation neural networks use continuously valued functions and supervised learning. That is, under supervised learning, the actual numerical weights assigned to element inputs are determined by matching historical data (such as time and weather) to

desired outputs (such as historical electric loads) in a pre-operational “training session”. Artificial neural networks with unsupervised learning do not require pre-operational training. Bakirtzis *et al.* [21] developed an ANN based short-term load forecasting model for the Energy Control Center of the Greek Public Power Corporation. In the development they used a fully connected three-layer feed-forward ANN and back propagation algorithm was used for training. Input variables include historical hourly load data, temperature, and the day of the week.

The model can forecast load profiles from one to seven days. Also Papalexopoulos *et al.* [22] developed and implemented a multi-layered feed-forward ANN for short-term system load forecasting. In the model three types of variables are used as inputs to the neural network: season related inputs, weather related inputs, and historical loads. Khotanzad *et al.* [23] described a load forecasting system known as ANNSTLF. ANNSTLF is based on multiple ANN strategies that capture various trends in the data. In the development they used a multilayer perceptron trained with the error back propagation algorithm. ANNSTLF can consider the effect of temperature and relative humidity on the load. It also contains forecasters that can generate the hourly temperature and relative humidity forecasts needed by the system.

An improvement of the above system was described in [24]. In the new generation, ANNSTLF includes two ANN forecasters, one predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these forecasts. The effects of humidity and wind speed are considered through a linear transformation of temperature. As reported in ANNSTLF was being used by 35 utilities across the USA and Canada. Chen *et al.* developed a three layer fully connected feed-forward neural network and the back propagation algorithm was used as the training method. Their ANN though considers the electricity price as one of the main characteristics of the system load. Many published studies use artificial neural networks in conjunction with other forecasting techniques (such as with regression trees [25], time series [26] or fuzzy logic [27]).

5) Expert Systems

Rule based forecasting makes use of rules, which are often heuristic in nature, to do accurate forecasting. Expert systems, incorporates rules and procedures used by human experts in the field of interest into software that is then able to automatically make forecasts without human assistance. Expert system use began in the 1960’s for such applications as geological prospecting and computer design. Expert systems work best when a human expert is available to work with software developers for a considerable amount of time in imparting the expert’s knowledge to the expert system software. Also, an expert’s knowledge must be appropriate for codification into software rules (i.e. the expert must be able to explain his/her decision process to programmers). An expert system may codify up to hundreds or thousands of production rules. Ho *et al.* [18] proposed a knowledge-based expert system for the short-term load forecasting of the Taiwan power system.

Operator’s knowledge and the hourly observations of system load over the past five years were employed to establish eleven day types. Weather parameters were also considered.

The developed algorithm performed better compared to the conventional Box-Jenkins method. Rahman and Hazim [29] developed a site-independent technique for short-term load forecasting. Knowledge about the load and the factors affecting it are extracted and represented in a parameterized rule base. This rule base is complemented by a parameter database that varies from site to site. The technique was tested in several sites in the United States with low forecasting errors. The load model, the rules, and the parameters presented in the paper have been designed using no specific knowledge about any particular site. The results can be improved if operators at a particular site are consulted.

6) Fuzzy Logic

Fuzzy logic is a generalization of the usual Boolean logic used for digital circuit design. An input under Boolean logic takes on a truth value of “0” or “1”. Under fuzzy logic an input has associated with it a certain qualitative ranges. For instance a transformer load may be “low”, “medium” and “high”. Fuzzy logic allows one to (logically) deduce outputs from fuzzy inputs. In this sense fuzzy logic is one of a number of techniques for mapping inputs to outputs (i.e. curve fitting).

Among the advantages of fuzzy logic are the absence of a need for a mathematical model mapping inputs to outputs and the absence of a need for precise (or even noise free) inputs. With such generic conditioning rules, properly designed fuzzy logic systems can be very robust when used for forecasting. Of course in many situations an exact output (e.g. the precise 12PM load) is needed. After the logical processing of fuzzy inputs, a “defuzzification” process can be used to produce such precise outputs. References [30], [31], describe applications of fuzzy logic to electric load forecasting.

7) Support vector machines

Support Vector Machines (SVMs) are a more recent powerful technique for solving classification and regression problems. This approach was originated from Vapnik’s [32] statistical learning theory. Unlike neural networks, which try to define complex functions of the input feature space, support vector machines perform a nonlinear mapping (by using so-called kernel functions) of the data into a high dimensional (feature) space. Then support vector machines use simple linear functions to create linear decision boundaries in the new space. The problem of choosing an architecture for a neural network is replaced here by the problem of choosing a suitable kernel for the support vector machine [33]. Mohandes [34] applied the method of support vector machines for short-term electrical load forecasting. The author compares its performance with the autoregressive method. The results indicate that SVMs compare favorably against the autoregressive method. Chen *et al.* [35] proposed a SVM model to predict daily load demand of a month. Their program was the winning entry of the competition organized by the EU NITE network. Li

and Fang [36] also used a SVM model for short-term load forecasting.

IV. FUTURE RESEARCH DIRECTIONS

In this paper we have discussed several statistical and artificial intelligence techniques that have been developed for short-, medium-, and long-term electric load forecasting. Several statistical models and algorithms that have been developed though, are operating ad hoc. The accuracy of the forecasts could be improved, if one would study these statistical models and develop mathematical theory that explains the convergence of these algorithms. Researchers should also investigate the boundaries of applicability of the developed models and algorithms. So far, there is no single model or algorithm that is superior for all utilities.

The reason is that utility service areas vary in differing mixtures of industrial, commercial, and residential customers. They also vary in geographic, climatologic, economic, and social characteristics. Selecting the most suitable algorithm by a utility can be done by testing the algorithms on real data. In fact, some utility companies use several load forecasting methods in parallel. As far as we know, nothing is known on a priori conditions that could detect which forecasting method is more suitable for a given load area. An important question is to investigate the sensitivity of the load forecasting algorithms and models to the number of customers, characteristics of the area, energy prices, and other factors. As mentioned above, weather is an important factor that influences the load. The usual approach to short-term load forecasting uses the forecasted weather scenario as an input.

However, one of the most important recent developments in weather forecasting is the so-called ensemble approach which consists of computing multiple forecasts. Then probability weights can be assigned to these ensembles. Instead of using the single weather forecast, weather ensemble predictions can be used as multiple inputs for load forecasts. These inputs generate multiple load forecasts. In recent papers [37, 38], the authors describe ensemble load predictions based on 51 weather ensembles and various statistical forecasting methods. There are two advantages of having load forecasts in the probabilistic form: (i) they can lead to a more accurate hourly forecast obtained by using multiple ensembles, for example, by averaging them; (ii) the probabilistic description of the future load can be used as an input to decision support systems to make important generation, purchasing, and switching decisions. In general, it is known from the appropriate mathematical models that the knowledge of the demand distribution leads to more cost efficient decisions than the knowledge of the expected demand. On a broader scale, we think that the important research and development directions are: (i) combining weather and load forecasting and (ii) incorporating load forecasting into various decision support systems.

V CONCLUSIONS

Accurate load forecasting is very important for electric utilities in a competitive environment created by the

electric industry deregulation. In this paper we have reviewed some statistical and artificial intelligence techniques that are used for electric load forecasting. We also discussed factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end use factors. Load forecasting methods use advanced mathematical modeling. Additional progress in load forecasting and its use in industrial applications can be achieved by providing short-term load forecasts in the form of probability distributions rather than the forecasted numbers; for example the so-called ensemble approach can be used. We believe that the enhancement of load forecasting will be achieved by the combination of two research areas; firstly, research in statistics and artificial intelligence and secondly, better understanding of load dynamics and the statistical properties in order improve modeling power.

REFERENCES

- [1] J. Dudhia and J.F. Bresch. A Global Version of the PSU-NCAR Mesoscale Model. *Monthly Weather Review*, 130:2989–3007, 2002.
- [2] H.S. Hippert, C.E. Pedreira, and R.C. Souza. Neural Networks for Short-Term Load Forecasting: A Review and Evaluation. *IEEE Transactions on Power Systems*, 16:44–55, 2001.
- [3] H.L. Willis. *Spatial Electric Load Forecasting*. Marcel Dekker, New York, 1996.
- [4] H. Chen, C.A. Canizares, and A. Singh. ANN-Based Short-Term Load Forecasting in Electricity Markets. *Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference*, 2:411–415, 2001.
- [5] S. Rahman. Formulation and Analysis of a Rule-Based Short-Term Load Forecasting Algorithm. *Proceedings of the IEEE*, 78:805–816, 1990.
- [6] C.W. Gellings. *Demand Forecasting for Electric Utilities*. The Fairmont Press, Lilburn, GA, 1996.
- [7] E.A. Feinberg, J.T. Hajagos, and D. Genethliou. Load Pocket Modeling. *Proceedings of the 2nd IASTED International Conference: Power and Energy Systems*, 50–54, Crete, 2002.
- [8] E.A. Feinberg, J.T. Hajagos, and D. Genethliou. Statistical Load Modeling. *Proceedings of the 7th IASTED International Multi-Conference: Power and Energy Systems*, 88–91, Palm Springs, CA, 2003.
- [9] E.A. Feinberg, J.T. Hajagos, B.G. Irrgang, R.J. Rossin, D. Genethliou and D.E. Feinberg. Load pocket forecasting software. Submitted to *IASTED Journal on Energy and Power Systems*.
- [10] R.F. Engle, C. Mustafa, and J. Rice. Modeling Peak Electricity Demand. *Journal of Forecasting*, 11:241–251, 1992.
- [11] O. Hyde and P.F. Hodnett. An Adaptable Automated Procedure for Short-Term Electricity Load Forecasting. *IEEE Transactions on Power Systems*, 12:84–93, 1997.
- [12] S. Ruzic, A. Vuckovic, and N. Nikolic. Weather Sensitive Method for Short-Term Load Forecasting in Electric Power Utility of Serbia. *IEEE Transactions on Power Systems*, 18:1581–1586, 2003.
- [13] T. Haida and S. Muto. Regression Based Peak Load Forecasting using a Transformation Technique. *IEEE Transactions on Power Systems*, 9:1788–1794, 1994.
- [14] W. Chartyoniu, M.S. Chen, and P. Van Olinda. Nonparametric Regression Based Short-Term Load Forecasting. *IEEE Transactions on Power Systems*, 13:725–730, 1998.
- [15] J.Y. Fan and J.D. McDonald. A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems. *IEEE Transactions on Power Systems*, 9:988–994, 1994.
- [16] M.Y. Cho, J.C. Hwang, and C.S. Chen. Customer Short-Term Load Forecasting by using ARIMA Transfer Function Model. *Proceedings of the International Conference on Energy Management and Power Delivery*, 1:317–322, 1995.
- [17] H.T. Yang, C.M. Huang, and C.L. Huang. Identification of ARMAX Model for Short-Term Load Forecasting: An Evolutionary Programming Approach. *IEEE Transactions on Power Systems*, 11:403–408, 1996.

- [18] D.B. Fogel. An Introduction to Simulated Evolutionary Optimization. *IEEE Transactions on Neural Networks*, 5:3–14, 1994.
- [19] H.T. Yang and C.M. Huang. A New Short-Term Load Forecasting Approach using Self-Organizing Fuzzy ARMAX Models. *IEEE Transactions on Power Systems*, 13:217–225, 1998.
- [20] M. Peng, N.F. Hubele, and G.G. Karady. Advancement in the Application of Neural Networks for Short-Term Load Forecasting. *IEEE Transactions on Power Systems*, 7:250–257, 1992.
- [21] A.G. Bakirtzis, V. Petridis, S.J. Kiartzis, M.C. Alexiadis, and A.H. Maassis. A Neural Network Short-Term Load Forecasting Model for the Greek Power System. *IEEE Transactions on Power Systems*, 11:858–863, 1996.
- [22] A.D. Papalexopoulos, S. Hao, and T.M. Peng. An Implementation of a Neural Network Based Load Forecasting Model for the EMS. *IEEE Transactions on Power Systems*, 9:1956–1962, 1994.
- [23] A. Khotanzad, R.A. Rohani, T.L. Lu, A. Abaye, M. Davis, and D.J. Maratukulam. ANNSTLF—A Neural-Network-Based Electric Load Forecasting System. *IEEE Transactions on Neural Networks*, 8:835–846, 1997.
- [24] A. Khotanzad, R.A. Rohani, and D. Maratukulam. ANNSTLF—Artificial Neural Network Short-Term Load Forecaster—Generation Three. *IEEE Transactions on Neural Networks*, 13:1413–1422, 1998.
- [25] H. Mori and N. Kosemura. Optimal Regression Tree Based Rule Discovery for Short-Term Load Forecasting. *Proceedings of IEEE Power Engineering Society Transmission and Distribution Conference*, 2:421–426, 2001.
- [26] T.W.S. Chow and C.T. Leung. Nonlinear Autoregressive Integrated Neural Network Model for Short-Term Load Forecasting. *IEE Proceedings on Generation, Transmission and Distribution*, 143:500–506, 1996.
- [27] S.E. Skarman and M. Georgioupolous. Short-Term Electrical Load Forecasting using a Fuzzy ARTMAP Neural Network. *Proceedings of SPIE*, 181–191, 1998.
- [28] K.L. Ho, Y.Y. Hsu, F.F. Chen, T.E. Lee, C.C. Liang, T.S. Lai, and K.K. Chen. Short-Term Load Forecasting of Taiwan Power System using a Knowledge Based Expert System. *IEEE Transactions on Power Systems*, 5:1214–1221, 1990.
- [29] S. Rahman and O. Hazim. Load Forecasting for Multiple Sites: Development of an Expert System-Based Technique. *Electric Power Systems Research*, 39:161–169, 1996.
- [30] S.J. Kiartzis and A.G. Bakirtzis. A Fuzzy Expert System for Peak Load Forecasting: Application to the Greek Power System. *Proceedings of the 10th Mediterranean Electrotechnical Conference*, 3:1097–1100, 2000.
- [31] V. Miranda and C. Monteiro. Fuzzy Inference in Spatial Load Forecasting. *Proceedings of IEEE Power Engineering Winter Meeting*, 2:1063–1068, 2000.
- [32] V.N. Vapnik. *The Nature of Statistical Learning Theory*. New York, Springer Verlag, 1995.
- [33] N. Christiani and J.S. Taylor. *An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods*. Cambridge University Press, Cambridge, 2000.
- [34] M. Mohandes. Support Vector Machines for Short-Term Electrical Load Forecasting. *International Journal of Energy Research*, 26:335–345, 2002.
- [35] B.J. Chen, M.W. Chang, and C.J. Lin. Load Forecasting using Support Vector Machines: A Study on EUNITE Competition 2001. Technical report, Department of Computer Science and Information Engineering, National Taiwan University, 2002.
- [36] Y. Li and T. Fang. Wavelet and Support Vector Machines for Short-Term Electrical Load Forecasting. *Proceedings of International Conference on Wavelet Analysis and its Applications*, 1:399–404, 2003.
- [37] J.W. Taylor and R. Buizza. Using Weather Ensemble Predictions in Electricity Demand Forecasting. *International Journal of Forecasting*, 19:57–70, 2003.
- [38] J.W. Taylor and R. Buizza. Neural Network Load Forecasting With Weather Ensemble Predictions. *IEEE Transactions on Power Systems*, 17:626–632, 2002.