Developing Efficient Algorithms for Load and Price Forecasting in Electric Power System: A Comprehensive Review

Dharmendra Kumar Mishra ,
NIELIT, Chandigarh, B.O. Lucknow
Ministry of C & IT, Gov.t of India

A.K.D. Dwivedi
NIELIT, Chandigarh, B.O. Lucknow,
Ministry of C & IT, Gov.t of India

S.P. Tripathi
Department of CSE
IET Lucknow

Abstract

Deregulation of the electric power industry worldwide raises many challenging issues. Forecasting the hourly market clearing prices (MCP), Load and other quantities (MCQ) in daily power markets is the most essential task and basis for any decision-making. One approach to predict the market behaviors is to use the historical prices, quantities and other information to forecast the future prices and quantities. The basic idea is to use history and other estimated factors in the future to "fit" and "extrapolate" the prices and quantities. There are many methods available in literature; each has its own merit and limitations. A number of Short Term Load Forecasting tools have been recently developed using nonlinear modelling methods, including those based on the Neural Network Modelling framework. In this paper, we study the various factors and methods used in power price and load forecasting.

Keywords: *Short-term, Demand Forecasting, Neural Networks, Genetic Algorithms, Fuzzy Rules.*

1. Introduction

Energy is the foundation for economic development of all the countries. Infrastructural growth of most of the key sectors like Transportation, Health and Education etc are dependent on the Energy. To ensure rapid, inclusive and sustainable growth of the Country, it has become imperative to increase the power production and restructure the power sector to minimize the power losses and to provide open access to everyone by setting up an exchange where electricity can be bought and sold as an essential commodity. This may provide conducive and competitive environment for all the vendors involved in power generation, transmission and its distribution. Electricity is characteristically different from other commodities that neither can be stored for long time nor can be released as per the decrease or increase in demand. Thus it is most important to forecast the demand of power for the next hour, next day or next month with utmost accuracy so that the generation, transmission and distribution mechanism can be controlled accordingly and power losses can be minimized. Restructuring process demands price transparency as the number of participants and the marketing operations are increased. Participants are demanding efficient tools for price forecasting in order to hedge their risk and survive in the competitive market. This paper highlights the main feature of electricity price forecasting and provides an insight into the development of future electricity price forecasting methods and indicates the potential future development of methodologies for accurate electricity price forecasting.

2. Load Pattern

The variation in power load occurring during each weekly cycle depends on the factors, such as –

a) **Day (d) -** The load characteristics on Saturday and Sunday are different from the usual weekdays, which is attributed to the fact that most business and industries are closed over the weekend, thus giving rise to an overall lower load demand. Weekend effect is also seen in the first part of Monday, which varies from regular weekdays.

b) **Time (t) -**Power consumption during the night is much lower than at daytime; furthermore, power consumption during the daytime varies with the time of the day. For example, the morning rush hour has a different load demand than the lunch hour or the afternoon period.

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c) **Weather factor** - The most important of the weather parameters are the temperature variables, representing the strongest correlation with weather-related load variations. Temperatures can be measured to a higher degree of accuracy relative to any of the other weather variables.

d) **Public Holidays** - The power load on the public holidays, are lower than regular weekdays.

All of these factors make the short-term load-forecasting problem highly non-linear with an infinite number of modelling characteristics and model data input combinations.

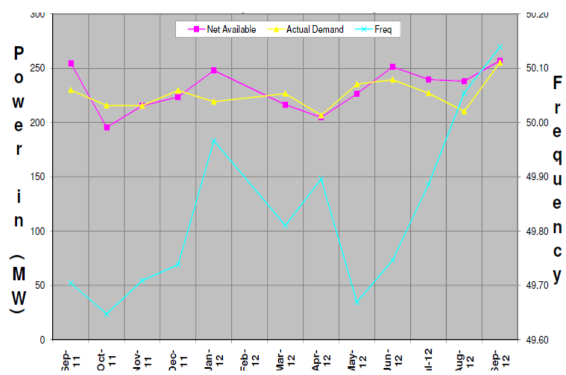

Figure 1. Power Demand (in MW) in Himachal Pradesh, India from 15-Sep-2011 to 14-Sep-2012

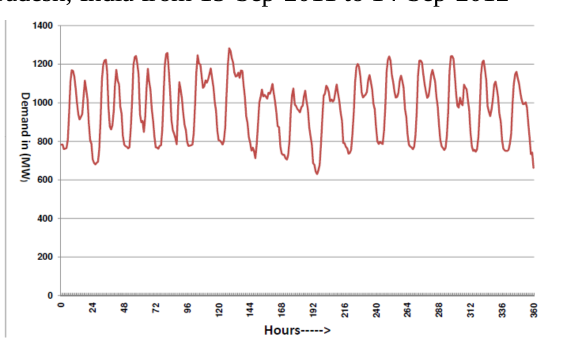

Figure 2. Hourly Demand (in MW) in Himachal Pradesh, India from 1-Jan-2012 to 9-Jan-2012

In Figure-1, we have plotted the demand, availability and frequency of the grid. But we can see that frequency is not showing any linear relationship with the demand. Price of the electricity is dependent on the frequency in the grid. In figure-2, it shows a within-day seasonal cycle of duration t_1=48 periods and within-week seasonal cycle of duration t_2=336 periods.

2. Load Estimation Criteria

Load forecasting plays an important role in planning and operation of power system. Selection of the variables affecting the forecast is the key factor in building a load-forecasting model. There is no general rule that can be followed in this process. It depends on engineering judgment and experience and is carried out almost entirely by trial and error. However, some statistical analysis can be very helpful in determining that which variables have significant influence on the system load.

In general, variables like hour and day indicators, weather-related inputs (temperature) and historical loads are used as variables in load forecasting. Some new variables like price can be more important input in load forecasting. In load forecasting modelling, interdependence between price and load can be the deciding factor, which would be reflected in pricing patterns of the market. The price-load relationship is neither linear nor stationary in time but price-load relationship may be relatively stable over shorter periods of time. Since the relationship between electricity price and load is complex and dynamic, research is needed to study how different customers' price response characteristics and locations affect the load forecasting.

The factors affecting the load forecasting can be represented as

L = f (day, weather, price)
Where '**f**' is a highly non-linear function.

In load forecast modelling, interdependence between price and load can be the deciding factor, which would be reflected in pricing patterns of the market. Accurate price forecasting helps utilities, independent power producers and customers to submit effective bids with low risks in order to maximize their benefits. Many activities in the competitive electricity markets, such as trading and risk management, are directly dependent on the quality of the price forecasting, in order to evaluate derivatives and devise hedging strategies. Electricity price depends on several factors such as load, bids of generating companies and load entities, gaming of market participants and several technical operating constraints. Volatile electricity prices in power markets are a new phenomenon that also needs to be considered as important factor as prediction of the prices themselves and their volatility are intrinsically connected.

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3. Methods of Prediction

There are many old methods of forecasting like time-of-day method, regression method, stochastic time series methods, state-space method, expert systems and new methods like neural network based load forecasting, fuzzy logic, genetic algorithm etc. The time scale involved for various activities in power system planning, operation & control varies from seconds, minutes, hours, and months to years. The statistical methods are not very useful as load and price variations are unpredictable some times as power system is highly complex and non-linear. Many conventional approaches are normally not appropriate due to their own limitations in predicting the non-stationary, highly volatile signals. Artificial intelligence (AI) methods, such as expert system (ES), artificial neural network (ANN), genetic algorithm (GA), evolutionary computation (EC), fuzzy logic, etc. have been emerged in recent years in power systems applications as effective tools. Artificial intelligence (AI) based methods are suitable to solve the challenging problems looming in the future of power systems. In proceeding section we discuss some commonly applicable models.

3.1. Artificial Neural Networks Model

Accurate and robust load forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydrothermal coordination, unit commitment, transaction evaluation, and system security analysis among other functions. Because of its importance, load forecasting has been extensively researched and a large number of models were proposed during the past several decades, such as Box-Jenkins models, ARIMA models, Kalman-filtering models, and the spectral expansion techniques-based models. Generally, the models are based on statistical methods and work well under normal conditions. However, they show some deficiency in the presence of an abrupt change in environmental or sociological variables, which are believed to affect load patterns. Also, the employed techniques for those models use a large number of complex relationships, require a long computational time, and may result in numerical instabilities.

Therefore, some new forecasting models were introduced recently. As a result of the development of Artificial Intelligence (AI), Expert System (ES) and Artificial Neural Networks (ANN) have been applied to solve the STLF problems. An ES forecast, the load according to rules extracted from expert's knowledge and operator's experience. This method is promising, however, it is important to note that the expert opinion may not always be consistent, and the reliability of such opinion may be in question.

Artificial Neural Networks have parallel and distributed processing structures. They can be thought of as a set of computing arrays consisting of series of repetitive uniform processors placed on a grid. Learning is achieved by changing the interconnection between the processors [1]. To date, there exist many types of ANNs, which are characterized by their topology and learning rules. As for the STLF problem, the BP network (Back-Propagated Delta Rule Networks) is the most widely used one. With the ability to approximate any continuous nonlinear function, the BP network has extraordinary mapping (forecasting) abilities. The BP network is a kind of multilayer feed forward network, and the transfer function within the network is usually a non-linear function such as the Sigmoid function.

The typical BP network structure for STLF is a three-layer network, with the nonlinear Sigmoid function as the transfer function [2-8]. An example of this network is shown in Figure 3(a). In addition to the typical Sigmoid function, a linear transfer function from the input layer directly to the output layer as shown in Figure 3(b) was proposed in [9] to account for linear components of the load. The authors of [9] have reported that this approach has improved their forecasting results by more than 1%.

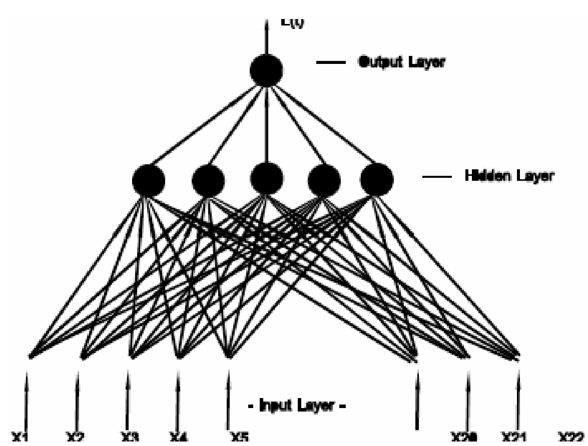

Figure 3(a). Feed Forward Back Propagation Neural Networks.

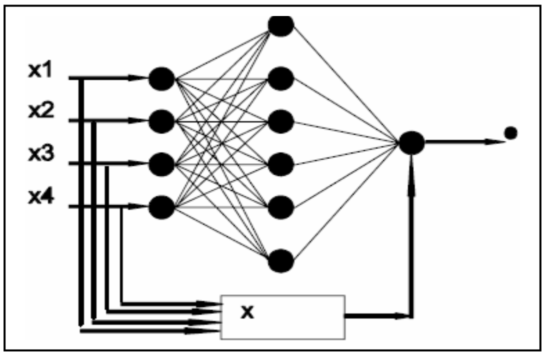

Figure 3(b). Jordan Recurrent Neural Networks

Because fully connected BP networks need more training time and are not adaptive enough to temperature changes, a non-fully connected BP model is proposed in [10,11]. The reported results show that although a fully connected ANN is able to capture the load characteristics, a non-fully connected ANN is more adaptive to respond to temperature changes.

3.2 Neural Networks Model

Generally commodity prices are compelled by supply and demand balance. In electricity markets the traded 'commodity' cannot be stockpiled economically, the constraints are defined by the system total capacity to satisfy demand at any given time [2]. This therefore causes electricity prices to have a high probability of volatility, which masks observable trends necessary for forecasting future values, especially in the short term. Short-term forecasts cover the period from a few minutes to about one week ahead. These are useful for dispatch and short-term or spot trading. Short term trading is meant to service the short-term variations in load and the actual prices are only known after matching of bids and offers by the market operator [1]. This presents a challenge in that to place effective bids; the traders need to have an idea of the future values of the demand and its corresponding price. This method utilized the artificial neural networks (ANN) to extract trends from past data of the same parameters and use that to predict possible future values. A data clustering approach is adopted that groups the data into sets with cut off points that vary from one day to the other. This creates zones of intersection, and to handle these points, fuzzy logic is used.

An artificial neural network (ANN) is a model that emulates the functional architecture of the human brain. In this research, a multi-layer ANN is adopted. This ANN consists of: an input layer, hidden layers and an output layer as shown in Figure 2. Except for the input layer, each neuron receives a signal that is a linearly weighted sum of the outputs from all the neurons in the preceding layer.

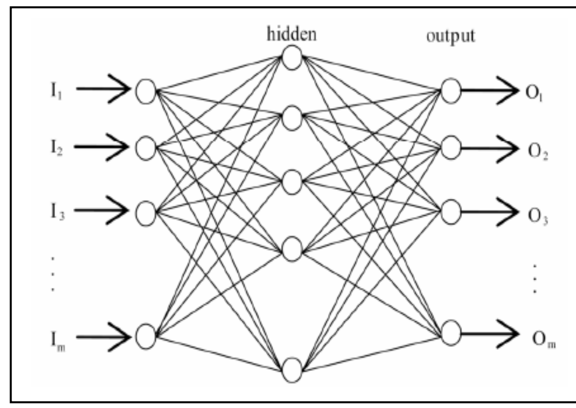

Figure 4. Radial Basis Function Network

3.3 Fuzzy Inference Model

Fuzzy inference is an implementation of fuzzy logic in which linguistic like rules map the input onto output space without strict specification of the input [3],[4].

Fuzzy Logic: if 'X' is a universe of discourse with elements denoted by 'x', then the fuzzy set 'A' in 'X' is defined as a set of ordered pairs,

$$\mathbf{A = \{x, \mu A(x) \mid x \varepsilon X\}.}$$

μA(x) is called the membership function of x in A. Figure-5 shows the triangular membership function used for 3 different fuzzy sets; Low, Medium and High.

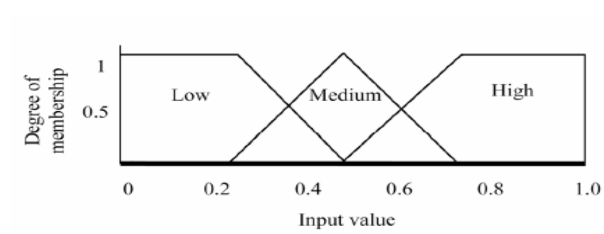

Figure 5. Triangular Membership

Fuzzy inference systems use fuzzy rules (IF - Then) and fuzzy reasoning, an inference procedure that obtains from a set of fuzzy rules and known facts. Three conceptual components: rule base (fuzzy rules selection); database (membership functions) and reason mechanism inference procedure thus form the basic structure of a fuzzy inference system.

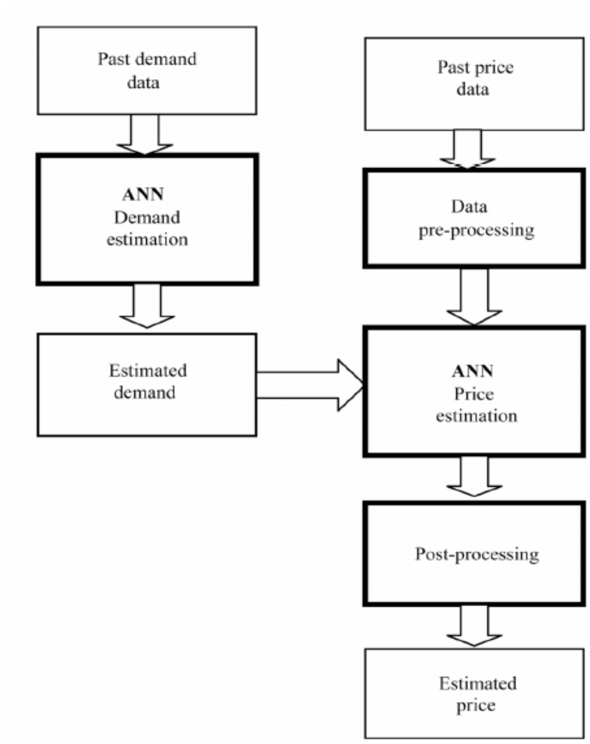

Figure 6. Structure of ANN based Price

A number of configurations based on the proposed approach were setup. A system with cascaded processing elements was setup as shown in Figure 4 below, which include data conditioning and classification blocks as part of pre-processing and post-processing for the price estimation path.

3.4 Probabilistic Neural Network

In recent years, ANNs (Artificial Neural Networks) have been applied to a variety of problems in the field of Power System Control [9], [10]. The application areas include, Economic load dispatch & loss reduction, Fault detection & diagnosis, Frequency control, Load forecasting, Security assessment & enhancement, voltage & reactive power control.

The computational neuroscience has 3 goals -

1. The computer aided simulation of some functionalities of the brain,
2. The understanding of the function of the brain in computational terms,
3. The application of neural concepts for innovative technical problem solving.

The theory of ANNs is mainly motivated by the second goal, i.e. the establishment of simple formal models of biological neurons and their interconnections called ANNs. In the power-engineering domain, the application of already simplified tools of ANNs to technical problems is the main objective. The ANNs are brain-inspired computers which may solve similar tasks as the biological brain. A number of STLF tools have been recently developed using non-linear modelling methods, including those based on the neural network-modelling framework. And if the underlying mechanism of the electric load data generating process is to be included into the analysis, a statistical approach may be the best. Certain types of ANN, especially a class of Radial Basis Function Networks (RBFN), can provide some statistical approaches.

Probabilistic Neural Networks (PNN) is a decades old powerful classification algorithm that can be cast in the form of neural network. Learning speed is better comparatively; however classification time may be slow and memory requirements are large. Nearly all standard statistical algorithms assume some knowledge of the distribution of the random variables used to classify. In particular multivariate normal distribution is frequently assumed and the training set used only to estimate the mean vectors and co-variance matrix of the populations. While some deviation from normality is tolerated, large deviations cause problems. Work till now in this field, shows neural networks can handle the most complex distributions. The three or four layered feed forward networks work satisfactorily for classifications. However it has two problems. One is that little is known how it operates, and what behaviour is expected of it, and other that training speed is slow. PNN has good mathematical credentials backing it, and trains faster, and is seen from applications that it trains as well as or better than feed forward networks. Its disadvantages are that it is relatively slow to classify, and that it requires large amounts of memory.

When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a complete transfer function on the output of the second layer picks the maximum of these probabilities. Here the activation function of a neuron is statistically derived estimates of probability density function (p.d.f) based on training patterns.

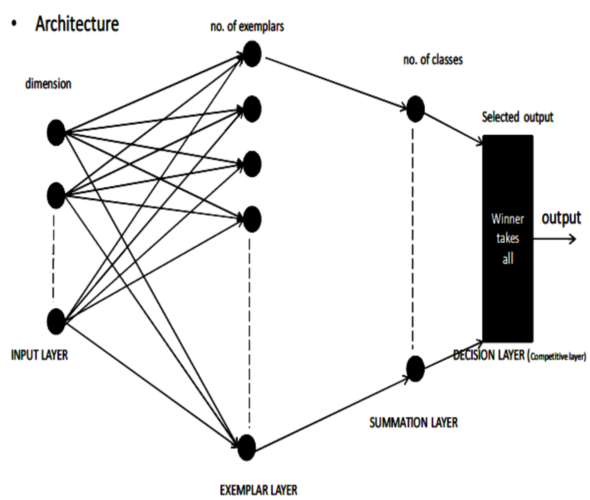

Figure 7. Probabilistic Neural Networks

The layers constituting the topology is organized as follows:

1. The input layer has m-units, to which m-dimensional vector is applied.
2. The hidden first layer has one pattern unit for each pattern exemplar; therefore each such unit is associated with the generic term in the summation for the $\mathbf{i^{th}}$ class.
3. The second hidden layer contains one summation unit for each class.
4. The output layer is the decision layer, selects the class with maximum posteriori probability.

Load and price forecasting are the two key issues for the participants of current electricity markets. However, load and price of electricity markets have complex characteristics such as nonlinearity, non-stationary and multiple seasonality, to name a few (usually, more volatility is seen in the behaviour of electricity price signal). A mixed model for load and price forecasting based on an iterative neural network based prediction technique is presented, which can consider interactions of these two forecast processes [24].

4. Conclusion

In this paper we outlined the various techniques applicable for load forecasting in power systems. Although the fundamental technologies of power generation, transmission, and distribution change quite slowly, the power industry has been quick to explore new technologies that might assist its search and to wholeheartedly adopt those that show benefits. The need for fast answers to complicated problems with uncertain and incomplete information/data undoubtedly grows as deregulation progresses. This work will present an enormous opportunity to solve the challenging problems looming in the future of power systems. The work will help to develop algorithms/ software for the short-term electric load forecasting of daily peak or valley loads and hourly loads in the competitive power market as well as price forecasting by using Artificial intelligence techniques. We hope that this paper will definitely be helpful for the researchers who are interested in the area of power optimization and forecasting.

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Dharmendra Kumar Mishra, Scientist-D, presently working as Branch Manager with National Institute of Electronics and Information Technology (Formerly DOEACC Society) Chandigarh, Extension Centre Lucknow. He has 21 years of experience with organizations of national repute. His research interest is artificial intelligence.