INTELLIGENT METHODS IN LOAD FORECASTING

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ABSTRACT

Load forecasting is of vital importance for any power system. It helps in taking many decisions regarding energy purchasing and generation, maintenance, etc. Further, load forecasting provides information which is able to be used for energy interchange with other utilities. Over the years, a number of methods have been proposed for load forecasting. This paper focuses on short term load forecasting by using a hybrid model of neural networks and fuzzy logic.

Keywords: fuzzy, load forecasting, neuro fuzzy, neural networks, regression

I. LOAD FORECASTING

Abundant advances have been made in developing intelligent systems, some inspired by biological neural networks, fuzzy systems and combination of them. Researchers from many scientific disciplines are designing Artificial Neural Network (ANNs) to solve a variety of problems in pattern recognition, prediction, optimization, associative memory and control. Conventional approaches have been proposed for solving these problems. Although successful applications can be found in certain well constrained environments, none is flexible enough to perform well outside its domain. Artificial Neural Network has been replacing traditional methods in many applications offering, besides a better performance, a number of advantages: no need for system model, tolerance bizarre patterns, notable adaptive capability and so on. Load forecasting is one of the most successful applications of ANN in power systems. Neuro-Fuzzy (NF) computing is a popular framework for solving complicated(complex) problems. If we have knowledge expressed in linguistic rules, we can build a Fuzzy Interface System (FIS), and if we have data, or can learn from a simulation (training) then we can use ANNs. For building an FIS, we have to specify the fuzzy sets, fuzzy operators and the knowledge base. Similarly, for constructing an ANN for an application the user needs to specify the architecture and learning algorithm. An analysis reveals that the drawbacks pertaining to these approaches seem to be complementary and therefore it is natural to consider building an integrated system combining the concepts. While the learning capability is an advantage from the viewpoint of FIS, the formation of linguistic rule base will be the advantage from the viewpoint of ANN. Short-term load forecasting (STLF) refers to forecasts of electricity demand (or load), on an hourly basis, from one to several days ahead. The short-term load forecasting (one to twenty four hours) is of importance in the daily operations of a power utility. It is required for unit commitment, energy transfer scheduling and load dispatch. Many algorithms have been proposed in the last few decades for performing accurate load forecasting. The most commonly used techniques include statistically based techniques like time series, regression techniques and box-jenkis models and computational intelligence method like fuzzy systems, ANNs and Neuro-fuzzy systems. There exist large forecasting errors using ANN when there are rapid fluctuations in load and temperatures. To cope with such uncertainties in load forecasting problem forecasting methods using fuzzy logic approach have been employed. In this regard hybrid methods of neural networks and fuzzy logic are also reported. For developing the forecasting models, we used the actual hourly electrical load data provided by the power plant in Andhra Pradesh.

Forecasting is an integral part of electric power system operations as it is the primary prerequisite for achieving the goal of optimal planning and operation of power systems. The load dispatcher at main dispatch center must anticipate the load pattern well in advance so as to have sufficient generation to meet the load requirements. Overestimation may cause the startup of too many generating units and lead to an unnecessary increase in the reserve and the operating costs. Underestimation of the lo\
ad forecast results in failure to provide the required spinning and standby reserve and stability to the system, which may lead into collapse of the power system network. Load forecast errors can yield suboptimal unit commitment decisions.

In the real-time dispatch operation, forecasting error causes more electricity purchasing cost or breaking contract penalty cost to keep the electricity supply and consumption balance. Hence accurate forecasting of the load is an essential element in power system.

II. TYPES OF FORECAST

Depending the period of the forecast done, it is classified into three different types. They are:

- Short term load forecasting, which forecasts within a time period of one day to one month.
- Medium term load forecasting, which forecasts within a time period of one month to one year.
- Long term load forecasting with a time period of more than one year.

In this, we are focusing on the short term load forecasting.

Short term load forecasting (STLF) refers to forecasts of electricity demand (or load), on an hourly basis, from one to several days ahead. In the daily operations of a power utility, the short term load forecasting is of vital importance. It is required for unit commitment, energy transfer scheduling and load dispatch. The short term load forecasting has played a greater role in utility operations with the emergence of load management strategies. The development of an accurate, fast and robust short-term methodology is of importance to both the electric utility and its customers.

Short term load forecasting has gained more importance and greater challenges with the recent trend of deregulation of electricity markets. Precise forecasting is the basis of electrical trade and spot price establishment for the system to gain the minimum electricity purchasing cost in the market environment. In the real-time dispatch operation, forecasting error causes more purchasing electricity cost or breaking-contact penalty cost to keep the electricity supply and consumption balance.

III.FORECAST TECHNIQUES

Short term load forecasting includes both conventional techniques & artificial intelligence techniques.
A few of them have been listed below.

- Regression method
- Fuzzy logic approach
- Neural network approach
- Neuro-fuzzy approach, etc.

Regression method is a conventional approach whereas the rest three are artificial intelligence methods.
The main important single-most parameter in the short term load forecast is the relationship between the load and the weather. This relationship is to be understood for making a reliable load forecast. The relationship between the weather and the load varies with the day of the week, segment of the day, season, etc.The weather-load relationship varies with the season, day of the week, and segment of the day.

Several factors, such as time factors and weather data, etc should be considered for short-term load forecasting. The load is influenced by the weather conditions. As a matter of fact, the most important factor in short term load forecasting is the weather. There are a lot of weather parameters available such as temperature, humidity, wind cover, sunshine, etc. But only temperature and humidity are the most commonly used parameters.

IV NEURAL NETWORKS

An artificial neural network is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks.. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform ''intelligent'' tasks similar to those performed by human brain.

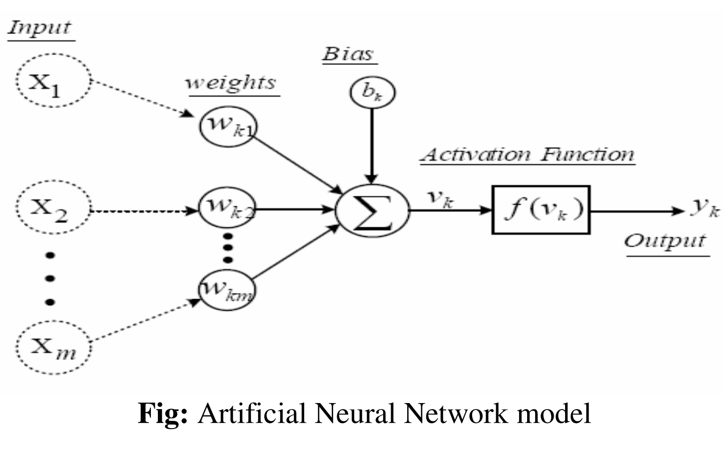

Fig: Artificial Neural Network model

When load forecasting is dealt by using neural networks, we must select one of the number of the available architectures (such as Hopfield, back propagation, Boltzmann, etc), the number of layers and elements, the connectivity between them , usage of unilateral or bilateral links and the number format to be used by inputs and outputs.

There will be differences in the estimation of performance depending on the different models. Generally back propagation is used. A back propagation network topology includes 3 layers r 4 layers, the transfer function may be linear or non linear or a combination of both. The network may be fully connected or non-fully connected. The application of neural networks in power utilities has been growing in acceptance over the years. The main reason behind this is because the capability of the artificial neural networks in capturing process information in a black box manner.

RBFN: Among the various ANN architectures the conventional back propagation momentum learning technique and RBFN can be used successfully to forecast the load demands. The RBFN was reported to be more accurate and less time consuming. The main problem associated with the back propagation in the forecasting is it's slow convergence. The RBFN was found to overcome these limitations to a certain extent. Radial Basis Function (RBF) neural network has an input layer, a hidden layer and an output layer. The neurons in the hidden layer contain Gaussian transfer functions whose outputs are inversely proportional to the distance from the center of the neuron. RBF networks are similar to K-Means clustering and PNN/GRNN networks. The main difference is that PNN/GRNN networks have one neuron for each point in the training file, whereas RBF networks have a variable number of neurons that is usually much less than the number of training points. For problems with small to medium size training sets, PNN/GRNN networks are usually more accurate than RBF networks, but PNN/GRNN networks are impractical for large training sets.

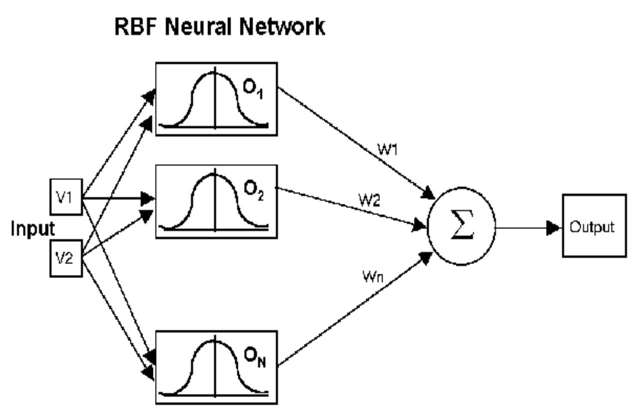

Fig:

RBF networks have three layers:

1. Input layer – There is one neuron in the input layer for each predictor variable. In the case of categorical variables, N-1 neurons are used where N is the number of categories. The input neuron (or processing before the input layer) standardizes the range of the values by subtracting the median and dividing by the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer.
2. Hidden layer – This layer has a variable number of neurons (the optimal number is determined by the training process). Each neuron consists of a radial basis function

centered on a point with as many dimensions as there are predictor variables. The spread (radius) of the RBF function may be different for each dimension. The centers and spreads are determined by the training process. When presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function to this distance using the spread values. The resulting value is passed to the summation layer.

3. Summation layer – The value coming out of a neuron in the hidden layer is multiplied by a weight associated with the neuron (W1, W2, ...,Wn in this figure) and passed to the summation which adds up the weighted values and presents this sum as the output of the network.

Training RBF Networks

The following parameters are determined by the training process:

1. The number of neurons in the hidden layer.
2. The coordinates of the center of each hidden-layer RBF function.
3. The radius (spread) of each RBF function in each dimension.
4. The weights applied to the RBF function outputs as they are passed to the summation layer.

V.FUZZY LOGIC

Fuzzy logic is a form of many-valued logic; it deals with reasoning that is approximate rather than fixed and exact. In contrast with traditional logic theory, where binary sets have two-valued logic: true or false, fuzzy logic variables may have a truth value that ranges in degree between 0 and 1. Furthermore, when linguistic variables are used, these degrees may be managed by specific functions. Under fuzzy logic an input is associated with certain qualitative values. For instance the temperature of a day may be ''low'', ''medium'' or ''high''.

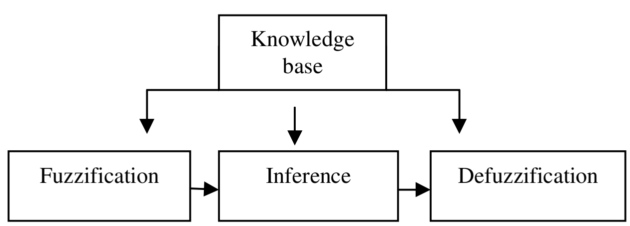

Fig: Block diagram of a fuzzy system

In the operation and management of power systems, fuzzy load forecasting plays a paramount role. Fuzzy logic usage has got several advantages. There is no need of a mathematical model mapping inputs to outputs and the absence of a need for precise inputs. Properly designed fuzzy logic systems can be very robust when used for forecasting with such generic conditioning rules. An exact output is needed in many situations. The logical processing of fuzzy inputs is followed by ''defuzzification'' to produce precise outputs.

VI. NEURO-FUZZY MODEL

In the field of artificial intelligence, Neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy was proposed by J. S. R. Jang. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of Neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules.

Several different ways to combine fuzzy logic with neural networks technique have been proposed by researchers in order to improve the overall forecasting performance. A Neuro fuzzy system is about taking an initial fuzzy inference systems and tuning it with a back propagation algorithm based on the collection of input-output data.

The objective of the work is to develop an algorithm to forecast hourly load, by incorporating weather conditions like temperature, humidity, etc. In this work, an attempt is made to implement the above forecast using fuzzy set classified neural network approach.

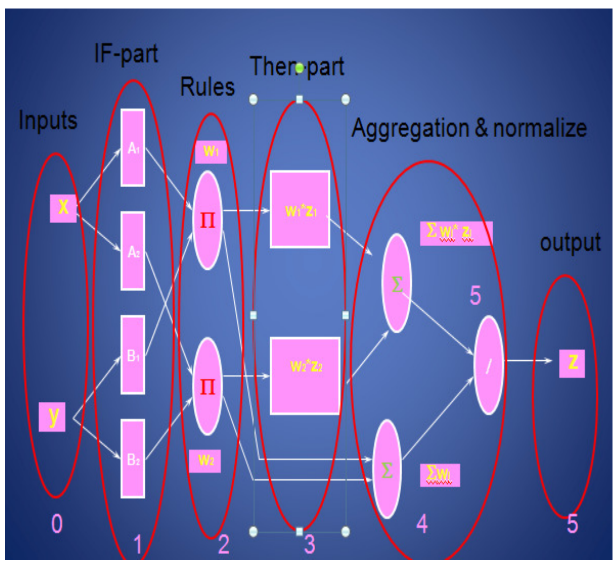

Fig: Neuro-Fuzzy Model

The work presented here is divided into three steps:

- Fuzzy Set Based Classification: Classification of training data using Fuzzy Set.
- Training of Neural Network: Training of the neural network for each hour of each day for which the load is to be forecasted using the training data of that particular class to which that hour belongs.
- Short term load forecasting: Forecasting of hourly load using trained neural network.

VII.MULTIPLE LINEAR REGRESSION

Multi linear regression is an approach to modeling the relationship between a scalar variable y and more than one explanatory variable denoted by x1, x2, etc. This is extensively used in practical applications. This is because models which depend linearly on their unknown parameters are easier to fit than models which are non-linearly related to their parameters and because the statistical properties of the resulting estimators are easier to determine.

Regression is used to fine tune the initial estimates of the load. It is done only if the number of records in the similar set exceeds a certain minimum number. Statistically, this minimum is one plus the number of variables used in regression. Similar set of data is adjusted and regression is made over it using a certain subset of weather variables. It gives a weight factor for each variable. And hence, the least-square error estimation of the load is determined for each hour in the target segment. Linear or nonlinear regression may be used. Only if the range of regression is limited, the linearity is justifiable. Although the load is known to be a nonlinear function of all the significant variables, a linear model may be assumed if the samples are all within a small neighborhood around the target point. It might be necessary, however, to use nonlinear models. This would be done by replacing one variable or more by certain point function. This might be useful to account for certain known non-linearity, especially at extreme temperature points.

In the multiple linear regression method, the load is found in terms of explanatory variables such as weather and non-weather variables which influence the electrical load. The load model using this method is expressed in the form as:

$$y(t) = a_0 + a_1 x_1(t) + \cdots + a_n x_n(t)$$

Where,

y(t) = electrical load.
x(t) = explanatory variables correlated with *y(t)*.
a_n =regression coefficients.

The explanatory variables of this model are identified on the basis of correlation analysis on each of these (independent) variables with the load (dependent) variable. Experience about the load to be modeled helps an initial identification of the suspected influential variables. The least square estimation technique is usually used for the estimation of the regression coefficients.

In the MLR application, the hourly load is modeled as: (i) Base Load Component and (ii) Weather Sensitive Component which is function of different weather variables. These weather variables include dry bulb temperature, dew point temperature and wind speed. The relationship between the weather sensitive component and most of the weather variables is not linear, but are rather transformed from current and previous lag time values.

VII.CONCLUSION

Precise load forecasting is very essential for electric utilities in a spirited environment created by the electric industry. In this paper we appraise 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. The evolution in load forecasting will be achieved in two ways. One is getting excellence in statistics and artificial intelligence and the other is to have good understanding of the load dynamics. Neural network alone cannot work for forecasting better. If neural network is combined with fuzzy logic then it can handle the forecasting problems well.

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