SHORT TERM LOAD FORECASTING METHODS, A COMPARATIVE STUDY

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ABSTRACT

Load forecasting is a very important function in electrical power systems. Accurate load forecasting is the need for economic cost saving. Short-Term Load Forecasting (STLF) is one of the forecasting methods that have a time frame of a few hours to about a day. STLF is required for adequate scheduling and operation of power systems. For the past several decades, there have been various methods used in load forecasting. Being a highly required activity both from a power system and economic point of view, extensive research is being made in the area of load forecasting. Some of the methods proposed earlier, and still being used are Box-Jenkins models, Auto Regressive Integrated Moving Average (ARIMA) models, Kalman filtering models, and the spectral expansion techniques-based models. Recent techniques are based on Artificial Intelligence methods like artificial neural networks (ANN), fuzzy logic, expert systems, support vector methods (SVM). Each technique has its own advantages and shortcomings. This paper does a comparative study of the methods with their positives and limitations.

Keywords: - *load forecasting, time series, regression, neural networks, support vector*

1. INTRODUCTION

Electrical load forecasting is an important function in power systems from the point of economic operation, planning, generation, and distribution. There are many tools and methods developed and are being improvised for this crucial activity.

Box-Jenkins models, ARMA, Kalman filtering are some of the conventional models used for quite some time. Generally, these 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. Some of the newer forecasting tools have been Artificial Intelligence (AI), Expert System (ES) and Artificial Neural Networks (ANN), Support Vector Machines (SVM) that have been applied to solve the load forecasting problems [1].

2. LOAD FORECASTING

Load forecasting is a way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system [2]. The typical steps in load forecasting are gathering of data, selecting the input set for patterns, load forecasting, and analyzing the results. STLF has been useful in safe and economical planning operation of an electrical power system. It has been also used in start-up and shut-down schedules of generating units, overhaul planning and load management [3].

Factors influencing system load behaviour are: [4]

* Time of day, the day of the week, workdays, holidays, and weekends
* Weather factors include temperature, humidity, precipitation, wind speed, cloud cover, light intensity
* Economic factors, such as the degree of industrialization, price of electricity and load management policy have significant impacts on the system load growth/decline trend
* Random disturbance factor like start and shut down of large loads, erratic loads etc.

Load forecasting can be classified as:
a. Long-term forecasting: Months to years
Used to supply electric utility company management with prediction of future needs for expansion, equipment purchases, or staff hiring
b. Mid-term forecasting: Weeks to months
Used for the purpose of scheduling fuel supplies and unit maintenance
c. Short-term load forecasting: Hours to weeks
Used to schedule the generation and transmission of electricity
d. Very short-term load forecasting: Shorter than a day
Used to supply necessary information for the system management of day- to-day operations and unit commitment

Characteristics of loads: [5]
Time dependant loads can vary over the week. Loads on weekdays and weekends are different. Even weekdays neighbouring weekends, like Mondays and Fridays, loads can be different from that midweek. Holidays can have load patterns similar to weekends if they are midweek, but may vary if they are neighbouring the weekends. Religious festival holidays can have a different pattern than non religious holidays.

During a typical weekday, loads may be higher in mornings and evenings compared to midday.
In weather dependant loads, temperature is the most important factor, along with humidity. These cause loads to rise based on the comfort level. In addition to time and weather, economical factors like price of electricity also plays an important role in load variation. In general, load can be considered as a factor of time, weather, random events, and price [6].

3. METHODS OF LOAD FORECASTING

Load forecasting methods can be broadly classified as parametric and artificial intelligence methods. Parametric methods can be regression and time series.

Some of the methods of load forecasting can be: [2]
* Time Series
* Regression Methods
* Neural Networks
* Expert Systems
* Support Vector Machines

4. PARAMETRIC METHODS

Time series methods depend on historical load data to predict future load. Time series forecasting can be termed as the act of predicting the future by understanding the past [7]. These models assure that the load term in stationary and treat any abnormal data as bad data [8]. Load is considered as a time series signal with known seasonal, weekly, and daily periodicities. These periodicities give a rough prediction of the load at the given season, day of the week, and time of the day. The difference between the prediction and the actual load can be considered as a stochastic process. Stochastic means situations, patterns or phenomenon which are unpredictable. Time series models ignore weather data leading to inaccurate prediction.

The Stochastic time series methods may be Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), or the more natural tool for load forecasting, ARIMA with Exogenous Variables (ARIMAX).

ARMA and ARIMA use the time and load as the only input parameters [9]. ARMA models are usually used for stationary time series data while ARIMA is an extension of ARMA to non-stationary processes. A stationary time series model means that properties like mean, variance, covariance etc. of the series do not vary with time. If a series in non-stationary, it has to be stationarized using mathematical transformations like differencing. A stationarized series is relatively easy to predict. ARIMA is best suited for stationary process where the data exhibits a consistent pattern over time.

ARIMA is an extension of AR and MA models. AR (Autoregressive) model is a linear model of a time series. AR(1) means autoregressive model of order 1 [10]. Order determines how many time lags are used to forecast the present time.

A first order AR model, AR(1) is given by-
$x_t=\delta+\varphi x_{t-1}+w_t$

A second order AR model, AR(2) is given by-
$x_t=\delta+\varphi_1 x_{t-1}+ \varphi_2 x_{t-1+} w_t$
δ is a constant, φ is the AR coefficient, w_t is the error, called white noise.

MA (Moving Average) model uses past forecast errors in a regression-like model [12]. Here the error is multiplied by the coefficient.
$x_t=\mu+w_t+\theta_1 w_{t-1}$ -- First order, MA(1)
$x_t=\mu+w_t+\theta_1 w_{t-1}+ \theta_2 w_{t-2}$ -- Second order, MA(2)

Autoregressive Moving Average (ARMA) is a combination of both AR and MA. To convert it into a stationary model, they are integrated into one, which is called as Autoregressive Integrated Moving Average (ARIMA).

Box-Jenkins ARIMA method is slow as it requires autocorrelation function for identifying proper ARMA models. ARMA model assumes load at that hour by the historical data of the previous hours. It is accurate with larger data set, but requires larger computational time. Spectral expansion technique uses Fourier series method where load pattern is considered as a number of sine waves with different frequencies. But this method is not accurate as load patterns are not perfectly periodic [12]. According to study by Hongzhan et al.[13], ARIMA is only suited for the linear part of the load data. For non-linearity, AR, MA, or ARIMA are not suited

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Kalman filter technique is a recursive estimation method. Here the present state is obtained by the operation between past value extrapolation and the current ones. One of the methods in forecasting is to use state space model to model the load on an hourly basis, while Kalman filter is used to recursively estimate the optimal load forecast parameters for each hour of the day [14]. But given the non-linear nature of the load, this technique may not allow an accurate estimate. Stelios A Markoulakis et al [15] state that a combination of Kalman Filter and neural system like Neural Fuzzy Inference System can work better for accurate forecasting.

Regression methods include weather related data while analysing load behaviour [16]. Alex Papalexopoulos et al.[17] included holiday data and temperature data in the regression technique, as electrical load is dependent on these two factors as well. While time series models assume load as a function of time, where present load depends on previous load values, regression takes weather data as well. Weather variables are handled separately by extracting the weather sensitive parts of the load data [18].

5. NON PARAMETRIC METHODS

Artificial intelligence methods consist of Artificial Neural Networks (ANN), Fuzzy logic, Expert Systems (ES), Machine Learning, and Hybrid. The time series methods, while being simple, have the limitation of being unable to handle nonlinear data, which is a common feature in load data. They are superior to the time series and regression models in terms of accuracy.

Artificial neural networks (ANN) can be classified into several categories based on supervised and unsupervised learning methods and feed-forward and feedback recall architectures.

The most commonly used ANN model is multilayered perceptron (MLP) which has an input and output layer, and one or more hidden layers between these two. ANN consists of processing elements called neurons. An artificial neuron has more than one inputs and a single output. They are connected with each other. The processing ability of the network is stored in the inter-node connection strengths, which are called weights. These weights are obtained by learning or adapting from a set of training patterns. A set of systematic steps called learning rules needs to be followed when developing an ANN. Further, the learning process requires learning data to discover the best operating point of the ANN. They can be used to learn an approximation function for some observed data [19].

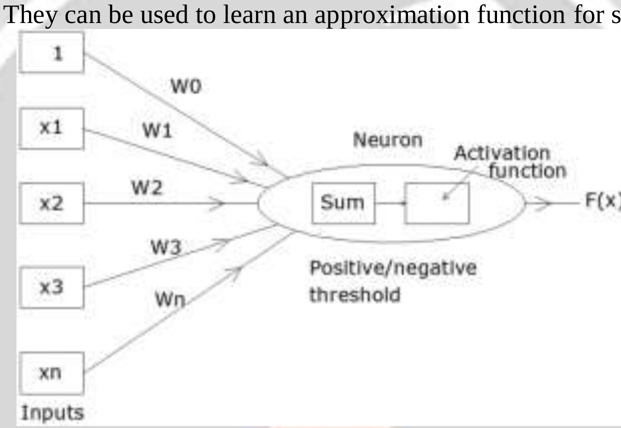

Fig -1: Model of an artificial neuron

Output function, F(x) is a sigmoid function given by-

$$F(x) = \frac{1}{1+e^{-sum}}$$

where

$$sum = \sum_{i=0}^{n} x_i W_i$$

The sum is the weighted sum of the inputs multiplied by the weights between one layer and the next. The activation function used is a sigmoid function, which is a continuous and differentiable approximation of a step function [20].

The architecture of the ANN comprises of-
-input layer: Contains neurons equal to the number of inputs
-hidden layer(s): The number of hidden layers and the number of neurons in each layer depends on the complexity
-output layer: Usually it has one neuron, and its output ranges from 0 to 1, that is, greater than 0 and less than 1. But multiple outputs can be present [21].

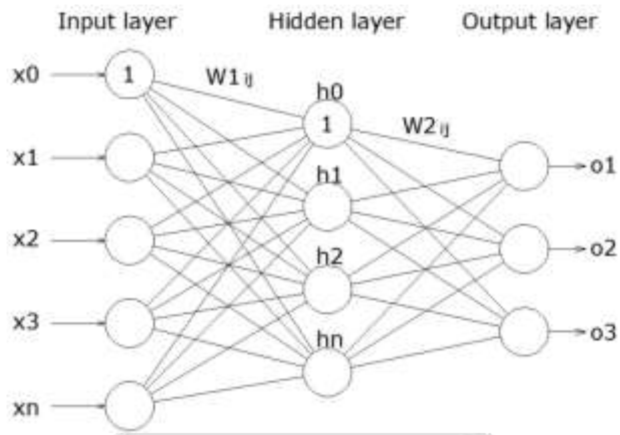

Fig -2: Neural network architecture

Back propagation algorithm is the most commonly used method in training the neural network. Here the difference in targeted output, and the output got, is propagated back to the layers and the weights adjusted. A back propagation neural network (BPNN) uses a supervised learning method and feed-forward architecture. It is one of the most frequently utilized neural network techniques for classification and prediction.

One of the most interesting properties of neural networks is their ability to work and forecast even on the basis of incomplete, noisy, and fuzzy data. Furthermore, they do not require a priori hypothesis and do not impose any functional form between inputs and output. For this reason, neural networks are quite practical to use in the cases where knowledge of the functional form relating inputs and output is lacking, or when a prior assumption about such a relationship should be avoided [22]. ANN requires previously known data for the analysis and study of load. Electrical load varies with time, season, temperature, holidays etc. Historical data related to these factors have been used in a study, which concludes that ANN delivered accurate load predictions under varying conditions such as the above [23] [24].

The main limitation of neural networks is over fitting of data. Also, training of the network is time consuming. If data is overfitted, that is, trained to extreme accuracy, it is rigid, and may not be suitable for future forecasting [25], that is, the pattern cannot be used in a general way. ANN can get stopped at the local minima, and may not be able to be optimized.

One of the recent methods used in pattern classification and regression is Support Vector Machines (SVM), developed in 1995 by Vapnik [26]. It was based on statistical learning theory (SLT). The basic idea of SLT is that the system, when it is input data, it delivers output as a function that can be used to predict future data. In a non-linear decision surface, support vectors are points or elements of the set that lie close to the decision surface. SVMs convert a non-separable set of points in input space into a separable set of points, by deriving the best separation hyper plane. SVMs extend the margin around the hyper plane [27]

One of the main advantages of SVM over ANN is its ability to solve both linear and nonlinear problems, without getting stuck in local mimina.

6. CONCLUSIONS

Electrical load forecasting is a complex activity that deals with diverse data set. As discussed above, there are different methods for predicting the load. Based on the literature review of the various methods used in load forecasting, one can conclude that one single method is unsuitable. A combination of time series methods with the soft computing methods like artificial intelligence methods will yield more accurate results. With the advent of SVM, and its improved version, Least Square SVM (LS-SVM), various papers have dealt with load forecasting by combining the positive factors of ANN and SVM [28][29].

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