A Review of very Short-Term Load Forecasting (STLF) using Wavelet Neural Networks

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ABSTRACT

For an Accurate load forecasting holds a great saving potential for electric utility corporations since it determines its main source of income, particularly in the case of distributors. Precise load forecasting helps the electric utility to make unit commitment decisions, reduce spinning reserve capacity and schedule device maintenance plan properly. In this paper we surveyed on waveletneural network approach for short- term loads forecasting. We will also study on previous literature for finding the method of advantage and disadvantage.

Keywords: Short term Load forecasting, wavelet neural network, artificial intelligence.

I.INTRODUCTION

The quality of the short-term hourly load forecasting with lead times ranging from one hour to several days ahead has a significant impact on the efficiency of operation of any electrical utility. Many operational decisions such as economic scheduling of the generating capacity, scheduling of fuel purchase and system security assessment are based on such forecasts. Accurate and robust load forecasting is of great importance for power system operation. It is the basis of economic dispatch, hydro-thermal 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 such opinion may be in question. Over the past two decades, ANNs have been receiving considerable attention and a large number of papers on their application to solve power system problems has appeared in the literature. This paper presents an extensive survey of ANN-based STLF models. Although many factors affect the accuracy and efficiency of the ANN-based load forecaster, the following six factors are believed to be the most important ones.

A. WAVELET NEURAL NETWORK

To perform accurate predictions after pre-filtering, load properties are analyzed in Data analysis shows that the load data have different components: a very fast changing component from five to fifteen-minute resolutions, a fast changing component from fifteen-minute to one-hour resolutions, and a slow changing component with hourly, weekly, and monthly patterns. The WNN method is developed to capture the complicated load properties. To accurately capture load features at multiple frequencies, a wavelet technique is used to decompose the loads into several frequency components. Due to the use of convolution in the wavelet transform, additional data need to be padded at the end side of the load segment in real-time. Relationships among the padding parameters are discussed and derived. Different padding strategies are then tested, and the best one is determined via the test data set. each load component is properly transformed and then fed with other time and date indices to a separate neural network. Predictions from individual neural networks are combined to form the forecasts.

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II. LITRATURE REVIEW

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 boxjenkis models [] and computational intelligence method like fuzzy systems, ANNs [6, 7, 8, 9, 10, 11] and neuro-fuzzy systems

Load Demand prediction, as such, was there since earlier times however it is hardly surprising that there is considerable work happening in the areas of forecasting for electric demand prediction since smart meters have been put to use. Various approaches have been suggested for the same using range of Load forecasting techniques like SVM, KNN, ANN, and Wavelet transform and Curve Fitting methods.

Prakash Ranganathan& Nygard [2] suggested an approach using M5 decision tree classifiers to predict the demand. However it didn't take into consideration other factors like weather, nature of the day [2]. Wen Chen and Yi-Ping Chen applied heat index (temperature & humidity) along with ANN to predict the demand but there was no mention of the smart meter data in the approach [1, 3]. Hourly load forecasting using ANN used only average daily loads and thus limiting accuracy. Chakhchoukh & Panciatici considered stochastic characteristics of load and proposed use of RME (ratio of median based estimator) as against traditional double exponential smoothing but it didn't considered any data mining techniques to its advantage. Apparently the RME approach worked well for normal days. Xiaoxia Zheng implemented a modeling approach based on least squares support vector machine (LS SVM) within the Bayesian evidence framework for short-term load forecasting. Under the evidence framework, the regularization and kernel parameters can be adjusted automatically, which can achieve a fine tradeoff between the minimum error and model's complexities.Yan Cao, Zhong Jun Zhang & Chi Zhou proposed SVM based model that takes weather factods into consideration to improve the accuracy. Koo & Kim [1] used smart meter data along with KNN & forecasting models to further improve the accuracy but didn't consider the weather factors into consideration. Besides the KNN was on stationary pool of data and didn't consider any continuous flow.

Zhang et.al in [4] presented application of bacteria foraging optimized neural network (BFO NN) for short term electric load forecast. The author used BFO to find optimized weights of neural network while minimizing the MSE. Simulation results also showed that BFONN converges more quickly than Genetic algorithm optimized neural network (GANN).

Park et al. [12] presented an ANN approach to electric load forecasting in which the ANN is trained with the back propagation algorithm. Peng et al [13] proposed a procedure for choosing the training cases, which are most similar to the forecasted inputs.

Khotanzad et al [14] presented a load forecasting system known as ANNSTLF, which predicts the next 24 hours load. It includes two ANN forecasters. One of them predicts the base load and the other forecasts the change in load. The final forecast is computed by an adaptive combination of these two forecasts. The effect of humidity and wind speed is considered through a linear transformation of temperature. Till date, several researchers dealt with the application of various neural networks to Short Term Load Forecasting with varying success [15]. Although neural networks are capable of handling nonlinearity between the electric load and the weather factors that affect the load, they somehow lack to fully handle unusual changes that occur in the environment. The topology of a neural network determines the degrees of freedom available to model the data. If the neural network is too simple then the network will not be able to learn the function relating the input to the output and an over-complex network will learn the noise in the data and will not be able to generalize.

W. Brockmann and S. Kuthe [16] proposed several models to forecast electricity usage, from simple statistical models up to hybrid crisp-fuzzy, neuro-fuzzy models based on rules and learning [6]. Their simplest model describes load as an average for the two years 1997 and 1998. This model is later improved by shifting the days of the week. However, it was still unable to account for holidays that do not occur on same date each year.

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Another model proposed in [16], considers load as having a base value with oscillating variations superimposed. Additionally, an offset was included in the nominal load by means of a holiday indicator. Fuzziness is introduced because the load and the oscillation of various holidays differ in amplitude and time. The effect of temperature on load variation was ignored as it was considered noise. The best model presented in [6] scored as the third place in the EUNITE competition in terms of MAPE. D. Esp proposed the use of an Adaptive Logic Network (ALN) to model electric load prediction [17]. ALN is a form of non-parametric, non-linear modeling technique broadly similar to ANNs. In his approach, D. Esp used additional data such as maximum illumination (taken from England's records) and load/temperature records from 1996 (requested separately to the organizers), to fine tune the model.

As is described in [17] by D. Esp , the model assumed that the average temperatures from 1997 and 1998 were an approximation to the temperature on January 1999; as such data were not available. The performance of the model was evaluated by predicting the load for January 1996. This model obtained the second place in the EUNITE competition in terms of MAPE.

In [18], Chang, Chen, andLin used support vector machines to predict electricity load. In support vector regression, time series prediction is considered an optimization problem subjected to some constraints. In their experiments, Chang et al. used local modeling to generate predictions, finding segments in the time series that closely resembled the segment at the points immediately preceding the point to be predicted. Conversely, global modeling was also employed by training the model to predict the load of a particular day. Attributes such as maximum loads of past seven days, whether a day was a holiday or not, which day of the week was a particular day etc., were used in the global modeling. Temperature data were discarded. Moreover, all days in January 1999 were treated as non-holidays to simplify the prediction. In spite of these simplifications, the model of Chang et al. obtained the first place in the EUNITE competition in terms of MAPE. There were some similarities among the approaches used by the participants in the EUNITE contest. Some of them used time series analysis or polynomial regression; others fuzzy logic or fuzzy time series prediction; auto-associative ANN, feed forward ANN or Kohonen maps were also employed. Additionally, most approaches discarded temperature data since it is difficult to predict. The prediction methods that obtained the highest marks in the contest ([17][18]) were not based on the application of feed forward ANNs, but instead on ALN and support vector machines. One motivation for the work described in this paper was to determine if we could improvement the prediction results reported in the EUNITE contest by using a simple feed forward ANN model.

III. CHALLENGES OF SHORT TERM LOAD FORECASTING

Actual load data putforths many challenges to design a predictive neural net structure Prominent of those challenges are, data pre-processing, input parameter selection, type of neural net structure selection, computational complexity and training algorithm. Computational complexity is dependent on the structural complexity and training algorithm. This factor becomes important for real time implementation of algorithms in power generation and transmission equipment. Since in power systems the next days' power generation must be scheduled every day, day ahead short-term load forecasting (STLF) is a necessary daily task for power dispatch. Its accuracy affects the economic operation and reliability of the system greatly. Under prediction of STLF leads to insufficient reserve capacity preparation and in turn, increases the operating cost by using expensive peaking units. On the other hand, over prediction of STLF leads to the unnecessarily large reserve capacity, which is also related to high operating cost. In spite of the numerous literatures on STLF published since 1960s, the research work in this area is still a challenge to the electrical engineering scholars because of its high complexity. How to estimate the future load with the historical data has remained a difficulty up to now, especially for the load forecasting of holidays, days with extreme weather and other anomalous days. With the recent development of new mathematical, data mining and artificial

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intelligence tools, it is potentially possible to improve the forecasting result.

With the recent trend of deregulation of electricity markets, STLF has gained more importance and greater challenges. In the market environment, precise forecasting is the basis of electrical energy trade and spot price establishment for the system to gain the minimum electricity purchasing cost. In the real-time dispatch operation, forecasting error causes more purchasing electricity cost or breaking-contract penalty cost to keep the electricity supply and consumption balance. There are also some modifications of STLF models due to the implementation of the electricity market.

IV. IMPORTANCE of neural network in short term load forecasting

Nowadays, short-term forecasts have become increasingly important since the rise of the competitive electricity markets. In this new competitive framework, short-term price forecasting is required by producers and consumers to derive their bidding strategies to the electricity market. Accurate forecasting tools are essential for producers to maximize their profits, avowing profit losses over the misjudgment of future price movements, and for consumers to maximize their utilities. Short-term load forecasting plays an important role in electric power system operation and planning [2]. An accurate load forecasting not only reduces the generation cost in a power system, but also provides a good principle of effective operation. The short-term forecasting can be used in generators macroeconomic control, power exchange plan and so on. And the prediction is from one day to seven days in the future, or a little longer time. Whereas the ultra-short-term forecasting can predict the situation in a day or in an hour, and it's mainly used in Prevention and control emergency treatment and frequency control. With the deepen reform of electricity, the formation of power market and the independent and self-financing of electricity enterprises, power load forecasting becomes more and more important[4]. How to improve the accuracy of power load forecasting is a valuable research. Generally speaking, long-term accuracy of the forecast will be lower, while short-term will be higher.

1. Neural networks are extremely powerful computational devices.
2. Massive parallelism makes them very efficient
3. They can learn and generalize from training data – so there is no need for enormous feats of programming.
4. They are particularly fault tolerant – this is equivalent to the "graceful degradation" found in biological systems.
5. They are very noise tolerant – so they can cope with situations where normal symbolic systems would have difficulty.
6. In principle, they can do anything a symbolic/logic system can do, and more.

In deregulated environment, due to increase in competition in electricity market, the need for accurate load forecast will get importance in future. In deregulated environment, utilities must have to operate at highest possible efficiency which requires accurate load forecast. It can be performed using many types of methodologies such as statistical methods, regression approaches, fuzzy logic, genetic algorithms, time series methods and artificial neural network etc. [2]. Various type of load forecasting methods are given in [3] with their advantages. The load forecasting system was developed by Lijesen and Rosing in 1971 using statistical approaches [4]. Among modern and traditional techniques, artificial neural network is widely used, as it posses the ability to solve non linear relationship between load and the factors such as temperature, humidity obtained from historical load data. Many type of neural network models are used to solve load forecast

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problems for example, recurrent network, functional link and multi-layered feed forward network with one or more numbers of hidden layers. In this paper, multilayer feed forward network is used in short-term load forecasting. The most important aspect of artificial neural network in STLF is that a single architecture is used with same input-output structure for predicating hourly load of various size utilities in different region of a country. To determine some parameters of ANN model only customization is required. Therefore, there is no need to alter the other aspect of model

III. DISCUSSION

In above various literature survey presented by many Authors, we analyze regarding various or many existing research concept in terms of SVM, KNN, ANN, and Wavelet transform and Curve Fitting methods, which are given us to emerging method about wavelet neural network operation on the bases of electric power system that provide consistent accuracy and aware from the time. In STLF environment, The developed methods give load forecasts of one hour upto 24 hours in advance. The power sector in ISO New England has undergone various structural and organizational changes in recent past. The main focus of all the changes initiated is to make the power system more efficient, economically viable and better service oriented. All these can happen if, among other vital factors, there is a good and accurate system in place for forecasting the load that would be in demand by electricity customers. Such forecasts will be highly useful in proper system planning & operations.

IV. COCLUSION

In this survey, we have reviewed various accurate loads forecasting method which can potentially provide greater intelligence (smartness) to the upcoming smart grids. In our paper, we surveyed theshort term load forecasting regression using wavelet neural network for data filtering technique incorporated with electric power system.

The future work, we intend to explore the idea of load forecasting for our regression model in order to further improve its accuracy. In addition, we plan to rigorously test our method with multiple Hybrids wavelet neural network that improves the data redundancy and accuracy load forecast. The datasets from different countries/industries and fine tune the method so as to ensure its general usability.

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