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A Review of Artificial Intelligence Techniques for Short Term Electric Load Forecasting

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ABSTRACT: Electricity demand forecasting is a central and integral process for planning periodical operations and facility expansion in the electricity sector. Demand pattern is almost very complex due to the deregulation of energy markets. Therefore, finding an appropriate forecasting model for a specific electricity network is not an easy task. Although many forecasting methods were developed, none can be generalized for all demand patterns. Since many factors affect electric load data, machine learning methods are useful for electric load forecasting (ELF). On the one hand, it is important to determine the irrelevant factors as a preprocessing step for ELF. Therefore, artificial intelligence techniques have gained importance in reducing estimation errors. Artificial neural network, support vector machine, and adaptive neuro-fuzzy inference system are among these artificial intelligence techniques. In this paper, a state-of-the-art review of different artificial intelligence techniques for short-term electric load forecasting is comprehensively presented.

KEYWORDS: Electric Power, Time series, Electric Load Forecasting, Artificial Intelligence.

I. INTRODUCTION

Electricity as a product has very different characteristics compared to a material product. For instance, electricity energy cannot be stored as it should be generated as soon as it is demanded. Any commercial electric power company has several strategic objectives. One of these objectives is to provide end users (market demands) with safe and stable electricity [1]. Therefore, Electric Power Load Forecasting (EPLF) is a vital process in the planning of electricity industry and the operation of electric power systems. Accurate forecasts lead to substantial savings in operating and maintenance costs, increased reliability of power supply and delivery system, and correct decisions for future development. Electricity demand is assessed by accumulating the consumption periodically; it is almost considered for hourly, daily, weekly, monthly, and yearly periods. The EPLF is classified in terms of the planning horizon's duration: up to 1 day/week ahead for short-term, 1 day/week to 1 year ahead for medium-term, and more than 1 year ahead for long-term [2].

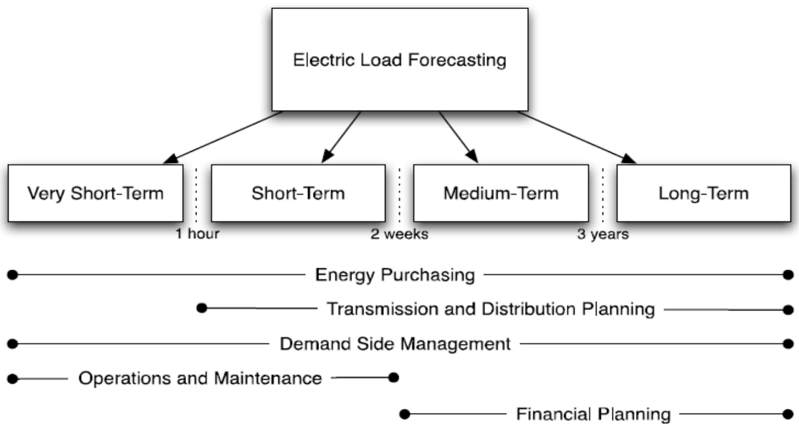

Figure 1: Electric load forecasting applications and classification

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Load forecasting is extremely important in electric energy generation, transmission, distribution and markets. Load forecast has been a central and an integral process in the planning and operation of electric utilities. The Purpose of load forecasting is proper planning and operation of a power utility requires an adequate model for electric power load forecasting [3]. Load forecasting plays a key role in helping an electric utility to make important decisions on power market, load switching, voltage control, network reconfiguration, and infrastructure development.

There are following types of load forecasting which are [4]:

Long-Term Electric Load Forecasting

Long-term electric load forecasting used to supply electric utility company management with prediction of future needs for expansion, equipment purchases or staff hiring. In long-term, among 3-year and 50 year electric load is predicted.

Medium-Term Electric Load Forecasting

Medium-term forecasting, used for the purpose of scheduling fuel supplies and unit maintenance. This is usually from a week to a year.

Short-Term Electric Load Forecasting

Short-term forecasting, it is used to supply necessary information for the system management of day-to-day operations and unit commitment.

Very Short-Term Electric Load Forecasting

Very short-term electric load forecasting which includes few minutes to an hour ahead forecasting of electric loads.

For strategic planning of the development of the electric power systems, both long-term and medium-term forecasts have great significance which includes scheduling of construction of new generation and transmission capacity, maintenance scheduling, as well as long-term demand side measurement and management planning [5-7]. However, an accurate STLF technique can alleviate operating costs, keep energy markets efficient, and provide a better understanding of the dynamics of the monitored system. On the contrary, an erroneous prediction might cause either a load overestimation, which leads to the excess of supply and reserve and consequently more costs and contract curtailments for market participants, or a load underestimation resulting in failures in gathering adequate provisions, hence more expensive complementary services [8].

II. SHORT TERM ELECTRICITY LOAD FORECASTING

Short-Term Load Forecasting is basically a load predicting system with a leading time of one hour to seven days, which is necessary for adequate scheduling and operation of power systems. It has been an essential component of Energy Management Systems (EMS). For proper and profitable management in electrical utilities, short-term load forecasting has lot of importance.

Factors Affecting Short Term Load Forecasting are:

Time Factor: Time is the most important factor in short term load forecasting because its impact on consumer load is highest. From observing load curve of several different grid stations it is found that the load curve has “time of the day” property, also it has “day of week”, “week of month” and “month of season” property[9].

Economic Factor: Since electricity nowadays became people’s daily life necessity so it has turned to be a commodity. Thus economy of the state has also an impact on the usage of electricity. Economic factor has more importance in long term forecasting, but it also can impact the load curve for short term load forecasting. Economic factors such as price of electricity, management of load and degree of industrialization have a significant impact on system average load and system maximum demand [10].

Weather Factor: Weather is the most important independent variable for load forecasting. The effect of weather is most prominent for domestic and agricultural consumers, but it can also alter the load profile of industrial consumers. Load forecasting models use weather forecast and other factors to predict the future load, thus to minimize the operational

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cost.. Unpredicted sea breeze, after moon thunderstorms, back door fronts is some of the environmental factors that can decrease the temperature and thus causing overestimated load forecast. Thus we are producing more power than required[11].

The weather factor includes:

Temperature: Temperature can also alter the conductivity of the transmission lines. Thus temperature can affect the overall carrying capability of the transmission lines. High temperature can increase not only the resistance of the transmission lines, but also it can alter the reactance of line, due to temperature induced expansion of the length of transmission line[12].

Humidity: Humidity is a term used for the amount of water vapors in air. Humidity has no effect on real temperature but it can intensify the severity of hot climate. So it is concluded from the above observation that for the prediction of daily load of domestic consumers we must consider apparent temperature instead of real temperature.

Random or Occasional Spikes: The power system consists of different types of consumers for example domestic, agricultural, industrial etc. The overall load of domestic consumers shows good statistical rules and is periodic in nature.

III. Short Term Load Forecasting Methods

Short term load forecasting methods are:

Similar Day Look up Approach: Similar day approach is based on searching historical data of days of one, two or three years having the similar characteristics to the day of forecast. The characteristics include similar weather conditions, similar day of the week or date [7].

Time Series Analysis: Time series forecasting is based on the idea that reliable predictions can be achieved by modeling patterns in a time series plot, and then extrapolating those patterns to the future. Using historical data as input, time series analysis fits a model according to seasonality and trend. Time series models can be accurate in some situations, but are especially complex and require large amounts of historical data [12].

Time series method has been most popular methodalthough it has several draw backs such as complex to use,require more time and historical data for prediction but intoday's most complex system and system of fastdevelopment in context of energy generation and demandmethod has difficulty to predict however it has been usingfor STLF. The remaining models of time series uses are:

- Autoregressive (AR) model
- Autoregressive moving-average (ARMA) model
- Autoregressive integrated moving-average(ARIMA) model

Regression based Approach: Linear regression is a technique which examines the dependent variable to specified independent. The independent variables are firstly considered because changes occur in them unfortunately. In energy forecasting, the dependent variable is usually demand of the electricity because it depends on production which on the other hand depends on the independent variables [8] [9].

Support Vector Machines: Support Vector Machines (SVM) is the most powerful and very recent techniques for the solution of classification and regression problems. In support vector machines, linear functions are used to create linear decision boundaries in the new space. In the case of neural network, the problem is in the choosing of architecture and in the case of support vector machine, problems occurs in choosing a suitable kernel.

Artificial Neural Networks: ANN is a soft technique used in various optimization processes. This method is able to perform non-linear modelling and adaptation. It does not require assumption of any functional relationship between load and weather variables in advance. We can adapt the ANN by exposing it to new data. The ANN is also currently being investigated as a tool in other power system problems such as security assessment, harmonic load identification, alarm processing, fault diagnosis, and topological observability [13].

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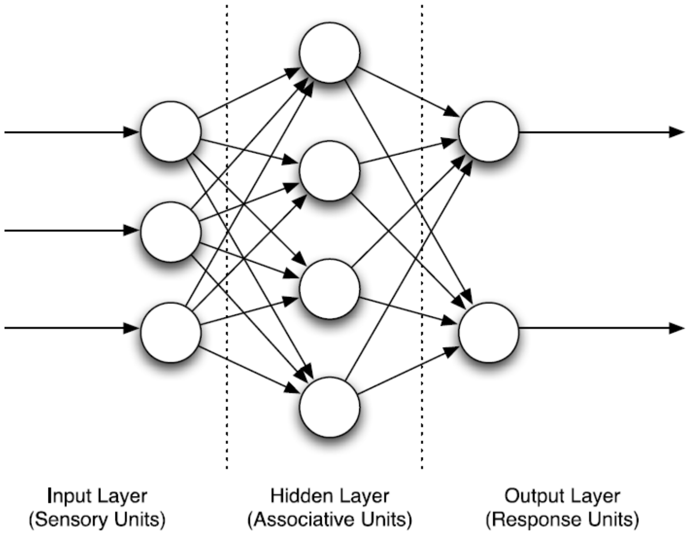

Figure 2: Feed-Forward ANN Topology

Fuzzy Logic: Fuzzy logic based on the usual Boolean logic which is used for digital circuit design. In Boolean logic, the input may be the truth value in the form of "0" and "1". In case of fuzzy logic, the input is related to the comparison based on qualities.

Adaptive Neuro-Fuzzy Inference System:

ANFIS is a class of multilayer feed-forward neural networks inwhich each neuron performs a specific function on incomingsignals, used to nonlinear prediction where past samples areutilized to forecast the sample ahead. The ANFIS is generallytrained by a hybrid algorithm combining the least squaresmethod and the gradient descent method. An ANFIS topology contains five layers with two inputs x andy, and each variable has two fuzzy sets A1, A2, B1, and B2, circleshows a fixed node, whereas a square illustrates an adaptivenode.

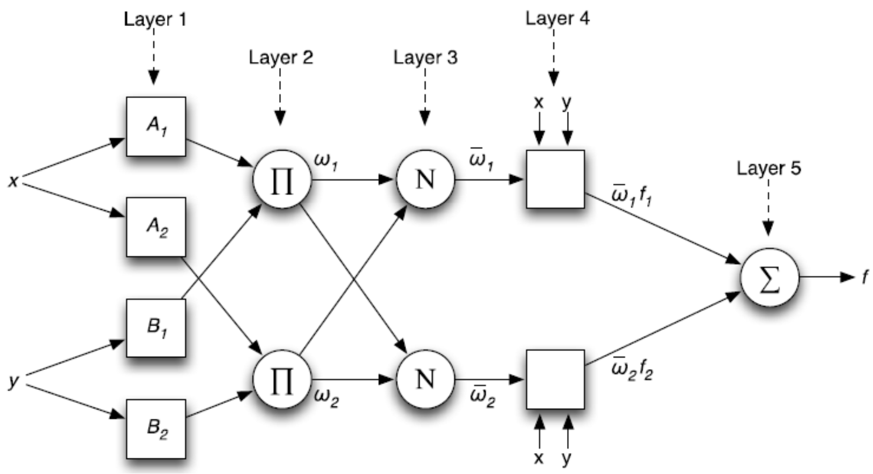

Figure 3: ANFIS Equivalent Topology

The main objective of the ANFIS design is to optimize theANFIS parameters. There are two steps in the ANFIS design.First is the design of the premise parameters and the other isthe training of the consequent parameters. There are severalmethods proposed for designing the premise parameter such asgrid partition, fuzzy c-means clustering and subtractiveclustering. Once the premise parameters are fixed, theconsequent parameters are obtained based on the input-outputtraining data.

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IV. RELATED WORK

McDonald et al.[11] presented an adaptive-time series model, andsimulated the effects of a direct load control strategy.

Barakat et al. [12] presented anew time-temperature methodology for load forecasting.In this method, the original time series of monthly peakdemands are decomposed into deterministic and stochasticload components, the latter determined by an ARMAmodel.

Mbamalu and El-Hawary [13] proposed aninteractive approach employing least-squares and theIRLS procedure for estimating the parameters of aseasonal multiplicative autoregressive model. The methodwas applied to predict load at the Nova Scotia PowerCorporation.

Hsu [14] presented an expert system using fuzzy set theory for STLF. The expertsystem was used to do the updating function. Short-termforecasting was performed and evaluated on the Taiwanpower system. Later, Liang and Hsu [15] formulated afuzzy linear programming model of the electric generationscheduling problem, representing uncertainties in forecastand input data using fuzzy set notation. The hybrid fuzzyneuraltechnique to forecasting load was later enhanced byDash [16].

Haida and Muto [17] presented a regression-based daily peak load forecasting method with a transformation technique. Their method uses a regression model to predict the nominal load and a learning method to predict the residual load.

Paarmann and Najar's [18]adaptive online load forecasting approach automaticallyadjusts model parameters according to changingconditions based on time series analysis. This approachhas two unique features: autocorrelation optimization isused for handling cyclic patterns and, in addition toupdating model parameters, the structure and order of thetime series is adaptable to new conditions.

Zheng et al.[19] applied a wavelet transform-Kalman filter method forload forecasting. Two models are formed (weathersensitive and insensitive) in which the wavelet coefficientsare modelled and solved by the recursive Kalman filteralgorithm.

Hippert et al. [20] designed a STLF system. The design tasks were divided into fourstages: data pre-processing, ANN design, implementation,and validation. Although the discussion was in the contextof ANN, a significant portion was also applicable to othertechniques.

Alfares and Nazeeruddin[21] covered a wide rangeof techniques classified into nine categories: (1) multipleregression; (2) exponential smoothing; (3) iterativereweighted least-squares; (4) adaptive load forecasting;(5) stochastic time series; (6) autoregressive moving averagemodels with exogenous inputs (ARMAX) based on geneticalgorithms; (7) fuzzy logic; (8) ANN; and (9) expertsystems. The paper described the methodologies briefly foreach category, and discussed their advantages and disadvantages.

Metaxiotiset al. [22] provided a chronologicalsummary of the development of various AI techniques,such as expert systems (ES), ANNs, and genetic algorithms.The advantages of AI techniques in STLF were summarizedboth conceptually and qualitatively.

Martin Längkvistet al. [23] proposed deep neural networks are applied to time series data with several kernel configurations. However, the usage of deep neural networks in electric forecasting is still limited due to the inability to access large volume of data and powerful computation machines

A. Baliyan et al.[24] proposed a multilayer ANN was to enhance the forecasting performance when the temperature forecast error increases. Recent research work of the ANN model for STLF included taking advantage of several meteorological forecasts. In order to adapt complex real-world data, there are two techniques.

Xiaoqin Wu [25] proposes a new approach for load forecasting inpower systems by using trajectory tracking stability theory.And based upon Lyapunov stability theory, the proposedmethod is essentially model independent and can ensure theprediction error convergence.

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Jian Zheng[26] explores Long-Short-Term-Memory (LSTM) based Recurrent Neural Network (RNN) to deal with this challenge. LSTM-based RNN is able to exploit the long term dependencies in the electric load time series for more accurate forecasting. Experiments are conducted to demonstrate that LSTM-based RNN is capable of forecasting accurately the complex electric load time series with a long forecasting horizon.

Tomas Vantuch [27] proposes an innovative algorithm entitled as ensemble of fuzzy linear regression (EFLR) and it bases on fuzzy linear regression combined with boosting mechanism. The fuzzy linear regression is optimized making use of multi objective optimization.

Junran Peng [28] used an adaptive network-based fuzzy inference system (ANFIS) model to construct theshort-term load forecasting model based on factors such as weather and date types, etc. Then, the model was trained bythe historical electric load data of eastern Czechoslovakia, and the prediction performance of the model is demonstrated.

V. CONCLUSION

Electricity demand forecasting represents the main task in the planning of electricity production because it determines the required resources to operate the electricity plants such as daily consumption of fuels. Furthermore, it is the corner stone of planning for electric plants and networks. In this research work a discussion on several statistical and artificial intelligence techniques for load forecasting that have been developed for short term electric load forecasting. Also a discussion on the factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end use factors is done. However, it is complicated to predict future electric loads accurately due to these influencing factors. It is therefore necessary to develop new methods for short term load forecasting to reduce the uncertainty of the predictions.

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