A LITERATURE SURVEY ON SHORT TERM ELECTRICITY LOAD FORECASTING METHODS

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ABSTRACT

Load forecasts are very important for the smooth functioning of the electrical industry. It has various applications, including energy purchasing and production, load switching, infrastructure development and contract evaluation. Energy planning and needs-based power generation plays an important role in this scenario. Electricity load forecasting knowledge can be used in the development of smart grids. Many mathematical methods have been developed for load prediction. This article analyzes various short-term load forecasting techniques that help predict performance for a short time. These different techniques include time series analysis, regression models, and deep learning models such as artificial neural networks and recurrent neural networks. A comparison of the merits and disadvantages of various load prediction methods is also performed.

INTRODUCTION

Load forecasts are just as important as the generation and transmission of energy. Keeping an eye on the system load is the basic requirement for any power system. This monitoring can be done on an hourly basis or over years. Appropriate monitoring of an unconventional power source must be undertaken as these power sources are not as flexible. For example, solar power generation is not controlled by human intelligence. The availability of fuel also requires the load forecast, so excess fuel needs to be available for the projected power generation.

At the time of deployment, the load forecast is determined to be performed in three different ways based on the time span of prediction.. Long-term load forecast (LTLF): This is mainly intended for system planning. It covers a timeframe of 10 to 20 years. Medium Term Load Forecast (MTLF): It is used to plan fuel supply and maintenance. It covers a few weeks or a month. Short-term load forecasting (STLF): It is carried out for the current operation and the planning of the power load system. This is usually one hour to one day [2] [3] [4] [5].

PREVIOUS WORKS ON LOAD FORECASTING:-

Jatin Bedi and Durga Toshniwal [6] proposed a Deep Empirical Fashion Decomposition deep learning model for power forecasting. This method combines the EMD method with the long-term storage network model to estimate the power requirements for each season, the day, and the time interval of one day. For this purpose, the EMD algorithm breaks down a load-time series signal into several intrinsic-mode functions (IMFs) and residuals. Then, an LSTM model is trained separately for each of the extracted IMFs and residuals. Finally, the forecast results of all IMFs are combined by summation to determine aggregate power demand.

Vincent Thouvenot, Audrey Pichavant, Yannig Goude, Anestis Antoniadis and Jean-Michel Poggi [7] came up with the idea to use multilevel estimators for non-linear additive models. It was a semi-parametric approach based on additive models. An automatic method for explaining variable selection in an additive model. It can be shown how mid-term forecast errors are corrected for short-term forecasts.

Another approach, proposed by Chun-Nam Yu, member, IEEE, Piotr Mirowski, member, IEEE, and Tin Kam Ho, IEEE Fellow, was a low-cost coding approach to household electricity demand in smart grids [8]. Sparse coding refers to the modeling of data signals as the sum of some basic elements. It finds its use in signal and image processing. Many natural signals are sparse in appropriately selected bases, e.g. B. Fourier base in speech, curvelets and wavelets in natural images.

Stacked Denoising Autoencoder [9] was proposed by Long Wang, Student Member, IEEE, Zijun Zhang, Members, IEEE and Jieqiu Chen. A class of deep neural networks and their extended version are used to predict the price of electricity hourly. Data collected in the US hubs of Nebraska, Arkansas, Louisiana, Texas, and Indiana are used. Two types of predictions are examined, the hourly online forecast and the hourly forecast for the predictive day. Calculation results show that SDA models are able to accurately predict electricity prices, and the enhanced SDA model further improves forecasting performance.

Hossam Mosbah and Mohamed El-Hawary, Life Fellow and IEEE, have been working on this multi-layered neural network [10]. A new computational approach for the use of backpropagation multilayered neural networks to predict the hourly electricity price for the next month, based on hourly important factors such as previous hourly load, hourly natural gas and hourly weather conditions for the January 2006 electricity load forecast for the Australian market. It includes three separate networks in a cascade topology and a parallel topology to get the best performance based on simulation results.

Recurring neural networks were used in the load prediction of Filippo Maria Bianchi1a, Enrico Maiorinob, Michael C. Kamp_meyera, Antonello Rizzib, Robert Jenssena [11]. This class of mathematical models is gaining new interest in researchers today, replacing many of the practical implementations of predictive systems previously based on static methods. Despite the undeniable expressiveness of these architectures, their recurring nature makes their understanding difficult and challenges the training process. Lately, new, important families of recurring architectures have emerged, whose applicability has not been fully explored in the context of load forecasting.

Jianwei Mi, Libin Fan, Xuechao Duan and Yuanying Qiu proposed an improved exponential smoothing-gap model [12]. To improve predictive accuracy, this article proposes a short-term performance load prediction method based on the improved exponential smoothing gray model. He first determines the main factor that affects the power load, using the gray correlation analysis. Then, the power load forecast is performed using the enhanced grayscale multi-variable model. The improved predictive model first performs the smoothing processing of the original power load data using the first exponential smoothing method. Second, the gray prediction model is set with an optimized background value using the smoothed sequence that matches the exponential trend. Finally, the inverse exponential smoothing method is used to restore the predicted value.

Merits and Demerits

Similar Day Approach: Easy to implement, flexible in application but has less accuracy and less parameters can be taken into consideration.

Multiple Linear Regression: Good accuracy, Easy to implement, update and automate. Problem in function selection, Needs explanatory variables, at least two year history required.

Time Series Analysis: Simple trend Formulation, easy to use, Prediction can be done only in a particular boundary, not much flexible.

Artificial Neural Network (ANN): Knowledge required in statistics and relted domain is minimal; during normal days this method has good accuracy. Heavy computation; over-parameterization; difficult to interpret, low accuracy during extreme weather condition.

Expert System: Easy , human interface so practically used. Less accuracy , largely affected by less data i.e less knowledge.

Fuzzy Logic: No need of mathematical model, No need of precise noise free data. Contains stages of calculation i.e. fuzzy and defuzzification.

Support Vector Machines: Simple Linear equation is used, accurate, flexible in application. Problems occurs in choosing a suitable kernel, complex to use

CONCLUSION

The forecast of electrical demand has become a very worrying issue in the energy industry as more and more electrical appliances became popular. The complexity of the forecasting problem grew. With the advent of conventional techniques to the soft techniques, several methods of optimization are being invented. Some of them are used in various aspects in the electrical industry. Smart Grid requires advanced methods for accurate and accurate monitoring of the energy system. Also, smart grid investments and technologies have presented new energy challenges, such as demand-response forecasts and renewable energy generation forecasts. The century-old energy forecasting field has found new life in the age of the Smart Grid. Many computer techniques are available, but all have some merits and disadvantages, as examined in this work. A good predicted result must be included
different parameters.

FUTURE WORK

As shown in this paper, there are many load forecasting methods with several advantages and disadvantages. This work can be extended by using some methods through analysis. A comparative analysis of the result of the practical load prediction can be carried out in some methods. After that, the best method can be recommended to several utilities.

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