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A Study on Recent Trends for Load Forecasting with Artificial Intelligence

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Abstract

In order to manage and maintain the power supply in distribution grids. The decision makers in the power grids must predict/forecast the energy demand with the least possibility of error. With the appropriate load forecasting, a stable, continuous and cost-effective power can be supplied to the consumers. Various factors can affect the accuracy of the load forecasting such as load density, geographical factors, population growth etc. Load forecasting is divided into three types: long-term load forecasting, medium-term load forecasting and short-term load forecasting. This paper presents an overview for load forecasting and its types. Out of which, STLF plays a very significant role in ensuring that power systems works efficiently, safely and economically. Various STLF techniques were proposed by the researchers that are discussed in literature survey, in order to optimize the distribution in electrical power grids. However, STLF is complex method as its prediction accuracy gets altered by the various complicated and non-linear external parameters. To overcome the drawbacks of STLF, a large number of STLF, MTLF and LTLF methods such as MLR, KBES etc. were proposed. From the literature survey conducted, it is observed that if these methods are incorporated with the artificial intelligence systems along with various dependency factors then the efficiency of these systems can further be increased..

Keywords: load forecasting, artificial intelligence, Short term load forecasting, Power systems etc.

1. Introduction

Load forecasting is a significant task in power system for its utility as storing of electric energy is an impossible process. Load forecasting assists in determining the electric load on the basis of the existing/historical data. It has the ability to manage and predict the patterns of energy consumption which in turn helps in monitoring load in future systems [1]. There are various factors affecting the load forecasting of the system. A few of them are historical data, land use, geographical factors, load density, population growth, alternate energy sources, etc.

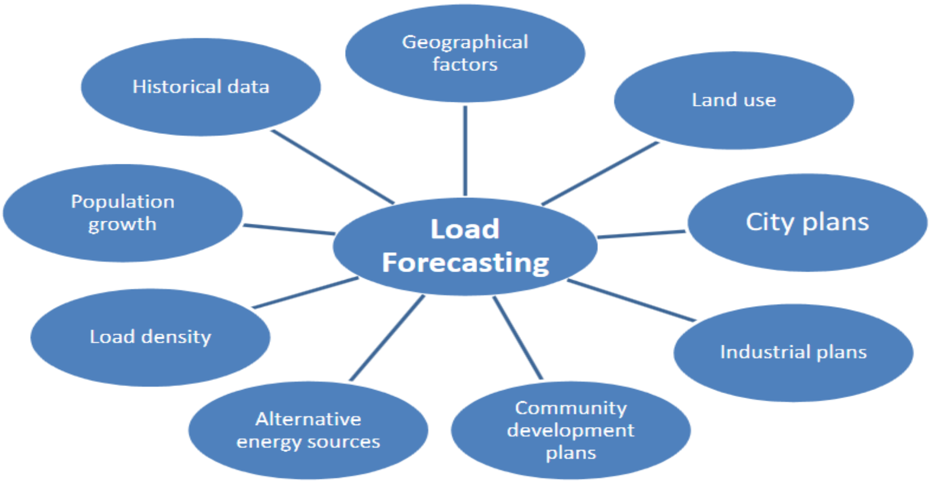

Fig 1. Factors affecting process of Load Forecasting

2.Advantages Of Load Forecasting

- Load forecasting helps the utility firm to schedule accurately as it knows potential usage or demand for the load.
- Minimize the service company's risks. Understanding the potential long-term load lets the business prepare and focus on future investment in output and transmission in an economically feasible manner.
- Helping to locate essential resources such as the fuels required to run the generating capacity, along with other assets needed to ensure that power generation and delivery to customers is unbroken and still economical. For short-, medium- and long-term planning, this is crucial.
- The load forecast helps in future planning in terms of plant scale, location, and type. The power generation of utilities is highly probable by identifying areas or regions with strong or increasing demand. This would reduce both the networks of transmission and delivery and the resulting losses.
- Assists in the decision-making and planning of power systems maintenance. The utility will know what to maintain to ensure it has the least impact on customers by knowing demand. For instance, because many people are working and the demand is very poor, they may decide to retain residential areas during the day.
- Usage of power generation plants as far as possible.

3.Challenges In Load Forecasting

- The outlook is focused on predicted environmental conditions. Sadly, the weather is sometimes unpredictable and the forecast may differ if the actual weather varies. In addition, numerous regions could have varying environmental patterns that will certainly impact the demand for electricity. This may have a negative impact on incomes, particularly if the utility generates more to meet the expected high demand, and then the consumption is much lower than that generated either using costly methods such as the generating of fossil fuels, etc.
- Due to changes in variables like pricing and the resulting demand dependent on those price changes, it is difficult to get reliable data on consumption behavior.
- The role of estimating the load is challenging because it is dynamic and may vary depending on the seasons, and the overall consumption can vary between two seasons.
- The various dynamic variables impacting energy demand are often difficult to incorporate into the projected models correctly. Furthermore, reliable demand estimates based on parameters such as temperature changes, moisture, and other variables influencing consumption cannot easily be obtained.
- The utilities will fail if they do not realize and determine for short-term load prediction a reasonable margin of error.

According to the time zone of the planning strategies, load forecasting can be divided into three categories [2]:

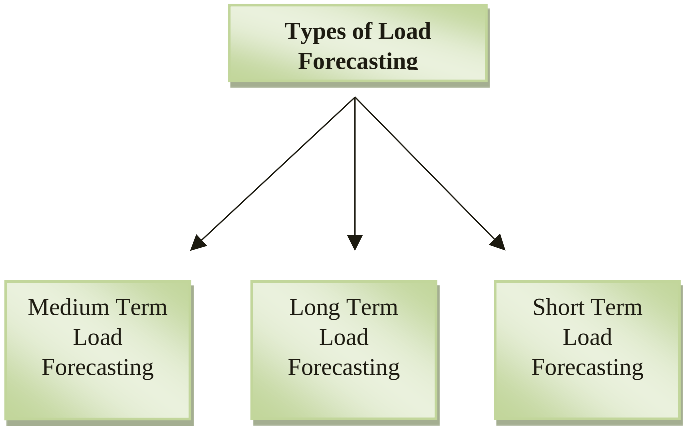

Fig 2. Different types of Load Forecasting

3.1.Medium Term Load Forecasting (Mtlf)

MTLF is an important stage in electric power system planning and operation. It is used in maintenance scheduling, and to plan for outages and major works in the power system. The proposed method is generic and can be implemented to the hourly loads of any power system [3].

3.2.Long Term Load Forecasting (Ltlf)

Long-term load forecasting is the first and primary step in planning the future requirements of generation, transmission, and distribution facilities in an electric grid. It is very essential for future network planning and expansion of the power system. In general, long-term forecasts span from one year ahead up to ten years and they are often complex in nature due to future uncertainties such as political factors, economic situation, per capita growth, etc [4].

3.3.Short Term Load Forecasting (Stlf)

This method of forecasting generally covers a period of between one hour and one week. It can lead to approximate charging flow and to decide which overburden can interfere. Short-term forecasts are used to provide compulsory information on everyday operating structure management and on unit interaction [5]. The STLF plays a very significant role in ensuring that power systems work efficiently, safely, and economically. A rigorous short-term load forecast is required for basic functions such as hydro-thermal coordination, unit commitment, safety assessment, and interchange evaluation [6]. Furthermore, the STLF is further divided into two basic models.

Peak Load Model: In this model, modelling of peak load is typically done as a function of the load on a daily or weekly basis. In those models, time is irrelevant. The peak model is further divided into two categories: a weather-independent base load and a weather-dependent variable load. Then, the variable load is inserted into the base load. By using linear or non-linear regressions, the parameters of this model are calculated. This model contains the data of the load curve’s shape, whereas this model does not specify peak time. Correlation over time cannot be predicted because the peak load model is fundamentally static

Load Shape Model: These models are examined at specific intervals of time. The load shape model is further divided into two types:-

• **Static Models**: These models are defined as a mixture of explicit time functions like sinusoids, exponentials, or polynomials. Static model attributes are computed using data of historical load and methods of linear regression or exponential smoothing

• **Dynamic Models**: In these types of models the load is not only influenced by the daytime but is also affected by the recent actions of UPEC 2007-1192, various climate conditions, and random inputs. Dynamic models could be combined with ARMA, state-space models, and ANN [7]

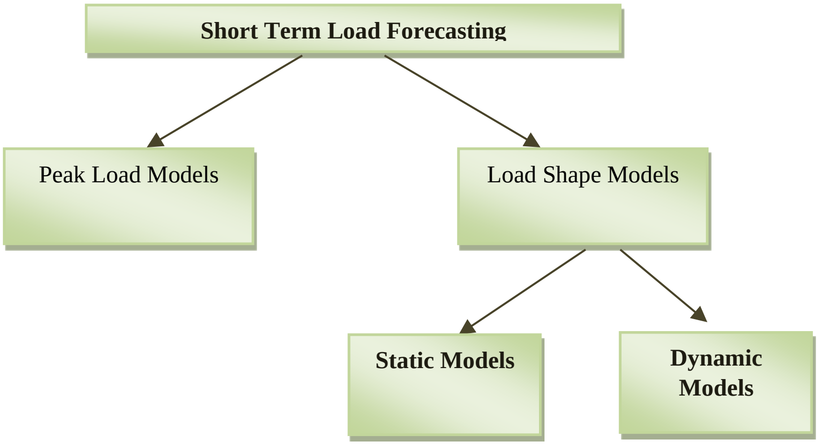

Fig 3. Different types of Models in STLF

4.Short Term Load Forecasting Methods

As represented in fig 4, the STLF is divided into six categories i.e. Multiple Linear Regression, General Exponential, State Space, Knowledge-Based Expert System, Stochastic Time Series, and Artificial Neutral Networks.

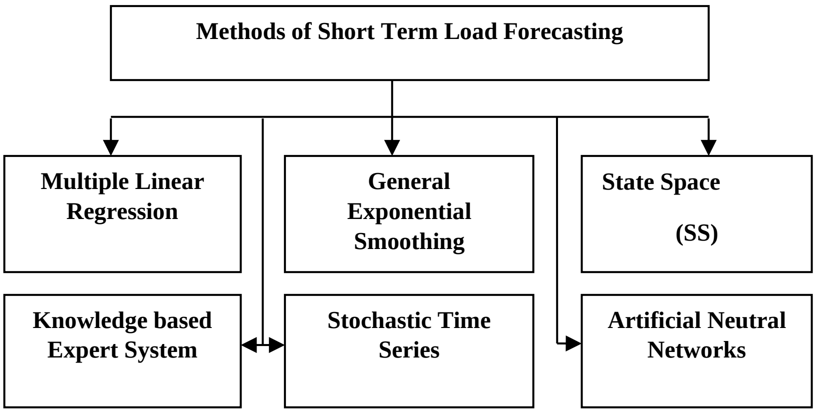

Fig 4. Methods of STLF

In the MLR method, the load is determined through independent variables such as environment and other factors that affect the electrical load. This approach works well for forecasting data that doesn't have a consistent trend or seasonal pattern [8] [9]. In the GES method, the linear combination of known frameworks of time and noise components is implemented. In the SS method, general methods which utilize the equations of measurements and state space are incorporated with methods of Multiple Linear Regression, General Exponential Smoothing, or Stochastic Time Series. The KBES is concerned with computer programs that are capable of making their own decisions to solve a problem of interest[9][12]. In the STS method, a linear filter with a white noise input is used to model a linear equation expressed in terms of prior load values[10]. In the ANN method, multivariate, non-linear, and nonparametric computer programs are trained on historic data. In addition to these methods, there are several other methods that are discussed in the next section [11].

5.Literature Survey

Various methods have already been proposed by different researchers to overcome various issues such as high energy consumption, data aggregation etc. in WSNs. Some of them are described here;

KunXie, et al. [12]:This paper provides a method for short-run power load forecasting together with the Elman neural network (ENN) and particle swarm (PSO). Firstly, the ENN and PSO algorithms theory are applied and the network efficiency analysis dependent on ENN parameters is evaluated. The optimization algorithm of the particle swarm is then used to look for the optimized ENN learning rate. The method is used in the short-term power projection, relevant to the resolution with ENN, to determine the capabilities of the method suggested in this article. Furthermore, a comparative experiment with the GRNN, initial ENN, and standard

Back-Propagation Neural network (BPNN) is performed on this approach (PSO – ENN) to show the usefulness of PSO – ENN. In addition, this experiment was carried out.

R. Gao, et al [13]: A method of short-term load estimation, based on the LS-SVM, and fluid control were suggested. The LS-SVM model, which consisted of evaluating load data and meteorological data, forecasted peak load, and valley load. Then the peak load and load of the valley were calculated by fluid rules based on error prediction data. The peak load and valley load with the same day load shift coefficient is mixed one day and one week before the fee. The 2008 Shan Dong electrical company's charging data and meteorological data were used for evaluating the prediction model. The findings show that the suggested methodology will increase the precision of the forecast.

P. Mukhopadhyay, et al. [14]: The demand for electricity in an area depends on a variety of factors such as population, regional growth, temperature, price of electricity, industrialization, etc. In determining the overall demand more accurately, weather plays a significant role. Precision in the forecast allows the device operator to maximize the generation and retain sufficient reserves in response to any contingency. The control area load only has a portion that is weather-prone, often load-prone, while others are weather-dependent. Short-term load forecasts shall not presume the contribution of seasonally dependent agricultural load and are thus presumed to be steady within a few days. This paper aims to build a model that uses furious reasoning to predict short-term weather and temperature for the future load.

S. Fan, et al. [15]: This paper addresses a large projection in Midwest USA for geographical loads and a small area load projection in a United Kingdom delivery feeder respectively. A multi-regional method that seeks an optimum area division in both stationary and intermittent weather and load conditions is addressed with respect to the load forecasts in the broad geographical zone. A two-stage hybrid module is also addressed for the load forecast on a small feeder. Risk assessment technologies are also recommended to evaluate unsecured load forecast based on time-domain and frequency-domain approaches.

Y. Min, et al. [16]: Mid-term power grid load forecasting is one of the fundamental works for energy planning. There are advantages and drawbacks to each power forecast model and its own application set. A load prediction model with variable weight is developed for this article. This enables the advantage of every single model to be maximized in various ranges. In addition, the residual correction technique from Fourier is used to reduce the absolute error of mixture model estimation. The experiments are conducted on the basis of sample data in a city. The findings indicate that the statistical accuracy of the mixture model is more for 94% than any single model. The forecasting accuracy is further increased to 95 percent after residual correction.

W. Shun-yu, et al. [17]: In this process, the local similar-day algorithm produces a change of load rate, and a change of load rate is obtained at the same time in the same working day according to the change rate. Then the above two values will determine a synthetic change rate and predict the next moment's load. This strategy can significantly reduce mistakes caused by sudden changes and increase global prediction output as well as load peak and load drop predictions.

J. Cui, et al. [18]: The sequence of power load is a dynamic nonlinear set of times. The long-term memory network (LSTM) has also been introduced to boost the RNN for short-term load forecasting since the time dynamic of the nonlinear time series can be recorded. The author developed the CEEMD-AE-LSTM load prediction model in order to further increase the accuracy of load forecast performance. The first thing to do is decompose the load series into many subsequences, with complementary ensemble analytical mode decomposition (CEEMD). Furthermore, each subsequence has estimated entropy (AE) and the subsequences with identical entropy values are combined into new sequences. Sequences are different. Researchers finally created the new LSTM networks and super-pose as the end load forecast result the output result of each LSTM network. Experimental findings reveal that, by compared relative error with an absolute percentage error, the CEEMD-AE-LSTM load forecasting model is above the single RNN and LSTM network. Consequently, the load prediction model of the CEEMD-AE-LSTM effectively predicts and upgrades short-term load prediction accuracy.

E. Akarslan and F. O. Hocaoglu[19]: Smart grid technology is being developed to make grid problems control more critical. One of the key grid control issues is load estimation. The objective of the study was to create an approach based on the adaptive Neuro-Fuzzy Inference System (ANFIS) to load projections for small regions with lower consumption. This is the purpose of the campus of AfyonKocatepe University. The requirement for the campus calculated and reported load times according to the planned ANFIS model. Throughout the proposed prediction model, only the demand factor is needed. Other parameters have been determined from this factor. The ANFIS model feedback in this scope predicts the load demand during the next hour, first-order utilization derivatives, true consumption, months, and hour. The experiment findings suggest that the suggested method is well prepared for small areas.

Faisal Mehmood Butt et al. [20]: For precise electrical load forecasting, effective management and better scheduling by the power companies are of great importance. In the load time series, there is a high degree of uncertainty that makes the specific short-term load forecast (STLF), medium-term load forecast (MTLF), and long-term load forecast difficult to make (LTLF). It suggested long short-term memory (LSTM), multilayer perceptron, and convolutional neural network (CNN) understand the connection in the time series to retrieve the local trends and to catch the same characteristics of short and medium forecast time series. These frameworks were developed to increase the precision of forecasting. Depending on the actual situation, the models were evaluated by carrying out detailed experiments to verify their stability and practicality. Squared Error, Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error were calculated in terms of output (MAE).

P. Borthakur and B.Goswami [21]: Throughout this article, for short-term load forecasting, a hybrid approach using data mining methods were indeed suggested. The method includes the AFTER (Aggregated Forecast through Exponential Reweighting) algorithm to integrate the k-means clustering-Naive Bayes classification algorithm and the ARIMA (Autoregressive Integrated Moving Average) method estimates to form a hybrid load forecasting model from the supply side. The deviation in the hybrid model's forecast also was fixed by using a neural network and minimized. To evaluate the validity of the developed system, the error of the forecast load was calculated using MAPE (Mean Absolute Percentage Error). The hybrid model forecast with the neural network error model substantially increases the supply side prediction accuracy of the load forecast compared to in individual forecast models considered.

Table I. Comparison table for different approaches available for load forecasting

Sr. No	Author Name	Technique Name	Year	Work Done
1	KunXie, et al.	Elman neural network with particle swarm optimization	2019	This paper provides a method for short-run power load forecasting together with the Elman neural network (ENN) and particle swarm optimization (PSO)
2	R. Gao, et al	Least square support vector machine combined with fuzzy control	2012	A method of short-term load estimation, based on the LS-SVM, and fluid control was suggested
3	P. Mukhopadhyay, et al.	Fuzzy Logics	2017	This paper aims to build a model that uses furious reasoning to predict short-term weather and temperature for the future load.
4	S. Fan, et al	Load forecasting technologies for different geographical distributed loads	2011	A multi-regional method that seeks an optimum area division in both stationary and intermittent weather and load conditions are addressed with respect to the load forecasts in the broad geographical zone.
5	Y. Min, et al	Combination forecasting mode	2015	A load prediction model with variable weight is developed for this article. This enables the advantage of every single model to be maximized in various ranges.
6	W. Shun-yu, et al	Local shape similarity corrective changing	2012	A very short-term method of load prediction based on modified local shapes was proposed
7	J. Cui, et al	Improved Long Short-Term Memory Network	2019	Developed the CEEMD-AE-LSTM load prediction model in order to increase the accuracy of load forecast performance.

8	E. Akarslan and F. O. Hocaoglu	Adaptive Neuro-Fuzzy Inference System	2018	This study proposed an approach based on the ANFIS system to load projections for small regions with lower consumption
9	Faisal Mehmood Butt et. Al	Artificial Intelligence	2021	It suggested LSTM, MLP, and CNN to understand the connection in the time series to retrieve the local trends and to catch the same characteristics of short and medium forecast time series.
10	P. Borthakur and B. Goswami	A Hybrid Approach Using Data Mining Methods	2020	The method includes the Aggregated Forecast through Exponential Reweighting algorithm to integrate the k-means clustering-Naive Bayes classification and the AIMAM estimates to form a hybrid load forecasting model from the supply side

6.. Conclusion

Load forecasting is one of the crucial factors in electrical power distribution systems to ensure the stability and reliability. From the literature survey it is observed that there are various factors that affect the accuracy of the load forecasting. A large number of STLF techniques such as ENN, PSO, SVM, AFTER etc. were proposed by the researchers in order to predict the weather and temperature conditions. In addition to this, various methods were suggested by the researchers to reduce the overload and increase the accuracy of the forecasting in electrical power distribution systems. After analyzing the various papers based on the STLF, MTLF and LTLF we find that there is a scope of improvement in these methods in order to predict the load accurately. Furthermore, it was observed that if these techniques are used along with the artificial intelligence and deep learning systems, more efficient and reliable forecasting systems can be achieved.

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