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Electrical Load Forecasting Methodologies and Approaches

Seemant TIWARI
Southern Taiwan University

Abstract: Load forecasting is indeed a strategy used mostly by power providers to predict the amount of power or energy required to match market dynamics at all moments. Electricity load prediction is a dangerous process trendy the electrical company's development besides theatres a dangerous character in electrical capacities allocation and power structure organization; as a result, it consumes increasingly gained research interest. As a result, the reliability of power demand prediction is critical for electricity resource planning and electrical management system. The increasing rise of database files in market research, together with data processing, created an urgent need development of an effective instrument process for capturing concealed and crucial understanding of load prediction from accessible enormous data sets. Many machine learning techniques, as a potential subset of computer engineering, are well suited to the answer to this issue. This text delivers an impression of authority weight prediction practices besides algorithms. Notwithstanding the complexity of all studied methods, the evaluation demonstrates that regression analysis itself is frequently utilized and economical for long-term prediction. Machine learning or artificially intelligent methods like Neural Networks, Support Vector Machines, and Fuzzy logic are ideal for short-term estimates.

Keywords: Artificial Neural Networks (ANNs), Prediction of load demand, Forecasting methods and algorithms, Time Series

Introduction

Forecasting is a critical component of the electricity system. Forecasting systems are now used for both wind power generation (Seemant & Ling, 2021), and wind speed (Tiwari, 2022). Forecasting electrical load is also beneficial to the power grid and power corporations. Electricity is an environmentally friendly and cost-effective type of energy that is indispensable in our everyday lives (Lin Y. et al., 2017). Electricity's importance has lately grown dramatically, which has also become an important issue in studies (Nalcaci et al., 2018). Furthermore, as likened to other conventional electricity sources like natural gas, coke, and petroleum, electrical energy is much more appropriate and effective for the requirements of an environmentally conscious community.

Furthermore, energy as a production differs from material goods in that it can't be held in quantity and must be produced as quickly as required. Furthermore, because of the liberalization of the electricity industry, including such energy glut and shortages, the sales volume for energy is complicated, which might result in faulty forecasts and severe loss of money. Furthermore, as the world's population grows and living conditions increase, world energy consumption is predicted to skyrocket. Additionally, industries are expanding, as is the use of increased electrical items and the advancement of technologies including micro-grids, electrical vehicles, and the manufacture of renewable energy. All of these issues brand managing the electric grid complex (Khamaira et al., 2018). As a result, when choosing on generating electricity, it is vital to forecast the requirements of energy.

The biggest issue in forecasting requests is deciding on a suitable method. With an annual increase rate of 4 to 7% in electrical energy usage, multiple features have now become leading in the production of generated electricity. Predicting energy demand has long been criticized for managing clients' needs, new activities, and maintaining power systems. The utilization of electricity in the shape of energy is referred to as an electricity network. The cost of electricity, consumption, and reliance on fossil fuels are all steadily rising. The creation of innovative electrical consumption prediction models to satisfy rising demands is a massive issue for any government concerned with energy or power generation. Because electric power is challenging to store in a reserve, forecasting energy needs is critical to ensuring an appropriate supply of electricity to power consumers. Predicted electric load numbers are utilized for: Choosing the quantity of fuel to allocate to distributed generators and maintaining them, distributed management and load preparation, and addressing the needs of customers throughout the year.

This work is divided into the following sections: Section 2nd discussed load forecasting categorization. The 3rd section classified load forecasting methodologies. Section 4th discussed the model chosen for their quality and source of data. Section 5th discussed a critical challenge in load forecasting. Section 6th discussed the benefits, and drawbacks of load forecasting. The last section is the conclusions besides future research.

Load Forecasting Categorization

Depending on the amount of power consumed, load forecasting could be divided into two categories. The first is spatial prediction, whereas the other is temporal prediction. Spatial prediction anticipates the power to the load for a specific area of the globe, like an entire nation, a province, or a specific town. Temporal prediction is the prediction of the energy demand for a given dealer or group of users for a specific interval of time, such as minutes, weeks, seasons, or years. Load predictions in respect of predicted durations into the following categories (Gordillo-Orquera et al., 2018).

Forecasting of Ultra-Short-Term Load

It is utilized for actual authority and can vary from very few minutes to an hour ahead. Used for the Systems of Energy Management as well.

Forecasting of Short-Term Load

This prediction approach typically spans a range of one hour to one week. This could help us estimate load flow and then formulate choices to avoid overburdening. Short-term prediction is employed to give necessary details for such platform's everyday processes including units' commitments. Additionally used to allocate fuels to diesel generators, perform short-term repairs, and pledge to generate units.

Forecasting of Medium-Term Load

The timeframe of this predicting approach ranges between six-seven days to one year. Predictions for various periods are critical for various functions inside a utility firm. Medium-term prediction is utilized for fuel supply planning and equipment maintenance. Often utilized in gasoline buying and pricing revision considerations.

Forecasting Long-Term Load

This predicting approach has a lengthier time frame than one year. It is employed to provide electrical power utility administration with a precise estimate of future development, component selection, or workforce employment requirements. It is also used for the development and increase of electricity generation. It plans to build additional power stations and cables.

Load Forecasting Methodologies

There have been several methodologies proposed for predicting power usage, which can be divided into two types modeling and methodologies. Such tactics and approaches take a more conventional methodology, employing principles like time-series data and linear regression approaches from the domains of AI (artificial intelligence) and computer intelligence (Hong, 2010). Univariate modeling, as well as multivariate modeling, are two different types of load demand prediction. Univariate methods, commonly known are time series analysis, include models in which the load is represented as a factor of its previously measured data.

Extracellular elements including such climate and the day kind are ignored in this prediction. Multiplicative autoregressive algorithms are instances of this kind of model, dynamic linear and nonlinear systems, thresholds auto-regressive concepts, and Kalman filtering (Abdel-Aal, 2008). Multivariate models are those in wherein demand is represented as a consequence of certain external features, most notably meteorological and sociological variables. Box and Jenkins transfer functions, ARMAXS modeling, non-parametric regression, and curve fitting processes are a few applications. Multivariate approaches are often known as causality approaches (Jain, 2009). Below is a summary of various concepts.

Models Based on Regression

Such methods are applied to create correlations among load demand and independent variables such as maximum temperature, minimum temperature, as well as date information, which are mostly employed in linear regression. Forecasting in regression appears to mean estimating a quantity, whether it be upcoming, present, or previous concerning the available data. The nonlinear link between power systems and moderating variables causes difficulties in determining the appropriate models. It is simple to create a connection among the model's O/P and I/P parameters. Such structures are simple to implement as well as manage. Multiple regression methods are also available to express the demand as a consequence of external inputs (Hahn et al., 2009).

In (Fan et al., 2014), this study outlines a method for building a model through ensemble modeling for estimating energy use for the following day. Ensemble programming is a machine learning technique where more than different base algorithms are combined to get a final output. Ensemble Learning as well as Ensemble Training is accomplished in two stages: In the initial phase, a no. of regular methods were produced, whether simultaneously or in succession, while in the second step, basis modeling is employed to produce the ultimate output through employing various clustering strategies. The genetic algorithms are utilized to calculate values for every one of the regular models employed in this approach. In Hong Kong, the approach is employed to predict electrical load requirements for a complex. Multiple Linear Regression was found to necessitate additional time for computing time inside this study.

Neural Networks

Warren McCulloch and Walter Pitts developed the artificial neural network (ANN) technique in 1990 as an alternate methodology to time series prediction. ANNs are being used effectively in a variety of fields, particularly predicting and categorization. ANN methods have recently been widely utilized and investigated as a technique for electricity load prediction and also have achieved popular success in recent years (Adhikari & Agrawal, 2013). The neural net is essentially a non-linear device susceptible to non-linear logistic regression. It depicts a knowledge acquisition approach that's been influenced either by the way the human-natural systems, including the mind, may analyze a particular piece of data. Inside this procedure, the ANNs attempt to discover constants and trends in the data received train through history, and afterward deliver extended outcomes based on the previously current information. An ANN is made up of numerous linked functional units (PE) named neurons that change their dynamic state reaction to exogenous variables (Kuster et al., 2017).

In (Slobadan et al., 2013), this research introduced an ANN methodology using a regression methodology; the records of electricity needs utilized in this research were obtained from Jeddah, Saudi Arabia. The electrical demand was forecasted using this method, and comparing it with certain other approaches revealed that Artificial Neural Network is superior in terms of outcomes. A randomly generated no. the producer was employed to generate the weights for the various input parameters in System. The things performed by the method are separated into two cycles: preparation of data in the first step and forecasting of electricity in the second phase.

In a short-term load-predicting approach that uses ANN, the research is split into two stages a first stage is employed aimed at data foundation, then the additional portion is utilized to forestall power usage expanding a neural network. It has been established that there is a very significant nonlinear link between everyday load demand and everyday temperatures. Three input parameters are utilized as input data: Last day's electrical consumption, Temp., as well as daily types. The "Modified Back Propagation" methodology is utilized to understand Artificial Neural Networks inside this method. Sigmoid initiation is utilized across overall hidden layers throughout neural network training.

Methodologies to Time-Series

Prediction in time series seems to imply approximating upcoming standards founded on ancient measurements of time-series data (Himanshu et al., 2008). The Time Series Technique commonly referred to as Univariate or Multivariate is one of the fundamental procedures utilized in energy consumption forecasting. Univariate analysis has the benefit of not necessitating additional time-series data from outside I/P (Abdel-Aal, 2008). A Time Series Technique, in the form of univariate methods, is utilized to forecast short-term electricity energy needs. Univariate methods were utilized to forecast electrical energy requests; in this research, such methods employed previous investigational results while disregarding additional associated variables. Univariate Process Methods include Multiplicative Autoregressive Methods, Threshold Autoregressive Methods, Dynamic Linear Methods, and Kalman Filtering Techniques. Multivariate approaches are also utilized to anticipate electrical power usage, however, in this research, such methods employed several external elements such as sociological variables, temperatures, and others (Hahn et al., 2009). These methods have the drawbacks of being time-demanding, requiring a lot of humanoid involvement, and then potentially fetching mathematically unreliable (Jain, 2009).

In (Gonzalez-Romera et al., 2006), this study attempts to service a two-step approach. The first step represents the tendency in electricity load demand, although the second step represents the variation in that tendency. When compared with the direct estimation of electricity load predictions, the findings of this technique are excellent.

Support Vector Machine

Support vector machines are regression and categorization methods developed by Vapnik in 1992. SVM was originally designed to solve pattern categorization difficulties. Following that, Vapnik expanded the usage of SVM to be used in regression techniques. Over the past two decades, SVM has gained popularity not just for pattern classification and regression analysis, in addition for predicting and tackling time series modeling issues. The fundamental goal of SVMs is to deduce particular decision rules with a better prediction capability by selecting a specific group of training data named support vectors (Weron, 2006).

A nonlinear mapping of the I/P space into such an advanced dimension is used in SVM methods, and then an ideally separated hyper-plane is generated. As a result, the complexities and accuracy of SVM algorithms are not directly impacted by the I/P vector. While creating SVM methods, the training method is similar to that used for addressing a linearly controlled quadratic software design challenge. As a result, in contrast to many other systems' training, SVM responses seem to be constantly universally optimal and distinct. But at the other hand, the fundamental flaw of SVM is that they demand a large number of computing, which significantly increases the temporal complexities of the responses (Zhang et al., 2017).

Fuzzy Logic

Fuzzy logic seems to be a modification of the ordinary Boolean concept, but rather than receiving some 0 or 1, that has certain subjective limits connected with this. In those other terms, a temp could be lower, middle, or higher; nevertheless, employing fuzzy logic permits outcomes to be determined using noise or fuzzy input without the necessity for exact mappings of input to output. Fuzzy approaches are extremely advantageous when dealing with uncertainty and are critical for human specialists' information literacy. A membership function could be expressed for just any fuzzy numbers, in which a function about any fuzzy numbers, or a membership function, demonstrates particular continuous curves that change from 0 to 1 or conversely, and the location of a matching transition reflects the period's fuzzy boundaries. To produce good predicting outcomes, fuzzy theories are frequently integrated with many other methodologies (Weron, 2006).

Azeem (2012), in these kinds of instances, fuzzy logic could be employed. The mathematical formula either doesn't exist or is too complicated to encode. The mathematical formula is just too sophisticated to be analyzed quickly enough yet for actual use. On the defined processor architectures, the statistical approach integrates far too much RAM. The experts are accessible to describe the model of development guidelines and the fuzzy systems that describe the features of every parameter. The processes are either too sophisticated, non-linear, or unknown to construct employing typical techniques.

Methods of Hybridization

This method integrates upwards of two methods or strategies in regulations to overcome the disadvantage of the originating methodology. Thus a strategy is referred to as a hybrid strategy. By combining the benefits of multiple single prediction models, hybrids or mixture methodologies and approaches can achieve greater predicting effectiveness over single methodologies so they are commonly utilized in several predicting domains. Therefore in regard, there are many multiple predicting methodologies, mathematical programming, and information processing approaches accessible for constructing various hybrid methodologies (Zhang et al., 2017). As a result, fresh research has shifted their main investigation attention to the creation of successful hybrid methodologies to boost forecasting accuracy (Wang et al., 2019). As a result, it is appropriate to seek out newer hybrid approaches that are offered to include new technical foundations (Verdejo et al., 2017).

Model Chosen for Their Quality and Source of Data

We discovered the significant findings through numerous research creations: methodology, set of data, I/P, O/P, methodology of training, and utilization of the suggested scientific study. Table 1 shows an overview of the research. Table 2 lists some of the most common textbooks on the topic of load forecasting models.

Table 1. Overview of the research

Ref.	I/P	O/P	Set of Data	Methodology	Methodology of Training	Utilize
Friedrich et al., 2015	Data on power and meteorology	Abu Dhabi, short-term load prediction	SCADA municipality of Abu Dhabi Emirate's energy supplier and Masdar area's monitoring system	Neural network	Algorithms of Levenberg-Marquardt	Electrical load usage forecasting
Prakash et al., 2014	Information on electricity and meteorology	Uttarakhand(State) short-term load prediction	Dehradun city load-shedding unit	Neural network	Formula of Levenberg-Marquardt	Electric load usage estimation
Slobadan et al., 2013	The method's inputs include loading and temp readings collected for a particular client on the electricity network	Short-term load prediction	Load data from the old days	Artificial neural network	The initial approach used a singular NN using 24 O/P to anticipate the load demand, whereas the other used 24 independent NN with just 1 O/P.	Predicting the hour load could be done rather well.
Deng, 2010	Energy consumption	Electricity consumption forecast	Details source China's national bureau of statistics	Linear Regression, ANN	Backpropagation	Long-term electricity forecast for China
Jain, 2009	Information on electric load	Load prediction	Data from the previous two years	SVM	SVM Clustering	Load forecast for the coming day

Table 2. Covers some of the most widely used textbooks

Title	Ref.
An Introductory Study on Time Series Modeling and Forecasting	Adhikari & Agrawal, 2013
Electrical Load Forecasting: Modeling and Model Construction	Soliman et al., 2010
Forecasting: Principles and Practice	Hyndman & Athanasopoulos, 2018
Short-Term Load Forecasting by Artificial Intelligent Technologies	Hong et al., 2019
Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach	Weron, 2006

A Critical Challenge in Load Forecasting

Estimating power demands has entered a mature stage. Predictions reaching the short range (a few seconds, hour, or coming days) to the lengthy period (up to 12-15 years ahead) were becoming highly prevalent since the reorganization of power networks. Several nations have followed a policy of containment and commercialized their energy networks, transforming electrical into a precious asset with market values. Demand forecasts are a hard process. Firstly, since the demand sequence is dynamic and has multiple layers of periodicity, the demand at a particular hour is reliant not just on the prior hour's longer load, but as well as the demand at the exact hours of the prior date, and the exact hourly demand the day before its same amount the prior week. Furthermore, there are numerous relevant external things to consider, particularly weather-related factors (Hippert et al., 2001). Such problems can be tackled utilizing a variety of techniques and approaches such as auto-regressive methods, dynamically linear or nonlinear approaches, fuzzy inference, fuzzy-neural concepts, Box and Jenkins transfer functions ARMAX methodologies, and neural network (NN), among others.

In the energy market, predicting demands and pricing are linked to activity, and errors in load prediction will spread to price prediction. Power prices have unique properties. It is distinguished by at least three key characteristics. One of these is its lack of energy storage, therefore implying that costs are strongly reliant on electricity consumption. The second distinguishing feature is the periodic nature of power prices at various levels (every day, monthly, and yearly periodicity), and the last is its uncertain issues to deal with. The hourly price changes in today's highly aggressive power sector contain elements like instability, non-stationarity, repeated periodicity, peaks, and high intensity. A price crash can be induced by economic power, that is a freak incident, as well as by unanticipated events including transmission delays, transmitting delays, and production consequences. Additional elements that can influence it include energy prices, production plant operating costs, weather patterns, and, perhaps most importantly, the equilibrium among complete system demand and supply. Power price predicting uses are classified into three timeframes: short-term prediction, medium-term prediction, and long-term prediction.

Benefits and Drawbacks of Load Forecasting

It allows the power corporation to strategy effectively because they have a good grasp of upcoming spending or load profile. Load predicting is used to prepare for the upcoming regarding the scope, position, and kind of upcoming output growth. It ensures the most efficient use of power generation plants. Prediction prevents under-generation and over-generation. Helpful for determining the necessary assets, like fuels necessary to run energy is converted as well as other materials necessary to provide continuous and cost-effective electricity production and distribution to customers. This is critical for any short, medium, or long-term management.

Taking a decision primarily based on a prediction might lead to monetary devastation for such a company, hence choices should not be created purely on a prediction. Accurate forecasting of tomorrow is impossible. Because of the subjective nature of predicting, a company might generate a variability of situations founded on the analysis of the information. Corporations must never depend entirely on prediction models. Furthermore, a company can utilize prediction in combination with other tools, instruments for assessment to provide the maximum possible data to the organization concerning the future.

Conclusions and Future Research

Various prediction algorithms for electricity load prediction have already been thoroughly examined in this study. Numerous factors, including the development's volume, the forecast horizons timescales, temporal determination, I/P, O/P, information pre-processing, and so on have indeed been assessed and inspected. The investigation also looked at certain trends in the application of such approaches. Several of these, including regression analysis-based methods like artificial neural networks (ANN), which are the greatest commonly used methods in electrical estimates, are now more suitable and favored for electricity load projections. Artificial neural networks (ANN) methodologies are primarily utilized in this context for short-term estimates wherein electricity and energy ingesting rates are far more intricate. Regression methods, in contrast, hand, are still commonly utilized and effective for long-term prediction wherein regularity and variations become less important. Furthermore, support vector machine (SVM) algorithms are used in a large fraction of studies, indicating a growing interest in them. In contrast, statistical methods (particularly the Box-Jenkins modeling group) are no longer as prominent as they once were, yet their contribution cannot be overlooked. Furthermore, the special focus could have been paid to studying extremely short-term and mid-term load predicting to address the identified vacuum in the area.

Scientific Ethics Declaration

The author declares that he is solely responsible for the scientific, ethical, and legal aspects of the paper published in EPSTEM.

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Author Information

Seemant Tiwari
Southern Taiwan University of Science and Technology
Yung Kang District, Tainan City-71005, Taiwan
Contact E-mail: *da82b203@stust.edu.tw*

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