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Review TEE

Support Vector Machine Inspired Load Forecasting of a State University in Haryana

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Abstract

Estimating the possible environmental impact and determining probable capital requirements are made easier with a solid grasp of electricity demand. Beginning in the middle of the 20th century, demand forecasting for electric power networks was studied theoretically. Prior to that, the study of demand forecasting had not developed because of the small scale of power networks. With the use of statistical prediction techniques, plans for the electric power industry have been created. For fuel management, maintenance scheduling, and budget planning, electric utility companies require monthly peak and annual load forecasts. The approach based on regression models, neural networks, and support vector machines for load forecasting—that is, the maximum and minimum load of the Maharshi Dayanand University (MDU) substation in Rohtak, Haryana—is compared in this paper. Many contributing elements have been investigated and tried. The system created to forecast the greatest and minimum electric demand and consumption in the MDU is presented in the study. Comparing the selected system to other methods in the study, it was found that the support vector machine (SVM)-based model forecasted the load most accurately. The study conducted at the MDU in Rohtak, Haryana, focuses on forecasting the maximum and minimum electrical loads at the university's substation. It compares three machine learning techniques: regression models, artificial neural networks (ANNs), and SVMs. The findings indicate that the SVM-based model outperforms the others in predicting both peak and minimum loads. SVMs are particularly effective in handling nonlinear, high-dimensional datasets, which are common in electrical load forecasting. They are less prone to overfitting compared to neural networks, especially when dealing with limited or noisy data. SVMs also offer robust generalization capabilities, making them suitable for scenarios where accurate predictions are crucial for operational planning and energy management. In contrast, regression models, while straightforward and interpretable, often struggle with capturing complex, nonlinear relationships inherent in load data. ANNs can model nonlinear patterns but require extensive data and careful tuning to avoid overfitting, and they may demand significant computational resources. SVMs balance complexity and performance, offering accurate predictions without the extensive data requirements of ANNs. Accurate load forecasting is vital for the MDU's substation to ensure efficient energy distribution, maintenance scheduling, and budget planning. Implementing an SVM-based forecasting model can lead to better resource allocation and operational efficiency, ultimately supporting the university's energy management objectives.

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INTRODUCTION

Modern system theory and optimization approaches are used to develop and operate large-scale systems as efficiently as possible, with the goal of saving a significant amount of money. Long- and short-term load forecasts are crucial because understanding the future power system loads is the first requirement for accomplishing this goal.

Effective scheduling of spinning reserve allocation is made possible for the system operator by load forecasting, with lead times ranging from a few minutes to several days. The capacity to generate, transmit, or distribute system additions, as well as the kind of facilities needed for transmission expansion planning, annual hydro-thermal maintenance schedule, etc., are all determined using long- and medium-term projections. The energy sector has remained the backbone of the economies, and global growth is expected to show twice the demand within the next 2–3 decades [1]. Proper planning, control, and capacity are what the energy sector must properly handle prior to predictions that need to be done accurately to avoid problems; a huge amount can be lost if an error is incurred during forecasting [2–5]. Box–Jenkins ARIMA is a weather-insensitive approach that uses a set of old load data to determine future load demand [6–9]. Load forecasting uses a set of different models and techniques that have various advantages and disadvantages; therefore, a proper choice must be made to achieve better accuracy.

Importance of Load Forecasting

With emerging economies, growing living standards, and an increased population, it is projected that power demand will increase by 85% by 2040 [1]. Load forecasting plays a vital role in planning, allocating, and fulfilling load demand in the most economical manner. Short-term forecasting (hours to days) helps predict the hourly variation in power consumption at various time zones, such as peak hours, solar hours, and normal hours. Medium-term forecasting (day to month) helps predict scheduling and operation variables with time, while long-term forecasting (months to years) helps plan future utilities. The goal is to achieve high accuracy in prediction, as it was found that a 1% error in forecasting can cost you 10 million pounds per year [2]. Power generation needs to be done on a demand basis as power storage batteries and devices find a deficiency at higher ratings, and it becomes crucial to know how the load may vary, which will assert power demand from the generating units. Thus, from a sustainability perspective, a method with some technical nomenclature is required, known as load forecasting [11]. Based on time schedules, there are three types of load forecasting: short-term, medium-term, and long-term.

Short-term load forecasting shares an observational and research span varying from one day to several weeks, which can be used for the analysis of transmission constraints, security, economic load dispatch, and operating schedules of generating units. Medium-term load forecasting shares an observational and research span varying from one week to several months and can provide data essential for maintenance, fuel supply, financial graphs, and tariff impacts. Long-term load forecasting shares an observational and research period from one year to several years, and data collected from this plan is important for understanding the expanding and technological needs of generating units, transmission, and distribution networks. Therefore, the evaluation of the generating capability and demand requirement is necessary for the best-synchronized operation of the power system, and with forecasting of future demand, perfect planning can be made to accomplish future demand goals [10].

Forecasting data are altered by various factors, such as load, previous load, geographical and physical conditions, number of customers and their types, economics, and devices [12]. Smart grids challenge the design of techniques against demand response and boost productivity when peak hours hit without increasing capacity [13]. Operating decisions are made by these networks according to consumption [14].

General techniques for load forecasting (LF) include regression models, time series, neural networks, expert systems, fuzzy logic, end-use models, and econometric models [1]. The goal of this study is to introduce an improved LF technique that uses an intelligent support vector machine (SVM) based model. Forecasting the demand for electricity is generally more complex in rapidly expanding economies, where structural changes may have a major effect on that demand. Variations in growth patterns, socioeconomic circumstances, frequency of special events, and subsidized energy tariffs are the reasons for this.

However, it is possible to ascertain the accuracy, suitability, and credibility of the established classical forecasting techniques while searching for more improvements by considering the nature of growth, socioeconomic conditions, the occurrence of special events, and subsidized energy tariffs. Factors affecting economic activities and consumption patterns have a significant impact on electricity consumption. The following factors have been identified for their significant contribution to long-term electricity demand [2].

FACTORS AFFECTING LOAD FORECASTING

While addressing the issues of efficiency, optimal operation, planning, dependability, and growth demands, the electrical power sector identified accurate load forecasting as a key responsibility [15–18].

To improve the accuracy of load forecasting, researchers must focus on the sensitive characteristics of load demand [19] and conduct systematic reviews using reliable sources that include many approaches and models that are practically right [20–24]. Root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error are assessment metrics used in load forecasting [25, 26]. To maximize the accuracy of forecasting methods, further attention must be paid to methods, time intervals, and input parameters, which still constitute a significant portion of the research activity [27].

Various factors affect the demand for electrical power, such as environmental, seasonal, economic, and random events. This must include factors in our observations to avoid upscaling or downscaling errors in the forecasting process. These factors, along with the previous and present data, when compiled together with the help of various forecasting techniques and software programs, give birth to a more precise format of load forecasting. Some of the factors affecting load forecasting are as follows:

- Temperature
- Humidity
- Precipitation
- Light intensity
- Wind speed
- Pressure
- Historical information (monthly trends/seasonal differences)
- Price variables
- Random disturbances

A reliable load forecasting methodology must "correctly" gauge the effects of key factors on electricity demand. In this study, an SVM-based model is proposed to determine the maximum and minimum loads of a day at a state university. This model was validated by comparing it with a regression model and a neural network based model for calculating the maximum and minimum loads of the day.

PROPOSED MODEL

One of the most important factors for electric power firms is electric load, which dictates their primary revenue stream, especially for distributors. The topic of forecasting the highest and minimum electric demands of the Maharshi Dayanand University (MDU), a state university, is addressed in this study. Several nonlinear models have been examined and applied to a real-world scenario using data from an MDU substation to address this forecasting issue.

Subsequently, a few steps were finalized to forecast the load of a particular area. The following important factors have been considered for the forecasting of the maximum minimum load of the MDU:

- Population (POP),
- Number of households (HH),
- Gross domestic product (GDP),
- Index of industrial production (IIP),

- Consumer price index (CPI) and
- Electric power consumption of the previous day (CON).

Data regarding these factors were collected for the last 30 days from a substation in the MDU. In addition, some data are available on some websites, such as the economic database of India.

Error is calculated as:

Error = Output by model – Actual Output

$$\% \text{ error} = \frac{\text{Error}}{\text{Actual output}} \times 100$$

Mean absolute percentage error (MAPE) has been calculated as:

$$\text{MAPE} = \frac{\sum|\%\text{error}|}{\text{No.of years}}$$

REGRESSION MODEL

Finding an equation that depicts the relationship between the variables was performed using this method. Regression can be applied to inference, hypothesis testing, modeling of causal relationships, and prediction (including time series data forecasting). Fulfilling these underlying assumptions is crucial for these regression applications. The fact that it requires far more expertise to analyze a model than to fit one is one reason why regression is misused. Neural networks are typically linked to nonlinear data, whereas statistical methods are linked to linear data. For many years, statistical techniques have been effectively applied to time series forecasting. The steps of the model are represented by the flowchart in Figure 1.

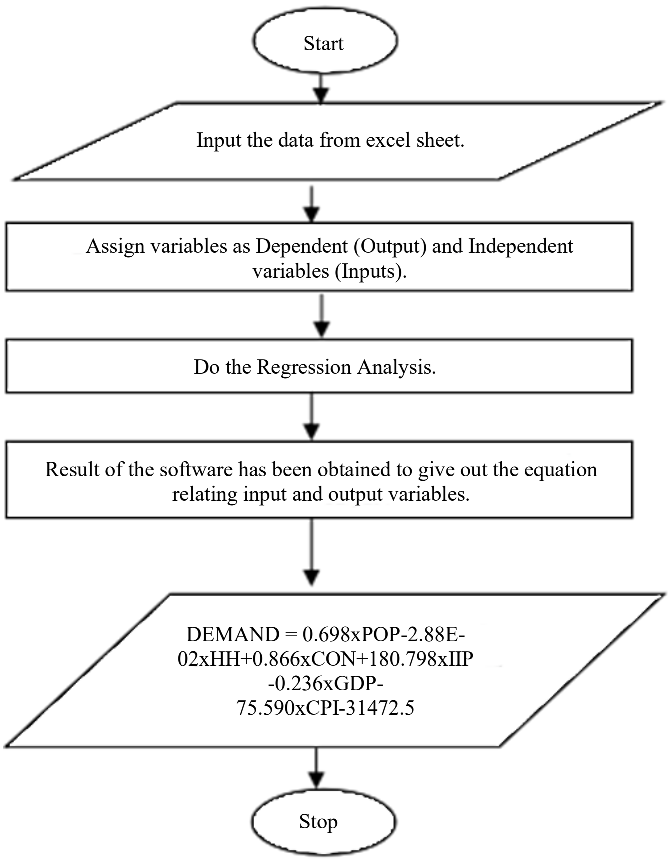

Figure 1. A flowchart represents the general steps for a regression model.

Using these coefficients for each of the input variables, an empirical formula was formulated by the researcher as

DEMAND = 0.698xPOP – 2.88E-02xHH + 0.866xCON + 180.798xIIP + 0.236xGDP – 75.590xCPI – 31472.5

Error is calculated as:

Error = Output by model – Actual Output

$$\% \text{ Error} = \frac{\text{Error}}{\text{Actual output}} \times 100$$

Mean absolute percentage error (MAPE) has been calculated as:

$$\text{MAPE} = \frac{\sum|\%\text{error}|}{\text{No.of years}}$$

It has been found that the MAPE and maximum absolute percentage error (Max. APE) obtained by the regression model using SPSS software are 6.63% and 12.2%, respectively, and from this, it has been concluded that the error obtained is high in the statistical methods of modeling.

NEURAL NETWORK BASED MODEL

In essence, neural networks are nonlinear circuits with a proven ability to fit nonlinear curves. A network's output is a mathematical function of its inputs, which can be either linear or nonlinear. In addition to the actual network inputs, the inputs can be the outputs of other network components. Backpropagation neural networks employ supervised learning and continuous-valued functions. In other words, supervised learning matches historical data (such as time and weather) to intended outputs (such as past electric loads) in a pre-operational "training session" to determine the actual numerical weights assigned to constituent inputs. A flowchart representing the steps of the Neural Network (NN) model is shown in Figure 2. It has been found that the MAPE and Maximum Absolute Percentage Error (Max APE) occurred by Neural Network Model using MATLAB (MATrix LABoratory) software are 4.63% and 10.02%, respectively.

SUPPORT VECTOR MACHINES BASED MODEL

A support vector machine was proposed by Vapnik [28], which aims to simplify the problem of classification of data, which is further upgraded to tackle nonlinear regression. This method is called Support Vector Regression (SVR) and is one of the most common forms of SVM. The goal of SVR is to produce a model that can predict the output for a set of inputs. SVM uses the Storage Resource Management (SRM) process to minimize the structural risk, which shows higher efficiency than the neural network that uses the Electronic Records Management (ERM) process to minimize the empirical risk. On the one hand, ERM minimizes errors during the training, while SRM works on the upper bound of the probable risks to be minimized.

The SVM is a machine learning tool capable of dealing with classification and regression problems. SVM aims to create a decision line called a hyperplane that can categorize the number of dimensions into classes, such that in the future, new data can be placed in the correct category. SVM. To create a hyperplane, extreme points/cases called support vectors are used, and hence, the process is termed as a support vector machine.

A potent supervised learning method, called a support vector machine, is frequently used in load forecasting, and the process of projecting future energy uses a database that is available, as shown in Figure 3. Finding a hyperplane in a multidimensional space that best separates various classes (such as energy demand levels) or, in the case of regression, fits the database, which is the main objective of SVMs in load forecasting. By using this model, the output demand for all years was calculated, and the % error was determined. Demand for all years was calculated by putting six inputs for all years, one by one, into the SVM-based model. It has been found that the MAPE and Maximum Absolute Percentage Error (Max APE) occurred by the adaptive neuro-fuzzy inference system (ANFIS) Model using MATLAB software are 2.9% and 7.62% respectively.

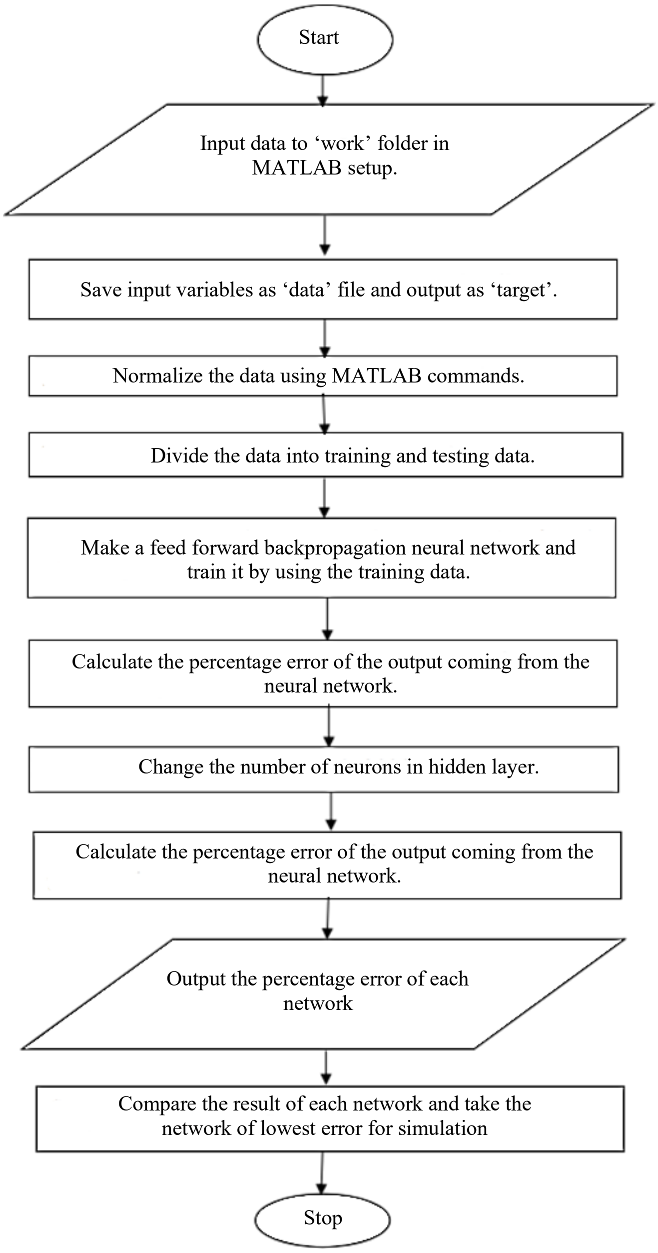

Figure 2. Flowchart of the NN model.

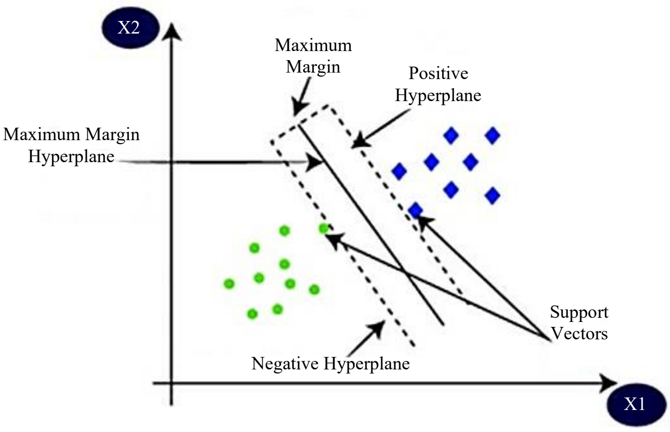

Figure 3. SVM's decision plan.

Table 1. Comparison between the % errors of all three models.

Type of model	MAPE (%)	Max. APE (%)
Regression	6.63	12.2
Neural network	4.63	10.02
SVM	2.9	7.62

SIMULATION RESULTS AND ANALYSIS

In this research, three models were proposed for the maximum minimum daily load of MDU: Rohtak. The first method was based on a regression method. The second method is based on a neural network. The third method was based on the SVM model. Real data from a substation at the MDU were used to illustrate the performance of the proposed model. The regression model is linear; thus, the results are not accurate in the forecast. Table 1 has been made by using all the above three models and all the results obtained. Hence, it can be concluded that the SVM-based model is better than both the models used earlier.

CONCLUSIONS

Because of their versatility in managing nonlinear systems, their capacity to learn from past data, and their capacity to generalize solutions based on input data, the results demonstrated that NN and SVM performed better in LF than the regression model. This thesis presents a novel research project that creates a neuro-fuzzy hybrid model to enhance long-term load forecasting. Additionally, based on the data, we conclude that the SVM outperforms the NN. According to the findings, the suggested model was more effective at predicting future loads with a lower percentage error for the following year. Utilizing the benefits of modern techniques to handle and formalize forecasters' experience and knowledge is an advantage of the suggested framework. It is evident from the results of these studies that the suggested composite model can be employed as a compelling and successful tool for load forecasting. The forecast demands are satisfied by increasing the prediction accuracy and adjusting to changing client needs.

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