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# Implementation of Smart Grid across the Country as Load Forecasting Helps to Provide Reliable And Quality Power Supply

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## ABSTRACT

*For any power company to decrease losses and boost efficiency, accurate load forecasting of energy demand is critical. Load Forecasting aids in the provision of a stable and high-quality power supply to consumers, which is critical for the deployment of Smart Grid across the country. In this study, we will analyse some of the available approaches for load forecasting and compare the performance of each method using the RMSE value as a performance metric. The approach with the lowest RMSE score has a higher level of accuracy and is more trustworthy. In our analysis, we also took into account the holidays and the temperature of the area, as these factors have a significant impact on the load consumption patterns of customers.*

**Key Words: -**Data Mining, Load Forecasting, Regression, Smart Grid, RMSE

## I. INTRODUCTION

The Smart Grid [1] is a computerised electrical grid that connects utilities and customers using cutting-edge technology to provide a dependable, sufficient, and high-quality power supply. The Smart Grid also includes the integration of renewable energy sources to satisfy the demand of diverse regions by supporting micro-grids that serve as mini-power plants. Figure 1 depicts some of the Smart Grid's characteristics. Descriptions of each category's load forecasting. There are nine different types of load forecasting techniques. In the following parts, one section is devoted to each category, with a brief description of the approach and a literature evaluation that includes a representative selection of the most important articles in the field. Multiple regression, exponential smoothing, iterative reweighted least-squares, adaptive load forecasting, stochastic time series, and ARMAX models based on genetic algorithms are the nine kinds of load forecasting approaches to be examined, in approximately chronological order. Irrational logic; Load forecasting[2]is a significant and critical activity in power utility planning and operations. For generation and distribution of energy without losses, power utilities must comprehend many elements such as client kinds, geographic location, and other considerations. It is commonly known that electricity cannot be stored in large quantities and that it must be utilised as soon as it is created. As a result, reliable demand forecasting is required for the effective operation of electricity utilities. Load forecasting is divided into three categories: short-term, medium-term, and long-term forecasting. Short and medium term forecasting are for periods of one day to one week, and long term forecasting is generally for periods of more than a year. Many scholars have looked at the issue of electric load forecasting, but none have been able to agree on a single accurate forecasting system that can be utilised in all parts of the world. This is due to the fact that consumer consumption, as well as temperature and other elements that impact forecasts, differ from one place to the next.

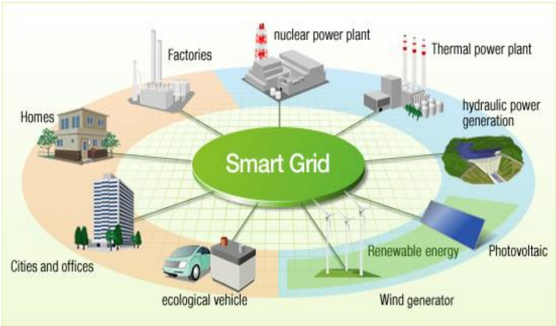


**Figure 1 Shows an Overview of Smart Grid Architecture**

## II. LITERATURE REVIEW

There are several approaches for forecasting electric load, however for the sake of this study, we will investigate the following machine learning methods: - a. Regression (number 3): A statistical procedure in which one value is claimed to be reliant on another is known as regression. The dependant variable is commonly referred to as the dependant value, whereas the independent variable is referred to as the other variable. This model creates an equation that may be used to forecast future values as and when needed. The dependent and independent variables are clearly separated in the equation.

Y = a + bX -------------------------------- (1)

We can see from Eq. (1) that 'Y' is the dependent variable and 'X' is the independent variable, with the constants 'a' and 'b' defining the intercept value (the value of y when the value of x is zero) and the slope, respectively.

**b. Exponential smoothing [4]:** One of the most often utilised approaches for load forecasting is exponential smoothing. This was the initial approach: develop a model based on historical data, then use the model to anticipate load. This is also one of the analysis-related prediction models. The formula can be represented as an equation (2)

$Y$n = $Y$n−1+ (Xn−1 − $Y$n−1 ---------------------- (2)

Where $Y$ n is the forecasted value, $Y$n−1 is previous forecast, $\alpha is$ known as the smoothing constant (α≥0 but α≤1),X$t$−1 is value of actual demand of the preceding period.

**c. Simple Moving Average (SMA)[5]:** The SMA is the most basic of the moving averages methods. The average value of a characteristic over a specified number of periods is computed using a simple moving average (SMA). A 5-day simple moving average is calculated by dividing the five-day total of closing prices by five. A moving average is a calculation that is done on the fly. Old data is discarded as new data becomes ready and available for analysis. The formula can be represented as an equation (3)

M (t) = A (t) +A (t-1) +A (t-2)….A (t-N+1) / N ------ (3)

Here M is the Moving Average value and A (t) up to A (t-N+1) gives the values of the previous time period values.

**d. Decomposition Method [6]:** Decomposition technique is a broad phrase that refers to a variety of approaches to solving issues. The goal here is to break down the problem into several subproblems and tackle each one separately. It's a good way to get an analytical solution for a number of systems that don't have linear behaviour. The formula can be represented as an equation (4)

$$Xa = U\mathit{T}a\mathit{S}a\mathit{C}aQa \qquad \text{------------------------------------} \qquad (4)$$

Here in the above equation (4) the value of Q denotes the random error.

## III. METHODOLOGY

For each of the approaches and performance measures, the historical dataset from 2006 to 2009 is analysed using the Machine Learning Tool Weka 3.6.11[9] programme, and the results are recorded to be recognised using the software. The root mean square error (RMSE) number is used as a benchmark for measuring the performance of a machine learning tool-built model. We do 10-fold cross validation for the analysis to ensure efficient and reliable results. The data is first created in excel sheet format, then converted to CSV format, and finally input into the Weka software's explorer tab for analysis. The value of RMSE is taken into consideration while evaluating the performance for a specific dataset. The Root Mean Square Error (RMSE) (also known as the root mean square deviation, RMSD) is a commonly used measure of the difference between values predicted by a model and actual values observed in the simulated environment. Individual differences are referred to as residuals, and the RMSE is used to combine them into a single predictive power score.

## IV. ANALYSIS AND COMPARISON

The entire dataset was first converted to CSV format and then loaded into the machine learning programme Weka. Following this, we used the choose feature to select the variables that will be used in the analysis. This generates a graphical output that displays each variable together with its data, such as the number of different values. This leads us to pick a technique for comparison, which we do by selecting and applying a method with 10% cross-validation. Following the study, we summarised the results by mapping the RMSE values to the data mining approach used to generate them. This is plotted against each other to compare the results of each approach graphically. This is one of the metrics used in load forecasting performance study to compare the accuracy of the considered model with MAPE (Mean Absolute Percentage Error) The Square Root of Mean Square Error (RMSE) formula is provided below.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{1,i} - X_{2,i})^2}{n}} \qquad \text{-----------} \qquad (5)$$

The lower the Root Mean Square Error, the better the performance of the dataset. The performance of each approach is shown in the table below, with the method with the lowest RMSE values having the most accuracy compared to the other ways.

We have taken different number of instance values for analysis.

The same was then displayed using the graphical tool as a line graph. The RMSE values are on the X-axis, while the number of instance values in the historical dataset utilised for the study is on the Y-axis. As the number of instances values grows, we can notice a steady shift in the RMSE values as well, demonstrating that multi-layer perception has a lower RMSE value, indicating superior performance than the other methods utilised in the investigation. The mean square error value is derived using the method in equation (5) and is thus a superior performance indicator for appraising the outcomes. The load on the system is the most important factor in forecasting, and it may also be used to anticipate energy prices. This may also be utilised to help a power provider better analyse and avoid losses, as well as improve operational efficiency.

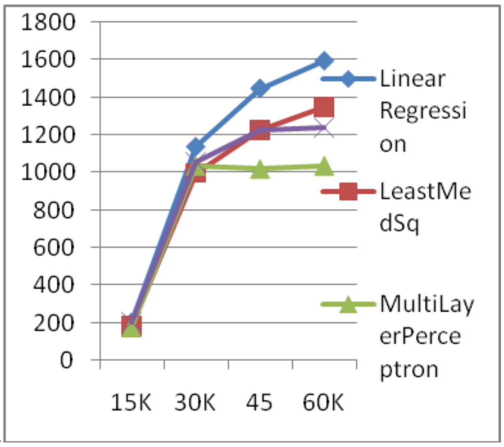


**Figure 2 Shows the Graphical Analysis of Performance Comparison**

## V. CONCLUSION

The performance of each approach was analysed and tabulated, along with the RMSE values acquired for each, and it can be shown that Multi-Layer Perception, which is a sort of Artificial Neural Network, outperforms the other ways. Since a result, we can infer that this technique is most suited for doing load forecasting in a smart grid context, as it is also scalable in light of the massive data input from smart metres. This strategy may be used to large geographical areas since it works for any number of instances that have metre reading data.

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