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Short-Term Load Forecasting Using Conventional and AI Techniques

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Abstract: Short-term load forecasting (STLF) ensures efficient energy management, economic dispatch, and grid stability in modern power systems. However, their performance is often constrained by assumptions of linearity and stationarity in the data. In contrast, Artificial Neural Networks (ANN) offer a data-driven, non-linear approach that captures complex relationships in time series data, thereby demonstrating significant potential in enhancing forecasting accuracy. This paper comprehensively compares conventional statistical methods (AR, ARMA, ARIMA) with Artificial Neural Networks for STLF. The analysis explores their performance under various forecasting horizons, data resolutions, and real-world scenarios, emphasizing their adaptability to changing load patterns. The research highlights that while ARIMA performs well for linear and stationary data, its accuracy diminishes when dealing with highly non-linear, dynamic loads. On the other hand, ANNs, with their inherent capacity to model non-linearities, exhibit superior accuracy, particularly when integrated with data pre-processing techniques and optimized training algorithms. The study assesses the effectiveness of different approaches using datasets of actual electrical loads. Findings show the accuracy, resilience, and scalability benefits of AI-based methods, opening the door for their incorporation into contemporary energy systems. The limits of conventional forecasting techniques for trustworthy energy management are addressed by artificial intelligence, as this comparative study highlights.

Keywords: *Short Term Load Forecasting (STLF); Autocorrelation Function (ACF); Partial Autocorrelation Function (PACF); Auto Regressive analysis (AR); Auto Regressive Moving Average analysis (ARMA); Auto Regressive Integrated Moving Average analysis (ARIMA); Artificial Intelligence (AI); Artificial Neural Network (ANN); Mean absolute percentage error (MAPE); Mean square error (MSE).*

1. INTRODUCTION

Short-term load forecasting (STLF) is a critical aspect of power system operation and planning. It describes the forecasting of electricity demand across brief time periods, from a few minutes to several days in advance. Utility firms may guarantee a dependable power supply by using accurate load forecasts. one of the parts as to address these limitations and application, Artificial Neural Networks (ANN) have emerged as a promising alternative. ANNs are computer models that can learn intricate, nonlinear relationships in data because they are modeled after the human brain. Because they can handle big datasets and model complex patterns in load behavior, they have demonstrated good performance in load forecasting tasks [1]. The technology lowers operating expenses and optimizes resource allocation. It is a crucial instrument for improving power systems' economic efficiency and lowering the possibility of overloading or underusing the resources used for power generation. (Kusum, 2017) [2],

The best ARIMA model to utilize for predicting a given time series can be determined using a methodical set of guidelines. Every form of regression model, including those that employ lags and differences, random walks, exponential smoothing, and others, has its own set of guidelines and statistical processes. All of these models are variations of the more generic ARIMA class of time series models. Understanding this implies that, in theory, the only model-type option you should utilize in the Stat Graphics forecasting process is ARIMA. [3], Applying prediction using ANN and ARIMA techniques is the second step. Both models, ARIMA and ANN, were used to examine the outcomes at the end, and the error factors (MSE and MAPE%) were used to compare the models. [4], Autoregressive In time series, ARIMA is the most popular technique in the series family because linear patterns are the most adaptable of all-time series methods [5,6]. Furthermore, the ARIMA model has the advantages of being a studied technology and using a simpler methodology when compared to artificial neural networks, the second generation of forecasting systems. Accurate electrical load forecasting is essential for power production, transmission, and distribution networks' planning and operational strategies. Power utilities rely on precise load forecasting for a number of economic components, including financial scheduling of generating capacity, fuel purchase scheduling, security analysis, power development planning, maintenance scheduling, and generating unit dispatching. It comprises the accurate forecasting of electric

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load locations and magnitudes over the different planning horizon periods.[7],

One of the key challenges in creating reliable forecasters is the limited ability of ANN-based forecasters to extrapolate modeled correlations outside of the training data set. It's likely that some input values from this domain will produce estimates that are wildly off. The severity of this issue is greatly influenced by the neural network's design. Networks with an excessive number of input variables or hidden neurons that provide a good accuracy under normal conditions are more likely to display this behavior than parsimoniously constructed networks. This problem can be lessened by predicting relative load increments rather than actual loads because daily patterns of relative load increments are more reliable than daily load curves.In other words, two days with different temperatures will have different load levels, but their relative load increase curves will remain quite similar. This suggests that the forecast accuracy won't significantly decrease even if the weather conditions weren't present in the training data.[9],

Because of their ease of use and capacity to capture the temporal dependence of the load data, ARIMA models are frequently employed in STLF applications. The autoregressive (AR), integrated (I), and moving average (MA) are the three building blocks of ARIMA models [11]. The dependence of the load on historical errors is modeled by the MA component, the trend of the load data is modeled by the I component, and the dependence of the load on historical values is modeled by the AR component. The order of the AR and MA components, the degree of differencing in the I component, and other characteristics of the three components can be altered to customize ARIMA models [12]. ARIMA models, however, make the assumption that the load data exhibits a consistent pattern, which isn't necessarily the case for applications involving power systems.

Additionally, it's possible that ARIMA models miss nonlinear interactions between the load and other influencing factors like occupancy and weather. The ARIMA model algorithm's formula is ARIMA(p,d,q), The AR model's order is denoted by p, the differencing model's by d, and the MA model's by q. Statistics such as maximum likelihood estimation can be used to assess these characteristics and are selected based on the attributes of the time series under examination. Once the parameters have been evaluated, the ARIMA model can be used to forecast future values of the time series. The model forecasts the next value in the series by analyzing prior data based on its AR and MA components. This procedure is carried out recursively to produce a forecast for a predetermined number of time steps into the future, updating the error term and producing a fresh prediction for the subsequent time step using this anticipated value [10].

Assume for the time being that we consider only one meaningful value from each of the models of AR and MA. Additionally, we had to perform a differencing operation once to make the graph stationary after it was initially non-stationaryAs a result, ARIMA (1,1,1) can be used to represent the ARIMA model that will be produced by adding the values of the other two models and the Integral operator.In [3][13], as The costs of large, interconnected forecasting errors may not always exhibit the same behavior as the MSE and RMSE. The costs associated with anticipating errors rise linearly with the size of the errors, according to MAE. It is commonly used to circumvent the problem where forecasting errors are overestimated by MSE and RMSE compared to expected real expenses. The true costs may rise even faster than the square of the error anticipated in MSE and RMSE, and this assumption is often wrong.

The current study examines the connection between consumers' savings from energy storage and the precision of load forecasts. Eleven distinct load projections, each with varying accuracy, are used to create the simulations for every customer. The actual load prediction time series is referred to as the basic level (100%), while the forecast error time series is scaled to change the forecasting accuracy. The real load data matches the ideal forecast (0%). With a 20% step size every hour, the linear range of error scaling under investigation is selected to be between 0% and 200%. The annual cost savings for clients as well as the different forecast accuracy criteria (MSE, RMSE, NRMSE, MAE, and MAPE) have been computed using the simulations. The MAE of monthly peak powers (MAEmax) was also computed because reducing monthly peak powers accounts for the majority of the savings; the findings are shown as percentages of cost savings because the monetary value of the savings is dependent on the load profile of the customer. [14] All power system options benefit considerably from these computations and error identification; all of the main issues are described here.

2. METHODOLOGY

2.1 Load Forecasting:

Since electrical energy cannot be stored, it must always be generated when needed, Electric power companies must therefore forecast the load on their systems beforehand. We refer to this pre-calculated load estimation as load forecasting, and it is an essential procedure in the planning and operation of electric power systems. The practice of predicting a future occurrence, outcome, or trend using statistical and historical data is known as load forecasting.

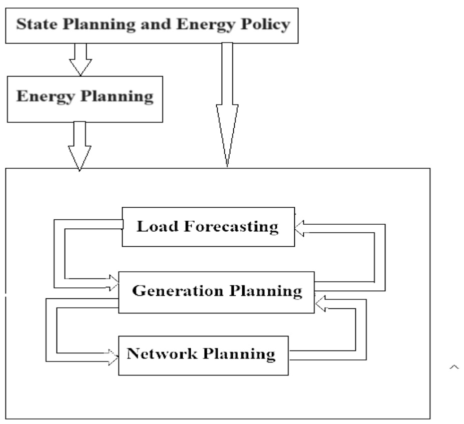


Fig.1. Load Forecasting Flow chart

2.2 Different Types of Load Forecasting:

Load forecasting is generally classified into three categories. These are

1. Short Term Load Forecasting (STLF)

2. Intermediate-Term Loads Forecasting

3. Long-range Load Prediction

4. Analogous Day Loads Forecasting

2.2.1. Short Term Load Forecasting:

The time frame for this forecasting technique is typically one hour to one week. It can help us make decisions that prevent overloading and provide guidance when calculating load flow. The data required for day-to-day operations and unit commitment system management is provided by short-term forecasting.[10],

2.2.2.Medium Term Load Forecasting:

The time frame for this forecasting technique is one week to a year. In order to balance generation and demand, medium-term forecasting is utilized for unit management and fuel supply scheduling, which includes arranging maintenance, coordinating load dispatch, and settling prices.

2.2.3. Long Term Load Forecasting:

Electric utility firm management receives accurate forecasts of future employment, equipment procurement, and growth demands using this forecasting technique, which has a time period of more than a year [15].

2.2.4. Anomalous Day Load Forecasting:

"Anomalous day load forecasting" is the process of predicting patterns in energy consumption for days that substantially differ from typical or anticipated behavior. Extreme weather, holidays, unique events, or unforeseen shifts in consumer behavior are a few possible causes of these anomalies [16].

2.3 Short Term Load Forecasting

Short-term load forecasting is essential to power system management and planning because it offers critical information for optimal decision-making processes. Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Moving Average (ARMA), and Auto Regressive (AR) models are examples of statistical and mathematical models that have historically been used to address STLF. However, there has been a paradigm change towards more data-driven and adaptive forecasting methodologies with the introduction of Artificial Intelligence (AI) tools, especially machine learning and neural network-based systems.[17]

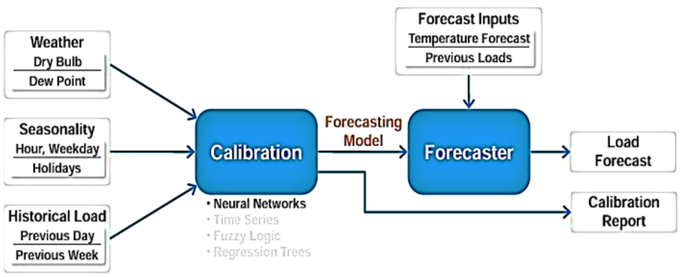


Fig.2. Load Forecasting Model

2.3.1 Basics of Forecasting

• Forecasting is a Stochastic task: Forecasting is a stochastic task by nature, not deterministic. There is no such thing as "certain" in prediction. The outcomes of a forecasting process should be in a probabilistic structure, such as a forecast under this or that scenario, a probability density function, a prediction interval, or some quantile of relevance, because forecasters deal with unpredictability. Point forecasts, such as the future expected value of a random variable, continue to be the most popular forecasting output form because many practical decision-making systems are unable to handle probabilistic inputs.

• Not Every Forecast Is Correct: Because predicting is stochastic, the response variable is never completely predictable. Other reasons that could cause us to make inaccurate forecasts include poor software, improper techniques, and bad data. Applying best practices is the forecaster's responsibility in order to steer clear of these avoidable problems.

• Forecasts can be improved: From an accuracy perspective, at least, there is always room for improvement because not all forecasts are accurate. Improving the utility is the aim of forecast improvement.

• Error spread: Nobody wants to make unexpectedly large mistakes. Forecasts become more useful when the uncertainty is decreased, which is achieved by decreasing the variance or range of the mistakes. Sometimes the corporation may even give up some of the central tendency of the error (like MAPE) to minimize the spread (like the standard deviation of APE).

2.4 Problem Statement

This study focuses on STLF using hourly load data over two months, and advanced AI techniques, specifically Artificial Neural Networks (ANNs), will be used in combination with traditional methods such as Auto Regressive (AR), Auto Regressive Moving Average (ARMA), and Auto Regressive Integrated Moving Average (ARIMA) models, with and without temperature inputs. The primary objective of this study is to thoroughly evaluate and compare the effectiveness of these conventional and AI-based methods in STLF. This evaluation will encompass various metrics including accuracy, robustness, and computational efficiency. By rigorously assessing the strengths and weaknesses of each method, this study seeks to compare the performance of conventional and AI-based techniques in STLF, with the aim of identifying the most effective strategies for power system operators and planners.

2.4.1 Objectives

1. To evaluate the precision and reliability of conventional methods (auto regression, auto regression moving average, and auto regression integrated moving average) in short-term load forecasting (STLF), historical load data must be analyzed.
2. To assess the extent to which artificial intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs), enhance STLF accuracy and reliability when compared to conventional methods.
3. To use both traditional and AI-based methods to examine how weather and other external factors affect the demand for power and how to incorporate them into forecasting models.
4. To identify the strengths and limitations of conventional and AI-based techniques in STLF, including considerations such as data preprocessing requirements, model complexity, interpretability, and computational efficiency.
5. To explore methods for integrating AI techniques into existing STLF frameworks and assessing their compatibility with operational requirements and constraints in power system planning and operation.
6. To provide recommendations and guidelines for power system

operators and planners regarding the selection and implementation of STLF techniques based on the comparative analysis of conventional and AI-based approaches.

2.5. Time Series Analysis

In Short-Term Load Forecasting (STLF), time series analysis is used to forecast future power demand by examining historical load data that is gathered at regular intervals. In order to help identify the underlying dynamics, patterns, and trends in time series data, it encompasses a variety of models and statistical techniques. The concept of stationarity is fundamental to time series analysis in STLF and is necessary for both forecast accuracy and model development.

2.5.1 Stationarity:

The term "stationarity" describes a time series' statistical qualities that stay constant across time. A stationary time series has the following traits:

1. Constant average: The time series' average value doesn't change over time.
2. Constant variance: Over time, the data points' variability or dispersion around the mean stays constant.
3. Autocovariance that is constant: Autocovariance, or the relationship between observations at various times, doesn't change throughout time.

Stationarity is important in time series analysis since many statistical models, such as AR and MA models, rely on it to generate accurate forecasts. Data non-stationarity may lead to inaccurate estimations and conclusions.

2.5.2. Non-Stationarity:

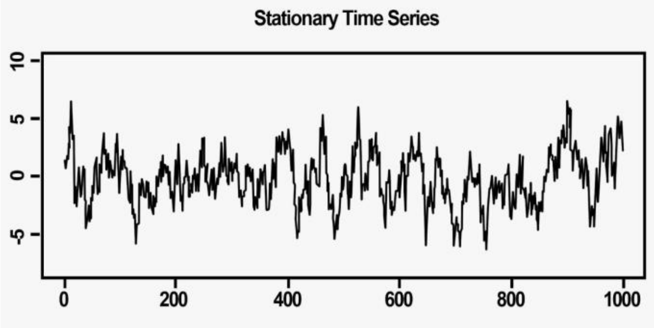
Non-stationarity occurs when one or more of the characteristics of stationarity are violated within a time series. Common causes of non-stationarity include trends, seasonality, and structural breaks:

1. Trend: An organized upward or downward shift in the data over time that points to a long-term shift in the underlying mechanism
2. Seasonality: Consistent, dependable patterns that recur at predetermined times, including daily, weekly, or monthly cycles.
3. Structural breaks: Unexpected adjustments or modifications to the procedure that generates the data, frequently brought on by outside influences or interventions.

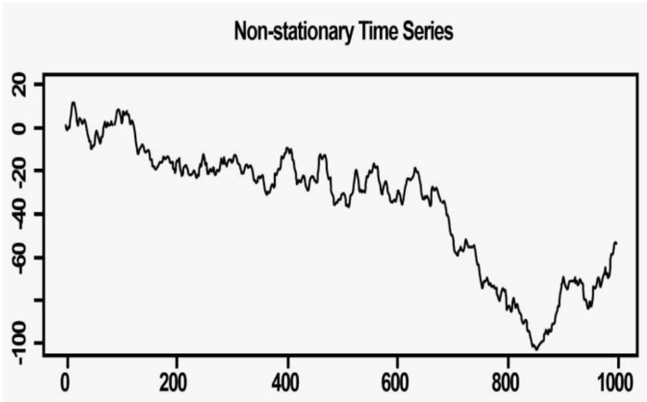
Non-stationarity can be an issue in time series analysis and forecasting since traditional models may not accurately capture the underlying dynamics of the data. In these cases, the data may be transformed into a stationary form using techniques like seasonal adjustment, detrending, or differencing prior to modeling.[17]

Auto Correlation Function (ACF): The association between a time series and itself at various delays is graphically shown by the ACF plot. One metric for measuring how strongly two variables are related is the correlation coefficient.

Partial Auto Correlation Function (PACF): After removing the effects of earlier lags, the PACF plot graphically shows the correlation between a time series and itself at various lags. The order of an MA model can be determined using the PACF diagram.



3(a)



3(b)

Fig. 3(a): Time Series Stationary and 3(b) Non-Stationary

2.6. Method evaluation

2.6.1 Conventional Methods

2.6.1.1 Auto Regressive Model (AR)

An Auto Regressive (AR) model uses historical behavior data to predict future behavior. When the time series values exhibit a correlation with their preceding and succeeding values, this sort of analysis is employed. It forecasts future actions based solely on historical data. Using one or more historical values from the same series, linear regression is applied to the data from the present series.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t \ldots (1)$$

The auto regressive coefficients, where Yt is the value at time t, c is a constant, $\phi 1$, $\phi 2$,..., εt is the white noise error term, and Yt-1, Yt-2,..., Yt-p are the historical values.

The value that comes right before the current value is what AR (1) auto-regressive processes rely on. As an alternative, AR (2) computes the current value using the preceding two values. White noise, on the other hand, is processed by AR (0) and is independent of terms.

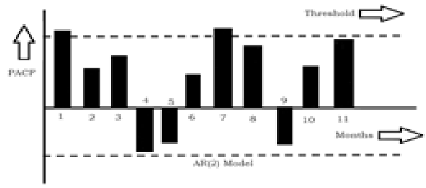


Fig. 4: Auto Regressive Model - AR(2)

Coefficients with these variances are calculated using the least squares approach. These forecasting ideas and methods are used by technical analysts to anticipate the price of securities.[19]

2.6.1.2 The ARMA, or auto-regressive moving average model

This model is the result of combining the AR and MA models. Using the residuals and the effect of previous lags, this model predicts the time series' future values.

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \ldots (2)$$

The moving average parameters are $\theta 1$, $\theta 2$,. θq, and the error term at time t is εt. the auto regressive parameters are $\phi 1$, $\phi 2$,...,ϕp, and yt is the time series value at time t.

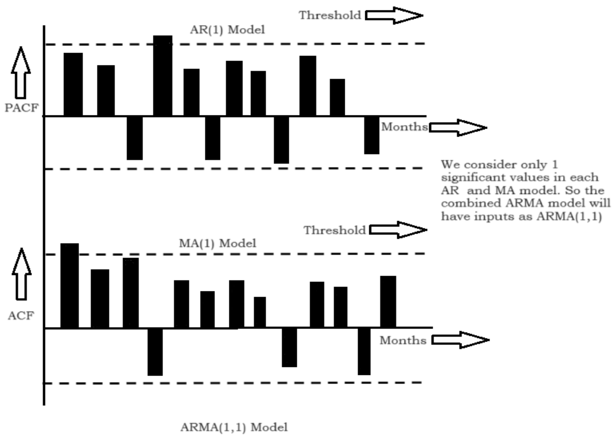


Fig. 5: ARMA (1,1) Auto Regressive Moving Average Model

The MA and AR values are shown in the graphs above along with the related significant values. For the purposes of this discussion, let us assume that each AR and MA model has a single meaningful value. From the total of the values of the other two models, the ARMA model—which is of the order of ARMA (1,1)—will be obtained. [20, 21]

2.6.1.3 ARIMA stands for Auto Regressive Integrated Moving Average.

The ARIMA model and the ARMA model are fairly similar, with the exception of the addition of a new element known as Integrated(I), or differencing, which in the ARIMA model stands for I. "Integrated" (I) series are those that require differentiation in order to become stationary. The delays of the stationarized series are known as "Auto Regressive" (AR) terms. Forecast error lags are represented by "moving average" (MA) terms.

Construction of an ARIMA model:

1. If required, standardize the series using deflating, logging, exponential smoothing, differencing, etc.
2. Analyze the autocorrelation and partial autocorrelation patterns to determine whether lags of the stationarized series and/or prediction errors should be included in the forecasting equation.
3. Determine whether all of the pattern has been described and whether all of the coefficients are significant by fitting the suggested model and looking at its residual diagnostics, particularly the residual ACF and PACF plots.
4. There are still patterns in the ACF and PACF that could point to the need for additional AR or MA keywords.

The ARIMA model can be represented as ARIMA(1,1,1) since it will be obtained from the sum of the values of the other two models and the Integral operator.[2][13][21] if we suppose that the graph was initially non-stationary and that we only take into account one significant value from the AR model and one from the MA model, and that we have to do a differencing operation once to make the graph a stationary set.

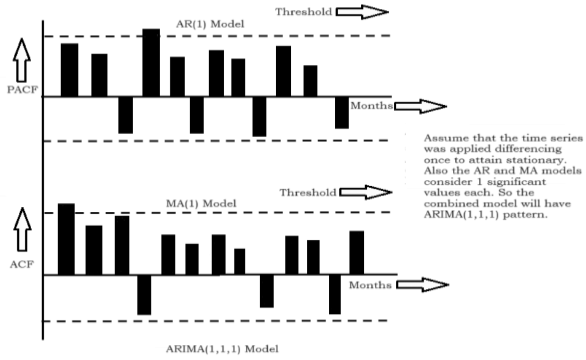


Fig. 6: ARIMA(1,1,1) is an auto-regressive integrated moving average.

2.6.2 Introduction to AI Techniques

The use of artificial intelligence (AI) techniques has revolutionized STLF in power networks, which provide sophisticated computational methods for evaluating historical load data and producing precise forecasts of future electricity demand. These artificial intelligence (AI) approaches increase the accuracy and reliability of forecasts by identifying complex patterns and relationships in the data using sophisticated algorithms and machine learning techniques. Artificial neural networks, also known as ANNs, are a common AI technique in STLF. Artificial Neural Networks (ANNs) are powerful models that can learn nonlinear correlations in data and produce predictions based on historical load data, weather, and other relevant variables. The structure and operations of the human brain serve as an inspiration for them. In general, AI techniques in STLF offer several advantages, including:

1. Enhanced accuracy and reliability of load forecasts.
2. The capacity to identify intricate and nonlinear patterns in the data.
3. Adaptability to diverse data distributions and forecasting scenarios.
4. Incorporation of expert knowledge and qualitative insights into the forecasting process.
5. Flexibility to handle high-dimensional and time-varying data.[13][22]

2.6.2.1 Artificial Neural Networks (ANNs)

Neural networks, also referred to as artificial neural networks (ANN), are non-linear networks for mathematical processing that are based on the architecture of the human brain. One input layer, one or more hidden layers, and one output layer make up their three layers. Because neural networks are very capable of self-learning, the conversion from input to output is not preprogrammed but rather learned. Every layer is made up of several neurons, and each neuron is coupled to neurons in neighboring layers of varying weights. After being received by the neural network's input layer, the signals go sequentially through each hidden layer before arriving at the output layer. Synaptic weights serve as the link between neurons in neural networks. These neurons can receive several inputs and produce a single output. The output from the input is determined by adding the bias and the weighted values.

$$Y = \sum_{i=1}^{n} W_i Z_i \ldots\ldots (3)$$

where b is the bias and w is the weight, z is the input, and y is the output.

This training is done through a series of iterations to fine-tune the synaptic weights, and these iterations continue until an acceptable inaccuracy or a predefined threshold is reached. The training process's goal is to reduce the error between the model's output and the target value. and the equation provides the error function.

$$E(W) = \frac{1}{2}\sum_{j}^{N} \|y(Z_i W) - t_i\|^2 \qquad (4)$$

Here, t stands for the intended value, y for the model's output, and E for the total error.

To minimize the discrepancy between the output and the actual value, the network then uses backpropagation to iteratively modify the connection weights [23].

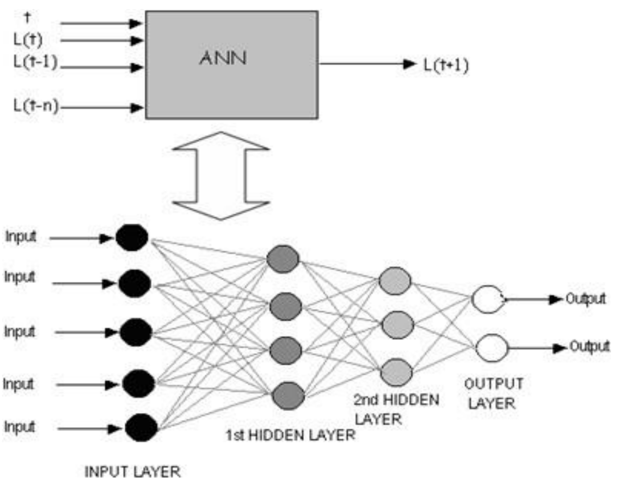


Fig.7*: Artificial Neural Networks*

This study offers an approach that combines time series and regression techniques. The method uses an ANN with multiple layers for perceptrons. The ANN tracks historical load trends to predict (i.e., extrapolate) a load pattern using recent load data, much like the time series approach does. Weather data is used to model the algorithm. The ANN is capable of handling tasks like adaptation and non-linear modeling. It is not necessary to presuppose that the load and weather factors have a functional relationship. By exposing the ANN to fresh data, we can adapt it.[24], The most often used ANN-based model for load forecasting is the static model, which is a forward neural network. The following equation can be used to explain this concept.

$$L_{t+k} = f(t, L_t, L_{t-1} \ldots L_{t-n},, W_t, W_{t-1} \ldots W_{t-r}, W_{t+k}) + \mathcal{E}_{t+k} \ldots (5)$$

Lt: load at time t; Wt: the weather factor vector as seen at time t; Weather forecast for time t+k is represented by ϴt+k. ´t+k: random load part. Here, t is the time of day, and k is the time lead of the prediction.

A neural network approximates the non-linear function "f." Because of the weather relationship's comparatively large time constant, variables that describe weather conditions can be disregarded for STLF, which has maximum lead times of 60 to 90 minutes. Consequently, It is possible to simplify the model as

$$L_{t+k} = f(t, L_t, L_{t-1} \ldots L_{t-n}) + \mathcal{E}_{t+k} \ldots (6)$$

The above model (4.4) is used by the trained neural network to compute load forecast L t+1 based on recent time and load data. In this instance, A feed-forward the data was forecasted 24 hours ahead of time using an ANN using a back propagation technique. Predicting load as a time-dependent conditional expectation and expected weather is the aim of STLF between hours and days. The most recent observed load measurement significantly affects only a few early projections. Here, utilizing recent load trends, the emphasis is on predicting relative changes in load. Consequently, a brief word can be expressed as

$$L_{t+k} = L_t(1 + \delta_{t+k}) \ldots (7)$$

In this instance, the anticipated relative load increase is δ t+1, that is defined as follows:

$$\delta_{t+1} = (L_{t+k} - L_t)/L_t \ldots (8)$$

A neural network forecasts δ t+1 based on the time and "n" recent relative load increases.

$$\delta_{t+1} = h\left(t, \delta_{t,} \delta_{t-1}, \ldots \delta_{t-n}\right) \ldots (9)$$

This technique has been applied to the power plant data in conjunction with the conventional ANN-based forecasts that were previously presented. When compared to the conventional ANN-based forecaster, our method enables us to make two significant advancements. It is more dependable and guarantees more precision. Certain input variable values from this domain are likely to result in highly inaccurate predictions. The phenomenon's sensitivity is highly depending on the architecture of neural networks. Such behavior is more likely to occur in networks with an excessive amount of hidden neurons or input variables that offer a high degree of accuracy under typical circumstances, Rather than proportionately increasing the burden, This can be replicated more easily than daily load curves. Stated otherwise, two relative increments will continue to be fairly equal. According to this, the training data reflects the forecast accuracy. Consequently, the second method increases precision and dependability. For network training, a layered perception type ANN is subjected to the Generalized Delta Rule (GDR). [4], [8], and [25],

ANN Advantages:

• High parallelism encourages quick processing and resilience to hardware failures.
• Data fit is improved by non-linearity.
• The model can be used to unlearned data thanks to generalization.

• Noise insensitivity, which permits precise forecasting even in the presence of measurement mistakes and ambiguous data.
The model's internal architecture can be updated in response to the changing environment thanks to learning and adaptability.

2.6.2.2 Load Forecasting using ANN

The load forecast system considers the following characteristics as input factors:

If "i" is the day that is predicted, Hourly loads are scheduled for day I-2 two days in advance, Hourly loads the day prior to the i-1 forecast day. The anticipated hour of the predicted day 1, 2, 3,………….. 24

Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday, and Wednesday are all considered to be the most anticipated day of the week.

Outputs are:

load prediction for every hour of the day. The predictor variables that are utilized as model inputs are produced by the gen Predictors function. For forecasting in the short future, these consist of load from the previous week at the same time and day. Examine and contrast the predicted and actual loads.

Make a visual to calculate the forecast error and compare the actual and projected loads. Measure the forecaster's performance not only with the visualization but also with metrics like MAE, MAPE, RMSE, and daily peak forecast error.

3. Simulation Analysis

3.1 Properties of Load Data

The load curve that must be its made up of hourly load information, In reality, they are hourly averages. Consequently, One way to conceptualize the load curve is as a sequence of actual values can display the typical load during an hour. Although the number of observations is restricted to 24 each day, the models analyzed can be applied in scenarios where the interval between observations is less. This paper uses a Hyderabad energy utility's hourly electric load demand as the test case. Additionally accessible is the significant district's hourly temperature data. The data collection spans roughly two months since the data for January and February of 2022 are available. However, there are only 24 observations made every day, the models examined can be used in situations where the time between observations is shorter. Hourly load data, which are actually hourly averages, make up the load curve that needs to be predicted; thus, the load curve can be viewed as a sequence of actual values that represent the average load during an hour. Even longer time periods for testing may be preferred. This paper uses a Hyderabad energy utility's hourly electric load demand as the test case. Additionally accessible is the significant district's hourly temperature data. The data collection spans roughly two months since the data for January and February of 2022 are available.The load curves for Monday through Friday are the first five patterns in the series, and they are fairly similar. After that, there are two distinct routines for Saturday and Sunday. After that, the weekly process is repeated.

However, most people's activities during the day tend to be simultaneous (e.g., working, lunch, watching TV, etc.); the daily rhythm varies throughout the year. Conversely, however, people's Daytime synchronized behavior leads to in a light load at night.

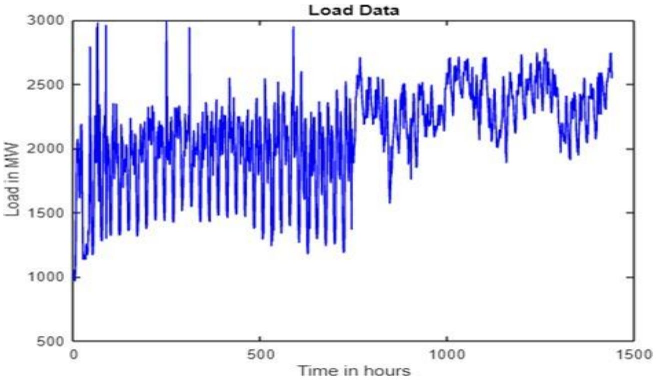


Fig.8: Load Data

3.2 STLF using Conventional Methods in MATLAB

3.2.1. Classification of Data

The hourly data is separated into two categories: training data and testing data. Every piece of information is part of the training data, except for the last 24 hours, which are reserved for testing. Prior to being incorporated into the AR model, the training data is detrended to make it stationary. Nevertheless, detrending is not necessary for ARMA and ARIMA models. During training, the model parameters are carefully chosen to minimize mistakes and provide accurate predictions. After training is finished, The load for the upcoming day is predicted by the model. The average square error

3.3. Simulation Results

3.3.1 Simulation results for Auto Regressive (AR) method

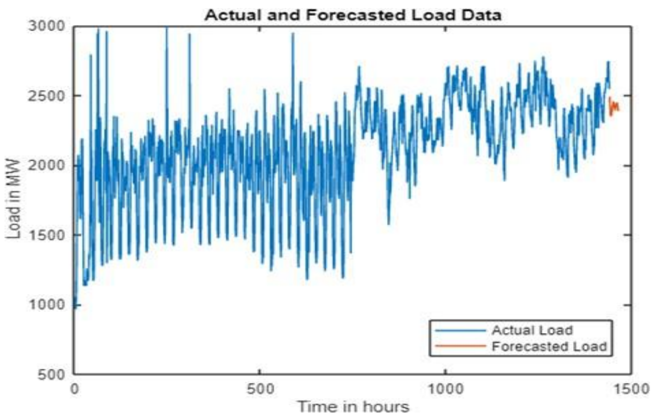


Fig.9: Actual and Forecasted Load Data using AR model

Fig. 9 displays the actual load and the predicted load data generated by the AR model. The actual load data for 60 days makes up the training dataset (January and February load data) covering hours 0–1440. The AR model then forecasts the load for the following 24 hours using this training data.

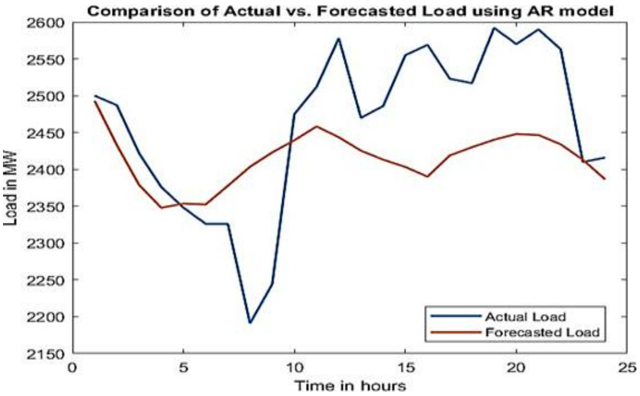


Fig.10: Comparison of Actual vs. Forecasted Load using AR model

The graph in Fig. 10 illustrates the direct comparison between the testing data and the predicted loadThis graph shows us how well the actual and anticipated numbers match. The Mean Square Error (MSE), which shows the average difference between the expected and actual values, is also calculated. For predictions to be accurate, the predicted values should be closer to the actual ones, which is shown by a lower MSE.

Mean Squared Error for the AR model = 11048.9811 kW.

3.3.2 Simulation results for Auto Regressive Moving Average (ARMA) method

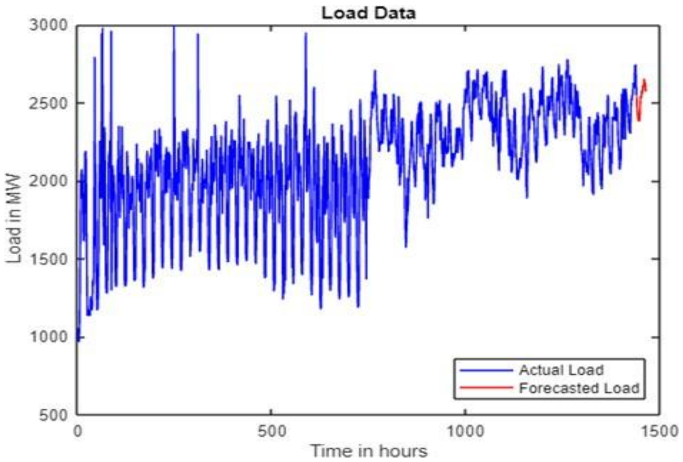


Fig.11: Actual and Forecasted Load Data using ARMA model

Fig. 11 displays the ARMA model's prediction of the load data for the following 24 hours along with the actual load data (training data). When applying the ARMA approach, two important model parameters are considered: the AR model order, denoted by "p," and the MA model order, denoted by "q." These parameters are determined using the inherent characteristics of the time series data, such as stationarity, as well as data gathered using statistical methods like the ACF and PACF. The AR component of the ARMA model predicts future values by looking at patterns and relationships in historical data.On the other hand, by carefully examining the errors or residuals from previous projections, the MA component predicts future values. The ARMA model provides a comprehensive approach to time series forecasting by integrating the AR and MA components, utilizing each one's advantages to identify and forecast intricate patterns in the data.

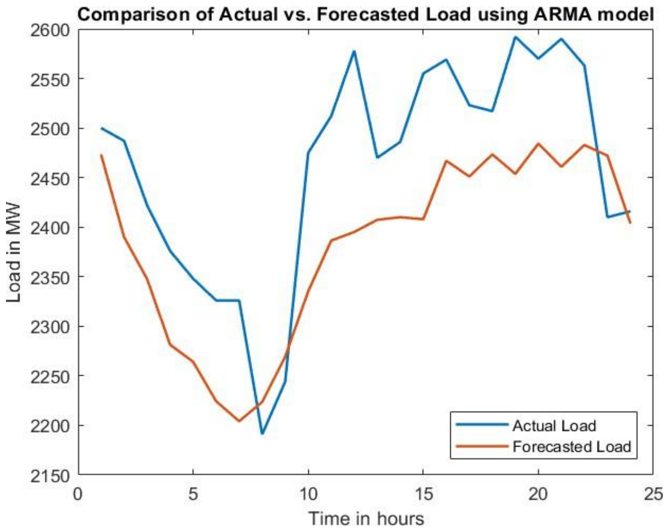


Fig.12: Comparison of Actual vs. Forecasted Load using ARMA model

The comparison between the testing data and the predicted load is shown graphically in Fig. 12. This graph makes it evident how closely the expected and actual numbers match. In addition to this visual assessment, we use a statistical metric known as the MSE to calculate the average error between the projected and actual load values.

Mean Squared Error for the ARMA model = 9565.6374 kilowatts (kW).

3.3.3 Simulation results for Auto Regressive Integrated Moving Average (ARIMA) method

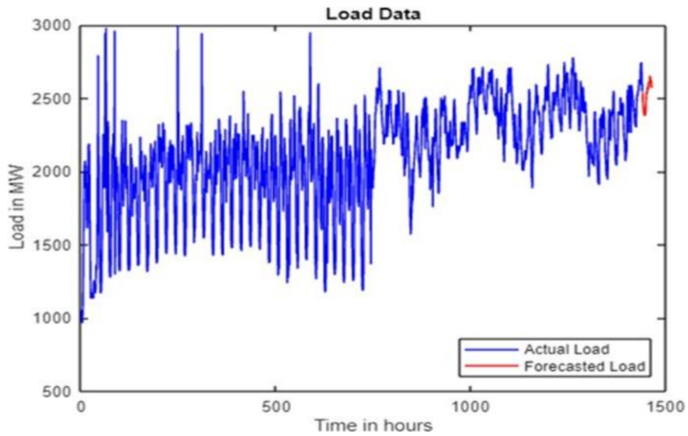


Fig.13: Actual and Forecasted Load Data using ARIMA model

Fig. 13 presents a comparison between the load data that was actually recorded and the load data that the ARIMA model predicted. Unlike ARMA, ARIMA adds a parameter called "d," which indicates the number of differencing operations required to make the time series data stationary. Many time series forecasting techniques rely on stationarity, which ARIMA solves by enabling differencing to stabilize the data. The ARIMA model is defined by three essential parameters: "d" representing differencing, "p" representing the Auto Regressive (AR) model order, and "q" representing the Moving Average (MA) model order. These parameters are the result of careful consideration of the autocorrelation structure and the need for stationarity in the analysis of the time series data. The ARIMA function is used to forecast the load for the upcoming 24 hours.

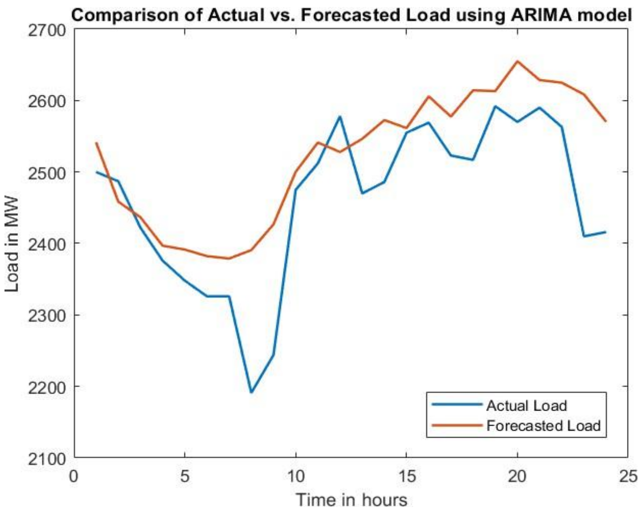


Fig. 14: Comparison of Actual vs. Forecasted Load using ARIMA model

The graph in Fig.14 illustrates the direct comparison between the testing data and the predicted load. Accurate predictions are indicated by a lower Mean Squared Error (MSE), which shows that predicted values are closer to real ones.

Mean Squared Error for the ARIMA model = 7984.373 kW.

3.3.4 Comparison between Conventional Methods

The AR, ARMA, and ARIMA techniques are frequently employed approaches in time series analysis and forecasting, each having unique advantages and uses. Because AR models estimate future events based on existing data, they are particularly effective at detecting linear links in a time series. They offer a simple yet effective forecasting tool and perform best in situations where the data shows consistent trends and seasonality. However, by combining moving average and auto regressive elements, ARMA models are able to identify both short-term and long-term dependencies in the data. Although they concentrate on stationary behavior, their increased adaptability makes them appropriate for datasets with non-linear correlations. By integrating differencing, ARIMA models build upon the capabilities of ARMA models, allowing them to handle non-stationary data by converting it into a stationary form. Due to their adaptability, ARIMA models are suitable for a variety of time series data since they can accommodate non-linear patterns and successfully capture trends and seasonality. In conclusion, AR models are simple and effective, ARMA models are simple and flexible, and ARIMA models are robust and versatile, meeting the various demands of forecasting and time series analysis tasks.

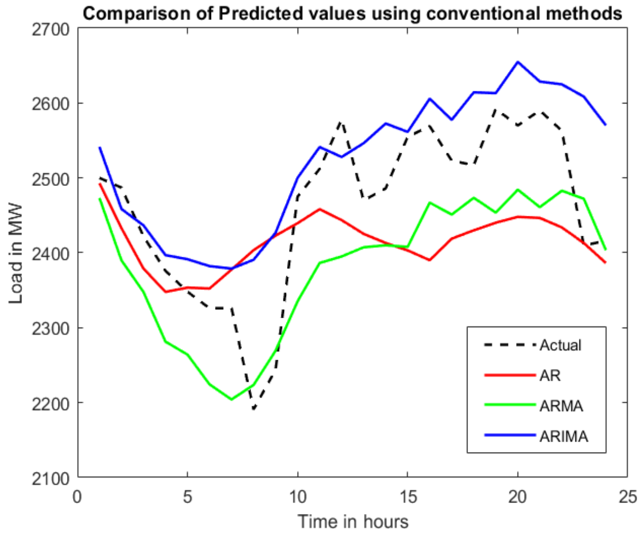


Fig. 15: Comparison of Predicted values of Actual data and AR, ARMA, ARIMA model

The comparison of the predicted load using AR, ARMA, and ARIMA directly with the testing data, as shown in the graph in Fig.15, which allows us to compare the degree to which the predicted values match the actual ones in various methods. We also compute Mean Square Error (MSE), which gives us important information about how accurate our forecasts are by revealing the typical magnitude of errors in our forecasts. A lower MSE suggests that our forecasted values are more closely matched with the actual data, signifying higher precision and reliability in our predictive model. Ultimately, our aim is to minimize the MSE, thereby ensuring that our forecasts closely track the real-world load data for more dependable predictions.

Mean Squared Error for the AR model = 11048.9811 kW.

Mean Squared Error for the ARMA model = 9565.6374 kW.

Mean Squared Error for the ARIMA model = 7984.3733 kW.

From the above MSE values obtained we can observe that error is least in ARIMA model compared to AR and ARMA models.

3.4 STLF using Artificial Neural Networks (ANN) in MATLAB

In order to ensure normalized input, this approach first separates the data into training and testing sets before scaling the data. An ANN with one or more layers that are concealed, just one output layer neuron, and varying quantity of input layer neurons is then initialized using a predefined design. To create non-linearity and regulate output scaling, the hyperbolic tangent sigmoid (tansig) and pure linear (purlin) activation functions are used, respectively. To promote effective learning, the network's weights and biases are set up correctly during initialization. The training process is set with a default of 1000 epochs, and a goal is defined to minimize the error to zero. The network is trained using the Levenberg-Marquardt algorithm, a powerful optimization technique suitable for small to medium-sized networks, known for its speed and efficiency in converging to an optimal solution. In this study, load forecasting is conducted using Artificial Neural Networks (ANN), exploring two distinct scenarios: One does not take temperature into account, whereas the other does, combining temperature information with daily-hourly load data. We intend to assess the impact of temperature parameters on the accuracy and effectiveness of the forecasting model by examining these two scenarios. Since load forecasting relies solely on historical load data, in the first scenario, the ANN may detect patterns and trends in the load data alone. This approach provides a baseline for comparison and emphasizes the performance improvements achieved by adding more environmental elements.

3.4.1 Simulation results

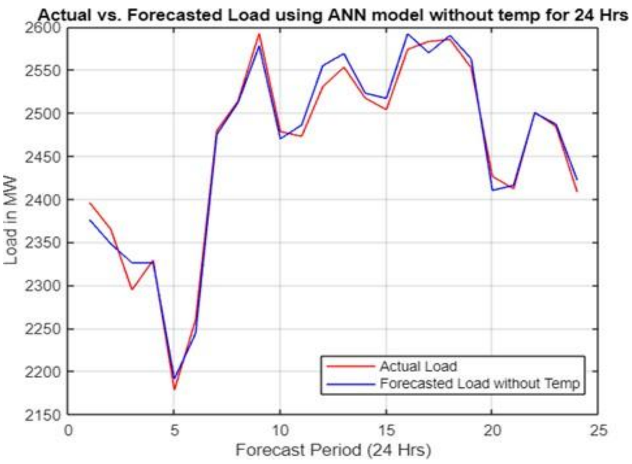


Fig. 16: Actual vs. Forecasted Load using ANN model without temp for 24 Hrs.

Fig.16 compares the actual (testing data) and expected load during a 24-hour period using the ANN model, omitting the effects of temperature. This graph illustrates how well the anticipated load matches the actual load data, demonstrating the ANN model's accuracy and performance in anticipating load demand.

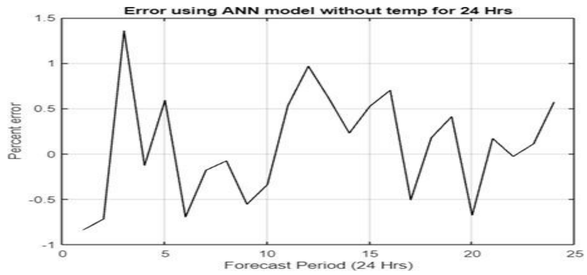


Fig. 17: Error using ANN model without temp for 24 hrs.

Plotting of the percent error for the 24-hour projected period without temperature impacts is shown in Fig.17. Percent error is an important metric to measure how accurate forecasts or estimations are in comparison to the actual or real values.

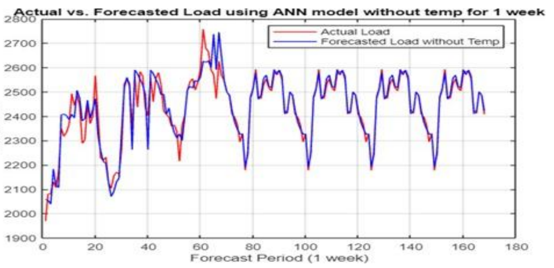


Fig. 18: Actual vs. Forecasted Load using ANN model without temp for 1 week

The graph in Fig.18, compares the actual (testing data) and expected load over a one-week period using the ANN model without accounting for temperature. The accuracy of the ANN model's long-term load demand prediction is comprehensively summarized in this chart.

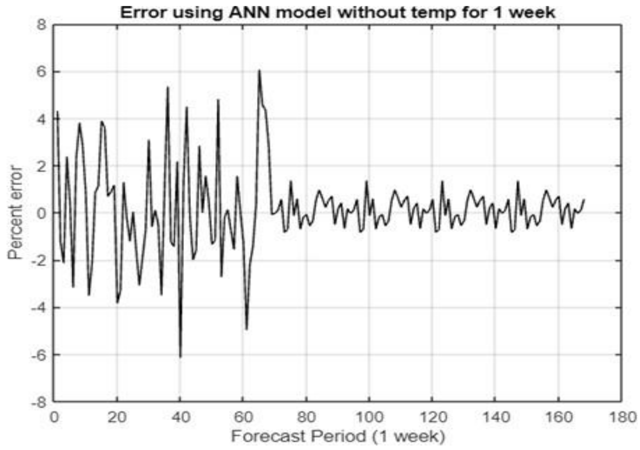


Fig. 19*:* Error using ANN model without temp for 1 week

A graphic showing the percent error for the predicted load over a week, without taking temperature into account, is shown in Fig.19. One essential indicator for evaluating how well estimates or projections match actual or true values is percent error. This graph highlights places where projections differ from actual load numbers, offering insightful information about the forecasting model's performance.

3.5 Comparison between conventional and ANN methods

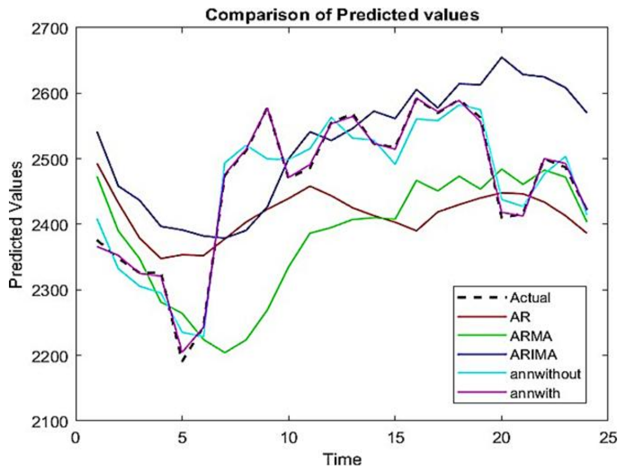


Fig. 20: Comparison of Predicted values of Conventional and ANN model

The graph in Fig.20, shows a detailed comparison of the anticipated load using both conventional (AR, ARMA, and ARIMA) and artificial neural network (ANN) approaches over a 24-hour period with the actual load (testing data). Mean Square Error, or MSE, is computed here. A lower MSE indicates greater precision and dependability in our predictive model since it shows that our predicted values match the real data more closely. Our ultimate goal is to reduce the MSE in order to make predictions that are more reliable by closely matching the actual load data.

The results obtained by different techniques are presented below:

Mean Squared Error (AR): 11048.9811 kW

Mean Squared Error (ARMA): 9565.6374 kW

Mean Squared Error (ARIMA): 7984.3733 kW

Mean Squared Error (ANN): 198.244 kW

From the above results it can be observed that error is reduced drastically in ANN when compared to Conventional techniques.

Even though conventional methods provide good results these methods are not suitable for non-linear complex time series data. Therefore, by incorporating AI Techniques like ANN accuracy is greatly improved as strength lies in its capacity to autonomously learn and adapt to the underlying nature and intricacies of the data, without relying on predefined assumptions about the data's structure. Also, ANN can recognize complex relationships and patterns within the data, allowing for more accurate predictions. Unlike traditional methods, ANN can uncover hidden patterns and non-linear dependencies, making it highly suitable for handling diverse and intricate time series datasets. These techniques represent a significant advancement in time series forecasting, empowering analysts to tackle the challenges posed by increasingly complex datasets with greater precision and efficacy

4. Conclusion

In conclusion, this paper examined STLF by examining two months' worth of hourly load data using both conventional and AI techniques. We now know the following: While traditional methods like AR, ARMA, and ARIMA models are good at predicting loads, they struggle to spot complex patterns and variables that affect power use. On the other hand, AI techniques, especially ANNs, yield better results in STLF. They are better at handling intricate load patterns and offer more accurate estimates.

Comparing traditional methods to AI techniques, we found that AI methods generally give more accurate predictions and make less errors. They're also good at dealing with big, nonlinear datasets. Plus, AI methods cut down on errors even more. Overall, this project offers useful insights into the best ways to forecast short-term load. By using advanced AI methods and addressing key challenges, power system operators and planners can improve their forecasting abilities, leading to better management of electricity demand and a more stable grid. The ability to combine the qualities of many short-term forecasting techniques into hybrids can enhance performance and robustness without requiring a lot of development work. Such model integration's primary obstacle is the need for proficiency with a wide range of modeling techniques. Our goal was to demonstrate that consideration should be given to the performance analysis, creation, and selection of error detection criteria. Ignorantly applying so-called standard criteria may result in subpar artificial intelligence approach creation, adjustment, and choice for short-term prediction in practical settings.

References

[1] A.N.Jha G. Mallesham "Short term load forecasting using Artificial neural networks" National Conference on Sensors and Instrumentation, 2002.

[2] Kusum, S. (2017). Short-term Load Forecasting: A Review. Journal of Electrical Engineering & Technology, 12(3), 1019-1030.

[3] Robert Nau "Notes on Non-seasonal ARIMA Models" Fuqua school of Business, Duke University.

[4] Elsevier Ltd; International Conference on Power, Energy and Electrical Engineering (PEEE 2022); Energy Reports 9 (2023) 550–557 "Short term load forecasting based on ARIMA and ANN approaches" Science Direct, Jan. 2023.

[5] Goswami K, Ganguly A, Sil AK. Day ahead forecasting and peak load management using multivariate auto regression technique. In: 2018 IEEE applied signal processing conference (ASPCON) IEEE. 2018, p. 279–82.

[6] Ahmed KMU, Al Amin MA, Rahman MT. Application of short-term energy consumption forecasting for household energy management system. In: 2015 3rd international conference on green energy and technology (ICGET) IEEE. 2015, p. 1–6.

[7] Almeshaiei,E., Soltan, H. "A methodology for Electric Power Load Forecasting". Alexandria Engineering Journal. 2011, 50, 137-44.

[8] Arvanitidis, A.I.; Bargiotas, D.; Daskalopulu, A.; Laitsos, V.; Tsoukalas, L.H. "Enhanced Short-Term Load Forecasting Using Artificial Neural Networks". *Energies* 2021.

[9] Ravinder.S.Dahiya and A.N. Jha," Short Term Load Forecasting Using ANN", NSC Proc.,pp 59- 65, 2001.

[10] Akhtar, S.; Shahzad, ; Zaheer, A.; Ullah, H.S.; Kilic, H.; Gono, R.; Jasinski, M.; Leonowicz, Z. "Short-Term Load Forecasting Models: A Review of Challenges, Progress, and the Road Ahead". Energies 2023, 16, 4060.

[11] Mosavi, A.; Salimi, M.; Ardabili, S.F.; Rabczuk, T.; Shamshirband, S.; Varkonyi-Koczy, A.R. State of the Art of Machine Learning Models in Energy Systems, a Systematic Review. *Energies* 2019, *12*, 1301. [Google Scholar] [CrossRef]

[12] Cai, M.; Pipattanasomporn, M.; Rahman, S. Day-ahead building-level load forecasts using deep learning vs. traditional time-series techniques. *Appl. Energy* 2018, *236*, 1078–1088. [Google Scholar] [CrossRef].

[13] Cheng, L.; Yu, T. "A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems". Int. J. Energy Res. 2019, 43, 1928–1973.

[14] Koponen, P.; Ikäheimo, J.; Koskela, J.; Brester, C.; Niska, H. "Assessing and Comparing Short Term Load Forecasting Performance". Energies 2020, 13, 2054.

[15] Lindberg, K.B.; Seljom, P.; Madsen, H.; Fischer, D.; Korpås, M. "Long-term electricity load forecasting: Current and future trends". Util. Policy 2019, 58, 102–119.

[16] Alfares, H.K., Nazeeruddin, M. "Electric load forecasting: literature survey and classification of methods". International Journal of System Science. 2002, 33, 23-34.

[17] Soliman, S.A., Ahmad, M.A. "Electrical Load Forecasting: Modeling and Model Construction", Elsevier, 2010.

[18] "Stationarity & Seasonality Time Series Forecasting #1" *YouTube*, uploaded by Nachiketa Hebbar, 14 July 2020,

[19] "Auto Regression(AR) Model| Time Series Forecasting #2" *YouTube*, uploaded by Nachiketa Hebbar, 27 Jan2021, https://youtu.be/Ia9irWcWt8s?si=YL340FHU-Cc9LQZY.

[20] "Moving Average (MA) Models| Time Series Forecasting #3" *YouTube*, uploaded by Nachiketa Hebbar, 20 July 2020, https://youtu.be/Lgy3ANiVJos?si=bnadL_oYHedKOvBA.

[21] "ARMA & ARIMA Model| Time Series Forecasting #4" *YouTube*, uploaded by Nachiketa Hebbar, 20 July 2020, https://youtu.be/8t11SmVD8dU?si=cEzr1QsgaFi_kuS1.

[22] Zhang, L.; Wen, J.; Li, Y.; Chen, J.; Ye, Y.; Fu, Y.; Livingood, W. "A review of machine learning in building load prediction". Appl. Energy 2021, 285, 116452.

[23] "Neural Network In 5 Minutes | What Is A Neural Network? | How Neural Networks Work" *YouTube*, uploaded by SimplilearnOfficial, 19 June 2019, https://youtu.be/bfmFfD2RIcg?si=KX49fgx_L4J3_fJA.

[24] "Neural Network Architectures" *YouTube*, uploaded by JOSHUA TALKS, 17 August 2020, https://youtu.be/P-6RI9gOck?si=IEXluxJ0mUtzOTbF

[25] Bedi, J.; Toshniwal, D. "Deep learning framework to forecast electricity demand". Appl. Energy 2019, 238, 1312–1326.