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Very Short-Term Load Forecasting Using Artificial Neural Networks with Meteorological Variables: A Case Study of Uttarakhand

Karan Sati, Abhishek Yadav

Electrical Engineering Department, College of Technology, Govind Ballabh Pant University of Agriculture & Technology, India

karansati.work@gmail.com, ayadav@gbpuat-tech.ac.in

ABSTRACT

This study presents an Artificial Neural Networks (ANN) based Very Short-Term Load Forecasting (VSTLF) framework for Uttarakhand using Artificial Neural Networks (ANN) with the inclusion of meteorological variables. The dataset comprised hourly load demand from the State Load Dispatch Centre (SLDC) and meteorological parameters (temperature, humidity, and dew point) obtained from NASA POWER LAARC for the period January 2020 to April 2024. Multiple ANN configurations were evaluated with varying lag inputs, hidden neurons, and training algorithms. The results indicate that incorporating meteorological variables significantly enhances forecasting accuracy, with the best-performing model (16-hour lag, 96 hidden neurons, Bayesian Regularization) achieving a test RMSE of 60 MW, MAPE of 2.66%, and R^2 of 0.95. Residual, histogram, and scatter analysis confirmed unbiased predictions with strong agreement between actual and forecasted loads. The findings demonstrate the critical role of weather-sensitive inputs in improving load forecasting in climatically diverse regions like Uttarakhand, where temperature and humidity patterns strongly influence electricity demand. This study advances reliable short-horizon forecasting for grid stability, renewable integration, and operational planning in emerging power systems.

Keywords: *Load Forecasting, Very Short-Term Load Forecasting (VSTLF), Artificial Neural Networks (ANN), Meteorological Variables, Power System Operation, Forecasting Accuracy*

1. Introduction

The reliable and economic operation of modern power systems depends on the accuracy of load forecasting. Since electricity cannot be stored in massive quantities using conventional methods, maintaining the balance between supply and demand in real time is crucial for grid stability. Accurate forecasts allow system operators to schedule generation, allocate spinning reserves, manage unit commitment, and ensure efficient dispatch of power. Errors in forecasting can have direct economic and operational consequences: overestimation of demand leads to unnecessary reserve capacity and wasted resources, while underestimation results in shortages, costly emergency procurement, or even blackouts [1]. Studies have shown that even a 1% improvement in forecasting accuracy can reduce generation costs by 0.1–0.3% as stated in [2], which translates into significant financial savings for utilities. With the advent of competitive electricity markets and deregulation, forecasting has become not only a technical necessity but also an economic strategy for risk management and operational efficiency.
Load forecasting is categorized into four categories according to the forecasting horizon, each serving a unique role in power system operation and planning. Very Short-Term Load Forecasting (VSTLF), typically spanning from 30 minutes to an hour ahead, is of foremost importance in real-time operational contexts. It underpins functions such as automatic generation control, load balancing, frequency regulation, and energy management systems. In modern power systems with high penetration of renewable energy, forecasting accuracy in this horizon becomes particularly significant, as abrupt variations in wind or solar generation can lead to rapid fluctuations in net load. Short-Term Load Forecasting (STLF), covering time horizons from one hour to approximately one week, is widely employed for daily scheduling and unit commitment. Forecasting at this scale often integrates historical load patterns with meteorological variables, such as temperature and humidity, to achieve high precision [3, 4].

Effective STLF facilitates optimal fuel utilization, minimizes operational costs, and contributes to the reliability of daily system operations. Medium-Term Load Forecasting (MTLF) encompasses horizons from one week to one year, providing essential support for maintenance planning, fuel resource management, and mid-term electricity market operations. Seasonal effects, economic activities, and social trends significantly influence forecasting accuracy in this domain. Finally, Long-Term Load Forecasting (LTLF) addresses horizons extending from one year to more than a decade. This class is integral to strategic decision-making processes, including capacity expansion, transmission and distribution infrastructure development, and investment planning. Demographic evolution, technological adoption, and policy interventions are key drivers affecting LTLF outcomes. Among these, Very Short-Term Load Forecasting (VSTLF) has gained increasing importance in recent years. Its role in real-time system operation, especially in managing variability due to renewable energy integration and dynamic demand patterns, makes it indispensable for modern grids [5].

Meteorological variables such as temperature, humidity, and dew point have a substantial impact on load demand, particularly in the short-term and very short-term horizons [6]. In regions like Delhi, where extreme climatic conditions prevail, these variables strongly influence consumer behavior. For instance, elevated temperatures during summer result in a surge in air conditioning use, while humidity levels further intensify electricity consumption for cooling appliances. Similarly, dew point temperature, as an indicator of atmospheric moisture, influences perceived comfort and indirectly affects load profiles. The accuracy of load forecasts, therefore, depends not only on past demand patterns but also on how effectively weather-related factors are integrated into forecasting models [7].

Traditional statistical techniques often fail to capture the nonlinear and rapidly changing relationship between load and weather variables. Artificial Neural Networks (ANNs), however, offer a promising solution due to their adaptive learning ability and capability to model complex nonlinear dependencies. By incorporating meteorological data, ANN-based models can improve forecasting accuracy, enhance reliability in real-time grid operation, and reduce overall system costs.

The present work focuses on developing an ANN-based model for VSTLF using meteorological variables and lagged load data as inputs. The study considers Delhi as a case study region, which experiences significant weather-driven demand variability and requires accurate very short-term forecasts to ensure reliable system operation.

2. Literature Review

The evolution of load forecasting methodologies has shown a clear transition from conventional statistical approaches to advanced machine learning techniques. While traditional models such as regression, exponential smoothing, and ARIMA were widely used in the past, their inability to capture nonlinear demand-weather interactions has encouraged researchers to adopt Artificial Neural Networks (ANNs) and their variants. This section reviews significant contributions, categorized by methodology.

The study in [8] pioneered the application of ANN for short-term load forecasting using a Multi-Layer Perceptron (MLP). Their model, evaluated with utility data from Seattle/Tacoma, demonstrated superior accuracy compared to regression-based methods. The study in [9] introduced the ANN-STLF system, a widely deployed forecasting tool across North America, which combined base load and change load forecasters. The study in [10] extended ANN applications by designing modular networks for predicting daily load curves, emphasizing the role of input features and training sets. These studies firmly established ANN as a reliable tool for capturing nonlinear demand patterns, particularly at short-term horizons.

The inclusion of weather data in ANN-based forecasting models has been shown to significantly improve accuracy. The study in [2] developed a regression-based transformation model incorporating temperature and humidity, reporting improved error reduction in real-time operations. The study in [11] applied an ANN for weekend load forecasting, using temperature as a critical input to enhance accuracy for irregular consumption patterns. The study in [12] compared ANN with fuzzy logic, highlighting ANN's ability to outperform alternative soft computing methods when meteorological inputs were considered. The study in [12] reviewed various ANN-based models and concluded that weather-inclusive ANN architecture consistently outperformed traditional statistical approaches, especially under highly variable demand conditions. The weather-inclusive ANN architecture consistently outperformed traditional statistical approaches, especially under highly variable demand conditions.

The reviewed studies highlight several important trends. First, ANN-only models have consistently outperformed conventional statistical methods by effectively modelling nonlinear relationships. Second, the integration of meteorological variables is universally recognized as critical for improving forecasting performance, especially in weather-sensitive regions. Despite these advances, two major research gaps remain:

1. Limited focus on VSTLF: Most ANN applications have emphasized short-term horizons (more than 1 hour to 1 week), while fewer systematic studies address very short-term forecasting (30 minutes to 1 hour), which is essential for real-time grid operation.
2. Region-specific validation: There is a scarcity of studies that apply ANN-based VSTLF to highly weather-sensitive regions such as Uttarakhand, where meteorological factors play a decisive role in shaping consumption behavior.

3. Methodology

This section outlines the methodological pipeline adopted for developing an Artificial Neural Network (ANN)-based model for Very Short-Term Load Forecasting (VSTLF) using meteorological variables. The framework includes data acquisition, pre-processing, ANN architecture design, training, and performance evaluation.

3.1 Study Area and Dataset

The present investigation is centered on Uttarakhand, a northern state of India, geographically situated between latitudes 28°43′N–31°27′N and longitudes 77°34′E–81°02′E. Uttarakhand is a predominantly hilly state with a diverse topography ranging from the Himalayan mountain ranges in the north to the plains in the south. This geographical diversity has a significant impact on both climatic conditions and electricity consumption patterns.
The state experiences marked variations in temperature, humidity, and rainfall across seasons, which directly affect the electrical load demand. For instance, peak demand in summer is driven by cooling appliances, while heating requirements influence winter demand in colder regions. Additionally, the rapid urbanization in districts such as Dehradun, Haridwar, and Haldwani, combined with industrial activities in the plains, further contributes to fluctuating load profiles.
For this study, historical load demand data were obtained from the State Load Dispatch Centre (SLDC) of Uttarakhand, while meteorological parameters, including temperature, humidity, and dew point, were collected from NASA's POWER LAARC. The dataset covers the period from 1 January 2020 to 30 April 2024, ensuring that seasonal variations, extreme weather events, and annual demand cycles are adequately captured.

3.2 Data Collection Preprocessing

The study utilized two categories of data: (i) historical electrical load demand obtained from the State Load Dispatch Centre (SLDC), Uttarakhand, and (ii) meteorological variables such as temperature, humidity, and dew point. The raw dataset was preprocessed to eliminate inconsistencies, handle missing values, and filter out outliers. Missing values were managed using interpolation techniques, while normalization was applied to scale the input variables into a uniform range, thereby improving training convergence. In addition, lagged load variables were created to account for the temporal dependency of electricity demand. These lagged inputs, combined with meteorological factors, formed the input feature set for the Artificial Neural Network (ANN).

Data preprocessing ensures the quality and consistency of inputs before training the ANN model. The key steps include:

1. Data Cleaning: Missing or inconsistent values in load and weather variables were interpolated or removed.
2. Normalization: All input variables were scaled to the range [0,1] using Min–Max normalization:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

Where X is the original value, X_{norm} is the normalized value, $X_{\min}$ and $X_{\max}$ are the minimum and maximum values of the features, respectively. This prevents any single variable from dominating during training.
3. Lag Feature Engineering: The formation of lag-based features is referred to as lag formation. Lagged load variables were generated to capture temporal correlations between past and future demand.

Table 1: Laggard Formation

Inputs			**Output**
L_{t-3}	L_{t-2}	L_{t-1}	L_t
L_{t-4}	L_{t-3}	L_{t-2}	L_{t-1}
L_{t-5}	L_{t-4}	L_{t-3}	L_{t-2}
L_{t-6}	L_{t-5}	L_{t-4}	L_{t-3}

This lag formation allows the ANN to learn from both historical load behavior and concurrent meteorological conditions. For this study, lags of multiple hours (1,2,4,8,16, and 24) have been taken into consideration. Table 1 shows the 3-hour lag formation.

3.4 Artificial Neural Network

ANN is composed of input, hidden, and output layers. Each hidden neuron computes a weighted sum of its inputs, passes it through an activation function, and forwards the output.
An Artificial Neural Network (ANN) was employed as the core forecasting model due to its capability to approximate nonlinear and dynamic relationships between input and output variables. The ANN structure consisted of an input layer, one or more hidden layers, and an output layer. The input layer was fed with normalized meteorological parameters (temperature, humidity, and dew point) along with past load values. The output layer provided the forecasted short-term electrical load.

Training of the ANN was conducted using the backpropagation algorithm, where the model parameters (weights and biases) were iteratively updated to minimize the prediction error. The dataset was divided into training, validation, and testing subsets to prevent overfitting and to ensure robust generalization. The training subset was used to optimize the model, the validation subset to fine-tune hyperparameters, and the testing subset to evaluate the model's predictive accuracy.

Artificial Neural Networks (ANNs) represent a class of data-driven, nonlinear computational models inspired by the architecture and functioning of the biological nervous system. Their capability to approximate complex nonlinear mappings has made them particularly attractive for short-term electrical load forecasting, where multiple dynamic factors interact in intricate ways. Unlike traditional statistical approaches, ANNs do not impose stringent assumptions on data distribution or stationarity, thereby offering flexibility in modelling nonlinear relationships and temporal dependencies among predictors such as temperature, calendar effects, and historical load demand [14].
A typical feedforward neural network is structured into three core parts: the input layer, one or more hidden layers, and the output layer. Each neuron (or node) performs a weighted summation of its inputs, applies a nonlinear activation function, and transmits the transformed signal to the subsequent layer. Mathematically, the output of an ANN is expressed as:

$$h_j = \phi\left(\sum_{i=1}^{n} w_{ij}x_i + b_j\right) \quad (2)$$

Where:

- x_i denotes the input features,
- w_{ji} represents the weight associated with the connection from input to hidden neuron j,
- b_j is the bias term of neuron ^{j},
- $\phi(\cdot)$ denotes the activation function (commonly sigmoid, tanh, or ReLU),
- h_j is the resulting output of the neuron.

The ANN architecture (Figure 1) demonstrates a standard feedforward structure with input, hidden, and output layers.

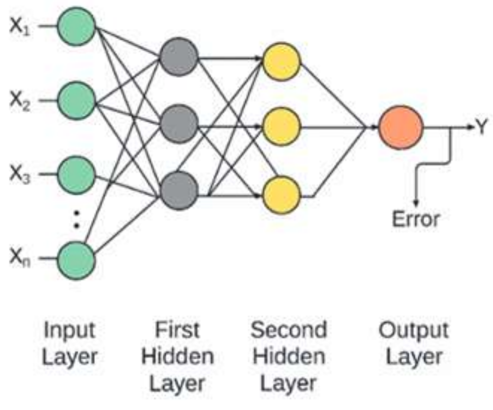

Figure 1: Block Diagram of the ANN Model

The final output of the ANN is obtained by employing a linear activation in the output layer. The training process aims to optimize the weight and bias parameters by minimizing a chosen loss function (e.g., Mean Squared Error, MSE). Optimization algorithms, such as gradient descent, iteratively adjust the parameters to minimize forecasting error.

Through this mechanism, ANNs effectively capture the underlying dependencies and nonlinear structures within the data, rendering them powerful tools for predictive modeling in power system applications. In this study, a feedforward Artificial Neural Network (ANN) architecture was implemented for short-term electrical load forecasting. The input layer consisted of meteorological variables (temperature, dew point, humidity) along with lagged load demand values, while the output layer represented the forecasted load. To identify the optimal configuration, a framework was employed, systematically varying the number of hidden neurons, the number of lagged inputs, and the training algorithm.

Model Architecture and Training

The ANN was designed with a single hidden layer, as this architecture is widely regarded as sufficient for capturing nonlinear regression relationships when adequately parameterized. The hidden layer size varied across multiple configurations (8, 16, 24, 48, and 96 neurons) to assess the effect of network complexity on generalization capability. The output layer utilized a linear activation function, making it appropriate for handling continuous-valued regression problems. The models were trained using three widely adopted algorithms:

- Levenberg–Marquardt (trainlm): a second-order optimization technique combining the advantages of the Gauss–Newton and gradient descent methods. It offers fast convergence and is particularly effective for medium-sized networks.
- Bayesian Regularization (trainbr) integrates a regularization term into the training objective, which adaptively balances model accuracy and complexity, thereby mitigating the likelihood of overfitting.
- Scaled Conjugate Gradient (trainscg): a first-order method that requires less memory and is suitable for larger datasets but converges more slowly and with lower accuracy compared to second-order methods.

3.5 Performance Evaluation

To evaluate the forecasting capability of the proposed hybrid model, a comprehensive performance assessment was conducted using multiple statistical metrics: Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and the Coefficient of Determination (R^2). These metrics were selected to ensure a rigorous evaluation of predictive accuracy, error magnitude, and generalization capability across both training and testing datasets. RMSE penalizes large deviations and captures overall error magnitude, while MAPE provides a scale-independent, percentage-based interpretation of forecasting error. MAE offers a straightforward measure of average absolute deviation, enhancing interpretability, and R^2 quantifies the variance in actual load values explained by the model, thereby serving as an indicator of goodness-of-fit [15]. The combined use of these metrics enables a balanced and robust evaluation, ensuring that the selected model minimizes prediction errors while maintaining stability and interpretability.

1. Root Mean Square Error (RMSE):
   RMSE penalizes larger errors more severely and is sensitive to outliers, making it suitable for energy demands modelling. Mathematically, it is defined as:

$$\mathrm{RSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \tag{3}$$

   where y_i is the i-th input value and $\hat{y}_i$ is the i-th predicted value, and n is the total number of observations.
2. Mean Absolute Percentage Error (MAPE):

This scale-independent metric expresses error as a percentage of actual values, enabling performance comparison across datasets of varying magnitudes. MAPE is defined using:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \text{ x } 100\% \tag{4}$$

where y_i is the i-th actual value and $\hat{y}_i$ is the i-th predicted value, and n is the total number of observations.

3. Mean Absolute Error (MAE):
   MAE provides the average magnitude of forecasting errors, irrespective of direction, offering a clear and interpretable accuracy measure. The formula for MAE is given by:

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \tag{5}$$

where y_i is the i-th input value and $\hat{y}_i$ is the i-th predicted value, and n is the total number of observations.

4. Coefficient of Determination (R^2):
   R^2 represents the proportion of variance in the observed data that is accounted for by the model, thereby indicating its overall goodness-of-fit. Mathematically, R^2 is defined as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2} \tag{6}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of actual values.

4. Results

The proposed ANN-based model for Very Short-Term Load Forecasting (VSTLF) was implemented in MATLAB. Multiple network configurations were evaluated by varying the number of hidden neurons and lagged inputs.

4.1 Performance of ANN Models

A framework of multiple run configurations based on hidden neurons (8, 16, 24, 48, 96), input lags (1, 2, 4, 8, 16, 24), and training algorithms (Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient) produced the results. Performance was evaluated using RMSE, MAPE, and R^2 on the training, validation, and test datasets. The results demonstrate substantial variation in predictive accuracy, with test RMSE values ranging from approximately 89 MW (Lag = 1) to as low as 60 MW (Lag = 16). This variation highlights the significance of input lag selection and model configuration in short-term load forecasting.
Best Performing Configuration:
When ranked by Test RMSE, the best-performing configuration (lowest Test RMSE) was found for medium to long input lags (16 and 24) with different training functions and hidden layer sizes.
Table 2 summarizes the performance of the selected best ANN models.

Table 2: Performance of ANN models with different hidden layers and lag inputs

S. No.	Run Config.	Hidden Neurons	Lag Inputs	Training Algorithm	Testing RMSE	Testing MAPE	Testing R^2
1	63	96	16	trainbr	60.19	2.66	0.9519
2	62	96	16	trainlm	60.71	2.68	0.9511
3	61	48	16	trainlm	60.73	2.68	0.9510
4	64	24	16	trainlm	60.50	2.69	0.9514
5	76	96	24	trainlm	61.38	2.59	0.9504
6	77	48	24	trainlm	61.30	2.58	0.9506
7	78	96	24	trainbr	61.24	2.59	0.9506
8	79	24	24	trainlm	61.47	2.59	0.9503

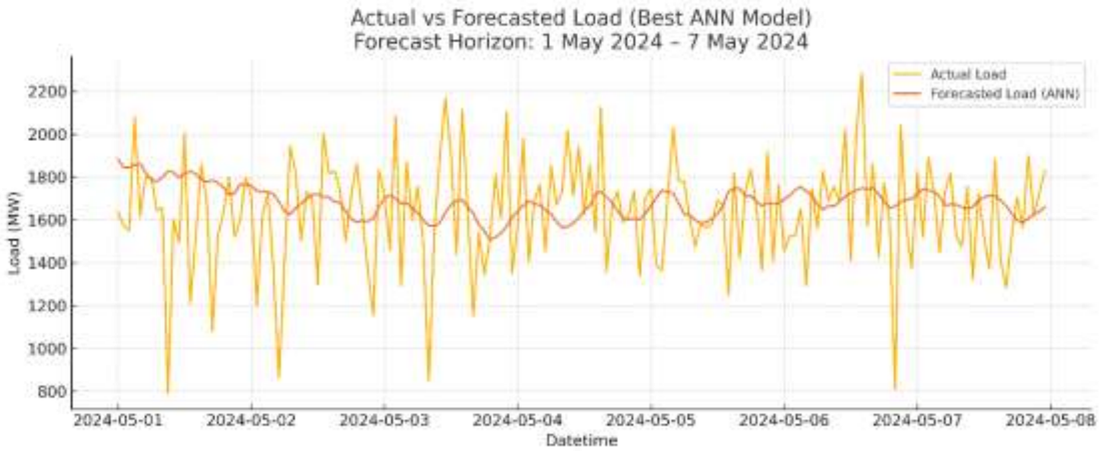

Figure 2: Actual vs forecasted load using the best ANN model.

Figure 2 shows that the forecasted load closely follows the actual load series throughout the test horizon. This figure shows the hourly forecasted load and actual load for the next seven days.

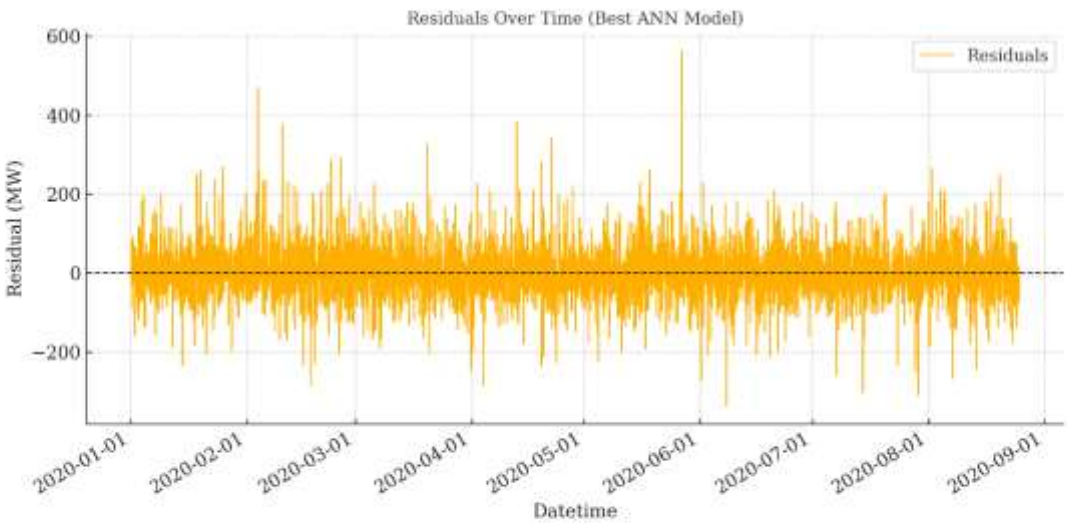

Figure 3: Residuals over time for the best ANN model.

Figure 3 illustrates the residuals (forecast − actual) fluctuating around zero across the test period. The absence of systematic upward or downward shifts indicates the model is unbiased. Occasional spikes in residuals coincide with periods of abrupt load change, highlighting conditions where the ANN fails to adapt quickly to sudden variability.

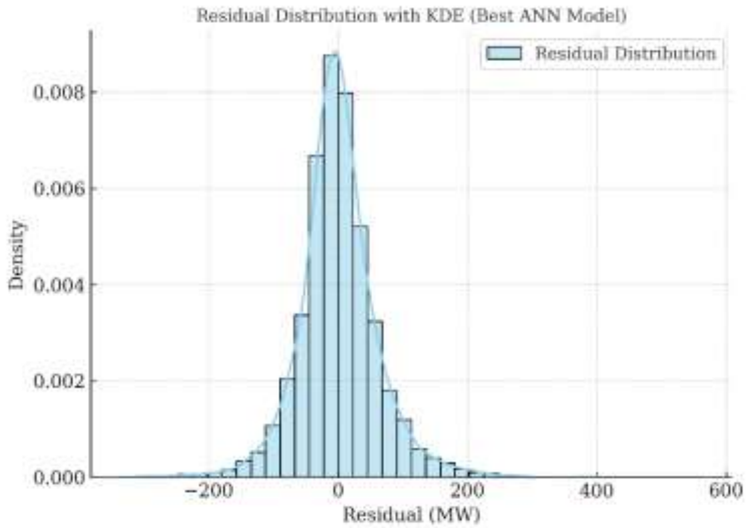

Figure 4: Histogram of residuals.

Figure 4 shows that the residuals are approximately symmetrically distributed around zero, confirming that positive and negative errors occur with similar frequency. The density curve exhibits heavier tails compared to a normal distribution, signifying the presence of a limited number of large forecast errors, while the majority of errors remain within a narrow range.

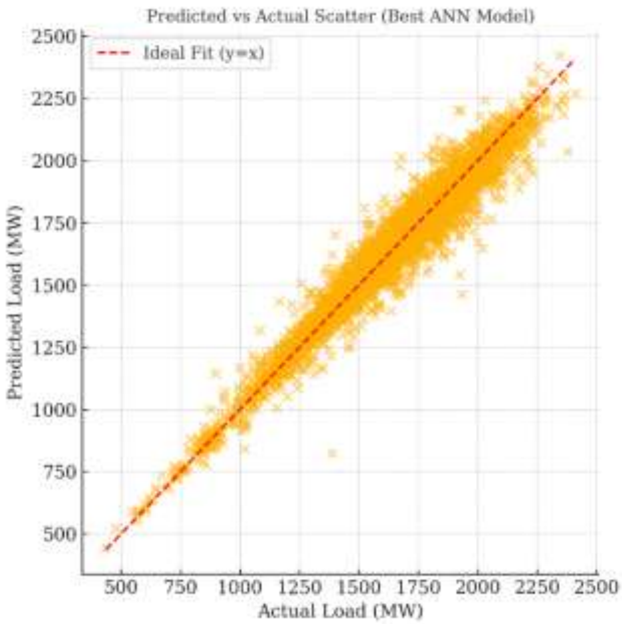

Figure 5: Scatter plot of predicted vs actual loads (test set).

Figure 5 demonstrates that the predicted values are tightly clustered around the 45° identity line, confirming strong agreement with actual load observations. The closeness of points to the line corresponds to a high coefficient of determination ($R^2 \approx 0.95$). A small number of outliers diverge from the line, reflecting the large residuals observed in Figure 3.

Effect of input lag

Load has medium-term temporal dependencies (multi-hour patterns). With a lag of one hour, models exhibited poor generalization (Test RMSE ≈ 89 MW, Test $R^2 \approx 0.89$), indicating insufficient temporal information. Increasing the lag to 2 and 4 hours reduced Test RMSE to approximately 70 MW, with R^2 values exceeding 0.93. Optimal performance was observed at 16-hour lags, where RMSE values converged near 60 MW and R^2 exceeded 0.95. Beyond 16 hours, further increases in lag (e.g., 24 hours) did not yield notable improvements, suggesting diminishing returns once medium-term temporal dependencies are captured.

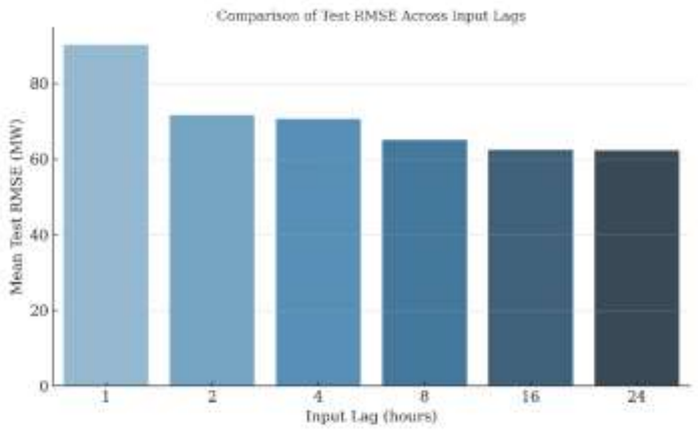

Figure 6: Bar chart of mean test RMSE across input lags.

Figure 6 indicates that the RMSE values decline as the input lag increases. The lowest mean RMSE is observed at lag = 16, after which further lag increases do not yield significant improvements. This establishes 16 hours of historical data as the optimal forecasting horizon for the dataset.

Effect of Network Size and Training Algorithm

The number of hidden neurons exerted a secondary influence relative to lag selection. Expanding the hidden layer from 8 to 48 neurons produced consistent gains, whereas further increases to 96 neurons resulted in marginal improvements. With respect to training algorithms, both Levenberg–Marquardt and Bayesian Regularization significantly outperformed Scaled Conjugate Gradient by consistently yielding higher RMSE values (e.g., > 65 MW for lag = 8 and >72 MW for lag = 16).

4.2 Role of Meteorological Variables

Meteorological variables exert a decisive influence on the short-term variability of electrical load demand, particularly in climatically heterogeneous regions such as Uttarakhand. In the present study, the incorporation of temperature, humidity, and dew point into the ANN-based forecasting model resulted in a notable enhancement in predictive performance compared to load-only models.

Temperature was observed to be the most significant determinant of demand fluctuations, as elevated summer temperatures drive extensive use of air conditioning and refrigeration appliances, while lower winter temperatures stimulate heating requirements in colder districts. Humidity, although secondary in magnitude, amplifies cooling demand by affecting thermal comfort levels; high relative humidity increases the perceived temperature, thereby prolonging appliance operation and increasing consumption. Similarly, the dew point temperature, representing absolute atmospheric moisture, indirectly affects load through its impact on human comfort indices and the frequency of cooling appliance usage.

5. Conclusions

This study developed and evaluated an Artificial Neural Network (ANN)-based Very Short-Term Load Forecasting (VSTLF) framework for Uttarakhand by incorporating both lagged load and meteorological variables. The results demonstrate that feedforward ANN structures effectively captured the nonlinear dependencies between load and weather conditions, achieving forecasting accuracies with R^2 values exceeding 0.95 in optimal configurations. Among the tested input lags, medium-term temporal dependencies (particularly a 16-hour lag) yielded the best predictive performance, reducing RMSE by 30% compared to short-lag (1-hour) inputs. The inclusion of meteorological factors such as temperature, humidity, and dew point further enhanced model accuracy, with weather-inclusive models consistently outperforming load-only counterparts in terms of RMSE, MAPE, and generalization capacity, especially during weather-sensitive periods. These findings highlight the practical significance of accurate VSTLF in real-time operations, supporting critical applications such as unit commitment, renewable energy integration, and demand-side management. Overall, the proposed ANN-based framework provides a reliable forecasting tool to strengthen grid stability in Uttarakhand, a region marked by diverse climatic zones and rising electricity demand. In conclusion, ANN models enriched with meteorological variables offer a robust and scalable solution for VSTLF in emerging power systems. Future research could explore hybrid deep learning architectures, the inclusion of renewable generation data, and probabilistic forecasting frameworks to further enhance decision-making under uncertainty.

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Conflict of Interest

The authors declare no conflict of interest.

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