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IntelliForecast: A Machine Learning Framework with Feature Engineering for Efficient Forecasting of Electricity Load

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Abstract: Modern smart grids of electricity align with the sustainable development goals of the United Nations (UN). Since electricity production and distribution are crucial in sustainable development, research in this area is highly significant. Artificial Intelligence (AI) has emerged as a powerful tool for addressing various challenges across real-life applications, including smart grids. In this regard, electricity load forecasting is indispensable for efficiently managing the demand-supply balance in electricity. This paper aims to develop and propose an intelligent machine learning framework, IntelliForecast, that integrates feature engineering with advanced machine learning models for short-term electricity load forecasting. Specifically, we propose two algorithms: Hybrid Feature Engineering (HFE) for selecting significant features and Learning-based Electricity Load Forecasting (LbELF) for efficient forecasting. Empirical results reveal that the IntelliForecast framework achieved the highest forecasting accuracy of 95.60% for hourly predictions using a Neural Network model optimized with Random Search Optimization (RSO), outperforming Multilinear Regression (MLR) and standalone Neural Network (NN) models. Additionally, the framework reduced Mean Absolute Percentage Error (MAPE) to 0.0169, showcasing its robustness in accurate and efficient forecasting. Our framework can be embedded into modern smart meters, enabling real-time forecasting and facilitating energy trading.

Keywords: Electricity Load Forecasting, Machine Learning, Artificial Intelligence, Feature Engineering, Smart Grid

1. Introduction

Numerous opportunities are emerging due to the power system's rapid development of new infrastructure. An intelligent power grid is a sophisticated power transmission and distribution network that uses control, communication, and information technologies to increase the grid's economy, efficiency, dependability, and security [1]. Many governments worldwide now prioritize replacing or upgrading outdated energy systems from several decades ago using smart grid technology.

One of the main forces behind an SG is information technology (IT), and various IT systems and methodologies, including AI, HPC, data mining, data warehousing, and database management, can be employed to support the efficient operation of an SG [2]. Because of this, there is a significant gap between the expected and actual results of the SG. This gap will need to be filled in the coming years by combining the expertise of IT and energy experts to develop technologies that support these new scenarios. These technologies will include (i) innovative algorithms. (ii) grid monitoring and controlling. (iii) Technology-driven approaches are to be used locally.

Most attributes and suggested situations rely on rapid, precise, and trustworthy energy forecasts. Understanding the specific output and/or consumption of commercial and residential buildings, businesses, and distributed power plants is necessary for distributed demand and supply to work. However, the cost of collecting this data is relatively significant regarding workforce and equipment. However, with the widespread implementation of smart metering in the emerging smart grid, energy firms may now use remote metering to obtain minute-by-minute precision on energy output and/or consumption in every household. Consequently, gathering and analyzing time-series data to create forecasts based on past values is possible. This one is more accurate, scalable, and non-intrusive than previous forecasting techniques. We show that our models are scalable across various consumption profiles and validate them using actual power usage data. Regarding short-term power consumption forecasting, a wide range of approaches have been used, and their results have outperformed those of conventional methodologies. In particular, it has been demonstrated that machine learning can reliably forecast uncertain electricity usage. Implementation is impacted by computational complexity. Alternative models prioritizing simplicity and precision, such as FNT trained by MOO, compete [3]. Power plants require accurate short-term load forecasting (STLF), especially when using intermittent renewable energy sources. The report offers valuable information, a workable model for Panama's electrical infrastructure, and suggestions for broader uses [4]. SVM and ANN, two types of machine learning, perform better. The research emphasizes sustainable planning by tying together energy consumption, the economy, and the environment [5]. An innovative machine-learning algorithm maximizes MAPE with a 17% gain [6]. Short-term forecasting uses a unique CNN-based approach that uses statistical characteristics better than LSTM, especially in scenarios with little data [7]. By outperforming SVM and RF, deep learning improves grid management and renewable energy adoption decisions [8]. RBF kernel and other machine-learning models have also proven successful [9]. A unique hybrid model combines FCRBM forecasting, GWDO optimization, and MMI-based feature selection. Significantly outperforms benchmark models in terms of accuracy and pace of convergence [10]. The literature review observed a need to improve short-term electricity load forecasting efficiency by exploiting feature engineering and ML models. Our contributions to this paper are as follows.

1. We proposed an ML framework known as IntelliForecast, which is equipped with a feature engineering methodology and ML models such as Neural Networks (NN), Multilinear Regression (MLR), and NN, along with Random Search Optimization (RSO).
2. We proposed two algorithms: hybrid Feature Engineering (HFE) and learning-based Electricity Load Forecasting (LbELF). The former is meant to select features that contribute to improving the efficiency of ML models for forecasting, while the latter is intended to perform actual forecasting of electricity load.
3. We built an application to test our framework and achieved the highest accuracy, 95.60%, compared to state-of-the-art methods. Our framework can be embedded into modern smart meters for short-term forecasting and helps traders trade excess energy.

The paper is structured as follows: Section 2 reviews the literature, while Section 3 covers our proposed methodology. Section 4 presents the results of our empirical study. Section 5 discusses the work in this paper and provides the study's limitations. Section 6 concludes our work and bestows possible future scope.

2. Related Work

This section reviews prior works on forecasting electricity load. Jawad *et al.* [1] observed that the cost of electricity is determined by wind, nuclear, hydro, and petroleum sources. Planning at a cheap price is aided by accurate regional forecasts. The study by Muzaffarabad connects consumption to temperatures. Weather influences demand, and associated data improves forecasts, providing worldwide insights for economical electricity planning. Yildiz *et al.* [2] explored essential power load forecasting for commercial buildings, emphasizing improved ANLs for campus loads. Regression highlights the influence of occupancy while having trouble with peak demand. Vantuch *et al.* [3] found that electricity needs a perfect generation-demand balance because of its widespread use. Implementation is impacted by computational complexity. Alternative models prioritizing simplicity and precision compete, such as FNT trained by MOO. Madrid and Antonio [4] planned power plants require accurate short-term load forecasting (STLF), especially when using intermittent renewable energy sources. The report offers valuable information, a workable model for Panama's electrical infrastructure, and suggestions for broader uses. Solyali and Davut [5] observed that with smart grids in particular, electricity load prediction is essential for contemporary power systems. SVM and ANN, two types of machine learning, perform better. The research emphasizes sustainable planning by tying together energy consumption, the economy, and the environment. Future research should investigate GRU and LSTM techniques.

Adnan *et al.* [6] investigated decentralized power generation using smart grids and found that LF is essential. An innovative machine learning algorithm maximizes MAPE with a 17% gain. Andriopoulos et al. [7] found that electrical load forecasting is necessary for integrating renewable energy. Short-term forecasting uses a unique CNN-based approach that uses statistical characteristics better than LSTM, especially in scenarios with little data. Shizadi *et al.* [8] impact of climate change need precise medium- to long-term forecasting of power usage. Deep learning improves grid management and renewable energy adoption decisions by outperforming SVM and RF. Future research can evaluate other time-series techniques and investigate model enhancements. Aurangzeb [9] observed that it is difficult to forecast a single household's short-term power usage in a smart grid. RBF kernel and other machine learning models have proven to be successful. Hafeez et al. [10] found that accurate electric load forecasting is essential for power grid choices. A unique hybrid model combines FCRBM forecasting, GWDO optimization, and MMI-based feature selection. Significantly outperforms benchmark models in terms of accuracy and pace of convergence.

Wang *et al*. [11] investigated both ac and dc drives used in drilling rigs frequently that result in severe harmonic distortion, which can damage equipment. It was a passive filter that addressed problems well. Banitalebi *et al.* [12] précised electricity consumption forecasting is necessary to ensure uninterrupted supply. A two-phase approach improves the performance of neural networks and considerably lowers mean absolute error [13]. Bellahsen and Dagdougui [14] found that accurate energy demand forecasting is essential for system operations and cost reductions. The autocorrelation function (ACF), random forest method, and building-level data work together to improve accuracy and highlight the importance of historical and climatic factors. The calendar data shows little impact, perhaps because of collinearity. Lin *et al*. [15] investigated energy trading in deregulated electricity markets where accurate short-term load forecasting is essential. The suggested ensemble model outperforms benchmarks in accuracy by combining VMD and ELM and optimizing them using DE.

Garcia *et al.* [16] maintained the stability of the electricity system requires probabilistic load forecasting. Using various measures, we show that combining Association Rules and Neural Networks increases prediction intervals without sacrificing accuracy. Khwaja *et al*. [17] presented Bag-BoostNN, an ensemble machine-learning approach that outperforms current techniques by reducing bias and variation in short-term load forecasting by combining bagging and boosting. Ahmad *et al.* [18] suggested a cutting-edge deep learning-based method for predicting power load. Redundancy reduction, hybrid feature selection, and classification using optimized SVM and ELM are the three steps of a three-step model. The accuracy of the upgraded approaches is 10% and 7% greater than that of SOTA techniques. Kuster *et al*. [19] investigated 41 articles and 113 instances to compare models for electricity forecasting. Long-term research favors regression, but short-term research depends on machine learning, particularly time series analysis and artificial neural networks. A taxonomy is offered to help with the selection of an educated model. Singla et al. [20] used accurate load data from a 66kV substation to create a machine learning-based artificial neural network (ANN) for short-term load forecasting (STLF). Accurate findings are produced by the suggested technique, which helps with load control and system dependability.

Pallonetto *et al.* [21] evaluated the methods for short-term load forecasting by contrasting Support Vector Machines (SVM) with Long Short-term Memory Networks (LSTMs). The paper proposes possible hybrid models to increase accuracy and presents three prediction models for evaluating flexibility [22]. Future efforts will focus on finding anomalies and evaluating how demand response strategies affect flexibility building. Ertugrul and Faruk [23] presented the Recurrent Extreme Learning Machine (RELM), a tool for precisely forecasting power load. Regarding dynamic and time-ordered datasets, RELM performs better than standard approaches, exhibiting remarkable performance and faster and more excellent accuracy training. Dong et al. [24] presented a hybrid model that combines kernel density estimation, deep belief network, and K-nearest neighbors (KNN). Tackling high computing costs and deterministic restrictions improves the efficiency and accuracy of deep learning forecasting. Experimental data validate its superiority and resilience. Kalbitzer *et al.* [25] discussed precise electric demand forecasting in the context of the Smart Grid and suggested a two-phase methodology that combines SVM classification with feature engineering (XGBoost and Decision Tree). The results indicate a 98% accuracy rate in predicting market data.

Hwang *et al.* [26] focused on accurately estimating the power used by 28 business buildings. A two-step machine learning model achieves >27.5% improvement in accuracy, significantly outperforming current approaches and supporting efficient power grid management. Eseye *et al.* [27] provided a Binary Genetic Algorithm-based machine learning feature selection method for precise short-term electricity demand forecasting in decentralized energy systems. The approach beats the competition and achieves a promising MAPE of 1.96%. Cao *et al.* [28] précised that estimating energy usage in healthcare facilities is essential. Particularly at finer temporal granularities, two ensemble models—XGBoost and Random Forest—performed better than the others. Key variables were determined using feature analysis. Bouktif *et al.* [29] forecasted the short-term electric load is essential to utility efficiency. Using GA and PSO tuning, LSTM deep learning models surpass benchmarks and enhance accuracy by optimizing input sequences. Luo *et al.* [30] explored electrical load predicted using a self-adaptive deep learning model with dynamic architecture for reliable and accurate forecasts. This model makes use of RSPSO.

Saxena *et al.* [31] ordered to help with cost reductions and effective demand response measures, a hybrid model that combines ARIMA, logistic regression, and artificial neural networks precisely predicts peak electric load days. Arens *et al*. [32] suggested a home energy management system (EMS) that uses a linear algorithm to optimize the cost of power. The EMS enhances performance and cost savings when secondary EV consumption profiles are integrated with a precise load forecast algorithm. Future studies must examine cost estimations, real-world EV mobility patterns, and uncertainties. Chen *et al.* [33] presented a novel approach for precise short-term electrical load forecasting: theory-guided deep-learning load forecasting (TgDLF). Future studies will examine how well TgDLF computes and whether it can be used under unusual load circumstances. Elkamel *et al.* [34] focused on accurate energy projections that facilitate the planning of electrical power, averting surplus generation. The success of a multichannel CNN model highlighted model selection and variable relevance in forecasting.

Tong *et al*. [35] used to support vector regression and layered denoising auto-encoders, a deep learning model that outperforms simple SVR and ANNs in improving day-ahead electrical load predictions.

Shen *et al*. [36] worked on the increased power load forecasting accuracy using the SELNet ensemble model, which combines deep learning and data processing. When tested in Texas, it performs better than other models, demonstrating its efficacy all year round. Gul *et al.* [37] used a Korean dataset to test ARIMA and CNN-Bi-LSTM models focusing on mid-term predictions. Through hyperparameter optimization, the models demonstrate potential gains in accuracy. Yeom and Kwak. [38] presented a TSK-ELM that incorporates autonomous knowledge representation for short-term electricity-load forecasting. Experimental data shows it performs better than traditional ELMs, especially when using hybrid learning techniques. Subsequent investigations seek to combine ELM with deep learning for practical problem-solving. Das *et al*. [39] stated that a significant worldwide energy user depends on HVAC and Miscellaneous Electric Loads (MEL). Deep Learning prioritizes GRU and Bi-LSTM models for larger prediction horizons to maximize energy management. Ghimire *et al*. [40] integrated a hybrid multi-algorithm framework that combines ANN, EDLSTM, and ICMD to accurately forecast energy demand (G). Surpasses standards, improving market analysis and identifying seasonality. The literature review observed a need to enhance short-term electricity load forecasting efficiency by exploiting feature engineering and ML models.

Mathumitha *et al.* [41] thoroughly analyzed innovative building energy consumption forecasting techniques, emphasizing residential and commercial sectors. It addresses issues like occupant behavior, load variations, and weather variability. Several forecasting methods are examined in the research, focusing on how well deep learning (DL) models—in particular, deep neural networks, or DNNs—improve prediction accuracy. Multivariate analysis is used in the suggested hybrid model to improve forecasting. A new deep-learning technique will be created in future research to further increase residential building accuracy. Rifat et al. [42] presented PredXGBR-1, a short-term load forecasting model that predicts hourly electrical demand using Extreme Gradient Boosting (XGBoost) with short-term lag characteristics. The model achieves an R2 value of 0.99 and a mean absolute percentage error (MAPE) of 0.98–1.2%, outperforming conventional techniques and other machine learning models like LSTM. The ability of the suggested model to adjust to changes in demand is its main advantage. Further optimizations may be investigated in future research; however, there may be difficulties with long-term forecasting and model scalability. Gang *et al.* [43] addressed the shortcomings of conventional approaches by integrating machine learning techniques into its SVR-based framework for forecasting regional power consumption. Using actual data from China's Guangdong Province, the solution was evaluated. The findings indicate that socioeconomic development and weather variability influence demand variations. The predictive accuracy of the SVR model is higher than that of other models. The study highlights the significance of local economic variables and recommends that future investigations look at other machine-learning methods and the consequences of low-carbon economic growth. Moises *et al.* [44] assessed many AI methods (RF, SVR, XGBoost, MLP, LSTM, and Conv-1D) for predicting building electrical loads to maximize energy efficiency. LSTM performs better than other models with fewer errors, according to test results on a single-family home in the United States. A key factor in LSTM's effectiveness is its effective modeling of historical input features. The study emphasizes that LSTM and other deep learning (DL) models perform better than machine learning (ML) models. The requirement for more extensive validation, hyperparameter adjustment, and power profile adaption are among the limitations. Future research might concentrate on system integration and real-time forecasting. Wen *et al*. [45] suggested a hybrid deep learning approach to enhance short-term power demand forecasting for smart grids by combining Temporal Convolutional Networks (TCN), Gated Recurrent Units (GRU), and an attention mechanism. The approach achieves above 95% accuracy on several datasets and reduces parameters, FLOPs, and inference time by up to 48.8%, outperforming baseline models. The method improves cost-effectiveness, stability, and efficiency for smart grid operations. Future research should investigate different datasets to enhance model interpretability and generalizability. One of the limitations is the reliance on datasets. Karan Kumar *et al*. [46] introduced a Quantum Support Vector Machine (QSVM) for smart grid Home Energy Management Systems (HEMS) that estimates electricity load. The AMPD2 dataset is used for testing, and QSVM outperforms conventional forecasting techniques with an accuracy of 97.3% and low RMSE (0.14) and MAE (0.380). QSVM's capacity to manage intricate, nonlinear consumption patterns and generate accurate predictions is highlighted. Applying it to various datasets may be the subject of future research. One limitation is the inability to generalize findings to different datasets and contexts.

Arvind R. *et al*. [47] investigated using Support Vector Regression (SVR) to enhance energy management and power generation forecasts in grid-connected microgrids. The SVR model, tested on various energy sources, improved supply-demand balance by 10% and increased the usage of renewable energy by 12% while achieving lower error metrics than conventional techniques. There may be an opportunity for improvement as the model's accuracy was somewhat affected in some instances. Future research will integrate blockchain, IoT, and sophisticated machine-learning approaches to improve microgrid resilience and model performance. Wen and Liu [48] discuss the integration of prosumers into electrical grids in this research, emphasizing enhancing the accuracy of energy forecasting through cutting-edge techniques such as time series analysis, Fast Fourier Transform, and Light Gradient Boosting Machine models. The method increased forecasting by 9.4% and obtained an R2 of 0.96 when tested on Enefit's dataset. The study focuses on energy pattern temporal dynamics and feature selection. Future research could overcome dataset generalization and processing efficiency constraints by investigating additional predictive modeling and policy implications for prosumer integration. M.Zulfiqar *et al*. [49] proposed a hybrid short-term load forecasting (STLF) model that improves forecasting accuracy, stability, and convergence by combining locally weighted support vector regression (LWSVR) with feature engineering (FE) and adaptive grasshopper optimization (AGO).

The model outperformed previous models, exhibiting higher accuracy and computing efficiency when tested on data from Australia and the United States. However, the model's failure to consider additional significant elements limits its applicability. Future research will incorporate dynamic model selection, integrating renewable energy, and adding more characteristics. Gaurav and Nuttanan [50] evaluated machine learning models (LSTM, GRU, XGBoost, LEAR, and DNN) and statistical models (GARCH, SV) for daily electricity price predictions in New Zealand. The research demonstrates that GARCH and SV models outperform machine learning methods, increasing predicting accuracy by 2-3% over LEAR, particularly when feature selection approaches are used. Among the models' drawbacks is their simplicity compared to more sophisticated methods; further research should include hourly forecasting, hybrid model ensembles, and sophisticated statistical models.

3. Proposed Methodology

We proposed a framework based on ML models and feature engineering for efficient electricity load forecasting. Our framework, illustrated in Figure 1, is known as IntelliForecast. The framework takes a historical electricity consumption dataset and performs various activities such as exploration and cleaning, time series analysis, feature engineering, and load forecasting. Exploration of the dataset is required to analyze data and find the need for pre-processing. Cleaning makes the dataset more relevant by removing missing data and eliminating redundant instances. After completion of pre-processing, time series analysis is performed on the data for possible decomposition, statistical tests are performed to visualize trends in the data, and autocorrelation is reflected in the given data. As part of time series analysis, a test known as Augmented Dickey-Fuller (ADF) is carried out to enable a higher-order regressive process. Subsequently, the framework has provision for feature engineering, which results in the best features and then forecasts the electricity load using ML models.

Neural Network (NN), Multilinear Regression (MLR), and NN with Random Search Optimization (NNRSO) are the three ML models used in the framework for forecasting based on their prediction capabilities. To identify the qualities that have the most significant influence on the accuracy of future consumption value predictions, feature engineering is used to identify contributing features. Different experiments are then constructed for electricity load forecasting.

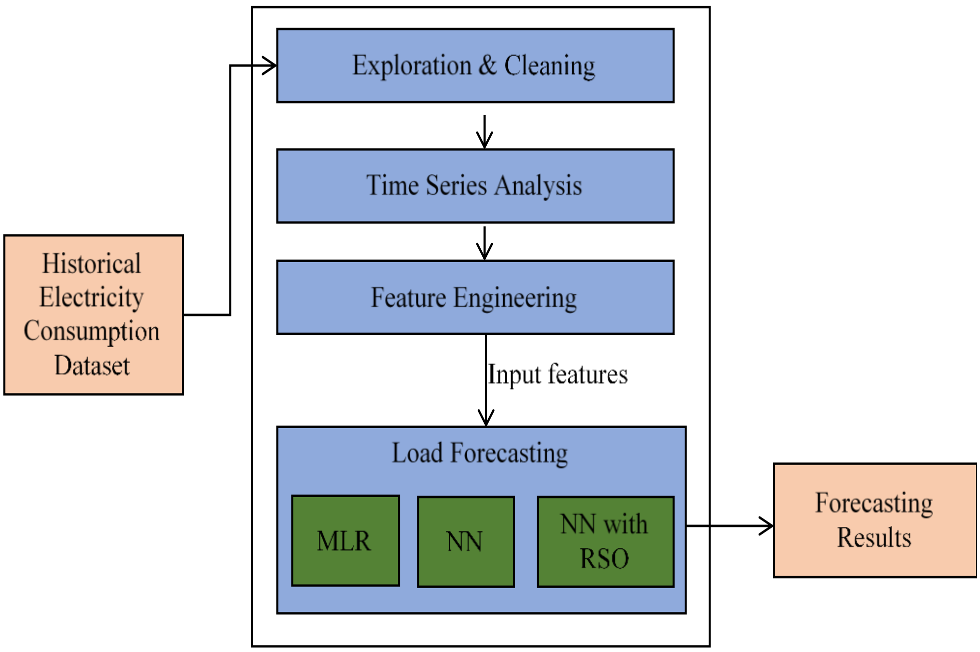


Figure 1. Proposed framework known as IntelliForecast for electricity load forecasting

We integrate the chosen historical consumptions to provide features to different modeling methodologies. The feature selection used in this study is to improve the performance of ML models. It involves identifying the most significant features for models by defining a hybrid feature selection method that exploits Pearson correlation as the filter method and Random Forest as the wrapper method.

3.1 Hybrid Feature Engineering

We proposed a hybrid feature engineering method based on a filter and wrapper combination. The filter method is based on Pearson correlation, while the wrapper uses the RF method. The Pearson correlation quantitatively indicates the linear association between two variables. Its value ranges from -1 to 1, with a value nearer negative or positive 1 signifying a strong linear connection. The linear correlation based on the Pearson correlation coefficient (r_{XY}) may be computed using Equation (1). The range of the data illustrating the link between the two variables gets smaller as r_{XY} rises. The values of the two variables are near the straight line if r_{XY} is near the absolute value of 1, strengthening the linear connection between the two variables. The data gets more dispersed as r_{XY} declines. There is no linear association between the two variables when r_{XY} is 0.

$$r_{XY} = \frac{\sum_{i=1}^{Z}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{Z}(X_i-\bar{X})^2}\sqrt{\sum_{i=1}^{Z}(Y_i-\bar{Y})^2}} \quad (1)$$

Where z is the quantity of observations, X and Y are variables, and X and Ȳ represent the averages of X and Y.

An ensemble learning technique called random forest creates numerous decision trees by randomly sampling learning-only data. It compiles the decision tree results and uses a majority vote to determine the outcome. Continuous learning makes up for the drawbacks of decision trees, whose outcomes vary greatly depending on the training set. Additionally, a feature concentrates more on the incorrect response from prior learning. Random forest generates different decision trees by bagging and randomized node optimization. When creating a decision tree, one technique to choose specific data points and base choices only on them is bagging. It is said as follows:

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x'), \quad (2)$$

When f_b denotes a regression tree, x' is the average prediction overall regression trees, and B stands for the total number of trials. A few of the input variables are chosen at random, rather than all, at each split node of a decision tree. To build decision trees and a randomly created forest, repeat this method. Randomized node optimization minimizes the variance in tree performance and finds branches to split by focusing on specific aspects while setting criteria for node data division. This is a result of a decreased connection between individual trees. Pruning is unnecessary because of this, enabling excellent accuracy and quick and easy learning and testing.

3.2 Machine Learning Models

The proposed framework, shown in Figure 1, uses MLR, NN, and NN with RSO for electricity load forecasting [51]. The MLR model [52] is a probability-based approach in which logit transformation is employed, as expressed in Eq.3 and Eq. 4.

$$Logit(pi) = 1/(1 + exp(-pi)) \quad (3)$$

$$Ln(pi/(1 - pi)) = Beta\_0 + Beta\_1 * \times\_1 + \ldots\ldots + B\_k * K\_k \quad (4)$$

In MLR, logit(pi) is the response variable, while x is the independent variable. It uses a coefficient or beta variable, which is estimated using maximum likelihood estimation. It has an iterative approach to convergence. The eventual model is represented in Eq. 5.

$$\log\frac{y_{n,t+1}}{1-y_{n,t+1}} = [X_{n,,t}, y_{n,t}]\theta_n + \epsilon_n \quad (5)$$

Where regression coefficients are denoted as $\theta_n = (\theta_{n,1}, \theta_{n,2}, \ldots\ldots, \theta_{n,k+1})^T$. Random errors are denoted as ϵ_n. At a givn time $X_{n,,t}$ *and* $y_{n,t}$ are used to predict $y_{n,t+1}$.

Neural Network (NN) [53] is a model based on the human brain's neurons. It has a layered approach consisting of input, hidden, and output layers. Each layer of the network gets its inputs from the previous layer. The inputs of different nodes in a given layer are combined using a weighted approach. The linear weighted combination can be expressed as in Eq. 6.

$$z_j = b_j + \sum_{i=1}^{4} w_{i,j}x_i. \quad (6)$$

About the hidden layer, a nonlinear function is employed to generate output for the next layer, as expressed in Eq. 7. It is similar to a Sigmoid function to reduce the effect of inputs and ensure that the network is free from outliers.

$$a_j = \frac{1}{1+exp(-(b_j+\sum_{i=1}^{4} w_{i,j}x_i))} \quad (7)$$

NN with RSO [54] exploits Random Search (RS) for hyperparameter optimization. Since hyperparameters of any ML model can be tuned based on the dataset available, optimization based on RS has its significance. The optimization process involves backpropagation, and the hyperparameter optimization procedure's generalization error can be expressed as in Eq. 8.

$$\mathbb{E}_{X\sim\mathcal{G}_x}\left[L\left(X;\ A_\lambda\left(X^{(train)}\right)\right)\right], \quad (8)$$

$$\lambda^* = \arg\min_{\lambda\epsilon\Lambda} \mathbb{E}_{X\sim\mathcal{G}_x}\left[L\left(X;\ A_\lambda\left(X^{(train)}\right)\right)\right] \quad (9)$$

The process can be expressed in Eq. 9 in the given hyperparameter space. The RSO approach used with NN for parameter optimization is expected to influence forecasting performance.

3.3 Proposed Algorithms

We proposed two algorithms: hybrid Feature Engineering (HFE) and learning-based Electricity Load Forecasting (LbELF). The former is meant to select features that contribute to improving the efficiency of ML models for forecasting, while the latter is intended to perform actual forecasting of electricity load.

Algorithm 1. Hybrid Feature Engineering (HFE)

Input: Historical electricity consumption dataset D, threshold th
Output: Selected features F
1. Begin
2. F←GetFeatures(D)
3. For each feature f in F
4. score←ApplyFilterMethod(f, F)
5. If score<th Then
6. remove f from F
7. End If
8. F←ApplyWrapper(F)
9. Return F
10. End

As presented in Algorithm 1, it takes historical electricity consumption dataset D and threshold th (empirically determined) as inputs and returns selected features that contribute to efficient forecasting. It uses the filter method (Pearson correlation) and wrapper method (RF) hybrid approach to finalize contributing features.

Algorithm 2. Learning-based Electricity Load Forecasting (LbELF)

Input: Historical electricity consumption dataset D, ML pipeline P
Output: Results of electricity load forecasting R, performance statistics P
1. Begin
2. (T1, T2)←SplitData(D)
3. F←Apply HFS(T1)
4. For each model m in P
5. Train the model m
6. R←Forecast(T2)
7. P←Evaluate(ground truth, R)
8. Display R
9. Display P
10. End For
11. End

As presented in Algorithm 2, it takes historical electricity consumption dataset D and ML pipeline inputs and performs forecasting. The given dataset is divided into two parts, known as training data T1 and test data T2. The feature selection algorithm is applied to choose the best features. ML models use the selected features for efficient learning and forecasting. The algorithm uses MLR, NN, and NNBSO models as pipelines. Each model is trained with selected features and then used for forecasting.

3.4 Evaluation Methodology

Several metrics evaluate the performance of the ML models used in the empirical study. They include the R2 score, Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Mean Absolute Error (MAE).

$$R^2 = 1 - \frac{RSS}{TSS} \tag{10}$$

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{11}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{12}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{13}$$

The coefficient of determination (R2), as expressed in Eq. 10, measures how well an ML model is in forecasting. A higher R2 score indicates better performance. As expressed in Eq. 11, MAPE is used to measure forecasting accuracy. A lower MAPE value means better performance. MSE, as described in Eq. 12, shows the average squared difference between forecasted and actual electricity load. A lower MSE indicates better performance. MAE, as expressed in Eq. 13, is used to show the mean absolute difference between forecasted and actual electricity load. A lower MAE indicates better performance.

4. Experimental Results

This section presents the experimental results of the proposed framework and compares it with existing methods. Experiments are made with the dataset collected from [51]. The results are observed in terms of time series analysis and electricity load forecasting using three ML models: Neural Network (NN), Multilinear Regression (MLR), and NN with Random Search Optimization (NNRSO). The experiments were conducted using an hourly resolution for electricity load forecasting. The proposed IntelliForecast framework demonstrated consistent performance across all time intervals, with the highest forecasting accuracy of 95.60% observed in hourly predictions using the NNRSO model. The evaluation metrics, including R^2 (0.9775) and MAPE (0.0169), further confirm the robustness of the model for hourly forecasting. Future work may explore extending the framework for multi-day or weekly aggregation predictions.

4.1 Time Series Analysis

Decomposition and trend analysis are made to visualize trend analysis, while partial autocorrelation and autocorrelation are carried out to visualize and know the degree of similarity. Figure 2 presents trends in the time series data linked to the historical electricity consumption dataset.

As presented in Figure 3, visualization of the results of partial autocorrelation is provided to reveal the degree of similarity to ascertain the lagged version of time series data against successive periods.

As presented in Figure 4, autocorrelation results are visualized to reveal the degree of similarity and ascertain a lagged version of time series data against successive periods.

As presented in Figure 5, the correlation among features is visualized. Correlation among variables can have an impact on forecasting capabilities. For instance, the higher correlation between two features reflects that if one feature is modified, it is affected in the other variable.

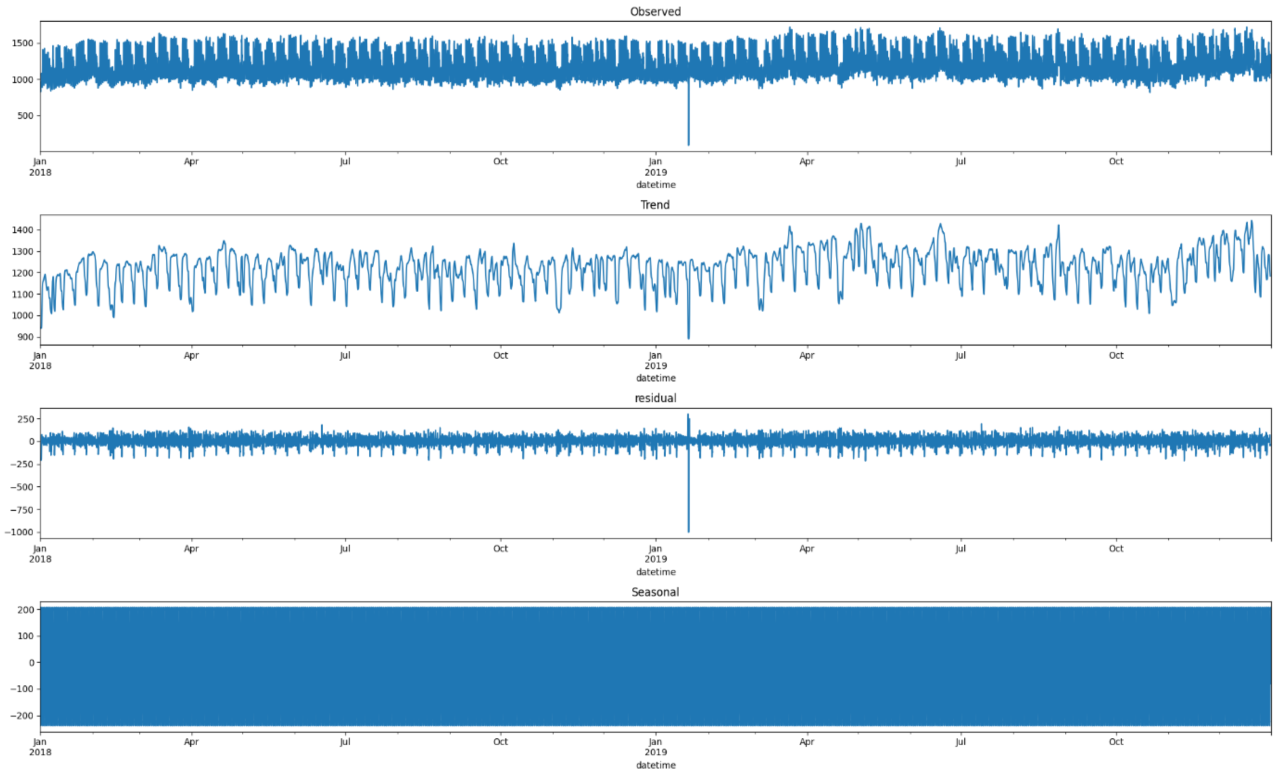


Figure 2. Visualization of trend analysis

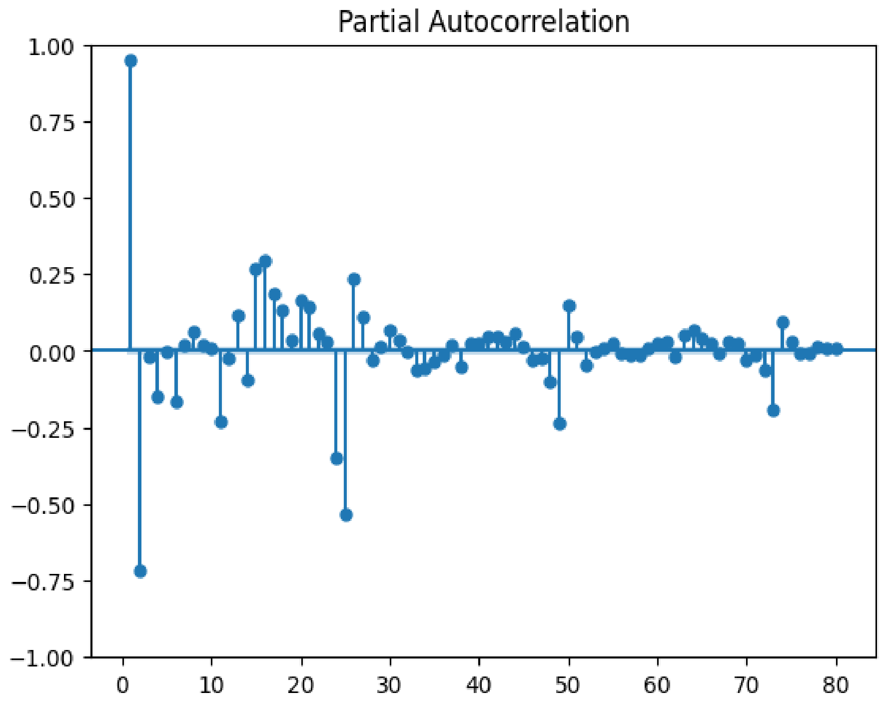


Figure 3. Visualization of partial autocorrelation analysis

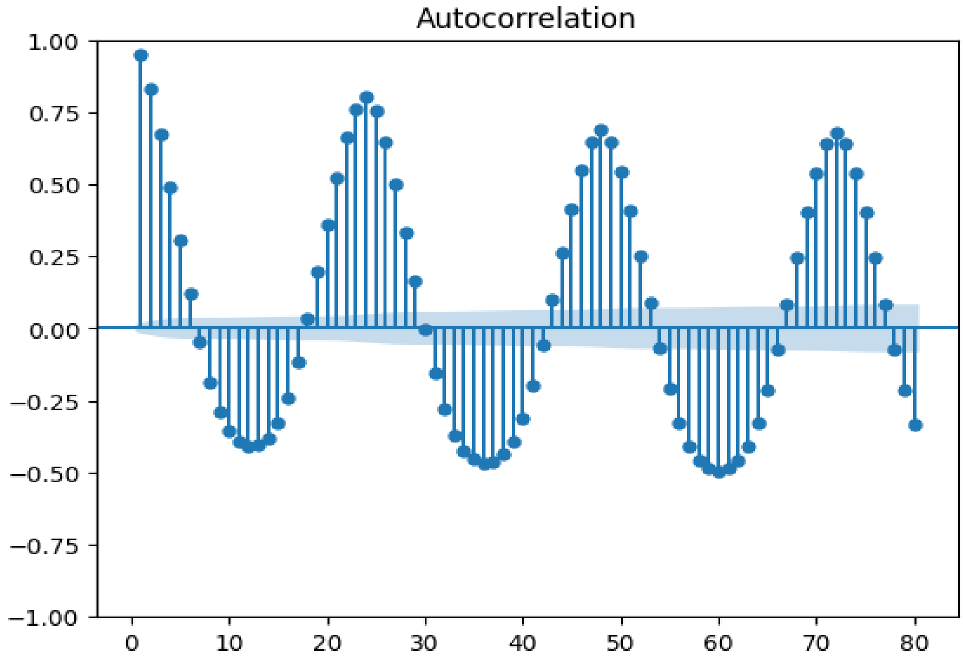


Figure 4. Visualization of autocorrelation analysis

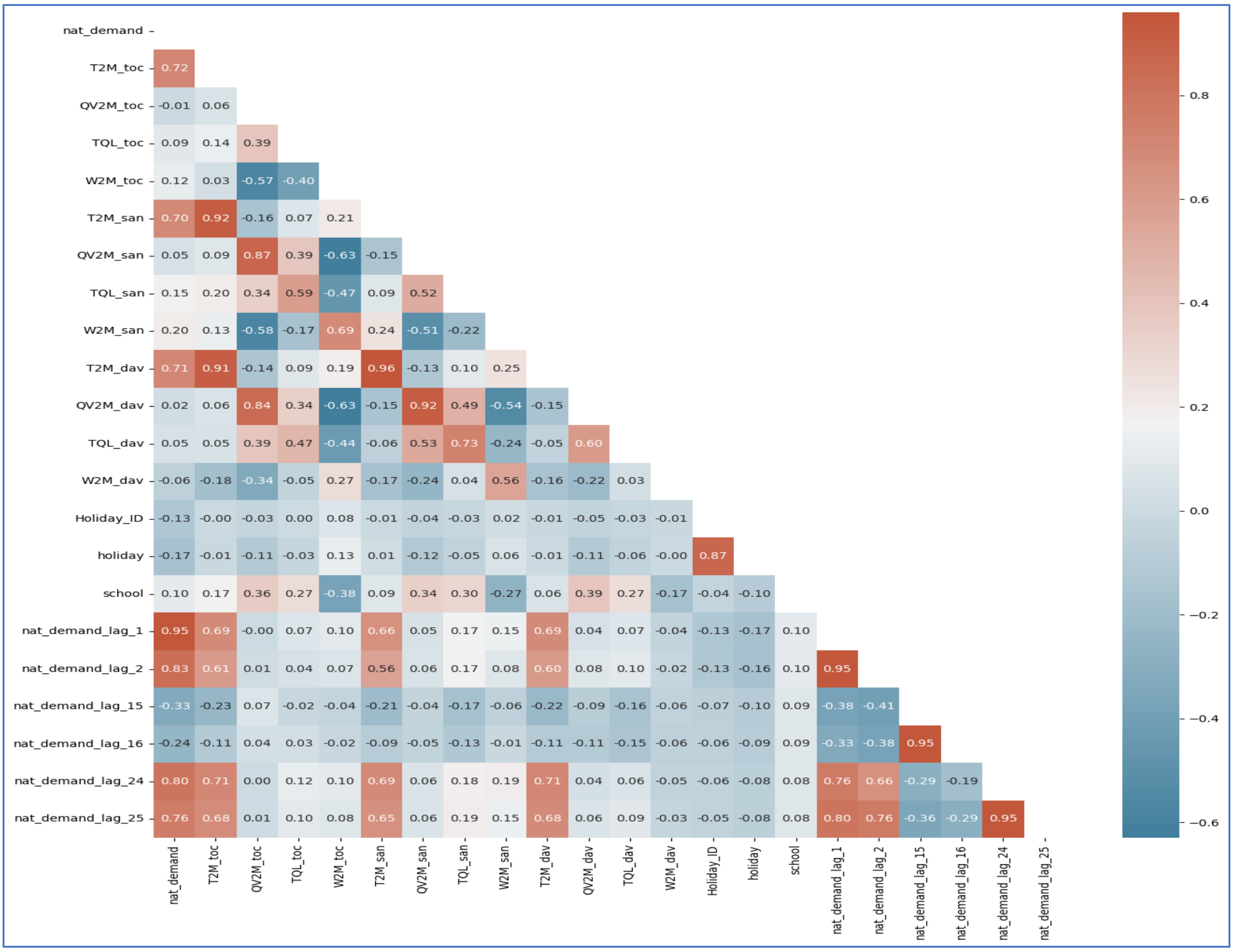


Figure 5. Correlation plot showing feature correlations

4.2 Results of Forecasting

This section presents the results of electricity load forecasting from different ML models used in the empirical study. All these models are enabled with the proposed feature engineering methodology for leveraging forecasting performance.

Figure 6 presents the MLR model's forecasting performance. The actual load and forecasted load are in megawatt-hours (MWh). A lower difference between actual and predicted load indicates better forecasting performance.

Figure 7 presents the MLR model's forecasting performance. The actual load and forecasted load are in megawatt-hours (MWh). A lower difference between actual and predicted load indicates better forecasting performance.

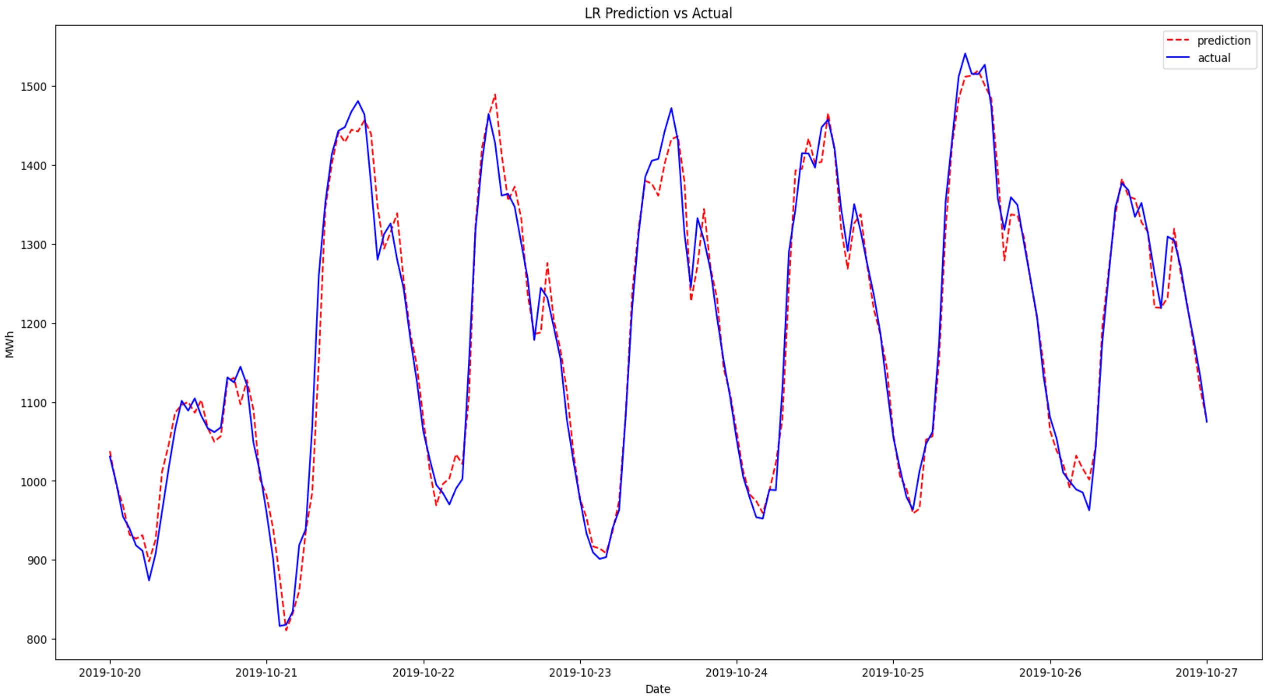


Figure 6. Forecasting performance of MLR model

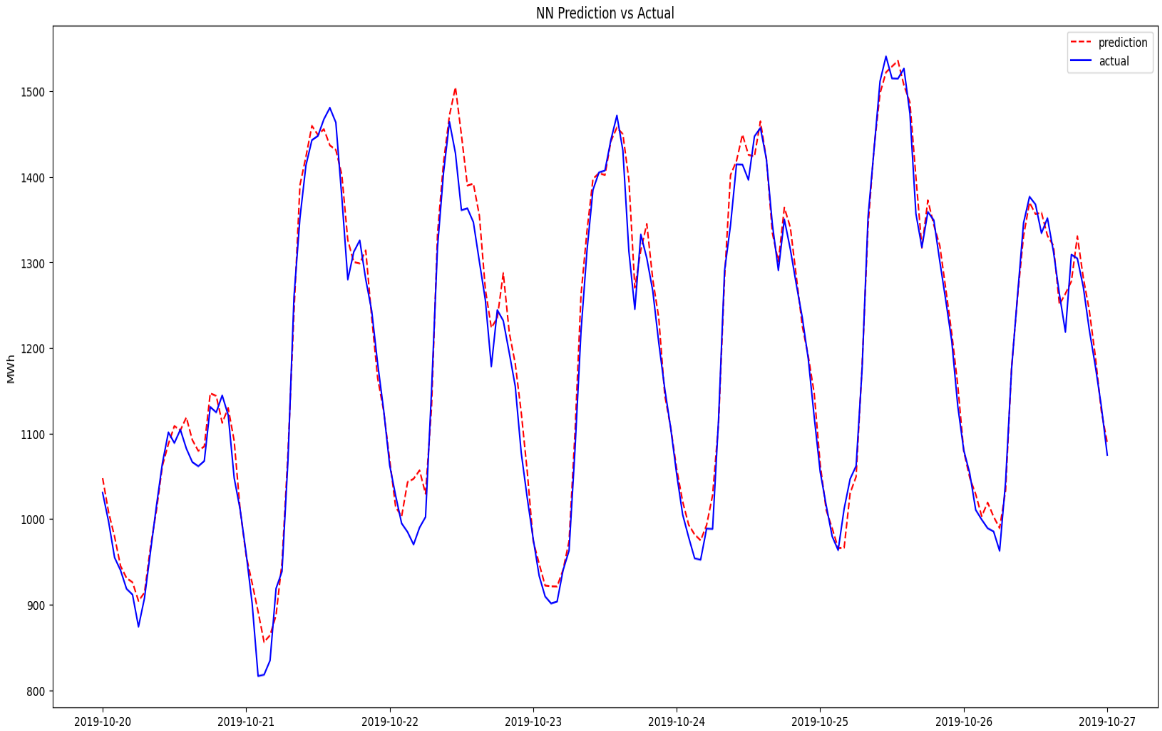


Figure 7. Forecasting performance of the NN model

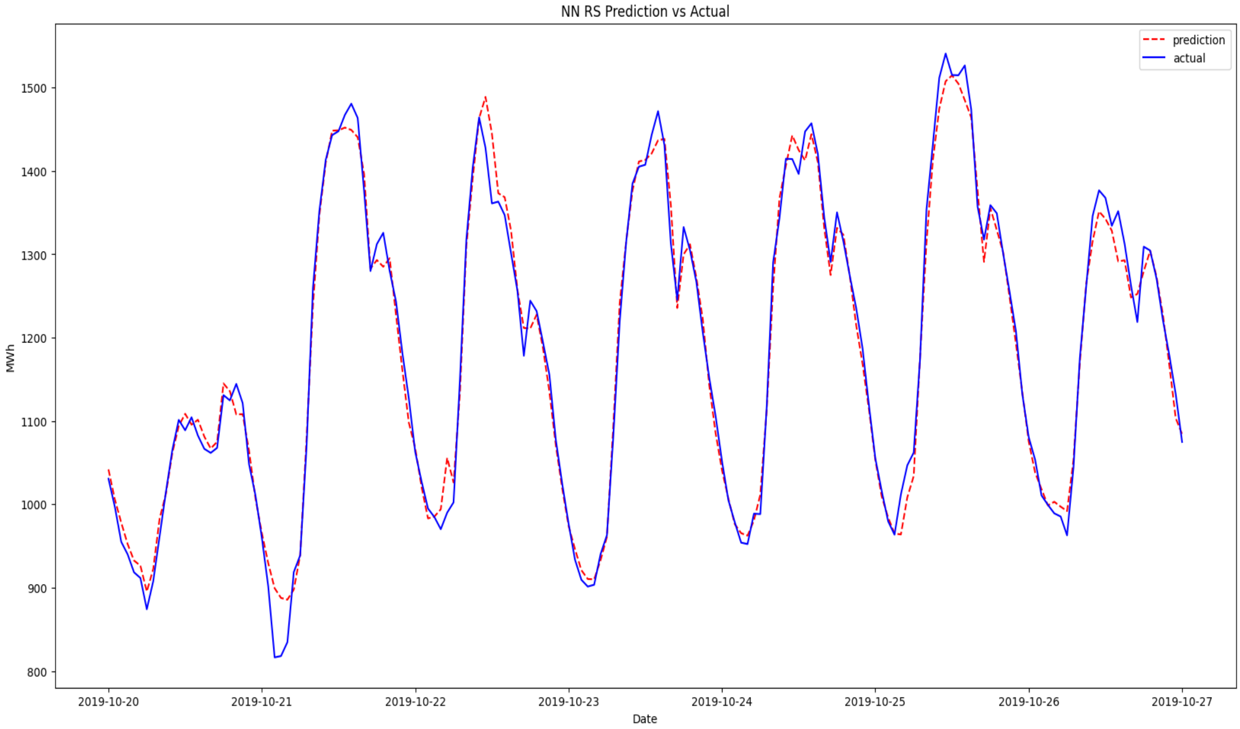


Figure 8. Forecasting performance of NNRSO model

Figure 8 presents the NNRSO model's forecasting performance. The actual load and forecasted load are in megawatt-hours (MWh). A lower difference between actual and predicted load indicates better forecasting performance.

4.3 Performance Comparison

This section presents performance comparisons among various ML models used in this study. Observations are made in terms of different performance metrics discussed in Section 3.4. Each model is found to have different performances based on its modus operandi in forecasting electricity load.

Table 1 presents performance comparisons among ML models regarding R2, MAPE, MSE, and MAE.

As presented in Figure 9 (a), the performance of three ML models in forecasting the electricity load is observed in terms of the R2 score. MLR method showed 0.9716 as the R2 score, the NN model achieved 0.9766, and the NNRSO could achieve the highest R2 score with 0.9775. A higher R2 score indicates better performance. NNRSO outperformed the other two models due to its approach to hyperparameter optimization toward performance enhancement. As presented in Figure 9 (b), the performance of three ML models in forecasting electricity load is observed in terms of MAPE. MLR method showed 0.0184 as MAPE, the NN model achieved 0.0173, and the NNRSO could achieve the highest MAPE with 0.0169. A lower in the MAPE indicates better performance. NNRSO outperformed the other two models due to its approach to hyperparameter optimization toward performance enhancement.

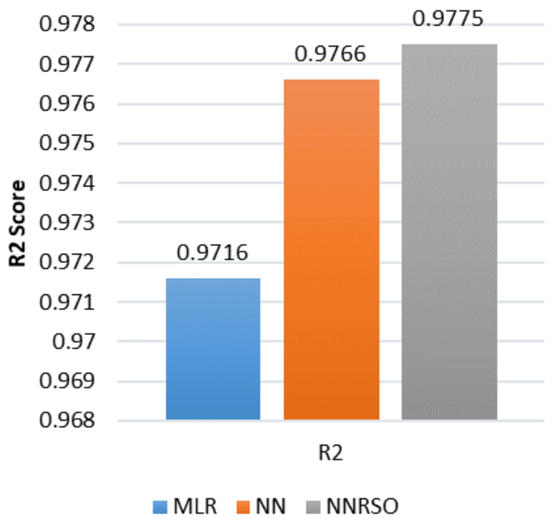
As presented in Figure 9 (c), the performance of three ML models in forecasting electricity load is observed in terms of MSE. MLR method showed 1032.8347 as MSE, the NN model achieved 850.8084, and the NNRSO could achieve the highest MSE with 817.1749. Lower in the MSE indicates better performance. NNRSO outperformed the other two models due to its approach to hyperparameter optimization toward performance enhancement. Figure 9 (d) shows three ML models' performance forecasting electricity load observed regarding MAE. MLR method showed 23.0518 as MAE, the NN model achieved 21.6164, and the NNRSO could achieve the highest MAE with 21.5433. A lower in the MAE indicates better performance. NNRSO outperformed the other two models due to its approach to hyperparameter optimization toward performance enhancement.

5. Discussion

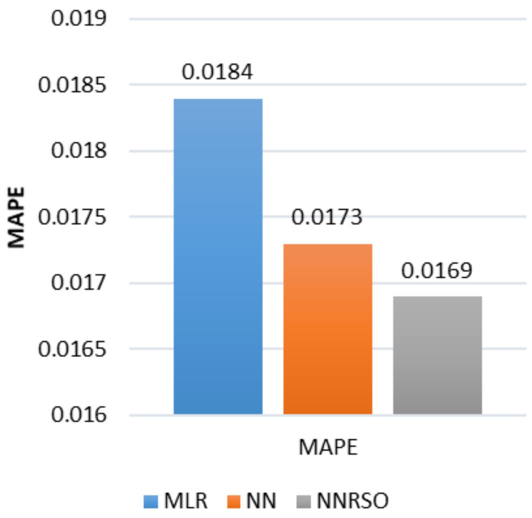
The proposed IntelliForecast framework exhibited strong forecasting performance, notably with the NNRSO model finding the best accuracy at 95.60% and the lowest MAPE for 0.0169 among examined models. The reasons for this improved performance are twofold: (I) hybrid feature engineering (HFE) enhances the model's ability to focus on relevant attributes, and (II) Random Search Optimization (RSO) efficiently tunes hyperparametric values to improve generalization capability.

Table 1. Performance comparison among ML models

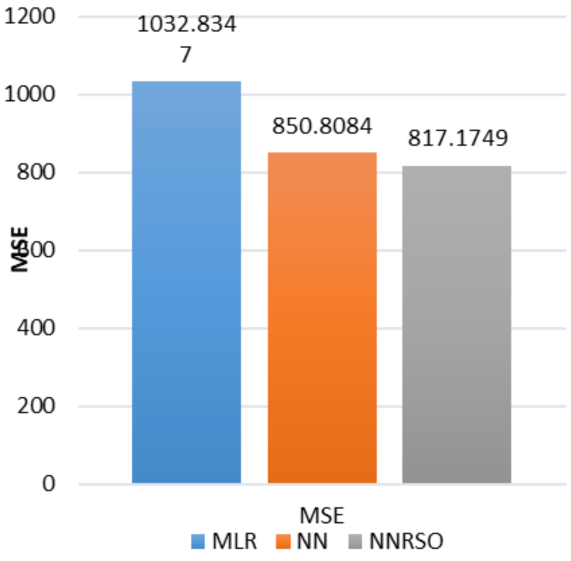
Forecasting Model	Performance			
	MAPE	MAE	MSE	R2
MLR	0.0184	23.0518	1032.835	0.9716
NN	0.0173	21.6164	850.8084	0.9766
NNRSO	0.0169	21.5433	817.1749	0.9775



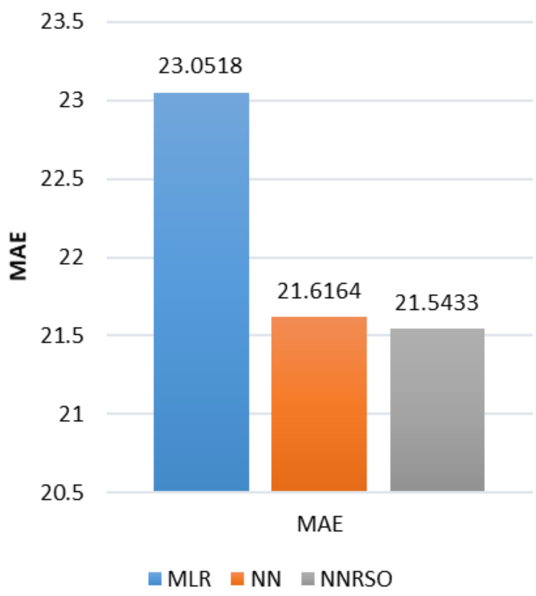
(a) R2 Score Comparison



(b) MAPE Comparison



(c) MSE Comparison



(d) MAE Comparison

Figure 9. Performance comparison of all ML modes

HFE is effective because it considers the Pearson correlation in a filter method and Random Forest importance scores in a wrapper method. This combined mechanism enables only statistically and model-wise relevant features to be chosen, making it robust to noise and helping to combat overfitting. Thus, the NN and NNRSO models got better learning and predictive capabilities due to diversified input features.

From the view of modeling, neural network architectures inherently show great superiority over traditional regression models, such as MLR, in identifying non-linear dependencies and temporal trends in electricity consumption data. This case with the NNRSO model also demonstrates the increment, although within slight difference when accounted with statistical tests, in performance due to hyperparameter tuning, which is reported in multiple works. For example, in previous studies done by Adnan et al. [6] and Hafeez *et al.* [10], it has been proven that optimization approaches, such as metaheuristics, enhance forecasting performance as they have been capable of optimizing model parameters significantly better than hand-made or grid search options.

These findings of the work of Bouktif *et al.* [13] and Wen *et al.* [45] show that when deep learning models are used in conjunction with comprehensive feature selection or selection approaches, the accuracy in prediction increases significantly. But unlike studies like Das *et al.* [39], which highlighted gated recurrent units and bidirectional LSTM models for long-horizon forecasts, the current study explicitly targets short-term, hourly time-step forecasts. In this light, shallow ANN models with appropriate feature engineering and hyperparameter tuning were enough and computationally efficient.

The existing methodology is also considerably different from the hybrid ensembles or data transformation-based approaches. For instance, Pallonetto et al. —The IntelliForecast framework kept consistent across time intervals. It retained a streamlined model structure, while hybrid models [9, 21] with statistical and learning techniques were thoroughly investigated to enhance peak load prediction and scalability. In the same spirit, ensemble-based models, such as the Bag-BoostNN model introduced by Khwaja et al. [17] and the hybrid three-stage approach introduced by Ahmad et al. While [18] obtained strong results, our single-model pipeline using NNRSO achieves similar accuracy with lower architectural complexity and cost of training. This gives credence to the idea that when properly input features are selected and optimized, few variables have the potential to outperform more complicated models.

From the perspective of differences, Wen and Liu [48] used prosumer datasets and employed time-frequency feature extraction. At the same time, the present study deployed traditional time-series decomposition and statistical correlation for feature engineering. While the methodology may differ extensively, the forecasting performance is competitive, illustrating that if fundamental aspects like feature selection and model tuning are made with precision, a more straightforward, faster approach can nevertheless return significant accuracy. These findings also support the conclusions of studies like Eseye *et al.* [27] and Zulfiqar *et al*. [49], highlighting the importance of feature engineering and adaptive optimization for scalable and accurate load forecasting models.

In conclusion, this study's empirical findings provide evidence that electricity load forecasting systems can be considerably improved through hybrid feature engineering and tuned neural network models. The results add to an increasing literature suggesting that well-designed, optimized implementations of shallow learning models may be adequate substitutes for more profound, resource-hungry platforms, especially for short-term forecasting situations in smart grid use cases.

5.1 Limitations

The findings of this paper inspire several future possibilities. For example, how data granularity, such as obtaining data in minutes, would affect prediction accuracy and what approach should be used in the feature selection process. Alternatively, how to handle the days that result in a substantial forecast error, further work will incorporate a more robust prediction procedure into the feature selection approach to address missing information more dependably. Another direction is that these models might be included in a subsequent generation of smart meters, enabling them to produce on-site predictions regarding energy production and/or consumption for the upcoming hours. Additionally, they could be used to exchange surplus energy with other smart meters.

6. Conclusion and Future Work

We proposed an ML framework known as IntelliForecast, which is equipped with a feature engineering methodology and ML models such as Neural Network (NN), Multilinear Regression (MLR), and NN along with Random Search Optimization (RSO). The framework has provisions for exploration and cleaning, time series analysis, feature engineering, and electricity load forecasting. We proposed two algorithms: Hybrid Feature Engineering (HFE) and Learning-based Electricity Load Forecasting (LbELF). The former is meant to select features that contribute to improving the efficiency of ML models for forecasting, while the latter is intended to perform actual forecasting of electricity load. An empirical study has revealed that the proposed framework achieved the highest performance with the NN model with RSO. Our framework can be embedded into modern smart meters for short-term forecasting and help trade excess energy. These results encourage the integration of our IntelliForecast framework into contemporary smart meters for online energy forecasting and trading approaches. Using mineral-level data (1min data) can also further boost this. Combining renewable energy sources with actual forecasting can also optimize generation features for the grid under changing supply conditions. Future work can improve the feature selection process for handling missing or noisy data, hybrid models capable of dealing with deep learning and statistical models for different prediction scenarios, or extend the framework for long-term predictions such as daily, weekly, or seasonal forecasts. Another promising direction for feature improvement is the development of real-time adaptive modules to respond dynamically to changes in consumption patterns and incorporate decision-making algorithms for energy trading and grid optimization.

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Authors Contribution Statement

G. Uday Kiran: conceptualization, investigation, Data Curation, Methodology, Software, Writing - Original Draft. V. Srilakshmi: conceptualization, investigation, Data Curation, Methodology, Software, Writing - Original Draft. B. Lavanya: Formal analysis, Writing - Review & Editing. B. Priyanka: Formal analysis, Writing - Review & Editing. All the authors read and approved the final version of the manuscript.

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Data Availability

The data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

Has this article screened for similarity?

Yes

Competing Interests

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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