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ENHANCING ENERGY EFFICIENCY IN SMART CITIES THROUGH ELECTRICITY LOAD FORECASTING USING ADVANCED ML MODELS

Moeez Hassan[1], Javairia Shahid[2], Hina Amjid[3], Usama Asif[4], Muhammad Sajjad[*5], Abdul Jabbar[6]

[1,2,3,4]*School of Software Engineering, Minhaj University Lahore, Pakistan.*
[*5,6]*School of Computer Science, Minhaj University Lahore, Pakistan.*

[1]moeezmehar32@gmail.com, [2]javairia.shahid203@gmail.com, [3]hinaamjad486@gmail.com,
[4]usamaasif.labengr-se@mul.edu.pk, [*5]engineersajjad07cs21@gmail.com,
[6]aj512039@gmail.com

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Corresponding Author: *
Muhammad Sajjad

Abstract

In these rapidly changing times of smart cities, a smart use of energy has become a financial rescue buoy. The forecasting of electricity loads is crucial for the stability of the grid, for resource allocation; however, it also becomes more and more important in the context of integrating wind and solar energy into the grid. Nonetheless, precise prediction is difficult when energy usage changes differently due to the variability of weather, human activity, and renewable generation. Some traditional statistical models, including linear regression and autoregressive type approaches, often fail to model the non-linear and multi-dimensional information underlying the data, resulting in a suboptimal forecasting performance. To address these limitations, this paper applies state-of-the-art machine learning and time series techniques to improve the forecasting accuracy of electricity load. Support Vector Regression (SVR), Random Forest (RF), Gradient Boosting (GB), Long-Short Term Memory (LSTM), the Facebook Prophet, Extreme Gradient Boosting (XGBoost), and Linear Regression are used for prediction. Taking advantage of an extensive electricity consumption dataset as well as time series characteristics and context features, we obtain better forecasting with the proposed model. RF was the best performing among all the models with Lowest MAE=0.021, Extremely low RMSE = 0.014, and Highest R^2*=0.982 (Almost perfect). These results validate the potential of advanced machine learning based models to provide data capitalism-driven energy management solutions for smart cities.*

INTRODUCTION

Load forecasting for the electric power industry in smart grid applications mainly deals with forecasting future electric load demand, helping power systems to utilize it in an efficient way. The smart grids in the current cities have a number of serious problems, such as uncertain energy consumption, putting new energy, grid instability operations, and resource waste. These challenges have been major obstacles in the energy industry, and particularly for reliable and sustainable power generation. Historically, electricity load forecasting has been conducted using simple statistical approaches and historical consumption patterns that do not appropriately account for the dynamic and complex nature of energy demands today. With the electricity load prediction for smart cities, it is necessary to have a high-precision prediction method for energy suppliers and grid operators. Such forecasts, derived from historical data and many parameters, will easily allow you to optimize resource allocation, grid stability, and the integration of renewable energy production.

The other goal of the smart city vision is to make urban systems like buildings, transportation, industry, and others more sustainable and effective. Of these, energy infrastructure is especially important. The efficient consumption of electricity in a smart city is associated with minimizing the waste of energy, decreasing the cost, and alleviating environmental pollution, which demands the cooperation of various types of technologies and smart solutions. Robust, efficient, and responsive delivery of electricity continues to be the ultimate goal, especially as grids need to adjust in response to local demand, while ensuring efficiency and quality [1].

In order to overcome these issues, a lot of research work has been conducted on energy management and analysis forecasting. Load forecasting, as its name suggests, involves predicting future electricity demand, allowing for minimising energy wastage and improved generation and distribution planning. Upcoming smart city technologies as IoT and AI, are being massively adopted for handling random demand profiles and enabling the integration of renewables. This movement underlines the general trend of urban smartification since the 1990s, guided by the increasing incorporation of technology such as computer-interaction, specialisation, and autonomy. As a result, the smart infrastructure of today, underpinned by sensors, cloud computing, machine learning, and the Internet of Things (IoT), lies at the heart of efficient urban energy systems and improved quality of living for citizens [2].

Load forecasting can be distinguished into four categories depending on the time horizons: Very Short-Term Load Forecasting, Short-Term Load Forecasting, Medium-Term Load Forecasting, and Long-Term Load Forecasting. VSLF and STLF have their direct applications in grid real-time operations, whereas MTLF and LTLF feed the long-term planning, capacity estimation, and cost control.

The load forecasting method predicts future electricity usage based on analysis of past and current consumption data. This functionality in smart grids is done with the help of smart energy meters that keep track of how much electricity has been used, from households to commercial buildings to large industrial establishments. These smart meters collect the data, which is processed centrally and used in forecasting models to forecast the load requirement as depicted in Figure 1 [3]. However, there are several challenges to improving electricity load prediction and energy efficiency in smart cities:

Develop advanced machine learning and artificial intelligence techniques to improve and enhance prediction models. Identifying the impact of factors like climate, human actions, and new technologies on electricity usage. Improving energy management approaches for different users, which may be domestic, commercial, or industrial.

Machine Learning (ML) is a component of AI that allows systems to learn from patterns of data to make predictions and decisions without the need to be programmed for each task. In the realm of smart cities, ML is utilized to model complex and dynamic energy consumption behaviors. One of these energy load forecast strategies is when ML is applied to predict one hour ahead energy demand for the next day. This method aggregates the results of the tothe p five single models into a strong ensemble model for better accuracy. It also now involves predictions about energy use as well, for further energy-efficient smart buildings. The proposed work compares various forecasting algorithms, inputs, objectives, and Multiple Prediction Horizons for Residential and Non-Residential buildings in a smart city environment [4]. By comparing traditional statistical methods to those based on machine learning for a set of five building types, particularly focusing on predictions of peak demand, the results suggest that ML-based models outperform traditional approaches and provide greater potential for optimizations of energy efficiency.

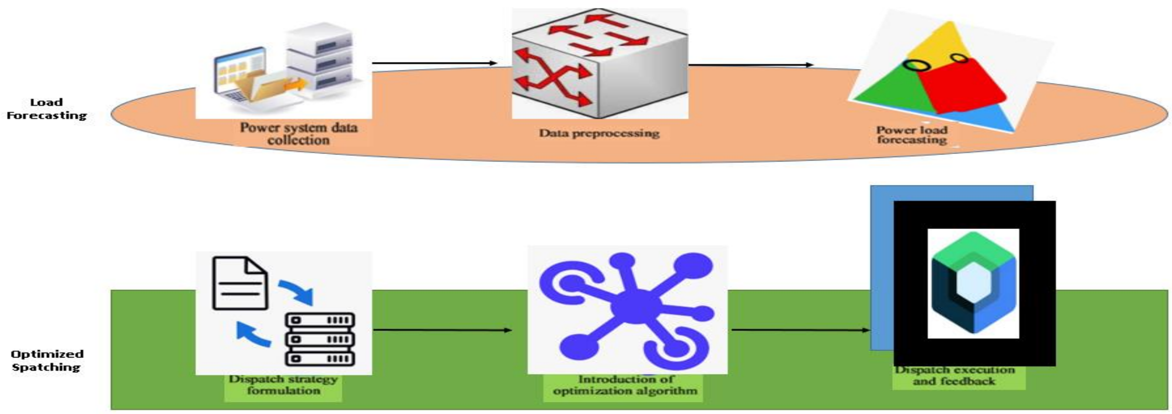


Figure 1: Process of Load Forecasting

The Machine Learning (ML) incorporation within the energy sector might be a disruptive factor to accurate electricity production, real demand response, energy saving, as well as renewable integration. Such models can also support utilities in operational scheduling and cost reduction, as well as meet sustainability targets in diverse urban infrastructures.

Literature Review:
Recent advancements in artificial intelligence, deep learning, and IoT have revolutionized diverse domains such as healthcare, transportation, and smart city infrastructure. In the healthcare sector, CNN-based approaches have been applied to mobile applications for skin disease classification with a focus on user privacy [1], innovative fungal disease diagnosis [2], and recognition of Urdu handwritten alphabets for linguistic preservation [3]. Intelligent ammunition detection systems employing CNNs have also enhanced security operations [4]. In the smart city domain, IoT-enhanced autonomous parking solutions leveraging transfer learning [5] and autonomous parking lot detection with multi-sensor data fusion [8] have been developed. Waste management has benefited from automatic image-based waste segregation through intelligent agents integrated with CNNs [6]. Transportation systems have seen major advancements through adaptive IoT-based smart road traffic congestion control systems [7], an adaptive approach for congestion management [12], and machine learning–based traffic modeling for improved flow optimization [15]. In addition, cloud- and IoT-based smart car parking systems have been designed using fuzzy-inference integration [10]. The field of computer vision continues to grow with deep learning analysis for image classification [9] and multimodal intelligent systems for real-time decision-making [11]. Furthermore, innovations in sustainable energy have been achieved through nanofluid-based parabolic trough solar collectors for environmental efficiency [13]. Collectively, these studies highlight the versatility and transformative potential of AI, deep learning, and IoT in solving complex, real-world challenges across multiple sectors.

Recently, a number of efforts have been undertaken to investigate the status quo of electrical loads and demands with the objective of developing better approaches to predict electricity load more accurately and effectively. Key contributions in the area have greatly advanced the prediction techniques, ranging from classical statistical methods to current ML methods for different problems of control, supervision, and power grid operation. Among these, one of the most important is the demand-supply gap that causes an energy shortage. The realization of smart city ideas, in particular, is applying smart grids, new rules for the direct application in real time of intelligent systems to the grid management.

Several studies have been conducted on the development of advanced machine learning (ML)based models for enhancing the accuracy of electricity load prediction in smart grid environments [5]. Introduced a data-driven approach based on Multidirectional LSTMs (MLSTMs) for predicting smart grid reliability. In comparison with LSTM, GRU, and RNN models, the MLSTM had significantly better predictions in accuracy, highlighting its capacity in time-series data management. Similarly, Gao et al. proposed the EMD-GRU-FS (Empirical Mode Decomposition-Gated Recurrent Units-Feature Selection) method. Their model was able to achieve an accuracy of more than 95% for the four datasets, which indicates the good generalization ability of the forecasting model for short-term load [6].

In another work by Zekić-Sušac et. al., ensemble models consisting of decision trees, gradient-boosted trees, and random forests were established. The ensemble method forecasted 10 years of 10-minute interval Spanish electricity consumption data effectively by using a weighted average with respect to the past model performance [7]. Zhou et al. similarly integrated EMD with LSTM to improve the model accuracy of short-term forecasting for seasonal variation, and summer/winter MAPEs of up to 2.24%/2.52% suggest good adaptability to time variance [8].

Thokala worked on Artificial Neural Networks (ANN) to handle historical load nonlinearity and improve prediction accuracy for building-level energy forecasts [9]. He et al. proposed a new hybrid model by fusing VMD-LSTM-BOA, showing great power with a far lower MAPE of 0.4186% and R^2 reached 0.9945, which is much better than MLPR, RF, and SVR [10]. Shen et al. introduced a rolling prediction method via XGBoost and HABoost, which was successfully used in the German electricity market. Furthered this study using a hybrid AS-GCLSSVM model optimized with two approaches, GWOR and ACF, to enhance the week-ahead forecasting accuracy with a trade-off in time consumption [11] [12].

Liu et al. employed CNN models for forecasting hourly electric load and achieved better results compared to SVM, RF, and DT models with a 7-history input and a 3-day prediction horizon [13]. Similarly, a hybrid wavelet transformation with LSTM and Radial Basis Functions (RBF) model, able to address multiple influencers such as weather and renewable inputs. Jung et al. also confirmed the best performance of LSTM for monthly energy forecasts, with more than 10 million, providing additional evidence of scalability for deep learning [14] [15] [16].

Liao et al. demonstrated that XGB is better than RF, in short-term (day-ahead 24 hours) electricity load forecasting and obtained a lower RMSE of 2.01. Abumohsen et al. confirmed the performance of LSTM against SVR and ANN with 1.8% MAPE, promoting this method for short-term forecasting in smart grids. Lastly, on the other hand, stressed the importance of single models that predict the electricity load and price at once and called for neural architectures to automatically learn the features without human-crafted preprocessing [17] [18].

Predicting load allows utilities to anticipate demand variations, lessening uncertainty, and to program maintenance activities without interfering with supply used Linear Regression (LR) is used to determine the significant weather-related independent variables like wind speed and humidity for load forecasting. Their results confirm the potential of regression models to highlight correlations of the energy request with exogenous phenomena [19] [16].

Kontogiannis et al. proposed a fused model based on XGBoost and Decision Trees (DTs) and fuzzy logic to generate intelligible rules to facilitate load behavior. Their method showed that a two-objective optimisation model that integrates ML methods and fuzzy inference systems can increase prediction accuracy and explanation, not only compared to a single-objective optimisation model. Alahi et al. focused on the potential future of energy-efficient smart buildings in the context of the application of AI and IoT, and flexibility, adaptability, and sustainability are the key factors [20][21].

Alhussein et al. introduced a CNN-LSTM hybrid model for weekly load prediction, with better accuracy but using relatively small and carefully preprocessed datasets [4]. Li et al. presented a CNN–GRU model trained with Earthworm Optimization (EWO) employed for dynamic tuning of hyperparameters and achieved a good performance on three years of electric load data, being superior to the conventional ML techniques such as SVM and ELM [22].

Aslam et al. examined eight years of ISO-NE electricity consumption and employed DT · RF classifiers for feature selection, and SVM and CNN for prediction. They also used a herd immunity-inspired coronavirus CNN optimization algorithm to optimize hyperparameters, which improved the overall accuracy while reducing overfitting [23].

Chen developed a filter and wrap technique of combining multiple windows and a Doppler feature set for load prediction over the EEMD decomposition technique. Model's dynamic structure adaptation using cluster-specific off-peak data outperformed models without any adaptation [24].

Ding et al. suggested a Hybrid Model based on RF-RFE for feature selection and a DNN that includes two kinds of models for the week-ahead electricity demand prediction. The performance of the model is evaluated on New York ISO data and compared to standard CNNs, showing a significant improvement on feature-rich scenarios [25].

For the versatility to model nonlinear relationships and efficiency with relatively small datasets, Support Vector Regression (SVR) has been widely adopted. Bargam et al. and Laouafi et al. utilized SVR, and suggestions for improvements are: incremental learning with PSO for hyperparameter optimization. Their methods obtained low MAPE, which illustrates the capability of the model for small-size load forecasting [26] [27].

Abumohsen, Owda, & Owda also used a Neural Network-PSO hybrid to forecast Iranian load power data. Their model obtained a high level of accuracy; its MAPE was reported to be 0.0338 and MAE at 0.02191, demonstrating the efficiency of evolutionary optimization for neural network fine-tuning [1].

Tudose et al. proposed a CNN model with two-layer inputs (meteorological features and past consumption) in Algeria's day-ahead prediction. Their combined method achieved an MAPE of 3.14%, demonstrating the effectiveness of fusion for multi-source input [28].

Zuazo et al. have applied the SVR and NARX models using 15-minute resolution data for daily and monthly load alternatives. The performance of SVR was better than NARX at most runs (for the commercial use training set, all the runs) and had higher accuracy (84–94 %).

Darab et al. introduced a Gaussian process mixture model for short-term load prediction in LVN. They included the temperature factor as well as the time series data for 1–4 day ahead prediction with good performances in terms of MAPE and MAE [29].

Nano et al. utilized multiple linear regression (MLR) and long-memory stochastic processes to predict hourly loads in Puget Sound and Brazil utilities. These classical models, while easier, remain relevant when data interpretability and execution speed are preferred [30].

Aribowo et al. used GRNN and PRNN along with a hybrid filter-wrapper approach and Firefly optimization to select the essential features. SVR was selected for the final solution as it performed well after features were reduced [31].

H. Kim et al. used sticky hierarchical clustering and k-means for time series clustering on AMI user smart meter data written in dynamic time warping (DTW) space. They found that multi-household prediction could improve accuracy results, and DTW could be used to obtain a clear cluster border rather than traditional periodogram-based methods [15] [16].

Recent advancements in artificial intelligence, deep learning, and IoT have revolutionized diverse domains such as healthcare, transportation, and smart city infrastructure. In the healthcare sector, CNN-based approaches have been applied to mobile applications for skin disease classification with a focus on user privacy [32], innovative fungal disease diagnosis [33], and recognition of Urdu handwritten alphabets for linguistic preservation [34]. Intelligent ammunition detection systems employing CNNs have also enhanced security operations [35]. In the smart city domain, IoT-enhanced autonomous parking solutions leveraging transfer learning [36] and autonomous parking lot detection with multi-sensor data fusion [37] have been developed. Waste management has benefited from automatic image-based waste segregation through intelligent agents integrated with CNNs [38]. Transportation systems have seen major advancements through adaptive IoT-based smart road traffic congestion control systems [39], an adaptive approach for congestion management [40], and machine learning–based traffic modeling for improved flow optimization [41]. In addition, cloud- and IoT-based smart car parking systems have been designed using fuzzy-inference integration [42]. The field of computer vision continues to grow with deep learning analysis for image classification [43] and multimodal intelligent systems for real-time decision-making [44]. Furthermore, innovations in sustainable energy have been achieved through nanofluid-based parabolic trough solar collectors for environmental efficiency [45]. Collectively, these studies highlight the versatility and transformative potential of AI, deep learning, and

IoT in solving complex, real-world challenges across multiple sectors

Proposed Methodology:

Load forecasting in electricity grids presents challenges like fluctuation of consumption due to meteorological factors, irregularity of consumer behavior, and integration of alternative energy sources. Such complexities are difficult to handle in traditional approaches. ML techniques may tackle these challenges, since they can capture non-linear relationships, deal with the missing values and the outliers in the dataset, and improve the accuracy of predictions with feature engineering and model optimization. The adoption of these technologies for the accurate prediction led to higher energy efficiency & grid stability in nifty cities. The main aim of this research is to develop a model for monitoring electricity load demand. There will also be a time history of loads. PSOCT can be used to forecast electricity demand accurately and better distribute energy in order to forecast electricity load. Leverage its extensive ML capabilities to do so. This leads to better forecasts that are crucial in the case of load forecasting. The electricity load is highly precise. Also, the climate and time of day are important for the power consumption, and incorporating several features at the same time enhances prediction performance. In this study, an ML model is proposed as shown in Figure 3. The proposed model consists of four modules: the dataset Module, the Data preprocessing module, the Learning module, and the Evaluation module.

Dataset Module:

This information is about electricity load forecasting, which predicts the coming load based on past use of electricity. Load forecasting is essential for utilities to supply the necessary demand and Supply and to operate efficiently.

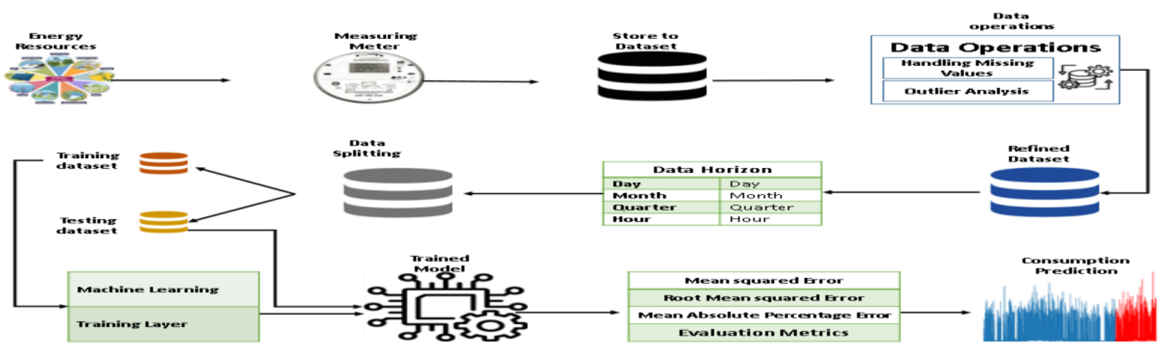


Figure 3: Proposed model for electricity load prediction

It consists of features like Date & time, that is timestamp of the entry, this can be up to hours or may be in minutes; Load and actual electricity consumption in MW or KW/h; temperature & humidity (weather data), which leads to peak consumption. It is also used to generate holiday and weekday/weekend status indicators, and hence takes into account the load variations due to dissimilar days of the week or holidays. The dataset consists of 36,721 instances. This is an important dataset useful for modeling of predicting electricity load and electricity supply management.

Data Preprocessing Module:

In the data preprocessing module, different operations are performed on the dataset, like missing values are handled put putting the average value of attributes that contain continuous values and the mode that contains discrete values. Outliers, as shown in Figure 4 using a boxplot, are also managed here by putting the extreme values.

The general form, variability, and median of statistical data are also revealed by these box charts. They consist of a grid of box charts, one for every dataset feature. Outliers (dots outside the whiskers), the median: the line inside the box, and the Interquartile Range (IQR, the size of the box) all serve to illustrate the central tendency and dispersion of the data in a box plot.

Demand, MA_X-4, Weeks X-2, X-3, and X-4: The dispersed distributions displayed by these features are essentially centered around their medians. The data has occasional lower-than-normal values when there are outliers below the lower whisker, but the spread of these variables is more or less normal. Day of Week and Hour of Day: These two variables, presumably categorical, exhibit even distribution without young, old points. This would imply the values are more or less evenly distributed along each of their categories. Weekend: A perfect separation between the two groups and no within-variability within each category is demonstrated by this dummy variable, which is most likely set to 0 for weekdays and 1 for weekends. Both Holiday & Holiday ID**.**

There are many zero entries in these variables, meaning that holidays are uncommon for these data. These few outliers indicate that when holidays do occur, they could be indicative of separate behaviors or consequences. T2M_toc (Temperature): It is a feature whose values are concentrated around the median, and most of them are the same. There are, however, some outliers on the high side: Some readings about extreme temperature, which are rare in the dataset. Furthermore, these box plots provide an easy and quick way to help you grasp the spread of individual feature central tendency, dispersion, and the outliers that need to be taken care of in the analysis.

In Figure 5, we see a Heatmap of the association between certain structures in a dataset, with the color of the box showing the direction and degree of the associations. Strong positive correlations are indicated with red color, negative ones - blue color. Weeks X-2, X-3, X-4, and MA_X-4, for example, have a strong positive correlation with the DEMAND variable and with each other, suggesting that historical demand and moving averages are reliable indicators of present demand. However, factors such as weekends and holidays have a negative impact on demand, which is why demand is typically lower on these days. T2M_toc (probable temperature) is also positively related to demand; this means the higher the temperature, the more the demand. The matrix is useful to probe which factors are important to predict a demand, in detail, time series, and seasonal factors. Simulations make use of a variety of machine learning algorithms specialized for different types of tasks. XG Boost specializes in structured data, being a strong algorithm in the area of boosting by combining models. For time-series predictions, long-term sequential data relationships are well-suited for LSTM. Facebook Prophet is an algorithm that produces the best forecasts for time series data that has multiple seasonality with non-linear or linear growth. Logistic Regression is a simple binary classifier. SVR is a regression technique that predicts continuous values by the use of hyperplanes, while RF is a model that enhances the accuracy of predictions by taking the average of multiple decision trees. These algorithms provide a variety of advantages when implementing predictive modeling. The results of several ML models for the power load forecasting are displayed in the table (4.1 & 4.2) with different evaluation measurements for the analysis of power load forecasting below:

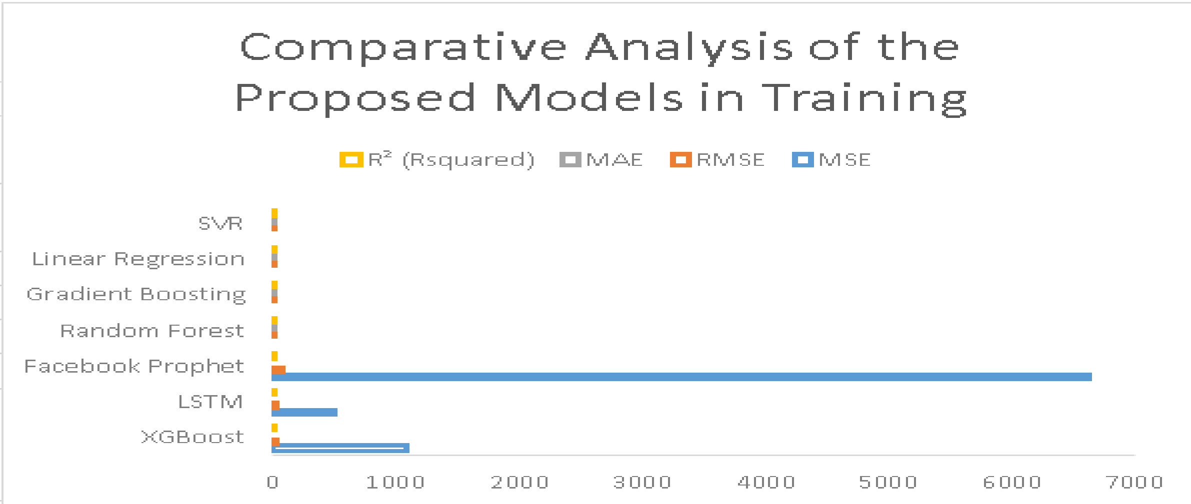
Learning Module

Table 4 and Figure 6 compare the efficiency performance in terms of different metrics when the different ML techniques are employed for electric load prediction. It is noteworthy that RF, GB, LR, and SVR attain nearly-zero MSE and RMSE, suggesting near-perfect prediction. LSTM is also efficient, with a rather low RMSE of 22.35, which demonstrates its effectiveness. Facebook Prophet, on the other hand, has the largest MSE and RMSE, suggesting that its predictions are not reliable for this dataset.

Table 4: Comparative Analysis of the Proposed Models in Training

Model	MSE	RMSE	MAE	R^2 (Rsquared)
XGBoost	1090.196	33.018	–	0.970
LSTM	499.960	22.350	–	0.986
Facebook Prophet	6633.233	81.445	–	0.821
Random Forest	–	0.007	0.005	0.998
Gradient Boosting	0.001	0.025	0.018	0.976

Linear Regression	0.001	0.035	0.025	0.954
SVR	0.001	0.038	0.031	0.945



The error measures MAE: RF has the minimum error, next is GB, and next is SVR, which once again indicates the accuracy of these methods. RF gives nearly a perfect fit (0.998) in terms of R-squared, while LSTM (0.986) and GB (0.976) come next, and Facebook Prophet gives an R-squared of 0.821. It is observed that RF achieves the most favorable results in this evaluation in terms of all metrics.

Table 5 compares different ML tactics according to how well they performed on testing. GB, RF, SVR, and LR still have virtually zero MSE numbers showing close predictability. LSTM results are also quite pleasing with a low RMSE of 22.44, XG Boost provides a little bit higher errors, but good enough as compared to an RMSE of 42.79. Facebook Prophet, by contrast, does rather poorly, with a much higher RMSE and MSE, which means the predictions are less reliable.

Table 5: Testing Results of the Proposed Models

Model	MSE	RMSE	MAE	R^2 (Rsquared)
XGBoost	1831.192	42.792	-	0.950
LSTM	503.58	22.44	-	0.985
Facebook Prophet	165511.829	406.831	-	-3.850
Random Forest (RF)	~	0.021	0.014	0.982
Gradient Boosting	0.001	0.027	0.018	0.970
Linear Regression	0.001	0.034	0.023	0.953
SVR	0.002	0.040	0.032	0.935

The R-squared also echoes this, with RF, LSTM, and GB having high R-squared (when 1 is the highest and negative numbers indicate a very bad fit), and FBprophet having negative R-squared (as an indication of the bad fit). For MAE, RF shows the best error, then GB and LR. In general, RF performs best on the test with the nearest neighbor method accuracy.

From the results as shown in Table-6, it can be seen that the proposed model, which is built using the RF, outperforms the conventional regression models applied, and with a minimum RMSE error of 0.021, the predicted load values are closer to the actual load values, ensuring that the energy management and the grid stability are managed precisely.

Table 6: The Results of the Proposed Model Compared with Literature

Literature	Algorithms	RMSEs
A. Tsanas [33]	IRLS	3.14
Castelli [34]	GSGP	1.06
T. Le [35]	GA-ANN	1.625
Proposed Model	**RF**	**0.021**

Conclusion

The application of techniques for electricity load forecasting faced some tasks, especially for dealing with complicated features such as changing weather and energy use patterns. Early models, such as Linear Regression, did not perform as accurately, evidenced by high RMSE, as the values were higher for previous models; they were unable to accurately predict load demands. Even for advanced models such as GA-ANN and MLP were improved, they still could not make good take into account non-linearity and uncertainties, particularly in situations of dealing with the integration of renewable energy sources and handling time-series data processing. ML attempts to overcome such limitations by integrating more complex algorithms. Models such as RF and Gradient Boosting could handle large datasets and complex variables, while giving us better predictions. These methods are based on ensemble learning, which is believed to better capture the different patterns and the interactions of the data, leading to more robust predictions. Additionally, the incorporation of the LSTM helped to control the sequential dependencies across the time-series data, thereby improving predictability. In this paper, we demonstrate the competitiveness of the proposed model by adopting state-of-the-art ML algorithms in handling time-series-based power data, including renewable power sources, and in providing accurate, actionable conclusions for smart grid applications.

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