Long-term Energy Demand Analysis using Machine Learning Algorithms: A Case Study in Bangladesh

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***Abstract*—In each energy sector from production to consumption machine learning and statistical models have intimidated the power system for the past few decades. Among these, energy demand analysis is one of the approved research projects in Bangladesh due to its necessity. Such a study introduces energy consumption forecasting along with necessary environmental featured variables. These energy demands vary depending on short-term, medium-term, and long-term analysis. Although, this paper utilizes long-term energy demand research while predicting energy consumption. The dataset in the study includes three years of monthly data consisting of more than one million samples and diverse consumer types with versatile features of the capital of Bangladesh, Dhaka (mainly Uttara). Different machine learning models like; Random Forest, k-neighrest Neighbors regression, Extreme Gradient Boosting Method, and Light Gradient Boosting Method have been used and in order to evaluate them various performance constraints have been utilized. Among the models, KNN has performed considerably well. It has the result of about 0.9447 as R^2, 163.9 as RMSE, and 28.7 as MAE. Such study will surely subsidize upgrading to the power system management of Bangladesh.**

Keywords—demand-side management energy consumption, energy demand, energy management policy, long-term prediction, machine learning models

I. Introduction

Energy consumption and production worldwide play a significant role in numerous sustainability solutions, such as addressing climate change and promoting resource preservation. Historically, industrialized nations have been the primary consumers of energy [1]. Nevertheless, this scenario is presently evolving. Developing countries, spurred by industrialization, enhanced living standards, and population expansion, are experiencing a swift rise in energy usage. Consequently, the current estimation of worldwide energy consumption is about 580 million terajoules which assesses the necessity of understanding what factors lead to this massive energy consumption [2]. Energy consumption patterns changed from the beginning of the Industrial Revolution. The rising of different non-renewable and renewable energies like solar, hydro, harvesting sea waves, wind, etc. have led to complex energy consumption patterns. Diverse energy consumption patterns are associated with different energy resources [3]. Factors like per capita income can affect annual energy consumption. Out of this energy consumption, in 2021, about 28 petawatt-hours of electrical energy were generated globally [4]. Subsequently, Total energy consumption is divided into different fuel types based on consumption rates demonstrated in Fig. 1 [5].

When electricity production exceeds electricity demand, several problems arise. Firstly, the overproduction of electricity can lead to economic waste since the costs of generating power are incurred without corresponding customer revenue. Secondly, operating power plants, especially those that need to ramp up and down frequently to balance supply and demand, can cause additional wear and tear on equipment. This can lead to higher maintenance costs and potentially shorter lifespans for power generation equipment. Besides, power plants running on fossil fuels might continue to produce power even when it is not needed, leading to wasted resources. Thus, comes the necessity of demand-side energy management. Developing an effective power management plan requires a thorough study of energy consumption. Astoundingly, machine learning (ML) is crucial in demand-side management (DSM). It helps to optimize electricity use and balance it with supply. Meanwhile, DSM is designed to encourage people to change how much and when they use electricity, especially during high demand.

Contrariwise, as consumer preferences tend to advance over time, this creates uncertainties in daily energy consumption patterns [6]. In the last decade, worldwide energy demand has increased significantly. The rapid increase in global population coupled with industrialization, economic growth, rising comfort demands, and social progress has greatly affected global energy consumption and environmental issues [7].

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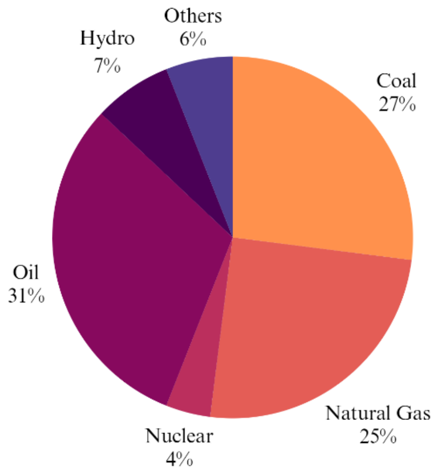


Fig 1. World Energy Consumption in 2020 [5].

For these issues, artificial intelligence (AI)- based methods using machine learning and deep learning algorithms have gained significant attention for their accurate forecasting. Energy estimation mainly influences two categories of prediction. One of them is ELF (Energy Load Forecasting), and EGF (Energy Generation Forecasting) [8]. The four categories of ELF/EGF are: i) VSTF / VSTG (very short-term Load / Generation Forecasting). This implies the forecasting should be ranged for the next few minutes. Based on past data of electricity consumption or generation this has been predicted for immediate understanding of the near future. ii) STLF / STGF (Short-term Load/generation Forecasting). Here forecasting of power consumption or generation ranges for the next hour up to the next day or week. iii) MTLF / MTGF (Middle-term Load / Generation Forecasting). Forecasting for the next weeks or months. iv) LTLF / LTGF (Long-term Load / Generation Forecasting). Predict Load or generation for next year [8]. The data on which the prediction is performed usually contains information about temperature, air, and humidity. In some cases, the speed of wind is also considered valuable. Different categories of ELF/EGF require different types of ML algorithms to predict properly.

Model estimation can be categorized into two main types among many others. One of them is the classical statistics technique and the other is the machine learning approach. The former includes many models starting from Multiple regression to Autoregressive Integrated Moving Average (ARIMA) models etc. The latter, machine learning, on the other hand, uses historical data to get trained and then predict. Different models like Support Vector Machine (SVM), Adaptive Boosting (AdaBoost), Extreme Gradient Boosting (XGboost), Random Forest (RF), Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), etc. are very popular to predict load, but each of them shows dominance over other in very specific conditions. Solyali et al. have presented a machine learning algorithm comparison regarding approaches for forecasting short- or long-term electricity load using SVM, Adaptive Neuro-fuzzy Inference System (ANFIS), ANN, and Multiple linear regression (MLR). Out of the four, the Support Vector Machine (SVM) has performed better in terms of long-term forecasting, and the Artificial Neural Network (ANN) has performed better in short-term forecasting. As part of future work, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) implementations have been mentioned [9]. On the other hand, Taheri et al. have shown that the Deep Recurrent Neural Network (DRNN) model is better than both the Support Vector Machine (SVM) and Gradient Boosting (GB) in terms of accuracy. The use of Gaussian Process (GP) has reduced computational time to a factor of 0.47 in medium to long-term forecasting of energy consumption [10]. In the next paper, wind and solar generation have been taken into consideration by Paterakis et al. Prediction accuracy has been determined by RMSE, Normalized Root Mean Square Error (NRMSE), and MAPE. A Multi-Layer Perceptron (MLP) has been presented and compared with different prediction methods to predict aggregated energy, validated by a dataset provided by Scholt Energy Control B.V. The MLP intensified by Deep Learning has resulted in higher accuracy [11].

Vantuch *et al*. have shown in comparison that boosting algorithms outperform other models. The authors have compared models such as Support Vector Regression (SVR), Artificial Neural Networks (ANN), Random Forest Regression (RFR), eXtreme Gradient Boosting (XGB), and a model named FNT, which is a 'Flexible Neural Tree', an ensemble of genetically evolved trees optimized for performance but requiring the highest computational capacity among the others. However, XGB and RFR have performed better and have the lowest computational complexity compared to the others [12]. Another study by Ahmad et al. has been conducted regarding load prediction for medium- and long-term forecasting. In this study, AdaBoost models, as well as Artificial Neural Networks with Nonlinear Autoregressive Exogenous Multivariable Inputs (ANN-NAEMI) and Multivariate Linear Regression Model (MLRM) models, have been tested at the district level. AdaBoost has dominated among them [13]. Somu et al. have presented eDemand. The novelty lies within the Haarlet wavelet-based mutation operator that has been applied and is usable for most types of forecasting, namely short, mid, and long-term forecasting [14]. Another work has been introduced by Somu et al., which is a deep learning framework known as kCNN-LSTM, that integrates clustering algorithms (represented by k) into forecasting the energy consumption of buildings [15]. In another paper, Ghazal et al. have applied machine learning techniques in IoT devices for advanced energy management. They have introduced an EDF-FMLA model used as a forecasting system in an intelligent smart meter. This model is essentially a decision-based cloud fusion model implemented to predict the load. Support Vector Machine (SVM) and Deep Extreme Learning Machine (DELM) techniques are fused together, achieving an accuracy of 90.70% in predicting energy consumption [16].

In Bangladesh, there is still insufficient research on energy demand side analysis in the management policy sector of the power system. To bridge the gap this paper proposed ML-models' utilization with adequate data availability in a promising area with versatile features along with meteorological parameters for long-term load prediction.

In section II, the paper illustrates the modeling of different machine learning models used in this paper. Again, in section III, the detailed properties of the dataset and the estimation process have been demonstrated. Afterward, thorough modeling of energy consumption prediction systems as well as the comparison among them has been signified in section IV. It also establishes the final discussion and results regarding the practical data. Finally, it dissolves with featured valuation and observations followed by conclusion in section V.

II. MODELING OF MACHINE LEARNING ALGORITHMS

Prediction with machine learning models has carried certainty to each corner of the world's application. Excelling to that many novel algorithms are present today for estimating any probable future outcome apart from the conventional ones. Some machine learning models used in this paper have been described below.

A. K-NEAREST NEIGHBORS (KNN) REGRESSION

K-nearest neighbors as a regression model use different distance measurement techniques to best fit the algorithm. Among the distance measurement methods, Minkowski distance, Euclidean distance, Manhattan distance, Chebyshev distance, and Cosine similarity are the popular ones. Using these methods, the model identifies the possible 'k' numbers of future target features. In this paper, the hyperparameter setup used: n_jobs=-1, n_neighbors=5 (others default). Thus, few of the distance measurement techniques are:

Manhattan: $(p = 1)$

$$d(x_i, x_k) \stackrel{\text{def}}{=} \sum_{j=1}^{D}\left|x_i^{(j)} - x_k^{(j)}\right| \tag{1}$$

Euclidean: $(p = 2)$

$$d(x_i, x_k) \stackrel{\text{def}}{=} \left(\sum_{j=1}^{D}\left|x_i^{(j)} - x_k^{(j)}\right|^2\right)^{\frac{1}{2}} \tag{2}$$

Cosine:

$$s(x_i, x_k) \stackrel{\text{def}}{=} \cos\left(\angle(x_i, x_k)\right) = \frac{\sum_{j=1}^{D} x_i^{(j)} x_k^{(j)}}{\sqrt{\sum_{j=1}^{D}(x_i^{(j)})^2}\sqrt{\sum_{j=1}^{D}(x_k^{(j)})^2}} \tag{3}$$

B. RANDOM FOREST (RF)

Being an ensemble ML algorithm, random forest (RF) can randomly sample the entire data into multiple decision trees based on different optimization methods. This algorithm optimizer has the nonparametric model as:

$$f_{ID3}(x) \stackrel{\text{def}}{=} \Pr(y = 1|x) \tag{4}$$

$$S \stackrel{\text{def}}{=} \{(x_i, y_i)\}_{i=1}^{N} \tag{5}$$

$$f_{ID3}^{S} \stackrel{\text{def}}{=} \frac{1}{|S|}\sum_{(x,y)\in S} y \tag{6}$$

-where S is known as set of labeled examples and (6) denotes the constant model where the sampling begins with (5) [17] . In order to determine the leaf node, the set of examples is divided with pieces of S_- and S_+, so that all the features j=1, 2, 3, …, d and even the threshold t would have the entropy $H(S_-, S_+)$ as follows:

$$H(S_-, S_+) \stackrel{\text{def}}{=} \frac{|S_-|}{S}H(S_-) + \frac{|S_+|}{S}H(S_+) \tag{7}$$

As the algorithm uses multiple trees to train the model, it basically uses either the bagging or boosting method to sample, but in this paper, the model has used a bagging algorithm (sampling with replacement (S_b)) [17]. This sampling continues till $S_b = N$. Now, if the model has created B random samples then the number of decision trees would also be B. Thus, for any future estimation of a new example of x:

$$y \leftarrow \hat{f}(x) \stackrel{\text{def}}{=} \frac{1}{B}\sum_{b=1}^{B} f_b(x) \tag{8}$$

However, overfitting is the challenge of such an ensemble model. This RF model has the hyperparameter setup as: n_estimators=20, criterion="poisson", random_state=0, n_jobs=-1 (others default).

C. EXTREME GRADIENT BOOSTING (XGBOOST) METHOD

Using the level-wise tree growth method, the ensemble extreme gradient boosting model conducts L1 (lasso) and L2 (ridge) regularization processes. The model has the following objective:

$$L^{(t)} = \sum_{i=0}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{9}$$

-where, y_i = actual observation, $\hat{y}_i^{(t-1)}$ = estimated observation, l = function of CART (classification and regression tree) learner (summation of tth and $(t+1)$th trees), t = iteration, L = loss function, $\Omega(f_t)$ = regularization. Another way to express a gradient boosting model:

$$f = f_0(x) \stackrel{\text{def}}{=} \frac{1}{N}\sum_{i=1}^{N} y_i \tag{10}$$

$$\hat{y}_i \leftarrow y_i - f(x_i) \tag{11}$$

$$f \stackrel{\text{def}}{=} f_0 + \alpha f_1 \tag{12}$$

-where $\hat{y}_i$ is the residual and α is known as the hyperparameter or learning rate for the boosting model and new decision tree f_1 [17]. In this paper, the hyperparameter setup used: n_estimators=30, max_depth=5, eta=0.1, subsample=1, colsample_bytree=1 (others default).

D. LIGHT GRADIENT BOOSTING (LIGHT-GBM) METHOD

Stochastic gradient boosting has been used for estimation with the hyperparameter method in the light gradient boosting ensemble algorithm. Nevertheless, the model has greater training speed while learning and so developed outcomes, as a result of gaining the skill to select features by automatic large gradient boosting.

$$L = \frac{1}{n}\sum_{i=0}^{n}(y_i - \gamma_i)^2 \tag{13}$$

where L = the loss function, γ_i = predictive observation of the ith sample, y_i= actual observation of the ith sample, n = the sample numbers. Depending on L, the algorithm conducts to minimize the error in each step as well as computes associated residuals by the following formulas [17] :

$$\frac{dL}{d\gamma} = -(y_i - \gamma_i) = -(observed - predicted) \tag{14}$$

$$r_{im} = -\left[\frac{\partial L(y_i, F(x_i))}{\partial F(x_i)}\right]_{F(x)=F_{m-1}(x)} \; for\ i = 1,2,\ldots,n. \tag{15}$$

$$\gamma_m = \arg_\gamma min \sum_{i=0}^{n} L\left(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)\right) \tag{16}$$

$$F_m(x) = F_{m-1}(x) + v_m h_m(x) \tag{17}$$

-where, r_{im}= pseudo residual, $F(x_i)$ = previous model, m = number of decision trees, $h_m(x_i)$ or $h_m(x)$ = decision tree made on residuals, $F_m(x)$ = new prediction, $F_{m-1}(x)$ = previous prediction, v_m = learning rate [0-1]. Furthermore, light-GBM precisely models the regression by updating each decision with respect to the previous loss function and residuals it has encountered. The hyperparameter setup of the model used in the paper: num_leaves=5, n_estimators=20, subsample_for_bin=10000, random_state=42, n_jobs=-1 (others default).

III. Data Properties and Estimation

For the modeling purpose the software that has been utilized is Jupyter notebook with a core i-9 14-th gen intel processor, 1TB SSD storage, 8GB NVIDIA GeForce RTX 4070 graphics, and 32GB RAM personal computer. Moreover, the data has been gathered from Dhaka Electric Supply Company Limited (DESCO). The dataset mainly consists of ten features including the target variable which is the energy consumption in kWh. The other features are SND (location name in Dhaka), ACCOUNT_NO (electricity meter card number), MONTHLY_SPENT_MONEY (BDT), TARIFF (35 types of consumers), YEAR [2021-2023], MONTH [1-12], RELATIVE_HUMIDITY (%), AVERAGE_TEMPARATURE (°C), MAXIMUM_TEMPARATURE (°C). After merging all the local data together, the total sample of the dataset has been stated as around 1.8 million.

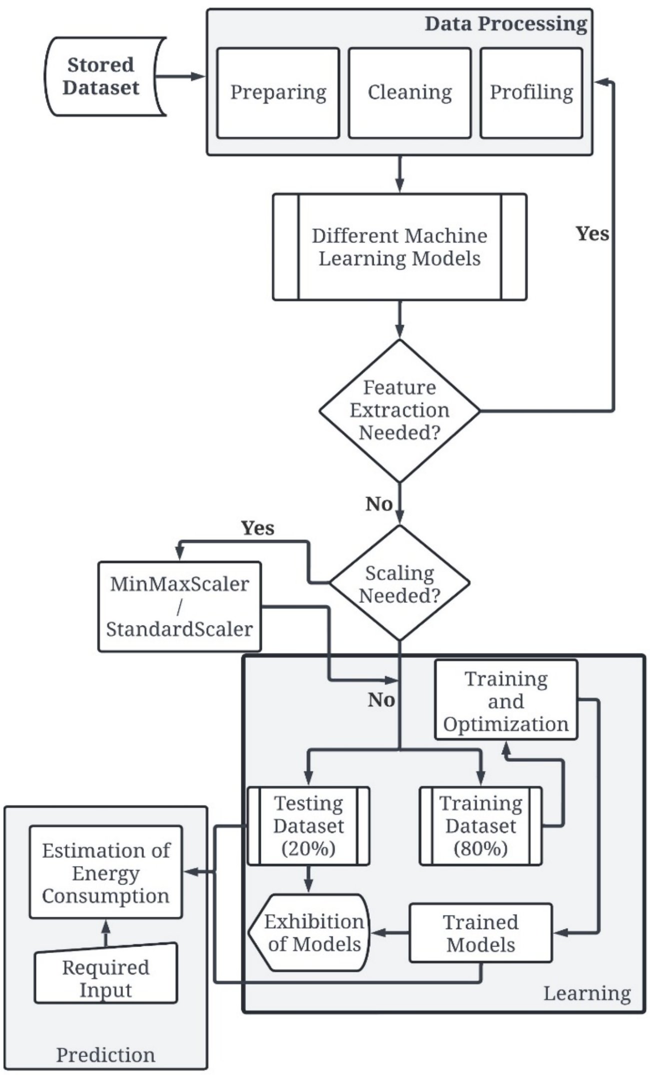


Fig 2. Flow Chart of the Proposed Modeling Structure.

Prior to different machine learning models, the stored dataset has undergone an extensive feature extraction process as needed. After the comprehensive data processing, the entire data is then lead to the scaling process based on the ML models. In this modeling, Random Forest (RF), k-neighrest Neighbors (KNN) regression, Extreme Gradient Boosting Method (XGBoost), and Light Gradient Boosting Method (Light-GBM) have been used. Afterward, in the learning process, the data has been divided into an 80:20 ratio as training:testing dataset as shown in Fig. 2. The training set has to be trained and optimized with certain parameters according to the output requirement. Using both the trained model and the testing set parameters certain performance parameters have been displayed which are: coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE), and root mean square error ($RMSE$). The mathematical representations of such parameters are:

$$R^2 = \left[\frac{\sum_{i=1}^{N}(y_{predict,i} - \bar{y}_{data})^2}{\sum_{i=1}^{N}(y_{data,i} - \bar{y}_{data})^2} \times 100\right] \% \tag{18}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_{predict,i} - y_{data,i})^2}{N}} \tag{19}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N} |y_{data,i} - y_{predict,i}| \tag{20}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_{predict,i} - y_{data,i})^2 \tag{21}$$

where, $y_{predict,i}$ = the predicted energy consumption, $y_{data,i}$ = the actual energy consumption or the test data, N = the sample sizes, $\bar{y}_{data}$ = the average of the energy consumption, R^2 = coefficient of determination, CV = coefficient of variance, $RMSE$ = root mean square error, MAE = Mean Absolute Error and MSE = Mean Square Error.

Subsequently, the same set of training and testing data have been used to predict new future data based on long-term prediction. Finally, such output data and the testing data have been compared to determine the above-mentioned performance parameters in a precise way. Eventually, getting all the results from different ML models have been presented in Table II which can then be compared and assumed to get the best-fitted one.

IV. Evaluation of ML models

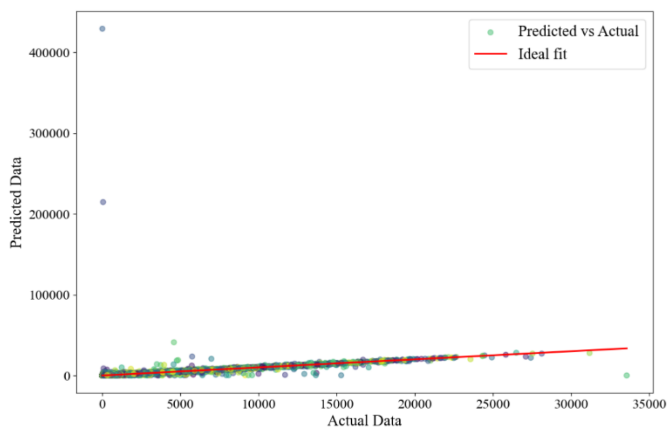
After learning and training the algorithms, ML models are evaluated using some performance parameters like coefficient of determination (R^2), mean absolute error (MAE), mean square error (MSE), and root mean square error ($RMSE$). Table I has displayed the outcomes of the algorithms applied in the Uttara city energy consumption related dataset.

Subsequently, the same set of training and testing data have been used for all the ML models like Random Forest (RF), k-neighrest Neighbors (KNN) regression, Extreme Gradient Boosting Method (XGBoost), and Light Gradient Boosting Method (Light-GBM). Afterward, some performance parameters like R^2, $RMSE$, MSE, and MAE have been applied to judge the algorithms' compatibility in terms of forecasting. In Table I it is comprehensible that KNN has the strongest pursuit in energy estimation while dealing with complex tariff contents as well as multiple weather-like parameters. It has around 94% of accuracy in the coefficient of determination section along with very low MAE which is 28.7. As KNN has the ability to use the kernels wisely to determine the best fitted 'k' number of neighbors to evaluate the future prediction, it is mostly prominent in the modeling era. Likewise, XGBoost and Light-GBM are not lagging either XGBoost has got around 87% accuracy in the prediction part where the error is stated as 37. Again, similar to the boosting part to XGBoost, Light-GBM has achieved 81% accuracy. On the contrary, as RF has the overfitting issue and as for the complexity pattern it has performed poorly with only around 25% accuracy with 8.5 MAE.

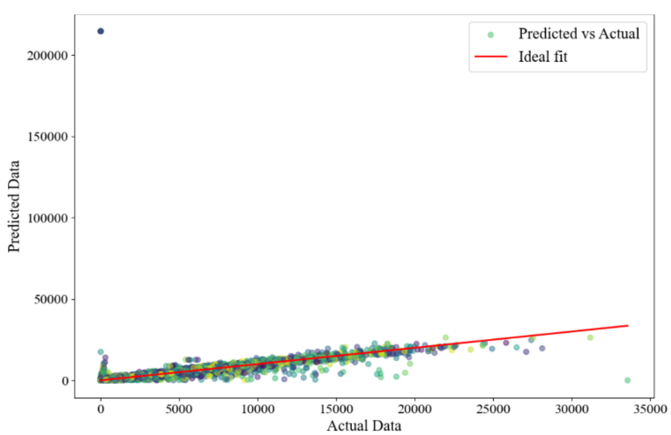
TABLE I. TABLE TYPE STYLES

Model Name	R^2	MSE	$RMSE$	MAE
RF	0.2460	366301.5	605.2	8.5
KNN	**0.9447**	26875.5	**163.9**	**28.7**
XGBoost	**0.8740**	61206.6	**247.4**	**37.0**
Light-GBM (boosting_type = 'gbdt')	0.8100	92287.7	303.8	68.9

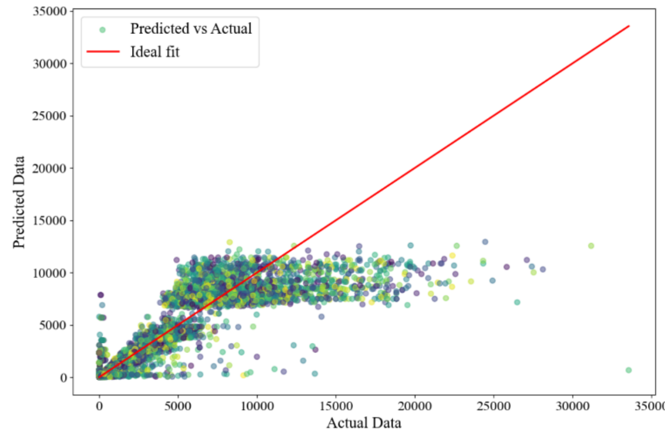
Fig. 3 illustrates the comparison of all four model's accuracy based on test-data and predicted-data. All the graphs from (a)-(d) also portray a similar scheme as Table I. As (b) which is KNN has plots around the best-fitted red line other than any other models.



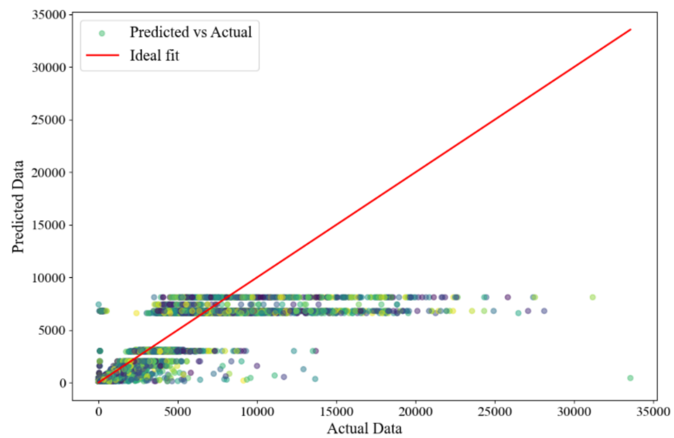
(a) RF



(b) KNN



(c) XGBoost



(d) Light-GBM

Fig 3. Accuracy graph of ML models [(a) RF, (b) KNN, (c) XGBoost, and (d) Light-XGB].

V. CONCLUSION

This paper has presented a proposed model of forecasting energy demand on a long-term basis with comparison among different machine learning algorithms like Random Forest (RF), k-neighrest Neighbors (KNN) regression, Extreme Gradient Boosting Method (XGBoost), and Light Gradient Boosting Method (Light-GBM). As KNN has the tremendous ability to recognize sequences from earlier patterns while handling a sizeable amount of data, it has the highest accuracy rate of 94% with approximately 28.7 error rates. Likewise, Light-GBM and XGBoost have some perks in them as well. With excelling scaling properties both these models have shown 81% and 87% accuracy respectively; whereas in the computational perspective, XGBoost has quicker computational time. Contrarily, RF has displayed 25% accuracy with meager error rates. Such tradeoff can absolutely be utilized in any power sector application-based platform with this modeling. Especially, a developing country like Bangladesh which is currently facing power issues, can consider such a study in practical use so that there could be proper power management policy stability. Hence, the future aim of the paper is to introduce hybrid models and state comparisons with the existing ones along with big data.

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