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Predicting Mining Excavator Fuel Consumption using Machine Learning Techniques

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Abstract

Fuel consumption represents about 30% of the total energy used in surface mines. Modelling and prediction of fuel consumption of mining equipment, including excavators is a valuable tool in assessing both energy cost and greenhouse gas emissions. However, only a few studies have reported on fuel predictions in mining operations. This study presents the implementation of four machine learning techniques (Random Forest, Gradient Boosting, k-Nearest Neighbor and Multi-Layer Perceptron Neural Networks) in mining excavator fuel consumption modelling and prediction based on collected dataset. Multiple regression analysis was used as a baseline study. Coefficient of correlation (R), root mean squared error (RMSE) and mean absolute error (MAE) were the statistical metrices used to assess the performance of the various models. The results indicate that all the implemented machine learning algorithms performed better than the multiple linear regression model. Although all the machine learning models gave good performance in predicting fuel consumption, the Gradient Boosting algorithm showed superior performance with high R value (0.7330) and lowest errors (RMSE = 762.58, MAE = 582.15). The Random Forest model showed poor performance in analyzing and explaining the datasets. This study has shown the possible application of machine learning models in predicting surface mine excavation energy using operating parameters. These models can therefore be used to analyze and improve mining excavator energy consumption through the control of crucial factors which significantly impact on energy consumption.

1. Introduction

In surface mining operations, heavy equipment is usually required for excavation, transportation and placement or disposal of materials. Excavation and haulage are the processes responsible for digging up material from the ground, be it waste or ROM, and transporting it to its next location. In its simplest form, there are two main pieces of mining equipment, excavators and trucks; grouped together they are often referred to as excavator (or shovel) and truck fleets. Excavators sit on top of the material being removed and scoop it up from below them into the truck on the level below [1]. Open-pit excavators are the prime extracting equipment used and they perform over 80% of the total work content [2]. In this regard, evaluation of their energy consumption determines to a greater extent the efficient operation of the whole mining excavation process. Three main factors affecting fuel consumption are operator practices, operating conditions and equipment [3]. During equipment

operations, energy is consumed in two main ways; excavator loading and idle. Diesel and electricity are used as sources of energy for the equipment used in the excavation [4].

Truck operation is one area of focus amongst literature analyzing haulage and excavation energy efficiency. Siami-Irdemoosa and Dindarloo, [5] developed a neural network approach for creating a prediction model of truck fuel consumption that could be used to compare alternate operating conditions. Kecojevic and Komljenovic, [6] analyzed several truck models under different load conditions to find correlation between fuel consumption and engine load and propose opportunities for improved operation. Sahoo et al., [7] develop a nonlinear optimisation model mine road topology and truck dynamics for reducing the fuel consumption of trucks. Salama et al., [8] used discrete event simulation and mathematical programming to analyze the energy consumption of alternative haulage methods, including in-pit conveyors, a long-term, strategic planning decision.

The assessment of excavator/shovel energy consumption has also been studied. Vukotic and Kecojevic, [9], conducted an analysis of shovel energy consumption data, to identify the impact that shovel operators have on energy efficiency. Awuah-Offei and Frimpong, [10], used dynamic simulation of a shovel to identify the specific operating conditions that yield the highest energy efficiency of the equipment. Another research contributes an original mixed integer linear programming formulation that schedules haulage activity to minimize the truck and shovel energy consumption required to meet production targets [11]. Another research proposed a model using an artificial neural network (ANN) to predict an excavator's hourly energy consumption and CO_2 emissions under different site conditions. The proposed ANN model includes five input parameters: digging depth, cycle time, bucket payload, engine horsepower, and load factor [12]. In an extensive study involving twenty-six types of construction equipment, excavators accounted for 15% of the total energy consumption and CO_2 emissions from construction equipment and machinery [13]. Therefore, it becomes necessary to model and predict excavator fuel consumption, particularly, in the mining industry to control critical operating parameters that can ensure efficient utilization of mining excavators [14].

This study aims to predict daily excavator fuel consumption per excavator operational activities in a surface mine site using Random Forest (RF), k-Nearest Neighbor (k-NN), Gradient Boosting (GB) and Multi-Layer Perceptron Neural Networks (MLP neural networks). The models were assessed and compared in predicting fuel consumption. Average daily excavator worked hours, average daily excavator availability (%), average percentage excavator utilization, total excavator bucket payload (bcm) were the input parameters and daily excavator fuel consumption as the output.

1.2 Brief Description of the Various Models

1.2.1 Random Forest

RF is a robust ensemble learning approach among machine learning techniques [15]. A final decision is made based on multiple decision trees. To ensure accuracy of the final decision, the number of trees in the forest must be sufficient [16]. In practical problems, RF is applied to both classification and regression problems. For classification problems, RF recapitulates the decisions from trees and makes a final decision based on the majority vote. However, for regression problems, it calculates the average value of the decision trees and uses it as the final decision. RF performs data sampling using the bootstrap technique when implemented in any problem. Sub-samples are divided randomly into small databases, and each tree represents a full growth based on each sub-sample. Finally, the majority vote or average value of the trees is used to evaluate the problem [16].

1.2.2 MLP Neural Networks

Artificial neural networks are popular owing to their similarities with the human brain in machine learning [16]. To develop an ANN, two problems should be considered: structure of the ANN; and training algorithm. The structures of ANNs often include three types of layers, namely the input layer, hidden layer(s), and output layer. The input and output layers are single layers, whereas the hidden layer(s) can consist of one or more layers. MLP neural networks are a popular form of an ANN with multiple layers [17], [18]. There are numerous training algorithms that can be applied to train an ANN model [19]. Of these, feed-forward and back-propagation are two of the most popular training algorithms used to train ANNs. MLP neural nets also use similar algorithms to train a network [17]. To solve problems, MLP neural nets use the input neurons to receive information from the outside environment. Data are then encoded and forwarded to the hidden neurons, where the calculations occur as in a 'black box'. Weights are the result of this processing, and they are the parameters used to explain the relationship between neurons. Finally, the hidden layers send the outcomes to the output neuron(s). Trial and error approach was used to determine the network structure and Figure 1 illustrates the general structure of the MLP Neural Networks used to predict fuel consumption in this study.

1.2.3 k-Nearest Neighbor

The k-NN is classified as a lazy learning-based algorithm in machine learning [20]. Its main concept is finding, collecting, and saving information from the nearest neighbors without learning. This algorithm calculates the Euclidean distance from all nearest neighbors [21]. It then sorts the distances in ascending order and selects the nearest neighbors around it [22]. In general, the implementation steps of the k-NN algorithm are straightforward; it includes calculation of Euclidean distance and selection of number of neighbors. Several neighbors can reduce the variance of a model; however, a small number of neighbors may be an essential pattern for the k-NN model, and it should not be ignored. Therefore, a balance between over-fitting and under-fitting is considered to be the most suitable method for the selection of the number of neighbors in the k-NN algorithm. The grid search technique is a good candidate for selecting the number of neighbors [16].

1.2.4 Gradient Boosting

The GB has emerged recently as a prime machine learning model. GB is very efficient on data that has been structured i.e. where the information has been grouped into columns and rows and datasets which are medium sized with the existence of at most a few million-sized populations [23]. GB is basically an ensemble approach that operates by training several individual students, often decision trees. Unlike in a RF where the trees are parallel trained, in a GB, the trees are sequentially trained with each tree learning from the mistakes of the preceding tree. The hundreds of weak learners are aggregated to construct a single robust ensemble learner with the contributions of each student learned during training via Gradient Descent (therefore the weights of each tree will be a model parameter) [24].

1.2.5 Multiple Linear Regression

Regression analysis is a common predictive modelling technique. The model can be written with more than one explanatory variable as shown in Eq. (1).

$$y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \ldots + \alpha_n X_n \quad (1)$$

where n is the number of input parameters, y is the output variable, α_i regression parameters (i = 0,1,2,3,…,n) and X_i is the input variable (i = 1,2,3,…,n).

In the MLR model, the least-square approach is usually used for approximation. If the regression coefficients are obtained, a projection equation may be used to estimate the value of a continuous output (target) as a linear function of one or more disparate inputs. The relevance of regression models depends on the way models are interpretable and easy to use. The main logical drawback however, of all regression methods is that the relationship can only be established but the underlying causal process can never be guaranteed [25].

It is worth mentioning that the various machine learning algorithms applied in this study, including the MLR model, were implemented using the scikit-learn library in Jupyter Notebook (Python (version 2.7.9)) programming environment.

2. Methodology

2.1 Data Description

In this study, data was collected from Mine X in the Western Region of Ghana. For this study, 172 historic datasets, collected over a period of 172 days, were obtained. Since the mine operates 2 shifts per day, each row of the input dataset represents average values of the 2 shifts. The collected datasets comprised of the following parameters: daily excavator worked hours (h), daily excavator availability (%), daily excavator utilization (%), total excavator bucket load (bcm) as the input parameters and daily excavator fuel consumption as output. Statistical description of the entire datasets is shown in Table 1. Table 2 also shows the correlation matrix within the data collected.

Table 1. Statistical description of the entire datasets

	Worked hours (h)	% Avail	% Util	Total load (bcm)	Fuel Used (L)
count	172	172	172	172	172
mean	11.60	0.80	0.65	12241.67	4011.09
std	2.37	0.15	0.12	2086.44	1113.81
min	6.61	0.44	0.35	8022.00	1450.00
10%	8.81	0.62	0.52	9401.00	2728.70
25%	9.85	0.67	0.57	10790.50	3335.00
50%	11.43	0.84	0.63	12215.00	3845.50
75%	13.12	0.94	0.73	13760.00	4516.50
90%	14.67	0.97	0.80	15056.80	5516.50
max	19.05	1.00	0.92	17766.00	7347.00

Table 2. Correlation matrix of the entire dataset

	Worked hours	*% Avail.*	*% Util.*	*Total load*	*Fuel used*
Worked hours	1				
% Avail	0.495861	1			
% Util	0.695882	0.52742	1		
Total load	0.558049	0.168386	0.388557	1	
Fuel used	0.416465	0.303479	0.525094	0.435515	1

2.2 Data Selection and Normalization

In partitioning the datasets, the simplest approach based on the random splitting approach was followed. Hence, out of the 172 datasets, 137 datasets representing 80% of the data selected for training and the remaining 20% of the datasets for testing the model. The training datasets were used exclusively for the construction of the various models. The test datasets were employed as unseen data to determine the models' performance. The test data set performance is ultimately called the realistic engineering performance. In machine learning, subsets (training and testing datasets) must be chosen to be representative of the whole data collection. Samanta et al., [26] demonstrated that a random sampling of small dataset is very likely to improperly give high and low output levels within the train and test datasets. Problems involving dataset division were solved by earlier researchers using Kohonen networks and genetic algorithms [27],[28]. A manual approach, which is applied in this study, involves multiple shuffles to get statistically similar subsets at 95% significant level [27]. Table 3 and 4 shows the statistical properties of both the training and testing data subsets for the various variables, including their percentiles (0.1, 0.25, 0.5, 0.75, 0.9). To avoid over-fitting in the models, Box–Cox transformation technique [29] was applied. The Box–Cox technique transformed the independent variables into normal shapes. The transformation of the values has the form:

$$y(\lambda) = \begin{cases} \frac{y^{\lambda}-1}{\lambda}, & \text{if } \lambda \neq 0; \\ \log y, & \text{if } \lambda = 0. \end{cases} \quad (2)\ [30]$$

Where, λ is referred to as lambda, which varies from -5 to 5. All values of λ are considered and the optimal value for the data is selected [30].

Table 3. Descriptive statistics on training data

	Worked Hours (h)	% Avail	% Util	Total load (bcm)	Fuel used (L)
count	137	137	137	137	137
mean	11.53	0.80	0.65	12265.44	3996.93
std	2.30	0.14	0.12	2045.13	1112.77
10%	8.74	0.63	0.52	9472.40	2708.60
25%	9.85	0.67	0.57	10808.00	3307.00
50%	11.38	0.83	0.63	12222.00	3834.00
75%	13.02	0.94	0.74	13856.00	4527.00
90%	14.58	0.97	0.81	15020.80	5444.40

Table 4. Descriptive statistics on testing data

	Worked Hours (h)	% Avail	% Util	Total load (bcm)	Fuel used, (L)
count	35	35	35	35	35
mean	11.87	0.80	0.64	12148.66	4066.54
std	2.62	0.16	0.11	2269.99	1132.41
10%	9.14	0.61	0.54	9377.20	2906.00
25%	9.84	0.66	0.57	10262.00	3467.50
50%	11.66	0.84	0.61	12054.00	3850.00
75%	13.31	0.96	0.69	13567.50	4490.50
90%	15.11	0.97	0.77	14891.60	5376.60

2.3 Model Formulation

It is necessary to determine the proper set of parameters, which enable the generation of reliable models for prediction while avoiding the implementation of the default configuration suggested by software packages in assessment of the overall performance of the various ML algorithms. In addition, investigations that test a new algorithm and evaluates it with other approaches may be skewed through enhanced understanding of one of the algorithms [31]. Hence, parameter tuning of the various models is therefore very essential to address generalization/overfitting problem.

2.3.1 RF

In the formulation of the RF model, the range of values for the minimum samples split (1-5), the number of estimators (1-500) at 10 intervals, maximum depth (1-8) at interval of 1 and the maximum leaf nodes (1-20) at interval of 2, which are the critical parameters of RF, were evaluated to establish the optimum values via a grid-search technique using the training dataset. Breiman [30] demonstrated that by increasing the number of trees, the generalization error always converges; hence, preventing the overtraining problem.

2.3.2 KNN

To build the KNN model, a trial and error approach was conducted with k set in the range of 1–30, at an interval of 1 to establish the optimal k-value for the model. The Euclidian distance weight function was used for the prediction, in this case, closer neighbors of a query point will have a greater influence than neighbors which are further away. Also, the algorithm used was set to 'auto', which will attempt to decide the most appropriate algorithm (ball tree, kd tree and brute force) based on the training values passed to the model.

2.3.3 GB

Likewise, with loss functions '*huber*' and '*Is*' as well as number of estimators from 10 to 500 at 10 intervals was used to determine the best parameters for the GB algorithm using the grid-search technique on the training datasets. The maximum depth of the tree, which greatly affects the model performance was assessed from 1 to 20, at 1 interval.

2.3.4 MLP neural networks

For the MLP neural network model, the common concerns include the structure (the number of hidden layers and nodes), training algorithm, and overfitting problem. To overcome the over-fitting problem, the Box cox transformation was applied. To design the optimal structure of the MLP neural networks model, a trial and error procedure was used. Finally, the best structure was designed with four hidden layers (70,70,60,20) as shown in Figure 1.

2.4 Model Performance Assessment

Performance indices of Mean Absolute Error (MAE) (Eqn. 3), Root Mean Squared Error (RMSE) (Eqn. 4) and correlation coefficient (*R*) (Eqn. 5) were used to assess the performance of the models on the testing datasets. Afterwards, the best model was selected and recommended for practical applications. The three indices are computed as follows:

$$MAE = \left[\frac{\sum_{t=1}^{m}|(A_t - P_t)|}{m}\right] \quad (3)$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(A_t - P_t)^2} \quad (4)$$

$$R = \frac{\sum_{t=1}^{m}\left(A_t - \bar{A}\right)\left(P_t - \bar{P}\right)}{\sqrt{\sum_{t=1}^{m}\left(A_t - \bar{A}\right)^2} \times \sqrt{\sum_{t=1}^{m}\left(P_t - \bar{P}\right)^2}} \quad (5)$$

where m, A_t, P_t, $\bar{A}$ and $\bar{P}$ the total number of samples, the measured field values, the predicted field values, the mean of the measured field values and the mean of the predicted values respectively. It is worth mentioning that a model with R value closer to 1 and a lower MAE and RMSE is deemed a better model compared to the other competing models.

3. Results and Discussion

3.1 Model Developed

For the RF modelling, the best number of estimators was 300 according to the grid search techniques. A maximum depth of 8 and maximum leaf nodes of 30 was selected for the model. Also, in the GB algorithm, the *huber* loss function along with 300 number of estimators and a maximum depth of 6 was obtained from the grid search technique to develop the model. Moreover, a k-NN model with k = 8, and the Euclidian distance were used in the modelling process.

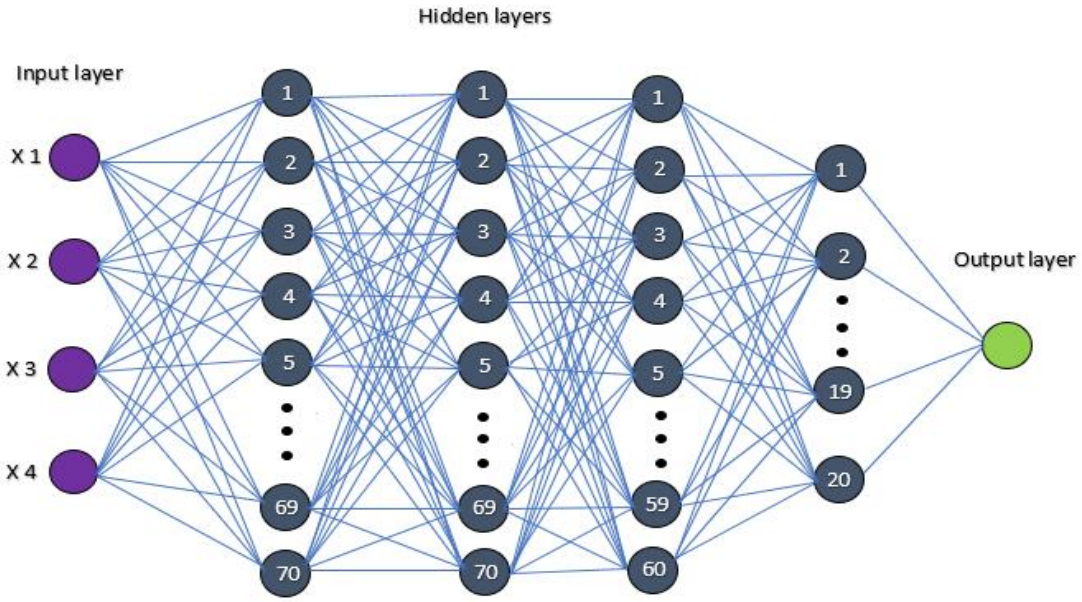


Figure 1. MLP Neural Networks structure

3.2 Model Performance

Based on the developed machine learning models for predicting excavator fuel consumption, it has been shown that the models were appropriately developed with good performances. The testing dataset was then used to evaluate their accuracy in practical engineering. The performance of the

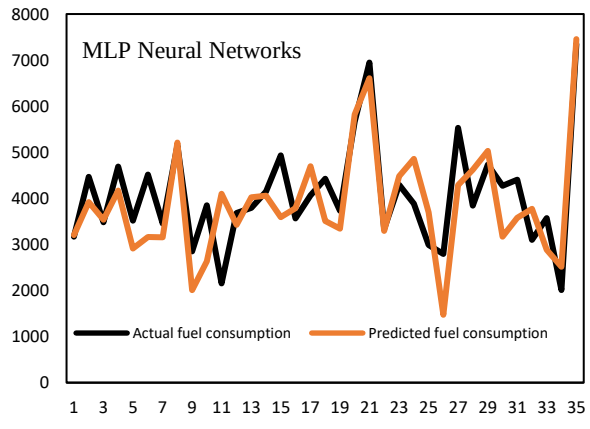
fuel predictive models is summarized in Table 5. It can be seen that the machine learning algorithms were good candidates for predicting excavator fuel consumption, based on the datasets collected from the mine in this study. The relationship between the input variables and fuel consumption was properly explained by the machine learning algorithms, even though the correlations between them were considerably low, as shown in Table 2.

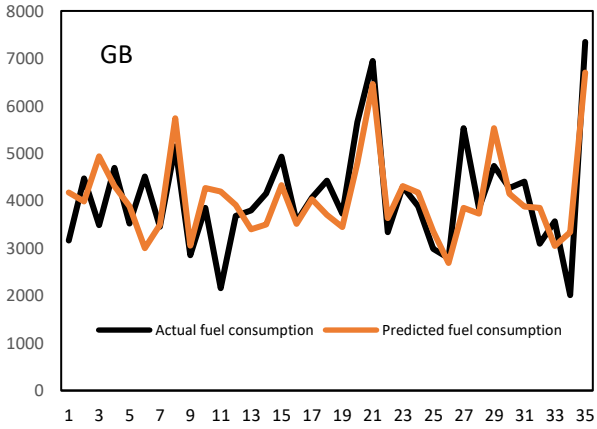
As seen in Table 5, though the MLP neural networks gave the highest R value (0.7854), thus, higher correlation between the measured and predicted fuel consumption, the GB exhibited the most superior performance in excavator fuel consumption prediction (i.e. lowest RMSE, MAE and a high *R* value). The error values of the MLP neural networks were slightly higher than the GB model. In contrast, among the machine learning models, RF model demonstrated the poorest performance in predicting the excavator fuel consumption. The k-NN algorithm performed slightly better than the RF algorithm though it did not learn anything from the datasets; however, its performance was still poor due to large errors. The MLP neural networks and GB models demonstrated high learning capabilities based on neurons and decision trees, respectively. They analyzed and explained the dataset more efficiently compared with the RF and k-NN models.

Table 5. Performance of the various models on the Testing dataset

	RMSE	MAE	*R*
MLP NN	772.36	614.46	0.7854
RF	831.61	647.20	0.6826
GB	**762.58**	**582.15**	**0.7330**
KNN	796.79	595.70	0.7200
MLR	889.89	619.73	0.6218

Based on the comparison of results in Table 5, it is clear that all the machine learning models were well-developed, and were better predictors than the MLR model, which gave the lowest *R*, highest RMSE and the second highest MAE. The multiple regression technique is linear and, hence, could not consider the non-linearities. Moreover, there are some important statistical assumptions for application of multiple regressions such as the assumptions of linearity, normality, non-multi-collinearity, and homoscedasticity. In another study concerning mining truck fuel efficiency modelling, neither of the assumptions was met, resulting in poor outputs from the multiple linear regressions [32].





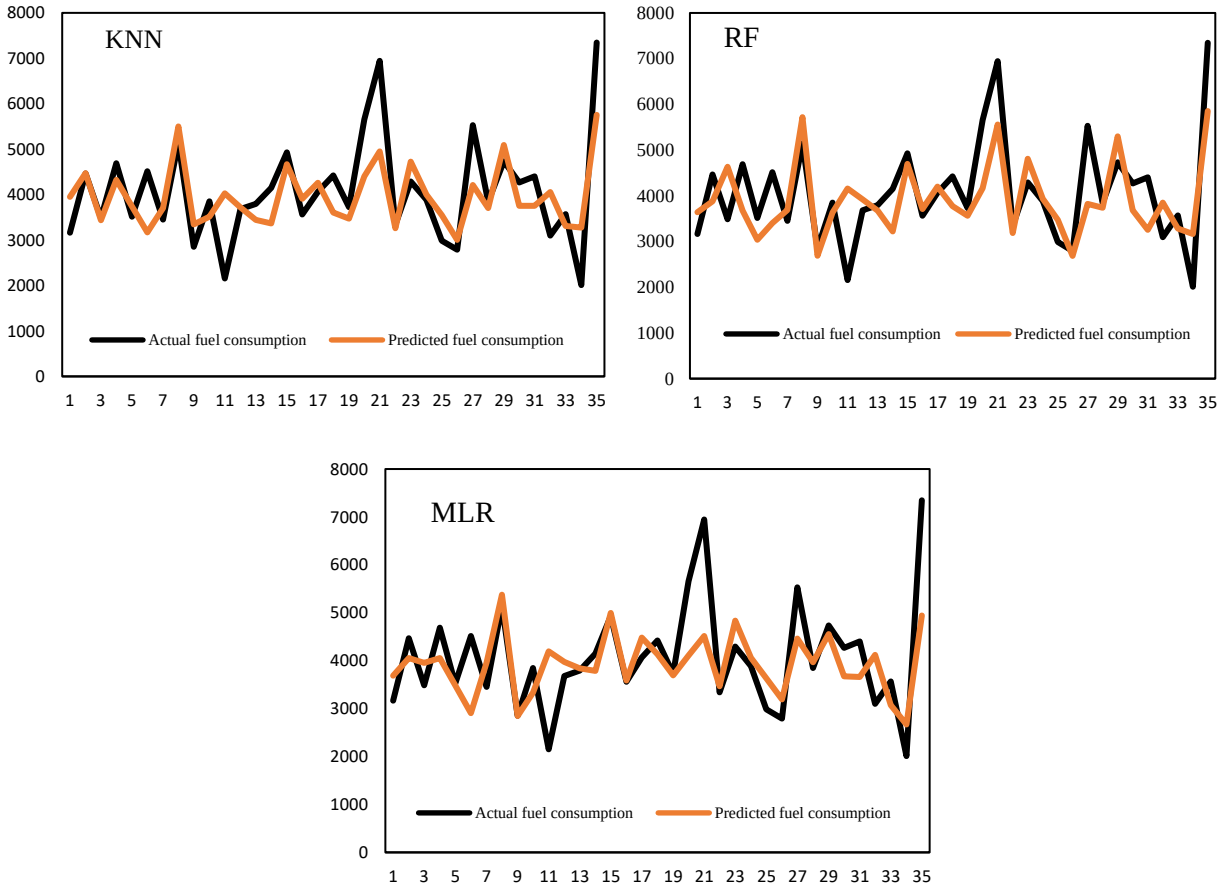
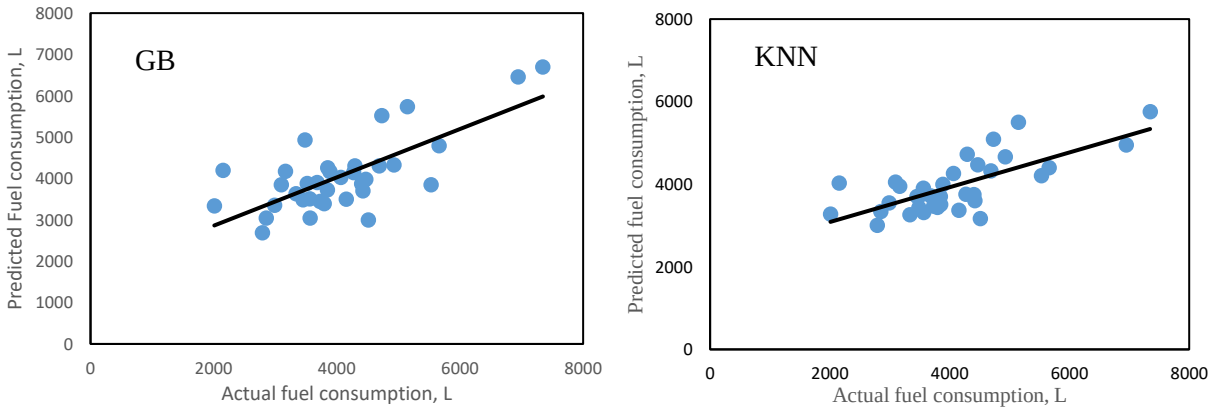


Figure 2. Relationship between actual and predicted fuel consumption based on testing datasets for the various models.

For further assessment of the performance of the developed machine learning models, the measured and predicted values of excavator fuel consumption were compared as depicted in Figure 2 and 3. The predicted values of fuel consumption using GB and MLP neural networks models were closest to the actual values. The predictions from the other models agreed with the results obtained in Table 5.



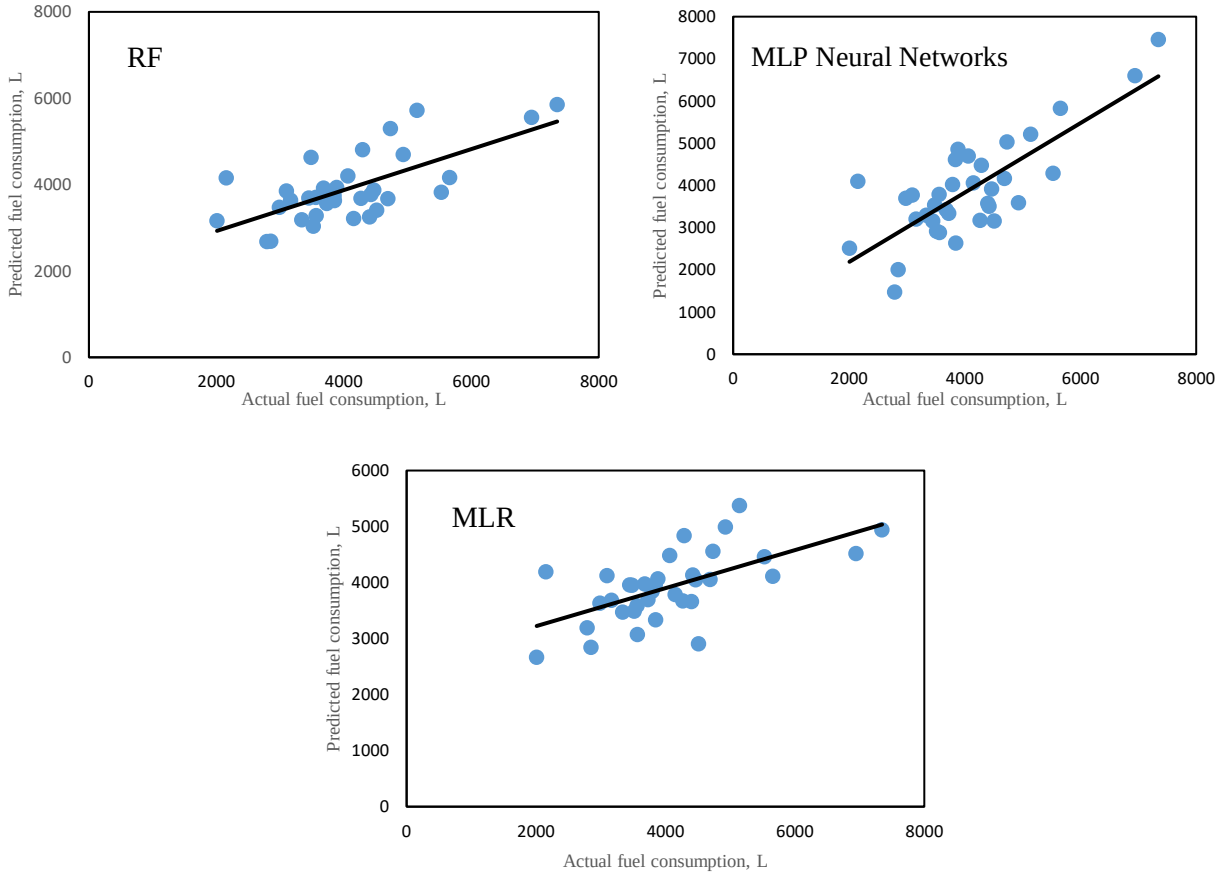


Figure 3. Correlation between actual and predicted fuel consumption based on testing datasets for the various models

4. Conclusion

In conclusion, this study has shown that machine learning models including k-NN, GB, RF and MLP neural networks can predict excavator fuel consumption with better performances. GB gave the best performance; showing slightly better performance than MLP neural networks with high *R* value (0.7330) and lowest errors (RMSE = 762.58, MAE = 582.15). k-NN was the third performing model in predicting the excavator fuel consumption with RF showing poor performance with large errors (*R* = 0.6826, RMSE = 831.61, MAE = 647.2). In essence, all the machine learning models performed better than the MLR (*R* = 0.6218, RMSE = 889.89, MAE = 619.73). Running the models with large datasets can improve upon the accuracy of the models. Mining professionals can incorporate these machine learning models to analyze and improve surface mining excavator energy consumption through the control of crucial factors which significantly impact on fuel consumption.

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