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Application of Machine Learning Techniques to Predict Haul Truck Fuel Consumption in Open-Pit Mines

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Abstract

The haul trucks consume a significant energy source in open-pit mines, where diesel fuel is widely used as the main energy source. Improving the haul truck fuel consumption can considerably decrease the operating cost of mining, and more importantly, reduce the pollutants and greenhouse gas emissions. This work aims to model and evaluate the diesel fuel consumption of the mining haul trucks. The machine learning techniques including multiple linear regression, random forest, artificial neural network, support vector machine, and kernel nearest neighbor are implemented and investigated in order to predict the haul truck fuel consumption based on the independent variables such as the payload, total resistance, and actual speed. The prediction models are built on the actual dataset collected from an Iron ore open-pit mine located in the Yazd province, Iran. In order to evaluate the goodness of the predicted models, the coefficient of determination, mean square error, and mean absolute error are investigated. The results obtained demonstrate that the artificial neural network has the highest accuracy compared to the other models (coefficient of determination = 0.903, mean square error = 489.173, and mean absolute error = 13.440). In contrast, the multiple linear regression exhibits the worst result in all statistical metrics. Finally, a sensitivity analysis is used to evaluate the significance of the independent variables.

1. Introduction

The need for energy has been globally boosted as the community and industrial demands have steadily grown. Although renewable energy has become the interest of many industries, non-renewable energy still provides more than 80%. The primary non-renewable energy sources are natural gas, oil, and coal, responsible for most greenhouse gas (GHG) emissions [1].

The mining industry has been in practice for many centuries to extract the minerals from the earth. Therefore, it has been a significant contributor to the current improvement of modern life. Thus, such a main industry consumes a large amount of energy, and supplying the required energy has been a major challenge for mining stockholders. The main operational categories in mining processed include extraction, transportation, and ore processing [2, 3]. Haul trucks are utilized for material transportation from the pits to the desired destinations (plants, stockpiles or waste dumps) based on the material types (ore or overburden/waste). About half of the total operating costs in open-pit mines are associated with the haulage systems [4, 5]. The continuous global increase in energy prices, energy demand, and environmental problems related to GHG emissions highlight an important challenge for the mining industry. Diesel fuel as the traditional energy source is the primary power source in surface mining due to its cost and transportation flexibility, especially in the mines located remotely. The electrical power is the second-ranked energy source if the mine location uses the electricity network grid. In addition,

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underground mining prefers to use electrical power in order to reduce exhaust gas and decrease safety hazards and ventilation costs. Moreover, stationary machinery such as comminution circuits, dewatering pumps, and ventilation pumps mostly uses electrical power [3].

According to a survey by the Department of Energy of the US [6], the mining industry's energy is 2% gasoline, 10% coal, 22% natural gas, 32% electricity, and 34% diesel. The energy used most for material handling is diesel fuel at 87% [6]. Also, material transportation accounts, on average, more than a third of energy consumption in the mines [7], which is the highest consumption of energy, followed by processing and extraction.

A study has shown that loading and hauling activities have the largest share in GHG emissions [8]. Haul trucks are operated with other machinery including loaders, excavators, and shovels, regarding the production capacity and site layout [2]. In the haulage operations of mining, the haul trucks consume a significant amount of fuel, and generate a remarkable amount of emissions [9]. The haul truck fuel consumption in mining is unique, and requires customized research. Mining roads (ramp) have more difficult conditions than highways, and the amount of dust produced is usually higher. In addition, the haul truck payload may exceed 300 tons. Moreover, the cycles of this operation are shorter than transportation in the other industries.

Improving the haul truck fuel consumption has a significant effect on reducing the pollutants and GHGs. Therefore, this has led to some research works in order to improve the haul trucks' energy efficiency. The most important studies on the haul truck fuel consumption and the related issues are as follows. Kecojevic and Komljenovic [10] have examined the effects of engine load factors and power on a truck's fuel consumption, and have determined the amount of a truck's CO_2 emission. The authors have considered the original equipment manufacturers haul trucks for this objective. The study conducted by Antoung and Hachibli [11] have addressed the technological concerns of power-saving and motor efficiency improvement in mining machinery. They mainly focused on the technical functioning of the mining equipment and motor components, and how to reduce friction can be achieved. In another study, an integrated data environment system has been developed by Bogunovic et al. [12] to analyze the energy consumed in an open-cast coal mine. Chingooshi et al. [13] have studied mining smart energy management strategies and have highlighted the critical parameters of creating opportunities to increase energy efficiency. Sahoo et al. [14] have provided a generic benchmarking model for dump truck energy consumption in surface mines based on vehicle dynamics, engine characteristics, and mine's topography. Kecojevic et al. [15] have established the relationships among energy production, energy consumption, and energy cost, as these factors relate to the extraction of a surface bituminous coal mine. Carmichael et al. [16] have investigated the haul truck fuel consumption costs and gas emissions in surface mining operations. In this research work, the simulations performed do not consider the variables related to the hauling truck fuel consumption. Liu et al. [17] have compared carbon emissions and energy consumption for transportation belt conveyors and truck based on the theory in surface coal mines. A process analysis-life cycle analysis has been constructed to determine the carbon emission factors and a calculated energy consumption model.

Siami-Irdemoosa and Dindarloo [18] have predicted fuel consumption of haul trucks by utilizing an artificial neural networks model based on the cyclic activities. They determined the haul truck fuel consumption in one cycle as the dependent variable and loaded travel time, loaded idle time, empty travel time, loading time, etc., as the independent variables. Soofastaei et al. [19] have investigated the payload variance on haul truck fuel consumption in Australia's surface coal mine. They also looked at GHGs and costs of haul truck fuel consumption. Rodovalho et al. [20] have created a method to identify and analyze the variables related to the hauling truck fuel consumption in open-pit mines. In this research work, the mathematical modeling tools and statistical analysis techniques accompanied with multiple linear regressions have been used to investigate road maintenance and construction variables on fuel consumption of haul trucks. The cyclic activities' effects on fuel consumption of haul trucks have been studied by Dindarloo and Siami-Irdemoosa [21] using the partial least squares regression and the autoregressive integrated moving average methods. An artificial neural network (ANN) has been developed by Soofastaei et al. [9] to predict haul truck fuel consumption in the surface mines. They determined the haul truck fuel consumption based on the truck weight, total resistance, and truck speed according to the best engine performance of the haul trucks. Peralta et al. [22] have considered a truck's maintenance effect on the truck energy consumption in the mining operations. Truck-specific fuel consumption was estimated using the regression analysis based on the equipment reliability, gross mass weight, and distance as the independent variables. Jassim et al. [23] have developed an ANN model for predicting off-highway trucks' energy consumption and CO_2 emissions. They used discrete event simulations in order to generate synthetic data for training and testing the prediction model according to a database and various project conditions.

Regarding the energy challenges and future emission policy, it is essential to determine a robust and intelligent prediction model built on the real-world collected data to be integrated with the mining industry's fuel management system. In other words, a significant amount of real data is currently available; however, providing an approach that can simultaneously reduce the trucks' fuel costs and their environmental responsibilities could bridge some of the issues in the mining sector. Thereby, the main questions of this research are: what are the most effective variables in the haul truck fuel consumption and how these variables can best predict the haul trucks fuel consumption? In the real mining operations, the relationship between the actual technical variables is generally complicated. Artificial intelligence and machine learning (ML) are the most advanced tools used to solve and optimize different practical problems, and also can be very effective in determining the complex relationship between the variables. The main aim of this research work is to determine the best model for predicting the haul truck fuel consumption with a comprehensive comparison between the machine learning models. In this work, the main controllable technical variables of the real dataset were used to predict the fuel consumption of haul trucks in an open-pit mine using the machine learning models that were not considered in the previous studies to the best of our knowledge. In addition, several well-known machine learning models, some of which have been used for the first time for this prediction, have been studied and compared based on a large actual dataset collected from a large-size open-pit mine to achieve the most accurate results. In summary, the research steps were carried out as what follows. In the first step, the variables affecting the haul truck fuel consumption were investigated and the most important ones were selected. After collecting the required data, pre-processing and data analysis were performed. Then five machine learning models were developed to predict the haul truck fuel consumption and validated, and finally, the best model was selected and discussed.

2. Methodology

A major subset of artificial intelligence is machine learning, which aims to deploy computer programs for automatic learning and improve the experience without explicit programming [24]. This research work aimed to investigate the various machine learning models' feasibility and performance to predict the haul truck fuel consumption in an open-pit mine according to the actual dataset. This research work provides one of the unique large-scale studies that have been recorded for mining haul trucks to build and evaluate the models.

In addition to the previously mentioned studies in predicting the fuel consumption of haul trucks in mines, the machine learning models have been used in other fields of mining engineering. Ohadi et al. [25] have employed the decision tree and random forest (RF) models in order to predict rock fragmentation and movement of the blasting process in the open-pit mines. Bastami et al. [26] have used the artificial neural network, gene expression programming, and multiple regression models in order to predict the blasting costs in limestone mines. The values of peak particle velocity in mine blasting have been predicted and compared using the artificial neural network and multivariate regression analysis by Bakhsandeh Amnieh et al. [27]. Srivastava et al. [28] have predicted the blast-induced ground vibration by machine learning models. Support vector machines (SVM) and random forests were used and compared in their study. Lashgari and Sayadi [29] have determined the overhaul and maintenance cost of loading equipment in surface mining, while the univariate regression and multiple regression have been used in this study. Different machine learning models, i.e. RF, SVM, ANN, kernel nearest neighbor (K-NN), decision tree, and M5Tree have been investigated to predict ore production at a limestone open-pit mine by Choi et al. [30]. The semi-autogenous grinding mill energy consumption in mining operations has been predicted by Avalos et al. [31] based on several machine learning models including multiple regression, k-nearest neighbor, support vector machine, neural network, long short-term memory, and gated recurrent units. Betrie et al. [32] have presented the machine learning models to predict the acid mine drainage quality in copper concentration. They used ANN, SVM, K-NN, and model tree (M5P) for their study. Khademi Hamidi et al. [33] have predicted the performance of hard rock TBM using the rock mass rating system using the multiple regression models in a case study. Accordingly, five machine learning models including multiple linear regression (MLR), RF, ANN, SVM, and k-NN have been investigated and developed to predict the haul truck fuel consumption. These algorithms have been used successfully in many other fields. The framework of the methodology for predicting fuel consumption of haul trucks that have been applied in the present paper is demonstrated in Figure 1.

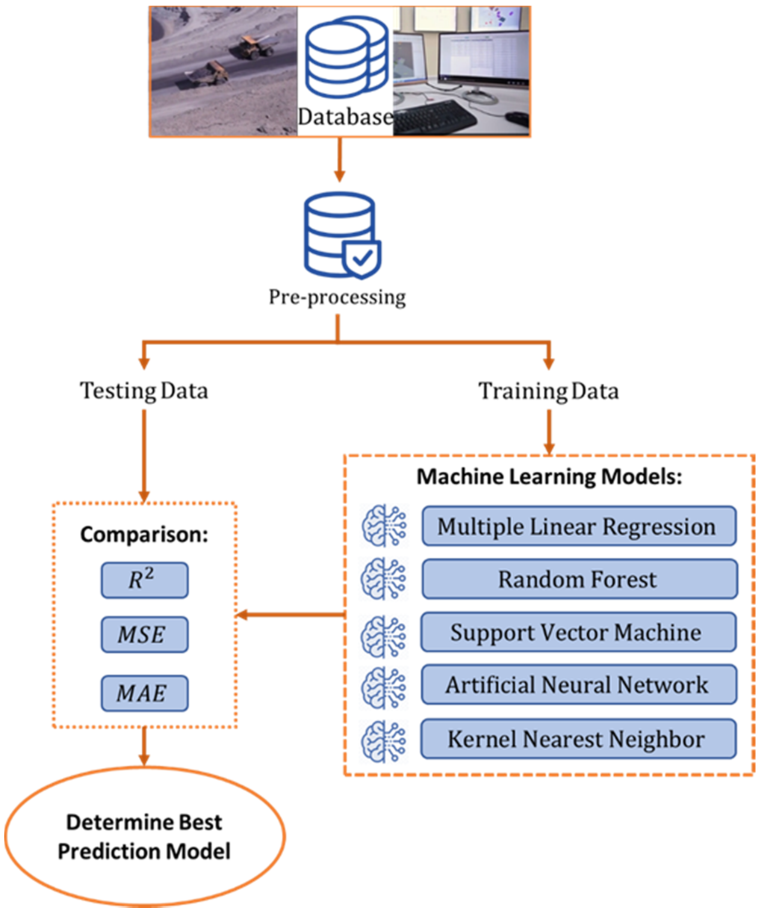

Figure 1. Framework for predicting haul truck fuel consumption.

Multiple linear regression

One of the easiest and most intuitive approaches of prediction is multiple linear regression. This method explains the relevance of one or more independent variables with one dependent variable. The model for an MLR was developed based on the most general equation (Equation (1)) [34].

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_r X_r + e \quad (1)$$

where, for r = n observations:

Y = dependent variable
X_r = independent variables
β_0 = intercept (constant term)
β_r = coefficients for each independent variable
e = model residual

The advantages of MLR are that it performs very well for linearly separable data, it is easier to implement and interpret, and can extrapolate beyond a dataset. On the other hand, the assumption of linearity between variables, sensitivity to outliers, and being prone to overfitting are the disadvantages of this model [35, 36]. An MLR model's compatibility can be checked with a coefficient of determination (R^2) value between 0 and 1. A higher value of R^2 demonstrates a strong association between the independent and dependent variables. A model with the highest R^2 can be designed using the stepwise, backward, and forward regression adjustments.

Random forest

Random forest is a group learning technique among machine learning methods [37]. RF combined the decision trees to increase the accuracy and stability of the prediction. This method uses the average random selection of predictor variables, where the predictor variables can be in any type including categorical and numerical types in a continuous or discrete shape. The hierarchical structure of the trees allows for the automatic interaction between the predictor variables of the model. Since the RF trees are not sensitive to skewed distributions, missing values, and outliers, they are among the most effective ML prediction techniques [37]. RF has several advantages. It is relatively fast, simple, robust to outliers and noise, avoids overfitting, and is less dependent on the tuning parameters. However, this algorithm is substantially slow and time-consuming. The computational cost increases as the number of generated trees increases, and may change significantly by a small change in the data [38, 39]. The framework of the RF algorithm for predicting the haul truck fuel consumption is demonstrated in Figure 2.

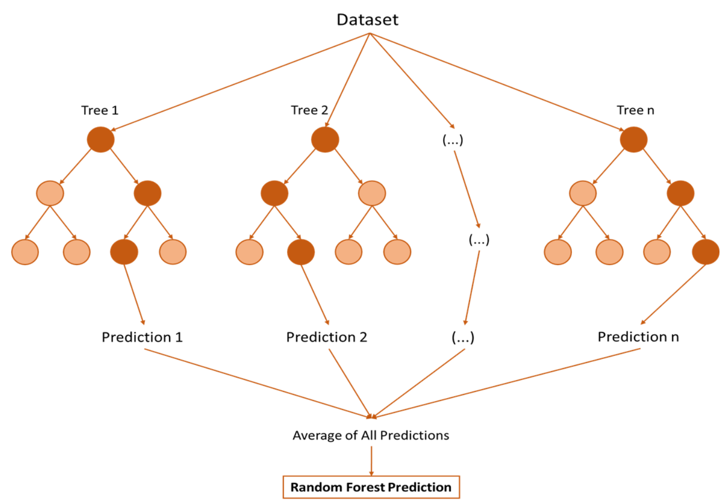

Figure 2. Random forest structure.

2.3. Artificial neural networks

Artificial neural networks (ANNs) simulate the behavior of a biological neural network, particularly the brains of humans [40], and it can be seen as a simplified mathematical model of biological neural networks [41]. Artificial neural networks can use models more easily and accurately through complex natural systems with large inputs. It is an innovative and useful tool for solving complex problems [42].

The basic layout of this technique consists of layers and neurons. It comprises the input, hidden, and output layer(s). In each layer, the neurons are connected according to a specific network structure. The neurons' number in the hidden layer affects the accuracy of the prediction model. This model is trained to represent a dataset based on the learning algorithms [43]. The relationship between the output and input must be established by training the created neural network structure.

If the systems are very complex, the dataset required for training may be increased, and some pre-processing is required. After training the network structure, ANNs can generate reliable and fast solutions, even in the datasets [36]. This practice's architectures are different based on the flow of information and the number of layers. It is important to adjust the optimal network size to avoid memorizing the dataset and even noise and reduce the training time. During training, the inputs and outputs of the layers are calculated using random weights and biases. An activation function is applied upon every layer, and one layer's output is transferred as the input to the next layer.

Some of the advantages of ANNs include the ability to deal with non-linear data, easily identify complex relationships between dependent and independent variables, strong fitting, and handling noisy data. In contrast, some of the disadvantages of ANNs are apt to overfitting, prone to become stuck in a local optimum, and difficult to interpret and high processing time for large neural networks [36, 44]. Figure 3 illustrates a schematic structure of ANNs.

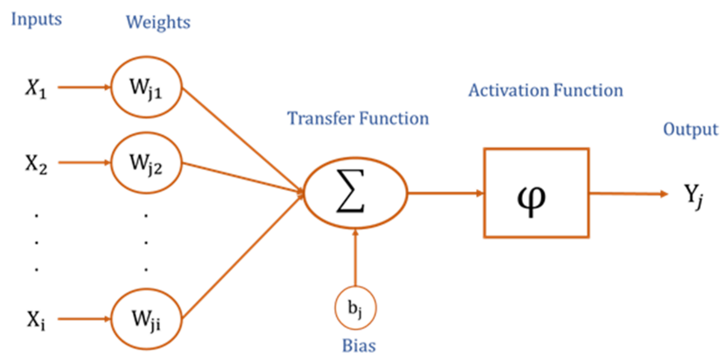

Figure 3. General structure of ANNs model.

2.4. Support vector machine

One of the supervised learning techniques is support vector machines used for the regression and classification problems based on the associated learning algorithms [45]. SVMs have impressive results on proper precision, accuracy, and generalization. SVMs are effective for both the linearly separable and not separable datasets. When the data is not linearly separable, it can be easily separated using a hyperplane, and applying a transformation from one dimension to another. Each class or cluster among the data points is disconnected in the SVM model by drawing a parallel line/hyperplane. This model's entered data is transformed into a special area, where the solution based on the optimization techniques occurs [46]. The data nearest from the hyperplane are known as the support vectors. The hyperplane should be selected to minimize the distances from the data points to the optimal separating hyperplane. Depending on the problem's characteristics, different kernel functions can be applied: radial basis function (RBF), linear, sigmoid or polynomial. RBF was used as a kernel type in this study's SVM model. The gamma (g) and penalty parameter (C) are the controllable kernel function parameters in this function. The K-fold cross-over algorithm was performed to detect the parameters g and C.

The advantages of SVM include learning useful information from a small training set, strong generation capability, and effectiveness in high-dimensional spaces. On the downside, it does not perform well on big data, is sensitive to kernel function parameters, and is computationally time-consuming [36, 47].

2.5. Kernel nearest neighbor

Kernel nearest-neighbor (K-NN) is a very simple and non-parametric method used for the machine learning regression and classification approaches [48]. This method's main concept is finding, collecting, and saving the nearest neighbors' information without learning [48]. This process calculates the distance from all N neighbors. The distances are arranged in the ascending order, and then select the nearest. In general, K-NN calculates the distance between each datum and the mean of a class, and selects the number of neighbors. The nearest neighbors' average classes are established by determining a specific k number, and the new target is devoted to the closest class to its neighbors [49]. Common distance metrics choices include Euclidean, Manhattan, Minkowski, and Chebyshev [50]. The appropriate number of neighbors is extremely important because it can reduce the variance of a model. The smaller k is, the more complex the model is and the higher the risk of overfitting.

Conversely, the larger k is, the simpler the model is and the weaker the fitting ability. The K-NN benefits include apply to massive data, suitable to non-linear data, robust to noise, fast training, and easy to implement. Mutuality, the drawback of K-NN includes low accuracy on the minority class, slow testing, sensitive to noise, and need a large storage space [36].

2.6. Model validation

Several evaluation metrics are applied to evaluate the prediction model's performance and compare them. In this work, R^2, mean square error (MSE), and mean absolute error (MAE), which are frequently used in the literature, were utilized for assessing and comparing the performance success of the machine learning models. The formulas of R^2, MSE, and MAE are given in Equations. (2), (3), and (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y - y')^2}{\sum_{i=1}^{N}(y - \bar{y})^2} \quad (2)$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{I=1}^{N}(y - y')^2 \quad (3)$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{I=1}^{N}|y - y'| \quad (4)$$

In the above equations, y represents the actual value, $\bar{y}$ and y' indicate the mean and predicted value of y, respectively. The total number of observations is N.

3. Case study

This work is based on the datasets collected from the Chadormalu Iron ore mine, located 165 km west of the Yazd city in Iran. The geological reserve of the Chadormalu iron ore mine is 400 million tons, and the minable reserve is 330 million tons with an average grade of iron 55%. The ore minerals consist predominantly of magnetite and hematite. The shovel-truck system is used for the haulage operations of ore and waste materials in this mine.

An incorrect estimation of a mine's energy requirement can lead to many problems in the mine management decisions. Although the truck manufacturers provide approximate estimates on their various trucks' fuel consumption, due to the various mines' different conditions, the actual fuel consumption of the trucks is associated with considerable uncertainties. In other words, the mines' specific situation leads to a remarkable deviation in the actual fuel consumption and the estimated one by the manufacturers.

This work collected and analyzed the required data to provide a prediction model of the haul truck fuel consumption. In order to obtain the real data, more than 400,000 fuel consumption recorded data for several haul trucks from December 2019 to January 2020 was used in this case study. CAT 777D, as the mining haul truck in this mine, was selected for this work, in which net power and nominal payload were 699 kW and 91 tons, respectively. The haul trucks were equipped with a Vital Information Management System (VIMS) and loaded by Komatsu PC 2000-8 shovels during the study period.

The haul truck fuel consumption is a function of various variables including mine plan, mine layout, dumpsite design, production rate, engine operating, equipment maintenance, age, speed, payload, cycle time, idle time, rolling resistance, tire wear, parameters and transmission shift patterns, and operator practices [51]. Many variables affect the haul trucks' productivity in mining. The most significant effective variables are categorized into six main groups, and presented in Figure 4.

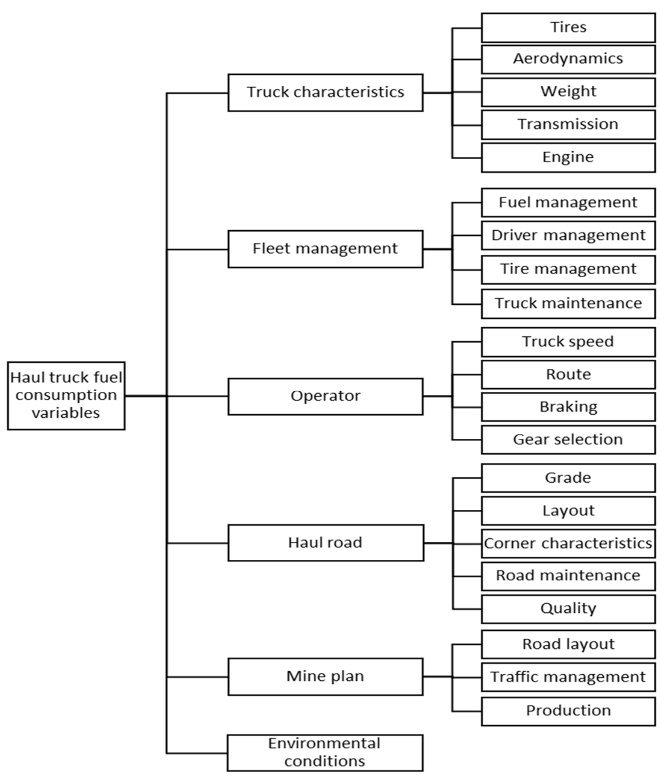

Figure 4. Haul truck fuel consumption effective variables [51].

A large dataset of real hauling operation was collected and investigated to accurately estimate the haul trucks' fuel consumption. This can help to have a model enabling engineers and managers to tune the fuel consumption strategies. Therefore, the effects of truck speed, truck payload, and total resistance (TR) on the haul truck fuel consumption were investigated. In this research work, the effective variables were selected based on their controllability. The summation of rolling resistance (RR) and grade resistance (GR) is the total resistance (Equation (5)) [9].

$$\mathrm{TR} = \mathrm{RR} + \mathrm{GR} \tag{5}$$

RR is a parameter that determines the resistance of rolling a wheel over the road's surface, and calculates the rolling friction force. RR mainly depends on the characteristics of the machine's tire and the condition of the road surface. GR represents the gradient of the haul road, and is calculated by dividing the vertical rise of the road over the horizontal length of the road. A positive GR shows the up-hilling condition, while a negative GR shows that the truck is moving down the hill. The material characteristics covered the road surface, and the road surface condition highly affects RR. Table 1 gives RR for the different types of the road surface.

Table 1. Typical rolling resistance [9].

Condition of road	Rolling resistance (%)
Concrete, bitumen	1.5
Smooth dirt and compacted dry gravel	2.0
Semi-compacted dry dirt and gravel	3.0
Firm sludge	4.0
Loose gravel	10.0
Soft spongy sludge	16.0

In the hard and well-maintained haul road, RR is about 2%. Road quality on the bench and near the end of the dump is declining, and RR might rise to 3%. As the road conditions worsen, especially in wet periods, RR will increase to 4%. In very bad and poor conditions, RR can be increased up to 10%–16%, although this status usually happens on very short parts of the road and in a short time.

The dataset includes the following records: date, time, payload (P), grade resistance (GR), speed (S), rolling resistance (RR), total resistance (TR), and fuel consumption (FC). The data was recorded using the onboard sensors, practical observations, and between-variables calculations. Most of the important variables were attainable via the onboard data logging instruments. Table 2 demonstrates a sample of the dataset. Table 3 shows the details of the dependent and independent variables.

Table 2. A sample of dataset collected from Chadormalu iron mine.

Date	Time	Truck ID	Truck state	P (tons)	S (km/h)	GR (%)	RR (%)	TR (%)	FC (L/h)
14/12/2019	9:40:31	TB204	Loaded	71	17	6.5	2.0	8.5	168
24/12/2019	0:22:12	TB209	Loaded	85	13	8.0	3.0	11.0	190
15/01/2020	8:59:53	TB205	Empty	0	35	0.0	2.0	2.0	70
15/01/2020	20:52:35	TB209	Idle	0	0	0.0	0.0	0.0	13
17/01/2020	9:02:51	TB201	Loaded	78	22	6.0	2.0	8.0	188
18/01/2020	7:10:39	TB205	Loaded	65	18	6.5	4.0	10.5	182
18/01/2020	2:18:12	TB201	Empty	0	32	8.0	2.0	6.0	66
19/01/2020	1:07:29	TB205	Loading	0	0	0.0	0.0	0.0	12
19/01/2020	1:25:09	TB203	Empty	0	25	7.0	2.0	5.0	48

Table 3. Independent and dependent variables statistical features.

Variable	Minimum	Maximum	Mean	Median	Standard Deviation
Payload (tons)	0	99	38.92	58.0	37.17
Speed (km/h)	0	39	15.02	16.0	11.03
Total resistance (%)	0	14.4	4.73	5.0	3.62
Fuel consumption (L/h)	9	193	98.93	86.0	71.0

4. Results and discussion

This work used five different machine learning techniques in order to predict the haul truck fuel consumption in an Iron ore mine. Prioritization between the prediction models was conducted according to the accuracy and success of the prediction to determine a model with the best performance on the dataset. Data preprocessing was performed on the obtained dataset for training the models. The dataset was divided into 20% for testing and 80% for training in order to ensure the training accuracy. All the numerical investigations and the machine learning implementation described above were conducted using Scikit-learn library and Python programming language. Scikit-learn, also known as sklearn, is a free machine learning library for the Python programming language [52].

The fuel consumption formula is found in Equation (6) by the best MLR model, where the R^2 values are 80.91% and 81.09% for the training and testing dataset, respectively.

$$FC = 11.113 + 1.111 \times P + 0.728 \times S + 7.10 \times TR \tag{6}$$

Figure 5 illustrates the relationship between the actual fuel consumption values predicted with the MLR model in the training and testing phase.

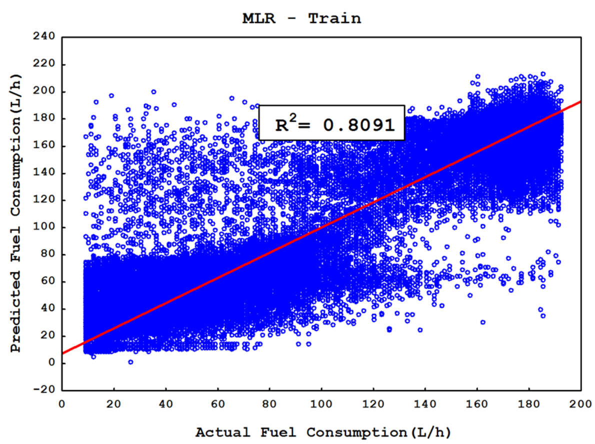

Figure 5. Relationship between actual and predicted values of FC with MLR model.

A sufficient number of trees in the random forest modeling was used to control the model accuracy and assure the sub-decision trees' aim. In this work, 200 trees were selected to satisfy this requirement. Figure 6 displays the relationship between the predicted and actual fuel consumption values with the RF model.

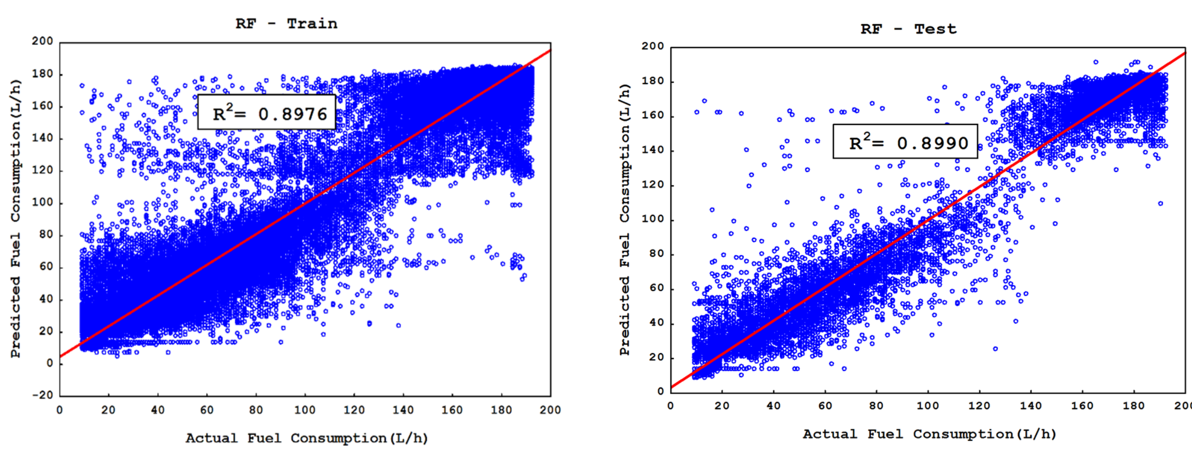

Figure 6. Relationship between actual and predicted values of FC with RF model.

The best structure of the neural networks was identified for this work by examining different networks and different activation functions. A two-layer network was implemented in this work. The two-layer ANNs with one hidden layer approximate all the desired functions. The linear and sigmoid functions were performed in the output and hidden layers, respectively, and a sufficient number of neurons was selected in the hidden layer. The number of suitable neurons in this layer can prevent overfitting and under-fitting the network [53]. In order to dominate this subject, the optimal neurons' number for the hidden layer was ascertained by trial and error, and by calculating the R^2 and MSE values for the training and testing dataset (Table 4).

In the present work, the proper neurons' number in the hidden layer was determined to be 20 in order to achieve the network's best performance. The characteristics of the ANN model's optimal structure for predicting the haul truck fuel consumption are presented in Table 5.

The accuracy of the results of the ANN model compared to the actual data of FC in the training and testing phase is illustrated in Figure 7.

Table 4. MSE and R2 values of ANN model with various neurons' number.

Neurons' number in the hidden layer	Train		Test	
	R^2	MSE	R^2	MSE
1	0.82660	873.32	0.83254	881.92
2	0.88275	590.51	0.88985	595.70
3	0.88706	568.78	0.89250	566.24
4	0.89254	541.21	0.88960	544.52
5	0.89663	520.61	0.89842	520.98
6	0.89799	513.76	0.89945	512.68
7	0.89841	511.65	0.89856	516.55
8	0.89821	512.64	0.89954	515.80
9	0.89891	509.14	0.89735	507.36
10	0.89985	504.41	0.90015	512.54
11	0.89895	508.94	0.90180	507.53
12	0.90013	502.97	0.89756	513.25
13	0.89908	508.24	0.90040	510.62
14	0.90056	500.81	0.90285	502.36
15	0.90025	502.37	0.90006	499.46
16	0.90070	500.12	0.90120	503.77
17	0.90090	499.31	0.89986	498.90
18	0.90220	492.68	0.90128	496.30
19	0.90150	496.28	0.90462	490.42
20	0.90270	490.15	0.90418	485.28
21	0.90200	493.62	0.90386	486.25
22	0.90250	490.97	0.90326	492.35
23	0.90182	494.45	0.90237	492.15
24	0.90227	492.73	0.90012	495.84
25	0.90238	493.90	0.90136	496.21

Table 5. The ANN model's optimal structure.

Training function	Levenberg–Marquardt
Hidden layers' number	1
Output layer' activation function	Linear
Hidden neurons' number	20
Hidden layer' activation function	Sigmoid

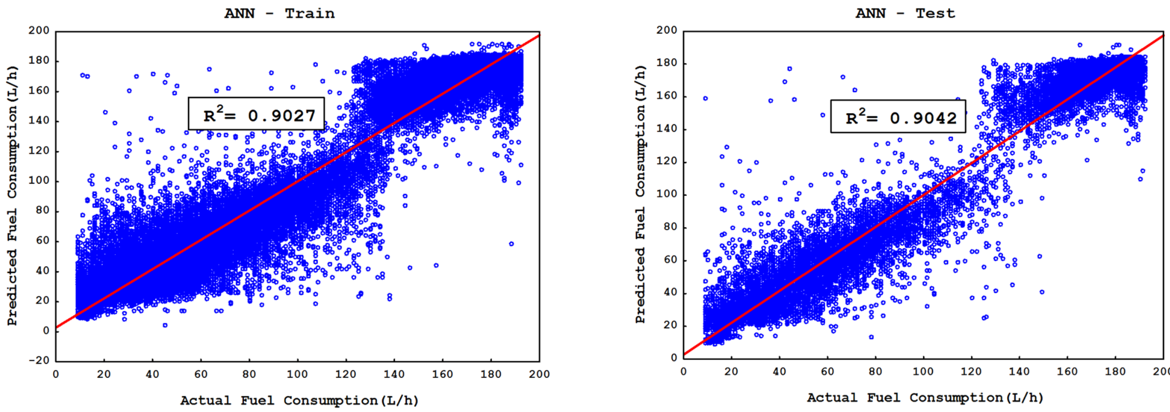

Figure 7. Relationship between actual and predicted values of FC with ANN model.

In the support vector machine model, the c-epsilon and maximum iteration values were considered 1.e5 and 1000000, respectively. The best SVM model for predicting the haul truck fuel consumption was defined with C = 1 and g = 0.250 (i.e. MSE = 563.107 and R^2 = 0.888). The amount of consistency resulting from the SVM model with the actual data is shown in Figure 8.

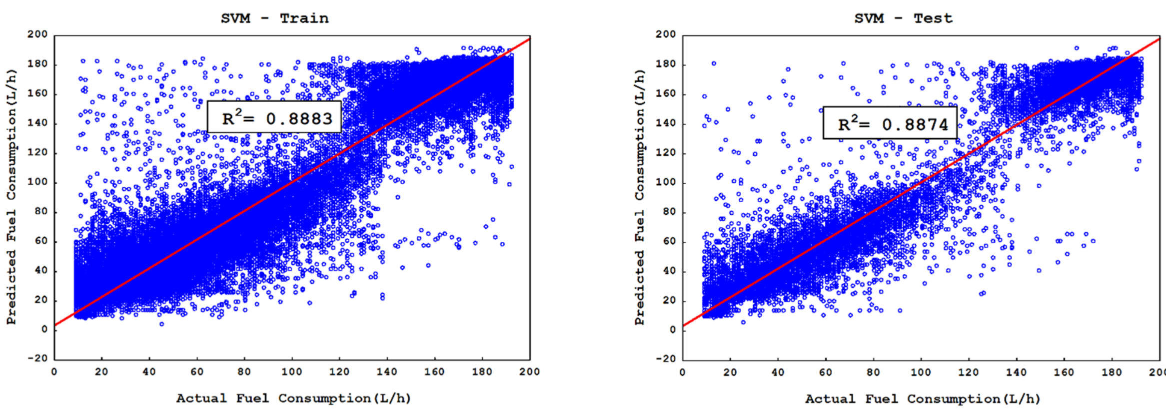

Figure 8. Relationship between actual and predicted values of FC with SVM model.

In the Kernel nearest-neighbor system, the processing time is significantly increased by increasing the dataset and k size. In this work, the best result for predicting the haul truck fuel consumption was observed, in which k is 7 for the k-NN model (Figure 9).

The correlation between the actual and predicted haul truck fuel consumption values with the K-NN model is presented in Figure 10.

The spread of real data and predicted haul truck fuel consumption data by different models had been done in the form of box plots for comparison (Figure 11). It could be seen from Figure 11 that the outcomes of some of the models were closer to actual than others, although none of the models was able to predict the minimum or maximum value correctly. According to Figure 11, it can be concluded that the prediction of a number of the models was closer to actual than the others. The SVM, ANN, and K-NN results for the median, second and third quarters are close to the actual values. These three models seem to have a better performance than the other models in overall prediction. Table 6 shows the calculated error metrics' values of the machine learning models.

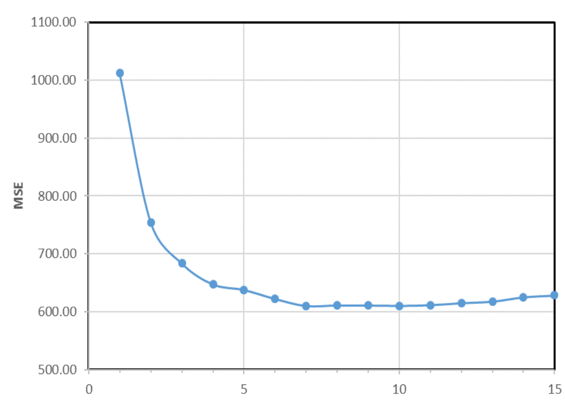

Figure 9. Configuration of k-NN model.

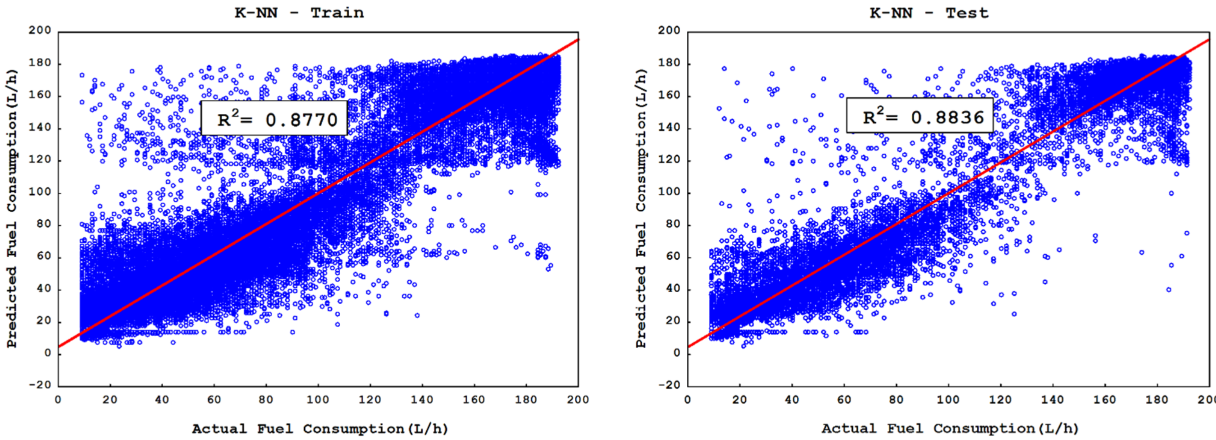

Figure 10. Relationship between actual and predicted values of FC with K-NN model.

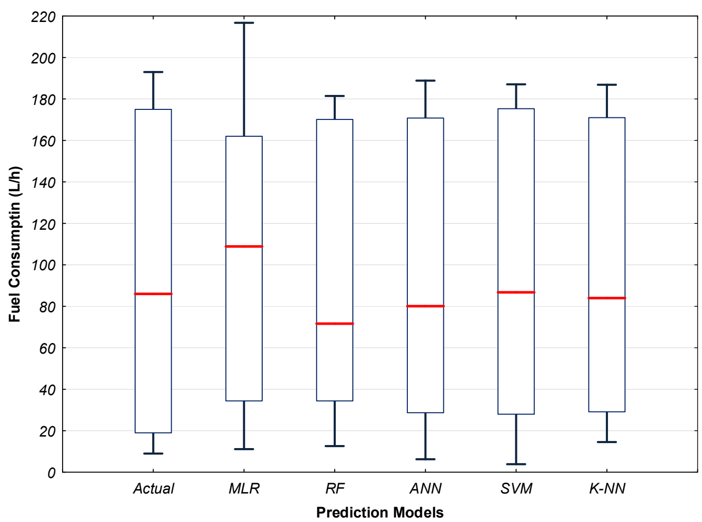

Figure 11. Comparison of outputs of different models.

Table 6. Performance metrics for prediction models.

Model	Train			Test			All		
	R^2	MSE	MAE	R^2	MSE	MAE	R^2	MSE	MAE
MLR	0.809	961.333	21.359	0.811	957.633	21.364	0.809	960.593	21.360
RF	0.898	515.774	13.975	0.899	511.336	13.934	0.898	514.887	13.966
ANN	0.903	490.148	13.448	0.904	485.276	13.409	0.903	489.173	13.440
SVM	0.888	563.107	13.671	0.887	568.298	13.727	0.888	564.145	13.682
K-NN	0.877	610.068	15.155	0.884	607.287	15.046	0.879	609.687	15.134

Table 6 shows that the coefficient of determination varies between 80.9% and 90.4% depending on the machine learning model. The MLR model's poorer performance can be due to the complex relationships between the haul truck fuel consumption and the affective variables. However, each model's success is acceptable for predicting haul truck fuel consumption. According to the results (Table 6), the ANN model has the highest R^2 and the lowest value of MSE with 90.3% and 489.173, respectively. A smaller MAE value is obtained with 13.440 in the ANN model. Therefore, ANN has the best performance in all evaluation metrics among all the other models to predict the haul truck fuel consumption in this work.

4.1. Sensitivity analysis

Sensitivity analysis is utilized in order to evaluate and determine each independent variable's relative importance in the prediction model. In this research work, a sensitivity analysis based on the Garson algorithm [54] was performed using the absolute values of the ANN model's connection weight, as illustrated in Equation(7). However, it does not explain the relevance between the predicted model's dependent and independent variables.

$$RI_{ik} = \frac{\sum_{j=1}^{N_h}((W_{ij}/\sum_{i=1}^{N_i} W_{ij}) \times W_{jk})}{\sum_{i=1}^{N_i}(\sum_{j=1}^{N_h}((W_{ij}/\sum_{i=1}^{N_i} W_{ij}) \times W_{jk}))} \times 100 \quad (7)$$

where RI_{ik} indicates the relative importance of the independent variable (x_i) on the predicted value (y_k), W_{jk} and W_{ij} indicate the connection weights of the hidden-output layer and the input-hidden layer, respectively, and (N_i) and (N_h) denote the input and hidden neurons' number, respectively.

The sensitivity analysis results clearly show the significant effect of these independent variables on the output (Figure 12). This work indicates that the payload, with the relative importance of 47.9%, has the maximum influence on the haul truck fuel consumption.

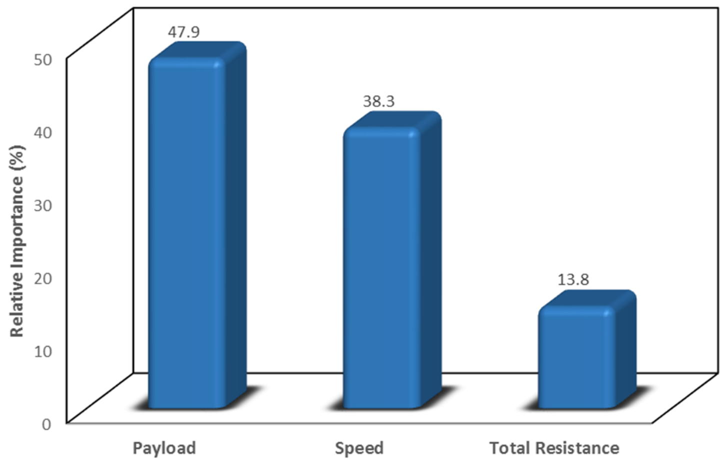

Figure 12. Relative importance of different independent variables.

5. Conclusions

In open-pit mines, a significant share of fuel consumption and greenhouse gas (GHG) emissions are related to the hauling trucks. Thus, predicting the haul truck fuel consumption is a very effective tool for GHG and cost reduction in the mining operations. Payload, speed, and total resistance are considered as the main variables affecting the fuel consumption of the haul trucks in this work. Five machine learning models including MLR, RF, ANN, SVM, and K-NN were investigated in order to design the worthiest prediction model of haul truck fuel consumption by utilizing more than 400,000 actual records of fuel consumption accumulated from a large-size Iron mine. The following results were obtained:

- A comprehensive comparison between the developed ML models was performed, and ANN was determined as the best model to predict the haul truck fuel consumption in this work.
- ANN has the highest accuracy compared to the other models such that it achieves the highest R^2 of 90.3% and the lowest value of MSE and MAE of 489.173, and 13.440, respectively.
- The sensitivity analysis showed that payload was the most influential independent variable in the fuel consumption of haul trucks in this work, with a relative importance of 47.9%.

The application of this research work can be extended to the other mining categories, and will help the management teams predict their various parts' energy consumption. Due to the haul trucks' different performances in different routes and various operating conditions in open-pit mines, it is possible for cost reduction and energy saving by providing appropriate operational solutions. Applying this methodology and other effective activities in mine fleet management such as allocation and dispatching can reduce the cost and GHG, which can be considered in the future studies in order to improve the mining haulage efficiency.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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کاربرد تکنیک‌های یادگیری ماشین برای پیش‌بینی مصرف سوخت کامیون‌ها در معادن روباز

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چکیده:

کامیون‌های باربری منابع انرژی قابل توجهی را در معادن روباز مصرف می‌کنند، جایی که سوخت دیزل به طور گسترده به عنوان منبع اصلی انرژی استفاده می‌شود. بهبود مصرف سوخت کامیون‌ها می‌تواند به طور قابل توجهی هزینه عملیاتی معدنکاری و مهمتر از آن، آلاینده‌ها و انتشار گازهای گلخانه‌ای را کاهش دهد. هدف این تحقیق مدل سازی و ارزیابی مصرف سوخت دیزل کامیون‌های معدنی است. تکنیک‌های یادگیری ماشین شامل رگرسیون خطی چندگانه، جنگل تصادفی، شبکه عصبی مصنوعی، ماشین بردار پشتیبان و الگوریتم k نزدیک‌ترین همسایه به منظور پیش‌بینی مصرف سوخت کامیون بر اساس متغیرهای مستقل مانند میزان بار، مقاومت کل جاده و سرعت واقعی پیاده‌سازی و بررسی شده است. مدل‌های پیش‌بینی بر اساس مجموعه داده‌های واقعی جمع‌آوری‌شده از یک معدن روباز سنگ آهن واقع در استان یزد ساخته شده‌اند. به منظور ارزیابی عملکرد مدل‌های پیش‌بینی شده، ضریب تعیین، میانگین مربعات خطا و میانگین خطای مطلق بررسی شده است. نتایج نشان می‌دهد که شبکه عصبی مصنوعی بالاترین دقت را نسبت به مدل‌های دیگر دارد (ضریب تعیین = ۰/۹۰۳، میانگین مربع خطا = ۴۸۹/۱۷۳ و میانگین خطای مطلق = ۱۳/۴۴۰). در مقابل، رگرسیون خطی چندگانه بدترین نتیجه را در تمام معیارهای آماری نشان می‌دهد. در نهایت، از تحلیل حساسیت برای ارزیابی اهمیت متغیرهای مستقل استفاده شده است.

کلمات کلیدی: مصرف سوخت، کامیون معدنی، یادگیری ماشین، پیش بینی، معادن روباز.