Optimum Fleet Selection Using Machine Learning Algorithms[1]

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ABSTRACT

This paper presents the machine learning method (ML), a novel approach that could be a profitable idea to optimize fleet management and achieve a sufficient output to reduce operational costs by diminishing trucks' queuing time and excavators' idle time based on the best selection of the fleet. The performance of this method has been studied at the Zenouz kaolin mine to optimize the type of loader and the number of trucks used to supply the processing plant's ore demands. Accordingly, the five years' data, such as date, weather conditions, number of trucks, routes, loader types, and daily hauled ore, have been collected, adapted, and processed to train five practical algorithms, including linear regression, decision tree, K-nearest neighbour, random forest, and gradient boosting algorithm. By comparing the results of the algorithms, the gradient boosting algorithm was determined to be the best fit and predicts test data values with 75% accuracy. Subsequently, 11,322 data were imported into the machine as various scenarios and daily hauled minerals as output results were predicted for each working zone individually. Finally, the data with the minimum variation of the required scheduled value selected and its related data containing loader type and the number of demanded trucks have been indicated for each day of the working year.

1. Introduction

Fleet management and scheduling are the most significant components of operations in the mining cycle. So, hauling costs, including 60% of operating costs, play a crucial role in the mining economics, influencing production costs and final product price (Li, 1990). In open-pit mining, the complexity of operations, coupled with an uncertain and dynamic environment, limits the certainty of the predictions. Consequently, to achieve the production targets and decrease operational costs, the best accuracy in predictions with a minimum of opportunity lost in fleet management should be reflected by considering all the factors, although small, which are coupled to each other. Accordingly, for far years, various methods have been performed and accomplished by many scientists and industrial companies to optimize fleet management by analyzing multiple situations. Lizotte and Bonates (1987) proposed a method to minimize shovel idle time, maximizing immediate truck use and allotting trucks to shovels to meet specific production purposes. Hashemi and Sattarvand (2015) presented a dispatching simulation model in ARENA simulation software with the objective function of minimizing truck waiting times that have developed hauling cycle and a 7.8% improvement obtained by applying a flexible assignment of the trucks for the loaders compared to the fixed assignment system. Temeng and Otuonye (1998) used the

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goal-programming-based dispatching model to maximize production rate and maintain ore quality compared to linear programming. Rodrigo et al. (2013) performed a novel system productivity simulation and optimization modelling framework. In their model, equipment availability is a variable in the expected productivity function of the system. The framework is used for allocating trucks by route according to their operating performances in a truck–shovel system of an open-pit mine to maximize the overall productivity of the fleet. In 2010, Topal and Ramazan (2010) presented a mixed-integer programming model (MIP). Their model provides substantial cost savings for equipment scheduling by optimizing truck usage. Gu et al. (2010) presented a dynamic management system of ore blending in an open-pit mine based on GIS/GPS/GPRS uses technologies from space, wireless location, wireless communication, and computers to control the ore quality and ensure the stability of the ore grade. Cox et al. (2018) used a genetic algorithm to develop cyclic automata for dispatching trucks in mines. Ahangaran et al. (2012) discussed the changing trend of programming and dispatching control algorithms and automation conditions. Finally, a real-time dispatching model compatible with the requirement of trucks with different capacities was developed by using two techniques of flow-networks and integer programming (IP). Additionally, the use of innovative methods in recent years has improved the performance of the transport systems in mines. Upadhyay and Askari-Nasab (2018) presented a framework using a discrete event simulation model (DES) of mine operations, which interacts with a goal programming (GP) based mine operational optimization tool to develop an uncertainty-based short-term schedule. This framework allows the planner to make proactive decisions to achieve the mine's operational and long-term objectives. Baek and Choi (2020) proposed a deep neural network (DNN)-based method for predicting ore production by truck-haulage systems in open-pit mines, and assisted comprehension of truck-haulage-system characteristics along with discrete haulage-operation sequences and support the prediction of ore production through training of DNN-based deep learning models without the need to develop additional algorithms. Moradi-Afrapoli et al. (2021) presented a new mixed-integer linear programming model (MILP) to solve the truck dispatching problem in surface mines. This paper's results showed that fuzzy linear programming (FLP) model improved the ore production and truck wait time in the queues by more than 15%. In 2021, Mohtasham et al. (2021a) presented a multi-objective optimization model based upon a mixed-integer linear goal programming (MILGP) model, which determines the optimal production plan of the shovels and allocation plan of the trucks and shovels in order to maximize production, meet desired head grade and tonnage at the ore destinations, and minimize fuel consumption of trucks. Yeganejoo et al. (2021) performed development, implementation, and validation of an integrated simulation and optimization tool that is capable of predicting productivity of truck fleet and determining optimal fleet size based on the historical data collected from the active mine. Mohtasham et al. (2021b) proposed new strategies based on mixed-integer non-linear programming (MINLP) models for the equipment sizing (ES) problem to verify the overall efficiency of the fleet. The developed models estimate the optimal size of trucks concerning the match factor value with two different strategies; the first strategy deals with each loader type, and the second one is applied simultaneously with all types of loaders. Upadhyay et al. (2021) presented a simulation-based fleet productivity estimation and fleet size determination algorithm developed to be used in open-pit mines to estimate fleet productivity and predict the required fleet size to meet the production schedules in the presence of technical uncertainties. Results showed that the developed simulation-based algorithm could predict fleet productivity with more than 20% higher accuracy and lower dependency on haulage distances.

The mentioned studies have individual problems, including disregarding past expertise in mining operations, limited flexibility for change in the production process, and ignoring actual working situations in mines.

This paper uses machine learning methods (ML), a novel approach known as a subfield of Artificial Intelligence (AI) methods, which could be a beneficial approach to reach the best fitting with environmental conditions and work situations to optimize fleet management and attain an adequate output. While fleet management is related to several factors and procedures, ML methods consider work situations like routes, types of machinery, time, and weather conditions. Furthermore, these methods also help planners to have reliable and accurate predictions.

2. Machine Learning (ML)

ML has become one of the most critical topics within development organizations looking for innovative ideas to leverage data assets to help the business gain a new level of understanding. ML is a form of AI that enables a system to learn from data rather than through explicit programming. Resurging interest in machine learning is due to growing volumes and varieties of available data, computational processing that is cheaper and more powerful, and affordable data storage. Machines that learn can more quickly highlight or find patterns in data that human beings would have otherwise missed. Consequently, ML techniques can be used to enhance humans' abilities to solve problems and make informed inferences on a wide range of problems. ML techniques are divided into three sections: supervised learning, unsupervised learning, and reinforcement learning, each of the sections has individual performance. Figure 1 shows a division of ML techniques and their sub-fields.

ML uses various algorithms that iteratively learn from data to improve, describe data, and predict outcomes. As the algorithms ingest training data, it is possible to produce more precise models based on that data. An ML model is the output generated when a machine learns by a learning algorithm with data. Then, when the predictive model is provided with data, it will predict based on the data that trained the model (Judith Hurwitz, 2018). In this paper, five regression techniques from supervised learning are employed. Figure 2 illustrates the flowchart of the optimum model selection operation using the ML algorithms.

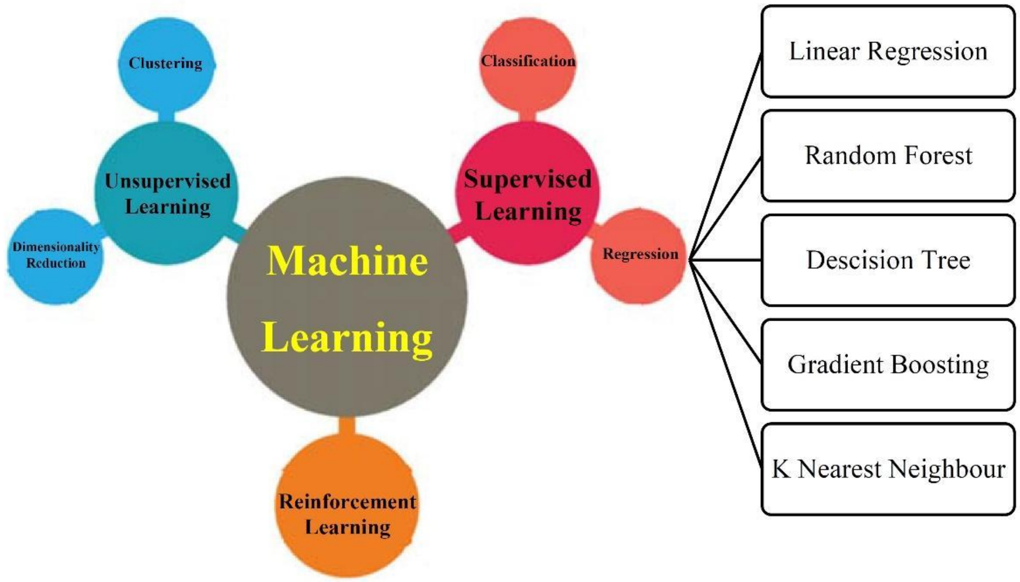

Figure 1. Types of machine learning methods and their subclasses.

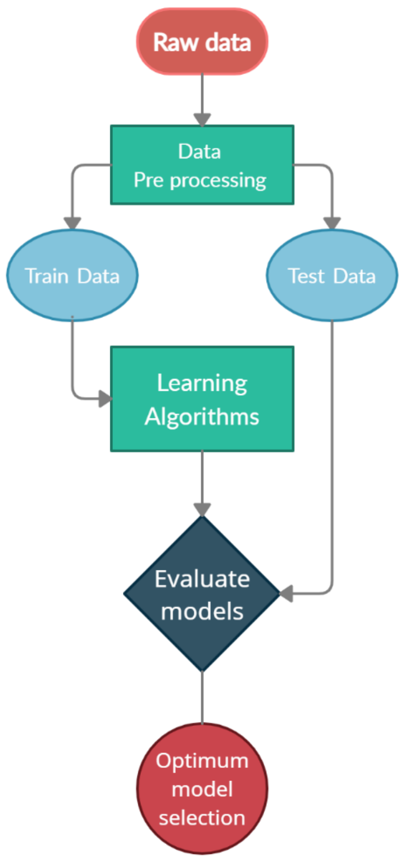

Figure 2. Optimum model selection flowchart.

3. Case Study

Zenouz kaolin mine is located near Zenouz city, approximately 15 km North of Marand city of East Azerbaijan, Iran.

Zenouz kaolin mine is the largest kaolin mine in the Middle East, producing approximately 1,700,000 tonnes of raw kaolin and supplying nearly 70% of the kaolin in the region. This mine includes five working zones. Each zone has its own characteristics and provides processing plant demands individually. The mining method in this mine is open-pit mining, and kaolin is extracted by blasting, loaded by various types of excavators, and hauled by trucks to the processing plant and low-grade stockpiles. Figure 3 shows the location of different zones and stockpile

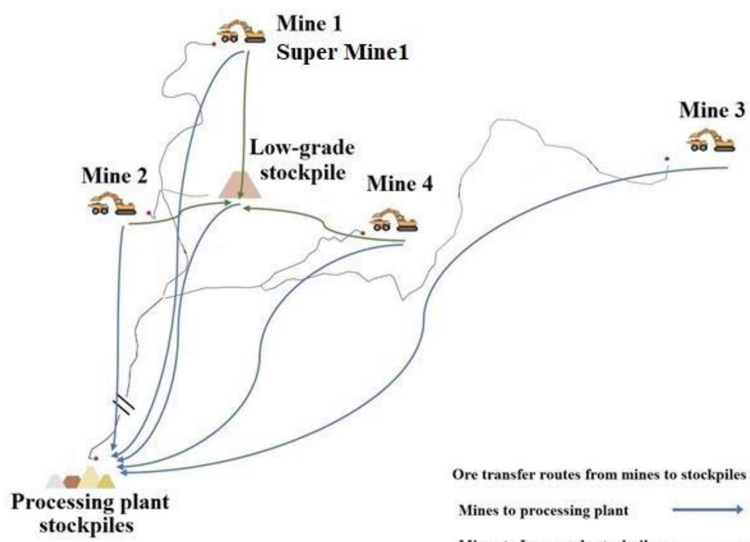

Figure 3. Working zones, low-grade stockpile and processing plant stockpiles locations.

3.1. Data Collection

By collecting the last five years' records (from May 2017 to May 2021) in eight different divisions, the 1976 data has been regarded as machine learning input data. On the other hand, they have been converted into numerical data to transform descriptive data into something understandable and agreeable to the machine. These eight categories and their related numerical forms are presented as follows:

3.1.1. Month

This information is considered because the amount of minerals hauled varies by month. Therefore, numbers 1 to 12 are allocated to the data for April to March, as shown in Table 1.

Table 1. Months and their related numerical values.

Mont h	Encoded data	Month	Encoded data	Month	Encoded data
April	1	August	5	December	9
May	2	September	6	January	10
June	3	October	7	February	11

July	4	November	8	March	12

3.1.2. Weather Condition

Weather conditions influence the operation of the hauling systems because operators and equipment perform differently in various weather conditions. Since weather conditions affect the amount of ore haulage, related data on this factor have been collected and divided into five situations, shown in Table 2.

Table 2. Weather conditions and related encoded data

Weather condition	Encoded
Cloudy	0
Foggy	1
Rainy	2
Snowy	3
Sunny	4

3.1.3. Season

According to experimental observations, the amount of mineral transportation varies in different seasons. Hence, this parameter has also been analyzed for better consideration as training data and has been presented in Table 3.

Table 3. Seasons and related encoded data

Season	Encoded
Spring	1
Summer	2
Fall	0
Winter	3

3.1.4. Weekday

Due to several spatial and temporal constraints, truck drivers' weekend driving behaviour is expected to differ considerably from their weekday driving style. Thus, the weekdays have also been considered and evaluated in Table 4.

Table 4. Weekdays and related encoded data.

Weekday	Encoded	Weekday	Encoded
Monday	1	Friday	0
Tuesday	5	Saturday	2
Wednesday	6	Sunday	3
Thursdays	4		

3.1.5. Number of Trucks

In Zenouz kaolin mine, two models of trucks, Sahand-WD615 and Mercedes-Benz-OM335, are used, and the carrying capacity of each is 26 tons on average. The number of trucks that haul minerals from different zones to stockpiles is also considered analyzable data in machine learning.

3.1.6. Routes

Zenouz mine complex includes six loading spots and two delivery points (see Figure 3). Regarding the distances of these zones from the stockpiles and considering the production plan, this parameter has also been separated into nine divisions, shown in Table 5.

Table 5. Routes and related abbreviations and encoded data.

Route	Abbreviation of routes	Encoded
LG-stockpile to plant	LGP	0
Mine 1 to plant	M1P	1
Mine 1 to LG-stockpile	M1LG	2
Mine 2 to plant	M2P	3
Mine 2 to LG-stockpile	M2LG	4
Mine 3 to plant	M3P	5
Mine 4 to plant	M4P	6
Mine 4 to LG-stockpile	M4L	7
Super Mine1 to plant	SP	8

3.1.7. Loader Types

Because different types of excavators load trucks, the efficiency of these machines has been investigated. Four types of excavators are used as loaders at the studied site, which were taken into account as part of the input data. Table 6 displays these loaders as well as the numerical data associated with them. Table 7 shows examples of the collected data, and Table 8 shows the final table after converting the data to numerical data.

Table 6. Types of excavators and their related encoded data.

Loader type	Encoded
Hyundai 250	0
Hyundai 320	1
Komatsu 200	2
Komatsu 220	3

Table 7. Sample of collected data.

Row	Month	Weather condition	Season	Weekday	No. of tucks	Routes	Loader	Hauled ore (tonne)
50	5	Sunny	Summer	Monday	6	M1 to plant	Hyundai 320	382.800
51	5	Sunny	Summer	Thursday	12	M1 to plant	Hyundai 320	1,131.310

52	5	Sunny	Summer	Friday	18	M1 to plant	Hyundai 320	2,129.650
53	5	Sunny	Summer	Saturday	18	M1 to plant	Hyundai 320	2,277.940
54	5	Sunny	Summer	Wednesday	14	M4 to plant	Hyundai 320	2,036.88

Table 8. Encoded value of the data presented in Table 7.

Row	Month	Weather condition	Season	Weekday	No. of tucks	Routes	Loader	Hauled ore (tonne)
50	5	4	2	1	6	1	1	382.800
51	5	4	2	4	12	1	1	1,131.310
52	5	4	2	0	18	1	1	2,129.650
53	5	4	2	2	18	6	1	2,277.940
54	5	4	2	6	14	1	1	2,036.88

4. Data Pre-Processing

4.1. Important Data

Since weekdays have insignificant impacts on model learning and creation basis on their low impact rates on the learning process (see Figure 4) and due to the unpredictability of the weather in the long term, their inclusion in the continuation of modelling has been omitted. Furthermore, five parameters, including season, month, number of trucks, routes, and loader types, have been used as input data. The data was processed and validated through efficient techniques to train the machine properly. Min-Max scaling and k-fold validation were used in this paper to standardize data and validate the implied prediction model, respectively.

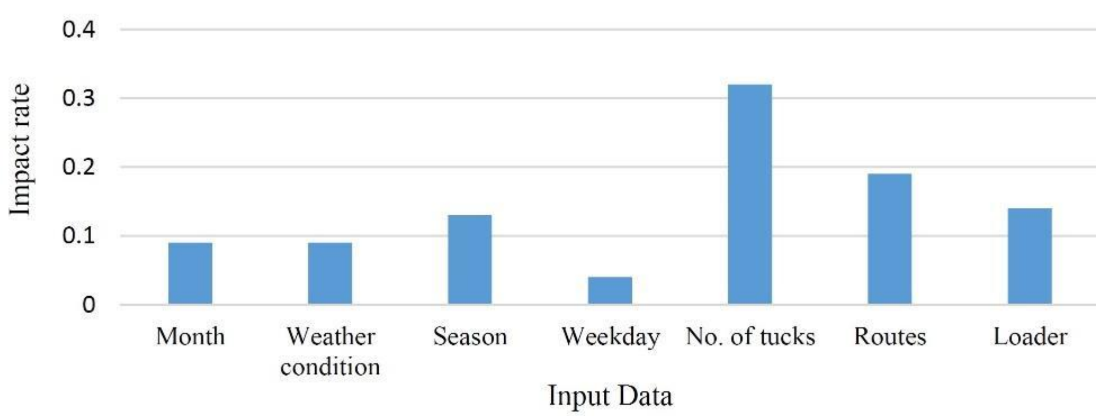

Figure 4. Impact rate of each parameter on the hauled ore.

4.2. Standardization

Considering the input data have different dimensions, to train the machine practicable, data converted to a similar scale via the min-max scaler. This method scales and translates each feature individually such that it is in the given range on the training set, between zero and one. Table 9 presents an example of data scaled by the Min-Max scaler.

Table 9. Standardized sample data presented in Table 8 by min-max scaling method

Row	Month	Season	No. of tucks	routes	Loader	Hauled ore (tonne)
50	0.363636	0.66666667	0.16666	0.125	0.33333	382.800
51	0.363636	0.66666667	0.33333	0.125	0.33333	1131.310
52	0.363636	0.66666667	0.5	0.125	0.33333	2129.650
53	0.363636	0.66666667	0.5	0.125	0.33333	2277.940
54	0.363636	0.66666667	0.38888	0.75	0.33333	2036.88

4.3. K-fold validation

K-fold cross-validation effectively partitions the data into K chunks, K-1 of which form the training set R, and the last chunk serves as the validation set V. Cross-validation iterates through all combinations of assignments of chunks to R and V. This procedure repeated for all K choices for the validation set and the performance of the model from the K runs averaged (Shalev-Shwartz and Ben-David, 2013). Figure 5 shows how this method runs. In this paper, 20% of the data is considered to be test data representing 395 values of 1975.

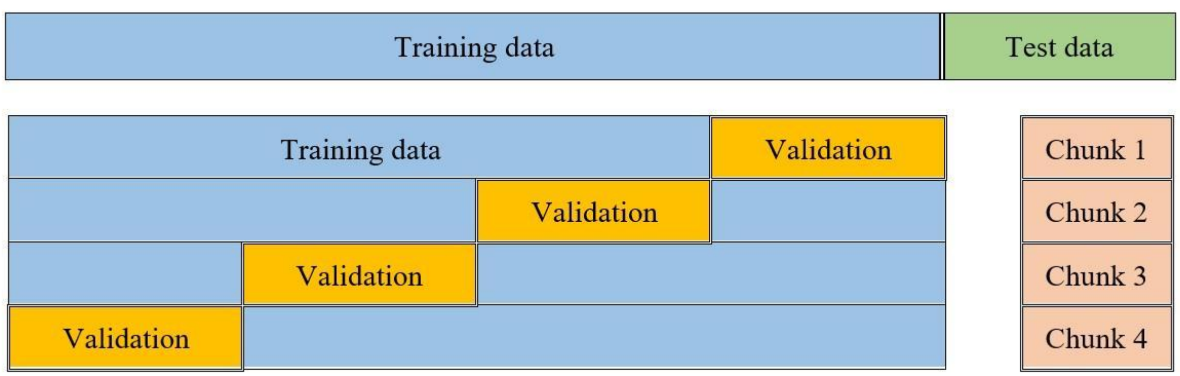

Figure 5. K-fold validation performance.

4.4. R2 score

The R^2 coefficient (Equation 1) represents the proportion of variation in the model's predicted result based on its features and real data (Raschka and Mirjalili, 2019).

$$R^2_{(ytrue,\ ypred)} = 1 - \frac{\sum(ytrue - ypred)^2}{\sum(ytrue - \bar{y})^2} = \frac{RSS}{TSS} \quad (1)$$

In which R^2 is the coefficient of determination, RSS is sum of squares of residuals, and TSS is total sum of squares.

5. Modelling

After collecting data, excluding insufficient data, and processing them, 1,580 and 395 data points were imported into the machine as training and test data, respectively. In machine learning, dozens of unique algorithms perform specialized purposes including, regression, clustering, and classification. The amount of hauled ore is continuous data; therefore, regression methods that deliver a continuous type of data was selected in this paper. The following sections describe the validation of the five algorithms.

5.1. Linear regression (LR)

The LR is a linear approach for modelling the relationship between scalar response and one or more explanatory variables. In LR, the relationships are modelled using linear predictor functions whose unknown model parameters are estimated from the data (Shalev-Shwartz and Ben-David, 2013). By running the algorithm on the processed input data, a model with 62% accuracy was achieved. Figure 6 shows the real and predicted values of the data from number 50 to 150.

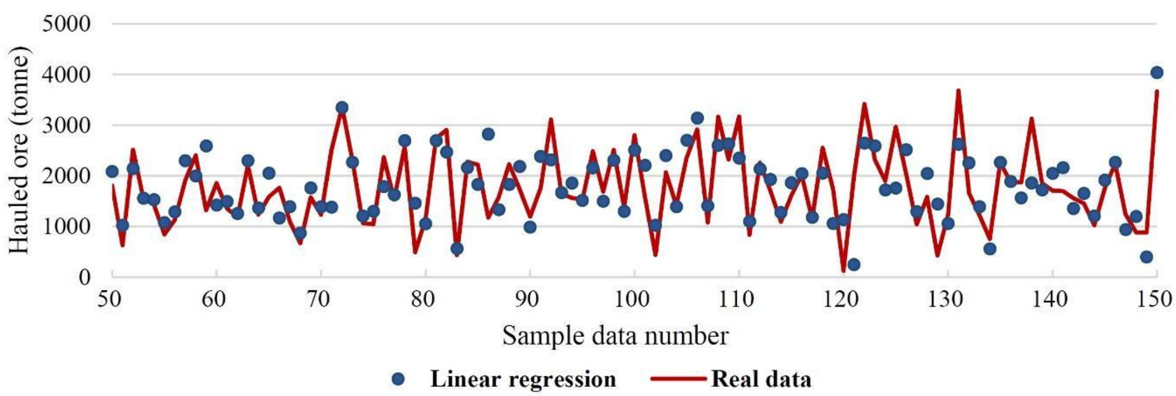

Figure 6. Comparison between real data and prediction of linear regression algorithm.

5.2. Decision Tree Regression (DTR)

The DTR algorithms are based on heuristics such as a greedy approach, where the tree is constructed gradually, and locally optimal decisions are made at the construction of each node [18]. By attempting this algorithm, predicted data have fitted to real data with 63% accuracy. Figure 7 compares real data, and DTR algorithm predicted data.

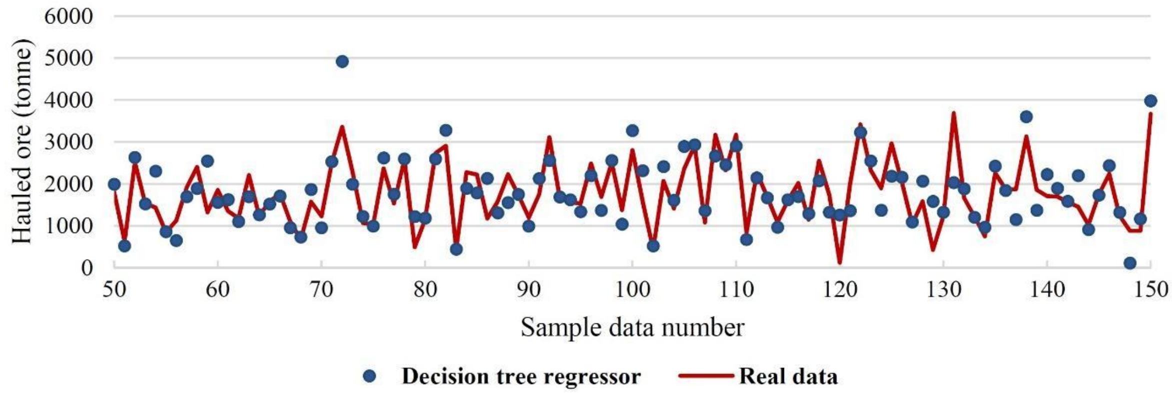

Figure 7. Comparison between real data and prediction of decision tree regression algorithm.

5.3. K-nearest Neighbors Algorithm (KNN)

The KNN algorithm is a supervised learning technique used to classify or predict new data points based on the relationship to nearby data points (Theobald, 2017). Actual and predicted values using the KNN algorithm are shown in Figure 8. The accuracy of the KNN prediction is 65%.

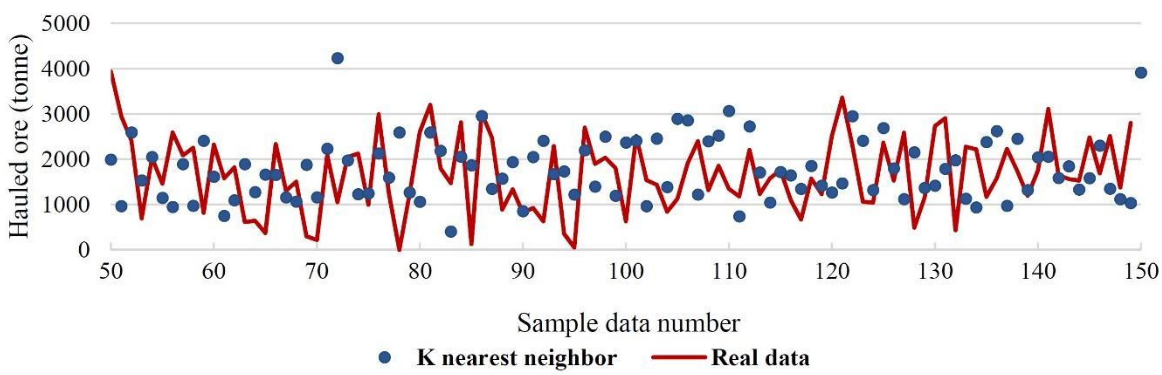

Figure 8. Comparison between real data and prediction of K nearest neighbour algorithm.

5.4. Random Forests (RF)

The RF is a regressor consisting of a collection of decision trees. The prediction of the random forest is obtained by a majority vote over the predictions of the individual trees, and also, RF generally outperform decision trees' performance (Shalev-Shwartz and Ben-David, 2013) with the implementation of this algorithm. Figure 9 shows the difference between the actual and predicted values by RF regression algorithm for the obtained accuracy of 73%.

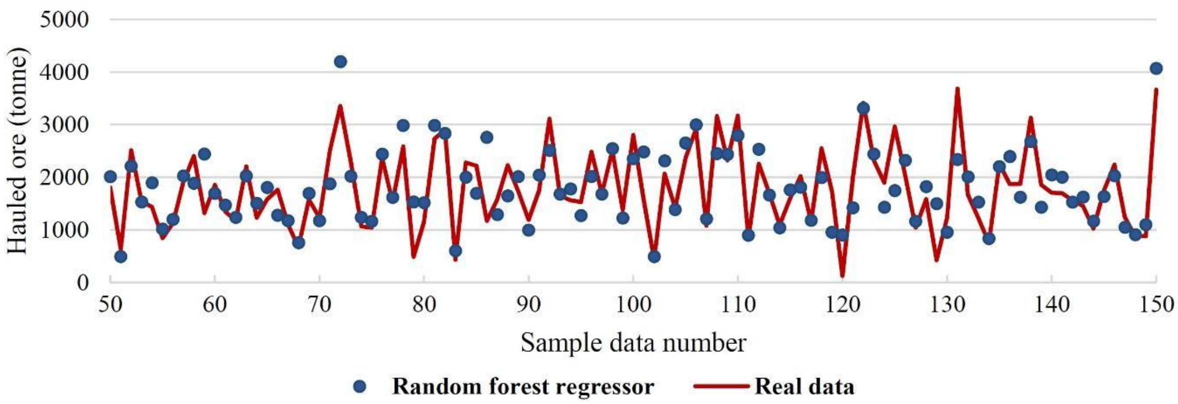

Figure 9. Comparison between real data and prediction of the random forest regression algorithm.

5.5. Gradient Boosting (GB)

Rather than selecting combinations of binary questions at random (like random forests), GB selects binary questions that improve prediction accuracy for each new tree. The way this works is that mistakes incurred with the training data are recorded and then applied to the next round of training data. At each iteration, weights are added to the training data based on the results of the previous iteration. A higher weighting is applied to instances that were incorrectly predicted from the training data, and instances that were correctly predicted receive less weighting. The training and test data are then compared, and errors are again logged in order to inform weighting at each subsequent round (Theobald, 2017). Figure 10 shows that the GB algorithm could predict the data with 75% accuracy.

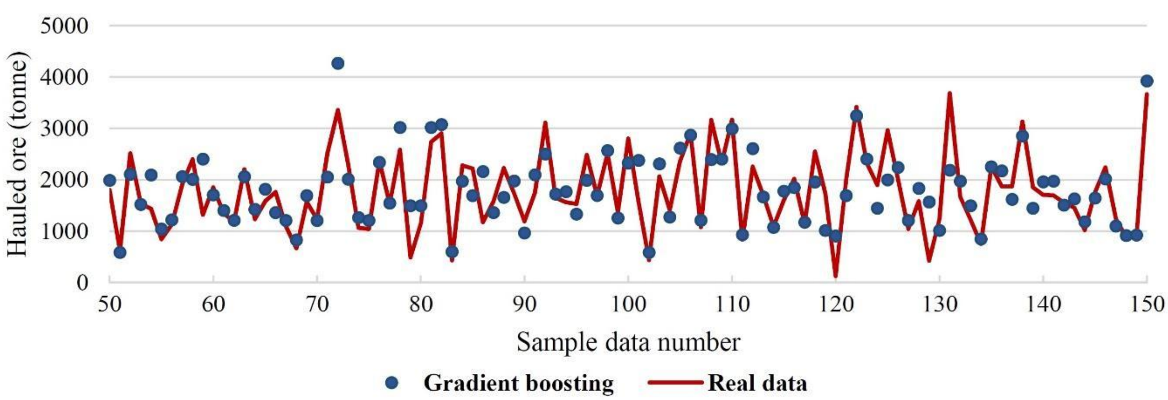

Figure 10. Comparison between real data and prediction of gradient boosting regression algorithm.

6. Model Selection

The gradient boosting algorithm was chosen as the best among the investigated algorithms. With 75% accuracy, this algorithm was used for the rest of the study after measuring the implemented algorithms to achieve an optimal model using the R^2 score formula. Each algorithm's efficiency is depicted in Figure 11.

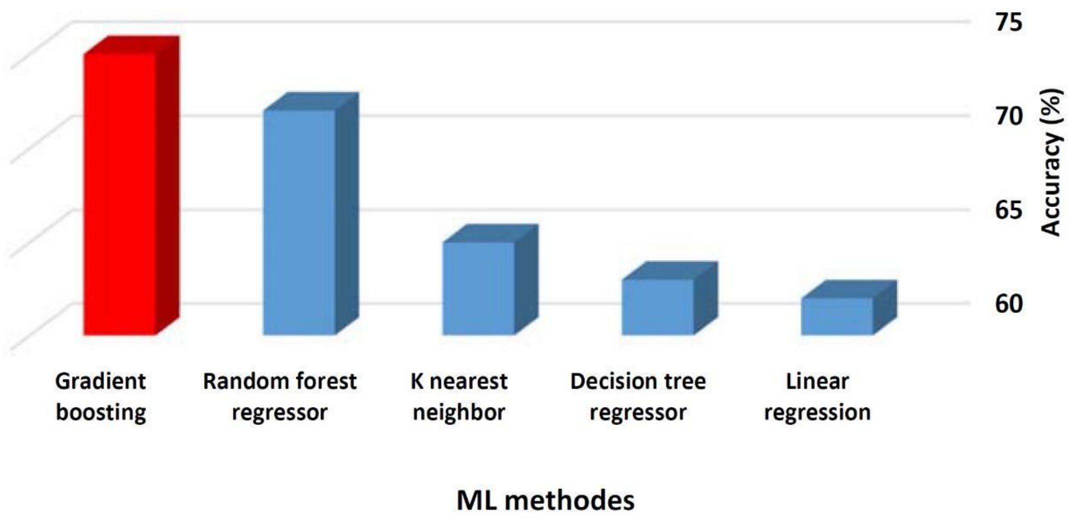

Figure 11. Implemented algorithms accuracy in percent.

7. Ore Transport Schedule

Mine Planning team calculates the required monthly ore production from each mine based on the processing plant's required monthly feed. Table 10 shows the calculated monthly amount of ore from different zones.

While there are some limitations, simultaneous loading in more than three working zones is not possible. As a result, working days for different zones have been planned according to Table 11. The Table 12 indicates an estimate of the required daily ore quantity to cover the processing plant's annual demand depending on this plan.

Table 10. Ore annual haulage scheduling (ktonne).

Month	SUP. to P	M1 to P	M2 to P	M3 to P	M4 to P	M1 to LG	M2 to LG	M4 to LG	LG to P	Total ore to the plant
1	0	60	15	0	0	15	0	0	0	75
2	12	65	17	0	0	20	0	0	0	94
3	15	65	17	14	0	20	0	0	0	111
4	15	65	17	14	25	20	10	5	0	136
5	15	65	17	0	33	30	0	5	0	130
6	15	65	17	0	33	30	0	5	0	130
7	10	65	17	0	33	30	10	5	0	125
8	8	65	17	0	33	30	0	5	0	123
9	0	65	17	0	33	25	0	5	0	115
10	0	65	17	0	33	25	8	3	0	115
11	0	65	17	0	20	25	0	3	0	102
12	0	60	15	0	0	16	0	3	10	85
Annual ore to the plant										1,341

Table 11. Working zones daily ore hauling schedule plan.

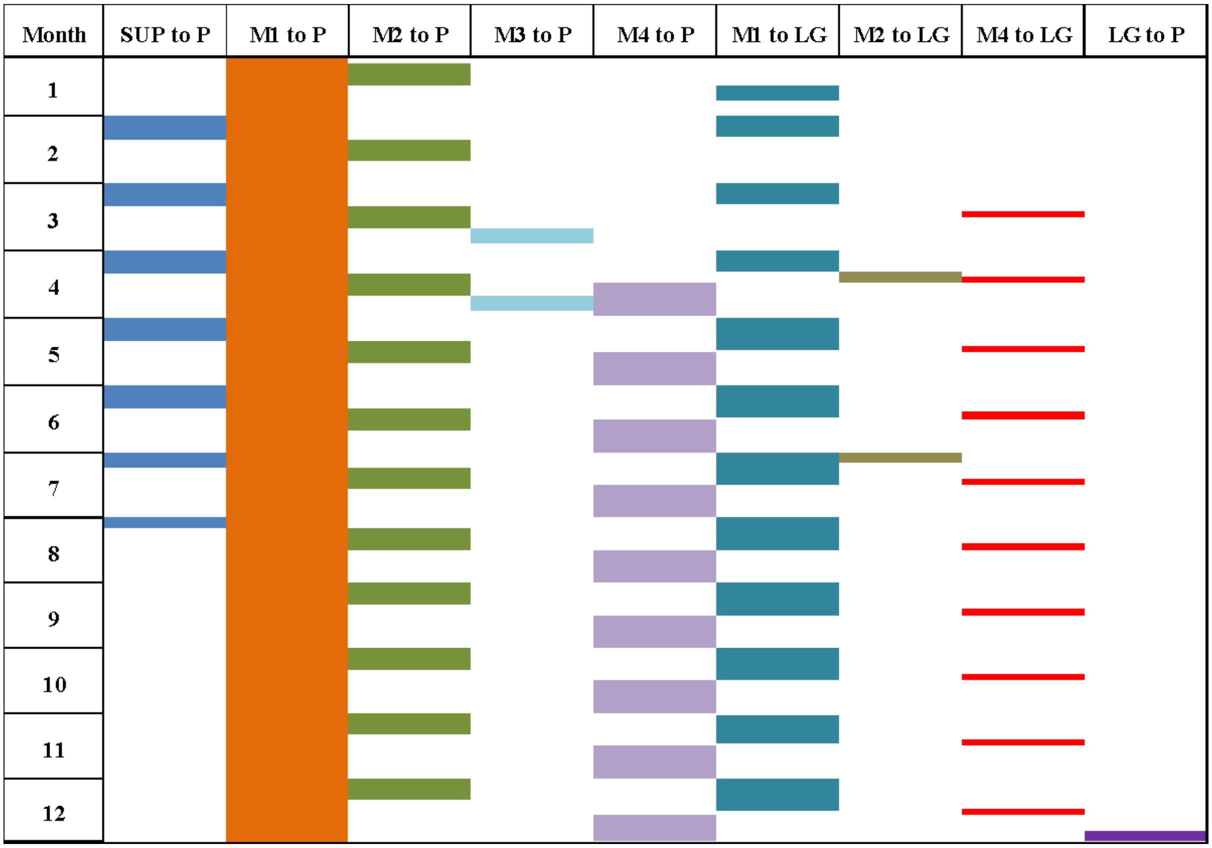

Table 12. Daily ore production schedule.

Month	SUP. to P	M1 to P	M2 to P	M3 to P	M4 to P	M1 to LG	M2 to LG	M4 to LG	LG to P
1	0	2000	1500	0	0	2143	0	0	0
2	1200	2097	1700	0	0	2000	0	0	0
3	1500	2097	1700	2000	0	2000	0	0	0
4	1500	2097	1700	2000	1667	2000	2000	1667	0
5	1500	2097	1700	0	2200	2000	0	1667	0
6	1500	2097	1700	0	2200	2000	0	1667	0
7	1429	2167	1700	0	2200	2000	2000	1667	0
8	1600	2167	1700	0	2200	2000	0	1667	0
9	0	2167	1700	0	2200	1667	0	1667	0
10	0	2167	1700	0	2200	1667	2000	1000	0
11	0	2167	1700	0	1333	1667	0	1000	0
12	0	2000	1500	0	0	1067	0	1000	2000

The algorithm used 1,258 individual scenarios after measuring the daily required ore amount. As a result, the minimum difference between the predicted and required data values were calculated, and the optimal fleet was selected based on related items to this data. According to Figure 12, for instance, the machine anticipates a Hyundai 320 excavator and 19 trucks as the ideal fleet in April to transport ore from Mine 1 to the plant's stockpiles.

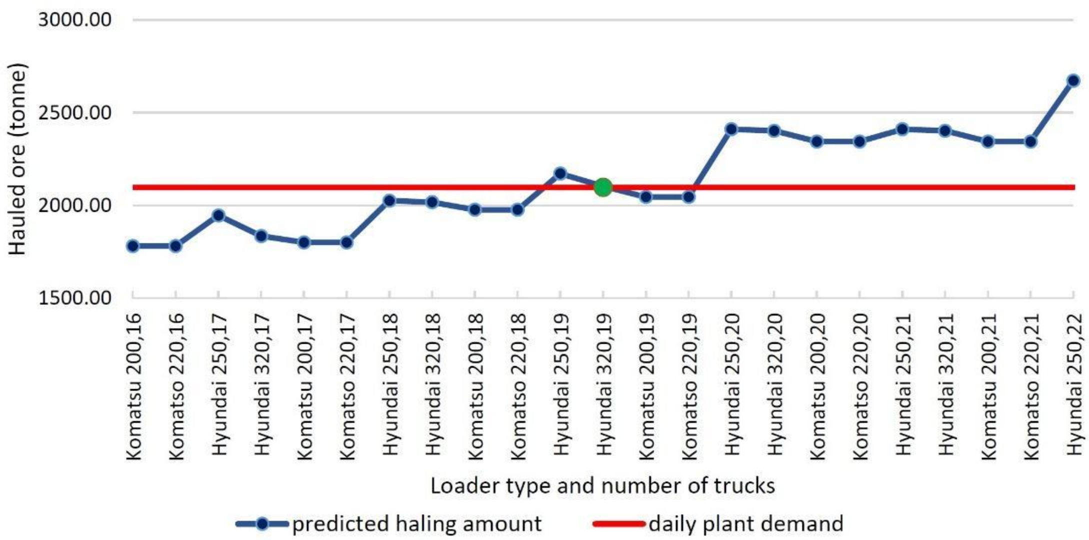

Figure 12. Optimum loader type and number of trucks selection.

Using 11,322 scenarios as input data for five loading points and two mineral discharge stockpiles, the most suitable fleet was selected. Table 13 shows the best loader and number of trucks that different zones should use in 12 months.

Table 13. Optimum fleet to supply processing plant demands.

	Sup. to plant		Mine1 to plant		Mine2 to plant		Mine3 to plant		Mine4 to plant		Mine1 to LG		Mine2 to LG		Mine4 to LG		LG to plant	
Month	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks	Loader	# trucks
1			H250	17	H320	10					H250	11						
2	H320	9	H250	18	H320	11					H250	11						
3	H320	11	H320	19	H250	11	K200	12			K220	11						
4	K200	12	H320	19	H320	11	K200	12	K200	10	K220	11	K200	11	K200	10		
5	K200	12	H320	19	H250	11			H320	13	K220	11			H320	11		
6	K200	12	H320	19	H250	11			H320	13	K220	11			H320	11		
7	H320	11	H320	19	H250	11			K200	13	H250	11	K200	11	H320	12		
8	K220	10	H320	19	H250	11			K200	13	H250	11			H320	12		
9			K220	21	K200	12			K200	13	H250	10			H320	12		
10			H250	19	H320	11			H320	13	K220	10	K220	11	K220	9		
11			K220	18	H320	11			K200	10	H250	10			K200	8		
12			H320	16	K200	10			K200	6	H250	8			K200	8	H320	17

K200 (Komatsu 200) H250 (Hyundai 250)
K220 (Komatsu 220) H320 (Hyundai 320)

8. Conclusions

According to estimations, mineral transportation costs cover a large share of the operating costs and are becoming a challenge in mining management. So, implementing optimization in this operation can minimize the loss of capital costs, reduce the final price of the mineral, and increase profitability. In this paper, ML method was used as an innovative approach to simulate operations, which was executed in the Zenouz kaolin mine to optimize fleet selection. Consequently, the Gradient Boosting Regressor, an excellent algorithm, was chosen and taught by various operational and conditional data to fit and predict the most beneficial fleet. Finally, the best daily required fleet to supply ore transportation to stockpiles was obtained by matching the processing plant ore demands and predicted values and finding the minimum difference between these values. As a result, the suggested fleet reduces truck queuing and excavators' idle times, accounting for a considerable portion of energy consumption and capital wasting.

9. References

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