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Predicting open-pit mine production using machine learning techniques

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Keywords

Mine production, Artificial neural network, Open-pit mining, Mining excavator, Machine learning

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Predicting open-pit mine production using machine learning techniques

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Abstract

In mining, where production is affected by several factors, including equipment availability, it is necessary to develop reliable models to accurately predict mine production to improve operational efficiency. Hence, in this study, four (4) machine learning algorithms – namely: artificial neural network (ANN), random forest (RF), gradient boosting regression (GBR) and decision tree (DT) – were implemented to predict mine production. Multiple Linear Regression (MLR) analysis was used as a baseline study for comparison purposes. In that regard, one hundred and twenty-six (126) datasets from an open-pit gold mine were used. The developed models were evaluated and compared using the correlation coefficient (R^2), mean absolute percentage error (MAPE) and variance accounted for (VAF). It has been shown in this study that the ANN model can best estimate open-pit mine production by comparing its performance to that of the other machine learning models. The R^2 , MAPE, RMSE and VAF of the models were 0.8003, 0.7486, 0.7519, 0.6538, 0.6044, 4.23%, 5.07%, 5.44%, 6.31%, 6.15% and 79.66%, 74.69%, 74.10%, 65.16% and 60.11% for ANN, RF, GBR, DT and MLR, respectively. Overall, this study has shown that machine learning algorithms predict mine production with higher accuracy.

Keywords: mine production, artificial neural network, open-pit mining, mining excavator, machine learning

1. Introduction

Mining activities typically involve the continuous excavation and transport of vast amounts of materials using high-performance equipment. Loading and transporting of materials are around 50% of the overall mine operating costs of open pit mines [1]. As such, the nature of a loading and truck transport system must be done efficiently to reduce energy consumption and maximise mine production or reach production targets [2,3]. Depending on the nature and preparation of the production process (drilling, blasting, loading, and transport), the efficiency and production output of a mine can vary considerably from another mine [4,5]. Thus, significant variations

between production targets set during the planning stage and the actual production are common in mining. These variations can be attributed to ore quality variability within an orebody, mining equipment availability and reliability, design-related issues with mining processes and other factors [6]. It is worth noting that the performance of the mining equipment is dependent primarily on utilisation, availability, and its rated capacity [7–9].

When there is uncertainty surrounding technical and equipment issues, actual production might differ from targets. Thus, it is vital to conduct thorough investigations into the main reasons why these variations do occur [10]. In mining, production efficiency is affected by a number of technical aspects, which include blast or ground conditions and

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equipment performance. Due to the uncertainty of equipment availability, the actual production may vary from the anticipated output.

In that regard, a variety of statistical and deterministic simulation models have been developed and employed to assess mining equipment selection, maintenance and configuration of the transport fleet so as to estimate production [11–13]. Theoretically, researchers have suggested mathematical relations for estimating the production of excavating and loading equipment. These mathematical relations are typically dependent on availability and utilisation of the equipment [14,15]. Furthermore, several other existing empirical and statistical methods are based on algorithms that take into account the sequential nature of duties carried out by trucks and excavators. It is worth mentioning that these conventional empirical estimation methods produce undesirable outputs when compared to the actual values obtained from the field.

It is noteworthy that several other research studies have employed machine learning and deep learning algorithms in the mining industry to model and predict critical issues such as blast vibrations [16–18], geology [19,20] and mineral processing [21–23]. Furthermore, mine shovel failure has been accurately forecasted using support vector machines in Dindarloo and Siami-Irdemoosa [24]. In the estimation of mine production, Baek and Choi [25] conducted a study to predict ore production and crusher utilisation of a truck haulage system in a limestone underground mine using a deep neural network approach. Five hidden layers and 300 hidden layer nodes in the model structure gave the best prediction results. In Baek and Choi [26], two ANN models were built for morning and afternoon haulage sessions, respectively. According to the study, the MAPE for morning and afternoon were 4.78% and 5.26%, respectively, with a determination coefficient of 0.99 each. Furthermore, in Choi et al. [27], machine learning models including ANN, support vector machine (SVM), random forest (RF), classification and regression tree (CART) and k-nearest neighbours were used to estimate ore production in an open-pit limestone mine in South Korea. Among the models, the SVM algorithm performed better with the highest accuracy. Additionally, in Edwards and Griffiths [28], hydraulic excavator cycle time, output and excavation cost were predicted using ANN and multiple linear regression (MLR) models. They found out that the ANN model provided a significant improvement over the MLR model with a sum square error of 0.194 and a MAPE of 7%, indicating a 14% reduction on the equivalent MLR model. Other studies

concerning construction and infrastructural projects indicate that ANN has the potential to estimate equipment productivity better than MLR [29,30].

Based on the literature, it has been found that limited machine learning models have been applied for the prediction of surface mine production. Hence, it is difficult to establish the best strategy for forecasting mine output using machine learning algorithms. Thus, this study is aimed at implementing four different machine learning techniques in predicting surface mine production to ascertain their prediction accuracy and generalisation power. The methods implemented are the random forest (RF), artificial neural network (ANN), gradient boost regression (GBR) and decision trees (DT). A multiple linear regression (MLR) was implemented to serve as a baseline for comparison purposes in this study. It is worth mentioning that no research work has been done to holistically compare the predictive performance of RF, ANN, GBR, DT and MLR as an attempt to explore the best case to predict mine production based on the average daily number of trucks, average percentage excavator utilisation and average daily excavator worked hours.

The various models were evaluated and compared using the coefficient of determination (R^2), mean absolute percentage error (MAPE), variance accounted for (VAF), and root mean squared error (RMSE). This article will potentially serve as a guideline for more research into the use of machine learning for the modelling and forecasting of mining production.

The remaining part of the paper is organised as follows: the mine and data description are outlined in Section 2. Section 3 presents the methodology. Here, a concise description of the RF, GBR, ANN, DT and MLR models is provided. In Section 4, the model development processes, as well as performance indicators, are presented. The obtained results and their discussions, along with the challenges and future perspectives of the research, are detailed in Section 5 and Section 6. Section 7 finally presents the conclusion of the paper.

2. Mine and data description

2.1. Description of the mine

Data from Mine X in the Ashanti Region of Ghana were collected for this study. Mine X is situated approximately 180 km to the northwest of the capital, Accra. There are four pits in the area of study: Pits W, X, Y and Z. The field of mining in the research area is shown in Figure 1. The mine employs drill and blast as the means of fragmenting the



Fig. 1. Study area.

rock mass. For blasthole drilling, a 4.2-m-long rod with a diameter of 127 mm is used. Vertically drilled blast holes in a staggered design have a burden and spacing of 4×4.5 and a stemming height of 3 m. Ammonium nitrate fuel oil (ANFO) is the main explosive in the mine. At the bottom of each hole, a detonator and a booster are placed to ensure a successful explosion. 400 g of pentolite booster is usually used for competent rock formations and 250 g for soft to medium-hard formations, as well as for charging trim holes to ensure the walls' stability. Usually, down lines with a 500 ms delay are used. Generally, down lines with a 500 ms delay are used. Surface connectors are normally used with different lengths and delays, like 0 ms, 17 ms, 25 ms and 67 ms. The charged holes are blasted by a non-electronic initiation device. Secondary breaking of the boulders is done by a rock breaker before they are fed into the crushers. The fragmented rocks are carried onto dump trucks by excavators and are transported to the processing plant for gold extraction. In order to achieve an average grade and tonnes of material to process at the plant, the engineers produce a blending plan per day.

2.2. Datasets description

One hundred and twenty-six (126) historical datasets were taken from Pit W of Mine X over a 126-day timeframe for this analysis. The following

parameters are presented in the data sets: average trucks, average daily excavator hours, average daily excavator worked hours, average daily excavator breakdown hours, average percentage excavator utilisation and daily production. Since the mine runs 2 shifts a day, the average values of both shifts are seen in each row of input. The statistical overview of the whole dataset is seen in [Table 1](#). [Table 2](#) also shows the correlation within the entire dataset.

3. Methodology

3.1. Artificial neural network model

The ANN is a well-known artificial intelligence computational method commonly used in all fields of engineering, including mining engineering. The architecture is focused on the configuration of the human brain with its network of layers and neurons. In other words, ANN addresses challenges through information acquisition [25,31]. The ANN training method performs constant weight and bias adjustments in order to attain output based on an error minimisation function. Many training algorithms are available for the training of an ANN model. The feed-forward and back-propagation algorithms are two of the most often used ANN training algorithms [32]. The execution process of the ANN algorithm during training is illustrated in [Figure 2](#).

Table 1. Statistical description of the entire datasets.

(p-value)	Breakdown hours (hr) 0.102316	Worked hours (hr) 0.000002	Utilisation (%) 0.006462	Number of trucks 0.000000	Production (bcm/d)
count	126	126	126	126	126
mean	5.03	10.78	64.64	9.36	11805.44
std	3.45	1.53	10.83	1.49	1634.64
min	0.00	7.59	35.35	6.00	8022.00
10%	0.56	8.94	51.64	7.00	9436.00
25%	1.24	9.64	56.98	8.00	10829.00
50%	5.38	10.62	63.19	10.00	11620.00
75%	8.11	11.79	72.17	10.00	13160.00
90%	9.00	12.80	78.38	11.00	14028.00
max	11.18	14.87	91.16	12.00	15078.00

3.2. Random forest regressor model

Breiman [34] presented RF as an ensemble machine learning algorithm. It is in the category of decision tree algorithms, which can solve problems in regression and classification. The RF regressor has been designed basically to solve regression problems. It requires the growing of many decision trees through the bagging of bootstraps [35]. It is based on the cumulative outcomes of several decision trees in reaching a final decision. The RF regressor collects the source matrix consisting of values of the various characteristics evaluated for the particular training field, with the RF regressor generating a set of K-regression trees, then performs an average of the output [34,36,37]. The RF regressor is, however, known to take significantly longer to train than decision trees because it generates a large number of trees. It is quite complicated [38].

3.3. Gradient boosting regressor model

The GBR has emerged recently as a prime machine learning model. GBR is very efficient on data that has been structured, i.e., where the information has been grouped into columns and rows and on datasets that are medium-sized, with the existence of at most a few million-sized populations. GBR is basically an ensemble approach that operates by training several individual decision trees. Unlike RF, where the trees are parallelly trained, in a GBR, 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 student or learner with the contributions of each student learned during training via Gradient Descent (therefore, the weights of each tree will be a model parameter). GBR, however, will continue to improve to reduce all errors to a minimum. This can lead to overfitting by overemphasising outliers [39].

3.4. Decision tree regressor model

DT is a non-parametric supervised learning approach used for regression and classification. DT approximates a sine curve with a set of if-then-else decision rules by learning from data. As the tree gets deeper, the more complicated the laws for decision-making are and the more suitable the model becomes [40]. A DT establishes a tree structure for regression models. A concise description of the underpinning theory of the regression tree, which best suits this research, is presented in this section. Multiple regressions and recursive segregation are performed on the dataset to trigger the DT. The data division mechanism is replicated from the root node within every inner node of the tree rule until a previously defined stop condition is achieved [41]. When the induction of the tree is complete, tuning can be implemented in order to boost the tree’s ability to generalise by reducing the complexity of its structure. The models then create a series of rules that can be used to forecast via the repeated splitting process.

Table 2. Correlation matrix of the data.

	Breakdown hours	Worked hours	Utilisation (%)	Number of trucks	Production
Breakdown hours	1				
Worked hours	-0.303	1			
Utilisation (%)	-0.263	0.462	1		
Number of trucks	0.082	0.281	0.302	1	
Production	-0.014	0.538	0.467	0.621	1

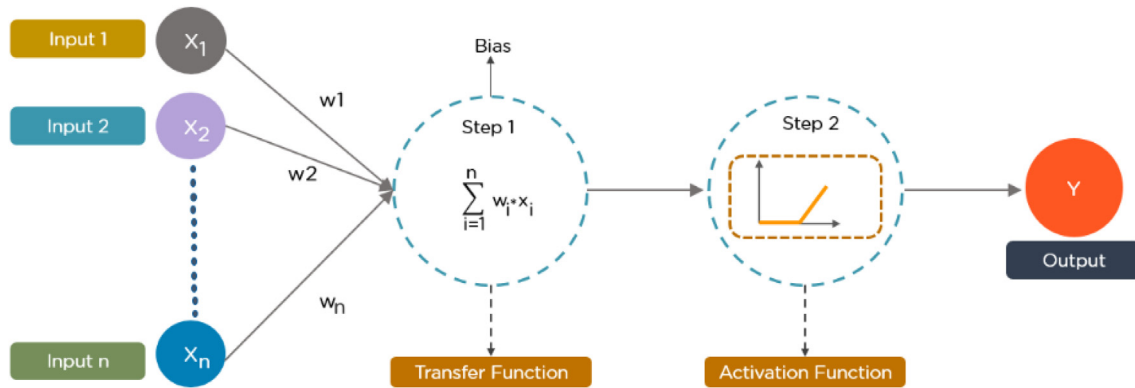


Fig. 2. Execution process of the ANN algorithm during training. Reproduced from [33].

3.5. Multiple linear regression model

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

$$y = \alpha_0 + \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \dots + \alpha_n X_n \quad (1)$$

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

In the MLR model, the least-squares approach is usually used for approximation. If the regression coefficients are obtained, a projection equation is 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.

These models were implemented herein to predict and evaluate mine production in an open-pit gold mine in Ghana with excavator and truck operating conditions. Three input factors in the input layer were used to predict mine production, the average daily number of trucks, the average daily excavator worked hours and the average percentage of excavator utilisation.

4. Model development

4.1. Data selection and data preprocessing

The simplest approach based on the holdout cross-validation approach was followed to partition the datasets. During the splitting, 88 datasets, representing 70% of the entire 126 datasets, were selected for training, while the remainder,

accounting for 30% of the datasets, were exploited for testing the trained model. In order to evaluate the models' efficiency, the test datasets were used as unseen data while the training datasets were used exclusively for model development. Essentially, the realistic engineering performance of the various models is determined by the efficiency of the test dataset.

A preliminary regression analysis was performed, utilising the four acquired input parameters (average daily excavator breakdown hours, average daily number of trucks, average percentage excavator utilisation, and average daily excavator worked hours) with their corresponding p -values in order to choose the optimal input parameters, the construction of the various models. Table 1 shows that the p -value for average daily excavator breakdown hours (0.102316) is greater than the alpha value (0.05); hence it was not deemed qualified to be used as an input parameter for the model development. During the data preparation, pre-processing and cross-correlation of the parameters were performed. The correlation coefficient was used to analyse the correlation between the output and input variables of the entire dataset, as outlined in Table 2.

Thus, the training and testing subsets were chosen to be statistically similar subsets at the 95% significance level in order to be representative of the entire dataset. The statistical properties of both the training and testing data subsets, with corresponding percentiles (0.1, 0.25, 0.5, 0.75, 0.9) used for the different models, are shown in Table 3. The obtained data subsets (training and testing) used to develop all the models are shown in Table 3.

4.2. Data normalisation

The input parameters used in this research were normalised into the range $[-1, 1]$ with Equation (2)

Table 3. Statistical description of training and testing data subsets used.

	Input						Output	
	Worked hrs		Utilisation (%)		No. of trucks		Production (bcm/d)	
	Training	Testing	Training	Testing	Training	Testing	Training	Testing
count	88	38	88	38	88	38	88	38
mean	10.74	10.87	64.77	64.37	9.44	9.16	11839.91	11725.63
std	1.46	1.69	11.13	10.25	1.44	1.62	1690.14	1516.90
10%	9.11	8.77	52.48	51.17	8.00	7.00	9452.80	9875.60
25%	9.72	9.47	57.08	56.61	8.00	8.00	10801.00	10885.00
50%	10.62	10.77	62.05	63.76	10.00	10.00	11676.00	11410.00
75%	11.77	12.34	72.66	71.75	10.00	10.00	13287.00	12944.25
90%	12.55	12.96	79.09	77.39	11.00	11.00	14133.30	13519.10

[42] before the creation of the ANN model in order to ensure consistency of values, regardless of varying units in the different input parameters.

$$P_i = P_{min} + \frac{(Q_i - Q_{min}) \times (Q_{max} - P_{min})}{(Q_{max} - Q_{min})} \quad (2)$$

where P_i is the normalised data, Q_i represents the observed data, Q_{min} and Q_{max} represents the minimum values and maximum of the observed data with P_{max} and P_{min} values set at 1 and -1, respectively.

4.3. Model formulation

It is necessary to determine the proper set of parameters that enable the generation of reliable models for prediction by avoiding the implementation of the default configurations suggested by software packages to research the overall performance of the various machine learning algorithms. In addition, experiments that test new algorithms and compare them with other approaches may be skewed by the enhanced understanding of the algorithms studied if model parameters are not optimised [43]. 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 with Python (version 2.7.9).

4.3.1. ANN

Python environment was used to perform these analyses and train the data: generating plots with Matplotlib [44], Pandas [45] handled the datasets, Scikit-learn [46] was also implemented for data analysis, and the ANN was implemented using Keras [47] on top of TensorFlow [48]. The structure (input, hidden, and output layers) of the ANN model was configured, and the activation function for each layer was defined. The optimizer and number of epochs (training rounds) were also

determined to begin the actual model training on the training dataset. This research aimed to determine the optimal structure for an ANN model used for prediction by creating and testing several different models, ranging from two to five hidden layers. Each hidden layer’s neuron size was evaluated from 100 to 500 in 100-neuron intervals. All activation functions were changed to ReLU [49] in the input layer and hidden layers and weight updates were performed with the Adam Optimizer [50]. The trained ANN model is used to predict the test data, and the prediction error is calculated. To prevent model over-fitting, the early stopping technique [51] was used to monitor MAPE for both training and testing events after every iteration. Training is stopped when the error on the test begins to worsen (overfitting).

4.3.2. RF regressor

In the formulation of the RF regressor model, various range values of the critical parameters (minimum samples split, number of estimators, maximum depth and maximum leaf nodes) were investigated via a grid-search technique using the training dataset [52] to ascertain the optimum RF regressor model. Thus, a minimum sample split of 1–5, number of estimators of 1–500 with a step size of 10, maximum depth of 1–8 with a step size of 1, and maximum leaf nodes of 1–20 with a step size of 2, were applied. It is demonstrated that by increasing the number of trees, the generalisation error always converges, thereby preventing the overtraining problem [34,53,54].

4.3.3. GB regressor

In the development of the GBR model, the huber [55] and least square [56] loss functions, as well as a number of estimators from 10 to 200 at ten intervals, were used to determine the best parameters for the GBR algorithm using the grid-search technique on the training datasets. The maximum depth of the

tree, which greatly affects the model's performance, was assessed from 1 to 10 at one interval.

4.3.4. DT regressor

A number of DT training parameters, such as measurement of dissimilarity, tree depth and the minimum sample number to be present at each leaf node, must be defined [57]. The measure of dissimilarity affects the manner in which data is split throughout each node. The minimum sample number and tree depth for each leaf node are parameters influencing the complexity of the structure of the tree: the more levels and the fewer minimum nodal observations, the higher the complexity of the model structure. Therefore, to ensure the highest prediction accuracy, it is important to calibrate these parameters, preventing the generation of complicated structures that overfit the dataset and end up losing their generality [58]. The mean absolute percentage error was used to calculate the quality of a split in this study. The DT regressor was evaluated using tree depths from 1 to 10, with a minimum number of samples per node between 1 and 5, at an interval of 1 to obtain generalizable and stable models. Further, the best splitter was used to develop the DT model.

4.4. Model performance assessment

Mean Absolute Percentage Error (MAPE) [Eq. (3)], coefficient of determination (R^2) [Eq. (4)], variance accounted for (VAF) [Eq. (5)], and root mean squared error (RMSE) [Eq. (6)] were used to assess the performance of the training and testing datasets of the developed models [57]. Then, for practical

applications, the best model was chosen and suggested. The following were used to calculate the four indices:

$$MAPE = \left[\frac{\sum_{t=1}^m \left| \frac{A_t - P_t}{A} \right|}{m} \right] \times 100\% \quad (3)$$

$$R^2 = 1 - \frac{\sum_{t=1}^m (A_t - P_t)^2}{\sum_{t=1}^m (A_t - \bar{A})^2} \quad (4)$$

$$VAF = \left[1 - \frac{\text{var}(A_t - P_t)}{\text{var}(A_t)} \right] \times 100 \quad (5)$$

where m , A_t , P_t , \bar{A} and \bar{P} the total number of samples, the actual values, the predicted field values, the mean of the actual values and the mean of the predicted values, respectively. A model with an R^2 and VAF value closer to 1 and a MAPE closer to 0% is considered a superior model than the other model.

5. Results and discussion

5.1. Model developed

According to the numbers of hidden layers and hidden layer neurons in the ANN model, the MAPE and coefficient of determination (R^2) for the test dataset are illustrated in Figures 3 and 4, respectively. The MAPE gradually decreased, while the coefficient of determination (R^2) increased as the number of neurons in the hidden layers increased.

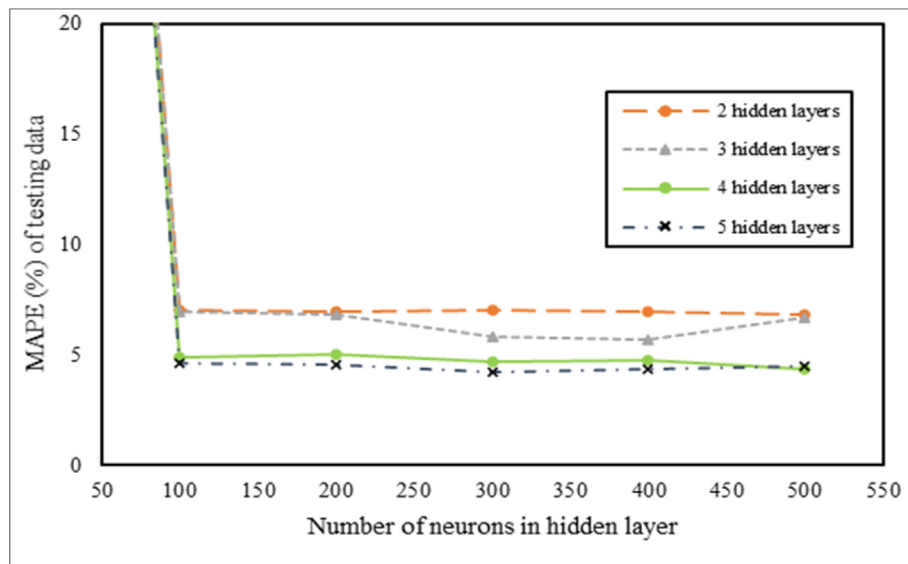


Fig. 3. ANN model configurations based on MAPE.

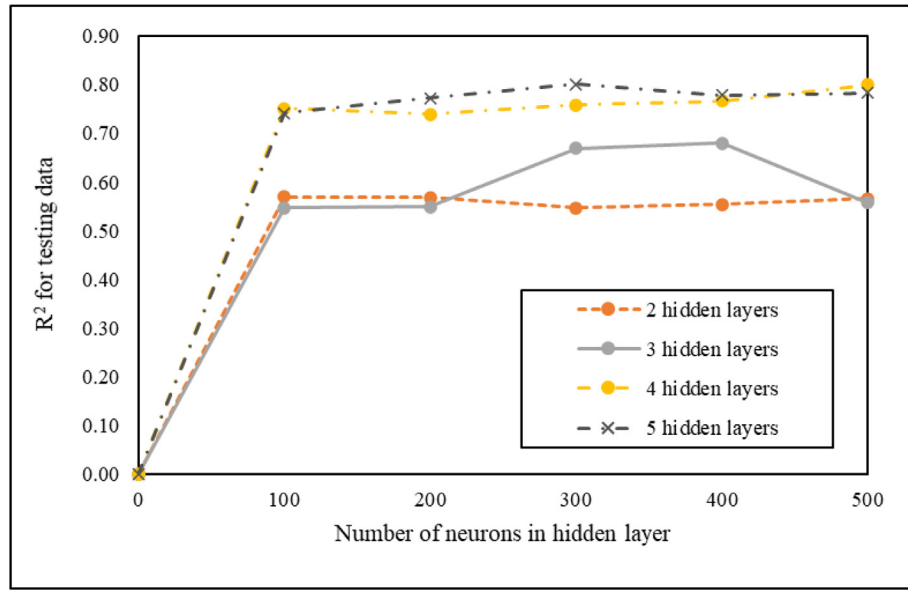


Fig. 4. ANN model configurations based on coefficient of determination (R²).

Increasing the number of hidden layers also resulted in an improvement in both the R² and MAPE. The R² for the testing dataset was the highest (0.8003) and the lowest MAPE (4.23%) when the number of hidden layers was 5 and the number of neurons in the hidden layers was 300 (Figs. 3 and 4). Ultimately, the ANN model with 5 hidden layers and 300 neurons for each hidden layer was determined to be the best structure for the ANN model. Thus, for this study, 5 hidden layers with 300 neurons in each hidden layer was used as the model structure, as shown in Figure 5.

For the RF regressor, the obtained results showed that the RF model with a number of trees = 300, a minimum sample split of 2, and a maximum depth

of 4 gave the lowest MAPE and highest R² value using the grid search technique. Moreover, GBR with a number of estimators = 30 with the least square loss function and a maximum depth of 3, was determined as the best model from the grid search approach. Further, the best splitter gave the best DT model along with a maximum depth of 3 and a minimum sample leaf of 1. The developed MLR model is shown in Equation (6).

$$P = 1271.4692 + 424.2250WH + 1917.7604U + 504.9406NT \tag{6}$$

where P is the production, WH is the worked hours, U is the utilisation, and NT is the number of trucks. The optimal training results, based on the R² and

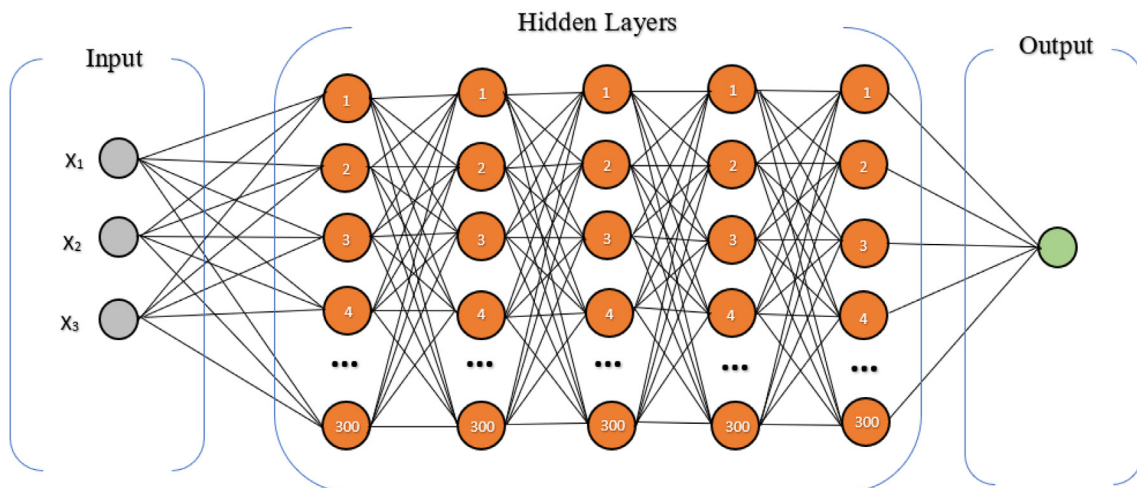


Fig. 5. Optimal ANN model structure.

Table 4. Comparison of results obtained from the different models on the training dataset.

Model	Training		
	R ²	MAPE (%)	VAF (%)
ANN	0.81	4.69	80.37
RF	0.81	5.42	80.12
GBR	0.86	5.42	83.65
DT	0.68	6.40	68.01
MLR	0.53	8.26	52.88

Table 5. Comparison of results obtained from the different models on the testing dataset.

Model	Testing		
	R ²	MAPE (%)	VAF (%)
ANN	0.8003	4.23	79.66
RF	0.7486	5.07	74.69
GBR	0.7519	5.44	74.10
DT	0.6538	6.31	65.16
MLR	0.6044	6.15	60.11

MAPE criteria, are presented in Table 4. Table 5 indicates the optimal testing results based on the R², MAPE and VAF criteria.

5.2. Model performance assessment

Based on the test data, the performance of the developed predictive models was assessed by means of R², MAPE and VAF. The obtained results are shown in Table 5. As shown in Table 5, the ANN model performed very well in predicting mine production, as it produced the highest R² value of 0.8003 and the lowest MAPE value of 4.23% on the testing datasets. This indicates that the ANN generalises better on the unseen test dataset than the other models, as it was able to predict 95.77% of the actual unseen production data accurately. The non-linear relationship between the parameters was better taken into account by ANN compared to the other non-linear models investigated. The ANN properly predicted 80% (R²) of the variance in mine production, whereas just 20% was incorrect. Moreover, the ANN gave the highest VAF value of 79.66%.

From Table 5, the RF regressor predicted mine production with R², MAPE and VAF of 0.7486, 5.07% and 74.69%, respectively, which was the second-best performing machine learning algorithm. It can also be gleaned from Table 5 that the GBR model was the third-best performing algorithm in predicting mine production, as it had an R² value of 0.7519, MAPE of 5.44% and a VAF of 74.10%. Furthermore, the DT regressor model had a higher R² and VAF value

compared to the MLR model, which in turn had a lower MAPE than the DT regressor model.

This finding suggests that ANN is the most effective model for estimating mine production. Among the machine learning models, the poorest performance on the testing datasets were given by the DT regressor approach. This could be due to its inadequacy in predicting continuous values [37]. This is because the DT regressor continues to generate new nodes in order to fit the continuous data values, and the tree eventually gets too complex to interpret. It thus loses its ability to generalise as a result. Hence producing inaccurate predictions based on unseen data. For an open-pit mine, the DT models are unreliable for making output predictions due to their larger margins of error. A similar observation was reported by [26]. Nevertheless, it can generally be observed that the machine learning models are better at predicting mine production than the MLR model. The MLR model, as a baseline model for this study, assumes linearity and does not clearly understand the hidden causal effects or patterns of the input parameters on mine production, hence its poor performance. The MLR model accounts for 60% (R²) of the variance in mine output while disregarding the remaining 40% (Table 5).

The predicted production values by the various models are compared to the actual production values and plotted as presented in Figures 6–10. With reference to Figures 6–10, it can be observed that all the approaches presented in this study had predicted production values that were closer to the actual production. However, a careful look at Figures 6–10 reveals that, generally, the machine learning models, with the exception of the DT regressor, had their predictions match up with the actual with smaller amounts of variation than the MLR model. This further reveals the capability and superiority of machine learning in predicting surface mine production in this study.

The ANN was able to learn the hidden patterns within the datasets during training and generalise well on unseen data (test data). It can be seen that the strength of the relationship between predicted and actual daily production for the ANN model is stronger than that for the MLR model. Comparatively, the prediction error was decreased by almost 2% using the ANN model. DT is vulnerable to data that is noisy [40]. A small amount of noise might make it unstable, resulting in less accurate predictions. Furthermore, it usually results in data overfitting, which leads to incorrect predictions. This is because it continues to generate new nodes

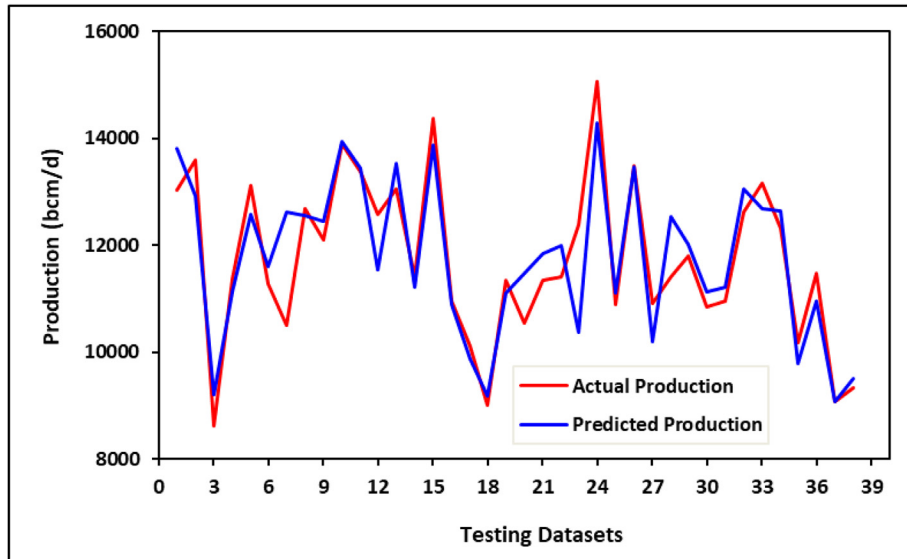


Fig. 6. Relationship between testing predicted and actual results using ANN.

in order to fit the data (even noisy data), and the tree eventually gets too complex to interpret. It thus loses its ability to generalise as a result of this phenomenon [41].

6. Challenges and future directions

Prediction has gained popularity in recent years and is now being used in a wide variety of fields. Despite machine learning’s popularity in mining and geo-engineering, the literature demonstrates that it has received little attention when it comes to assessing and forecasting mine production. This

research has presented a technique utilizing machine learning models to assess the efficiency of excavator and dump truck utilisation in order to predict mine production in an open-pit operation. This study indicates that the parameters modelled to predict mine production can be carefully monitored to effectively reduce excavator idle times and unnecessary down times during operations [59,60]. In fact, these machine learning approaches will help to confidently consider the working patterns of excavators and dump trucks in connection with the mining output that is forecasted. In addition, due to their better predictions, ANN algorithms can be

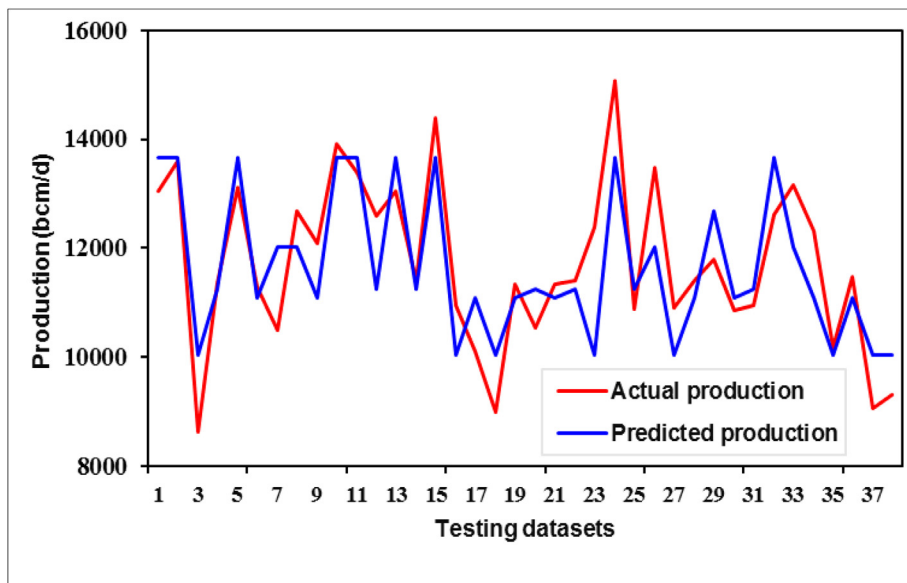


Fig. 7. Relationship between testing predicted and actual results using DT Regressor.

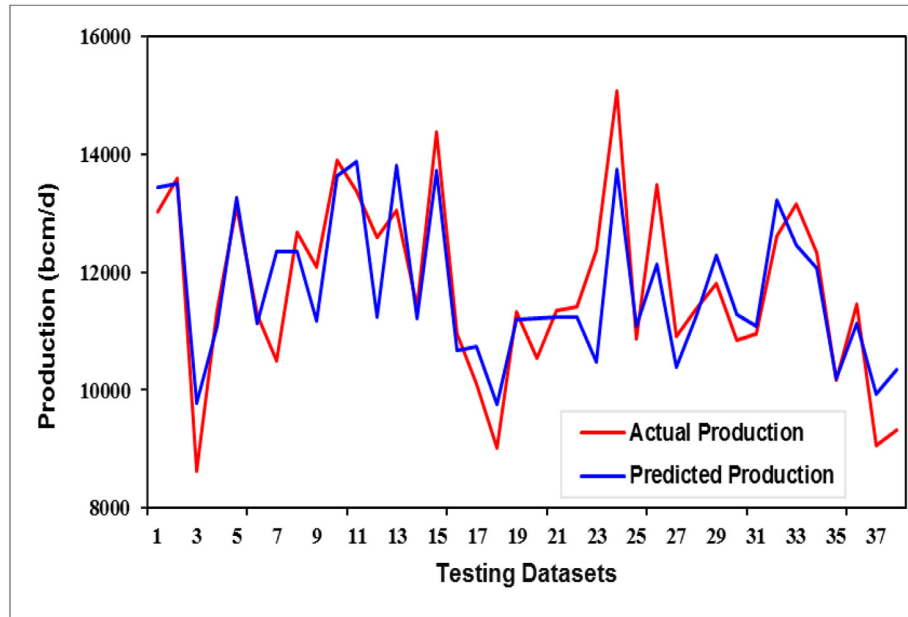


Fig. 8. Relationship between testing predicted and actual results using RF Regressor.

used to maximise the most sensitive factors affecting the output in order to reach production goals. Particularly, efficient excavator utilisation (reducing idle times) would not only minimise production loss but also reduce unnecessary fuel consumption [61]. As revealed in Table 2, increasing the number of trucks during operations can positively improve excavator utilization, which, in turn, increases the mine production.

Yet, as mines are dynamic systems where the working environment regularly changes, it is

important to update the ANN model frequently with the newest training data and tune the model parameters to take these features into account. However, in order to design and anticipate mine production, more study is needed into the usage of alternative machine learning models other than the ones employed in this article. Moreover, determining an efficient equipment utilisation pattern by incorporating these machine learning algorithms in assessing and predicting mine production can also offer mining companies the opportunity to operate

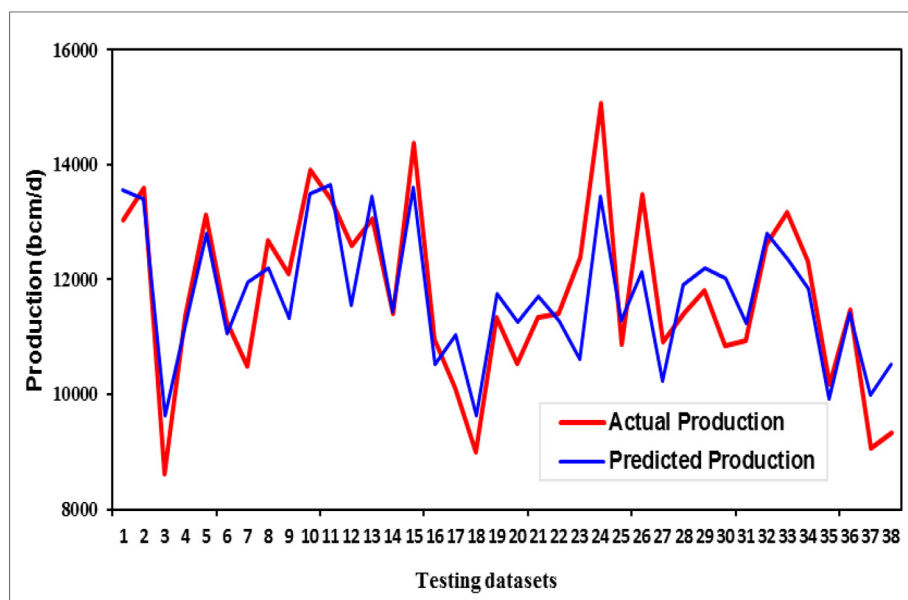


Fig. 9. Relationship between testing predicted and actual results using GBR.

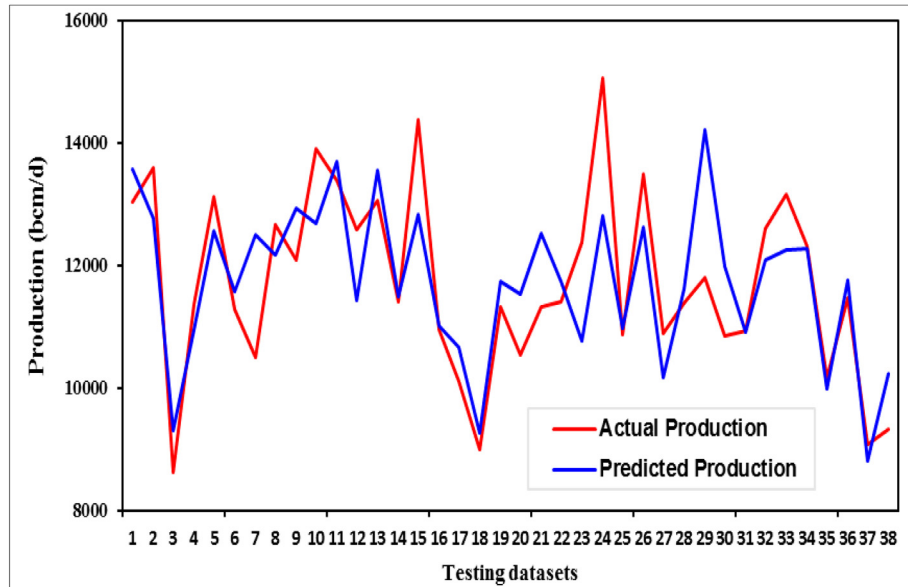


Fig. 10. Relationship between testing predicted and actual results using MLR.

their fleets more efficiently in order to achieve maximum productivity. Also, desktop application software can be built for the developed model to produce hands-on predictions for a mining company. It is proposed that larger data sets be explored in future studies with these machine learning techniques to hopefully improve their accuracy in predicting daily mine production.

7. Conclusion

This research evaluated the performance of machine learning algorithms; ANN, RF, GBR and DT regressor, as well as MLR, to predict daily surface mine production. In that regard, 126 datasets were collected and used in this study. Input parameters of average daily number of trucks, average percentage excavator utilisation, and average daily excavator worked hours were used for the development of the various models, whereas daily production served as the output parameter. Among the models implemented, ANN was found to be more efficient in predicting mine production with a coefficient of determination (R^2) of 0.8003, MAPE of 4.23% and VAF of 79.66% on the testing data followed by the RF with R^2 , MAPE and VAF of 0.7486, 5.07% and 74.69%, respectively. The results indicate that the developed ANN model is more reliable. Among the machine learning models, the DT regressor model was the least performing algorithm in predicting mine production with higher errors (R^2 , MAPE and VAF of 0.6538, 6.31% and 65.16%, respectively). From the results, it is possible to predict mine production more accurately when using the machine

learning models rather than the multiple regression analysis, which gave R^2 , MAPE and VAF of 0.6044, 6.15% and 60.11%, respectively. Moreover, it was determined that the ANN model can best estimate open-pit mine production by comparing its performance to that of other machine learning models. Overall, this study has shown that machine learning techniques can be relevant in modelling and predicting mine production in an open pit mine site.

Ethical statement

The authors state that the research was conducted according to ethical standards.

Funding body

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Conflicts of interest

None declared.

References

- [1] Alarie S, Gamache M. Overview of solution strategies used in truck dispatching systems for open pit mines. *Int J Surf Min Reclamat Environ* 2002. <https://doi.org/10.1076/ijsm.16.1.59.3408>.
- [2] Arteaga F, Nehring M, Knights P. The equipment utilisation versus mining rate trade-off in open pit mining. *Int J Min Reclamat Environ* 2018;32:495–518. <https://doi.org/10.1080/17480930.2017.1306674>.
- [3] Santelices G, Pascual R, Lüer-Villagra A, Mac Cawley A, Galar D. Integrating mining loading and hauling equipment selection and replacement decisions using stochastic linear

- programming. *Int J Min Reclamat Environ* 2017;31:52–65. <https://doi.org/10.1080/17480930.2015.1115589>.
- [4] Edwards DJ, Holt GD, Harris FC. Predicting downtime costs of tracked hydraulic excavators operating in the UK opencast mining industry. *Construct Manag Econ* 2002;20:581–91. <https://doi.org/10.1080/01446190210163552>.
- [5] Fisonga M, Mutambo V. Optimization of the fleet per shovel productivity in surface mining: case study of Chilanga Cement, Lusaka Zambia. *Cogent Eng* 2017;4:1386852. <https://doi.org/10.1080/23311916.2017.1386852>.
- [6] Ozdemir B, Kumral M. Appraising production targets through agent-based Petri net simulation of material handling systems in open pit mines. *Simulat Model Pract Theor* 2018. <https://doi.org/10.1016/j.simpat.2018.06.008>.
- [7] Lanke AA, Hoseinie SH, Ghodrati B. Mine production index (MPI)-extension of OEE for bottleneck detection in mining. *Int J Min Sci Technol* 2016;26:753–60. <https://doi.org/10.1016/j.ijmst.2016.05.050>.
- [8] Soofastaei A, Karimpour E, Knights P, Kizil M. Energy-efficient loading and hauling operations. *Green Energy Technol* 2018;121–46. https://doi.org/10.1007/978-3-319-54199-0_7.
- [9] Kaba FA, Temeng VA, Eshun PA. Application of Discrete event simulation in mine production forecast. *Ghana Min J* 2016;16:40. <https://doi.org/10.4314/gmj.v16i1.5>.
- [10] Sehulsoe TC, Musingnini C. Characterizing a mining production system for decision-making purposes in a platinum mine. *J South African Inst Min Metall* 2017. <https://doi.org/10.17159/2411-9717/2017A/117r2a11>.
- [11] Hall RA, Knights PF, Daneshmend LK. Pareto analysis and condition-based maintenance of underground mining equipment. *Min Technol* 2000;109:14–22. <https://doi.org/10.1179/mnt.2000.109.1.14>.
- [12] Markeset T, Kumar U. Application of LCC techniques in selection of mining equipment and technology. *Mine Plan Equip Sel* 2000;2018:635–40. <https://doi.org/10.1201/9780203747124-120>. Routledge.
- [13] Moradi Afrapoli A, Tabesh M, Askari-Nasab H. A stochastic hybrid simulation-optimization approach towards haul fleet sizing in surface mines. *Min Technol* 2019;128:9–20. <https://doi.org/10.1080/1080/25726668.2018.1473314>.
- [14] Manyele SV. Investigation of excavator performance factors in an open-pit mine using loading cycle time. *Engineering* 2017;9:599–624. <https://doi.org/10.4236/eng.2017.97038>.
- [15] Mohammadi M, Rai P, Gupta S. Performance evaluation of bucket based excavating, loading and transport (BELT) equipment – an OEE approach. *Arch Min Sci* 2017;62:105–20. <https://doi.org/10.1515/amsc-2017-0008>.
- [16] Arthur CK, Temeng VA, Ziggah YY. Novel approach to predicting blast-induced ground vibration using Gaussian process regression. *Eng Comput* 2020;36:29–42. <https://doi.org/10.1007/s00366-018-0686-3>.
- [17] Paneiro G, Rafael M. Artificial neural network with a cross-validation approach to blast-induced ground vibration propagation modeling. *Undergr Sp* 2020. <https://doi.org/10.1016/j.undsp.2020.03.002>.
- [18] Yang H, Hasanipannah M, Tahir MM, Bui DT. Intelligent prediction of blasting-induced ground vibration using ANFIS optimized by GA and PSO. *Nat Resour Res* 2020;29:739–50. <https://doi.org/10.1007/s11053-019-09515-3>.
- [19] Nwaila GT, Zhang SE, Frimmel HE, Manzi MSD, Dohm C, Durrheim RJ, et al. Local and target exploration of conglomerate-hosted gold deposits using machine learning algorithms: a case study of the witwatersrand gold ores, South Africa. *Nat Resour Res* 2020;29:135–59. <https://doi.org/10.1007/s11053-019-09498-1>.
- [20] Qi X, Wang H, Pan X, Chu J, Chiam K. Prediction of interfaces of geological formations using the multivariate adaptive regression spline method. *Undergr Sp* 2020. <https://doi.org/10.1016/j.undsp.2020.02.006>.
- [21] Avalos S, Kracht W, Ortiz JM. Machine learning and deep learning methods in mining operations: a data-driven SAG mill energy consumption prediction application. *Mining, Metall Explor* 2020. <https://doi.org/10.1007/s42461-020-00238-1>.
- [22] Li S, Sari YA, Kumral M. Optimization of mining–mineral processing integration using unsupervised machine learning algorithms. *Nat Resour Res* 2020;29:3035–46. <https://doi.org/10.1007/s11053-020-09628-0>.
- [23] Wang X, Huang L, Yang P, Yang C, Xie Q. Online estimation of the pH value for froth flotation of bauxite based on adaptive multiple neural Networks**Sponsor and financial support: the national natural science foundation of China (61304126, 61304019) and foundation for innovative research groups. *IFAC-PapersOnLine* 2016;49:149–54. <https://doi.org/10.1016/j.ifacol.2016.10.112>.
- [24] Dindarloo SR, Siami-Irdemoosa E. Data mining in mining engineering: results of classification and clustering of shovels failures data. *Int J Min Reclamat Environ* 2017;31:105–18. <https://doi.org/10.1080/17480930.2015.1123599>.
- [25] Baek J, Choi Y. Deep neural network for ore production and crusher utilization prediction of truck haulage system in underground mine. *Appl Sci* 2019. <https://doi.org/10.3390/app9194180>.
- [26] Baek J, Choi Y. Deep neural network for predicting ore production by truck-haulage systems in open-pit mines. *Appl Sci* 2020;10:1657. <https://doi.org/10.3390/app10051657>.
- [27] Choi Y, Nguyen H, Bui X-N, Nguyen-Thoi T, Park S. Estimating ore production in open-pit mines using various machine learning algorithms based on a truck-haulage system and support of internet of things. *Nat Resour Res* 2021;30:1141–73. <https://doi.org/10.1007/s11053-020-09766-5>.
- [28] Edwards DJ, Griffiths IJ. Artificial intelligence approach to calculation of hydraulic excavator cycle time and output. *Inst Min Metall Trans Sect A Min Technol* 2000. <https://doi.org/10.1179/mnt.2000.109.1.23>.
- [29] Kassem M, Mahamedi E, Rogage K, Duffy K, Huntingdon J. Measuring and benchmarking the productivity of excavators in infrastructure projects: a deep neural network approach. *Autom Construct* 2021;124:103532. <https://doi.org/10.1016/j.autcon.2020.103532>.
- [30] Ok SC, Sinha SK. Construction equipment productivity estimation using artificial neural network model. *Construct Manag Econ* 2006;24:1029–44. <https://doi.org/10.1080/01446190600851033>.
- [31] Kim Y, Lee SS. Application of artificial neural networks in assessing mining subsidence risk. *Appl Sci* 2020;10:1302. <https://doi.org/10.3390/app10041302>.
- [32] da Silva IN, Hernane Spatti D, Andrade Flauzino R, Liboni LHB, dos Reis Alves SF. Artificial neural network architectures and training processes. *Artif Neural Networks* 2017:21–8. https://doi.org/10.1007/978-3-319-43162-8_2. Cham: Springer International Publishing.
- [33] An Overview and Applications of Artificial Neural Networks n.d. <https://www.analyticsvidhya.com/blog/2022/03/an-overview-and-applications-of-artificial-neural-networks-ann/>(accessed March 12, 2023).
- [34] Breiman L. Random forests. *Mach Learn* 2001. <https://doi.org/10.1023/A:1010933404324>.
- [35] Johnson RW. An introduction to the bootstrap. *Teach Stat* 2001;23:49–54. <https://doi.org/10.1111/1467-9639.00050>.
- [36] Guo L, Chehata N, Mallet C, Boukir S. Relevance of airborne lidar and multispectral image data for urban scene classification using Random Forests. *ISPRS J Photogrammetry Remote Sens* 2011. <https://doi.org/10.1016/j.isprsjprs.2010.08.007>.
- [37] Rodriguez-Galiano V, Sanchez-Castillo M, Chica-Olmo M, Chica-Rivas M. Machine learning predictive models for mineral prospectivity: an evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geol Rev* 2015. <https://doi.org/10.1016/j.oregeorev.2015.01.001>.
- [38] Mbaabu O. Introduction to random forest in machine learning [internet]. 2020. Retrieved from: <https://www.section.io/engineering-education/introduction-to-random-forest-in-machine-learning/>.

- [39] Zhang Y, Haghani A. A gradient boosting method to improve travel time prediction. *Transport Res C Emerg Technol* 2015. <https://doi.org/10.1016/j.trc.2015.02.019>.
- [40] Pekel E. Estimation of soil moisture using decision tree regression. *Theor Appl Climatol* 2020;139:1111–9. <https://doi.org/10.1007/s00704-019-03048-8>.
- [41] Jena M, Dehuri S. Decision tree for classification and regression: a state-of-the art review. *Inform* 2020. <https://doi.org/10.31449/INF.V44I4.3023>.
- [42] Bowden GJ, Maier HR, Dandy GC. Optimal division of data for neural network models in water resources applications. *Water Resour Res* 2002. <https://doi.org/10.1029/2001wr000266>.
- [43] Mas JF, Flores JJ. The application of artificial neural networks to the analysis of remotely sensed data. *Int J Rem Sens* 2008; 29:617–63. <https://doi.org/10.1080/01431160701352154>.
- [44] Hunter JD. Matplotlib: a 2D graphics environment. *Comput Sci Eng* 2007. <https://doi.org/10.1109/MCSE.2007.55>.
- [45] McKinney W. Data structures for statistical computing in Python. *Proc. 9th Python Sci. Conf.* 2010:56–61. <https://doi.org/10.25080/Majora-92bf1922-00a>.
- [46] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: machine learning in Python. *J Mach Learn Res* 2011;12:2825–30.
- [47] Moolayil J. Learn Keras for deep neural networks: a fast-track approach to modern deep learning with Python. 2019.
- [48] Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, et al. TensorFlow: a system for large-scale machine learning. In: *Proc. 12th USENIX Symp. Oper. Syst. Des. Implementation, OSDI.* 2016; 2016.
- [49] Yu Y, Adu K, Tashi N, Anokye P, Wang X, Ayidzoe MA. RMAF: Relu-Memristor-like activation function for deep learning. *IEEE Access* 2020;8:72727–41. <https://doi.org/10.1109/ACCESS.2020.2987829>.
- [50] Kingma DP, Ba J. Adam: a method for stochastic optimization. In: *3rd int conf learn represent ICLR 2015 - conf track proc*; 2014.
- [51] Ying X. An overview of overfitting and its solutions. *J Phys Conf Ser* 2019;1168:022022. <https://doi.org/10.1088/1742-6596/1168/2/022022>.
- [52] Ogutu JO, Piepho H-P, Schulz-Streeck T. A comparison of random forests, boosting and support vector machines for genomic selection. *BMC Proc* 2011;5:S11. <https://doi.org/10.1186/1753-6561-5-S3-S11>.
- [53] Li Y, Zou C, Berecibar M, Nanini-Maury E, Chan JCW, van den Bossche P, et al. Random forest regression for online capacity estimation of lithium-ion batteries. *Appl Energy* 2018. <https://doi.org/10.1016/j.apenergy.2018.09.182>.
- [54] Liu D, Fan Z, Fu Q, Li M, Faiz MA, Ali S, et al. Random forest regression evaluation model of regional flood disaster resilience based on the whale optimization algorithm. *J Clean Prod* 2020. <https://doi.org/10.1016/j.jclepro.2019.119468>.
- [55] Gupta D, Hazarika BB, Berlin M. Robust regularized extreme learning machine with asymmetric Huber loss function. *Neural Comput Appl* 2020;32:12971–98. <https://doi.org/10.1007/s00521-020-04741-w>.
- [56] Yang S-H, Hu B-G. A stagewise least square loss function for classification. In: *Proc. 2008 SIAM int. Conf. Data min.* Philadelphia, PA: Society for Industrial and Applied Mathematics; 2008. p. 120–31. <https://doi.org/10.1137/1.9781611972788.11>.
- [57] San Millan-Castillo R, Morgado E, Goya-Esteban R. On the use of decision tree regression for predicting vibration frequency response of handheld probes. *IEEE Sensor J* 2020;20: 4120–30. <https://doi.org/10.1109/JSEN.2019.2962497>.
- [58] Pal M, Mather PM. An assessment of the effectiveness of decision tree methods for land cover classification. *Remote Sens Environ* 2003. [https://doi.org/10.1016/S0034-4257\(03\)00132-9](https://doi.org/10.1016/S0034-4257(03)00132-9).
- [59] Park S, Choi Y, Park H-S. Simulation of shovel-truck haulage systems in open-pit mines by considering breakdown of trucks and crusher capacity. *J Korean Soc Rock Mech* 2014; 24:1–10. <https://doi.org/10.7474/TUS.2014.24.1.001>.
- [60] Park S, Choi Y, Park H. Optimization of truck-loader haulage systems in an underground mine using simulation methods. *Geosystem Eng* 2016;19:222–31. <https://doi.org/10.1080/12269328.2016.1176538>.
- [61] Siami-irdemoosa E, Dindarloo SR. Prediction of fuel consumption of mining dump trucks : a neural networks approach. *Appl Energy* 2015;151:77–84. <https://doi.org/10.1016/j.apenergy.2015.04.064>.