ARTICLE IN PRESS

Resources Policy xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Forecasting mining capital cost for open-pit mining projects based on artificial neural network approach

Hongquan Guo[a], Hoang Nguyen[b,*], Diep-Anh Vu[c], Xuan-Nam Bui[d,e]

[a] School of Resources and Safety Engineering, Central South University, Changsha, Hunan, 410083, China
[b] Institute of Research and Development, Duy Tan University, Da Nang, 550000, Viet Nam
[c] Department of Basic Economics, Faculty of Economics and Business Administration, Hanoi University of Mining and Geology, 18 Vien st., Duc Thang ward, Bac Tu Liem dist., Hanoi, Viet Nam
[d] Department of Surface Mining, Mining Faculty, Hanoi University of Mining and Geology, 18 Vien st., Duc Thang ward, Bac Tu Liem dist., Hanoi, Viet Nam
[e] Center for Mining, Electro-Mechanical Research, Hanoi University of Mining and Geology, 18 Vien st., Duc Thang ward, Bac Tu Liem dist., Hanoi, Viet Nam

ARTICLE INFO

Keywords:
artificial neural network
Artificial intelligence
Mining capital cost
Open-pit mining
Resources policy

ABSTRACT

This study considered and developed four artificial intelligence (AI) techniques to estimate mining capital cost (MCC) for open-pit copper mining projects with high accuracy, including artificial neural network (ANN), random forest (RF), support vector machine (SVM), and classification and regression tree (CART); 74 observations of mining projects were collected and analyzed to predict MCC based on five input variables. Root-mean-squared error (RMSE), coefficient of correlation (R^2), mean absolute error (MAE), and absolute percentage error (APE), were used to evaluate the performance/quality/accuracy of the models. The results of this study indicated that ANN, RF, SVM and CART models were advanced techniques in predicting MCC with high accuracy. Of those, the ANN model yielded the most dominant accuracy/performance with an RMSE of 138.103, R^2 of 0.990, MAE of 114.589, and APE of 7.770%. The remaining models (i.e. RF, SVM, CART) yielded lower performance with RMSE in the range of 172.975–379.691, R^2 in the range of 0.924–0.987, MAE in the range of 134.982–301.196, and APE in the range of 10.339%–19.384%. The results of the sensitivity analysis of this work also revealed that production capacity includes MineAP and MillAP, were the two most essential parameters on the MCC predictive models. They should be used as the primary input parameters for estimating MCC in actual.

1. Introduction

Mining capital cost (MCC) is one of the essential criteria for assessing the feasibility of an open-pit mine (or underground mine). The MCC heavily influences the net present value (NPV) of the projects over the lifetime of the mine. In open-pit mining, optimization issues in designing and mining planning have been made (e.g. Ahmadi and Shahabi, 2018; Dimitrakopoulos et al., 2002; Dimitrakopoulos et al., 2007; Leite and Dimitrakopoulos, 2007; Menabde et al., 2018; Moreno et al., 2017; Ramazan and Dimitrakopoulos, 2018). The primary purpose of the optimisation problem above is to achieve maximum value of NPV for mines. The cost of procurement of equipment and capital construction are two significant factors that affect the MCC of the mine (Mohutsiwa and Musingwini, 2015). Of those, equipment size is directly related to the MCC in each project (Bozorgebrahimi et al., 2005). The advanced techniques in mining industry are also the influence methods on MCC as well as NPV of an open-pit mine (Demirel et al., 2018; Mai et al., 2018; Miao et al., 2017; Richmond, 2018; Rimélé et al., 2018; Ristovski et al., 2017). In briefly, MCC is a factor that has a great effect on the success of an open-pit mine project. Therefore, it needs to be precise estimated to minimize the risks, as well as increase the feasibility of mining projects.

Review of literature showed that the MCC forecasting studies are poor with simple methods (Dehghani and Ataee-pour, 2012; Lima and Suslick, 2006). The underestimation of the MCC has led to significant risks in the mining process during the past four decades (Bertisen and Davis, 2008). According to Castle (1985), the majority of mining projects with the real MCCs exceed 10–15% of the predicted values, on average exceeding 35% in the surveying of 17 mining projects from 1965 to 1980. In another study, Bennet (1996) was investigated 16 mining projects from 1990 to 1995 with MCC exceeded 27% in an average. Thomas (2001) was also showed that the percentage of MCC exceeded 17% due to the escalating rate of inflation in the surveying of 21 mining projects. Investigation of 60 mining projects by Gypton (2002) from 1980 to 2001 showed that MCCs exceeded 22%. Underestimating the MCC will lead to a higher NPV than its actual value. In

* Corresponding author.
E-mail address: nguyenhoang23@duytan.edu.vn (H. Nguyen).

https://doi.org/10.1016/j.resourpol.2019.101474
Received 14 December 2018; Received in revised form 14 June 2019; Accepted 14 August 2019

contrast, overestimating MCC will lead to lower NPV than reality.

For estimating MCC, some scientists have attempted to investigate and study different techniques (Bertisen and Davis, 2008; Huang et al., 2012; Mular, 1982; Niazi et al., 2006; Shafiee and Topal, 2012). However, the regression method was still the most popular method for the development of MCC predictive models (Smith and Mason, 1997). Many scientists have used univariate regression methods to estimate the MCC for mining projects (Petrick and Dewey, 1987; Prasad, 1969; Stebbins, 1987; Weiss, 1979). The general equation of MCC is described as follows (Darling, 2011):

$$MCC = k \times X^n \tag{1}$$

where k denotes a unit cost related to X; X indicates a variable to be causal of MCC, and n means a force to manage a changing tendency of the curve.

In addition, the O'Hara model was also a popular method used for forecasting MCC (O'Hara, 1980a, 1980b). The polynomial least square was O'Hara's approach. It was developed based on the data collection of MCC in Canadian as an empirical technique (Bertisen and Davis, 2008). The O'Hara method investigated the produce point; however, other vital points were disregarded. It was calculated as equation (2) as follows:

$$MCC = US\$600{,}000 \times T^{0.6} \tag{2}$$

where T denotes daily ore milled (tons). Should be noted that MCC in equation (2) was calculated in US dollars for mid-1989 (Easley and O'hara, 2004).

As mentioned, the O'Hara method was not considered other parameters for estimating MCC. Therefore, the significant errors can occur in MCC estimation resulting. To overcome the drawback of the O'Hara method, Sayadi et al. (2014) applied the multivariate regression (MR) method to predict MCC. The cost of operating and capital of the excavator was estimated based on the MR method (Oraee et al., 2011). Also, the capital, as well as the operating cost of a constitution machine, can be predicted based on the MR method (Arfania et al., 2017).

In recent years, artificial intelligence (AI) techniques have been applied in resources policy and estimating MCC as the advanced methods (e.g. Ahmadi and Shahabi, 2018; Dehghani and Bogdanovic, 2018; Fan et al., 2016; He et al., 2015; Pierdzioch et al., 2016). Artificial neural network (ANN) was also an alternative technique for the MR method in estimating capital cost (Smith and Mason, 1997). Nourali and Osanloo (2018b) developed a CART model for forecasting MCC using 28 observations. The feasibility of their CART model was interpreted through root-mean-squared error (RMSE) of 219.36 and mean absolute error (MAE) of 178.5. In another study, Nourali and Osanloo (2018a) also developed another soft computing model, i.e. SVR model, for estimating MCC based on 52 observations. Kernel ridge regression (KRR) method was also applied to determine MCC in their study for the comparison and evaluation purposes. A promising result was demonstrated in their research with an RMSE of 87.375 and MAE of 9.447, for their SVR model. In contrast, the KRR model only reached lower performance with an RMSE of 2311.856 and MAE of 1679.815.

Review of literature shows that AI techniques for estimating MCC are rarely used for mining projects. Whereas, new AI models for predicting MCC with high accuracy are needed to ensure the feasibility of the project, as well as to estimate the NPV of the project accurately. Therefore, ANN was applied in this study to predict MCC. Accordingly, three ANN models were developed in this study for estimating MCC. Three benchmark algorithms were also considered and prepared for predicting MCC, including random forest (RF), support vector machine (SVM), and classification and regression tree (CART). A database with 74 observations was collected from 74 open-pit mining projects for this aim. The rest of this paper is organised as follows. Section 2 presents the materials used in this study. Section 3 describes the methods used. The results of this study are showed and discussed in section 4. Finally, the conclusions are given in section 5.

Table 1
Features of the MCC database used in the present research.

Element	MineAP	SR	MillAP	RMG	LOM	MCC
Min.	4.0	0.2	185.0	0.20	10.0	406.0
Mean	34.108	1.976	574.703	0.762	26.932	2463.76
Max.	64.0	5.05	1215.0	2.84	48.0	6373.0

2. Materials

In this section, the dataset used for predicting MCC was presented. In this study, a dataset with 74 observations was collected from 74 open-pit copper mining projects. In mining projects, production capacity was considered as the most critical factor for capital cost estimation (Dagdelen, 2001; Hustrulid et al., 2013b). Based on production capacity, equipment capital cost can be calculated. According to Long (2011), capacity should be used to estimate capital cost even though distance and stripping ratio from the railway were insisted by other scientists with a trustworthy range of error. Nourali and Osanloo (2018a) was recommended that annual mine production (MineAP), million tons; stripping ratio (SR); annual production of the mill (MillAP), thousand tons; reserve mean grade % Cu EQU (RMG) and the mine life (LOM) should be used to estimate MCC. However, they did not mention which factor(s) are the most influential factor(s) on MCC in their study. Therefore, five input variables include MineAP, SR, MillAP, RMG, LOM were used to estimate MCC in this study. The effectiveness of the input variables will be analysed in this study. Table 1 summaries the dataset used in this study.

3. Background of the methods used

3.1. Artificial neural network

Inspired by the human biological neural network, ANN has been researched and developed since the 1970s. Its structure consists of 3 parts: input layer, hidden layer(s), and output layer (Yegnanarayana, 2009). In each layer, neurons are considered as the information processing unit of ANN (He and Xu, 2010). They are interconnected by weights and bias-based algorithms, such as the Levenberg-Marquardt, Quasi-Newton, conjugate gradient, back-propagation, multiple linear perceptrons, Newton, and gradient descent (Haykin et al., 2009; Yegnanarayana, 2009). In the input layer, the number of neurons depends on the number of input variables of the data. Typically, each neuron in the input layer takes care of an input variable from an external environment. Herein, five neurons were used in the input layer, i.e. MineA, SR; MillAP, RMG and LOM. After receiving information from input variables, neurons in the hidden layers perform coding, calculating the weights, biases, and sending them to the hidden layer (s). In an ANN, the number of hidden layers can be one or more. In theoretical, one hidden layer is enough for an ANN model which can handle every problem (Nguyen et al., 2018). More complex problems require an ANN model with multiple hidden layers rather than one hidden layer (De Villiers and Barnard, 1993; Nguyen et al., 2019b). In the hidden layer(s), the determination of the number of hidden neurons is a complex problem. Nguyen et al. (2018) recommended that too little or too many hidden neurons lead to underfitting or overfitting in ANN. Some previous scientists have proposed methods for determining the number of neurons that are reasonable for ANN (e.g. Hecht-Nielsen, 1987; Kaastra and Boyd, 1996; Kanellopoulos and Wilkinson, 1997; Masters, 1993; Ripley, 1993; Wang, 1994). However, there are still many issues to discuss these heuristics. After receiving information from the input layer, hidden neurons continue to compute, process and transfer data to the output layer, where the MCC is estimated. The general structure of an ANN model for estimating MCC in this study is shown in Fig. 1. Also, the back-propagation algorithm was applied in

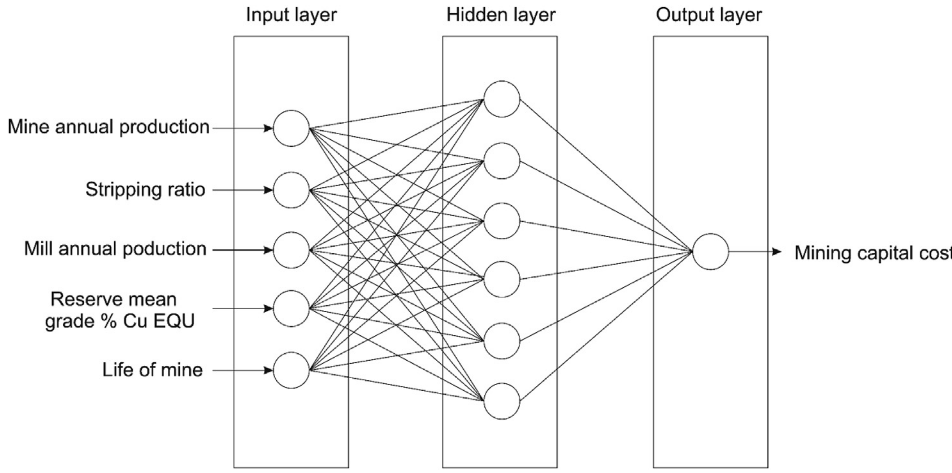

Fig. 1. General structure of an ANN model for forecasting MCC in this study.

Algorithm 1 Backpropagation Algorithm

procedure TRAIN
  $X \leftarrow$ Training Data Set of size mxn
  $y \leftarrow$ Labels for records in X
  $w \leftarrow$ The weights for respective layers
  $l \leftarrow$ The number of layers in the neural network, 1...L
  $D_{ij}^{(l)} \leftarrow$ The error for all l,i,j
  $t_{ij}^{(l)} \leftarrow 0$. For all l,i,j
  $For\ \ i = 1$ to m
    $a^l \leftarrow feedforward(x^{(i)}, w)$
    $d^l \leftarrow a(L) - y(i)$
    $t_{ij}^{(l)} \leftarrow t_{ij}^{(l)} + a_j^{(l)} \cdot t_i^{l+1}$
  if $j \neq 0$ **then**
    $D_{ij}^{(l)} \leftarrow \frac{1}{m} t_{ij}^{(l)} + \lambda w_{ij}^{(l)}$
  else
    $D_{ij}^{(l)} \leftarrow \frac{1}{m} t_{ij}^{(l)}$
    where $\frac{\partial}{\partial w_{ij}^{(l)}} J(w) = D_{ij}^{(l)}$

Fig. 2. Pseudo-code of the back-propagation algorithm in training ANN.

this study to forecast MCC; thus, the pseudo-code of the back-propagation algorithm is shown in Fig. 2.

3.2. Random forest

As a useful technique for forecast problems, the Random Forest (RF) algorithm was introduced by Breiman (2001). The development of the RF model based on the idea of an election and a forest. There, each tree in the forest represents a voter. The set of votes and percentages by category is the basis for making the final decision by the RF algorithm (Nguyen and Bui, 2018). For each of the trees, RF implements the bagging method to generate a randomly training dataset (Sirikulviriya and Sinthupinyo, 2011). The splitting features are also semi-randomly selected by the RF. A random subset of a specified proportion is provided from the possible splitting features space. RF's pseudocode is illustrated in Fig. 3.

3.3. Support vector machine

Support vector machine (SVM) is one of the benchmark machine learning algorithms, which was widely applied in statistical communication (Deka, 2014; Mountrakis et al., 2011; Orru et al., 2012). It was first introduced by Cortes and Vapnik (1995) for classification problems, called SVC. Subsequently, Vapnik et al. (1997) developed the SVM algorithm for the regression problems in 1997, called SVR. It is the most common application form of SVM. In this work, the SVR algorithm was applied to estimate MCC since the database used in this work is numeric. For SVR, the cost function for the development of the model ignores any training dataset that is near to the predictive model (within a threshold ε). Therefore, the model constructed by SVR only depends on a subset of the training dataset (Basak et al., 2007). For non-linear regression problems, SVR employs an approximation as follows:

$$f(x) = \sum_{i=1}^{N} \left(\alpha_i^* - \alpha_i\right). k\left(x_i, x\right) + b \tag{3}$$

where N is the input patterns space; α_i^* and α_i denote the Lagrange multipliers; $k(x_i, x)$ indicates the kernel functions.

To define the Lagrange multipliers α_i^* and α_i, the following function is applied:

$$R_{reg}[f] = \frac{1}{2}\|\omega^2\| + C\sum_{i=1}^{l} L_\varepsilon(y) \tag{4}$$

where $\|\omega^2\|$ denotes the complexity of the model; C is the trade-off constant; ε denotes the insensitive loss function, i.e. $L_\varepsilon(y)$.

$$L_\varepsilon(y) = \begin{cases} 0, for|f(x) - y| < \varepsilon \\ |f(x) - y| - \varepsilon otherwise \end{cases} \tag{5}$$

3.4. Classification and regression tree

In data mining or machine learning, decision tree algorithms are one of the effectiveness branches for prediction problems. Of the decision tree algorithms, CART was introduced as an effective technique to solve both regression and classification problems (Breiman, 2017; Lewis, 2000). It was proposed by Breiman et al. (1984) based on an independent framework and unknown the relationship between input and output variables. One of the outstanding features of the CART method is it can detect the critical level of input variables (Bui et al., 2019). Furthermore, the CART model is not sensitive to outliers (Nguyen et al., 2019a). This is a plus for the CART model in processing and working with data include many outliers. To develop a CART model, the pseudo-code of the one can be applied, as shown in Fig. 4.

3.5. Performance indices for evaluating

For evaluating the accuracy/performance of the mentioned models (i.e. ANN, RF, SVM, CART), three performance indices were used and computed, including RMSE, R^2 and MAE.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

```
Algorithm 1: Pseudo code for the random forest algorithm
To generate c classifiers:
for i = 1 to c do
   Randomly sample the training data D with replacement to produce D_i
   Create a root node, N_i containing D_i
  Call BuildTree( N_i )
end for

BuildTree(N):
if N contains instances of only one class then
   return
else
   Randomly select x% of the possible splitting features in N
   Select the feature F with the highest information gain to split on
   Create f child nodes of N , N_1 ,..., N_f , where F has f possible values ( F_1, … , F_f )
   for i = 1 to f do
      Set the contents of N_i to D_i , where D_i is all instances in N that match
      F_i
      Call BuildTree( N_i )
   end for
end if
```

Fig. 3. Pseudo-code of the RF algorithm.

```
d=0, endtree=0
Note(0)=1, Node(1)=0, Node(2)=0
while endtree<1
        if
Node(2^d – 1) + Node(2^d) + … + Node(2^(d+1) – 2) = 2 – 2^(d+1)
                endtree = 1
        else
                do i = 2^d – 1, 2^d, …, 2^(d+1) – 2
                        if Node(i) > -1
                                Split tree
                        else
                                Node(2i + 1) = -1
                                Node(2i + 2) = -1
                        end if
                end do
        end if
d = d + 1
end while
```

Fig. 4. Pseudo-code of the CART algorithm.

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{8}$$

In which, the number of observations is described by n; y_i and $\hat{y}_i$ indicate the actual and forecasted values; $\bar{y}$ represents mean of real observations.

4. Results and discussion

As regarded, three ANN models, RF, SVM, and CART models are developed in this study for estimating MCC based on the training dataset. The steps and structure of the algorithms, computational steps, as well as the inputs in respect of each AI technique, were presented and highlighted. Then, the results were presented and discussed. Before developing the mentioned models, the original dataset includes 74 observations were divided into two sections for training and testing processes. Of the whole dataset, 80% (~ 62 experimental datasets) was used for the development of the models, called the training process. The remaining 20% (~ 12 experimental datasets) was used to check the reliability/accuracy of the constructed models, drawn the testing process. This scale (i.e. 80/20) was recommended by the previous researchers to ensure the balance of the models (Gao et al., 2019; Moayedi et al., 2019; Nguyen et al., 2019c; Zhang et al., 2019). Note that, all the models were developed based on the same training dataset (i.e. 62 observations), and tested by the same testing dataset (i.e. 12 observations).

For ANN models, three main steps were conducted, including determination of the hidden layers; determination of the hidden neurons, and calculate the weights and biases of the ANN models. For the decision of the hidden layers, it is complicated to define how many hidden layers is the best for the ANN model in estimating MCC. As introduced above, an ANN model using one or two hidden layers can explain every trouble. Therefore, a “trial and error” procedure for the number of hidden layers was performed during the development of the ANN model. It was set equal to 1 and 2, respectively. To prevent the generation of a complexity ANN model, the hidden neurons were tested in the range of 7–12. Back-propagation algorithm was applied to train the ANN models. To avoid overfitting, the min-max scale technique was involved with the range of [-1,1] (Shang et al., 2019); 120 repetitions were performed to determine the initial weights. Eventually, three ANN models for predicting MCC were defined, including ANN 5-9-1, ANN 5-8-8-1 and ANN 5-12-7-1 models. The structure of the developed ANN models for estimating MCC in this study are shown in Figs. 5–7.

For the development of the RF model, two significant hyper-parameters were considered for testing the accuracy of the model, including *the number of trees in the forest* (n) and *randomly selected predictor* (*mtry*). To ensure the forest enrich, n was set equal to 2000 (Nguyen et al., 2018); *mtry* is the remaining hyper-parameter which was used to control the quality/accuracy/reliability of the RF model. A grid search technique of *mtry* with *mtry* lies in the range [1, 50], was performed to find out the optimal model; 10 fold cross-validation technique (Fushiki, 2011) was used in this study to improve the accuracy of the RF model. Based on the RMSE values, the best RF model was defined at *mtry* = 36 with the lowest RMSE, as shown in Fig. 8. Note that, all the input variables and the training dataset are the same as those used for the development of the ANN models.

To develop the CART model, *complexity parameter* (*cp*) is the only hyper-parameter used to control the performance/accuracy of the CART model. A grid search procedure was also applied to find out the optimal value of *cp*, with *cp* was set equal to 0, 0.05 and 0.1; The similar resampling technique (i.e. 10-fold cross-validation) was also applied for the CART modelling. As shown in Fig. 9, *cp* = 0 is the optimal value for the CART model in estimating MCC. Note that, all the input variables

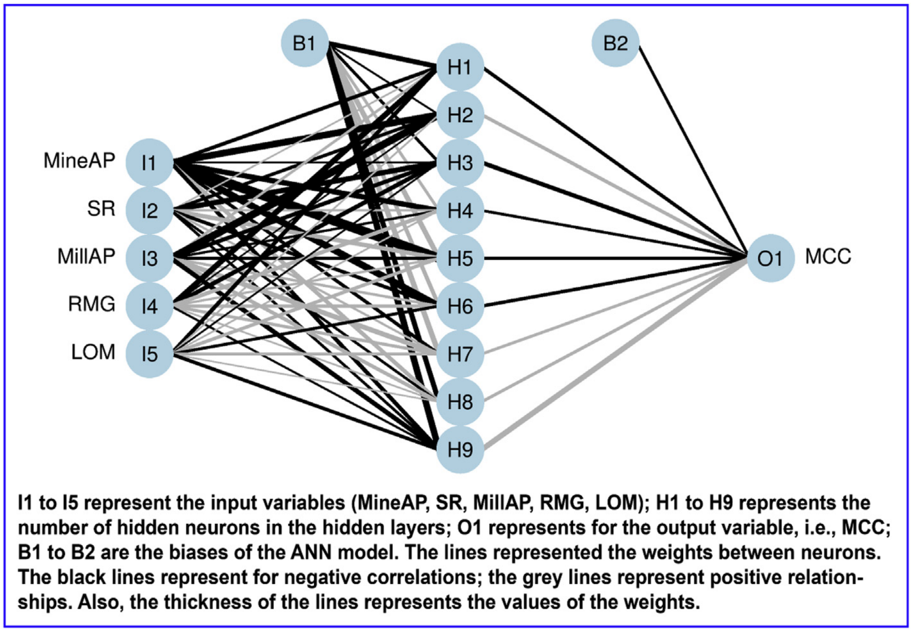

Fig. 5. The ANN 5-9-1 model for estimating MCC in this study.

and the training dataset are the same as the development of the ANN and RF models.

For the SVM model development, the radial basis kernel function was applied to train the SVM model in this work. Accordingly, cost (C) and sigma (σ) were used to control the accuracy of the SVM model. A "trial and error" procedure with 100 SVM models was conducted in this study with different values of C and σ (Fig. 10). The similar techniques, as well as the same input variables and the same training dataset, were applied during developing the SVM model as those used for the development of the RF and CART models. Based on the RMSE values, the best SVM model was found at $c = 81.685$ and $\sigma = 0.023$.

Once the models were developed, an unseen dataset (i.e. testing dataset) was applied to evaluate the performance/accuracy of the developed models. To have a complete conclusion, the performance of the models should be assessed on both training and testing phases. Herein, RMSE, R^2 and MAE were calculated according to equations (4)–(6). The indices of the model performances for forecasting MCC in the present research is calculated in Table 2.

Based on the obtained results in Table 2, the ANN models performed very well for estimating MCC. They obtained a promising performance with an RMSE in the range of 151.225–196.100, R^2 in the range of 0.981–0.988, and MAE in the range of 116.437–149.479. Likewise, the ANN models were also performed very well on the testing phase with an RMSE in the range of 138.103–278.425, R^2 in the range of 0.963–0.990, and MAE in the range of 114.589–236.655. Among three ANN models developed, the ANN 5-12-7-1 model was the most dominant model with an RMSE of 138.103, MAE of 114.589, and R^2 of 0.990. The SVM model also provided quite well performance in estimating MCC with an RMSE of 172.975, MAE of 134.982, and R^2 of 0.987, on the testing phase. Next is the RF model with the performance was acceptable in

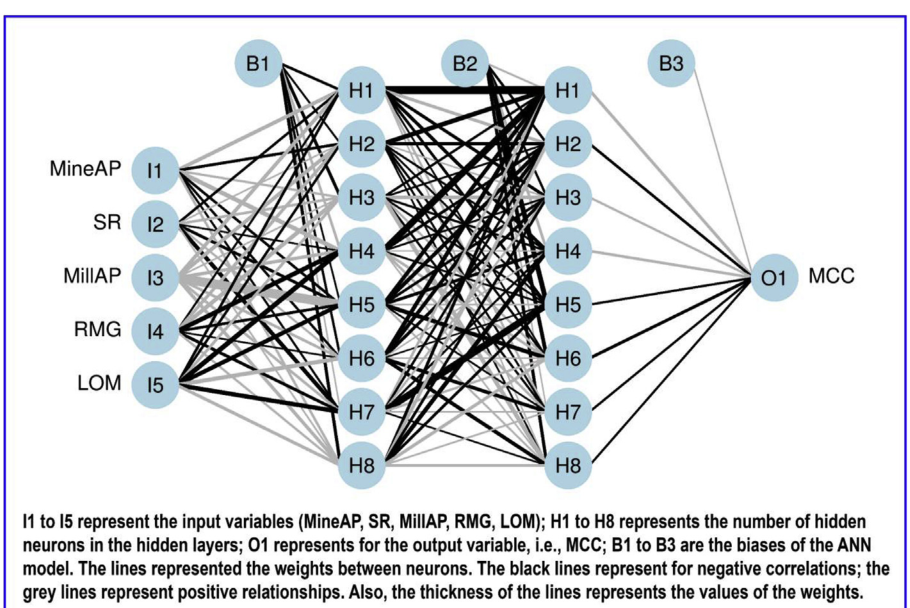

Fig. 6. The ANN 5-8-8-1 model for estimating MCC in this study.

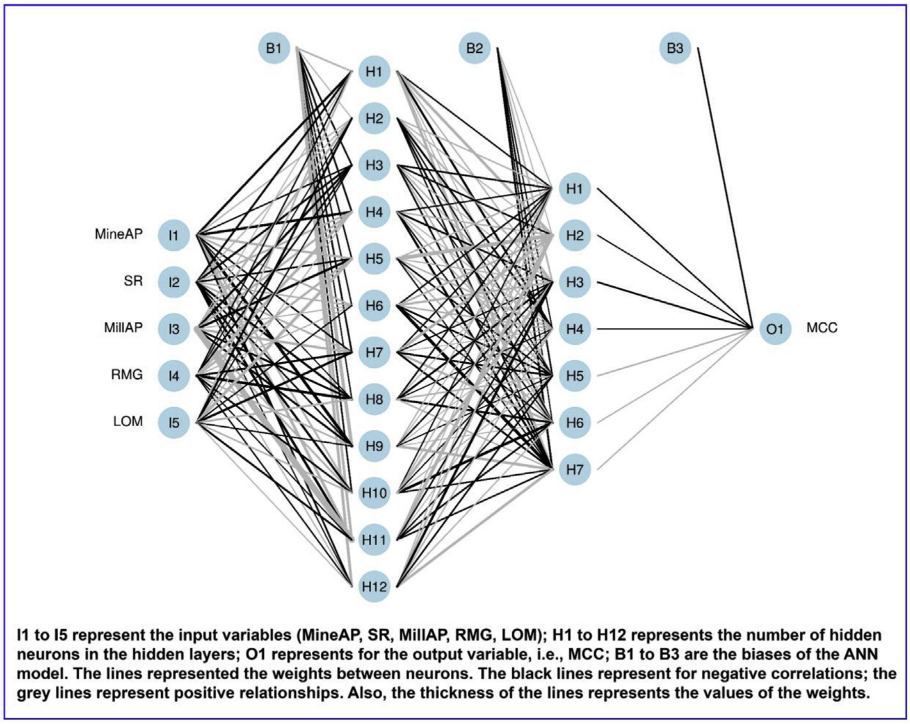

Fig. 7. The ANN 5-12-7-1 model for estimating MCC in this study.

estimating MCC (i.e. RMSE = 231.959, MAE = 146.278, R^2 = 0.976, and on the training phase; RMSE = 299.311, MAE = 222.966, R^2 = 0.960, on the testing phase). In contrast, the CART model yielded the poorest performance in the present study with an RMSE of 496.362, MAE of 404.791, and R^2 of 0.921, on the training phase; RMSE of 379.691, MAE of 301.196, and R^2 of 0.924, on the testing phase. Fig. 11 shows the performance of the models based on the actual and predicted values of the testing phase.

It can be seen that the AI techniques rely on mining and processing rates and an average grade of material. Depending on the production schedule, mining and processing rates may vary due to supply uncertainty. In reality, the supply of the mines is different depending on the specific time/period. It is an uncertain problem during the life of mines. It affects the production schedule of the mines, as well as mining capital cost (Jaeger, 2006). However, forecast the supply uncertainty is a challenge for mining companies. The main factors responsible for the

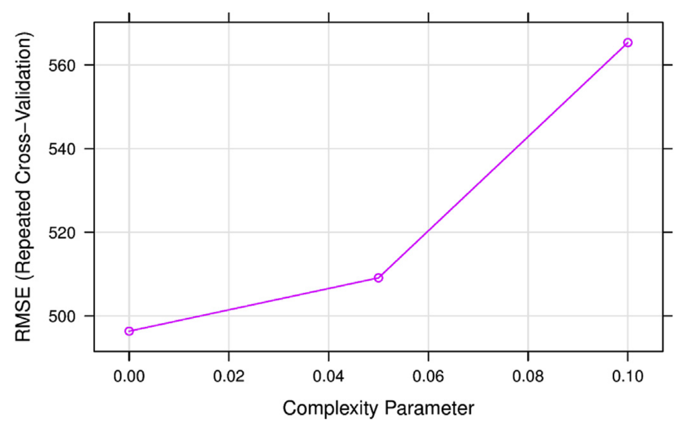

Fig. 9. RMSE of the CART model in predicting MCC in the present work.

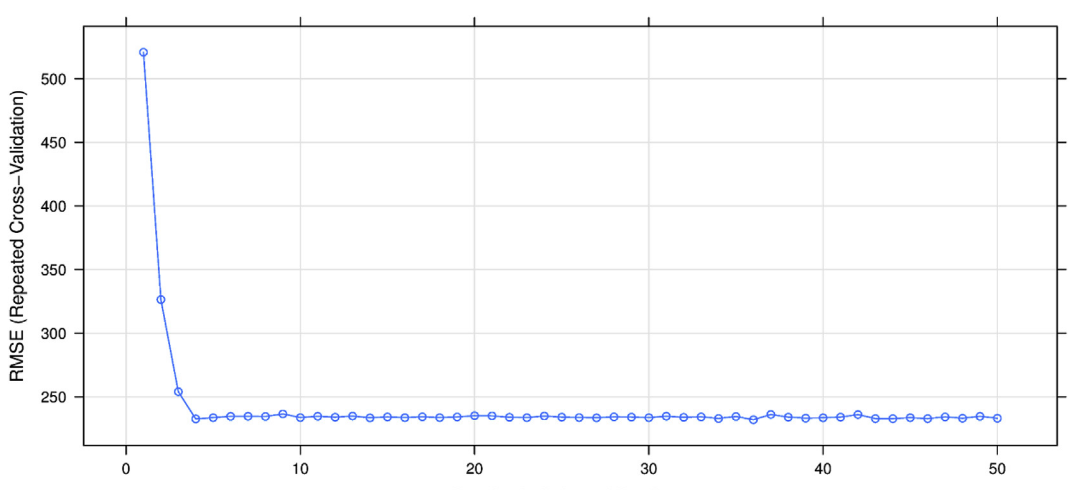

Fig. 8. Performance of the RF model for estimating MCC in this study.

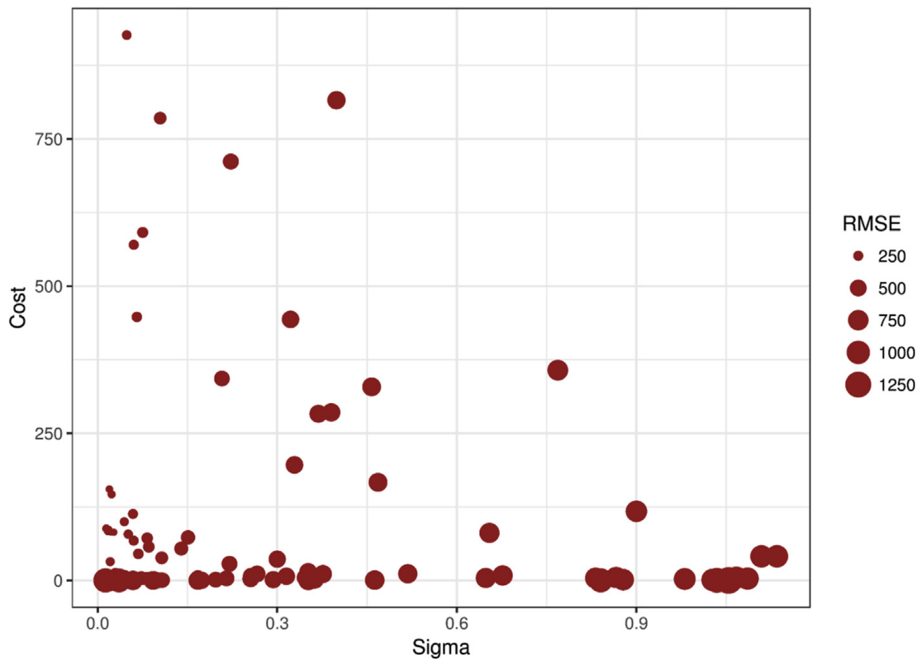

Fig. 10. RMSE of the SVM technique for predicting MCC.

Table 2
The MCC predictive models and their performance/accuracy in this study.

Model	Training phase			Testing phase		
	RMSE	R^2	MAE	RMSE	R^2	MAE
ANN 5-9-1	196.100	0.981	149.479	278.425	0.963	236.655
ANN 5-8-8-1	186.050	0.983	140.584	247.988	0.970	219.080
ANN 5–12-7-1	**151.225**	**0.988**	**116.437**	**138.103**	**0.990**	**114.589**
SVM	221.300	0.979	175.293	172.975	0.987	134.982
CART	496.362	0.921	404.791	379.691	0.924	301.196
RF	231.959	0.976	146.278	299.311	0.960	222.966

Note: The best model was shown in bold type.

supply certainty are economy, politics, and society. Therefore, it is challenging to predict the supply certainty accurately and set is as an input variable for forecasting MCC. Moreover, the supply-demand of the mines is often not publicly released. Thus, we omitted this factor and considered AI models based on specific parameters in the current study (i.e., annual mine production, stripping ratio, reserve mean grade % Cu EQU, mill annual production, and life of mine).

Furthermore, the milling rate seems to depend on the cut-off grade rather than the average grade. Higher the cut-off grade, lower would be the quantity of material to be processed, and vice versa. However, using dynamic cut-off grade is only suitable for specific mines without being able to represent many mines. Thus, for each developed AI model for each mine, the predicted results will be incorrect when applied to other mines. Like to the supply certainly factor, a dynamic cut-off grade of each mine is different. They should be considered as a case study for specific mine. In the current study, we investigated a total of 74 open-cast mining projects and forecasted their mining capital cost. Based on confident, fixed and capable elements representing most of the mines, we have developed six AI models that can accurately describe and predict mining capital cost for the mines. The obtained results of this study with high accuracy demonstrated the suitability and representation of input variables.

As mentioned, the feasibility of a mining project is assessed through the MCC value. Accurate estimation of MCC helps the NPV of mining projects is optimise. According to Hustrulid et al. (2013a), the acceptable absolute percentage error (APE) for MCC predictions should not exceed 10%. Based on this criteria, the predicted values of the model and percentage error on each observation, as well as on the APE values were computed, as shown in Fig. 12 and Table 3.

Based on Table 3, it can be seen that the percentage error of the ANN model was the lowest among the developed models in this study for estimating MCC. Take a closer Table 3 showed that the APE values were exceeded 10% on the observations 3, 4 and 9, by the ANN model. The remaining observations yielded a promising result with APE in the range of 0.027–7.759 on the selected ANN model (i.e. ANN 5-12-7-1). Remarkable, the average error only reached 7.770 on the testing phase by the selected ANN model. Whereas, the remaining models provided higher average error, i.e. 10.339 for the SVM model; 16.750 for the RF model; 19.384 for the CART model.

For evaluating the effect of the input variables in estimating MCC, a sensitivity analysis procedure was conducted in this study. The results showed that MineAP and MillAP were the most influential parameters on the MCC predictive model, as shown in Fig. 13. They should be used as the significant parameters for forecasting MCC in practical.

5. Conclusion

MCC is an essential criterion for evaluating the feasibility of an open-pit mining project. An accurate estimation of MCC is needed to manage the funds and determine the NPV for the mine. Based on the findings of this study, it can conclude that AI techniques are the advanced techniques in estimating MCC for open-pit mines with high reliability. ANN, RF, SVM, and CART were the advanced techniques that were developed in this study for estimating MCC. Of these, ANN was considered as the most superior technique in estimating MCC with an RMSE of 138.103, MAE of 114.589, and R^2 of 0.990, for the performance of the ANN 5-12-7-1 model, respectively. The SVM model was also performed well in predicting MCC with an RMSE of 172.975, MAE of 134.982, and R^2 of 0.987. The remaining models were presented quite well for estimating MCC, but lower than the ANN 5-12-7-1 and SVM models. Notably, the CART model yielded most miserable performance with an MAE of 301.196, RMSE of 379.691, and R^2 of 0.924. As a conclusion, the ANN 5-12-7-1 model should be applied in actual for estimating MCC for open-pit copper mines. The average percentage error of 7.770 was the promising result for predicting MCC by ANN in

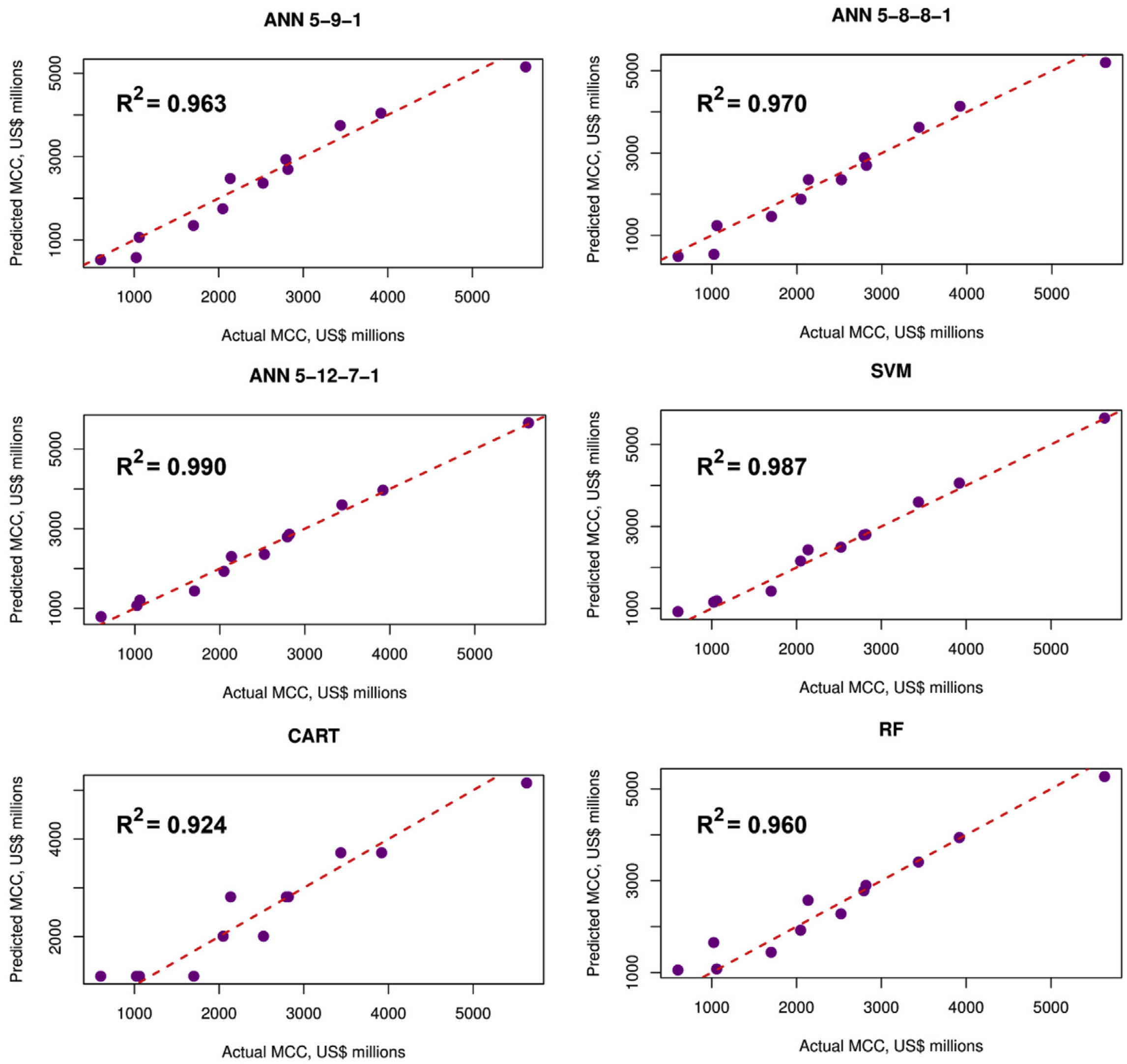

Fig. 11. Actual versus predicted values on the testing dataset for estimating MCC.

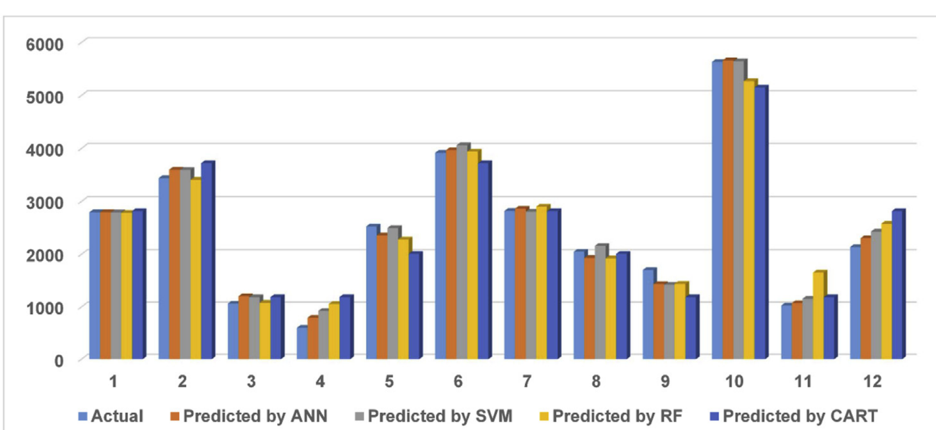

Fig. 12. Comparison of predicted values on the testing dataset by the models.

this study.

Although the results of this study are very positive; however, the supply of the mines should be further considered and researched as an input variable since its impact on the production schedule, mining and processing rates, as well as mining capital cost.

Declarations of interest

None.

Table 3
Percentage error of the models on the testing dataset.

Testing dataset	Absolute percentage error (%)			
	ANN	SVM	RF	CART
Observation 1	0.027	0.094	0.455	0.723
Observation 2	4.702	4.602	0.889	8.210
Observation 3	13.765	12.206	1.676	12.189
Observation 4	31.355	53.472	75.011	97.355
Observation 5	6.587	1.150	9.734	20.458
Observation 6	1.236	3.554	0.537	5.099
Observation 7	1.462	0.499	2.859	0.135
Observation 8	5.786	5.374	6.169	1.971
Observation 9	15.528	16.355	15.297	30.154
Observation 10	0.486	0.219	6.428	8.547
Observation 11	4.547	12.771	61.446	16.023
Observation 12	7.759	13.768	20.505	31.751
Average	**7.770**	**10.339**	**16.750**	**19.384**

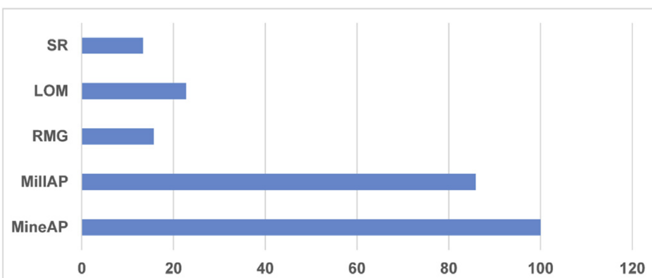

Fig. 13. Influencing level of the input variables for estimating MCC in this study.

Acknowledgements

This research was supported by Hanoi University of Mining and Geology (HUMG), Hanoi, Vietnam; Duy Tan University, Da Nang, Vietnam; and the Center for Mining, Electro-Mechanical research of HUMG.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2019.101474.

References

Ahmadi, M.R., Shahabi, R.S., 2018. Cutoff grade optimization in open pit mines using genetic algorithm. Resour. Policy 55, 184–191.
Arfania, S., Sayadi, A., Khalesi, M., 2017. Cost modelling for flotation machines. J. S. Afr. Inst. Min. Metall 117, 89–96.
Basak, D., Pal, S., Patranabis, D.C., 2007. Support vector regression. Neural Inf. Process. Lett. Rev. 11, 203–224.
Bennet, R., 1996. Technical due diligence requirements for mining project finance. In: Randol at Vancouver 1996 85th Annual Global Mining Opportunities and 2nd Annual Copper Hydromet Rountable, Conference Proceedings.
Bertisen, J., Davis, G.A., 2008. Bias and error in mine project capital cost estimation. Eng. Econ. 53, 118–139.
Bozorgebrahimi, A., Hall, R., Morin, M., 2005. Equipment size effects on open pit mining performance. Int. J. Surf. Min. Reclam. Environ. 19, 41–56.
Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32.
Breiman, L., 2017. Classification and Regression Trees. Routledge.
Breiman, L., Friedman, J., Olshen, R., Stone, C., 1984. Classification and Decision Trees. Wadsworth, Belmont, pp. 378.
Bui, X.N., Nguyen, H., Le, H.A., Bui, H.B., Do, N.H., 2019. Prediction of blast-induced air over-pressure in open-pit mine: assessment of different artificial intelligence techniques. Nat. Resour. Res. https://doi.org/10.1007/s11053-019-09461-0.
Castle, G., 1985. Feasibility studies and other pre-project estimates: how reliable are they. In: Proceedings of the Finance for the Minerals Industry.
Cortes, C., Vapnik, V., 1995. Support vector machine. Mach. Learn. 20, 273–297.
Dagdelen, K., 2001. Open pit optimization-strategies for improving economics of mining projects through mine planning. In: 17th International Mining Congress and Exhibition of Turkey, pp. 117–121.
Darling, P., 2011. SME Mining Engineering Handbook. SME.
De Villiers, J., Barnard, E., 1993. Backpropagation neural nets with one and two hidden layers. IEEE Trans. Neural Netw. 4, 136–141.
Dehghani, H., Ataee-pour, M., 2012. Determination of the effect of operating cost uncertainty on mining project evaluation. Resour. Policy 37, 109–117.
Dehghani, H., Bogdanovic, D., 2018. Copper price estimation using bat algorithm. Resour. Policy 55, 55–61.
Deka, P.C., 2014. Support vector machine applications in the field of hydrology: a review. Appl. Soft Comput. 19, 372–386.
Demirel, N., Taghizadeh, A., Khouri, S., Tyuleneva, E., 2018. Optimization of the excavator-and-dump truck complex at open pit mines–the case study. In: E3S Web of Conferences. EDP Sciences, 01006.
Dimitrakopoulos, R., Farrelly, C., Godoy, M., 2002. Moving forward from traditional optimization: grade uncertainty and risk effects in open-pit design. Min. Technol. 111, 82–88.
Dimitrakopoulos, R., Martinez, L., Ramazan, S., 2007. A maximum upside/minimum downside approach to the traditional optimization of open pit mine design. J. Min. Sci. 43, 73–82.
Easley, D., O'hara, M., 2004. Information and the cost of capital. J. Financ. 59, 1553–1583.
Fan, X., Wang, L., Li, S., 2016. Predicting chaotic coal prices using a multi-layer perceptron network model. Resour. Policy 50, 86–92.
Fushiki, T., 2011. Estimation of prediction error by using K-fold cross-validation. Stat. Comput. 21, 137–146.
Gao, W., Raftari, M., Rashid, A.S.A., Mu'azu, M.A., Jusoh, W.A.W., 2019. A predictive model based on an optimized ANN combined with ICA for predicting the stability of slopes. Eng. Comput. https://doi.org/10.1007/s00366-019-00702-7.
Gypton, C., 2002. How have we done? Eng. Min. J. 203, 40.
Haykin, S.S., Haykin, S.S., Haykin, S.S., Elektroingenieur, K., Haykin, S.S., 2009. Neural Networks and Learning Machines. Pearson education, Upper Saddle River.
He, K., Lu, X., Zou, Y., Lai, K.K., 2015. Forecasting metal prices with a curvelet based multiscale methodology. Resour. Policy 45, 144–150.
He, X., Xu, S., 2010. Artificial neural networks. Process Neural Networks. Theory Appl. 20–42.
Hecht-Nielsen, R., 1987. Counterpropagation networks. Appl. Opt. 26, 4979–4984.
Huang, X.X., Newnes, L.B., Parry, G.C., 2012. The adaptation of product cost estimation techniques to estimate the cost of service. Int. J. Comput. Integr. Manuf. 25, 417–431.
Hustrulid Kuchta, M., Martin, R.K., 2013a. Open Pit Mine Planning and Design, Two Volume Set & CD-ROM Pack. CRC Press.
Hustrulid, W.A., Kuchta, M., Martin, R.K., 2013b. Open Pit Mine Planning and Design, Two Volume Set & CD-ROM Pack. CRC Press.
Jaeger, W.K., 2006. The hidden costs of relocating sand and gravel mines. Resour. Policy 31, 146–164.
Kaastra, I., Boyd, M., 1996. Designing a neural network for forecasting financial and economic time series. Neurocomputing 10, 215–236.
Kanellopoulos, I., Wilkinson, G.G., 1997. Strategies and best practice for neural network image classification. Int. J. Remote Sens. 18, 711–725.
Leite, A., Dimitrakopoulos, R., 2007. Stochastic optimisation model for open pit mine planning: application and risk analysis at copper deposit. Min. Technol. 116, 109–118.
Lewis, R.J., 2000. An Introduction to Classification and Regression Tree (CART) Analysis, Annual Meeting of the Society for Academic Emergency Medicine in San Francisco, California.
Lima, G.A.C., Suslick, S.B., 2006. Estimating the volatility of mining projects considering price and operating cost uncertainties. Resour. Policy 31, 86–94.
Long, K., 2011. Statistical Methods of Estimating Mining Costs, SME Annual Meeting and Exhibit and CMA 113th National Western Mining Conference 2011. pp. 147–151.
Mai, N., Topalt, E., Ertent, O., 2018. A new open-pit mine planning optimization method using block aggregation and integer programming. J. S. Afr. Inst. Min. Metall 118, 705–714.
Masters, T., 1993. Practical Neural Network Recipes in C++. Morgan Kaufmann.
Menabde, M., Froyland, G., Stone, P., Yeates, G., 2018. Mining Schedule Optimisation for Conditionally Simulated Orebodies, Advances in Applied Strategic Mine Planning. Springer, pp. 91–100.
Miao, H., Jinsheng, Z., Dexin, N., 2017. Ga-based resource transportation scheduling optimization of open-pit mine. In: Smart Grid and Electrical Automation (ICSGEA), 2017 International Conference on. IEEE, pp. 247–250.
Moayedi, H., Moatamediyan, A., Nguyen, H., Bui, X.-N., Bui, D.T., Rashid, A.S.A., 2019. Prediction of ultimate bearing capacity through various novel evolutionary and neural network models. Eng. Comput. https://doi.org/10.1007/s00366-019-00723-2.
Mohutsiwa, M., Musingwini, C., 2015. Parametric estimation of capital costs for establishing a coal mine: South Africa case study. J. S. Afr. Inst. Min. Metall 115, 789–797.
Moreno, E., Rezakhah, M., Newman, A., Ferreira, F., 2017. Linear models for stockpiling in open-pit mine production scheduling problems. Eur. J. Oper. Res. 260, 212–221.
Mountrakis, G., Im, J., Ogole, C., 2011. Support vector machines in remote sensing: a review. ISPRS J. Photogrammetry Remote Sens. 66, 247–259.
Mular, A.L., 1982. Mining and Mineral Processing Equipment Costs and Preliminary Capital Cost Estimations. Canadian Institute of Mining and Metallurgy Montreal.
Nguyen, H., Bui, X.-N., 2018. Predicting blast-induced air overpressure: a robust artificial intelligence system based on artificial neural networks and random forest. Nat. Resour. Res. 28 (3), 893–907. https://doi.org/10.1007/s11053-018-9424-1.
Nguyen, H., Bui, X.-N., Bui, H.-B., Cuong, D.T., 2019a. Developing an XGBoost model to predict blast-induced peak particle velocity in an open-pit mine: a case study. Acta Geophys. 67, 477–490.
Nguyen, H., Bui, X.-N., Bui, H.-B., Mai, N.-L., 2018. A comparative study of artificial

neural networks in predicting blast-induced air-blast overpressure at Deo Nai open-pit coal mine. Vietnam. Neural Comput. Appl. 1–17.

Nguyen, H., Drebenstedt, C., Bui, X.-N., Bui, D.T., 2019b. Prediction of blast-induced ground vibration in an open-pit mine by a novel hybrid model based on clustering and artificial neural network. Nat. Resour. Res. https://doi.org/10.1007/s11053-019-09470-z.

Nguyen, H., Moayedi, H., Jusoh, W.A.W., Sharifi, A., 2019c. Proposing a novel predictive technique using M5Rules-PSO model estimating cooling load in energy-efficient building system. Eng. Comput. https://doi.org/10.1007/s00366-019-00735-y.

Niazi, A., Dai, J.S., Balabani, S., Seneviratne, L., 2006. Product cost estimation: technique classification and methodology review. J. Manuf. Sci. Eng. 128, 563–575.

Nourali, H., Osanloo, M., 2018a. Mining capital cost estimation using Support Vector Regression (SVR). Resour. Policy 62, 527–540. https://doi.org/10.1016/j.resourpol.2018.10.008.

Nourali, H., Osanloo, M., 2018b. A regression-tree-based model for mining capital cost estimation. Int. J. Min. Reclam. Environ. 1–13.

O'Hara, T., 1980a. A Parametric Cost Estimation Method for Open Pit Mines. Society of mining engineers (SME), New York.

O'Hara, T.A., 1980b. Quick guide to the evaluation of ore bodies. Cim. Bull. 73, 87–99.

Oraee, B., Lashgari, A., Sayadi, A.R., 2011. Estimation of Capital and Operation Costs of Backhoe Loaders.

Orru, G., Pettersson-Yeo, W., Marquand, A.F., Sartori, G., Mechelli, A., 2012. Using support vector machine to identify imaging biomarkers of neurological and psychiatric disease: a critical review. Neurosci. Biobehav. Rev. 36, 1140–1152.

Petrick, A., Dewey, R., 1987. Microcomputer Cost Models for Mining and Milling. Mineral Resource Management by Personal Computer.

Pierdzioch, C., Risse, M., Rohloff, S., 2016. A boosting approach to forecasting the volatility of gold-price fluctuations under flexible loss. Resour. Policy 47, 95–107.

Prasad, L., 1969. Mineral Processing Plant Design and Cost Estimate.

Ramazan, S., Dimitrakopoulos, R., 2018. Stochastic Optimisation of Long-Term Production Scheduling for Open Pit Mines with a New Integer Programming Formulation, Advances in Applied Strategic Mine Planning. Springer, pp. 139–153.

Richmond, A., 2018. Direct Net Present Value Open Pit Optimisation with Probabilistic Models, Advances in Applied Strategic Mine Planning. Springer, pp. 217–228.

Rimélé, M.A., Dimitrakopoulos, R., Gamache, M., 2018. A stochastic optimization method with in-pit waste and tailings disposal for open pit life-of-mine production planning. Resour. Policy 57, 112–121.

Ripley, B.D., 1993. Statistical aspects of neural networks. Network. chaos Stat. Probabilistic Asp. 50, 40–123.

Ristovski, K., Gupta, C., Harada, K., Tang, H.-K., 2017. Dispatch with confidence: integration of machine learning, optimization and simulation for open pit mines. In: Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM, pp. 1981–1989.

Sayadi, A.R., Khalesi, M.R., Borji, M.K., 2014. A parametric cost model for mineral grinding mills. Miner. Eng. 55, 96–102.

Shafiee, S., Topal, E., 2012. New approach for estimating total mining costs in surface coal mines. Min. Technol. 121, 109–116.

Shang, Y., Nguyen, H., Bui, X.-N., Tran, Q.-H., Moayedi, H., 2019. A novel artificial intelligence approach to predict blast-induced ground vibration in open-pit mines based on the firefly algorithm and artificial neural network. Nat. Resour. Res. 1–15.

Sirikulviriya, N., Sinthupinyo, S., 2011. Integration of Rules from a Random Forest. International Conference on Information and Electronics Engineering, pp. 194–198.

Smith, A.E., Mason, A.K., 1997. Cost estimation predictive modeling: regression versus neural network. Eng. Econ. 42, 137–161.

Stebbins, S.A., 1987. Cost Estimation Handbook for Small Placer Mines.

Thomas, S., 2001. Project development costs—estimates versus reality. In: Mineral Economics and Management Society, Tenth Annual Conference, Houghton, Michigan.

Vapnik, V., Golowich, S.E., Smola, A.J., 1997. Support vector method for function approximation, regression estimation and signal processing. Adv. Neural Inf. Process. Syst. 281–287.

Wang, C., 1994. A Theory of Generalization in Learning Machines with Neural Network Applications.

Weiss, A., 1979. Computer Methods for the 80's in the Mineral Industry. Society of Mining Engineers of AIME xxvi+ 975, 26 x 18 cm, Illustrated, 1979.

Yegnanarayana, B., 2009. Artificial Neural Networks. PHI Learning Pvt. Ltd.

Zhang, X., Nguyen, H., Bui, X.-N., Tran, Q.-H., Nguyen, D.-A., Bui, D.T., Moayedi, H., 2019. Novel soft computing model for predicting blast-induced ground vibration in open-pit mines based on particle swarm optimization and XGBoost. Nat. Resour. Res. https://doi.org/10.1007/s11053-019-09492-7.