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Developing a novel artificial intelligence model to estimate the capital cost of mining projects using deep neural network-based ant colony optimization algorithm

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ABSTRACT

This study aims to propose a novel artificial intelligence model for forecasting the capital cost (CC) of open-pit mining projects with high accuracy. It is a unique combination of a deep neural network (DNN) and ant colony optimization (ACO) algorithm, abbreviated as ACO-DNN. In this model, MineAP (annual mine production), SR (stripping ratio), MillAP (annual production of the mill), RMG (reserve mean grade), and LOM (life of mine) were used to consider the CC of open-pit mining projects. A series of simple and complex artificial neural networks (ANN) was developed for forecasting CC of 74 copper mining projects herein. Subsequently, the ACO algorithm has been applied to optimize the developed ANN and DNN models to improve the accuracy of them. Finally, an optimal hybrid model was defined (i.e., ACO-DNN 5-25-20-18-15-1) with superior performance than other models (i.e., RMSE of 130.988, R^2 of 0.991, MAE of 115.274, MAPE of 0.072, and VAF of 99.052). The findings of this study showed that the DNN models could predict the CC for open-pit mining projects with more accuracy than those of the simple ANN models. In particular, the ACO algorithm played an essential role in improving the accuracy of forecasting models. Also, MineAP, MillAP, SR, and LOM have been confirmed as critical parameters that affect the accuracy of the selected model in forecasting the CC of open-pit mining projects, especially MineAP. In conclusion, this study offers a useful tool to improve resource policies of mining projects, especially copper mining projects.

1. Introduction

In mining projects, the capital cost (CC) of mining usually includes two main groups (1) the initial and (2) working capital costs (start-up and stay-in-business capital costs) (Mohutsiwa and Musingwini, 2015). The costs usually focus primarily on infrastructure, equipment,

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Algorithm: The pseudo-code of the ACO algorithm

```
Input: Instance x ∈ I of Π_opt
        Set algorithm parameters ()
        i, j ← 0
        For j=1 to colonies do
            Ant s_0 ← creat sub-colony and release
            Agent
            While not-termination conditions
                On sub-colony do
                    i = i+1
                    Manage_ants activity ()
                    Manage_Pheromone ()
                    Manage_Daemon Action ()
                    Selection Procedure ()
                    Compute solution quality ()
            End while
            j = j+1
            S_best ← candidate to be optimal solution
            Update pheromone on arc ()
        End for
Output: S_best "candidate" to be the best found solution x ∈ I
```

Fig. 1. Pseudo-code for the ACO algorithm.

mine-site development, and exploration, keeping the mine running, to name a few. Besides, advances in mining technology also have significant impacts on the CC for open-pit mining projects (Wheeler, 2019). Meanwhile, the changing speed of science and technology of the mining industry is enormous (Aznar-Sánchez et al., 2019). Therefore, many mining companies are facing various risks of finance due to the uncertainty in the CC estimation in open-pit mining projects.

In mine design, the CC for open-pit mining projects is considered as one of the critical criteria to evaluate the feasibility of mining projects. In addition, it is also one of the factors that significantly influence the net present value (NPV) of mining projects (O'Regan and Moles, 2006). Many scholars attempted to study and optimize the uncertainty issues of open-pit/underground mines (e.g., mine planning, mine design, cut-off grade, and scheduling, to name a few) aiming to improve the NPV of the projects (Ahmadi and Bazzazi, 2019; Asad and Dimitrakopoulos, 2013; Ben-Awuah et al., 2016; Goodfellow and Dimitrakopoulos, 2016; Ramazan, 2007; Souza et al., 2010). Nevertheless, their reports do not seem to provide a high accuracy level in estimating NPV due to the uncertainty in the CC estimation for mining projects (Dehghani and Ataee-pour, 2012; Rendu, 2002; Shafiee and Topal, 2012). Therefore, it is useful for mining companies and economists to improve the accuracy of the CC estimation in evaluating and forecasting NPV of mines.

From the CC estimation point of view, many approaches were proposed by previous researchers. For example, Niazi et al. (2006) reviewed and evaluated a variety of technologies developed over the years for estimating product costs. Besides, Huang et al. (2012) also employed an estimation of the product cost for mining projects. Subsequently, the CC for mining projects can be estimated and analyzed based on technologies and product costs. Besides, approaches to univariate and multivariate regression models were also considered to forecast the CC of mining projects (Darling, 2011; Long and Singer, 2001; Pytel et al., 2013; Sayadi et al., 2012; Smith and Mason, 1997; Stebbins, 1987). Polynomial least square technique was also used to estimate the CC of mining projects by O'Hara (1980). However, the accuracy level does not seem to satisfy the mining companies with the error percentage which lies in the range of 10% to 100% (Noakes and Lanz, 1993). To overcome the disadvantages of the abovementioned traditional methods, Nourali and Osanloo (2018a, 2018b) used machine learning algorithms, such as support vector regression (SVR) and regression tree (CART) for estimating the CC for open-pit mining projects. Their studies provided a promising result with an error percentage of less than 10%. Guo et al. (2019) also developed an artificial neural network (ANN) model that the accuracy

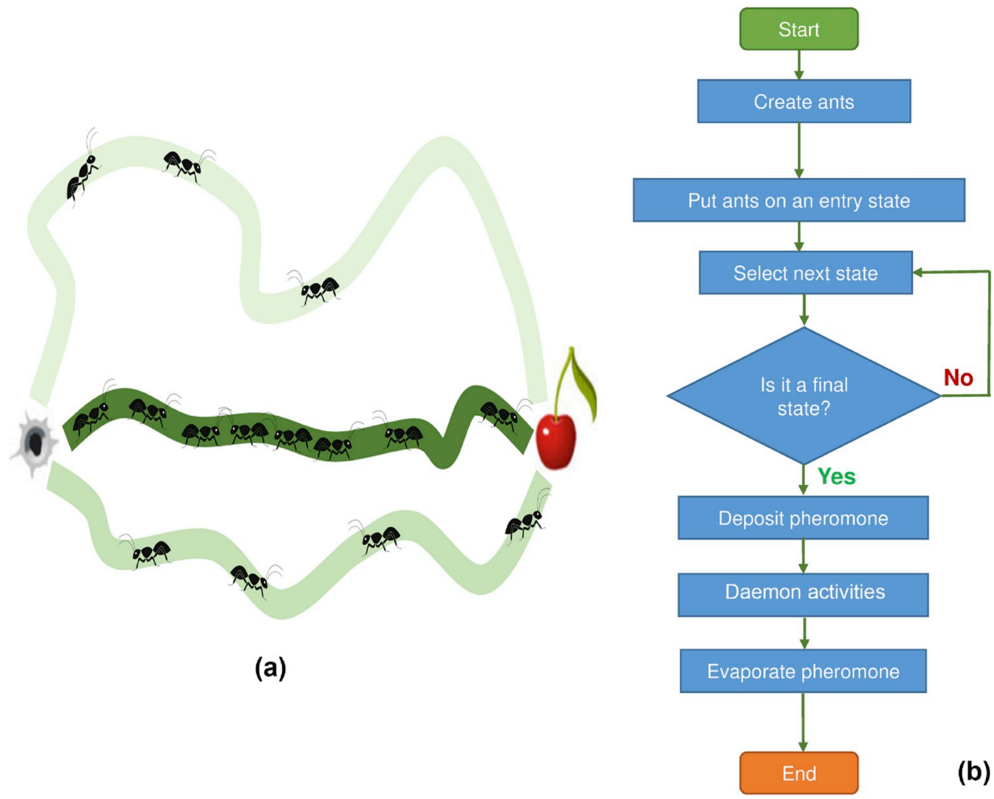

Fig. 2. Paths and pheromone of ants and their flowchart. (a) Paths of ants and the amount of corresponding pheromone (Mirjalili, 2019); (b) Flowchart of the ants for optimization.

was improved (i.e., mean absolute percentage error of 7.77%).

A review of relevant works showed many approaches that can be applied to forecast the CC for open-pit mining projects, especially artificial intelligence (AI) approaches that offer higher accuracy. Nevertheless, previous studies did not seem to be optimized. They were only considered as the traditional techniques/models in artificial intelligent applications (Loterman et al., 2012; Nguyen and Bui, 2018). Whereas hybrid machine learning algorithms with the combination of optimization algorithms are considered to be the perfect solution to forecasting problems aiming to improve the accuracy of models (Dellermann et al., 2019; García and Kristjanpoller, 2019; Shang et al., 2019). In addition, deep learning for ANN is also evaluated as a new approach to minimize errors of forecasting models (Elola et al., 2019; Hassanpour et al., 2019). Therefore, this study investigated the feasibility of deep neural network (DNN) and optimization algorithms for forecasting the CC for open-pit mining projects. Finally, a DNN model was optimized by the ant colony optimization (ACO) algorithm for estimating the CC for open-pit mining projects in this study, namely ACO-DNN model. To have a comprehensive assessment of the proposed model, ten ANN and DNN models were optimized by the ACO algorithm and compared to each other. The ANOVA test was applied to assess the strength, as well as the statistical significance of the developed models. The remainders of this study are structured as follow:

- Section 2 summarizes the principle of ACO, ANN, and DNN.
- The methodology is presented in section 3. Herein a novel AI method (i.e., ACO-DNN) is proposed for estimating the CC of open-pit mining projects.
- Section 4 describes the performance metrics used to evaluate the models' performance.
- Section 5 describes the dataset used and its characteristics.
- The models' development process is detailed in section 6.
- Section 7 presents and discusses the results of the study.
- Section 8 investigates the importance of the input variables for predicting the CC of open-pit mining projects.
- Finally, conclusions are given in section 9.

2. Principle of ACO, ANN, and DNN

2.1. Ant colony optimization (ACO)

First introduced in 1999 by Dorigo and Di Caro (1999), ACO has become one of the widely used swarm optimization algorithms in the statistical and machine learning community. The main concept of the ACO is based on the stigmergy in nature (Mirjalili, 2019). It uses environmental manipulation to communicate with each other. In their communication, environmental manipulation is communicating unique. Individuals should move close to this unique method of communication in order to have the best local connection (Dorigo et al., 2000).

In ACO, individuals (i.e., ants) constantly search for food sources around their nests at random. When food is found, they mark their paths with a distinctive sign, namely pheromone (Dorigo and Stützle, 2019). However, the pheromone amount highly depends on the quantity and quality of the food source. If a route has a high concentration of pheromones, it means that the path leads to an abundance of high-quality food (Nguyen et al., 2020). Based on the concentration of the pheromone, other ants can find the path to the highest quality food source and bring them back to their nest. In another interesting study, ants are able to accurately count and remember their steps (Haferlach et al., 2007). Therefore, based on the concentration of pheromones, they can find the shortest/most optimal path. The pseudo-code of the ACO algorithm is shown in Fig. 1, and the paths of ants, as well as the amount of pheromone and their flowchart, are illustrated in Fig. 2. In Fig. 2, the paths of ants and the amount of the corresponding pheromone are illustrated. Based on the amount of pheromone, ants can find out the optimal path, as shown in the flowchart (Fig. 2b). Accordingly, the number of

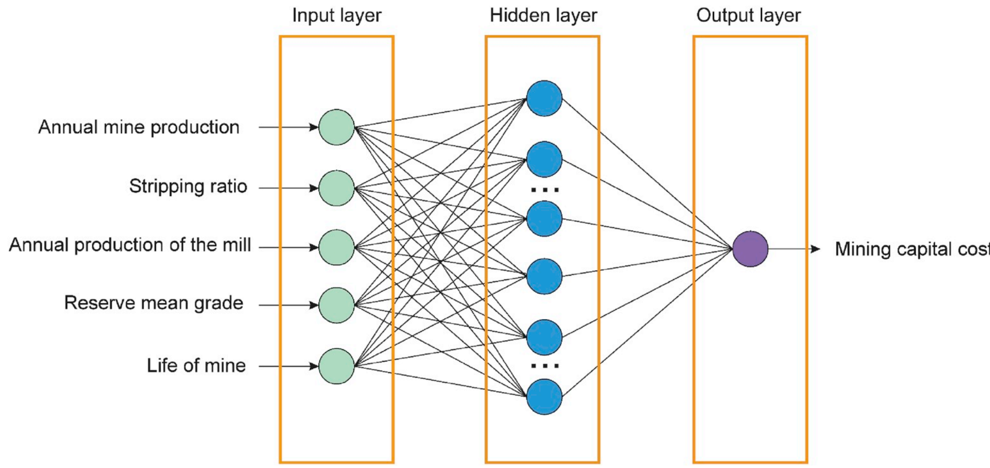

Fig. 3. General architecture of ANN/DNN for predicting the CC of mining projects in this study.

ants/populations are needed for starting. Subsequently, the ants implement a global search for the state. If the state found out is the final one, they deposit pheromone as a unique signal for other ants. Otherwise, they search for other states to continue. Once the final state is found, daemon activities are conducted aiming to create the dispersion of pheromone. The other ants can easily recognize the marked state based on the evaporation of pheromone.

2.2. Artificial neural network (ANN) and deep neural network (DNN)

ANN has previously been applied to predict and simulate many physics problems with high performance. In recent years, it was also considered for forecasting the economy, as well as policy and social issues (Alameer et al., 2019; Fan et al., 2016; Franco-Sepúlveda et al., 2019; Guo et al., 2019; Wang et al., 2019). In theoretical, ANN uses neurons which are separated in many layers to process the problems in real-life. It mimics the operations of the human brain to analyze and respond to the received information, in which, the layers are divided into three groups: input, hidden, and output layers (Fig. 3). The neurons in the layers are linked together through weights and the deviations between weights (i.e., biases). The accuracy of the ANN model depends on the weights and biases (Aljarah et al., 2018; Whitley et al., 1990).

In recent years, ANN has been growing strongly in many different forms, such as simple ANN (with only one hidden layer), complex ANN (with multiple hidden layers), convolutional neural network (CNN), and recurrent neural network (RNN), to name a few. Of those, ANN is the most common and widely used form in many areas (Armaghani et al., 2019; Asteris et al., 2016; Nguyen et al., 2018a, 2018b; Shang et al., 2019). Like other AI techniques, ANN can be trained through supervised or unsupervised learning methods. The performance of ANN models highly depends on the number of hidden layers and hidden neurons. The complex ANN models with multiple hidden layers are called deep neural network (DNN) (Deng et al., 2013). Theoretically, an ANN model with the low hidden layer(s) can improve the training time, and keep hidden layers as small as possible to avoid overfitting, too (Lawrence et al., 1997). However, the predictive power of ANN increases as hidden layers increases. Indeed, a DNN with eight hidden layers was applied for phone recognition (Mohamed et al., 2009). Another DNN was also developed from the RNN method with multiple hidden layers for processing language problems (Mikolov et al., 2010). In this paper, both ANN and DNN

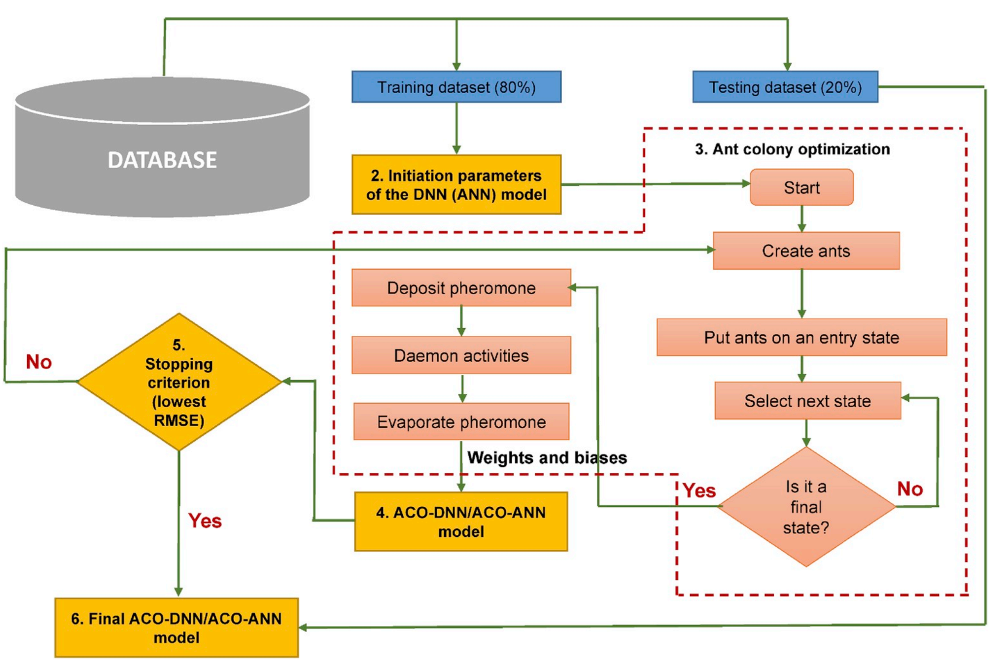

Fig. 4. Global search of the ant colony and optimization of DNN (ANN) by the ACO algorithm.

(with multiple hidden layers) were considered to predict the CC of mining projects. Fig. 3 illustrates the general architecture of ANN/DNN for predicting the CC of open-pit mining projects in this paper.

Basically, the principle of ANN and DNN is the same; however, their structure, the numbers of hidden layers, as well as the training algorithm, are different. In this paper, the main difference between ANN and DNN is the numbers of hidden layers. Whereas the ANN model includes only one hidden layer, there are multiple hidden layers in the DNN. In Fig. 3, raw information (i.e., MineAP, SR, MillAP, RMG, LOM) is embedded in the input layer. Then, a given transformation is applied to input values. In the hidden layer, the activity of each hidden unit is determined. Herein, one hidden layer is illustrated in Fig. 3, and the lines represent weights. For the ANN model, determined weights are transmitted to the output neuron (output layer) to predict the CC of mining projects. Whereas, the pre-determined weights in the previously hidden layer(s) are used as the input values for the next hidden layer.

3. Methodology

As mentioned above, the accuracy of the ANN and DNN models depends highly on the weights. Therefore, an optimization algorithm (i.e., ACO) is applied to optimize the weights of ANN and DNN models herein, called ACO-ANN and ACO-DNN models. The back-propagation algorithm (BPA) is used to train ANN and DNN models for estimating the CC of mining projects in the study.

Some previous research tend to "simplify" ANN models in term of engineering, as well as resources policy, with one or two hidden layers (Fan et al., 2016; Nguyen et al., 2018a, 2019b; Wang et al., 2019). However, some recent studies showed that ANN models with more than two hidden layers are able to provide better results than simple ANN models (Bouwmans et al., 2019; Dwivedi et al., 2018; Lacey et al., 2018; Lee et al., 2019; Li et al., 2018), and they are called DNN. Thus, this study investigated the feasibility of simple ANN models (one and two hidden layers), contrasted with DNN models in estimating the CC of mining projects. Furthermore, the ACO algorithm is applied to optimize the ANN and DNN models, abbreviated as ACO-ANN and ACO-DNN models. Accordingly, weights and biases of the ANN and DNN models are adjusted by the global search of the ant colony to reach the optimal performance. During the global search of the ant colony, root-mean-square error (RMSE) is used as the objective function to evaluate the fit of each position that the ants found. The lowest RMSE is the optimal goal of the models, and it was selected as the stopping criterion. The searching, as well as the optimization processes by the ACO algorithm for the DNN model (or ANN model) in estimating the CC of mining projects, are illustrated in Fig. 4.

4. Performance indices for evaluating

To form the model evaluation, this study used five statistical indexes, including mean absolute error (MAE), mean absolute percentage error (MAPE), RMSE, variance accounted for (VAF), and coefficient of determination (R^2). They are computed as follow:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{\text{Capital cost},i} - \widehat{y}_{\text{Capital cost},i}\right| \tag{1}$$

$$\mathrm{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_{\text{Capital cost},i} - \widehat{y}_{\text{Capital cost},i}}{y_{\text{Capital cost},i}}\right| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{\text{Capital cost},i} - \widehat{y}_{\text{Capital cost},i}\right)^2} \tag{3}$$

$$\mathrm{VAF} = \left(1 - \frac{\mathrm{var}\left(y_{\text{Capital cost},i} - \widehat{y}_{\text{Capital cost},i}\right)}{\mathrm{var}\left(y_{\text{Capital cost},i}\right)}\right) \times 100 \tag{4}$$

$$\mathrm{R}^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_{\text{Capital cost},i} - \widehat{y}_{\text{Capital cost}}\right)^2}{\sum_{i=1}^{n}\left(y_{\text{Capital cost},i} - \overline{y}_{\text{Capital cost}}\right)^2} \tag{5}$$

where $y_{\text{Capital cost},i}$ is the i^{th} of the experimental CC of the mining projects; $\widehat{y}_{\text{Capital cost},i}$ is the i^{th} of the estimated CC of the mining projects; $\overline{y}_{\text{Capital cost}}$ is the mean of measured values of the CC of the mining projects; n indicates the number of observations in the training or testing datasets.

5. Material

In mining investment, there are many factors which have impacts on the capital cost of a project, such as geotechnical variability, existing infrastructure availability, site location (remoteness), brownfield or greenfield expansion, project completion timeline (i.e., initial investment decision to first production), regulatory environment, ore body knowledge confidence (change in plan risk), financing costs (cost of capital), processing technology, workforce productivities and foreign exchange costs (Bridge, 2004; Ferguson et al., 2011; O'Hara, 1987; Sánchez et al., 2015; Shafiee and Topal, 2012). Geotechnical localized uncertainty impacts measurement error, inherent variability, and transformation uncertainty (Phoon and Kulhawy, 1999). Therefore, it might lead to inaccuracy in estimating mining production, as well as the CC of mining projects. The existing infrastructure does not seem to be designed for multiple purposes, and it may be related to the dispute between policymakers and mining firms, as well as its policy objectives (Collier and Ireland, 2018). Furthermore, it is difficult to estimate the value of the existing infrastructure for a mining project. Thus, it is complicated to define the availability of the existing infrastructures, and its effect on the mining capital costs as well. In addition, the other factors, such as site location, project completion timeline, regulatory environment, processing technology, and workforce productivity, to name a few, are taken into account as the indirect factors that have affected the mining capital costs (Bluszcz and Kijewska, 2016; Mular, 1982; O'Regan and Moles, 2006).

A review of mining CC estimation works shows that production capacity is one of the most critical factors determining the CC of mining projects, as well as the risk factors for mining in short/long-term (Cairns and Shinkuma, 2003; Godoy and Dimitrakopoulos, 2004; Mohutsiwa and Musingwini, 2015). Accordingly, mine production and mill production were evaluated as the critical parameter that can effect on the CC of mining projects (Dagdelen, 2001; Hustrulid et al., 2013). Stripping ratio and the railroad distance were also used to predict the CC in the study of Long (2011). Nevertheless, the mining capacity for ore and waste is still widely used for estimating the CC of mining projects (Camm, 1992; Duckworth and John, 2016; Wellmer et al., 2007). As mentioned above, the mining capital cost usually focuses primarily on infrastructure, equipment, mine-site development, and exploration, and keeping the mine running. Moreover, Guo et al. (2019); Nourali and Osanloo (2018a) indicated that the reserve mean grade, stripping ratio, annual mine production, annual production of the mill, and life of mines are influencing factors on the mining capital cost. They claimed that these parameters should be used to predict the mining capital cost. Consequently, this study uses five input variables; reserve mean grade, stripping ratio, annual mine production, annual mill production, and life of mine, to estimate the CC of the mining projects.

Herein, 74 open-pit mining projects were collected based on the critical parameters as recommended by the previous researchers (Nourali and Osanloo, 2018a, b). Accordingly, 52 copper mines properties were extracted from the Copper Mine Project Profiles, which was investigated in Nourali and Osanloo (2018a). In addition, 22 other copper mines properties in China, India, Iran, Malaysia, and Vietnam were also investigated with similar features. Finally, a total of 74 copper mines properties were investigated in this study. A summary of the input

Table 1
Summary of the CC database used in this work.

Features	MineAP (million tons)	SR	MillAP (thousand tons)	RMG (% Cu)	LOM (year)	CC (million USD)
Min.	4.00	0.200	185.0	0.2000	10.00	406
1st Qu.	23.00	1.230	373.0	0.4250	21.00	1273
Median	36.00	2.120	540.5	0.7000	27.00	2176
Mean	34.11	1.976	574.7	0.7619	26.93	2464
3rd Qu.	45.75	2.598	781.5	0.9675	32.00	3436
Max.	64.00	5.050	1215.0	2.8400	48.00	6373

MineAP (annual mine production); SR (stripping ratio); MillAP (annual production of the mill); RMG (reserve mean grade); LOM (life of mine); CC (capital costs).

and output variables is contained in Table 1, which includes only the range of the dataset used herein. It is also worth noting that Table 1 does not show the relationship between the inputs and output variables. To evaluate the relationship between input variables, a correlation matrix of the input variables is showed in Fig. 5. It can be seen that the correlation of the input variables is not high [-0.5, 0.75]. In other words, it is interesting to take into account the relationship between the CC of mining and the input variables, as well as estimating the CC of mining projects based on these input parameters.

The size of the dataset used in this study is not large. Theoretically, a large dataset can give better training in machine learning (Berthold and Hand, 2003; Pedrycz and Chen, 2014); however, many studies have been successfully applied with a small dataset depending on the complexity of the solved problems (Bui et al., 2019; Nguyen et al., 2020; Pasini, 2015; Zhang and Ling, 2018). Also, data preprocessing techniques (i.e., transformation, k-fold cross-validation) can be applied to improve the accuracy of AI models for small and moderate datasets (Karsznia and Weibel, 2018; Maronidis et al., 2011; Stratigopoulos et al., 2009). And they were applied during development of the models in this study. On the other hand, a review of the previous studies indicates that Nourali and Osanloo (2018a, 2018b) successfully developed two benchmark AI models (i.e., SVR and CART) for estimating the CC using only used 52, even 28 observations. These primary rationales show that the size of the database used herein (i.e., 74 observations) is sufficient to investigate, develop, and evaluate the feasibility of advanced artificial intelligence models for estimating the CC of open-pit mining projects. Therefore, the dataset with 74 observations was considered to develop AI models in this study. The performance of the artificial intelligence models for estimating the CC of open-pit mining projects is presented in the next sections.

6. Developing the AI models for estimating the CC of mining projects

In this section, the ACO-ANN and ACO-DNN models are developed to predict the CC of mining projects. All the models are programmed and designed on the R environment (version 3.6.0). Before developing the models, the dataset is divided into two parts for training and testing processes. Of those, 62 cooper mines properties (~80%) were selected randomly for the training process; then, 12 remaining copper mines

Table 2
Summary of the training dataset.

Features	MineAP	SR	MillAP	RMG	LOM	CC
Min.	4.00	0.200	185.00	0.20	11.00	406
1st Qu.	23.00	1.147	362.80	0.41	22.00	1273
Median	35.50	1.955	526.00	0.66	28.00	2176
Mean	33.98	1.857	566.10	0.72	27.40	2462
3rd Qu.	45.75	2.465	781.50	0.96	32.00	3454
Max.	64.00	4.230	1215.00	2.00	48.00	6373

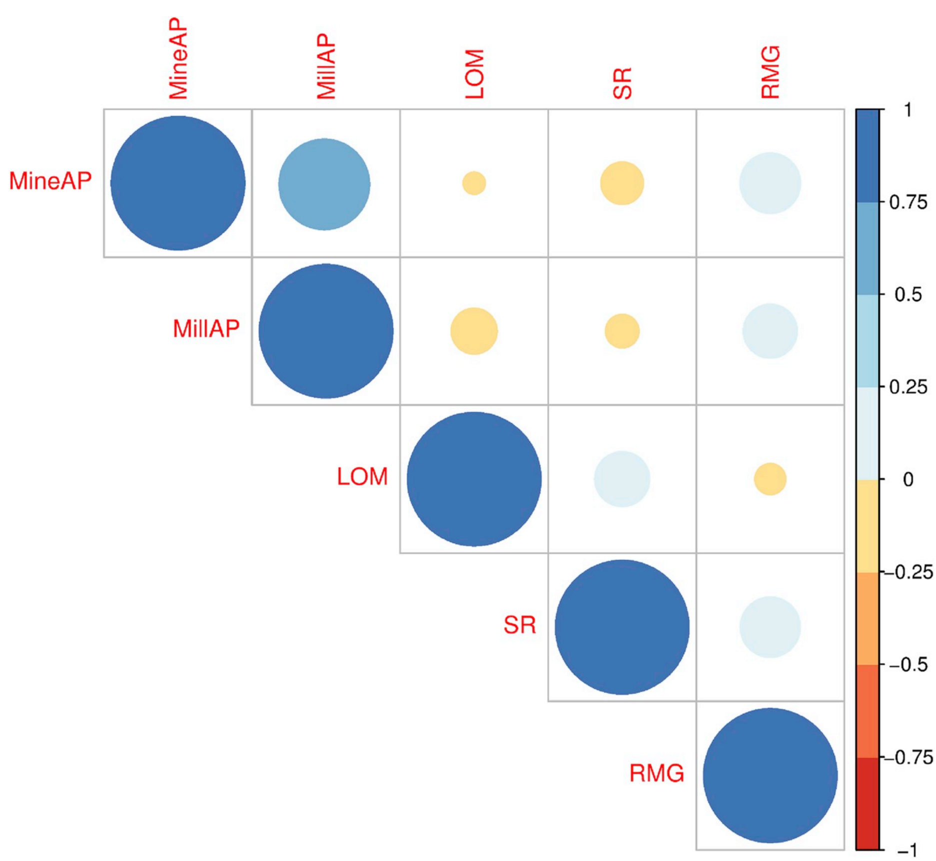

Fig. 5. Correlogram of the input variables in the used dataset.

Table 3
Summary of the testing dataset.

Features	MineAP	SR	MillAP	RMG	LOM	CC
Min.	11.00	0.30	346.0	0.28	10.00	602
1st Qu.	23.00	2.305	458.50	0.635	20.00	1540
Median	36.50	2.530	620.00	0.910	25.00	2330
Mean	34.75	2.590	619.0	0.978	24.50	2474
3rd Qu.	44.25	3.060	747.2	1.028	31.25	2973
Max.	60.00	5.050	1003.0	2.840	36.00	5631

properties (~20%) were used for testing the models' performance. The training and testing datasets are summarized in Tables 2 and 3.

Primarily, the process of developing ACO-ANN and ACO-DNN models is divided into two main steps, as illustrated in Fig. 4. Accordingly, the initial ANN and DNN models are needed to create first, as the first step. Subsequently, their parameters, such as weights and bias, are optimized by the ACO algorithm to improve the accuracy of the models. In the first step, the trial and error method were applied for the determination of the hidden layers and the hidden neurons. Previous literature has noted the potential to overfitting or underfitting an ANN/DNN model (Nguyen et al., 2019a, 2019c; Shang et al., 2019); therefore, the min-max scale technique was applied for the dataset used with the range of [-1, 1] to avoid overfitting/underfitting. Also, 5-fold cross-validation technique was applied to improve the performance of the ANN/DNN models in this study. Finally, two ANN models with only one hidden layer and eight DNN models with two, three, four, five, and six hidden layers were developed. The ACO algorithm can now perform optimization of weights and biases for the developed ANN and DNN models.

To optimize the initial ANN and DNN models, the parameters of the ACO algorithm need to be well-established. The target size of the ant colony was set equal to 50, 100, 150, 200, 250, 300, 350, 400, 450, 500, respectively, to test the effect of the initial ants. Subsequently, the percentage of pheromone was set equal to 5%. The process of finding the optimal food source for the ants was conducted based on the concentration of pheromones and the number of ants in the established colonies. RMSE is used as a criterion to evaluate the search results of ant colonies. Accordingly, the lowest RMSE was defined as the convergence criterion of the optimization process. To ensure that the ants' search process reaches the optimal value (the lowest RMSE), the search is repeated 1000 times/iterations until RMSE reaches the lowest and

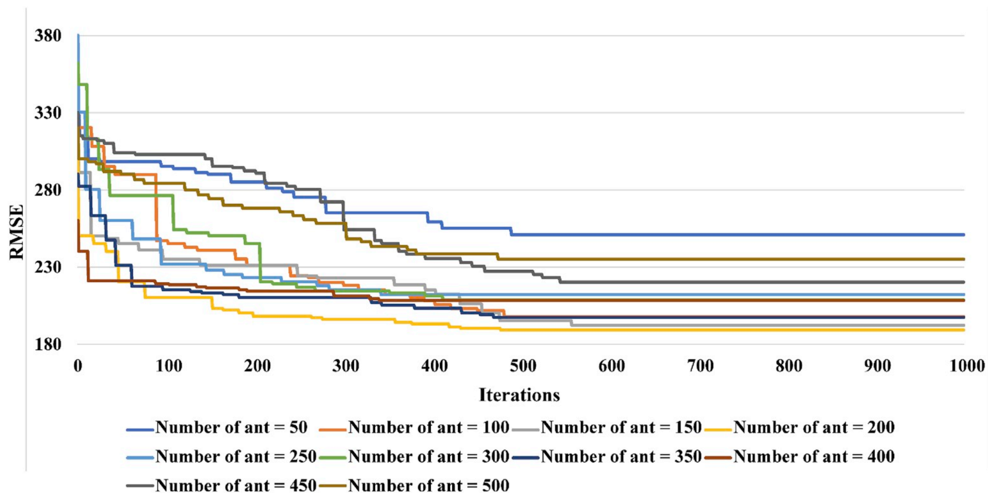

Fig. 6. ACO-ANN 5-9-1 performance on the training process.

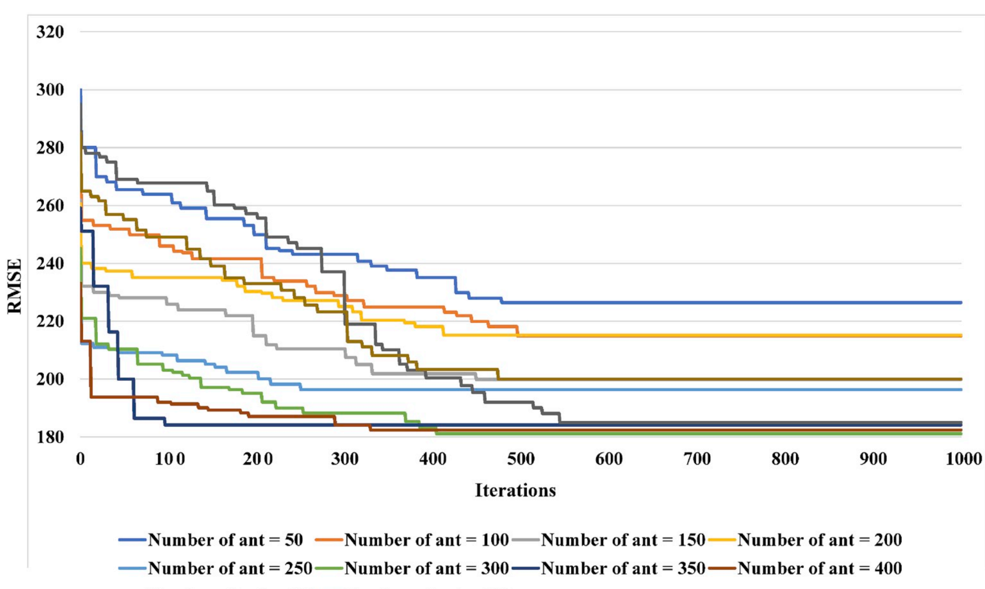

Fig. 7. ACO-ANN 5-12-1 performance on the training process.

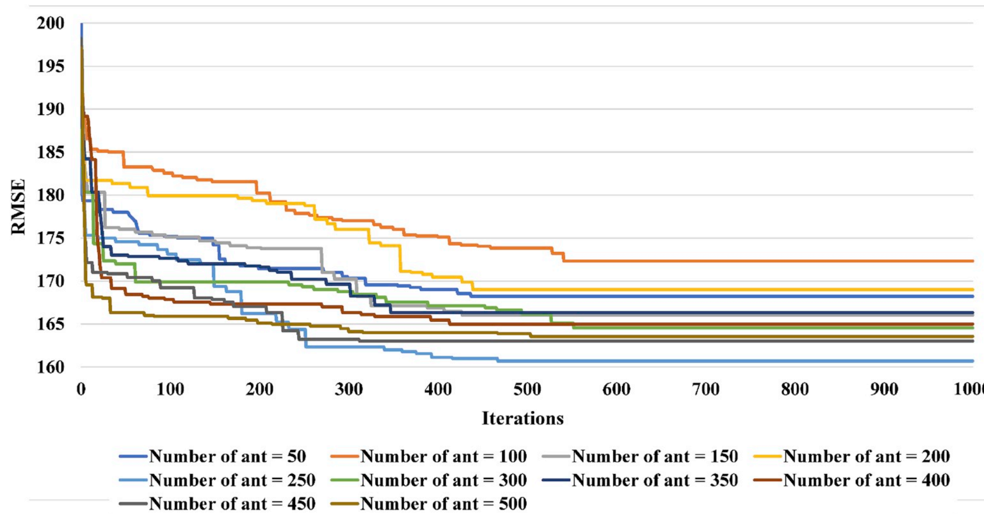

Fig. 8. ACO-DNN 5-15-8-1 performance on the training process.

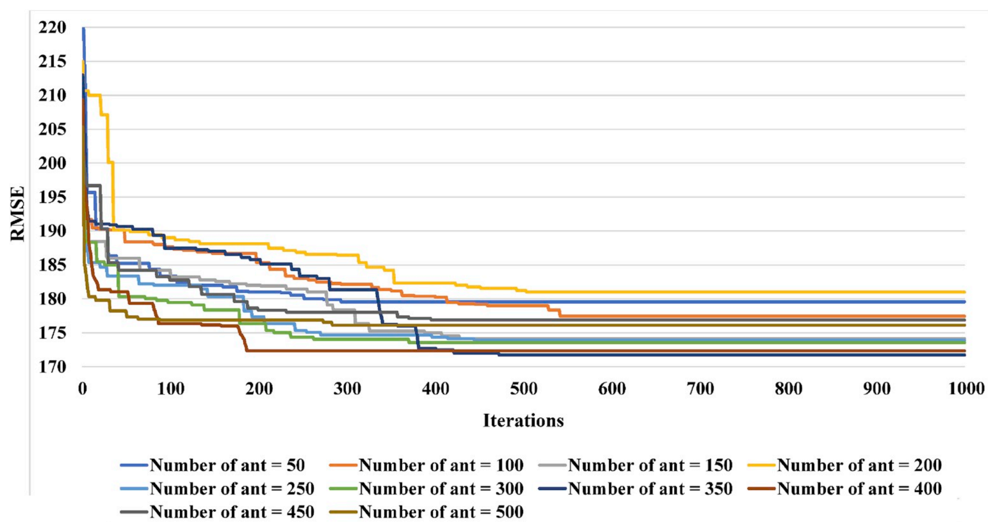

Fig. 9. ACO-DNN 5-20-12-1 performance on the training process.

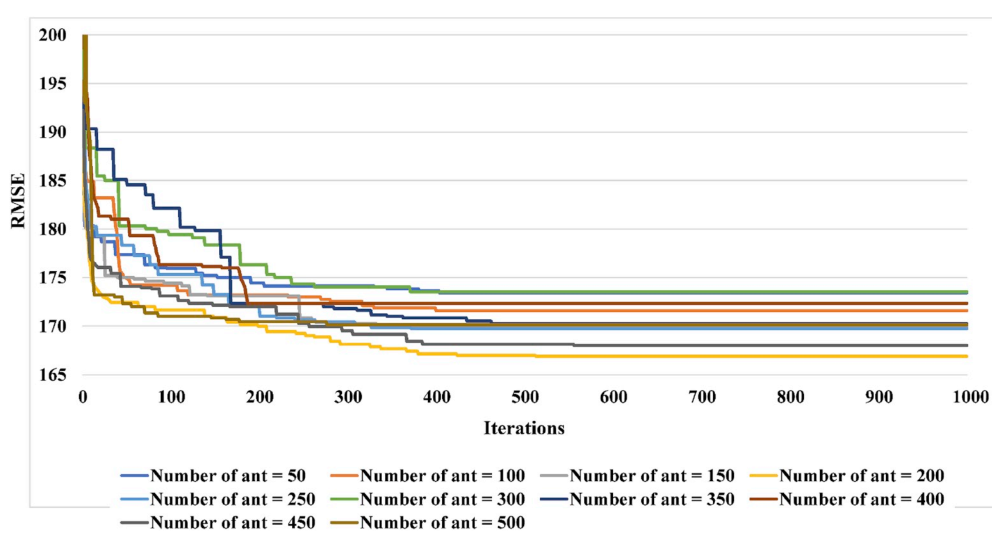

Fig. 10. ACO-DNN 5-15-12-13-1 performance on the training process.

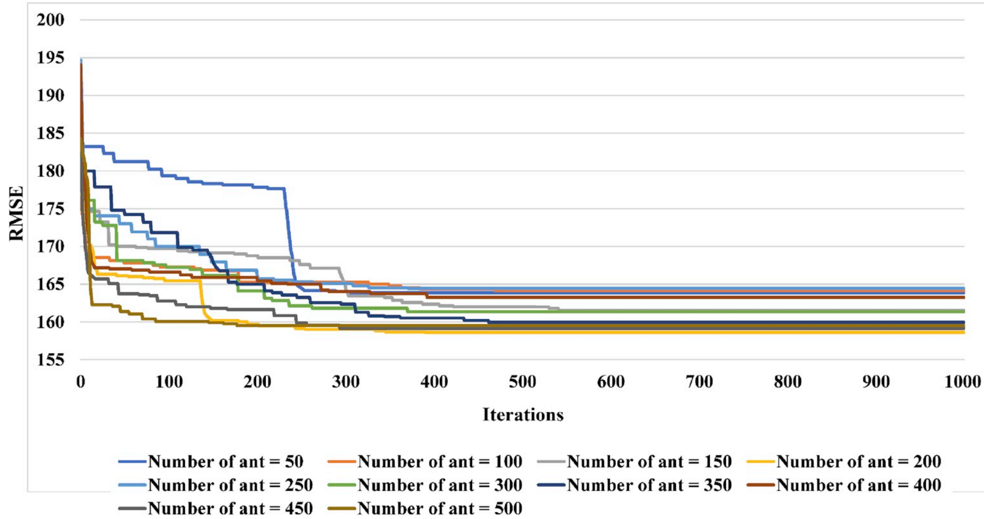

Fig. 11. ACO-DNN 5-20-15-10-1 performance on the training process.

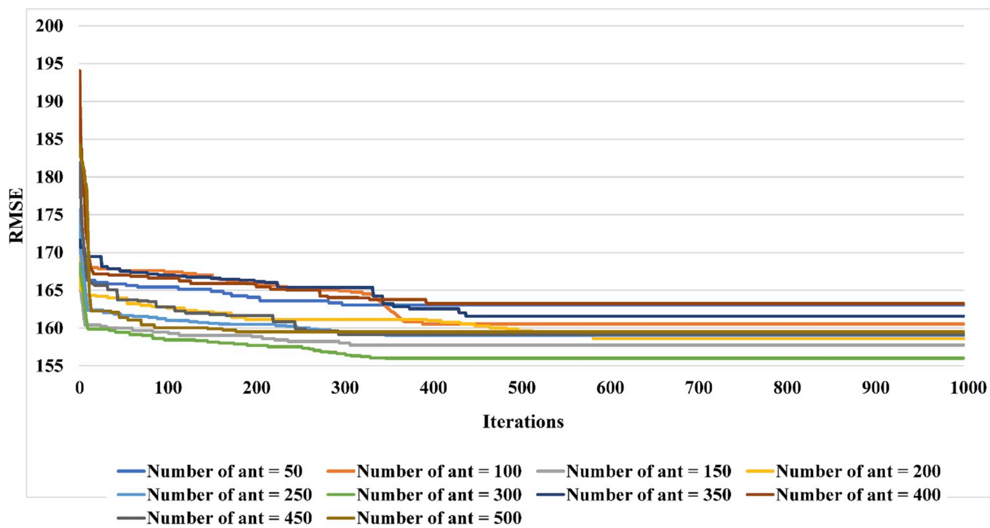

Fig. 12. ACO-DNN 5-25-20-18-15-1 performance on the training process.

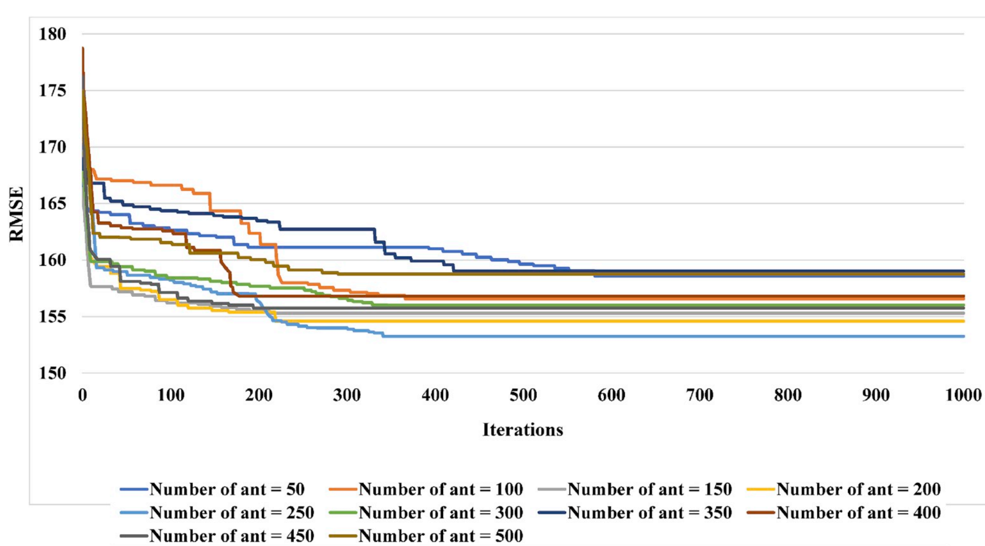

Fig. 13. ACO-DNN 5-30-25-20-18-1 performance on the training process.

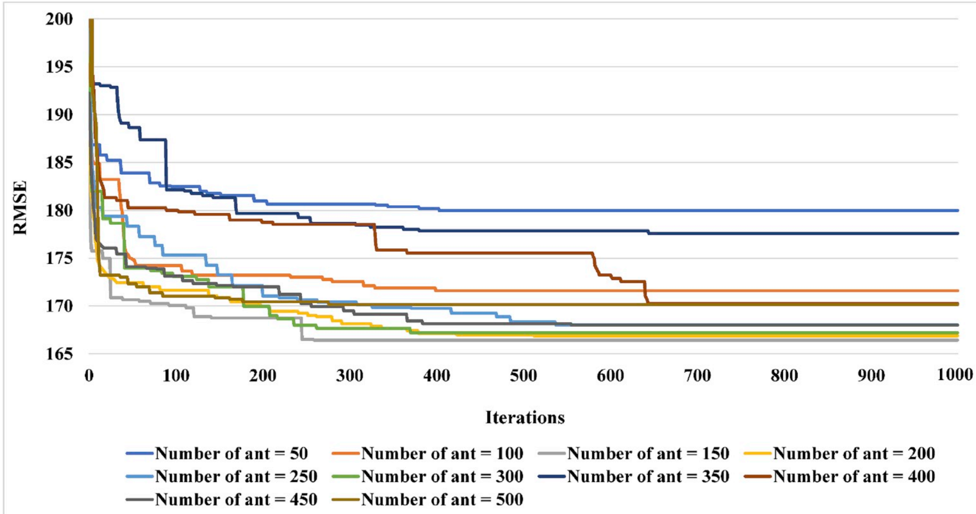

Fig. 14. ACO-DNN 5-30-25-20-15-10-1 performance on the training process.

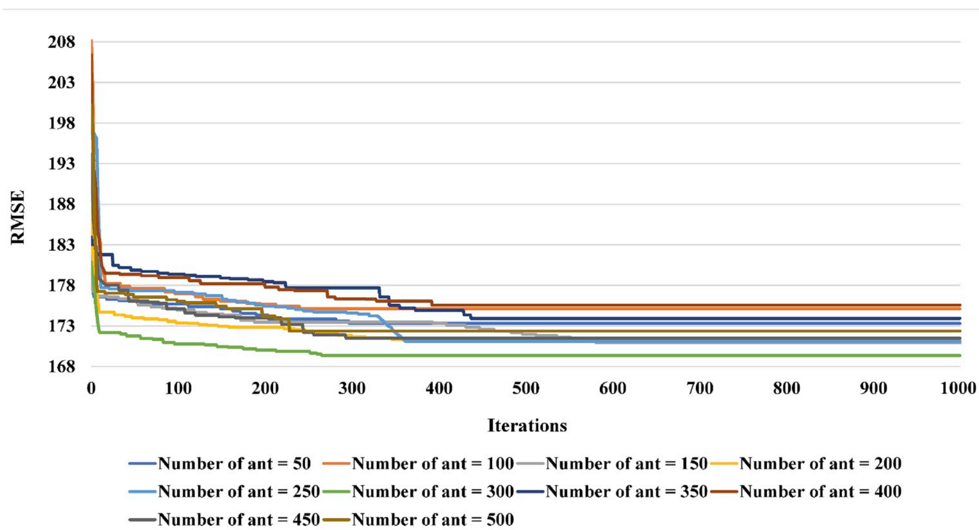

Fig. 15. ACO-DNN 5-32-25-23-18-12-8-1 performance on the training process.

Table 4
Optimal parameters of the developed models on the training dataset.

Model	Optimal parameters and performance			
	Hidden layers	Number of ants	Number of iterations	RMSE
ACO-ANN 5-9-1	1	200	478	189.280
ACO-ANN 5-12-1	1	300	404	184.140
ACO-DNN 5-15-8-1	2	250	468	160.700
ACO-DNN 5-20-12-1	2	350	473	171.715
ACO-DNN 5-15-12-13-1	3	200	513	166.883
ACO-DNN 5-20-15-10-1	3	200	391	158.587
ACO-DNN 5-25-20-18-15-1	4	300	330	156.013
ACO-DNN 5-30-25-20-18-1	4	250	342	153.246
ACO-DNN 5-30-25-20-15-10-1	5	150	260	166.440
ACO-DNN 5-32-25-23-18-12-8-1	6	300	266	169.358

constant value. The performance of optimizing the ANN and DNN models are shown in Figs. 6–15.

7. Analysis and discussion

From the obtained results in Figs. 6–15, the optimal parameters of the developed models on the training dataset were listed in Table 4. Additionally, the correlation between hidden layers, performance, and optimal parameters of ACO is analyzed in Fig. 16.

Accordingly, we can see that the accuracy of the models (i.e., RMSE) does not depend on the number of ants. The optimal number of iterations for each model is also different in Table 4. However, the number of iterations seem to have a positive correlation with RMSE. In contrast, the number of hidden layers seems to have a negative relationship with RMSE on the training dataset. Remarkably, the number of iterations of the ants have a high negative correlation with the number of hidden layers of ANN/DNN. In other words, the global search of the ants is random, and they must implement more iterations to find out the optimal parameters for the ANN and DNN models with fewer hidden layers.

Once the ANN and DNN models have been optimized by the ACO

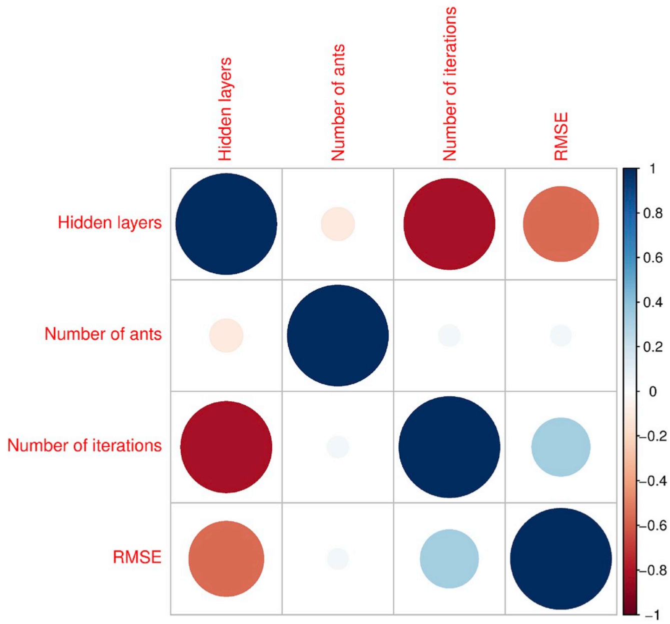

Fig. 16. Correlation between hidden layers, performance and optimal parameters of ACO.

algorithm (i.e., ACO-ANN and ACO-DNN), their performance is aggregated and compared to find out the most optimal model for forecasting the CC of mining projects. RMSE, R^2, MAE, MAPE, and VAF were used as the criteria to evaluate the quality of the developed models. Besides, the color intensity rating (CIR) method was also applied to rate and assess the results of the developed models (Koopialipoor et al., 2019). The forecast results, as well as the accuracy of the models, are shown in Tables 5 and 6.

As shown in Table 5, performance metrics, especially RMSE, MAE, and MAPE revealed that all the ten models overcame the underfitting/overfitting issues. It is an important issue to assess the strength of the proposed model within the constraints of the used dataset. The results demonstrated that the pre-processing technique (i.e., scaled dataset in [-1, 1]) and pre-train method using 5-fold cross-validation helped the models overcome the disadvantage of the sample size issues. However, it is complicated to define which model is the best or the worst. Therefore, the ranking method was applied for the performance metrics (i.e., RMSE, R^2, MAE, MAPE, and VAF), as calculated in Table 6. Accordingly, the developed models (10 models) were sort ordered from 1 to 10. In which, the value of 1 denotes the lowest performance, and 10 means the highest performance. Each performance metric was ranked separately; then, they were merged as a total ranking for model evaluation. Using the CIR method, it is easy to observe which model is the best and which model is the worst in this study. Table 5 shows that the ACO-ANN 5-9-1 model provided the worst performance in estimating the CC of mining projects herein with an accuracy of 95.840% and the total ranking of 13, corresponding to the CIR of the white color. In contrast, the ACO-ANN 5-25-20-18-15-1 model provided the best performance with the accuracy is up to 99.052% and the total ranking of 92, corresponding to the CIR of the darkest red color.

The examination of the depth of learning of different neural networks in this study showed that deep learning neural networks (i.e.,

Table 5
Developed AI models for estimating MCC and their performance.

Model	Training process					Testing process				
	RMSE	R^2	MAE	MAPE	VAF	RMSE	R^2	MAE	MAPE	VAF
ACO-ANN 5-9-1	189.280	0.982	144.034	0.077	98.192	282.953	0.962	238.344	0.121	95.840
ACO-ANN 5-12-1	181.141	0.983	137.487	0.071	98.344	233.217	0.974	209.567	0.127	97.020
ACO-DNN 5-15-8-1	160.700	0.989	118.869	0.073	98.854	196.258	0.980	160.985	0.106	97.957
ACO-DNN 5-20-12-1	171.715	0.985	137.911	0.077	98.511	239.197	0.975	187.404	0.118	96.887
ACO-DNN 5-15-12-13-1	166.883	0.986	124.482	0.073	98.594	164.982	0.987	149.196	0.092	98.497
ACO-DNN 5-20-15-10-1	158.587	0.987	123.354	0.072	98.731	183.391	0.981	161.312	0.079	98.142
ACO-DNN 5-25-20-18-15-1	156.003	0.988	119.710	0.065	98.772	130.988	0.991	115.274	0.072	99.052
ACO-DNN 5-30-25-20-18-1	153.246	0.988	115.848	0.065	98.815	155.399	0.987	139.753	0.080	98.703
ACO-DNN 5-30-25-20-15-10-1	166.440	0.986	123.503	0.068	98.602	220.622	0.976	179.861	0.134	97.428
ACO-DNN 5-32-25-23-18-12-8-1	168.979	0.986	122.367	0.066	98.559	199.735	0.980	173.135	0.122	97.807

Table 6
Ranking of the developed models.

Model	Training process					Testing process					Total rank
	Rank for RMSE	Rank for R^2	Rank for MAE	Rank for MAPE	Rank for VAF	Rank for RMSE	Rank for R^2	Rank for MAE	Rank for MAPE	Rank for VAF	
ACO-ANN 5-9-1	1	1	1	1	1	1	1	1	4	1	13
ACO-ANN 5-12-1	2	2	3	6	2	3	2	2	2	3	27
ACO-DNN 5-15-8-1	7	10	9	3	10	6	5	7	6	6	69
ACO-DNN 5-20-12-1	3	3	2	1	3	2	3	3	5	2	27
ACO-DNN 5-15-12-13-1	5	4	4	3	5	8	8	8	7	8	60
ACO-DNN 5-20-15-10-1	8	7	6	5	7	7	7	6	9	7	69
ACO-DNN 5-25-20-18-15-1	9	8	8	9	8	10	10	10	10	10	92
ACO-DNN 5-30-25-20-18-1	10	8	10	9	9	9	8	9	8	9	89
ACO-DNN 5-30-25-20-15-10-1	6	4	5	7	6	4	4	4	1	4	45
ACO-DNN 5-32-25-23-18-12-8-1	4	4	7	8	4	5	5	5	3	5	50

Note: the values of 1 is the worst and 10 is the best.

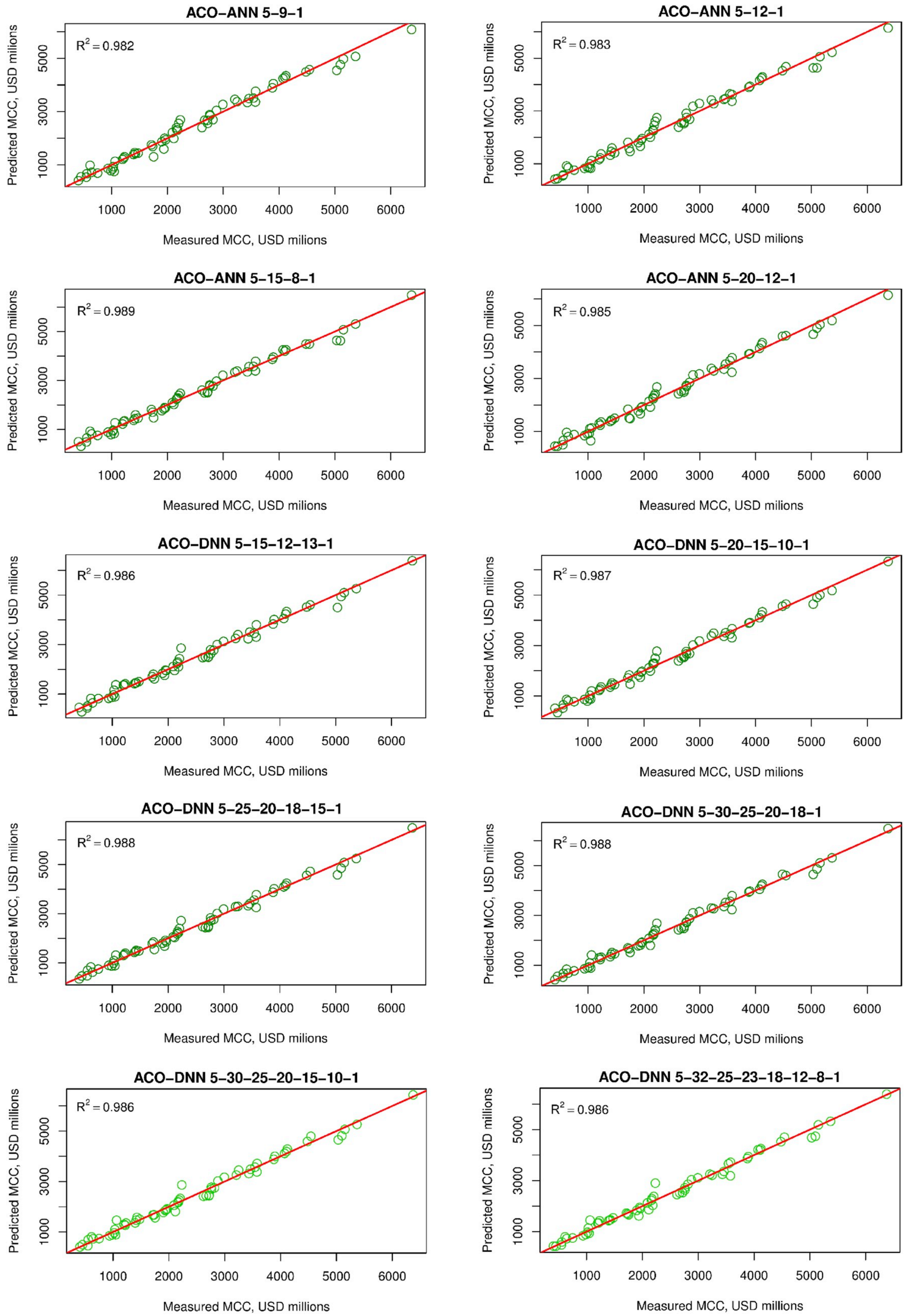

Fig. 17. Training performance of the ACO-ANN and ACO-DNN models.

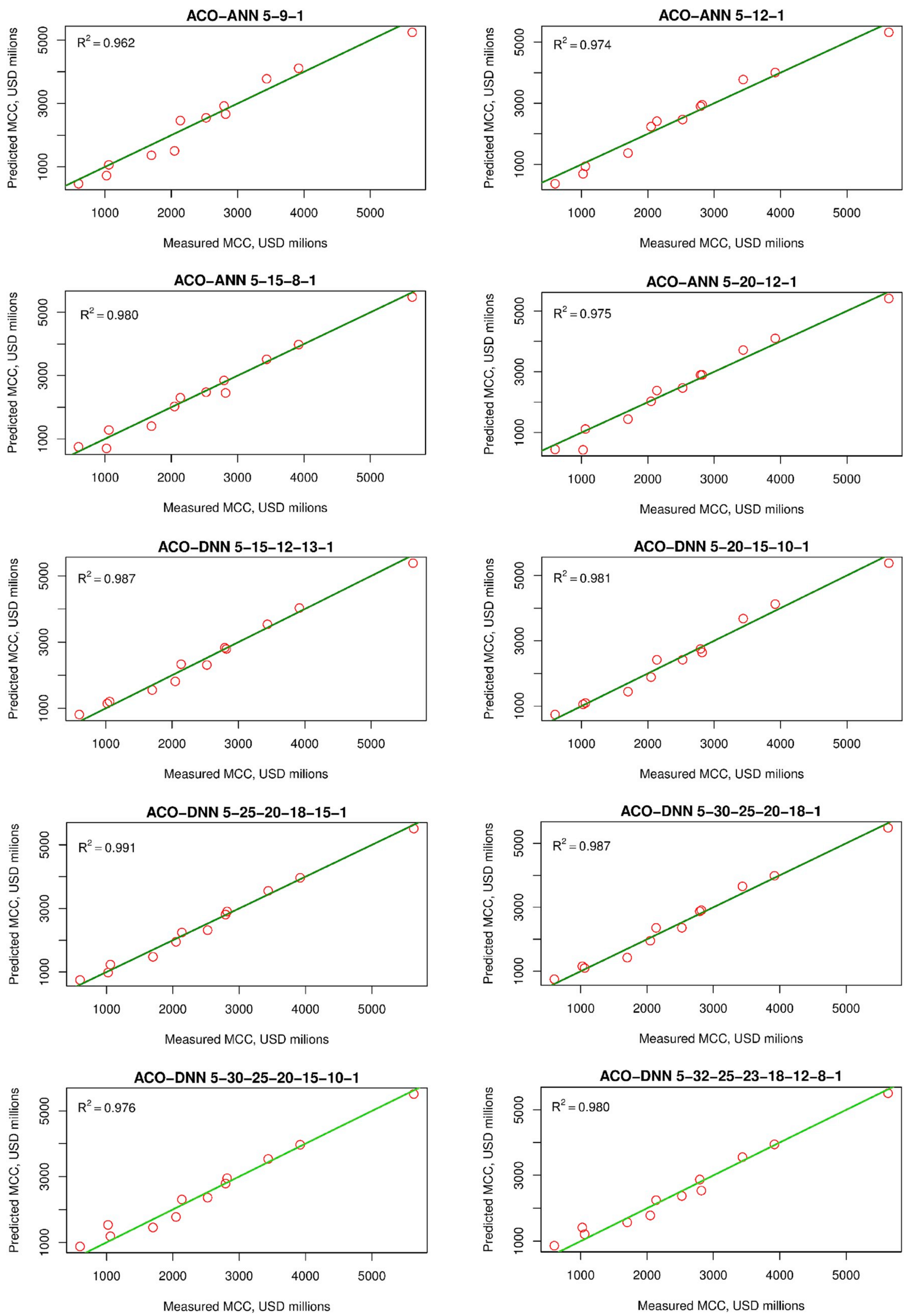

Fig. 18. Testing performance of the ACO-ANN and ACO-DNN models.

Table 7
ANOVA test results of the models for predicting the CC of open-pit mining projects.

Model	Training phase		Testing phase	
	F value	Pr (>F)	F value	Pr (>F)
ACO-ANN 5-9-1	177.3	<2e-16	30.34	7.01e-16
ACO-ANN 5-12-1	176	<2e-16	31.11	4.00e-16
ACO-DNN 5-15-8-1	174.4	<2e-16	33.92	<2e-16
ACO-DNN 5-20-12-1	175.9	<2e-16	29.96	9.31e-16
ACO-DNN 5-15-12-13-1	175.9	<2e-16	38.19	<2e-16
ACO-DNN 5-20-15-10-1	176.1	<2e-16	35.59	<2e-16
ACO-DNN 5-25-20-18-15-1	175.5	<2e-16	35.82	<2e-16
ACO-DNN 5-30-25-20-18-1	174	<2e-16	36.42	<2e-16
ACO-DNN 5-30-25-20-15-10-1	174.2	<2e-16	39.75	<2e-16
ACO-DNN 5-32-25-23-18-12-8-1	176	<2e-16	39.15	<2e-16

DNN) have an improved accuracy than those of ANN models in predicting the CC of mining projects. The DNN models with four hidden layers have significantly improved efficiency compared to the ANN and DNN networks with fewer hidden layers. However, considering the DNN models with five and six hidden layers show that their performance is lower than those of the DNN models with four hidden layers, although the number of hidden layers is higher. This finding indicates that DNN models with four hidden layers are the most suitable for the mining capital cost database used herein. Also, the complexity of DNN models with five or six hidden layers seems to reduce the performance of the computing models. Besides, the number of neurons in each hidden layer also significantly affects the accuracy of the CC forecasting model. Considering the two best DNN models shows that the performance of the ACO-DNN 5-30-25-20-18-1 model was lower than those of the ACO-DNN 5-25-20-18-15-1 model; meanwhile, the number of hidden neurons of the ACO-DNN 5-30-25-20-18-1 model is higher than the ACO-DNN 5-25-20-18-15-1 model (as shown in Tables 5 and 6). We can also see similar results for the ACO-DNN 5-15-8-1 and ACO-DNN 5-20-12-1 models. Whereas the accuracy of the ACO-DNN 5-15-8-1 model obtained approximately 98%, the ACO-DNN 5-20-12-1 model only got the accuracy of about 97%.

In general, the ANN and DNN models-optimized by the ACO algorithm are robust models for forecasting the CC of mining projects. The mean absolute percentage error of the developed models lies in the range of 7.2% to 12.1%. Compared to previous studies with non-AI methods, the accuracy of the developed models in this study is outstanding, especially the ACO-DNN 5-25-20-18-15- 1 model with a mean absolute percentage error of 7.2%. Whereas, it was 35% in a survey of Castle (1985); 27% in a study of Bennet (1996); 17% in a study of Thomas (2001) and 22% in a survey of Gypton (2002). In comparison with the previous studies which were developed by Nourali and Osanloo (2018b, 2019) using SVR and CART models, the optimal ACO-DNN model in this study is better with the mean absolute percentage error of 7.2%, whereas the studies of Osanloo (2018, 2019) was ±8%. Also, compared to the study of Guo et al. (2019) using the ANN model, this study provided a lower mean absolute percentage error (i.e., MAPE = 7.2%), whereas, the study of Guo et al. (2019) provided a MAPE of 7.8%. Figs. 17 and 18 show the accuracy of the ACO-ANN and ACO-DNN models in estimating the CC of open-pit mining projects on the training/testing datasets.

Additionally, to assess the strength of the models, the ANOVA test (Cuevas et al., 2004) on the variation between the developed models was analyzed to prove that the results are statistically significant and vital, as shown in Table 7. Accordingly, all ten developed models are statistically significant with P-value less than 0.05. However, it is hard to conclude which model is the best if only based on the ANOVA test results in Table 7 due to the P-value is very small (<2e-16) upon most of the models. Therefore, an overall combination of Tables 5–7 is the best way for evaluating the performance of the models, as well as their statistically significant in this study. In other words, these analyses demonstrated that the developed ACO-ANN and ACO-DNN models are robust statistical models with high accuracy for predicting CC of open-pit mining projects, especially the ACO-DNN 5-25-20-18-15-1 model.

8. Sensitivity analysis

From the abovementioned results, the ACO-DNN 5-25-20-18-15-1 model was selected as the optimal model for estimating the CC of open-pit mining projects. It is a deep neural network optimized by the ACO algorithm with four hidden layers; therefore, the Olden's sensitivity method (Olden and Jackson, 2002; Olden et al., 2004) was selected to take into account the effects of input variables on the CC predictions. The results show that MineAP, MillAP, SR, and LOM are the most significant parameters that affect the accuracy of the CC predictive model (i.e., the proposed ACO-DNN 5-25-20-18-15-1 model). In contrast, RMG does not seem to profoundly affect the accuracy of the selected model, as shown in Fig. 19. It is worth noting that MineAP, MillAP, SR, and LOM are considered as the influential parameters for the CC of mining projects when using the proposed ACO-DNN 5-25-20-18-15-1 model. Of those, the MineAP parameter is evaluated

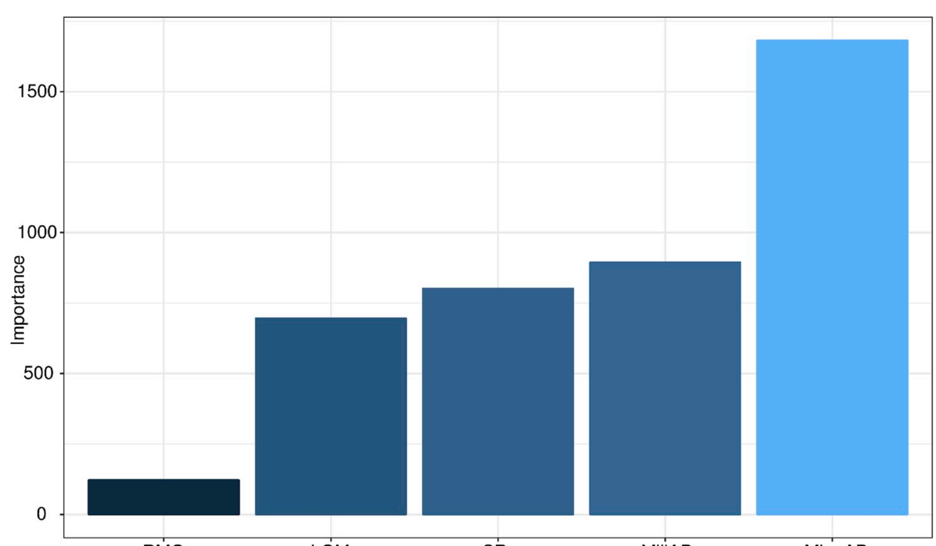

Fig. 19. Input variables and their effect on the CC prediction of the selected model.

Table 8
Comparison of the performance of the proposed ACO-DNN 5-25-20-18-15-1 model.

Model	Important inputs	Performance		
		RMSE	R^2	MAE
Guo et al. (2019) (ANN)	MineAP, MillAP	138.103	0.990	114.589
This study (ACO-DNN)	MineAP, MillAP, SR, and LOM	130.988	0.991	115.274

as the most crucial parameter for the CC prediction in open-pit mining projects. Comparing with the conclusion in the study of Guo et al. (2019), it can be seen that the proposed ACO-DNN 5-25-20-18-15-1 model appreciated four out of five input parameters when forecasting the CC of a mining project (i.e., MineAP, MillAP, SR, and LOM). Whereas, Guo et al. (2019) only appreciated two out of five input variables (i.e., MineAP and MillAP). Indeed, annual production of mines and mills, and the stripping ratio typically vary over the life of every operation. Generally, these are key variables in a cutoff grade optimization process to maximize project value. Thus, this finding indicates that DNN's deep learning considered and assessed the importance of multiple variables in predicting the CC of mining projects which is matching with the cutoff grade optimization process. Reviewing and evaluating the significance of many input variables combined with the optimization process of the ACO algorithm improved the accuracy of this study, as compared in Table 8.

9. Conclusion

Accurate forecasting of the CC for open-pit mining projects is the goal of investors, as well as mining businesses. It helps investors and mining businesses have specific strategies for business development. Besides, the accurate forecast of the CC for open-pit mining projects also allows investors and mining enterprises to assess the necessity for particular policies to change and improve the efficiency of mining investment. This study proposed a deep neural network for predicting the CC for open-pit mining projects with high accuracy (i.e., mean percentage error of 7.2%) based on the optimization of the ACO algorithm, namely ACO-DNN 5-25-20-18-15-1 model. The findings indicated that the DNN models could predict the CC of mining projects more accurate than those of the simple ANN models. In addition, the combination of DNN and optimization algorithms (e.g., ACO) was considered a perfect approach for improving the accuracy of the DNN models in estimating the CC for open-pit mining projects. Remarkable, the MineAP, MillAP, SR, and LOM are the parameters that need special attention in forecasting and evaluating the CC for open-pit mining projects.

Declaration of competing interest

None.

Acknowledgments

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