Chapter 7

Application of cubist algorithm, multi-layer perceptron neural network, and metaheuristic algorithms to estimate the ore production of truck-haulage systems in open-pit mines

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1 Introduction

The extraction of ore from a mine and its transportation to the processing plant consists of unit operations such as drilling, blasting, loading, and transportation. The productivity and profitability of a mine can vary significantly depending on the design and operation of the production process. Therefore, it is important to design, operate, and manage production processes composed of unit operations efficiently [1–4]. In particular, it is very important to design and operate a mine's haulage system efficiently because the cost of transporting ore and waste accounts for more than half of the total production cost [2].

To date, many researchers have conducted studies to optimize the variables of the haulage system or to predict ore production, which is one of the major performance indicators. Researchers have implemented a variety of deterministic and stochastic simulation models to solve the problem of determining the equipment required for a haulage system and the capacity of a vehicle. Different

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estimation methods, such as expert systems, fuzzy set theory, genetic algorithms (GAs), multi-criteria decision-making, computer-based simulation techniques, and various mathematical decisions, are used to simulate and optimize mine haulage systems [5–10]. In addition, studies on discrete event simulations to solve the haulage problem related to mines have been actively conducted [11–18]. Furthermore, studies are being conducted to predict or optimize variables and performance indicators for mine haulage systems through machine learning using big data collected from mines. Soofastaei et al. [19] utilized an artificial neural network (ANN) and a GA to optimize the parameters related to the fuel consumption of trucks used in haulage systems. Park et al. [20] developed a machine learning model that can predict truck travel time employing underground mine data collected using the Internet of Things (IoT) and diagnosed and evaluated the condition of the transport route. Baek and Choi [21] developed a deep neural network (DNN)-based model to analyze truck haulage and operational conditions and predict ore production. In addition, Choi et al. [22] evaluated the validity of various machine-learning algorithms for predicting ore production in open-pit mines.

Machine learning has been widely applied in mining and geoengineering; however, the development of machine learning models able to evaluate and predict ore production efficiently is insufficient. Therefore, in this study, we developed a multi-layer perceptron (MLP) neural network model that combines metaheuristic algorithms and can estimate ore production using data collected from mines. To this end, data on the haulage system of a limestone mine in Korea were collected. In addition, gray wolf optimization (GWO), particle swarm optimization (PSO), and the GA were considered as metaheuristic algorithms for optimizing the MLP, and thus GWO-MLP, PSO-MLP, and GA-MLP models were developed to predict the ore production of truck haulage systems of open-pit mines. Furthermore, a standalone MLP model was developed for comparison with the hybrid models.

2 Dataset used

A limestone mine operated by Hanil Cement Co., Ltd. in South Korea (coordinates: 128° 19′ 58″ E; 37° 1′ 59″ N) was selected as the study area to estimate the ore production of the truck-haulage system in open-pit mines. The mine produces approximately 8.1 million tons of limestone annually. Limestone ore is produced by ten shovels, two loaders, and three dozers, and the produced ore is transported to the shaft by 15 dump trucks (with loading capacities of 45, 60, and 84 tons). The mine has two ore-processing shafts. The ore dumped on the shaft is immediately crushed and then transferred to a cement plant using a belt conveyor.

For data acquisition, an IoT-based mine management system operating in the study area was used. The system utilizes four wireless access points (APs) and Global Positioning System (GPS) tags installed in the mine to track the location of equipment and mine workers and monitor the operational status in real time. Therefore, the production manager can verify the operating status of the mine in real time. Packet data are transmitted by the wireless APs to the web server and consist of the tag recognition date, tag recognition time, IP address identifying the wireless AP, and tag location date. In this study, 16,217 observations were collected from the aforementioned limestone mine in South Korea to estimate the ore production (output-Y) of the truck-haulage system in open-pit mines. The dataset contains 16 input variables: Relative operation start time (X1), relative operation end time (X2), the interval between operation start and end times (X3), number of dispatched 45-ton trucks (X4), number of dispatched 60-ton trucks (X5), number of dispatched 84-ton trucks (X6), utilization of dumping zone A by the 45-ton trucks (X7), utilization of dumping zone B by the 45-ton trucks (X8), utilization of dumping zone A by the 60-ton trucks (X9), utilization of dumping zone B by the 60-ton trucks (X10), utilization of dumping zone A by the 84-ton trucks (X11), utilization of dumping zone B by the 84-ton trucks (X12), average stay time of trucks at dumping zone A (X13), average stay time of trucks at dumping zone B (X14), average travel time of trucks from dumping zone A to loading points (X15), and average travel time of trucks from dumping zone B to loading points (X16). Operations, stays, and travel times (min) used as input variables are expressed in relative terms to adjust the scale of the variables. For example, if an operation starts at 8:30 AM and ends at 11 AM, the relative operation start and end times can be set to 0 min and 150 min, respectively.

Downscaling techniques for big data are considered a powerful solution to reduce the computational cost of machine learning problems, as the long-running time of large-scale data is a drawback for engineers and developers [23–26]. In this study, the ore production dataset consisting of 16,217 observations was reduced to 3000. It was reduced to a small dataset without losing its properties. The dataset (3000 observations) was then divided into three sections. First, 80% of the dataset (2400 samples) was randomly selected to train and validate the model, and the remaining 20% (600 samples) were used to test the model. The 2400 samples were again divided in a 7:3 ratio and divided into a training dataset (1680 samples) and a validation dataset (720 samples), respectively. Finally, the practical engineering of the model was evaluated using the testing dataset. Table 1 presents the statistics of the dataset (scaled-down dataset) for the 16 input variables used to estimate the ore production.

TABLE 1 Summary of the dataset used in this study.

Characteristics	Variables								
	X1 (min)	*X2 (min)*	*X3 (min)*	*X4 (number)*	*X5 (number)*	*X6 (number)*	*X7 (ratio)*	*X8 (ratio)*	*X9 (ratio)*
Min.	0	30	30	0	0	0	0	0	0
First Qu.	28	113.5	30	3	1	4	0	0	0
Median	58	154	60	3	2	4	0.44	0.5	0
Mean	65.5	146.4	80.94	3.648	1.843	4.056	0.4475	0.5229	0.2708
third Qu.	98	186	120	5	3	5	0.93	1	0.67
Max.	180	210	210	6	3	5	1	1	1

Characteristics	Variables								
	X10 (ratio)	*X11 (ratio)*	*X12 (ratio)*	*X13 (min)*	*X14 (min)*	*X15 (min)*	*X16 (min)*	*Y*	–
Min.	0	0	0	0	0	0	0	45	–
First Qu.	0	0	0.5375	0	1.45	0	7.49	1416	–
Median	0.95	0	1	1.74	1.61	8.27	9.64	2505	–
Mean	0.583	0.2394	0.741	1.364	2.11	7.11	8.734	2962	–
Third Qu.	1	0.33	1	1.99	1.99	11.65	11.41	4059	–
Max.	1	1	1	11.47	29.98	88.68	61.52	11,979	–

3 Methodology

A multi-layer perceptron (MLP) was developed to estimate the ore production of the truck-haulage system in open-pit mines. In addition, different metaheuristic algorithms, including GWO, PSO, and GA, were utilized to optimize the model. First, a dataset of 3000 samples, consisting of 16 input variables, was collected from a limestone mine in South Korea. The importance of the input variables was then analyzed by applying the cubist algorithm (CA), and the GWO-MLP, PSO-MLP, and GA-MLP models were developed using the selected variables.

3.1 Selection of input variables using the cubist algorithm

The CA was used to analyze the importance of the input variables and select the variables to develop a model. The CA is a rule-based algorithm and a complement of C5.0, which is mainly used for classification. It is based on different approaches proposed by Quinlan [27–29]. Unlike other algorithms, the CA has several properties [30]: (1) Different types of pruning, smoothing, and rule creation processes; (2) optional boosting procedures; and (3) adjustable estimation with the possibility of choosing nearby units for the training dataset [31]. The process of building a tree is similar to that of other decision algorithms. However, the CA considers the weighted linear combination of two trees, including an actual tree and its parents, and then performs pruning. The weights for each tree are calculated based on the covariance of the tree residuals and the variance of the difference between the residuals. Models with lower errors are given more weight than other models. After determining the weight of each model, the adjusted error rate is calculated by removing each rule from the rule set. If the adjusted error rate increases when deleting a rule, the rule is omitted from the set [32,33].

In this study, the importance of the 16 input variables for estimating ore production was analyzed using the CA (Fig. 1). The results showed that the most important input variables in the ore production prediction model were X3, X5, and X2. In particular, the interval between the start and end times of the operation (X3) was found to be the most important factor. In general, it was confirmed that the importance of the input variables related to operation time, number of dispatched trucks, travel time, and stay time was high. In contrast, the importance of the input variables (X7–X12) related to the dumping zone utilization rate was generally low. Notably, the importance of the input variable X10 for the utilization rate of dumping zone B by 60-ton trucks was the lowest. Therefore, the model was developed using 15 variables, excluding X10, as input variables to estimate the ore production of the truck-haulage system in open-pit mines.

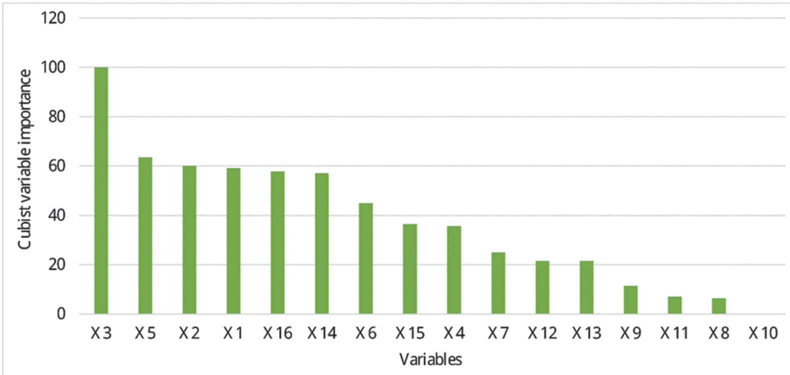

FIG. 1 Analysis of the importance of variables using the cubist algorithm.

3.2 Multi-layer perceptron neural network

The artificial neural network (ANN) technology is well established as a powerful mathematically based solution that is similar to the human brain and promises stable connections between inputs and outputs in practice [22,34]. Therefore, ANNs are designed to solve most problems, in practice, rather than humans [35–39]. The ANN was first introduced by McCulloch and Pitts [40], and ANN-based models have been widely used in many investigations. To develop ANNs, the structure of the ANN and the training algorithm must be considered. The ANN structures consist of three types of layers: Input, hidden, and output layers [41]. The input and output layers consist of a single layer. However, the hidden layer consists of one or more layers [42]. The MLP neural network consisting of one or more layers is a well-established form of ANN commonly used by researchers.

There are various training algorithms for training ANN models, but feed-forward and back-propagation are the most widely used. For MLP neural networks, a similar algorithm is used to train the network. The general operating principle of an MLP neural network is as follows. First, information is received from the external environment through input neurons. Second, the data are encoded and passed to hidden neurons, where calculations occur. Weights are the parameters used to describe the relationship between neurons and are the result of this process. Finally, the result of the hidden-layer calculation is sent to the output neuron. In this section, a hybrid model based on an MLP neural network is used to estimate ore production.

3.3 Metaheuristic algorithm for optimizing the multi-layer perceptron

A metaheuristic algorithm was used to optimize the MLP neural network to estimate the ore production of the truck-haulage system of open-pit mines.

Metaheuristics are a set of intelligent strategies for improving the efficiency of heuristic procedures [43]. Laporte and Osman [44] defined metaheuristics as an iterative generation process that intelligently combines different concepts to explore and exploit a search space and then guides a subordinate heuristic. In addition, they defined learning strategies as those used to structure information to find near-optimal solutions efficiently. In this work, the MLP neural network was optimized using nature-inspired algorithms, such as GWO, PSO, and GA. The GWO, PSO, and GA algorithms provide the biases and weights of the MLP and receive the RMSE and R^2 values for the training data. The variables of the MLP, such as weights and biases, represent a series of values for training and are sent to the GWO, PSO, and GA optimization algorithms.

Gray wolf optimization (GWO)

GWO is a powerful metaheuristic algorithm proposed by Mirjalili et al. [45] and has strengths in terms of solution accuracy, minimum computational effort, and aversion to premature convergence [46]. GWO was inspired by the gray wolf, a member of the Canidae family, which leads the predators at the top of the food chain. Gray wolves are characterized by living in packs of 5–12 individuals. The leader of a pack of wolves is in charge of the pack and is referred to as the alpha. Beta reinforces the alpha's guidelines throughout the pack and delivers feedback to the alpha wolf. The lower level in the hierarchy of gray wolves is called the omega and they serve as the scapegoat. In addition, if a wolf is not alpha, beta, or omega, it is referred to as a delta. Delta wolves are scouts, sentinels, elders, hunters, and caretakers. The behavior of the GWO for hunting the prey can be formulated mathematically. The position of the alpha wolf is assumed to be the best answer in the proposed GWO algorithm, and the positions of beta and delta are the second-and third-best answers, respectively. Omega represents the remaining answers to the problem. In the GWO algorithm, hunting is instructed by alpha, beta, and delta, and omega follows them. Details of the formulation of prey-hunting behavior in gray wolf packs can be found in Nimma et al. [46].

Particle swarm optimization (PSO)

PSO is an algorithm developed by Kennedy and Eberhart [47] based on swarm behavior, such as that of fish and birds in nature. x_i and v_i, which indicate the position and velocity of the particle, can be updated using the following formulas:

$$\boldsymbol{v}_i^{t+1} = \boldsymbol{v}_i^t + \boldsymbol{\alpha\varepsilon_1}\left[\boldsymbol{g}^* - \boldsymbol{x}_i^t\right] + \boldsymbol{\beta\epsilon_2}\left[\boldsymbol{x}_i^* - \boldsymbol{x}_i^t\right], \tag{1}$$

$$\boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \boldsymbol{v}_i^{t+1}, \tag{2}$$

where ε_1 and ε_2 represent two random vectors, and each entry has a value between 0 and 1. The parameters α and β are the learning parameters or acceleration constants. A new position is generated by mutations of the pattern-search type, and selection is performed implicitly through the current global best solution g^* and the individual best x_i^* found thus far. However, as shown in accelerated PSO, the current global best is very important for selection, but the role of the individual best is not clear. Therefore, PSO mainly consists of mutation and selection, and there is no crossover. This means that PSO can have high mobility in particles with a high degree of exploration. However, the use of g^* is seen as highly optional. Although it helps to speed up convergence, it can lead to premature convergence, even if it is not the right optimal solution to the problem of interest.

Genetic algorithm (GA)

The GA was first developed by Holland [48] and extended by Whitley [49] and Houck et al. [50]. The GA is widely applied to optimize scientific and engineering problems, and many researchers have used GA optimization methods [37,51–52]. The main advantage of the GA is that it has the potential to find solutions by solving highly complex or nonlinear problems. A suitable function must be processed and developed in the GA by optimizing many parameters, such as the population size and genetic operator rates. In particular, these parameters affect the convergence of the algorithm and the results of the network. GA-based methods involve chromosomes of fixed lengths [34]. Chromosomes encode issues that are transformed into a linear binary string system between 0 and 1, which is the main reason for generation. Chromosomes are evaluated according to their random properties and are selected by particular genetic operators from the remaining chromosomes to produce new generations of chromosomes. Crossovers select a range of 0–1 between the mutation and parents' work. This process is repeated continuously until the best is generated through measurements according to the network performance.

4 Results and discussions

This study combined the MLP neural network technology with three metaheuristic algorithms, namely, GWO, PSO, and GA, to predict the ore production of truck haulage systems in open-pit mines. In addition, a standalone MLP model was developed for comparison with three hybrid models. In this section, the development and comparison results of the standalone MLP model and the hybrid model are presented.

One of the most important parameters affecting the proposed metaheuristic algorithms (GWO, PSO, and GA) is the number of swarms or population sizes. This will assist in the use of the best-fit ensemble with a hybrid MLP-based model. The optimization process considered different swarm sizes of 50–500 in increments of 50. A total of 1000 iterations were performed for the optimization calculations for each proposed prediction network. In addition, the main objective function was set to the RMSE value, and the performance error was measured for each iteration. Fig. 2 shows the training results of the hybrid model using the training dataset. The GWO-MLP prediction method was optimized

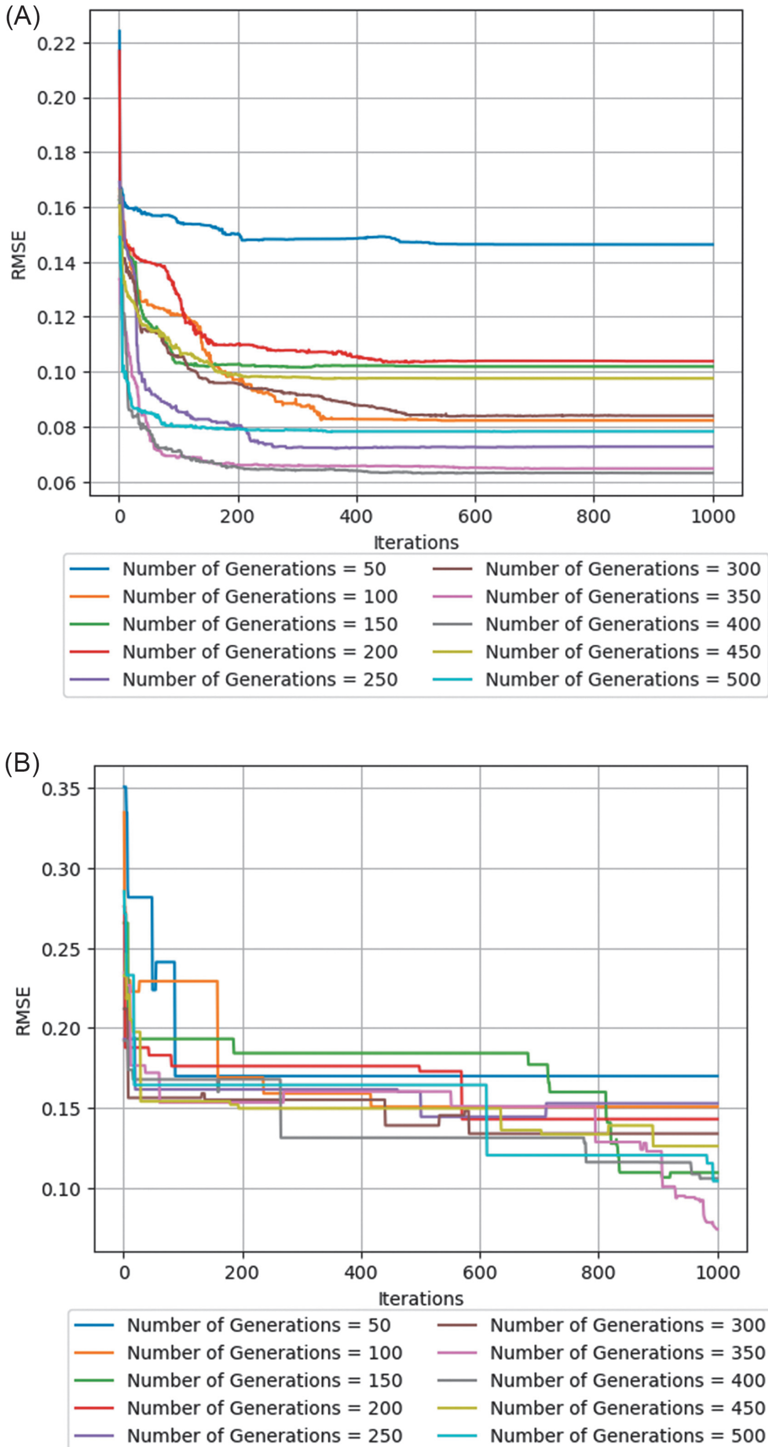

FIG. 2 Training performance of the hybrid models for predicting ore production. (A) Convergence of the GWO-MLP model. (B) Convergence of the PSO-MLP model.

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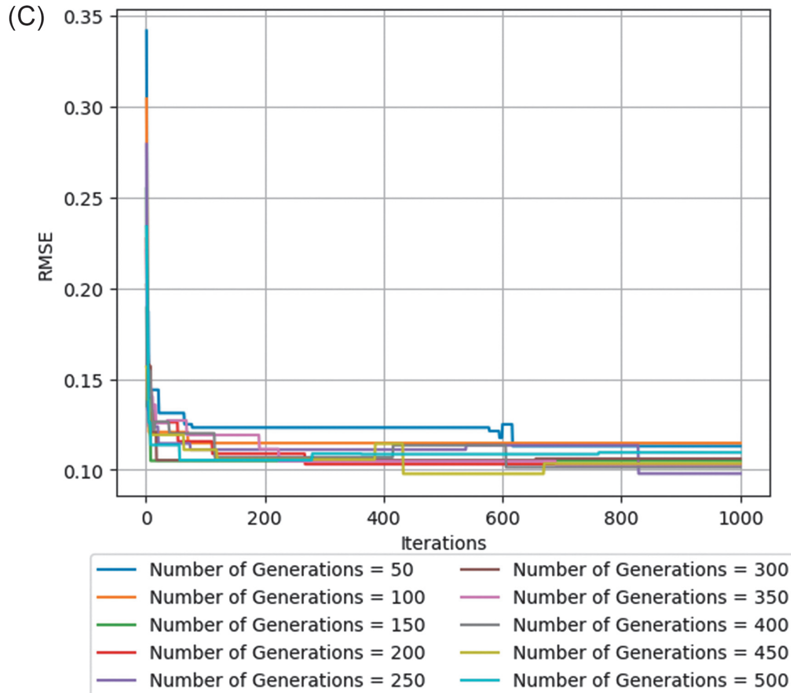
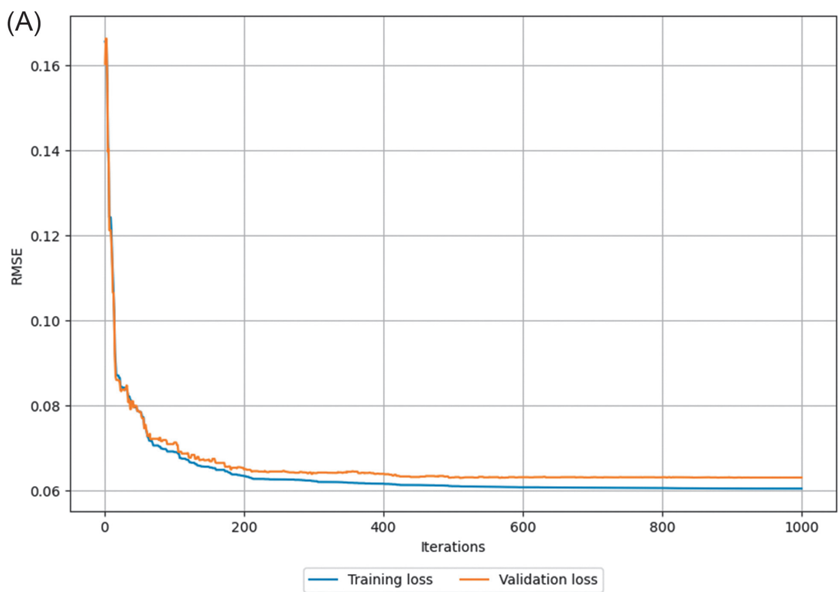


FIG. 2, CONT'D (C) Convergence of the GA-MLP model.

after approximately 500 iterations and exhibited the best performance (RMSE: 713.795) when the swarm size was 400. The PSO-MLP model was optimized after approximately 800 iterations, and the best RMSE was found to be 890.124 when the swarm size was 350. However, for swarm sizes of 350, 400, 450, and 500, if the number of iterations is increased to more than 1000, the RSME is likely to be lowered. Finally, the GA-MLP was optimized after approximately 800 iterations. The RMSE was the lowest (1102.081) when the swarm size was 250. Regarding the performance of the hybrid model on the training dataset, GWO-MLP was the best, followed by PSO-MLP and GA-MLP. It should be noted that the RMSE values in Fig. 2 are normalized in the range of 0–1, corresponding to the unscaled values, as mentioned above.

In this study, a dataset (2400 samples) and a testing dataset (600 samples) were constructed for training and validation with 3000 scaled-down ore production datasets at a 4:1 ratio. Fig. 3 shows a graphical visualization of the training and validation losses during the training and validation phases of the hybrid models. The GWO-MLP, PSO-MLP, and GA-MLP models all show that both the training and validation losses decrease and stabilize at a certain point.



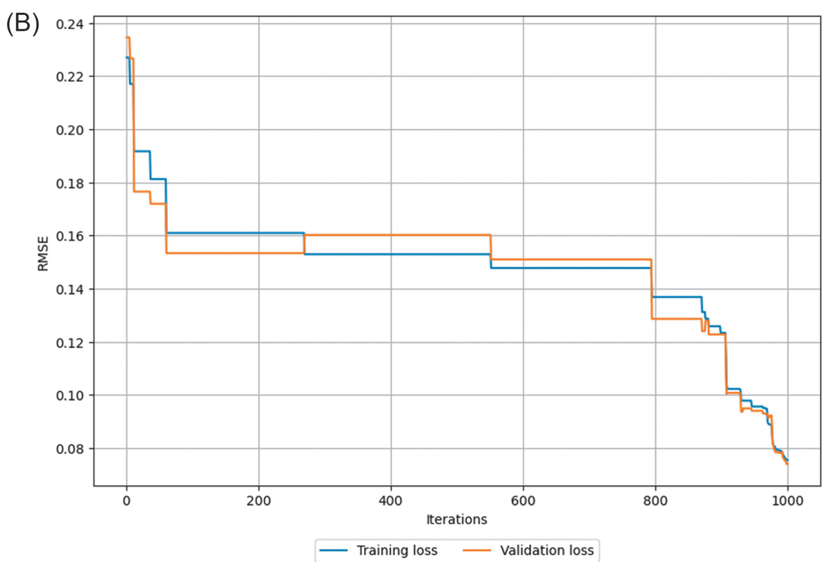


FIG. 3 Comparison of the models in the training and validation phases. (A) GWO-MLP model. (B) PSO-MLP model.

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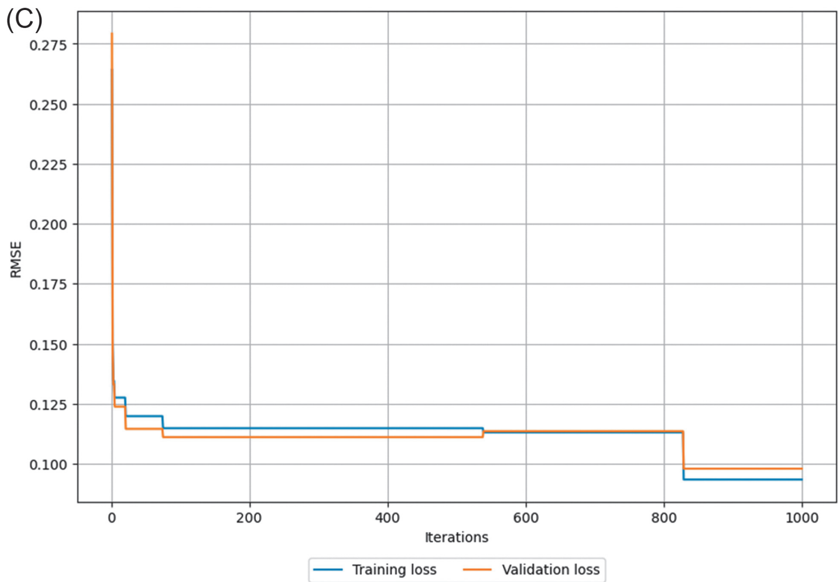

FIG. 3, CONT'D (C) GA-MLP model.

It is evident from the results that the hybrid models based on metaheuristic algorithms were developed appropriately with high performance. After developing the model, the performance of the model was evaluated using training, validation, and testing datasets. Table 2 summarizes the performance of the ore production estimation model for the training, validation, and testing datasets. Considering the performance values of the developed machine learning model, it can be observed that GWO-MLP achieved the best performance in ore production estimation with the lowest RMSE and highest R^2. In contrast, the GA-MLP model had the lowest performance in estimating ore production in open-pit mines. Comparing the performance of the four models, their performance is arranged in the following order: GWO-MLP, standalone MLP, PSO-MLP, and GA-MLP.

TABLE 2 Performance metrics of the models.

	Training		Validation		Testing	
Model	*RMSE*	R^2	*RMSE*	R^2	*RMSE*	R^2
GWO-MLP	713.795	0.877	744.425	0.851	657.921	0.893
PSO-MLP	890.124	0.809	873.559	0.795	882.876	0.807
GA-MLP	1102.081	0.707	1155.485	0.642	1055.324	0.724
MLP	735.624	0.870	740.473	0.853	767.496	0.854

Fig. 4 shows the correlation between the actual and estimated ore production in the training dataset. It can be observed that the performance of the PSO-MLP and GA-MLP models is rather low when the ore production is 8000 tons or more. In contrast, GWO-MLP and the MLP neural network are effective in most ore production levels, and their R^2 values are also relatively high, at 0.877 and 0.870, respectively. According to the comparison of results in Fig. 4, the GWO-MLP and MLP neural network models are well-developed and have good accuracy. In particular, the predicted value of ore production using the GWO-MLP model was the closest to the measured value.

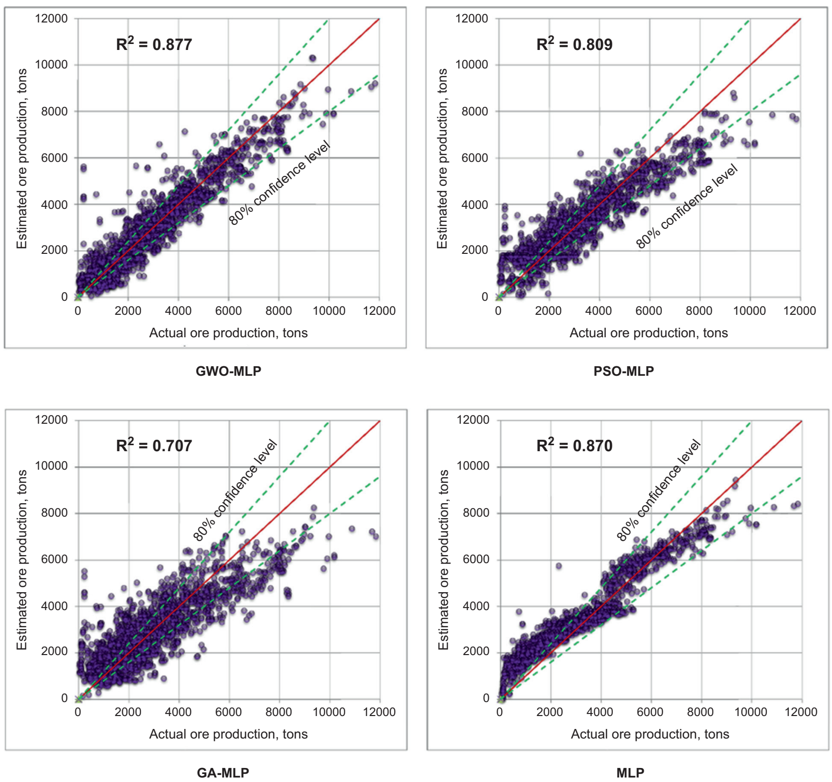

FIG. 4 Correlation between actual and estimated ore production values on the training dataset.

Fig. 5 shows the correlation between the actual and estimated ore production using the validation dataset. The results of the correlation analysis using the validation dataset are similar to those of the training dataset. However, Fig. 5 shows that the R^2 value of the MLP neural network is higher than that of GWO-MLP, although the difference is small.

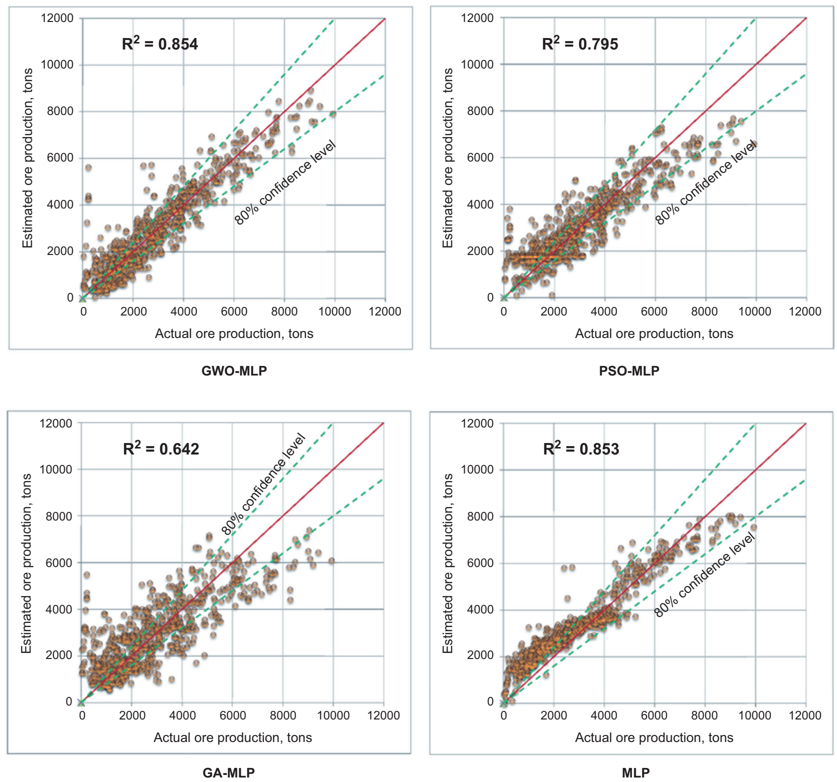

FIG. 5 Correlation between actual and estimated ore production values on the validation dataset.

In this study, a downscaling technique was used to reduce the original dataset from 16,217 to 3000 observations. The performance of MLP neural networks combined with metaheuristic algorithms was sufficient for both the training and validation datasets derived from the scaled-down dataset. However, a testing dataset was required to assess the representation of the scaled-down dataset and to confirm the performance of the developed model. In other words, it is necessary to verify the developed model through the testing dataset and confirm that the scaled-down dataset can accurately represent the properties of the original dataset. The testing data set consisted of 600 observations corresponding to 20% of 3000 observations. Fig. 6 shows the correlation between the actual and estimated ore production in the testing dataset. The GWO-MLP model exhibited the best performance on the testing dataset. The GA-MLP model still showed the lowest performance, similar to that evaluated on the training and validation datasets. In addition, the rest of the models showed similar performances to those obtained in the training and validation datasets.

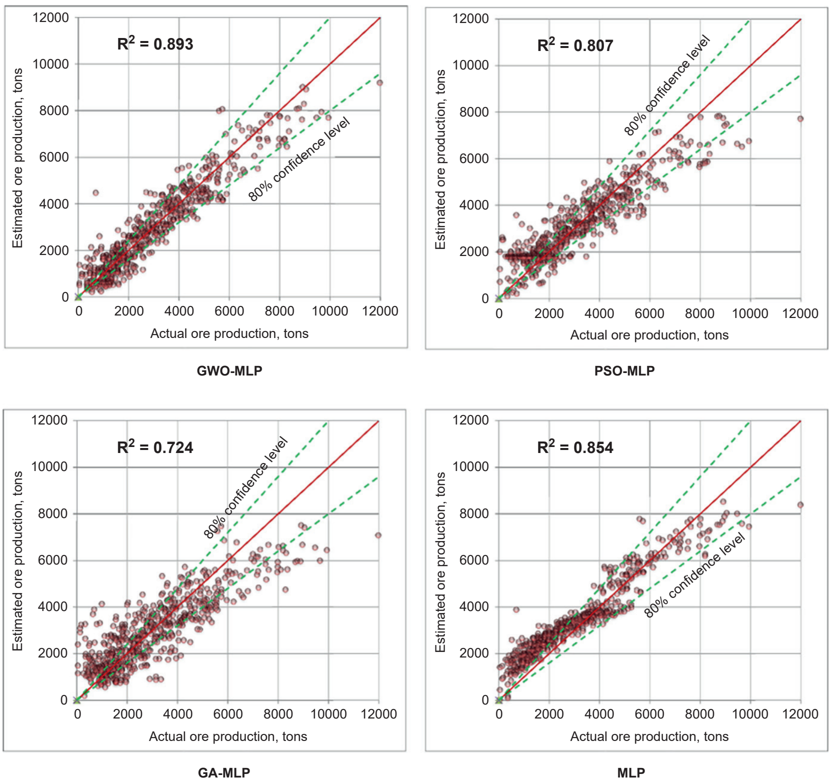

FIG. 6 Correlation between actual and estimated ore production values on the testing dataset.

5 Conclusion

In this study, machine learning was implemented to estimate ore production in open-pit mines with high accuracy. The GWO-MLP, PSO-MLP, and GA-MLP models were developed by combining algorithms based on the metaheuristics of GWO, PSO, and GA with the MLP neural network. In addition, a standalone MLP model was developed, and the results of a comparison of the predictive performance of ore production in open-pit mines were presented. The scaled-down dataset was again divided into 4:1 and consisted of a dataset for training and validating the model (2400 samples) and a dataset for testing the model (600 samples). In addition, 70% of the 2400 observations were used as training datasets for model training, and the remaining 30% were used as validation datasets for model validation. Subsequently, the developed model and properties of the scaled-down dataset were verified. Among the four models developed to estimate ore production in open-pit mines, the GWO-MLP model exhibited the highest estimation accuracy. Meanwhile, the GA-MLP model exhibited the lowest performance. The estimation performances of the models appeared in the order of GWO-MLP, MLP, PSO-MLP, and GA-MLP, and it was confirmed that the performance was the same for the training, validation, and testing datasets. Therefore, not all metaheuristic algorithms are suitable for the optimization process of MLP models; in particular, PSO-MLP and GA-MLP showed much lower performance than the standalone MLP model.

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