Artificial Neural Network and Firefly Algorithm for Estimation and Minimization of Ground Vibration Induced by Blasting in a Mine

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It is of a high importance to introduce intelligent systems for estimation and optimization of blasting-induced ground vibration because it is one the most unwanted phenomena of blasting and it can damage surrounding structures. Hence, in this paper, estimation and minimization of blast-induced peak particle velocity (PPV) were conducted in two separate phases, namely prediction and optimization. In the prediction phase, an artificial neural network (ANN) model was developed to forecast PPV using as model inputs burden, spacing, distance from blast face, and charge per delay. The results of prediction phase showed that the ANN model, with coefficient of determinations of 0.938 and 0.977 for training and testing stages, respectively, can provide a high level of accuracy. In the optimization phase, the developed ANN model was used as an objective function of firefly algorithm (FA) in order to minimize the PPV. Many FA models were constructed to see the effects of FA parameters on the optimization results. Eventually, it was found that the FA-based optimization was able to decrease PPV to 17 mm/s (or 60% reduction). In addition, burden of 3.1 m, spacing of 3.9 m, and charge per delay of 247 kg were obtained as the values optimized by FA. The results confirmed that both developed techniques of ANN and FA are powerful, accurate, and applicable in estimating and minimizing blasting-induced ground vibration and they can be used with caution in similar fields.

KEY WORDS: Ground vibration, Optimization, Minimization, Artificial neural network, Firefly algorithm.

INTRODUCTION

Blasting is universally the most popular method for fragmenting in situ rock for excavation in mining and construction activities (Mehrdanesh et al. 2018). However, such operations typically release huge volumes of useless energy, which bring about some environmental effects such as air blast or air overpressure, flyrock, ground vibrations, back-break, and many others (Khandelwal and Singh 2006; Monjezi et al. 2011a, b; Armaghani et al. 2014, 2018; Han et al. 2020). Among all of environmental side effects of blasting, ground vibration is highlighted as one of the most serious (Monjezi et al. 2010; Hajihassani et al. 2015; Jahed Armaghani et al. 2015; Hasanipanah et al. 2015). Blasting-induced ground vibration has undesirable impacts not only on the integrity of structures but also on groundwater in the neighboring region (Singh and Singh 2005; Khan-

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delwal and Singh 2009). Therefore, it is of high significance to predict properly the magnitude of blast-induced ground vibrations in order to decrease as much as possible its environmental impact at the time of blasting or in the wake of such operation.

After detonation of explosive materials within a blast hole, the chemical reactions of explosives can lead to formation of high pressure gases. The gas pressure formed in the former step, which decays or dissipates rapidly, will crush rock mass around the blast hole (Armaghani et al. 2015a, b). Then, a wavy motion is generated in the ground by straining waves that are conveyed to neighboring rock masses (Duvall and Petkof 1958). According to Dowding and Hryciw (1986), the generated straining waves, which are elastic waves, spread to lower levels of the ground when their intensity decreases. The waves formed in this way are actually in the form of ground vibrations.

In general, two parameters affect blast-induced ground vibration significantly, namely peak particle velocity (PPV) and frequency. The literature shows that PPV can be used to measure ground vibration because it has been recognized as a key indicator that can be taken into account to control the criteria of structural damages (e.g., Khandelwal et al. 2011; Nateghi 2011). A few decades ago, numerous empirical predictors have been introduced for the prediction of blasting-generated PPV. However, according to the literature, such methods were not successful in doing the defined task (e.g., Hasanipanah et al. 2016, 2018) and this is due to their limited connections with the number of effective factors of PPV (i.e., distance from blast face, maximum charge per delay). Nevertheless, the PPV is influenced by other factors that can be grouped as controllable and non-controllable such as powder factor, spacing, and burden (Monjezi et al. 2016). In addition, multiple regression methods have been developed for PPV approximation (Hudaverdi 2012), although such methods have not been found to be highly reliable in cases where new available data differ from the original data (Mohamed 2011).

Recently, some soft computing and machine learning techniques have been proposed for accurate estimation of blasting-generated PPV (e.g., Zhou et al. 2016a, b; Nguyen et al. 2019a, b). The capability of such techniques to predict accurately issues related to engineering and sciences has been highlighted by many researchers (Shi et al. 2012; Zhou et al. 2016a, b, 2019a, b; Wang et al. 2018a, b; Chen et al. 2019a, b; Hajihassani et al. 2019; Huang et al.

2019; Koopialipoor et al. 2019; Sarir et al. 2019; Xu et al. 2019a, b; Yang et al. 2018a, b). By investigating 150 blasting events, Khandelwal and Singh (2006) attempted to predict PPV using an empirical method and a soft computing technique (i.e., artificial neural network or ANN). Their findings confirmed the superiority of ANN over the empirical method in terms of accuracy. An adaptive neuro-fuzzy inference system (ANFIS) was developed by Iphar et al. (2008) and Armaghani et al. (2015a, b) for prediction of PPV. Fisne et al. (2011) introduced a fuzzy inference system (FIS) to assess and estimate PPV for 33 blast-generated events in Akdaglar quarry (Turkey). Based on the blasting parameters investigated at the Bakhtiari Dam located in Iran, another soft computing method, i.e., support vector machine (SVM) was developed by Hasanipanah et al. (2015) for prediction of PPV. Many predictive techniques such as gene expression programming (GEP), imperialism competitive algorithm (ICA), ANN-based models, extreme gradient boosting machine (XGBoost), clustering ANN, regression tree, particle swarm optimization (PSO), hybrid ANFIS-based models, and hybrid support vector regression (SVR)-based models, have also been proposed and applied for PPV prediction (Shirani Faradonbeh et al. 2016; Hasanipanah et al. 2016; Shahnazar et al. 2017; Armaghani et al. 2018; Nguyen et al. 2019a, b; Zhang et al. 2019; Chen et al. 2019a, b). Table 1 summarizes some of the previous investigations from 2011 to 2019, with their developed models and respective input parameters for PPV prediction. From Table 1, it is apparent that new models with acceptable prediction accuracy still need to be investigated and developed for PPV estimation.

Therefore, the present study was conducted in two phases, namely prediction and optimization. In the prediction phase, an ANN model was constructed and introduced to predict blast-induced PPV. Then, in the second phase, the developed ANN technique was used as input to optimization to minimize blast-induced ground vibration using the firefly algorithm (FA), which is a powerful optimization technique.

BACKGROUND OF APPLIED METHODS

The following steps were for the prediction and minimization of blast-induced PPV with the help of ANN and FA (Fig. 1): (a) identify the input and output parameters; (b) predict blast-induced ground

Table 1. Some of the previous researches to predict ground vibration

Study	Predictive model	Input parameter
Monjezi et al. (2011a, b)	ANN	DI, HD, MC, ST
Ghasemi et al. (2013)	Fuzzy model	DI, S, B, MC, N ST
Hajihassani et al. (2014)	ICA–ANN	E, BS, MC, ST, DI, PF, Vp
Hajihassani et al. (2015)	PSO–ANN	RQD, BS, HD, MC, S_d, ST, DI, PF
Armaghani et al. (2015a, b)	ANFIS	DI, MC
Shirani Faradonbeh et al. (2016)	GEP	MC, HD, ST, B, D, S, PF, DI
Khandelwal et al. (2017)	Regression tree	DI, MC
Shahnazar et al. (2017)	PSO–ANFIS	DI, MC
Armaghani et al. (2018)	ICA	DI, MC
Zhang et al. (2019)	PSO–XGBoost	S, B, PF, MC, DI
Nguyen et al. (2019a, b)	ANN, clustering	S, B, PF, MC, DI
Chen et al. (2019a, b)	MFA–SVR	BS, MC, ST, E, Vp DI

E: Young's modulus, B: burden, S: spacing, MC: max charge per delay, ST: stemming, DI: distance from the blast face, HD: hole depth, D: hole diameter, PF: powder factor, BS: burden to spacing ratio, RQD: rock quality designation, N: number of row, S_d: sub-drilling, Vp: p-wave velocity, MFA: modified firefly algorithm
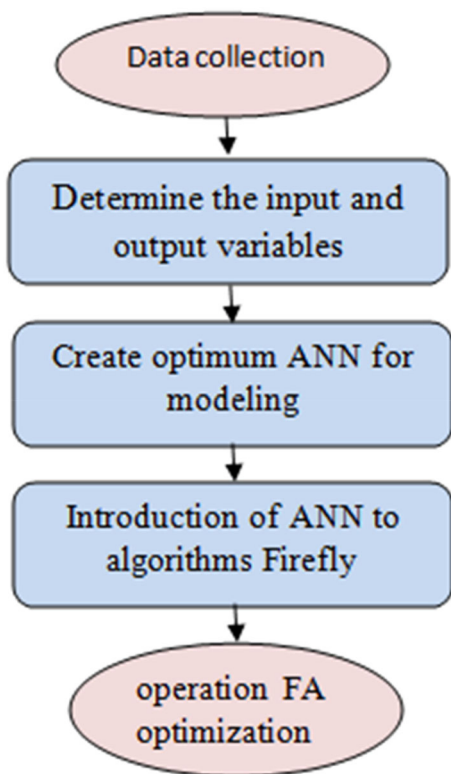

Figure 1. Different steps for estimating and minimizing blast-induced PPV.

vibrations by adopting an ANN-based technique; and (c) introduce the developed ANN model to FA model to minimize blast-induced ground vibrations. In the following subsections, detailed backgrounds of ANN and FA are given for better understanding of their modeling procedure.

Artificial Neural Networks

An ANN simulates the neural system of a human brain (Trippi and Turban 1992). It consists of a number of interconnected layers, each of which contains computational components (neurons). An ANN is able to solve nonlinear problems. Its power is largely highlighted when they are applied to tasks such as feature selection and function approximation (Simpson 1990; Kosko 1992). When an ANN is to be applied, the initial step is defined as systemic training, which needs a database with model inputs and outputs. In the modeling procedure of multilayer perception (MLP), a number of tactics need to be taken into account; in contrast, the back-propagation algorithm enjoys more advantages compared to other approaches already proposed in the literature (Momeni et al. 2015). The MLP networks consist of at least the following three parts: input layers, hidden layers, and output layers. The nature of a given problem determines how many neurons should exist within the hidden layer. In the training process, a certain weight is initially allocated to each connection between the nodes that exist within each layer. To evaluate the efficiency level of the network, the connection weight needs modifications. Figure 2 shows a general model of an ANN wherein x signifies input, w denotes weight, $\sum$ represents summation, and f stands for activation function. The neuron (also named unit, cell, or node) is a processing ele-
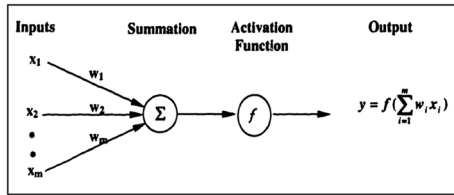
Figure 2. A simple model of a neuron (Mehrotra et al. 1997).

ment that takes several inputs, weights them, and then sums them up.

Firefly Algorithm Structure

Among the most effective types of algorithms applied to optimization problems, the nature-inspired ones (e.g., firefly algorithm, FA) play a significant role in this field. FA has been designed based on the social behaviors of fireflies in nature. Most of these captivating insects generate short and recurring flashes. Factors such as rhythm, rate, and amount of time of flashes affect the process of attracting both sexes to each other. Therefore, the flashing behavior of a firefly is actually a signal system for attracting other fireflies flying in the neighboring area.

FA was proposed by Yang (2010) based on a light intensity physical formula that drops when the square of the distance rises. This phenomenon can be in relation with the objective function that should be optimized. Typically, three rules make the fundamental base of FA. (1) All fireflies are unisex; as a result, regardless of sex, they will be attracted to each other. (2) Intensity of light generated affects attractiveness, and attractiveness reduces when the insects get more distant. (3) A firefly's light intensity is determined by fitness function.

To design a FA properly, there is a need to define two significant items: attractiveness formulation and variation of light intensity. Designers can use these two items when adapting various FAs in order to satisfy the requirements of the problem in hand. In a standard FA, a firefly's light intensity (I), which represents the solutions, is proportional to the values of fitness function $I(s)$ and $F(s)$, while the

light intensity $I(r)$ is changed based on the following equation (Yang 2010):

$$I = I_0 e^{-\gamma r} \tag{1}$$

where I_0 stands for the source's light intensity, and the fixed light absorption coefficient γ is applied to the estimation of the light absorption. At $r = 0$, the singularity in the expression I/r^2 is evaded through the integration of the impacts of the inverse square law. The fireflies' attractiveness (β) is proportional to $I(r)$. Therefore, analogous to Eq. 1; β is expressed as:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{2}$$

where β_0 stands for attractiveness at $r = 0$. Based on the base FA, the distance between X_i and X_j is indicated as Euclidean distance; thus:

$$r_{ij} = X_i - X_j = \sqrt{\sum_{k=1}^{n} (X_{i,k} - X_{j,k})^2} \tag{3}$$

where n signifies the problem dimensionality. The ith firefly's movement attracts another more attractive firefly j. This can be expressed as:

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2}(x_i - x_j) + \alpha \varepsilon_i \tag{4}$$

where ε_i stands for a random number taken from the Gaussian distribution. The movement of a firefly consists of three different items: the ith firefly's current position, attraction to another firefly with higher attractiveness, and a random walk that includes α as an index for randomization. If $\beta_0 = 0$, then, the movement only affects the random walk. In addition, parameter γ significantly affects the speed of convergence process. In general, it varies between 0.1 and 10. In brief, three parameters control FA, namely attractiveness (β), randomization parameter (α), and absorption coefficient (γ). FA has two distinguished usage performances; the first one appears in the case $\gamma - 0$ and the latter in the case $\gamma - \infty$; when $\gamma - 0$, then $\beta = \beta_0$.

Note that throughout the search space, attractiveness is fixed. Such behavior is a certain instance of PSO. When $\gamma - \infty$, then the second term is detached from Eq. 4, and the movement of a firefly will be a random walk indicating a version of stimulated annealing. Indeed, each utilization of FA may take

place between its two usage performances (Fister et al. 2013).

FIELD STUDY AND DATA SOURCE

In this study, we selected the Hozak limestone mine, which is located along the Karaj-Qazvin highway, Alborz state, Iran. The mine area is a part of the Central Alborz Range. The largest and most important residential and industrial areas around the mine include Abyek city and Abyek and Siporex cement factories. The Hozak limestone belongs to the Lar Formation. The oldest sediments in the area are Paleozoic in age. They include the Soltanieh dolomite, the Chile Formation, the Ziggon Sandstone Formation, the quartzite–sandstone of the Dorood Formation, and the Rime Gray Lime Formation. The Paleozoic sediments are overlain by the Elika Formation (dolomite and limestone), followed by the Shemshak Formation (gray-brown to mudstone and siltstone with charcoal sandstones). These formations underlie the area's coal mines, including Hugh and Esquite. A field view of the Hozak limestone mine is presented in Figure 3.

In order to prepare and establish a database, the results of a blasting operation in the Hozak limestone mine were used. To do that, 154 blasts were evaluated and their PPV results, which were recorded by a Vibraloc ABEM seismograph, were considered. Several blasting design factors such as burden (B), spacing (S), charge per delay (CPD), and distance from blast face (DI) were also determined before the blasting. It should be noted that the operations were conducted with the use of blast holes with 76 mm diameter. The main explosive applied to these operations was the ammonium-nitrate fuel oil (ANFO).

All 154 datasets were evaluated in order to remove outlier data, and eventually, three datasets were removed. Hence, the modeling procedure of this study was applied using 151 datasets with B, S, DI, and CPD as model inputs and PPV as model output. The range, mean, and standard deviation of these variables are shown in Table 2. In addition, the

Figure 3. The Hozak mine long view.

Table 2. Input and output variables and their relevant statistical information

Parameter	Group	Unit	Symbol	Min	Max	Mean	SD
Burden (B)	Input	m	B	2.5	3.8	3.094	0.335
Spacing (S)	Input	m	S	3.5	5.3	4.324	0.438
Distance from the blast face (DI)	Input	m	DI	256	1650	809.848	345.134
Charge per delay (CPD)	Input	kg	CPD	225	3745	2007.013	895.114
Peak particle velocity (PPV)	Output	mm/s	PPV	13	97	42.411	20.812

Electronic Supplementary Material provides box plots of the input and output data.

MODELING AND OPTIMIZATION OF GROUND VIBRATION

ANN Modeling

After the required data were gathered and the input/output parameters determined, a number of models were built using ANN to predict PPV. To estimate accurately the blast-induced ground vibrations, different ANN predictive models were built with various structures. The established database was separated into two parts. Specifically, 80% of the dataset was dedicated to training, while the remaining 20% was allocated to testing. In nonlinear predictive applications, results of higher quality can be obtained using only one hidden layer when computing the validation criteria. Eventually, an ANN model with 1-hidden layer and 23 neurons demonstrated the best results. In addition, among all available transfer functions, the exponential and logistic functions returned the best outcomes for prediction of PPV. Figure 4 shows the suggested ANN structure to estimate blast-induced ground vibration.

For the ANN model developed in this study, the coefficient of determination (R^2) of the testing and training results was 0.977 and 0.9384, respectively. Figures 5 and 6 present the measured values and predicted PPVs, respectively, for the training and testing stages. These figures show clearly that the predicted PPVs are very close to the measured ones. This confirms the capability of ANN in predicting blast-induced PPV.

The precision of a model is examined by taking into consideration it outputs with respect to the measured values. In this study, to evaluate the precision of the ANN model, five indices, namely root mean square error (RMSE), mean absolute error (MAE), R^2, variance accounted for (VAF), and $a20$ were considered and calculated. The literature reported successful and efficient uses of these indices for evaluation purposes (Armaghani et al. 2017; Koopialipoor et al. 2018; Tonnizam Mohamad et al. 2018; Asteris et al. 2019; Asteris and Nikoo 2019). Equations 5–9 present the formulas of the mentioned indices.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y - y')^2}{\sum_{i=1}^{N}(y - \tilde{y})^2} \tag{5}$$

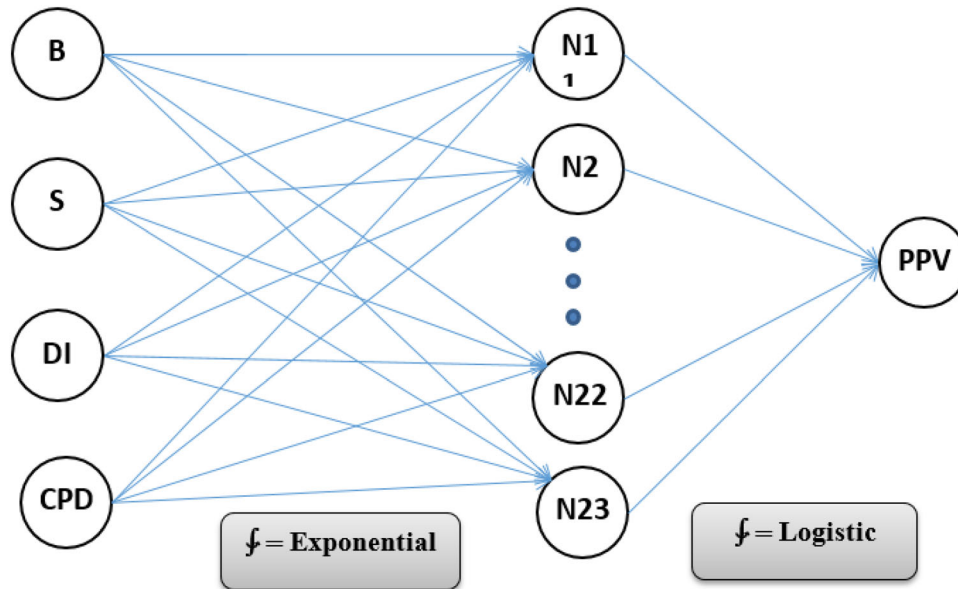$$VAF = \left[1 - \frac{VAR(y - y')}{VAR(y)}\right] \times 100 \tag{6}$$

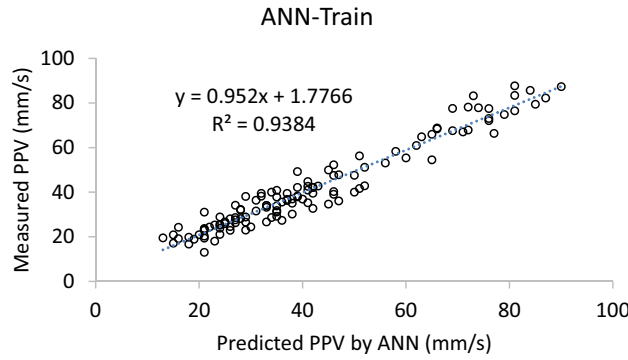**Figure 4.** The suggested ANN structure.

Figure 5. Actual and predicted blast-induced ground vibration (training set).
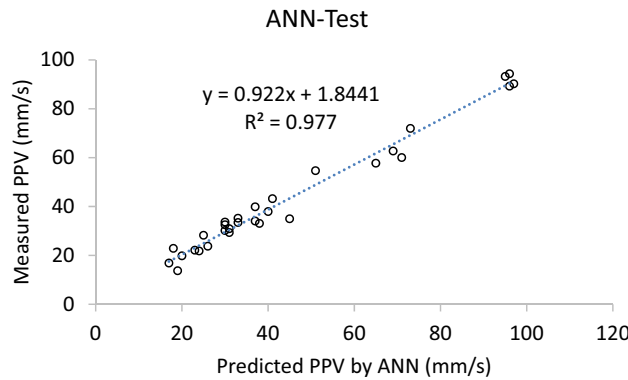

Figure 6. Actual and predicted blast-induced ground vibration (testing set).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y - y')^2} \qquad (7)$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y' - y| \qquad (8)$$

$$a20 = \frac{m20}{N} \qquad (9)$$

where y, y' and $\tilde{y}$ are the measured, predicted and mean values, respectively, N is the total number of dataset, and $m20$ is obtained by dividing measured PPVs by predicted PPVs. The prediction performance results for the training and testing stages of the developed ANN model are presented in Table 3. The obtained R^2, VAF, RMSE, MAE, and $a20$ were 0.9384, 93.82%, 4.483, 0.231, and 0.9 for the training

Table 3. Performance prediction results for train and test stages of ANN model

Stage	Performance Index				
	R^2	RMSE	VAF (%)	MAE	A20-index
Train	0.9384	4.843	93.82	0.231	0.9
Test	0.977	4.38	97.391	1.644	0.83

stage and 0.977, 97.391%, 4.38, 1.644, and 0.83 for the test stage. These reveal that the ANN model is a powerful and applicable model for PPV prediction.

After the ANN modeling, a necessary step is to apply sensitivity analysis and to investigate the ef-
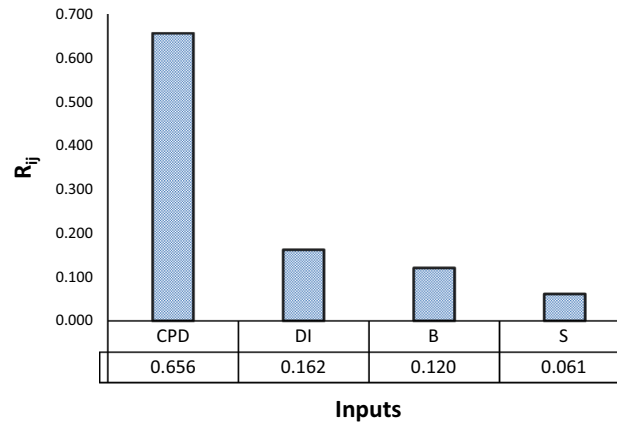
Figure 7. Results of PPV sensitivity analysis.

fects of the input variables on blast-induced PPV. To this end, the cosine amplitude method was used; thus:

$$r_{ij} = \frac{\sum_{k=1}^{m} X_{ik} X_{jk}}{\sqrt{\sum_{k=1}^{m} X_{ik}^2 \sum_{k=1}^{m} X_{jk}^2}}. \qquad (10)$$

The value of r_{ij} ranges between 0 and 1. Values closer to 1 indicate higher effect on the output. The sensitivity analysis results (Fig. 7) show that the CPD, with r_{ji} value of 0.656, is the most effective input predictor of PPV, while S, with r_{ji} value of 0.061, has the least impact on PPV.

Optimization by FA

The FA can be used determine the blasting pattern parameters through optimization. Different FA-based models were created with the use of various modifiable parameters. Figure 8 depicts the optimization process conducted using FA to optimize blasting parameters. Following the accomplishment of several analyses, the most suitable FA variables were achieved and are recorded in Table 4. FA requires an objective function, which in this study is the developed ANN model obtained from the previous section. In fact, the ANN model has the task of simulating the objective function. Eventually, the optimal pattern parameters (the improved version compared to the initial pattern) in order to reduce blast-induced ground vibration were obtained by FA as shown in Table 5. In addition, the differ-

ence percentages of the parameters compared to their mean values were calculated (Table 5); thus, blast-induced ground vibration was reduced by 60% if there are 1% increment of burden, 10% reduction of spacing, 88% reduction of charge per delay. All the differences percentages were calculated based on mean values in the original database. As can be seen in Table 5, CPD is the most effective parameter for reducing PPV as the system output. It should be mentioned that CPD is also found to be one of the most effective parameters in previously developed empirical and computational models (Armaghani et al. 2014, 2015a, b; Ghoraba et al. 2016; Monjezi et al. 2016; Shahnazar et al. 2017). This parameter has also been determined as the most effective inputs in the sensitivity analysis discussed in the previous section. The results of optimization confirmed that FA is a powerful technique that is able to minimize blast-induced ground vibration up to 60% in this study. In fact, this technique, due to its powerful, can be used in other optimization problems in other engineering fields.

CONCLUSIONS

In the present paper, for the purpose of alleviating blast-induced ground vibrations, first, required data were collected and the input variables, i.e., spacing, burden, charge per delay, distance from blast face were prepared. As the system output, PPV was specified. After that, several parametric analyses were done with the use of ANN for estimation of PPV. The MAE, RMSE,
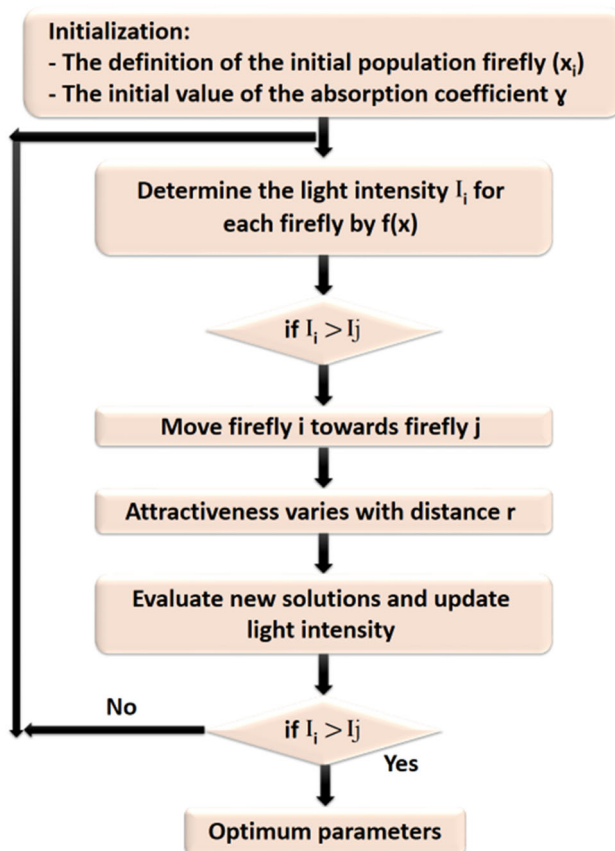
Figure 8. The optimization process using FA to optimize blasting parameters.

Table 4. Controllable FA parameters used for optimization

Parameter	Symbol	Value
Maximum number of repetitions	MaxIt	400
Number of fireflies	npop	151
Light absorption coefficient	γ	1
Randomization parameter	α	0.2
Space width	δ	0.05
Amount attractiveness of $r = 0$	β	0.7

and VAF of the obtained ANN model were 0.231, 4.483, and 93.82%, respectively, for the training set and 1.644, 4.38, and 97.391%, respectively, for the testing set. These results reveal that the ANN is a powerful, accurate, and applicable approach for estimating PPV. In the optimization phase, FA was used to minimize PPV where the developed ANN model was considered as the objective function. Various effective parameters of FA were identified and utilized in the optimization. The results of FA showed that it was able to minimize PPV to 60% compared to its mean value. This can be achieved when burden is 3.1 m (1% increment), spacing is 3.9 m (10% reduction), and charge per delay is 247 kg (88% reduction). The results of this study indicated that ANN and FA are usable for similar conditions and for the same model inputs and their ranges.

Table 5. Optimal pattern parameters obtained by FA to reduce ground vibration

Parameter	Original mean value	Obtained by FA	Difference (%)
B (m)	3.09	3.1	1, increment
S (m)	4.32	3.9	10, reduction
CPD (kg)	2007	247	88, reduction
PPV	42.41	17	60, reduction

ELECTRONIC SUPPLEMENTARY MATERIAL

The online version of this article (https://doi.or g/10.1007/s11053-020-09697-1) contains supplementary material, which is available to authorized users.

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