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ORIGINAL PAPER

Prediction of ground vibration due to quarry blasting based on gene expression programming: a new model for peak particle velocity prediction

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Abstract Blasting is a widely used technique for rock fragmentation in opencast mines and tunneling projects. Ground vibration is one of the most environmental effects produced by blasting operation. Therefore, the proper prediction of blast-induced ground vibrations is essential to identify safety area of blasting. This paper presents a predictive model based on gene expression programming (GEP) for estimating ground vibration produced by blasting operations conducted in a granite quarry, Malaysia. To achieve this aim, a total number of 102 blasting operations were investigated and relevant blasting parameters were measured. Furthermore, the most influential parameters on ground vibration, i.e., burden-to-spacing ratio, hole depth, stemming, powder factor, maximum charge per delay, and the distance from the blast face were considered and utilized to construct the GEP model. In order to show the capability of GEP model in estimating ground vibration, nonlinear multiple regression (NLMR) technique was also performed using the same datasets. The results demonstrated that the proposed model is able to predict blast-induced ground vibration more accurately than other developed technique. Coefficient of determination values of 0.914 and 0.874 for training and testing datasets of GEP model, respectively show superiority of this model in predicting ground vibration, while these values were obtained as 0.829 and 0.790 for NLMR model.

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Introduction

The rock excavation is one of the most important works in the surface mines. For this purpose, blasting operation is the most common and economical technique among available techniques. Nevertheless, in the blasting operations, a large amount of explosive energy is wasted to create environmental impacts like flyrock, ground vibration, air overpressure, and back break which can affect surrounding area (Khandelwal and Singh 2006, 2007; Khandelwal and Kankar 2011; Ebrahimi et al. 2015). Among these environmental issues, ground vibration is recognized as an undesirable phenomenon which may lead to damage to surrounding structures, adjacent rock masses, roads, underground workings, slopes, railroads, the existing ground water conduits, and the ecology of the nearby area (Singh and Singh 2005; Toraño et al. 2006; Ozer et al. 2008; Verma and Singh 2011; Faramarzi et al. 2014; Dindarloo 2015a). Hence, proper estimation of ground vibration may minimize/reduce the blasting environmental problems.

Chemical reaction of explosive may create high-pressure gas, when explosive material is detonated in a blast hole.

Then, the created gas pressure crushes the surrounding rock mass to the blast hole. The detonation pressure decays or dissipates quickly. After that, in the ground, a wave motion is produced by the strain waves conveyed to the adjacent rocks (Duvall and Petkof 1959). The strain waves are propagated as the elastic wave when the stress wave intensity reduces to the ground level (Dowding 1985). These waves are known as ground vibration.

Normally, ground vibration can be recorded based on two factors, i.e., frequency and peak particle velocity (PPV). According to many researchers (Bureau of Indian Standard 1973; Kahriman 2002; Singh 2004; Singh and Singh 2005; Sawmliana et al. 2007), PPV is set as an index for measuring ground vibrations as it is an important indicator for controlling the structural damage criteria. During a few past decades, in order to predict PPV produced by blasting, many vibration predictors have been proposed empirically (e.g., Duvall and Petkof 1959; Langefors and Kihlstrom 1963; Davies et al. 1964; Ambraseys and Hendron 1968; Roy 1993). In the mentioned predictors, PPV values are obtained from two factors, i.e., maximum charge per delay and distance from the blast face. Nevertheless, as a result, these empirical approaches are not good enough, whereas high degree of PPV estimation is required to determine blast safety area. This is maybe due to incorporation of only limited numbers of influential parameters on PPV (maximum charge per delay and distance from the blast face) in these predictors, whereas it is also influenced by other controllable or non-controllable parameters like burden, spacing, stemming, and powder factor (Singh and Singh 2005; Khandelwal and Singh 2007). Apart from empirical predictors, statistical techniques have been widely utilized for PPV prediction (e.g. Verma and Singh 2011, 2013a; Hudaverdi 2012). In these techniques, some other input parameters related to blasting design, rock mass properties, and explosive material were utilized for ground vibration prediction (e.g., Singh and Singh 2005; Khandelwal and Singh 2009; Hajihassani et al. 2015b; Dindarloo 2015a). However, the implementation of statistical techniques is not reliable if new available data are different from the original ones (Khandelwal and Singh 2009; Mohamed 2011; Verma and Maheshwar 2014).

During the recent years, soft computing techniques have also been extensively applied and developed to predict ground vibration caused by blasting. Many scholars highlight the successful use of these techniques in the field of ground vibration prediction. Khandelwal and Singh (2006) examined empirical predictors and artificial neural network (ANN) model to predict PPV and frequency values obtained from 150 blasting events and concluded that ANN results are more accurate compared to empirical predictors. In another study of ground vibration prediction, Monjezi et al. (2011) developed ANN, empirical and statistical models for blasting operations conducted in Siahbisheh pumped storage dam, Iran. They used a database comprising of 182 datasets in order to predict PPV and concluded that ANN can implement better in predicting PPV compared to other proposed models. Iphar et al. (2008) and Jahed Armaghani et al. (2015) developed the adaptive neuro-fuzzy inference system (ANFIS) for estimating PPV induced by blasting. A fuzzy inference system (FIS) model was proposed by Fisne et al. (2011) for evaluation and prediction of 33 PPV values obtained from the Akdaglar quarry, Turkey. Another fuzzy model was employed and suggested for indirect determination of PPV using 6 different controllable input parameters in the study carried out by Ghasemi et al. (2013). They highlighted the high-performance prediction of the fuzzy model in estimating PPV. Mohamed (2011) proposed both ANN and FIS models for estimating PPV and reported that FIS approach can provide slightly higher performance capacity in approximating PPV. Based on obtained blasting parameters from Bakhtiari Dam, Iran, Hasanipanah et al. (2015) utilized and introduced a support vector machine (SVM) model to estimate PPV. Dindarloo (2015b) developed a SVM model for estimating 100 PPV values collected from Golegohar iron ore mine, Iran. They used 12 model inputs of both controllable and non-controllable parameters in order to predict PPV and found that the developed model is a versatile tool for predicting PPV. Two hybrid intelligent techniques namely particle swarm optimization (PSO)-ANN and imperialism competitive algorithm (ICA)-ANN were developed in the studies carried out by Hajihassani et al. (2015a, b), respectively. A summary of previous investigations in the field of PPV prediction and their prediction performances are shown in Table 1.

Gene expression programming (GEP) which is the developed version of genetic programming (GP) and genetic algorithm (GA), has been used to solve engineering problems (e.g. Teodorescu and Sherwood 2008; Alkroosh and Nikraz 2011; Mollahasani et al. 2011; Ozbek et al. 2013). GEP is a new algorithm which can introduce relationships between input parameters to estimate output. Utilization of the GEP algorithm in the field of rock mechanics and mining engineering has only been limited into a few studies. For instance, Baykasoglu et al. (2008) and Çanakcı et al. (2009) proposed new models based on GEP for solving problems related to compressive and tensile strength of the rock with high degree of accuracy. Ozbek et al. (2013) and Dindarloo and Siami-Irdemoosa (2015) developed GEP models for prediction of the uniaxial compressive strength (UCS) of the rock samples. Their study represented a good agreement between the measured UCS and predicted by GEP model. Ahangari et al. (2015) proposed two models, i.e., GEP and ANFIS to estimate settlement induced by tunneling and indicated the

Table 1 Summary of previous investigations in the field of PPV prediction

Reference	Technique	Input	No. of dataset	R^2
Iphar et al. (2008)	ANFIS	DI, MC	44	0.98
Monjezi et al. (2011)	ANN	HD, ST, DI, MC	182	0.95
Khandelwal et al. (2011)	ANN	DI, MC	130	0.92
Mohamed (2011)	ANN, FIS	DI, MC	162	ANN = 0.94 FIS = 0.90
Fisne et al. (2011)	FIS	DI, MC	33	0.92
Li et al. (2012)	SVM	DI, MC	32	0.89
Mohamadnejad et al. (2012)	SVM, ANN	DI, MC	37	SVM = 0.89 ANN = 0.85
Ghasemi et al. (2013)	FIS	B, S, ST, N, MC, DI	120	0.95
Monjezi et al. (2013)	ANN	MC, DI. TC	20	0.93
Jahed Armaghani et al. (2014)	PSO-ANN	S, B, ST, PF, MC, D, N, RD, SD	44	0.94
Hajihassani et al. (2015b)	ICA-ANN	BS, ST, PF, MC, DI, Vp, E	95	0.98
Hasanipanah et al. (2015)	SVM	DI, MC	80	0.96
Dindarloo (2015b)	SVM	RD, E, UCS, TS, Js, B, S, HD/B, SC, ST, DPR, DI	100	0.99
Hajihassani et al. (2015a)	PSO-ANN	BS, MC, HD, ST, SD, DI, PF, RQD	88	0.89
Jahed Armaghani et al. (2015)	ANFIS	DI, MC	109	0.97

Burden (B); Spacing (S); hole length (HL); stemming (ST); powder factor (PF); blastability index (B); support vector machine (SVM); maximum charge per delay (MC); rock density (RD); hole diameter (D); hole depth (HD); burden to spacing (BS); number of row (N); particle swarm optimization (PSO); subdrilling (SD); distance from the blast face (DI); total charge (TC); rock quality designation (RQD); Young's modulus (E); imperialist competitive algorithm (ICA); p-wave velocity (Vp); adaptive neuro-fuzzy inference system (ANFIS); fuzzy inference system (FIS); coefficient of determination (R^2); uniaxial compression strength (UCS); tensile strength (TS); joint spacing (Js); hole depth-to-burden ratio (HD/B); specific charge (SC); delay per row (DPR)

superiority of their developed GEP model compared to ANFIS predictive model in settlement prediction. More specifically, in the field of ground vibration prediction, a GEP technique was employed and proposed for prediction of the frequency of the adjacent ground vibrations in the study conducted by Dindarloo (2015a).

As far as the authors know, there is no study developing GEP technique for predicting PPV induced by blasting. Therefore, in the present study, a model based on the mentioned model is proposed to estimate PPV values obtained from a granite quarry in Penang, Malaysia. To show the ability of GEP model in predicting PPV, nonlinear multiple regression (NLMR) analysis was also performed.

Materials and methods

Gene expression programming

Gene expression programming (GEP) is a data-driven method that firstly introduced by Ferreira (2001). Unlike GP and GA techniques that have been widely applied in the field of rock mechanics and mining engineering (Baykasoglu et al. 2008; Ozbek et al. 2013; Güllü 2012; Ahangari et al. 2015; Dindarloo 2015a), GEP is not yet a well-established technique in the mentioned fields. GEP is the developed version of GP and GA and can surmount their shortcomings such as difficulties of applying genetic operators on trees (Ferreira 2001; Baykasoglu et al. 2008; Teodorescu and Sherwood 2008). The main difference between these three algorithms is related to the nature of the individuals or solutions. In GA, the individuals are expressed as binary (0 and 1) strings with the fixed length which are called chromosomes. While, in GP, the solutions are computer programs (CPs) that follow the Lost of Irritating Superfluous Parentheses (LISP) language and are able to express as parse trees with different sizes and shapes. The structure of individuals in GEP is somehow a combination of two previous algorithms. In GEP, similar to GA, individuals are considered as linear chromosomes with the fixed length and similar to GP, they can be shown in tree structure with different sizes and shapes called expression tree (ET) (Ferreira 2001; Zhou et al. 2003; Kayadelen 2011; Güllü 2012; Dindarloo 2015a). GEP algorithm consists of five main components namely terminal set, function set, fitness function, operator(s), and stop condition. The fundamental steps of GEP algorithm are shown in Fig. 1. The process of GEP modeling can be summarized as follows:

- Step 1 Certain number of chromosomes is generated randomly based on the number of population
- Step 2 The chromosomes of initial population are expressed as ET and mathematical equations

Step 3 The fitness of each chromosome is evaluated according to the fitness function, and if the stopping conditions are not reached, the best of first generation is selected based on roulette wheel method

Step 4 In the fourth step, the genetic operators (core of GEP algorithm) are applied to the remaining chromosomes in order to create modified individuals. These operators are described later

Step 5 After applying genetic operators on the chromosomes, they create the next generation and this process is repeated for a specified number of generations

A linear chromosome in GEP is created using terminals and functions. Depending on the problem to be solved, terminals or input parameters may be consisted of numerical constants. In GEP, some simple mathematical operators (e.g., +, −, ×, and ÷), nonlinear functions (e.g., sin, cos, tan, arctan, and sqrt), logical and Boolean operators are selected as function set(s).

Chromosomes in GEP include a series of linear symbolic strings with fixed length that are composed of one or two genes. Each gene includes a head and tail. The head contains symbols that represent both functions and terminals, whereas the tail is composed of only terminals. The length of the head (h-head size) is an input parameter of the algorithm and according to the nature of the problem, its complexity can be determined. There is no a definite way for determining value of the head size, so head size should be obtained through trial-and-error method according to suggestions of previous GEP studies (e.g., Ferreira 2006; Baykasoglu et al. 2008; Teodorescu and Sherwood 2008; Alavi and Gandomi 2011; Dindarloo 2015a). The tail length (t) which is a function of h and the number of arguments of the function ($n$max), is expressed as follows (Ferreira 2001; Teodorescu and Sherwood 2008; Güllü 2012):

$$t = h(n_{\max} - 1) + 1 \quad (1)$$

The sum of h and t is equal to the chromosome length. Karva is a new language that was developed to read and express the information encoded in the chromosomes (K-Expression) (see Fig. 2a). Karva language is created using functions, terminals, and constants that are placed in a linear string. The numbers at the top of the terminals or functions are their position in the chromosome. Each gene on a chromosome is decoded in the form of sub-ET, and finally, these sub-ETs create a more complex version of ET (multi sub-ET). Expression of the gene as a sub-ET is simple and straightforward. To correctly express of the gene, there are four rules that are presented in the studies conducted by Ferreira (2001, 2006):

- The root node of ET must contain a function which is located in the first position (position No. 0) of chromosome.
- Each function has an argument number but, the argument number of terminals is zero. For example, the functions of +, −, *, / have two arguments while Q is composed only one argument. According to the number of argument of function, each node split to sub-nodes.
- Terminals and functions according to their positions in the chromosome are listed from top to down and left to right in each line.
- This process continues until a line containing terminal is formed.

As an example, Fig. 2a shows the three-genic chromosome with length 45 ($h = 7$, $t = 8$) that each of the gene can be expressed to a sub-ET (see Fig. 2b), and eventually the equations related to each sub-ETs can be extracted by reading from left to right and bottom to top (see Fig. 2c). When the sub-ETs are in the form of algebraic or Boolean expression, any algebraic or Boolean functions (with more than one argument) can be used to link the sub-ETs in order to obtain multi-subunit ET. Note that, the most widely used functions for algebraic sub-ETs are addition or multiplication, while they are OR and IF for Boolean sub-ETs. A

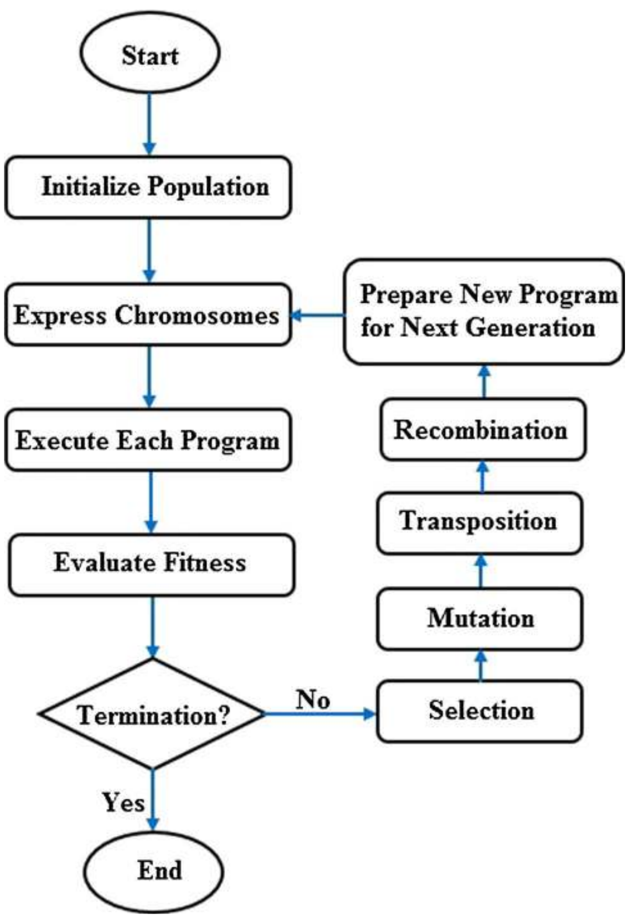


Fig. 1 Flowchart of GEP algorithm

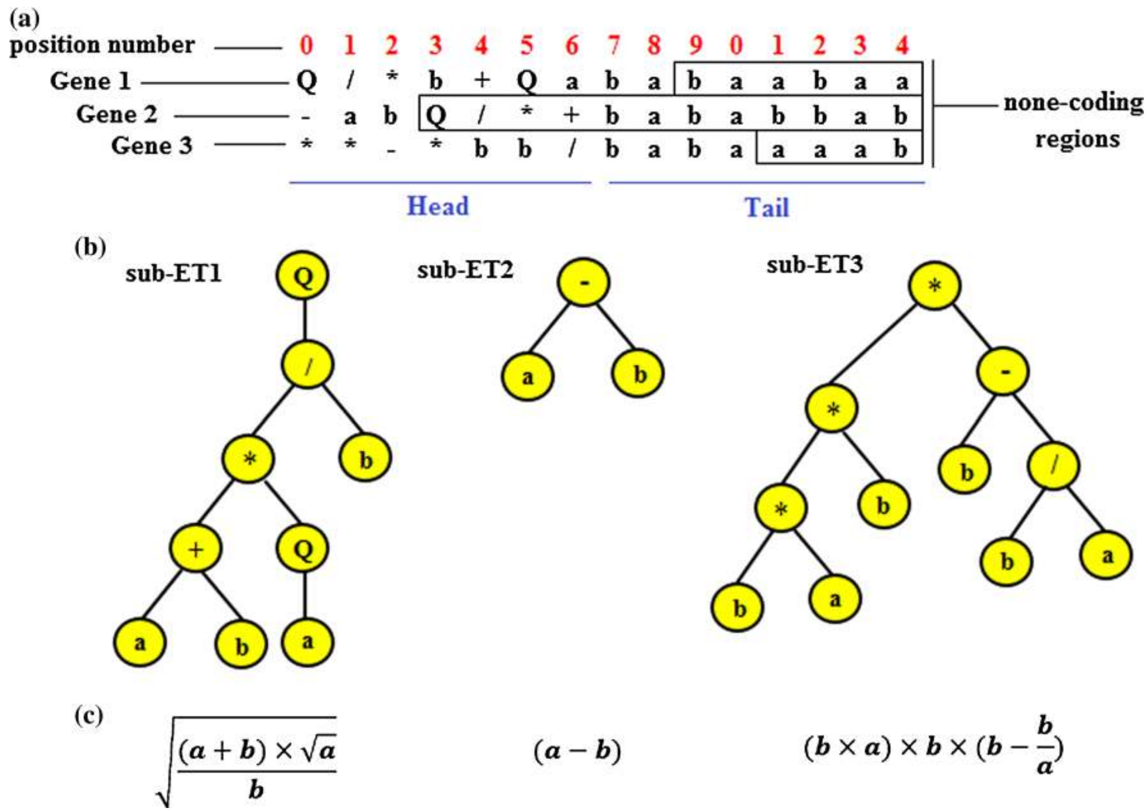


Fig. 2 Different expressions of three-genic chromosome, **a** K-Expression, **b** expression tree, **c** mathematical equations

part of the chromosome that can be expressed in an ET is named as open reading frame (ORF) (Yang et al. 2013).

Genetic operators

Genetic operators have an important role in all of the genetic algorithms and creation of the next generation. Changes in the rate of genetic operators led to a fundamental change in the structure of the algorithm. So, the appointment of them is very important in the GEP design. In the following sections, some explanations about genetic operators including mutation, inversion, transposition, and recombination and their implementations are described.

Mutation

Mutation can occur anywhere in the chromosome, but the structure of the chromosomes should be saved. In the heads, a mutation can replace any symbol with another function or terminal, but in the tails this replacement causes the terminal change with another terminal. Mutation has a rate that is the division of a number of mutations into the chromosome length (Güllü 2012). It is suggested that the mutation rate should be usually used in the range of 0.01–0.1 (Ferreira 2002; Teodorescu and Sherwood 2008; Kayadelen 2011).

Inversion

Inversion operator reverses a small segment (1–3 positions) only in the head of chromosomes and may be used with low probability. Ferreira (2001) and Brownlee (2011) suggested an inversion rate of 0.1 for this operator.

Transposition

This operator selects a fragment of the chromosome (insertion sequence) that can be jump to another position in the chromosome. There is three types of transposition operators: (1) a fragment with a function or terminal in the first position duplicate into the head (IS transposition), (2) short fragment with the function in the first position duplicate and move to the first position of the chromosome (RIS transposition), and (3) randomly selected genes are transposed to the beginning point of the chromosome (gene transposition). All types of these operators have a rate that is varied between 0.1 and 1 (Ferreira 2001; Baykasoglu et al. 2008; Yang et al. 2013).

Recombination

Similar to transposition operator, there are three kinds of recombination (also called crossover) in GEP algorithm. In all of them, two chromosomes are selected randomly.

These three recombination operators include one-point recombination, two-point recombination, and gene transposition. Ferreira (2001, 2006) recommended the value of 0.7 for sum of these three operators. More information regarding these operators can be found in the studies conducted by Ferreira (2001, 2006) and Brownlee (2011).

Case study and input selection

In order to develop predictive models for indirect measure of PPV, a granite quarry in Penang state, Malaysia, was selected and subsequently its blasting operations were investigated. Pulau Pinang coated by two main granite pluton, i.e., Pluton Penang north and south. Pluton is divided into three main units which are recognized as granite Tanjung Bunga, granite Feringgi, and mikrogranit on the top. While south Penang Pluton consists of muscovite–biotite granite that contains more mikrolin, especially in the south of the island. Generally, main rock type observed in the studied site is granite. The thickness of the top soil is usually less than three feet, and it is more sandy clay with humus and tree roots. A view of studied quarry is shown in Fig. 3.

The purpose of blasting in this site is to produce aggregates for various construction works with capacity range of 500,000–700,000 tons per year. In this quarry, depending on the weather condition, 2 or 3 blasting operations were conducted per week. ANFO and dynamite were used as the main explosive material and initiation, respectively. Blasting operations were conducted using blast hole diameters of 76 and 89 mm. In addition, minimum and maximum numbers of blast holes were 18 and 84, respectively. Moreover, values of 865.6 and 9420.5 kg were designed for minimum and maximum of total explosive weights in these blasting operations. In these events, some of the controllable blasting parameters, e.g., burden, spacing, stemming length, hole diameter, hole depth, total charge, number of hole, maximum charge per delay, powder factor, sub-drilling, and distance from the blast face were measured. Additionally, PPV vales were monitored using Vibra ZEB seismograph having transducers for PPV measurement. Note that, measured distances between the blast face and monitoring point were ranging from 285 to 531 m. These distances were selected because of a distance of about 400 m between the studied quarry site and surrounding residential area. In total, 102 blasting operations and their pattern parameters were identified in this study.

As mentioned earlier, according to many scholars (Duvall and Petkof 1959; Langefors and Kihlstrom 1963; Roy 1993; Singh et al. 2008; Monjezi et al. 2012), maximum charge per delay (MC) and distance from the blast face (DI) are the most effective factors on PPV. In addition, burden, spacing, and burden-to-spacing ratio have been extensively utilized for predicting PPV by some researchers (Ghasemi et al. 2013; Jahed Armaghani et al. 2014; Ghoraba et al. 2015; Hajihassani et al. 2015a, b) in their predictive models. Apart from that, powder factor, stemming, and hole depth were set as input parameters in various studies (Monjezi et al. 2011; Jahed Armaghani et al. 2014; Hajihassani et al. 2015a). Hence, in this research, burden-to-spacing ratio, stemming length, powder factor, the maximum charge per delay, hole depth, and distance from the blast face were selected and set as input parameters to predict PPV. A summary of input and output data utilized in the modelling analysis of this study is shown in Table 2.

Results and discussion

This section presents modelling procedures of the developed models to predict PPV values produced by quarry blasting operations. As mentioned before, BS, HD, ST, PF,

Fig. 3 View of the studied quarry

Table 2 Summary of the data used in the modelling and their categories

Parameter	Unit	Symbol	Category	Min	Max	Mean
Burden-to-spacing ratio	–	BS	Input	0.70	0.92	0.82
Hole depth	m	HD	Input	5.2	23.2	14.1
Stemming length	m	ST	Input	1.9	3.6	2.63
Powder factor	kg/m^3	PF	Input	0.23	0.94	0.65
Maximum charge per delay	kg	MC	Input	45.8	305.6	179.6
Distance from the blast face	m	DI	Input	285	531	379.5
Peak particle velocity	mm/s	PPV	Output	0.13	11.05	5.34

MC, and DI were utilized as input parameters in this study to predict PPV. The following sections describe modelling design of GEP and NLML techniques in predicting PPV.

PPV prediction by GEP model

The main objective of using GP in this study is to find a function for PPV prediction. Eventually, a model in form of $\mathrm{PPV} = f(\mathrm{BS}, \mathrm{HD}, \mathrm{ST}, \mathrm{PF}, \mathrm{MC}, \mathrm{D})$ is obtained where BS, HD, ST, PF, MC, and D are input variables to predict PPV. The process of GEP design was performed considering the presented flowchart in Fig. 1. As a first step of design, whole 102 datasets were divided randomly to training and testing datasets. Training datasets were used for PPV model development, while testing datasets were performed to check the performance prediction of the developed model. Swingler (1996) and Looney (1996) suggested 20 and 25 % of whole dataset for testing purpose, respectively. Furthermore, Nelson and Illingworth (1990) introduced a range of (20–30 %) for evaluation of the performance capacity of the developed model. Based on the suggested percentages, 20 % of data (20 datasets) was selected for testing and validation purpose and remaining 80 % (82 datasets) was chosen to develop PPV models. In GEP design, the software of Gene Xpro Tools 4.0 was performed. In this study, several GEP models with different parameters (number of chromosomes, head size, number of genes, linking function and etc.) based on literature's recommendations (e.g., Baykasoglu et al. 2008; Mollahasani et al. 2011; Güllü 2012; Yang et al. 2013; Dindarloo, 2015a) were conducted and finally, five models with highest performance prediction were chosen (see Table 3). To propose GEP models, each randomly selected dataset was presented separately to the software. BS, HD, ST, PF, MC and D are inputs of the system that are also known as terminal sets in GEP algorithm. There are many function sets that can be used to relate input and output parameters. Nevertheless, evaluation and utilization of all of them may increase the complexity degree of the proposed model. So, determination of the function sets is a critical task in design of GEP models.

The GEP functions used in this study are comprised of simple mathematical operators like $\{+, -, \times, \div\}$ and also some non-linear functions like {sin, cos, tan, A tan, Ln, Exp, ^2, ^3, 3Rt, Sqrt}. Using trial-and-error procedure and considering the suggestions of Ferreira (2001), multiplication ($\times$) and addition (+) are used for linking of the genes. As it can be seen in Fig. 1, genetic operators should be applied, respectively, on chromosomes. The researchers have suggested the values of 0.044, 0.1, 0.1, 0.3, 0.3, and 0.1 for mutation, inversion, transposition (IS, RIS and Gene transposition), one-point recombination, two-point recombination, and gene recombination, respectively (Ferreira 2001; Baykasoglu et al. 2008). So, these values were fixed for the constructed five models. As a criteria of fitness function for determining the optimal solution, mean absolute error (MAE) was selected for models No. 1, 2, 3 and 5, while root-mean-square error (RMSE) was performed for model No. 4. The equations of MAE and RMSE are expressed as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|X_{\mathrm{ipred}} - X_{\mathrm{imes}}\right| \quad (2)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}\left|x_{\mathrm{ipred}} - x_{\mathrm{imes}}\right|} \quad (3)$$

where x_{imes} and x_{ipred} are actual and predicted values by GEP, respectively, and n is the number of data (fitness cases). To evaluate the performance of five models, some performance indices including coefficient of determination (R^2), variance account for (VAF) and RMSE were computed. The definition of the R^2 and VAF are given as follows:

$$R^2 = 1 - \frac{\sum_{(i=1)}^{N}\left(x_{\mathrm{imes}} - \mathrm{x}_{\mathrm{ipred}}\right)^2}{\sum_{i=1}^{N}\left(x_{\mathrm{imes}} - \bar{x}\right)^2} \quad (4)$$

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}\left(x_{\mathrm{imes}} - x_{\mathrm{pred}}\right)}{\mathrm{var}\ \left(x_{\mathrm{imes}}\right)}\right] \times 100 \quad (5)$$

where $\bar{x}$ is the mean value of the x. The results of the performance indices for five built GEP models are listed in Table 4. GEP algorithm selects the best individual (chromosome) based on fitness function (e.g. MAE). As shown in Table 4, model No. 1 with the MAE values of 0.755 and 0.851 for training and testing datasets, respectively, outperforms the other developed models. Considering other performance indices and evaluation criteria, it was found

Table 3 Selected GEP models with their parameters

GEP parameters	Value				
	GEP model number				
	1	2	3	4	5
Terminal set	BS, HD (m), ST (m), PF (kg/m^3), MC (kg), D (m)				
Fitness function	MAE	MAE	MAE	RMSE	MAE
Number of chromosomes	32	42	24	31	30
Head size	8	9	5	7	8
Number of genes	5	3	5	4	3
Linking function	Multiplication	Multiplication	Multiplication	Addition	Addition
Number of generation	2500	2500	2500	2500	2500

that the model No. 1 shows the best results compared to other constructed models.

The best chromosome belongs to the generation of 2477 (from 2500 generations) which consists of five genes where each gene shows the formation of a sub-ET (see Fig. 4a). The connections of these five sub-ETs by multiplication function cause a formation of ET. The length of the chromosome is 17 ($h = 8$, $t = 9$). K-Expression of the selected GEP model is given in Fig. 4b.

Finally, the mathematical formula of each gene belong to their sub-ETs can be extracted [see Eqs. (6)–(10)], and overall predictive relationship for PPV estimation can be achieved by multiplying the Equations of (6)–(10) as it can be seen in Eq. (11). Therefore, this equation can be used in practice for predicting PPV before conducting blasting operation.

$$\text{Gene1} : \text{Cos}\left(\frac{\text{ST}}{\text{MC} - \text{HD}} + \text{Sin}\left(\sqrt[3]{\text{D}}\right)\right)^3 \quad (6)$$

$$\text{Gene 2} : \text{Cos}\left(\frac{-5.142486\text{BS} + \text{D}}{-5.142486\text{MC}}\right) + \text{Exp}(-1.776978) \quad (7)$$

$$\text{Gene3} : \left(\sqrt{\text{PF}} - \text{Ln}\left(\sqrt[3]{\text{ST}}\right)\right) + \text{Sin}\left(\text{BS}^3\right) \quad (8)$$

$$\text{Gene3} : \left(\sqrt{\text{PF}} - \text{Ln}\left(\sqrt[3]{\text{ST}}\right)\right) + \text{Sin}\left(\text{BS}^3\right) \quad (9)$$

$$\text{Gene5} : \text{BS} + 6.570953 - \text{PF} \quad (10)$$

$$\text{PPV} = \text{Gene 1} \times \text{Gene 2} \times \text{Gene 3} \times \text{Gene 4} \times \text{Gene 5} \quad (11)$$

The graphs of the predicted PPV values obtained from selected GEP model against the measured PPV values for training and testing datasets are displayed in Fig. 5a. This shows high reliability of the GEP technique in predicting PPV induced by blasting operation.

PPV prediction by NLMR model

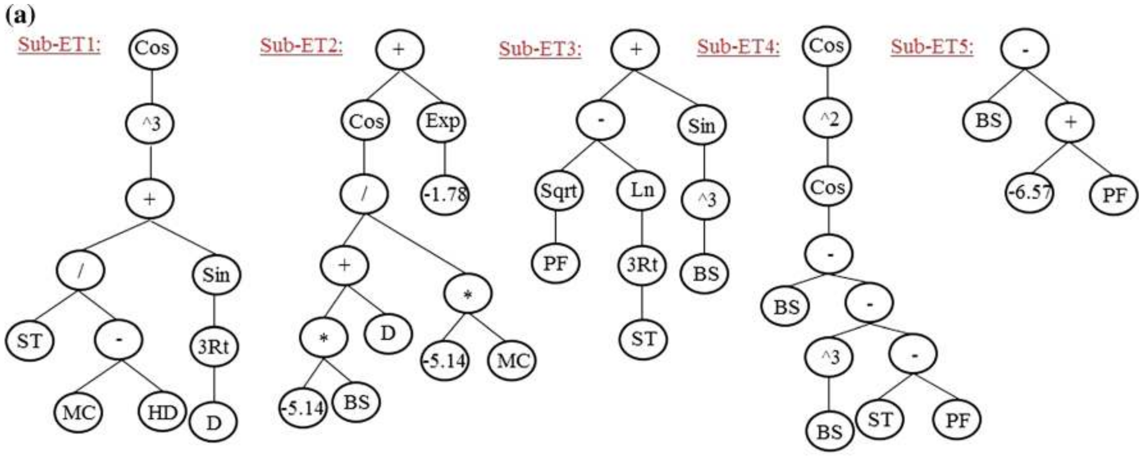
The regression analysis is a statistical tool that is used to recognize the relationships between variables. The purpose of multiple regressions is to learn more about the relationships between several independent variables and dependent variable(s) (Verma and Singh 2013b; Tripathy et al. 2015; Ghiasi et al. 2016). In the NLMR technique, both nonlinear and linear relationships, e.g., exponential, logarithmic, and power, can be employed. The NLMR approach is used for the establishment of mathematical formulas to make a prediction on dependent variables based on known independent variables in the geotechnical engineering field (Yagiz et al. 2009; Yagiz and Gokceoglu 2010; Shirani Faradonbeh et al. 2015).

Since GEP is conceptually non-linear, NLMR model is selected to develop PPV predictive model for comparison purpose. In this regard, using simple regression models and considering the same training and testing datasets of GEP

Table 4 Values of performance indices for constructed GEP models

GEP model	Training				Testing			
	R^2	RMSE	VAF	MAE	R^2	RMSE	VAF	MAE
1	0.914	0.920	91.304	0.755	0.874	0.963	87.107	0.851
2	0.842	1.266	84.087	0.938	0.864	1.420	73.886	1.033
3	0.834	1.276	83.369	0.936	0.875	1.487	82.017	1.133
4	0.837	1.260	83.694	0.991	0.880	1.079	84.438	0.861
5	0.871	1.126	87.071	0.845	0.871	1.361	86.903	1.168

(a)



(b)

0	1	2	3	4	5	6	7	8	9	0	1	2	3	4	5	6
Cos	^3	+	/	Sin	ST	-	3Rt	MC	HD	D	ST	BS	BS	5.41	ST	MC
+	Cos	Exp	/	1.78	+	*	*	D	5.14	BS	-5.14	BS	5.14	MC	PF	D
+	-	Sin	Sqrt	Ln	^3	PF	3Rt	BS	ST	7.47	D	D	D	BS	PF	HD
Cos	^2	Cos	-	BS	-	^3	-	BS	ST	PF	7.794	HD	BS	PF	PF	6.102
-	BS	+	6.57	PF	6.57	3Rt	HD	D	6.57	-6.57	-6.57	PF	HD	D	D	MC

Fig. 4 **a** Sub-ETs for the selected gene model, **b** K-Expression of the selected GEP model

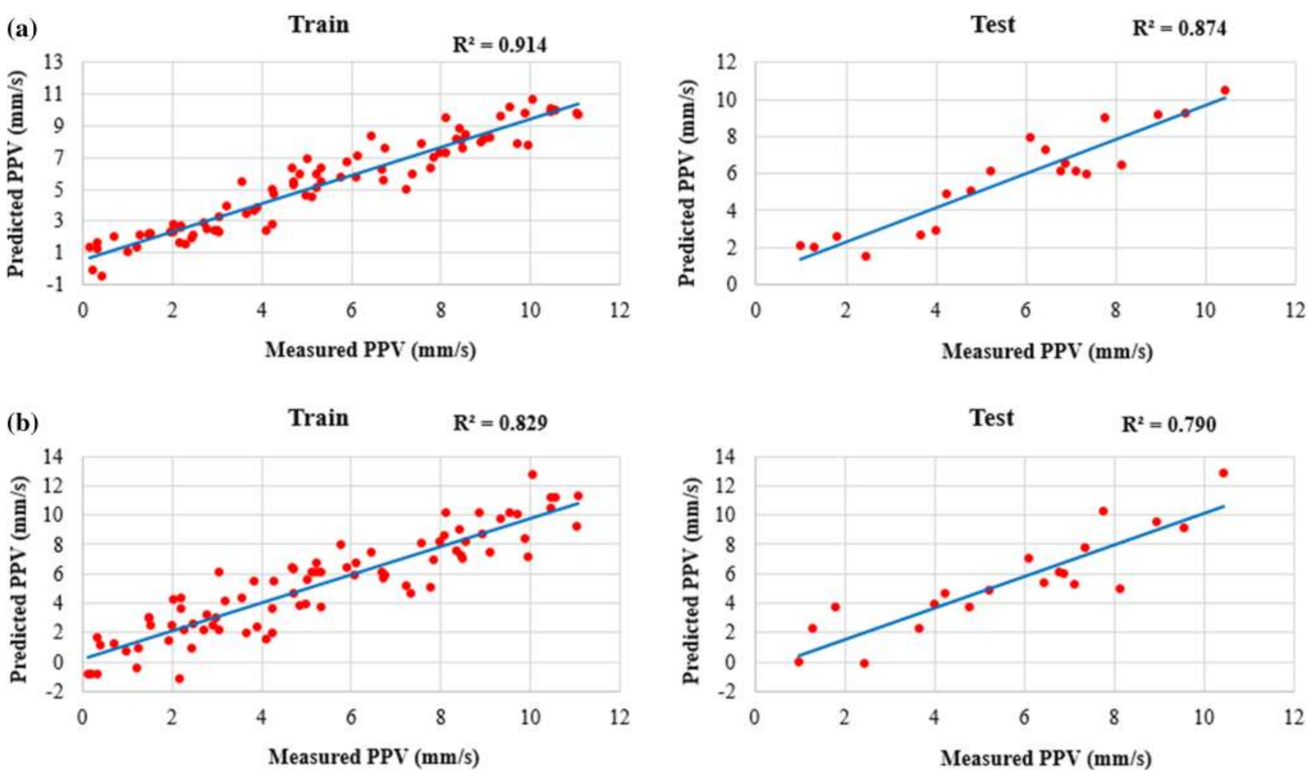


Fig. 5 Measured and predicted PPV for training and testing datasets. **a** Using GEP, **b** using NLMR

modelling, a NLMR equation was developed. In constructing the NLMR model, results of BS, HD, ST, PF, MC and D were used as model inputs. NLMR model was built using statistical software package of SPSS version 16 (SPSS 2007). The developed NLMR equation for estimating PPV is presented as follows:

$$\begin{aligned} \mathrm{PPV} = {} & 4.585 \times \mathrm{BS}^{7.28} + 0.227 \times \mathrm{HD} - 4.158 \times \mathrm{ST} \\ & + 1.139 \times \mathrm{PF}^{2.144} + 0.014 \\ & \times \mathrm{MC}^{0.779} - 0.036 \times e^{0.009 \times D} + 11.86 \end{aligned} \qquad (12)$$

PPV value obtained from the Eq. (12) is expressed as mm/s. Predicted PPVs by NLMR technique and measured PPVs for training and testing datasets is illustrated in Fig. 5b. R^2 values of 0.829 and 0.790 for training and testing datasets express suitable performance prediction of the proposed NLMR model. Evaluation of the developed NLMR equation will be discussed later.

Comparison of the model performances

A GEP model was developed to predict the PPV produced by blasting. For comparison purposes, NLMR technique was also used and proposed for PPV estimation. These models were constructed using six input parameters namely BS, HD, ST, PF, MC and D. In this study, R^2, VAF, MAE and RMSE were calculated to check the performance prediction of the developed GEP and NLMR models. Theoretically, a predictive model is excellent when $R^2 = 1$, VAF $= 100$ %, MAE $= 0$ and RMSE $= 0$. Considering testing datasets, values of 0.874, 87.107, 0.851, and 0.963 were obtained for R^2, VAF, MAE, and RMSE, respectively, indicate higher degree of accuracy provided by GEP model, while these values were achieved as 0.790, 69.261, 1.221, and 1.498 for NLMR technique. In addition, for training datasets, these values were obtained as 0.914, 91.304, 0.755 and 0.920 for GEP model, while values of 0.829, 80.878, 1.125, and 1.365 were achieved for NLMR model. As a result, by developing GEP model, for instance, RMSE results are decreased from 1.498 to 0.963 and from 1.365 to 0.920 for testing and training datasets, respectively. In addition, similar trends can be found for results of other performance prediction, i.e., R^2, VAF, MAE. The results show that the developed GEP model can provide higher performance prediction for estimating PPV compared to NLMR.

In order to have a better comparison, the measured and predicted PPVs using GEP and NLMR models are plotted for testing datasets as shown in Fig. 6. This figure demonstrates that obtained results by GEP model are closer to measured PPVs compared to obtained results by NLMR predictive model. It should be mentioned that the direct use of the developed models to predict PPV for other conditions is not recommended.

Sensitivity analysis

Sensitivity analysis was carried out to recognize the relative influence of the each parameter in the network system by the cosine amplitude method (Yang and Zang 1997). This method is used to obtain similarity relations between the involved parameters. To apply this method, all of the data pairs were expressed in common X-space. To undertake this technique, all data pairs should be utilized to build a data array X as follows:

$$X = \{x_1, x_2, x_3, \ldots, x_i, \ldots, x_n\} \tag{13}$$

Each of the elements, xi, in the data array X is a vector of lengths of m, that is:

$$x_i = \{x_{i1}, x_{i2}, x_{i3}, \ldots, x_{im}\} \tag{14}$$

The strength of the relation between the dataset, xi and xj, is presented as follows:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik}x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{ik}^2}} \tag{15}$$

The rij values were obtained as 0.891, 0.925, 0.819, 0.917, 0.972 and 0.932 for BS, HD, ST, PF, MC and D,

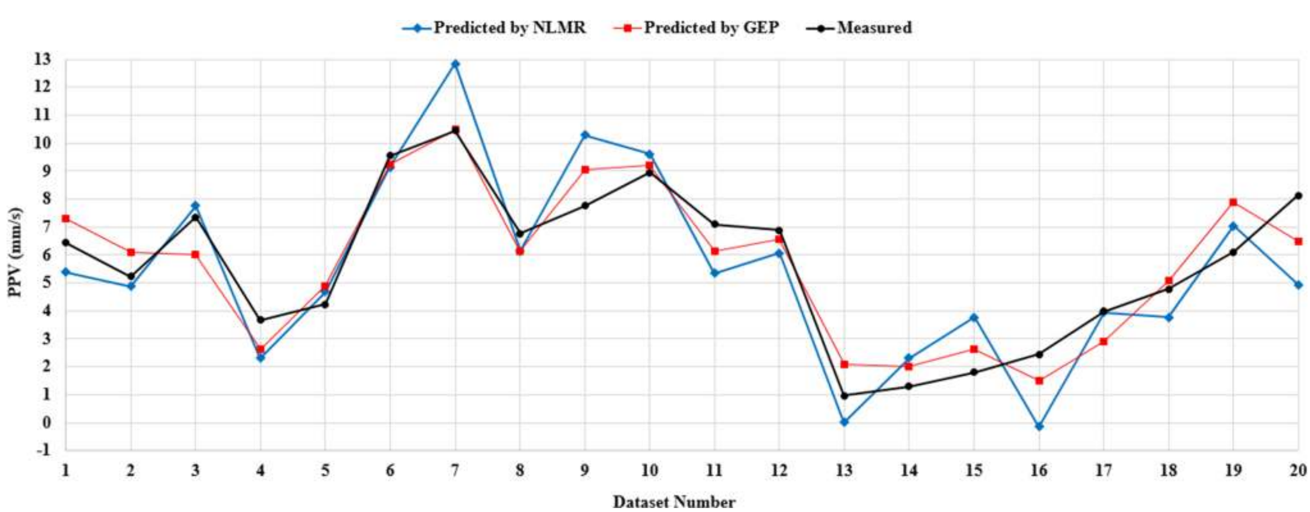


Fig. 6 Comparison between measured and predicted PPVs by GEP and NLMR models for testing datasets

respectively. These results show that among all inputs, MC and D are the most influential parameters on PPV.

Conclusion

Ground vibration is one of the undesirable side effects of blasting operation. Therefore, an accurate evaluation/prediction of ground vibration is essential to minimize/reduce the potential risk of damage. An attempt has been done to estimate PPV values induced by blasting developing both GEP and NLMR models. In the analyses of GEP and NLMR models, burden-to-spacing ratio, stemming length, powder factor, the maximum charge per delay, hole depth, and distance from the blast face were set as model inputs. After developing the predictive models for PPV prediction, several performance prediction, e.g., R^2, RMSE, VAF, and MAE were computed to evaluate the proposed models. The obtained results indicate that the developed GEP equation is practically able to predict PPV with higher performance prediction as compared to obtained results of NLMR model. R^2 equal to 0.874 for testing datasets recommends the superiority of the GEP model in predicting PPV, while for NLMR, this value is obtained as 0.790. It is important to note that the proposed models of this study are applicable only in the studied quarry site and in the mentioned ranges of the used data. The obtained strength of the relations indicates that maximum charge per delay and distance from the blast face are the most effective parameters on PPV.

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References

Ahangari K, Moeinossadat SR, Behnia D (2015) Estimation of tunnelling-induced settlement by modern intelligent methods. Soils Found 55(4):737–748

Alavi AH, Gandomi AH (2011) A robust data mining approach for formulation of geotechnical engineering systems. Eng Comput (Swansea, Wales) 28(3):242–274

Alkroosh I, Nikraz H (2011) Correlation of pile axial capacity and CPT data using gene expression programming. Geotech Geol Eng 29(5):725–748

Ambraseys NR, Hendron AJ (1968) Dynamic behavior of rock masses: rock mechanics in engineering practices. Wiley, London

Baykasoglu A, Güllü H, Canakci H, Ozbakır L (2008) Prediction of compressive and tensile strength of limestone via genetic programming. Expert Syst Appl 35:111–123

Brownlee J (2011) Clever algorithms: nature-inspired programming recipes. Jason Brownlee, Melbourne

Bureau of Indian Standard (1973) Criteria for safety and design of structures subjected to underground blast. ISI Bull IS-6922

Çanakcı H, Baykasoğlu A, Güllü H (2009) Prediction of compressive and tensile strength of Gaziantep basalts via neural networks and gene expression programming. Neural Comput Appl 18(8):1031–1041

Davies B, Farmer IW, Attewell PB (1964) Ground vibrations from shallow sub-surface blasts. Engineer 217:553–559

Dindarloo SR (2015a) Prediction of blast-induced ground vibrations via genetic programming. Int J Min Sci Technol 25(6):1011–1015

Dindarloo SR (2015b) Peak particle velocity prediction using support vector machines: a surface blasting case study. J South Afr Inst Min Metall 115(7):637–643

Dindarloo SR, Siami-Irdemoosa E (2015) Estimating the unconfined compressive strength of carbonate rocks using gene expression programming. Eur J Sci Res 135(3):309–316

Dowding CH (1985) Blast vibration monitoring and control. Prentice-Hall, Englewoods Cliffs, pp 288–290

Duvall WI, Petkof B (1959) Spherical propagation of explosion of generated strain pulses in rocks. USBM, RI-5483

Ebrahimi E, Monjezi M, Khalesi MR, Jahed Armaghani D (2015) Prediction and optimization of back-break and rock fragmentation using an artificial neural network and a bee colony algorithm. Bull Eng Geol Environ. doi:10.1007/s10064-015-0720-2

Faramarzi F, Ebrahimi Farsangi MA, Mansouri H (2014) Simultaneous investigation of blast induced ground vibration and airblast effects on safety level of structures and human in surface blasting. Int J Min Sci Technol 24(5):663–669

Ferreira C (2001) Gene expression programming: a new adaptive algorithm for solving problems. Complex Syst 13(2):87–129

Ferreira C (2002) Gene expression programming in problem solving. In: Roy R et al (eds) Soft Computing and Industry, Springer, London, p 635–653

Ferreira C (2006) Gene expression programming: mathematical modeling by an artificial intelligence, 2nd edn. Springer, Germany

Fisne A, Kuzu C, Hüdaverdi T (2011) Prediction of environmental impacts of quarry blasting operation using fuzzy logic. Environ Monit Assess 174:461–470

Ghasemi E, Ataei M, Hashemolhosseini H (2013) Development of a fuzzy model for predicting ground vibration caused by rock blasting in surface mining. J Vib Control 19(5):755–770

Ghiasi M, Askarnejad N, Dindarloo SR, Shamsoddini H (2016) Prediction of blast boulders in open pit mines via multiple regression and artificial neural networks. Int J Min Sci Technol. doi:10.1016/j.ijmst.2015.12.001

Ghoraba S, Monjezi M, Talebi N, Moghadam MR, Jahed Armaghani D (2015) Prediction of ground vibration caused by blasting operations through a neural network approach: a case study of Gol-E-Gohar Iron Mine, Iran. J Zhejiang Univ Sci A. doi:10.1631/jzus.A1400252

Güllü H (2012) Prediction of peak ground acceleration by genetic expression programming and regression: a comparison using likelihood-based measure. Eng Geol 141:92–113

Hajihassani M, Jahed Armaghani D, Monjezi M, Mohamad ET, Marto A (2015a) Blast-induced air and ground vibration prediction: a particle swarm optimization-based artificial neural network approach. Environ Earth Sci 74:2799–2817

Hajihassani M, Jahed Armaghani D, Marto A, Tonnizam Mohamad E (2015b) Ground vibration prediction in quarry blasting through an artificial neural network optimized by imperialist competitive algorithm. Bull Eng Geol Environ 74:873–886

Hasanipanah M, Monjezi M, Shahnazar A, Jahed Armaghani D, Farazmand A (2015) Feasibility of indirect determination of blast induced ground vibration based on support vector machine. Measurement 75:289–297

Hudaverdi T (2012) Application of multivariate analysis for prediction of blast-induced ground vibrations. Soil Dyn Earthq Eng 43:300–308

Inc SPSS (2007) SPSS for windows (Version 160). SPSS Inc, Chicago

Iphar M, Yavuz M, Ak H (2008) Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neurofuzzy inference system. Environ Geol 56:97–107

Jahed Armaghani D, Hajihassani M, Mohamad ET, Marto A, Noorani SA (2014) Blasting-induced flyrock and ground vibration prediction through an expert artificial neural network based on particle swarm optimization. Arab J Geosci 7(12):5383–5396

Jahed Armaghani D, Momeni E, Abad SVANK, Khandelwal M (2015) Feasibility of ANFIS model for prediction of ground vibrations resulting from quarry blasting. Environ Earth Sci 74:2845–2860

Kahriman A (2002) Analysis of ground vibrations caused by bench blasting at can open-pit lignite mine in Turkey. Environ Earth Sci 41:653–661

Kayadelen C (2011) Soil liquefaction modeling by genetic expression programming and neuro-fuzzy. Expert Syst Appl 38:4080–4087

Khandelwal M, Kankar PK (2011) Prediction of blast-induced air overpressure using support vector machine. Arab J Geosci 4:427–433

Khandelwal M, Singh TN (2006) Prediction of blast induced ground vibrations and frequency in opencast mine: a neural network approach. J Sound Vib 289:711–725

Khandelwal M, Singh TN (2007) Evaluation of blasting induced ground vibration predictors. Soil Dyn Earthq Eng 27:116–125

Khandelwal M, Singh TN (2009) Prediction of blasting induced ground vibration using artificial neural network. Int J Rock Mech Min Sci 46:1214–1222

Khandelwal M, Kumar DL, Yellishetty M (2011) Application of soft computing to predict blast-induced ground vibration. Eng Comput 27(2):117–125

Langefors U, Kihlstrom B (1963) The modern technique of rock blasting. Wiley, New York

Li DT, Yan JL, Zhang L (2012) Prediction of blast-induced ground vibration using support vector machine by Tunnel excavation. Appl Mech Mater 170:1414–1418

Looney CG (1996) Advances in feed-forward neural networks: demystifying knowledge acquiring black boxes. IEEE Trans Knowl Data Eng 8(2):211–226

Mohamadnejad M, Gholami R, Ataei M (2012) Comparison of intelligence science techniques and empirical methods for prediction of blasting vibrations. Tunn Undergr Space Technol 28:238–244

Mohamed MT (2011) Performance of fuzzy logic and artificial neural network in prediction of ground and air vibrations. Int J Rock Mech Min Sci 48:845–851

Mollahasani A, Alavi AH, Gandomi AH (2011) Empirical modeling of plate load test moduli of soil via gene expression programming. Comput Geotech 38(2):281–286

Monjezi M, Ghafurikalajahi M, Bahrami A (2011) Prediction of blastinduced ground vibration using artificial neural networks. Tunn Undergr Space Technol 26:46–50

Monjezi M, Dehghani H, Singh TN, Sayadi AR, Gholinejad A (2012) Application of TOPSIS method for selecting the most appropriate blast design. Arab J Geosci 5(1):95–101

Monjezi M, Hasanipanah M, Khandelwal M (2013) Evaluation and prediction of blast-induced ground vibration at Shur River Dam, Iran, by artificial neural network. Neural Comput Appl 22:1637–1643

Nelson M, Illingworth WT (1990) A practical guide to neural nets. Addison-Wesley, Reading

Ozbek A, Unsal M, Dikec A (2013) Estimating uniaxial compressive strength of rocks using genetic expression programming. J Rock Mech Geotech Eng 5(4):325–329

Ozer U, Kahriman A, Aksoy M, Adiguzel D, Karadogan A (2008) The analysis of ground vibrations induced by bench blasting at Akyol quarry and practical blasting charts. Environ Geol 54:737–743

Roy PP (1993) Putting ground vibration predictors into practice. Colliery Guard 241:63–67

Sawmliana C, Roy PP, Singh RK, Singh TN (2007) Blast induced air overpressure and its prediction using artificial neural network. Min Technol 116(2):41–48

Shirani Faradonbeh R, Monjezi M, Jahed Armaghani D (2015) Genetic programing and non-linear multiple regression techniques to predict backbreak in blasting operation. Eng Comput. doi:10.1007/s00366-015-0404-3

Singh TN (2004) Artificial neural network approach for prediction and control of ground vibrations in mines. Min Technol 113(4):251–256

Singh TN, Singh V (2005) An intelligent approach to prediction and control ground vibration in mines. Geotech Geolog Eng 23:249–262

Singh TN, Dontha LK, Bhardwaj V (2008) Study into blast vibration and frequency using ANFIS and MVRA. Min Technol 117:116–121

Swingler K (1996) Applying neural networks: a practical guide. Academic Press, New York

Teodorescu L, Sherwood D (2008) High energy physics event selection with gene expression programming. Comput Phys Commun 178:409–419

Toraño J, Ramírez-Oyanguren P, Rodríguez R, Diego I (2006) Analysis of the environmental effects of ground vibrations produced by blasting in quarries. Int J Min Reclam Environ 20(4):249–266

Tripathy A, Singh TN, Kundu J (2015) Prediction of abrasiveness index of some Indian rocks using soft computing methods. Measurement 68:302–309

Verma AK, Maheshwar S (2014) Comparative study of intelligent prediction models for pressure wave velocity. J Geosci Geomatic 2(3):130–138

Verma AK, Singh TN (2011) Intelligent systems for ground vibration measurement: a comparative study. Eng Comput 27:225–233

Verma AK, Singh TN (2013a) A neuro-fuzzy approach for prediction of longitudinal wave velocity. Neural Comput Appl 22(7–8):1685–1693

Verma AK, Singh TN (2013b) Comparative study of cognitive systems for ground vibration measurements. Neural Comput Appl 22(1):341–350

Yagiz S, Gokceoglu C (2010) Application of fuzzy inference system and nonlinear regression models for predicting rock brittleness. Expert Sys Appl 37(3):2265–2272

Yagiz S, Gokceoglu C, Sezer E, Iplikci S (2009) Application of two non-linear prediction tools to the estimation of tunnel boring machine performance. Eng Appl Artif Intell 22(4):808–814

Yang Y, Zang O (1997) A hierarchical analysis for rock engineering using artificial neural networks. Rock Mech Rock Eng 30:207–222

Yang Y et al (2013) A new approach for predicting and collaborative evaluating the cutting force in face milling based on gene expression programming. J Netw Comput Appl 36(6):1540–1550

Zhou C, Xiao W, Tirpak TM, Nelson PC (2003) Evolving accurate and compact classification rules with gene expression programming. IEEE Trans Evol Comput 7(6):519–531