

Estimation of blast-induced ground vibration through a soft computing framework

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Received: 16 October 2016 / Accepted: 10 February 2017 / Published online: 28 February 2017
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Abstract Blasting is considered as the most common technique for rock breakage in surface mines, tunneling and large infrastructural development projects. Ground vibration, as one of the most adverse effects induced by blasting operations, can cause substantial damage to structures in the nearby environment. Therefore, there is a need to make accurate predictions of blast-induced ground vibration for minimizing the environmental effects. The present paper explores the possibility of using the genetic algorithm (GA) to create a new predictive model for estimating blast-induced ground vibration at Bakhtiari dam region, Iran. In this regard, two form of equations, i.e., power and linear forms, were developed by GA. Maximum charge weight per delay (W) and distance between monitoring station and blasting point (D), as the most influential parameters on

the ground vibration, were used as the input or independent variables for modeling. Also, the peak particle velocity (PPV) parameter, as a descriptor for evaluating blast-induced ground vibration, was considered as the output or dependent variables for modeling. In total, 85 blasting events were considered and the D , W and PPV parameters were precisely measured. The selected GA forms were then compared with the several empirical prediction models. Finally, it was found that the GA power form (with root-mean-square error (RMSE) 0.45 and coefficient of multiple determination (R^2) of 0.92) was more acceptable model for predicting PPV than the GA linear form and the empirical prediction models.

Keywords Blasting operation · Ground vibration · GA · Empirical models

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1 Introduction

Drilling and blasting technique is an inseparable part of the rock fragmentation process in opencast mines.

Only a fraction of 20–30% of the explosive energy is used for the desired rock fragmentation and the rest of it goes waste in undesirable generation of flyrock, backbreak, air-overpressure and ground vibration [1–10]. Among these adverse effects, ground vibration is the most undesirable effect induced by mine blasting operations which can cause severe damage to the surrounding structures [11–14]. Therefore, accurately forecasting the blast-induced ground vibration is very significant especially for the minimizing the environmental effects and the determining the blast-safety area. The effective parameters on ground vibration may be divided into two main groups, controllable and uncontrollable parameters [15–18]. Controllable parameters

are burden, spacing, stemming, blast-hole depth, blast-hole diameter, number of rows, powder factor, maximum charge weight per delay (W) and total charge. This group of parameters can be changed by the explosive engineers. In the second group, uncontrollable parameters such as rock and discontinuities properties cannot be changed by the explosive engineers. An overview of the relevant literature reveals that the W and distance between monitoring station and blast-point (D) are the most effective parameters on the ground vibration [5, 13]. Normally, ground vibration can be recorded based on several factors, i.e., frequency, acceleration and peak particle velocity (PPV). Among them, PPV is the most principal factor for vibration measurement and widely applied by many researchers [19–22]. During a few past decades, many empirical prediction models have been proposed for the prediction of PPV [23–27]. Table 1 gives some empirical models for PPV prediction [28–31]. In the presented models in this Table, PPV, W and D are in terms of mm/s, kg and m, respectively. According to some researches [5, 14], the performance prediction of the empirical models are not good enough in many case studies, high degree of PPV prediction is required to determine blast-safety area. For instance, Lapčević et al. [32] used several empirical models for predicting the blast-induced PPV in Bor copper mine, Serbia. Their results indicated that the conformity between the measured and predicted PPV values by empirical models was poor. To achieve a better solution quality (prediction accuracy), many researchers highlighted the application of soft computing approaches in solving various engineering areas, especially in the field of mining and civil applications [33–43]. Fuzzy logic (FL) was developed for PPV prediction in the study conducted by Ghasemi et al. [14]. To evaluate the performance of the developed FL model, several empirical models were also used. Finally, it was discovered that FL model can predict PPV better than empirical models. Verma and Singh [2]

Table 1 the empirical prediction models used in this study

Empirical models	Equation
USBM [28]	$PPV = k \times \left[\frac{D}{\sqrt{W}} \right]^n$
Langefors-Kilhstrom [29]	$PPV = k \times \left[\sqrt{\frac{W}{D^3}} \right]^n$
Ambraseys–Hendron [14]	$PPV = k \times \left[\frac{D}{W^{0.33}} \right]^n$
Indian Standard [14]	$PPV = k \times \left[\frac{W}{D^{2.5}} \right]^n$
Davies et al. [14]	$PPV = k \times D^a \times W^b$
Roy [30]	$PPV = n + \left[k \times \left[\frac{D}{\sqrt{W}} \right]^{-1} \right]$
Rai-Singh [31]	$PV = k \times D^a \times W^b \times e^{(c \times D)}$

employed support vector machine (SVM), artificial neural network (ANN) and empirical models for the estimation of PPV at one of the largest opencast mines in India. They concluded that the SVM provided more accurate predictions in comparison with ANN and empirical models. In the other study of soft computing methods, Monjezi et al. [34] investigated the results of blast-induced PPV at Shur river dam, Iran. They used ANN and several empirical models to predict PPV. Based on their result, ANN can estimate PPV with higher level of accuracy in comparison with empirical models. A comprehensive study to estimate blast-induced PPV at four quarry sites in Malaysia was presented by Jahed Armaghani et al. [44] using adaptive neuro-fuzzy inference system (ANFIS), ANN and empirical models. The results indicated that the ANFIS model presents better performances when compared with ANN and empirical models. Amiri et al. [22] proposed a new combination of ANN and K-nearest neighbors (KNN) models for the prediction of PPV. In their study, 75 datasets were used and W and D were set as the input parameters. The results revealed that the ANN-KNN as an acceptable tool can estimate PPV with high degree of accuracy. In the other research conducted by Fouladgar et al. [42], cuckoo search algorithm and empirical models were employed for the PPV prediction. They also used W and D as the model inputs. Their results indicated that the proposed cuckoo search model perform quite well compared to results empirical model and is quite practical for use. In the present research work, genetic algorithm (GA) is proposed to develop a precise and reliable model for predicting the PPV in Bakhtiari dam, Iran. For comparison aims, several empirical models were also developed. The rest of this paper is organized as follows.

The GA is shortly described in Sect. 2. Details of the studied case are given in Sect. 3. The development of the GA and empirical models for the prediction of PPV is explained in Sect. 4. The accuracy of the predictive models is evaluated in Sect. 5, and then conclusion is given in Sect. 6.

2 Genetic algorithm

Holland [45] introduced GA as a technique for stochastic search and optimization. In GA modeling, the mechanism of natural selection and the evolution process of biological species are imitated. The stochastic optimization is referred to a technique wherein solution space is searched through producing potential solutions by using a random number generator [46, 47].

For the aim of advancement, GA only needs an evaluation of objective function value in case of each decision variable. This is because the GA needs no definite

information to guide the search [48]. As suggested in the literature, the difference between the shortest and the longest time of response for the optimization in the GA is larger in comparison with that of the traditional gradient methods. Furthermore, the GA is not able to assure constant times for the optimization response. GA comprises individuals who are candidate solutions that mature steadily in a way to be converged to an optimal solution. In the GA, each candidate solution is represented by a linear string that comprises chromosomes shown by 0 and 1 s. There are two terms in GA: the population size that is the total number of solutions and generation that refers to each iteration of the optimization process. In the GA, three basic genetic operators, namely crossover, reproduction and mutation, should be performed in order to form the next generation [49, 50].

Offspring (i.e., new individuals) are created in the crossover operator by the combination of definite parts of the individuals (parent). The best chromosomes are chosen by the reproduction operator, and then the chosen chromosomes are transferred directly to the next generation. A random change is appeared in a chromosome’s elements (allele) by the mutation operator. In the binary system, mutation refers to flipping a bit’s values where 0 becomes 1 and 1 becomes 0. Those small random changes occurred in a chromosome’s allele cause genetic diversity and make GA capable of searching a wider space. The following steps are summarized steps of a GA:

1. Formation of an initial population.
2. Evaluation of chromosomes in the population.

1. Moving the most suitable chromosomes to the next generation.
2. Application of the crossover and mutation function for the formation of new chromosomes.
3. Repetition of Step 2 till meeting the stopping criterion.
4. Returning the finest chromosome as the solution.

More explanations about GA algorithm can be found in many studies [51–54].

3 Field investigation

An extensive research program was carried out to estimate blast-induced PPV at Bakhtiari dam, in Iran. The site is located in the southwest of Iran, Lorestan province, between 48°46'34"E longitude and 32°57'41"N latitude (see Fig. 1). The most important aims to construct Bakhtiari dam are the generation of 3000 GW/h per annum, the control of floods, hydroelectric energy generation and preventing annual destruction. Table 2 summarizes some descriptions of the Bakhtiari dam. In this area, the type of bed rock is limestone and Mary limestone. Drilling and blasting method was performed for the tunneling in this site. In this regard, Jumbo Drill Machine and ammonium nitrate fuel oil (ANFO) were mainly used for drilling and blasting operations, respectively. Blasting operations were also conducted using blast-hole diameters of 150 and 165 mm. In order to provide an access road between Bakhtiari dam

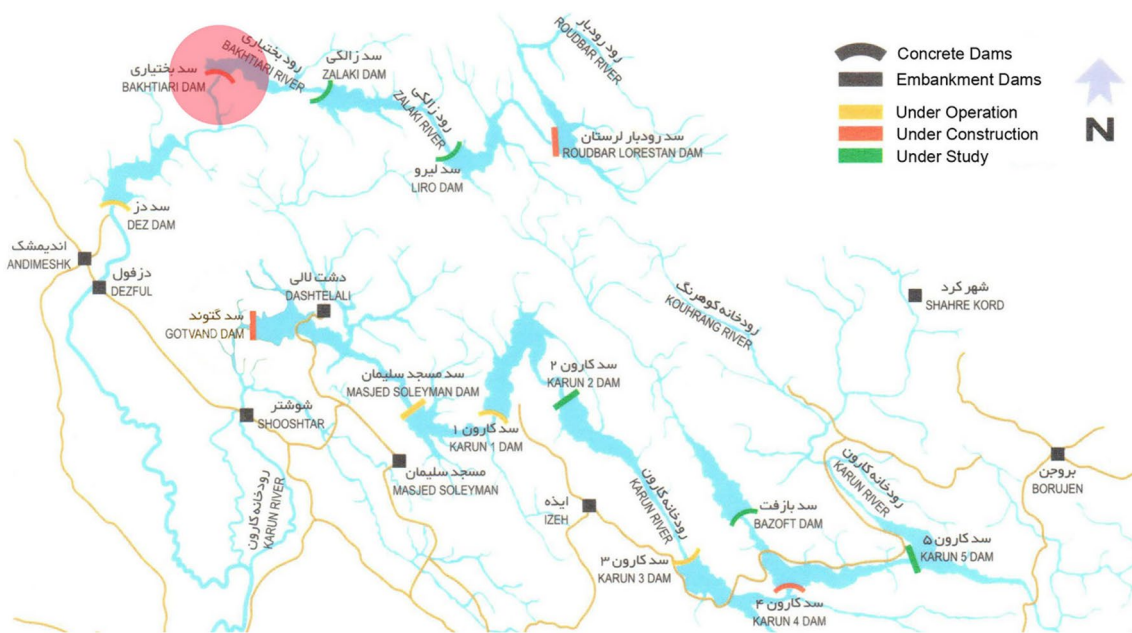


Fig. 1 Location map of the Bakhtiari dam site [55]

Table 2 The properties of the Bakhtiari dam

Body specifications		Dam reservoir	
Item	Quantity	Item	Quantity
Dam type	Double arc concrete	Total volume of reservoir	5200 million m ³
Height from foundation	315 m	Profitable volume of reservoir	3027 million m ³
Crest length	434 m	Water normal level	830
Crest width	10 m	Area of reservoir	58.7 km

Table 3 The range of used parameters in this study

Parameter	Unit	Symbol	Min	Max
Maximum charge weight per delay	kg	<i>W</i>	7	35
Distance between blast-point and monitoring station	m	<i>D</i>	32	175
Peak particle velocity	mm/s	PPV	1.89	8.90

and the nearest city, several tunnels should be excavated. In some cases, the railway tunnels are located on the side of access road. Therefore, ground vibration prediction, as one of the environmental impacts of blasting, is of interest in the mentioned site. For this aim, 85 blasting events were monitored and the two influential parameters on the ground vibration namely *W* and *D* were measured. The values of PPV, as the most common descriptor for evaluating the blast-induced ground vibration, were carefully measured for all 85 blasting operations, using MR2002 SYSCOM seismograph. It is worth mentioning that the mentioned seismograph was installed at the ground surface around the tunnel. In order to measure the values of *D*, GPS (global positioning system) was used. Also, the values of *W* were measured by controlling the blast-hole charge and based on blasting design. Table 3 summarizes the range of utilized variables in the current study. In addition, a graphical summary of the utilized variables in the modeling analysis is illustrated in Fig. 2.

4 Prediction of PPV

In this study, estimation capabilities of the GA and empirical prediction models were investigated for the prediction of blast-induced PPV. The development of the predictive models is explained in this section.

4.1 Prediction of PPV by empirical models

In this research, several empirical models were used for the PPV prediction induced by blasting operations at Bakhtiari dam (see Table 1). The presented site constants in Table 1 (*k*, *n*, *a*, *b* and *c*) can be computed by using regression analysis. For this work, statistical software package of

SPSS version 16 [56] was used in the present study. The values of the site constants for the used empirical models are given in Table 4. Figures 3, 4, 5, 6, 7, 8 and 9 illustrate the values of coefficient of multiple determination (R^2) for measured and predicted PPV values by empirical models. What is clear from Figs. 3, 4, 5, 6, 7, 8 and 9, is that the prediction capabilities of the empirical models are in the average range. More details regarding the performance of the empirical models in comparison with GA models will be given in Sect. 5.

4.2 Prediction of PPV by GA

The GA is used to develop a nonlinear equation for the prediction of blast-induced PPV. In order to increase the ability of models in diagnosing relation among inputs and outputs, it is recommended that the values of input and output parameters be normalized. Therefore, the used datasets were normalized as the first work. The normalization of dataset can be calculated by using Eq. 1.

$$X_n = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

In Eq. 5, *X*, X_{min} , X_{max} and X_n denote the actual, minimum, maximum and normalized values of the measured parameter, respectively. In the second step, power and linear equations were developed and the weighting factors of the developed equations can be optimized by GA. Note that, Hasanipanah et al. [57] used the power form and based on their results, this form of equation had a good performance in the field of PPV prediction. Hence, this form as well as linear form was used in the present paper. The general forms of power and linear equation with two independent variables, including *W* and *D*, can be formulated as given in Eqs. 2 and 3.

$$PPV = x_1 + x_2 \cdot W^{x_3} + x_4 \cdot D^{x_5} \quad (2)$$

$$PPV = x_1 + x_2 \cdot W + x_3 \cdot D \quad (3)$$

In the next step, considering the fitness function, presented in Eq. 4, the best weighting factors can be computed through the GA.

$$\text{MeanSquareError} = \frac{1}{n} \times \sum_{i=1}^n \left[(PPV_m - PPV_p)^2 \right] \quad (4)$$

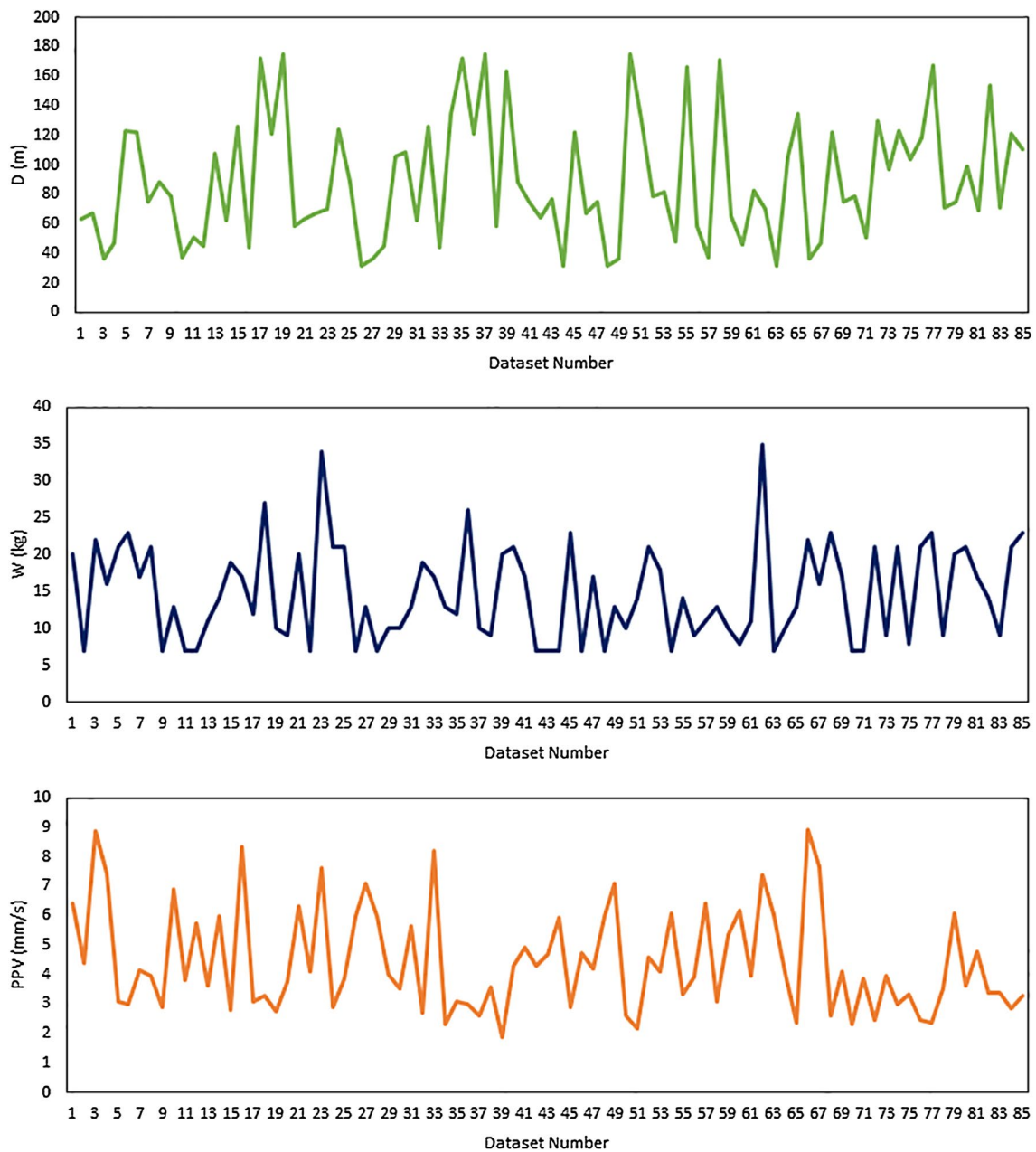


Fig. 2 a graphical summary of measured parameters in the present research

Table 4 the values of site constants computed by SPSS version 16

Empirical Model	Site constants				
	<i>k</i>	<i>n</i>	<i>a</i>	<i>b</i>	<i>c</i>
USBM	43.71	-0.76	-	-	-
Langefors-Kilhstrom	29.18	0.96	-	-	-
Ambraseys–Hendron	61.28	-0.76	-	-	-
Indian Standard	5.12	0.55	-	-	-
Davies et al.	49.6	-	-0.76	0.34	-
Roy	64.36	1.13	-	-	-
Rai-Singh	1.6	-	0.28	0.39	-0.01

where PPV_m , PPV_p and n represent the measured and predicted PPV as well as number of cases, respectively. Theoretically, the model will be excellent, if $MSE = 0$. In GA coding (where is implemented in MATLAB Software environment), the several parameters including the number of generations, the number of population, the mutation percentage on population (the mutation probability) and the crossover percentage on population (the crossover probability) should be considered. The appropriate values of these parameters can be identified by using trial-and-error method. Note that, when MSE is close to zero, the appropriate values of GA parameters are

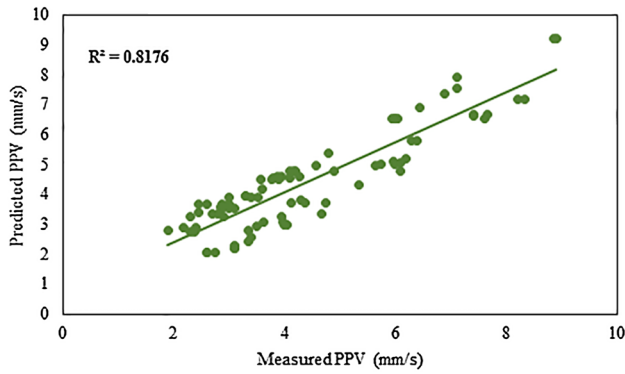


Fig. 3 Measured and predicted PPVs using USBM

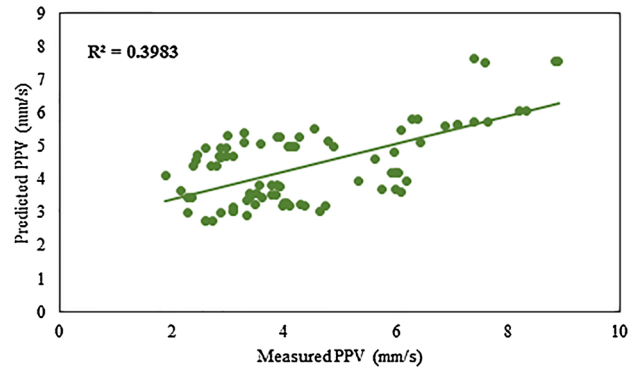


Fig. 6 Measured and predicted PPVs using Indian Standard

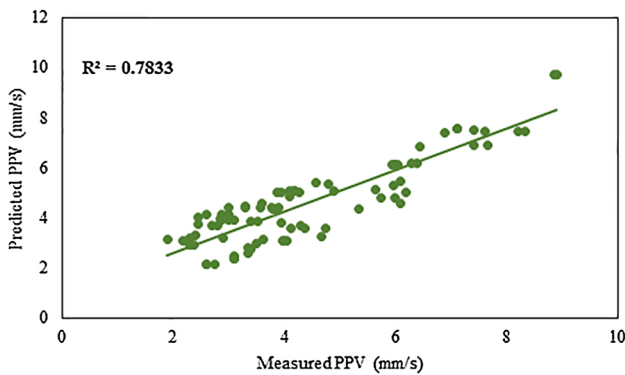


Fig. 4 Measured and predicted PPVs using Langefors-Kilhstrom

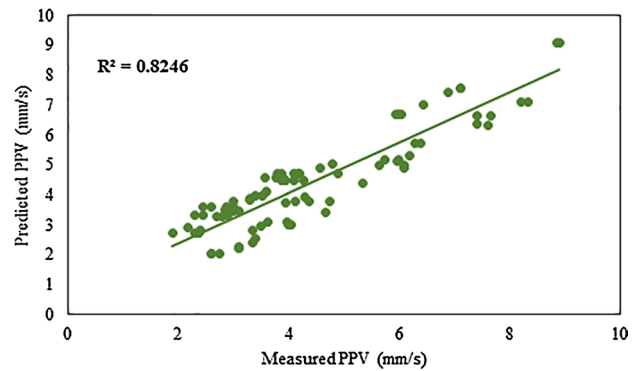


Fig. 7 Measured and predicted PPVs using Davies et al

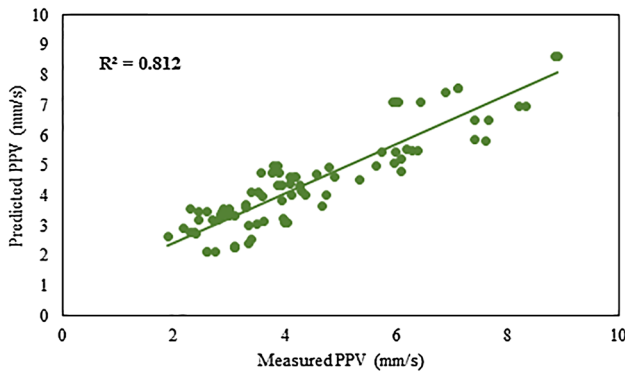


Fig. 5 Measured and predicted PPVs using Ambraseys-Hendron

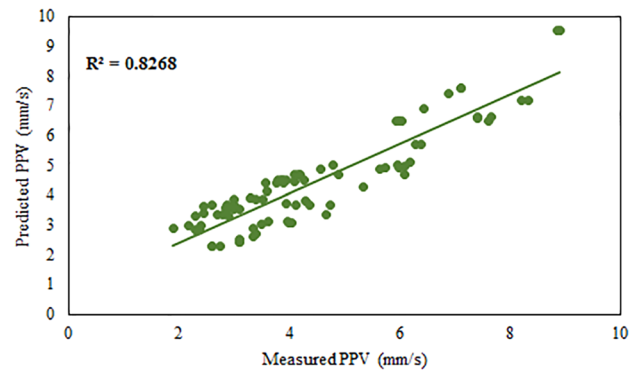


Fig. 8 Measured and predicted PPVs using Roy

obtained. Based on trial-and-error method used in the presented paper, the optimum values of these parameters for both GA models are given in Table 5. Considering the presented parameters in Table 5, the power and linear models optimized by GA were developed and formulated as below:

$$PPV = -11.82 + (40.58 \times D^{-0.2}) + (6133.6 \times W^{-4.25}) \quad (5)$$

$$PPV = 6.75 - (0.03 \times D) + (0.045 \times W) \quad (6)$$

Figures 10 and 11 show the values of R^2 for measured and predicted PPV by GA power and GA linear equations. As shown in Figs. 10 and 11, the GA power and GA linear models are capable of predicting PPV very well. Nevertheless, the performance of GA power model is slightly better than the GA linear model. More details regarding the performance of the proposed GA models for the PPV prediction will be given in Sect. 6.

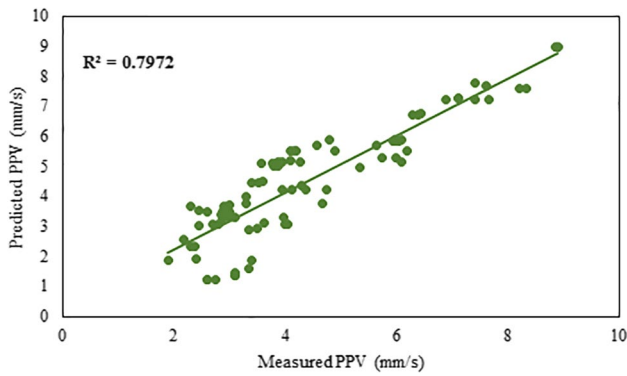


Fig. 9 Measured and predicted PPVs using Rai-Singh

Table 5 The obtained values of the GA parameters

Parameter	Value
Number of generations	400
Number of population	350
Mutation percentage on population	9%
Crossover percentage on population	70%

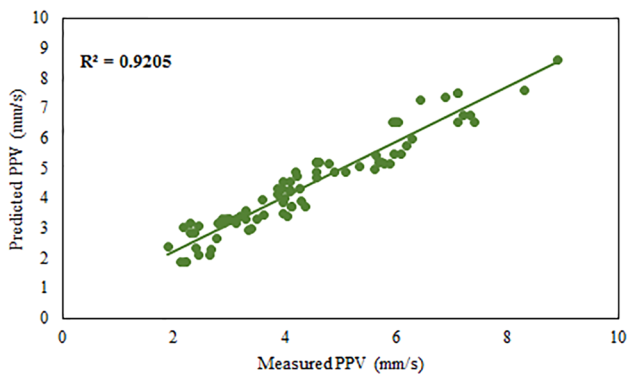


Fig. 10 Measured and predicted PPVs using GA power form

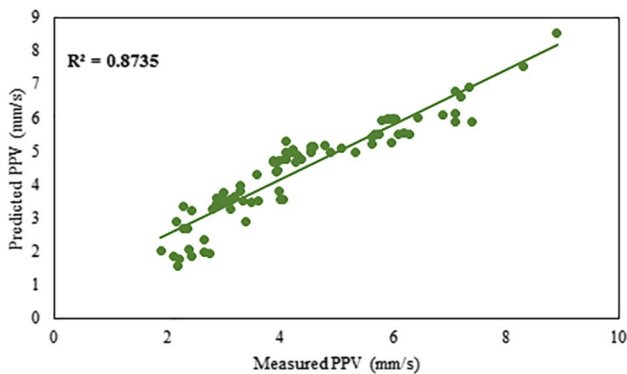


Fig. 11 Measured and predicted PPVs using GA linear form

5 Evaluation of the predictive models

In this section, the accuracy of the developed models in predicting PPV is evaluated using R^2 , root-mean-square error (RMSE), variance account for (VAF) and nash and sutcliffe (NS) criteria.

$$R^2 = \frac{\left[\sum_{i=1}^n (x_i - x_{\text{mean}})^2 \right] - \left[\sum_{i=1}^n (x_i - x_p)^2 \right]}{\left[\sum_{i=1}^n (x_i - x_{\text{mean}})^2 \right]} \tag{7}$$

$$\text{RootMeanSquareError} = \sqrt{\frac{1}{n} \times \sum_{i=1}^n \left[(x_i - x_p)^2 \right]} \tag{8}$$

$$\text{VAF} = \left[1 - \frac{\text{var}(x_i - x_p)}{\text{var}(x_i)} \right] \times 100 \tag{9}$$

$$\text{NS} = 1 - \frac{\sum_{i=1}^n (x_i - x_p)^2}{\sum_{i=1}^n (x_i - \bar{x})^2} \tag{10}$$

where x_i and x_p are the measured and predicted PPV values, and n is also number of datasets. It is worth noting that the $R^2=1$, $RMSE=0$, $VAF=100$ and $NS=1$ indicate the best approximation. Table 6 suggests the values of mentioned criteria for the all predictive models. Based on Table 6, the $RMSE$ values were obtained as 0.73, 0.83, 0.75, 1.35, 0.73, 0.72, 0.84, 0.45 and 0.58 for USBM, Langefors-Kilhstrom, Ambraseys–Hendron, Indian Standard, Davies et al., Roy, Rai-Singh, GA power and GA linear forms, respectively. Also, the R^2 values were obtained as 0.817, 0.783, 0.812, 0.4, 0.824, 0.826, 0.797, 0.92 and 0.873 for USBM, Langefors-Kilhstrom, Ambraseys–Hendron, Indian Standard, Davies et al., Roy, Rai-Singh, GA power and GA linear forms, respectively. In addition, the highest value of VAF and NS are obtained for GA power form in comparison with the obtained criteria results from GA linear form and empirical prediction models. The results summarized in Table 6 show the GA power form has strong potential to indirect estimation of blast-induced PPV and can get more accurate predicting results than the GA linear form and the empirical prediction models.

6 Conclusion

In the presented research, GA is proposed to develop an acceptable and accurate model to estimate ground vibration induced by blasting operations at Bakhtiari dam region, Iran. For this aim, two form of GA model, i.e., power and linear forms were proposed and the weighting factors of

Table 6 statistical criteria results for the predictive models

Model	Statistical criteria			
	RMSE	R^2	VAF (%)	NS
USBM	0.73	0.817	81.66	0.82
Langefors-Kilhstrom	0.83	0.783	77.99	0.77
Ambraseys–Hendron	0.75	0.812	81.16	0.81
Indian standard	1.35	0.4	39.64	0.39
Davies et al.	0.73	0.824	82.41	0.82
Roy	0.72	0.826	82.65	0.83
Rai-Singh	0.84	0.797	76.77	0.76
GA power	0.45	0.92	93.23	0.92
GA linear	0.58	0.873	88.95	0.87

the proposed forms were optimized by GA. In this regard, 85 blasting operations were considered and the values of D and W, as the most effective parameters on the ground vibration, were measured. Also, the values of PPV, as the most common descriptor for evaluating the blast-induced ground vibration, were precisely recorded for the all 85 blasting operations. In order to develop the GA forms, W and D were used as the independent parameters, while PPV was used as the dependent parameter. In GA modeling, the optimum values of GA parameters were determined using trial-and-error method. In this study, the values of 400, 350, 9% and 70% were selected for the number of generations, number of population, mutation percentage on population and crossover percentage on population, respectively. For comparison aims, seven empirical prediction models, including USBM, Langefors-Kilhstrom, Ambraseys–Hendron, Indian Standard, Davies et al., Roy and Rai-Singh models, were also developed by same datasets. To check the applicability and reliability of the all predictive models, several statistical criteria, i.e., R^2 and RMSE, VAF and NS, were computed. Based on obtained results, the lowest value of RMSE and also the highest value of R^2 , VAF and NS are obtained for GA power form in comparison with the other predictive models. For instance, a high R^2 value of 0.92 was obtained for the GA power predictions. As a conclusion, it was found that the GA power form, as a powerful tool can predict ground vibration better than GA linear form as well as empirical prediction models. It is worth mentioning that the developed models in the current paper are specific to Bakhtiari dam region. The application of these models directly in other sites is not recommended, and some modifications are necessary based on blasting pattern and geological conditions.

Acknowledgements The authors would like to extend their appreciation to manager, engineers and personnel of Bakhtiari dam, especially Mr. Alireza Farazmand, for providing the needed information and facilities that made this research possible.

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