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ORIGINAL ARTICLE

The potential application of particle swarm optimization algorithm for forecasting the air-overpressure induced by mine blasting

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Abstract In tunneling projects and open-pit mines, drilling and blasting is a common method for fragmenting the rock masses. Although fragmentation is the main aim of blasting, the adverse effects such as air-overpressure (AOp) and ground vibration are unavoidable. Among these unwanted effects, AOp is considered as one of the most important effects which can cause damage to nearby structures. Therefore, precise estimation of AOp is required for minimizing the environmental problems. This article proposes three new models for predicting blast-induced AOp at Shur river dam area, Iran, optimized by particle swarm optimization (PSO). For this aim, 80 blasting events were investigated and the requirement parameters such as maximum charge per delay, distance from the blast-face and rock mass rating were measured. To evaluate the acceptability and reliability of the proposed PSO models, artificial neural network (ANN) has also been performed. After modeling, the capability of the constructed predictors has been evaluated using the statistical criteria such as coefficient of determination (R^2) and mean square error (MSE). Eventually, it was found that the PSO-linear model (with $R^2=0.960$ and MSE = 4.33) possessed superior predictive ability than the PSO-power model (with $R^2=0.923$ and MSE = 8.89), PSO-quadratic model (with $R^2=0.926$ and MSE = 10.14), ANN model (with $R^2=0.897$ and MSE = 9.98) and USBM model (with $R^2=0.872$ and MSE = 16.28).

Keywords Blasting · AOp · PSO · ANN

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1 Introduction

Drilling and blasting is a common method for fragmenting the rock mass in dam constructions, tunneling projects as well as open-pit mines. The main purpose of the blasting is the appropriate fragmentation, nevertheless, the unwanted effects such as ground vibration, air-overpressure (AOp) and backbreak are inevitable [1–5]. Among them, AOp is defined as a shock wave which is refracted horizontally by density variations into the atmosphere [6]. In the literature, precise estimation of AOp has been highlighted by researchers for minimizing the environmental problems. It is a well-established fact that the different parameters can cause AOp. These parameters are categorized into two main groups; blast design parameters and properties of rock mass [7–9]. Blast design or controllable parameters, such as specific charge, weight charge per delay (W), burden, spacing, time delay interval, sub-drilling, weight charge, stiffness ratio and type of explosive material can be changed by the engineers, Whereas properties of rock mass cannot be changed by the engineers. Based on some studies [7, 9, 10], W and distance from the blast-face (*D*) are the most effective parameters on AOp. In the recent years, the application of soft computing methods for solving the engineering problems has been highlighted by some researchers [11–16]. By reviewing the previous studies, several soft computing methods such as artificial neural network (ANN), fuzzy interface system (FIS), adaptive neuro-fuzzy inference system (ANFIS) genetic programing (GP) and support vector machine (SVM) have been employed in forecasting the AOp. Khandelwal and Singh [7] employed the ANN, United States Bureau of Mines (USBM) model and regression analysis for forecasting the AOp. In their study, W and D were used as the model inputs. Based on their results, ANN was more acceptable than regression analysis and USBM for forecasting the AOp. In the other study, Mohamed [17] used FIS and ANN for predicting the AOp. He used also W and D as the input parameters. His results proved that accuracy of FIS was superior to that of ANN. A comprehensive study to forecast AOp was done by Khandelwal and Kankar [9] using SVM and USBM models. Their results showed significant capability of the SVM compared to USBM in forecasting AOp. In the other study of soft computing methods, Hajihassani et al. [18] developed a hybrid model of ANN and particle swarm optimization (PSO) for forecasting the AOp. For comparison aims, USBM and ANN model were also used in their studies. Based on their obtained results, the accuracy of hybrid model was superior to those of ANN and USBM models. Recently, ANFIS and ANN were employed for AOp prediction by Jahed Armaghani et al. [19]. Their results indicated that the ANFIS possessed superior predictive ability than the ANN, since a very close agreement between the measured and the predicted values was obtained. In the present research, a new practical model is proposed to forecast AOp at Shur river dam, Iran, using PSO. In the other words, a non-linear equations is proposed which optimized by PSO. To evaluate the acceptability and reliability of the proposed PSO model, artificial neural network (ANN) has been also performed. In summary, the present paper is structured as follows:

The field investigation has been explained in Sect. 2. The AOp prediction by PSO is presented in Sect. 3. The results of the predictive models are presented and discussed in Sect. 4 and finally, the main conclusions of this research work are drawn.

2 Field investigation

In the present study, the requirement datasets were collected from Shur river dam region, in Iran, between 55°51′47″ longitudes and 30°1′48″ latitudes. A view of Shur river dam region is shown in Fig. 1. Bench blasting was the most main method for rock breakage in this site. In each blasting, maximum numbers of rows and blast-holes were 6 and 66, respectively, while their minimum numbers were 2 and 25, respectively. Moreover, ANFO with the specific gravity of 0.85–0.95 gr/cm^3 was used as the explosive material in each blasting. AOp was one of the undesirable effects induced by mine blasting in this site. Hence, a research program was carried out for evaluating and predicting the AOp. For this

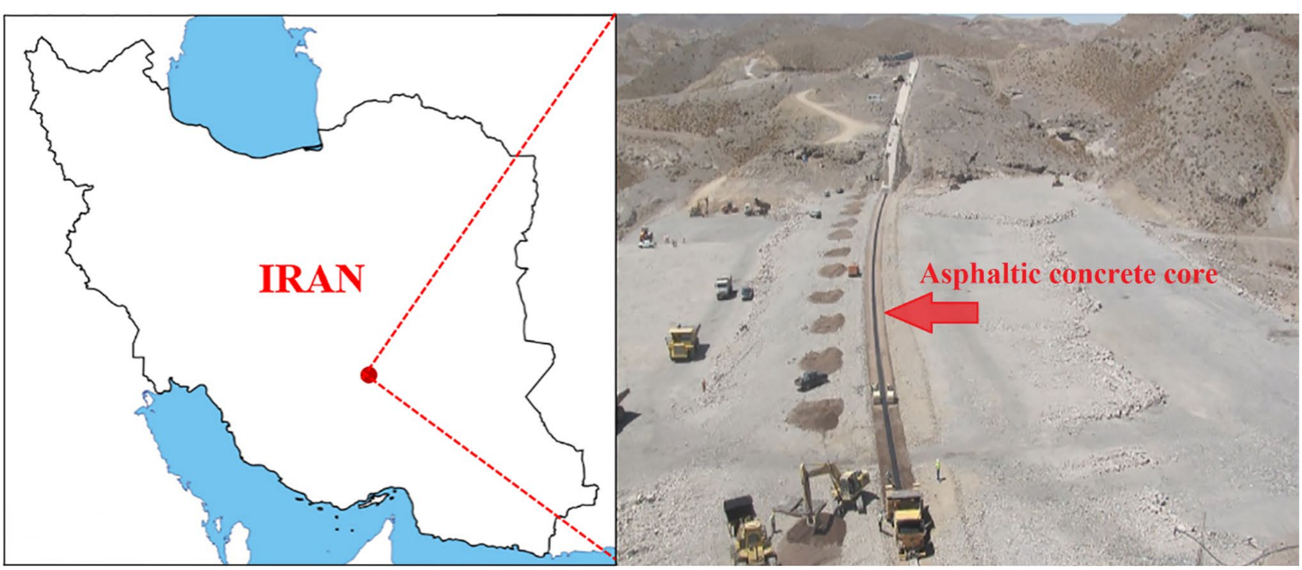

Fig. 1 A view of Shur river dam

work, 80 blasting events were monitored and the effective parameters on AOp were measured. According to Kuzu et al. [20], Khandelwal and Kankar [9], W and D are the most effective parameters on AOp. Hence, W and D were measured for all monitored blasting events. In addition, the values of rock mass rating (RMR) were determined for these operations. In other words, W, D and RMR were considered as the independent parameters for forecasting the AOp. For measuring the AOp values, Minimate Pulse instrument was installed in different locations and its distances from shot-points were measured by GPS. This instrument can record the AOp values in the range of 88 dB (7.25×10^{-5} psi or 0.5 Pa) and 148 dB (0.0725 psi or 500 Pa). More details regarding to measured datasets are summarized in Table 1 and Fig. 2.

3 Prediction of AOp

In the present research work, PSO and ANN were employed for predicting the AOp. For modeling PSO and ANN models, the prepared datasets were divided into two subsets, i.e., train and test. In this regard, 80 and 20% of total datasets were adopted for training and testing, as recommended in many studies [4, 5, 13, 19]. In other words, 64 and 16 datasets were employed for building and testing the models. Table 2 also shows the basic statistics of the train and test sets.

3.1 Prediction of AOp using PSO

PSO is a population-based search algorithm based on an analogy with the collective motion of biological organisms [21]. According to some studies, the principal of the PSO are the cognitive of swarm and social behavior [21]. This algorithm has faster convergence than genetic algorithm as well as has few parameters to adjust and is also easy to implement [22–24]. More explanations regarding PSO algorithm can be viewed in many studies (e.g., Momeni et al. [22]; Ghasemi et al. [23]). PSO is extensively applied for solving real world problems, so far. Day by day the number of researchers being interested in PSO increases rapidly. For instance, Jahed Armaghani et al. [19], Tonnizam Mohamad et al. [24] and Ghasemi et al. [23] employed the PSO in the field of rock engineering. Based on their obtained results, PSO is a powerful algorithm for optimizing aims in this field. According to mentioned descriptions, PSO is used for optimizing three linear and non-linear equations for predicting the AOp. In the other words, two forms of non-linear equations including power and quadratic and a linear equation are proposed in the present study, so that the coefficients of these equations were optimized by PSO. Considering the input (independent) parameters, the linear, power and quadratic forms are shown as following:

$$\mathrm{AOp}_{\mathrm{linear}} = A_0 + A_1 \cdot W + A_2 \cdot D + A_3 \cdot \mathrm{RMR} \quad (1)$$

$$\mathrm{AOp}_{\mathrm{power}} = A_0 + A_1 \cdot W^{A_2} + A_3 \cdot D^{A_4} + A_5 \cdot \mathrm{RMR}^{A_6} \quad (2)$$

$$\begin{aligned}\mathrm{AOp}_{\mathrm{quadratic}} = A_0 &+ A_1 \cdot W + A_2 \cdot D + A_3 \cdot \mathrm{RMR} \\ &+ A_4 \cdot W^2 + A_5 \cdot D^2 + A_6 \cdot \mathrm{RMR}^2\end{aligned} \quad (3)$$

where *W, D* and RMR are the model inputs. The $A_0, A_1, A_2, A_3, A_4, A_5$ and A_6 are the coefficients so that these coefficients will be optimized by PSO in the present study. For this aim, a PSO code was implemented in MATLAB Software environment. In PSO modeling, various parameters, i.e., number of particles, number of iterations, coefficients of velocity equation (C_1 and C_2) and inertia weight should be determined. To obtain the number of particles, trial and error method is employed in the present study. In this regard, various numbers of particles were used and their performances were evaluated based on coefficient of determination (R^2), as shown in Table 3. From Table 3, it was found that the model no. 9 with the numbers of particles of 350 indicates the best performance. Therefore, the value of 350 was considered as the numbers of particles in the present study. By reviewing the previous studies, the various number of iterations were tested and based on obtained results the value of 450 was considered as the numbers of iterations. Afterwards, the values of coefficients of velocity equation (C_1 and C_2) and inertia weight should be determined. Based on expert opinions as well as the previous researchers, the value of 0.75 was also selected as the inertia weight. In addition, Table 4 shows the using of various values for the C_1 and C_2. According to this Table, the values of 2 and 2 were considered as the C_1 and C_2. Based on above, the values of 350, 450, 0.75, 2 and 2 were chosen as the numbers of particles, numbers of iterations, inertia weight, C_1 and C_2. Note that, the mentioned values were assigned for the linear form. In case of power and quadratic forms, the mentioned steps were reconsidered and based on obtained results, the values of the numbers of particles, numbers of iterations, inertia

Table 1 The measured parameters in the present study for forecasting AOp

Type of data	Symbol	Range		
		Min	Mean	Max
Input	*W* (kg)	180	784	1450
	D (m)	308	559	944
	RMR	38	45	55
Output	AOp	111.6	130.9	147.3
No. of samples	80			

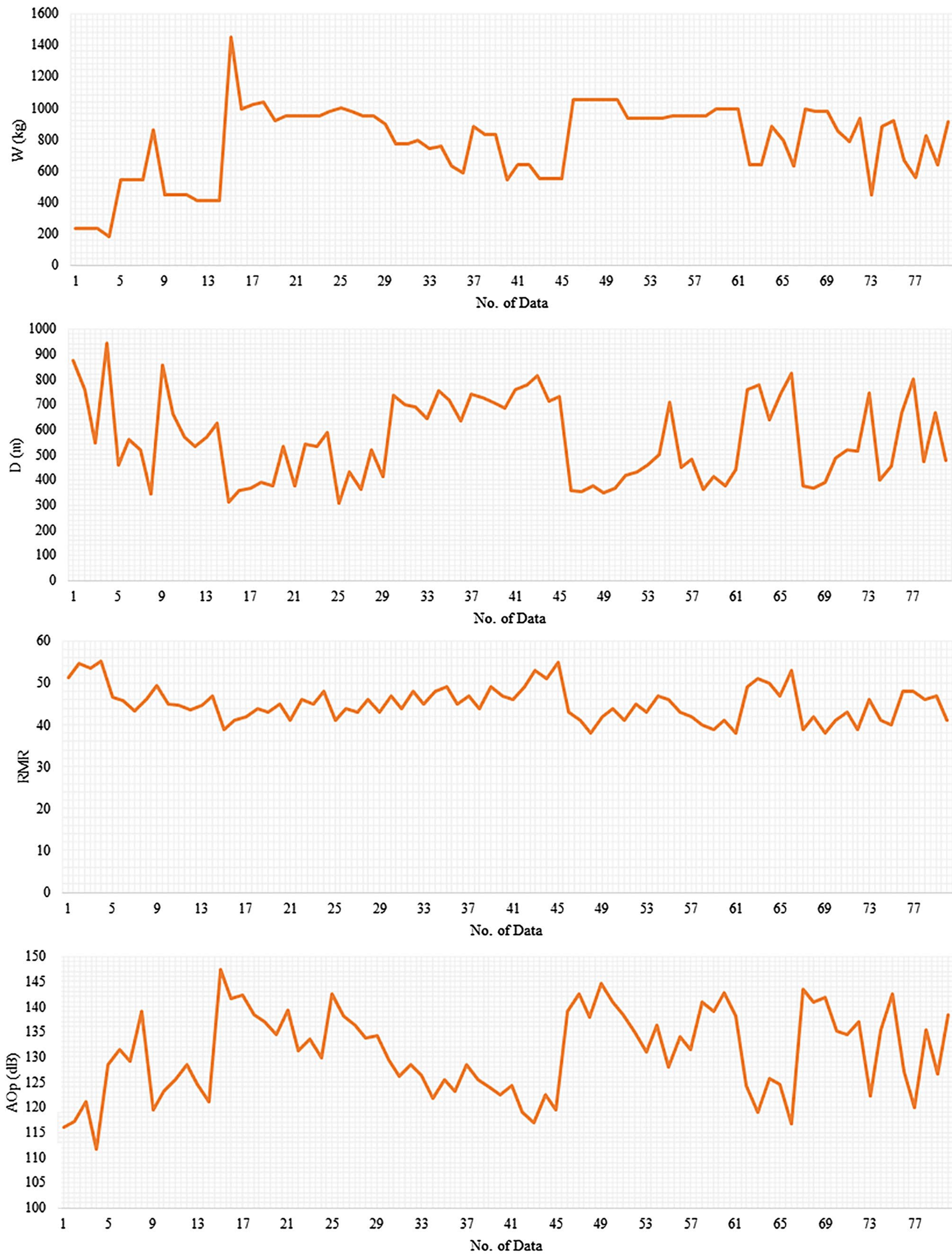

Fig. 2 A view of the measured parameters in the present study

Table 2 The basic statistics of the train and test sets in this research

	No. of samples	Parameters	Min	Mean	Max
Train set	64	W (kg)	180	780	1450
		D (m)	308	559	944
		RMR	38	46	55
		AOp (dB)	111.6	130.5	147.3
Test set	16	W (kg)	450	801	955
		D (m)	366	557	823
		RMR	38	44	53
		AOp (dB)	116.7	132.6	143.5

Table 3 Results of PSO models for various number of particle

Model no.	Number of particle	Network result	
		R^2	
		Train	Test
1	25	0.855	0.843
2	50	0.861	0.835
3	75	0.854	0.849
4	100	0.866	0.845
5	150	0.879	0.858
6	200	0.874	0.861
7	250	0.881	0.867
8	300	0.899	0.881
9	350	0.914	0.911
10	400	0.902	0.895
11	500	0.889	0.873

Table 4 Results of PSO modeling for various coefficients of velocity equation (C_1 and C_2)

Model no.	(C_1 and C_2)	Network result	
		R^2	
		Train	Test
1	(2 and 2)	0.949	0.960
2	(1.5 and 1.5)	0.933	0.925
3	(1.75 and 1.75)	0.919	0.923
4	(1.5 and 1.75)	0.941	0.937
5	(1.75 and 1.5)	0.935	0.926
6	(2.25 and 1.75)	0.921	0.913
7	(1.75 and 2.25)	0.931	0.934

weight, C_1 and C_2 are given in Table 5. Considering these values, the linear, power and quadratic forms optimized by PSO were formulated, as shown in below:

$$\mathrm{AOp}_{\mathrm{linear}} = 154.5 + 0.011W - 0.028D - 0.037\mathrm{RMR} \tag{4}$$

Table 5 The values of PSO parameters for the power and quadratic forms

Form of equation	PSO parameters				
	No. of particles	No. of iterations	Inertia weight	C_1	C_2
Power	400	350	0.75	1.5	1.5
Quadratic	300	400	0.75	2	2

$$\mathrm{AOp}_{\mathrm{power}} = -47.77 + 0.1W^{0.72} + 371.3D^{-0.08} - 47.77\mathrm{RMR}^{1} \tag{5}$$

$$\begin{aligned}\mathrm{AOp}_{\mathrm{quadratic}} = {} & 1.27 + 0.001W - 0.06D + 6.87\mathrm{RMR} + 7.04 \\ & \times 10^{-6}W^2 + 3.08 \times 10^{-5}D^2 - 0.078\mathrm{RMR}^2\end{aligned} \tag{6}$$

The above equations were constructed based on training datasets. In the second step, the performance of these equations will be evaluated using testing data sets. More details about the performance of PSO models is suggested in Sect. 4.

3.2 Prediction of AOp using ANN

The good performance and effectiveness of ANN have been approved in the complicated systems [25, 26]. An ANN has the layers, i.e., input, hidden and output layers. The input and output parameters are adopted in the input and output layers, respectively. In the present study, W, D and RMR are the model inputs, while, the AOp is considered as the model output. The most important task in ANN modeling is to select the appropriate neurons in hidden layers. By reviewing the previous studies, it was found that using one hidden layer is sufficient for solving any problems. Hence, one hidden layer is employed in the present study. Then, the numbers of neurons in this hidden layers should be determined. For this work, various models have been constructed and their performances have been compared, as shown in Table 6. Based on Table 6, model No. 4 with the four neurons in hidden layer has the best performance in both train and test. Hence, the appropriate structure of ANN in the presented research work has 3 neurons (W, D and RMR) in the input layer, 4 neurons in the hidden layer and 1 neuron (AOp) in the output layer. The comparison between the ANN model via PSO models have been suggested in the next section.

4 Analysis of the results

In this study, three forms of equations, i.e., linear, power and quadratic forms, were proposed for predicting the AOp, so

Table 6 R^2 values of the developed ANN models

Model no.	Neurons in hidden layer	Network Result											
		Run 1		Run 2		Run 3		Run 4		Run 5		Average	
		R^2		R^2		R^2		R^2		R^2		R^2	
		Train	Test	Train	Test	Train	Test	Train	Test	Train	Test	Train	Test
1	1	0.832	0.825	0.842	0.823	0.841	0.824	0.823	0.812	0.847	0.835	0.837	0.823
2	2	0.861	0.854	0.869	0.843	0.875	0.869	0.857	0.853	0.876	0.834	0.867	0.850
3	3	0.856	0.842	0.853	0.841	0.877	0.848	0.859	0.851	0.865	0.869	0.862	0.850
4	4	0.873	0.877	0.879	0.858	0.892	0.886	0.907	0.897	0.879	0.895	0.886	0.882
5	5	0.845	0.851	0.856	0.843	0.877	0.834	0.868	0.873	0.882	0.855	0.865	0.851
6	6	0.882	0.835	0.849	0.829	0.844	0.841	0.854	0.866	0.857	0.859	0.857	0.846

that their coefficients were optimized by PSO. To check the performance of the constructed equations, ANN model was also employed. For constructing the predictive models 64 datasets were used and then 16 new datasets were used to test the constructed models. Aside from the mentioned ANN and PSO models, an empirical model presented by United States Bureau of Mines (USBM) [27] is used in the present study. Based on obtained results from the regression analysis, the constructed USBM model is formulated as following:

$$\mathrm{AOp} = 248.37\left(\frac{D}{W^{0.33}}\right)^{-0.15} \tag{7}$$

The accuracy of the predictors was evaluated based on several statistical functions, i.e., R^2, variance account for (VAF), mean absolute bias error (MABE) and mean squared error (MSE).

$$R^2 = \frac{\left[\sum_{i=1}^{n}\left(x_i - x_{\mathrm{mean}}\right)^2\right] - \left[\sum_{i=1}^{n}\left(x_i - x_p\right)^2\right]}{\left[\sum_{i=1}^{n}\left(x_i - x_{\mathrm{mean}}\right)^2\right]} \tag{8}$$

$$\mathrm{MSE} = \frac{1}{n} \times \sum_{i=1}^{n}\left[\left(x_i - x_p\right)^2\right] \tag{9}$$

$$\mathrm{VAF} = \left[1 - \frac{\mathrm{var}\left(x_i - x_p\right)}{\mathrm{var}\left(x_i\right)}\right] \times 100 \tag{10}$$

$$\mathrm{MABE} = \frac{1}{n} \times \sum_{i=1}^{n}\left|x_i - x_p\right| \tag{11}$$

where, n is the number of the selected data sets, x_p is the predicted value and x_i is the actual value.

Table 7 shows the obtained R^2 and MSE for the predictive models. From Table 7, it was proved that the lowest values for the MSE and MABE as well as the highest values for the VAF and R^2 were obtained from PSO-linear model. The R^2 of 0.960 shows that prediction of AOp by PSO-linear model is very accurate and closer to measured AOp values. Figures 3, 4, 5, 6 and 7 also illustrate the scatter plots of AOp predicted by the models for both training and testing data sets. Moreover, when considering the achieved results of the MSE for the predictive models, values of 4.33, 8.89, 9.98, 10.14 and 16.28 were obtained from PSO-linear, PSO-power, ANN, PSO-quadratic and USBM models, respectively, which demonstrates a higher accuracy of PSO-linear model. In the present study, sensitivity analysis was also performed using Yang and Zang [28] met hod:

Table 7 The values of statistical functions for the predictive models

Model	Statistical functions							
	R^2		MSE		VAF (%)		MABE	
	Train	Test	Train	Test	Train	Test	Train	Test
USBM	0.892	0.872	8.11	16.28	88.85	86.08	2.45	3.81
ANN	0.907	0.897	6.64	9.98	90.60	88.33	2.34	2.66
PSO-linear	0.949	0.960	3.68	4.33	94.82	95.05	1.59	1.67
PSO-power	0.941	0.923	4.27	8.89	94.04	90.50	1.70	2.47
PSO-quadratic	0.929	0.926	5.32	10.14	92.55	89.55	1.93	2.50

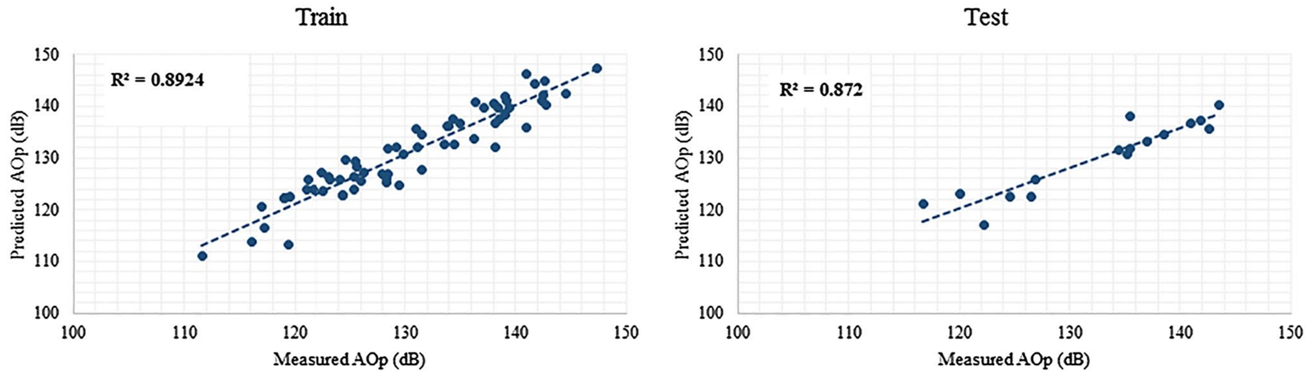

Fig. 3 The performance of the USBM for forecasting the AOp

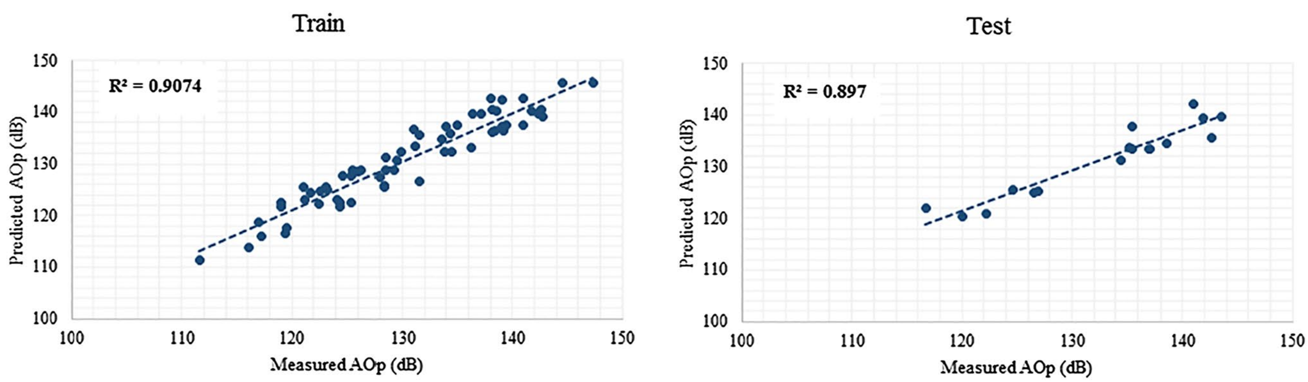

Fig. 4 The performance of the ANN for forecasting the AOp

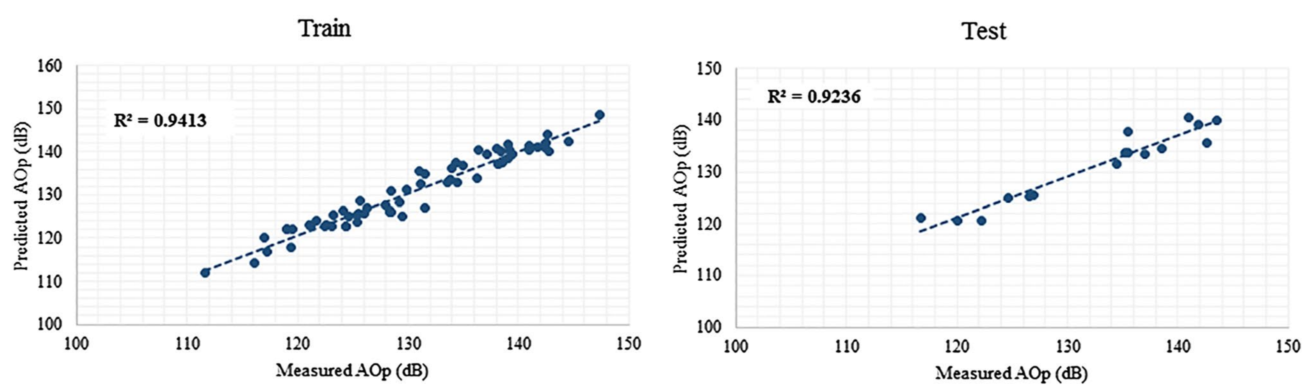

Fig. 5 The performance of the PSO-power for forecasting the AOp

$$r_{ij} = \frac{\sum_{k=1}^{n} (y_{ik} \times y_{ok})}{\sqrt{\sum_{k=1}^{n} {y_{ik}}^2 \sum_{k=1}^{n} {y_{ok}}^2}} \tag{12}$$

where y_i and y_o denote the input and output parameters, respectively. Based on obtained results from the sensitivity analysis, RMR with r_{ij} of 0.988 was the most effective parameter on the AOp in the present research work, while, the values of r_{ij} for the W and D were 0.969 and 0.941, respectively.

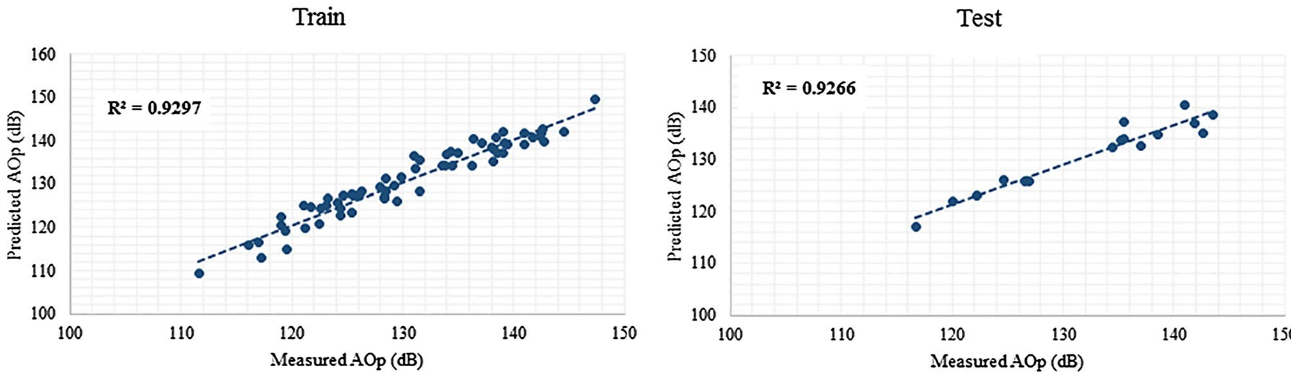

Fig. 6 The performance of the PSO-quadratic for forecasting the AOp

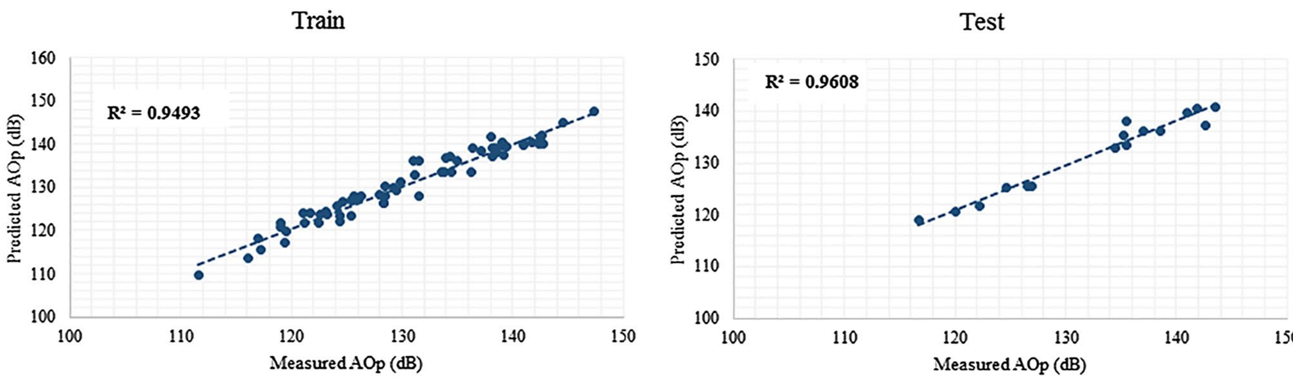

Fig. 7 The performance of the PSO-linear for forecasting the AOp

5 Conclusion

The aim of this research work is to obtain a novel predictive model for forecasting the AOp induced by mine blasting at Shur river dam region, Iran. AOp is an undesirable effect induced by blasting operations in surface mines and proper predictions of AOp is a necessary task in this field. This paper presents three PSO-based models, namely linear, power and quadratic which use PSO for optimizing aims. In addition, ANN and USBM models were also employed in the same datasets for comparison purposes. In this regard, 80 blasting were investigated and the values of AOp were carefully measured and set as the models output. Also, the values of W, D and RMR were measured and these parameters were set as the input parameters. The prepared datasets were divided into train and test categories, so that 64 and 16 datasets were adopted as the training and testing. After constructing the models, four statistical criteria, i.e., VAF, R^2, MABE and MSE were employed for evaluating the accuracy of the constructed models. Based on obtained results, it was proved that the PSO-linear model (with R^2 of 0.960, MSE of 4.33, VAF 95.05 and MABE of 1.67) has better performance of PSO-power model (with R^2 of 0.923, MSE of 8.89, VAF 90.50 and MABE of 2.47), PSO-quadratic model (with R^2 of 0.926, MSE of 10.14, VAF 89.55 and MABE of 2.50), ANN model (with R^2 of 0. 897, MSE of 9.98, VAF 88.33 and MABE of 2.66) and USBM (with R^2 of 0.872, MSE of 16.28, VAF 86.08 and MABE of 3.81). The achieved results show that the proposed PSO-based models, especially PSO-linear model, can be introduced with confidence for future research works on formulating new predictors for forecasting the blast-induced AOp.

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