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ORIGINAL ARTICLE

A novel intelligent approach to simulate the blast-induced flyrock based on RFNN combined with PSO

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Abstract
This research focuses to propose a new hybrid approach which combined the recurrent fuzzy neural network (RFNN) with particle swarm optimization (PSO) algorithm to simulate the flyrock distance induced by mine blasting. Here, this combination is abbreviated using RFNN–PSO. To evaluate the acceptability of RFNN–PSO model, adaptive neuro-fuzzy inference system (ANFIS) and non-linear regression models were also used. To achieve the objective of this research, 72 sets of data were collected from Shur river dam region, in Iran. Maximum charge per delay, stemming, burden, and spacing were considered as input parameters in the models. Then, the performance of the RFNN–PSO model was evaluated against ANFIS and non-linear regression models. Correlation coefficient (R^2), Nash and Sutcliffe (NS), mean absolute bias error (MABE), and root-mean-squared error (RMSE) were used as comparing statistical indicators for the assessment of the developed approach's performance. Results show a satisfactory achievement between the actual and predicted flyrcok values by RFNN–PSO with R^2, NS, MABE, and RMSE being 0.933, 0.921, 13.86, and 15.79, respectively.

Keywords Flyrock distance · Recurrent fuzzy neural network · Particle swarm optimization · Adaptive neuro-fuzzy inference system

1 Introduction

In the surface mines and tunneling projects, flyrock is considered as an undesirable effect induced by blasting operation. Aside from flyrock, several undesirable effects, such as ground vibration, air-blast, and noise, are inevitable [1–4].

The most influential parameters on flyrock can be categorized into two main parts, i.e., controllable and uncontrollable parameters [1–7]. For example, burden, spacing, delay times, and maximum charge per delay are the controllable parameters. In other words, the blasting designer can change the amount of the controllable parameters. On the other hand, uncontrollable parameters such as the strength of the rock mass are the natural and can be not changeable. Flyrock is known to have resulted in damages to structures and fatalities as well as human injuries in the vicinity of mines. Hence, achieving a high-precision model to forecast blast-induced flyrock is very important for assessing the environmental damages. In the recent years, the artificial intelligence-based models have been employed to the prediction aims [5–21], especially in the field of blast-induced flyrock. Artificial neural network (ANN) and empirical models were used to predict the flyrock by Monjezi et al. [22]. Their prediction results showed that the accuracy of the ANN was higher compared with empirical models. Amini et al. [23] predicted the values of the blast-induced flyrock through ANN and support vector machine (SVM). Their obtained results show that the SVM yields the better performance

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for the prediction of blast-induced flyrock as compared to ANN. In another study, Trivedi et al. [24] employed multi-variable regression analysis (MVRA), ANN and adaptive neuro-fuzzy inference system (ANFIS) models to forecast the flyrock distance. According to the obtained results, the ANFIS model with a high accuracy was able to forecast the flyrock as compared to ANN and MVRA. Like to Trivedi et al. [24], ANN and ANFIS models were offered to predict flyrock by Jahed Armaghani et al. [3], and their results proved the acceptability and reliability of the ANFIS model. The scope of this paper is to build an advanced and accurate model to forecast the values of blast-induced flyrock in the Shur river dam region, Iran. For this work, a new hybrid approach combined the recurrent fuzzy neural network (RFNN) with particle swarm optimization (PSO) algorithm is proposed in the present research work. In other words, PSO is used to optimize the RFNN. The proposed RFNN–PSO is a novel artificial intelligence-based model in this field and the results obtained will be useful to promote new future research works.

2 Field investigation

The main aim of the present research work is to propose a new hybrid of RFNN and PSO in the field of flyrcok prediction. The requirement data sets for developing the proposed RFNN–PSO model were collected from Shur river dam region, in Iran. For a better understanding, a view of the location site is shown in Fig. 1. In addition, the extensive details about the Shur river dam region can be found in [25–29]. In the used database, 72 sets of data including four input parameters and one output parameter are considered. Input parameters include burden, spacing, stemming, and maximum charge per delay, while the output parameter is the flyrock distance. To measure the flyrock distance values, a handheld Global Positioning System (GPS) was used. All data were divided into two subsets, i.e., training and testing. In all the predictive models, the used data for training and testing sets were 58 and 14 of total 72 actual data, respectively. In other words, 58 sets of data were allotted to training data of model construction and the remained 14 data were allocated for test data used to assess the reliability of the developed model.

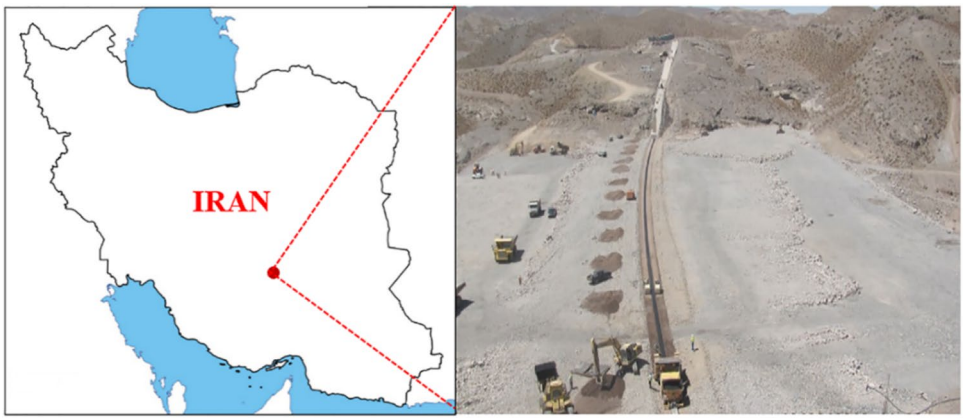


Fig. 1 A view of Shur river dam region in Iran

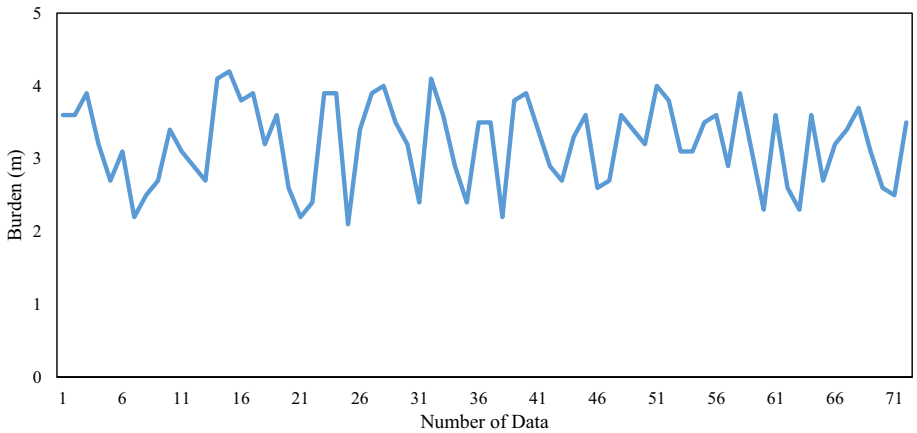


Fig. 2 A statistical view of the burden parameter

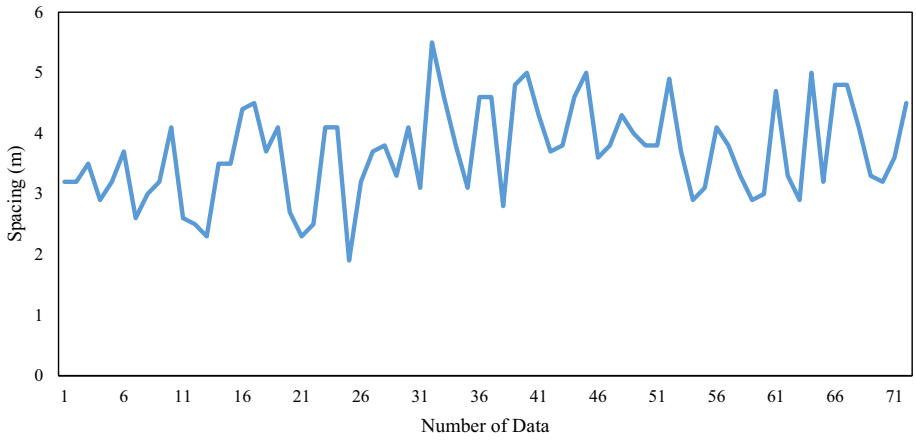


Fig. 3 A statistical view of the spacing parameter

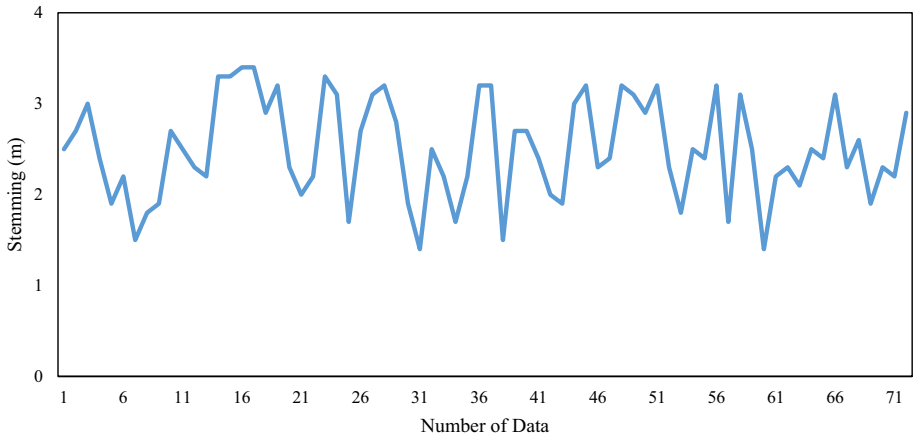


Fig. 4 A statistical view of the stemming parameter

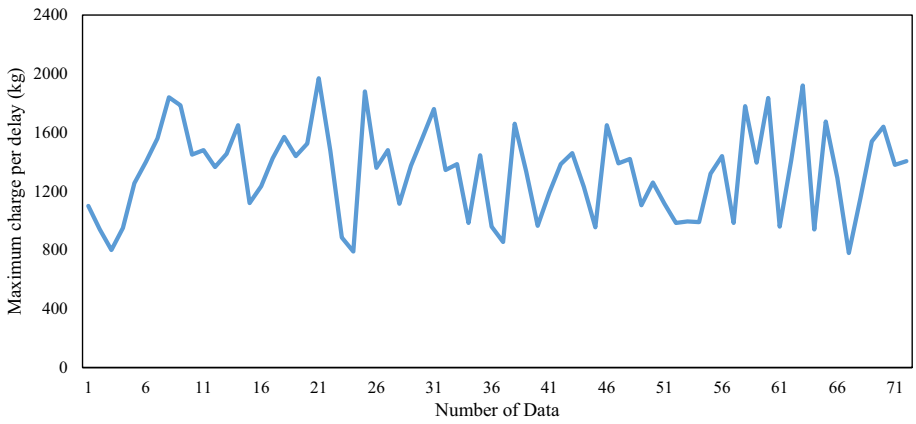


Fig. 5 A statistical view of the maximum charge per delay parameter

Figures 2, 3, 4, 5, 6 show the statistical view of the input and output parameters. In addition, the range of the input and output parameters is listed in Table 1.

3 Development of the predictive models

3.1 RFNN–PSO

In the present research work, a novel hybrid of RFNN and PSO is proposed to predict the flyrock. An overall schematic diagram of the structure of the RFNN is shown in

Fig. 7 [30]. In this diagram, *N, M*, and *P* are considered as the number of inputs, the term for each variable, and the output variable, respectively [30]. As shown in Fig. 7, the RFNN consists of six layers, so that each membership function has a recurrent connection. Extensive details about the RFNN and its implementation can be found in [30–32]. In the present study, PSO is used to optimize the RFNN. In RFNN–PSO modeling, the PSO parameters, i.e., coefficients of velocity equation (C_1 and C_2) and inertia weight, should be evaluated. Table 2 represents various combinations of C_1 and C_2, and their achieved results. In Table 2, seven models were created, and then, their performances were checked using correlation coefficient (R^2) and root-mean-squared error (RMSE). It is worth mentioning that the highest total rank value indicates the most accurate model. In addition, the values of rank value will be between 0 and 7, since we have developed seven different models. Based on Table 2, model No. 2, with the highest total rank value, has the better performance than the others. Hence, the values of 1.5 and 1.5 were

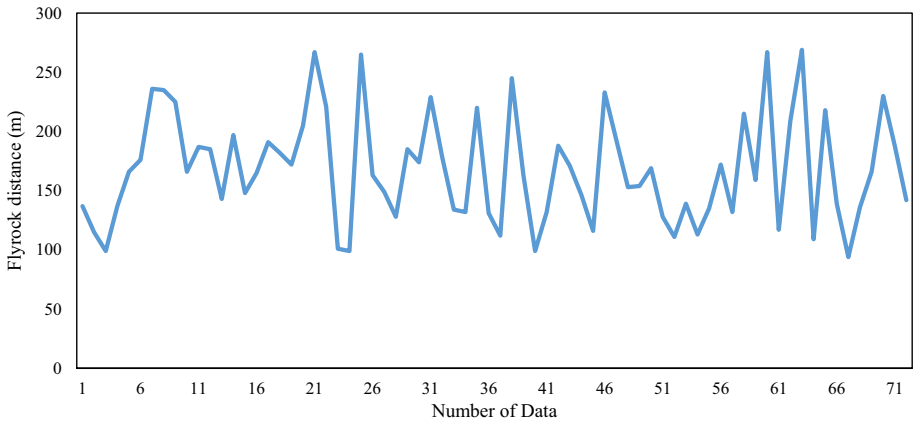


Fig. 6 A statistical view of the flyrock parameter

Table 1 The range of input and output parameters used in this research

Parameter	Unit	Category	Min	Max	Mean	STDEV
B	m	Input	2.1	4.2	3.21	0.567
S	m	Input	1.9	5.5	3.68	0.776
S_T	m	Input	1.4	3.4	2.50	0.547
MC	kg	Input	780	1970	1332.08	299.164
Flyrock distance	m	Output	94	269	168.12	46.030

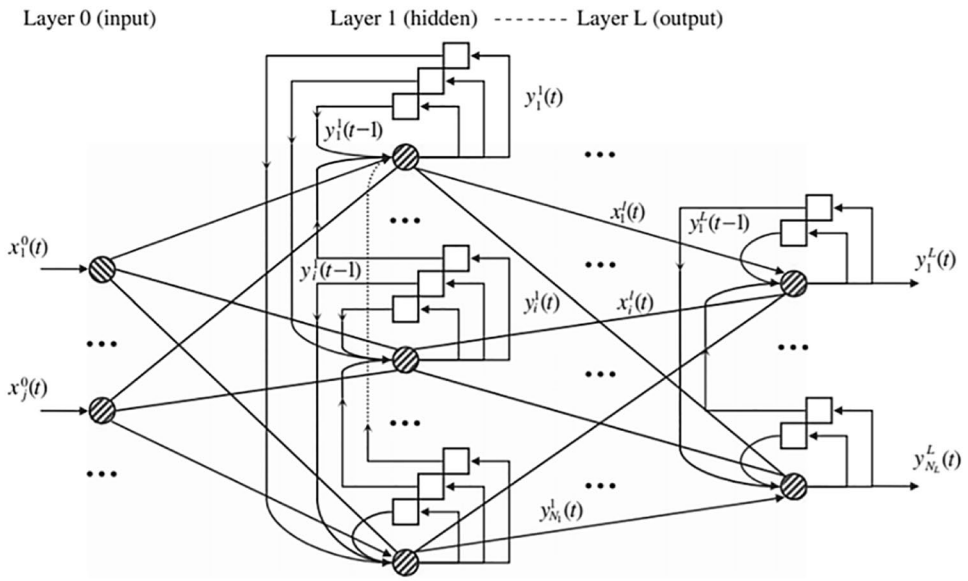


Fig. 7 The Structure of the RFNN model

Table 2 Results of RFNN–PSO for various C_1 and C_2

Model no.	C_1	C_2	RFNN–PSO result				Rank value				Total Rank
			Train		Test		Train		Test		
			R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	
1	2	2	0.953	0.107	0.872	0.500	2	2	1	1	6
2	1.5	1.5	0.974	0.079	0.933	0.105	6	6	7	7	26
3	1.75	1.75	0.941	0.12	0.903	0.138	1	1	3	3	8
4	1.5	1.75	0.986	0.058	0.890	0.125	7	7	2	4	20
5	1.75	1.5	0.955	0.103	0.913	0.412	3	3	5	2	13
6	2.25	1.75	0.969	0.080	0.918	0.110	5	5	6	6	22
7	1.75	2.25	0.964	0.093	0.910	0.119	4	4	4	5	17

selected for the C_1 and C_2 in the RFNN–PSO modeling. Based on some related studies (such as Hasanipanah et al. [29]; Jahed Armaghnai et al. [33]; Shahnazar et al. [34]), the value of 0.75 was also selected as the inertia weight. The performance of the developed RFNN–PSO model in comparison with the other models is discussed in Sect. 4.

3.2 ANFIS

In the recent years, the application of ANFIS has been highlighted for the predicting aims by many researchers (e.g., Samui et al. [35]; Koçaslan et al. [36]). In the modeling of ANFIS, three strategies, i.e., fuzzy c-mean clustering (FCM), subtractive clustering method (SCM), and grid partitioning (GP), can be considered. Considering the data sets used in the present research, the prediction capabilities of these strategies are computed, as shown in Table 3. According to the obtained results, both of the GP and FCM strategies can predict flyrock in the same average ranges and better than the SCM strategy. On the other hand, run of 2 for the FCM has the higher R^2 value for testing data sets. Hence, the FCM strategy is chosen as the best ANFIS model in this study. The performance of the developed ANFIS model in comparison with the other models will be discussed in Sect. 4.

3.3 Non-linear regression models

In this study, two forms of non-linear regression models are developed to predict the flyrock. These models are given as follows:

$$\text{Flyrock} = a + a_1 B^3 + a_2 S^3 + a_3 {S_\text{T}}^3 + a_4 \text{MC}^3, \quad (1)$$

where B (burden), S (spacing), S_T (stemming), and MC (max charge per delay) are as the independent parameters. a and b are the intercept, and a_i and b_i are also the partial regression coefficients. Considering the training data, the followed non-linear regression models are created:

$$\text{Flyrock} = 147.29 - 1.87B^3 + 0.3S^3 + 2.13{S_\text{T}}^3 + 18 \times 10^{-7}\text{MC}^3. \quad (2)$$

In this equation, B, S, S_T, and MC are in terms of m, m, m, and kg, respectively. The accuracy of the created non-linear regression models in comparison with the other models is discussed in Sect. 4.

4 Analysis of the results

In this section, the performance of the RFNN–PSO, ANFIS, and non-linear regression models is evaluated and compared using statistical performance metrics. The performance parameters include RMSE, Nash and Sutcliffe (NS), median

Table 3 The prediction capabilities of GP, SCM, and FCM strategies for predicting flyrock

Model no.	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
GP	0.854	0.725	0.854	0.725	0.854	0.725	0.854	0.725	0.854	0.725	0.8545	0.7251
SCM	0.884	0.577	0.883	0.577	0.883	0.577	0.883	0.577	0.883	0.577	0.8839	0.577
FCM	0.871	0.711	0.876	0.743	0.871	0.711	0.871	0.711	0.874	0.699	0.8729	0.715

absolute error (MEDAE), mean absolute bias error (MABE), and R^2 [37–44].

1. Nash and Sutcliffe (NS) (1970):

$$\mathrm{NS} = 1 - \frac{\sum_{i=1}^{n} \left(M_i - P_i\right)^2}{\sum_{i=1}^{n} \left(M_i - \bar{M}\right)^2}. \tag{3}$$

2. Median absolute error (MEDAE):

$$\mathrm{MEDAE} = \mathrm{median}(M_i - P_i). \tag{4}$$

Mean absolute bias error (MABE):

$$\mathrm{MABE} = \frac{1}{n} \times \sum_{i=1}^{n} \left|P_i - M_i\right|. \tag{5}$$

Lower RMSE, MEDAE, and MABE are the better model prediction. In addition, NS and R^2 order from 0 to 1, while the model has healthy predictive ability when it is near to 1. The obtained values for the mentioned statistical performance metrics are given in Table 4. It is worth mentioning that the training data were used to develop the predictive models, while the testing data will be applied to test and check the performance of the developed models. As shown in Table 4, the smallest RMSE, MEDAE, and MABE values for testing set have been obtained from the RFNN–PSO with 15.79, 13.70, and 13.86, respectively. In addition, the highest NS and R^2 values for testing set have been obtained from the RFNN–PSO with 0.921 and 0.933, respectively. In addition, the values of R^2 for the all predictive models are shown in Figs. 8, 9, and 10. According to the summarized results in Table 4 as well as the showed R^2 values in Figs. 8, 9, and 10, RFNN–PSO has been found a superior predictive model in comparison to ANFIS and non-linear regression models.

5 Conclusion

The application of computational methods using the artificial intelligence models in the field of flyrock prediction has attracted enormous attention in the last few decades. Flyrock is one of the most undesirable effects induced by mine blasting. Hence, accurately prediction of flyrock is very important, especially for the safety issues. This research reports on an effort to forecast the blast-induced flyrock using a novel hybrid of RFNN and PSO. In other words, PSO is used to optimize the RFNN. For comparison aims, ANFIS and non-linear regression models are also used. For developing the predictive models, a database including four input parameters and one output parameter was prepared. The data used in the predictive models were divided into two parts: 58 data were reserved for training and developing the models and the remaining 14 data were used to test the models. RMSE, R^2, NS, MEDAE, and MABE, as the statistical performance

Table 4 Values of the statistical performance metrics used in the present research

Analysis	Equation 3		ANFIS		RFNN–PSO	
	Train	Test	Train	Test	Train	Test
R^2	0.718	0.852	0.876	0.743	0.974	0.933
MEDAE	12.28	12.50	8.38	9.22	2.47	13.70
RMSE	20.95	18.92	15.15	30.46	6.92	15.79
MABE	15.25	14.44	10.92	21.47	4.46	13.86
NS	0.76	0.88	0.87	0.70	0.974	0.921

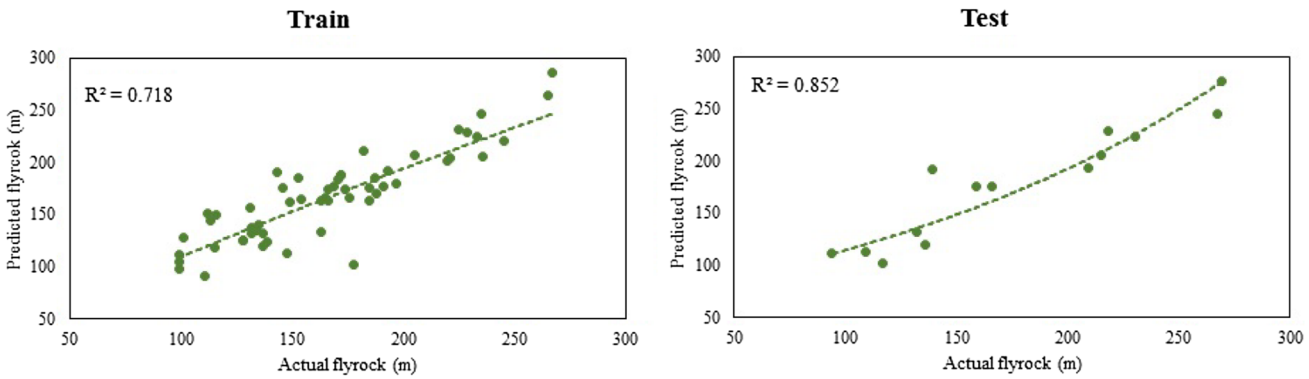


Fig. 8 The actual vs the predicted flyrock(s) using Eq. 3

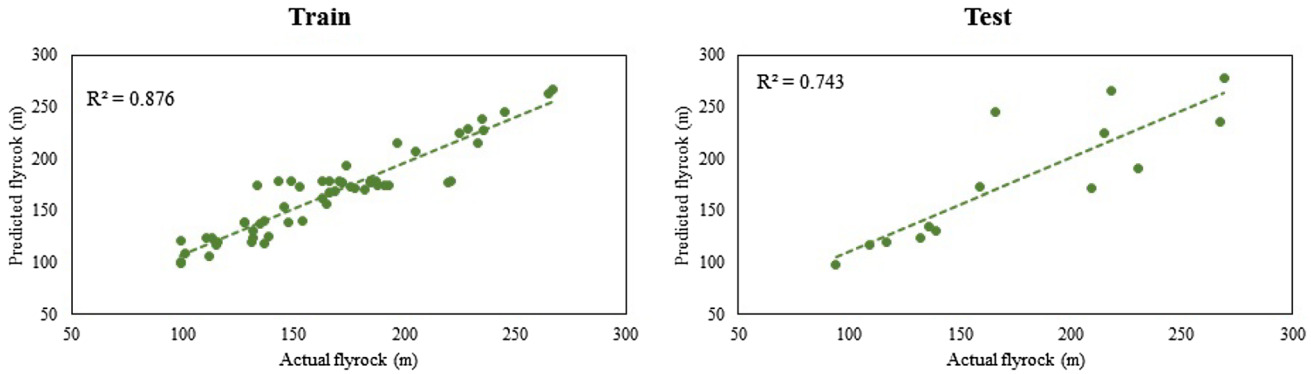


Fig. 9 The actual vs the predicted flyrock(s) using ANFIS

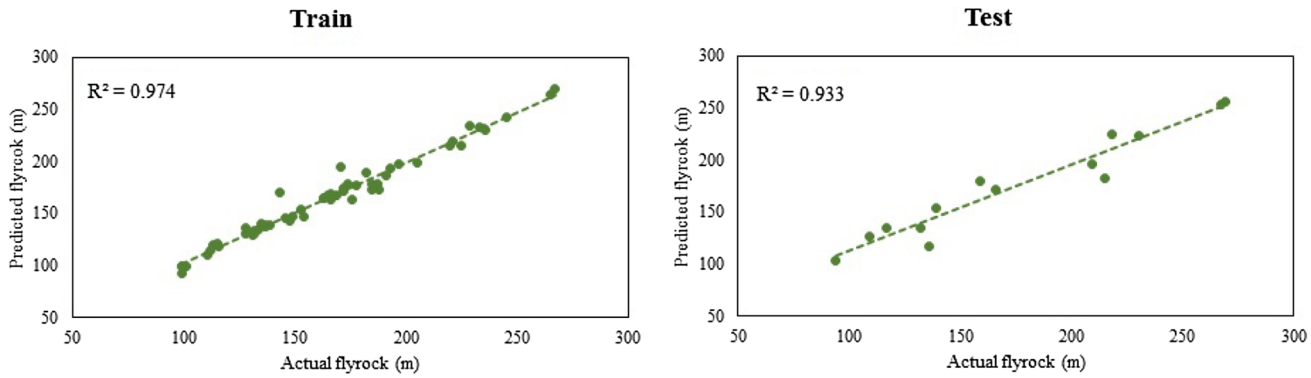


Fig. 10 The actual vs the predicted flyrock(s) using RFNN–PSO

metrics, were then used to evaluate the efficiency of the developed models between the actual and predicted values of flyrock. According to the obtained results, RFNN–PSO exhibited a higher performance than ANFIS and non-linear regression models. RFNN–PSO model with the R^2 of 0.933 predicted the values of flyrock better than the ANFIS with the R^2 of 0.743 and non-linear regression models with the R^2 of 0.877 and 0.852. As a conclusion, RFNN–PSO model has the potential to be used in different fields of mining/geotechnical engineering in the future studies.

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