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## Stochastic fractal search-tuned ANFIS model to predict blast-induced air overpressure

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### Abstract

Air overpressure (AOp) induced by rock blasting is an undesirable phenomenon in open-pit mines and civil construction works. The prediction of AOp has been always a complicated task since many parameters have potential to affect the propagation of air waves. This study aims to assess the capability of a new hybrid evolutionary model based on an integrated adaptive neuro-fuzzy inference system (ANFIS) with a stochastic fractal search (SFS) algorithm. To assess the reliability and acceptability of ANFIS-SFS model, the particle swarm optimization (PSO) and genetic algorithm (GA) were also compared with ANFIS. The proposed models were developed using a comprehensive database including 62 sets of data collected from four granite quarry sites in Malaysia. Performances of the ANFIS-SFS, ANFIS-GA, and ANFIS-PSO models were checked using statistical functions as the performance criteria. The obtained results showed that the proposed ANFIS-SFS model, with root mean square error of 1.223 dB, provided much higher generalization capacity than the ANFIS-PSO (RMSE of 1.939 dB), ANFIS-GA (RMSE of 2.418 dB), and ANFIS (RMSE of 3.403 dB) models in terms of predicting AOp. This clearly demonstrates the effectiveness of SFS to provide a more accurate model in the AOp prediction field.

**Keywords** Blasting · Air overpressure · ANFIS · Optimization algorithms

### 1 Introduction

In recent decades, the number of surface mining operations has dramatically grown across the world. In these operations, the widely used methods of drilling and blasting are of the lowest expense. With every explosion, a huge volume of energy is released in the form of temperature and

pressure. Only a small part of the energy released is applied to fragmenting and displacing the rock mass. The rest of the energy causes adverse effects such as air blast, blast vibrations, flyrock, dust, and noise [1–12]. Once blast takes place, explosion-induced gases are suddenly released to atmosphere, which produces air pressure waves. The unspent volume of energy that still exists in these gases elevates the air pressure level exceeding the normal atmospheric level. This phenomenon is recognized as air overpressure (AOp). The AOp can be created due to many reasons, including the gases released into the air after detonation, the rock face displacement, ground vibrations, stemming blowout, and displacement that occurs around the bore hole. In case of any certain block, a different combination of the above issues may form [13].

The air pressure wave propagation has been described as a function of distance; it has been standardized using the cube root of the charge mass [14, 15]. Generally, AOp is an atmospheric pressure wave that contains audible sound with high frequency in addition to sub-audible sound with low frequency that is too low to be heard by human beings. In case there is a sufficient amount of sound pressure, the sound waves may lead to damage. AOp does not result in

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damage, but causes annoyance; it might lead to a conflict between the managers of the mine and people living in the neighboring area [15, 16].

It is possible to design blasts in a way to keep vibrations and AOp levels in an acceptable limit [15, 17]. Once the waves pass from a certain point, the air pressure rapidly rises; then, it is fallen slowly; afterward, it returns to the ambient value after some oscillations. In this wave, the maximal excess pressure is recognized as the peak air overpressure, which is normally gauged in decibels (dB) with considering the linear frequency weighting (L). Equation (1) can change AOp to dB.

$$AOp = 20 \log \left( \frac{P}{P_r} \right) \quad (1)$$

where  $P_r = 2 \times 10^{-6}$  Pa (pressure of the lowest audible sound) and  $P$  is the measured AOp in terms of Pa. It is not easy to predict the maximum level of AOp at a certain location with a high accuracy; the reason is the uncontrollable and unpredictable impacts of predominant atmospheric conditions [15]. The cube root is the most commonly used factor in predicting AOp, which incorporates both the distance from the blast face ( $D$ ) and the maximum charge per delay (MC). An overview of blast design parameters is also shown in Fig. 1. In this figure,  $B$ ,  $S$ , and  $T$  are the burden, spacing, and stemming variables, respectively.

In recent years, practitioners and researchers have applied a variety of artificial intelligence techniques to different mining, civil, and geo-engineering applications [18–39]. Khandelwal and Singh [16] developed an ANN for the purpose of predicting AOp. The results obtained by their developed mode were compared to those of the multivariate regression analysis (MVRA). The comparative study confirmed that ANN outperformed the other predictor in terms of predicting AOp. For AOp prediction, support vector machine (SVM) was also developed by Khandelwal

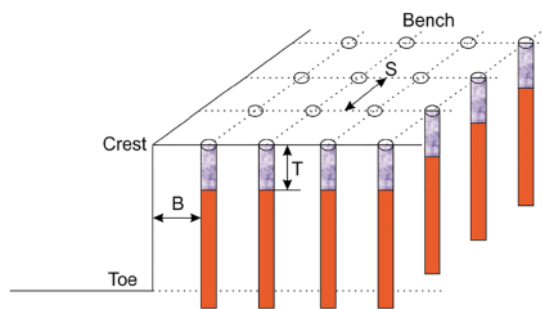


Fig. 1 A view of the blasting pattern structure [50]

and Kankar [40]. SVM was found as an efficient model to predict the AOp in comparison with the generalized predictor equation, and the results showed the superiority of the SVM to the rival in doing the defined task. In the study conducted by Hajihassani et al. [41], the implementation of a hybrid evolutionary model based on integrated neural network (NN) with particle swarm optimization (PSO) was investigated to estimate AOp. The results obtained using the PSO-NN were compared with those of the empirical formula. Findings confirmed that their proposed model performed efficiently regarding the accurate prediction of AOp. Hasanipanah et al. [42] established some models based on ANN, FS, and ANFIS to predict AOp. According to their results, ANFIS showed better performance than the ANN and FS models. In another study, Hasanipanah et al. [43] developed a practical hybrid model by integrating support vector regression (SVR) with PSO for the aim of the AOp prediction. Their statistical results revealed the superiority of PSO-SVM model over SVM in terms of the accuracy level. Alel et al. [44] suggested the application of multi swarm algorithm (MSO) to predict the AOp value and showed its effectiveness in this field. Recently, Nguyen et al. [45] have offered several types of ANN in estimating the AOp. AminShokravi et al. [46] presented the linear and nonlinear equations for the AOp prediction through PSO. According to their results, the prediction accuracy of the PSO-based models was excellent. In another study, hybridization of the random forest (RF) and ANN models for the purpose of predicting AOp was tested by Nguyen and Bui [47]. They showed that the proposed ANN-RF model produced better results than the RF and ANN models. For the same purpose, Zhou et al. [48] offered a hybrid optimization method based on firefly algorithm (FFA) and fuzzy system (FS). They demonstrated the successful application of FFA-FS as an efficient model for predicting AOp. Nguyen and Bui [49] predicted the AOp value through hybridizing the genetic algorithm (GA) with the boosted smoothing spline. To check the acceptability of the GA-boosted smoothing spline model, several other soft computing models were also implemented. According to their results, the proposed GA-boosted smoothing spline model is useful as an alternative model for the prediction of AOp. In another study, Bui et al. [50] offered several soft computing models such as ANN,  $k$ -nearest neighbors, SVM, RF, and boosted regression trees for the prediction of AOp. They used 113 datasets gathered from an open-pit mine in Vietnam. Their results indicated that ANFIS outperformed the other predictive models in terms of root mean square error (RMSE). For the same purpose, the Cubist, gradient boosting machine, and RF models were investigated by

Nguyen et al. [51]. They concluded that the lowest RMSE and the highest effectiveness were offered by the Cubist model.

The present study develops a practical hybrid evolutionary model using an integrated adaptive neuro-fuzzy inference system (ANFIS) with a stochastic fractal search (SFS) algorithm aiming at predicting the blast-induced AOp. To assess the reliability and acceptability of the ANFIS-SFS model, two hybrid models of ANFIS optimized with PSO and genetic algorithm (GA) were also used. At the final step, a comparison was made on the predictions made by the models in terms of the accuracy level of the predicted values.

## 2 Research significance

Study of blasting is especially important to identify the undesirable phenomena, thereby minimizing potential damage to the surroundings. It is well known that the AOp is one

of the most particular concerns induced by mine blasting. Therefore, the present study aims to present the accurate and practical models to predict AOp. To this aim, an integrated expert system comprising of ANFIS and SFS algorithm is proposed, and then to check its results, GA and PSO algorithms are also developed. To our knowledge, the ANFIS-SFS model has not been used to predicting the blast-induced AOp in different timescales as of yet.

## 3 Sources of database

Four quarry sites of granite rock located in Malaysia were taken into consideration, and totally 62 blasting operations were meticulously studied [41]. More specifically, the sites are near the Johor city that is the capital of the Johor State, Malaysia (see Fig. 2). In the sites studied, granite quarry is blasted by means of blast holes of 75, 89, and 115 mm of diameter and the main explosive is ANFO (ammonium



Fig. 2 Sites studied for the prediction of AOp [41]

**Table 1** Descriptive statistics for modeling parameters

Parameter	Minimum	Maximum	Mean	Standard error	Standard deviation	Skewness
HD	10	25	15.145	0.495	3.896	0.760
PF	0.34	0.76	0.518	0.014	0.109	-0.027
MC	60	171	88.153	3.422	26.946	1.392
T	1.7	3	2.087	0.034	0.268	1.060
B	1.5	3.2	2.366	0.061	0.483	0.293
S	2.65	4	3.318	0.053	0.421	-0.220
RQD (%)	60	91	76.823	1.222	9.618	-0.174
NoH	12	63	39.871	1.620	12.757	-0.060
D	300	600	498.387	18.179	143.140	-0.699
AOp	89.1	126.3	105.095	1.274	10.034	0.263

HD depth of the blast holes, PF powder factor, MC maximum charge per delay, T stemming, B burden, S spacing, RQD rock quality designation, NoH number of holes, D distance from the blast point, AOp air overpressure

nitrate/fuel oil). The stemming material used in this study is fine gravels. Table 2 describes the blasting sites of the case studies. The parameters taken into account in the data gathering process were *B*, *T*, *S*, powder factor (PF), depth of the blast holes, and rock quality designation (RQD). In each of the blasting operations, AOp was checked by means of VibraZEB instrument. This instrument recorded AOp values that were in the range of 88 dB to 148 dB. In all cases, AOp was measured in front of the quarry bench and roughly perpendicular to it. Remember that *D* ranged from 300 to 600 m in various sites. Descriptive statistics for modeling parameters are shown in Table 1 and Fig. 3. Note that Fig. 3 shows the values of all parameters used in the modeling processes gathered from 62 blasting events. It is worth mentioning that the other parameters such as *B*, *S*, and *T* were determined using blasting design pattern.

#### 4 Predicting the blast-induced AOp

This section describes how SFS, PSO, and GA were implemented to improve the ANFIS performance. The proposed models were first trained using 50 datasets out of 62 datasets (80%); then, they were tested using the rest of datasets (20%).

#### 4.1 Integrated ANFIS with SFS

The ANFIS algorithm, as a popular machine learning method, has been widely used in order to address complex nonlinear problems [52–56]. This efficient algorithm integrates the neural network with the fuzzy inference system [57]. ANFIS makes use of least squares and gradient descent algorithms to perform a learning model [58]. ANFIS has been found a powerful tool applicable effectively to prediction problems. In the following, a five-layer ANFIS is described [58].

Within the first layer, i.e., the fuzzification layer, all nodes are supposed as adaptive inputs.

$$O_i^1 = \mu A_i(x_1) \quad \text{for } i = 1, 2, \dots, n \quad (2)$$

$$O_i^1 = \mu B_{i-2}(x_2) \quad \text{for } i = 3, 4, \dots, n \quad (3)$$

where  $\mu A_i(x_1)$  and  $\mu B_{i-2}(x_2)$  stand for Gaussian membership functions and *n* denotes the number of fuzzy sets for different input variables [58].

Within the second layer, i.e., the product layer, every node evaluates the firing strength of specific rule with the use of Eq. 4.

$$O_i^2 = \omega_i = \mu A_i(x_1) \mu B_i(x_2) \quad \text{with } i = 1, 2 \quad (4)$$

Within the third layer, i.e., the normalized layer, the normalization process is carried out with the use of Eq. 5 with

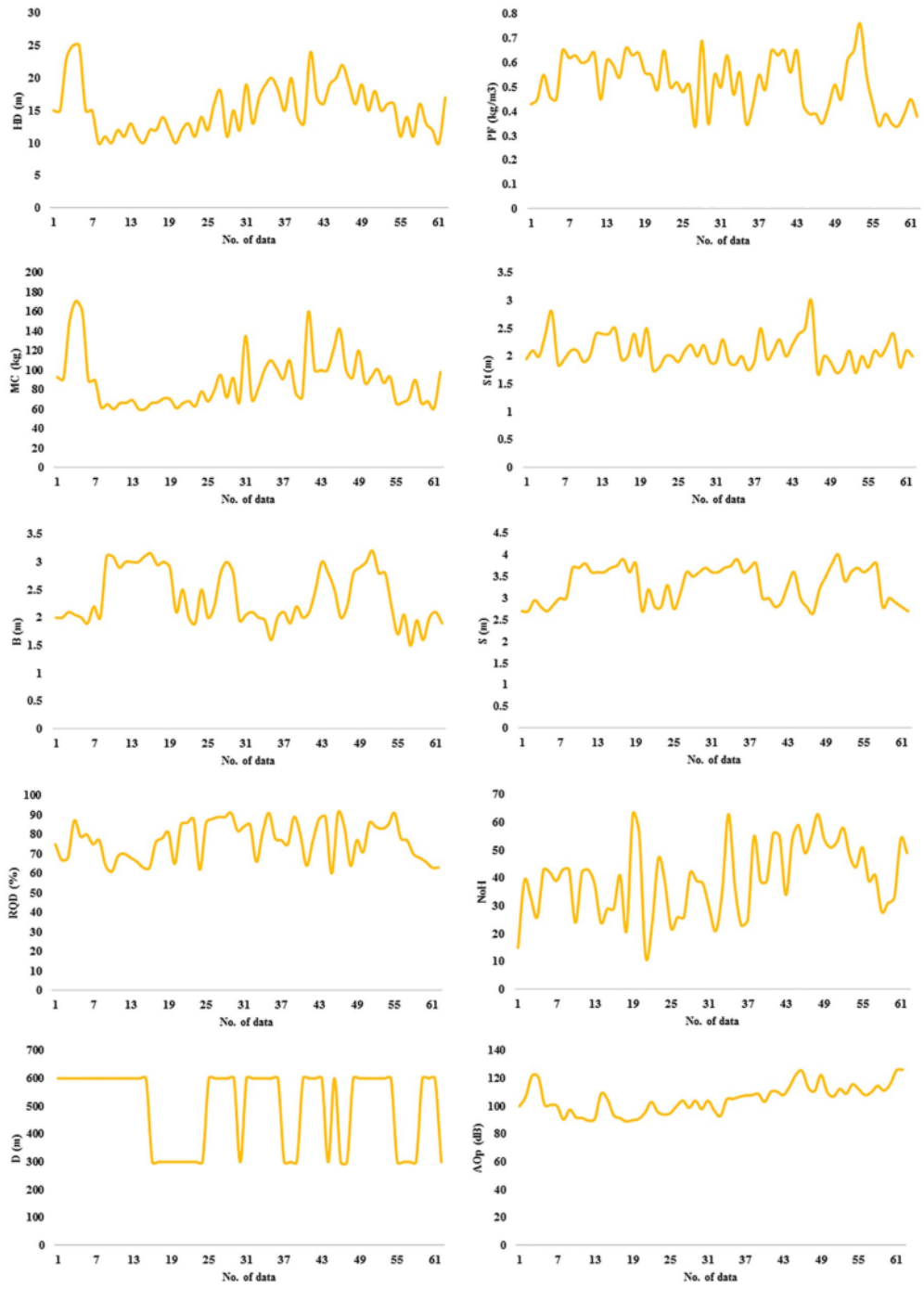


Fig. 3 A view of all parameters used in this study and their values

the summation of the  $i$ th rule's firing strength ratio to all rules' firing strength [58].

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \quad (5)$$

Within the fourth layer, the defuzzification process is carried out. In this layer, each node is adaptable with Eq. 6:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i (k_1^i x + k_2^i y + k_0^i) \quad (6)$$

where  $w_i$  signifies the output of the third layer and  $\{k_1^i, k_2^i, k_0^i\}$  represents the variable sets of  $\bar{w}_i$  node.

Within the fifth layer, i.e., the output layer, the output is formed through summation of the output of the previous layer using Eq. (7):

$$O_i^5 = \text{overall output} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}; \quad i = 1, 2 \quad (7)$$

In ANFIS, three different models are involved, i.e., the fuzzy C-Means clustering (FCM), subtractive clustering (SCM), and grid partitioning (GP). According to the literature that has confirmed FCM as the most effective model, it was chosen for the ANFIS algorithm to be applied to prediction purposes. FCM is elaborated in detail by Nikafshan Rad et al. [57].

In recent years, meta-heuristic algorithms have been successfully implemented when solving a variety of problems, especially for optimization purposes. For instance, SFS is a meta-heuristic algorithm that has been designed based on the natural phenomenon of growth. This algorithm has been found effective in improving ANFIS and optimizing the membership functions elements. More specifically, it is

widely known that ANFIS suffers from limitations like quiet convergence and getting trapped in local optima. SFS has the capacity required for enhancing the convergence rate of ANFIS and also helping it to keep distance from local minima. With the use of diffusion, the particles that exist within the new algorithm will be capable of searching the search space with a higher efficiency. Two key parts of optimization in SFS are diffusion and updating processes. During the process of diffusing, each particle diffuses around its current position in a way to satisfy intensification property.

On the other hand, during the process of updating, SFS finds the way each particle in the group can update its own position rather than updating the other particles' position. Based on Fig. 4 [59], the optimal particle created from the diffusing process in SFS is the isolated particle that is admitted; the others are then rejected. In addition, the process of updating gives motivation to researchers to explore properties in meta-heuristic algorithms. At the diffusion step, two statistical techniques exist that can be used for particles production: Levy flight and Gaussian. Early studies have reported faster concentration of the Levy flight in comparison with the Gaussian walk in little generations. However, in exploring global optima, the Gaussian walk is more encouraging [60]. For more detailed information in regard to the SFS algorithm, the study conducted by Salimi [59] can be referred to. The pseudocode of the ANFIS-SFS is presented in Fig. 5.

### 4.2 ANFIS integrated with PSO and GA

To examine the performance quality of SFS in ANFIS, two popular optimization algorithms, i.e., GA and PSO [61–65], were considered and also applied to the optimization of ANFIS. Additionally, to minimize prediction errors in the present study, a number of parameters were taken into consideration. In the implementation of the models, two techniques were adopted: least square and back-propagation. The optimal number of fuzzy rules was determined using the trial-and-error method.

When modeling GA-ANFIS, the maximum iteration was fixed at 300, and the minimum error was fixed at  $1e-5$ . Moreover, the mutation and crossover rates were set to 0.3 and 0.7, respectively. Furthermore, various values ranging from 50 to 400 were examined in order to reach the optimal number of populations (see Table 2). As can be seen in this table, with fixing the number of populations at 250, the minimum RMSE was obtained. The inertia weight and the

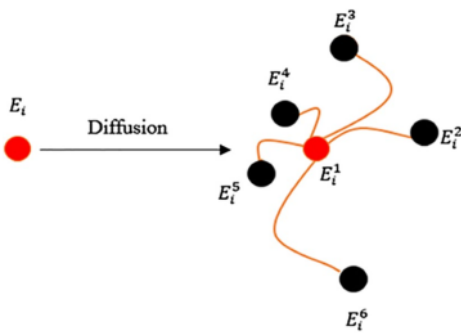


Fig. 4 Particle diffusion [59]

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 Integrated ANFIS with a SFS
 

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1: Set the input
2: Initialize a random population size, No. Rules, No. generations, the maximum diffusion walk (k), the side walk.
3: While h<Max No. of Iterations Do
4:   Create the population size (particles)
5:   Calculate the fitness function based on Error function
6:   For every Particle in the population Do
7:     Call Diffusing Process:
8:       For j=1 to k Do
9:         A new point will be created:  $GW1 = Gussian(\mu_{BP}, \sigma) + (\varepsilon_{XBP} - \varepsilon'_{XPI})$ 
10:        End for
11:      End Call
12:    End for
13:End while
14:  Call Updating Process:
15:  First Updating Process
16:  First, all parameters of ANFIS are ranked
17:  For Every Point of population( $P_i$ ), Do
18:    For each component in Population, Do
19:      If rand [0,1]> $P_{ai}$ 
20:        Update the ANFIS parameters
21:      End If
22:    End For
23:  Second Updating Process:
24:  All points determined by the first updating process are re-ranked
25:  For Every Point of population( $P'_i$ ) of ANFIS parameter, Do
26:    If rand [0,1]> $P'_{ai}$ 
27:      Update the position:
28:        
$$P''_i = P'_i - \hat{\varepsilon} \times (P'_i - BP) | \hat{\varepsilon} \leq 0.5$$

29:        
$$P''_i = P'_i + \hat{\varepsilon} \times (P'_i - P'_r) | \hat{\varepsilon} > 0.5$$

30:      End If
31:    End For
32:  End For
31: Train the optimized ANFIS parameters based Stochastic Fractal Optimization
32: Calculate MSE for ANFIS testing result
  
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Fig. 5 ANFIS-SFS pseudocode



**Table 2** Selection of the proper population size in ANFIS-GA

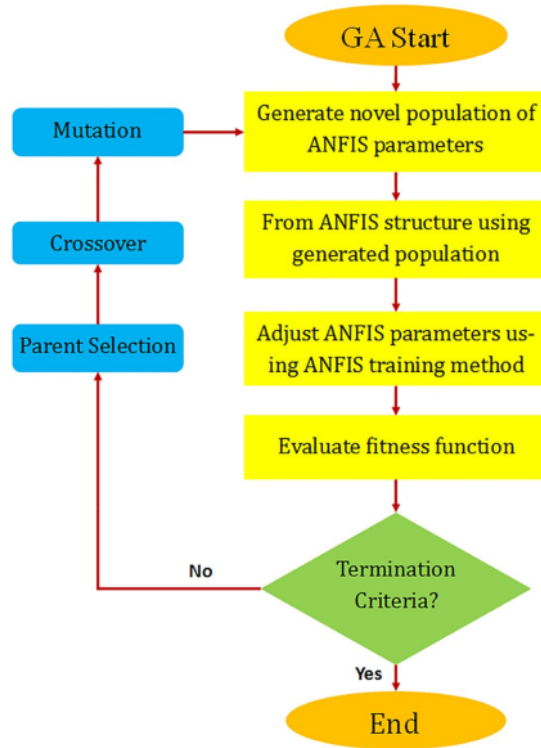
Population size	Network result	
	RMSE	
	Train	Test
50	5.431	5.196
100	4.560	4.239
150	4.672	4.198
200	4.145	3.802
<b>250</b>	<b>3.771</b>	<b>3.039</b>
300	3.819	3.327
350	3.995	3.891
400	4.347	4.105

**Table 3** Selection of the proper  $C_1$  and  $C_2$  in ANFIS-PSO modeling

$C_1$	$C_2$	Network result	
		RMSE	
		Train	Test
1.333	2.667	4.311	3.919
2.667	1.333	4.128	3.877
1.5	1.5	3.722	3.540
2	2	3.295	2.712
1.75	1.75	2.919	2.327
1.5	1.75	3.118	2.774
1.75	1.5	3.541	3.229

**Table 4** Selection of the proper number of particles in ANFIS-PSO modeling

No. of particle	Network result	
	RMSE	
	Train	Test
50	4.116	3.882
100	3.866	3.559
150	3.528	3.327
200	3.291	2.580
250	2.887	2.115
300	3.157	2.766
350	3.418	3.382
400	3.701	3.644



**Fig. 6** ANFIS-GA chart [61]

number of iterations in ANFIS-PSO were set to 1 and 1000, respectively. Moreover, various values were examined for the aim of choosing the optimal number of particles and coefficients of velocity equation ( $C_1$  and  $C_2$ ), as shown in Tables 3 and 4. These tables show that the minimum RMSE were attained for  $C_1 = C_2 = 1.75$  and the number of particles = 250. As a result, these values were applied to experiments carried out in the present paper. Figures 6 and 7 illustrate the ANFIS schemes optimized using the GA and PSO algorithms.

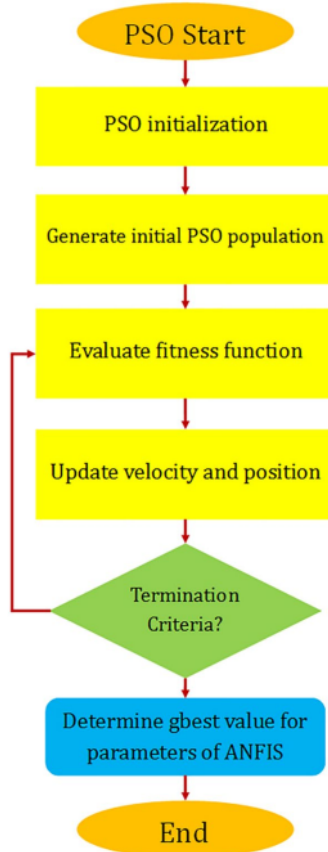


Fig. 7 ANFIS-PSO chart [61]

### 5 Results and discussion

The present paper was aimed at examining the efficiency of the SFS algorithm in optimizing ANFIS to predict blast-induced AOp. In this section, the way the ANFIS-SFS model performed in regard to the AOp prediction is discussed; after that, the results obtained from the proposed ANFIS-SFS model will be compared to those of the other models. As mentioned earlier, a total of 62 datasets were applied to this study, among which 50 datasets were allocated to training and 12 datasets were allocated to testing purposes. Then, ANFIS-SFS model performance was assessed regarding RMSE, mean absolute error (MAE), mean average percentage error (MAPE), and coefficient of determination ( $R^2$ ) [66–80]:

$$MAE = \frac{1}{n} \sum_{i=1}^{22} |A_i - P_i| \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (A_i - P_i)^2}{n}} \tag{9}$$

$$MAPE = \left[ \frac{1}{n} \sum_{i=1}^{44} \frac{|A_i - P_i|}{A_m} \right] \times 100 \tag{10}$$

where  $n$  stands for the number of data ( $n=62$ ), and  $A_i$  and  $P_i$  signify the actual and predicted AOp values, respectively. Table 5 presents the RMSE, MAE, and MAPE (%) values attained by the predictive models. The table shows that the SFS-ANFIS outperformed the others in terms of predicting the AOp value. In addition, Figs. 8, 9, 10, and 11 demonstrate the actual versus estimated AOp values with the use of all predictive models. Accordingly, SFS was found more

Table 5 Assessment of the performance of the prediction models used in this study

Statistical functions	Prediction models							
	ANFIS		ANFIS-GA		ANFIS-PSO		ANFIS-SFS	
	Train	Test	Train	Test	Train	Test	Train	Test
RMSE	4.569	3.403	3.450	2.418	2.817	1.939	1.814	1.223
MAE	4.234	3.242	3.194	2.325	2.626	1.891	1.694	1.133
MAPE (%)	4.112	2.843	3.101	2.039	2.550	1.659	1.645	0.994
$R^2$	0.904	0.873	0.945	0.935	0.963	0.965	0.987	0.986

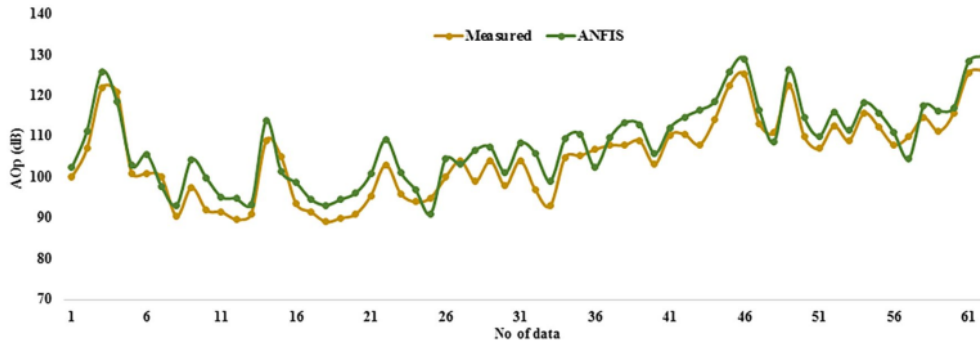


Fig. 8 Use of ANFIS in predicting AOp

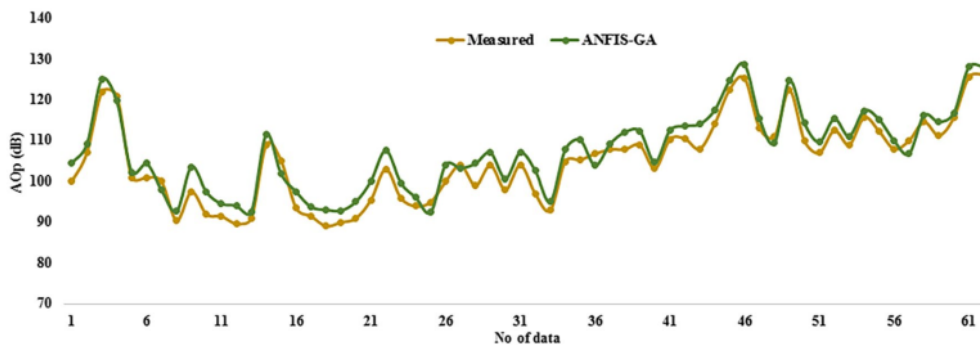


Fig. 9 Use of ANFIS-GA in predicting AOp

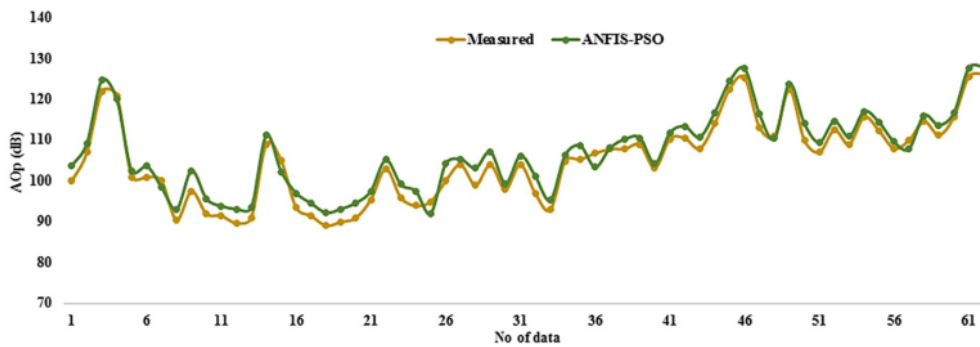


Fig. 10 Use of ANFIS-PSO in predicting AOp

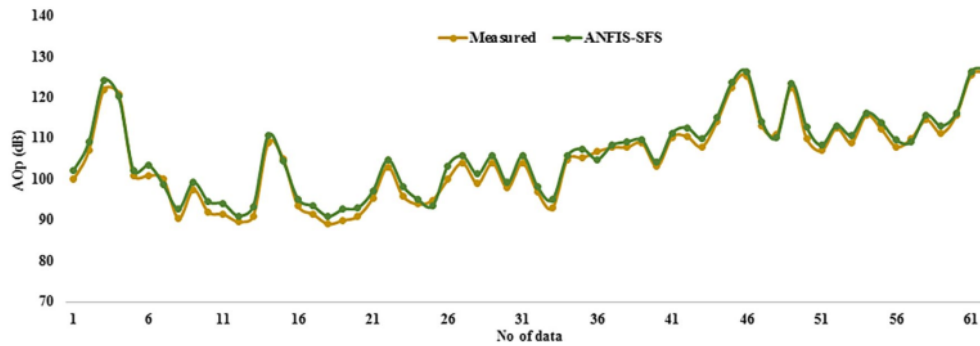


Fig. 11 Use of ANFIS-SFS in predicting AOp

effective in comparison with GA and PSO in regard to the ANFIS improvement. For a better understanding, the Taylor diagrams for both training and testing phases are shown in Fig. 12. Observing Fig. 12, it can be seen that the proposed ANFIS-SFS model was more effective than the others. In addition, the Yang and Zang's [81] method was used to conduct a sensitivity analysis for the aim of showing the relative effect of HD, PF, MC,  $T$ ,  $B$ ,  $S$ , RQD, NoH, and  $D$  upon AOp:

$$r_{ij} = \frac{\sum_{k=1}^n (y_{ik} \times y_{ok})}{\sqrt{\sum_{k=1}^n y_{ik}^2 \sum_{k=1}^n y_{ok}^2}} \quad (11)$$

The values of  $r_{ij}$  indicate the impact of each input upon the output. With the use of Eq. 10, the values of  $r_{ij}$  for HD, PF, MC,  $T$ ,  $B$ ,  $S$ , RQD, NoH, and  $D$  were calculated, as shown in Fig. 13. These results confirmed that  $T$  was the most effective parameter upon AOp.

## 6 Conclusions

Any blasting operation unavoidably leads to different undesirable effects such as air overpressure (AOp). As a result, it is of high importance to predict AOp with a high accuracy in a way to determine properly the safe regions around the operation sites. This paper represents several hybrid evolutionary models based on ANFIS optimized by SFS, PSO, and GA to predict AOp. It is worth mentioning that this is the first work that predicts AOp through ANFIS-SFS model. A database was created containing 62 datasets collected from blasting events performed at four quarry sites in Malaysia [41]. More specifically, the database included 62 sets of data, nine independent parameters, and one dependent parameter. In the predictive models, the independent parameters were set as inputs, and the dependent parameter (AOp) was set as output. Finally, some statistical functions were designed to demonstrate the capacity and superiority of the proposed models in the prediction of AOp. The conclusions of this study are as follows: (1) The use of SFS, GA, and PSO algorithms had a positive impact on the ANFIS

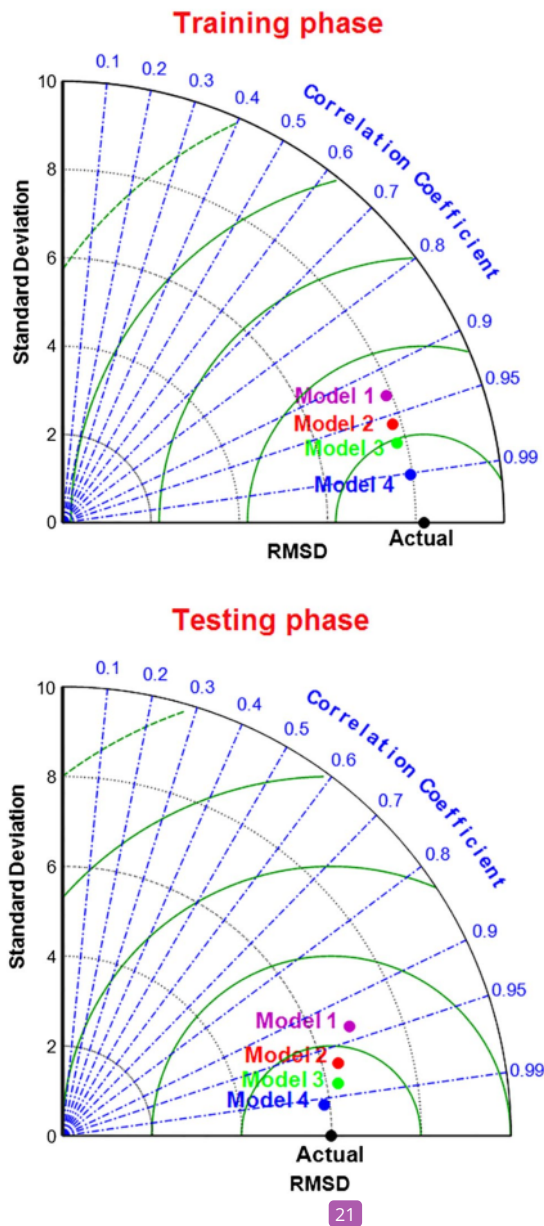
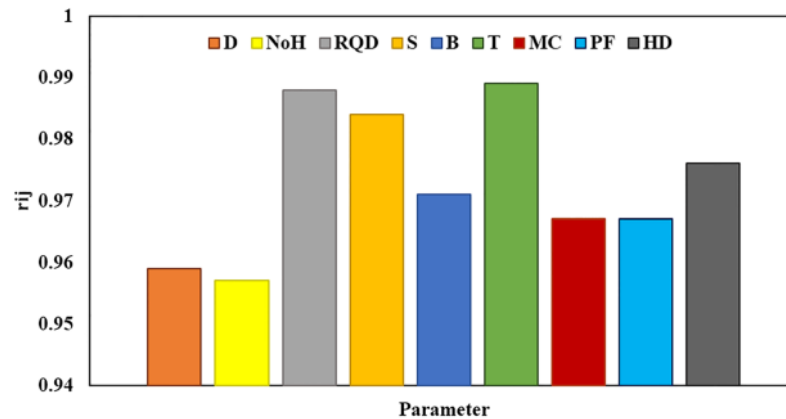


Fig. 12 Obtained Taylor diagrams from model 1: ANFIS, model 2: ANFIS-GA, model 3: ANFIS-PSO, and model 4: ANFIS-SFS for both training and testing phases

perform<sup>42</sup> ce. (2) The results obtained in this research confirmed that the ANFIS-SFS was the most effective model in regard to accuracy in AOp prediction. In case of ANFIS-SFS, the values of  $R^2$ , RMSE, MAE, and MAPE were obtained as 0.986, 1.223, 1.133, and 0.994%, respectively. As a result, SFS could meaningfully enhance the ANFIS performance quality. (3) The ANFIS-SFS model can have the capacity required for addressing other prediction problems that appear generally in the context of r<sup>16</sup> blasting. (4) Obtained results show that the ANFIS-SFS model can be used with confidence for fut<sup>40</sup> research works on predicting the AOp. (5) According to the sensitivity analysis results, the stemming ( $T$ ) was the most effective parameter on the intensity of AOp. (6) To enhance the ANFIS performance, other meta-heuristic algorithms, including the green heron optimization algorithm, gradient evolution algorithm, firework algorithm, honey bee mating optimization, and interior search algorithm, can be implemented, too.

**Fig. 13** Results of sensitivity analysis

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