

# Application of two intelligent systems in predicting environmental impacts of quarry blasting

Danial Jahed Armaghani<sup>1</sup> · Mohsen Hajihassani<sup>2</sup> · Masoud Monjezi<sup>3</sup> ·  
Edy Tonnizam Mohamad<sup>1</sup> · Aminaton Marto<sup>1</sup> · Mohammad Reza Moghaddam<sup>4,5</sup>

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**Abstract** Blasting, as the most frequently used method for hard rock fragmentation, is a hazardous aspect in mining industries. These operations produce several undesirable environmental impacts such as ground vibration, air-overpressure (AOp), and flyrock in the nearby environments. These environmental impacts may cause injury to human and damage to structures, groundwater, and ecology of the nearby area. This paper is aimed to predict the blasting environmental impacts in granite quarry sites through two intelligent systems, namely artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). For this purpose, 166 blasting operations at four granite quarry sites in Malaysia were

investigated and the values of peak particle velocity (PPV), AOp, and flyrock were precisely recorded in each blasting operation. Considering some model performance indices including coefficient of determination ( $R^2$ ), value account for (VAF), and root mean square error (RMSE), and also using simple ranking procedure, the best models for prediction of PPV, AOp, and flyrock were selected. The results demonstrated that the ANFIS models yield higher performance capacity compared to ANN models. In the case of testing datasets, the  $R^2$  values of 0.939, 0.947, and 0.959 for prediction of PPV, AOp, and flyrock, respectively, suggest the superiority of the ANFIS technique, while in predicting PPV, AOp, and flyrock using ANN technique, these values are 0.771, 0.864, and 0.834, respectively.

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✉ Masoud Monjezi  
monjezi@modares.ac.ir

Danial Jahed Armaghani  
danielarmaghani@yahoo.com

Mohsen Hajihassani  
mohsen\_hajihassani@yahoo.com

Edy Tonnizam Mohamad  
edy@utm.my

Aminaton Marto  
aminaton@utm.my

Mohammad Reza Moghaddam  
m110\_erfan@yahoo.com

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## Introduction

Blasting is a common technique of rock fragmentation in quarry and mining operations as well as some civil engineering applications such as tunneling and road construction. In quarry operations, blasting consists of drilling several rows of blast-holes almost parallel to the free face of the bench. These operations create several environmental impacts such as air overpressure, ground vibration, flyrock, and back-break around the blasting zone (Monjezi and Dehghani 2008; Fisse et al. 2011; Jahed Armaghani et al. 2013; Hajihassani et al. 2014a; Ebrahimi et al. 2015). There are some empirical equations for prediction of these environmental impacts. Nevertheless, these equations just consider limited numbers of influential parameters on them whereas these impacts are

<sup>1</sup> Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

<sup>2</sup> Construction Research Alliance, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia

<sup>3</sup> Department of Mining, Tarbiat Modares University, Tehran, 14115-143, Iran

<sup>4</sup> South Tehran Branch, Islamic Azad University, Tehran, Iran

<sup>5</sup> Saman Zamin Hamgam Engineering Company, Tehran, Iran

also affected by other effective factors such as blast geometry and geological conditions (Douglas 1989; Singh and Singh 2005). As a result, empirical approaches are not accurate enough, while sometimes prediction of the environmental impact values with higher accuracy is essential to minimize environmental damage due to blasting operations (Jahed Armaghani et al. 2013; Hajihassani et al. 2014a).

Ground vibration is defined as a wave motion which spreads away from the blast to nearby areas (Khandelwal and Singh 2009; Bakhshandeh Amnieh et al. 2012). The ground vibrations can be determined in terms of peak particle velocity (PPV) and frequency. As mentioned in several standards (Bureau of Indian Standard 1973), PPV is considered as a vibration index, which is an important indicator to control the structural damage criteria. High ground vibration can cause damage to the surrounding structures, groundwater, and ecology of the nearby area (Singh and Singh 2005; Monjezi et al. 2010a; Hajihassani et al. 2014b). Several parameters such as blast design, distance between the blast-face and monitoring point, rock mass mechanical properties, explosive charge weight per delay, and geological conditions are the most influential parameters on ground vibration induced by blasting (Wiss and Linehan 1978; Khandelwal and Singh 2006).

Air overpressure (AOp) is created by a large shock wave from explosion point to the free surface. The pressures of AOp waves contain an audible high-frequency and subaudible low-frequency sound. Normally, four main sources can cause AOp waves in blasting operations: air pressure pulse which is rock displacement at bench face, rock pressure pulse which is induced by ground vibration, gas release pulse which is the escape of gases through rock fractures, and finally stemming release pulse which is the escape of gases from the blasthole when the stemming is ejected (Wiss and Linehan 1978; Siskind et al. 1980; Morhard 1987). AOp may cause damage to structures and should be kept below critical ranges (Kuzu et al. 2009; Rodriguez et al. 2010). AOp is influenced by several factors such as explosive charge weight per delay, blast geometry, distance between blast-face and monitoring point, length of stemming, geological discontinuities, and blasting direction (Konya and Walter 1990; Khandelwal and Kankar 2011).

Excessive random throw of rock fragments beyond the blast safety area can be defined as flyrock (Khandelwal and Monjezi 2013; Raina et al. 2014). In the mechanism of flyrock, three parameters namely rock mass mechanical strength, charge confinement, and explosive energy distribution are in an affective relationship to each other and any mismatch between these parameters can create flyrock (Bajpayee et al. 2004). When flyrock happens, huge energy is used to throw the rock rather than creation of fragmented rock (Roy 2005). Flyrock induced by blasting can cause damage to structures and injury to human (Keckojevic and

Radomsky 2005; Roy 2005; Khandelwal and Monjezi 2013). Inadequate burden and spacing, inadequate stemming, inaccurate drilling, overloaded holes, excessive powder factor, and unfavorable geological conditions may produce flyrock (Hemphill 1981; Bhandari 1997).

Utilizing soft computing methods such as artificial neural network (ANN) (Khandelwal et al. 2011; Tonnizam Mohamad et al. 2012; Monjezi et al. 2013a), fuzzy inference system (FIS) (Mohamed 2011), and adaptive neuro-fuzzy inference system (ANFIS) (Iphar et al. 2008) for prediction of blasting environmental impacts are recently highlighted in literatures. In this study, two intelligent systems namely ANN and ANFIS were used to predict blasting environmental impacts including PPV, AOp, and flyrock using the datasets obtained from four granite quarry sites in Malaysia.

## Prediction methods of blasting environmental impacts

### Peak particle velocity

Various empirical predictors have been established to predict PPV by several scholars (Duvall and Petkof 1959; Langefors and Kihlstrom 1963; Davies et al. 1964; Bureau of Indian Standard 1973; Ghosh and Daemen 1983; Roy 1993). However, in a particular blasting, predicted PPV values obtained by these predictors are different and there is no homogeneity in their results. Furthermore, these empirical predictors only consider two influential parameters including charge per delay and distance from blast-face whereas PPV is also influenced by other effective parameters such as blast geometry and geological conditions (Jahed Armaghani et al. 2013).

Apart from the empirical predictors, soft computing techniques have been extensively used to predict PPV. ANN and regression analysis were applied to predict PPV by Singh and Singh (2005). They demonstrated that ANN is a more accurate technique in comparison to regression analysis for PPV prediction. Fisne et al. (2011) utilized fuzzy logic approach and classical regression analysis to predict PPV using 33 datasets obtained from Akdaglar quarry in Turkey. In their research, charge weight and distance from blast-face were considered as input parameters. They concluded that the predicted PPVs obtained from fuzzy model were much closer to the measured values in comparison to those predicted by statistical models. Monjezi et al. (2013a) predicted PPV values using different empirical equations and ANN technique. They compared the computed results with the actual field data obtained from Shur River Dam in Iran. Finally, they found that the results of ANN model are more accurate in comparison to those of empirical equations. In the other study, Saadat et al. (2014) predicted 69 PPV values obtained from Gol-E-Gohar iron mine in Iran by using ANN. For the sake of comparison, they compared the

ANN results with common empirical approaches and multiple linear regression (MLR). It was found that the ANN approach performs better in comparison to empirical and MLR models.

### Air overpressure

Many attempts have been made to develop empirical approach for prediction of AOp induced by blasting. Rodriguez et al. (2007) established semi-empirical method for prediction of AOp due to blasting outside a tunnel. Their method was surveyed with several cases, and they found that it can be used under different conditions. A new empirical relationship for prediction of AOp was developed by Kuzu et al. (2009) using two parameters including the distance between blast-face and monitoring point as well as weight of explosive materials. They concluded that the proposed equation predicts AOp with reasonable degree of accuracy. Segarra et al. (2010) proposed a new AOp predictive equation using recorded data from two quarries. AOp values were measured from 122 records in 40 blasting operations in the rocks with low to very low strength. Finally, they presented a predictive equation with 32 % of accuracy.

In addition to empirical methods, the use of soft computing approaches for AOp prediction is recently highlighted. An ANN model was presented for prediction of AOp by Khandelwal and Singh (2005) using weight of explosive as well as distance between blast-face and monitoring point. They compared the ANN results with the US Bureau of Mines (USBM) predictor and MLR technique and concluded that the ANN yields better estimation of AOp values compared to other methods. Mohamed (2011) used ANN and FIS to predict AOp. He compared the results of predictive models with the values obtained by regression analyses and observed field data. From that study, it was found that the ANN and fuzzy models are accurate predictive models for AOp estimation. Support vector machine (SVM) technique was applied to predict AOp by Khandelwal and Kankar (2011) using 75 datasets obtained from three mines in India. They compared AOp values predicted by SVM with the results of generalized predictor equation. The results demonstrated that the estimated values of AOp using SVM are much closer to the actual values. A combination of PSO and ANN approaches was presented to predict AOp by Hajihassani et al. (2014a). Two empirical formulas were also established to predict AOp values using distances of 300 and 600 m. Finally, they found that the PSO-ANN technique is an applicable tool to predict AOp with high degree of accuracy.

### Flyrock

Several empirical equations have been established by some researchers to predict flyrock distance. An empirical equation

based on hole and rock diameters was developed by Lundborg et al. (1975) as follows:

$$L_m = 260 \times D^{2/3} \quad (1)$$

$$T_b = 0.1 \times D^{2/3} \quad (2)$$

in which  $L_m$  is the maximum throw of the rock (m),  $D$  is hole diameter (in.), and  $T_b$  is the rock size (m). Another equation was proposed using stemming length and burden parameters by Gupta (1990), as given below:

$$L = 155.2 \times D^{-1.37} \quad (3)$$

where  $L$  is the ratio of stemming length to burden, and  $D$  is the distance of thrown fragments (m). Ghasemi et al. (2012a) developed an empirical equation for flyrock prediction using dimensional analysis as follows:

$$F_d = 6946.547 \left[ B^{-0.796} S^{0.783} S_t^{1.994} H^{1.649} D^{1.766} (P/Q)^{1.465} \right] \quad (4)$$

where  $B$  is burden,  $S$  is spacing,  $S_t$  is stemming,  $H$  is blasthole length,  $D$  is diameter of blasthole,  $P$  is powder factor, and  $Q$  is mean charge per blasthole. Coefficient of determination ( $R^2$ ) equals to 0.83 shows the high prediction performance of the proposed equation.

In another empirical study, Trivedi et al. (2014) proposed an equation to predict flyrock distance using multivariate regression analysis. To do this, they monitored 95 blasting operations of four opencast limestone mines in India and relevant blasting parameters were recorded. Proposed flyrock equation is as follows:

$$\text{Flyrock} = \frac{10^{5.1} q_l^{0.51} q^{0.14}}{B^{0.93} ST^{0.64} \sigma_c^{0.75} \text{RQD}^{0.93}} \quad (5)$$

where  $q_l$  is linear charge concentration,  $q$  is specific charge,  $\sigma_c$  is unconfined compressive strength,  $ST$  is stemming length,  $B$  is burden, and RQD is rock quality designation.  $R^2$  of 0.815 was obtained for their developed model.

Apart from the empirical methods, prediction of flyrock using artificial intelligent methods has been reported by many researchers. Monjezi et al. (2011b) predicted 192 datasets of flyrock induced by blasting operations by using ANN. From their study, it was found that the ANN technique can predict flyrock with high degree of accuracy. Rezaei et al. (2011) used FIS model to predict flyrock and compared the FIS results with conventional statistical approaches. They clearly found that the efficiency of the developed FIS model is much better than that of statistical models. Ghasemi et al. (2012b) predicted flyrock distance using two predictive models namely ANN and FIS models. They indicated that both models are able to

predict flyrock distance in which the FIS model yields higher performance in comparison to the ANN approach. Neuro-genetic predictive model was utilized to predict flyrock and back-break by Monjezi et al. (2012). They compared the proposed model with the regression analysis and concluded that the proposed model is a better tool in prediction of flyrock. Amini et al. (2012) presented two intelligent approaches namely SVM and ANN to estimate flyrock distance. They used hole diameter, hole length, burden, spacing, stemming, powder factor, and specific drilling as inputs. After comparison, it was found that the SVM method is more precise than ANN technique. In the other study of flyrock prediction, Khandelwal and Monjezi (2013) used SVM and MLR techniques to estimate flyrock of Soungun Copper Mine, Iran. After comparison of these methods, they introduced SVM as a better option for close flyrock prediction. Table 1 shows some recent studies with their performances in predicting PPV, AOp, and flyrock induced by blasting.

### Artificial neural network

The ANN is a soft computation technique inspired by the human brain information process. A typical ANN consists of three main constituents, namely learning rule, network architecture, and transfer function (Simpson 1990). There are two major types of ANN: recurrent and feed-forward. Shahin et al. (2002) recommend that if there is no time-dependent parameter in the ANN, the feed-forward (FF)-ANN can be employed. The multilayer perceptron (MLP) neural network is one of the most well-known FF-ANNs (Haykin 1999; Rezaei et al. 2012; Monjezi et al. 2013b). MLP consists of a number of nodes or neurons in three layers (input, hidden, and output) linked to each other by weights. Du et al. (2002) and Kalinli et al. (2011) reported on the high efficiency of MLP-ANNs in approximating various functions in high-dimensional spaces. Nevertheless, the ANN needs to be trained before interpreting the results. Among many kinds of learning algorithms to train MLP-FF, the back-propagation (BP) algorithm is the most extensively utilized (Dreyfus 2005). In a BP-ANN, the imported data in the input layer starts to propagate to hidden neurons through connection weights (Kuo et al. 2010). The input from each neuron in the previous layer,  $I_i$ , is multiplied by an adjustable connection or weight,  $W_{ij}$ . At each node, the sum of the weighted input signals is computed and then, this value is added to a threshold value known as the bias value,  $B_j$  (see Eq. 6). To create the output of the neuron, the combined input,  $J_j$ , is passed through a non-linear transfer function  $f(J_j)$ , such as a sigmoidal function (see Eq. 7). However, in general, the output of each neuron provides the input to the next layer neuron. This procedure is continued until the output is generated. To achieve the error, the created output is checked against the desired output. The

BP training can change the weights between the neurons iteratively in a way that minimizes the root mean square error (RMSE) of the system. More details of the BP algorithm can be seen in the classic artificial intelligence books (Fausett 1994).

$$J_j = \sum (w_{ij}I_i) + B_j \quad (6)$$

$$y_i = f(J_j) \quad (7)$$

### Adaptive neuro-fuzzy inference system

ANFIS developed based on the Takagi and Sugeno (1985) FIS by Jang (1993). ANFIS is considered as a universal predictor which is able to approximate real continuous functions Jang et al. (1997). In fact, ANFIS integrates the principles of ANN and FIS and, therefore, potentially presents all benefits of them in a unique framework. By determining the optimum distribution of membership functions, ANFIS is able to analyze the relationships between the input and target data using the hybrid learning. As in Fig. 1a, ANFIS structure consists of premise and consequent parts. The equivalent architecture of ANFIS including five layers is shown in Fig. 1b. Regarding the applicability of ANFIS in prediction of the nonlinear relationship between input and output data, it has been widely used in various applications of engineering.

In order to describe the procedure of ANFIS, it is assumed that the FIS under consideration consists of two inputs ( $x, y$ ) and one output ( $f$ ) and the rule base includes two fuzzy rule set “if-then” as follows (Jang 1993):

Rule I If  $x$  is  $A_1$  and  $y$  is  $B_1$ , then  $f_1 = p_1x + q_1y + r_1$

Rule II If  $x$  is  $A_2$  and  $y$  is  $B_2$ , then  $f_2 = p_2x + q_2y + r_2$

in which  $p_i, q_i$ , and  $r_i$  are the consequent parameters to be settled. According to Jang (1993) and Jang et al. (1997), an ANFIS with five layers and two rules can be described as follows:

Layer I Every node  $i$  in layer I produces a membership grade of a linguistic label. For example, the node function of the  $i$ th node is

$$Q_i^1 = \mu_{A_i}(x) = \frac{1}{1 + \left[ \left( \frac{x - v_i}{\sigma_i} \right)^2 \right]^{b_i}} \quad (8)$$

in which  $Q_i^1$  and  $x$  are the membership function and input to node  $i$ , respectively.  $A_i$  is the linguistic label related to node  $i$ , and  $\sigma_i, v_i, b_i$  are parameters that

**Table 1** Recent works on PPV, AOp, and flyrock prediction using soft computation techniques

Reference	Technique	Input	Output	No. of dataset	R <sup>2</sup>
Iphar et al. (2008)	ANFIS	DI, C	PPV	44	R <sup>2</sup> =0.98
Bakhshandeh Amnieh et al. (2010)	ANN	ST, DI, C, N	PPV	29	R <sup>2</sup> =0.99
Monjezi et al. (2011a)	ANN	HD, ST, DI, C	PPV	182	R <sup>2</sup> =0.95
Khandelwal et al. (2011)	ANN	DI, C	PPV	130	R <sup>2</sup> =0.92
Mohamed (2011)	ANN, FIS	DI, C	PPV	162	R <sup>2</sup> <sub>ANN</sub> =0.94 R <sup>2</sup> <sub>FIS</sub> =0.90
Fisne et al. (2011)	FIS	DI, C	PPV	33	R <sup>2</sup> =0.92
Li et al. (2012)	SVM	DI, C	PPV	32	R <sup>2</sup> =0.89
Mohamadnejad et al. (2012)	SVM, ANN	DI, C	PPV	37	R <sup>2</sup> <sub>SVM</sub> =0.89 R <sup>2</sup> <sub>ANN</sub> =0.85
Ghasemi et al. (2013)	FIS	B, S, ST, N, C, DI	PPV	120	R <sup>2</sup> =0.95
Monjezi et al. (2013a)	ANN	C, DI, TC	PPV	20	R <sup>2</sup> =0.93
Jahed Armaghani et al. (2013)	ANN-PSO	S, B, ST, PF, C, D, N, RD, SD	PPV	44	R <sup>2</sup> =0.94
Hajihassani et al. (2014b)	ANN-ICA	BS, ST, PF, C, DI, Vp, E	PPV	95	R <sup>2</sup> =0.98
Ghoraba et al. (2015)	ANN	BS, DI, C, ST, HL	PPV	115	R <sup>2</sup> =0.98
Khandelwal and Singh (2005)	ANN	DI, C	AOp	56	R <sup>2</sup> =0.96
Mohamed (2011)	ANN, FIS	DI, C	AOp	162	R <sup>2</sup> <sub>ANN</sub> =0.92 R <sup>2</sup> <sub>FIS</sub> =0.86
Khandelwal and Kankar (2011)	SVM	DI, C	AOp	75	R <sup>2</sup> =0.85
Tonnizam Mohamad et al. (2012)	ANN	HD, S, B, N, D, ST, PF	AOp	38	R <sup>2</sup> =0.93
Hajihassani et al. (2014a)	ANN-PSO	HD, S, B, ST, PF, N, DI, C, RQD	AOp	62	R <sup>2</sup> =0.86
Monjezi et al. (2010b)	ANN	HD, BS, ST, PF, SD, N, C, RD	Flyrock	250	R <sup>2</sup> =0.98
Rezaei et al. (2011)	FIS	HD, S, B, ST, PF, SD, RD, C	Flyrock	490	R <sup>2</sup> =0.98
Monjezi et al. (2011b)	ANN	HD, BS, ST, PF, D, SD, C, B	Flyrock	192	R <sup>2</sup> =0.97
Monjezi et al. (2012)	ANN-GA	HD, S, B, ST, PF, SD, D, C, RMR	Flyrock	195	R <sup>2</sup> =0.89
Amini et al. (2012)	SVM, ANN	HL, S, B, ST, PF, SD, D	Flyrock	245	R <sup>2</sup> <sub>ANN</sub> =0.92 R <sup>2</sup> <sub>SVM</sub> =0.97
Tonnizam Mohamad et al. (2013)	ANN	HD, BS, ST, PF, C, D, N, RD, SD	Flyrock	39	R <sup>2</sup> =0.97
Jahed Armaghani et al. (2013)	ANN-PSO	S, B, ST, PF, C, D, N, RD, SD	Flyrock	44	R <sup>2</sup> =0.94
Monjezi et al. (2013b)	ANN	HD, S, B, D, C	Flyrock	310	R <sup>2</sup> =0.98
Khandelwal and Monjezi (2013)	SVM	HL, S, B, ST, PF, SD	Flyrock	187	R <sup>2</sup> =0.95
Marto et al. (2014)	ANN-ICA	RD, HD, BS, ST, PF, C, Rn	Flyrock	113	R <sup>2</sup> =0.98
Trivedi et al. (2014)	ANN	B, ST, q <sub>i</sub> , q, σ <sub>c</sub> , RQD	Flyrock	95	R <sup>2</sup> =0.98
Ghasemi et al. (2014)	ANN, FIS	HL, S, B, ST, PF, C	Flyrock	230	R <sup>2</sup> <sub>ANN</sub> =0.94 R <sup>2</sup> <sub>FIS</sub> =0.96

HL hole length, S spacing, B burden, ST stemming, PF powder factor, SD specific drilling, SVM support vector machine, C maximum charge per delay, D hole diameter, HD hole depth, RD rock density, BS burden to spacing, N number of row, B blastability index, GA genetic algorithm, RMR rock mass rating, PSO particle swarm optimization, Sb subdrilling, DI distance from the blasting face, TC total charge, RQD rock quality designation, ICA imperialist competitive algorithm, E Young’s modulus, Vp p wave velocity, q<sub>i</sub> linear charge concentration, q specific charge, σ<sub>c</sub> unconfined compressive strength

make changes in the shape of the membership function. The existing parameters in this layer are related to the premise part (see Fig. 1a).

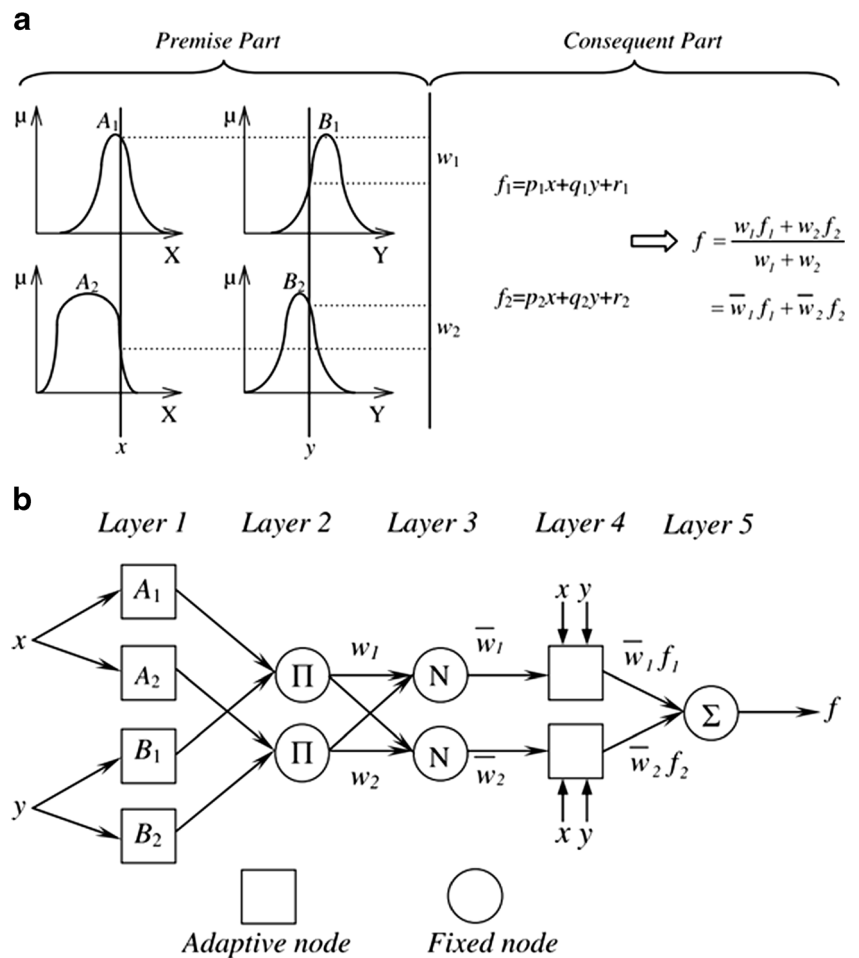
Layer II Each node in layer II computes the firing strength of each rule via multiplication:

$$Q_i^2 = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad i = 1, 2 \quad (9)$$

Layer III The ratio of firing strength of the *i*th rule to the sum of firing strengths of all rules is calculated in this layer.

$$Q_i^3 = W_i = \frac{w_i}{\sum_{j=1}^2 w_j} \quad i = 1, 2 \quad (10)$$

**Fig. 1** **a** Sugeno fuzzy model with two rules; **b** equivalent ANFIS architecture (Jang et al. 1997)



Layer IV Every node  $i$  in layer IV is a node function whereas  $W_i$  is the output of layer III. Parameters of this layer are related to consequent part.

$$Q_i^4 = W_i f_i = W_i(p_i x + q_i y + r_i) \tag{11}$$

Layer V The incoming signals are summed in this layer and form the overall output.

$$Q_i^5 = \text{Overall output} = \sum W_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{12}$$

**Site description and data collection**

To provide a sufficient number of datasets for prediction of blasting environmental impacts, four granite quarry sites were studied in Johor area, Malaysia. Table 2 shows the descriptions of these sites. The purpose of blasting operation in these

quarries is to produce aggregate with capacity of 160,000 to 380,000 t per month. Depending on the weather conditions, 6 to 12 blasting operations are carried out per month in these quarries.

The minimum bench height of 10 m was investigated in Kulai quarry whereas maximum bench height (28 m) was observed is Bukit Indah quarry. A range of rock mass weathering zones from moderately weathered (MW) to completely weathered (CW) was identified in Taman Bestari, Senai Jaya, Kulai and Bukit Indah quarries (Alavi Nezhad Khalil Abad et al. 2014). In addition to mentioned weathered zones, residual soil (RS) was investigated only in Bukit Indah quarry. In identification of weathering zones, suggested method proposed by International Society of Rock Mechanics (ISRM 2007) was utilized. Schmidt hammer test was also conducted based on ISRM (2007) in order to estimate rock mass strength. Range of Schmidt hammer rebound values (Rn) was obtained between 19 and 37. Furthermore, values of 40.7 and 99.8 were obtained as minimum and maximum of uniaxial compressive

**Table 2** Description of granite quarry sites used in this study

Quarry name	Distance to Johor (km)	Latitude	Longitude	Bench height (m)
Taman Bestari	17	1° 60' 41" N	103° 78' 32" E	7–17
Senai Jaya	27	1° 36' 00" N	103° 39' 00" E	13–24
Kulai	35	1° 39' 21" N	103° 36' 11" E	10–22
Bukit Indah	18	1° 93' 12" N	103° 35' 08" E	15–28

strength (UCS), respectively. It should be noted that the uniaxial compression tests were conducted on limited block samples collected from the quarries. As a jointing degree or fracturing of the rock mass, RQD can be used to represent the geological discontinuities. RQD is measured as a percentage of the drill core in lengths of 100 mm or more. This parameter was measured in the selected blasting operations. Minimum and maximum values of 22.5 and 61.25, respectively, were achieved for RQD results.

A total number of 166 blasting operations were investigated, and related parameters of blasting were measured. Various blasting parameters including spacing, burden, stemming length, maximum charge per delay, powder factor, and distance from the blast-face were recorded. It should be mentioned that hole diameter of 115 mm was used for all blasting operations. ANFO and dynamite are used as the main explosive material and initiation, respectively. The blastholes are stemmed using fine gravels.

In each blasting, PPV and AOp values were recorded using VibraZEB seismograph with transducers for PPV and AOp measurement. The AOp values were monitored using linear L-type microphones connected to the AOp channels of recording units. The VibraZEB records AOp values ranging from 88 dB ( $7.25 \times 10^{-5}$  psi or 0.5 Pa) to 148 dB (0.0725 psi or 500 Pa). The microphones have an operating frequency response from 2 to 250 Hz, which is adequate to measure AOp accurately in the frequency range critical for structures and human

hearing. The distance between the monitoring point and the center of blast-face ranged from 65 to 710 m. To measure the flyrock distances in quarry sites, the surface of benches were colored and two video cameras were placed to monitor the flyrock projections. After each blasting, the relevant videos were reviewed to find the locations of the maximum flied rocks. According to Table 1, the widely used input parameters in predicting PPV and AOp are maximum charge per delay and distance from the blast-face. In addition, according to Siskind et al. (1980), the most effective parameters on PPV and AOp are maximum charge per delay and distance from blast-face. In the case of flyrock, the extensively utilized input parameters are burden, spacing, stemming length, powder factor, and maximum charge per delay (see Table 1). Moreover, several researchers obtained these parameters as the most influential one on flyrock resulting from blasting (e.g., Monjezi et al. 2010b, 2011b, 2013b; Rezaei et al. 2011). Therefore, in this study, maximum charge per delay and distance from the blast-face were used as model inputs for prediction of PPV and AOp, while burden to spacing ratio (having effects of both burden and spacing), stemming length, powder factor, and maximum charge per delay were set as input parameters in predicting flyrock distance. Summary of the measured data is tabulated in Table 3. Figures 2, 3, and 4 illustrate the frequency distributions of PPV, AOp, and flyrock distance used in this study.

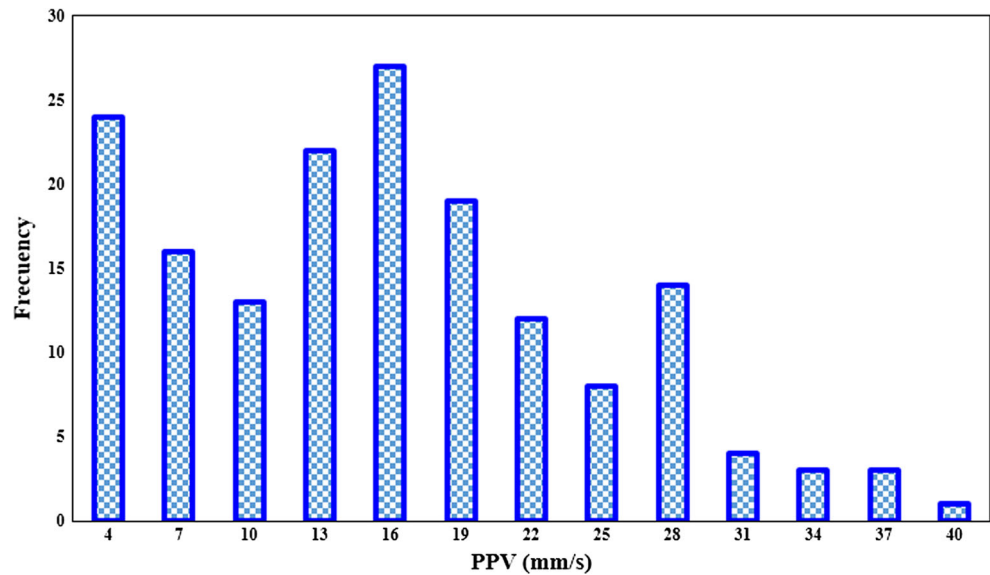
**Application of intelligent systems in predicting PPV, AOP, and flyrock**

To predict PPV, AOp, and flyrock induced by quarry blasting, two intelligent systems namely ANN and ANFIS were developed. As mentioned earlier, maximum charge per delay and distance from the blast-face were selected as inputs to predict PPV and AOp, while maximum charge per delay, distance from the blast-face, burden to spacing ratio, and stemming

**Table 3** Summary of measured parameters in the predictive models

Parameter	Unit	Symbol	Min	Max	Mean	St. deviation
Burden to spacing	–	BS	0.41	0.91	0.75	0.103
Stemming length	m	ST	1.4	4	2.87	0.619
Powder factor	kg/m <sup>3</sup>	PF	0.24	0.98	0.69	0.197
Maximum charge per delay	kg	C	69.79	309.09	202.44	64.534
Distance from the blast-face	m	DI	65	710	329	142.961
Peak particle velocity	mm/s	PPV	1.21	37.44	14.4	8.673
Air-overpressure	dB	AOp	89.30	137.8	113.2	12.159
Flyrock distance	m	–	39	258	140.2	48.521

**Fig. 2** Frequency distribution of measured PPV values



length were set as input parameters for flyrock prediction. The modeling procedures of the ANN and ANFIS techniques are described in the following sections.

### Prediction of PPV, AOp, and flyrock using ANN

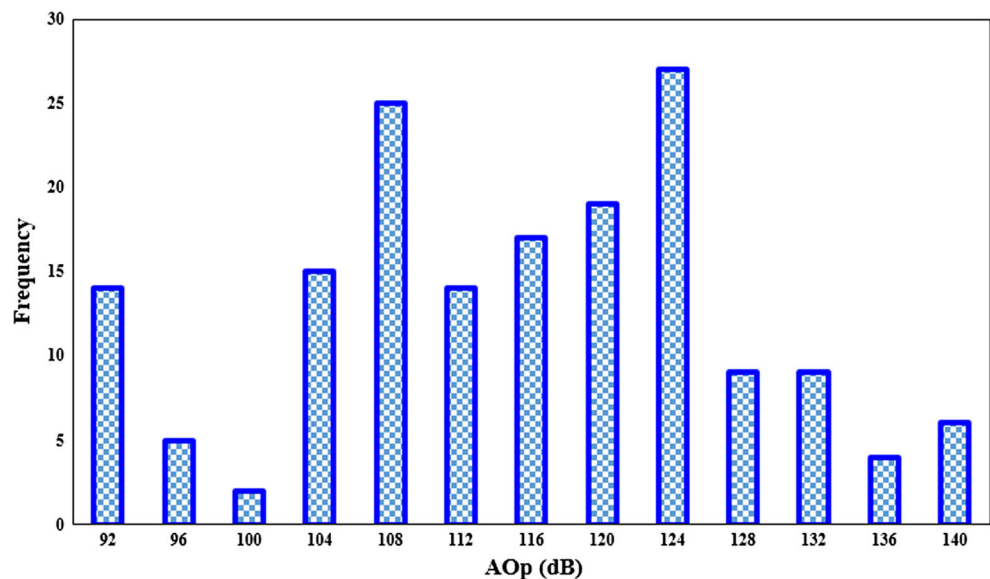
An attempt was made to predict PPV, AOp, and flyrock using ANN technique. To do this, all data were normalized in the range of (0,1) using the following equation:

$$X_{\text{norm}} = (X - X_{\text{min}}) / (X_{\text{max}} - X_{\text{min}}) \quad (13)$$

where  $X$  is the measured value,  $X_{\text{norm}}$  represents the normalized value of the measured parameter, and  $X_{\text{min}}$  and  $X_{\text{max}}$  are

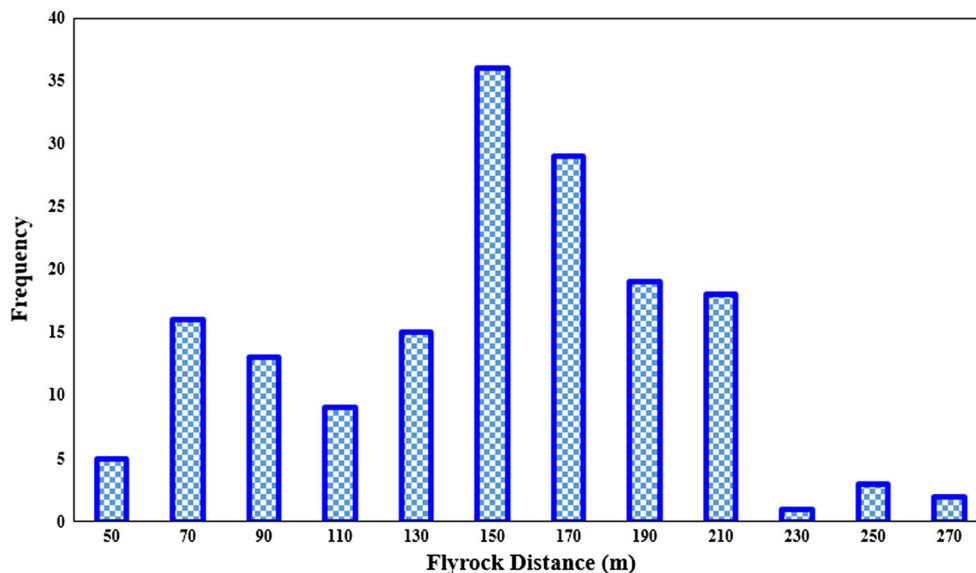
the minimum and maximum values of the measured parameters in the dataset. The performance of the ANN models depends strongly on the suggested architecture of the network as mentioned in the studies by Hush (1989) and Kanellopoulos and Wilkinson (1997). Therefore, determination of the optimal architecture is required to design an ANN model. The network architecture is defined as the number of hidden layer(s) and the number of nodes in each hidden layer(s). According to various researchers (e.g., Hecht-Nielsen 1987; Hornik et al. 1989; Baheer 2000), one hidden layer can solve any complex function in a network. Hence, in this study, one hidden layer was selected to construct the ANN models. In addition, determining neuron number(s) in the hidden layer is the most critical task in the ANN architecture as

**Fig. 3** Frequency distribution of measured AOp values





**Fig. 4** Frequency distribution of measured flyrock distances



stated by Sonmez et al. (2006) and Sonmez and Gokceoglu (2008). Table 4 tabulates some equations related to determination of number of neuron proposed by several scholars. Based on this table, the number of hidden neuron in the range of 1 to 5 should be used for PPV and AOp prediction (using two inputs and one output), while this range is between 1 and 9 for flyrock prediction (using four inputs and one output).

In this study, all datasets were divided randomly to training and testing datasets. The idea behind using some data for testing is to check the performance capacity of the developed model. In the studies by Swingler (1996) and Looney (1996), testing dataset was recommended as 20 and 25 % of whole dataset, respectively, while a range of 20 to 30 % of whole data was suggested for testing in the study by Nelson and Illingworth (1990). Considering these recommendations, 20 % (33 datasets) of whole datasets (166 datasets) was selected randomly as testing datasets, whereas the remaining 133 datasets were used for training the system. In order to determine the optimum number of neurons in the hidden layer,

several ANN models were constructed using one hidden layer and mentioned number of hidden neurons for prediction of PPV, AOp, and flyrock as presented in Table 5. In this table, five iterations were modeled for each hidden node in all outputs and average results of these iterations were presented. According to average results, considering  $R^2$  value of both training and testing datasets, model nos. 5, 4, and 6 outperform the other ANN models for prediction of PPV, AOp, and flyrock, respectively. Hence, in construction of ANN models, values of 5, 4, and 6 were selected as number of hidden neurons to predict PPV, AOp, and flyrock.

In the next step of ANN modeling, five different datasets were selected to develop ANN models for prediction of PPV, AOp, and flyrock. A visual basic code was written to choose the random datasets through the randomizer function (Zorlu et al. 2008). Using the suggested ANN structure for each output and five different randomly selected datasets, totally 15 ANN models were constructed for all outputs (see Tables 6, 7, and 8). The testing datasets were also simulated for each train as shown in these tables. It should be noted that in constructing ANN models in this study, using trial-and-error procedure and recommended values in different studies (Yagiz et al. 2009; Jahed Armaghani et al. 2014), the learning rate and momentum coefficient were considered as 0.1 and 0.9, respectively.

**Table 4** The proposed equations for number of neurons in hidden layer

Heuristic	Reference
$\leq 2 \times N_i + 1$	Hecht-Nielsen (1987)
$(N_i + N_0) / 2$	Ripley (1993)
$\frac{2 + N_0 \times N_i + 0.5 N_0 \times (N_0^2 + N_i) - 3}{N_i + N_0}$	Paola (1994)
$2N_i / 3$	Wang (1994)
$\sqrt{N_i \times N_0}$	Masters (1994)
$2N_i$	Kaastra and Boyd (1996)
	Kanellopoulos and Wilkinson (1997)

$N_i$ : number of input neuron,  $N_0$ : number of output neuron.

**Prediction of PPV, AOp, and flyrock using ANFIS**

To develop a predictive ANFIS model in predicting environmental impacts of blasting, 166 quarry blasting operations were investigated results of these operations were used. In ANFIS analyses, similar to ANN modeling, the best architecture should be determined. To this aim, using a trial-and-error procedure, several ANFIS models were built to determine the

**Table 5**  $R^2$  of trained ANN models to predict PPV, AOp, and flyrock

Output	Model no.	Nodes in hidden layers	Network result											
			Iteration 1		Iteration 2		Iteration 3		Iteration 4		Iteration 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
PPV	1	1	0.741	0.749	0.733	0.781	0.726	0.783	0.473	0.405	0.740	0.743	0.683	0.692
	2	2	0.784	0.706	0.783	0.651	0.769	0.659	0.755	0.729	0.757	0.734	0.770	0.696
	3	3	0.751	0.704	0.753	0.766	0.755	0.750	0.770	0.632	0.787	0.605	0.763	0.691
	4	4	0.754	0.621	0.760	0.797	0.766	0.815	0.750	0.842	0.780	0.798	0.762	0.775
	5	5	0.773	0.869	0.768	0.839	0.780	0.778	0.750	0.780	0.767	0.824	0.768	0.818
AOp	1	1	0.779	0.858	0.797	0.779	0.259	0.411	0.790	0.814	0.776	0.841	0.680	0.741
	2	2	0.825	0.776	0.792	0.780	0.812	0.819	0.825	0.766	0.819	0.771	0.815	0.782
	3	3	0.806	0.826	0.803	0.845	0.828	0.728	0.805	0.83	0.805	0.846	0.809	0.815
	4	4	0.819	0.819	0.857	0.829	0.863	0.812	0.837	0.812	0.843	0.821	0.844	0.819
	5	5	0.86	0.712	0.846	0.722	0.817	0.806	0.839	0.787	0.843	0.753	0.841	0.756
Flyrock	1	1	0.371	0.421	0.396	0.163	0.398	0.241	0.333	0.653	0.411	0.253	0.382	0.345
	2	2	0.446	0.310	0.448	0.237	0.469	0.246	0.520	0.262	0.475	0.302	0.472	0.271
	3	3	0.490	0.194	0.489	0.349	0.564	0.279	0.482	0.269	0.441	0.565	0.493	0.331
	4	4	0.470	0.469	0.615	0.419	0.548	0.406	0.65	0.530	0.648	0.426	0.586	0.450
	5	5	0.587	0.495	0.601	0.456	0.593	0.474	0.651	0.342	0.639	0.529	0.614	0.459
	6	6	0.799	0.785	0.833	0.809	0.828	0.789	0.772	0.812	0.805	0.611	0.807	0.761
	7	7	0.685	0.593	0.741	0.788	0.728	0.686	0.794	0.810	0.731	0.623	0.736	0.701
	8	8	0.812	0.698	0.759	0.609	0.794	0.786	0.791	0.805	0.754	0.677	0.782	0.715
	9	9	0.841	0.493	0.780	0.513	0.803	0.765	0.778	0.654	0.799	0.766	0.801	0.638

**Table 6** Performance indices of each model and their rank values in predicting PPV

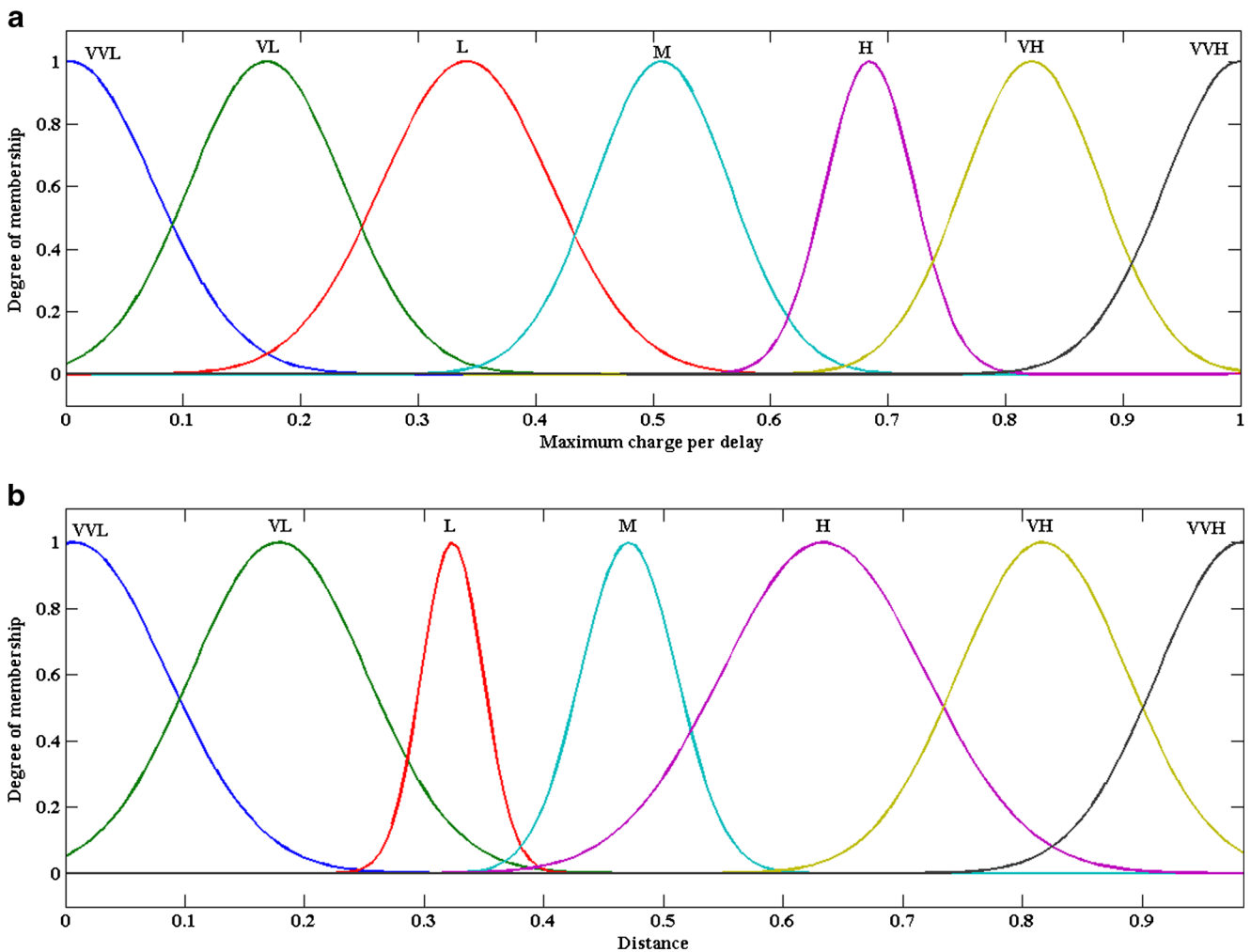
Method	Model	$R^2$	RMSE	VAF	Rating for $R^2$	Rating for RMSE	Rating for VAF	Rank value
ANN	Train 1	0.806	0.102	80.575	5	5	5	15
	Train 2	0.785	0.110	78.471	3	4	3	10
	Train 3	0.790	0.113	79.022	4	3	4	11
	Train 4	0.779	0.115	77.915	2	1	2	5
	Train 5	0.762	0.114	76.202	1	2	1	5
	Test 1	0.734	0.137	73.239	2	2	3	7
	Test 2	0.771	0.113	76.544	4	5	4	13
	Test 3	0.741	0.113	71.475	3	5	2	10
	Test 4	0.696	0.121	66.736	1	3	1	5
	Test 5	0.798	0.118	79.399	5	4	5	14
ANFIS	Train 1	0.953	0.049	95.324	2	2	1	5
	Train 2	0.971	0.040	97.196	5	5	5	15
	Train 3	0.960	0.048	96.021	4	3	3	10
	Train 4	0.971	0.042	97.093	5	4	4	13
	Train 5	0.959	0.050	95.887	3	1	2	6
	Test 1	0.924	0.076	92.351	4	1	4	9
	Test 2	0.922	0.062	91.533	3	4	2	9
	Test 3	0.939	0.058	93.721	5	5	5	15
	Test 4	0.920	0.064	91.673	2	3	3	8
	Test 5	0.922	0.072	88.968	3	2	1	6

**Table 7** Performance indices of each model and their rank values in predicting AOp

Method	Model	$R^2$	RMSE	VAF	Rating for $R^2$	Rating for RMSE	Rating for VAF	Rank value
ANN	Train 1	0.841	0.099	84.104	5	5	5	15
	Train 2	0.819	0.105	81.863	1	2	1	4
	Train 3	0.826	0.105	82.566	2	2	3	7
	Train 4	0.837	0.103	83.745	4	4	4	12
	Train 5	0.828	0.104	82.816	3	3	2	8
	Test 1	0.801	0.117	78.545	1	1	1	3
	Test 2	0.859	0.107	85.458	4	3	5	12
	Test 3	0.838	0.104	83.152	3	4	3	10
	Test 4	0.834	0.108	80.521	2	2	2	6
	Test 5	0.864	0.101	84.831	5	5	4	14
ANFIS	Train 1	0.961	0.050	96.052	1	1	1	3
	Train 2	0.971	0.043	97.019	5	5	5	15
	Train 3	0.968	0.045	96.757	3	3	3	9
	Train 4	0.970	0.044	97.011	4	4	4	12
	Train 5	0.967	0.046	96.714	2	2	2	6
	Test 1	0.932	0.063	93.073	2	3	2	7
	Test 2	0.947	0.058	94.715	4	4	5	13
	Test 3	0.935	0.063	93.510	3	3	3	9
	Test 4	0.949	0.056	94.276	5	5	4	14
	Test 5	0.927	0.069	92.284	1	2	1	4

**Table 8** Performance indices of each model and their rank values in predicting flyrock

Method	Model	$R^2$	RMSE	VAF	Rating for $R^2$	Rating for RMSE	Rating for VAF	Rank value
ANN	Train 1	0.781	0.103	78.077	2	2	2	6
	Train 2	0.812	0.095	81.130	3	3	3	9
	Train 3	0.824	0.089	82.310	4	4	4	12
	Train 4	0.776	0.109	77.548	1	1	1	3
	Train 5	0.846	0.083	84.376	5	5	5	15
	Test 1	0.790	0.104	78.457	2	3	2	7
	Test 2	0.807	0.102	80.287	4	4	4	12
	Test 3	0.834	0.106	82.291	5	2	5	12
	Test 4	0.785	0.085	78.342	1	5	1	7
	Test 5	0.802	0.109	78.485	3	1	3	7
ANFIS	Train 1	0.988	0.024	98.798	5	5	5	15
	Train 2	0.975	0.032	97.432	3	3	3	9
	Train 3	0.969	0.038	96.871	1	1	1	3
	Train 4	0.985	0.028	98.470	4	4	4	12
	Train 5	0.971	0.035	96.999	2	2	2	6
	Test 1	0.959	0.044	95.908	5	5	5	15
	Test 2	0.940	0.070	93.944	3	1	3	7
	Test 3	0.934	0.065	93.128	1	2	2	5
	Test 4	0.935	0.057	92.804	2	4	1	7
	Test 5	0.951	0.063	95.134	4	3	4	11



**Fig. 5** Membership functions assigned for the input parameters of PPV: **a** maximum charge per delay and **b** distance

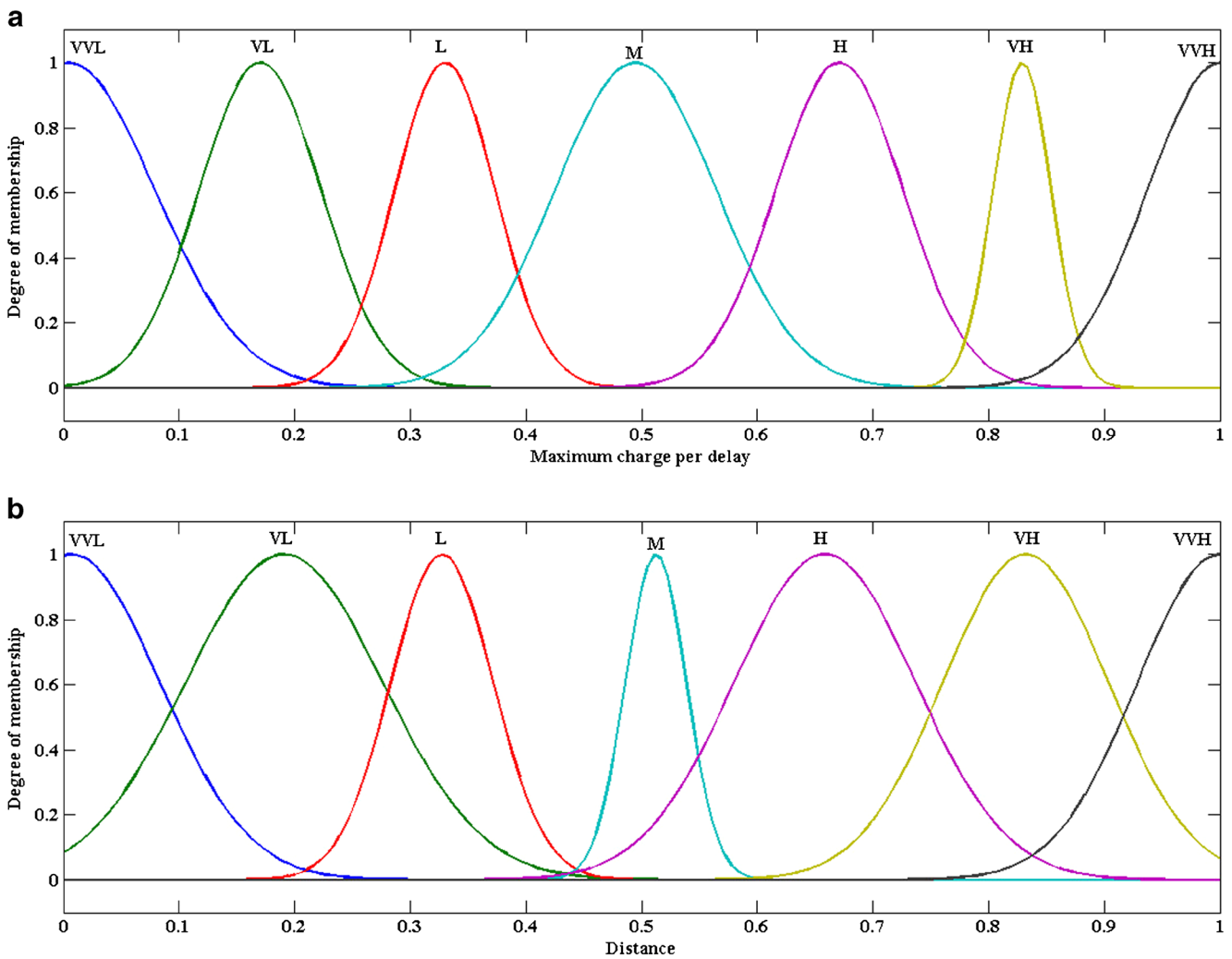
number of fuzzy rules in predicting PPV, AOp, and flyrock separately. The Gaussian membership function, as a well-known membership function in fuzzy systems, was employed in the modeling (Jahed Armaghani et al. 2014). Eventually, each input parameter with seven fuzzy rules outperforms the other ANFIS models in predicting PPV and AOp, while the value of 3 was obtained for prediction of flyrock. Therefore, a number of 49 fuzzy rules ( $7 \times 7$ ) show the best performance for PPV and AOp prediction and 81 fuzzy rules ( $3 \times 3 \times 3 \times 3$ ) indicate the best performance for flyrock prediction. In determining the number of fuzzy rules, the results of RMSE were only considered. The linguistic variables were set as very very low (VVL), very low (VL), low (L), medium (M), high (H), very high (VH), and very very high (VVH) in modeling PPV and AOp, while these linguistic variables were assigned as L, M, and H for flyrock prediction.

In the next step, considering the suggested ANFIS structure, using the same selected datasets in ANN modeling, 15 ANFIS models were constructed for all output as shown in

Tables 6, 7, and 8. In addition, these models were checked using the data assigned for testing datasets. Figures 5, 6, and 7 show the normalized membership functions of input parameters for prediction of PPV, AOp, and flyrock, respectively. The presented membership functions were assigned after training the system. Furthermore, for the output, a linear type of membership function was utilized. It is worth noting that the RMSE results were not decreased after epoch numbers of 10, 14, and 45 for best models of PPV, AOp, and flyrock, respectively. In this study, all ANN and ANFIS models were constructed using Matlab version 7.14.0.739 (Demuth et al. 2009).

### Analysis of the results

In this research, two nonlinear techniques namely ANN and ANFIS were developed to predict environmental impacts of quarry blasting including PPV, AOp, and flyrock distance. During the modeling process of this study, all 166 datasets were randomly divided to five different datasets (training



**Fig. 6** Membership functions assigned for the input parameters of AOp: **a** maximum charge per delay and **b** distance

and testing) for development of intelligent models. Some performance indices including  $R^2$ , amount of value account for (VAF), and RMSE were computed to check the capacity performance of all predictive models:

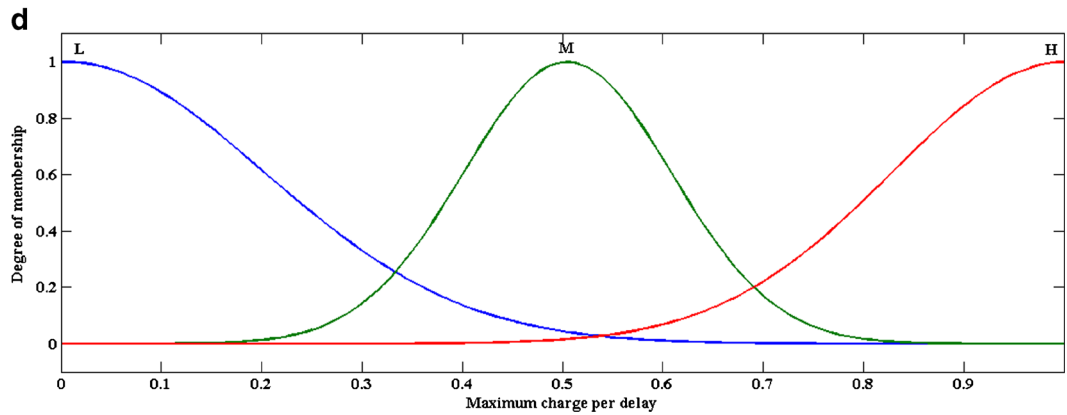
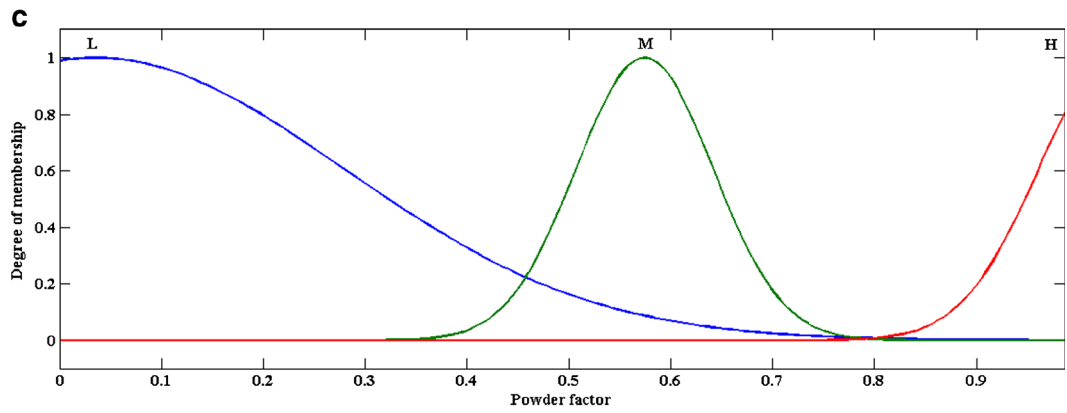
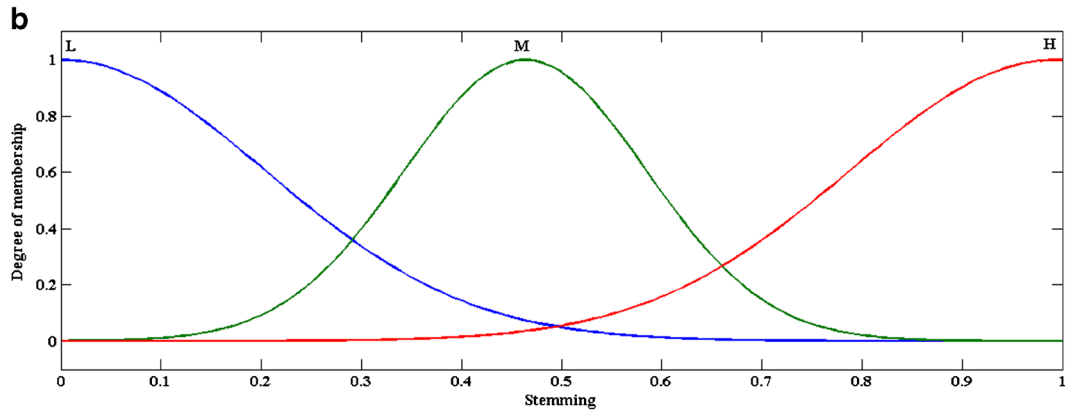
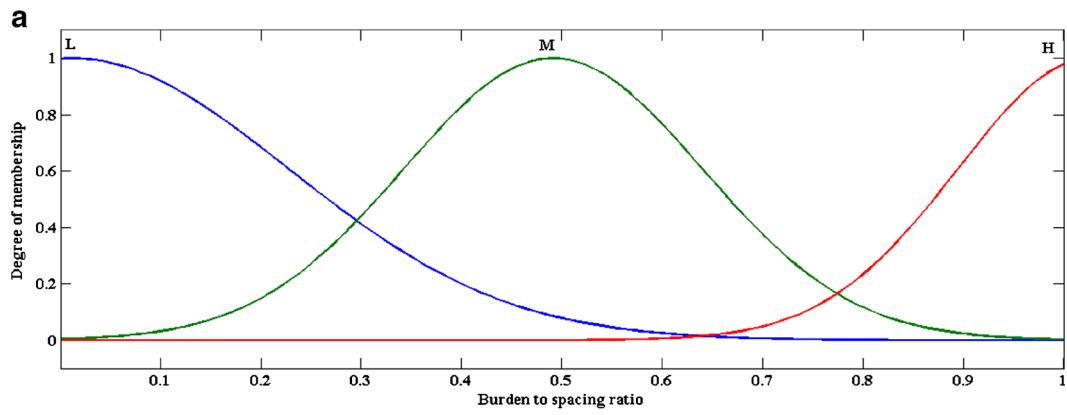
$$R^2 = 1 - \frac{\sum_{i=1}^N (y - y')^2}{\sum_{i=1}^N (y - \bar{y})^2} \tag{14}$$

$$VAF = \left[ 1 - \frac{\text{var}(y - y')}{\text{var}(y)} \right] \times 100 \tag{15}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y - y')^2} \tag{16}$$

where  $y$ ,  $y'$ , and  $\bar{y}$  are the measured, predicted, and mean of the  $y$  values, respectively,  $N$  is the total number of data, and  $P$  is

the number of predictors. Theoretically, the model will be excellent if the VAF is 100 and RMSE is zero. Results of models performance indices ( $R^2$ , RMSE, and VAF) for all randomly selected datasets based on training and testing are presented in Tables 6, 7, and 8 in predicting PPV, AOp, and flyrock, respectively. High performances of the training dataset indicate that the learning step of the models is successful if the testing dataset reveals that the model generalization ability is satisfactory. As it can be seen in Tables 6, 7, and 8, selecting the best models is too difficult. To overcome this difficulty, a simple ranking procedure suggested by Zorlu et al. (2008) was used to select the best models. A ranking value was calculated and assigned for each training and testing dataset separately (see Tables 6, 7, and 8). Each performance index was ordered in its class and highest rating was assigned to the best result. For instance, in the case of PPV (see Table 6),  $R^2$  values of the train datasets for ANN technique were obtained as 0.806, 0.785, 0.790, 0.779, and 0.762, respectively. Therefore, their ratings were assigned as



◀ **Fig. 7** Membership functions assigned for the input parameters of flyrock: **a** burden to spacing ratio, **b** stemming, **c** powder factor, and **d** maximum charge per delay

5, 3, 4, 2, and 1, respectively. This procedure was repeated for all performance indices. After this process, the obtained ratings for each dataset (training and testing) were summed, separately. For example, for prediction of PPV (see Table 6), the rating values of ANN training dataset 1 were 5 for  $R^2$ , 5 for RMSE, and 5 for VAF, so the performance rating was computed as 15. The final stage of selecting the best models is to calculate the total rank by summing up the rank value of each dataset (training and testing). Total ranking of training and testing datasets for two intelligent systems in predicting blasting environmental impacts is shown in Table 9.

**Table 9** Results of total rank for all outputs obtained from five randomly selected datasets

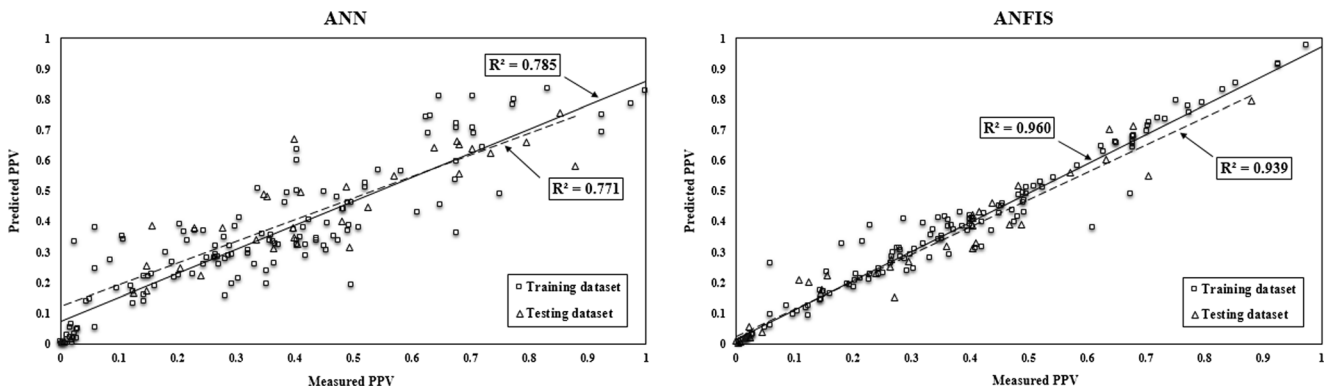
Output	Technique	Model	Total rank
PPV	ANN	1	22
		2	23
		3	21
		4	10
		5	19
	ANFIS	1	14
		2	24
		3	25
		4	21
		5	12
AOp	ANN	1	18
		2	16
		3	17
		4	18
		5	22
	ANFIS	1	10
		2	28
		3	18
		4	26
		5	10
Flyrock	ANN	1	13
		2	21
		3	24
		4	10
		5	22
	ANFIS	1	30
		2	16
		3	8
		4	19
		5	17

According to this table, model nos. 2 and 3 exhibited the best performance of PPV prediction for ANN and ANFIS techniques, respectively, while model nos. 5 and 2 yielded the best results of ANN and ANFIS, respectively, in predicting AOp. In addition, the best ANN and ANFIS models for prediction of flyrock distance are model nos. 3 and 1, respectively. Based on the presented results, considering both training and testing datasets, the prediction performances of the ANFIS models are higher than the ANN models.

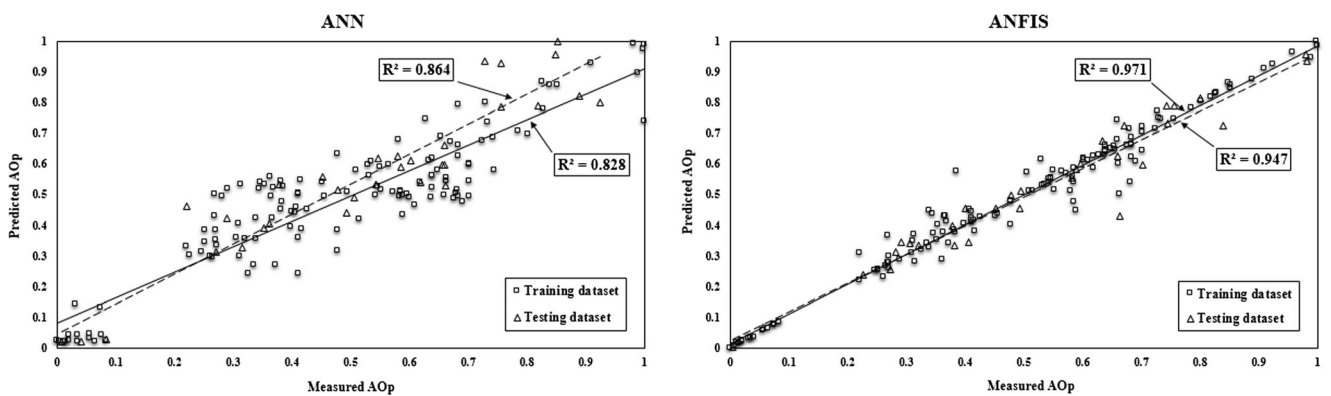
The graphs of predicted PPV, AOp, and flyrock using the ANN and ANFIS techniques against their measured values for training and testing datasets are shown in Figs. 8, 9, and 10, respectively. As shown in these figures, the ANFIS model can perform better in the prediction of blasting environmental impacts in comparison to ANN predictive models. In these figures,  $R^2$  values of testing datasets equal to 0.939, 0.947, and 0.959 for prediction of PPV, AOp, and flyrock, respectively, suggest the superiority of the ANFIS technique in predicting blasting environmental impacts, while implementing ANN model, these values are 0.771, 0.864, and 0.834 in predicting PPV, AOp, and flyrock, respectively.

### Summary and conclusion

Two intelligent systems (ANN and ANFIS) were developed to predict blasting environmental impacts using 166 datasets obtained from four granite quarry sites in Malaysia. For this purpose, the blasting parameters such as burden, spacing, stemming, powder factor, and maximum charge per delay, as well as environmental impacts including PPV, AOp, and flyrock were precisely recorded in each blasting event. Several ANN and ANFIS models were constructed to predict environmental impacts of quarry blasting. In this study, based on previous researches, maximum charge per delay and distance from the blast-face were used as inputs for prediction of PPV and AOp, while burden to spacing ratio, stemming length, powder factor, and maximum charge per delay were set as input parameters in predicting flyrock distance. Considering some model performance indices including  $R^2$ , RMSE, and VAF and also using simple ranking method, the best ANN and ANFIS models were selected among all constructed models. The results indicated that the ANFIS technique can provide higher performance capacity in predicting blasting environmental impacts compared to ANN model.  $R^2$  values of testing datasets equal to 0.939, 0.947, and 0.959 for prediction of PPV, AOp, and flyrock, respectively, suggest the higher performance capacity of the ANFIS technique



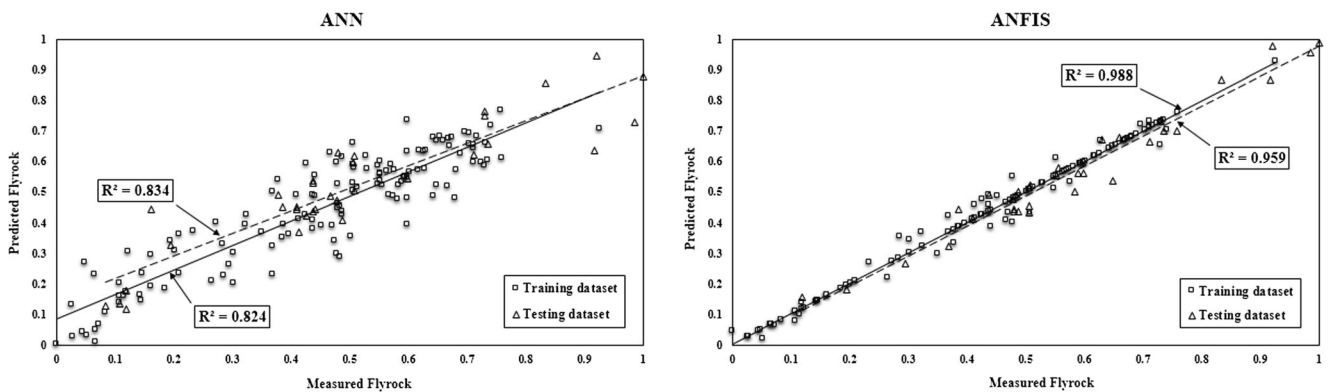
**Fig. 8** Correlation between normalized measured and predicted values of PPV using ANN and ANFIS techniques



**Fig. 9** Correlation between normalized measured and predicted values of AOp using ANN and ANFIS techniques

in predicting blasting environmental impacts, while in predicting PPV, AOp, and flyrock performing ANN approach, these values are 0.771, 0.864, and 0.834, respectively. Although all proposed models in this study are applicable for prediction of blasting environmental impacts, they can be

used depending on the condition. When higher accuracy is required, the ANFIS model would be the proper alternative as it combines the advantages of the ANN and FIS techniques to demonstrate a high prediction capacity in nonlinear engineering problems.



**Fig. 10** Correlation between normalized measured and predicted values of flyrock distance using ANN and ANFIS techniques



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