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Development of a fuzzy model for predicting ground vibration caused by rock blasting in surface mining

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Abstract

Ground vibration is an integral part of the rock blasting process in surface mines, which may cause severe damages to structures and plants in the nearby environment. Therefore, its prediction plays an important role in the minimization of environmental impacts. The peak particle velocity (PPV) is an important predictor for ground vibration. In this paper, first a fuzzy logic model was developed to predict PPV based on collected data from blasting events in Sarcheshmeh copper mine, located in the southwest of Iran. The predictive fuzzy model was implemented on the fuzzy logic toolbox of MATLAB using the Mamdani algorithm. Then, the PPV was predicted by conventional empirical predictors used in blasting practice and also by multiple regression analysis. Finally, a comparative analysis between the results obtained by the fuzzy model and common vibration predictors was carried out. The results indicated the high predictive capacity of fuzzy model, which can be used as a reliable predictor of ground vibration for the studied mine.

Keywords

Blasting operation, ground vibration, peak particle velocity, fuzzy logic, empirical predictors, multiple regression

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1. Introduction

In most surface mines, the blasting operation is the first element of the ore extraction process. The primary purpose of blasting is rock fragmentation and displacement of the broken rocks. For this purpose, the blasting operation requires a large amount of explosives. Singh and Singh (2005) indicated that fragmentation and displacement of broken rocks use only 20–30% of the total amount of explosive energy. The remainder of the energy is wasted away in the form of environmental side effects, such as ground vibration. The ground vibration is usually described as a time-varying displacement, velocity or acceleration of a particular point (particle) in the ground.

Ground vibration caused by blasting operations is acoustic waves that propagate through the rocks. It differs from the ground vibrations caused by earthquakes in terms of seismic source, amount of available energy and travelled distances (Giraudi et al., 2009). Over years, many studies have been conducted to assess and control ground vibration due to blasting operations (Blair and Jiang, 1995; Bhandari, 1997; Siskind, 2000; Kahriman, 2002; Valdivia et al., 2003; Kahriman, 2004; Kuzu and Ergin, 2005; Singh et al., 2006; Uysal et al., 2007; Kuzu, 2008; Ozer et al., 2008; Ak et al., 2009; Mesec et al., 2010; Singh and Verma, 2010). The intensity of ground vibration arising from rock blasting depends on various parameters. These parameters can be broadly divided into two categories, namely, controllable parameters and uncontrollable parameters. Controllable parameters can be changed

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and include blast geometry, type and amount of used explosive, stemming, priming and initiation, while uncontrollable parameters are natural and cannot be changed and include distance, geological conditions, initiation timing errors and meteorological conditions.

Ground vibration traveling through the ground may damage the surrounding environment and nearby structures when it reaches a certain magnitude. High intensity ground vibration not only creates problems for the nearby population, but also adversely affects the integrity of the structures in the mine area. Sometimes, it provokes the population and can put mines into closure. High intensity vibration also damages the ground water and harms the ecology of the nearby area. Therefore, the effects of ground vibration on building structures and human beings need to be predicted, monitored and controlled by the blasting engineers as part of optimizing the blasting operation. In order to predict and evaluate the blast vibration effects and consequences, different indicators have been proposed, such as peak particle velocity (PPV), peak particle acceleration (PPA) and peak particle displacement (PPD). Among these indicators, the PPV has been used frequently in different standards and it has been found to be a reliable indicator for evaluation and prediction of losses associated with ground vibration. A number of investigators have studied ground vibration resulting from blasting and have developed several empirical equations for predicting the PPV using statistical techniques (Duvall and Petkof, 1959; Langefors and Kihlstrom, 1963; Davies et al., 1964; Ambraseys and Hendron, 1968; Indian Standard Institute, 1973; Ghosh and Daemen, 1983; Gupta et al., 1987; Pal Roy, 1991; Rai and Singh, 2004). These empirical PPV predictor models are basically based on two parameters, maximum charge per delay and distance from blast site, and do not include other effective parameters. Because of the large number of influencing parameters and complex interrelation among these parameters, empirical methods may not be fully suitable for such problems. In order to overcome these shortcomings, artificial intelligence techniques are now being used as alternate statistical techniques. In recent years, some researchers have tried to develop new predictive models using artificial intelligence techniques, especially an artificial neural network (ANN) incorporating two or more parameters affecting the ground vibration (Singh and Singh, 2005; Khandelwal and Singh, 2006, 2007; Iphar et al., 2008; Mohamed, 2009; Khandelwal et al., 2009; Khandelwal and Singh, 2009; Bakhshandeh Amnieh et al., 2010; Fisne et al., 2010; Monjezi et al., 2010; Verma and Singh, 2010; Dehghani and Ataee-pour, 2011; Kamali and Ataei, 2011; Mohamed, 2011). The researchers found that the artificial intelligence is a useful tool for better prediction of PPV.

In this paper, an effort has been made to predict PPV with the help of the fuzzy logic approach using data collected from blasting events in Sarcheshmeh copper mine, Iran. The same data have been also used for the prediction of PPV using multiple regression analysis and empirical vibration predictors. The basic idea is to find the scope and suitability of the fuzzy logic for prediction of PPV over the widely used conventional vibration predictors. It should be noted that Fisne et al. (2010) have recently developed a fuzzy model for predicting PPV based on two parameters, charge weight per delay and distance from blast location, for quarry operations in Istanbul, Turkey. The main difference between their study and the present study is that in addition to the two mentioned parameters, this study considers other effective parameters on ground vibration, such as burden, spacing, stemming and number of holes per delay. In addition, in this study the performance of the fuzzy model is compared with common empirical predictor models, whereas Fisne et al. (2010) have compared their obtained results with only the United States Bureau of Mines (USBM) empirical model.

This paper is organized into eight sections. In Section 2, details of the case study and collected data are given, while in Section 3, the background of fuzzy logic is described. Details of fuzzy model development are given in Section 4 and in Sections 5 and 6, we describe the development of the multiple regression model and empirical predictor models, respectively, for prediction of PPV. In Section 7 the predictive capacity of all mentioned models is compared and in Section 8, results of this paper are given.

2. Case study: Sarcheshmeh copper mine

2.1. Mine description

Sarcheshmeh copper mine is the largest porphyry copper mine in Iran, which is situated 160 km southwest of Kerman and 50 km south of Rafsanjan city, at 31.2° N longitude and 56.1° E latitude (Bakhshandeh Amnieh et al., 2010). Figure 1 shows the location of Sarcheshmeh copper mine, which is 2600 m above sea level. The mine is located near the center of an elongated NNW–SSE mountain belt, which is principally composed of folded and faulted rocks, and extends intermittently from Turkey to the southeast Baluchestan of Iran.

The geology of Sarcheshmeh porphyry deposit is very complicated and various rock types can be found. The oldest host rock in this mine is Eocene

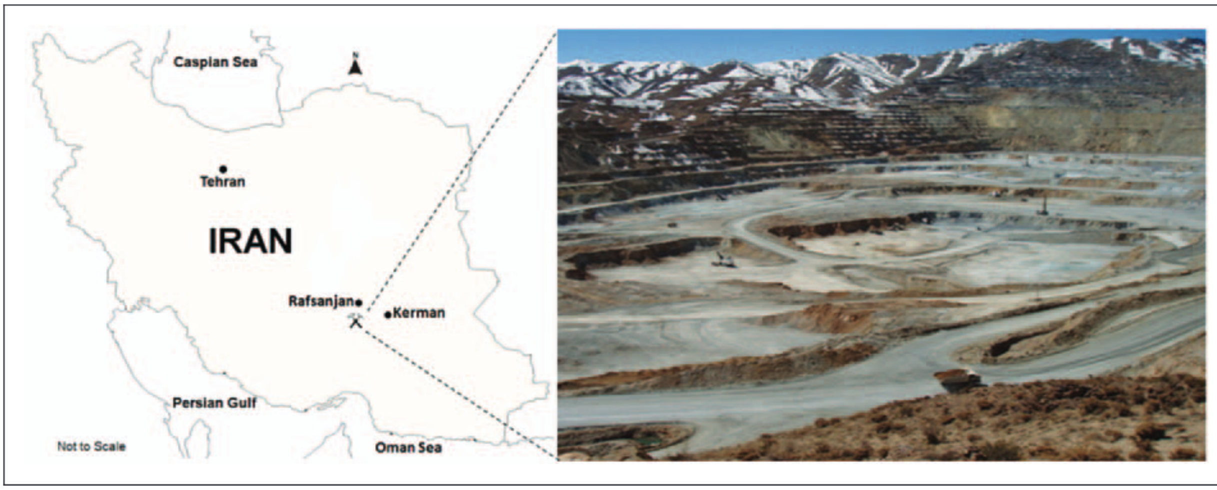

Figure 1. Sarcheshmeh copper mine.

Table 1. Basic descriptive statistics of the data collected from Sarcheshmeh copper mine

Parameters	Unit	Symbol	Min.	Max.	Mean.	Std. dev.
Burden	m	B	3.00	7.50	7.01	1.13
Spacing	m	S	4.00	11.00	9.29	1.75
Stemming	m	S_t	2.40	6.00	5.51	0.95
No. of holes per delay	–	N	6.00	32.00	14.08	5.33
Charge per delay	kg	Q	1332.00	9812.00	5595.21	2079.04
Distance from blast location	m	D	133.00	2845.00	1037.47	591.04
PPV	mm/s	PPV	0.49	53.55	9.31	9.00

andesite and other rock is Sarcheshmeh granodiorite stock. Waste rocks are mainly granodiorite dykes, including prophyric hornblende, prophyric feldspar and prophyric biotite. The ore zone is in the form of an ellipse with 2300 and 1200 m diameters. Mineralization in this deposit belongs to the late Tertiary era. The main minerals of the deposit are chalcopyrite, pyrite, chalcocite, cuprite and malachite. The proved reserve of the deposit is approximately 826 Mt, with an average grade of 0.78% of copper, 0.03% of molybdenum, 0.27 ppm of gold, 1.14 ppm of silver, 1.2 ppm of nickel and 0.9 ppm of cobalt.

The mine is extracted by open pit mining and the blasting operation is performed for rock excavation. The height and slope of the working benches are 12.5 m and 63.4°, respectively. The angle of the overall slope ranges from 30° to 35°. The width and slope of the ramp are 30 m and 5°, respectively. Ammonium nitrate and fuel oil (ANFO) is used as the main explosive material and dynamite cartridges are used as a primer, with bottom hole positioning. The blasting system is nonelectric and detonating cord is applied for initiation. Blast holes are drilled vertically in a staggered pattern and drilling cuttings are used as stemming materials. The diameter and depth of blast holes are 215 mm and 15 m, respectively. After each blast, broken rocks, using hydraulic shovels and trucks, are sent to the waste dump, oxide dump or primary crushers, depending on rock type. With the present design, mine production is about 40,000 ton per day.

2.2. Data collection

To do this study, the PPV due to ground vibration by blasting was measured for 120 blast events at various blasting patterns and distances from the blast face in Sarcheshmeh copper mine in a specific period of time. Burden, spacing, stemming, number of holes per delay, maximum charge per delay, distance from blast location to monitoring point and PPV were recorded in each blast event. Burden, spacing and stemming were measured by a tape meter and the number of holes per delay by controlling each blasting pattern. The distance from the blasting location to the monitoring point was measured carefully by means of a hand-held GPS (global positioning system) and the amount

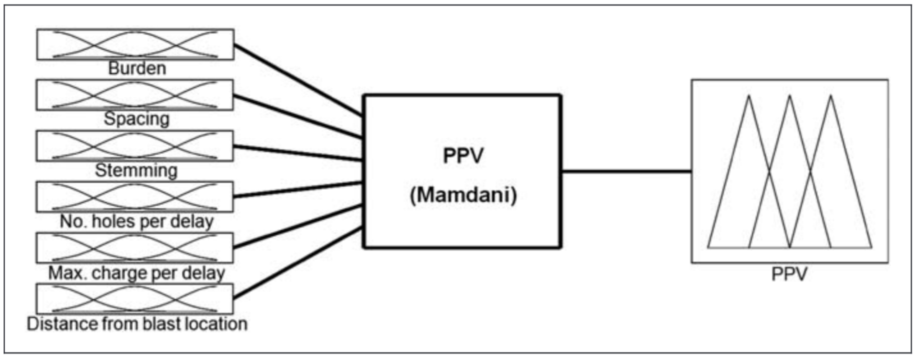

Figure 2. Input and output variables of the fuzzy model.

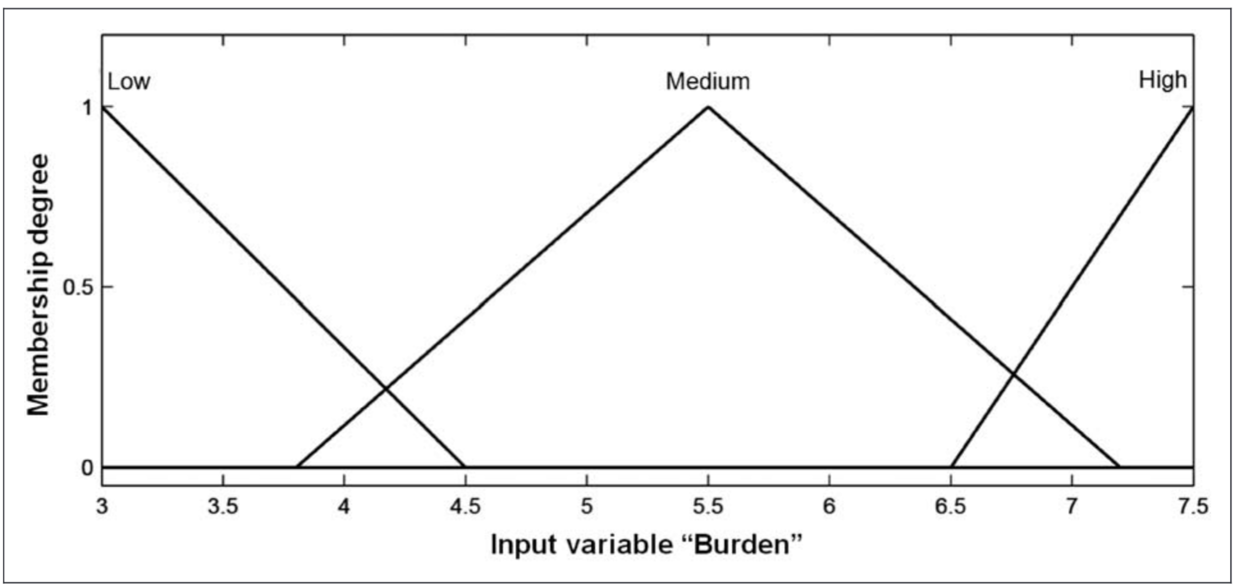

Figure 3. Fuzzy representation of burden.

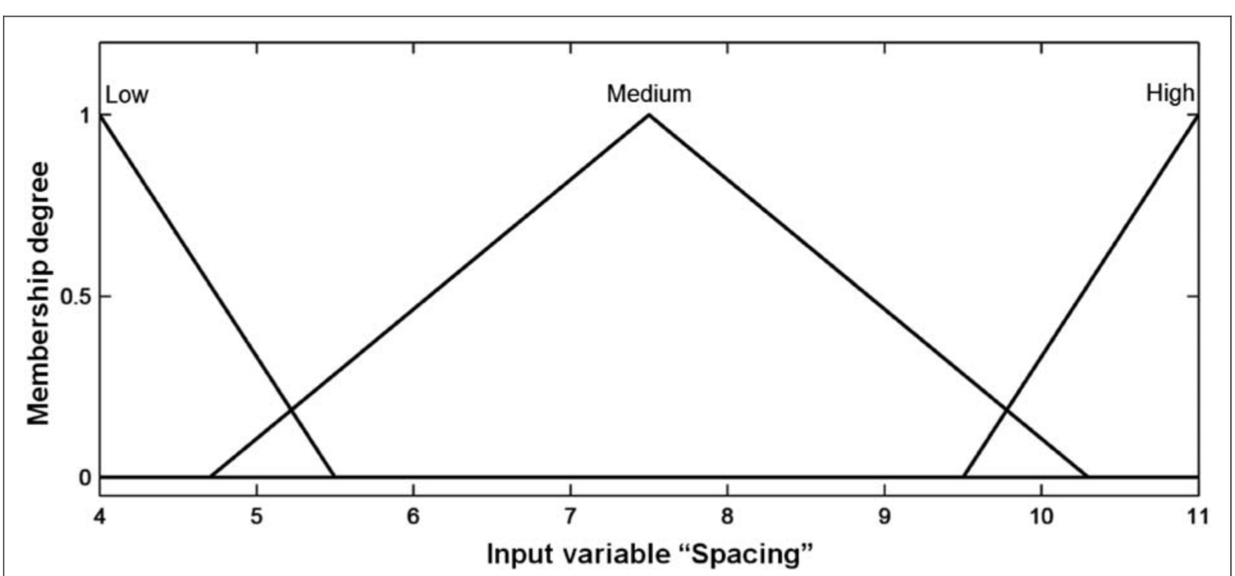

Figure 4. Fuzzy representation of spacing.

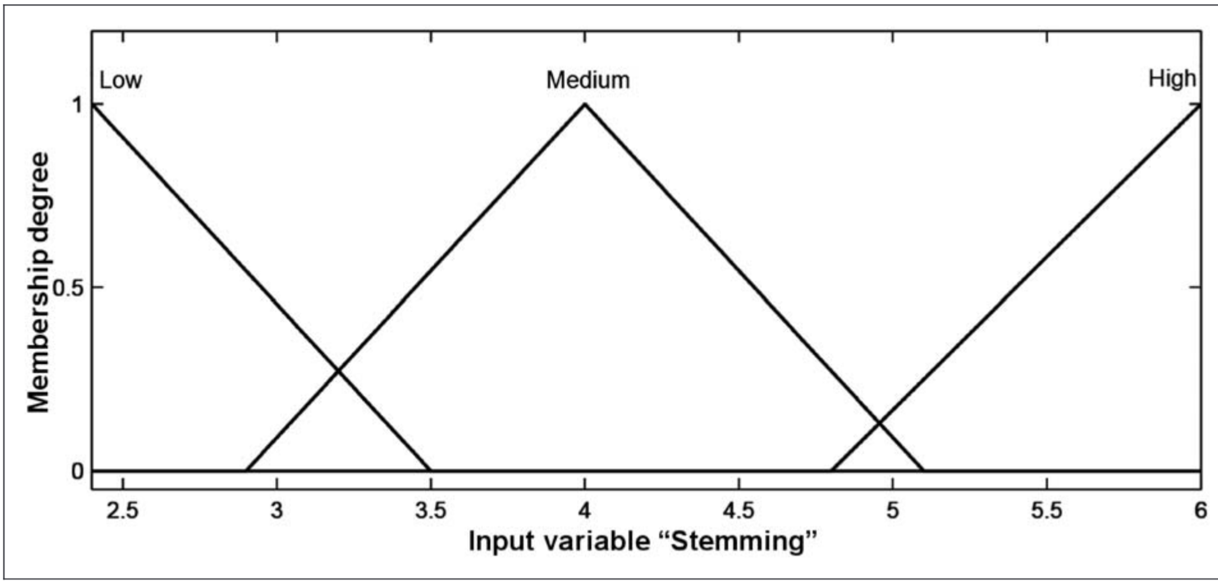

Figure 5. Fuzzy representation of stemming.

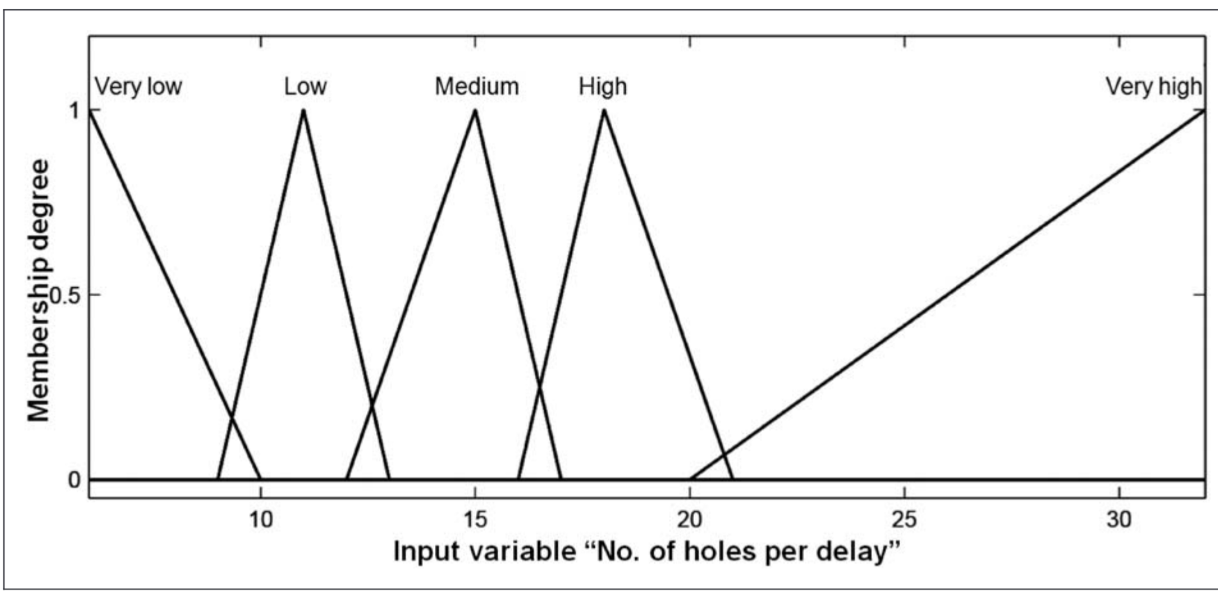

Figure 6. Fuzzy representation of number of holes per delay.

of maximum charge per delay was recorded for each blast by controlling the blast hole charge. Furthermore, the amount of dynamite used for priming was considered for determining the maximum charge per delay. PPV was measured by using the PDAS-100 digital seismograph. It should be mentioned that in all of the recorded blasts, the diameter of blast holes, depth of blast holes and delay time between blast holes are constant and equal to 152 mm, 15 m and 50 ms, respectively. The basic descriptive statistics of collected data are summarized in Table 1.

3. Fuzzy logic: basic concepts and definitions

The details of fuzzy logic are available in the literature (Zadeh, 1965; Ross, 1995), but it is explained briefly in the following. The fuzzy logic is a matter of the fuzzy set theory that in particular is used to deal with subjects having ambiguities and uncertainties. Fuzzy set theory was first formulized by Zadeh (1965) as a mathematical way to represent linguistic vagueness. A fuzzy set is an extension of a crisp set but does not have any sharp

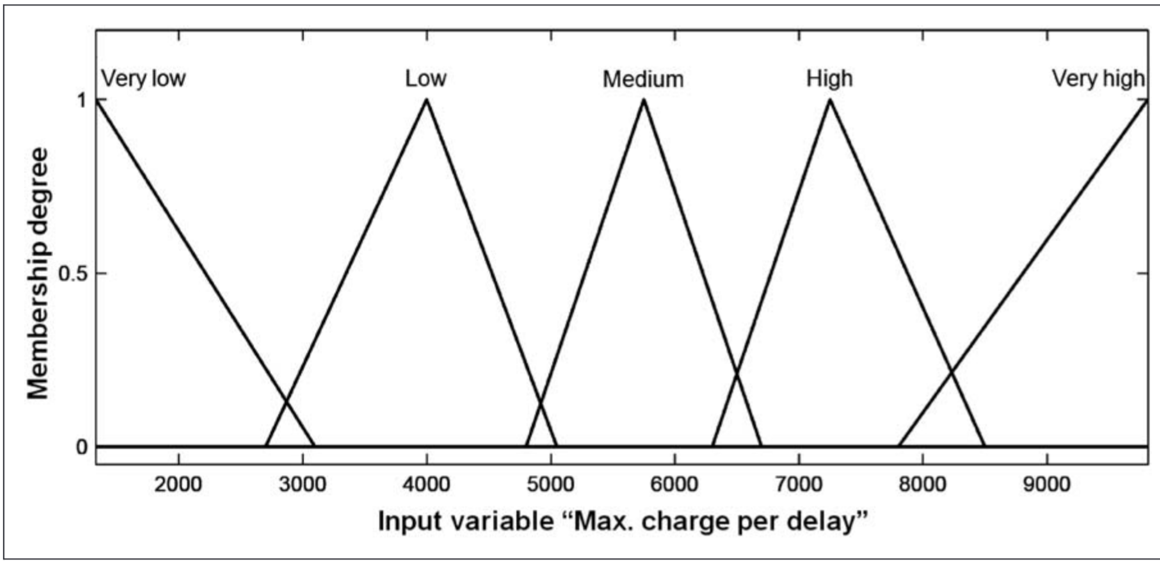

Figure 7. Fuzzy representation of maximum charge per delay.

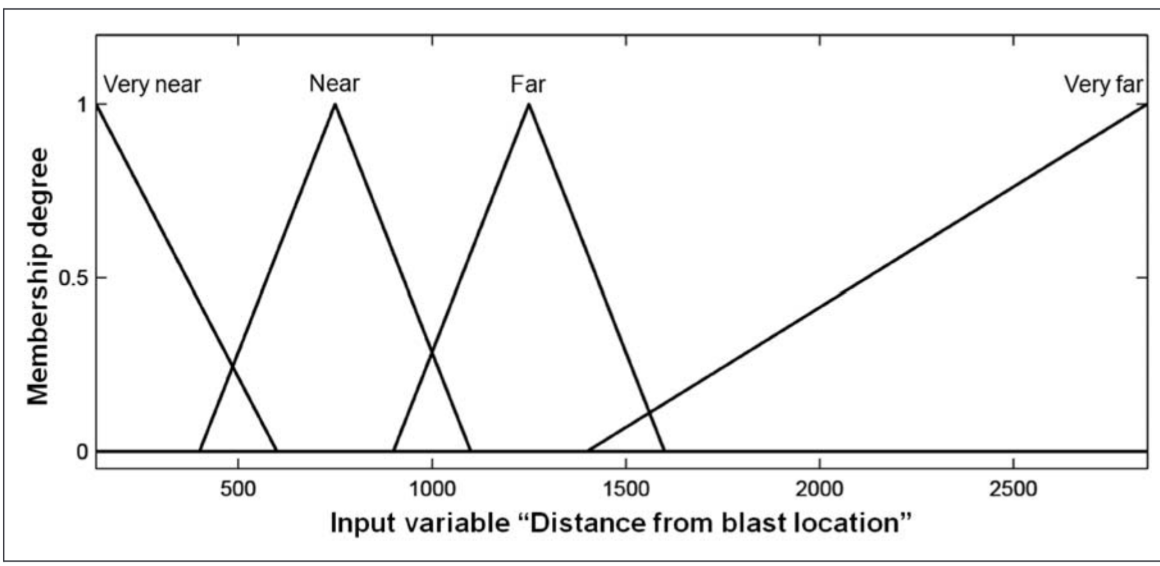

Figure 8. Fuzzy representation of distance from blast location.

and precise boundaries, unlike a crisp set (Aydin, 2004). A fuzzy logic system consists of four parts: (1) the fuzzification process; (2) knowledge base; (3) fuzzy inference system (FIS); and (4) defuzzification process. In the following, each one of these parts is described.

3.1. Fuzzification process

Fuzzy set performs numerical computation by using linguistic labels. Therefore, in the first part of the fuzzy logic system, crisp values of input and output variables should be converted to fuzzy values or linguistic information. This is called fuzzification and is done by membership functions.

3.2. Knowledge base

The knowledge base includes a data base and a rule base. The data base defines the membership functions of the fuzzy sets used in the fuzzy rules, whereas the rule base contains a number of fuzzy if–then rules. The if–then rules, also known as the fuzzy rules, provide a system for describing complex (uncertain, vague) systems by relating input and output parameters using linguistic variables. Generally, the fuzzy rules are

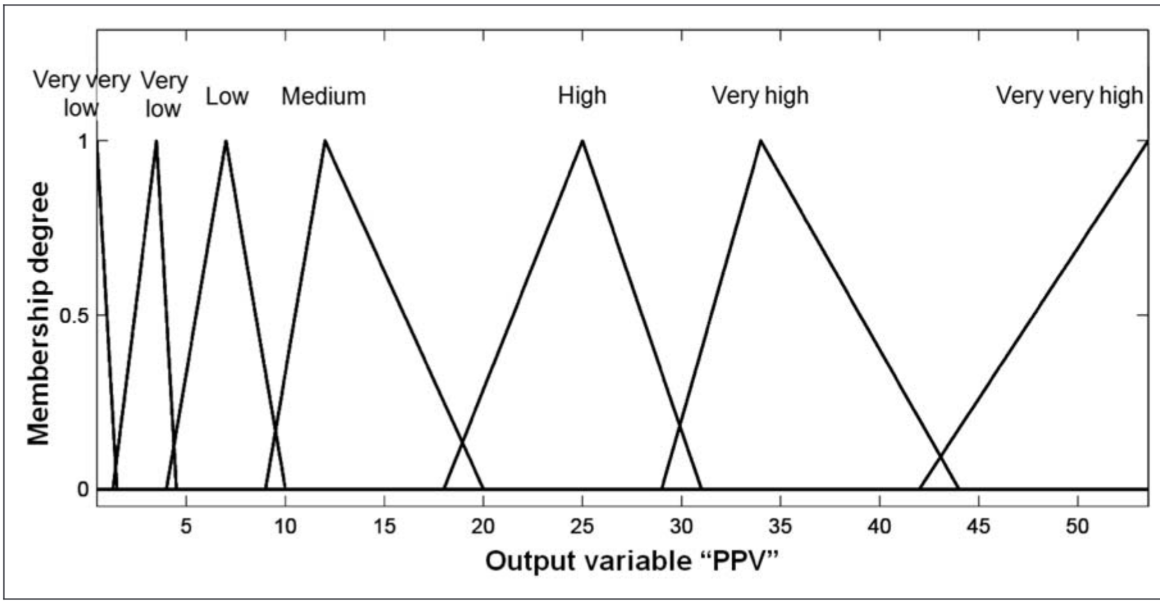

Figure 9. Fuzzy representation of peak particle velocity (PPV).

extracted from experts' judgments, engineering knowledge and experience.

3.3. Fuzzy inference system

The FIS, also known as the decision-making unit, performs the inference operations on the rules. In fact, fuzzy inference is the process of formulating an input fuzzy set map to an output fuzzy set using fuzzy logic. The core section of a fuzzy logic system is the FIS part, which combines the facts obtained from the fuzzification with the rule base and conducts the fuzzy reasoning process. There are several FISs that have been employed in various applications; the most commonly used include the Mamdani fuzzy model, the Takagi–Sugeno–Kang (TSK) fuzzy model, the Tsukamoto fuzzy model and the Singleton fuzzy model. The differences between these FISs lie in the consequents of their rules, and thus aggregation and defuzzification procedures differ accordingly.

3.4. Defuzzification process

The output generated by the FIS is always in the fuzzy (linguistic) form, but most of the time, the need for a crisp and representative value leads to usage of the defuzzifier. The application of the defuzzifier is to receive the fuzzy input and provide crisp output. In fact, it works in the opposite way to the fuzzifier.

During the past two decades, fuzzy logic has been successfully applied to many real world problems, especially in modeling complex and imprecise systems in the science and engineering fields, particularly mining, rock mechanics and engineering geology, by Fisne et al. (2010), Aydin (2004), Grima and Babuska (1999), Gokceoglu (2002), Gokceoglu and Zorlu (2004), Iphar and Goktan (2006), Tzamos and Sofianos (2006), Khademi Hamidi et al. (2010), Acaroglu (2011) and Ghasemi et al. (2011). In the next section, the proposed fuzzy model for predicting PPV is described in detail. Of course, it should be mentioned that all predictive models, including fuzzy, multiple regression and empirical predictors, are developed based on only 75% of the collected data (i.e. 90 datasets) and the rest (i.e. 30 datasets) are used for testing the model performances.

4. Development of the fuzzy model

In this section, a fuzzy model based on the Mamdani algorithm is introduced for prediction of PPV in Sarcheshmeh copper mine. The fuzzy model was implemented on the fuzzy logic toolbox of MATLAB ver. 7.6 (R2008a) software package. The model includes six input variables and one output variable. Figure 2 shows input and output variables in the MATLAB environment where burden, spacing, stemming, number of holes per delay, maximum charge per delay and distance from blast location are referred to as input and PPV is referred to as output.

In the model, triangular membership functions were adopted for describing input and output variables because of their simplicity and computational efficiency. The triangular membership function, as

Table 2. Representation of membership functions and their parameters

Variables	Linguistic variables	Linguistic values	Parameters
Inputs	Burden	Low	[3 3 4.5]
		Medium	[3.8 5.5 7.2]
		High	[6.5 7.5 7.5]
	Spacing	Low	[4 4 5.5]
		Medium	[4.7 7.5 10.3]
		High	[9.5 11 11]
	Stemming	Low	[2.4 2.4 3.5]
		Medium	[2.9 4 5.1]
		High	[4.8 6 6]
	No. holes per delay	Very low	[6 6 10]
		Low	[9 11 13]
		Medium	[12 15 17]
		High	[16 18 21]
		Very high	[20 32 32]
	Max. charge per delay	Very low	[1332 1332 3100]
		Low	[2700 4000 5050]
		Medium	[4800 5750 6700]
		High	[6300 7250 8500]
		Very high	[7800 9812 9812]
	Distance from blast location	Very near	[133 133 600]
		Near	[400 750 1100]
		Far	[900 1250 1600]
		Very far	[1400 2845 2845]
Outputs	PPV	Very very low	[0.49 0.49 1.5]
		Very low	[1.3 3.5 4.5]
		Low	[4 7 10]
		Medium	[9 12 20]
		High	[18 25 31]
		Very high	[29 34 44]
		Very very high	[42 53.55 53.55]

described in Equation (1), is used to convert the linguistic values in the range of 0–1:

$$
Triangular\,(x\,;a,b,c) = \left\{ \begin{array}{ll} 0 & if\ x \leq a \\ \dfrac{x-a}{b-a} & if\ a \leq x \leq b \\ \dfrac{c-x}{c-b} & if\ b \leq x \leq c \\ 0 & if\ c \geq x \end{array} \right\} \tag{1}
$$

where a, b, c are the parameters of the linguistic value and x is the range of the input parameters. The graphical representations of the membership functions of different input and output variables are shown in Figures 3–9. In addition, Table 2 shows the linguistic variables, their linguistic values and associated parameters.

The next stage of the FIS is the construction of the if–then rules, which are used to represent the fuzzy relationships between input and output fuzzy variables. In this paper, for constructing the rule base of the fuzzy model a total of 229 rules were utilized based on experts' experiences and data collected from the case studied mine. Figure 10 shows a fuzzy if–then rule editor including 11 rules of the model in MATLAB environment. In this figure, VVL stands for very very low, VL for very low, L for low, M for medium, H for high, VH for very high, VVH for very very high, VN for very near, N for near, F for far and VF for very far.

In the last stage, each result in the form of a fuzzy set is converted into a crisp (real output) value by the defuzzification process. In this model, the centroid of

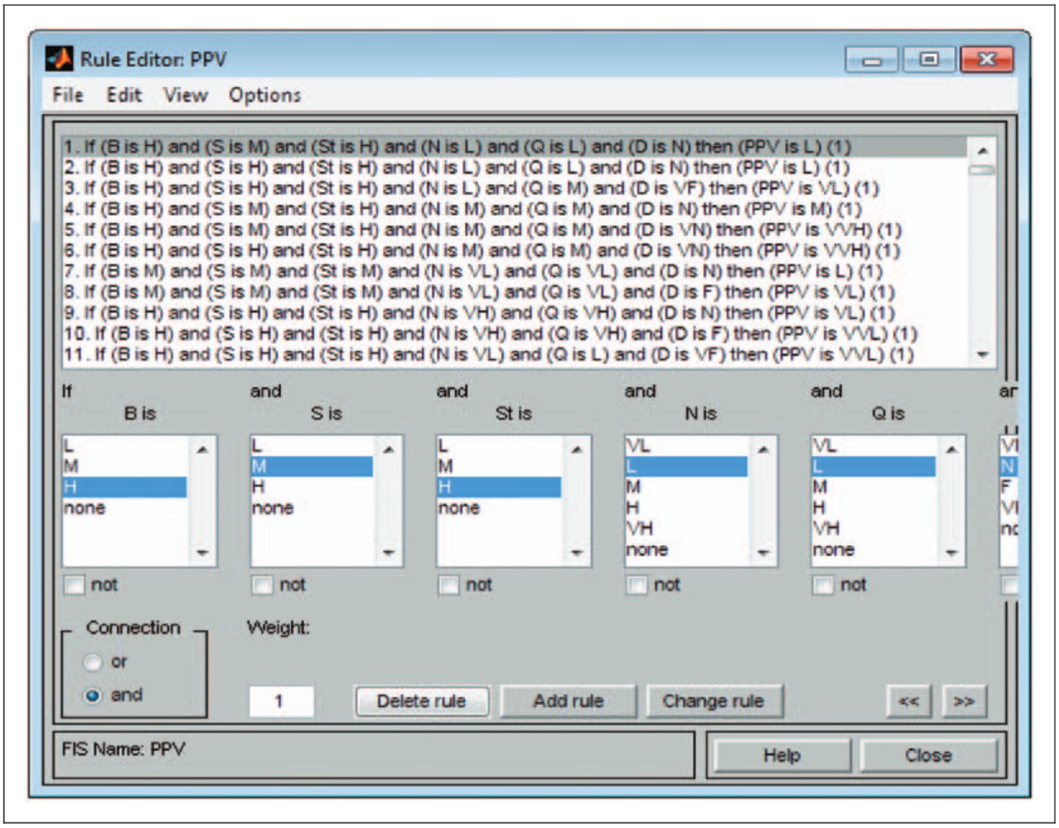

Figure 10. Fuzzy if–then rule editor for the proposed fuzzy model.

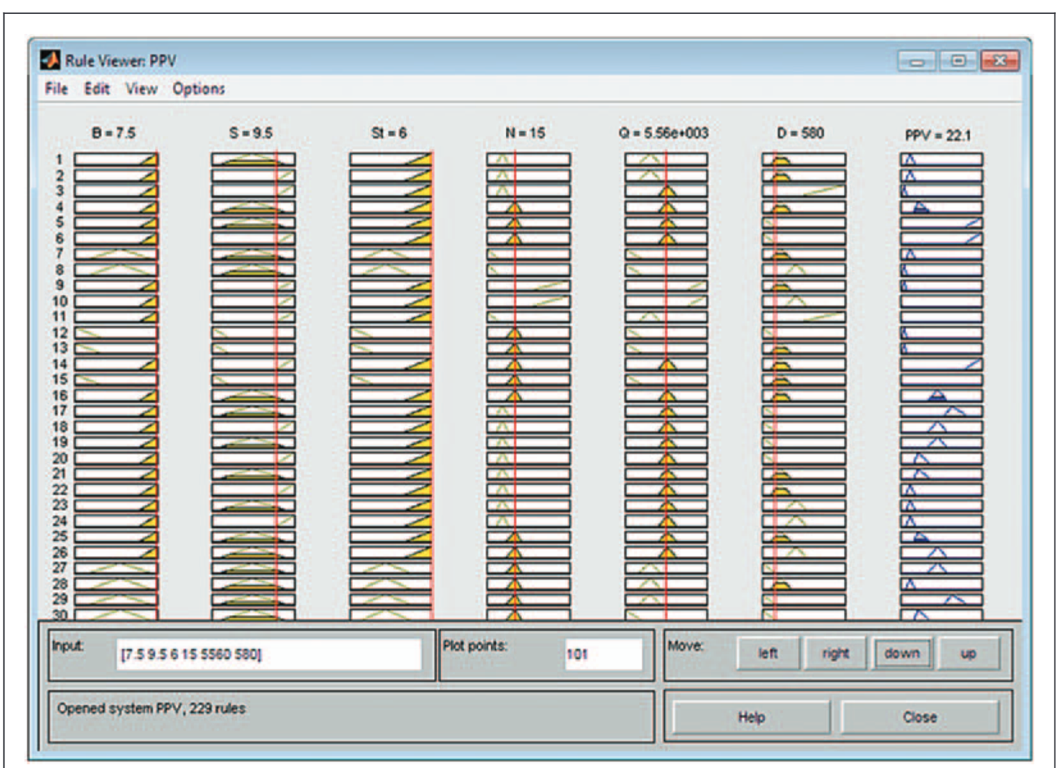

Figure 11. Fuzzy rule viewer for the proposed fuzzy model.

Table 3. Summary of the multiple regression model for prediction of PPV

Independent variables	Coefficient	Std. error	*t*-value	Sig. level
Constant	8.577	6.360	1.349	0.181
B	4.493	2.138	2.102	0.039
S	−2.394	1.078	−2.222	0.029
S_t	−0.419	1.608	−0.261	0.795
N	−0.250	0.198	−1.263	0.210
Q	0.001	0.001	1.289	0.201
D	−0.007	0.001	−5.609	0.000

Table 4. Most common empirical predictors for the prediction of peak particle velocity (PPV)

Name	Equation
USBM (Duvall and Petkof, 1959)	$PPV = K.[D/Q^{1/2}]^{-B}$
Langefors–Kihlstrom (1963)	$PPV = K.[Q^{1/2}/D^{3/4}]^{B}$
General predictor (Davies et al., 1964)	$PPV = K.\,D^{-B}.\,Q^{A}$
Ambraseys–Hendron (1968)	$PPV = K.[D/Q^{1/3}]^{-B}$
Indian Standard (1973)	$PPV = K.[Q/D^{2/3}]^{B}$
Ghosh–Daemen 1 (1983)	$PPV = K.[D/Q^{1/2}]^{-B}.\,e^{-\alpha.D}$
Ghosh–Daemen 2 (1983)	$PPV = K.[D/Q^{1/3}]^{-B}.\,e^{-\alpha.D}$
Gupta et al. (1987)	$PPV = K.[D/Q^{1/2}]^{-B}.\,e^{-\alpha.(D/Q)}$
CMRI predictor (Pal Roy, 1991)	$PPV = n + K.\,[D/Q^{1/2}]^{-1}$
Rai–Singh (2004)	$PPV = K.D^{-B}.Q^{A}.e^{-\alpha.D}$

Table 5. Obtained values of site constants

	Site constants				
Empirical predictor	K	B	A	n	α
USBM	71.810	0.922			
Langefors–Kihlstrom	19.547	1.257			
General predictor	14.240	0.946	0.668		
Ambraseys–Hendron	238.504	0.891			
Indian Standard	0.039	1.278			
Ghosh–Daemen 1	76.884	1.006			0.000
Ghosh–Daemen 2	319.697	1.023			0.000
Gupta et al.	68.082	0.849			0.724
CMRI predictor	75.994			0.904	
Rai–Singh	11.556	0.904	0.667		0.000

area (COA) method, which is a common method of defuzzification, was employed for the defuzzification process (Grima and Babuska, 1999). The crisp value adapting the COA defuzzification method was obtained by

$$z^* = \frac{\int \mu_A(z).\,z.\,dz}{\int \mu_A(z).\,dz} \tag{2}$$

where z^* is the crisp value for the z output and $\mu_A(z)$ is the aggregated output membership function.

The developed fuzzy model can provide an estimation of PPV when proper input data is entered into model. For example, as can be seen in Figure 11, when the input parameters are burden = 7.5 m, spacing = 9.5 m, stemming = 6 m, number of holes per delay = 15, charge per delay = 5560 kg and distance from blast location = 580 m, the predicted output PPV is 22.1 mm/s (whereas measured PPV is 21.05 mm/s).

5. Multiple regression model

The general purpose of multiple regression is to learn more about the relationship between several independent or predictor variables and a dependent or criterion variable. The mathematical form of the multiple regression is $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$, where the β values are regression coefficients. In this paper, multiple regression analysis was carried out on 90 blast vibration cases to determine the mathematical equation for PPV using statistical software package SPSS 16. The multiple regression model for predicting PPV is given in Equation (3) and the detailed results of the regression analysis are presented in Table 3:

$$\begin{aligned} PPV[mm/s] = {} & 8.577 + 4.493B[m] - 2.394S[m] \\ & - 0.419S_t[m] - 0.250N + 0.001Q[kg] \\ & - 0.007D[m] \end{aligned} \tag{3}$$

6. Empirical predictor models

As mentioned previously, there are several empirical equations that are used in blasting operations to estimate PPV. The most common equations are shown in Table 4. In these equations, D is the distance between the center of the explosive charge and the measuring unit in meters and Q is charge per delay in kilograms. Values of K, A, B, n and α are site constants that can be determined by regression analysis. In this paper, the site constants for Sarcheshmeh copper mine were determined from the regression analysis of the

Table 6. Comparison between measured peak particle velocity (PPV) and predicted PPV values by different predictive models

No. of blast events	Measured PPV (mm/s)	Predicted PPV (mm/s): Fuzzy model	Multiple regression	USBM	Langefors–Kihlstrom	General predictor	Ambraseys–Hendron	Indian Standard	Ghosh–Daemen 1	Ghosh–Daemen 2	Gupta et al.	CMRI predictor	Rai–Singh
1	8.44	7.00	12.96	9.18	8.95	8.91	9.36	7.58	8.15	7.77	11.32	9.07	9.39
2	13.45	19.80	13.78	8.45	8.80	8.90	8.10	10.15	7.44	6.58	10.37	8.37	9.50
3	21.05	22.10	14.77	10.83	10.96	10.99	10.66	10.54	9.76	9.01	12.87	10.67	11.55
4	53.55	48.80	15.36	15.61	16.04	16.14	15.06	15.41	14.54	13.40	17.55	15.42	16.70
5	2.27	3.01	6.56	3.33	2.69	2.56	4.11	1.21	2.70	3.02	6.70	3.62	2.77
6	0.91	0.71	7.78	6.49	7.09	7.26	5.97	10.65	5.58	4.63	8.22	6.51	7.90
7	5.47	2.37	11.17	9.79	10.80	11.07	8.88	15.57	8.74	7.31	11.58	9.66	11.82
8	0.50	0.76	0.31	2.65	2.53	2.51	2.79	2.52	2.10	1.94	4.75	3.02	2.81
9	27.80	20.60	14.69	12.79	12.82	12.82	12.66	11.46	11.70	10.99	14.84	12.60	13.35
10	16.90	19.80	14.08	8.77	8.98	9.04	8.54	9.52	7.75	6.99	10.74	8.67	9.61
11	33.90	30.80	15.60	21.61	20.76	20.55	22.11	13.91	20.73	20.84	23.54	21.56	20.75
12	1.23	0.75	4.90	2.10	1.93	1.90	2.31	1.68	1.63	1.56	4.52	2.55	2.13
13	9.18	11.70	2.80	7.31	6.66	6.52	7.98	4.36	6.36	6.47	9.72	7.28	6.89
14	2.39	2.88	7.42	3.87	3.68	3.64	4.09	3.28	3.18	3.00	6.01	4.11	3.99
15	4.33	3.02	12.36	8.46	8.89	9.00	8.05	10.62	7.45	6.53	10.35	8.38	9.62
16	11.10	9.24	12.26	7.31	7.37	7.40	7.24	7.58	6.35	5.78	9.30	7.28	7.92
17	34.10	36.10	16.08	28.58	29.87	30.15	26.91	27.47	28.13	26.11	29.90	28.88	30.37
18	16.50	17.20	14.27	13.20	13.59	13.69	12.73	13.63	12.11	11.06	15.17	13.01	14.29
19	8.81	6.97	19.91	8.76	8.16	8.03	9.34	5.69	7.75	7.75	11.09	8.67	8.44
20	7.57	6.97	13.23	8.22	8.67	8.79	7.80	10.57	7.23	6.30	10.10	8.15	9.41
21	12.55	14.70	13.58	9.01	9.52	9.65	8.53	11.50	7.99	6.98	10.90	8.90	10.29
22	6.37	6.95	10.88	6.91	6.82	6.81	7.00	6.42	5.98	5.56	8.97	6.91	7.29
23	14.9	18.30	10.64	10.15	10.02	9.99	10.21	8.79	9.09	8.59	12.25	10.00	10.51
24	4.05	2.99	8.74	4.96	5.31	5.40	4.66	7.67	4.16	3.49	6.67	5.09	5.94
25	3.22	3.03	7.23	4.09	3.99	3.97	4.21	3.96	3.37	3.10	6.11	4.30	4.36
26	1.82	3.00	8.31	4.40	3.89	3.79	4.97	2.47	3.65	3.75	6.94	4.58	4.09
27	18.45	19.70	10.25	9.18	8.95	8.91	9.36	7.58	8.15	7.77	11.32	9.07	9.39
28	9.15	11.60	5.43	4.86	4.77	4.75	4.97	4.69	4.07	3.76	6.88	5.00	5.17
29	10.93	9.24	12.27	7.32	7.38	7.40	7.25	7.59	6.36	5.79	9.31	7.29	7.93
30	14.55	19.80	13.47	8.38	8.43	8.45	8.32	8.32	7.38	6.78	10.41	8.30	8.98

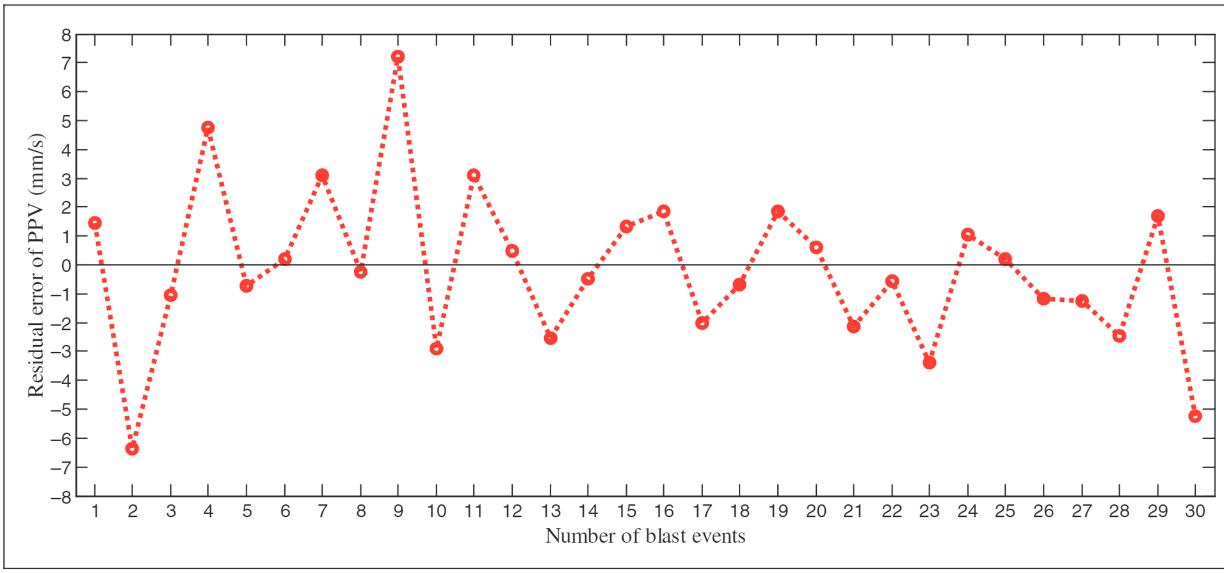

Figure 12. The difference between the values predicted by the fuzzy model and the measured values.

Table 7. Performance indices for models

Model	R^2 (%)	VAF (%)	RMSE	MAPE
Fuzzy	94.59	94.59	2.73	23.25
Multiple regression	34.55	29.57	9.94	107.07
USBM	64.36	52.61	8.84	74.42
Langefors–Kihlstrom	62.64	52.65	8.82	74.52
General predictor	62.12	52.56	8.81	74.81
Ambraseys–Hendron	65.25	51.58	8.96	75.94
Indian Standard	45.40	40.20	9.81	93.91
Ghosh–Daemen 1	63.30	51.87	9.30	63.37
Ghosh–Daemen 2	63.53	50.45	9.69	60.61
Gupta et al.	65.00	51.98	8.27	117.02
CMRI predictor	63.38	51.74	8.91	79.63
Rai–Singh	62.14	52.57	8.63	81.75

previously mentioned 90 cases using SPSS 16 software. The obtained values of site constants for the various predictor equations are given in Table 5.

7. Comparison of model performance

In this section the results obtained from different predictive models are compared and performances of the models are evaluated. It should be mentioned that the collected data from 30 blast events that were not incorporated in the models were used for testing and validating the models. Table 6 shows this comparison between the predicted PPV using the fuzzy model, multiple regression model and empirical predictor models with the measured PPV values. As shown in Table 6, the predicted PPVs by the fuzzy model are closer to the measured ones, whereas the results of multiple regression and empirical predictors vary widely. This indicates that the prediction of ground vibration using the fuzzy model is more accurate than that using other models. Fuzzy model errors vary between −6.35 and +7.20 mm/s, as can be seen in Figure 12.

The correlation coefficient (R^2) between the measured and predicted values is a good indicator to check the prediction performance of each model. Furthermore, in this paper, variance account for (VAF) (Equation (4)), root mean square error (RMSE) (Equation (5)) and mean absolute percentage error (MAPE) (Equation (6)) indices were calculated to control the prediction performance of models, as employed by Grima and Babuska (1999), Gokceoglu (2002) and Yilmaz and Kaynar (2011). If R^2 and VAF are 100 and RMSE and MAPE are 0, then the model will be excellent:

$$VAF = \left[1 - \frac{\mathrm{var}(A_i - P_i)}{\mathrm{var}(A_i)}\right] \times 100 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - P_i)^2} \tag{5}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{A_i - P_i}{A_i}\right| \times 100 \tag{6}$$

where A_i and P_i are the measured (actual) and predicted values, respectively, and N is the number of testing

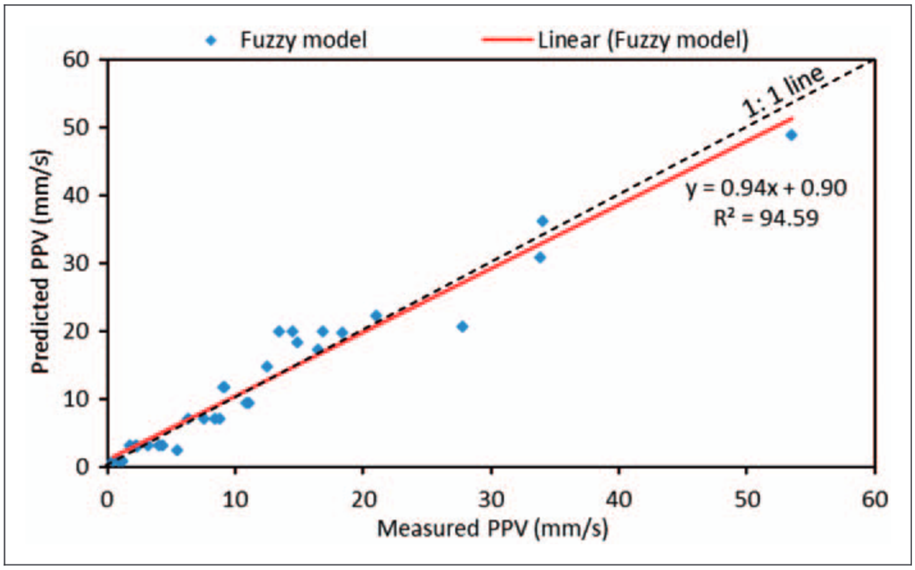

Figure 13. Measured versus predicted peak particle velocity (PPV) (fuzzy model).

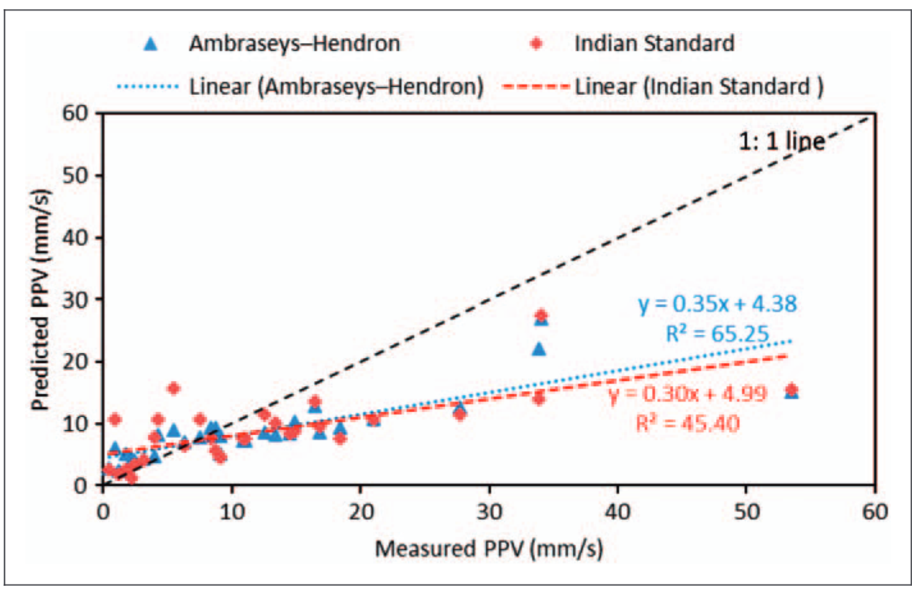

Figure 14. Measured versus predicted peak particle velocity (PPV) (Ambraseys–Hendron and Indian Standard predictors).

samples. The calculated indices are given in Table 7. The comparison of VAF, RMSE and MAPE indices and the correlation coefficient (R^2) for predicting PPV between these models indicated that the prediction performance of the fuzzy model is higher than that of the multiple regression and empirical models. Figure 13 shows the relationship between measured and predicted PPV values, with a good correlation coefficient for the fuzzy model. The multiple regression model with a correlation coefficient of 34.55% showed lower prediction performance in comparison with other models. As can be seen in Table 7, the prediction performance of empirical predictor models is approximately identical, except for the Indian Standard predictor. The correlation coefficient of these predictors varies between 45.40% for the Indian Standard and 65.25% for the Ambraseys–Hendron model (Figure 14).

8. Results and discussion

Ground vibration is an undesirable and important side product of rock blasting in the mining industry and its prediction is significantly important for controlling and eliminating associated environmental problems. In this paper, fuzzy logic, multiple regression and empirical predictors were used for the prediction of PPV (as a vibration indicator) and their results were compared. The models of fuzzy logic and multiple regression were constructed using six inputs and one output. The fuzzy model was developed based on the Mamdani algorithm and triangular fuzzy membership functions were adopted for describing input and output variables. In addition, it was constructed based on 229 if–then fuzzy rules and the COA method for defuzzification.

The results of the present paper can be explained as follows.

1. The results of the models for PPV prediction showed that the equation obtained from the multiple regression model has lower prediction performance in comparison with other models. The reason for this is that the developed regression model in this paper is based on the linear relationship between input and output variables, whereas the nature of the relationship is complex.
2. The empirical predictor models for PPV prediction revealed a high predictive capacity in comparison with the multiple regression model, but lower capacity than that of the fuzzy model. There are two main reasons for this; the first is that the empirical predictors are site specific and are not suitable for other sites and the second is that these predictors are based on only two parameters, maximum charge per delay and distance from blast location, and do not include other effective parameters.
3. In order to predict the PPV, the fuzzy model was applied successfully; it exhibited more reliable predictions than the regression and empirical models.
4. The practical outcome of the proposed fuzzy model, with acceptable accuracy, can be considered as a preliminary estimation of PPV and based on it many environmental impacts due to ground vibration can be controlled and reduced. It should be noted that the most important measure for controlling ground vibration is proper design of controllable blasting parameters. Therefore, the main recommendations for ground vibration control are: (1) reducing the maximum charge per delay using proper delay interval, reduced blast hole diameter and/or deck loading; (2) changing the blast geometry (including burden, spacing, stemming length and blast hole inclination) and/or type of explosive; (3) using a minimum of practical subdrilling length; (4) minimizing the degree of confinement by increasing the free face.
5. Based on these results, fuzzy logic is a useful and powerful means to enhance the efficiency of blasting operation in surface mining. The major advantage of the fuzzy model is that human judgment and intuition can be effectively used for prediction of PPV, which helps in field applications.
6. It should be noted that the proposed fuzzy model can be used only for predicting PPV in Sarcheshmeh copper mine and it should not be used directly for PPV prediction in other surface mines. However, the methodology employed in the present paper can also be used in other surface mines that employ blasting operation in order to predict PPV.
7. Finally, it is clear that the proposed fuzzy model can be improved based on more data, which can be obtained from blasting operations over time.

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