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ORIGINAL ARTICLE

Application of fuzzy logic for predicting roof fall rate in coal mines

Ebrahim Ghasemi · Mohammad Ataei

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Abstract Roof fall is one of the serious hazards associated with underground coal mining. Roof fall can cause fatal and non-fatal injuries on miners, stoppages in mining operations and equipment breakdowns. Therefore, accurate prediction of roof fall rate is very important in controlling and eliminating of related problems. In this study, the fuzzy logic was applied to predict roof fall rate in coal mines. The predictive fuzzy model was implemented on fuzzy logic toolbox of MATLAB® using Mamdani algorithm and was developed based on experts' knowledge and also a database including 109 datasets of roof performance from US coal mines. 22 datasets of this database were used to assess the performance of this fuzzy model. The comparison between obtained results from model and actual roof fall rate showed that the fuzzy model can predict roof fall rate very well.

Keywords Coal mining · Roof fall · Safety · Fuzzy logic · Mamdani algorithm

1 Introduction

There are several reasons that make underground coal mining one of the most hazardous activities, and the most important one is roof fall. Roof fall is the greatest safety hazard that underground coal miners deal with. Roof fall can cause detrimental effects on workers in the form of injury, disability or fatality and also on mining companies because of downtimes, interruptions in the mining operations, equipment breakdowns, etc. The hazardous nature of roof fall can be illustrated by the statistics of mine accidents. For example, US mine accident statistics indicated that during 10 years, 1996–2005, 7,738 miners were injured from roof falls in underground coal, metal, non-metal and stone mines [1]. Coal mines showed the highest injury rate, 1.75 injuries per 200,000 h underground work. Fatal injury trends from 1996 to 2005 were equally troubling, with 100 roof fall fatalities, while coal mines had the highest number of 82 (0.021 fatalities per 100,000 miners). In 1998, a total of 2,232 unplanned roof falls occurred in 884 US underground coal mines. These falls resulted in 419 injuries and 13 fatalities [2].

Unplanned roof failures in coal mines can be created by a number of different factors. These include geologic defects in the roof rock, moisture degradation of shales, extreme loading conditions under high cover, multiple seam mining and inadequate support to name just a few. Using statistical analysis of roof fall database from 37 coal mines in US, Molinda et al. [2] found relationships among the roof fall rate and coal mine roof rating (CMRR), primary roof support (PRSUP), intersection span and depth of cover. van der Merve et al. [3] investigated roof falls in South Africa coal mines carefully, and in their point of view, poor design of support systems, poor performance of support elements, poor mining conditions, unknown nature of the stress regime and weak roof rock were dominant causes. Molinda [4] found that the main reason of roof fall in coal mines is weak and defective roof and then explained the role of geological deficiencies on the occurrence of roof falls. Deb [5] used an extensive database of roof performance from US coal mines and fuzzy reasoning techniques to determine the relationships between coal mine roof rating (CMRR), primary roof support (PRSUP) and

E. Ghasemi (✉) · M. Ataei
Department of Mining, Petroleum and Geophysics Engineering, Shahrood University of Technology, Daneshgah Blvd., P. O. Box 3619995161, Shahrood, Iran
e-mail: ebrahim62.gh@gmail.com; e.ghasemi@shahroodut.ac.ir

intersection diagonal span with roof fall rate. Furthermore, recently extensive researches have been conducted to control and assess roof fall risk in coal mines. For example, Duzgun and Einstein [6] proposed a risk and decision analysis methodology for the assessment and management of roof fall risk in underground coal mines. In this study, they computed the probability of roof fall risk using statistical analysis of available roof fall data from mines in the Appalachian region, in the US, and also they computed the consequence of roof fall risk using relative cost criterion. Duzgun [7] proposed a risk assessment and management methodology for roof fall hazard in underground mines of the Zonguldak coal region, in Turkey. She computed the probability of roof fall by fitting a distribution function to the annual roof fall, while the consequence of roof fall was quantified based on a cost model. Palei and Das [8] collected geotechnical data from 14 roof fall incidents in an underground coal mine and conducted sensitivity analysis to examine the effects of the contributing parameters on support safety factor and the probability of roof fall. Shahriar and Bakhtavar [9] collected roof fall data from five coal regions, in Iran, and assessed and managed roof fall risk in these regions using a method that previously was applied in landslide risk assessment. Using roof fall data from five bord and pillar mines in India, Palei and Das [10] predicted the severity of roof fall accidents based on some major contributing parameters by the binary logistic regression model.

Roof fall is a complex issue in mining industry and its prediction is very difficult because of the complexity of geological conditions and variability in mining parameters. Correct prediction of roof fall rate can result in development of preventive and controlling measures for roof fall reduction. In this paper, using US roof fall database compiled by Molinda et al. [2], a fuzzy model for the prediction of roof fall rate in coal mines is presented.

2 Fuzzy logic

The details of fuzzy logic can be found in numerous literatures [11–13], but it is explained briefly in the following. Most of the world's knowledge is uncertain and imprecise, and thus, the description of all actual systems inherently contains incomplete and imprecise information. In order to deal with such situations, a fuzzy approach based on fuzzy logic seems to be the most appropriate. Fuzzy logic or fuzzy set theory was first presented by Zadeh [11] that provides a mechanism for representing linguistic constructs such as "many," "low," "medium," "often" and "few." In general, the fuzzy logic provides an inference structure that enables appropriate human reasoning capabilities. A fuzzy set is an extension of a crisp set but does not have any sharp and precise boundaries, unlike crisp set. A crisp set only allows full membership or no membership to every element of a universe of discourse, whereas a fuzzy set allows the degree of membership for each element to range over the unit interval between 0 and 1.

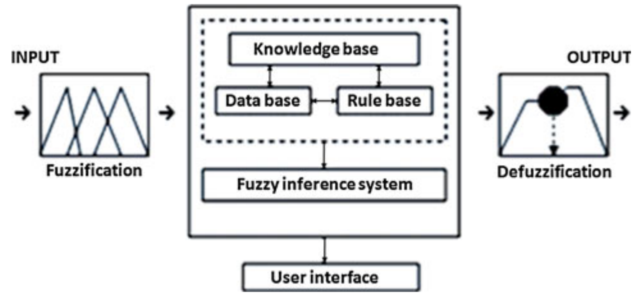


Fig. 1 A typical architecture of a fuzzy model [15]

Block diagram of a typical fuzzy logic system is presented in Fig. 1. As outlined in this figure, a fuzzy logic system consists of four parts [14]: (1) fuzzification process, (2) knowledge base, (3) fuzzy inference system and (4) defuzzification process. In the following, each one of these parts is described briefly.

2.1 Fuzzification process

Fuzzy set performs numerical computation by using linguistic labels. So, in first part of 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. The shape of the membership functions can be either linear (trapezoidal or triangular) or various forms of nonlinear (Gaussian, bell-shaped, S-shaped, etc.). The type of the membership function depends on the modeled problem, experts' knowledge and contexts [16].

2.2 Knowledge base

As presented in Fig. 1, knowledge base includes database and rule base. The database 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 extracted from experts' judgments, engineering knowledge and experience.

The if–then rule is generally made up of a premise (antecedent) and a consequent (conclusion) part. A fuzzy if–then rule assumes the form "if x is A then y is B" in which "x is A" is premise part and "y is B" is consequent part. Also, A and B are linguistic values defined by fuzzy sets or more specifically by membership functions. Most rule-based systems involve more than one rule. The process of obtaining the overall consequent from the individual consequents contributed by each rule in the rule base is known as the aggregation of rules. In determining an aggregation strategy, two simple extreme cases exit, namely conjunctive and disjunctive system of rules by using "and" and "or" connectives, respectively.

2.3 Fuzzy inference system

The fuzzy inference system (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, and the most commonly used include the following: 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.

Among different FISs, the Mamdani fuzzy model is one of the most commonly used in fuzzy logic for solving many real-world problem. The Mamdani FIS was proposed by Mamdani to control a steam engine and boiler combination by set of linguistic control rules obtained from experienced human operators [17]. The general "if–then" rule structure of the Mamdani algorithm is given in the following equation:

$$\text{If } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2} \text{ and} \ldots x_r \text{ is } A_{ir} \text{ then } y \text{ is } B_i \quad (\text{for } i = 1, 2, \ldots, k) \tag{1}$$

where k is the number of rules, x_i is the input variable, A_{ir} and B_i are linguistic terms, and y is the output variable.

Figure 2 is an illustration of a two-rule Mamdani FIS that derives the overall output z when subjected to two crisp inputs x and y [18]. As can be seen in the figure, the fuzzy output is the aggregation (max) of the two truncated fuzzy sets in Mamdani FIS model. The outputs are obtained after defuzzification by using the centroid of area (COA) method.

2.4 Defuzzification process

The output generated by the FIS is always in the fuzzy (linguistic) form, but most of the time, the need to a crisp and representative value leads to usage of the defuzzifier.

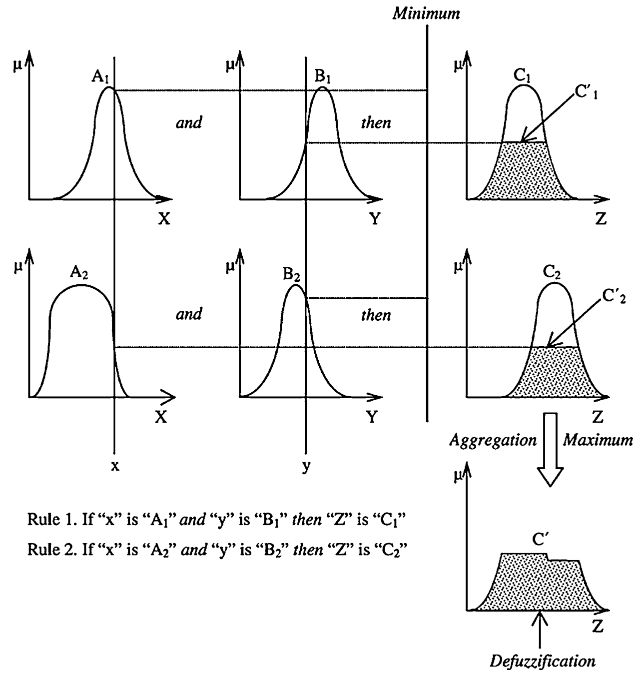


Fig. 2 Mamdani fuzzy inference system (FIS) scheme [18]

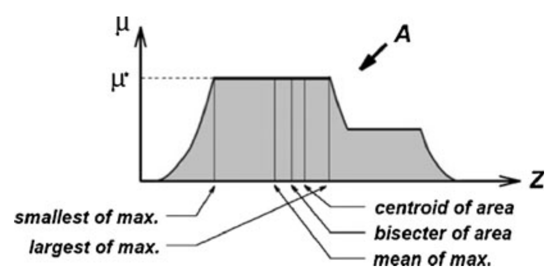


Fig. 3 Various defuzzification schemes for obtaining a crisp output

The application of the defuzzifier is to receive the fuzzy input and provide crisp output. In fact, it works opposite to the fuzzifier. There are a number of defuzzification methods in the literature such as centriod of area (COA) or center of gravity, mean of maximum (MOM), smallest of maximum (SOM), largest of maximum (LOM) and bisector of area (BOA). Figure 3 shows various defuzzification schemes for obtaining a crisp output.

3 Application of fuzzy logic

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 field especially mining, rock mechanics and engineering geology. For example, Nguyen and Ashworth [19], Habibagahi and Katebi [20], Sonmez et al. [21]

and Aydin [22] used fuzzy approaches for rock mass classification. Jiang et al. [23] and Deb [5] evaluated the performance of roof in coal mines using fuzzy set theory. Bascetin et al. [24] used fuzzy technique for the selection of surface mine equipments. Karadogan et al. [25] applied fuzzy set theory for the selection of underground mining method. Grima et al. [16], Acaroglu et al. [26], Khademi Hamidi et al. [27] and Acaroglu [28] employed fuzzy set theory for the prediction of TBM performance and trench excavation machines. Dodagoudar and Venkatachalam [29] employed fuzzy set theory for the assessment of rock slope stability. Tzamos and Sofianos [30] applied the fuzzy logic concept for the prediction of support system in tunnels. Fisne et al. [31], Monjezi et al. [32] and Rezai et al. [33] developed fuzzy models for the analysis and prediction of the effects of blasting operation such as ground vibration, flyrock and backbreak. Li et al. [34] and Li et al. [35] applied fuzzy models for the analysis of rock displacement and ground subsidence due to underground mining. Azimi et al. [15] applied fuzzy sets to predict the blastability of rock masses. Iphar and Goktan [36] developed a fuzzy model to predict rock mass diggability for surface mine equipment selection. Ataei et al. [37] used fuzzy logic for the determination of coal mine mechanization. Fuzzy set theory has been used for the prediction of rock properties such as uniaxial compressive strength, modulus of elasticity and brittleness by Gokceoglu [38], Kayabasi et al. [39], Gokceoglu and Zorlu [40], Sonmez et al. [41] and Yagiz and Gokceoglu [42].

4 Determining the parameters for the prediction of roof fall rate

Several geotechnical parameters are known to influence roof stability. Based on study conducted by Molinda et al. [2], major contributing parameters on roof fall are CMRR, PRSUP, intersection span and depth of cover. In the following, each of these parameters and their influence on roof fall are described.

CMRR Quality of roof rock has an important role in the occurrence of roof fall. Roof fall reports in coal mines showed that the weak roof was the main reason of fatal incidents. CMRR is an indicator for representing the quality of roof rock in coal mines that was developed by Molinda and Mark [43] and has a single rating between 0 and 100. When the CMRR value is approaching 0 the roof is weaker, while approaching 100 shows that the roof is stronger. One of the most important advantages of CMRR classification is that it considers natural causes of roof fall such as strength of roof rock, bedding and other discontinuities and groundwater.

PRSUP In underground coal mining, roof bolts are usually the only primary support systems overhead protection of miners. Therefore, its failure is a major factor in roof fall accidents and fatalities. Increasing the roof bolt density in many cases can be the simplest way for reducing roof fall risk. PRSUP is a roof bolt density indicator that is calculated by the following (2):

$$\mathrm{PRSUP} = \frac{L_\mathrm{b} \times N_\mathrm{b} \times C}{14.5 \times S_\mathrm{b} \times W_\mathrm{e}} \tag{2}$$

where L_b is length of the bolt in m, N_b the number of bolts per row, C the bolt capacity in KN, S_b the spacing between rows of bolts in m, and W_e entry width in m.

Intersection span Researches have shown that intersections are 8–10 times more likely to collapse than the equivalent length of entry or crosscut. Because unlike of entries and crosscuts, rock load applied on roof in intersections is proportional to the cube of the span [44]. One of the most important methods of decreasing roof instability at intersections is creating intersections with minimum possible span. According to Fig. 4, the intersection span is calculated as the sum of the two intersection diagonals.

Depth of cover Deep cover is one of the main reasons of roof fall accidents in underground coal mines, because increasing depth leads to increase in virgin stress levels in the rock mass, both vertically and horizontally. Therefore, achieving to sufficient stability is harder at high depth, and special precautions are required to ensure ground stability.

The purpose of presented paper is to construct a fuzzy logic model for predicting roof fall rate in underground coal mines. To do this, the database compiled from US coal mines was used. This database includes 109 datasets from 37 coal mines in 10 US states. The database was divided into two groups randomly: one group for training and developing fuzzy model including 80 percent of the datasets (i.e. 87 datasets) and the other group including rest of datasets (i.e. 22 datasets) for testing the model performance. Results of the basic descriptive statistical analysis performed on original database are given in Table 1.

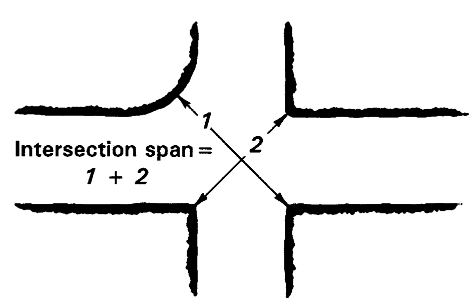


Fig. 4 Method of measuring intersection span [2]

Table 1 Basic descriptive statistics for the original database

Parameter (unit)	Symbol	Min	Max	Mean	SD
Coal mine roof rating	CMRR	28	78	47.72	11.1
Primary roof support	PRSUP	2.46	14.67	5.71	2.29
Intersection span (m)	IS	15.2	23.9	19.34	1.71
Depth of cover (m)	D	45.7	335.3	136.8	68.1
Roof fall rate	RFR	0	31.82	2.99	5.8

5 Fuzzy model to predict roof fall rate

In this section, a fuzzy model based on Mamdani algorithm is introduced for the prediction of roof fall rate in coal mines. Fuzzy model was implemented on fuzzy logic toolbox of MATLAB® ver. 7.6 software package [45]. In this model, max–min composition was selected as composition method of fuzzy relations because of being the most commonly used technique [13]. In this method, the rule-based system is described by the following equation:

$$\mu_{C_k}(z) = \max_k[\min[\mu_{A_k}(\text{input}(x)), \mu_{B_k}(\text{input}(y))]] \quad k = 1, 2, \ldots, r \tag{3}$$

where μ_{C_k}, μ_{A_k} and μ_{B_k} are the membership functions of output "z" for rule "k," input "x" and input "y," respectively.

As can be seen in the Fig. 5, the proposed fuzzy model includes four input variables (CMRR, PRSUP, intersection span and depth of cover) and one output variable (roof fall rate).

In the model, triangular and trapezoidal membership functions were adopted for describing input and output variables because of their simplicity and computational efficiency. The triangular and trapezoidal membership functions are shown in Fig. 6. In this figure, a, b, c and d 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

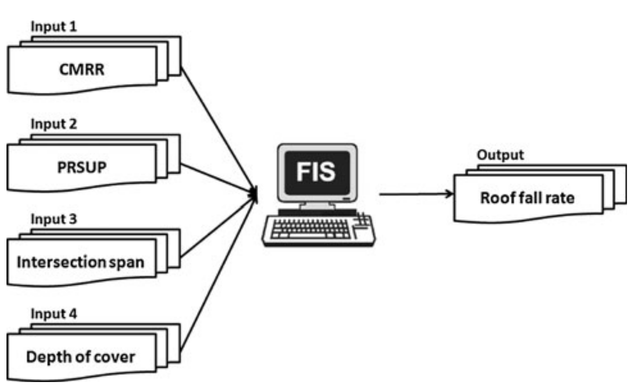
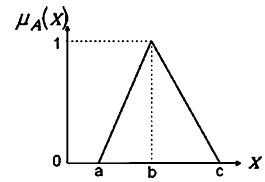
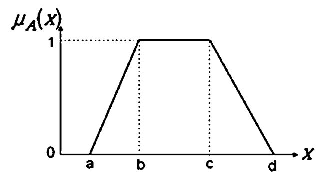


Fig. 5 Schematic illustration of the roof fall rate fuzzy model



$$\mu_A(x) = \begin{cases} 0 & \text{if } x \le a \\ \dfrac{x-a}{b-a} & \text{if } a < x \le b \\ \dfrac{c-x}{c-b} & \text{if } b < x \le c \\ 0 & \text{if } x > c \end{cases}$$



$$\mu_A(x) = \begin{cases} 0 & \text{if } x \le a \\ \dfrac{x-a}{b-a} & \text{if } a < x \le b \\ 1 & \text{if } b < x \le c \\ \dfrac{d-x}{d-c} & \text{if } c < x \le d \\ 0 & \text{if } x > d \end{cases}$$

Fig. 6 Triangular (*top*) and trapezoidal (*bottom*) membership functions

Fig. 7. In this figure, VL stands for very low, L for low, M for medium, H for high and VH for very high. 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 fuzzy model, a total of 180 rules were utilized based on experts' experiences and data compiled from the US coal mines. Figure 8 shows a fuzzy if–then rule editor including 11 rules of the model in MATLAB® environment.

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 COA method, which is a common method of defuzzification, was employed for defuzzification process [16]. The crisp value adapting the COA defuzzification method was obtained by:

$$z^* = \frac{\int \mu_A(z) \cdot z \cdot \mathrm{d}z}{\int \mu_A(z) \cdot \mathrm{d}z} \tag{4}$$

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

The fuzzy model developed here can provide an estimate of roof fall rate when proper input data were entered into model. For example, as can be seen in Fig. 9, when input parameters are CMRR = 28, PRSUP = 5.89, IS = 21 m and D = 152.4 m, the output predicted for roof fall rate is 1.99 (whereas according to Table 4 actual roof fall rate is 1.81).

6 Results and discussions

As mentioned before, 22 datasets, which were not incorporated in the model, were used for testing and validation

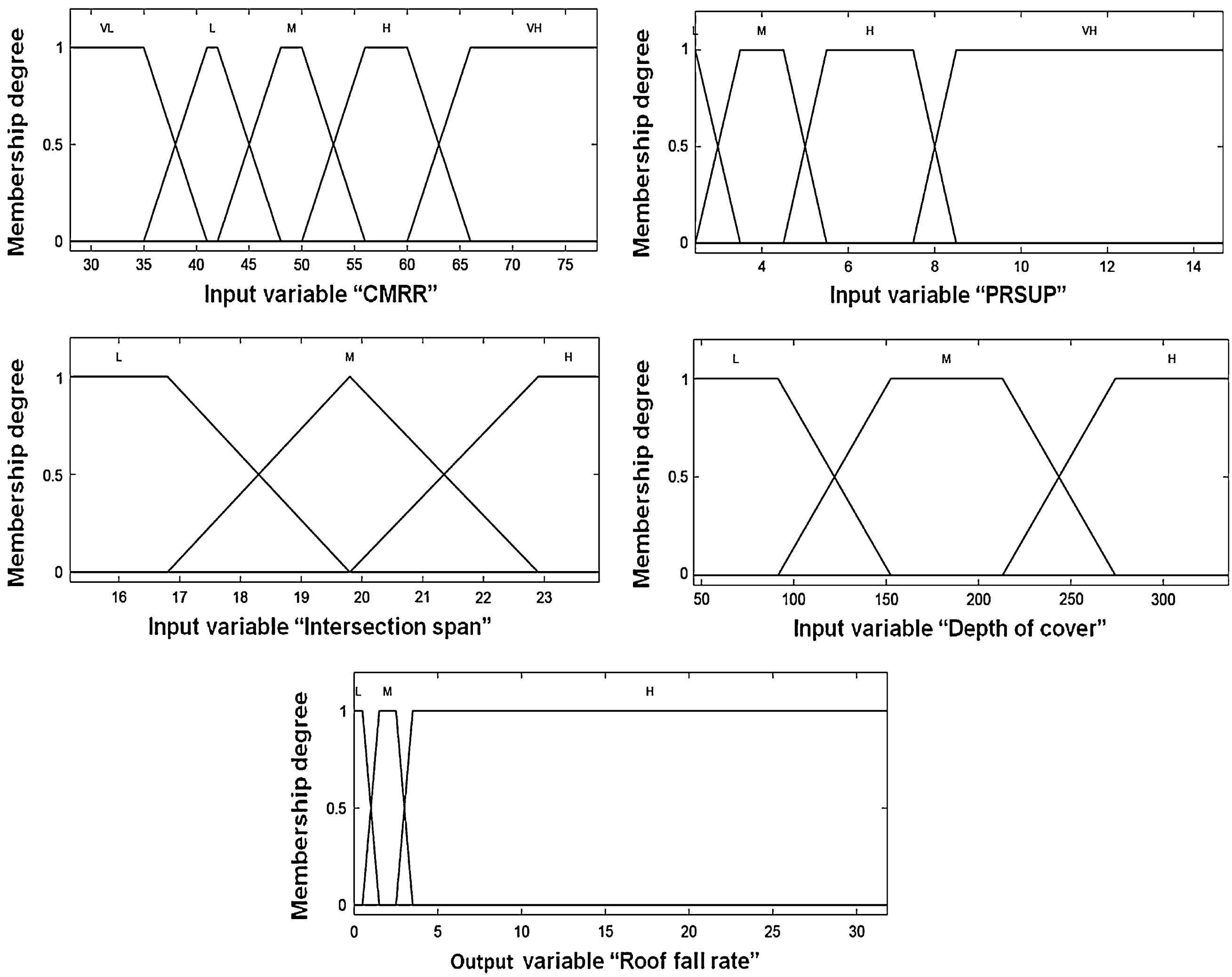


Fig. 7 Fuzzy representation of input and output variables

of the model. Regarding that the purpose of this paper is to predict the roof fall rate qualitatively, the output of the proposed model for each dataset is converted into qualitative information (low, medium and high) based on Table 3, then obtained result is compared with actual roof fall rate to test the model. As can be seen in Table 4, the proposed model can predict roof fall rate correctly in 19 cases (approximately 85% cases), and only in 3 cases (approximately 15% cases), the model cannot predict the desired roof fall rate.

The response plots for roof fall rate with different input variables for fuzzy model have been presented in Fig. 10. In Fig. 10a–f, the effects of two input parameters variability on roof fall rate have been shown, whereas two other parameters are constant, and their values can be seen on top of each figure. It can be concluded from Fig. 10 that the proposed rule-based fuzzy model is capable of predicting roof fall rate in the experimental domain quite efficiently as the rule covers a larger decision surface.

The results showed that the fuzzy logic is a useful and powerful means for predicting roof fall rate in coal mines. Other coal mines all over the world can use this model, and output of this model can be considered as a preliminary estimation of roof fall rate based on which mining managers and engineers can develop preventive measures for controlling roof, so hazards due to roof fall can be minimized. For example, if fuzzy model predicts that the roof fall rate in a coal mine is less than 1, based on Table 3, the probability of roof fall occurrence is low and no controlling measures are needed. If the fuzzy model predicts the roof fall rate between 1 and 3, the probability of roof fall occurrence in that mine is medium, and by developing a few controlling measures, the roof fall risk can be minimized to the least possible amount. Finally, when the fuzzy model predicts the roof fall rate more than 3, the

Table 2 Representation of membership functions and their parameters

Variables	Linguistic variables	Linguistic values	Type of MF[a]	Parameters
Inputs	CMRR	Very low	Trapezoidal	[28 28 35 41]
		Low	Trapezoidal	[35 41 42 48]
		Medium	Trapezoidal	[42 48 50 56]
		High	Trapezoidal	[50 56 60 66]
		Very high	Trapezoidal	[60 66 78 78]
	PRSUP	Low	Triangular	[2.46 2.46 3.5]
		Medium	Trapezoidal	[2.46 3.5 4.5 5.5]
		High	Trapezoidal	[4.5 5.5 7.5 8.5]
		Very high	Trapezoidal	[7.5 8.5 14.67 14.67]
	Intersection span	Low	Trapezoidal	[15.2 15.2 16.8 19.8]
		Medium	Triangular	[16.8 19.8 22.9]
		High	Trapezoidal	[19.8 22.9 23.9 23.9]
	Depth of cover	Low	Trapezoidal	[45.7 45.7 91.5 152.5]
		Medium	Trapezoidal	[91.5 152.5 213 274]
		High	Trapezoidal	[213 274 335.3 335.3]
Output	Roof fall rate	Low	Trapezoidal	[0 0 0.5 1.5]
		Medium	Trapezoidal	[0.5 1.5 2.5 3.5]
		High	Trapezoidal	[2.5 3.5 31.82 31.82]

[a] MF stands for membership function

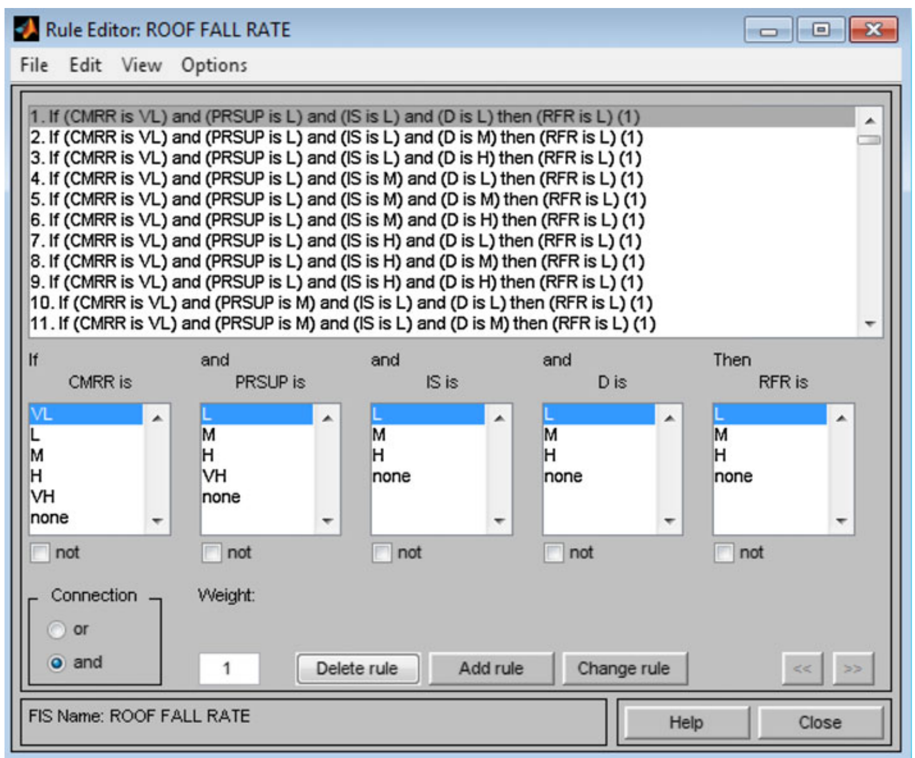


Fig. 8 Fuzzy if–then rule editor for proposed fuzzy model

probability of roof fall occurrence is very high, and only by developing extensive monitoring and controlling measures can decrease the roof fall risk to an acceptable level.

Among input parameters, CMRR and depth of cover are uncontrollable (depending on ground conditions so unchangeable) and two other parameters, PRSUP and intersection span, are controllable (depending on design of mine and mining conditions so changeable). Thus, the most practical controlling measures for decreasing roof fall risk are as follows:

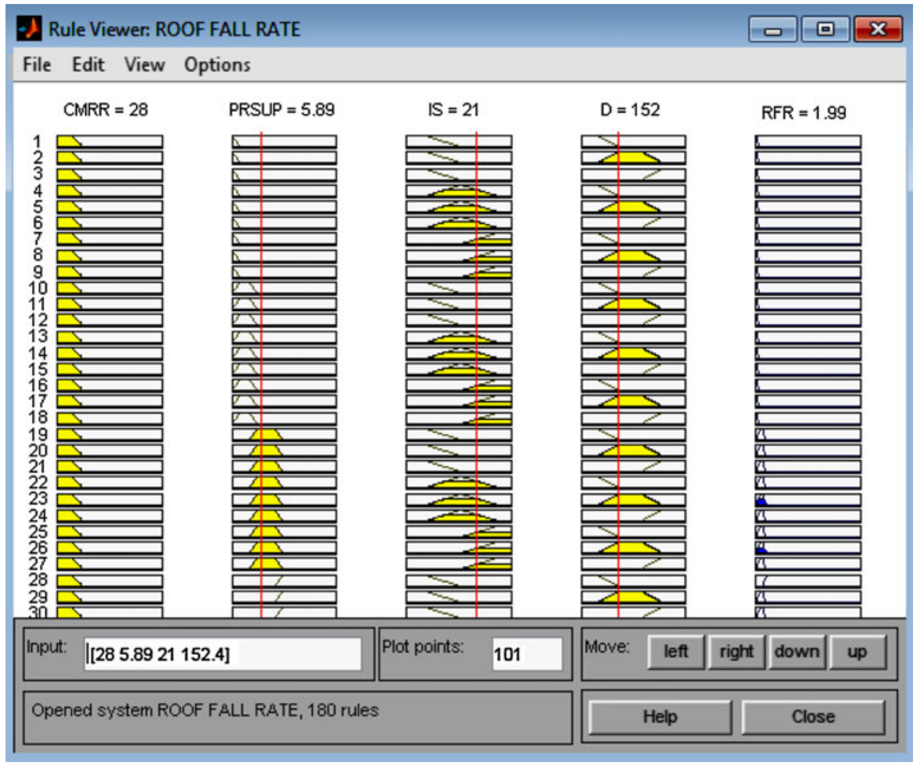


Fig. 9 Fuzzy rule viewer for proposed model

Table 3 Classification of roof fall rate

Roof fall rate	Roof fall class	Roof fall level and description
Less than 1	Low	Acceptable
		No controlling measures are needed
Between 1 and 3	Medium	Acceptable
		A few management review and controlling measures are needed
More than 3	High	Undesirable
		Extensive monitoring and controlling measures are needed

1. In mine design stage: creating intersections with minimum possible span.
2. In mining stage: increasing the roof bolt density using longer and stronger bolts especially in the intersections.

7 Conclusions

Roof fall is a common geotechnical hazard in coal mines, and it is generally complex and unpredictable due to uncertainty and variability in geological and mining

Table 4 Testing dataset used for evaluating the proposed model

No.	CMRR	PRSUP	IS (m)	*D* (m)	Roof fall rate actual	Roof fall rate predicted
1	28	5.89	21	152.4	1.81 (Medium)	Medium
2	30	6.07	17.4	91.4	4 (High)	Medium
3	32	8.67	16.5	243.4	2 (Medium)	Medium
4	35	4	19.5	61	0 (Low)	Low
5	37	13.24	17.7	76.2	6.26 (High)	High
6	37	9.93	17.7	121.9	12.07 (High)	High
7	38	4.32	18.3	182.9	0.65 (Low)	Low
8	40	6.25	18.6	228.6	0.52 (Low)	Medium
9	41	3.79	18	106.7	1.28 (Medium)	Medium
10	42	3.27	18.6	61	2.37 (Medium)	Medium
11	44	6.2	18.9	106.7	3.57 (High)	High
12	44	3.5	20.7	76.2	1.56 (Medium)	Medium
13	45	4.55	19.8	106.7	5.67 (High)	High
14	46	4.84	19.7	91.4	2.63 (Medium)	High
15	47	3.98	18.8	152.4	0 (Low)	Low
16	50	5.52	18.3	91.4	3.19 (High)	High
17	50	7.23	23.9	304.8	3.5 (High)	High
18	51	3.24	20.1	152.4	0 (Low)	Low
19	55	3.71	19.1	304.8	0.28 (Low)	Low
20	58	3.1	19.8	243.4	0 (Low)	Low
21	75	2.46	19.2	121.9	0 (Low)	Low
22	76	8.83	21	152.4	0.72 (Low)	Low

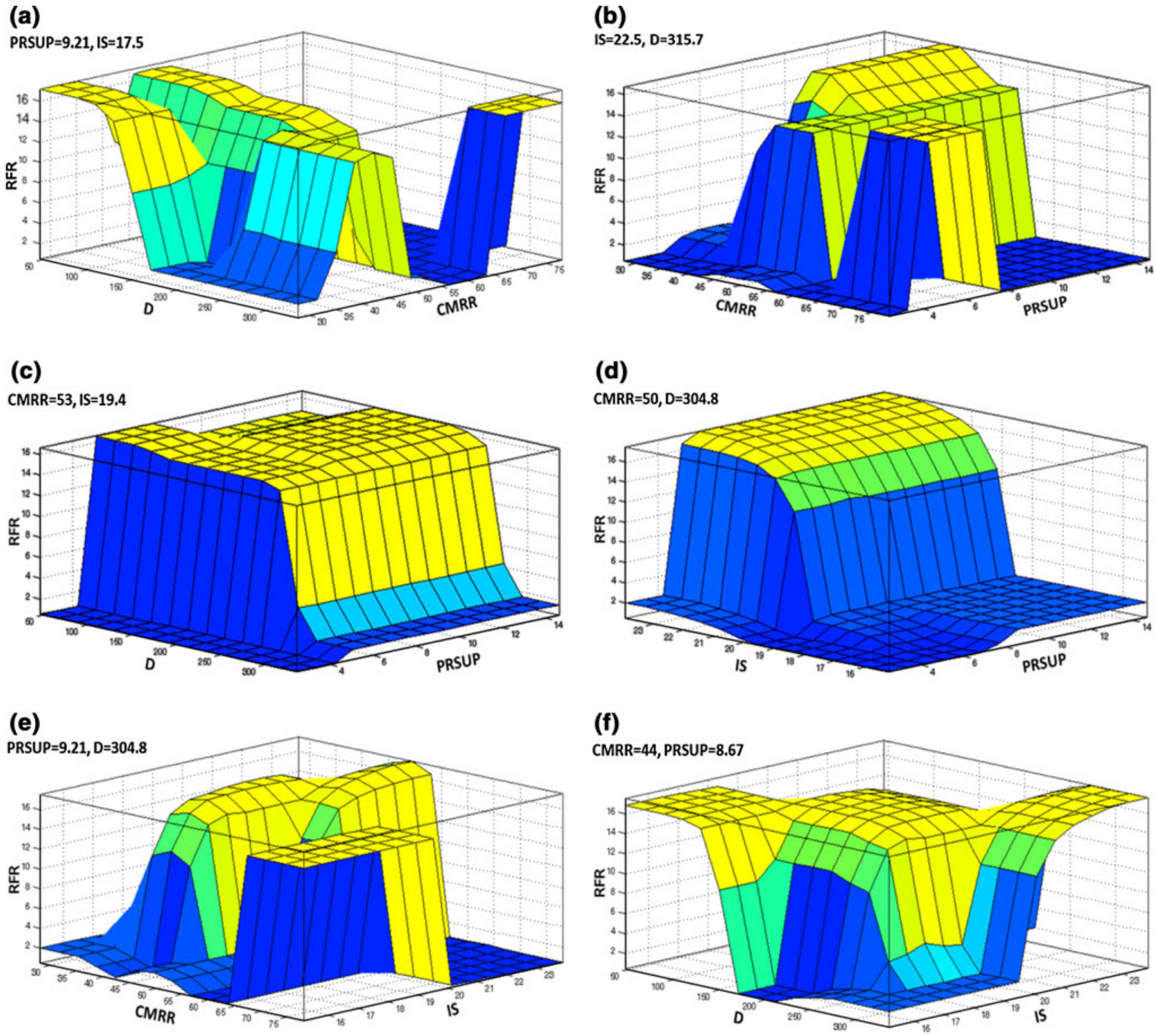


Fig. 10 Surface plots of roof fall rate with **a** depth of cover and CMRR, **b** CMRR and PRSUP, **c** depth of cover and PRSUP, **d** intersection span and PRSUP, **e** CMRR and intersection span, **f** depth of cover and intersection span

parameters. Recently, the application of fuzzy logic method has increased in almost all research areas, particularly including complexity and uncertainty. Therefore, in this paper using fuzzy logic method, a model was established to predict roof fall rate. The model was constructed using four inputs: CMRR, PRSUP, intersection span and depth of cover. Proposed fuzzy model was developed based on Mamdani algorithm, and triangular and trapezoidal fuzzy membership functions were adopted for describing input and output variables. Furthermore, 180 if–then fuzzy rules and COA method for defuzzification were used in order to develop fuzzy model. The results of the fuzzy model showed that fuzzy logic is a useful and powerful means to enhance the safety of underground coal mines. Practical outcome of the proposed model can be considered as a preliminary estimation of roof fall rate based on which controlling measures can be developed for the reduction of roof fall accidents. The major advantage of fuzzy model is that human judgment and intuition can be effectively used for the prediction of roof fall rate, which helps in field applications. Finally, it is clear that the presented fuzzy model can be improved based on more data that can be obtained from other underground coal mines over time.

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