SANTOSH KUMAR NANDA
AND
DEBI PRASAD TRIPATHY

Development of fuzzy logic based intelligent accident alarming system for opencast mine: a case study

Now-a-days safety issues are the major issues in any industry, workplace etc. Increasing accidents not only reduce the safety in workplace also affects the economic strength of the industry, state and the country. An accident alarming system is one of the solutions for preventing accident in industry. However, it is very difficult to make mathematical, intelligent model for approximate the accident, as accident is not a measurable quality. In general, accident is not a measurable quantity. Factors associated or related to accident issues are also not measurable. Hence, these issues are coming under high uncertainty problem. Here the only choice is fuzzy logic, which can be applied for approximating the above issues as fuzzy logic is a universal approximation. In this research article, an attempt has been made to design an intelligent accident alarming system with fuzzy logic. Initially a mathematical model was developed using Likert scale with the severity index value. After the development of the model, appropriate factors were determined, and then fuzzy logic was used to develop an intelligent alarming system for prediction of accidents for anopencast coal mine.

Keywords: *Safety, Likert scale, severity index, fuzzy logic, Mamdani Fuzzy Inference System*

1. Introduction

Safety is a primary concern for the human survival and development, which are the common values of human society. Safe production situation is a huge project and reflection of economical, industrial, educational, and scientific and technological development. Safety can be enhanced by minimizing the accidents in industry. Compared to other industries, accidents are major issue in mining industry as huge man-power used for production in mines. The various factors related to safety issues including technical factors, human and managerial. The different causative factors in underground coal mines can be roof fall, water, fire, coal-dust, gases, firedamp, inundation, blasting, electricity etc. The technological advancement cannot replace the human interaction in the overall process of the mining [1, 2].

Mr. Santosh Kumar Nanda, Tonkabi, Trivandrum, Kerala and Dr. Debi Prasad Tripathy, Department of Mining National Institute of Technology, Rourkela-769008, India. E-mail: santoshnanda@live.in / debi_tripathy@yahoo.co.in

Safety is a relative term compared for different mines, and it has to be told by making a scale which would not change with the change in extent and area of mine, with the change in opinion and ability of persons employed and with the change in production target of mine and effort done by changing in plan to achieve it. DGMS Circular defines risk assessment process in a mine but it does not focus on classifying mines on safety comparison at national or international basis [3]. Sometime it also fails to provide accident grading of different mines when mine is large or small, either it is mechanized, manual or semi mechanized and also do not consider the skills and ability of employees and other factors. Therefore forecasting the accident with intelligent system in mines is now a challenging issue at present [4]. In general, accident is not a measurable quantity. Factors associated or related to accident issues are also not measurable. Hence, these issues come under high uncertainty problem. Very few mathematical models are available in literature for approximate this type of high uncertainty problem [5,6, 12]. Hence the only choice is fuzzy logic, which can be applied for approximating the above issues as fuzzy logic is a universal approximator [7, 8]. Particularly for predicting accident in mining or construction areas is very difficult and need appropriate parameters [9,10, 11, 13]. Therefore, fuzzy system cannot directly apply to approximate accident. Before developing the intelligent model with fuzzy logic, it is essential to make a mathematical model to find the appropriate parameters for approximation of the accident in opencast mine.

To find the appropriate responsible parameters those have influences on accident in mines, Statistical Processing System (Likert scale) is required [5]. Likert scale determines the correlation values between the factors taken in questionnaire survey. After the development of the model, appropriate factors with high correlation value (servity index) are considered for development of an intelligence alarming system for prediction or approximation of accident for an opencast coal mine. As fuzzy logic is an universal approximator and successfully applied to many complex engineering applications and successfully handled uncertainties, therefore, fuzzy logic system is a well justified methodology for this proposed problem [15, 16] .

This research article is spread in four sections. Section-1 highlights the problem aspect of safety issues in opencast mines, Section-2 represents the methodology and description on fuzzy logic-based accident alarm system for opencast mines, Section-3 represents the simulation studies of the proposed model and Section-4 highlights the findings, recommendation and conclusion of the proposed study.

2. Development of fuzzy logic based accident alarming system for opencast mine

Accident measurement in opencast mine is treated as higher uncertainty problem. Directly any intelligent system cannot measure the high uncertainty problem like accident etc. Therefore, a statistical intelligent processing unit (SIPU) or a statistical process model (SPM) is required to find the dependent parameter for accident. Fig. 1 represents system hierarchy diagram of the proposed work. As per Fig.1, Likert scale system was used for finding the dependent factors for accident and according to severity index, suitable parameters were chosen.

2.1 Application of Likert scale for finding the suitable parameter for accident measures with the value of severity index

Perception and ability of individual are evaluated in questionnaire survey, observing the collective responses to a set of items. Frequencies of all responses are scored describing the overall importance of factors involved in analysis system concerned with safety. Likert-type scales are the basis of option formation of questionnaires so that the responses can be evaluated. Safety and accident analysis are unreliable without consideration of factors directly related to people working in mines which involves their attitude, dedication and skill towards productivity with safety.

Five-point Likert item questions were used for containing factors which have been identified to be responsible for their importance in opencast coal mine safety. Factors of production affecting the safety (Q-2), and factors of mine management, workers ability and factors on site (Q-1) are questioned. These factors are highly uncertain to be taken in common for other person and other mines, therefore companywise consideration of mines have been done to analyze number of accidents by various factors. The analysis of number of accidents contains unpredictability in it as it is a countable value, occurs at different places according to situation. Situation for accident cannot be told previously, and its situation can be just estimated by various factors as told above like production, safety, skill of workers, awareness, love of work and other. So, for prediction of degree of safety

Table 1: Factors that are influence accident in opencast mines

	(a) Management factors					
1.	Inspection delays	1	2	3	4	5
2.	Skill in loading and hauling machinery	1	2	3	4	5
3.	Lack of proper safety equipments	1	2	3	4	5
4.	Communication and coordination gap	1	2	3	4	5
5.	Lack of motivation and awareness	1	2	3	4	5
6.	Safety measures and laws enforced	1	2	3	4	5
	(b) Workers ability and attitude					
7.	Education	1	2	3	4	5
8.	Safety knowledge and state of emergency	1	2	3	4	5
9.	Attitude towards illegal operation of colleagues	1	2	3	4	5
	(c) Site factors					
10.	By explosive (blasting)	1	2	3	4	5
11.	Electricity leakage	1	2	3	4	5
12.	Loading/hauling machines	1	2	3	4	5
13.	Support installation machines	1	2	3	4	5
14.	Pre-mature collapse	1	2	3	4	5
	(d) Management personnel decision					
15.	Title or office post	1	2	3	4	5
16.	Monthly income	1	2	3	4	5
17.	Extent of current love of work	1	2	3	4	5
18.	Time on post	1	2	3	4	5
19.	Work concern and promoting of work culture in laborers	1	2	3	4	5
20.	Decision making capabilities	1	2	3	4	5
21.	Satisfaction of working conditions	1	2	3	4	5
22.	Status of life satisfaction	1	2	3	4	5

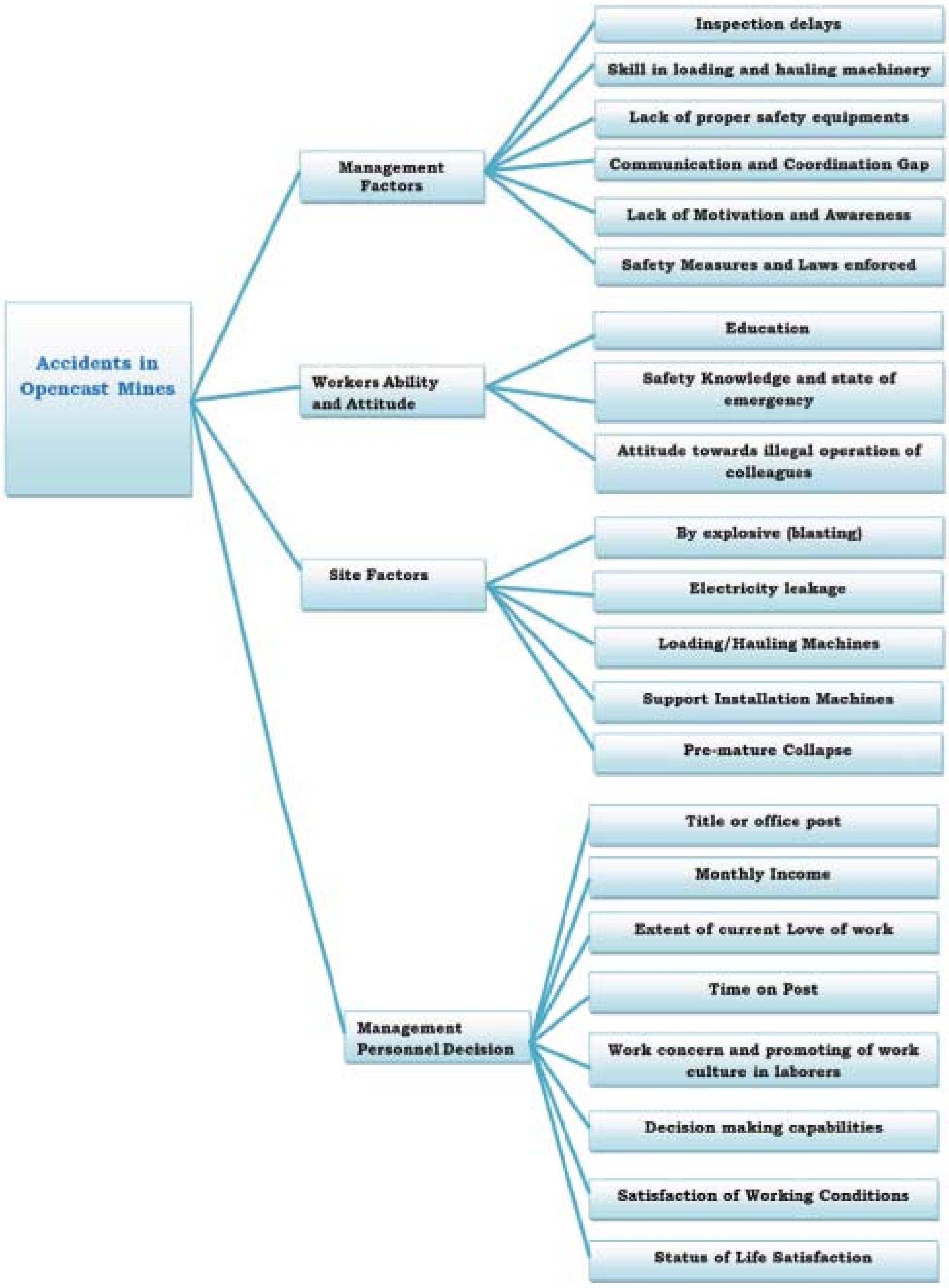


Fig.1 System hierarchy diagram of proposed problem

means range of accidents in the intelligent prediction models have been used, and fuzzy modelling has been identified as most appropriate model for its reorganization pattern and applicability. Five significant influencing factors (Table 1) identified through questionnaire survey were then surveyed by more 200 questionnaires recorded at sites on the Likert scale of 1 to 5 during data collection. Factors recorded were then statistically analyzed by calculating severity index (S.I.) (expression 1) as shown in Table 2. S.I. of the factors have been calculated by using Eqn. (1) as mentioned below [13]. These factors were ranked based on the values of S.I calculated as shown in Table 3.

$$Severity\ Index\,(S.I.) = \left(\frac{\sum_{i=1}^{5} a_i x_i}{5\sum_{i=1}^{5} a_i} \right) \quad \text{... (1)}$$

Total number of twenty-two factors (Table 1) are chosen for evaluating accident in opencast mine. The questionnaire survey comprised four different categories e.g. (a) management factor, (b) worker ability and attitude (c) site factors and (d) management personal decision. Each category was classified into different sub-categories and represented in Table 1. In questionnaire survey, every factor and sub factors are examined with a rank value of 1 to 5. Using Likert scale, calculating severity index, eight factors were selected with high severity index value. However, the best Five factors (high severity index value) Inspection delay (F1), Skill in loading and hauling machine operation (F2), Communication and coordination gap in management persons (F3), Lack of motivation, safety knowledge and state emergency knowledge (F4) and Safety measures and laws enforced (F5) were selected. Using these five most influencing factors, an intelligent system designed to approximate accident in opencast mines. The next section highlights the fuzzy logic system and procedure of the fuzzy based intelligent alarming system for approximate the accidents by taking all above selected parameters.

2.2 Preliminary introduction to fuzzy rule base system

This section introduces fuzzy systems. Detailed analysis on fuzzy system can be found in numerous literatures [14, 15]. Fig.2 represents the basic architecture of fuzzy logic system. A fuzzy rule-based system consists of four parts: fuzzifier, knowledge base, inference engine and defuzzifier. These four parts are described below:

- Membership function: The major issues in all fuzzy sets are how to determine fuzzy membership functions. The membership function fully defines the fuzzy set. A membership function provides a measure of the degree of similarity of an element to a fuzzy set. Membership functions can take any form, but there are some common examples that appear in real applications. Membership Function can either be chosen by the user arbitrarily, based on the user's experience (MF chosen by two users could be different depending upon their experiences, perspectives, etc.) or be designed using machine learning methods (e.g., artificial neural networks, genetic algorithms, etc.).There are different shapes of membership functions; triangular, trapezoidal, piecewise-linear, Gaussian, bell-shaped, etc.
- Inference engine: The inference system or the decision-making unit performs the inference operations on the rules. It handles the way in which the rules are combined. This block gives the information on the inference on rules. Generally Min-Max. Min-product, Max-product or Product-min inference used in this block. This block behaves like a decision kind of unit of entire fuzzy system block where it handles the way in which the rules are combined.
- Rule base: The above description shows the behaviour of a fuzzy expert system. Let X is the universe of discourse and x is the elements of X. A fuzzy set A in a universe of discourse X is characterized by a membership function A(x) which has a value ranging from 0 to 1. If there are n fuzzy sets associated with a given input x, then fuzzifier would produce n fuzzy sets as $A_1(x)$, $A_2(x)$...$A_n(x)$ with n number of membership function Ai,i = 1,2n. This process is called the fuzzification. After fuzzification the information goes to knowledge base which comprises a database and rule-base. Membership functions of the

Table 2: Calculated severity index of selected influence factors

Company						
Management and workmen factors and Mine site						
Factors		C1	C2	C3	C4	C5
1	Inspection delays	86.7	86.6	86.6	87.1	85.7
2	Skill in loading and hauling machine operation	86.8	85.9	88.1	83.4	87.2
3	Communication and coordination gap in management persons	86.3	86.5	87.3	87.1	86.7
4	Lack of motivation, safety knowledge and state of emergency knowledge	88.3	86.1	87.4	87.1	86.9
5	Explosion	47.8	46.2	48.1	45.4	47.5
6	Safety measures and laws enforced	84.1	86.2	88.4	86.9	69.5
7	Team internal politics and illegal attitude of workmen	65.8	64.9	64.4	64.1	53.8
8	Decision making capabilities of management personnel	63.5	63.1	62.9	62.8	52.5

TABLE 3: INPUTS AND OUTPUT WITH THEIR FUZZY AND FUZZY INTERVALS

	System's linguistic variable	Variables	Linguistic values	Fuzzy interval (in %)	Remarks
1.	Inputs	Factor-1	Low	5-20	Very important
			Medium	15-55	
			High	50-100	
		Factor-2	Low	5-20	Very important
			Medium	15-55	
			High	50-100	
		Factor-3	Low	5-20	Very important
			Medium	15-55	
			High	50-100	
		Factor-4	Low	5-20	Important
			Medium	15-55	
			High	50-100	
		Factor-5	Low	5-20	Moderate
			Medium	15-55	
			High	50-100	
2.	Output	Percentage of accident	Low	5-20	(green-color)
			Medium	15-45	(yellow-color)
			High	40-85	(violet-color)
			Very high	80-100	(red-color)

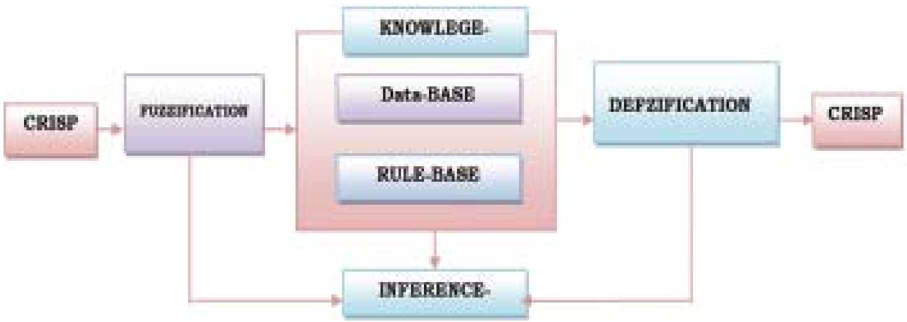


Fig.2 Basic structure of fuzzy logic system

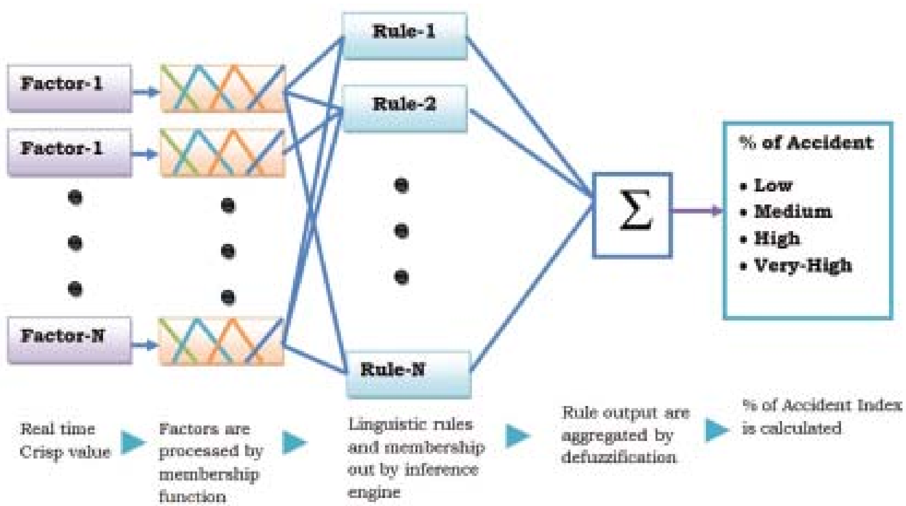


Fig.3 Architecture of the fuzzy inference system applied to accident alarming system

fuzzy sets are contained in the data base. The rule base is a set of linguistic statements in the appearance of IF-THEN rules with antecedents and consequents, correspondingly, with and or operators.

- Defuzzification: The output generated by the inference block is always fuzzy in nature. A real world system will always require the output of the fuzzy system to the crisp or in the form of real world input. The job of the defuzzifier is to receive the fuzzy input and provide real world output. In operation, it works in the opposite way to the input.

2.3 PROCEDURE FOR FUZZY RULE BASED ACCIDENT ALARMING SYSTEM

The procedure for fuzzy rule based accident alarming system for opencast mine is illustrated in Fig.3.

The structure of fuzzy inference system applied to accident alarming system is discussed as follows:

2.3.1 Selection of input and output variables

The first step in system modelling was the identification of input and output variables called the system variables. Only those inputs that affect, the output to a large extent was selected. The five important input variables were inspection delay (F1), skill in loading and hauling machine operation (F2), communication and coordination gap in management persons (F3), lack of motivation, safety knowledge and state emergency knowledge (F4) and safety measures and laws enforced (F5) selected. Inclusion of more number of inputs to the system requires more number of rules and hence the complexity increases. The universe of discourse was also decided on the basis of the physical nature of the problem. In the selection procedure, the above mentioned inputs and the output were taken in the form of linguistic format which displayed an important role in the application of fuzzy logic. For example, F1 = low, medium, high, F2 = low, medium, high, F3 = low, medium, high, F4 = low, medium, high, F5 = low, medium, high .The output variables were similarly divided into percentage of accident = low, medium, high, very high. A linguistic variable is a variable whose values are words or sentences in a natural or man-made language. All the input factors are also evaluated and represented with remark. Table 3 shows the linguistic variables, their linguistic value, remark on influence of the input parameters and associated fuzzy intervals.

2.3.2 Selection of membership function for input and output variables

Linguistic values were expressed in the form of fuzzy sets. A fuzzy set is usually defined by its membership functions. In general, triangular and trapezoidal membership functions were used to normalize the crisp inputs because of their simplicity and computational efficiency [16, 17].

$$traingle(x;a,b,c)=\begin{cases}0, & x\le a\\ \dfrac{x-a}{b-a} & a\le x\le b\\ \dfrac{c-a}{c-b} & b\le x\le c\\ 0, & c\le x\end{cases} \quad \text{... (2)}$$

$$traingle(x;a,b,c)=\max\left(\min\left(\frac{x-a}{b-a},\frac{c-x}{c-b}\right),0\right) \quad \text{... (3)}$$

The triangular membership functions as described in the above equations is used at here that converted the linguistic values in the range of 0 to 1. Where a, b, c are the parameters of the linguistic value and x is the range of the input parameters. In this proposed model, all the membership functions of inputs and output are represented in triangular membership function. Figs.4 to 9 represent the graphical representation of the membership function of input variables and output variable.

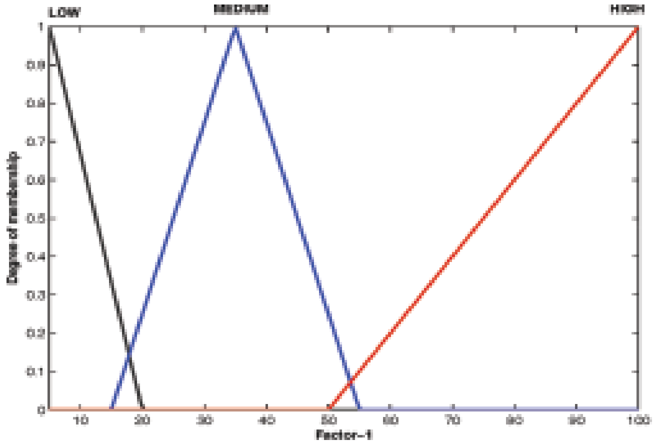


Fig.4 Graphical representation of membership function of factor 1

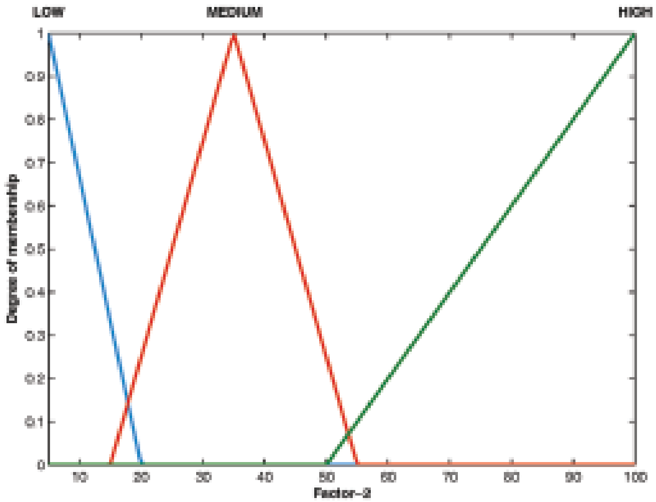


Fig.5 Graphical representations of membership function of factor 2

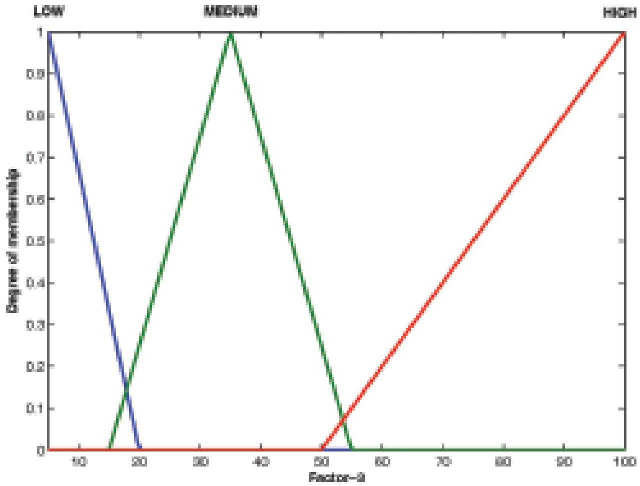
2.3.3 Formation of linguistic rule-base

The relationship between input and the output were represented in the form of IF-THEN rules. Let the 1st input (F1) was taken as A, the 2nd input (F2) as B, 3rd input (F3) as C, 4th input (F4) was taken as D and the 5th input (F5) was taken as (E) and the output (% of accident) is taken as Z. As per the fuzzy systems, all the inputs had three membership functions each, hence 243 rules were made. In Mamdani fuzzy model, Max-min inference was applied. The rule base a combination of rules of the Mamdani fuzzy system, were generated in the following ways:

R1 = IF A is A1 = Low AND B is B1 = Low AND C is C1 = Low AND D is D1 = Low AND E is E1 = Low THEN Accident (Z) is Z = Z1 = Low;

R2 = IF A is A1 = Low AND B is B1 = Low AND C is C1 = Low AND D is D1 = Low AND E is E2 = Medium THEN Accident (Z) is Z = Z1 = Low;

R243 = IF A is A3 = High AND B is B3 = High AND C is C3 = High AND D is D3 = High AND E is E3 = High THEN



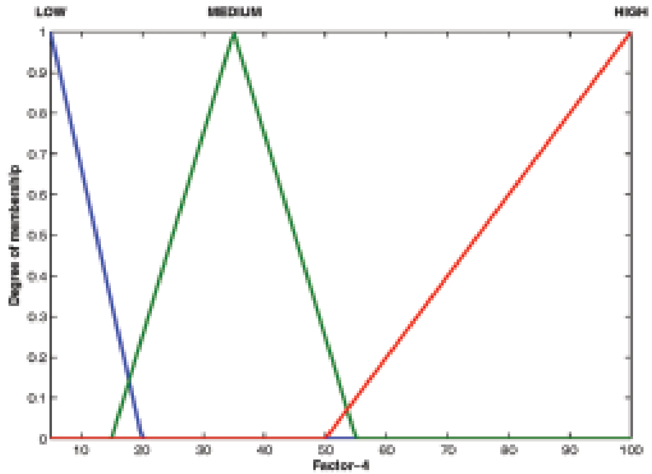


Fig.6 Graphical representations of membership function of factor 3

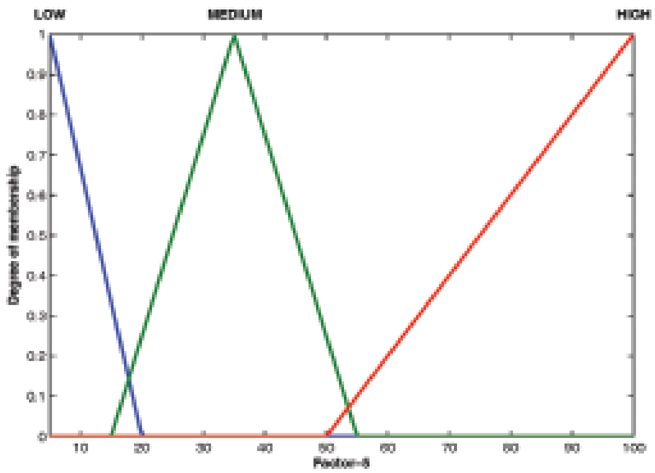


Fig.7 Graphical representations of membership function of factor 4

Accident (Z) is Z = Z3 = High;

2.3.4 Defuzziûcation

In this proposed model, centroid of area (COA) method of defuzzification is used for determining the output as

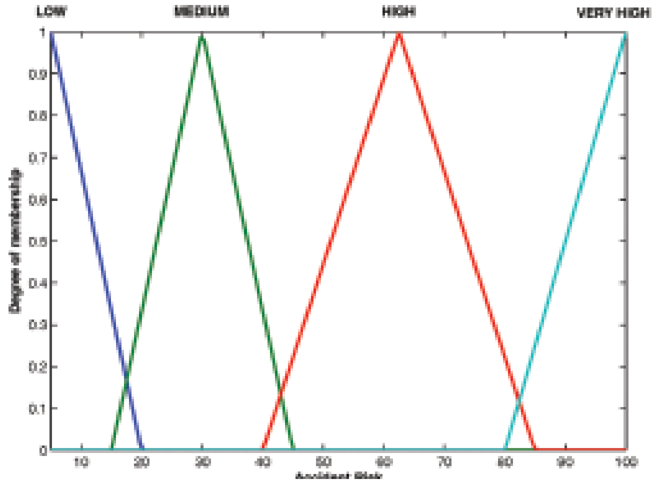


Fig.8 Graphical representations of membership function of factor 5

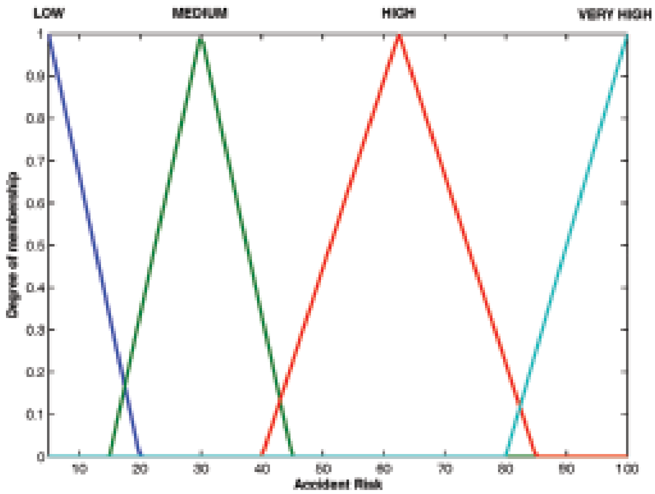


Fig.9 Graphical representations of membership function of output (accident risk)

expressed in equation (3) [18].

$$z_{COA} = \frac{\int_z \mu_A(z) z \, dz}{\int_z \mu_A(z) \, dz}$$

3. Simulation result and discussion

The proposed system models for accident risk were validated using simulation studies. The studies were carried out by using Matlab simulation environment. This proposed model was simulated using Intel Core i3 Processor, 3.3 GHz CPU, 4 GB ram and 64 bit operating system. The proposed system model for accident measure is validated using simulation studies. Before coming to the simulation, a mathematical model was designed with Likert scale as discussed in section 2.1. From this statistical analysis the non-measurable equantities were quantified using Likert scale. Out of several factors those partially and fully affect the accident in

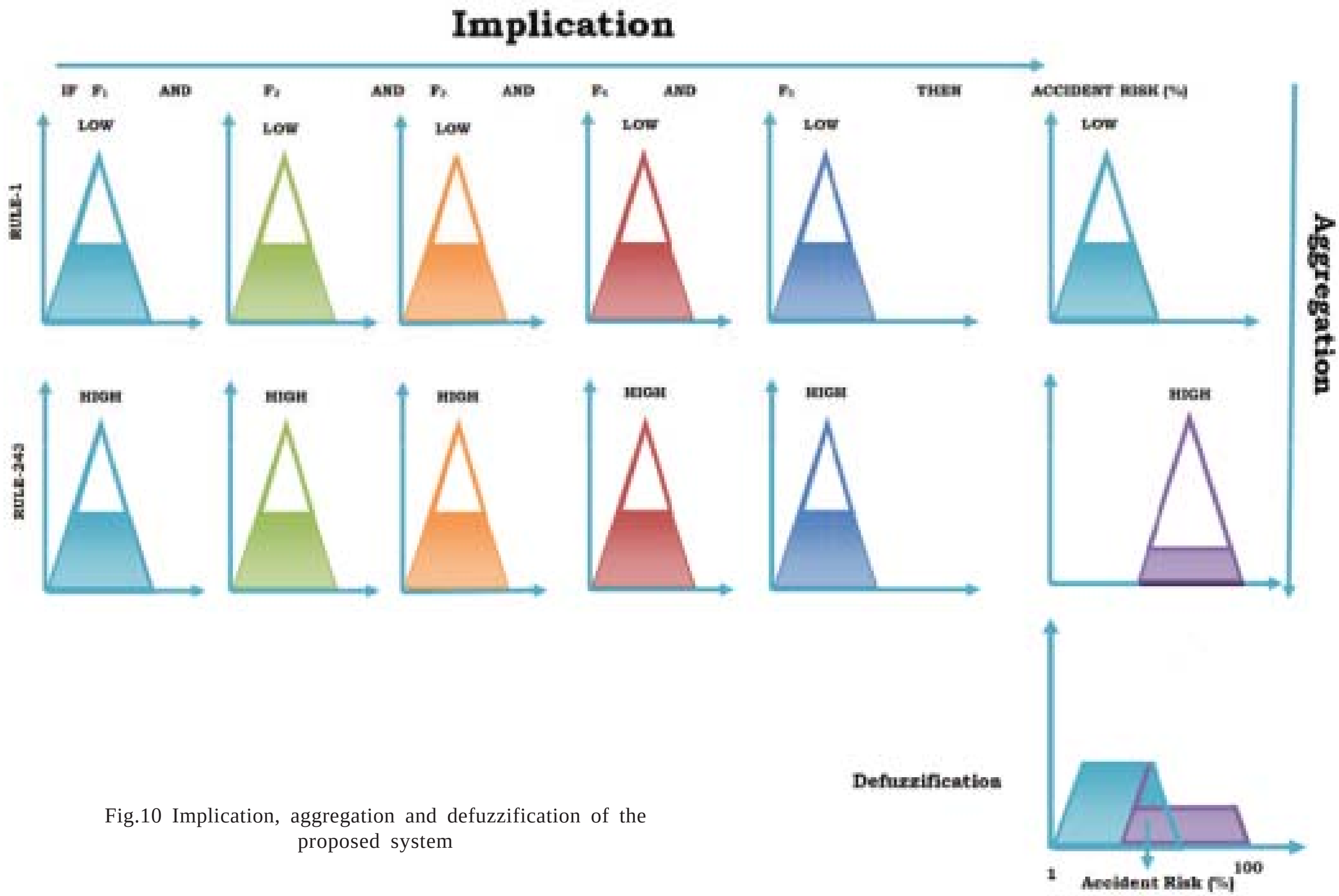


Fig.10 Implication, aggregation and defuzzification of the proposed system

opencast mines, influencing factors were selected. After the questionnaire survey, rank analysis of the Likert scale method was used. Severity index of included factors was calculated.

For this study the entire data was collected from Talcher coal mine, Odisha, India. The total no. of data is approximately 200. Using these samples and experimented severity index value of included parameters co-relations, co-efficient of each factor is calculated. From the analysis it is found that factor 1, factor 2, factor 5 are co-related value is more than 0.8 and these factors are highly responsible for the accidents in opencast mines and hence selected for model development.

The above analysis gives information of the influence parameters that affect the accident in opencast mines. However this analysis never makes a learning system using human intelligence. For this it is essential to make an intelligent model for analyzing system for this complex problem. Using the above analysis, other intelligent models like MLP, RBF, and genetic algorithm etc. are impossible to be implemented in reality. Hence, Mamdani fuzzy model was developed and discussed. The fuzzy parameters are successfully checked to ensure the performance of the design model. For Mamdani fuzzy inference system, the no. of rules are 243.

To make this system for software application, here another approach has been implemented using MATLAB GUI. For this type of high uncertainty problem, MATLAB is a suitable programming tool. The five factors represented in Table 3 were taken as input to system and the output is accident risk. Mamdani fuzzy inference system has been used and 243 rules are applied in this software. The fuzzy based accident alarming system aggression and implication is shown in Fig.10.

Using the concept of fuzzy implication, aggregation (MIN-MAX) and fuzzy defuzzification, typical fuzzy inference based accident prediction software is made and represented in Fig.11.

As per Table 3, the system is designed and the relationship between input parameters and output parameters are represented by 3D surface plot. To study the performance of the fuzzy system, 3D surface view plots were generated. As there are five inputs, hence twenty set of surface plots were generated. For each input set, there are four surface plots which are essentially plotted. All the surface plots are represented from Figs.12 to 14. Fig.12 represented the surface view plot of input 1 with other inputs with output. It generally represented the effectiveness of the output (% of accident) with factor 1 with factor 2, factor 3, factor 4 and factor 5 respectively. Fig.12(a) represents the characteristics of output with F1 and F2. From this figure it was observed that the output sharply increases with the value of F1 and F2 as the factor F1 and F2 are the very important factors as already

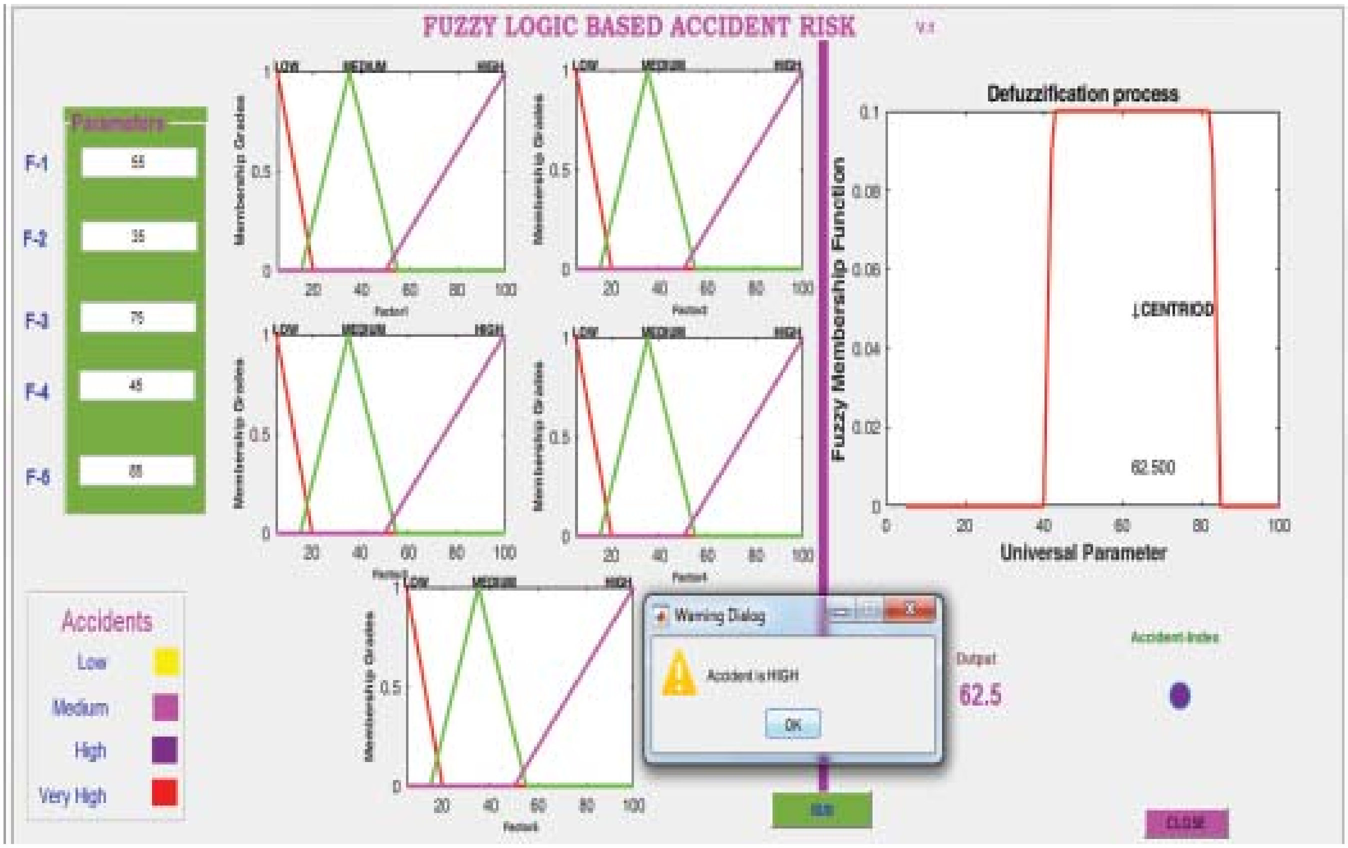


Fig.11 MATLAB GUI (software) for accident risk prediction in mines

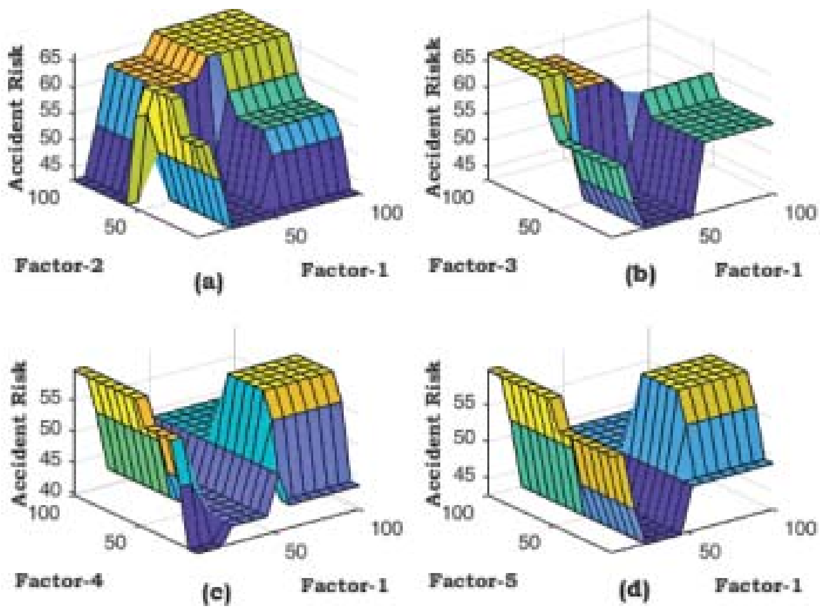


Fig.12 (a) Surface plot between % of accident with factor 1 and factor 2, (b) factor 1 and factor 3, (c) factor 1 and factor 4, (d) factor 1 and factor 5

represented in Table 3. Similar results are represented in Fig.12 (b). In Fig.11 (c) and Fig.11(d), the output linearly decreased with the increment value of F1, F4 and F5 as the factors F4 and F5 are the less important variables. Similarly, Fig.13 and 14 represent the effectiveness of output with other input variables.

4. Conclusions

In this proposed work, it is possible to design a fuzzy based intelligent alarming system for accident prediction for an opencast mine by using statistical processing system (Likert scale). The present analysis gives information of the influence parameters that affect the accident in opencast mines. However, this analysis never makes a learning system using human intelligence. However, using the human intelligence, other intelligent models like MLP, RPF, and genetic algorithm etc were difficult to be implemented, whereas fuzzy logic system is comparatively easy to make such intelligent system using human intelligence. From the simulation study the effectiveness of the proposed fuzzy intelligent model was also evaluated. As the system take very less CPU time 0.33 sec, it will easily be implemented in hardware. It is clearly observed from the simulation study, the proposed fuzzy logic system very successfully handles the uncertainties associated with this complex problem in opencast mine. The developed GUI (Software) helps mining

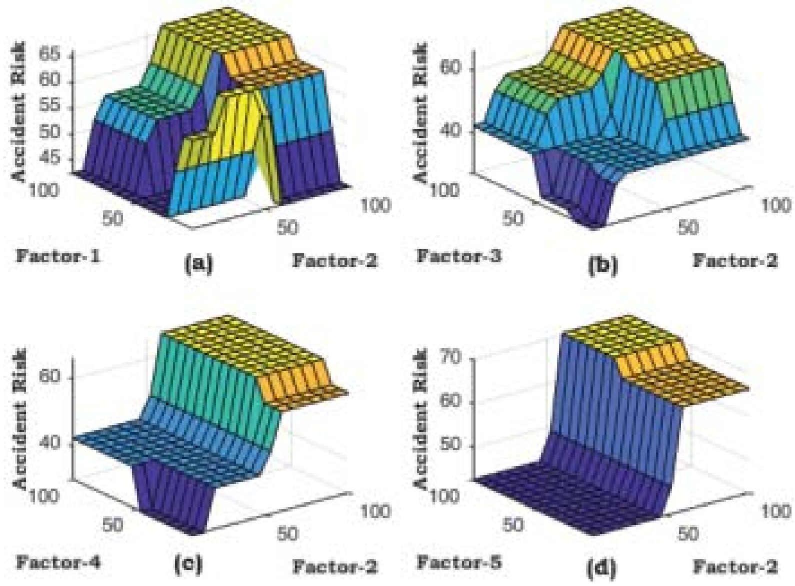


Fig.13 (a) Surface plot between % of accident with factor 2 and factor 1, (b) factor 2 and factor 3, (c) factor 2 and factor 4, (d) factor 2 and factor 5

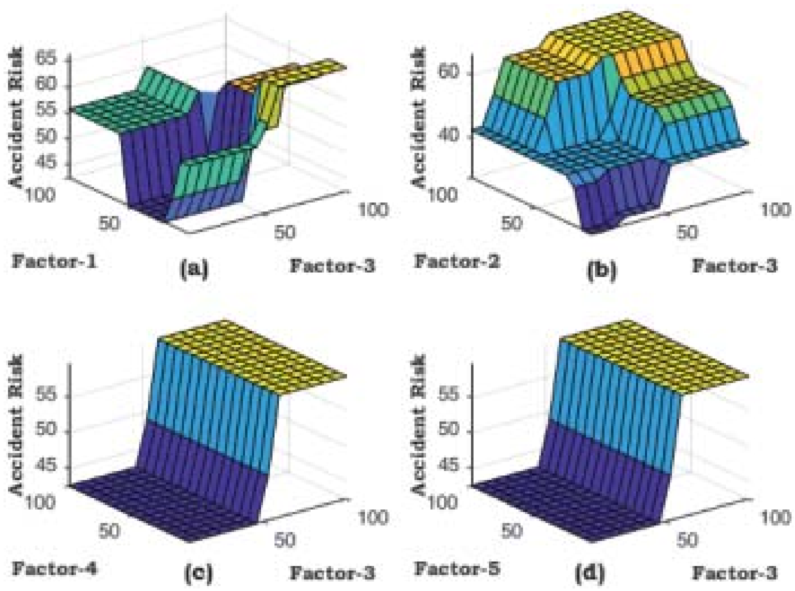


Fig.14 (a) Surface plot between % of accident with factor 3 and factor 1, (b) factor 3 and factor 3, (c) factor 3 and factor 4, (d) factor 3 and factor 5

industry to measure accident for enhancing the safety and helpful to save life in mines.

References

1. David A. Hofmann, Rick Jacobs, and Frank Landy, (1995): "High reliability process industries: Individual, micro, and macro organizational influences on safety performance," *Journal of safety research*, vol. 26, no. 3, pp.131-149.
2. Mallick S., and Mukherjee K. (1996): "An empirical study for mines safety management through analysis on potential for accident reduction," *Omega*, vol. 24, no. 5, pp.539-550.
3. DGMS,"DGMS Annual Report", Tech. Rep., 2007, http://dgmsindia.in/pdf/report/03-APPENDICES%202007(ENGLISH).pdf
4. Zadeh L. A., (1965): "Fuzzy sets," *Information and Control*, vol. 8, pp.338-353.
5. Mellinger G. D., Sylwester D. L., Gaffey W. R., and Manheimer D. I., (1965): "A Mathematical Model with Applications to a Study of Accident Repeatedness Among Children," *Journal of the American Statistical Association*, vol. 60, no. 312, pp. 1046-1059.
6. Asalor, J. O. (1995): "A general model of road traffic accidents," Applied Mathematical Modelling, vol.8, no.2, pp.133-138, 1984. [7] J. Yen, R. Langari, and L. A. Zadeh, Eds., Industrial Applications of Fuzzy logic and Intelligent Systems. IEEE Press, New York.
7. Wang L.-X. (1997): A Course in Fuzzy Systems and Control. Prentice Hall International, Inc., USA.
8. Gomase V. V., Jain S. and Bhure V. S., (2012): "Accident Prevention Using Fuzzy Logic," *International Journal of Engineeringand Innovative Technology* (IJEIT), vol. 2, no. 4, pp. 17–19.
9. Driss M., Saint-Gerand T., Bensaid A. and Benabdeli K., (2013): "Afuzzy logic model for identifying spatial degrees of exposure to the risk of road accidents (Case study of the Wilaya of Mascara, Northwest of Algeria)," in 2013 International Conference on Advanced Logistics and Transport (ICALT), Sousse, Tunisia, 29-31 May 2013, pp. 69-74.
10. Nidhi R. and Kanchana V., (2018): Analysis of Road Accidents Using Data Mining, Techniques, *International Journal of Engineering & Technology*, 7 (3.10), pp.40-44.
11. Dutta S., Sheikh T. A., Baruah S., Sharma P. and Roy S., (2016): "Accident Control Using Fuzzy Logic: Survey," *European Journal of Advances in Engineering and Technology*, vol.3, no.1, pp.62-65.
12. Tripathy Debi Prasad, Ala Charan Kumar, (2018): Identification of safety hazards in Indian underground coal mines, Journal of Sustainable Mining, Elsivier, 17, pp 175-183.
13. Al-Hammad and Assaf S., (1996): "Assessment of Work Performanceof Maintenance Contractors in Saudi Arabia," *J. Manage.Eng.*, vol. 12, no. 2, pp.4449.
14. Zadeh L. A., (1994): "Soft computing and fuzzy logic," *IEEE Software*, vol. 11, no. 6, pp. 48-56.
15. Nagy G., (1991): "Neural networks-then and now," *IEEE Transactions on Neural Networks*, vol. 2, no. 2, pp. 316–318.
16. Nanda S. K., Tripathy D. P. and Patra S. K., (2009): "Fuzzy inferencesystem-based noise prediction models for opencast mines," *International Journal of Mining, Reclamation and Environment*, Taylor & Francis, vol. 23, no. 4, pp. 242-260.
17. Nanda S. K., Tripathy D. P. and Patra S. K., (2011): "A soft computing system for opencast mining machineries noise prediction," *Noise Control Engineering Journal*, USA, vol. 59, no. 5, pp.432-446.
18. Jang J. S., Sun C. T., and Mizutan E., (2005): Neuro-Fuzzy and Soft Computing. Prentice Hall of India Private Limited, New Delhi.

Printed by Pradip Kumar Chanda at The Indian Press Pvt. Ltd. 93A Lenin Sarani, Kolkata 700 013 and published by him for Books & Journals Pvt. Ltd. from 62 Lenin Sarani, Kolkata 700 013.