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Research Article
Fuzzy Bayesian Network Model for Roof Fall Risk Analysis in Underground Coal Mines

[1]Mohammad Javadi, [1]Gholamreza Saeedi and [2]Kourosh Shahriar

[1]Department of Mining Engineering, Shahid Bahonar University of Kerman, Kerman, Iran
[2]Department of Mining and Metallurgical Engineering, Amirkabir University of Technology, Tehran, Iran

Abstract
Background and Objective: Roof fall is one of the greatest single hazards faced by underground coal miners. This accident may have detrimental effects on studyers in the form of fatal and non-fatal injuries as well as downtimes, equipment breakdowns, etc. Due to different impacts of contributing parameters on roof fall and ill-defined or even immeasurable nature of such factors, this problem is an uncertain and complex issue. As a result, development of a methodology for roof fall risk evaluation under uncertainty condition has a remarkable role on safety of underground coal miners. **Methodology:** This study proposes a new quantitative assessment framework, integrating the inference process of Bayesian networks and fuzzy set theory with the traditional probabilistic risk analysis. The constructed Fuzzy Bayesian Network (FBN) based model has 12 root nodes contributing to the failure of the leaf node. The geology maps and data related to mining equipment at Tabas Coal Mine (TCM) are used to determine the prior probability of FBN root nodes. In addition, weighted sum algorithm is used to populate the conditional probability table of intermediate and leaf nodes. **Results:** The new model quantifies uncertainty in roof fall and also provides an appropriate method for modeling complex relationships in underground mining. **Conclusion:** Finally, the proposed approach is illustrated with an application for the TCM and found to be a powerful technique for coping with uncertainties and predicting roof fall risk.

Key words: Roof fall risk, longwall mining, Bayesian network, fuzzy set theory

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Corresponding Author: Gholamreza Saeedi, Department of Mining Engineering, Shahid Bahonar University of Kerman, Kerman, Iran Tel: +983432112764

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Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Roof falls continue to be one of the greatest single hazards faced by underground coal miners. The complexity of geological deposit and variability of mining parameters lead to the occurrences of roof falls[1]. These accidents may have detrimental effects on studies in the form of injury, disability or fatality as well as mining company due to down times, interruptions in the mining operations, equipment breakdowns, etc[2]. The hazardous nature of roof falls in underground coal mine operations can be illustrated from the statistics of mine accidents. It accounted for 18.18% of all fatal accidents in coal mines, contributing about 35.29% of all fatal accidents in below-ground operations[3] in 2005.

Several factors such as geological and stress conditions, mine layout and environment contribute to occurrences of roof falls in underground coal mines[4]. Analyzing the roof fall risk during underground mining could increase the ability of mine designer and studies to reduce the detrimental effects of this hazard. Therefore, extensive research has been conducted to control and assess roof fall in coal mines. In these studies, it has been tried to find the relationship between the roof fall and contributing parameters. Kidybinski[5] classified roofs of mines in the United State for the selection of suitable mechanized support for longwalls. Unrug and Szwilski[6] proposed the roof quality index for determining the influence of strata control parameters on longwall mining design. Coal Mine Roof Rating (CMRR) has been introduced by Molinda and Mark[7] and similar to Bieniawski's RMR has a single rating between 0 and 100. When the CMRR value is close to 0, the roof is weaker while the value getting close to 100 shows that the roof is stronger. Mark[8] evaluated the stability of extended cut by using some contributing parameters like entry with, cut depth, CMRR and depth of cover. Using statistical analysis of roof fall database from 37 coal mines, Molinda *et al.*[1] found the relationships between the roof fall rate and CMRR, primary roof support, intersection span and depth of cover. Deb[9] analyzed the coal mine roof fall rate. In this study, the relationships between CMRR, primary roof support and intersection diagonal span with roof fall rate were determined by using fuzzy reasoning techniques. Duzgun and Einstein[2] proposed a risk and decision analysis methodology for assessment and management of risk associated with mine roof falls in underground coal mines. Duzgun[4] introduced a risk assessment and management methodology for roof fall risk in underground mines. The data was collected from Zonguldak coal region, in Turkey; then the probability of roof fall was computed by fitting a distribution function to the annual roof fall, while the consequence was quantified based on a cost model. Palei and Das[3] predicted the effects of contributing parameters such as number of bolts per row, anchorage strength of bolt, spacing between bolts, width of gallery, mean rock density and RMR on roof falls in underground coal mines. Palei and Das[10] proposed a model to predict the severities of roof fall accidents based on some major contributing parameters in bord and pillar underground coal minig by using logistic regression model. Ghasemi and Ataei[11] developed a fuzzy based model for predicting roof fall rate in coal mines based on Mamdani algorithm. Ghasemi *et al.*[12] developed a practical methodology for assessment and control of the roof fall risk during retreat mining in room and pillar coal mines. Razani *et al.*[13] applied a Fuzzy Inference System (FIS) to predict roof fall rate for controlling, mitigating and/or even eliminating the risk of roof fall. Gao *et al.*[14] presented a numerical approach to simulate shear failure of a coal mine roadway roof. The distinct element code, UDEC, incorporating a proposed Trigon logic was employed in this study. Oraee *et al.*[15] evaluated the effect of discontinuities characteristics on coal mine stability. For this aim, a practical rule-based approach was proposed to assess the risk of a roof fall.

The literature review shows that the behavior of the roof at longwall face has been given little attention. One of the major problems in predicting the roof fall risk at mine faces arises from the adherent complexity and uncertainty of contributing parameters related to the roof fall. Therefore, applying a proper technique that can simultaneously take into account both the complexity and inherent uncertainty connected with the roof fall problem helps designers to analyze the problem more accurately and precisely. In order to control the uncertainty of parameters affecting the roof fall at longwall faces, Bayesian Networks (BNs) which are based on probability theory can be utilized. Also, in order to increase the accuracy of BN results, the fuzzy logic can be applied.

The main aim of this study is to develop a Fuzzy Bayesian Network (FBN) model to evaluate the probability of roof fall in order to obtain a more accurate, precise and robust model. The new approach explicitly quantifies uncertainty in roof fall analysis and also provides an appropriate method for modeling complex relationships and factors in underground coal mining, such as causal relation between variables, common causal factors, formal use of experts' judgments and learning from data to update previous beliefs and probabilities. To show the capability and effectiveness of the constructed model, the data from Tabas Coal Mine (TCM) has been used as a case study.

Tabas Coal Mine (TCM) is the biggest and only fully mechanized coal mine in Iran which is located approximately

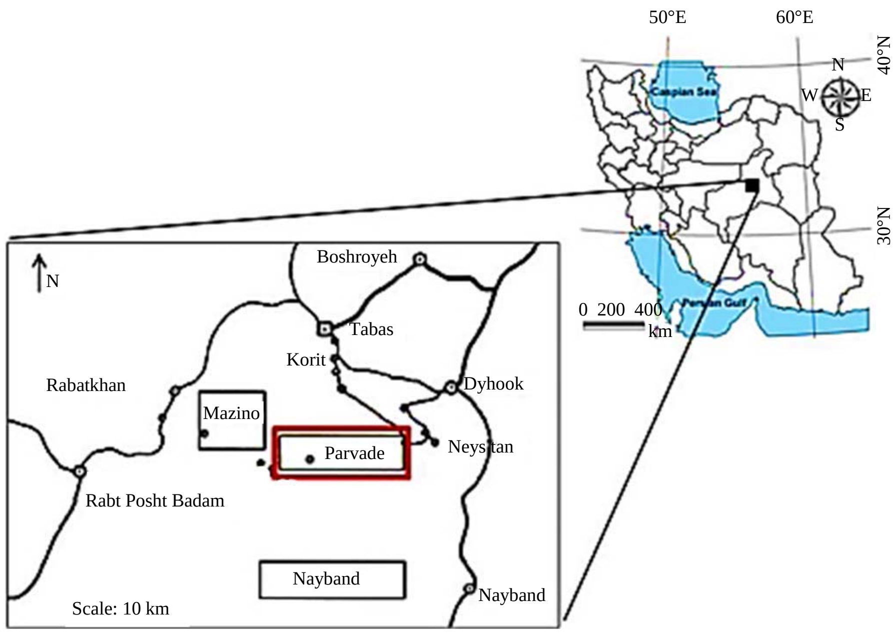

Fig. 1: Location map showing Tabas coal mine

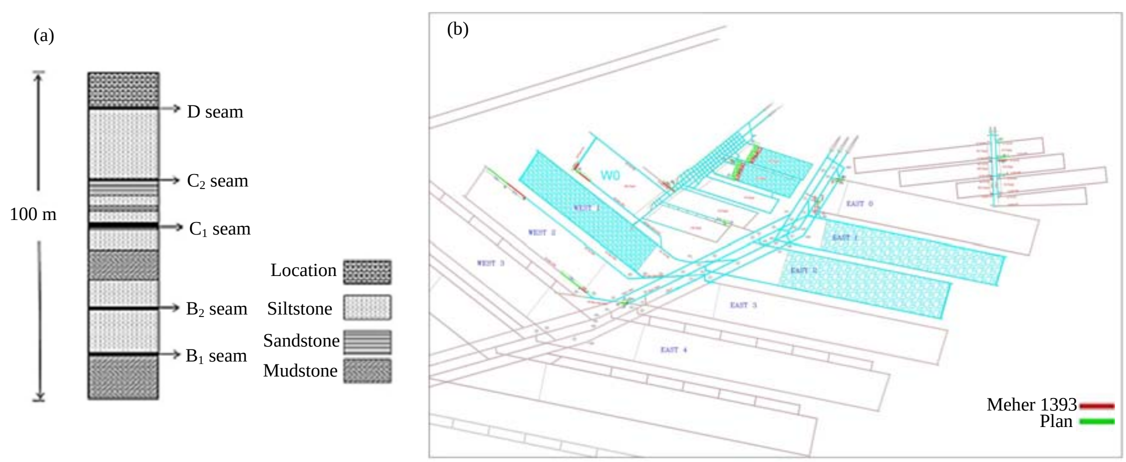

Fig. 2(a-b): (a) Location of panels in mine-field No. 1 and (b) Generalized stratigraphic column at TCM

75 km South of the city of Tabas (Fig. 1). It has three minable seams (C_1, B_1 and B_2). The C_1 seam located in the Tabas coal mine-field No. 1 is mined by longwall method. The thickness and dip of the C_1 seam mostly vary from 1.8-2 m and from 11-26 degrees, respectively. Low-strength sandstone and siltstone layers have been formed in the hanging wall of the coal seam. The mine foot wall consists of siltstone and mudstone seams. The location of panels in the mine-field and generalized stratigraphic column at mine[16] is shown in Fig. 2.

In this study, data collected from East 2 panel has been used. Panel width and length are 217 and 900 m, respectively. From October, 2010 to July, 2013, this panel was extracted (approximately 33 months).

MATERIALS AND METHODS

Fuzzy set theory: Fuzzy Set Theory (FST) was first introduced by Zadeh[17]. The FST provides a basis to generate powerful, widespread problem-solving techniques, especially in the field of decision making[18]. The FST has been employed in various studies such as multi criteria analysis system[19], wave parameters prediction[20], coronary heart disease risk assessment[21], rock brittleness prediction[22], building damage risk assessment on mining terrains[23], the fuzzy Risk Analysis and Management for Critical Asset Protection (RAMCAP) introduction in order to extend RAMCAP[24], risk evaluation of tunneling projects[25], risk assessment of mining equipment failure[26], green supply chain practices evaluation in the mining industry[27] and over break minimization in underground blasting operations[28].

A fuzzy subset A of U is defined by its membership function that can be any number between 0 and 1. Membership of 0 means that the value does not belong to set A, membership of 1 means that the value belongs to the set under consideration and membership anywhere between 0 and 1 determines the degree of membership.

A membership function of fuzzy number $\tilde{A}$ on R is described as $\mu_{\tilde{A}}(x)$: $R \rightarrow [0,1]$, which has the following characteristics[29]:

- $\mu_{\tilde{A}}(x)$ is the piecewise continuous function
- $\mu_{\tilde{A}}(x)$ is the convex fuzzy subset

Fuzzy number: In general, the FST uses triangular, trapezoidal or Gaussian fuzzy numbers to convert the uncertain numbers into fuzzy numbers[30]. Without loss of generality, Triangular Fuzzy Numbers (TFN) are often utilized to provide more precise descriptions and obtain more accurate results[31]. Thus, in this study, TFNs are used for representing probabilities of nodes in the FBN model.

A fuzzy number $\tilde{A}$ can be shown as:

$$\tilde{A} = (a, b, c)$$

where, $\tilde{A}$ is defined as a TFN and a, b and c are crisp numbers and $a \geq b \geq c$, so that a and c represent fuzzy probabilities between the lower and upper boundaries of evaluation information. A fuzzy number $\tilde{A}$ = (a, b, c) is called a TFN if its membership function is given by Eq. 1:

$$F(x) = \begin{cases} 0, & x \leq a \\ \frac{x-a}{b-a}, & a \leq x \leq b \\ 1, & x = b \\ \frac{c-x}{c-b}, & b \leq x \leq c \\ 0, & x \geq c \end{cases} \quad (1)$$

If assume two TFNs $\tilde{A}_1 = (a_1, b_1, c_1)$, $\tilde{A}_2 = (a_2, b_2, c_2)$ then mathematical operations are described as follows in Eq. 2:

$$\begin{aligned} &\tilde{A}_1 + \tilde{A}_2 = (a_1, b_1, c_1) \oplus (a_2, b_2, c_2) = (a_1 + a_2, b_1 + b_2, c_1 + c_2) \\ &\tilde{A}_1 - \tilde{A}_2 = (a_1, b_1, c_1) \Theta (a_2, b_2, c_2) = (a_1 - a_2, b_1 - b_2, c_1 - c_2) \\ &\tilde{A}_1 \times \tilde{A}_2 = (a_1, b_1, c_1) \otimes (a_2, b_2, c_2) = (a_1.a_2, b_1.b_2, c_1.c_2) \\ &\tilde{A}_1 \div \tilde{A}_2 = (\frac{a_1}{c_2}, \frac{b_1}{b_2}, \frac{c_1}{a_2}) \\ &k \times \tilde{A} = k \times (a, b, c) = (k.a, k.b, k.c) \end{aligned} \quad (2)$$

Fuzzy linguistic variable: The fuzzy linguistic variable is a variable with values as words or sentences in a natural language. It helps experts to evaluate the importance of the child node on its parents' with respect to other child nodes. In this study, a 5-point scale has been used (Table 1). Figure 3 shows linguistic variables used for determining the importance weight of each node on its parents.

Fuzzy Bayesian Network (FBN): A BN, also called a causal network or Bayesian belief network is a powerful tool for knowledge representation and reasoning under conditions of uncertainty[32]. This method is frequently applied in different aspects of science and engineering real world problems such as diagnosis, forecasting, automated vision, sensor fusion and manufacturing control[33]. It has been extended to other applications including software risk management[34], transportation[35], project scheduling[36], ecosystem and environmental management[37], new product development project assessment[38], risk analysis during tunnel construction[39], fall risk assessment of cantilever bridge projects[40], safety risk analysis in construction projects[41], safety and risk analysis of managed pressure drilling operation[42] and determination of safety integrity levels[43].

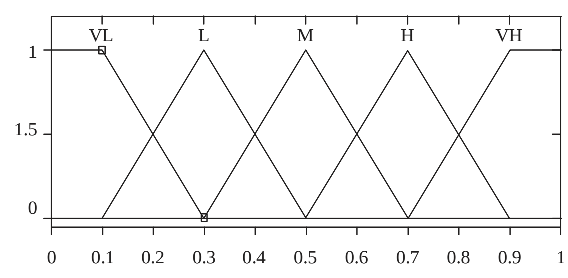

Fig. 3: Linguistic variables used in roof fall risk modelling

Table 1: Membership function of linguistic scale

Linguistic value	Fuzzy number
Very Low (VL)	0.0, 0.1, 0.3
Low (L)	0.1, 0.3, 0.5
Medium (M)	0.3, 0.5, 0.7
High (H)	0.5, 0.7, 0.9
Very High (VH)	0.7, 0.9, 1.0

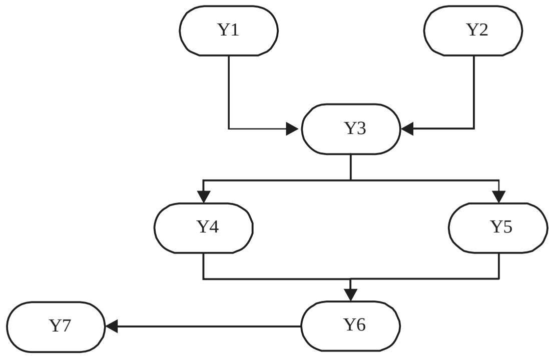

Fig. 4: A naive BN model

A BN has many advantages such as suitability for small and incomplete data sets, structural learning possibility, combination of different sources of knowledge, explicit treatment of uncertainty and support for decision analysis and fast responses[37].

Numerous uncertainties about roof fall items such as geological condition, mining parameters and stress condition make the roof fall analysis a complex issue. Uncertainty generally occurs for reasons including uniqueness (no similar experience) and variability and ambiguity (lack of clarity, data, structure and bias in estimates)[44]. One way to control the uncertainty of roof fall items is Bayesian belief networks. The BN is a combination of two different mathematical areas, namely graph theory and probability theory, which consists of a Directed Acyclic Graph (DAG) and an associated Joint Probability Distribution (JPD). A Bayesian belief network consists of qualitative and quantitative parts[45]. The qualitative part of a BN, the so-called structural learning is the graphical representation of independence holding among variables and has the form of a DAG that is popular in the statistics, machine learning and artificial intelligence societies. The quantitative part of a BN, the so-called parameter learning, finds dependence relations as joint conditional probability distributions among variables using cause and consequence relationships from the qualitative part and data of variables. The network is commonly represented as a graph, which is a set of nodes and arrows. The nodes represent the probabilistic variables and the arrows represent the causal relationships between these variables. Nodes, which are the starting ones and do not have an inward arrow are called the parent nodes. Other nodes, which have inward arrows connected to them are the child nodes. In order to run the calculations, it is necessary to define the states and probabilities for each node.

In a BN, for example as shown in Fig. 4, nodes without arcs directing into them and with no parents are root nodes (Y1 and Y2) having marginal prior probabilities assigned to them while nodes with arcs directing into them are intermediate nodes (Y3, Y4, Y5 and Y6), possessing Conditional Probability Tables (CPTs). Nodes such as Y7 with no children are leaf nodes[46]. Considering the DAG of Fig. 4, the JPD of the BN is the product of the conditional probability distributions of the variables Y1 = y1, Y2 = y2, . . . and Y7 = y7:

$$P(y_1, y_2, \ldots, y_7) = \prod_{i=1}^{7} P(y_i \mid y_{\text{Ø}(i)}) \tag{3}$$

where, Ø(i) in Eq. 3 are the parents of the node i in the DAG and y1, y2, . . . , y7 are the states of variables Y1, Y2, . . . , Y7. Thus, Eq. 4 gives the joint probability distribution of the BN in Fig. 4:

$$\begin{aligned} P(y_1, y_2, \ldots, y_7) = P(y_7 | y_6)\, P(y_6 | y_{4,} y_5) P(y_4 | y_3) \\ P(y_5 | y_3) P(y_3 | y_{1,} y_2) P(y_1) P(y_2) \end{aligned} \tag{4}$$

When constructing a BN model, researchers are faced with insufficient data relating to probabilities of root nodes. In the engineering practice, in the absence of sufficient data, it is necessary to study with rough estimates of probabilities[47]. Under such uncertain circumstances, it is considered inappropriate to use conventional BN to estimate the system failure probability. The FST offers an analysis frame that can deal with imprecision in input failure probabilities for the estimate of probability of the leaf root and such analysis is termed Fuzzy Bayesian Network (FBN).

With regard to the FBN, it is essential to choose the proper fuzzy probability measure as to conduct the fuzzy Bayesian inference. The fuzzy marginalization rule and fuzzy Bayesian rule can be calculated by Eq. 5 and 6, respectively. Here, T stands for the leaf root and Xi stands for the root nodes. Combing with Eq. 2, the FBN-based inference techniques can then be fulfilled:

$$P(T = t_j) = \sum_i P(X = x_i \otimes P(T = t_j | X = x_i) \tag{5}$$

$$P(X = x_j \mid T = t_j) = \left[P\,(X = x_i) \otimes P(T = t_j | X = x_i) \text{Ø} P(T = t_j) \right] \tag{6}$$

Proposed approach

Inputs: Various factors could affect the roof fall in underground mine projects. Table 2 shows the Common Cause (CC) items used in the last researches. One of the important matters in predicting the behavior of the rock mass

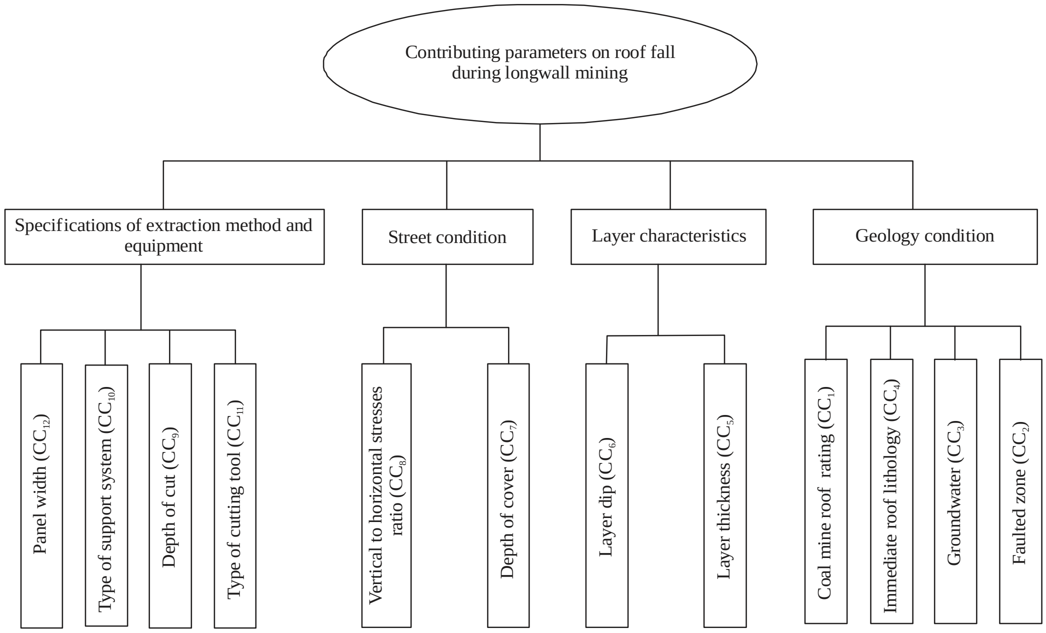

Fig. 5: Major contributing parameters on roof fall during longwall mining

Table 2: Common cause items used in the last researches

References	Parameters involved in model
Kidybinski[5]	Average roof rock strength
Unrug and Szwilski[6]	Roof quality index
Newman and Bieniawski[50]	Strata weatherability, high horizontal stresses and the roof support reinforcement factor
Molinda and Mark[7]	Groundwater, surcharge, rock strength, strong bed, discontinuities, spacing, cohesion, roughness, persistence, bedding contact and moisture sensitivity
Mark[8]	Entry with CMRR, cut depth and cover
Mark *et al.*[51]	Rock Quality Designation (RQD), Uniaxial Compressive Strength (UCS) and diametral point load testing
Deb[9]	ntersection diagonal span (IS), CMRR, primary roof support (PRSUP) and depth of mine
Duzgun and Einstein[2]	Injury, equipment damage, interruption and delay in operation and clean up
Palei and Das[3]	Number of bolts per row, anchorage strength of bolt, spacing between the bolts, width of gallery, mean rock density and Rock Mass Rating (RMR)
Palei and Das[10]	Width of gallery, Mining Height (MH), Depth of Cover (DOF), seam thickness, roof support status, immediate roof, face and specific
Ghasemi and Ataei[11]	CMRR, PRSUP, IS and DOF
Ghasemi *et al.*[12]	Geological, design and operational parameters
Razani *et al.*[13]	CMRR, DOF, MH, IS and PRSUP
Gao *et al.*[14]	Roadway geometery, matrix properties (density and E), contact properties (Kn and Ks), cohesion, friction and tensile strength
Oraee *et al.*[15]	structural data and the geometry and stability of wedges in underground coal mines

is to choose parameters with the highest effect on designing. Clearly, no single parameter can represent the behavior of the rock mass. Different parameters have different effects on the rock and only when combined together, can represent the behavior of the rock satisfactorily[48]. Regarding the fact that determining several parameters in the rock mass is difficult and partly impossible, methods or models need to be developed to simplify the real status of the environment[49].

In the present study, the most important factors affecting the roof fall at the longwall mine faces are divided into four groups (Fig. 5).

Model framework: The model employs a FBN methodology to conduct a causal analysis on important variables influencing the roof fall risk and provides probabilistic results which can improve our decisions. The schematic framework of the proposed model is portrayed in Fig. 6.

For constructing the model, first, the mining engineers are interviewed to establish the structure of the FBN model for the Roof Fall Risk (RFR). Then the logic diagram is subsequently used to build up the failure-consequence scenario from the top to bottom nodes using a DAG.

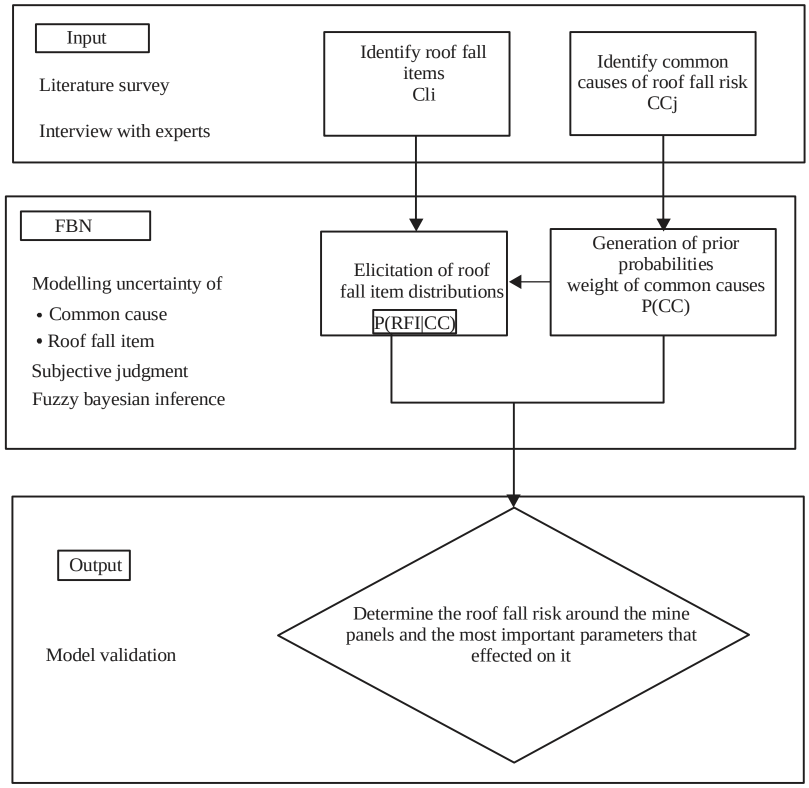

Fig. 6: A framework for using FBN roof fall risk analysis

Table 3: Descriptions of nodes in FBN model

		States				
Nodes	Descriptions	1	2	3	4	5
RFR	Roof fall risk	Very High	High	Moderate	Low	Very low
GC	Geology condition	Weak	Moderate	Good		
LC	Layer condition	Bad	Moderate	Good		
SC	Stress condition	High	Moderate	Low		
EM and E	Excavation method and equipment	Inadequate	Medium condition	Adequate		
CC_1	CMRR	CMRR<20	21<CMRR<40	41<CMRR<60	61<CMRR<80	81>CMRR
CC_4	Immediate roof lithology	Carbonized soft shale	Hard shale, weak sandstone	Sandstone or strong shale	Hard and thick sandstone or	Hard limestone or sandstone
CC_3	Water inflow	Flow	Seepage	Leakage	Wet	Dry
CC_2	Faulted zone (It)	>2.25	1.5-2.25	1-1.5	0.5-1	0.5>
CC_5	Dip	45-70	30-45	15-30	5-15	0-5
CC_6	Thickness	4.5<T<6	1.8<T<4.5	1.2<T<1.8	0.8<T<1.2	0.6<T<0.8
CC_7	Depth of cover	H>600	100<H<600	H<100		
CC_8	Vertical to horizontal stresses ratio	K>1	K = 1	K<1		
CC_{11}	Panel width	W>365	304<W<365	182<W<304	W<182	
CC_{10}	Type of support system	Frame	Chock	Shield	Chock shield	
CC_9	Cut depth	CD>1	0.5<CD<1	0.2<CD<0.5	CD<0.2	
CC_{12}	Cutting tool	Shearer	Pollow			

In accordance with what mentioned above, a FBN model is established (Fig. 7), where 12 root nodes contribute to the failure of the leaf node (roof fall risk). The descriptions and states of all nodes are illustrated in Table 3.

RESULTS

In order to validate the FBN based model, several steps by using data collected from the E2 panel of TCM was carried out. The first step is determining the prior probabilities of root

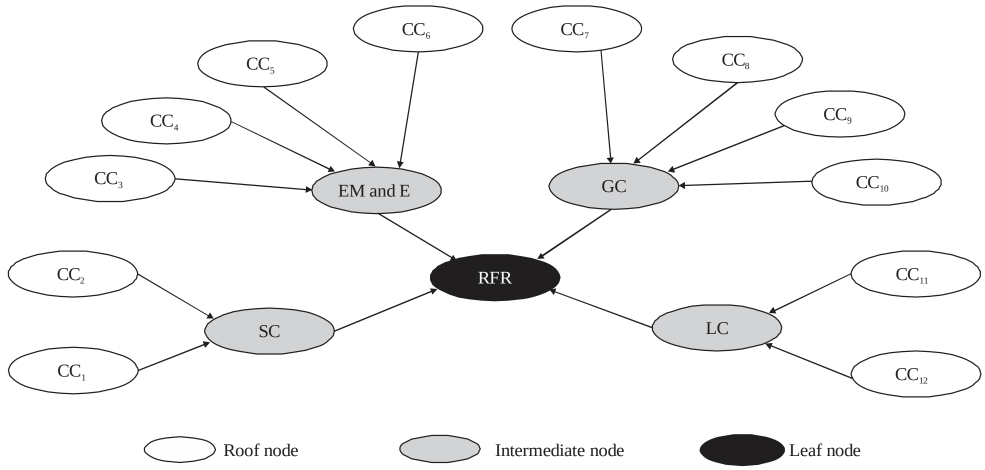

Fig. 7: Establish network model for RFR in longwall mining

Table 4: States of the root nodes in E2 panel zones

		Probability of variables in each state				
Common cause	Zone ID	S_1	S_2	S_3	S_4	S_5
CMRR	1	0	0	0	0	100
	2	0	70	30	0	0
	3	70	30	0	0	0
	4	80	20	0	0	0
	5	95	5	0	0	0
Fault zone	1	0	0	0	10	90
	2	0	0	0	20	80
	3	0	0	0	70	30
	4	0	70	30	0	0
	5	0	90	10	0	0
Water inflow	All zones	0	10	70	20	0
Immediate roof		0	70	30	0	0
Thickness		0	70	30	0	0
Dip		0	20	80	0	0
Depth of cover		0	100	0	-	-
K		100	0	0	-	-
Cut depth		0	10	70	20	-
Type of support		0	0	100	0	-
Panel width		0	0	100	0	-
Cutting tools		1	0	0	0	-

nodes. To do this, the panel was divided into zones. Zoning was done based on the changes in one of the geological parameters like the immediate roof, the faulted zone condition and the like. Then, the geology maps and data related to mining equipment are used to determine the prior probability of root nodes (CC_1-CC_{12}). The states of the root nodes in different zones are illustrated in Table 4.

Determining the Conditional Probability Table (CPT) of intermediate and leaf nodes is the next step. In this research, weighted sum algorithm proposed by Das[52] was used to populate the CPT. The input to the algorithm consists of a set of weights that quantifies the relative strengths of the influences of the parent-nodes on the child-node and a set of probability distributions over the child node for compatible parental configurations. These are elicited from the domain expert. So, to populate the CPTs a questionnaire was distributed among experts. The questionnaire asked the experts to express the relative weight of parental nodes on the child nodes using the linguistic variables presented in Table 1. The experts' opinions were integrated by using Eq. 3. Finally the integrated linguistic variables were defuzzified by using the best non fuzzy performance (BNP) method. The BNP value of the fuzzy number $\tilde{R}_i$ can be found using the Eq. 7:

$$BNP_i = \frac{\left[(UR_i - LR_i) + (MR_i - LR_i) \right]}{3} + LR_i \quad (7)$$

Table 5: Relative weight of parent's nodes

Child node	Parent node	Relative weight
Geology condition	CMRR	0.34
	Immediate roof lithology	0.27
	Groundwater	0.09
	Fault zone	0.30
Layer condition	Dip	0.62
	Thickness	0.38
Stress condition	Depth of cover	0.49
	Vertical to horizontal stresses ratio	0.51
Excavation method and equipment	Panel width	0.13
	Type of support system	0.30
	Depth of cut	0.37
	Cutting tool	0.20
Roof fall risk	Geology condition	0.45
	Layer condition	0.08
	Stress condition	0.37
	Excavation method and equipment	0.10

Table 6: Fuzzy JPD of the leaf node (RFR) in FBN model under zone No. 5 condition

	States			$P(RFR = s \mid GC = g_i, LC = l_i, EM\ and\ E = E_i, GC = g_j, SC = s_i)$				
Parents nodes	1	2	3	s = VH	s = H	s = M	s = L	s = VL
GC	0.45	0.06	0.06	0.109	0.045	0.032	0.024	0.037
	0.60	0.20	0.18					
	0.72	0.38	0.35					
LC	0.21	0.10	0.13	0.257	0.177	0.16	0.151	0.185
	0.38	0.29	0.34					
	0.57	0.51	0.64					
EM and E	0.11	0.04	0.44					
	0.23	0.16	0.59					
	0.38	0.33	0.72					
SC	0.33	0.26	0.01	0.516	0.423	0.431	0.437	0.483
	0.48	0.41	0.09					
	0.60	0.54	0.23					

The relative weight of the parent nodes are obtained and given in Table 5. Then the experts were asked to answer the following question using the linguestic variables from Table 1. Given the parental configuration {Comp $\left(Y_i = y_i^{s_i}\right)$}, what should be the probability distribution over the states of the child X?

In other words, we seek distributions of the type in Eq. 8:

$$\left\{P\left(x^0 \mid \left\{Comp(Y_i = y_i^{s_i})\right\}\right), P\left(x^1 \mid \left\{Comp(Y_i = y_i^{s_i})\right\}\right), \ldots, P\left(x^m \mid \left\{Comp\left(Y_i = y_i^{s_i}\right)\right\}\right)\right\},$$
$$1 \le i \le n,\ 1 \le s_i \le k_i \tag{8}$$

where, X is the child node and has states (x^0, x^1, ..., x^n) and Y_i are the parent's nodes which have states $\{y_i^1, y_i^2, y_i^{ki}\}$.

Finally, Eq. 9 was used to complete the CPTs:

$$P\left(x^1 \mid y_1^{s_1}, y_2^{s_2}, \ldots, y_n^{s_n}\right) = \sum_{j=1}^{n} w_j P\left(x^1 \mid \left\{Comp(Y_j = y_j^{s_j})\right\}\right),$$
$$l = 0, 1, \ldots, m \text{ and } s_j = 1, 2, \ldots, k_j \tag{9}$$

where, W_j is the relative weight of the node j.

The final aim of this study is to calculate the probability distribution in risk event under the combination of or root nodes, i.e., CC_1, CC_2,$\cdots$ and CC_{12}. In order to obtain this goal, in each zone the state of risk factors were treated as evidence input into a FBN model. As an example, the fuzzy JPD of the RFR node under the zone condition No. 5 is presented in Table 6.

At the end, for different zones the CPT of leaf node (RFR) was calculated and defuzzfied using Eq. 7. The correlation between the RFR values and values of the extraction rate in E2 panel can prove the reliability of the FBN model. Higher extraction rate shows lower roof fall risks and better studying conditions. In this study, the parameter R is

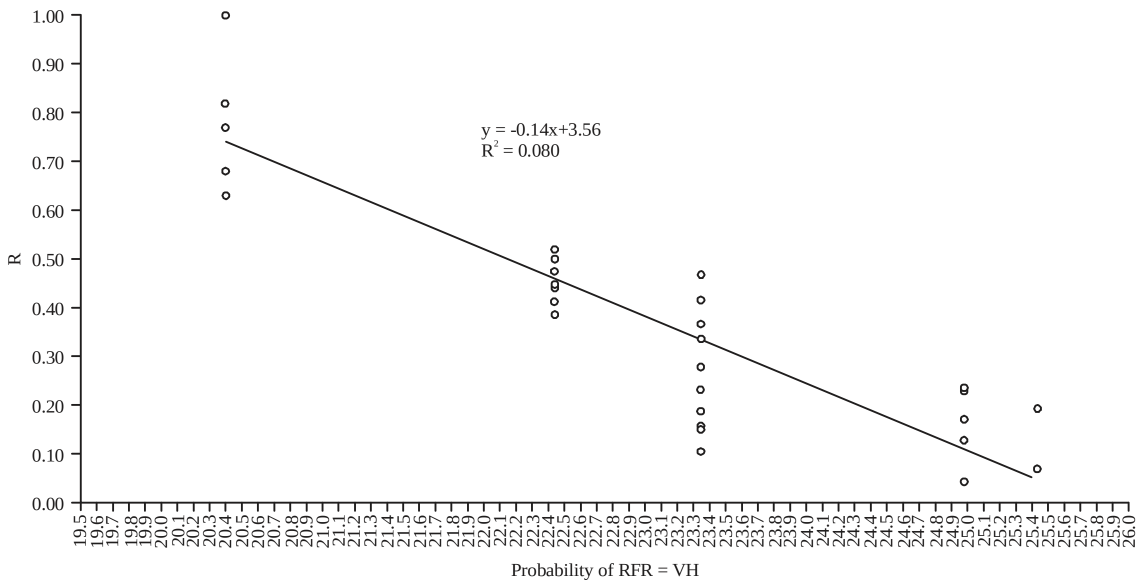

Fig. 8: Relation between RFR in VH state and R, a linear regression analysis

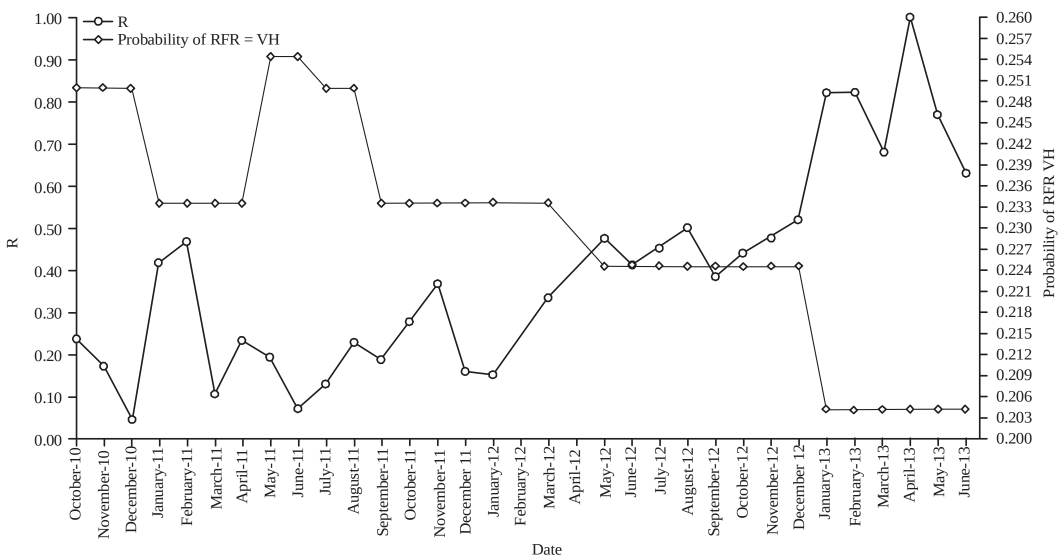

Fig. 9: Compatibility rate of the RFR in VH state with the R parameter

defined for determining the relation between the risk values and extraction rate. The extraction efficiency (R) is calculated from Eq. 10:

$$R = \frac{\text{Extraction rate}}{\text{Maximum extraction rate}} \times 100 \quad (10)$$

The relation between the RFR in VH state and extraction efficiency in the E2 panel is shown in Fig. 8. Also, the compatibility rate of the RFR values with the R is shown in Fig. 9.

DISCUSSION

Development of a methodology for analyzing the roof fall risk has a remarkable role on mine safety. Factors like the geological and stress conditions, mine layout and configuration contribute to occurrences of roof falls[4]. In the last studies, it has been tried to find the relationship between the roof fall and contributing parameters. Clearly, no single parameter can represent the behavior of the roof. In addition, only when different parameters combined together, can represent the behavior of the rock satisfactorily[48]. Also, last studies show there are no doubt that the condition of a mine roof can be better expressed by using fuzzy set theory rather than traditional set theory[9]. For this reason, some studies are done using fuzzy sets in the field of risk assessment in underground coal mining[9,11,13,53,54].

Another major problem in risk evaluation arises from the complexity and uncertainty of contributing parameters. One of the ways to overcome the problems like this is using a Bayesian network based model. Bayesian belief networks was developed for knowledge representation and reasoning under conditions of uncertainty. This approach has the wide application in the any phases of the risk analysis[34,39-42].

Considering the problems mentioned in the context of risk analysis, a new methodology was proposed, integrating the inference process of Bayesian networks and fuzzy set theory. The main advantage of this approach is considering all effective parameters on roof fall under uncertainty condition. Another advantage of FBN model is its possible utilization in new coal field where enough experience and data are not available.

CONCLUSION

The complex nature of geological condition and variability of mining configuration lead to the occurrence of roof falls. The presented approach was a probabilistic methodology of risk analysis which developed based on fuzzy Bayesian network model. This methodology can simultaneously take into account both the complexity and inherent uncertainty associated with the roof fall problems. Application of the proposed methodin Tabas coal mine show that the FBN based model is a powerful technique for coping with uncertainties and evaluating the roof fall risk at longwall face.

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REFERENCES

1. Molinda, G.M., C. Mark and D.R. Dolinar, 2000. Assessing Coal Mine Roof Stability Through Roof Fall Analysis. In: Proceedings, New Technology for Coal Mine Roof Support, NIOSH (Ed.). National Institute for Occupational Safety and Health, USA., pp: 53-72.
2. Duzgun, H.S.B. and H.H. Einstein, 2004. Assessment and management of roof fall risks in underground coal mines. Safety Sci., 42: 23-41.
3. Palei, S.K. and S.K. Das, 2008. Sensitivity analysis of support safety factor for predicting the effects of contributing parameters on roof falls in underground coal mines. Int. J. Coal Geol., 75: 241-247.
4. Duzgun, H.S.B., 2005. Analysis of roof fall hazards and risk assessment f or Zonguldak coal basin underground mines. Int. J. Coal Geol., 64: 104-115.
5. Kidybinski, A., 1977. Roof rock stability tests and powerd support selection systems for longwalls. USDI/CMI Joint Research Project No. 14-01-0001-1450, Report No. 2, State-of-the-Art Report.
6. Unrug, K.F.D.A. and A.B.D.A. Szwilski, 1980. Influence of strata control parameters on longwall mining design. Proceedings of the 21st US Symposium on Rock Mechanics (USRMS), May 27-30, 1980, Rolla, Missouri.
7. Molinda, G.M. and C. Mark, 1994. Coal Mine Roof Rating (CMRR): A Practical Rock Mass Classification for Coal Mines. U.S. Dept. of Interior, Bureau of Mines, USA., Pages: 83.
8. Mark, C., 1999. Application of the Coal Mine Roof Rating (CMRR) to extended cuts. Min. Eng., 51: 52-55.
9. Deb, D., 2003. Analysis of coal mine roof fall rate using fuzzy reasoning techniques. Int. J. Rock Mech. Mining Sci., 40: 251-257.
10. Palei, S.K. and S.K. Das, 2009. Logistic regression model for prediction of roof fall risks in bord and pillar studyings in coal mines: An approach. Safety Sci., 47: 88-96.
11. Ghasemi, E. and M. Ataei, 2013. Application of fuzzy logic for predicting roof fall rate in coal mines. Neural Comput. Applic., 22: 311-321.
12. Ghasemi, E., M. Ataei, K. Shahriar, F. Sereshki, S.E. Jalali and A. Ramazanzadeh, 2012. Assessment of roof fall risk during retreat mining in room and pillar coal mines. Int. J. Rock Mech. Min. Sci., 54: 80-89.
13. Razani, M., A. Yazdani-Chamzini and S.H. Yakhchali, 2013. A novel fuzzy inference system for predicting roof fall rate in underground coal mines. Safety Sci., 55: 26-33.
14. Gao, F., D. Stead and H. Kang, 2014. Simulation of roof shear failure in coal mine roadways using an innovative UDEC Trigon approach. Comput. Geotechnics, 61: 33-41.
15. Oraee, K., N. Oraee, A. Goodarzi and P. Khajehpour, 2016. Effect of discontinuities characteristics on coal mine stability and sustainability: A rock fall prediction approach. Int. J. Min. Sci. Technol., 26: 65-70.
16. Anonymous, 2005. Basic design of tabas coal mine project. Report-Mining, Vol. 1-5.
17. Zadeh, L.A., 1965. Fuzzy sets. Inform. Control, 8: 338-353.
18. Arunraj, N.S., S. Mandal and J. Maiti, 2013. Modeling uncertainty in risk assessment: An integrated approach with fuzzy set theory and Monte Carlo simulation. Accident Anal. Prevention, 55: 242-255.

19. Anagnostopoulos, K., H. Doukas and J. Psarras, 2008. A linguistic multicriteria analysis system combining fuzzy sets theory, ideal and anti-ideal points for location site selection. Exp. Syst. Applic., 35: 2041-2048.
20. Sylaios, G., F. Bouchette, V.A. Tsihrintzis and C. Denamiel, 2009. A fuzzy inference system for wind-wave modeling. Ocean Eng., 36: 1358-1365.
21. Khatibi, V. and G.A. Montazer, 2010. A fuzzy-evidential hybrid inference engine for coronary heart disease risk assessment. Exp. Syst. Applic., 37: 8536-8542.
22. Yagiz, S. and C. Gokceoglu, 2010. Application of fuzzy inference system and nonlinear regression models for predicting rock brittleness. Exp. Syst. Applic., 37: 2265-2272.
23. Malinowska, A., 2011. A fuzzy inference-based approach for building damage risk assessment on mining terrains. Eng. Struct., 33: 163-170.
24. Alidoosti, A., M. Yazdani, M.M. Fouladgar and M.H. Basiri, 2012. Risk assessment of critical asset using fuzzy inference system. Risk Manage., 14: 77-91.
25. Fouladgar, M.M., A. Yazdani-Chamzini and E.K. Zavakdskas, 2012. Risk evaluation of tunneling projects. Arch. Civil Mech. Eng., 12: 1-12.
26. Petrovic, D.V., M. Tanasijevic, V. Milic, N. Lilic, S. Stojadinovic and I. Svrkota, 2014. Risk assessment model of mining equipment failure based on fuzzy logic. Expert Syst. Applic., 41: 8157-8164.
27. Kusi-Sarpong, S., C. Bai, J. Sarkis and X. Wang, 2015. Green supply chain practices evaluation in the mining industry using a joint rough sets and fuzzy TOPSIS methodology. Resour. Policy, 46: 86-100.
28. Mohammadi, M., M.F. Hossaini, B. Mirzapour and N. Hajiantilaki, 2015. Use of fuzzy set theory for minimizing overbreak in underground blasting operations-A case study of Alborz Tunnel, Iran. Int. J. Min. Sci. Technol., 25: 439-445.
29. Chang, B., C.W. Chang and C.H. Wu, 2011. Fuzzy DEMATEL method for developing supplier selection criteria. Expert Syst. Appl., 38: 1850-1858.
30. Abbasbandy, S. and T. Hajjari, 2010. Weighted trapezoidal approximation-preserving cores of a fuzzy number. Comput. Math. Applic., 59: 3066-3077.
31. Li, P.C., G.H. Chen, L.C. Dai and L. Zhang, 2012. A fuzzy Bayesian network approach to improve the quantification of organizational influences in HRA framestudys. Safety Sci., 50: 1569-1583.
32. Cheng, J., D.A. Bell and W. Liu, 1997. Learning belief networks from data: An information theory based approach. Proceedings of the 6th International Conference on Information and Knowledge Management, November 10-14, 1997, Las Vegas, NV., USA., pp: 325-331.
33. Heckerman, D., A. Mamdani and M.P. Wellman, 1995. Real-world applications of Bayesian networks. Commun. ACM., 38: 24-26.
34. Fan, C.F. and Y.C. Yu, 2004. BBN-based software project risk management. J. Syst. Software, 73: 193-203.
35. Ulengin, F., S. Onsel, Y.I. Topcu, E. Aktas and O. Kabak, 2007. An integrated transportation decision support system for transportation policy decisions: The case of Turkey. Transp. Res. Part A: Policy Pract., 41: 80-97.
36. Khodakarami, V., N. Fenton and M. Neil, 2007. Project scheduling: Improved approach to incorporate uncertainty using bayesian networks. Proj. Manage. J., 38: 39-49.
37. Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Modell., 203: 312-318.
38. Chin, K.S., D.W. Tang, J.B. Yang, S.Y. Wong and H.W. Wang, 2009. Assessing new product development project risk by Bayesian network with a systematic probability generation methodology. Expert Syst. Applic., 36: 9879-9890.
39. Sousa, R.L. and H.H. Einstein, 2012. Risk analysis during tunnel construction using bayesian networks: Porto metro case study. Tunnelling Underground Space Technol., 27: 86-100.
40. Chen, T.T. and S.S. Leu, 2014. Fall risk assessment of cantilever bridge projects using Bayesian network. Safety Sci., 70: 161-171.
41. Zhang, L., X. Wu, M.J. Skibniewski, J. Zhong and Y. Lu, 2014. Bayesian-network-based safety risk analysis in construction projects. Reliabil. Eng. Syst. Safety, 131: 29-39.
42. Abimbola, M., F. Khan, N. Khakzad and S. Butt, 2015. Safety and risk analysis of managed pressure drilling operation using Bayesian network. Safety Sci., 76: 133-144.
43. Cai, B., Y. Liu and Q. Fan, 2016. A multiphase dynamic Bayesian networks methodology for the determination of safety integrity levels. Reliabil. Eng. Syst. Saf., 150: 105-115.
44. Khodakarami, V. and A. Abdi, 2014. Project cost risk analysis: A Bayesian networks approach for modeling dependencies between cost items. Int. J. Proj. Manage., 32: 1233-1245.
45. Van Der Gaag, L.C., 1996. Bayesian belief networks: Odds and ends. Comput. J., 39: 97-113.
46. Nielsen, T.D. and F.V. Jensen, 2009. Bayesian Networks and Decision Graphs. Springer Science and Business Media, USA.
47. Liu, H.T. and Y. Tsai, 2012. A fuzzy risk assessment approach for occupational hazards in the construction industry. Saf. Sci., 50: 1067-1078.
48. Bieniawski, Z.T., 1984. Rock Mechanics Design in Mining and Tunnelling. Balkema Publishing Co., Rotterdam.
49. Canbulat, I. and T. Dlokweni, 2002. Rating system for coal mine roofs. Safety in Mine Research Advisory Committee, COL 812, September, 2002, pp: 1-82.
50. Newman, D.A. and Z.T. Bieniawski, 1985. A modified version of the geomechanics classification for entry design in underground coal mines. Proceedings of the Society of Mining Engineers Fall Meeting, October 16, 1985, Albuquerque, NM., USA.

51. Mark, C., G.M. Molinda and T.M. Barton, 2002. New developments with the coal mine roof rating. Proceedings of the 21st International Conference on Ground Control in Mining, August 6-8, 2002, Morgantown, WV., pp: 294-301.
52. Das, B., 2004. Generating conditional probabilities for Bayesian networks: Easing the knowledge acquisition problem. arXiv Prepr. cs/0411034.
53. Nie, B.S., P.F. Zhao, J.H. Guo, P.P. Niu and G. Wang, 2012. Fuzzy comprehensive evaluation of coal mine safety investment structure based on the M(1,2,3) model. Energy Procedia, 16: 592-597.
54. Wang, Q., H. Wang and Z. Qi, 2016. An application of nonlinear fuzzy analytic hierarchy process in safety evaluation of coal mine. Saf. Sci., 86: 78-87.