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Scenario analysis of mine water inrush hazard using Bayesian networks

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ABSTRACT

Mine water inrushes involve in many unidentified or new risk factors due to the complex hydrogeological features arising with the increasing mining depth. This creates a higher level of complexity for disaster preparedness and leads to great difficulty in evaluating the hazard evolution and performing disaster response. This paper presented a framework using the Scenario Analysis methodology combined with the Bayesian networks for evaluating the probability of the occurrence of mine water inrush accident. Based on cases study of typical mine water inrush accidents and expert judgment, twelve scenario elements of four types for representing mine water inrush evolution were proposed and classified with different states. On the basis of the twelve classified scenario elements, the Bayesian network of mine water inrush was constructed. Through setting up different state combinations of the scenario elements, various probabilities of four mine water inrush scenarios including typical ones and catastrophically serious ones were calculated and analyzed. The proposed framework for evaluating the probabilities of the occurrence of mine water inrushes could be helpful to establish a "Scenario-Response" based disaster response strategy for mine water inrushes.

1. Introduction

With the increasing depths of mines, the hydrogeological features have become more complicated, and there has been a high frequency occurrence of mine water inrush disasters, especially in China. According to the accident record of State Administration of Work Safety, China, there had been totally 482 coal mine water inrush accidents from July, 2000 to June, 2015, which caused 2722 deaths. In the past decades, a lot of research work have been put on studying mine water inrush problems, mostly focusing on investigating the vulnerability and prediction of mine water inrushes through empirical coefficients, mathematical methods like the geographic information system (GIS), the analytic hierarchy process (AHP), the attribute mathematical theory and the artificial neural network (ANN) (Duan, 2003; Wu et al., 2011, 2015; Dong et al., 2012; Li et al., 2015), and studying the mechanisms of water inrushes (groundwater seepage, flow-stress-damage, etc.) based on physical experiments, numerical simulations or field measurements (Li et al., 2011; Bai et al., 2013; Zhang et al., 2014; Yin et al., 2015). However, few studies have been conducted on evaluating the inundation risk after water inrush (Li et al., 2013), which is very important for disaster preparedness and particularly of significance for disaster risk reduction decision-making at the time of disaster response.

Due to the complex hydrogeological features that arise with the increasing mining depth, mine water inrush hazards show more characteristics of unconventional emergencies and involve in many new or unidentified risk factors like the magnitude uncertainties (volume, impurity, pressure, initiated hydrogen sulphide, etc.), which could not be foreseeable at the disaster preparedness level. This creates a higher level of complexity and leads to great difficulty in evaluating the disaster evolution due to the lack of accurate accident information and similar experience. Therefore, the traditional "Preparedness-Response" disaster response strategy would not be a good choice that can successfully predict and deal with the mine water inrush hazard. For the variable uncertainties of water inrush hazard, new approaches are required. The Scenario Analysis methodology can be an alternative tool. Scenario Analysis was firstly used in military strategic planning, and has been successfully applied in many fields, such as environment (Tourki et al., 2013; Brown and Castellazzi, 2014; Wang and Yu, 2015), and economics (Ehlen and Vargas, 2013; Bateman et al., 2014). In recent years, the idea of scenario analysis has been applied to evaluate emergency strategies and disaster risk (Thulke et al., 2008; Zhang and Liu, 2012; Lv et al., 2013; Davies et al., 2015).

In this paper, the Scenario Analysis methodology combined with the Bayesian Network (BN) is used to analyze mine water

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inrushes and evaluate the risk of hazard evolvement. At first, a Bayesian network of mine water inrush hazard was built by cases study of typical coal mine water inrush accidents and expert judgement, which ensure that the Bayesian network has a good universality, and then the scenario analysis and probability evaluation of water inrush accidents with a variety of hazard uncertainties and risk factors were performed based on the proposed Bayesian network. The first run of risk parameters and results could be applied to a further scenario analysis of accident evolvement of mine water inrush. The proposed framework is helpful to establish a "Scenario-Response" based disaster response strategy, which would be an effective way to cope with mine water inrushes.

2. Method

2.1. Scenario analysis

The word of "Scenario" was firstly proposed in 1967, which put forward that the scenario is a description of a future situation and a transform tendency of the event from original state to future (Kahn and Wiener, 1967). Afterwards, many researchers devoted to the definition of scenario, and there are two main consistent conceptions of scenario: (1) Scenario is a rational description of the future evolution of event; (2) Scenario is not a simple imagination or prediction, it is a projection of event with credible, possible and relevant features (Schnaars, 1987; Tucker, 1999). According to the conception of the scenario, scenario analysis is considered to be a research process to create a series of possible "story" of future. Scenario analysis method was firstly improved as a qualitative method, but at present many quantitative methods have been combined to Scenario Analysis. In this paper, the BN and Dempster-Shafer theory are used to address quantitative scenario analysis. The main step of scenario analysis could be concluded as follows (Punjabi, 2005):

(a) Recognize the driving forces of the system. The first step of Scenario analysis is to identify the driving forces of the system. The driving forces are main factors to develop a comprehensive understanding of the system. The driving forces are collected by the interview experts who have the related knowledge.
(b) Classify the driving force into two kinds, i.e. probable trends and uncertainties. The classification of driving forces is also based on expertise judgement. The uncertainties of the system play an important role in subsequent scenario deduction.
(c) Develop scenarios based on the outcomes of uncertainties. The final step of scenario analysis is to build the scenario Bayesian network and improve it based on the information collected by the interview.

2.2. Bayesian networks

BN is an inferential model based on probability analysis and graphical theory. Conceptually, Bayesian network is a Directed Acyclic Graph (DAG), which is composed of nodes and directed edges, and it is a representative method to deal with problems focusing on illustrating relationship among a variety of variables. Using BN to analyze the uncertainties of engineering problems has recently draw considerable attention (Weber et al., 2012; Zhao et al., 2012; Khakzad et al., 2013; Cárdenas et al., 2014).

Fig. 1 is a simple model of BN. The arcs between Bayesian nodes represent cause-effect relationship between them. There are two types of nodes in Bayesian network. The nodes with links directed to them are called child node, while the nodes with edges depart to child nodes are called parent nodes. In Fig. 1, X_1 is the parent nodes of X_2 and X_3, also X_2 and X_3 are the parent nodes of X_4. The Bayesian network is a representation of the joint distribution over all the variables represented in the DAG. The joint probability distribution of a set of variables, based on their conditional independence, can be obtained as

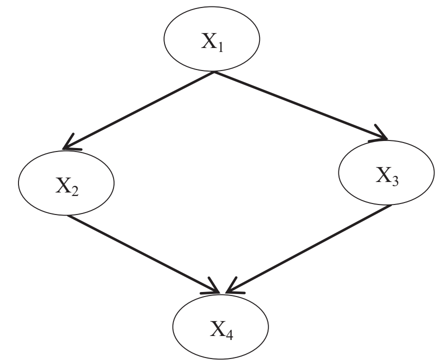

Fig. 1. Sample of Bayesian network.

$$P(S_1, S_2, \ldots, S_n) = \prod_{1}^{n} P(S_i/\mathrm{Pa}(S_i)) \quad (i = 1, 2 \ldots n) \tag{1}$$

where $\{S = S_1, S_2, \ldots S_n\}$ represent a set of variables, consisting of the nodes of BN. The marginal and the conditional probabilities can be computed for each node of the network based on the joint probability.

There are generally three ways to develop BN: (a) data learning, which is a popular way based on a large amount of statistical data; (b) taking advantage of expert knowledge, which is mostly for the cases in absence of historical data; (c) the combination of statistical data learning and expert judgement. For the kinds of phenomena or events that are with extreme circumstances or pretty new lacking of enough statistical data, it is suitable (or required) to employ expert judgement to develop the BN. Experiences show that expert judgement is a required and credible tool to develop BN structure and node conditional probabilities for the events in absence of statistical data (Trucco et al., 2008; Nordgard and Sand, 2010; Zhao et al., 2012).

BN is a good method for predicting inference. The calculating process of predicting inference using BN is dependent on Conditional Probability Table (CPT), which is generally obtained from statistical data or collected by experts' opinion. Taking X_4 as an example, if there are two states of each node in Fig. 1, the CPT of X_4 is shown in Table 1.

In this case, the probability of X_2 and X_3 can be calculated by CPT. By setting the state of X_1, the probability of X_4 can be calculated by Eq. (2):

$$P(X_4/X_1) = P(X_4/X_3, X_2)P(X_3/X_1)P(X_2/X_1) \tag{2}$$

where $P(X_2/X_1)$ and $P(X_3/X_1)$ is given in its CPT.

This paper is a typical application of predicting inference using BN. The inference engine of jtree_inf_engine(bnet) in Matlab BNT toolbox is employed to estimate various probabilities of mine water inrushes.

Table 1
Example of CPT of X_4 in Fig. 1.

	X_2	State 1		State 2	
	X_3	State 1	State 2	State 1	State 2
X_4	State 1	0.8	0.6	0.65	0.55
	State 2	0.2	0.4	0.35	0.45