Mine Water Environ (2017) 36:217–225
DOI 10.1007/s10230-017-0431-y

TECHNICAL ARTICLE

Prediction Reliability of Water Inrush Through the Coal Mine Floor

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Received: 17 June 2015 / Accepted: 18 January 2017 / Published online: 16 February 2017

Abstract Inrush of Ordovician limestone karst water through the mine floor occurs frequently in the Carboniferous-Permian coalfield in northern China. A probability index method was proposed to predict water inrushes using five indices: an aquifer water-bearing index, a structural index, an aquifuge index, an aquifer water pressure index, and an underground pressure index. Expert input was used to obtain weights for these five factors. Expert evaluation and statistical probability were then used to determine weights of the subsidiary factors, allowing the calculation of a water inrush probability index (*I*) and a threshold water inrush value for the Feicheng coalfield of 0.65. The Dempster-Shafer evidence theory was then used to determine a 74% degree of confidence for this prediction. Finally, the method was applied to the No. 9901 working face of the Taoyang coal mine. A subsequent 1,083 m^3/h water inrush that occurred there aligned with the statistical results.

Keywords Feicheng coalfield · Water inrush probability index · Multi-attribute decision · D-S evidence theory · Decision making model

Electronic supplementary material The online version of this article (doi:10.1007/s10230-017-0431-y) contains supplementary material, which is available to authorized users.

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Introduction

Northern China's Carboniferous-Permian coalfield is widely distributed in Shanxi, Hebei, Shandong, Henan, Jiangsu, Anhui, and Shaanxi provinces. The coalfield has a total area of about 727,600 km^2 and accounts for 60% of China's total coal resources. However, since the shallower seams are mostly depleted, deeper Carboniferous seams are now being mined. Complications arise because the geological structure is complex, the aquifuge is thin, and the underlying Ordovician limestone contains large quantities of water under high pressure. As a result, karst water inrush events occur frequently. In the past 40 years, over 200 Ordovician limestone karst water inrushes have occurred in the North China coalfield, causing more than 1300 deaths and 30 billion yuan in economic losses (Shi et al. 2015).

Prediction of water inrush events above confined aquifers and development of decision-making technology has long been a significant research topic in China. The traditional method of solving the problem is to use the water inrush coefficient (Ministry of Coal Industry 2009), an empirical parameter defined as the ratio between the water pressure of the aquifer and the aquifuge thickness (Wu et al. 2011). However, the water inrush coefficient method only considers those two factors, thus oversimplifying the complicated water inrush mechanisms.

With the development of computer technology, artificial intelligence technology has been widely used in various aspects of water science (Donglin et al. 2012; Valipour 2014, 2015a, b; Valipour et al. 2012, 2013; Valipour and Montazar 2012a, b; Wu and Zhou 2008; Wu et al. 2011). The Bayesian network (Donglin et al. 2012), the analytic hierarchy process (Wu et al. 2011), the artificial neural network (Wu et al. 2008), the multi-source information theory (Wu and Zhou 2008), and support vector machines (Shi et al. 2014) have all been applied to water inrush prediction. These methods consider many factors that may affect the water inrush processes, but just assess the probability that a water inrush will occur, and not the reliability of the results.

In this study, we introduced a decision-making method for predicting water inrush from the mine floor based on the water inrush probability index method and the Dempster–Shafer (D–S) evidence theory, and applied it to the Feicheng coalfield. The water inrush probability index method was proposed to assess the probability of floor water inrush. The D–S evidence theory was used to determine the reliability of the decision making.

Study Area

The Feicheng coalfield is situated in northern China and covers an area of about 120 km^2. It is one of the leading producers of coal in the Shandong province and produces about 7,700,000 t of coal annually. There are seven coal mines in the Feicheng coalfield, the: Yangzhuang, Caozhuang, Dafeng, Taoyang, Baizhuang, Guozhuang, and Chazhuang coal mines (Fig. 1).

The lithology in the study area (Fig. 2) consists of Ordovician (O), Carboniferous (C), Permian (P), Triassic (T), Paleogene (E), and Quaternary (Q) strata. The coal-bearing strata in the Feicheng coalfield belong to the Permian-Carboniferous system. There are 9 minable coal seams: the No. 3, 4, 5, 6, 7, 8, 9, and 10 coal seams. All of these seams are mined by the longwall method and all of the mines in this coalfield are threatened by water inrush from underlying confined limestone aquifers, including the Carboniferous Taiyuan formation and the confined Ordovician limestone aquifer. The Ordovician limestone, which unconformably underlies the Benxi formation, is the major threat. During exploitation of these seams in the 7 coal mines, 180 cases of water inrush from the floor strata have occurred (see supplemental table 1); about 76% of these from the Ordovician aquifer.

Main Factors of the Floor Water Inrush Decision-Making Model

After studying a large number of water inrush events in the Feicheng coalfield, we selected five main factors that significantly affect water inrush, the: aquifer water-bearing index, structure index, aquifuge index, aquifer water pressure index, and underground pressure index. These terms are defined below.

The Aquifer Water-Bearing Index

The aquifer water-bearing property refers to the productivity (quantity and duration) of the aquifer, which is a key factor in coal floor water inrush (Li and Chen 2016). Based on hydrological data and the regional geological analysis, the water source of most of the water inrush events in the Feicheng coalfield is the confined Ordovician limestone aquifer, which is about 800 m thick. The aquifer's water-bearing property is divided into four categories by the unit water inflow of drilling (q), according to the Regulations for Mine Water Prevention and Control (Ministry of Coal Industry 2009): the first class is the weakest, with $q \leq 0.1$ L (s·m); the second is weakly water-bearing, with $0.1 < q \leq 1.0$ L (s·m); the third is strongly water-bearing with $1.0 < q \leq 5.0$ L (s·m), and; the fourth class is strongest, with $q > 5.0$ L (s·m). The unit water inflow was obtained by conducting pumping tests. The Feicheng coalfield was then divided into four areas by the unit water inflow (Fig. 1). A case history analysis of water inrush events has indicated that most water inrushes are confined to the areas associated with the strong and strongest water-bearing areas.

The Structural Index

The geological structure is very closely related to water inrush. The coalfield is mainly controlled by fault structures; minor structures like small folds only influence the local area. In general, the structural outline of this coalfield belongs to the monoclinic structural type; the strata strikes in the NNE direction and dips 8°–20° to the north. There are four sets of faults in the inner region, with strikes to the NW, NE, NNE, and ENE, dividing the coalfield into fault blocks of different sizes (Fig. 1). Faults and the associated fractures make up the two main subsidiary factors of the structural index. The water inrush pathway is either a fault or a fracture, with folds having a negligible influence.

The Aquifuge Index

An aquifuge acts as a geologic barrier that prevents water in the underlying confined aquifer from bursting into mines

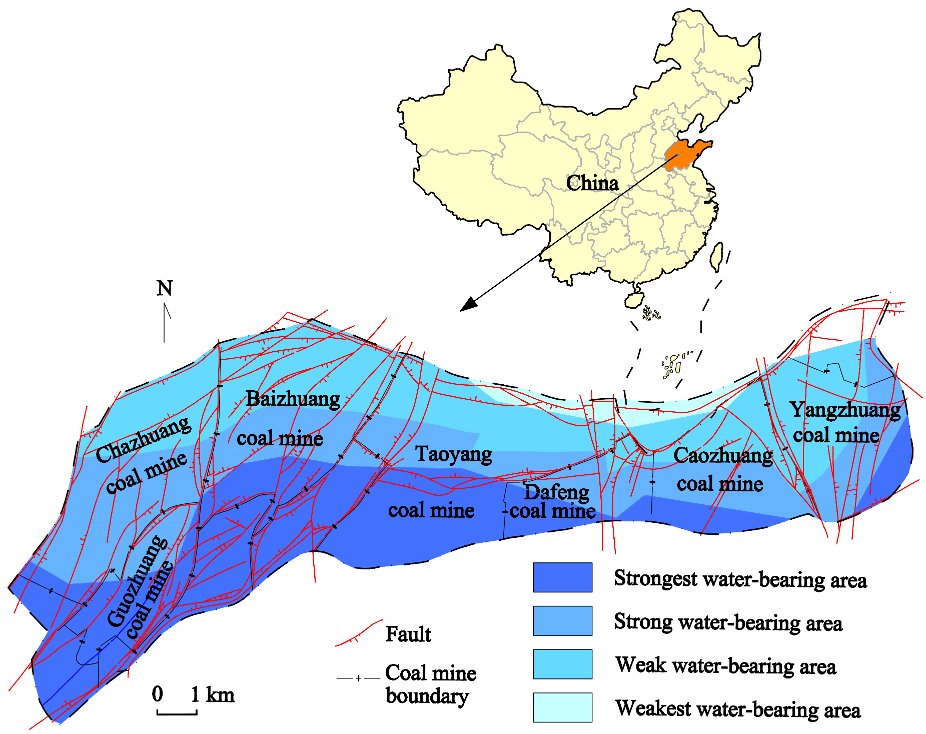

Fig. 1 Outline map of the Feicheng coalfield

(Wu et al. 2011). The water-resisting ability of the floor aquifuge depends on the aquifuge thickness, the lithology, and the degree of rock damage. These characteristics can all be determined using drilling logs. The studied cases of water inrush showed that the thicker the aquifuge between the mining horizon and the Ordovician aquifer, the greater the resistance to groundwater outbursts. With a high mechanical strength, a brittle sandstone aquifuge's resistance to water pressure is usually very strong (Meng et al. 2012).

The Aquifer Water Pressure Index

With increased water pressure, the relative risk of water inrush becomes greater (Wu and Zhou 2008). The water pressure of the aquifer can be determined by observing the groundwater level in hydrogeologic wells.

The Underground Pressure Index

As mining progresses, the surrounding floor rock will be partially destroyed by the underground pressure (Li and Chen 2016). The greater the pressure, the more severe the damage to the hydrologic barrier.

The Water Inrush Probability Index Method, Based on Multi-Attribute Decision Making

There are many factors that influence water inrush through the mine floor, and each factor contributes differently towards the occurrence of an inrush event (Shi et al. 1999). To quantify the contribution made by each factor to a water inrush event, a weight was assigned to each of the major factors based on statistical probability and expert opinions. A mathematical relationship was used to combine these factors to obtain the water inrush probability index (I) for a particular coalfield (Han et al. 2003). Then the minimum probability index was taken as a threshold value to predict a water inrush incident for a coalfield. A strict procedure was followed to calculate the water inrush probability index.

The Establishment of Weights and Calculation of the Water Inrush Probability Index

Mining practice shows that five main factors influence water inrush. Their degree of influence was quantified by assigning a weight to each factor; the more important the factor was, the heavier its weight. There are two ways to do this: probability theory and empirical evaluation. Based on practical experience, the field personnel who work in the Feicheng Mining Group Company and the professors who have cooperated with the mines in the coalfield established an index system for the water inrush probability index I (Fig. 3). Weights of $P_A = 0.5$, $P_S = 0.3$, $P_T = 0.1$, $P_W = 0.05$, and $P_R = 0.05$ were assigned to the aquifer water-bearing index (A), structural index (S), aquifuge index (T), aquifer water pressure index (W), and underground pressure index (R), respectively.

The water inrush probability index can be calculated as:

$$I = P_A A + P_S S + P_T T + P_W W + P_R R = 0.5A + 0.3S + 0.1T + 0.05W + 0.05R, \tag{1}$$

where I is the water inrush probability index; A, S, T, W, and R are the aquifer water-bearing index, structural index, aquifuge index, aquifer water pressure index, and underground pressure index, respectively, and; P_A, P_S, P_T, P_W and P_R are the weights of the above-mentioned factors.

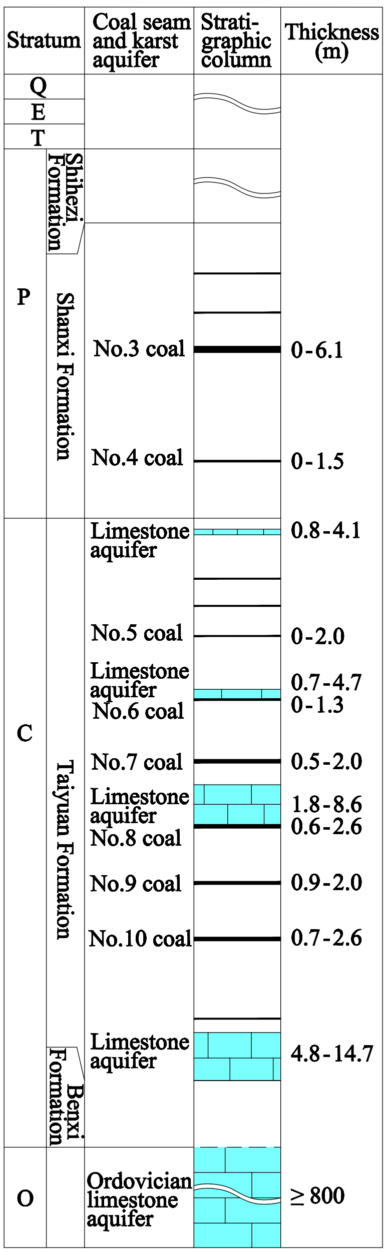

Fig. 2 The schematic geological profile

The aquifer water-bearing index depends on the water-bearing property of the Ordovician limestone in the different areas. The experts assigned weight indices of 1.0, 0.8, 0.6, and 0.4 to the strongest, strong, weak, and weakest water-bearing areas, respectively. That is to say, if a mining area was in the strongest area, $A = 1.0$; if in a strong area, $A = 0.8$, and so on (Fig. 3).

The structural index consists of two subsidiary factors, faults and fractures. In the 180 water inrush cases, 109 water inrushes were caused by faults, accounting for about 60% of the events; 71 water inrushes were attributable to fractures, accounting for the other 40%. Therefore, the weight of the fault index (P_F) was 0.6; the weight of the fracture index (P_J) was 0.4. The fault index (F) is controlled by four subsidiary factors: fault throw (h); fault category (normal or reversed fault) (n); fault combination (singular or multiple faults) (c); and the angle of the fault (r). The weights of the four indices are: $P_h = 0.5$, $P_n = 0.3$, $P_c = 0.15$, and $P_r = 0.05$. The fault throw index (h) is equal to 1 when the throw exceeds 20 m, $h = 0.8$ when the throw is between 10 and 20 m, and so on. If the fault is a normal fault, the fault category index (n) is 1.0, and if it is a reversed fault, $n = 0.4$. The fault combination index (c) is equal to 1.0 if two or more faults exist, $c = 0.8$ if not. When the angle of the fault is more than 70°, the fault angle index (r) is equal to 1.0; otherwise, $r = 0.5$. Two subsidiary factors, the fracture mechanics feature and the fracture density influence the fracture index. Their weights are $P_o = 0.6$ and $P_g = 0.4$, respectively. The mechanical index (o) is equal to 1.0, 0.6, or 0.1, corresponding to tensile joints, shear joints, and compressive joints, and the density index (g) is equal to 1.0 if there are more than 30 joints in 1 m^2, and so on (Fig. 3). Formulae from (2) to (5) were used to calculate the structural index (S).

$$S = P_F F + P_J J = 0.6F + 0.4J, \tag{2}$$

$$F = P_h h + P_n n + P_c c + P_r r = 0.5h + 0.3n + 0.15c + 0.05r, \tag{3}$$

$$J = P_o o + P_g g = 0.6o + 0.4g \tag{4}$$

$$h = \begin{cases} 1.0 \\ 0.8 \\ 0.6 \\ 0.4 \end{cases}, \quad n = \begin{cases} 1.0 \\ 0.4 \end{cases}, \quad c = \begin{cases} 1.0 \\ 0.8 \end{cases}, \quad r = \begin{cases} 1.0 \\ 0.5 \end{cases}, \quad o = \begin{cases} 1.0 \\ 0.6 \\ 0.1 \end{cases}, \quad g = \begin{cases} 1.0 \\ 0.6 \\ 0.1 \end{cases}. \tag{5}$$

The aquifuge index (T) is composed of three subsidiary factors: the aquifuge thickness (t), the lithological combination (b), and the degree of rock damage (d). Weights of 0.5, 0.2, and 0.3 were respectively given to the aquifuge thickness (t), the lithological combination (b), and the degree of rock damage (d). If the aquifuge thickness was more than 18 m, $t=1.0$; if the thickness was less than 18 m, $t=0.4$. If there was sandstone in the strata between the mining horizon and the aquifer, then $b=1.0$; if no sandstone, 0.6. Similarly, $d=1.0$, 0.7, 0.4, or 0.1, corresponding to stronger damage, strong damage, weak damage, and weaker damage (Fig. 3). Equations 6 to 7 were used to calculate the aquifuge index (T).

$$T = P_t t + P_b b + P_d d = 0.5t + 0.2b + 0.3d, \tag{6}$$

$$t = \begin{cases} 1.0 \\ 0.4 \end{cases}, \; b = \begin{cases} 1.0 \\ 0.6 \end{cases}, \; d = \begin{cases} 1.0 \\ 0.7 \\ 0.4 \\ 0.1 \end{cases}. \tag{7}$$

The weight given to the aquifer water pressure index (W) depends on the water pressure. The water pressure in the Feicheng coalfield is divided into five groups: more than 2 MPa, between 1.5 and 2 MPa, between 1 and 1.5 MPa, between 0.5 and 1 MPa, and less than 0.5 MPa. W is equal to 1.0, 0.8, 0.6, 0.4 or 0.2, corresponding to the different group (Fig. 3).

The underground pressure index (R) is influenced by the mining depth and the roof rock combination (Fig. 3). Different mining depths have different mining depth indices (m), and different roof rock combinations have different rock combination indices (f). Equations 8 to 9 were used to calculate the indices.

$$R = P_m m + P_f f = 0.7m + 0.3f, \tag{8}$$

$$m = \begin{cases} 1.0 \\ 0.6 \\ 0.2 \end{cases}, \; f = \begin{cases} 1.0 \\ 0.4 \end{cases}. \tag{9}$$

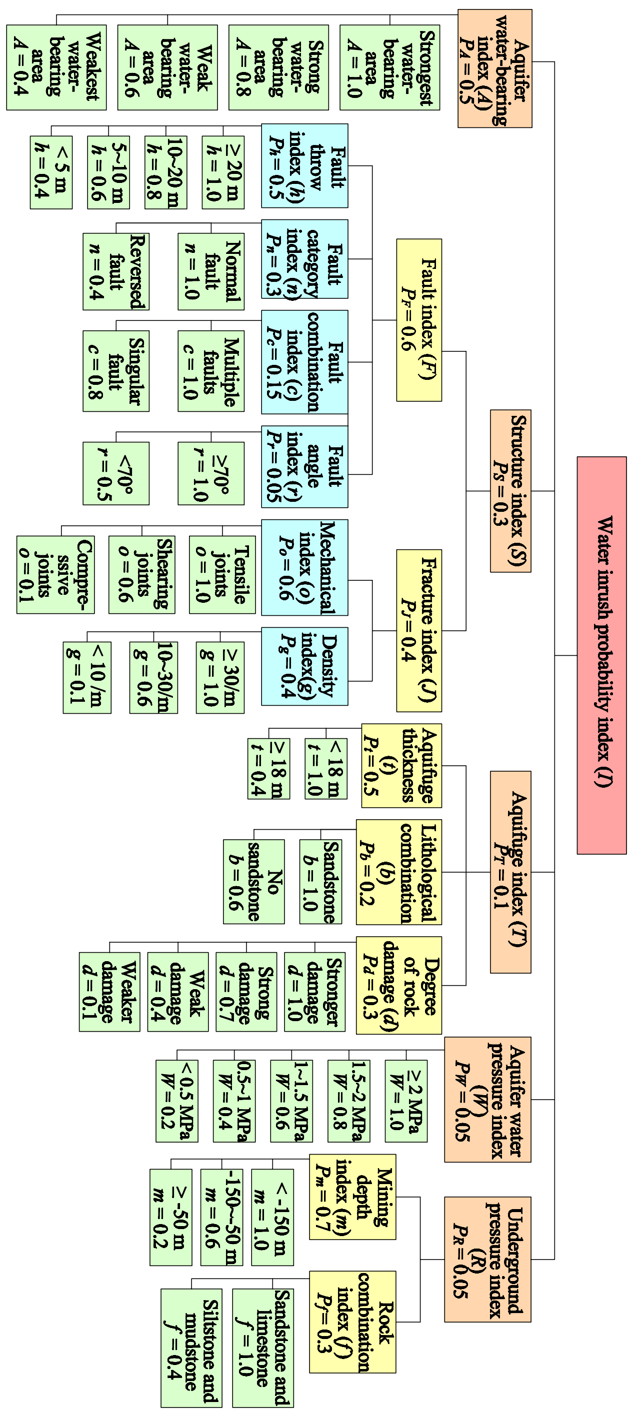

Fig. 3 The index system of the water inrush probability index

Decision Result

The water inrush probability indices of the seven water inrush cases in the Feicheng coalfield were calculated (Table 1) and a water inrush threshold value of 0.65 was obtained. In other words, if the water inrush probability index in this coalfield exceeds 0.65, the experts judged that water inrush though the floor is likely. Obviously, the accuracy and reliability of the prediction is affected by the various factors influencing water inrush and the mathematical model. The credibility of this method admittedly requires many water inrush cases for validation, and the quality of the conclusions derived by this method will be further improved as more data is added.

Decision-Making Regarding Water Inrush Based on the D–S Evidence Theory

The values of the five main factors (A, S, T, W, R) that influence the likelihood of water inrush merely reflects the probability of water inrush. While in practice there is a certain ambiguity or uncertainty in the likelihood of water inrush through the coal floor, there is no reflection of the confidence level in the water inrush probability index method. So the D–S evidence theory was applied to determine the reliability of the method. The D–S evidence theory is an extension of probability theory, with a weaker axiom system and a more rigorous reasoning process (Kang 1997; Liu et al. 1998), and allows us to better quantify uncertainty (Shafer 1976). As a means of decision-making fusion, with wide application to artificial intelligence, the D–S evidence theory can cover the shortcomings of the water inrush probability index method (Han and Zhou 2006).

Decision-Making Based on the D–S Evidence Theory

The basic process of information fusion (Sun et al. 2006) can be divided into the following steps (Wang et al. 2005; Wu et al. 2005):

a. On the basis of extensive analysis of the decision-making problem, the definitions of all possible propositions were used to apply the D–S theory, which is called a frame of discernment Θ (Gong 2007; Neshat and Pradhan 2015; Zhu 2005):

$$\Theta = \left\{ F_j \right\} \ (j = 1,\ 2,\ \cdots,\ K), \tag{10}$$

where F is the set of mutually exclusive and exhaustive propositions and K is the number of propositions.

b. Evidence aimed at the target information system was built based on the frame of discernment:

$$E = \left\{ E_i \right\} \ (i = 1,\ 2,\ \cdots,\ n), \tag{11}$$

where E_i is the i^{th} evidence and n represents the amount of evidence.

c. To set up the framework of the D–S theory, the basic probability assignment (BPA) or mass function (presented by m) was required, which is defined as the mapping of 2^{Θ} to the interval [0, 1] satisfying the following properties (Altınçay 2006):

$$m(\varnothing) = 0, \tag{12}$$

$$\sum_{L \subseteq 2^{\Theta}} m(L) = 1, \tag{13}$$

where Ø is an empty set of 2^{Θ}; L is the subset of the power set 2^{Θ} with a positive mass of belief, which is called the focal set element of $m(\cdot)$; and $m(\cdot)$ is the mass function.

d. Information was combined by applying Dempster's rule of combination. Let m_1 and m_2 be the mass functions of the two independent bodies of evidence. Then, the combined mass function m_{12} is defined by Dempster's rule of combination, as follows (Mathon et al. 2010):

$$m_{12}(J) = (m_1 \oplus m_2)(J) = \frac{\sum_{B \cap C = J} m_1(B) m_2(C)}{1 - \sum_{B \cap C = \varnothing} m_1(B) m_2(C)}, \tag{14}$$

where J is simply the resultant joint focal set element formed from the nonempty intersections of the focal set element; $m_{12}(J)$ is referred to as a joint basic probability assignment or mass function and represents the degree to which the combined evidence supports the premise that the unknown situation of a working face belongs exactly to the set J; B, C, $J \subseteq \Theta$.

e. Given the body of evidence with BPA m, we calculated belief (Bel) and plausibility (Pls) values for the body of evidence for a proposition (Neshat and Pradhan 2015). The lower bound of the probability for a set L, Bel(L),

Table 1 Decision matrix of water inrush cases and decision results in the Feicheng coalfield; *WF* working face no.; *MR* main roadway

Site	Mine	*A*	*S*	*T*	*W*	*R*	*I*	Note
WF 9101	Yangzhuang	0.8	0.79	0.43	0.6	0.44	0.73	Water inrush occurred, maximum water yield of 5273 m^3/h
WF 9204	Dafeng	0.8	0.6	0.43	0.8	0.44	0.69	Water inrush occurred, maximum water yield of 1628 m^3/h
WF 10204	Dafeng	0.8	0.49	0.52	1	0.82	0.69	Water inrush occurred, maximum water yield of 2035 m^3/h
WF 9901	Taoyang	0.8	0.39	0.43	1	0.82	0.65	Water inrush occurred, maximum water yield of 1083 m^3/h
WF 9507	Taoyang	1	0.39	0.43	0.8	0.82	0.74	Water inrush occurred, maximum water yield of 17,940 m^3/h
MR−210 m	Guozhuang	1	0.49	0.52	0.8	0.82	0.78	Water inrush occurred, maximum water yield of 32,970 m^3/h
WF 8101	Guozhuang	0.8	0.49	0.8	1	0.82	0.72	Water inrush occurred, maximum water yield of 16,540 m^3/h

is defined as the sum of all masses of all subsets (B) ($B \subseteq L$):

$$Bel(L) = \sum_{B \subseteq L} m(B). \tag{15}$$

The upper bound of the probability for a set L, Pls(L), is defined as the sum of all masses of the sets (B) intersecting L ($B \cap L \neq \varnothing$):

$$Pls(L) = \sum_{B \cap L \neq \varnothing} m(B). \tag{16}$$

Equations (17) and (18) represent the lower and upper probabilities, having the properties:

$$Bel(L) \leq Pls(L), \tag{17}$$

$$Pls(L) = 1 - Bel\left(\bar{L}\right), \tag{18}$$

where $\bar{L}$ is the negation of L; $Bel\left(\bar{L}\right)$, called the disbelief function, which is denoted by Dis and expressed as:

$$Dis(L) = 1 - Pls(L). \tag{19}$$

f. Decision rules were constructed. The prediction result F_a was ascertained according to the following rules (Yang and Wu 2007):

Rule 1: $Bel(F_a) = \max_j \left\{Bel(F_j)\right\}$;

Rule 2: $Bel(F_a) - Bel(F_j) > \varepsilon$;

Rule 3: $m(\Theta) < \gamma$, $\gamma \in R$ and $\gamma > 0$.

Rule 1 indicates that the prediction result must be the proposition with the biggest probability; rule 2 indicates that the probability of the prediction result must be ε bigger than all other propositions' probability; rule 3 indicates that evidence's uncertainty $m(\Theta)$ must be less than γ, where, ε and γ were determined according to practical application condition, and the values of ε and γ were selected as 0.35 and 0.002 in this study, respectively. With the premises of achieving the above three rules, prediction result F_a can be ascertained.

Application to Prediction of Water Inrush

We used the No. 9901 working face in the Taoyang coal mine as a research example. In a safety analysis of the working face, based on the D–S evidence theory, the frame of discernment was defined as:

$$\Theta = \{F_1, F_2, F_3\} = \{\text{water inrush, critical, no water inrush}\}, \tag{20}$$

where F_1 indicates the proposition "water inrush"; F_2 indicates the proposition "critical"; and F_3 indicates the proposition "no water inrush".

In this study, the five previously defined factors that significantly affect water inrush were considered as evidence: E_1, E_2, E_3, E_4, and E_5. Thus, the evidence of the frame of discernment was:

$$E = \{E_1, E_2, E_3, E_4, E_5\} = \{A, S, T, W, R\}. \tag{21}$$

The basic probability assignment of the evidence was given by the field personnel who work in the Feicheng Mining Group Company based on the decision matrix of the No. 9901 working face in the Taoyang coal mine (Table 1), as shown in Table 2. Then, we used Eq. (14) to combine the E_1, E_2, E_3, E_4, and E_5 to obtain the basic probabilities of the combined evidence (E_{12345}). Finally, the belief and plausibility measures were calculated based on the BPAs (Table 2).

With all the evidence combined together, the decision rules (Table 2) were applied. From the results, after fusion of the evidence of the No. 9901 working face, $Bel(F_1) = 0.74$ and $m(\Theta) = 0$. In other words, the "water inrush" proposition had the greatest probability, 0.74, as the probability of water inrush is at least 0.50 greater than the probability of all other propositions, and the uncertainty $m(\Theta)$ of the evidence was less than γ (0.002). Consequently, water inrush into the working face was predicted.

Combining the water inrush probability index and the D–S evidence theory to analyze the No. 9901 working face in the Taoyang coal mine of the Feicheng coalfield provided a more informed decision. The water inrush probability index, $I = 0.65$, obtained from the probability index method (Table 1), provided a judgement as to the likelihood of water inrush in term of decision rules, but the degree of confidence was unknown. However, the D–S evidence theory defined the "water inrush" BPA of the No. 9901 working face in Taoyang coal mine as 0.74 after fusions. In other words, the degree of confidence in the water inrush probability index $I = 0.65$, is 74%, providing a powerful indication of the reliability of the decision. In practice, a 1083 m^3/h water inrush from the floor occurred during exploitation of the No. 9901 working face, in alignment with the statistical results.

Conclusions

Since water inrush through the coal floor is determined by complex factors and variable geometry, simultaneous qualitative and quantitative analyses are required. We combined the water inrush probability index method and the D–S evidence theory to predict water inrush through the coal floor. This study indicated that using the probability index can guide site personnel to better predict whether water inrush through the coal floor will occur. The degree of confidence in the probability can be improved and uncertainty reduced

Table 2 Values of D–S evidence theory for prediction of water inrush in the No. 9901 working face in the Taoyang coal mine

Evidence	BPA				*Bel*			*Pls*			Decision result
	$m(F_1)$	$m(F_2)$	$m(F_3)$	$m(\Theta)$	$Bel(F_1)$	$Bel(F_2)$	$Bel(F_3)$	$Pls(F_1)$	$Pls(F_2)$	$Pls(F_3)$	
E_1	0.4	0.15	0.4	0.05	0.4	0.15	0.4	0.45	0.2	0.45	Uncertain
E_2	0.6	0.2	0.1	0.1	0.6	0.2	0.1	0.7	0.3	0.2	Uncertain
E_3	0.3	0.3	0.3	0.1	0.3	0.3	0.3	0.4	0.4	0.4	Uncertain
E_4	0.4	0.1	0.4	0.1	0.4	0.1	0.4	0.5	0.2	0.5	Uncertain
E_5	0.4	0.15	0.45	0	0.4	0.15	0.45	0.4	0.15	0.45	Uncertain
E_{12}	0.68	0.12	0.19	0.01	0.68	0.12	0.19	0.69	0.13	0.20	Uncertain
E_{123}	0.68	0.13	0.19	0	0.68	0.13	0.19	0.68	0.13	0.19	Uncertain
E_{1234}	0.73	0.06	0.21	0	0.73	0.06	0.21	0.74	0.06	0.21	Water inrush
E_{12345}	0.74	0.02	0.24	0	0.74	0.02	0.24	0.74	0.02	0.24	Water inrush

by fusion of the evidence. The validity and feasibility of the decision making model was successfully applied in the Feicheng coalfield.

Acknowledgements This research was financially supported by the National Natural Science Foundation of China (41572244), Ministry of Education Research Fund for the doctoral program (20133718110004), Shandong Province Nature Science Fund (ZR2015DM013), SDUST Research Fund (2012KYTD101), and the Taishan Scholars Construction projects. We thank the anonymous reviewers, the editors, and Mona Pelkey for their help in improving this manuscript.

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