Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 4586979, 17 pages
https://doi.org/10.1155/2022/4586979

Research Article

Selection of Compatible Coal Seam for Methane Drainage Operation Based on Uncertain Geological Conditions: A Hybrid Fuzzy Approach

Amir Jafarpour and Mehdi Najafi

Department of Mining and Metallurgical Engineering, Yazd University, Yazd, Iran

Correspondence should be addressed to Mehdi Najafi; mehdinajafi@yazd.ac.ir

Received 2 January 2022; Revised 5 February 2022; Accepted 7 March 2022; Published 12 April 2022

Academic Editor: Mahsa Valipour

Geological studies are very important at different steps of mining activities. Different uncertain geological criteria and factors show a significant impact during the underground mining operations and mineral extraction process. The current study reports on the evaluation and classification of coal seams for methane drainage-ability (MDA) through a fuzzy hybrid approach. This problem was investigated due to the importance of uncertain geological factors in the process of MDA and the necessity to evaluate safety operations in underground coal mines. The important criteria involved are depth, thickness, and uniformity of coal seam, joints and cleats conditions, roof quality, coal seam gas content, underground water condition, and permeability of coal seam. The two-stage fuzzy classification approach was used to analyze the effectiveness of the uncertain geological criteria. Also, fuzzy cognitive map (FCM) method was used to calculate weights for geological criteria. The used FCM method is based on the Hebbian algorithm and metaheuristic methods. The Hebbian learning algorithm is made from a hybrid learning algorithm of nonlinear heuristics and differential evolution. In addition, fuzzy intervals of criteria were calculated based on technical reports and other scientific studies. Then, the rank of each coal seam calculates by fuzzy T-norms. The proposed system was employed to classify the coal seams for MDA in Parvadeh coalfield, Iran. The results showed that the C_1, C_2, B_2, B_1, and D coal seams were classified in the "very good," "good," "moderate," "poor," and "very poor" categories, respectively. The proposed fuzzy hybrid approach provides a new logical tool in the selection of coal seam for methane drainage operation and can reduce the risk of methane drainage projects in underground coal mines.

1. Introduction

All coal seams contain methane gas (CH_4) ranging from 0.031 to more than 18.7 m3/ton, about 10% of which is compressed into cleats system, about 5% is dissolved in the coal-containing water, and the rest is absorbed chemically in the structure of the coal cleats matrix [1, 2]. In underground coal mining methods, controlling, monitoring, and extraction of coal seam/mine methane is a priority as a source of gas and reducing CO_2 gas production. This operation increases safety during mine extraction, emits fine dust, and reduces mine ventilation process costs, initial investment, downtime, air pollution, and greenhouse gas emissions [3,4]. Nowadays, the importance of applied geological sciences at various phases of mining operations cannot be ignored. The location, number, and drilling method of gas drainage holes can be determined by taking into account the uncertain geological parameters in conducting methane drainage-ability (MDA) operations. Therefore, geological studies are necessary procedures to be done in the coal mine methane drainage projects [5].

The methane drainage from the coal seams on a large scale can be accomplished through three different methods: Coal-Bed Methane (CBM), Coal Mine Methane (CMM), and Enhanced Coal-Bed Methane (ECBM). Methane can be captured before and after mining by pre- and postdrainage phases. Postdrainage may also involve drilling from the surface or from the underground caved spaces. Even more

than 70% of total methane emission to airways may come from overburden and underburden layers in some mines. CMM can be carried out simultaneously with or prior to mining operations. This is done to increase mine safety [6–8]. Many factors affect the efficiency of CMM/CBM drainage operations, an important part of which is uncertain geological criteria [9]. A few studies have been done on the evaluation, classification, and ranking of the coal seam for the MDA during the coal mining operation. Earlier research has focused on the problems such as the effect of factors on the methane drainage efficiency [10], production rate of the CBM [11], optimization of boreholes drilling pattern [12,13], and environmental problems of the methane drainage operations [14,15].

Perera et al. [16] optimized the CMM operation by examining the geological factors (coal seam porosity, cleats condition, temperature of seam, gas content, and methane gas pressure), which affect the operation. Lu et al. [10] analyzed the effect of the geological criteria (roof rock quality, coal intrinsic properties, coal density, *P*-wave velocity, uniaxial compressive strength, modulus of elasticity, and Poisson ratio) to evaluate the methane drainage efficiency of the coal mines. Also, Zhou et al. [17] performed simulation and optimization of the piping network for CBM operations. In addition to considering the influence of geological factors (gas content and geometrical properties of the coal layer), they examined the parameters related to the drilling pattern (diameter, length, angle of boreholes, and distance from each other) were also applied to the mathematical model. Wang et al. [18] evaluated the potential of CBM operation in coal mines of Xishan coalfield of China using fuzzy multilevel mathematical analysis. They also analyzed the influence of different geological criteria such as tectonics, coal stratification, and hydrology on MDA. Meng et al. [19] presented a mathematical model for the management of methane production in the CBM method through the consideration of geological factors (thickness and length of coal seam, water content, and coal density) and geomechanical parameters (Poisson ratio, modulus of elasticity, and cleats length). Najafi and Rafiee [20] developed an index for MDA of coal seams using the Fuzzy Rock Engineering System (FRES). They considered 17 parameters as the main factors affecting the methane drainage from coal seams. The result showed that the permeability of coal is the most interactive parameter.

On the other hand, the importance of uncertainty in solving mining problems, especially methane drainage of the underground coal mines, is significant. Some studies have been done on this target. Szlązak and Korzec [21] investigated the gas content of the coal seam considering the uncertainty of the amount of gas. In laboratory studies, they presented a significantly effective two-step methodology. Montiel et al. [22] also presented a general optimization of underground and open-pit mining operations taking into account geological uncertainty. In this study, an extraction sequence based on uncertainty and its general principles is presented, which had significant results. Also, assessment of the risk of underground mines with Failure Modes and Effects Analysis (FMEA) method is studied by Shariati [23]. A Fuzzy-FMEA method is presented in this study that solves the risk analysis in different mining problems.

In preoperation steps, the coal seams should be ranked via different methods based on effective parameters before designing and implementing methane drainage systems. Prioritization of coal seams is necessary because the fuzzy classification system can identify suitable sequestration of the coal seams. From a safety point of view, it is also important to identify which coal seam is in an unfavorable safety state and is hazardous. In terms of safety problems, the seams that are badly or abnormally conditioned by different criteria should be degasification very quickly. The current study examined the drainage-ability of the coal seams in Tabas (Parvadeh) coalfield in Iran by evaluating the effects of geological factors. Also, a classification system was presented by applying a fuzzy theory and fuzzy cognitive map (FCM) for each of the criteria, and the coal seams were ranked based on the effective factors. Also, in this study, the CBM drainage method has been considered due to the causal nature of the proposed model and the extent of its applications in underground coal mines.

The main purpose of the current study is to provide a hybrid algorithm based on metaheuristic methods and fuzzy theory that can be used to classify coal seams. The importance of classification is that using an engineering classification, it is possible to prioritize coal seams in order to start methane drainage operations. It is difficult to distinguish one underground coal seam from several existing seams for gas drainage operations. To this end, it is necessary to provide a technical and engineering approach to solve this problem. In this research, by considering several influencing factors and examining how they affect them, an algorithm is presented that has acceptable results.

The article is outlined as follows: in Section 2, the geological factors affecting the MDA operation are analyzed. In Section 3, the research methodology is described, including fuzzy theory and fuzzy cognitive map (FCM). In Section 4, a case study is reviewed and after discussing the results in Section 5, the main results of this research are presented in Section 6.

2. Materials

The geological factors are serious and influential parameters in methane drainage operations. Ignoring these factors can cause irreparable damage to an underground coal mine and even cause project closures. Therefore, the methane drainage process is impressed by geological parameters. The most important geological criteria affecting the CMM ability of the coal seams are depth, thickness, and uniformity of coal seam, condition of joints and cleats, roof quality, coal seam gas content, underground water condition, and permeability of coal seam [24–29].

2.1. Cleats and Joints Condition. Naturally, coal has discontinuities that can be referred to as cleats, joints, and discontinuous plates. Generally, the cleats are a fracture system in coal seams with a length of less than one meter and

a frequency of between 5 and 20 joints per meter. The cleats are usually upright and have two directions perpendicular to each other: the face cleats are longer and the layering plates cut off the coal that may extend over larger distances. The but cleats, which are usually short in length and may have curves, are discontinuous fractures that alternate the face cleat's permeability [30]. Gas production is highly dependent on cleat spacing and cleat interconnections [31]. By decreasing cleat spacing and increasing its interconnections, the potential of methane drainage is increased. The cleat aperture has an immense impact on reservoir permeability. The relationship between cleat spacing, aperture size, and permeability was studied by Laubach et al. [32] in the San Juan and Black Warrior basins (Figure 1).

2.2. Thickness of Coal Seam. The thickness of the seam is an important factor in determining the gas drainage-ability and has an impact on the amount of degasification and equipment selection. As the seam increases in thickness, the length of boreholes in the coal seam will increase, and more gas will thus be produced. Moreover, horizontal boreholes drilling in a thicker coal seam is easier. Black [33] studied 53 samples of coal seam thickness. He found that increased gas production was achieved from boreholes located in areas with greater seam thickness. Also, caving height depends on seam thickness [34]. Therefore, the greater the seam thickness, the higher the caving, and more gas will flow into the gob from overlying strata and into the mine.

2.3. Permeability of Coal Seam. Permeability refers to the ability of the coal to transmit gas when a pressure or concentration gradient occurs across it. Permeability has significant effects on the gas drainage from coal seams [5,35,36]. It is closely related to the cleat properties (spacing and aperture width) and the value of in situ stress on the cleat. Therefore, permeability may vary with changes in fluid pressure during gas drainage from coal seam [32,33,36]. Permeability of coal seam has a strong effect on the gas production profile and gas performance. In high-permeability coals, the horizontal boreholes can be used for reducing the gas content of longwall panels and maximizing gate road development [5]. According to research on different methane drainage projects, it has been found that the appropriate permeability rate for the CMM process is 30–50 mDarcy [37]. Nowadays, with the new technologies, the CMM process can be carried out on low permeable coal seams. The research shows that the minimum rate of permeability required for CMM operations is 1 mDarcy [38].

2.4. Depth of Coal Seam. By increasing the depth, the pressure from the overlying strata on the coal seam will be increased, which improves the absorption capacity of the coal [39]. The absorption capacity is greater in high-quality coals for a given depth. On the other hand, increasing the depth (vertical stress) of the seam causes the network of cleats and fractures to stick together, reducing the permeability of the coal seam [40]. Like the vertical stresses, the horizontal stresses tend to close up fractures [39]. The relationship between the absorption capacity and the type of coal and the depth (and pressure) is shown in Figure 2. It should be noted that as the depth of the coal seam increases, CMM operation becomes more difficult due to the need for more advanced equipment and higher operating costs.

2.5. Coal Seam Gas Content. Gas content is defined as the cubic meters of gas per ton of coal (t/m3). The gas content of coal refers to the volume of the absorbed phase in coal as the gas from coal is released [42]. Gas content is an important factor in relation to mine safety and mine planning and has become increasingly important in coal-bed methane resource assessment and recovery operation [33]. It is one of the key data in CBM resource estimation. The coals of subbituminous to low-volatile bituminous rage usually provide high gas content and natural permeability [5]. The gas content of coals with the same rank generally increases with increasing depth [43]. The coal rank is the most important factor that affects the methane adsorption capacity in coal beds. By increasing the rank of the coal, the gas holding capacity also increases.

2.6. Underground Water Condition in Mining Area. The presence of water in the panels and working faces of underground coal mines is extremely harmful, but the presence of water in the coal seam prevents the release of methane into the panels and working faces. On the other hand, dissolving methane gas in the water in the coal seams results in increased energy consumption of the drainage pumps and other equipment during the drainage operation.

2.7. Roof Quality. The discontinuities, fault, stratigraphy, and the strength of overlying and underlying strata have many effects on the gas production from coal seams. The appropriate spacing of faults can limit the dewatering required and allow quick gas to the surface, possibly enhancing the economy of a prospect [5]. The effect of fault on the coal seam gas is complex. It depends on the closure of fault and the permeability of the surrounding rock that touches the coal seam [44]. The faults and the associated weakness zones may be responsible for the high gas concentration encountered during mining [45]. Karacan et al. [1] studied the effects of impermeable faults on the gas drainage efficiency by numerical modeling. The results indicated that the faults caused increased production from the vertical borehole but left no effects on the gas production horizontal borehole. The gas content of surrounding rock of coal seams highly depended on the situation of geological structure.

However, one of the important parameters in the gas drainage from coal seams is the quality of the overburden rock of the coal seam. As the overburden rocks become more stable, the methane gas in the seam cannot move upward and is stored in the coal seam. On the other hand, by increasing the quality of the overburden rock mass, the stability of the drainage boreholes is increased and their destruction is prevented. It also makes drainage

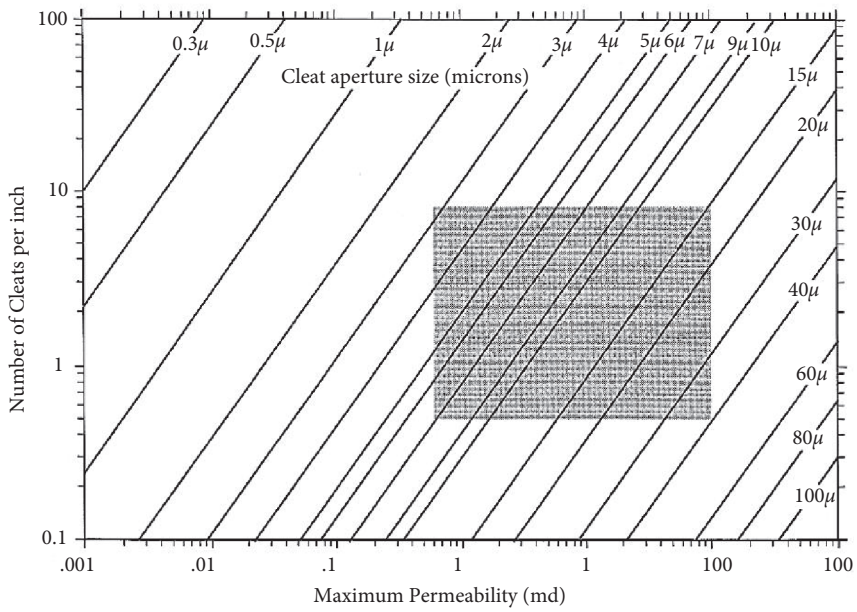

Figure 1: Relationship between cleat properties and permeability [32].

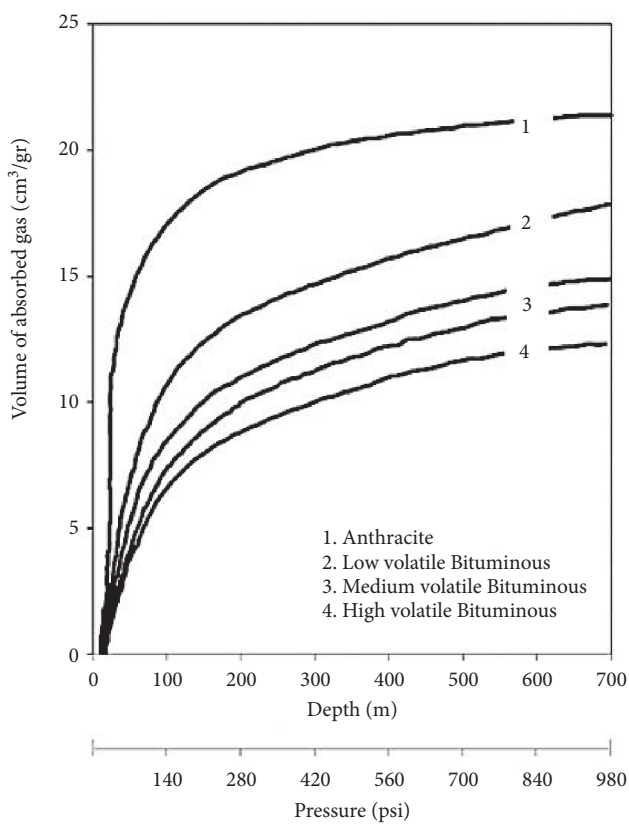

Figure 2: Relationship between volumes of gas stored in the seam, type of coal, and depth of deposition [41].

equipment more efficient. The roof quality index depends on parameters such as the uniaxial compressive strength (UCS) of the overburden and the immediate roof thickness. The roof quality index (Q_r) value is calculated from the following:

$$Q_r = 0.015 \times \sigma_M \times d, \tag{1}$$

where σ_M is the in situ compressive strength of roof rock (kg/cm^2) and d is immediate roof thickness (cm). Measuring the value of σ_M in situ is relatively difficult. Therefore, the

following equation can be used for the calculation of this parameter:

$$\sigma_M = \sigma_C \times k_1 \times k_2 \times k_3, \quad (2)$$

where σ_C is UCS of the overburden rocks (kg/cm^2), k_1 is the in situ strength coefficient, k_2 is creep coefficient, and k_3 is moisture coefficient. The k_1, k_2, and k_3 coefficients depend on the material of the roof rock and its properties and are determined according to Table 1.

The roofs with a quality index of 35 to 130 (kg/cm^2) are selected as the most suitable roof for longwall mining operations and the gas drainage processes, consequently [46].

2.8. Uniformity of Coal Seam. The faults are one of the most important geological structures in the underground coal mines, which may cause the immediate release of methane gas or as an impermeable barrier to methane release. The faults can also act as a conduit for the passage of gas flow through the covering layers into the extraction plant or vice versa. The reverse faults also act as a barrier to gas flow. In general, the best method of methane drainage from faulted layers is degasification using vertical, directional, and transverse boreholes [38]. When designing and executing coal mines that are extracted on faulted coal seams, special attention should be paid to the different states of the mine's input impedance to the fault and methane drainage method. The value of fault-induced coal seam displacement and the number of faults along the seam are the most important factors influencing coal extraction [47] and the MDA. The MDA of the coal seam is directly related to its uniformity. The uniformity of the seam is determined by the changes in the displacement index (the ratio of the seams displacement to its thickness), as follows:

$$I_t = \frac{t}{m}, \quad (3)$$

where t is the displacement of coal seam by fault (m) and m is the coal seam thickness (m). In this classification, the seam displacement index is shown as a fraction of the seam thickness. The uniformity of the seam is assigned to the seam as a score based on its displacement index.

3. Case Study: Parvadeh Coalfield in Tabas, Iran

Parvadeh is located in the Tabas region in the Southern-Khorasan province and 85 km south of Tabas city (Figure 3). This area is located in the geological divisions of Iran in the Central Iran area. Parvadeh coal deposit consists of five coal seams (C_1, C_2, D, B_1, and B_2). It has three minable seams (C_1, B_1, and B_2). The Parvadeh coalfield (in Iran) lies in a basin between two major north-south trending fault systems, the Kalmard fault to the west and the Nayband fault to the east. A third major fault is thought to exist in the west. The Nayband fault is still seismically active, a major earthquake occurring in 1978. Other faults in the area may also be active. Second-order structures trend east-west between these faults, including the Rostam, Zenowqan, and Quri-Chay faults and the Parvadeh anticline. The Rostam fault forms the northern boundary to the Parvadeh area. It is a reverse fault with a displacement of up to 700 m, downthrowing to the north. The Parvadeh anticline, lying immediately to the south of the Rostam fault, is asymmetric, with a steep (65°) northern limb. Deformation of the strata is severe in the zone adjacent to the Rostam fault with tight folding and numerous faults. Stratigraphically, the coal-bearing sequence is included in the Qadir member, some 1000 m in thickness, of the Nayband formation and is of Triassic age. The rocks are mostly mudstone with prominent coarsening up siltstone/sandstone sequences, often topped by extremely fossiliferous horizons. Locally developed, thin, marine limestones occur.

Table 1: Coefficients affecting the compressive strength of the roof rock.

Rock type	k_1	k_2	k_3
Sandstone	0.33	0.7	0.6
Limestone	0.42	0.6	0.4
Limestone and Claystone	0.5	0.6	0.4

The geological criteria used in the current study and the characteristics of the different seams of the Parvadeh coalfield are presented in Table 2.

4. Methods

In the current study, the fuzzy theory classification approach is used. The proposed approach is a two-step algorithm that uses the FCM method in the first step and fuzzy theory in the second step. The fuzzy cognitive map (FCM) is one of the causal methods based on metaheuristic approaches and due to its efficiency, it has been used to calculate the fuzzy weight of the effective criteria based on uncertainty geological factors. The second part of the algorithm is done according to previous studies and considering the weight obtained from the first stage of the algorithm. Then, the classification of the coal seams is done by the introduced algorithm. On the other hand, the approach presented in the current study is general, and data of an underground coal mine have been used to achieve the results and validate the proposed method. The consequent results of the current study can be used in other coal mines.

The model is designed based on available information and data. In other words, in the model, the available data affecting the methane drainage have been considered by researchers. Regarding the geology and condition of the coal cleats and joints, it should be noted that each coal seam will be scored using the available geological surveys and maps. Also, the cleats condition of the coal seam was obtained based on laboratory studies. This means that after sampling the coal seam, the status and number of coal cleats will be determined and was used in the model. The theoretical literature on the hybrid fuzzy method used in this study is briefly described below.

4.1. Fuzzy Theory. Zadeh [48] first proposed the "fuzzy sets" theory in 1965. This theory is introduced to solve decision-making (DM) problems in an atmosphere of

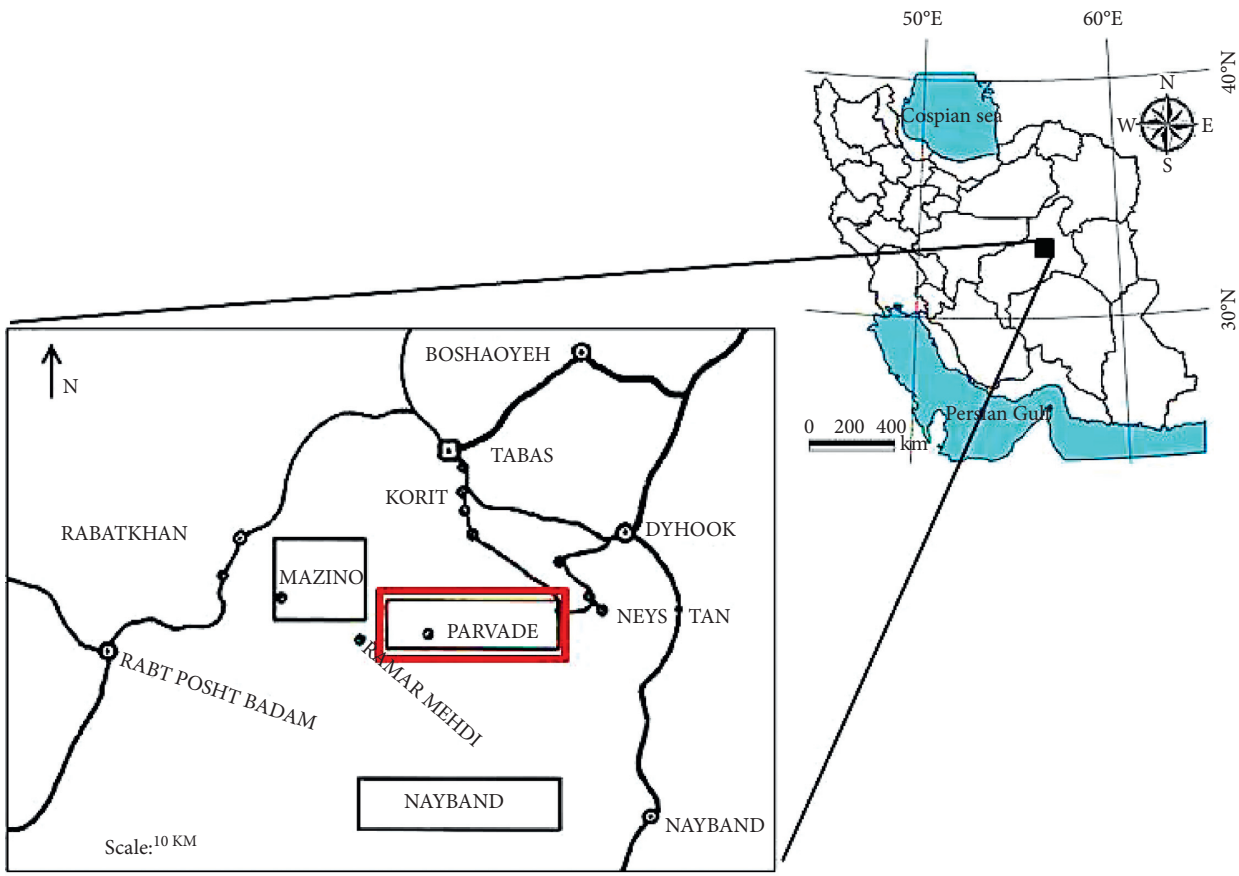

Figure 3: Geographical location of the studied mine in Iran.

Table 2: Characteristics of the geological criteria used in this study.

Seam	Depth (m)	Thickness (m)	Cleats (joint/m)	Uniformity	Gas content (m^3/ton)	Roof quality (MPa)	Water condition (m^3/min)	Permeability (mDarcy)
D	313	0.3	13	0.7	15.1	88.7	106	38
C_2	348	0.6	17	0.8	16.2	91.4	91	40
C_1	364	1.9	20	0.75	16.3	95.1	83	45
B_2	387	0.9	18	0.8	20.87	85.4	64	30
B_1	399	0.75	16	0.7	21.69	86.1	80	41

uncertainty for the ease of performing complex real-world calculations. On the other hand, decisions are accompanied by the uncertain situation and practitioners' comments as preliminary data for engineering DM should be in linguistic propositions (linguistic variables). The expert opinions are usually expressed in terms of quality that must be quantified with precision and applied in the DM process. For this purpose, the replacement of definitive values with fuzzy values has resulted in different fuzzy approaches. Consequently, the results of each approach have become more consistent with real-world conditions, and the efficiency of the approach has increased [49].

The fuzzy theory states that if the range of the {0,1} is converted to the interval [0,1], the crisp set is converted to the fuzzy set. In other words, by assuming the universal set U, the fuzzy set A in set U is defined as follows:

$$\begin{aligned} &A: U \longrightarrow [0.1]; \\ &A(u) \in [0.1]. \end{aligned} \tag{4}$$

Also, the fuzzy set A can be represented by the following:

$$A = \left\{ \frac{\mu_A(x_1)}{x_1}, \frac{\mu_A(x_2)}{x_2}, \ldots, \frac{\mu_A(x_n)}{x_n} \right\}, \tag{5}$$

where $\mu_A(x_1)$ is the degree of membership X_i in set A that changed in the interval [0,1] [50].

According to the fuzzy theory, the use of the degree of membership sets has replaced the definite sets. Also, the use of fuzzy numbers in fuzzy calculations has led to different types of fuzzy numbers being studied by researchers. The fuzzy numbers may be expressed in triangular, trapezoidal, or other forms. The use of triangular numbers is common in solving engineering problems with a fuzzy approach [51].

With these types of numbers, decision-makers can easily express the linguistic variables provided by experts with greater consistency than with fuzzy number facts.

In the current study, a classification algorithm is used based on fuzzy theory and uncertainty factors. The reason for using fuzzy logic is the results close to the real-world that this approach has shown in solving various engineering problems. The results of studies based on fuzzy theory show that various problems (including the presentation of classification algorithms) can be solved by fuzzy simulations. For this purpose, in the present study, a fuzzy two-step algorithm is used. The proposed hybrid algorithm, in the first step, calculates the weight of the effective criteria by a fuzzy method based on metaheuristic algorithms (FCM). Then, using the weights obtained from the first step, the algorithm classifies the coal layers based on fuzzy operators.

4.2. FCM Method. Given the ability of FCM to model complex systems with scarce and limited data, as well as the unavailability or cost-effectiveness of data collection, FCM can be a very useful modeling tool [52]. Also, the FCM method is a cognitive map (CM) that can use the relation between the components of a subjective perspective to calculate the effect of causal relationships with numerical in the interval [0,1] or [-1,1] [53]. Time series data and expert opinions can be used to draw such a CM. In the calculation-based CM method, time series data are used as inputs. Moreover, neural network logic is used to estimate map weights and relationships between variables [54].

In FCM, C_is represents the concepts or nodes that are linked together by weighted arcs. Each relation between the two nodes C_i and C_j has a weight equal to W_{ij}, indicating the degree of causality and the type of relationship between the nodes. On the other hand, $W_{ij} > 0$ indicates a positive causal relationship, $W_{ij} < 0$ indicates a negative causal relationship, and $W_{ij} = 0$ indicates no relationship between the two nodes or concepts [55]. There are six steps to explain a CM as follows:

(i) Identifying the concepts/nodes that affect the system

(ii) Determining the relationship between concepts

(iii) Weighting these connections and concepts based on field studies and expert opinion

(iv) Selecting the calculation method and limit functions

(v) Releasing all concepts/nodes with other concepts/nodes and calculating the result of the interaction between the concepts/nodes in each cycle

(vi) Continuing this process until stopping conditions such as chaotic behavior of the system or when the numbers of repetitions are reached

In the CM method, the accurate estimation of map weights by the experts is a serious problem. In recent years, learning algorithms have been used to increase metrics accuracy and map convergence and reduce dependency on expert opinion. The algorithms are categorized into three groups of learning algorithms based on Hebbian, population-based learning, and hybrid learning algorithms [56]. Also, according to the data of the current study, hybrid learning algorithms would be the best option. Because these algorithms are designed according to Artificial Intelligence Systems (AIS) and human brain functions, they are capable of training. On the other hand, the algorithms are capable of simultaneously analyzing the effects of various factors and have acceptable results in solving different engineering problems. These algorithms are a combination of the Hebbian learning algorithm and metaheuristic methods. Furthermore, they are suitable for weight modification of maps that combine time series data and expert opinions. In this study, the algorithms of this category are also used as a hybrid learning algorithm of nonlinear heuristics and differential evolution because they update nonzero weights in different iterations and maintains the relationships between the concepts defined in the original map [57]. Figure 4 shows the nonlinear Hebbian algorithm pseudocode (first stage of NHL-DE algorithm), and Figure 5 shows the pseudocode of differential evolution algorithm (second stage of NHL-DE algorithm).

In the presented pseudocode, A^0 denotes the initial state matrix of the system, W^0 denotes the initial weight matrix between the variables, $A^{(k)}$ and $A^{(k+1)}$ denote the new values of the variables in the k and k+1 iterations, η and γ denote positive and very integer small numbers (learning rate), $W_{ji}^{(k)}$ and $W_{ji}^{(k+1)}$ denote updated weights between variables i and j in k and k+1 iterations, and $\mathrm{WNHL}^{(k+1)}$ represents the final weight matrix between variables in the first step, sgn denotes sign function, and NP represents the population number [58].

4.3. Hybrid FCM Method and Fuzzy Approach. This study has employed the FCM method and fuzzy classification approach. According to the proposed method, the criteria weights are calculated via FCM and are used as part of the inputs of the fuzzy classification approach. Due to the desired performance of each of these methods in optimizing the evaluation of projects, they were also used in the current study. The main reason for this issue is the compatibility of these two approaches with the real situation, so the fuzzy numbers are used to make the algorithm's performance more consistent with the actual conditions. In this study, the geological criteria affecting the MDA (CMM/CBM-ability) of underground coal mines are used as the primary input in the FCM method. In fact, after identifying the geological criteria affecting the MDA, the FCM is drawn with these criteria. The reason for using this approach is to identify the causal relationships between the criteria that affect and how each criterion affects them. Therefore, the identified geological criteria are used as cognitive map concepts.

The causal relationship between the concepts in CM and the weighting of the identified relationships has been determined by experts in mining engineering, who also determined the most effective criteria identified by assuming each of the identified criteria is active in cognitive mapping and implemented a hybrid learning algorithm that indicates the extent to which each geological criterion has an effect on

First stage: Nonlinear Hebbian algorithm

Step 1: Read input concept state A^0 and initial weight matrix W^0

Step 2: Repeat for each iteration k

Step 3: Calculate A(k) through the following Equation:

$$A^{(k+1)} = f\left(A_i^{(k)} + \sum_{\substack{j \neq 1 \\ j=1}}^{N} A_j^{(k)},\ w_{ij}^{(k)}\right)$$

Step 4: Update the weight through the following Equation:

$$W_{ji}^{(k)} = \gamma W_{ji}^{(k-1)} + \eta A_i^{(k-1)}\left(A_j^{(k-1)} - \operatorname{sgn}\left(W_{ji}^{(k+1)} A_i^{(k-1)}\right)\right)$$

Step 5: Calculate the termination functions

Step 6: Continue until the termination conditions are met

Step 7: Return the final weights $W_{NLH}^{(k+1)}$ to the *Second stage* (DE algorithm)

Figure 4: The pseudocode of the NLH learning algorithm [56].

Second stage: Differential evolution algorithm (DE)

Step 1: Initialize the DE population in the neighborhood of $W_{NLH}^{(k+1)}$ and within the suggested weight constraints

Step 2: Repeat for each input concept state (k)

Step 3: Do steps (4)to (7) for i=1 to NP (number of population)

Step 4: *MUTATION* $W_i^{(k)} \rightarrow$ *Mutant_Vector*

Step 5: *CROSSOVER*(*Mutant_Vector*) →Trial_Vector

Step 6: Accept Trial Vector for the next generation if $F(Trial\_Vector) \leq F(W_i^{(k)})$

Step 7: Until the termination condition is met

Figure 5: The pseudocode of the DE learning algorithm [56].

MDA. After calculating the weight of the criteria by FCM, the fuzzy theory is used to classify the criteria. It is assumed that U is a set of evaluated elements, and $\prod = \{f_1, f_2, \ldots, f_m\}$ is a set of parameters that determine the quality of the elements under evaluation. Moreover, $E = \{e_1, e_2, \ldots, e_p\}$ is considered as a set of verbal results that e_k determines the quality of the category k. For each of the parameters f_j, for each value of k of the set $\{1, 2, \ldots, p\}$, a fuzzy class e_k is created. Because fuzzy class e_k is a fuzzy set that is controlled by f_j, the fuzzy set is designed by A_{jk} [59]. If qualitative categories are used by distance indexes, the objective function $Q^{(k)}(x)$ is defined as the membership function. $Q^{(k)}(x) = A_{jk}(x)$ is calculated by the following equations:

$$Q^{(1)}(x) = \frac{1}{1 + \exp\left[-c_j \times \left(x - d_j\right)\right]}, \quad j = 1, 2, \ldots, m, \tag{6}$$

$$Q^{(k)}(x) = \exp\left(-\frac{1}{2}\left(\frac{x - a_j}{b_j}\right)^2\right), \quad j = 1, 2, \ldots, m,\ k = 1, 2, \ldots, p-1, \tag{7}$$

$$Q_j^{(p)}(x) = \frac{1}{1 + \exp\left[-c_j \times \left(x - d_j\right)\right]}, \quad j = 1, 2, \ldots, m. \tag{8}$$

It should be noted that the number of qualitative categories is the same for all parameters f_j. By accepting three elements for set $u \in U$, the results of evaluation $R^u = (r_{jk}(u))_{mxp}$ can be obtained as in Figure 6.

Figure 6 shows a map of the multicriteria evaluation method, including the weight of the parameters and the corresponding matrix combined with a decision function, as follows [61]:

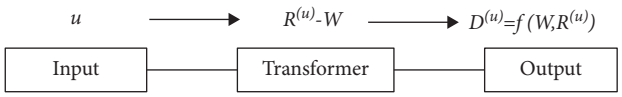

Figure 6: Multicriteria evaluation process [60].

$$\xi: U \longrightarrow F(E), \tag{9}$$

$$\begin{aligned} u &\longrightarrow \xi(u), \\ D^{(u)} &= f\left(W, R^{(u)}\right). \end{aligned} \tag{10}$$

In equations (9) and (10), f is the decision criterion used to evaluate the option.

One of the most important steps in evaluating fuzzy criteria and providing an optimal fuzzy classification system is the selection of the appropriate aggregation operator (T-norm). The operators (T-norms) are part of a fuzzy set that overlaps sets in the sense that they are used as a kind of societal turn. Numerous T-norms such as minimum (maximum) and maximum (minimum) transfer functions have been introduced in many studies (Table 3).

Each T-norm is a fuzzy transfer and has the role of calculation mechanism between fuzzy sets. Also, fuzzy operators act as intermediaries that enable the calculations of the fuzzy equations to be performed correctly and establish connections between different parts of the fuzzy equations and calculations. Fuzzy equations are different from classic mathematics and for this reason, many operators are made and presented to solve fuzzy-based computations. It is now widely accepted that any fuzzy set integrator can be used in multicriteria evaluation. So, decision-makers may choose a decision function that works best in decision-making. In this study, the operator introduced by Dubois and Prade [59] with minimum weight is used. Dubois and Prade operator was used because of the significant efficiency of this operator in solving fuzzy classification problems. In the literature of fuzzy theory's applications in mining engineering problems, usually, the Dubois and Prade operator was used, and the results of this T-norm is acceptable in real-world condition.

After applying the operator in the fuzzy class selection process for each option (coal seam), one can perform expert and engineering analysis of the results. Also, to validate the fuzzy classification results, each option category can be compared with the actual conditions in the mine (Figure 7).

5. Results and Discussion

According to the expert opinion and the relationships between the selected criteria by the FCM method, the fuzzy cognitive map is shown in Figure 8. Then, the causal relationships between the criteria using hybrid learning algorithms (nonlinear and hybrid learning algorithms) were examined, and the weights of each criterion were calculated as presented in Table 4.

After calculating the fuzzy weights of each criterion using the FCM method, all fuzzy weights are transformed into a nonfuzzy (11) [63]:

$$\widetilde{W}_i = \left(\prod_{i=1}^{3} w_j\right)^{1/3}. \tag{11}$$

Table 5 shows the degree of nonfuzzy significance of the criteria affecting the MDA using the FCM method.

After determining the importance of the geological criteria, the interval classification of the criteria was done in five distinct categories (classes): very good (VG), good (G), moderate (M), poor (P), and very poor (VP). The classification results for criteria are presented in Table 6. After determining the categories, the Gaussian and sigmoidal membership functions were defined for each criterion. Fuzzy functions have many forms, including triangles, trapezoids, and sigmoidal. The efficiency of sigmoidal functions is greater than other forms in various engineering problems and the results of this form are close to the real world. These functions are also more consistent with the nature of the problem in this study. The values required to analyze the data and provide the appropriate classification of the coal seams are usually curved forms. Thus, fuzzy sigmoidal functions are used in the current study.

Figure 9 shows the Gaussian membership functions defined for the criteria. After performing the above steps, five-category membership functions were defined for all criteria according to Table 6. The specified functions are presented in Table 7.

To classify the criteria and factors influencing the decision regarding the classification of coal seams for methane drainage, the results of previous studies were used. The technical reports of underground coal mines were very helpful in this regard. Authentic scientific sources, some of which are also mentioned in the text of the article, have also been used. The authors of this article, considering the fuzzy conditions of each criterion and reviewing previous studies, have presented a fuzzy classification (Table 6). It should be noted that models based on fuzzy theory have the ability that specialists can consider their desired intervals to solve an engineering problem. Of course, the authors have also used the experiences of experts and consulting engineers of the Parvadeh coal mine.

Due to the inverse relationship between the "depth of coal seam" and the "methane drainage-ability (MDA)," the curves related to this criterion are different from other diagrams. That means that the shallower depth of the seam (seams in slight deep of the ground) has greater MDA, which indicates a VG class. This argument is not true for other criteria and for other criteria, the opposite is true.

The opinions of geologists and methane drainage system experts have been used in deciding on various criteria affecting the MDA. In the current research, a fuzzy classification of factors affecting MDA is presented based on the experiences of coal mining experts who have experience in methane drainage.

After creating the classification system, the evaluation of this system was done using the presented functions obtained from Parvadeh coalfield data (Table 7). Therefore, at the first step, the fuzzy matrix was formed for each coal seam. The fuzzy matrix elements are represented as a_{ij}. Each element

Table 3: Some of the most important fuzzy aggregation operators (T-norms).

Researcher (s)	Year	Presented operators
Yager [62]	1978	$D^W(\mu_1, \mu_2, \ldots, \mu_m) = \wedge_{i=1}^{m}.\mu_i^{W_i}$
Dubois and Prade [59]	1980	$D^W(\mu_1, \mu_2, \ldots, \mu_m) = \wedge_{i=1}^{m}[(1-w_i)\vee\mu_i]$
Kaymak [61]	1998	$D^W(\mu_1, \mu_2, \ldots, \mu_m) = \mathrm{Max}[0.1 - (\sum_{i=1}^{m} w_i \times (1-\mu_i))^{1/\gamma}]$, $\gamma > 0$

represents the degree of membership of the corresponding criterion i in class j of the mentioned element. An example of the calculations for C_1 coal seam (Table 8) is provided below.

In the next step, the position of each seam was determined in the fuzzy classification by using Dubois and Prade operator (Table 9). It should be noted that the fuzzy calculations were done for each criterion and each fuzzy class.

$$D = f(W, R) \cdots [0.1208, 0.0815, 0.1682, 0.1138, 0.11584, 0.0888, 0.1364, 0.1320]$$

$$\mathrm{O}\begin{bmatrix} 0.0000 & 0.0991 & 0.5661 & 0.0000 & 0.0000 \\ 0.0322 & 0.1181 & 0.0000 & 0.0000 & 0.0000 \\ 1.0000 & 0.0000 & 0.0000 & 0.0075 & 0.0024 \\ 0.0003 & 0.7548 & 0.0795 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.4483 & 0.4674 & 0.0000 \\ 0.0000 & 0.1186 & 0.5083 & 0.0000 & 0.0000 \\ 0.0000 & 0.0000 & 0.5561 & 0.1862 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0038 & 0.9994 \end{bmatrix},$$

$$\begin{aligned} D^W &= f(W, R) \\ &= \wedge_{i=1}^{m}[(1-w_i)\vee\mu_i] \Longrightarrow d_i(u) \\ &= ((1-w_i)\vee r_{11}(u))\wedge\cdots\wedge((1-w_i)\vee r_{11}(u)), \\ \left.\begin{aligned} d_1(u) &= ((1-w_1)\vee r_{11}(u))\wedge\cdots\wedge((1-w_9)\vee r_{91}(u)) = 0.8680 \\ d_2(u) &= ((1-w_1)\vee r_{12}(u))\wedge\cdots\wedge((1-w_9)\vee r_{92}(u)) = 0.4674 \\ d_3(u) &= ((1-w_1)\vee r_{13}(u))\wedge\cdots\wedge((1-w_9)\vee r_{93}(u)) = 0.5661 \\ d_4(u) &= ((1-w_1)\vee r_{14}(u))\wedge\cdots\wedge((1-w_9)\vee r_{94}(u)) = 0.7548 \\ d_5(u) &= ((1-w_1)\vee r_{15}(u))\wedge\cdots\wedge((1-w_9)\vee r_{95}) = 0.8317 \end{aligned}\right\} &\Rightarrow D = f(W, R) \\ &= (\underline{0.8680}, 0.4674, 0.5661, 0.7548, 0.8317). \end{aligned} \tag{12}$$

The value of 0.8680 belongs to the "very good" category that has the seam of C_1. The results of the fuzzy classification for different coal seams in Parvadeh are presented in Table 9.

The C_1 seam located in Parvadeh coalfield is mined by a mechanized longwall retreat mining method. Currently, considering the high value of C_1 gas content, methane drainage operation is done by steeply methane drainage boreholes into the roof strata with the length of 40–90 m and 28–37-degree dip. The boreholes cut off the C_2 coal seam. The C_1 coal seam has low strength. In soft coal seams, drilling boreholes is very difficult because the holes fail and usually collapse, and drill bits get stuck in the holes. However, the C_1 seam is very accurate in the category of "very good," which is calculated by the proposed fuzzy classification system, which is very consistent with the real-field conditions. Also, the other seams have their own conditions. For example, seam C_2 has a significant gas volume because it is located above seam C_1, and the geological parameters of this seam are almost similar to seam C_1. Because of this, seam C_2 is placed close to seam C_1, in the "good" category. The seams B_2, B_1, and D were classified into "Moderate," "Poor," and "Very Poor" categories due to the fluctuations in the values of the geological criteria, indicating the fact that these seams are among the last priorities of the methane drainage operation.

The only way for proposed classification model validation is to compare the results of the current study with the real conditions of a coal mine in which methane drainage operation is processing. For this purpose, the largest and

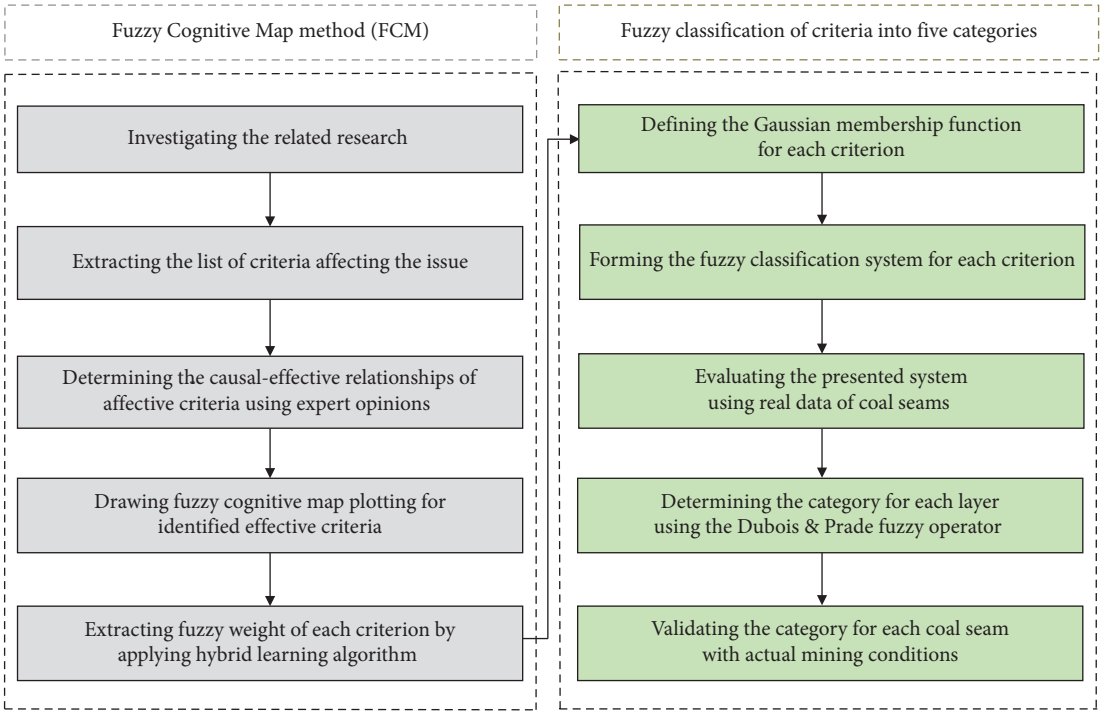

Figure 7: Flowchart of the various steps of the presented hybrid fuzzy approach.

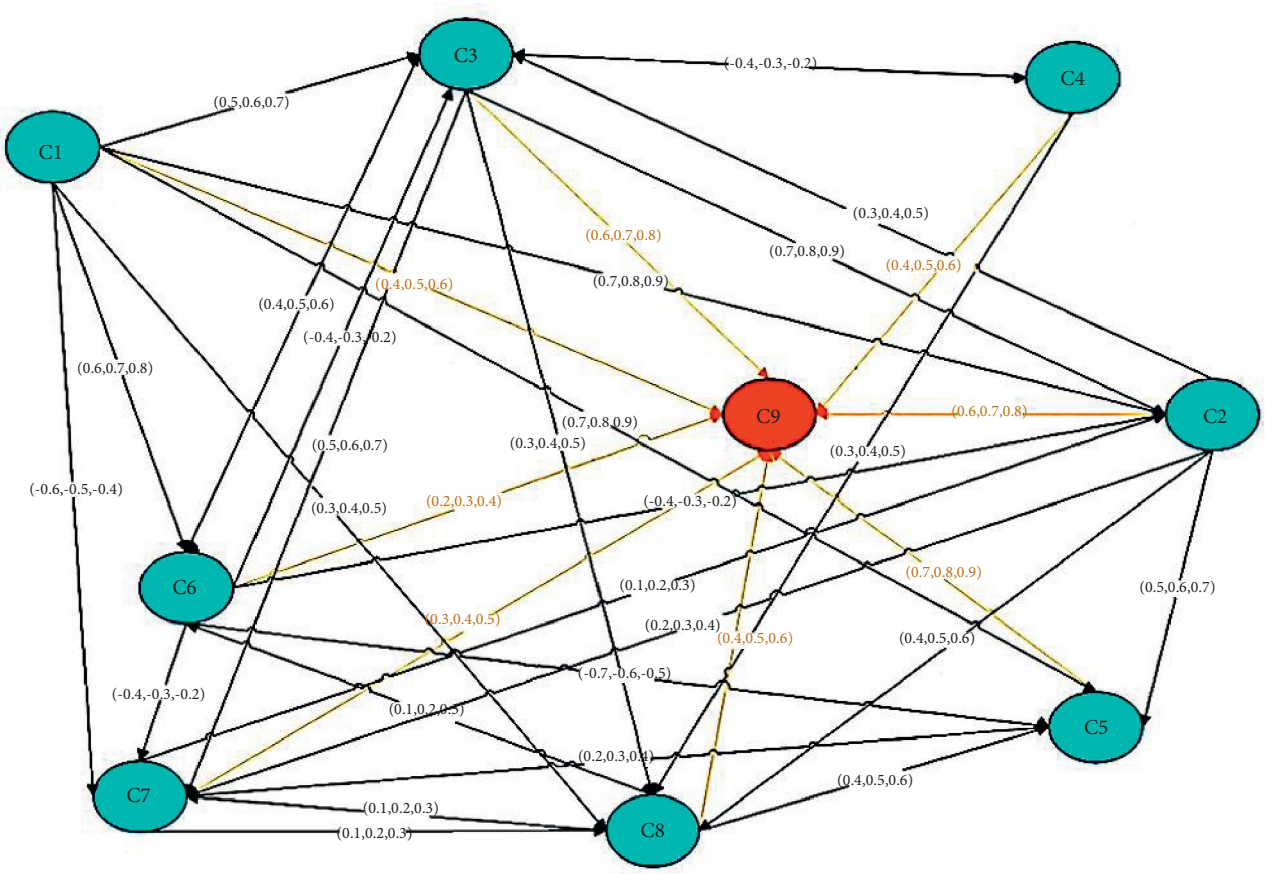

Figure 8: FCM to calculate the weight of different parameters affecting MDA (case study).

Table 4: The weights from the FCM method for each criterion.

Criteria	Symbol	Weights from learning algorithm		
		Lower limit	Middle limit	Higher limit
Depth of seam	C_1	0.4038	0.5053	0.6087
Thickness of seam	C_2	0.3132	0.3394	0.3586
Cleats	C_3	0.6631	0.6939	0.7281
Uniformity of seam	C_4	0.4716	0.4862	0.4921
Gas content	C_5	0.6177	0.6521	0.6945
Roof quality	C_6	0.3357	0.3764	0.3902
Water condition	C_7	0.5033	0.5304	0.6697
Permeability	C_8	0.5209	0.5445	0.5706
Methane drainage	C_9	-	-	-

Table 5: The importance degree (weight) of the geological criteria affecting MDA of coal seams.

Criteria	Symbol	Degree of importance ($\widetilde{W}_i$)
Depth of seam	C_1	0.1208
Thickness of seam	C_2	0.0815
Cleats	C_3	0.1682
Uniformity of seam	C_4	0.1138
Gas content	C_5	0.1584
Roof quality	C_6	0.0888
Water condition	C_7	0.1364
Permeability	C_8	0.1320

Table 6: The quantitative and qualitative classification of geological criteria affecting MDA.

Criteria	Quantitative and qualitative classification of criteria				
Depth of seam (m)	1–100 very shallow	100–200 shallow	200–400 nearly deep	400–600 deep	600 < very deep
Thickness of seam (m)	<0.5 very thin	0.5–4.5 thin	4.6–6 nearly thick	6–30 thick	30 < very thick
Cleats condition (joint/m)	0–3 very few	3–10 few	10–15 moderate	15–20 numerous	20 < very numerous
Uniformity of seam	0–0.5 very uniform	0.5–1.3 uniform	1.3–2 nearly uniform	2–2.8 nonuniform	2.8 < quite nonuniform
Gas content (m^3/ton)	0–5 very low gaseous	5–10 low gaseous	10–15 moderate gaseous	15–20 gaseous	20 < very gaseous
Roof quality (MPa)	5–40 very weak	40–100 weak	100–200 moderate	200–300 strong	300 < very strong
Underground water condition (m^3/min)	0–35 dry	35–70 wet	70–105 very wet	105–140 hydrous	140 < very hydrous
Permeability (mDarcy)	0–5 very little	5–15 little	15–30 moderate	30–45 very much	45 < much

most mechanized coal mine in Iran was studied for validation of the presented fuzzy classification model. The results of the presented model were compared with the information and data obtained from the real CBM operations in the mentioned mine. Also, the MDA obtained from the model was evaluated with the parameters obtained from the implementation of the real operation. The results show that the coal seam whose MDA is in the "good" class is in fact the same. Or the coal seam with "bad" MDA class is really evaluated for bad to drain the methane based on the criteria influencing the model.

Similar studies have not been performed on the fuzzy classification of coal seams and their prioritization based on methane drainage-ability. The results of the research were compared with the real conditions of the Parvadeh mine (case study). Parvadeh mine is the largest mechanized mine in Iran and methane drainage operations are carried out in it. The design and implementation of metamorphosis operations of this mine have been done by reputable consulting companies and are still ongoing. In order to validate the present study, the results of fuzzy calculations and classification were compared with the results of the design and implementation of consulting engineers of Tabas Coal Project, which indicates the concordance of the research results with the real world. It should be noted that the projects presented by consulting engineers are being implemented in the Parvadeh mine and the layers mentioned in this study have been selected from the same layers of activated coal so that a more accurate comparison can be made.

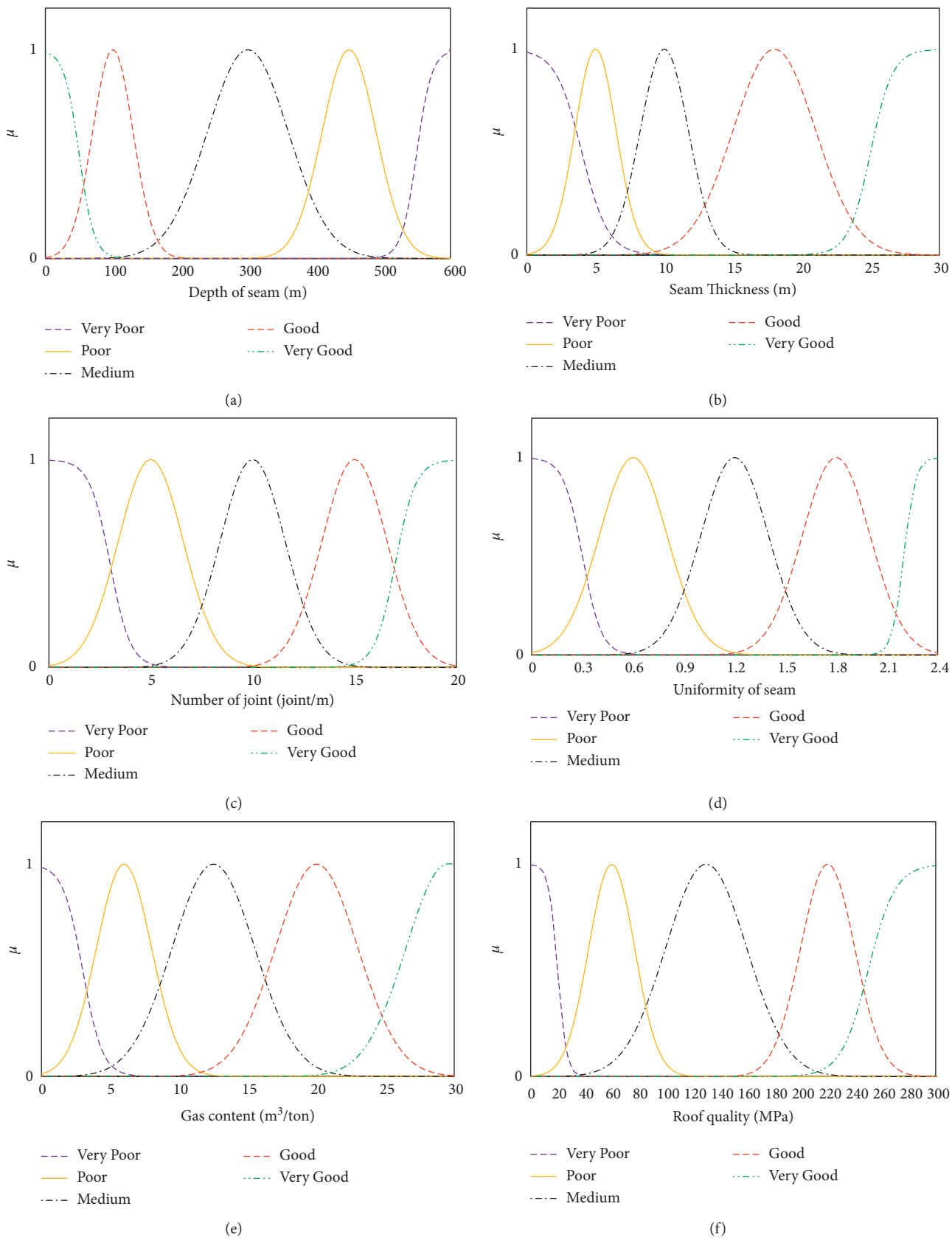

Figure 9: Continued.

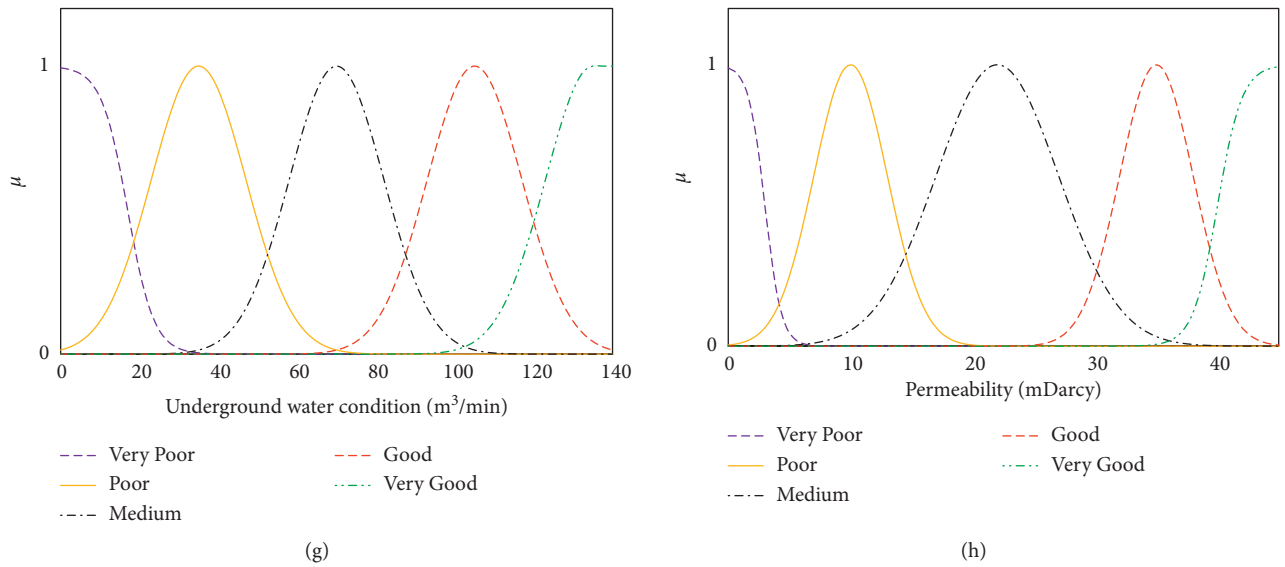

Figure 9: Membership functions of criteria.

Table 7: The presented functions for the evaluation of the MDA of coal seams.

Qualitative class	Thickness of seam	Depth of seam
Very poor	$Q_1^{(1)}(x) = 1/1 + \exp[4 \times (x - 1.05)]$	$Q_1^{(1)}(x) = 1/1 + \exp[(-0.09) \times (x - 550)]$
Poor	$Q_1^{(2)}(x) = \exp[-1/2(x - 5/1.5)^2]$	$Q_1^{(2)}(x) = \exp[-1/2(x - 450/40)^2]$
Moderate	$Q_1^{(3)}(x) = \exp[-1/2(x - 10/1.75)^2]$	$Q_1^{(3)}(x) = \exp[-1/2(x - 300/60)^2]$
Good	$Q_1^{(4)}(x) = \exp[-1/2(x - 18/3)^2]$	$Q_1^{(4)}(x) = \exp[-1/2(x - 100/30)^2]$
Very good	$Q_1^{(5)}(x) = 1/1 + \exp[(-1.25) \times (x - 25)]$	$Q_1^{(5)}(x) = 1/1 + \exp[(0.09) \times (x - 50)]$
Qualitative class	Uniformity of seam	Cleats
Very poor	$Q_1^{(1)}(x) = 1/1 + \exp[(18) \times (x - 0.3)]$	$Q_1^{(5)}(x) = 1/1 + \exp[(-2) \times (x - 5)]$
Poor	$Q_1^{(2)}(x) = \exp[-1/2(x - 0.6/0.2)^2]$	$Q_1^{(4)}(x) = \exp[-1/2(x - 5/1.6)^2]$
Moderate	$Q_1^{(3)}(x) = \exp[-1/2(x - 1.2/0.2)^2]$	$Q_1^{(3)}(x) = \exp[-1/2(x - 10/1.6)^2]$
Good	$Q_1^{(4)}(x) = \exp[-1/2(x - 1.8/0.2)^2]$	$Q_1^{(2)}(x) = \exp[-1/2(x - 15/1.6)^2]$
Very good	$Q_1^{(5)}(x) = 1/1 + \exp[(-18) \times (x - 2.2)]$	$Q_1^{(1)}(x) = 1/1 + \exp[2 \times (x - 17)]$
Qualitative class	Gas content	Underground water condition
Very poor	$Q_1^{(1)}(x) = 1/1 + \exp[1.4 \times (x - 3)]$	$Q_1^{(1)}(x) = 1/1 + \exp[0.3 \times (x - 35)]$
Poor	$Q_1^{(2)}(x) = \exp[-1/2(x - 6/2)^2]$	$Q_1^{(2)}(x) = \exp[-1/2(x - 35/12)^2]$
Moderate	$Q_1^{(3)}(x) = \exp[-1/2(x - 12.5/3)^2]$	$Q_1^{(3)}(x) = \exp[-1/2(x - 70/12)^2]$
Good	$Q_1^{(4)}(x) = \exp[-1/2(x - 20/3)^2]$	$Q_1^{(4)}(x) = \exp[-1/2(x - 105/12)^2]$
Very good	$Q_1^{(5)}(x) = 1/1 + \exp[(-1.4) \times (x - 29.5)]$	$Q_1^{(5)}(x) = 1/1 + \exp[(-0.3) \times (x - 135)]$
Qualitative class	Roof quality	Permeability
Very poor	$Q_1^{(1)}(x) = 1/1 + \exp[0.3 \times (x - 20)]$	$Q_1^{(1)}(x) = 1/1 + \exp[1.5 \times (x - 3)]$
Poor	$Q_1^{(2)}(x) = \exp[-1/2(x - 60/17)^2]$	$Q_1^{(2)}(x) = \exp[-1/2(x - 10/3)^2]$
Moderate	$Q_1^{(3)}(x) = \exp[-1/2(x - 130/30)^2]$	$Q_1^{(3)}(x) = \exp[-1/2(x - 22/5)^2]$
Good	$Q_1^{(4)}(x) = \exp[-1/2(x - 220/20)^2]$	$Q_1^{(4)}(x) = \exp[-1/2(x - 35/3)^2]$
Very good	$Q_1^{(5)}(x) = 1/1 + \exp[(-0.1) \times (x - 250)]$	$Q_1^{(5)}(x) = 1/1 + \exp[(-1.5) \times (x - 40)]$

Table 8: Fuzzy matrix of seam C_1.

Criteria	Seam data	Components of fuzzy matrix				
		VP	P	M	G	VG
Depth of seam	364	0	0.0991	0.5661	0	0
Thickness of seam	1.9	0.0322	0.1181	0	0	0
Cleats	20	1	0	0	0.0075	0.0024
Uniformity of seam	0.75	0.0003	0.7548	0.0795	0	0
Gas content	16.3	0	0	0.4483	0.4674	0
Roof quality	95.1	0	0.1186	0.5083	0	0
Water condition	83	0	0	0.5561	0.1862	0
Permeability	45	0	0	0	0.0038	0.9994

Table 9: Fuzzy classification for different seams of Parvadeh.

Seam	Fuzzy value	Fuzzy class
B_2	0.8317	Moderate
B_1	0.7066	Poor
C_2	0.8661	Good
C_1	0.8680	Very Good
D	0.6869	Very Poor

6. Conclusion

The results for the five coal seams in Parvadeh coalfield with different intrinsic, uncertain geological, and environmental conditions, using Dubois and Prade operator, showing that seam C_1 is located in the "very good" and seam C_2 is in "good" categories in terms of MDA. This can be accounted for by the high gas content, the very good condition of the generalization parameter, and the relatively high thickness of the seam C_1 relative to the other coal seams. On the other hand, seam B_2 is located in the "moderate" quality fuzzy class. The seam B_1 was also classified as "poor." At present, among these seams, the seam C_1 of the Parvadeh (Tabas coal mine) is mined by a full-mechanized longwall mining method, and the methane drainage operation is done in this mine. In order to validate the results of the study, the data from the drainage holes used in this mine were compared with the qualitative categories of each seam, indicating that the results of this classification system are in good agreement with the real conditions of the studied seams in the Tabas (Parvadeh) coalfield.

The results of this research can pave the way for future studies. Also, by comparing the obtained results with the real conditions and technical reports of the consulting engineers of Parvadeh Tabas mine, the compatibility of the results of this research with the real world was proved. The required suggestions were also provided to the managers of Parvadeh Tabas mine. The managerial and financial-economic aspects of this study should be evaluated in the form of another study. However, it can be noted that with the correct prioritization of coal seams, in addition to managing human and financial resources of underground coal mining projects, risk management due to methane gas condensation in the underground spaces of coal mines can also be done. Obviously, safety in underground coal mines is of special importance that by selecting the appropriate coal layers and performing methane drainage operations, we can see an increase in the level of safety of underground coal mining, which is of great importance from a managerial point of view. On the other hand, by selecting the appropriate layer for metamorphosis and performing metamorphosis operations from the desired layer, we can see the growth of the profitability of mines. Methane extracted from coal seams is a good source of income that can be a significant profit as a by-product of the mine.

Data Availability

The data that support the findings of the current study are available from Amir Jafarpour upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] C. Ö. Karacan and P. D. Warwick, "Assessment of coal mine methane (CMM) and abandoned mine methane (AMM) resource potential of longwall mine panels: example from Northern Appalachian Basin, USA," *International Journal of Coal Geology*, vol. 208, pp. 37–53, 2019.

[2] J. Hendel and J. Macuda, "Coal mine methane production by vertical boreholes drilled from surface," *International Multidisciplinary Scientific GeoConference: SGEM: Surveying Geology & Mining Ecology Management*, vol. 17, no. 1.2, pp. 127–133, 2017.

[3] C. Ö. Karacan, "Heterogeneous sorption and swelling in a confined and stressed coal during CO_2 injection," *Energy and Fuels*, vol. 17, no. 6, pp. 1595–1608, 2003.

[4] L. Zhang, T. Ren, N. Aziz, and C. Zhang, "Evaluation of coal seam gas drainability for outburst-prone and high-co2-containing coal seam," *Geofluids*, vol. 2019, Article ID 3481834, 14 pages, 2019.

[5] C. Ö. Karacan, F. A. Ruiz, M. Cotè, and S. Phipps, "Coal mine methane: a review of capture and utilization practices with benefits to mining safety and to greenhouse gas reduction," *International Journal of Coal Geology*, vol. 86, no. 2-3, pp. 121–156, 2011.

[6] J. Jiang, Y. Cheng, P. Zhang, K. Jin, J. Cui, and H. Du, "CBM drainage engineering challenges and the technology of mining protective coal seam in the Dalong mine, Tiefa basin, China," *Journal of Natural Gas Science and Engineering*, vol. 24, pp. 412–424, 2015.

[7] A. W. Bhutto, A. A. Bazmi, and G. Zahedi, "Underground coal gasification: from fundamentals to applications," *Progress in Energy and Combustion Science*, vol. 39, no. 1, pp. 189–214, 2013.

[8] M. Najafi, S. M. E. Jalali, and R. KhaloKakaie, "Thermal-mechanical-numerical analysis of stress distribution in the vicinity of underground coal gasification (UCG) panels," *International Journal of Coal Geology*, vol. 134-135, pp. 1–16, 2014.

[9] D. J. Xu and B. L. Hu, "Analysis on geologic factors affecting coal seam methane occurrence regularity," *Zhongzhou Coal*, vol. 2, 2009.

[10] T. Lu, Y. Guo, and X. Yang, "Coal seam fracturing by a high-pressure waterjet technique to increase efficiency of coal mine gas drainage," *Journal of the South African Institute of Mining and Metallurgy*, vol. 116, no. 1, pp. 79–84, 2016.

[11] Z. Likai, J. Youjun, Y. Tianhong, and L. Xiaoyu, "Analysis on production of coal bed methane considering the change in permeability of coal rock," *The Open Petroleum Engineering Journal*, vol. 9, no. 1, 2016.

[12] Z. Xie, D. Zhang, Z. Song, M. Li, C. Liu, and D. Sun, "Optimization of drilling layouts based on controlled presplitting

blasting through strata for gas drainage in coal roadway strips," *Energies*, vol. 10, no. 8, p. 1228, 2017.

[13] Z. Xin, B. Jiang, X. U. Qiang, L. Jiegang, Z. Yue, and D. Piaopiao, "Well pattern design and optimal deployment for coalbed methane development," *Petroleum Exploration and Development*, vol. 43, no. 1, pp. 89–96, 2016.

[14] H. Qianting, L. Yunpei, W. Han, Z. Quanle, and S. Haitao, "Intelligent and integrated techniques for coalbed methane (CBM) recovery and reduction of greenhouse gas emission," *Environmental Science and Pollution Research*, vol. 24, no. 21, pp. 17651–17668, 2017.

[15] J. Swiadrowski and K. Stanczyk, "Environmental aspects of underground coal gasification," *Chemik*, vol. 70, no. 5, pp. 239–242, 2016.

[16] M. S. A. Perera, P. G. Ranjith, A. S. Ranathunga, A. Y. J. Koay, J. Zhao, and S. K. Choi, "Optimization of enhanced coal-bed methane recovery using numerical simulation," *Journal of Geophysics and Engineering*, vol. 12, no. 1, pp. 90–107, 2015.

[17] J. Zhou, G. Liang, T. Deng, and S. Zhou, "Optimization design of coalbed methane pipeline network–coupled wellbore/reservoir simulation," *Advances in Mechanical Engineering*, vol. 9, no. 6, Article ID 1687814017708905, 2017.

[18] G. Wang, Y. Qin, Y. Xie et al., "Coalbed methane system potential evaluation and favourable area prediction of Gujiao blocks, Xishan coalfield, based on multi-level fuzzy mathematical analysis," *Journal of Petroleum Science and Engineering*, vol. 160, pp. 136–151, 2018.

[19] S. Meng, Y. Li, L. Wang, K. Wang, and Z. Pan, "A mathematical model for gas and water production from overlapping fractured coalbed methane and tight gas reservoirs," *Journal of Petroleum Science and Engineering*, vol. 171, pp. 959–973, 2018.

[20] M. Najafi and R. Rafiee, "Development of a new index for methane drainageability of a coal seam using the fuzzy rock engineering system," *Rudarsko-Geolosko-Naftni Zbornik*, vol. 34, no. 4, 2019.

[21] N. Szlązak and M. Korzec, "Method for determining the coalbed methane content with determination the uncertainty of measurements," *Archives of Mining Sciences*, vol. 61, no. 2, pp. 443–456, 2016.

[22] L. Montiel, R. Dimitrakopoulos, and K. Kawahata, "Globally optimising open-pit and underground mining operations under geological uncertainty," *Mining Technology*, vol. 125, no. 1, pp. 2–14, 2016.

[23] S. Shariati, "Underground mine risk assessment by using FMEA in the presence of uncertainty," *Decision Science Letters*, vol. 3, no. 3, pp. 295–304, 2014.

[24] R. M. Flores, G. Wang, D. Qin, Y. Xi, and L. R. Rukstales, "Advancing CMM drainage, quality, and utilization with horizontal directional-drilled boreholes in Duanshi Coal Mine, southern Qinshui Basin, China," *International Journal of Coal Geology*, vol. 209, pp. 1–13, 2019.

[25] S. Kędzior and M. Dreger, "Methane occurrence, emissions and hazards in the upper silesian coal basin, Poland," *International Journal of Coal Geology*, vol. 211, Article ID 103226, 2019.

[26] S. Tao, Z. Pan, S. Tang, and S. Chen, "Current status and geological conditions for the applicability of CBM drilling technologies in China: a review," *International Journal of Coal Geology*, vol. 202, pp. 95–108, 2019.

[27] C. Zheng, B. Jiang, S. Xue, Z. Chen, and H. Li, "Coalbed methane emissions and drainage methods in underground mining for mining safety and environmental benefits: a review," *Process Safety and Environmental Protection*, vol. 127, 2019.

[28] Y. Qin, T. A. Moore, J. Shen, Z. Yang, Y. Shen, and G. Wang, "Resources and geology of coalbed methane in China: a review," *International Geology Review*, vol. 60, no. 5-6, pp. 777–812, 2018.

[29] J. Brodny and M. Tutak, "Analysis of methane hazard conditions in mine headings," *Tehnički Vjesnik*, vol. 25, no. 1, pp. 271–276, 2018.

[30] L. Howard and H. L. Hartman, "Methane drainage," in *Handbook of Mining Engineering*, G. L. Finger, A. Michael, and Trevits, Eds., Society for Mining, Metallurgy and Exploration, Littleton, CO, USA, 1992.

[31] G. C. Meszaros, "Geosteering horizontal coalbed methane reservoirs: a case study," in *Proceedings of the Rocky Mountain Oil & Gas Technology Symposium*, Denver, CO, U.S.A, April 2007.

[32] S. E. Laubach, R. A. Marrett, J. E. Olson, and A. R. Scott, "Characteristics and origins of coal cleat: a review," *International Journal of Coal Geology*, vol. 35, no. 1–4, pp. 175–207, 1998.

[33] D. J. Black, N. Aziz, and T. Ren, "Enhanced gas drainage from undersaturated coal bed methane reservoirs," in *Proceedings of the 3rd Asia Pacific Coalbed Methane Symposium*, pp. 1–8, Brisbane, Australia, May 2011.

[34] S. Peng, H. Chen, R. Yang, Y. Gao, and X. Chen, "Factors facilitating or limiting the use of AVO for coal-bed methane," *Geophysics*, vol. 71, no. 4, pp. C49–C56, 2006.

[35] T. A. Moore, "Coalbed methane: a review," *International Journal of Coal Geology*, vol. 101, pp. 36–81, 2012.

[36] X. Cui and R. M. Bustin, "Controls of coal fabric on coalbed gas production and compositional shift in both field production and canister desorption test," *SPE Journal*, vol. 11, no. 01, pp. 111–119, 2006.

[37] D. P. Creedy, "An introduction to geological aspects of methane occurrence and control in British deep coal mines," *The Quarterly Journal of Engineering Geology and Hydrogeology*, vol. 24, no. 2, pp. 209–220, 1991.

[38] J. Ulery, "Managing excess gas emissions associated with coal mine geologic features," *Handbook for Methane Control in Mining*, NIOSH, Information Circular 9486, Pittsburgh, PA, USA, 2006.

[39] S. Paul and R. Chatterjee, "Determination of in-situ stress direction from cleat orientation mapping for coal bed methane exploration in south-eastern part of Jharia coalfield, India," *International Journal of Coal Geology*, vol. 87, no. 2, pp. 87–96, 2011.

[40] P. Thakur, "Coal seam degasification," *Coal Bed*, Methane, Elsevier, pp. 155–175, Amsterdam, Netherland, 2014.

[41] J. Esterle, *Gas in Coal: a Hazard and a Resource*, University of Queensland Australia, Brisbane, Australia, 2005.

[42] A. Saghafi, "Determination of the gas content of coal," in *Proceedings of the 2016 Coal Operators' Conference, Mining Engineering*, N. Aziz and B. Kininmonth, Eds., pp. 18–20, Wollongong, Australia, February 2016.

[43] A. G. Kim, *Estimating Methane Content of Bituminous Coalbeds from adsorption Data*, Bureau of Mines, Pittsburgh Mining and Safety Research Center, Pittsburgh, PA, USA, 1977.

[44] J. Ying, J. Yongli, and F. Hui, "Construction technology of steel roof waterproofing in ministry of foreign affairs of Congo," *Construction Technology*, vol. 2010, no. 10, pp. 105–107, 2010.

[45] J. D. McLennan, P. S. Schafer, and T. J. Pratt, "A guide to determining coalbed gas content: gas Research Institute," *Topical Report GRI*, vol. 94, no. 0396, p. 123, 1995.
[46] K. Unrug and T. B. Szwilski, "Method of roof quality prediction," in *Proceedings of the State-Of-The-Art of Ground Control in Longwall Mining and Mining Subsidence*, Morgantown, WV, USA, August 1982.
[47] J. J. Walsh and J. Watterson, "New methods of fault projection for coalmine planning," *Proceedings of the Yorkshire Geological Society*, vol. 48, no. 2, pp. 209–219, 1994.
[48] L. A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, no. 3, pp. 338–353, 1965.
[49] R. Mikaeil, E. J. Gharahasanlou, and A. Jafarpour, "Ranking and evaluating the coal seam mechanization based on geological conditions," *Geotechnical & Geological Engineering*, vol. 38, no. 3, pp. 3307–3329, 2020.
[50] R. E. Bellman and L. A. Zadeh, "Decision-making in a fuzzy environment," *Management Science*, vol. 17, no. 4, pp. B–141, 1970.
[51] S. Ghadernejad, A. Jafarpour, and P. Ahmadi, "The application of an integrated decision-making approach based on FDAHP and PROMETHEE for selection of optimal coal seam for mechanization (case study: tazareh coal mine complex, Iran)," *International Journal of Mining and Geological Engineering*, vol. 53, no. 1, pp. 15–23, 2019.
[52] E. I. Papageorgiou, C. Stylios, and P. P. Groumpos, "Unsupervised learning techniques for fine-tuning fuzzy cognitive map causal links," *International Journal of Human-Computer Studies*, vol. 64, no. 8, pp. 727–743, 2006.
[53] S. Tabatabaee, M. Ashour, S. R. Mohandes et al., "Deterrents to the adoption of green walls: a hybrid fuzzy-based approach," *Engineering Construction and Architectural Management*, 2021.
[54] M. Jahangoshai Rezaee, S. Yousefi, M. Valipour, and M. M. Dehdar, "Risk analysis of sequential processes in food industry integrating multi-stage fuzzy cognitive map and process failure mode and effects analysis," *Computers & Industrial Engineering*, vol. 123, pp. 325–337, 2018.
[55] M. A. Onari and M. J. Rezaee, "A fuzzy cognitive map based on Nash bargaining game for supplier selection problem: a case study on auto parts industry," *Operational Research*, pp. 1–39, 2020.
[56] E. Bakhtavar, S. Yousefi, and A. Jafarpour, "Evaluation of shaft locations in underground mines: fuzzy multi-objective optimization by ratio analysis with fuzzy cognitive map weights," *Journal of the South African Institute of Mining and Metallurgy*, vol. 119, no. 10, pp. 855–864, 2019.
[57] S. Yousefi and B. M. Tosarkani, "An analytical approach for evaluating the impact of blockchain technology on sustainable supply chain performance," *International Journal of Production Economics*, vol. 246, Article ID 108429, 2022.
[58] Y. Liu, J. Xiao, Y. Zheng, and L. Tang, "Effects of nitrogen levels and root barriers on nitrogen absorption of intercropping *Triticum aestivum* and Vicia faba," *Journal of Southwest Forestry University*, vol. 38, no. 1, pp. 72–78, 2018.
[59] D. Dubois and H. Prade, "New results about properties and semantics of fuzzy set-theoretic operators," in *Fuzzy Sets*, Springer, Boston, MA, USA, 1980.
[60] B. Tutmez, S. Kahraman, and O. Gunaydin, "Multifactorial fuzzy approach to the sawability classification of building stones," *Construction and Building Materials*, vol. 21, no. 8, pp. 1672–1679, 2007.
[61] U. Kaymak, *Fuzzy decision making with control applications*, PhD Thesis, Delft University of Technology, Delft, Netherlands, 1998.
[62] R. R. Yager, "Fuzzy decision making including unequal objectives," *Fuzzy Sets and Systems*, vol. 1, no. 2, pp. 87–95, 1978.
[63] Y. C. Liu and C. S. Chen, "A new approach for application of rock mass classification on rock slope stability assessment," *Engineering Geology*, vol. 89, no. 1-2, pp. 129–143, 2007.
[64] H. X. Li and V. C. Yen, *Fuzzy Sets and Fuzzy Decision Making*, CRC Press, Boca Raton, FL, USA, p. 347, 1995.