ESTIMATION OF COAL SEAM METHANE CONTENTS USING FUZZY LOGIC METHOD

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Keywords

Coal, underground mining, methane, fuzzy logic, mine safety

Abstract

The physical characteristics and chemical composition of the coal change as a result of coalification. Coal has a particular ability for sorption. One of the main dangers in underground coal mines is methane, which is also a problem for the environment because of gas emissions from coal mining. Numerous mechanisms, including gas migration, accumulation, and formation, affect methane content. Depending on the rank and depth of the coal seam, its quality and quantity vary significantly. Methane poses a significant threat as mining depths increase because of the possibility of explosion. Therefore, a critical issue for mine safety is the forecast of methane concentrations based on various and changing working conditions. In this study, the estimation of coal seam methane concentrations was performed using fuzzy logic, which offers a quick and reliable approach. The study's goal is to suggest a different approach to preventing potential mining accidents by predicting the amount of methane in coal seams using fuzzy logic. Therefore, a fuzzy inference system (FIS) model was developed by using Mamdani system. The field methane contents were compared to the model values. The findings show that the fuzzy logic model has a 92% success rate in making accurate predictions. The classifications established based on the measured value in the field and those predicted by the fuzzy model are similar.

KÖMÜR DAMARI METAN İÇERİKLERİNİN BULANIK MANTIK YÖNTEMİ İLE TAHMİNİ

Anahtar Kelimeler

Kömür, yeraltı madenciliği, metan, bulanık mantık, maden güvenliği

Öz

Kömürleşme işlemi, kömürün hem fiziksel özelliklerinde hem de kimyasal yapısında değişikliklere neden olur. Sorpsiyon kapasitesi, kömürün karakteristik bir özelliğidir. Metan, yeraltı kömür madenlerinde önemli tehtidlerden biridir ve ayrıca kömür madenciliğinden kaynaklanan gaz emisyonlarının çevresel bir sorunudur. Metan içeriği, gaz göçü, birikimi ve üretimi gibi bir dizi sürece bağlıdır. Kalitesi ve miktarı, kömür damarının derecesine ve derinliğine bağlı olarak büyük ölçüde farklılık gösterir. Üretim derinliklerinin artmasıyla birlikte metan, patlama riski nedeniyle önemli bir tehlike haline gelmektedir. Bu nedenle metan içeriklerinin farklı ve değişen çalışma koşullarına göre tahmin edilmesi maden güvenliği açısından önemli bir konudur. Bu çalışmada kömür damarı metan içeriklerinin tahmininde hızlı ve güvenilir bir çözüm sunan Bulanık Mantık yöntemi tercih edilmiştir. Çalışmanın amacı, Bulanık Mantık yöntemi ile kömür damarı metan içeriklerini tahmin ederek olası maden kazalarını önlemek için alternatif bir yol önermektir. Bu nedenle Mamdani sistemi kullanılarak bir bulanık çıkarım modeli geliştirilmiştir. Model sonuçları yerinde metan içerikleri ile karşılaştırılmıştır. Sonuçlar, Bulanık Mantık modelinin %92 başarı oranı ile güvenilir bir tahmin aracı olabileceğini göstermektedir. Bulanık modelin tahmin etmiş olduğu sınıf ile sahada ölçülen değere göre belirlenen sınıflar benzerdir.

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1. Introduction

Coalbed methane (CBM) is a natural gas that can be gathered from coal seams. While some gas constituents transfer into coal seams from other layers, CBM is generated in situ by thermal, microbial, or probably catalytic deterioration of inherent ingredients existent in coal. CBM primarily includes methane (CH_4) with the other constituents of nitrogen (N_2), heavier hydrocarbons, carbon dioxide (CO_2) ethane (C_2H_6), propane (C_3H_8), and butanes (C_4H_{10}) (Gao, Mastalerz and Schimmelmann, 2014). CBM is different from traditional gas basins or sandstone since it is deposited in the coal in a manner named adsorption. It is stored in natural fractures, butt cleats, face cleats, pores, and micro-pores. Methane is supposed to exist mainly in matrix pores (>95%), micro-pores in adsorbed conditions, and very little quantity in natural fractures (<5%). Methane occurs in two different forms in coal, generally called adsorbed gas and free gas. The free gas contains particles that are free to transfer in the fractures and pores. Most of CBM is in adsorbed condition on the micropores of the coal surface, thus coal is both the reservoir rock and resource for CBM (McPherson, 1993).

In the pores and fractures of coal under undisturbed conditions, there is an equilibrium between adsorbed gas and free gas. As mining operations get underway, the gas pressure gradient may cause flow-through natural or stress-induced fractures. Desorption is stimulated by the pores' low gas pressure. In other words, when the binding pressure that keeps the gases in coal is released, gas emission happens by diffusion. This principle continues during the methane extraction process. Due to production in deep coal seams, increased productivity, and increased coal fragmentation, methane emissions from coal have considerably increased during the past few decades. Methane must be under control at the working faces and other mine locations, according to existing standards for coal mines. A ventilation system that is well-designed can do this (Prasad, 2012).

CBM content is affected by various factors such as seam thickness, seam depth, coal rank, maceral composition (vitrinite, liptinite, inertinite), cleats/fractures, hydrodynamic properties, porosity and permeability, reservoir temperature, geothermal gradient, physical and chemical features of the coal (ash content, volatile matter, water content), pressure, magma intrusion (Islam and Hayashi, 2008; Hemza, Sivek and Jirásek, 2009; Kedzior, 2009; Zhu, Liu, Chen and Kang, 2017). Methane content is one of the most important parameters to be measured to characterize a coal seam, both in terms of mine safety and gas recovery. Within the scope of the present study, when some studies in the literature were examined, it has been seen that the methane content in coal seams was determined as the most important risk factor for mine safety (De-shun and Kai-li, 2011; Mahdevari, Shahriar and Esfahanipour, 2014; Mutlu and Sari, 2022). There are two causes to measure the coal seam methane contents and related strata: (1) Such data are essential in the valuation of methane emissions into working areas and, thus, these emissions can be diluted to the mandatory and safe threshold limit values. (2) The methane content of the layers is necessary data for computer models or other computational processes to assess the gas flows attained from methane drainage applications. There are two methods such as direct and indirect methods to evaluate the coal gas content. The direct measurement method consists of observations of gas release from coal samples. The indirect method is based on the adsorption isotherms, measuring other coal properties, and examining the relationships between these factors (McPherson, 1993; Prasad, 2012).

Coalbed methane is a type of unconventional natural gas storage, which exists in the coal seam and its adjacent rocks in reservoir type. Coalbed methane is not only one of the important disasters factors in coal mine production, but also is a prerequisite for commercial exploration and development of coalbed methane resources in a region. Therefore, whether it is for coal mine production safety, or for accurate evalu- ation and prediction of coalbed methane development prospects, coalbed methane content is one of the most important parameters (He, Zhao, Zhang, Gao and Yang,2016).

Since coalbed methane is a kind of complex and uncertain phenomenon, there is a need for methods to overcome complex and uncertain problems. The Fuzzy Logic is one of the most efficient artificial intelligence methods that can handle complex and unclear problems reliably and flexibly. Thus, the Fuzzy Logic method was used to estimate the methane contents of the coal seams in this study. The main object of the study is to guide the future CBM explorations and development studies in Zonguldak coalfield.

2. Literature Review

Many studies have been carried out by different researchers in the literature to assess and estimate coal methane content. Saghafi, Williams and Battino (1998) determined the methane content using the quick crush method and examined the variability in methane content of coal samples. Islam and Hayashi (2008) evaluated methane content based on exploration data and empirical methods. Hemza et al. (2009) analyzed the methane content of coal samples from experimental drilling. Two methods were used to determine methane content such as the Borowski method and the USBM method. Jianqing (2011) implemented the artificial neural network method to predict methane contents. Chatterjee and Paul (2013) estimated methane contents of coal seams using an empirical equation. Zawadzki, Fabijańczyk and Badura (2013) measured the methane content using the direct method and estimated the methane content using multivariable geostatistics. Two kinds of secondary measurements were preferred such as coal strength index and desorption factor. Kedzior (2015) determined methane contents using vacuum degasification in hermetic containers. Zhu et al. (2017) analyzed coalbed methane occurrences collecting the coal samples directly from coal mines and predicted the methane content using a mathematical model. Kędzior and Dreger (2019) measured the methane contents of coal samples in hermetic containers using vacuum degasification. These methods are reliable but largely time-consuming and complicated. Methane content prediction may require the application of other new approaches such as the fuzzy system. It is of great significance to examine the methane contents using a practical intelligence tool. To reduce occupational accidents caused by methane, methane contents of coal seams in an underground coal mine were evaluated in this study utilizing fuzzy logic.

3. Methodology

3.1. Methane

Methane is generated by chemical and bacterial processes on organic material. It is one of the most prevalent layer gases and evolved through the formation of both coal and petroleum. It is not poisonous but is principally hazardous since it is combustible and may constitute an explosive combination with air. For this reason, many thousands of miners can lose their lives. Association with air is sometimes described as firedamp. Methane has a density of just over half that of air. This leads to an unsafe behavior form of methane. It can generate layers or pools throughout the roofs of underground openings. Any gas explosion can increase along with those strata to emission resources. Methane combusts in the air with a faded blue flame. This can be examined over the diminished spark of a safety lamp at concentrations as small as 1¼ percent. With a plentiful air source, it burns to generate carbon dioxide and water vapor. Unfortunately, within the limits of mined openings and through explosions or fires, there might be inadequate oxygen to continue full ignition, causing the formation of the extremely lethal carbon monoxide (McPherson, 1993)

CBM has generally been considered a hazard since it may lead to a severe hazard to mine safety and efficiency owing to its explosion risk. One of the most significant responsibilities of ventilation in coal mines is to protect methane levels below the explosive limit by reducing methane emissions that emerge during mining. Methane can produce a localized high concentration region in a zone with low air quantities and velocities. It is ready to explode at any time when the methane concentration in the mine air is between 5% which is the lower explosion limit and 15% which is the upper limit. In this range, methane may simply ignite with an ignition source that can diffuse with coal dust in the environment. Figure 1 demonstrates the methane explosion diagram (Karacan, Ruiz, Cotè and Phipps,, 2011).

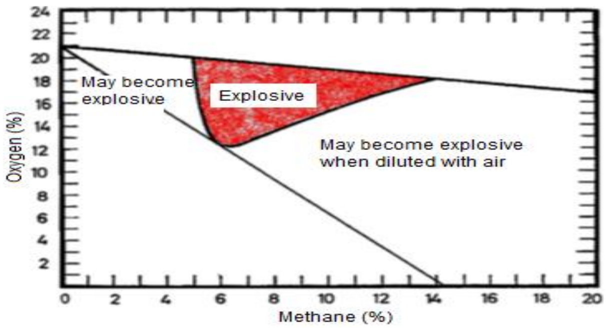

Figure 1. Methane Explosibility Diagram (Karacan et al., 2011)

Methane concentration increases in a mine air affect its explosion and/or ignition. Ignition of the methane-air mixture happens at temperatures less than 650 °C. Thus, a common reason for methane explosion is rock sparking. For example, sandstone tends to spark and ignite methane because of friction produced by a mining instrument (Kędzior and Dreger, 2019)

3.2. Fuzzy Logic Approach

The Fuzzy Logic is a problem-solving methodology that can instantaneously handle linguistic and numerical data. This method eases the control of a complex system. The Fuzzy Logic differs from traditional logic in that it uses linguistic expressions such as true or false, black or white, on or off. In conventional logic, while an object can take a value of zero or one, in the Fuzzy Logic, a statement can take any real value between 0 and 1. The steps of the Fuzzy Logic are explained as below (Zadeh, 1965):

Step 1: Determination of input and output fuzzy linguistic parameters. The first step in designing a Fuzzy Logic model is to select suitable inputs. These input variables should be able to fully represent the system.

Step 2: Fuzzification of the inputs using the input membership functions. The fuzzification process matches the crisp inputs to a fuzzy set membership degree using membership functions. (Shatnawi, Shatnawi, AlShara and Husari, 2021). These membership functions should incorporate the entire universe of discourse and represent a linguistic variable or a fuzzy set. Frequently used membership functions are Trapezoidal, Triangular, and Gaussian. The most commonly used among them are Triangular and

Trapezoidal since they are easy to symbolize the user's idea and require less calculation time (Zadeh, 1965). The trapezoidal curve is a vector function, x, and represented with four parameters such as a_1, a_2, a_3, a_4. Figure 2 shows a trapezoidal membership function. Its membership functions are expressed in Equation 1:

$$\mu_A(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2 \\ 1, & a_2 \le x \le a_3 \\ \dfrac{a_4 - x}{a_4 - a_3}, & a_3 \le x \le a_4 \\ 0, & x > a_4 \end{cases} \tag{1}$$

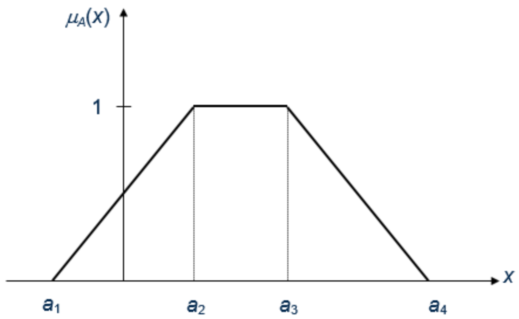

Figure 2. Schematic View of A Trapezoidal Membership Function (Yen and Langari, 1999)

Step 3: Determination of fuzzy rules. It consists of several If-Then rules. The "If" part of the rule is described as the antecedent and the "Then" part is described as the result. Fuzzy rules are presented as below:

If input1 is MF1 and/or input2 is MF2 and/or Then output is output MF

Step 4: Defuzzification of output distribution. In this step, the fuzzy variables are converted to crisp sets. This process is essential since the crisp values can only be used as inputs in the other systems in the real world. It is commonly necessary only when the Mamdani fuzzy model is used to design a controller. Other fuzzy inference systems are Larsen, Tagaki-Sugeno, and Tsukamoto. Unlike the Mamdani system, the outputs are identified using a specific function for the other two models and hence the output is crisp instead of fuzzy. This is illogical because a fuzzy model should be able to spread the fuzziness from inputs to outputs properly. There are different defuzzification methods in the literature such as Centroid of Area, the Bisector of Area, Mean of Maximum, Smallest of Minimum, and Largest of Maximum. The last two defuzzification techniques are rarely used because of their biased nature. The most commonly used method is the Centroid of Area method. This method uses the output distribution and obtains its center of mass to assert one crisp number. It is determined in Equation 2:

$$z = \frac{\sum_{j=1}^{q} Z_j u_c(Z_j)}{\sum_{j=1}^{q} u_c(Z_j)} \tag{2}$$

where μ_c is the membership in class, c at value Zj and z is the center of mass (Ross, 2017).

4. Application of the Fuzzy Logic Method

The literature contains some earlier studies on the use of fuzzy logic in the mining sector (Razani, Yazdani-Chamzini and Yakhchali, 2013; Danish and Onder, 2020). The application of the Fuzzy Logic methodology to estimate methane contents of the coal seams was implemented in Zonguldak coalfield which has five production enterprises such as Kozlu, Karadon, Üzülmez, Armutçuk, and Amasra. The methane content prediction analyses were performed for the coal seams belonging to Kozlu enterprise. The longwall mining method is implemented in all of the five enterprises of the basin. The location of Zonguldak coalfield was given in Figure 3.

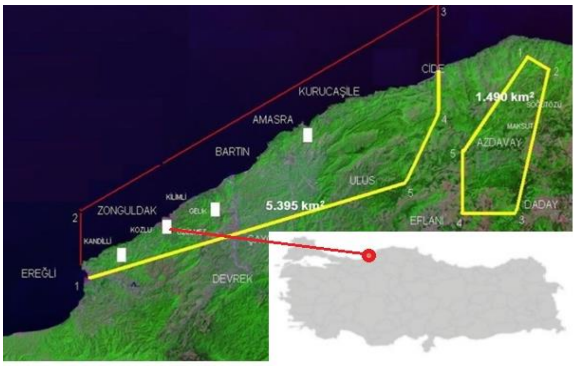

Figure 3. Location of Zonguldak Coalfield (THE, 2020)

The implementation steps of the fuzzy algorithm (Section 3.2) to estimate methane contents of Zonguldak coalfield were conducted as follows:

Step 1: Variables of seam depth (SD), seam thickness (ST), and moisture content (MC) were determined as input parameters according to the literature review in the Section 2. Methane content (GC) represents the output parameter of the Fuzzy Logic model. In the first step, fuzzy linguistic parameters were determined for input and output variables. Coal seams were classified into three categories based on their gassiness and depth by Thakur (2011) in Table 1. The coal seam thickness of

Zonguldak coalfield changes between 0.7 m and 30 m. The majority of the production has been provided from coal seams with a core thickness of greater than 3 m in recent years. The moisture content of the coal seams changes between 0.38 % and 3 % (Fisne and Esen, 2014). The thicker the coalbed, the larger is the amount of gas released, indicating that the reservoir volume of free and adsorbed gases restored in the coalbed (Chen et al., 2018). Based on these explanations the linguistic and membership function parameters of input and output were given in Table 2.

Step 2: Trapezoidal membership function was preferred based on the theoretical explanation presented in Section 3.2. The structure of the Fuzzy Logic model was shown in Figure 5. The membership functions of input and output parameters were given in Figure 6. The Fuzzy Logic was applied using MATLAB R2015a software.

Table 1.

Gassiness Classification of The Coal Seams (Thakur, 2011)

Category of mine	Depth (m)	Gas content (m³/t)
Mildly gassy	≤ 200	< 3
Moderately gassy	200-500	3-10
Very gassy	> 500	10-25

Table 2.

Linguistic and Membership Function Parameters of İnput and Output

Linguistic variable type	Linguistic variable descriptions	Linguistic Expression	Membership Function Parameters
Input	Seam depth (m)	Low (*L*)	[0 0 50 200]
		Medium (*M*)	[50 200 350 500]
		High (*H*)	[350 500 650 800]
	Seam thickness (m)	Low (*L*)	[0 0 1 2]
		Medium (*M*)	[1 2 3 4]
		High (*H*)	[3 4 5 6]
	Moisture content (%)	Low (*L*)	[0 0 0.5 1]
		Medium (*M*)	[0.5 1 1.5 2]
		High (*H*)	[1.5 2 2.5 3]
Output	Methane content (m³/t)	Mildly gassy (*MILG*)	[0 0 1 3]
		Moderate gassy (*MODG*)	[1 3 6 9]
		Very gassy (*VG*)	[6 10 14 25]

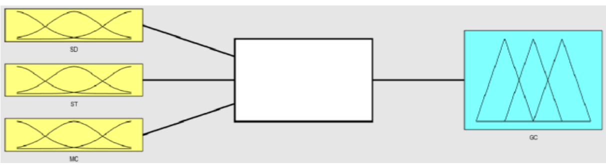

Figure 5. Fuzzy Logic Model of The Study

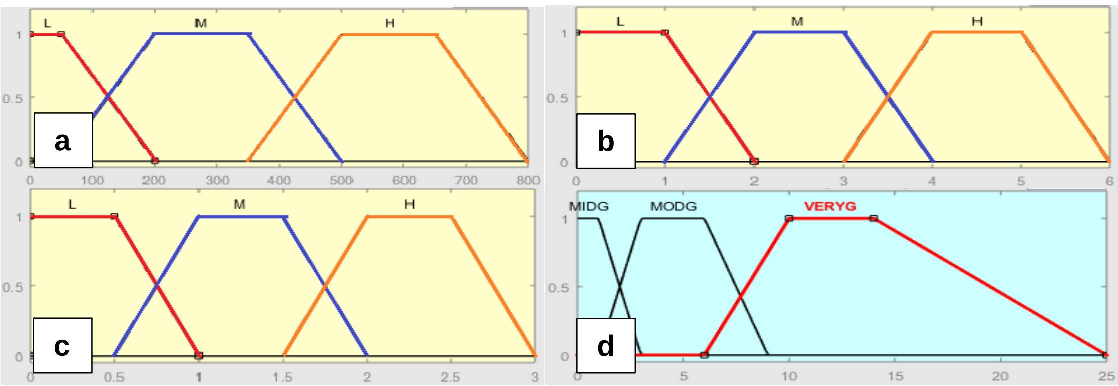

Figure 6. (a) Membership Function of SD, (b) Membership Function of ST, (c) Membership Function of MC, (d) Membership Function of GC.

<u>*Step 3*</u>: The Fuzzy Logic model consists of 9 input linguistic expressions (SD, ST, and MC variables have three linguistic expressions). Thus, 27 (3x3x3) rules were constructed. All fuzzy rules given in Table 3 were constructed with AND connection parameter.

Table 3.

Fuzzy Rules of The Model

Rules	Input			Output
	Seam Depth	Seam Thickness	Moisture Content	Gas Content
1	H	H	H	H
2	H	H	M	H
3	H	H	L	H
4	H	M	H	M
5	H	M	M	M
6	H	M	L	H
7	H	L	H	L
8	H	L	M	M
9	H	L	L	H
10	M	H	H	M
11	M	H	M	M
12	M	H	L	H
13	M	M	H	M
14	M	M	M	M
15	M	M	L	M
16	M	L	H	L
17	M	L	M	M
18	M	L	L	M
19	L	H	H	L
20	L	H	M	M
21	L	H	L	H
22	L	M	H	L
23	L	M	M	M
24	L	M	L	M
25	L	L	H	L
26	L	L	M	L
27	L	L	L	L

<u>*Step 4:*</u> Mamdani inference system and center of area defuzzification method were preferred based on the theoretical explanation presented in Section 3.2. The simulation steps of the Mamdani fuzzy inference system to estimate methane contents of the coal seams were presented in Figure 7. It uses the data such as SD, ST, and MC as crisp input and converts them into fuzzy inputs using membership functions as explained in Section 3.2. These fuzzy inputs were assessed using the fuzzy rules. Then, fuzzy outputs were formed. Finally, the fuzzy outputs were gathered into a single crisp output (GC).

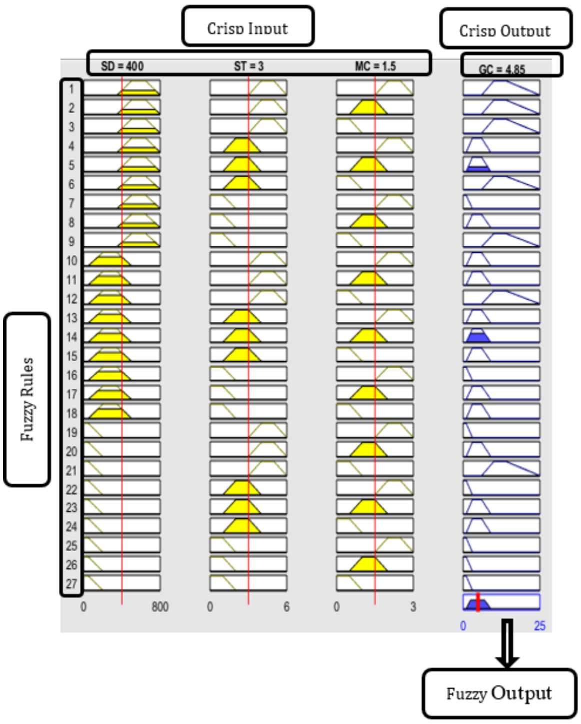

Figure 7. Graphical Demonstration of Fuzzy Rule-Base

5. Results and Discussion

The prediction of methane contents in underground coal mines based on various combinations of input parameters was presented in Figures 8 (a)-(c).

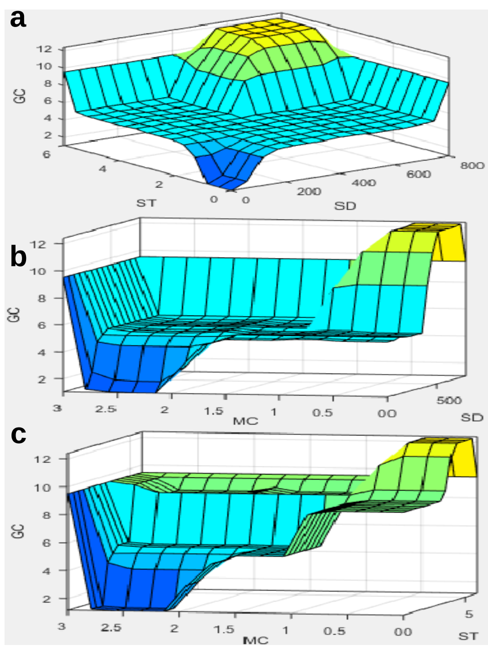

Figure 8. Surface Graphics of The İnput Parameters: (A) Seam Thickness-Seam Depth (Constant value of MC:1.5%), (b) Moisture Content- Seam Depth (Constant value of ST:3m) , (c) Moisture Content- Seam Thickness (Constant value of SD:400m).

Table 4

Fuzzy Logic Results

	Inputs				Output		
Seam	Seam Depth (m)	Seam Thickness (m)	Moisture Content (%)	Field Methane Contents (m^3/t)	Fuzzy Logic Results	Field Categories	Fuzzy Logic Categories
-425/22924 Raise (*S1*)	387	1.5	1.1	5	4.88	Moderate Gassy	Moderate Gassy
-425/22924 Raise (*S2*)	402	2	1.1	5	4.85	Moderate Gassy	Moderate Gassy
-425/22924 Raise (*S3*)	400	1.8	1.1	5	4.85	Moderate Gassy	Moderate Gassy
42036/43311 Raise (*S4*)	250	1.2	0.71	5.44	4.87	Moderate Gassy	Moderate Gassy
42036/42319 Raise (*S5*)	253	1.2	0.71	5.44	4.87	Moderate Gassy	Moderate Gassy
-260/-150 42319 Face (*S6*)	250	1.5	0.71	5.44	4.88	Moderate Gassy	Moderate Gassy
-260/-160 Raise (*S7*)	244	2.5	0.71	5.44	4.87	Moderate Gassy	Moderate Gassy
-360/42417 Raise (*S8*)	343	2	0.71	5.44	4.87	Moderate Gassy	Moderate Gassy
-260/-150 42319 Raise (*S9*)	250	1.5	0.71	5.44	4.88	Moderate Gassy	Moderate Gassy
-150/41217 Raise (*S10*)	110	2.5	0.71	5.44	4.87	Moderate Gassy	Moderate Gassy
-360/42417 Raise (*S11*)	356	2.2	0.71	5.44	6.58	Moderate Gassy	Moderate Gassy
-360/42400 Drifting road (*S12*)	364	2	0.69	7	8.02	Moderate Gassy	Moderate Gassy
-360/42417 Drifting road (*S13*)	360	2	0.69	7	7.33	Moderate Gassy	Moderate Gassy
-260/41305 Raise (*S14*)	228	2	3.2	8.97	9.5	Moderate Gassy	Moderate Gassy

To verify the performance of the developed fuzzy model, a comparison between predicted and field methane contents was performed. For this purpose, methane content prediction was conducted using the input parameters. The field methane contents were derived from Kursunoglu and Onder (2019). Predicted fuzzy results were given in Table 4.

The graphical representation of the results was shown in Figure 9. The results indicate that the fuzzy model can provide a reliable prediction way with a 92% success rate. Figure 10 shows which category the coal seams belong to according to the fuzzy logic results.

The figure indicates that all seams are in the moderate gassy category. In the study's fuzzy rules, it was also examined at how low the gas content is in comparison to instances when the production depth and seam thickness are low and the moisture content is high (Yin et al., 2012).

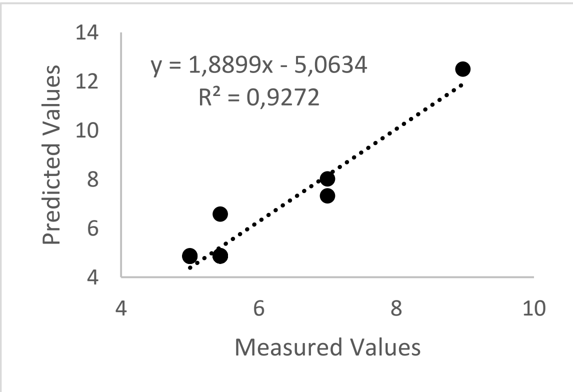

Figure 9. Comparison of The Measured and Predicted Values

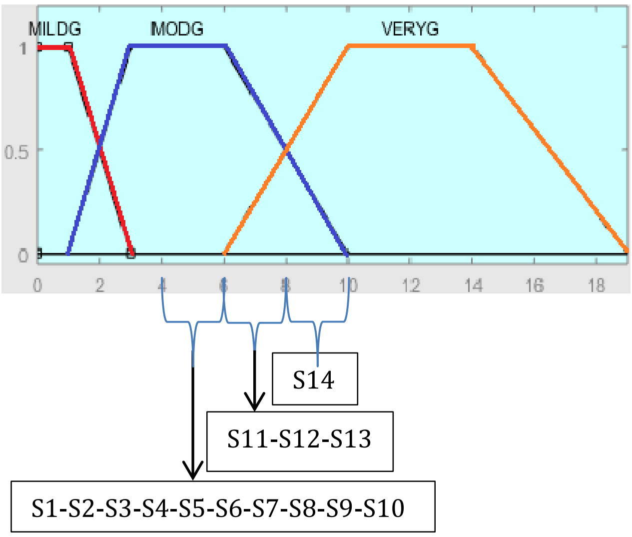

Figure 10. Fuzzy Logic Categories of Coal Seams

The proposed prediction model was used to predict the gas contents of 14 coal seams, and the prediction results were compared with the actual methane contents, which shows that the prediction model can effectively predict the gas contents. Compared with the existing prediction models such as back propagation and neural network method (Paul et al. 2021; YuMin et al., 2011), grey system theory (Zeng and Li, 2021), the quantification prediction model (Hu et al., 2014), the prediction accuracy of the presented model does not depend on a large number of sample learning, and overcomes the problem of slow convergence speed.

6. Conclusions

In this paper, a fuzzy logic model was developed to estimate methane content of the coal seams for an underground coal mine. Coal methane content is affected by many parameters such as mining factors, coal properties, and geological conditions. The input variables for the proposed model are seam depth, seam thickness, and moisture content. It is very complex and essential to predict methane content for underground coal mines. For this purpose, the Fuzzy Logic is a flexible and influential tool to assess the methane content of the coals. A comparison between the measurement and predicted values was conducted to examine the efficiency of the proposed model. The model results showed that the fuzzy model can be implemented with an R^2 value of 0.92. The fuzzy model's predicted categories and the classes established using measurements made in the field are parallel. As a result, the fuzzy model is successful in predicting the methane content of coal seams. The fuzzy logic technique lets for prior knowledge of methane content values in underground coal mines. It is possible in this way to reduce and foresee the accidents that may cause an outburst, fire, or explosion. It is suggested that prediction model can be appropriate for other coal mines in Zonguldak coalfield exhibiting different geotechnical, geological, and mining conditions. The fuzzy logic approach can be used to estimate the methane contents of the seams in other hard coal basins of Zonguldak in the future. Due to the flexible character of the fuzzy logic method, coal mines will be able to predict gas contents in the future in accordance with changing operational conditions.

Contribution of Researchers

The Nilüfer KURŞUNOĞLU contributed to the publication with the conceptualization, methodology, investigation, writing - original draft, writing- review & editing, visualization, supervision

Conflict of Interest

No conflict of interest was declared by the author.

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