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Original Article

Application of Fuzzy Logic for Predicting of Mine Fire in Underground Coal Mine

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A B S T R A C T

Background: Spontaneous combustion of coal is one of the factors which causes direct or indirect gas and dust explosion, mine fire, the release of toxic gases, loss of reserve, and loss of miners' life. To avoid these incidents, the prediction of spontaneous combustion is essential. The safety of miner's in the mining field can be assured if the prediction of a coal fire is carried out at an early stage.
Method: Adularya Underground Coal Mine which is fully mechanized with longwall mining method was selected as a case study area. The data collected for 2017, by sensors from ten gas monitoring stations were used for the simulation and prediction of a coal fire. In this study, the fuzzy logic model is used because of the uncertainties, nonlinearity, and imprecise variables in the data. For coal fire prediction, CO, O_2, N_2, and temperature were used as input variables whereas fire intensity was considered as the output variable.The simulation of the model is carried out using the Mamdani inference system and run by the Fuzzy Logic Toolbox in MATLAB.
Results: The results showed that the fuzzy logic system is more reliable in predicting fire intensity with respect to uncertainties and nonlinearities of the data. It also indicates that the 1409 and 610/2B gas station points have a greater chance of causing spontaneous combustion and therefore require a precautional measure.
Conclusion: The fuzzy logic model shows higher probability in predicting fire intensity with the simultaneous application of many variables compared with Graham's index.

1. Introduction

In recent years, the world is faced by energy challenges due to overwhelming increase in population. Coal is one of the sources of energy used in both the developed and the developing nations. For instance, in Turkey's vision 2023, the capacity of coal power plants projected an increase from 15 GW in 2015 to 30 GW in 2023. Coal alone is expected to contribute about 25% of the electricity demand. This shows that there will be an increase in coal consumption in Turkey by the year 2023 [1].

Spontaneous combustion of coal is one of the factors which cause direct or indirect gas and dust explosion, mine fire, the release of toxic gases, loss of reserve, and loss of miners' life. The carrying out of early assessment and prediction of spontaneous combustion play a key role in combatting with these problems.

In coal mining sector, spontaneous combustion is a big problem in both surface and underground mining. Coal low-temperature oxidation is the basic cause of self-ignition and self-heating during mining, storage, and transportation of coal [2]. Worldwide, spontaneous combustion accounts for 75–90% of all underground coal fire and 20% of underground metal mine fires [3]. In US, between the periods of 1990–1999, the estimated fire resulting from the spontaneous combustion are as follows: at underground coal mines 17% of the 87 fires were reported, whereas in surface coal mines 10% of the 215 fires occurred. Similarly, in all coal operation plants, 17% of the 91 fires are reported, and 17% of the 65 reported fires were from surface of underground coal mines [4]. In China, it is reported that 56% of all underground coal mines are likely to be affected by spontaneous combustion [5] and approximately 90% of mine fires are caused by spontaneous combustion. The issue of mine fire which does result from coal spontaneous combustion is a

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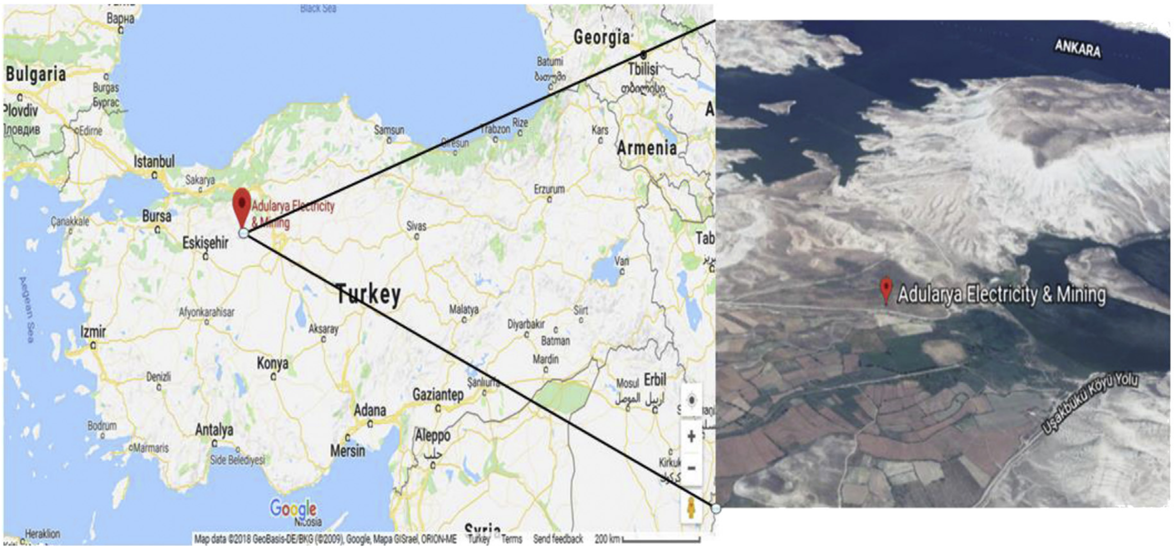

Fig. 1. Location of AUCM and Adularya power plant.

major problem in coal producing countries such as China, USA, India, Australia, Germany, and so on [6]. For instance, in Germany, the spontaneous combustion caused about 10 coal fires per year in the Ruhr area [7] and 75% of the coal fire in Indian's coal mines [8]. Between 1990 and 2000, six events of spontaneous combustion were reported in Karadon Colliery of Turkish Hardcoal Enterprise in the Zonguldak Basin [9]. Hence, other Turkish coal mines are no exception to this phenomenon.

Coal spontaneous combustion not only destroys coal reserve, but also emits greenhouse gases and toxic gases to the environment. Physical hazard and poor air quality caused by coal fire and coal mine fires increase the risk of community exposure to high concentration of contaminants known as aerosolized particles [10]. In China, it is reported that, each year, 20 to 200 million tonnes of coal were combusted through coal fires, which release about 1% of global carbon dioxide [11]. In addition, it is reported that, in a year, about 40 tonnes of mercury were released into the atmosphere worldwide due to coal fire, and nearly, and 3% of global carbon dioxide are said to be released by coal fires [12].

For ensuring safety, the prediction of spontaneous combustions is very important. Since 1941, an estimated number of three thousand miners lost their lives, and more than 100 thousand miners were injured in different Turkish mines owing to the gas explosion, mine collapse and mine fire [13].

Spontaneous combustion of coal is an inherent phenomenon in coal mining and is considered as a natural hazard during mining. Spontaneous combustion is a physical and chemical reaction occurring when coal is exposed to oxygen. An increase in hydrogen, carbon, moisture, and volatile matter, the existence of pyrite, the existence of sulfur, and a decrease in ash content could catalyze the cause of spontaneous combustion [14].

There are numerous methods used for early detection of spontaneous combustion in underground coal mines. These include the fuzzy logic method [6,15], monitoring of concentration of gases produced during spontaneous combustion [16–22], the electromagnetic radiation technique [23], temperature measurement [24–26], numerical modeling [27–29], statistical analysis [30], the gray model [31], the analytical method [32], remote sensing [33], and the radon detection method [34]. Out of these, the most widely used technique in initial prediction of spontaneous combustion and fire status is the gas indices, such as oxides of carbon ratio (CO/CO_2), Willet's ratio, Jones and Trickett ratio, Graham's ratio, Young's ratio, and so on. [35–37]. With the development of instruments for taking gas samples, predicting of coal fires, and coal spontaneous combustion by utilizing low-temperature hydrocarbons, such as C_2H_6, C_3H_8, C_2H_2, C_2H_4, C/H ratio, and Litton ratio, early prediction could be improved [2,35]. The main hydrocarbon ratios are shown as follows:

$$C_{CO}/C_{C_2H_2};\quad C_{CH_4}/C_{C_2H_6};\quad C_{C_2H_4}/C_{C_2H_6};\quad C_{C_3H_8}/C_{C_2H_6};\quad C_{C_2H_4}/C_{C_2H_2};\quad C_{C_2H_4}/C_{H_2} \tag{1}$$

where $C_{C_2H_2}; C_{C_2H_4}; C_{C_2H_6};$ *and* $C_{C_3H_8}$ are the concentrations of C_2H_2, C_2H_4, C_2H_6 and C_3H_8 gases respectively.

In this paper, the fuzzy logic method which is more accurate and reliable technique in predicting spontaneous combustion and fire monitoring is proposed. The fuzzy logic method is fast and therefore can alleviate the time consumption in decision making.

A lot of literatures have reported some works that have been done in this area. For instance Monjezi et al [38], reported a fuzzy logic model for prediction of rock fragmentation due to blasting. Similarly Razani et al [39], developed a fuzzy logic system for predicting the rate of roof fall in underground coal mines. Toraño, et al [40] also used a fuzzy logic system based on the virtual reality model approach for the installation of longwall coal mines. In another development, Muduli et al [6] proposed a fuzzy logic model based on online fire monitoring in underground coal mines, where temperature, oxygen, carbon dioxide, and carbon monoxide were considered as input variables, but according to Turkish mining regulation, measurement of carbon dioxide is not compulsory, and hence, Adularya Underground Coal Mine (AUCM) does not carry out

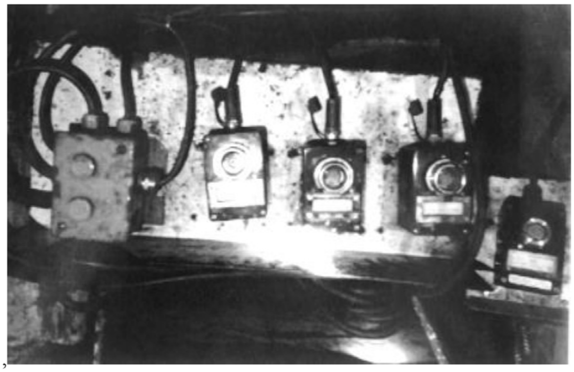

Fig. 2. The location of sensors for measuring the gas samples and temperature.

measurement of carbon dioxide. Grychowski et al [15] studied an offline fuzzy logic model for monitoring of fire hazard in the underground coal mine. He has also considered carbon dioxide as the input variable, but the main factor temperature, which is increasing during combustion and accelerates the spontaneous combustion of coal and coal fire, was not considered. Meanwhile, the concentration of oxygen was considered unreliable (21.25 and 21.09%) which is higher than the normal concentration of oxygen in the air (20.95%).

Although all the methods have made certain success in prediction of coal fire, fuzzy logic will be better because the high uncertainty and nonlinearity conditions will be efficiently handled with the linguistics variables. Fuzzy logic is based on the logic of approximation and uncertainty to generate decisions from the monitoring data. Fuzzy rules are extracted from expert opinion, knowledge, and experience which shows uncertainty and ambiguity in the fuzzy system. In addition, uncertainties exist at the measuring devices or monitoring sensors.

Fuzzy system is a nonlinear mapping of input data into output using fuzzy logic. This mapping is carried out using the fuzzification, fuzzy inference, and defuzzification. In addition, spontaneous heating of coal is a complex process, and there exists a nonlinear relationship between crossing point temperature and intrinsic parameters.

Recently, the application of the fuzzy logic model has attracted the attention of many researchers. In this study, the fuzzy inference system was applied to deal with high uncertainties and nonlinearities in predicting of spontaneous combustion of coal and coal fire.

2. Materials and methods

2.1. Material

AUCM is classified as a lignite coal mine, which is located at Mihalıççık. Mihalıççık is a town that is at distance of 128 km from the Eskişehir province, and 145 km from Ankara, the capital of Turkey (Fig. 1). It covers an area of 40 km^2 and produces 3.91 million tons of coal annually. Adularya power plant has been established in 2007, under the supervision of Naksan Holding Group with the capacity of 2 × 145 MW, and contributes about

Table 1
The mean values of data for each gas monitoring station in AUCM in 2017

Gas stations	Months	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
Main intake	O_2 (%)	20.64	20.83	20.91	20.89	20.82	20.94	21.15	21.15	20.77	20.80	20.93	20.84
	CO (ppm)	2.00	0.00	0.00	4.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Temperature (oC)	0.68	4.30	9.85	12.41	16.99	21.67	28.24	27.49	23.93	17.16	9.94	7.91
	N_2 (%)	79.20	79.06	78.57	78.73	78.28	78.98	78.78	78.76	79.16	79.15	79.02	79.1
510	O_2 (%)	20.96	20.60	20.83	20.82	20.81	20.76	20.84	20.84	20.84	20.96	20.97	20.96
	CO (ppm)	0.77	3.24	1.88	1.74	1.60	1.30	1.14	1.00	1.04	1.25	1.00	1.00
	Temperature (oC)	7.31	11.27	15.12	15.74	18.38	20.84	23.48	24.17	22.33	16.37	13.12	11.91
	N_2 (%)	78.94	79.29	79.11	79.11	79.11	78.15	78.04	79.08	77.71	78.96	78.95	78.99
1410	O_2 (%)	20.46	20.62	20.97	20.98	20.99	20.98	20.97	20.96	20.94	20.95	20.96	20.97
	CO (ppm)	4.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	0.00
	Temperature (oC)	25.02	27.41	26.24	26.00	25.97	26.75	26.71	27.46	27.04	26.99	26.13	25.54
	N_2 (%)	79.49	79.33	78.93	78.89	78.92	78.95	78.98	78.99	79.02	79.01	79.00	78.99
1409	O_2 (%)	20.82	20.75	20.91	20.86	20.87	20.86	20.83	20.81	20.80	20.90	20.88	20.89
	CO (ppm)	1.41	2.82	2.82	4.63	3.08	3.47	3.64	2.43	2.27	2.78	2.29	2.2
	Temperature (oC)	26.13	26.87	26.93	27.03	27.03	27.72	27.97	28.20	28.12	28.47	27.08	27.02
	N_2 (%)	77.99	78.89	78.68	78.70	78.73	78.49	78.61	78.62	78.89	78.73	76.44	79.06
610/2B	O_2 (%)	20.49	20.42	20.84	20.83	20.84	20.82	20.81	20.12	20.74	20.67	20.86	20.86
	CO (ppm)	2.93	5.03	3.53	4.58	2.85	2.76	2.81	2.34	2.37	1.88	1.48	1.38
	Temperature (oC)	27.31	28.06	27.11	26.90	27.02	28.06	28.69	28.88	29.03	28.68	28.61	28.13
	N_2 (%)	79.10	78.94	78.73	78.75	78.74	78.76	78.75	79.03	78.70	78.48	78.33	79.05
A06	O_2 (%)	20.06	19.27	19.92	20.16	20.15	20.32	20.36	20.02	20.05	20.10	19.85	20.18
	CO (ppm)	1.38	3.92	3.20	2.68	2.33	2.59	3.85	3.09	2.98	2.36	2.36	3.64
	Temperature (oC)	26.27	25.84	26.60	26.69	26.73	26.52	25.93	26.77	27.19	27.00	27.09	26.72
	N_2 (%)	79.89	80.67	79.85	79.63	79.75	79.22	79.6	76.83	79.88	78.78	80.06	79.64
610	O_2 (%)	20.90	20.85	20.88	20.17	20.81	20.82	20.80	20.62	20.82	20.91	20.89	20.90
	CO (ppm)	3.65	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Temperature (oC)	10.81	13.08	16.12	16.07	18.36	19.88	20.42	20.59	19.86	17.74	16.16	15.54
	N_2 (%)	78.62	78.67	78.48	79.4	78.77	78.59	78.50	78.97	78.09	78.70	78.83	78.57
Main return	O_2 (%)	20.33	19.78	20.23	20.18	20.16	20.17	20.51	20.35	20.27	20.29	20.29	20.46
	CO (ppm)	0.00	2.06	6.31	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Temperature (oC)	21.00	22.00	22.49	22.59	23.56	24.39	24.73	24.96	24.45	22.79	22.20	23.05
	N_2 (%)	79.57	80.12	79.66	79.79	75.61	79.70	79.43	79.58	79.65	79.64	79.62	79.47
D	O_2 (%)	20.88	20.88	20.83	20.82	20.76	20.64	20.60	20.64	20.76	20.95	20.64	20.45
	CO (ppm)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Temperature (oC)	15.9	15.54	16.95	17.00	18.39	19.62	20.37	20.33	19.43	18.53	17.02	16.88
	N_2 (%)	79.04	79.09	79.11	79.09	79.11	79.27	79.31	79.28	79.16	79.02	79.33	79.36
D 210	O_2 (%)	20.88	20.87	20.83	20.80	20.77	20.71	20.65	20.66	20.73	20.86	20.96	20.61
	CO (ppm)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Temperature (oC)	13.27	13.02	14.46	15.00	16.53	18.09	19.02	19.75	19.00	17.44	15.89	15.01
	N_2 (%)	79.02	79.00	79.10	79.12	79.15	79.19	79.24	79.31	79.24	79.11	79.01	79.30

AUCM, Adularya Underground Coal Mine.

1.17% of Turkey's electricity supply. Adularya coal mine is divided into three sections, A, D, and E. Currently, coal seam mine is ongoing at section A and has covered a length of 250 m of the working surface. In section D, all development and preparation works are ongoing with three Dosco Marks roadheaders for a new fully mechanized longwall method. Adularya coal mine is a fully mechanized coal mine, in which all actions from coal production in the mine and transportation to the power plant are mechanical. The mining method is mechanized longwall, where mining residual coals remain in the gob. These residual coals make the condition suitable for spontaneous combustion. The ‘U’ type ventilation system is applied to the working face, with volumetric air rate of 45.15 m3/sec and velocity of 2.11 m/sec.

Section E is not considered in this study. In this section, production is not going on, because this section is too close to the mined-out area. In this section, ventilation and water drainage are carrying out; just production is not on going. In addition, the development works have been made. This area has very much reserve; therefore, in the future, this area will be mined with other areas together.

Adularya coal mine works in three shifts with eight hours per shift. Every hour, gas samples, temperature, and air velocity are measured by sensors that are firmly situated on the side wall of the gallery with supports of the gallery (Fig. 2). The measurement of gas samples in section A is carried out at eight station points namely, main intake, 510, 1410, 1409, 610/2B, 610, A06, and main return, and two station points in section D namely, D and D210. In this paper, the data collected for 2017 are used to determine whether there is a threat of spontaneous combustion of coal and mine fire in the area. The mean values of the data for each gas monitoring station are listed in Table 1. Fig. 3 shows the gas monitoring station points and the general ventilation system of AUCM. In Fig. 3, the gas monitoring stations have the same monitoring sensors (temperature sensor, carbon monoxide sensor, oxygen sensor, and air velocity sensor) for monitoring the mine environment. They do not have any specific differences with respect to monitoring, but they have different condition with respect to safe and unsafe situation. The safe and unsafe situation of monitoring stations with more details will be discussed in results and discussion sections.

According to Turkish underground mine's regulation, it is compulsory to locate the sensors in main intake and in main return air ways, like main intake and main return monitoring stations (Fig. 3). In addition, in production areas, sensors must be located in intake and return air ways, like 610/2B and A06 monitoring stations (Fig. 3). In the areas which are ventilating by auxiliary ventilation, the sensors must be located in return air way, like 1409 and 1410 monitoring stations (Fig. 3).

2.2. Methods

2.2.1. Fuzzy inference system

The fuzzy inference system is a famous computing framework based on the principles of fuzzy set theory, fuzzy ‘IF-THEN’ rules, and fuzzy reasoning. The fuzzy system has been successfully applied in various fields such as data classification, automatic control, expert system, decision analysis, robotics, time series prediction, and pattern recognition [41].

A fuzzy logic model consists of four components such as fuzzifier, rules base, inference engine, and defuzzifier. The general structure of a fuzzy logic model is shown in Fig. 4. Before describing the fuzzy inference system, fuzzy set theory and crisp set theory would be discussed.

2.2.2. Fuzzy and crisp set theory

A fuzzy set is a generalization of a classical set or is a set without a crisp boundary and characterized by a characteristic function between zero and one ($\mu\in\{0,1\}$). In addition, each element is connected with a membership degree value and takes a membership value between zero and one [42]. This shows its flexibility in linguistic expressions, whereas in the crisp set each element takes a membership value of zero or one ($\mu\in\{0,1\}$) (Yes, No condition). In crisp set F, the membership or nonmembership of an element $x$is represented by the characteristic function$\mu_F of\ F$, expressed by

$$\mu_F(x) = \begin{cases} 1\ if\ x\in F \\ 0\ if\ x\notin F \end{cases} \quad (2)$$

In a fuzzy set P, with the input crisp set x is represented by the membership function, defined by

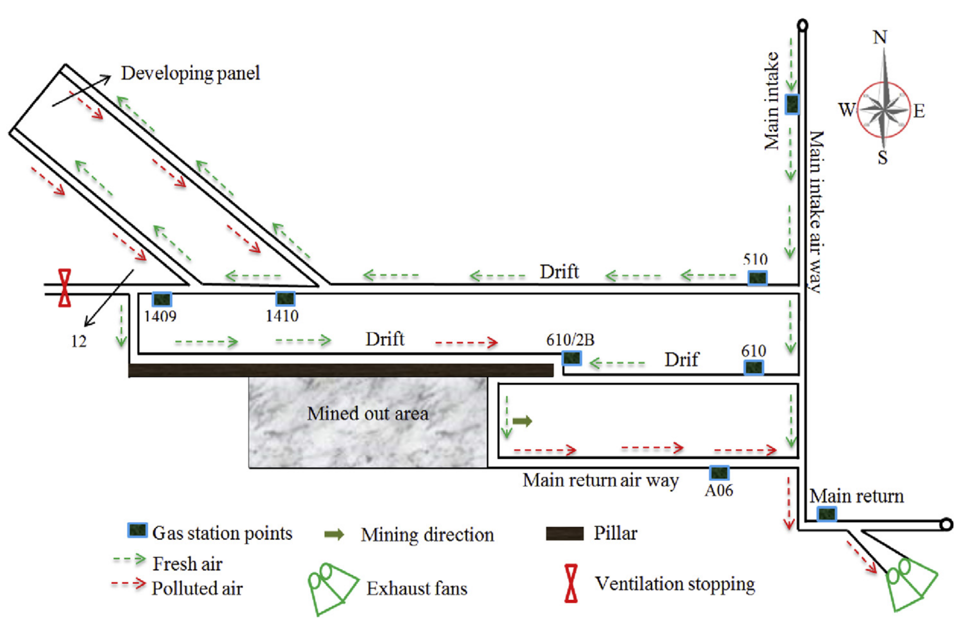

Fig. 3. The general ventilation system and gas station points of AUCM.

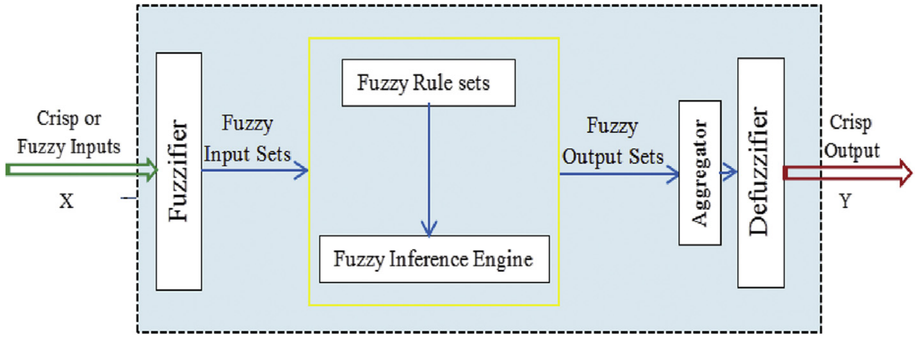

Fig. 4. The general structure of a fuzzy logic model.

$$P = \{x, \mu_p(x) | x \in F\} \tag{3}$$

where $F$is universal discourse and $\mu_p(x)$is the membership function for the fuzzy set P. The membership degree of $x$variables which is expressed as

$$\mu_p(x) \rightarrow [0, 1] \tag{4}$$

For example, if we consider a suffocated area with oxygen concentration less than 10%, according to crisp set theory those areas, which have above 10% oxygen concentration, will not be counted as suffocated areas but in the fuzzy set each area will be considered by their membership degree. If we assume area A with 20% oxygen concentration, area B with 15% oxygen concentration, area C with 9.99% oxygen concentration, and area D with 5% oxygen concentration, then, according to crisp set theory, area A and B will be considered as appropriate, whereas area C with 0.01% difference would be rejected. However, in the fuzzy set theory, area C with membership degree between zero and one will be considered as the appropriate area, and area D with membership degree of zero will be rejected (Fig. 5).

To run a fuzzy logic model, Fuzzy Logic Toolbox in MATLAB was used. For developing a fuzzy model, the first step is to introduce input and output variables and give them linguistics values, and for each linguistic value consider a membership function with their ranges. The concentration of CO, O_2, N_2, and CO_2 are commonly used as indicators for early predicting of coal fires and coal spontaneous combustion [2]. In this study, CO, O_2, N_2, and temperature

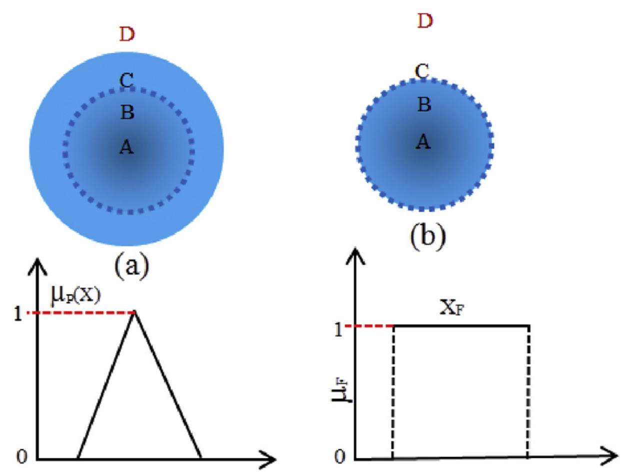

Fig. 5. Fuzzy set (a) and crisp set (b).

are selected as input variables whereas fire intensity is an output variable.

2.2.3. Fuzzy system components

Fuzzification: in fuzzy logic system, input can either be crisp or fuzzy sets, but the outputs are always fuzzy sets [41]. When the input is as crisp input sets, the fuzzifier is used for mapping the crisp input sets to fuzzy input sets. In the fuzzification part, the precise values are converted to imprecise values. In other words, for each crisp input variable, given linguistic values, and linguistic values characterized by their membership function, those variables whose values are words rather than numbers are called linguistic variables [43]. The temperature, CO, O_2, N_2 linguistic input variables, and fire intensity was considered as a linguistic output variable. Table 2 shows the input and output variables, linguistic values of variables, membership function, membership function's ranges, and membership function shapes. Various shapes of membership functions are used for presenting the linguistic values, such as trapezoidal, Gaussian, bell curve, triangular, and sigmoid. The trapezoidal shape of the membership function is used in this study, and for all inputs and output, graphical trapezoidal membership functions are illustrated in Fig. 6. The trapezoidal membership function could be specified by four parameters $\{a, b, c, d\}$ as follows:

$$Trapezoidal\ (x; a, b, c, d) = \begin{cases} 0, & x \le a. \\ \frac{x-a}{b-a}, & a \le x \le b. \\ 1, & b \le x \le c. \\ \frac{d-x}{d-c}, & c \le x \le d. \\ 0, & d \le x. \end{cases} \tag{5}$$

By using the MAX and MIN trapezoidal membership function is specified as follows:

$$Trapezoidal\ (x; a, b, c, d) = MAX\left(MIN\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{6}$$

where $a, b, c, and\ d$are the parameters of membership functions on the $x$coordinate and x is the considered crisp input value.

2.2.4. Fuzzy conditional statement and inference engine

These two components of the fuzzy logic model work closely together and constitute important modeling tools that are based on the fuzzy logic set theory and known as the backbone of the fuzzy logic system. The relationship between inputs and outputs are described by 'IF-THEN' rules (Equation 8), and fuzzy conditional

Table 2
The input and output variables, linguistic values, membership function shape, range, and membership function parameters

Variables		Linguistic values	Membership function shape	Ranges	Membership function parameters
Input variables	Nitrogen (N_2)	Low (L)	Trapezoidal	[0-85]	[0, 0, 20, 30]
		Moderate (M)	Trapezoidal		[20, 30, 50, 70]
		High (H)	Trapezoidal		[50, 70, 85, 85]
	Oxygen (O_2)	Low (L)	Trapezoidal	[0-20.95]	[0, 0, 5, 8]
		Moderate (M)	Trapezoidal		[5,8,14,18]
		High (H)	Trapezoidal		[14, 18, 20.95, 20.95]
	Temperature (T)	Low (L)	Trapezoidal	[0-45]	[0, 0, 10, 15]
		Moderate (M)	Trapezoidal		[10,15,20,30]
		High (H)	Trapezoidal		[20,30,45,45]
	Carbon monoxide (CO)	Low (L)	Trapezoidal	[0-0.006]	[0, 0, 0.001, 0.002]
		Moderate (M)	Trapezoidal		[0.001, 0.002, 0.004, 0.0045]
		High (H)	Trapezoidal		[0.004, 0.0045, 0.006, 0.006]
Output variable	Fire intensity (FI)	Very low (VL)	Trapezoidal	[0-3]	[0, 0, 0.2, 0.4]
		Low (L)	Trapezoidal		[0.2, 0.4, 0.45, 0.5]
		Moderate (M)	Trapezoidal		[0.45, 0.5, 0.75, 1]
		High (H)	Trapezoidal		[0.75, 1, 1.5, 2]
		Very high (VH)	Trapezoidal		[1.5, 2, 3, 3]

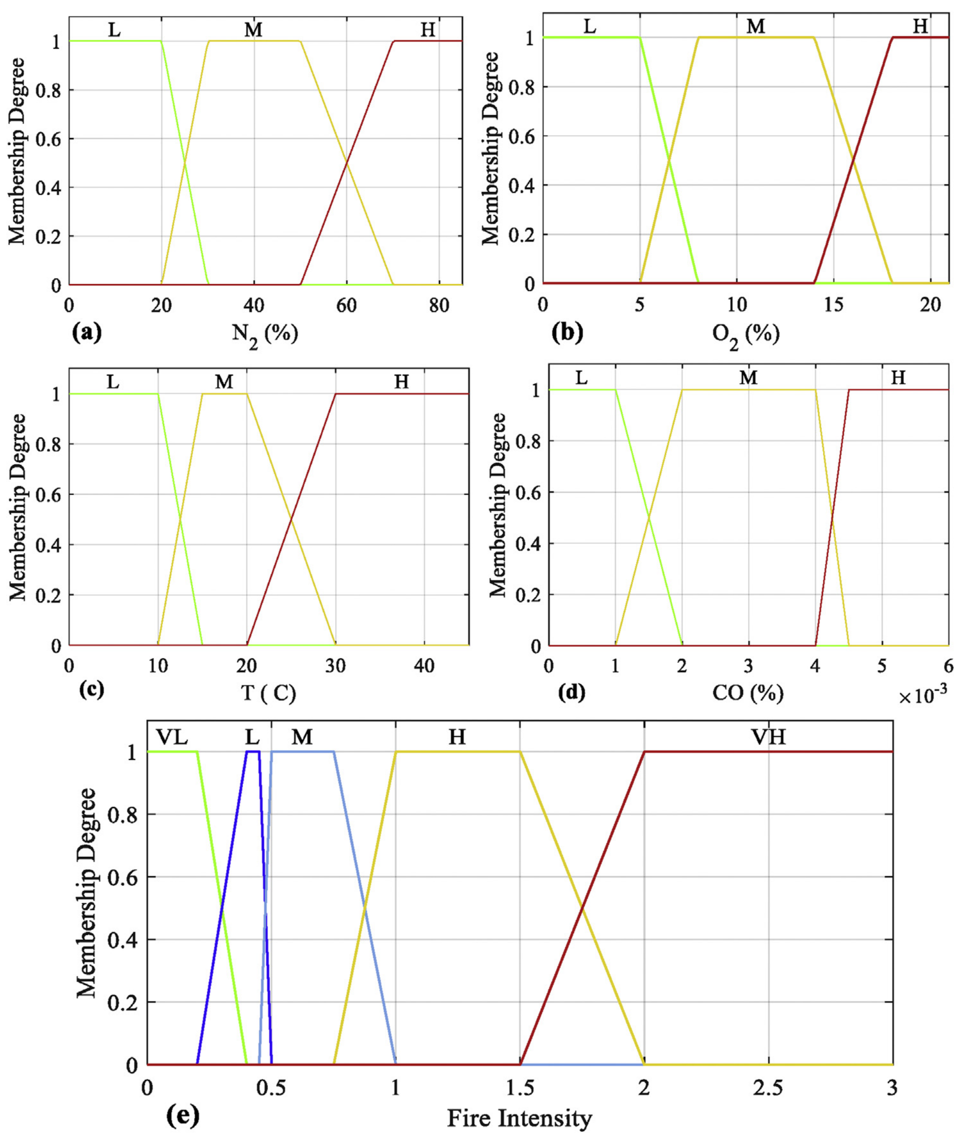

Fig. 6. The graphical trapezoidal shape membership function of fuzzy inputs; (a) nitrogen, (b) oxygen, (c) temperature, (d) carbon monoxide, and fuzzy output (e) fire intensity.

statement consists of antecedent and consequence sections. Fuzzy relations can be combined with various operators such as AND, OR, and NOT which are called MIN, MAX, and complement operators, respectively [41]. In this fuzzy model, the AND operator was used for creating fuzzy relations which is expressed as follows:

$$\mu_{fi}(x_i)\ and\ \mu_{fj}(x_j) = \mu_{fi}(x_i)\, I\, \mu_{fj}(x_j) = MIN\left(\mu_{fi}(x_i), \mu_{fj}(x_j)\right) \tag{7}$$

where $\mu_{fi}(x_i)$ *and* $\mu_{fj}(x_j)$ are the membership functions of F_i *and* F_j fuzzy sets, respectively.

$$R_i = IF(X_1 is\ A_{i1} and\ X_2 is\ A_{i2} and \ldots\ and\ X_n is\ A_{in})\ THEN(Y\ is\ D_i) \tag{8}$$

whereR_i is a number of $R_i th$ rules, $X_1, X_2, X_n$are inputs, Y is the output variable, $A_{i1}, A_{i2}\ A_{in}$are inputs, and $D_i$is the output linguistic value. In the (Equation 8) $(X_1 is\ A_{i1} and\ X_2 is\ A_{i2} and \ldots and\ X_n is\ A_{in})and(YisD_i)$are called antecedents and consequence, respectively.

The fuzzy conditional statement and inference engine are also called the fuzzy logic controller, in which the fuzzy engine processes all fuzzy inputs by using the fuzzy logic theories based on the sets of fuzzy 'IF-THEN' rules and creates fuzzy output sets, which are used in decision making (Fig. 7). In this paper, for predicting the coal fire with the fuzzy logic system, 81 'IF-THEN' rules (Equation 8) were created and are listed in Tables 3, 4.

2.2.5. Defuzzification

The nature of defuzzification operations is opposite to fuzzification. As mentioned in section 2.2.3 fuzzy logic model inputs can either be fuzzy sets or crisp sets, but the outputs are always fuzzy sets. To recognize the fire intensity, like other gas indices, the real world for decision making needs a crisp value, as shown in the general structure of the fuzzy logic model (Fig. 4); then, defuzzification has to be carried out. There are different defuzzification methods such as centroid of area (COA), bisector of area, mean of maximum, smallest of maximum, and largest of maximum. Among them, COA has been widely used in different applications [41]. In this study, COA, which is a widely used defuzzification method, was used and expressed as follows:

Table 3
Some samples of the full version of fuzzy rules

R#	IF-THEN rules
1	IF N_2 is Low and O_2 is Low and T is Low and CO is High THEN FI is High
2	IF N_2 is Low and O_2 is Low and T is Low and CO is Moderate THEN FI is Moderate
3	IF N_2 is Low and O_2 is Low and T is Moderate and CO is High THEN FI is Very high
4	IF N_2 is Moderate and O_2 is Low and T is Low and CO is High THEN FI is Very high
5	IF N_2 is Moderate and O_2 is Low and T is Low and CO is Moderate THEN FI is High
6	IF N_2 is High and O_2 is High and T is Moderate and CO is High THEN FI is Moderate
7	IF N_2 is High and O_2 is High and T is Moderate and CO is Moderate THEN FI is Low

FI, fire intensity.

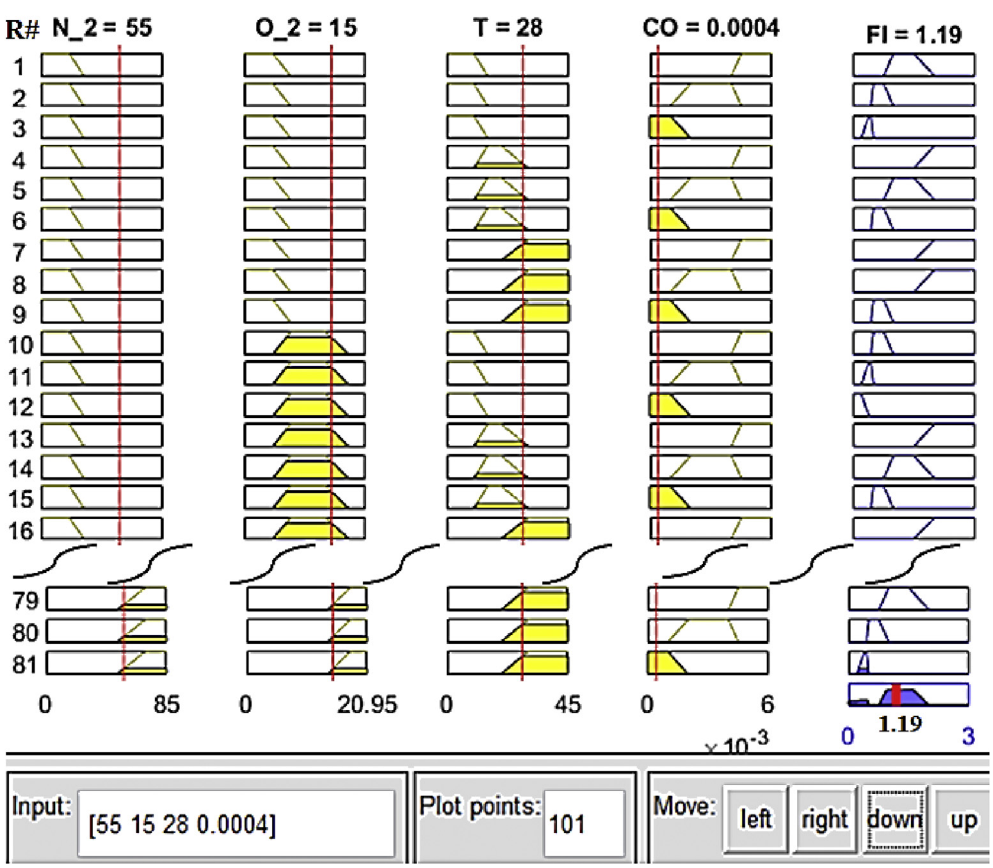

Fig. 7. Main structure of the fuzzy controller system and defuzzification steps.

Table 4
Complete abbreviation form of fuzzy rules for predicting coal fire

R#	Inputs				Output	R#	Inputs				Output	R#	Inputs				Output
	N_2	O_2	T	CO	FI		N_2	O_2	T	CO	FI		N_2	O_2	T	CO	FI
1	L	L	L	H	H	28	M	L	L	H	VH	55	H	L	L	H	H
2	L	L	L	M	M	29	M	L	L	M	H	56	H	L	L	M	M
3	L	L	L	L	L	30	M	L	L	L	M	57	H	L	L	L	L
4	L	L	M	H	VH	31	M	L	M	H	VH	58	H	L	M	H	VH
5	L	L	M	M	H	32	M	L	M	M	H	59	H	L	M	M	H
6	L	L	M	L	M	33	M	L	M	L	M	60	H	L	M	L	M
7	L	L	H	H	VH	34	M	L	H	H	VH	61	H	L	H	H	VH
8	L	L	H	M	VH	35	M	L	H	M	H	62	H	L	H	M	VH
9	L	L	H	L	M	36	M	L	H	L	M	63	H	L	H	L	M
10	L	M	L	H	M	37	M	M	L	H	H	64	H	M	L	H	H
11	L	M	L	M	L	38	M	M	L	M	L	65	H	M	L	M	L
12	L	M	L	L	VL	39	M	M	L	L	VL	66	H	M	L	L	VL
13	L	M	M	H	VH	40	M	M	M	H	H	67	H	M	M	H	M
14	L	M	M	M	H	41	M	M	M	M	M	68	H	M	M	M	L
15	L	M	M	L	M	42	M	M	M	L	L	69	H	M	M	L	VL
16	L	M	H	H	VH	43	M	M	H	H	VH	70	H	M	H	H	H
17	L	M	H	M	VH	44	M	M	H	M	H	71	H	M	H	M	M
18	L	M	H	L	M	45	M	M	H	L	H	72	H	M	H	L	L
19	L	H	L	H	H	46	M	H	L	H	H	73	H	H	L	H	M
20	L	H	L	M	M	47	M	H	L	M	L	74	H	H	L	M	L
21	L	H	L	L	VL	48	M	H	L	L	VL	75	H	H	L	L	VL
22	L	H	M	H	M	49	M	H	M	H	M	76	H	H	M	H	M
23	L	H	M	M	L	50	M	H	M	M	L	77	H	H	M	M	L
24	L	H	M	L	VL	51	M	H	M	L	VL	78	H	H	M	L	VL
25	L	H	H	H	VH	52	M	H	H	H	M	79	H	H	H	H	H
26	L	H	H	M	H	53	M	H	H	M	M	80	H	H	H	M	M
27	L	H	H	L	M	54	M	H	H	L	L	81	H	H	H	L	L

Note: VL: very low, L: low, M: moderate, H: high, VH: very high.

$$^{z}COA = \frac{\int_z \mu_A(z) z\, dz}{\int_z \mu_A(z)\, dz}, \tag{9}$$

where $\mu_A(z)$ is the aggregated membership function of output fuzzy set$A$, ^{z}COA is the crisp value.

In general, there are three commonly used fuzzy inference systems in the various application based on linguistic rules, such as Mamdani systems, Sugeno or Takagi, Sugeno and Kang (TSK) models, and Tsukamoto models [44]. The differences between the aforementioned fuzzy inference systems are in the consequents of their fuzzy rules, aggregation, and defuzzification. Thus, the result, after defuzzification in Mamdani system, has been given as a crisp output whereas in the TSK model the result is given as the polynomial function. For more clarification, typical fuzzy rules for Mamdani fuzzy system and TSK fuzzy system are given as follows:

$$Mamdani: \; IF\; X_1 is\; A^k_{i1} and\; X_2 is\; A^k_{i2}\; THEN\; Y^k is\; D^k_i \tag{10}$$

$$for\; k = 1, 2, 3, ..., r$$

whereA^k_{i1} *and* $A^k_{i2}$are fuzzy sets in the *kth* antecedent and D^k_i is the fuzzy set in the *kth* consequent.

$$TSK: \; IF\; X_1 is\; A_{i1} and\; X_2 is\; A_{i2} THEN\; Y\; is\; Y = f(a, b) \tag{11}$$

where A_{i1} *and* $A_{i2}$are fuzzy sets in the antecedent and $Y = f(a, b)$ is a crisp function in the consequent.

Consequently, for prediction of the coal fire in this work, Mamdani fuzzy inference system [45] is used because of its easiness to interpret and well accepted for human input.

Muduli et al [6] proposed a fuzzy logic model based on online fire monitoring in underground coal mines, where temperature, oxygen, carbon dioxide, and carbon monoxide were considered as input variables, and Grychowski et al [15] studied an offline fuzzy logic model for monitoring of fire hazard in the underground coal mine. He has also considered oxygen, carbon dioxide, and carbon monoxide as input variables, but the main factor temperature, which is increasing during combustion and accelerates the spontaneous combustion of coal and coal fire, was not considered. Meanwhile, the concentration of oxygen was considered unreliable (21.25 and 21.09%) which is higher than the normal concentration of oxygen in the air (20.95%). The differences of these studies and our study are in input variables, fuzzy rule base, and analyzed data.

In the fuzzy logic model suggested here, oxygen, carbon monoxide, temperature, and nitrogen were considered as input variables whereas fire intensity considered as an output variable. According to Turkish mine's regulation, measurement of carbon dioxide is not compulsory, and hence, AUCM does not carry out measurement of carbon dioxide. In this paper, we have generated 81 'IF-THEN' rules which are called as a backbone of the fuzzy logic

Table 5
Rating of fire intensity using Graham's ratio

Graham's ratio	Status
≤ 0.4	Indicates normal status
0.5	Indicates necessity for a thorough check-up
>0.5 < 1	Indicates heating almost certain
>1 < 2	Indicates heating in an advanced stage
>3	Indicates active fire
≥7	Indicates blazing fire

system which differ from other works. On the another hand, the membership function shape, range, and membership function parameters differ from existing researches. In addition, Muduli's et al [6] work was validated by statistical test, and ours was validated by Graham's index.

2.2.6. Fire ratios

Prediction of spontaneous combustion of coal based on the gas monitoring data is conducted using different gas indices. For predicting of spontaneous combustion, in underground coal mines, some important gas ratios proposed by different researchers such as oxides of carbon ratio (CO/CO_2), Willet's ratio, Jones and Trickett ratio, Graham's ratio, Young's ratio, dry ash-free oxygen index, desorbed hydrocarbon index, and ($N_2/(CO + CO_2)$) ratio.

Consequently, all the aforementioned fire indices have their own advantages, disadvantages, and limitation. The area in underground coal mines based on gas sampling is divided into two groups (1) ventilated areas and (2) sealed off areas. However, because the evaluation of gases which are taken from behind seals differs from the analysis of gases which are taken from the ventilated air, the fire ratios should be considered into two groups: (1) fire ratios for ventilated areas and (2) fire ratios for the sealed-off area [36]. Hence, Graham's ratio, CO/CO_2 ratio, Jones and Trickett's ratio, and so on are used for analyzing the ventilated areas, and desorbed hydrocarbon index, dry ash-free oxygen index, $N_2/(CO + CO_2)$ index, CO/CO_2 ratio, and so on are used for sealed off area analysis. As mentioned in section 1 according to Turkish mine's regulation, measurement of carbon dioxide is not compulsory; therefore, Graham's ratio was used. Advantages of Graham's ratio include the following: (1)it is used as an index for detecting the status of the fire in the early stage and in the development stages because of spontaneous combustion in underground coal mines, (2) it is widely accepted because of the availability of CO field sensor as a comparison to CO_2 sensor, (3) it does not involve carbon dioxide, and (4) can be used for ventilated areas. Owing to these advantages, Graham's ratio was selected for validation of fuzzy logic simulation.

2.2.6.1. Graham's ratio (GR). Graham's ratio which is widely used as an index for detecting the status of the fire in early stages as well as in development stages due to spontaneous combustion in underground coal mines [35,36]. This ratio is also named as Graham index and carbon monoxide index, and stated as carbon monoxide/oxygen deficiency, which means the release of carbon monoxide due to heating or spontaneous combustion causes oxygen consumption. The rating of fire intensity by Graham's ratio is shown in Table 5. This ratio is generally expressed as a percentage and is calculated by the following equation:

$$GR = 100 \times \frac{CO}{(0.265 \times N_2 - O_2)} \quad (12)$$

where N_2, O_2, and CO are the percentage of gas samples taken at any time and from anywhere in underground coal mines.

3. Results

As stated earlier, spontaneous combustion causes fire in underground coal mines, and various methods are used for detection and forecasting of coal fire in underground coal mines. During spontaneous combustion process, some gases are produced, and the detection of coal fire can be carried out by gas indicators, such as CO, CO_2, N_2, CH_4 and so on. As a result, many fire ratios are used to forecast and assess the fire status in underground coal mines. The most widely used fire ratios are oxides of carbon ratio (CO/CO2), Willet's ratio, Jones and Trickett ratio, Graham's ratio, Young's

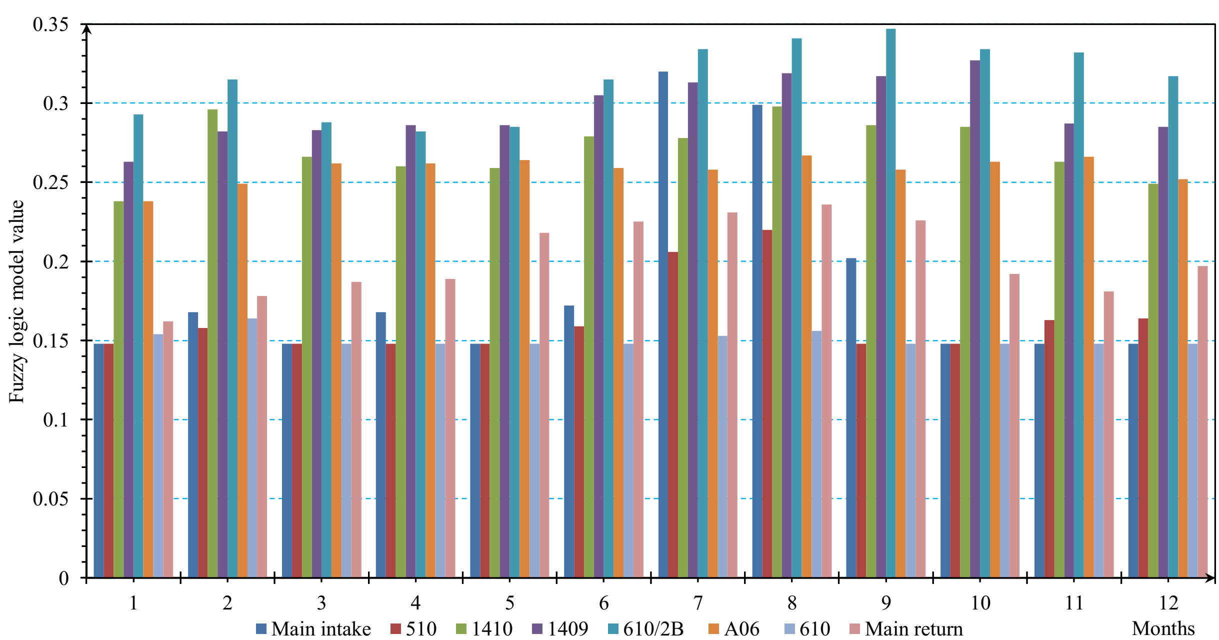

Fig. 8. Value of fuzzy model for each gas monitoring station in AUCM.

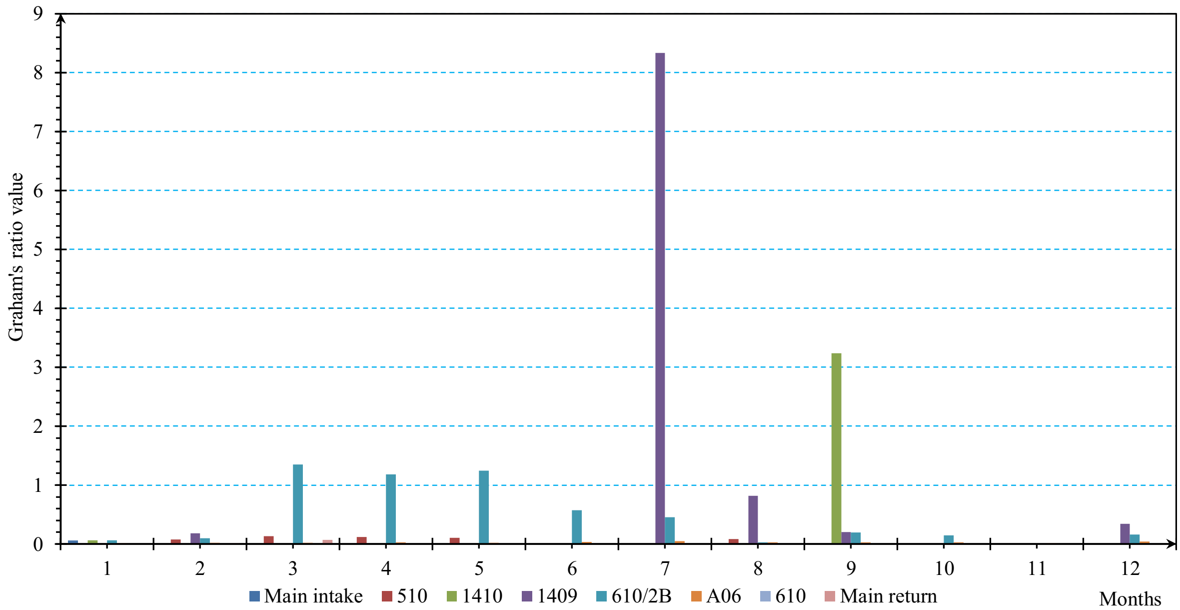

Fig. 9. Value of Graham's ratio for each gas monitoring station in AUCM.

ratio, dry ash-free oxygen index, desorbed hydrocarbon index, and ($N_2/(CO + CO_2)$) ratio. Among them, Graham's ratio, because of its easiness to interpret, can be used for early detection and advanced fire stages, as it does not involve carbon dioxide and can be used for both ventilated areas and sealed-off areas, is more accepted, and is widely used as a fire ratio (Equation 12). During spontaneous combustion of coal, the increase in temperature increases the production of gases with the consumption of oxygen in underground coal mines. The most determinant parameters for prediction of coal fire are oxygen, CO, CO_2, N_2, and temperature in underground coal mines.

Prediction of coal fire in AUCM with the fuzzy model was carried out for each gas station, and the results are shown in Fig. 8. Fig. 8 shows considerable values for 1409 and 610/2B gas station points; 1409 gas station is in under development gallery. 610/2B gas station point is near to working face and in the middle of drift which is mined into the coal seam and is parallel to the mine gob. In underground coal mines, when a coal seam is being mined, residual coals in the gob are subjected to low-temperature oxidation on exposure to air leakage of ventilation system, which may result in the ignition of residual coals. As a result, the longwall gob area is the main place for spontaneous combustion in AUCM which is in line with the result reported by Taraba and Michalec [46]. However, attention should be paid to these two points which is suspected for future spontaneous combustion, and therefore, precautionary action has to be taken. The result of fuzzy logic model for each gas monitoring station shows that the value increases gradually from main intake toward return airway. This result is in line with the results reported in the literature [6]. Fig. 8 also shows that the spontaneous combustion likely to increase seasonally; as shown in June, July, August, September, and October, the values are higher than those of other months. The value of the main intake gas station point in July, August, and September shows an increase in the fuzzy model (Fig. 8).

For validation of the fuzzy logic model, the result of the fuzzy logic model was compared with Graham's index result (Fig. 9). Fig. 9 shows that the values of Graham index increased at 1409 and 610/2B stations as well. Graham's index remains unchanged seasonally, but shows a high increase at 1409 and 1410 stations in July and September, respectively. In Fig. 9, if we decrease the value of 1409 monitoring station in month seven and value of 1410 monitoring station in month nine, the other monitoring station values will appear.

4. Discussion

AUCM was selected as a case study to assess whether is prone to coal fire or not. The data were collected from 10 gas monitoring

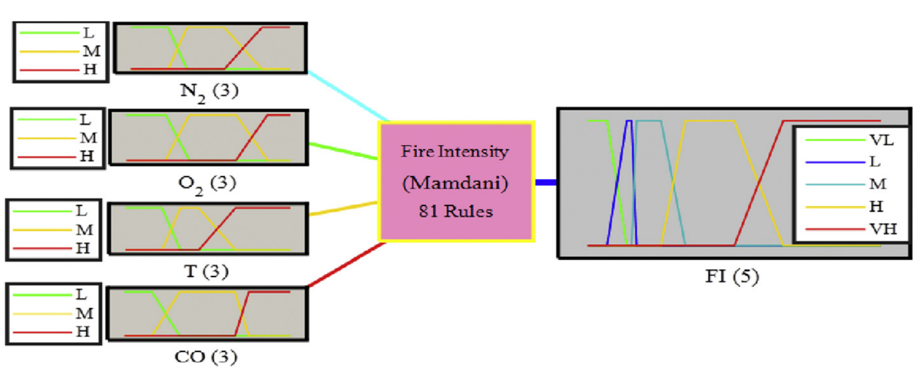

Fig. 10. Main structure of simulation model with four inputs and one output.

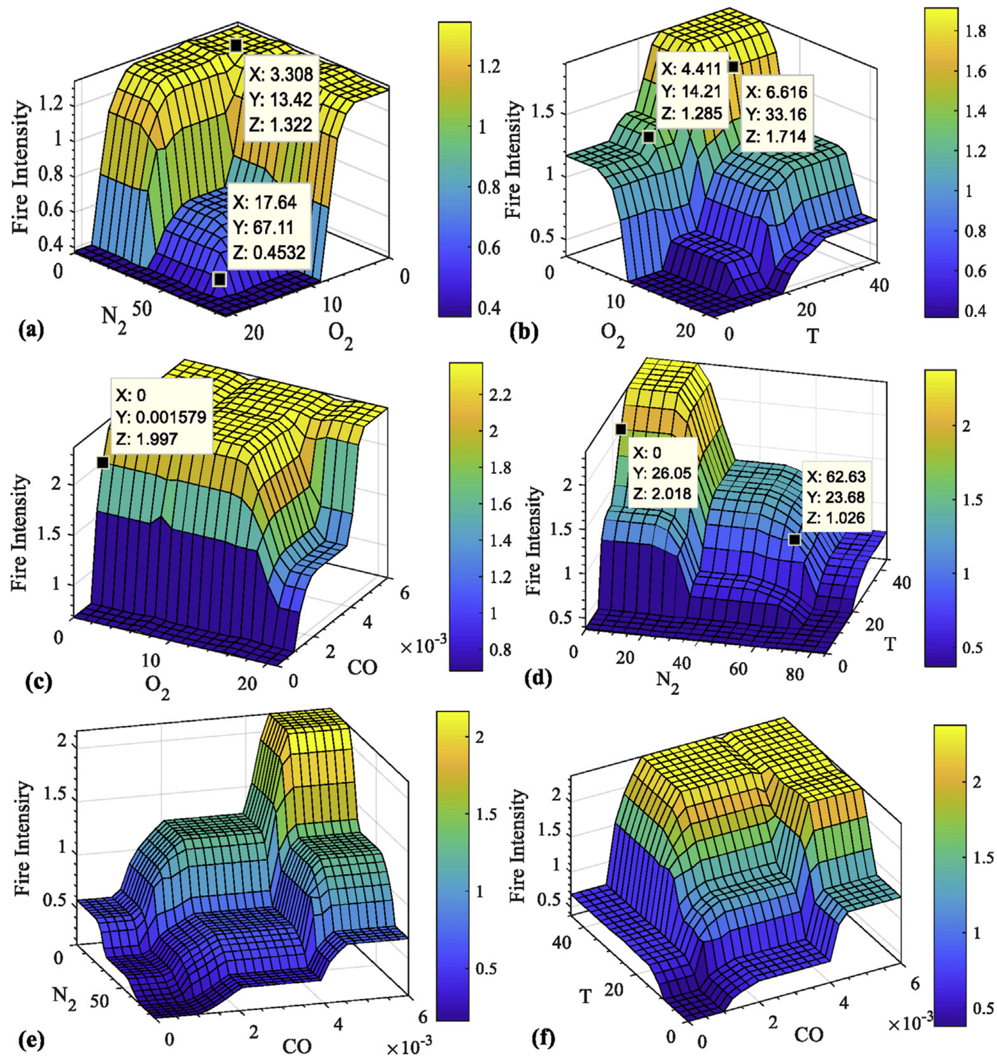

Fig. 11. Interpretation of fire intensity based on graphical fuzzy rules with various combination of inputs; (a) oxygen and nitrogen, (b) oxygen and temperature, (c) oxygen and carbon monoxide, (d) nitrogen and temperature, (e) nitrogen and carbon monoxide, (f) temperature and carbon monoxide.

stations in AUCM colliery in whole 2017 as shown in Table 1. In this study, a fuzzy logic model is proposed for predicting and assessing the fire status in AUCM. In the fuzzy logic model suggested here, N_2, O_2, CO, and temperature were used as inputs variables, and fire intensity was used as an output variable (Fig. 10). In simulating the fuzzy logic model, Fuzzy Logic Toolbox in MATLAB R2017a on a system with an Intel core i7-4500U, 1.80GHz CPU, and 16GB RAM running on Microsoft Windows 8.1Pro platform was used. As mentioned in section 2.2.1, the fuzzy logic system consist of four components; fuzzification, rule base, inference engine, and defuzzification. In the fuzzification step, crisp values which were introduced as inputs were converted to fuzzy inputs by giving them linguistic values (Table 2) and trapezoidal shape membership functions (Fig. 6). In rule base step, by using Equation 8, 81 'IF-THEN' rules were generated based on knowledge expert as shown in Table 4. For the case of the inference engine step, it is based on created rules which generated fuzzy output sets using Mamdani fuzzy inference system (Equation 10) and is a widely used inference system. The defuzzification step is done to obtain a crisp value for interpreting the fire status, like other fire indices, and fuzzy output defuzzified to crisp output by using the COA method (Equation 9).

Table 6
Rating of fire intensity with record to the fuzzy model

Fuzzy model	Comments
<0.3	Indicates normal status
≥0.3 < 0.48	Indicates certain heating
≥0.48 < 0.88	Indicates heating in an advanced stage
≥0.88 < 1.8	Indicates active fire
≥1.8 ≤ 3	Indicates blazing fire

As shown in Fig. 8, 1409 and 610/2B gas monitoring station points show considerable values. 1409 gas monitoring station is in the under development gallery; therefore, the air is polluted and the temperature is high because of the series of ventilation system and working of machines. The fresh air comes from the main intake airway, passes through 510, 1410 serially, and then ventilates 1409, but the main result for spontaneous combustion of coal is the intersection of two galleries (Fig. 3, point 12). The thickness of the pillar in this point is less, and owing to overburden pressure, cracks and fractures are formed; therefore, this phenomenon leads to air leakage into pillar, and in addition, mine air circulates the shortest way through formed cracks and fractures into pillar to ventilate next galleries and accelerate spontaneous combustion process in this gallery as a result. 610/2B gas monitoring station point is the most dangerous point in AUCM till now because the cross section of gallery is shrinking, and cracks and fractures are being formed because of overburden pressure. Therefore, when the crosscut of gallery is decreased, the air pressure goes up and air leakage occurred into the mine gob through cracks and fractures accelerate the spontaneous combustion phenomenon into the gob area. Fig. 10 also shows an increase for main intake gas in July, August, and September. Hence, it shows that the fuzzy model might be affected by increasing the air temperature in these months.

Fig. 11 shows, the fire intensity and accuracy of fuzzy rules with respect to various combinations of input variables. In Fig. 11a, the label shows if oxygen concentration is 3.3% and nitrogen concentration is 13.4%, then, the fire intensity is 1.3. In Fig. 11c, the label shows, if oxygen concentration is 0% and CO is 0.0015%, then, the fire intensity is 1.9. In addition, in Fig. 11d, the label shows, if nitrogen concentration is 0% and temperature is 26 ^{0}C, the fire intensity is 2. The rating of fire intensity for this fuzzy model is shown in Table 6. Assessing of fire intensity with a build-up fuzzy model is easy and time saving with respect to analyzing many variables simultaneously just by entering variable values in the input part, Fig. 7.

The values of Graham index increased at 1409 and 610/2B stations the same as those of the fuzzy logic model (Fig. 9). The value of Graham's index remains unchanged seasonally whereas the fuzzy logic model shows seasonally change. The increase of Graham's index value at 1409 and 1410 stations in July and September, respectively, caused by the carbon monoxide gas which released as a result of blasting works are realized in these galleries in July and September.

5. Conclusion

In this paper, a fuzzy logic model was developed for predicting the coal fire in AUCM as a case study area. The data was collected from AUCM at ten gas monitoring stations by sensors in the whole year of 2017. For predicting of coal fire, CO, O_2, N_2, and temperature were used as input variables and fire intensity as the output variable. In the fuzzy model, Mamdani inference system was used and ran Fuzzy Logic Toolbox in MATLAB environment for simulation. The results showed that the fuzzy logic system is more reliable for decision making of fire intensity with respect to uncertainties and nonlinearities of data. From the results, the 1409 and 610/2B gas monitoring station points are suspected areas for spontaneous combustion, and precautionary works have to be carried out. For validation of the fuzzy logic model, Graham's index was used and showed that the fuzzy model can assess fire intensity with many variables at the same time and produce a reasonable result.

Graham's index includes carbon monoxide and oxygen deficiency as variables whereas in the fuzzy logic system we have considered oxygen, carbon monoxide, temperature, and nitrogen as input variables. In addition, in the fuzzy logic system we can add more input variables which effect on coal fire such as relative humidity or other hydrocarbons. Rating of fire intensity by Graham's index is difficult because it has some gob (for example, between two and three what will happen), but in the fuzzy logic method this gob is eliminated by membership function. Fuzzy logic is fast and, therefore, can alleviate the time consumption in decision making. In addition, the fuzzy logic system should be incorporated to sensors for the design of an efficient and reliable online monitoring system for underground coal mines. The fuzzy logic model shows higher probability in predicting fire intensity with the simultaneous application of many variables compared with Graham's index.

Conflicts of interest

All authors have no conflicts of interest to declare.

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