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Applying an Automatic Gasometry System and a Fuzzy Set Theory to Assess the State of Gas Hazard During the Coal Mining Production Process

Jarosław Brodny,[1,*,#] Dariusz Felka[2,*,#] and Magdalena Tutak[1,*,#]

Abstract

One of the most dangerous hazards occurring in the process of underground mining production is a methane hazard caused by the release of methane gas into mine workings. The flammability and explosiveness of this gas lead to significant, and oftentimes catastrophic, consequences that endanger the ongoing mining operation. To reduce them, it is necessary to conduct research to reliably assess the status of this hazard. Having addressed this issue, the article presents the results of study aimed at developing an effective methodology for assessing the state of methane hazard. This methodology was based on the results of measurements in real conditions and a model developed using fuzzy set theory. The construction of the structure of this model is based on the method of clustering measurement data and fuzzy inference in accordance with the Takagi-Sugeno-Kang model. As a measure of the state of methane hazard, the value of the methane hazard index (MHI) – determined by the fuzzy model – was adopted, taking into account the results of measurements of ventilation parameters by the automatic gasometry system. The paper discusses the developed methodology and model as well as presents the results of the study for a real operating longwall. The comparative analysis carried out showed that both the developed methodology and model make it possible to obtain reliable values of the methane hazard index. The practical application of the findings, especially to support the process of mining production safety management, should improve this safety and the efficiency of the entire mining production process.

Keywords: Fuzzy model; Sensory systems; Underground coal mining; Methane hazard; Management system support.

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1. Introduction

Despite the dynamic development of renewable energy, hard coal continues to be one of the world's primary energy resources, as evidenced by its increasing output, among other examples.[1] In addition to its use in the energy sector, coal is also an important raw material in the production of coke used in steelmaking processes. In addition to energy and coke production, coal is also applied in many other areas of economic activity (*e.g.*, in the chemical industry). The widespread use of coal, and its great importance to the global economy, justifies taken measures to improve the safety and efficiency of its production process.

Hard coal mining is most often carried out in the process of underground coal mining by longwall systems.[2] This process is accompanied by a number of natural hazards resulting from the violation of the equilibrium state in the rock mass.[3-6] One of the most common, and also the most dangerous, is the methane hazard, the cause of which is methane emitted into the mine headings, mainly during the mining process. Methane, lingering in coal seams, is a colorless and lighter-than-air gas that becomes explosive and flammable when certain conditions are met. These characteristics make it a huge threat to the process of underground mining operations. Unfortunately, despite the increasing use of various types of drainage systems, methane

[1] *Silesian University of Technology, Akademicka 2A, 44-100 Gliwice, Poland.*

[2] *Łukasiewicz Research Network – Institute of Innovative Technologies EMAG, Leopolda 31, 40-189 Katowice, Poland.*

[#] *These authors contributed to this work equally.*

**Email:* jaroslaw.brodny@polsl.pl (J. Brodny); dariusz.felka@emag.lukasiewicz.gov.pl (D. Felka); magdalena.tutak@polsl.pl (M. Tutak)

emissions during mining operations are immensely high. It should also be noted that methane is a gas with good energy properties, which has a very negative impact on the environment (greenhouse effect). It is estimated that about 40% to 80% of total methane emissions enter mine headings directly from the mined seams and later into this environment.[7] The remainder enters these mine headings as well as collapsed goaves due to fractures from the rock mass surrounding the mined seams. Methane emissions into mine headings are therefore closely related to the process of underground coal mining, and at this stage, it is impossible to eliminate this gas from these processes.

Since methane hazard events pose a great threat to the crew and cause huge material losses in the coal production process, it becomes necessary to take measures to limit and/or reduce the impact of this hazard on the process. These measures are aimed at, on the one hand, reducing the amount of methane in coal seams as much as possible (through the process of drainage system), and, on the other hand, at reducing the events associated with the occurrence of this gas through the use of methods and systems that diagnose and forecast the safety of a given situation. In the latter area, the processes of assessing methane emissions and the state of methane hazard in the regions of mining operations are of key importance.

To date, the literature on predicting methane emissions and the magnitude of the methane hazard has used various approaches, which can be divided into empirical,[8-10] analytical,[11] statistical,[12-15] numerical,[16,17] and combined.[18,19] Therefore, the importance and timeliness of this problem causes great interest in it and results in a variety of methods used to reduce the negative impact of methane on the mining process.[20-25] The works show the variety of approaches used to diagnose and predict methane concentrations and the state of methane hazard in mine headings. This diverse approach testifies to the importance and relevance of this problem for the implementation of the mining production process and the constant search for new methods and ways to improve its safety. Particularly recently, the increasing use of model studies (CFD) and intelligent methods (*e.g.*, neural networks) to study these processes is noticeable. The use of new approaches is therefore fully justified, and the results obtained are used to plan and implement the mining process and improve its efficiency and, above all, safety. When taking into account the above factors and the need for greater use of intelligent methods to analyze the state of methane hazards, the paper presents a new method for diagnosing this state based on the fuzzy set theory. The key importance in method based on fuzzy set theory is ventilation data obtained from the automatic gasometry system. These data create the basis for ongoing analysis and assessment of the state of methane hazard in the studied mining region. Subsequently, the results obtained from these studies can be used for the process of forecasting this condition, such as based on neural networks.

The basis of the developed research methodology aimed at assessing the state of methane hazard in the mining region is a fuzzy model, the process of verification, validation and improvement, using the results of measuring ventilation parameters by the automatic gasometry system. Thus, the main objective of the research was to develop a new universal and effective method for diagnosing the state of methane hazard, using the fuzzy set theory and the results of measurements carried out by the automatic gasometry system. An immensely important element of this methodology is the reliance on the results of automatic gasometry systems, which are increasingly being used in practice. This is because it often happens that despite the use of advanced systems recording ventilation data, their use is very limited. The developed methodology provides opportunities for their use for advanced assessment of the state of methane hazard, and in further stages, not included in the study, also for forecasting this state. The purpose of the developed methodology was also to use the results of measuring these ventilation parameters in the area of the mining operation to assess the state of methane hazard in a more advanced way than previously used. During this assessment, the aggregated dimensionless methane hazard index (MHI) was used, which took into account the values of the indications of the automatic gasometry system. The following sections discuss how to determine the value of this index and the developed methodology, along with a model based on the fuzzy set theory. In order to evaluate the developed methodology, a comparative analysis of the results with those obtained by other methods was also performed. The results of this analysis indicate the great advantages and possibilities of practical application of the developed methodology and the results to improve the safety of the mining operation process.

After all, the process of reliable diagnosis and, in turn, forecasting of the state of methane hazard is of great significance for maintaining the continuity and efficiency of the entire mining production process.

2. Theoretical background of the model for predicting the state of methane hazard in the area of ongoing mining operations

The fuzzy set theory emerged as an alternative to the classical concepts of set theory and logic. The emergence of fuzzy set theory is associated with a study by of L. A. Zadeh[26,27] referring to the triple and multivalued logic introduced by J.

Lukashevich.[28] It describes phenomena that are difficult to define with ordinary mathematics due to vagueness and imprecision. L. A. Zadeh presented the assumptions of fuzzy inference with the definition of linguistic variables and conditional rules. Among his works, two are important,[29,30] in which, based on the theories of fuzzy logic, he introduced the idea of soft computing, which became the basis for combining various computing techniques and methods, such as fuzzy systems and artificial neural networks.[31,32] As it stands, the fuzzy set theory can be divided into mathematics, logic, uncertainty optimization, and fuzzy systems.[31-33]

The basic assumption of fuzzy set theory is to define the possible partial membership of an element in a set, without a sharp dividing line between belonging and not belonging to a given set, as in classical logic. Fuzzy sets provide an opportunity to define imprecise or ambiguous concepts. These concepts are defined in the non-fuzzy space of the analyzed data. Thus, a fuzzy set is defined as a set of pairs.[34-36]

$$A = \{(x, \mu_A(x)); x \in X\} \tag{1}$$

where: μ_A is a membership function of a fuzzy set, and X is fuzzy set space.

Closely related to the fuzzy set is the concept of membership function. Through the so-called degree of membership, contained between total membership and non-membership, it is determined to what extent a given element belongs to the fuzzy set. The shape of the membership function determines the value of a given argument. One possibility is to define a membership function composed of straight segments, the undoubted advantage of which is the ease of description. To define it, it is enough to give the values of the arguments representing the coordinates of the points that are the vertices of the polygon. Another type of membership functions are relations defined by nonlinear mappings, such as Gaussian, or other bell-shaped functions. Their shape makes it easier to analyze fuzzy systems and allows mapping a larger number of parameters of a fuzzy system, which is important when modeling more complex phenomena. A specific membership function is the so-called singleton, which is a one-element fuzzy set. The singleton takes value 1 for full membership of the set, while in other cases, it is assigned value 0.[37]

The general structure of the fuzzy system developed and used for the study is shown in Fig. 1. Fuzzy systems are often used in the field of data processing. The task of fuzzy systems is to process input signals according to an implemented inference mechanism in order to obtain a specific response at the output. These systems process both numerical and linguistic input values. The main difference between these values lies in the way they are represented. The numeric value is represented by itself, while the linguistic value is represented by the calculated degree of membership in the fuzzy set, described by the membership function. In the inference process, the fuzzy system requires the use of variables in fuzzy form, so it is necessary to use dedicated conversion mechanisms. Performing the conversion of numeric and linguistic values is carried out using fuzzifying (Fuzzifying block) and defuzzifying (Defuzzifying block) mechanisms. The calculation process uses an inference mechanism, also known as a fuzzy inference engine (Inference block). The calculation is based on an implemented rule base (Rule base block). The rule base is written in the form of fuzzy conditional "if-then" rules:

$$R = \{IF\ (\wedge_{n=1}^{N} X_n is\ A_n),\ THEN\ \{Y\ is\ B\}\} \tag{2}$$

where: X_n is input linguistic variables, Y is output linguistic variable, and A_n, B are linguistic values.

The properties of a given piece of knowledge of a fuzzy system in input/output processing are described by rules. The fuzzy area of the rule is defined by the premise of the rule. The conclusion, in turn, determines the output value for this area. When creating a rule base, it is necessary to maintain its completeness, *i.e.*, so that each input value activates a minimum of one rule and ensures continuity of operation without empty rules. At the same time, it must not contain rules that contradict each other, *i.e.*, those in which equal premise values give different rule conclusion values. The application of these rules makes it possible to determine the form of the resulting fuzzy set.

There are many types of fuzzy systems. The main feature that differentiates fuzzy systems from one another is the type of conclusion in fuzzy conditional rules. The output of a fuzzy model can be a linguistic or numerical value. According to the division proposed in one study,[38] fuzzy systems can be divided into several types, for which the output value is:

A weighted average of the degrees of activation of all rules;

The result of applying defuzzifying operations;

A weighted average of the degrees of activation of the rules, which are a linear combination of the values of the inputs and inference parameters.

When considering the overall structure, fuzzy systems can, in turn, be divided into multi-input-multi-output (MIMO) and multi-input-single-output (MISO) structures.

To design a fuzzy system, two types of information are required: quantitative (numerical) and qualitative (linguistic). The construction of the structure of the system consists primarily in determining the parameters of the membership function for all linguistic variables, as well as implementing the rule base. In fuzzy modeling, two approaches are usually

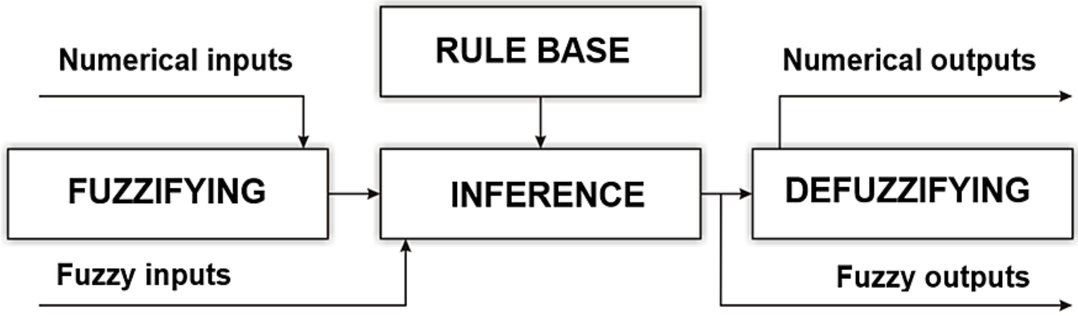


Fig. 1 Structure of the developed fuzzy system.

used to obtain this information. The first is to obtain knowledge from an expert. The structure and parameters are set arbitrarily based on their knowledge. The problem with this approach can be the difficulty of accurately determining model parameters and implementing complex mappings. Therefore, a common solution is to create a model with a pre-created rule base, which is then subjected to fine-tuning based on measurement data. The values of the membership function parameters for inputs and outputs are then determined, while the system structure itself is usually not further modified.

The second approach Is to automatically define rules based on numerical data. Given that each rule is described by its area of operation, such methods can be divided into the ones:

- With grid partition,
- With scatter partition,
- With tree partition.

The result of such an algorithm is the parameters of the system along with the organization of its structure. The use of this approach also allows the use of expert knowledge. In this case, part of the knowledge will come from the expert, and part from automatic rule extraction.

During the process of building the model, one should strive to simplify the structure and rule base as much as possible. This is due to the fact that the process of tuning the model with a complex and extensive base is not easy, and in some cases even impossible.

3. Materials and methods

3.1 Methodology of research proceedings

The main elements of the research process were the acquisition of data from the automatic gasometry system and their analysis in a model built on the basis of the fuzzy set theory. Therefore, the developed methodology involved the acquisition and preparation of measurement data and their analysis using the developed fuzzy model. An important part of the process also involved determining the value of the methane hazard index (MHI) and comparing it with normative values, in order to determine the degree of hazard. The general scheme of the research procedure, taking into account the methods used, is shown in Fig. 2.

The methodology also considered the characteristics of the studied region and the automatic gasometry network used. The developed methodology formed the basis for the research.

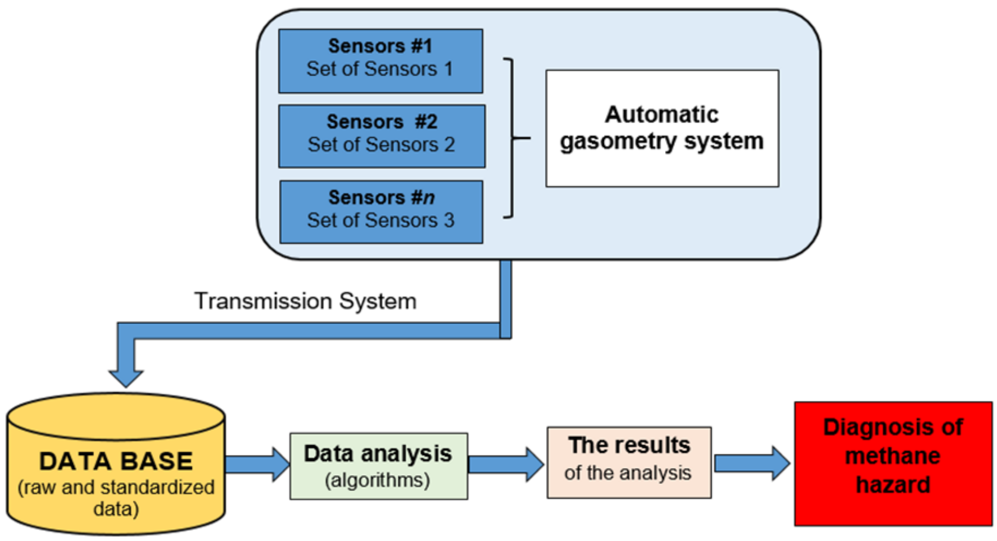


Fig. 2 Diagram of the research procedure for determining the degree of methane hazard in the region of underground mining operations.

3.2 Characteristics of the study area of mining operations

The developed methodology formed the basis for the research. An assessment of the state of methane hazard using the fuzzy set theory was made for a real mining region in one of Poland's underground coal mines.

The region under study included a longwall (mining) pit and headings (Fig. 3). The longwall being mined was characterized by a high methane-bearing capacity, and for this reason a drainage process was carried out in the region. A schematic diagram of the studied region with the location of the measurement sensors, being part of the automatic gasometry system, is shown in Fig. 3.

The investigated BS longwall was ventilated using the "Y" method. Ventilation air was supplied to the wall by the N-1 ramp and further by the N-2 tailgate. Part of the air from the N-1 ramp was directed toward the N-3 maingate, which was then combined with the air flowing out of the N-2 longwall. Air was discharged from the longwall by the N-3 maingate and the N-3 surface. The projected, at the stage of designing the exploitation, value of the criterial methane-bearing capacity for the region of this longwall was 12.76 m^3/min, and the efficiency of drainage systems – about 45%. On the other hand, the projected value of the criterial methane-bearing capacity was 23.2 m3/min. For the longwall area at such designed values of methane and drainage systems and for the extraction of 2000 Mg/day, 1217.78 m^3/min of fresh air had to be supplied, and to the longwall itself – 639.64 m^3/min.

The longwall mining region was covered entirely by an automatic gasometry system, which included the following sensors for measuring ventilation parameters of air flow and methane concentrations:

AS038 anemometer for measuring airflow velocity built into the N-2 maingate,

AS099 anemometer to measure air flow velocity built into the N-3 tailgate,

AS072 anemometer for measuring air flow velocity built into the N-3 rise gallery N-3,

MM137 sensor for measuring methane concentration built into the N-2 maingate,

MM116 sensor for measuring methane concentration built into N-3 tailgate,

MM104 sensor for measuring methane concentration, built into N-3 rise gallery,

Integrated WM46 sensor to measure the volume flow rate of methane in the methane drainage pipeline built into the N-3 Rise Gallery.

The values of ventilation parameters, recorded by these sensors, were the input data for the developed model. On their basis, the values of MHI were determined in the fuzzy model, including the state of this hazard in the studied region.

3.3 Characteristics of the automatic gasometry system used

The implementation of the research, the results of which are

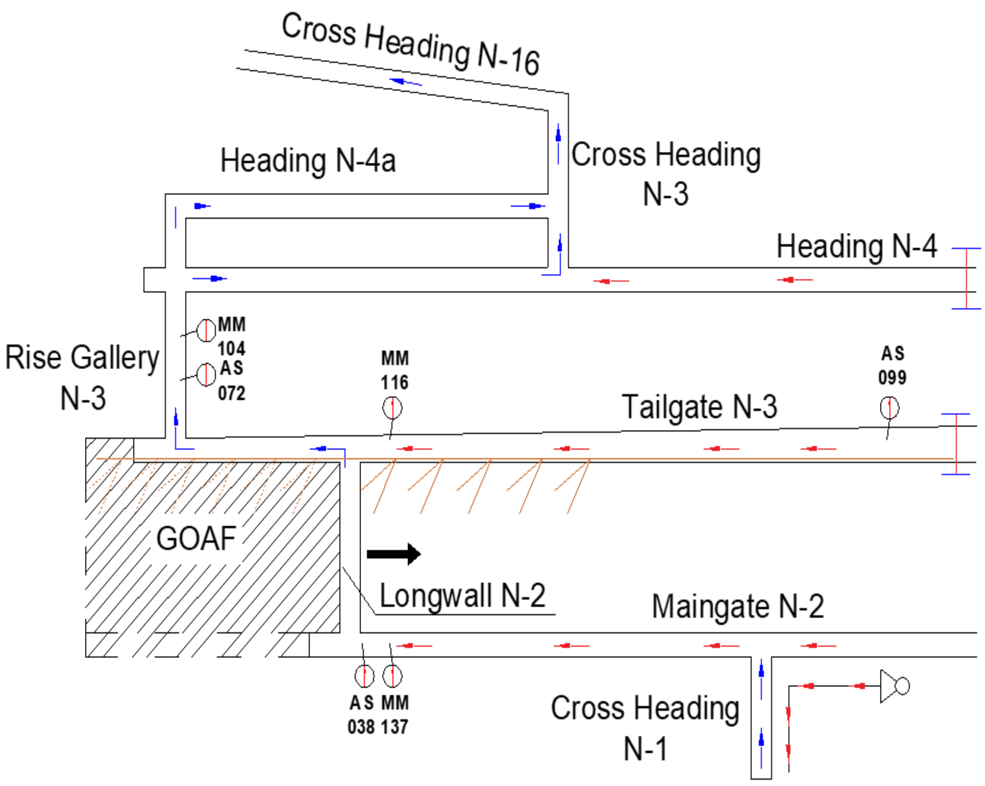


Fig. 3 The layout of an underground longwall with the location of the measurement sensors.

presented in the article, was based on data from the automatic gasometry system. The basis of this system was a system of sensors directly recording the physical and chemical quantities of air passing through mine headings. The data recorded by this system formed the basis for determining the value of MHI, which made it possible to determine the prevailing state of this hazard in the studied area.

Measurement of air ventilation parameters, also known as physicochemical parameters (velocity, pressure, and concentrations of mine gases) in underground coal mines was carried out using automatic gasometry sensors. These sensors include anemometers, automatic methane meters, oxygen meters, carbon monoxide and carbon dioxide sensors, as well as absolute pressure, humidity, and temperature sensors. These sensors are part of the mine's gas measuring system (SMP system), recording the values of the measured parameters in a discrete manner. Based on these indications, decisions are made as to whether the mining process should be performed. Indeed, it should be noted that in the event of exceeding the permissible values of methane concentration in the study area, energy is automatically shut down. In general, the SMP system provides quasi-continuous communication between the dispatcher and the underground equipment.

Therefore, automatic gasometry systems are part of the dispatching supervision system for industrial processes. This type of system distinguishes between an underground facility part and dispatching stations located on the surface (Fig. 4). The underground part consists of sensors for measuring air ventilation parameters and underground stations, which perform the functions of data concentrators and actuators. The surface stations, in turn, consist of data transmission systems and power supply systems. At the same time, they are an intermediate element for the computer part of the dispatching system.

The main components of this system are the sensors already mentioned for measuring ventilation parameters in mine headings (Fig. 5).

For measuring methane concentration, the MM-4 type methanometer (Fig. 5a), commonly used in Polish mines, was used. This device has proper metrological properties and short response time and uses thermocatalytic transducers for measurement. The basic properties of this methanometer are as follows:

It allows continuous measurement of methane concentration in the range of 0 ÷ 100 % CH4.

- The measuring range is within two subranges: 0 ÷ 5 % CH_4 and 5 ÷ 100 % CH4.
- The measurement error is:

± 0.1 % CH4 for concentrations of 0 ÷ 2 % CH4,
± 5 % indication for concentrations of 2 ÷ 5 % CH4,
± 3 % CH4 for concentrations of 5 ÷ 60 % CH4,
± 5 % indication for concentrations of 60 ÷ 100 % CH4,

It has two shutdown outputs with independently adjustable action thresholds.

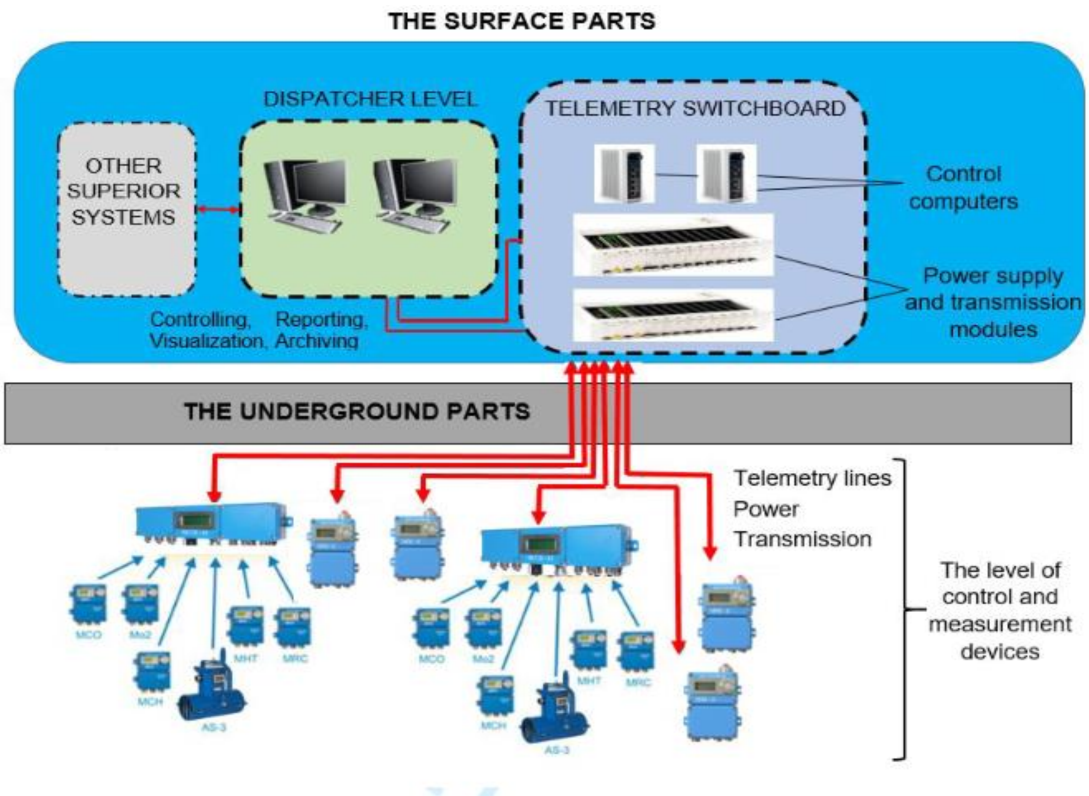


Fig. 4 Structure of the automatic gasometry system in the Polish underground coal mining.

a b c

Fig. 5 Sensors of the methane gas system in the studied region (a - methanometer, b - anemometer, c - integrated drainage sensor).

It has LED signaling.

It has automatic power off after exceeding the permissible concentrations.

There is a possibility of emergency power supply of the device from a battery.

An AS-3 type anemometer (Fig. 5b) was used to measure the speed of air flow in mine headings. This device can perform measurements using the time-based ultrasonic method. The device works with underground control panels and can be used as a portable one, powered by an intrinsically safe battery power supply.

The basic properties of the AS-3 anemometer, are as follows:

It allows continuous measurement of air flow velocity.

It has a voltage output signal in the range of 0.4 ÷ 2.0 V.

The measurement range is: 0.1 ÷ 10 m/s or -5 ÷ +5 m/s.

The measurement error is less than 5% ± 0.1 m/s.

The measurement resolution is 0.05 m/s.

To measure the amount of methane captured during the drainage process, an integrated drainage sensor of the ZCO type was used (Fig. 5c). It measures physical parameters (pressure, differential pressure at the orifice and temperature) and methane concentration. Its design is adapted for cooperation with a chamber measurement orifice installed in the drainage pipeline. Based on the results, using a simplified or iterative method, the amount of pure methane in the pipeline can be determined. These data can be automatically transmitted to the system's control panel. The basic parameters of this sensor are as follows:

Measuring range: methane concentration: 0 ÷ 100% CH_4, temperature: -10 ÷ +80 ºC, absolute pressure: 0 ÷ 110 kPa, differential pressure: 0 ÷ 2.5 kPa, KHT temperature range: -10 °C ÷ +40°C, KHT humidity range: 0 ÷ 95% (non-condensing), KHT pressure range: 800 ÷ 1200 hPa.

Measurement errors are:

For methane measurement: 3% CH_4 for concentrations 0 ÷ 60 %; 5 % of the indication for concentrations of 60 ÷ 100 % CH_4, for differential pressure measurement: less than 1% (25 Pa), for absolute pressure measurement: less than 2% (2 kPa), for temperature measurement: 1ºC.

The equipment shown was used to diagnose the degree of methane hazard in the studied region.

3.4 Methane Hazard Index (MHI)

The main task of the conducted research was to determine the value of MHI and compare it with normative values in order to assess the degree of methane hazard in the studied area. Thus, in the presented research, the value of this indicator is a measure of the degree of methane hazard and is determined on the basis of the calculated values of methane-bearing capacity. In order to determine methane in the mining longwall region, it is necessary to define the concepts of ventilation methane content (the balance of pure methane discharge for the studied region), absolute methane content (the sum of the discharge of methane emitted into the workings and the amount of methane drainage) and criterion methane content (the maximum absolute methane content at which the permissible concentrations of methane in the used air current will not be exceeded). Thus defined, the criterion methane content makes it possible to assess the methane hazard in the mining area. Its value can also be a condition for the necessary application of methane drainage or other measures to reduce the amount of methane emitted into the workings. This is particularly important in the case of determining lower values of the criterion methane content than the actual amount of methane occurring during mining.

The criterion value of absolute V_{CR} methane, within the conducted research, was determined from the following relationship:

$$V_{CR} = \frac{c_m \times V_s \times k}{100 \times n} + \frac{V_p\left(\frac{c_m}{n} - c_p\right)}{100 - \frac{c_m}{n}} - V_D, \frac{m^3}{min} \quad (3)$$

Due to the methane drainage process carried out in the area of operation, the final value of the criterion methane is:

$$V_{CR-0} = \frac{100 \times V_{CR}}{100 - E}, \frac{m^3}{min} \quad (4)$$

where: C_m - permissible methane content, %; C_p - concentration of methane in the refreshing current, %; V_P - discharge of refreshing air current, m^3/min; V_s - discharge of air in the wall, m3/min; V_D - discharge of methane flowing into the wall, m^3/min; k - coefficient of unevenness of air distribution in the wall, n - coefficient of unevenness of methane release, E - efficiency of methane drainage, %.

In order to reliably estimate the value of the criterion methane content, it is necessary to calculate the coefficient of unevenness of methane release n. This coefficient reflects the weekly fluctuation of methane concentration in ventilation air in the area of the longwall (for new designed longwalls, its value is 1.55). This coefficient is determined from the following relationship:

$$n = n_d \times n_t \quad (5)$$

where: n_d - coefficient of daily uneven methane release determining the ratio of the maximum methane concentration to the value of the average methane concentration during the day;
n_t - coefficient of weekly uneven methane release determining the ratio of the average methane concentration on the working day of the week with the highest concentrations to the value of the average methane concentration for the entire week.
Methane Hazard Index is calculated according to equation (6):

$$MHI = \frac{V_B}{V_{CR}} \quad (6)$$

where: V_B is absolute methane-bearing capacity, which is the sum of V_W ventilation methane-bearing capacity and the amount of methane captured by the drainage process, m^3/min; and V_{CR} is criterial methane-bearing capacity, m^3/min.

The ventilation methane-bearing capacity occurring in this equation determines the volumetric amount of methane emitted into the mine headings. On the other hand, the criterial methane-bearing capacity determines such a volumetric amount of methane that can be emitted into the headings so that the permissible concentrations of methane in the used air stream are not exceeded. The basis for determining these methane rates are measurements of ventilation air parameters carried out by the automatic methanometry system.

Thus, the determination of the value of the methane hazard index is aimed at identifying the state of methane safety by determining the ratio of the actual state of methane in the studied area (absolute methane-bearing capacity) to the critical state, the limiting measure of which is the criterial methane-bearing capacity.

Therefore, diagnosing the degree of methane hazard can be understood as estimating the current value of MHI in the region of the coal production process under way. This process, as already mentioned, involves the current estimation of the absolute methane-bearing capacity in relation to the criterial methane-bearing capacity.

In order to determine the degree of methane hazard on the basis of these measures, it is necessary to compare the values of MHI determined from the study with normative values. Thus, the process of assessing the state of safety is associated with the adopted ranges of values of this indicator. In the presented study, the evaluation of the state of methane hazard is based on the criteria used in Polish coal mines and included in the study.[39] A summary of the values of MHI along with the corresponding methane hazard states is presented in Table 1.

When analyzing the criteria for assessing the state of methane hazard, it can be concluded that for the value of the indicator of "0", there is the highest level of safety, while for the value of "1", there is a very high state of methane hazard. Thus, the dangerous state is when the value of absolute methane hazard approaches the criterion methane hazard value determined for a given excavation (geometry) and assumed ventilation parameters (ventilation air velocity).

In such a situation, it becomes necessary for mine services to take measures about improving the value of this indicator. These actions can range from reducing the intensity of mining (reducing methane emissions) to increasing the speed of air flow (faster removal of methane from the mining area).
Thus defined, MHI was the basis for determining, according to the developed methodology, the state of methane hazard in the studied region.

Table 1. State of methane hazard depending on the methane hazard index.

Value of methane hazard index	$MHI \geq 1.0$	$0.8 \leq MHI < 1.0$	$0.5 \leq MHI < 0.8$	$0.2 \leq MHI < 0.5$	$MHI < 0.2$
Level of methane hazard	Very high	Very low	Average	Low	No hazard

3.5 Model for analyzing the degree of methane hazard

Of key importance for the process of assessing the degree of methane hazard in the studied area is the analysis of changes in the amount of methane in the headings, and more broadly, the balance of the amount of methane for the entire longwall region characterized by absolute and criterion methane (equation 6). This analysis is implemented using a model developed based on the fuzzy set theory. The input values for this model, diagnosing the degree of methane hazard, are the indications of the measurement devices of the dispatching gasometer system. The number of inputs to the model (measurement data), depends on the ventilation scheme of the longwall and the drainage system used.

Four variants of the number of inputs to the model can be distinguished, in order to carry out the process of diagnosing the methane hazard:

Without refreshment and drainage– four devices: two pairs of anemometer/methananometer devices in the inlet and outlet air currents;

Without refreshment, with drainage – five devices: two pairs of anemometer/methanometer devices in the inlet and outlet air currents and a device for measuring the amount of methane captured in the drainage process;

With refreshment, without drainage – six devices: three pairs of anemometer/methanometer devices in the inlet, outlet and refreshing air currents;

With refreshment and drainage– seven devices: three pairs of anemometer/methanometer devices in the inlet, outlet and refreshing air current, and a device for measuring the amount of methane captured in the drainage process.

In the case under study, we are dealing with the last variant, that is, the refreshment and drainage process of the exploited seam. Therefore, the input parameters for the developed model are seven values of parameters recorded by the gasometry system. On the other hand, the output value from the model is MHI.

The general scheme of model construction for diagnosing the degree of methane hazard using the fuzzy set theory is shown in Fig. 6.

The fuzzy model for diagnosing methane hazard is a MISO-type system.

It consists of fuzzifying, inference and defuzzifying blocks. An additional element is the implemented rule base. The model is based on the inference of the Takagi-Sugeno-Kang system.[40,41] A feature of this system is the use of a polynomial function in the conclusion of conditional rules, which positively affects the computational efficiency of the model due to the lack of the need for complex defuzzification mechanisms. Fig. 7 shows an example of inference using this system.

The model's input values are subject to a fuzzifying operation (transforming them into fuzzy sets by calculating membership degrees). Using the inference mechanism and rule base, the resulting degrees of activation is calculated. The degrees of fulfillment of the premises are aggregated using the MIN operator. Based on the input values, the functions in the conclusion of the fuzzy rules are also determined, where the coefficients are the dropped coordinates of the centers of the output clusters. The output value of the model is determined by the weighted average of all elements of the model's rule base. The weights are the degrees of activation, and the elements are the functions in the rule conclusions.

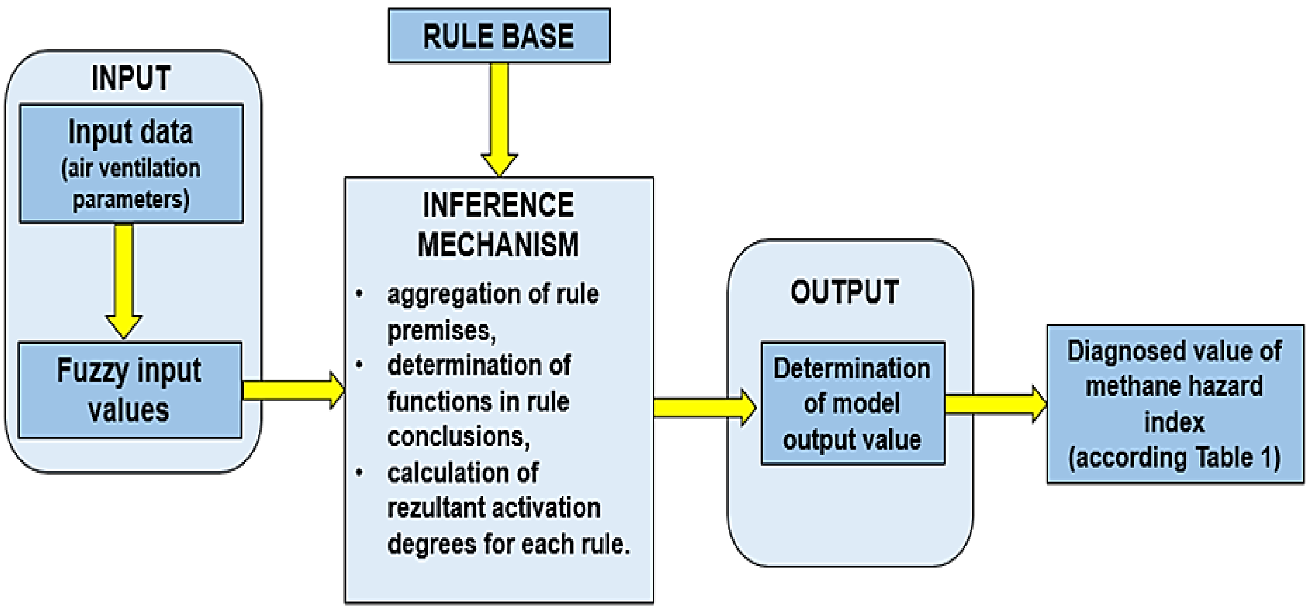


Fig. 6 Schematic diagram of the model for diagnosing the degree of methane hazard.

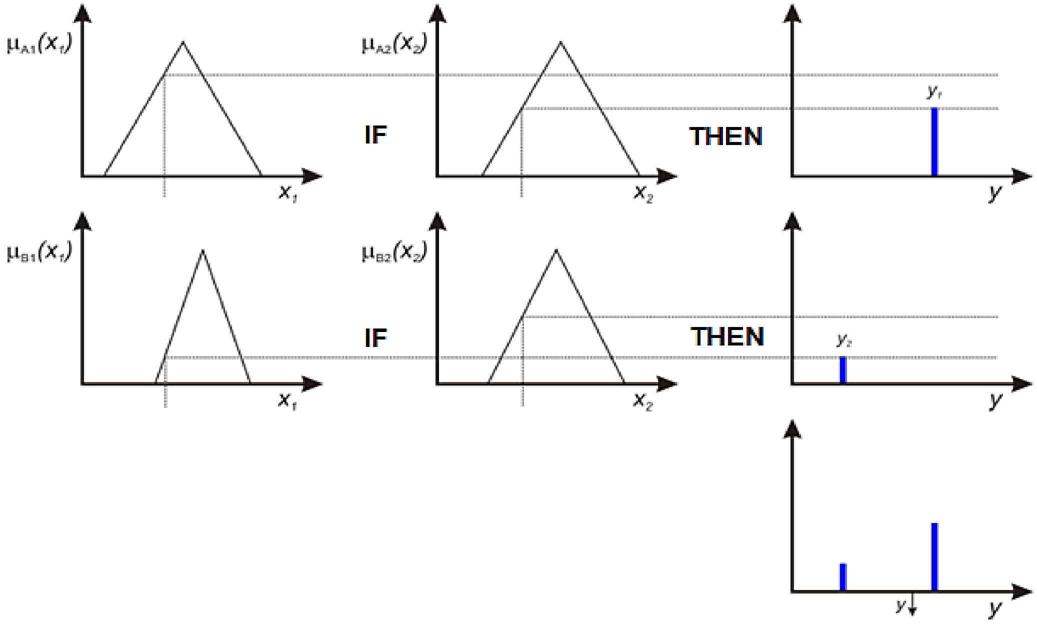


Fig. 7 Example inference using the Takagi-Sugeno-Kang system.

The construction of the model structure is based on the method of clustering the measurement data. This yields model parameters that describe the model's structure and operation. The clustering algorithm returns the location of cluster centers and, depending on the method chosen, the number of clusters. This parameter is extremely important, since the number of clusters equals the number of conditional rules in the rule base, and the coordinates of the centers of the clusters correspond to the position of the centers of the membership function of the fuzzy model. The parameters and shape of the functions defined in this way have a great impact on the accuracy of the model.

Figure 8 shows a schematic diagram of the fuzzy model built on the measurement data base, along with its structure and parameters, while Fig. 9 shows an example of the inference of a fuzzy model built on the same base. The model's input parameters are data from seven measuring devices, according to the applied ventilation variant of the studied longwall:

AS038 anemometer for measuring airflow velocity built into the N-2 maingate),

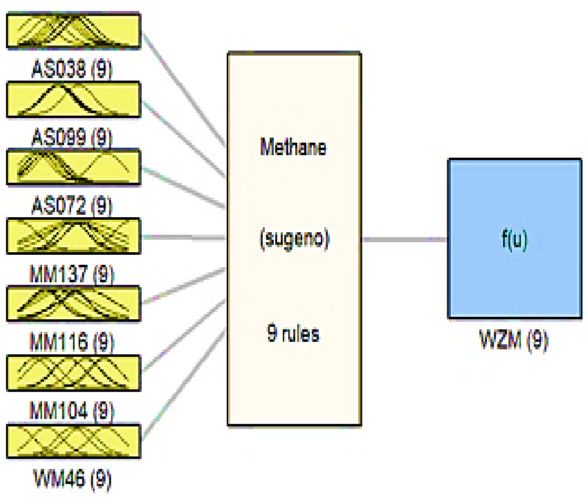
AS099 anemometer to measure air flow velocity built into the N-3 tailgate,

AS072 anemometer for measuring air flow velocity built into the N-3 rise gallery N-3,

MM137 sensor for measuring methane concentration built into the N-2 maingate,

MM116 sensor for measuring methane concentration built into N-3 tailgate,

MM104 sensor for measuring methane concentration,



MODEL NAME:	METHANE
Type:	Sugeno
Inputs / Outputs:	7 / 1
Number of functions for inputs:	9
Number of output functions:	9
Number of rules:	9
AND Operator:	prod
OR Operator:	probor
Defuzzification Method:	wtaver
Type of membership function:	gaussmf
Type of output function	linear

Fig. 8 Fuzzy model built using data from the studied area.

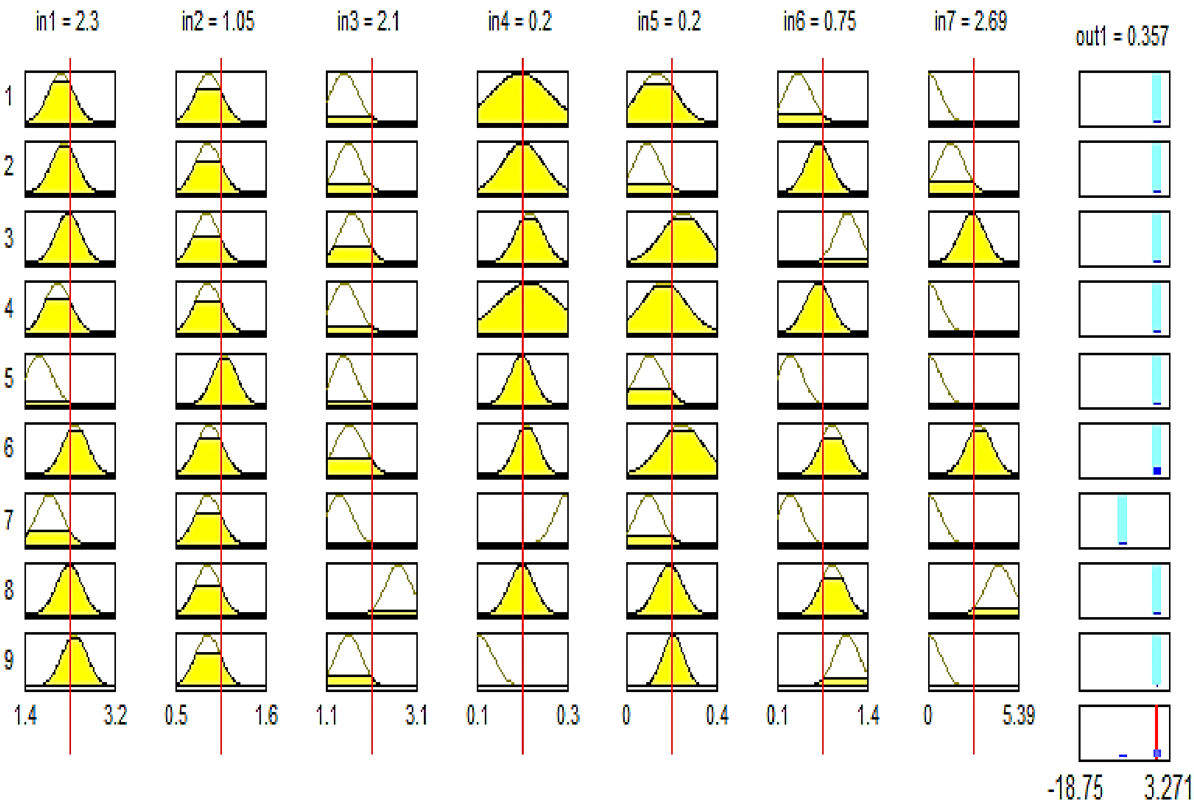


Fig. 9 Example of fuzzy model inference for data from the studied area.

built into N-3 rise galler, integrated WM46 sensor to measure the volume flow rate of methane in the methane drainage pipeline built into the N-3 Rise Gallery.

The output parameter from the model is the Methane Hazard Index (MHI).

The final result of the process of diagnosing the state of methane hazard, using the model developed in this way, is the course of changes in the value of MHI. This course is the basis for assessing the degree of methane hazard in the studied region.

3.6 Estimating forecast errors

Errors for the determined forecasts were calculated from the following relationships:

– Mean absolute percentage error (MAPE):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - y_i^*}{y_i}\right| \quad (7)$$

– Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2} \quad (8)$$

– Relative Root Mean Squared Error (RRMSE):

$$RRMSE = \sqrt{\frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - y_i^*)^2}{\sum_{i=1}^{n}(y_i^*)^2}} \quad (9)$$

where: y_i^* is the forecast variable at time t, y_i is the forecast variable at time t and n is the data set.

4. Results and discussion

In accordance with the developed methodology, a study was conducted at one of the coal mines in Poland (discussed in Section 3.2). The purpose of this research was to determine the degree of methane hazard in the area being mined. The research was conducted for a data set of 44,640 records registered during the operation of this longwall. The study used averaged one-minute measurements from seven sensors included in the automatic gasometry system and calculated values of MHI for a period of 31 days of continuous operation. The recorded data were divided into two parts, training (30,000 records) and testing (14,640 records). Basic information regarding the data set used for the study is presented in Table 2, and their statistical data in Table 3.

Table 2. Characteristics of the studied measurement data set.

Data type	Initial time:	Final time	Number of records	Number of variables
Training data	01-10 00:00:00	21-10 19:59:00	30000	8
Testing data	21-10 20:00:00	31-10 23:59:00	14640	8

Table 3. Basic descriptive parameters of the studied measurement data set.

Sensor/ parameter	Training data				Testing data			
	min	med	mean	max	min	med	mean	max
AS038, m/s	1.3000	2.1000	2.1322	2.6000	1.3000	2.1000	2.0134	2.4000
AS099, m/s	0.5000	0.9000	0.8738	1.6000	06000	0.9000	0.9444	1.6000
AS072, m/s	1.0000	1.5000	1.6084	2.9000	08000	1.7000	1.8191	2.8000
MM137, %	0.2000	0.3000	0.2746	0.4000	02000	0.3000	0.2957	0.4000
MM116, %	0.0000	0.2000	0.1626	0.4000	00000	0.2000	0.1723	0.4000
MM104, %	0.1000	0.6000	0.6222	1.3000	0.3000	0.5000	0.5103	0.9000
WM46, m^3/min	0.0000	0.8400	1.1136	3.1100	0.0000	1.8000	1.5575	2.6900
WZM	0.0330	0.1816	0.2162	0.9882	0.0323	0.1817	0.1899	0.5647

The recorded time variation of selected parameters registered by the automatic gasometry system is shown in Figs. 10 and 11. The time variation of airflow velocity recorded by anemometers (AS038, AS099 and AS072) is shown in Fig. 9, while the time variation of methane concentrations and drainage system efficiency is shown in Fig. 10.

Based on these measurement data, the values of the coefficient of irregular methane release were determined on a daily, weekly and total basis. This coefficient is important for determining the value of the criterial methane-bearing

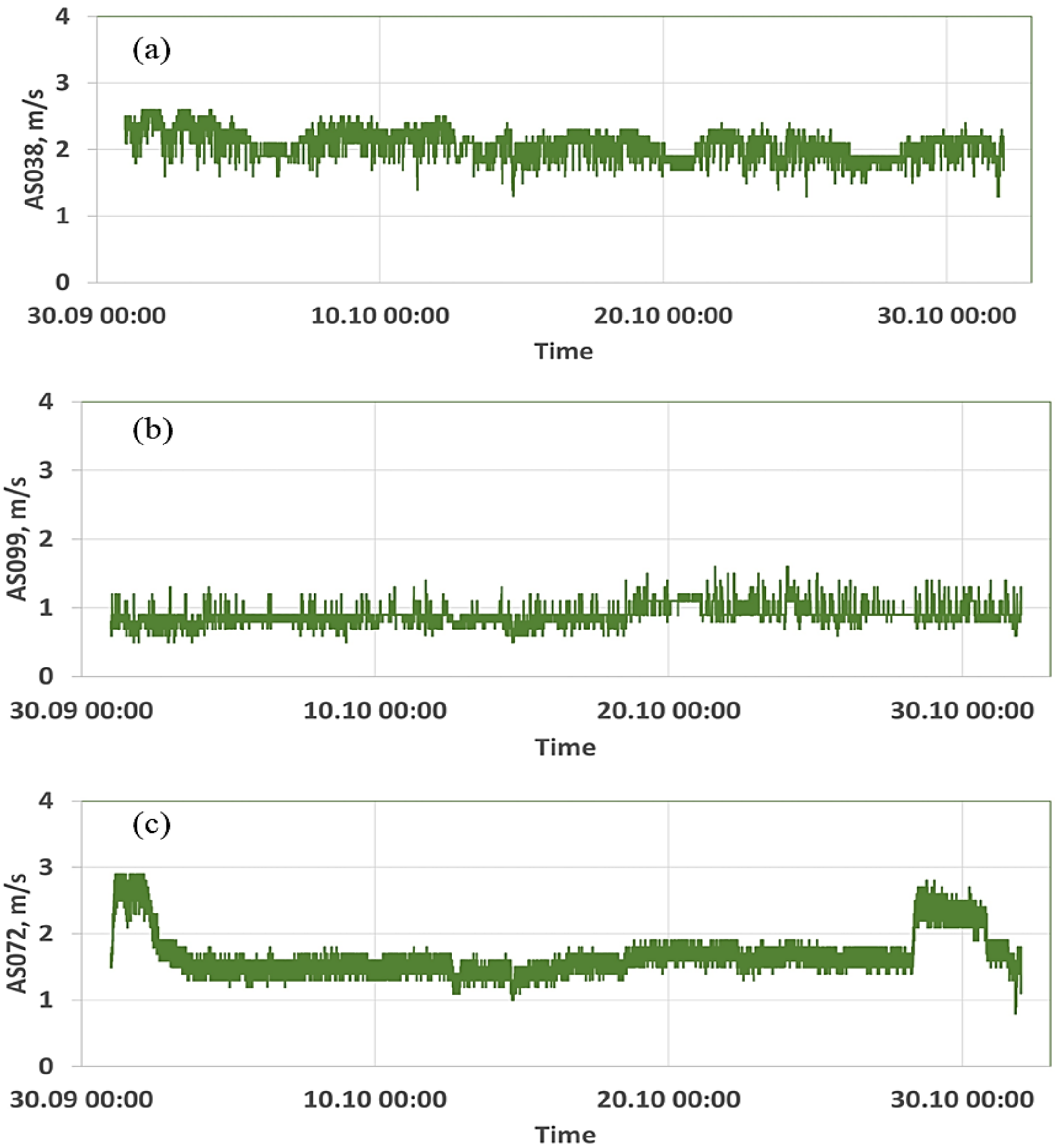


Fig. 10 Time waveforms of airflow velocity values recorded in the study region by sensors: AS038 (a), AS099 (b) and AS072 (c).

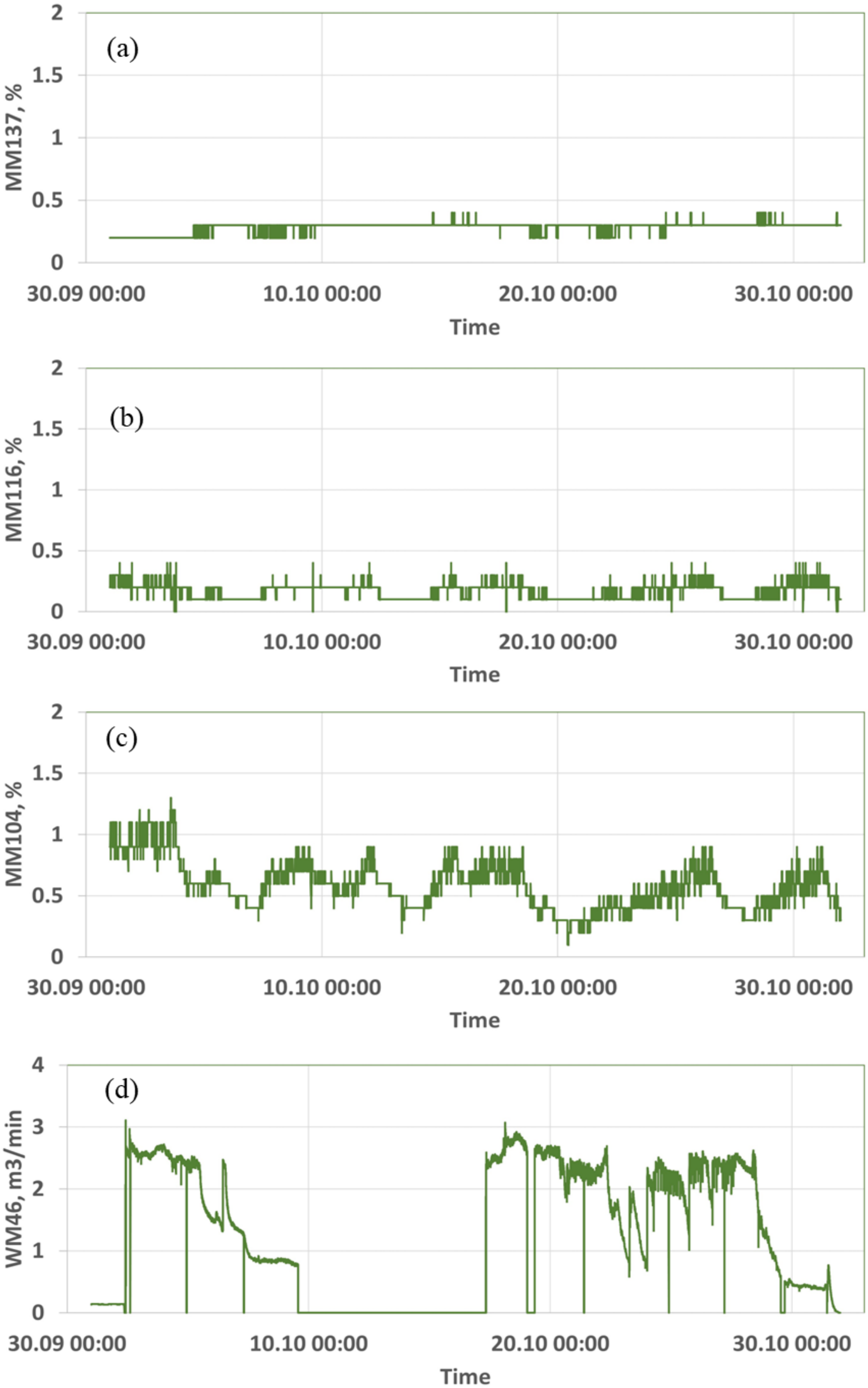


Fig. 11 Time waveforms of methane concentration (a-MM137-a, b-MM116, c-MM104) and drainage system efficiency (d-WM46) recorded in the studied area.

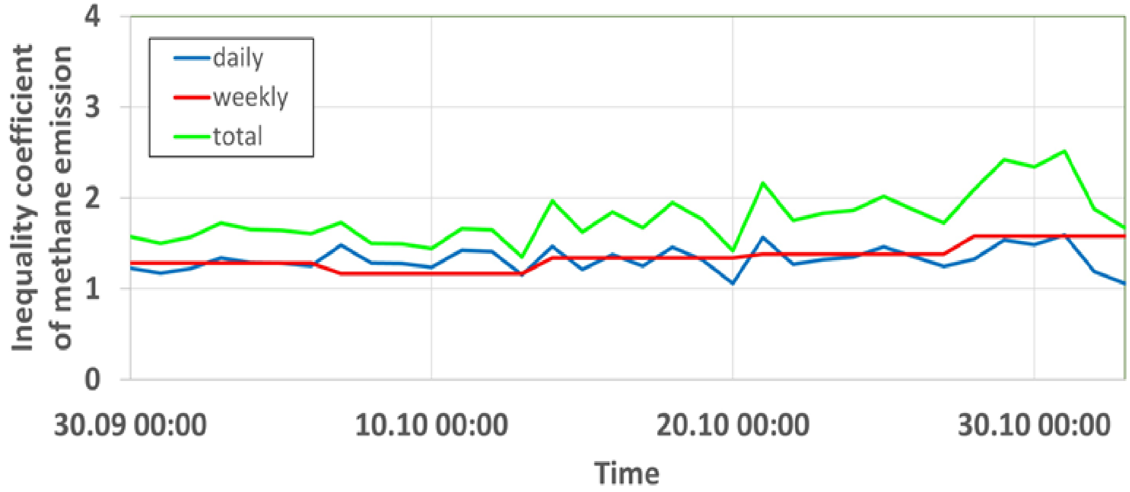


Fig. 12 Values of daily, weekly and total coefficient of irregular methane release in the studied area.

capacity and reflects the weekly fluctuation of methane concentration in ventilation air. The results obtained are shown in Fig. 12.

The results show that for the analyzed daily data set, and especially the total values, there are quite significant differences in the evenness of methane release. In the first half of the month, the coefficient remains at about 1.5. In subsequent days, its value increases to almost 2.5 at the end of the analyzed month.

Using the data recorded by the measurement sensors, the time waveforms of the current values of ventilation, absolute and criterial methane-bearing capacitys were determined. The value of the criterial value of absolute methane-bearing capacity is the basis for taking measures (*e.g.*, drainage) to reduce the release of methane into the headings. This is of particular importance when its calculated value is less than the methane-bearing capacity occurring during mining in the area of the longwall. The results are shown in Fig. 13.

The results are the basis for determining the current value of MHI, and subsequently the degree of methane hazard. The basis for this assessment is MHI, which is a measure of methane hazard in the studied region. In the case studied, the measurement data were divided into two groups. The training data were subjected to a clustering process in order to determine the parameters of a fuzzy model for diagnosing methane hazard, by determining the value of the MHI. The task of the testing data, on the other hand, was to verify the effectiveness of the clustering algorithm and, at the same time, the accuracy of determining the MHI. Two clustering methods were used for testing: c-means and subtractive clustering. Based on the results obtained from the clustering process, the structure of the fuzzy model was created, determining the value of MHI. The structure of the created fuzzy model along with its most important parameters is shown in Fig. 8.

Based on this model, an analysis was performed to determine the temporal changes in the value of the methane hazard index for the analyzed data. The results obtained in the form of the time waveforms of this index are shown in Fig. 14.

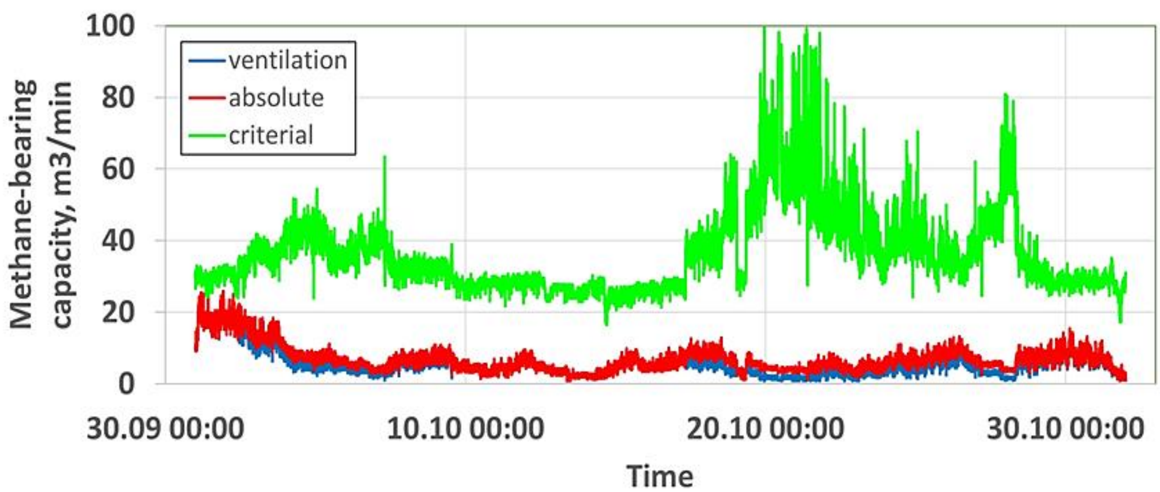


Fig. 13 Temporal waveforms of methane-bearing capacity in the studied region.

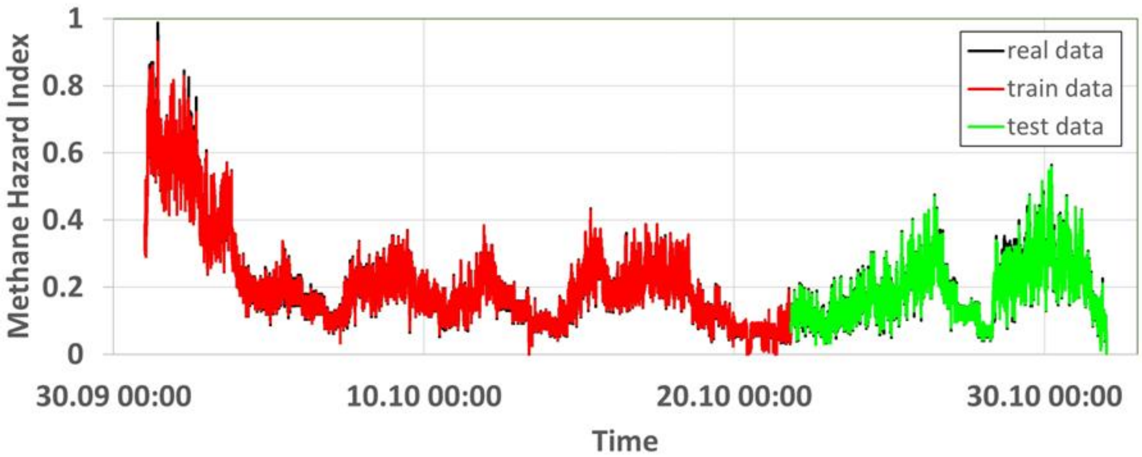


Fig. 14 Time waveforms of the methane hazard index for the period under study.

The actual data reproduce the values recorded in the entire data set, while the training and testing data are the values of MHI determined by the model based on the training and testing sets. It should be noted that the fuzzy model reproduced the values of MHI with high accuracy. When analyzing the data, one area of potential danger from the point of view of methane hazard can be identified. For the dataset for the period under study, values of MHI above 0.8 (high methane hazard) were recorded in the initial phase. The occurrence of such a condition is the basis for the mine services to take measures to reduce the value of MHI. In this case, decisions were made to reduce the speed of the shearer's feed (reduce the mining efficiency), which resulted in a reduction in methane emissions and the value of MHI. Therefore, it was not necessary to interrupt the mining process.

For the presented research, an error analysis was also carried out, determining the differences between expected and actual values. A distribution of these errors was also made for the training and testing data in the form of histograms (Fig. 15). The results show that the error values are clustered around the expected value, *i.e.*, the "zero" value. For the test data set, not many error values deviating significantly from the expected value were obtained. Therefore, it can be concluded that for the analyzed data set, the values of MHI determined by the fuzzy model are close to the values obtained from analytical calculations.

In order to determine the relationship between the recorded ventilation parameters and the determined value of the methane hazard index (MHI), an analysis of its correlation with the measurement data was also carried out. The results are presented in the form of a correlation matrix in Fig. 16. This is a symmetrical matrix, determining the strength of the relationship between the analyzed variables.

Based on the results of this analysis, a summary of the influence of explanatory variables on the value of MHI is presented in Table 4. The greatest influence on the value of this index is exerted by the recorded methane concentrations and airflow velocities for the sensors deployed in the used air current (sensors AS072, MM104). This result confirms the significant influence of these parameters on methane-bearing

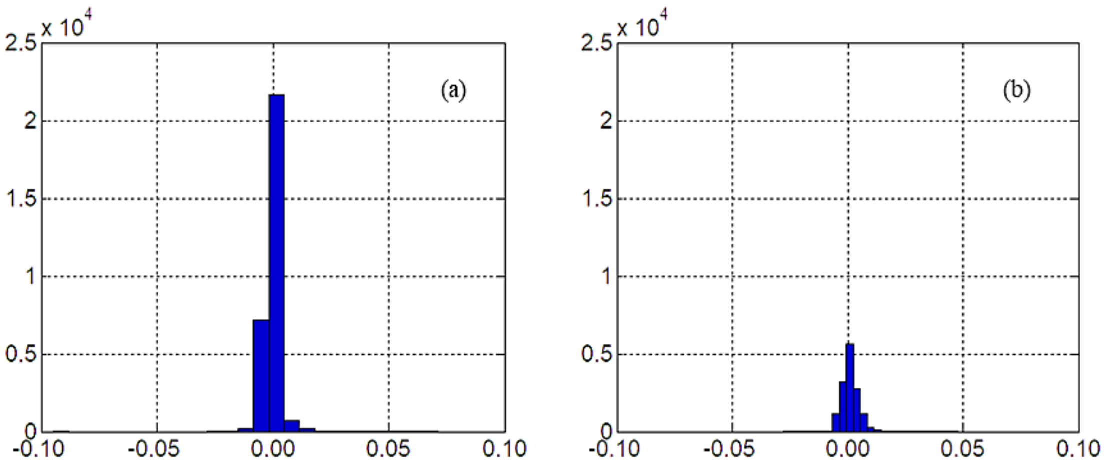


Fig. 15 Error distributions for the values of the methane hazard index (a-the training, b-testing data).

Table 4. Summary of the values of correlation coefficients of studied parameters with the diagnosed variable (MHI).

Sensor/parameter	Correlation	Correlation strength
AS038	0.5078	moderate
AS099	-0.4394	moderate
AS072	0.7291	high
MM137	-0.5781	moderate
MM116	0.5801	moderate
MM104	0.8680	high
WM46	-0.0708	none

capacity in the area of mining operations. The remaining variables are characterized by lower strength of correlation or lack thereof (sensors AS099, MM137).

In the next stage of the study, the results obtained from the model tests were compared with manual measurements of ventilation parameters carried out in the studied area.

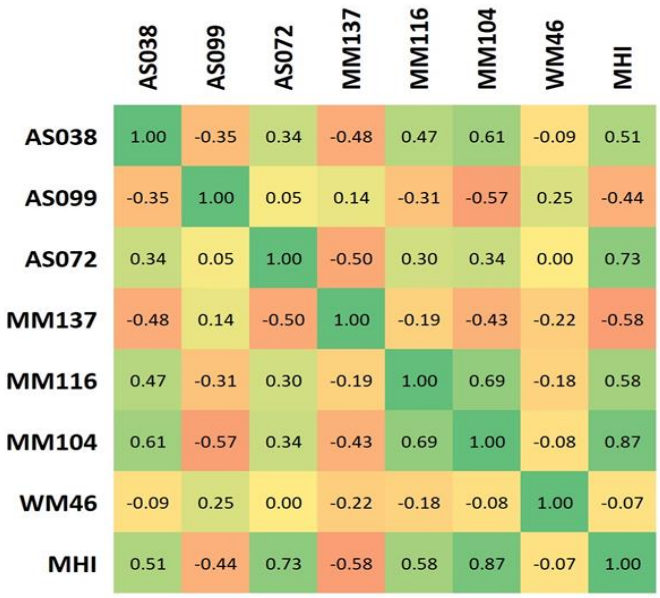


Fig. 16 Results of the correlation study between the measured parameters and the value of MHI.

Manual measurements were carried out once a day. Based on them, the values of the criterial methane-bearing capacity were determined, which were compared with the average values obtained from the data from the automatic gasometry system. The results are presented and compared in Table 5. The compilation does not include days off (weekends), on which no operations were carried out and no manual measurements were taken. At this point, it is worth noting that the method developed and presented in the paper, using the system of automatic gasometry, provides the possibility of continuous diagnosis of the state of methane hazard, even on days off from operation.

Table 5. Summary of the determined average values of the criterial methane-bearing capacity in the studied area and their comparison with the values determined on the basis of manual measurements made by the mine services.

Day	Criterion methane content			
	Based on manual measurements, m^3/min	From the IT system, m^3/min	Δ, m^3/min	Δ, %
01.10	36.69	29.99	-6.70	18.26
02.10	35.07	32.42	-2.65	7.56
03.10	28.33	36.85	8.52	30.07
04.10	46.06	42.40	-3.66	7.95
07.10	39.87	35.92	-3.95	9.91
08.10	37.55	32.59	-4.96	13.21
09.10	43.89	30.41	-13.48	30.71
10.10	47.59	27.96	-19.63	41.25
11.10	36.84	28.40	-8.44	22.91
14.10	42.83	25.74	-17.09	39.90
15.10	36.06	25.76	-10.30	28.56
16.10	40.70	27.04	-13.33	33.56
17.10	27.21	34.40	7.19	26.42
18.10	37.41	42.98	5.57	14.89
21.10	53.95	61.25	7.30	13.53
22.10	54.93	47.60	-7.33	13.34
23.10	51.11	39.12	-11.99	23.46
24.10	21.97	41.67	19.70	89.67
25.10	38.09	37.80	-0.29	0.76
28.10	50.69	42.86	-7.83	15.45
29.10	36.82	29.57	-7.25	19.69
30.10	37.00	29.14	-7.86	21.24
31.10	46.22	28.03	-18.19	39.36
Mean	40.30 ±8.34	35.21 ±8.53	-5.07 ±9.60	24.42 ±17.99

When analyzing the results, differences can be noted. They are mainly due to the variability of methane concentrations and air flow velocity that occur throughout the day. Manual measurements, although made at one hour each day, fail to take into account the changing conditions throughout the day. It is also evident that at the end of the month, where after the increase in the anemometer readings in the consumed air current, the values gradually decrease, which at higher methane concentrations translates into lower values of criterion methane content. Manual measurements did not show this. In addition, these measurements can also be subject to errors (*e.g.*, the measurement on 24.10, where, with stable ventilation conditions, the measurement showed a more than twofold decrease in the value of criterion methane content). Unfortunately, many mines still operate systems based on manual measurements, the results of which, as the analysis presented here shows, can differ significantly from the actual conditions found in the mining areas. On the other hand, a high convergence of the results of the two methods occurs in the case of stable ventilation conditions.

In the next stage, a comparative analysis of the test results was performed with other applied methods of data analysis. The following methods were included in the analysis:

linear regression (Linear) – reference model,
tree regression (Fine Tree),
random forest regression (Bagged Trees),
gradient-boosted tree regression (Boosted Trees).

The performance of all these methods was measured by the error values of the analysis. This analysis was performed by estimating the following errors: mean absolute percentage error of diagnosis (MAPE), root mean square error (RMSE) and relative root mean square error (RRMSE).

The results are shown in Table 6, which includes the values of errors produced in the process of diagnosing the value of the methane hazard index by the fuzzy model for three different ways of splitting the data (Fuzzy c-means clustering, subtractive clustering and grid partition), and by the four methods of data analysis indicated.

The results clearly indicate that for all testing sets, the fuzzy model based on differential clustering achieved the best results. The fuzzy model based on fuzzy c-means clustering also achieved good results – better than the reference model. However, the advantage of this method is the running time of the algorithm, which is much shorter than in the subtractive clustering method. A good result, better than the reference model, was still achieved by a model based on Random Forests, however, worse than fuzzy models based on data partitioning by the fuzzy clustering method. The remaining models obtained results worse than the reference model. By far the worst results were obtained for the model using grid-based data partitioning. The large number of rules generated by this model did not translate into the efficiency of its inference. The values of the obtained errors for this model are at an unacceptable level.

In the last stage of the research, an analysis was performed with regard to the behavior of the developed model in the case of incomplete or erroneous measurement data.

Disturbances in the data recording system can be the result of sensor damage, loss of connectivity or calibration of the measuring device. Therefore, the purpose of this part of the study was to determine what effect these random adverse events would have on the determined value of the MHI. In this regard, all tested methods (four) were analyzed, as well as the built fuzzy model for two variants of measurement data clustering (fuzzy c-means clustering, subtractive clustering). For the analyzed set of measurement data, tests were carried out for seven cases involving the absence of one of the sensors (data from this sensor). The results obtained, in the form of the magnitude of the diagnostic errors for the tested data, are shown in Table 7.

Table 6. Summary of the error values of diagnosing the methane hazard index by the fuzzy model for three different ways of splitting the data and by other methods of data analysis.

Parameter	Fuzzy c-means clustering	Subtractive clustering	Grid partition	Linear regression	Tree regression	Random forest regression	Gradient-boosted tree regression
MAPE	4.8916	1.8890	214.97	12.391	11.908	8.8662	19.274
RMSE	0.0153	0.0050	0.3134	0.0357	0.0502	0.0252	0.0593
RRMSE	42.9	14.0	877.9	100.0	140.6	70.6	166.1

Table 7. Summary of the values of diagnostic errors of the methane hazard index in the absence of one of the sensors for all tested methods.

Missing sensor	Fuzzy c-means clustering		Subtractive clustering		Linear regression		Tree regression		Random forest regression		Gradient-boosted tree regression	
	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE	RMSE	RRMSE
AS038	0.0246	65.6	0.0208	55.5	0.0375	100.0	0.0490	130.7	0.0431	114.9	0.0590	157.3
AS099	0.0195	58.6	0.0127	38.1	0.0333	100.0	0.0517	155.3	0.0272	81.7	0.0593	178.1
AS072	0.0695	93.3	0.0698	93.7	0.0745	100.0	0.0713	95.7	0.0663	89.0	0.0741	99.5
MM137	0.0167	38.5	0.0097	22.4	0.0434	100.0	0.0497	114.5	0.0353	81.3	0.0540	124.4
MM116	0.0142	37.6	0.0088	23.3	0.0378	100.0	0.0493	130.4	0.0234	61.9	0.0606	160.3
MM104	0.0750	83.3	0.0754	83.8	0.0900	100.0	0.1091	121.2	0.0887	98.6	0.0934	103.8
WM46	0.0151	40.5	0.0160	42.9	0.0373	100.0	0.0488	130.8	0.0255	68.4	0.0581	155.8
Mean	0.0335 ±0.0267	59.6 ±22.466	0.0305 ±0.0291	51.4 ±28.094	0.0505 ±0.0223	100.0 ±0.0000	0.0613 ±0.0226	125.5 ±18.233	0.0442 ±0.0246	85.1 ±17.829	0.0655 ±0.0138	139.9 ±30.569

Table 8. Summary of the magnitude of diagnosis errors of the methane hazard index in the case of random outliers or out of range for testing data.

Parameter	Fuzzy c-means clustering	Subtractive clustering	Linear regression	Tree regression	Random forest regression	Gradient-boosted tree regression
RMSE	0.0361	0.0371	0.0899	0.0985	0.0527	0.0875
RRMSE	40.2	41.3	100.0	109.6	58.6	97.3

When analyzing the results, it can be concluded that the best results were obtained for models based on fuzzy clustering of measurement data. This is evidenced by the average error values from the entire test, better than the reference model. Similar conclusions can be drawn from the analysis of individual tests. The fuzzy models showed significantly better accuracy and higher efficiency for most of the cases tested. Only the simulation of the absence of an anemometer and methanometer in the used air current caused problems for these models. The reason for this is the great importance of these measuring devices in the process of estimating the degree of methane hazard. As a whole, models not based on fuzzy clustering, in addition to Random Forest, performed significantly worse than the reference model.

In this part of the study, the developed model and other methods were also tested for erroneous measurement data and out-of-range values, such as during calibration of measurement equipment.

Table 8 presents a summary of the magnitude of diagnostic errors in the value of MHI in the case of random outliers or out-of-range values for test data.

For the tested variant, the best results were recorded for models based on fuzzy clustering of measurement data. Error values for the test set were better than the reference model and other methods. The best results were obtained for the model based on fuzzy c-means clustering. It should also be pointed out that most methods scored better than the reference model in this test.

Thus, analyzing the results obtained, it can be concluded that among the tested methods, the developed methodology and the fuzzy model guarantee by far the most reliable values of MHI.

5. Conclusions

Methane hazard is one of the most troublesome and dangerous hazards occurring in the process of underground mining. Its cause is methane, a flammable and explosive gas, the presence of which is inseparable from the process. The great importance of coal as a raw material for power generation and for the production of coke means that the problem of methane hazard is now faced practically in most coal mines around the world. Events resulting from its ignition and/or explosion cause huge material losses and a threat to the health and lives of workers. Therefore, in order to create favorable conditions for the implementation of the mining process, it is necessary to take measures to reduce the possibility of such dangerous events.

The methodology developed and presented in this paper for assessing the state of methane hazard based on the results of measuring ventilation parameters by the automatic gasometry system and using fuzzy set theories to diagnose this state is a new approach to the study of this issue. This is mainly due to the fact that the theory of fuzzy sets, treated as one of the intelligent methods, is used to assess the state of methane hazard, and further to support the management of occupational safety and production efficiency in the mine.

The developed methodology makes it possible to quickly, effectively and practically continuously determine the value of MHI and, taking into account the adopted criteria, conduct a continuous assessment of the state of methane hazard in the studied area. Continuity and the possibility of diagnosing this state even in periods when the mining process is not carried out is undoubtedly its advantage. The universality of this methodology should also be emphasized. This is because it allows adaptation to different ventilation systems and the number of sensors. The latter possibility is particularly significant. In a mining environment, which in many cases is unpredictable, the inclusion in this type of system of the possibility of failure or disconnection of any of the sensors should be considered a great advantage.

Another positive element of the developed methodology is the reliance on actual results of measuring ventilation parameters in the studied area. In addition to the reliability of the data, the advantage of this approach is that the process of acquiring them is based on existing infrastructure and in most cases does not require additional investment. This creates favorable conditions for broad practical application of the developed methodology.

Thus, referring to the developed methodology (and model), it can be said that its application has enabled the acquisition of new knowledge (including tacit knowledge) in terms of:

acquisition of reliable quantitative data on ventilation parameters, including in particular on methane concentrations in the studied area (their time distributions),

continuous determination of the value of the methane hazard index during the mining process, and through comparison with the adopted criteria for determining the state of methane hazard in the area.

The error analysis of the determined values of the MHI is also important for the reliability of the findings. The results obtained from this analysis indicate the high reliability of the analyses performed, and thus also of the diagnosis made.

The research and its results do not exhaust the possibilities of using intelligent systems to analyze the state of methane hazard during the mining production process. As mentioned earlier, the findings can also be successfully used to forecast the state of methane hazard. In this case, other methods, such as artificial neural networks, can be adopted for analysis.

In the future, an important element of the whole process of diagnosing and possibly forecasting the state of methane hazard is also the wider use of the acquired information to support the process of managing mining operations. In this regard, it is necessary to specifically quantify the impact of these solutions on the safety and efficiency of the mining production process.

It is therefore reasonable to conclude that the developed methodology offers great opportunities for practical application and improvement of the quality of management of these processes.

The solution presented in the article is a novel and previously unused approach to the problem of diagnosing and, further, forecasting methane hazard in underground coal mines. The developed neuro-fuzzy model can be successfully used to forecast the methane hazard in real time and enable the adjustment of methane prophylaxis to the level of this hazard to ensure mining safety.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

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