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THE USE OF FUZZY SYSTEMS IN THE DESIGNING OF MINING PROCESS IN HARD COAL MINES

WYKORZYSTANIE SYSTEMÓW ROZMYTYCH W PROJEKTOWANIU PROCESU WYDOBYWCZEGO W KOPALNIACH WĘGLA KAMIENNEGO

This article presents examples of solutions supporting the design of certain elements of the mining process in coal mines. The focus is on two fuzzy systems: the first supports the selection of equipment for longwall faces (FSES); and the second supports the estimation of production results (FSOE). System FSES generates proposals for equipment in designed longwall faces. The module of fuzzing in this system enables a fuzzing operation for the following quantitative variables: longwall length; longwall height; longitudinal and crosswise incline of the longwall, workability of the coal and thickness of rock vein in a given section of the longwall. The knowledge base includes over 100 fuzzy rules indicating possible options for equipment under specified site conditions.

After a proposal of equipment is generated, it is then possible to insert the values obtained into the second system FSOE, which estimates output for a given shift time using the chosen parameters. The module of fuzzing in system FSOE includes 9 variables, which are crucial in determining shift output for the given longwall face. The knowledge base in this system contains over 2000 rules.

As a result of the operation of both systems, the designer receives both a proposal of equipment for the designed longwall face and the size of shift output under the given conditions.

Operation of the two systems has been presented using a case study.

Keywords: coal mine, mining process, fuzzy logic, fuzzy systems, modelling

Logika rozmyta pozwala na płynne i stosunkowo dokładne opisanie istotnych zależności pomiędzy zmiennymi o charakterze nieprecyzyjnym lub mało dokładnym, które są danymi wejściowymi do procesu projektowania. Prowadzony przez system rozmyty proces wnioskowania na podstawie zapisanych w bazie wiedzy reguł pozwala na uogólnienie posiadanej przez projektantów wiedzy, a także prowadzenie wnioskowania w sposób zbliżony do rozumowania eksperta.

W artykule zaprezentowano przykłady opracowanych rozwiązań wspomagających projektowanie wybranych elementów procesu wydobywczego w kopalniach węgla kamiennego. Przedstawiono dwa systemy rozmyte, pierwszy wspomagający dobór wyposażenia do projektowanych wyrobisk ścianowych (FSES) oraz drugi wspomagający szacowanie wyników produkcyjnych (FSOE).

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System FSES umożliwia wyznaczenie propozycji wyposażenia dla projektowanych wyrobisk ścianowych. Moduł rozmywania w tym systemie umożliwia przeprowadzenie operacji rozmycia następujących zmiennych ilościowych: długość ściany, wysokość ściany, nachylenie podłużne i poprzeczne ściany, urabialność węgla oraz grubość przerostów w przekroju ściany. Baza wiedzy obejmuje ponad 100 reguł rozmytych wskazujących w konkluzjach możliwe do zastosowania wyposażenie, w określonych warunkach wyrobiska.

Po wyznaczeniu proponowanego wyposażenia, możliwe jest wprowadzenie otrzymanych wartości do drugiego systemu FSOE, który umożliwia oszacowanie wydobycia zmianowego dla zadanych parametrów. Moduł rozmywania systemu FSOE obejmuje 9 zmiennych, które konieczne są do wyznaczenia wydobycia zmianowego w projektowanym wyrobisku. Baza wiedzy tego systemu zawiera ponad 2000 reguł.

W efekcie działania obu systemów projektant otrzymuje propozycję wyposażenia dla projektowanego wyrobiska ścianowego oraz oszacowaną wielkość wydobycia zmianowego dla podanych warunków. Wyniki te może wykorzystać w procesie projektowania wybranych elementów procesu wydobywczego (wyrobisk ścianowych) lub weryfikacji przyjętych planów produkcyjnych.

Działanie opracowanych systemów zaprezentowano na wybranym przykładzie wyrobiska ścianowego.

Słowa kluczowe: kopalnia węgla kamiennego, proces wydobywczy, logika rozmyta, systemy rozmyte, modelowanie

Introduction

One of the basic tasks of a coal mine is to assure the required level of production and to protect the supply of raw materials within. This can be done through proper implementation of the mining process. The mining process is a specific kind of production process, which is based on the acquisition of non-renewable deposits (warehouse-transport process).

The specificity of the mining process results from the fact that this process is carried out between nature and man, entailing specific consequences for its operational course. The conditions for conducting mining activities (uncertainty and risk related to the geology of deposits and other natural threats) compel designers to accumulate knowledge such as relevant information and past experience in an effort to improve the accuracy of design decisions.

In the design of mining activities, knowledge plays a specific role in the cutting and selection order of the deposit, the selection of equipment suitable for longwall face conditions, as well as the estimation of longwall face progress. For example, the selection of equipment for longwall face conditions can be done according to basic principles adapted to the producer's technical specifications; but an experienced designer knows that, in a given deposit, the geological and mining conditions can make it impossible to realize the planned amount of output. This knowledge comes from common experiences and specific rules that guide a given designer.

Tacit knowledge can be obtained through the formulation with use of the expert methods (interviews, questionnaires, expert observations), or through advanced techniques of data exploration (with the use of algorithms designed to generate such knowledge). Obtained knowledge concerning the mining process can be stored in knowledge base systems (e.g. expert systems) (Brzychczy, 2011). In order to do this, knowledge must be appropriately represented e.g. as rules.

Rules made by the experts are often characterized by a lack of precision, due to the informal nature of human reasoning and the lack of reliable schemes of inference. In order to save these rules, it is possible to use fuzzy logic in the database, which enables a process of inference even when descriptions of the researched phenomenon are imprecise. Fuzzy logic also makes possible a general description of rules obtained in the process of knowledge discovery from data (Brzychczy, 2012).

Making inferences in a way similar to the way an expert reasons (using the base of fuzzy rules) is made possible by fuzzy systems, the theoretical basis of which is described further in the article.

1. Logic and fuzzy systems

Fuzzy systems are based on the theory of fuzzy logic. Fuzzy logic was developed by Lotfi A. Zadeh in the 1960s (Zadeh, 1965). It is an extension of classical reasoning closer to human reasoning. Fuzzy logic is used in process improvement and in various optimization tasks. One of the first examples of its application was controlling the Sendai metro in Japan. The control system was developed based on the experience of an engineer who, for many years accumulated practical knowledge about controlling the metro system. His observations and proper use of fuzzy logic led to the creation of an automatic control system by Hitachi (Abel, 1991), (Piegat, 1999). The next achievements based on the principles of fuzzy sets or fuzzy numbers led to the fruition of increasingly newer and more developed fuzzy systems.

The basic concept in fuzzy logic is fuzzy set A in X (formula 1). This is a set of pairs such that (Piegat, 1999); (Nowicki, 2009):

$$A = \{(x, \mu_A(x),)x \in X\}\mu_A : X \to [0,1] \tag{1}$$

where μ_A is a function of membership, describing for each $x \in X$ the value of this element's membership $\mu_A : X \to [0,1]$ to the fuzzy set A and $A \subseteq X$

The function of this membership thus assigns to each element x of a variable, a certain value from the range [0,1] and this value is called the degree of membership. In classic sets, the value is assigned as 1 when the element completely belongs to the set or 0 when it does not belong at all. In fuzzy logic theory, the element can belong to the set to a certain degree, meaning the function of membership can take the values from the whole unit bracket [0,1]. We can therefore distinguish three cases:

- $\mu_A(x) = 1$, which means full membership to set A,
- $\mu_A(x) = 0$, which means total lack of membership to set A,
- $0 < \mu_A(x) < 1$, which means partial membership of element x to set A.

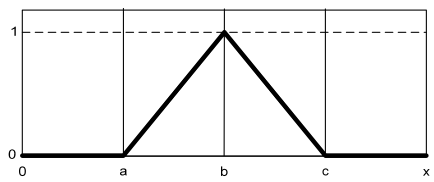
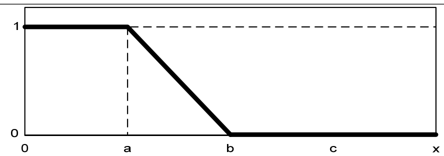
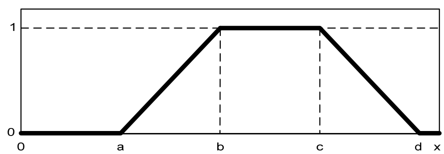
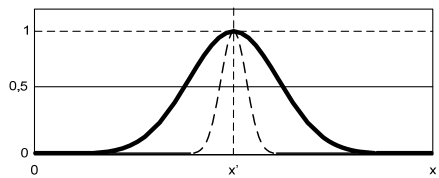
The membership function can be expressed as a continuous or discreet diagram, a formula, table, sum, or a vector of membership. In practice, for the creation of fuzzy systems, functions of membership are used, with different forms. Among the most common forms of the membership functions are: triangle, trapezoid, the letters “L”, “S” and the Gaussian function.

The selected membership functions are shown in Table 1.

Functions of membership described using polygons or segments have many advantages, and a small number of parameters will suffice to define them. They are characterized by ease of parameter modification, on the basis of system input and output measurement values (Piegat, 1999). Describing the membership function using the Gaussian function entails many difficulties. Above all, the Gaussian function is symmetric, which means that the criteria of unifying fuzzy sets are not met. There is also the need to identify two parameters of the function. These factors hinder the acquisition of simple, locally linear surfaces of the fuzzy model. On the other hand, the function as such facilitates theoretical analysis of fuzzy systems, because its derivatives can be set to any level (Piegat, 1999).

TABLE 1

Selected forms of the membership function and their graphic presentation

Type of function	**Sets and membership functions**	**Graphic representation of membership functions**
triangular	$\mu_A(x;a,b,c)=\begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ \frac{c-x}{c-b}, & b < x \le c \\ 0, & x > c \end{cases}$	
”L” shape	$\mu_A(x;a,b)=\begin{cases} 0, & x \le a \\ \frac{b-x}{b-a}, & a < x \le b \\ 1, & x > c \end{cases}$	
trapezoidal	$\mu_A(x;a,b,c,d)=\begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ 1, & b < x \le c \\ \frac{c-x}{c-b}, & c < x \le d \\ 0, & x > d \end{cases}$	
Gaussian function	$\mu_A(x;\mathrm{x}',\sigma)=e^{-\frac{1}{2}\left(\frac{\mathrm{x}-\mathrm{x}'}{\sigma}\right)^2}$	

Source: Original work

Fuzzy systems are models which process information using fuzzy rules.
They are made up of 4 elements (Fig. 1):

1. A fuzzification module, which converts system input, i.e. acute numerical values into fuzzy ones. This is done via the membership function of defined fuzzy sets.
2. A knowledge base which stores the set of rules representing the knowledge about the problem. These rules can come from different sources: from experts appointed on the basis of qualitative modelling; and from algorithms which automatically generate knowledge.
3. A mechanism of inference, which simulates human reasoning through a fuzzy inference process according to the logic stored in the rules.
4. A defuzzification module, which converts a fuzzy set indicated by the inference result into acute values.

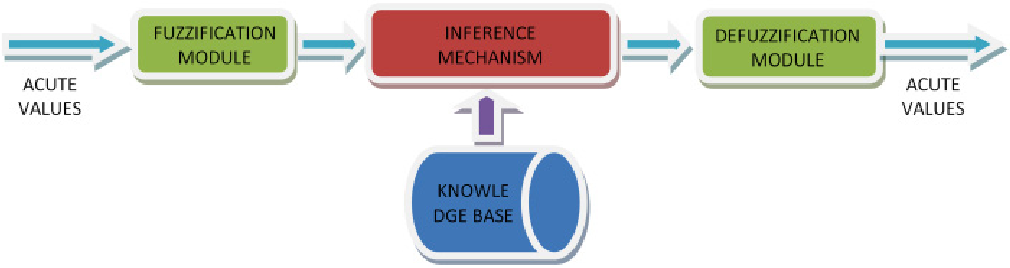


Fig. 1. Fuzzy system scheme
Source: Original work based on (Nowicki, 2009)

System works as follows: after inserting the input data, quantitative variables are converted into linguistic variables; then, inference is done according to the knowledge base, which contains fuzzy rules (representing knowledge about the problem being analysed); and finally, in the defuzzification module, the resulting fuzzy set is converted into numerical values.

The inference mechanism comprises a crucial element of the fuzzy system. It uses the knowledge base, and the rules contained within it. The "rule of inference" can be understood as a method of deriving conclusions from premises. This process can be carried out using the rules: *modus ponendo ponens* (inference through statement); *modus tollendo tollens* (inference through denial); conditional syllogism of the stoics; or the principles of distribution (Łęski, 2008). "If-then" rules can be obtained in the following manner:

- Specification of the premises, and then the conclusion.
- Specification of the conclusions of a rule, and then the selection of its premises.
- Independent determination of premises and conclusions.

Among the basic methods of inference is the Mamdani model. Systems using this model rely on a base of rules and the use of linguistic operators, and inference is done through the aggregation of fuzzy sets resulting from all the rules. Thus, the fuzzy set is the resulting set.

The second group is comprised of systems based on the Takagi-Sugeno-Kanga model. In this model – in contrast to the Mamdani model – the base of rules is fuzzy only in the first part; that is to say, the "if" part. In the second part – the "then" part – functional relationships occur.

Obtaining a result from the fuzzy system is possible through the defuzzification operation. This involves the determination of a qualitative or quantitative value for the output variable, based on knowledge of the nature of the resulting fuzzy set. There are several methods of defuzzification. The most common are (Łęski, 2008; Nowicki, 2009):

- Method of maximum (MD), in which the output value is the maximum value of the argument from the set of argument values of the membership function for the resulting fuzzy set.
- Method of height (HM), where the output value is affected by all the activated premises, and not just those that have the biggest impact on the given fuzzy set for the output variable. In this method, fuzzy sets of the output variable are converted into single-element sets (Singletons).
- Method of gravity centre (COG), in which the output variable is the centre of gravity for the shape created by the output fuzzy set.

Fuzzy systems enable effective modelling of complicated and advanced technological processes. Inference based on fuzzy rules, as well as the possibility of conducting analysis using quantitative and qualitative variables, can also be used in the designing of mining process. Examples of developed solutions in this field are presented later in this article.

2. Designing of mining process

The designing of mining process can be divided into the following stages:
1. Work study.
2. Searching solutions.
3. Evaluation and selection of solutions.
4. Detailed design.
5. Implementation of design solutions.

The basic mode of operations during work study is the accumulation of knowledge concerning the designed task (e.g. market analysis, diagnosis of the formal legal situation, familiarization with input data related to task data, or to geological documentation of the deposit in the case of a mine), specification of requirements and constraints for the formulated design problem, and indication of evaluation criteria for solutions with regard to uncertainty and risk.

In the case of mining process, the main design tasks are:
- Identification of longwall faces taking part in the mining process, as well as the essential surface infrastructure (elements of spatial structure).
- Selection of equipment and the organization of work.
- Specification of time intervals for mining activities.

Next in the modelling stage is the generation of potential design solutions, which are subjected to preliminary selection. The result of this stage is a set of descriptions of possible solutions.

In the next stage is the evaluation of solutions and selection of the best, for which detailed design is subsequently carried out. Then, design documentation is drawn up, which is essential for implementing the chosen design solution.

It should be highlighted that the quality of a design solution depends mainly on the stages of modelling and optimization. The designer can use different methods at different stages, which can significantly influence the design process and its results. Among these methods are algorithmic methods (i.e. systematic search methods, linear and nonlinear programming, dynamic programming, network programming, methods of mathematical statistics, the Monte Carlo method) and heuristic methods, including: greedy algorithms; simulated annealing; evolutionary algorithms; swarm algorithms; artificial immune systems; artificial neural networks and elements of fuzzy logic.

More and more frequently, fuzzy logic finds use in the modelling of complex manufacturing systems. Its use in issues related to the process of mining, as well as in underground and surface mines, has been described *inter alia* in (Benović et al., 2013; Vujic et al., 2011; Bazzazi et al., 2009; Grychowski, 2008; Bascetin & Kesimal, 1999; Nguyen, 1985; Hosseini et al., 2012; Dezyani et al., 2006; Li, 2009; Razani et al., 2013; Karadogan et al., 2008).

This article focuses on the possibilities of using fuzzy logic in the design of mining process in an underground coal mine, with reference to selected elements of its spatial and technical structure.

3. Proposition of fuzzy systems supporting the design of selected elements in the mining process

The selection of technical and technological equipment, as well as the organization of mining works to the geological and mining conditions, fundamentally affect the economic and production results of mines (Snopkowski & Sukiennik, 2012, 2013).

Longwall faces are a main source of production (output) in an underground coal mine. Under Polish conditions, they are conducted using longwall systems (Snopkowski & Napieraj, 2012).

Introduced later in this article solutions are developed for equipment selection and the organization of mining activity in longwall faces. These solutions enable determination of production results in designed longwall faces – fuzzy systems *FSES* and *FSOE*.

3.1. Fuzzy system supporting equipment selection for designed longwall faces – *FSES* (Fuzzy System for Equipment Selection)

The selection of equipment for a designed longwall face involves specifying the machines and other equipment in longwall complex, which includes: a longwall coal-cutting machine (shearer); conveyor machinery; and sections of mechanized longwall support.

The basic factors affecting the selection of shearer according to conducted surveys (Brzychczy & Kęsek, 2007; Brzychczy & Napieraj, 2014) are: thickness of the deposit in the exploited area; thickness of rock vein in a given longwall section; crosswise inclination of the longwall; longitudinal inclination of the longwall; workability of the coal; category of methane hazard and longwall height. When choosing conveyor equipment, the following are taken into account: crosswise inclination of the longwall; longitudinal inclination of the longwall; length of the longwall and the type of shearing equipment being used. Selection of a mechanized longwall support is influenced by: thickness of the deposit; spoil in the roof; crosswise inclination of the longwall; floor class, ceiling class; level of rock burst hazard; longwall height and the method of roof protection.

In the *FSES* system, a part of the abovementioned parameters affecting the selection of longwall face equipment (quantitative variables), was expressed using fuzzy sets. These sets, along with specific membership functions (included in the *FSES* fuzzy system model) are shown in table 2.

In order to obtain a fuzzy rules knowledge base, data concerning the operating conditions of 250 longwall faces (and their equipment) from two multi-mine mining companies were used. Fuzzy rules were determined according to the algorithm described in (Wang & Mendel, 1992). In arranging machines and other equipment, an algorithm of association rules was used (Brzychczy, 2009).

A fragment of the base of determined fuzzy rules for the *FSES* system (consisting of over 100 rules) is shown in table 3. Due to the multitude of different types of mechanized longwall supports, the minimal limits of the operation range for these devices were declared for each fuzzy set describing the "longwall height" variable.

Table 4 shows different combination rules for shearing equipment and conveyor machinery.

TABLE 2

Functions of membership for select parameters in the FSES system

<table>
<tr><th>Variable</th><th>Sets and membership functions</th><th>Graphic representation of membership functions in fuzzy sets</th></tr>
<tr><td>Longwall length, l [m]</td><td>

$$\mu_{(short)}(l)=\begin{cases}1 & \text{for} \quad l\le 150\\ \dfrac{175-l}{25} & \text{for} \quad 150<l\le 175\\ 0 & \text{for} \quad l>175\end{cases}$$

$$\mu_{(medium)}(l)=\begin{cases}0 & \text{for} \quad l\le 150\\ \dfrac{l-150}{25} & \text{for} \quad 150<l\le 175\\ 1 & \text{for} \quad 175<l\le 250\\ \dfrac{275-l}{25} & \text{for} \quad 250<l\le 275\\ 0 & \text{for} \quad l>275\end{cases}$$

$$\mu_{(long)}(l)=\begin{cases}0 & \text{for} \quad l\le 275\\ \dfrac{l-250}{25} & \text{for} \quad 250<l\le 275\\ 1 & \text{for} \quad l>275\end{cases}$$

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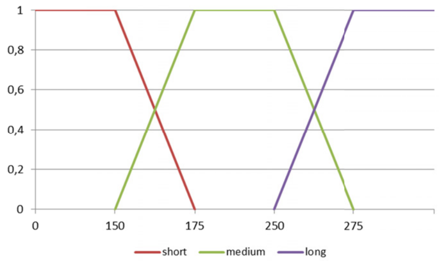

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<tr><td>Longwall height, h [m]</td><td>

$$\mu_{(low)}(h)=\begin{cases}1 & \text{for} \quad h<1\\ \dfrac{2-h}{1} & \text{for} \quad 1<h\le 2\\ 0 & \text{for} \quad h>2\end{cases}$$

$$\mu_{(medium)}(h)=\begin{cases}0 & \text{for} \quad h<1\\ \dfrac{h-1}{1} & \text{for} \quad 1<h\le 2\\ 1 & \text{for} \quad 2<h\le 3\\ \dfrac{4-h}{1} & \text{for} \quad 3<h\le 4\\ 0 & \text{for} \quad h>4\end{cases}$$

$$\mu_{(high)}(h)=\begin{cases}0 & \text{for} \quad h<3\\ \dfrac{h-3}{1} & \text{for} \quad 3<h\le 4\\ 1 & \text{for} \quad h>4\end{cases}$$

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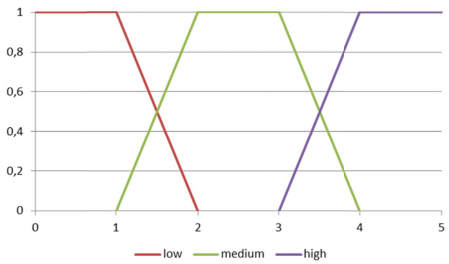

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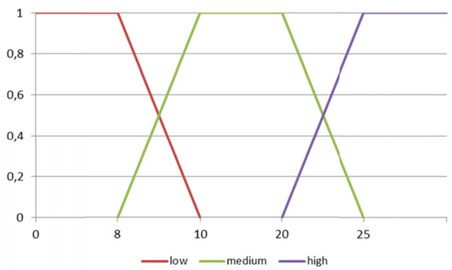
<tr><td>Longitudinal inclination of the longwall, c [°]</td><td>

$$\mu_{(low)}(c)=\begin{cases}1 & \text{for} \quad c\le 8\\ \dfrac{10-c}{2} & \text{for} \quad 8<c\le 10\\ 0 & \text{for} \quad c>10\end{cases}$$

$$\mu_{(medium)}(c)=\begin{cases}0 & \text{for} \quad c\le 8\\ \dfrac{c-8}{2} & \text{for} \quad 8<c\le 10\\ 1 & \text{for} \quad 10<c\le 20\\ \dfrac{25-c}{5} & \text{for} \quad 20<c\le 25\\ 0 & \text{for} \quad c>25\end{cases}$$

$$\mu_{(high)}(c)=\begin{cases}0 & \text{for} \quad c\le 20\\ \dfrac{c-20}{5} & \text{for} \quad 20<c\le 25\\ 1 & \text{for} \quad c>25\end{cases}$$

</td><td>



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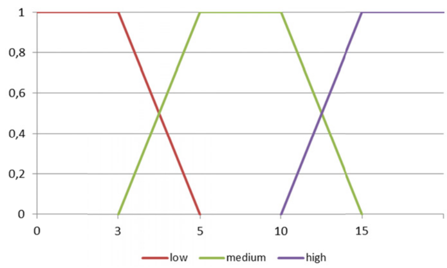
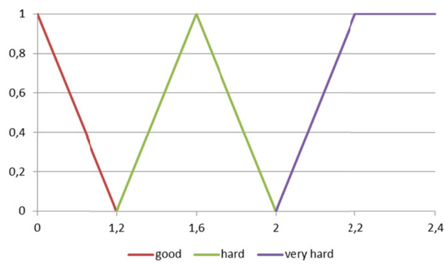
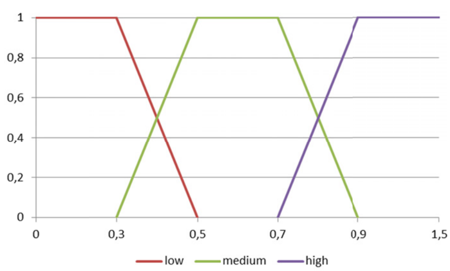
</table>

TABLE 2. CONTINUED

Crosswise inclination of the longwall, ***p*** [°]	$\mu_{(low)}(p)=\begin{cases}1 & \text{for} \quad p\le 3\\ \dfrac{5-p}{2} & \text{for} \quad 3<p\le 5\\ 0 & \text{for} \quad p>5\end{cases}$ $\mu_{(medium)}(p)=\begin{cases}0 & \text{for} \quad p\le 3\\ \dfrac{p-3}{2} & \text{for} \quad 3<p\le 5\\ 1 & \text{for} \quad 5<p\le 10\\ \dfrac{15-p}{5} & \text{for} \quad 10<p\le 15\\ 0 & \text{for} \quad p>15\end{cases}$ $\mu_{(high)}(p)=\begin{cases}0 & \text{for} \quad p\le 10\\ \dfrac{p-10}{5} & \text{for} \quad 10<p\le 15\\ 5 & \text{for} \quad p>15\end{cases}$	
Coal workability (coefficient ***f***)	$\mu_{(good)}(f)=\begin{cases}1 & \text{for} \quad f\le 0\\ \dfrac{1,2-f}{1,2} & \text{for} \quad f\le 1,2\\ 0 & \text{for} \quad f>1,2\end{cases}$ $\mu_{(hard)}(f)=\begin{cases}0 & \text{for} \quad f\le 1,2\\ \dfrac{f-1,2}{0,4} & \text{for} \quad 1,2<f\le 1,6\\ \dfrac{1,6-f}{0,4} & \text{for} \quad 1,6<f\le 2\\ 0 & \text{for} \quad f>2\end{cases}$ $\mu_{(very\,hard)}(f)=\begin{cases}0 & \text{for} \quad f\le 2\\ \dfrac{f-2}{0,2} & \text{for} \quad 2<f\le 2,2\\ 1 & \text{for} \quad f>2,2\end{cases}$	
Thickness of rock vein in a given longwall section, **g** [m]	$\mu_{(low)}(g)=\begin{cases}1 & \text{for} \quad g\le 0,3\\ \dfrac{0,5-g}{0,2} & \text{for} \quad 0,3<g\le 0,5\\ 0 & \text{for} \quad g>0,5\end{cases}$ $\mu_{(medium)}(g)=\begin{cases}0 & \text{for} \quad g\le 0,3\\ \dfrac{g-0,3}{0,2} & \text{for} \quad 0,3<g\le 0,5\\ 1 & \text{for} \quad 0,5<g\le 0,7\\ \dfrac{0,9-g}{0,2} & \text{for} \quad 0,7<g\le 0,9\\ 0 & \text{for} \quad g>0,9\end{cases}$ $\mu_{(high)}(g)=\begin{cases}0 & \text{for} \quad g\le 0,7\\ \dfrac{g-0,7}{0,2} & \text{for} \quad 0,7<g\le 0,9\\ 1 & \text{for} \quad g>0,9\end{cases}$	

Source: Original work

TABLE 3

Fragment of the fuzzy rule base for the FSES system

Rule no.	Premises IF … and ... and …										Conclusions	
	l =	*h* =	*p* =	*c* =	*f* =	*g* =	Floor class =	Ceiling class =	Category of methane hazard.=	Category of rock bust hazard. =	THEN min/max support system range =	THEN shearer type =
1	medium	high	high	low	very hard	low	II	I	II	I	According to type / above 3,5 m	KGE 750
2	long	high	low	low	good	low	III	V	IV	III	According to type / above 3,5 m	Eickhoff SL300
3	medium	high	low	low	good	low	II	III	0	I	According to type / above 3,5 m	KSW 2000E
4	medium	medium	low	low	hard	low	I	I	0	0	1,5m to 3,5m	KGS 600
5	medium	high	low	medium	hard	medium	III	III	III	I	According to type / above 3,5 m	JOY 4L
6	medium	high	medium	low	good	low	I	III	I	0	According to type / above 3,5 m	KSW 620EZ
7	long	medium	medium	low	very hard	low	II	III	0	III	1,5m to 3,5m	KSW 1140E
8	medium	medium	medium	medium	hard	medium	III	III	III	I	1,5m to 3,5m	Electra 1000
9	medium	medium	low	low	good	medium	I	III	0	0	1,5m to 3,5m	KSW 880EU
10	short	medium	low	low	good	medium	VI	IV	IV	0	1,5m to 3,5m	KSW 460N
11	medium	low	medium	low	good	low	II	IV	IV	0	According to type / to 1,5 m	Strug GH 1600
12	short	medium	medium	low	hard	low	III	I	0	0	1,5m to 3,5m	KGE 710FM
13	medium	medium	low	medium	good	medium	I	I	IV	0	1,5m to 3,5m	KSW 475
14	medium	high	low	low	very hard	medium	II	III	0	I	According to type / above 3,5 m	JOY 7LS6

Source: Original work

TABLE 4

Rules of combination for shearing equipment and conveyor machinery

Rule no.	Premise IF shearer =	==>	Conclusion THEN conveyor =	Confidence (%)
1	Eickhoff SL300	==>	RYBNIK 850	36,3636
2	Electra 1000	==>	RYBNIK 850	100,0000
3	JOY 4L	==>	RYBNIK 850	56,2500
4	JOY 7LS6	==>	RYBNIK 1100	100,0000
5	KGE 710FM	==>	RYBNIK 850	60,0000
6	KGE 750	==>	RYBNIK 850	81,2500
7	KGS 600	==>	RYBNIK 750	43,7500
8	KSW 1140E	==>	RYBNIK 850	66,6667
9	KSW 2000E	==>	RYBNIK 1100	100,0000
10	KSW 460N	==>	RYBNIK 750	41,0256
11	KSW 475	==>	RYBNIK 850	64,7059
12	KSW 620EZ	==>	RYBNIK 850	100,0000
13	KSW 880EU	==>	RYBNIK 850	46,6667
14	Strug GH 1600	==>	PF 4/1032	100,0000

Source: Original work

For each type of shearer, rules with the highest confidence coefficient were chosen (CC). This coefficient shows the relationship between the number of shearer combinations *K* with a given conveyor device *P*, and the number of occurring shearers *K*, which can be shown with the formula:

$$CC = \frac{P(K \cup P)}{K} \cdot 100\% \tag{2}$$

where: P – is the number of occurrences of given elements of a longwall complex.

A diagram of the developed system (FSES) is shown in figure 2.

Inference in the system is done in two stages. After the insertion of data and the fuzzification, inference based on fuzzy rules stored in the system knowledge base is conducted. Then are shown the minimal intervals for the operation range of the mechanized longwall support and for active rules, the defuzzification is conducted using the max method (MD). The result is a proposition of longwall shearer which is suitable for use under the given conditions. The next stage of inference uses association rules for the pairing of shearers and conveyors for a given element of the longwall complex.

After determining the proposition for the given longwall complex, it is possible to specify the duration and output for each production cycle according to fuzzy system FSOE, which is described later in this article.

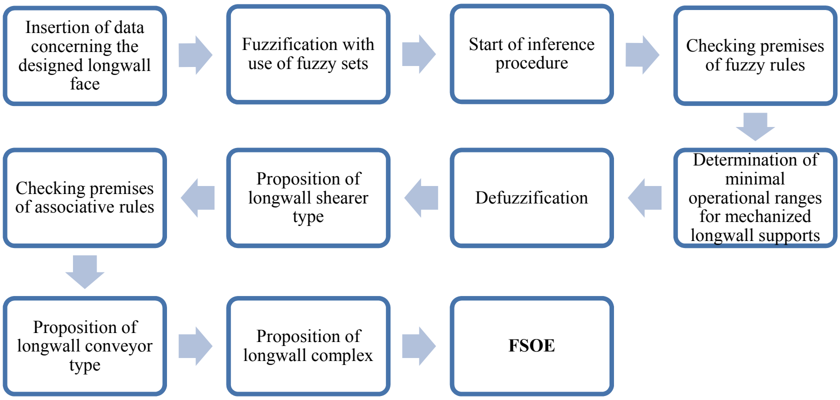


Fig. 2. Operational scheme of FSES system
Source: original work

3.2. Fuzzy system FSOE (Fuzzy System for Output Estimation) for supporting estimation of production results

The production process realized in longwall faces of coal mines is characterized by the fact that its operation is influenced by many factors. These factors are related to geological, technical, organizational and mining conditions.

Fuzzy system *FSOE* is a continuation of system *FSES* and enable to estimate the duration of the production cycle and the level of shift output in coal mines. The results can be used when making decisions concerning the design and management of the mining process.

System *FSOE* makes inferences according to the scheme shown in figure 3. First, based on inserted input data, a fuzzy set is determined for the duration of the production cycle; which in turn, then becomes an input parameter for the magnitude of shift output.

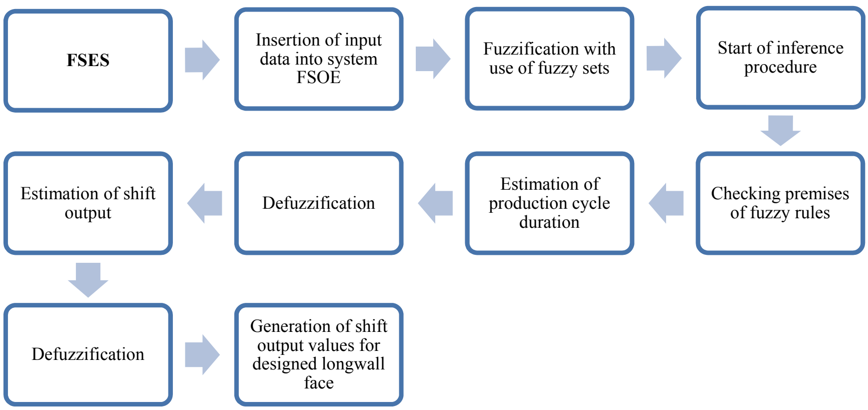


Fig. 3. Operation scheme for fuzzy system FSOE
Source: Original work

The duration of a production cycle is the sum of the individual elements realization times (Snopkowski & Napieraj 2012) e.g. cleaning with use of the shearer within a section ($x_p - d_k$), cutting with use of the shearer within a section ($L - x_p$), slotting with use of the shearer within a section ($x_o + d_k + p + s$), cutting with use of shearer within a section equal to ($x_o + d_k + p + s$), turning station replacement, and driving unit replacement. It can be expressed by the formula:

$$T_c = \frac{1}{V_{cz}}(x_p - d_k) + \frac{1}{V_r} \cdot (L - x_p) + \left(\frac{1}{V_z} + \frac{1}{V_r}\right) \cdot (x_o + d_k + p + s) + t_z + t_n \tag{3}$$

where:

- T_c — production cycle duration [min],
- L — longwall length [m],
- V_r — shearer operational advance rate [m/min],
- V_z — advance rate of the slotting shearer [m/min],
- V_m — shearer maneuver advance rate (shearer advance rate during cleaning the shearer route) [m/min],
- x_p — distance between shearer stoppage place and longwall-roadway crossing [m],
- d_k — shearer length [m],
- x_o — distance between shifted conveyor and support[m],
- p — minimal distance between shifted conveyor and shearer [m],
- s — distance between support and shearer [m],
- t_z — turning station replacement time [min],
- t_n — turning drive unit replacement time [min].

A part of these parameters is shown as fuzzy sets which, along with their functions of membership, are shown in table 5.

TABLE 5

Fuzzy sets and functions of membership for parameters inserted into the FSOE system

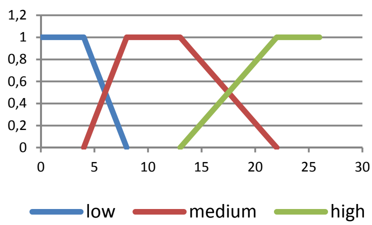
Parameter	**Sets and membership functions**	**Graphic representation of membership functions in fuzzy sets**
V_m – shearer maneuver advance rate, [m/min]	$\mu_{(low)}(V_m) = \begin{cases} 1 & \text{for} \quad V_m \le 4 \\ \frac{8 - V_m}{4} & \text{for} \quad 4 < V_m \le 8 \\ 0 & \text{for} \quad V_m > 8 \end{cases}$ $\mu_{(medium)}(V_m) = \begin{cases} 0 & \text{for} \quad V_m \le 4 \\ \frac{V_m - 4}{4} & \text{for} \quad 4 < V_m \le 8 \\ 1 & \text{for} \quad 8 < V_m \le 13 \\ \frac{22 - V_m}{9} & \text{for} \quad 13 < V_m \le 22 \\ 0 & \text{for} \quad V_m > 22 \end{cases}$ $\mu_{(high)}(V_m) = \begin{cases} 0 & \text{for} \quad V_m \le 13 \\ \frac{V_m - 13}{9} & \text{for} \quad 13 < V_m \le 22 \\ 1 & \text{for} \quad V_m > 22 \end{cases}$	

TABLE 5. CONTINUED

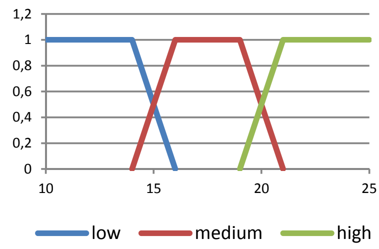
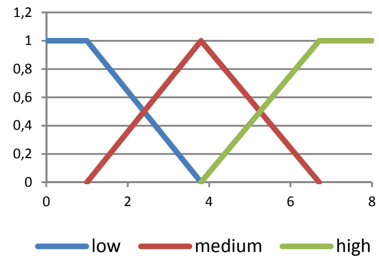
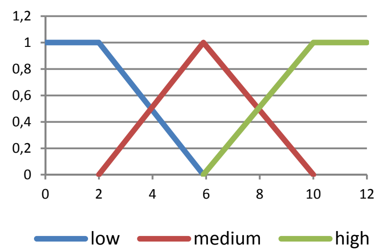
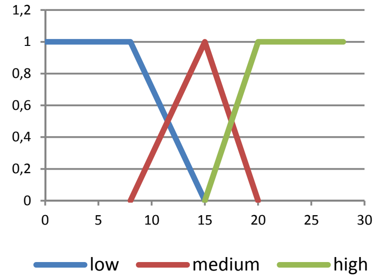
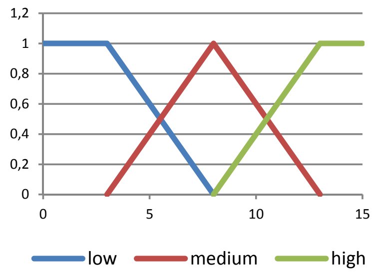
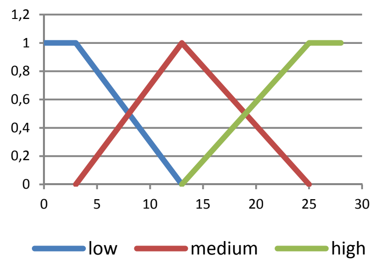
x_p – distance between shearer stoppage place and longwall-roadway crossing, [m]	$\mu_{(low)}(x_p)=\begin{cases}1 & \text{for} \quad x_p \le 14 \\ \frac{16-x_p}{2} & \text{for} \quad 14 < x_p \le 16 \\ 0 & \text{for} \quad x_p > 16\end{cases}$ $\mu_{(medium)}(x_p)=\begin{cases}0 & \text{for} \quad x_p \le 14 \\ \frac{x_p-14}{2} & \text{for} \quad 14 < x_p \le 16 \\ 1 & \text{for} \quad 16 < x_p \le 19 \\ \frac{21-x_p}{2} & \text{for} \quad 19 < x_p \le 21 \\ 0 & \text{for} \quad x_p > 21\end{cases}$ $\mu_{(high)}(x_p)=\begin{cases}0 & \text{for} \quad x_p \le 19 \\ \frac{x_p-19}{2} & \text{for} \quad 19 < x_p \le 21 \\ 1 & \text{for} \quad x_p > 21\end{cases}$	
V_r – shearer operational advance rate [m/min]	$\mu_{(low)}(V_r)=\begin{cases}1 & \text{for} \quad V_r \le 1 \\ \frac{3,8-V_r}{2,8} & \text{for} \quad 1 < V_r \le 3,8 \\ 0 & \text{for} \quad V_r > 3,8\end{cases}$ $\mu_{(medium)}(V_r)=\begin{cases}0 & \text{for} \quad V_r \le 1 \\ \frac{V_r-1}{2,8} & \text{for} \quad 1 < V_r \le 3,8 \\ \frac{6,7-V_r}{2,9} & \text{for} \quad 3,8 < V_r \le 6,7 \\ 0 & \text{for} \quad V_r > 6,7\end{cases}$ $\mu_{(high)}(V_r)=\begin{cases}0 & \text{for} \quad V_r \le 3,8 \\ \frac{V_r-3,8}{2,9} & \text{for} \quad 3,8 < V_r \le 6,7 \\ 1 & \text{for} \quad V_r > 6,7\end{cases}$	
V_z – advance rate of the slotting shearer [m/min]	$\mu_{(low)}(V_z)=\begin{cases}1 & \text{for} \quad V_z \le 2 \\ \frac{5,9-V_z}{3,9} & \text{for} \quad 2 < V_z \le 5,9 \\ 0 & \text{for} \quad V_z > 5,9\end{cases}$ $\mu_{(medium)}(V_z)=\begin{cases}0 & \text{for} \quad V_z \le 2 \\ \frac{V_z-2}{3,9} & \text{for} \quad 2 < V_z \le 5,9 \\ \frac{10-V_z}{4,1} & \text{for} \quad 5,9 < V_z \le 10 \\ 0 & \text{for} \quad V_z > 10\end{cases}$ $\mu_{(high)}(V_z)=\begin{cases}0 & \text{for} \quad V_z \le 5,9 \\ \frac{V_z-5,9}{4,1} & \text{for} \quad 5,9 < V_z \le 10 \\ 1 & \text{for} \quad V_z > 10\end{cases}$	

TABLE 5. CONTINUED

s – distance between support and shearer [m]	$\mu_{(low)}(s)=\begin{cases}1 & \text{for} \quad s\le 8\\ \dfrac{15-s}{7} & \text{for} \quad 8<s\le 15\\ 0 & \text{for} \quad s>15\end{cases}$ $\mu_{(medium)}(s)=\begin{cases}0 & \text{for} \quad s\le 8\\ \dfrac{s-8}{7} & \text{for} \quad 8<s\le 15\\ \dfrac{20-s}{5} & \text{for} \quad 15<s\le 20\\ 0 & \text{for} \quad s>20\end{cases}$ $\mu_{(high)}(s)=\begin{cases}0 & \text{for} \quad s\le 15\\ \dfrac{s-15}{5} & \text{for} \quad 15<s\le 20\\ 1 & \text{for} \quad s>20\end{cases}$	
t_z – turning station replacement time [min]	$\mu_{(low)}(t_z)=\begin{cases}1 & \text{for} \quad t_z\le 3\\ \dfrac{8-t_z}{5} & \text{for} \quad 3<t_z\le 8\\ 0 & \text{for} \quad t_z>8\end{cases}$ $\mu_{(medium)}(t_z)=\begin{cases}0 & \text{for} \quad t_z\le 3\\ \dfrac{t_z-3}{5} & \text{for} \quad 3<t_z\le 8\\ \dfrac{13-t_z}{5} & \text{for} \quad 8<t_z\le 13\\ 0 & \text{for} \quad t_z>13\end{cases}$ $\mu_{(high)}(t_z)=\begin{cases}0 & \text{for} \quad t_z\le 8\\ \dfrac{t_z-8}{5} & \text{for} \quad 8<t_z\le 13\\ 1 & \text{for} \quad t_z>13\end{cases}$	
t_n – turning drive unit replacement time [min]	$\mu_{(low)}(t_n)=\begin{cases}1 & \text{for} \quad t_n\le 3\\ \dfrac{13-t_n}{10} & \text{for} \quad 3<t_n\le 13\\ 0 & \text{for} \quad t_n>13\end{cases}$ $\mu_{(medium)}(t_n)=\begin{cases}0 & \text{for} \quad t_n\le 3\\ \dfrac{t_n-3}{10} & \text{for} \quad 3<t_n\le 13\\ \dfrac{25-t_n}{12} & \text{for} \quad 13<t_n\le 25\\ 0 & \text{for} \quad t_n>25\end{cases}$ $\mu_{(high)}(t_n)=\begin{cases}0 & \text{for} \quad t_n\le 13\\ \dfrac{t_n-13}{12} & \text{for} \quad 13<t_n\le 25\\ 1 & \text{for} \quad t_n>25\end{cases}$	

Source: Original work

Table 6 shows selected rules used in the system inference process at this stage of work. These rules were determined on the basis of timing research conducted in longwall faces of Polish coal mines. The knowledge base contains over 2000 rules.

TABLE 6

Combinations of selected FSOE system rules for estimation of production cycle duration

Rule no.	**Premise IF … and ... and …**								==>	**Conclusion THEN**
	V_m =	x_p =	V_r =	V_z =	s =	t_z =	t_n =	l =		T_c =
1	medium	medium	high	medium	low	low	low	short	==>	low
2	low	medium	high	medium	high	low	low	short	==>	low
3	low	high	high	high	low	low	low	short	==>	low
4	medium	low	high	low	medium	medium	high	short	==>	medium
5	medium	medium	low	medium	low	medium	medium	medium	==>	medium
6	high	high	high	high	high	high	high	long	==>	medium
7	high	medium	low	low	high	medium	high	long	==>	high
8	medium	low	low	low	low	low	high	long	==>	high
9	low	low	low	low	high	high	high	long	==>	high

Source: Original work

The level of shift output from a longwall face depends not only on the duration of the production cycle, but also on: longwall height; shearer web; disposable shift time. The relationship is described by the following equation:

$$W_{zm} = \frac{T_d \cdot h \cdot z \cdot \gamma \cdot l}{T_c} \tag{4}$$

where:

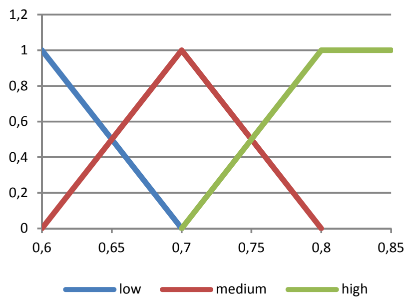
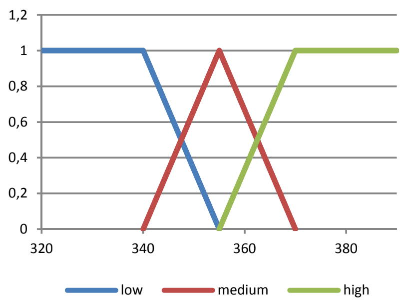
T_d — disposable shift time [min/zm],
T_c — duration of the production cycle [min],
h — longwall hight [m],
z — shearer web [m],
l — longwall length [m],
γ — coal specific weight [Mg/m^3].

Table 7 summarizes the membership functions for these parameters, which are also included in the fuzzing module of the *FSOE* system.

Table 8 shows selected rules used in the second stage of FSOE system inference.

TABLE 7

Fuzzy sets and membership functions of the abovementioned parameters for the FSOE system – c.d.

Parameter	Sets and membership functions	Graphic representation of membership functions in fuzzy sets
z – shearing web [m]	$\mu_{(low)}(z) = \begin{cases} 1 & \text{for} \quad z \le 0,6 \\ \frac{0,75 - z}{0,05} & \text{for} \quad 0,6 < z \le 0,7 \\ 0 & \text{for} \quad z > 0,8 \end{cases}$ $\mu_{(medium)}(z) = \begin{cases} 0 & \text{for} \quad z \le 0,6 \\ \frac{z - 0,7}{0,05} & \text{for} \quad 0,6 < z \le 0,7 \\ \frac{0,8 - z}{0,05} & \text{for} \quad 0,75 < z \le 0,8 \\ 0 & \text{for} \quad z > 0,8 \end{cases}$ $\mu_{(high)}(z) = \begin{cases} 0 & \text{for} \quad z \le 0,75 \\ \frac{z - 0,75}{0,05} & \text{for} \quad 0,75 < z \le 0,8 \\ 1 & \text{for} \quad z > 0,8 \end{cases}$	
T_d – disposable shift time [m/zm]	$\mu_{(low)}(T_d) = \begin{cases} 1 & \text{for} \quad T_d \le 340 \\ \frac{355 - T_d}{15} & \text{for} \quad 340 < T_d \le 355 \\ 0 & \text{for} \quad T_d > 355 \end{cases}$ $\mu_{(medium)}(T_d) = \begin{cases} 0 & \text{for} \quad T_d \le 340 \\ \frac{T_d - 340}{15} & \text{for} \quad 340 < T_d \le 355 \\ \frac{370 - T_d}{15} & \text{for} \quad 355 < T_d \le 370 \\ 0 & \text{for} \quad T_d > 370 \end{cases}$ $\mu_{(high)}(T_d) = \begin{cases} 0 & \text{for} \quad T_d \le 355 \\ \frac{T_d - 355}{15} & \text{for} \quad 355 < T_d \le 370 \\ 1 & \text{for} \quad T_d > 370 \end{cases}$	

Source: Original work

TABLE 8

Combination of selected FSOE inference rule used to determine shift output

Rule no.	Premise IF … and … and …					==>	Conclusion THEN
	$T_c =$	$h =$	$z =$	$T_d =$	$l =$		$W_{zm} =$
1	high	low	low	low	short	==>	low
2	medium	low	low	low	short	==>	low
3	high	low	medium	low	short	==>	low
4	low	low	medium	high	long	==>	medium
5	medium	medium	high	high	medium	==>	medium

TABLE 8. CONTINUED

6	high	high	medium	high	long	==>	medium
7	low	high	high	high	long	==>	high
8	medium	high	high	high	long	==>	high
9	low	high	medium	high	long	>	high

Source: Original work

Operation of fuzzy systems is presented with use of a case study in chapter 3.3.

3.3. Case study

The designed longwall face is characterized by the parameters presented in Table 9.

TABLE 9

Longwall face parameters

Longwall length = 220 m	**Longwall height = 4,2 m**
• Transverse inclination = 1,5°	• Longitudinal inclination 3,2°
• Floor class = II	• Roof class = III
• Coefficient f = 1,1	• Thickness of rock vein in coal seam = 0,2 m
• Category of methane hazard = lack	• Level of rock burst threat = I

Source: Original work

The above data were inserted into fuzzy system FSES which, on the grounds of the rule base and the inference process conducted (table 3 rule 3), proposed shearer type *KSW 2000E*, as well as requirements regarding the range of longwall support system (*according to type/above 3,5 m*). In addition, on the basis of the rules for combining machines with other equipment (table 4 rule 9), it proposed the last element of the longwall complex – conveyor *Rybnik 1100*. The obtained data were then inserted into *FSOE* system to estimate the shift output in the designed longwall face. The input parameters were supplemented by the following data:

- d_k – shearer length, d_k = 10 [m],
- x_o – distance between shearer stoppage place and longwall-roadway crossing, x_o = 3,2 [m],
- p – minimal distance between shifted conveyor and shearer, p = 5,25 [m],
- γ – coal specific weight, γ = 1,35 [g/m^3].

As a result of the inference process, a fuzzy set was generated for the duration of the production cycle (table 6 rule 5), which was then defuzzied by the geometric method of gravity center (COG), thus yielding the numerical value T_c = 91,22 [min]. This value was then used to estimate shift output (activating rule 5 table 8). Likewise, in this case the end results were determined using by the COG method.

In the analysed case for the given parameters of the designed longwall face and selected equipment, the shift output determined by system *FSOE* amounted to 3664 [Mg/zm].

4. Summary

The mining process is a process of production affecting the economic state of countries in possession of mineable natural resources. Its design includes distinguished structures; and in terms of space, technology and time, it should take into account the knowledge accumulated by mines and mining enterprises in order to improve the quality of design decisions. The storage and use of this knowledge is enabled by systems with a knowledge base, which also include elements of fuzzy logic (creating i.e. fuzzy systems).

This work has introduced fuzzy systems, which can be applied when designing elements of the mining process. The first of them is system *FSES*, which facilitates the selection of equipment according to the conditions of longwall faces. The fuzzification module in this system makes possible a fuzzy operation for the following quantitative variables: longwall length; longwall height; longitudinal and cross-wise incline of the longwall; workability of coal and the thickness of rock vein in a given longwall section. The knowledge base includes over 100 fuzzy rules for determining equipment suitable for use under the specified conditions of an longwall face. After determination of the proposed equipment, it is then possible to insert the values obtained into the second system *FSOE*, which enables estimation of shift output according to the selected parameters. The fuzzification module in system *FSOE* includes 9 linguistic variables, which are necessary for determining shift output in the designed longwall face. The system knowledge base contains over 200 rules. As a result of the operation of both systems, the designer receives both a proposition for longwall face equipment, and the estimated shift output under given conditions. These results can be used when designing certain elements of the mining process (longwall faces) or the verification of adopted plans.

Fuzzy logic allows a smooth and relatively precise description of key relationships between variables of imprecise nature which serve as input data for the design process. The fuzzy inference conducted by the system on the basis of rules saved in the knowledge base generalizes the knowledge possessed by the designer, as well as a method of inference is similar to that of the reasoning of an expert. Fuzzy systems can effectively support – among other things – the design of selected elements of the mining process, as presented in the above article.

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