DEVELOPMENT OF A FUZZY INFERENCE SYSTEM FOR AVOIDING COLLISION OF BUCKET WHEEL EXCAVATOR EQUIPPED WITH ELECTROMAGNETIC (EM) SENSORS WITH HARD ROCK INCLUSIONS

OPRACOWANIE SYSTEMU WNIOSKOWANIA ROZMYTEGO DLA UNIKNIĘCIA KOLIZJI KOPARKI WIELONACZYNIOWEJ KOŁOWEJ WYPOSAŻONEJ W CZUJNIKI ELEKTROMAGNETYCZNE (EM) Z WTRĄCENIAMI NIEURABIALNYMI

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This study aims to the development of a Fuzzy Inference System (FIS) that will guide the operator of a Bucket Wheel Excavator (BWE) equipped with geophysical sensors to avoid collision of the excavating buckets with the hard rock formations. The developed FIS uses the probability of occurrence of a hard rock formation (estimated from the measurements of the geophysical sensor) and the operational data of the BWE to estimate the risk for collision and the diggability of the excavated material. The structural and operational characteristics of the used BWEs as well as the applied mining practices were used to modify the structure and the inference rules of the FIS and to maximize the exploitation of the existing factual and experiential knowledge.

Keywords: *fuzzy expert systems, BWE, hard rock inclusions, collision avoidance*

W artykule zaprezentowano wyniki badań mających na celu opracowanie Systemu Wnioskowania Rozmytego (FIS), który będzie wspomagał operatora koparki wyposażonej w czujniki geofizyczne, aby uniknąć kolizji koła czerpakowego z twardymi formacjami skalnymi. Opracowany system FIS wykorzystuje prawdopodobieństwo wystąpienia nieurabialnej skały (oszacowanego na podstawie pomiarów czujnika geofizycznego) oraz dane operacyjne koparki w celu oszacowania ryzyka kolizji i urabialności wybieranych utworów. Cechy konstrukcyjne i użytkowe używanych koparek, a także stosowane praktyki górnicze zostały wykorzystane do modyfikacji struktury i zasad wnioskowania FIS oraz maksymalizacji wykorzystania istniejącej wiedzy faktycznej i empirycznej.

Słowa kluczowe: *system Wnioskowania Rozmytego, koparka wielonaczyniowa kołowa, wtrącenia nieurabialne, unikanie kolizji*

INTRODUCTION

Recent advances in FIS have provided a new approach in solving many problems related to mineral industry, a traditional economic activity which is heavily based on the experiential knowledge. The success of Fuzzy Inference Systems (FIS) is mainly due to their similarity to human perception and reasoning, and their intuitive handling and simplicity, which are important factors for the acceptance and usability of the mining systems. FIS have the ability to handle imprecise or incomplete information and to incorporate them into decision–making processes, based on the knowledge of an expert. The literature review of the recently published related articles indicates that there are an increasing number of FIS applications in almost all fields of mineral industry (Galetakis and Vasileiou, 2013).

In this study we suggest a Fuzzy Inference System (FIS) that aids the operator of a Bucket Wheel Excavator (BWE) equipped with geophysical sensors to avoid collisions of the excavating buckets with the hard rock inclusions and other problematic in digging materials, which can cause severe damages to BWE. After extensive comparison, ranking and evaluation via field testing of several geophysical methods we have identified that, in the typical geologic environment of lignite mines employing BWEs, the Electromagnetic Method (EM) measuring the electrical resistivity of the subsurface materials are the most promising in detecting local features such boulders and hard layers (Overmeyer et al., 2007; Galetakis et al., 2016; Vafidis et al., 2016). Thus a continuously working geophysical EM sensor mounted on the BWE scans the slope few cuts ahead of the face and measures the electrical resistivity of geological formations. The received data form EM sensor, after pre-processing and corrections, are sent an automated algorithm to estimate the probability of occurrence of a hard rock formation at the position of measurement, and sends this information to expert system module. The developed expert system (FIS) uses the probability of occurrence of a hard rock formation and the operational data of the BWE to estimate the risk for collision and the diggability of the excavated material.

More specifically a Mamdani type FIS was created, within Matlab programming environment. The development of the FIS included the selection of its inputs (the probability of occurrence of a hard rock formation at a specific position S, the distance of bucket wheel to S, the slewing speed of bucket wheel and the apparent resistivity values of the excavated material), the fuzzyfication-membership functions, the inference rules and the defuzzyfication method. Two outputs were selected for the FIS, the risk for collision of the bucket wheel with a hard rock formation and the diggability of the excavated formation. The training of the developed FIS was based on collected data regarding structural and operational characteristics of the used BWEs and the applied mining practices. This information was used to modify the structure and the inference rules of the FIS and to maximize the exploitation of the existing factual and experiential knowledge.

FUZZY INFERENCE SYSTEMS

FIS have emerged from the field of „Artificial Intelligence", in which expert systems, artificial neural networks, genetic algorithms, and agent-based software have also dominated. Fuzzy inference systems are computing frameworks, based on the concepts of fuzzy set theory. FIS can be considered as a process for mapping a given input data set to an output set, using fuzzy logic. The mineral industry sector has been particularly receptive to these methods, since many of the mining operations and processes are understood and controlled in empirical ways. The goal of the design of the fuzzy inference system is to capture the knowledge of a human expert relative to some specific domain and code this in a computer in such a way that the knowledge of the expert is available to a less experienced user (Tripathi 2011, Dennis 1996).

FIS have been applied with success in mining (Kesimal & Bascetin, 2002; Taboada et al., 2006, Galetakis and Vasiliou 2010), mineral processing (Chuk et al., 2005) mineral exploration (Luoa & Dimitrakopoulos, 2003) and other fields of mineral industry (Meech, 2006). Their success is mainly due to their similarity to human perception and reasoning, and their intuitive handling and simplicity, which are important factors for the acceptance and usability of the mining systems.

FIS uses fuzzy logic, instead of Boolean logic, to reason about data in the inference mechanism. Fuzzy logic, initiated in 1965, by Zadeh, is a multi-valued logic that allows intermediate values to be defined between conventional evaluations, like true/false, yes/no, high/low, etc. (Zadeh, 1997). Notions like "rather thick" or "very thin" can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking. Unlike the classical Boolean set allowing only 0 or 1 value, the fuzzy set is a set with a smooth boundary allowing partial membership. The degree of membership in the set is expressed by a number between 0 and 1, with 0 indicating entirely not in the set, 1 indicating completely in the set and a number in between meaning partially in the set.

The basic structure of a general FIS, shown in Figure 1, consists of three subsystems: a fuzzifier, a rule base and a defuzzifier. While the fuzzifier and the defuzzifier have the role of converting external information in fuzzy quantities and vice versa, the core of a FIS is its knowledge base, which is expressed in terms of fuzzy rules and allows for approximate reasoning (Czogala & Leski, 2000). Fuzzification refers to the process of taking a crisp input value and transforming it into the degree required by the terms. The fuzzification subsystem measures the values of input variables, performs a scale mapping that transfers the range of values of input variables into corresponding universes of discourses and finally performs the function of fuzzification that converts input data into suitable linguistic values, which may be viewed as labels of fuzzy sets. Such a function is called the membership function and it is determined by the experts. Typically, a FIS can be classified according to three main types of models that are distinguished in the formalization of the fuzzy rules (Castellano et al., 2002). The knowledge base is consisting of a set of fuzzy „if-then" rules which capture the relation between input and output linguistic variables. The developed FIS is the Mamdani type, which incorporates the following fuzzy rule schema:

IF x is A then y is B

where: A and B are fuzzy sets defined on the input and output domains, respectively. Mamdani FIS type was proposed as the first attempt to solve control problems, by a set of linguistic rules obtained from experienced human operators. The main feature of such type of FIS is that both the antecedents and the consequents of the rules are expressed as linguistic constraints. As a consequence, a Mamdani FIS can provide a highly intuitive knowledge base that is easy to understand and maintain, though its rule formalization requires a time consuming defuzzification procedure. FIS have been successfully applied in several engineering and scientific fields as automatic control, data classification, decision analysis, expert systems and many others.

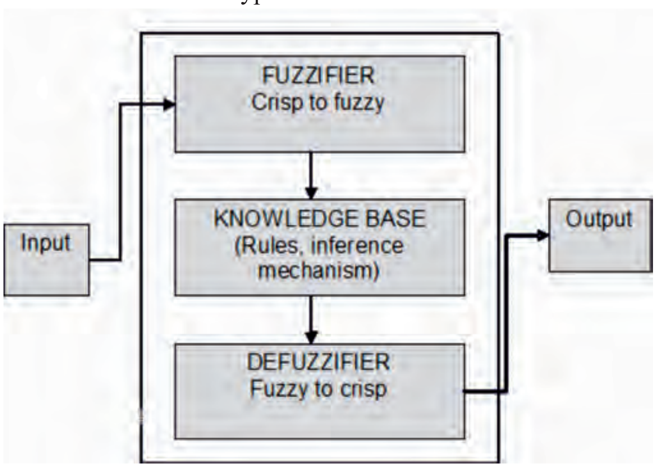

Fig. 1. Scheme of a Fuzzy Inference System (FIS)
Rys. 1. Schemat Systemu Wnioskowania Rozmytego(FIS)

DEVELOPMENT OF A FUZZY INFERENCE SYSTEM

For the development of the FIS, the Fuzzy Logic Toolbox of the Mathworks was implemented (Mathworks, 1999). The steps for the development of the FIS were:

- Definition and fuzzification of the input/output variables.

- Creation of the inference rules (application of the fuzzy operator (AND, OR) in the antecedent and implication from the antecedent to the consequent).

- Aggregation of the consequents across the rules.

- Defuzzification.

During the first stage the initial structure and the parameters of the developed FIS were chosen. The final structure and the FIS and the optimal values of parameters were determined during training. During the training process typical selective mining cases representing different operational conditions were given to FIS as input data and the obtained results were compared to that evaluated by an expert (mining engineers). Furthermore the rules inference mechanism and the response surface plot were examined. Based on the results of this comparison FIS parameters were changed until satisfactory result was achieved (Fig.2).

Definition of input/output variables

Based on the description of mining operations and the experts' opinion, the inputs selected for the developed FIS were considered the probability of occurrence of a hard rock formation at a specific positon S, the distance of bucket wheel to S, the slewing speed of bucket wheel and the apparent resistivity values of the excavated material. Two outputs were selected for the FIS, the risk for collision of the bucket wheel with a hard rock formation and the diggability of the excavated formation. The structure of the FIS, consisting of four inputs, two outputs and 12 rules, is shown in Figure 3.

Input variables

For the probability of occurrence of a hard rock formation at a specific positon S, three linguistic fuzzy variables, named low, medium and high were used. For the distance of bucket wheel to S, three linguistic fuzzy variables, named small, medium and large were used. For the slewing speed of bucket wheel, two linguistic fuzzy variables, named low, and high were used. For the apparent resistivity values of the excavated material, three linguistic fuzzy variables, named low, medium and high were used.

Output variables

For the risk for collision of the bucket wheel with a hard rock formation, three linguistic fuzzy variables, named low, average and high were used. For the diggability of the excavated formation, three linguistic fuzzy variables, named easy, average and difficult were used.

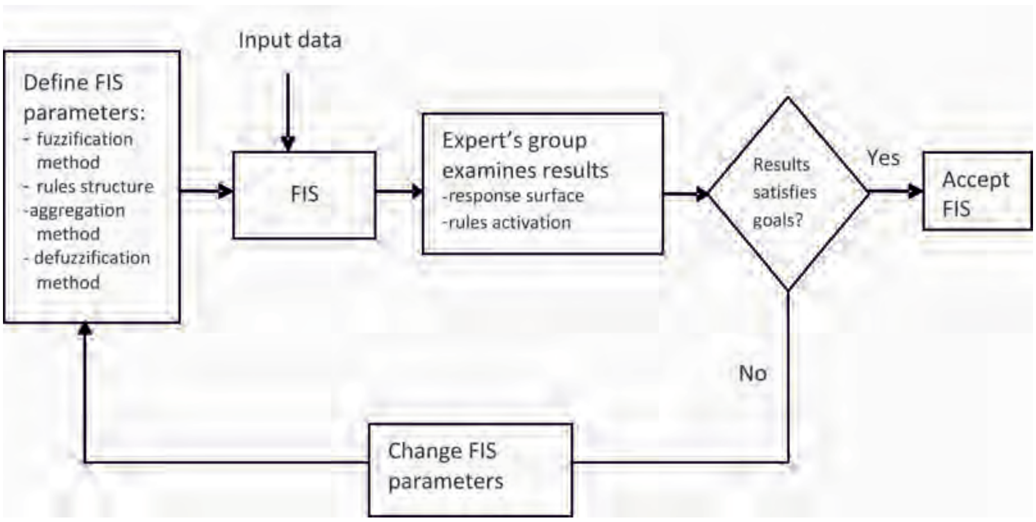

Fig. 2. Strategy for developing a FIS for the determination of the collision risk
Rys. 2. Strategia opracowania FIS w celu określenia ryzyka kolizji

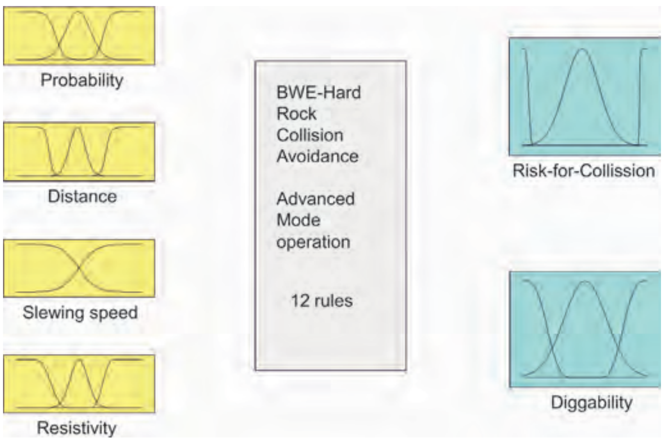

Fig. 3. FIS development in Matlab programming environment (Fuzzy Logic Toolbox)
Rys. 3. Rozbudowa FIS w środowisku programowania Matlab (Fuzzy Logic Toolbox)

Fuzzification of variables

The fuzzification of the FIS input/output variables converts them to linguistic variables, which are fuzzy sets that are used to add semantic sense to the analysis. The shape of the fuzzy variables is given by the fuzzy membership functions. A degree of membership to a linguistic variable is assigned to each value of the input variable. In this step, the degree μl, to which each input variable belongs to the appropriate fuzzy set via membership functions, is determined. The input is always a crisp numerical value and the output is a fuzzy degree μ of membership in the qualifying linguistic set (always in the interval between 0 and 1). The membership functions, used for the fuzzy values of the fuzzy variables, are selected based on expert's experience. The parameters of membership functions were optimized during the training of the FIS. The parameters of the membership func-

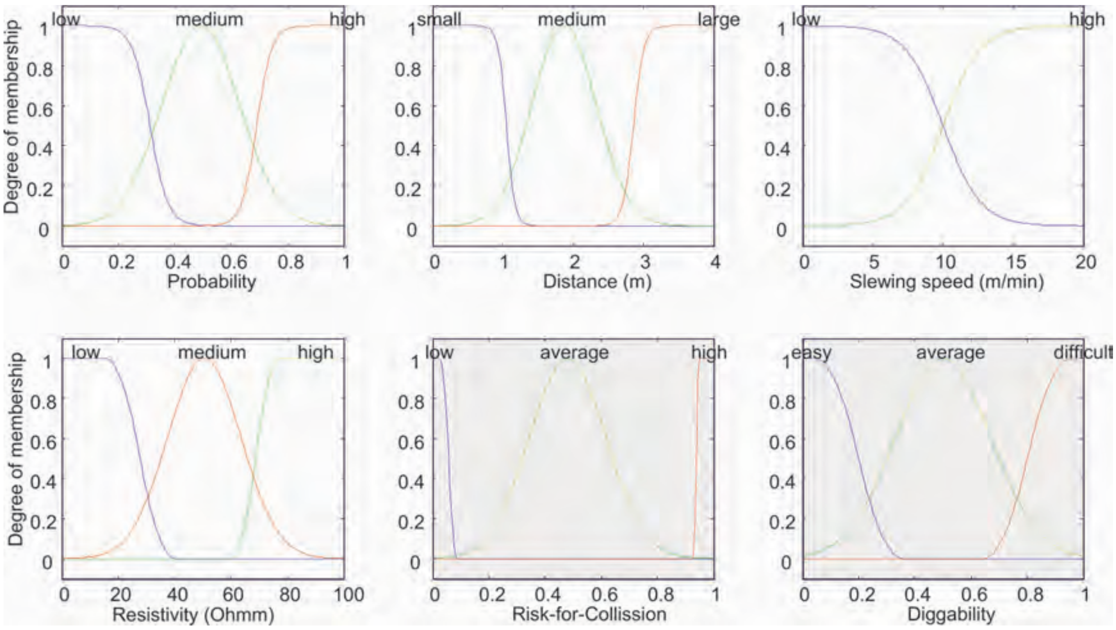

Fig. 4. Membership functions of input/output variables
Rys. 4. Funkcje przynależności zmiennych wejściowych / wyjściowych

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1. If (Probability is low) or (Distance is large) then (Risk-for-
Collision is low) (1)

2. If (Probability is medium) and (Distance is medium) and (Speed is
low) then (Risk-for-Collision is low) (1)
3. If (Probability is medium) and (Distance is medium) and (Speed is
high) then (Risk-for-Collision is average) (1)

4. If (Probability is medium) and (Distance is small) and (Speed is
low) then (Risk-for-Collision is low) (1)
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Fig. 5. Typical set of rules of the developed FIS
Rys. 5. Typowy zestaw reguł opracowanego FIS

tions, which determined during the training process, are shown in Figure 4.

Inference rules and aggregation process

The rules of the FIS are obtained from information gathered by mining engineers and operators' experience and were optimized during the training of the FIS. Finally, the developed knowledge base of the FIS consists of 12 rules. The fuzzy operator AND was applied to all fuzzy antecedents. The structure of a typical rule consists of the antecedent, the inference and the weigh. The weigh indicates the importance of a particular rule compared to the others. In the developed FIS, all rules have the same weigh. Typical set of rules of the developed FIS is shown in Figure 5. The results of all rules are combined with the aggregation process into a single fuzzy set for the output variable. From the available aggregation methods (maximum, probabilistic or and summation) the summation method was used.

Defuzzification

The input for the defuzzification process is the aggregate output fuzzy set and the output is a crisp number. The most popular defuzzification method is the centroid, which calculates the centre of the area under the curve. Other available methods are: bisector, middle of maximum (the average of the maximum value of the output set), largest of maximum, and smallest of maximum. In the developed FIS the centroid method was used. The inference mechanism of the developed FIS, which consists of four inputs, 12 rules and two outputs, is shown in Figure 6. Information flows from left to right, to a single output for each rule. Outputs from all rules are aggregated to form outputs fuzzy set. The response surface for Risk of Collision as function of the Probability (of hard rock occurrence) and the Distance (BW to hard rock) is shown in Figure 7.

FIS versions for Simple and Advanced Mode operation

Two different versions of the Fuzzy Inference System (FIS) were developed. The first version, presented above, was named AMFIS and it is used during the advanced mode operation of the real-time automated algorithm for data processing and evaluation. The second version, named SMFIS, is used during the simple mode operation of the real-time automated algorithm for data processing and evaluation. The SMFIS has less inputs (the probability and the distance) and rules compared to AMFIS.

FIS INTEGRATION AND TESTING IN SOUTH FIELD MINE

The integration of the developed FIS into the overall system for real-time monitoring of the excavation process of the BWE (Fig. 8) included:

- connection of the FIS to the automated algorithm for the estimation of the probability of occurrence of a hard rock for-

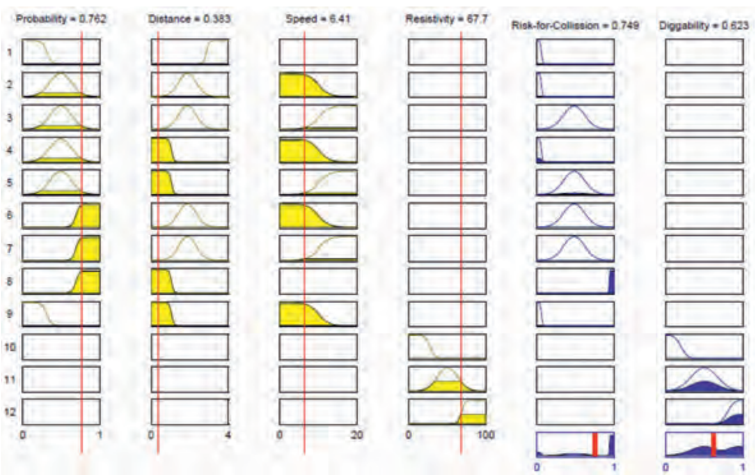

Fig. 6. Fuzzy inference mechanism and defuzzification method
Rys. 6. Mechanizm wnioskowania rozmytego i metoda defuzji

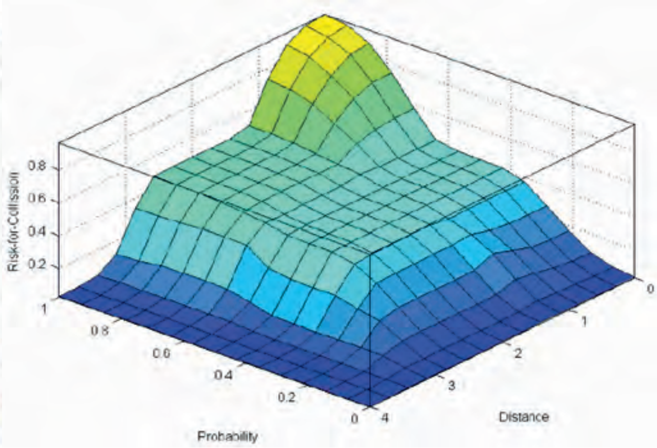

Fig. 7. FIS response surface for Risk of Collision as function of the Probability (of hard rock occurrence) and the Distance (BW to hard rock)
Rys. 7. Powierzchnia odpowiedzi FIS dla ryzyka kolizji w funkcji prawdopodobieństwa (występowania nieurabialnego wtrącenia skalnego) i odległości (koła wielonaczyniowego do wtrącenia skalnego)

mation based on the measurements of the electrical resistivity of the excavated material obtained by the EM sensor

- development of a graphical user-interface (visualization unit) providing all necessary information, including this obtained by the fuzzy expert system, in a comprehensive way, to the operator of the BWE was also developed. As shown in Figure 9 the developed visualization unit includes four panels.

The first panel (top left) displays the excavation process via live streaming obtained by a camera connected to the system. The second panel (bottom left) displays the outputs of the fuzzy expert system (risk for collision of the BW with a hard rock formation and diggability of excavated material) as well as the probability of occurrence of a hard rock formation. These values are displayed in colored scale in order to be easily visible and

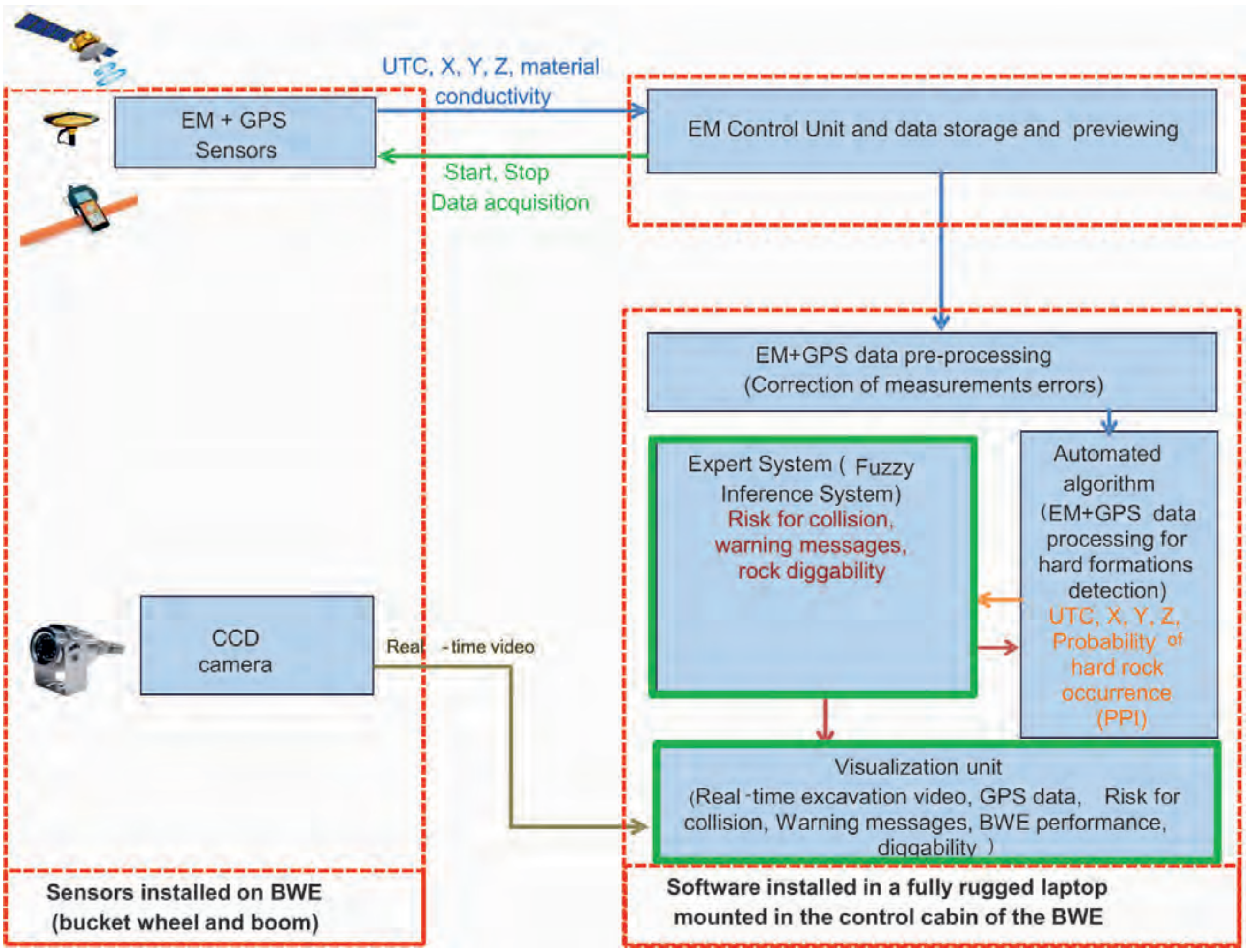

Fig. 8. Overall system for real-time monitoring of the excavation process of the BWE
Rys. 8. Ogólny system monitorowania w czasie rzeczywistym procesu urabiania wielonaczyniową koparką kołową

Fig. 9. Visualization unit providing all necessary information to the operator of the BWE during real-time mine face inspection tests in South Field mine at Ptolemais area (Greece)
Rys 9. Okno wizualizacji dostarczające operatorowi wszystkie niezbędne informacje podczas urabiania zabierki w czasie rzeczywistym w kopalni South Field na obszarze Ptolemais (Grecja).

understood by the operator of the BWE. When risk of collision exceeds a certain level an audio alarm is also activated and short messages in form of warnings of advices for the operator of the BWE are displayed. The third panel (top right) includes the buttons controlling the measuring units during the excavation process and for creating plots of the resistivity measurements. The fourth panel (bottom right) displays the current resistivity measurements. Depending on the mode of real-time operation (simple or advanced) this panel can also provide information regarding the position BW and the slewing speed of the boom.

The above described system was tested in South Field mine (Ptolemais, Greece) operated by the Public Power Corporation (PPC). The system was mounted in a BWE operating on the first bench of the mine, where hard rock inclusions (mainly conglomerates) in forms of lenses occur. Results indicated that the system was able detect the presence of hard rock inclusions in the excavating area and to generate early warnings alarms for the operator of the BWE. The use of the fuzzy expert system results in the gradual detection of collision and this is very convenient for BWE operator.

CONCLUSIONS

The use of fuzzy logic have allowed to capture and incorporate the existing experiential knowledge about excavated material properties and the mining with BWE in a very efficient way in the developed fuzzy expert system used to estimate the risk of collision of bucket wheel with hard rock formations. The use of fuzzy logic results in the gradual detection of collision and this was very convenient for BWE operators. Furthermore the developed fuzzy expert system can be simply adjusted through membership functions to include new factual knowledge while the fuzzy set of rules can be easily extended to incorporate additional experiential knowledge. This will allows the application of the developed system in different mining environments.

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Architectural details of Wrocław