COMMUNICATIONS

DECISION SUPPORT SYSTEM FOR VENTILATION OPERATORS BASED ON FUZZY METHODS APPLIED TO IDENTIFICATION AND PROCESSING OF GAS–DYNAMIC IMAGES

Izabella V. Lokshina — Richard C. Insinga *

This paper discusses a decision support system (DSS) based on fuzzy methods that are applied to the identification and processing of gas-dynamic images received during monitoring and control processes of underground coal mine atmospheres. The DSS supports the ventilation operator's decisions under complex and unanticipated gas-dynamic situations on the working face.

K e y w o r d s: decision support system, fuzzy methods, monitoring and control processes in underground facilities

1 INTRODUCTION

With the increase of the depth of underground mining operations and processes, gas emissions, stratum temperature, and gas-dynamic activity also increase, causing a growing number of incidents. That's why continuous and active monitoring and control of underground coal mine atmospheres is very important as well as contributing to the effective functioning of ventilation and degasification systems.

Continuous improvement and modernization of ventilation automated control systems (VACS) could not eliminate human (operator) participation in the control loop.As a result, in addition to traditional VACS supporting software, a decision support system (DSS) was developed based on processing of gas-dynamic images to support the VACS operator's decisions under complex and unexpected gas-dynamic situations on the working face.

2 DSS: EVOLUTION OF IDEA

Coal mine atmospheres are an extremely complex to monitor and control. Complexity is due to the fact that the object could never be completely observed and that the majority of information received is stochastic and non-structured. Coal mine atmosphere measurements are extremely complex to interpret, because of the many gas-dynamic situations and their occurrences in the working face of underground coal mines. Consequently, it causes great difficulties in effective decisions and necessary control actions of the ventilation operators.

On the other hand, there are a number of experienced operators and experts who are able to interpret complex gas-dynamic situations and occurrences based on their great experience and knowledge for decision-making, using only partial coal mine atmosphere measurements.

Decision support and decision-making for coal mine atmosphere monitoring and control is an ideal task for Artificial Intelligence (AI). And the best solution is a system providing the identification of the gas-dynamic situations on the working face and offering some reasonable suggestions for possible actions to the ventilation operator.

Traditionally, both VACS and ventilation operator perform monitoring and control functions. The human tasks during the control process consist of (1) determining the prognosis levels of gas contents in the mine atmosphere, measured by the active automated gas protection system (AGPS); (2) supervising VACS performance; (3) operative decision-making when atypical situations occur; and (4) supervising performance of the accident liquidation plan (ALP) when emergency situations occur. The DSS for ventilation operators was based on the gas-dynamic image classification system, which has been produced using a gas-dynamic image processing procedure.

The idea to apply Artificial Intelligence methods in coal mine atmosphere monitoring and control was not new and original. In the middle of the 1980's, three expert systems for methane and dust concentration control (UFEL, SHEARER, IDSS) were created in the USA and the UK. At the same time period, two prototype expert systems for methane concentration control were created in Russia: the first was based on the principle of situational control under uncertainty (PROVETRIVANIE), and the second was based on analysis of quantitative

* Division of Economics and Business State University of New York, Ravine Parkway, Oneonta, NY 13820, USA, lokshiiv@oneonta.edu, insingrc@oneonta.edu

First version of this paper was presented at SympoTIC ´03, 26-28 October 2003, Bratislava, Slovakia

ISSN 1335-3632

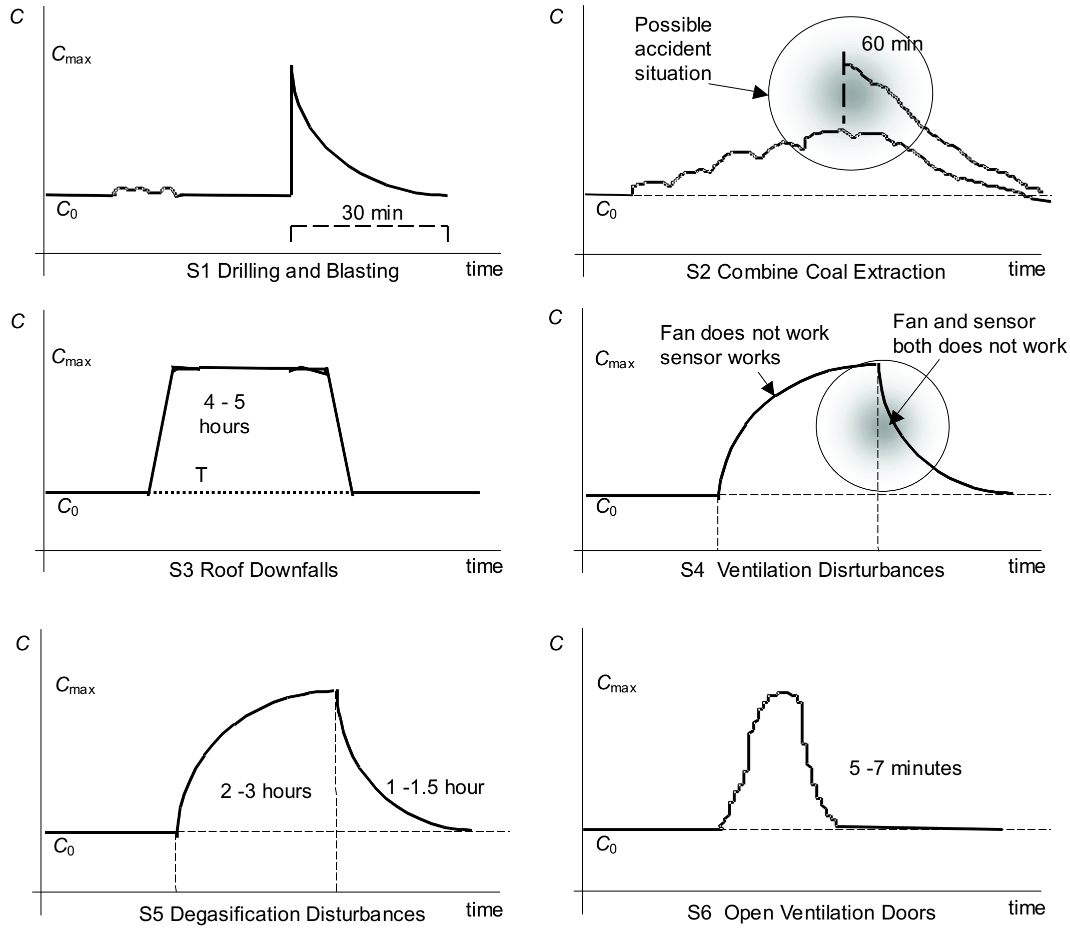

Fig. 1. Examples of gas-dynamic images.

symptoms and expert estimation of gas-dynamic parameters realization (METEX) [2, 3].

However the idea to apply fuzzy methods to gas-dynamic images processing was really new and original. Models and algorithms of all the mentioned above systems were based on productive- and frame-based methods of knowledge representation. Fuzzy methods of knowledge representation have been never used for mine atmosphere monitoring and control before the system described in this paper was created [3].

3 FUZZY MODELS

The job description of a ventilation operator related to coal mine atmosphere monitoring and control includes these activities:

- Supervision of the gas-dynamic situations on the working faces;
- Identification of Mine Ventilation System (MVS) parameters for control corrections;
- Determination of the reasons for variations of the gas-dynamic situations;
- Decision-making in the case of considerable methane deviations;
- Emergency ventilation control;
- Statistical reports producing.

Gas-dynamic situations observed by a ventilation operator on the working face were correlated with a great number of mining-geological, mining-technological, and mining-technical factors.

Gas-dynamic situations on the working face were classified as gas-dynamic processes in MVS and emergency situations.

The general formula of mine atmosphere monitoring and control in logic format was:

$$F1 \wedge F2 \wedge F3 \rightarrow F4 \vee F5\,,$$

where $F1$ – mining-geological parameters,
$F2$ – technological processes parameters,
$F3$ – technical parameters of MSV,
$F4$ – gas-dynamic processes in MSV,
$F5$ – emergency situations.

Based on the formula below, the ventilation operator activities were produced in logic format, which could be considered as determination of possible reasons for methane concentration deviations.

$$F2 \wedge F3 \rightarrow F4\,.$$

For decision-making, a ventilation operator uses the following information:

– Methane concentration records obtained (recorded) from different points of working faces;
– Mining technology information;
– Planned and actual mining status;
– Schemes of working face ventilation and topological information;
– Placement and location of methane concentration sensors;
– Information about disturbances in ventilation and degasification systems.

Based of this information, it was possible to diagnose the operative situation on the working face and to identify the reasons for methane concentration deviations. For the most part, single mining-technological and technical factors caused strictly certain classes of occurrences with definite shapes of gas-dynamic spectrums or gas-dynamic images, which were always observed in the records of methane concentration.

Several examples of some of these gas-dynamic images are presented at Fig. 1.

The classes of gas-dynamic images in the records of methane concentration were also the perfect instruments used to separate the real occurrences and the disturbances caused by electronic devices and communication channels.

Fuzzy classification of gas-dynamic situations on the working face was developed as a system of fuzzy rules, connecting the set of the gas-dynamic images (S_i, $i = [1,m]$) and their fuzzy attributes (B_j, $j = [1,n]$, $B_j = [0;1]$) with high maximum value of belief function.

For example, several fuzzy classification rules, describing classes of gas-dynamic images $S_1 - S_6$ shown in Fig. 1, are shown below.

$$B_1[0.5-0.6] \wedge B_2[0.5-0.6] \wedge B_3[0.5-0.6] \wedge B_4[0.1-0.6] \wedge B_5[0.1-0.2] \wedge B_6[0.9-1] \rightarrow S_1[0.9-1]\,,$$

$$B_1[0.5-0.6] \wedge B_2[0-0.1] \wedge B_3[0-0.3] \wedge B_4[0.1-0.3] \wedge B_5[0.3-0.4] \wedge B_6[0-0.1] \rightarrow S_2[0.9-1]\,,$$

$$B_1[0.8-0.9] \wedge B_2[0.2-0.4] \wedge B_3[0.2-0.3] \wedge B_4[0.2-0.3] \wedge B_5[0.2-0.3] \wedge B_6[0-0.1] \rightarrow S_3[0.9-1]\,,$$

$$B_1[0.9-1.0] \wedge B_2[0-0.2] \wedge B_3[0-0.3] \wedge B_4[0.1-0.2] \wedge B_5[0-0.3] \wedge B_6[0-0.1] \rightarrow S_4[0.9-1]\,,$$

$$B_1[0.5-0.9] \wedge B_2[0.8-1.0] \wedge B_3[0.5-0.6] \wedge B_4[0.4-0.6] \wedge B_5[0.1-0.7] \wedge B_6[0-1] \rightarrow S_5[0.9-1]\,,$$

$$B_1[0.8-1.0] \wedge B_2[0.3-0.5] \wedge B_3[0.1-0.6] \wedge B_4[0.4-0.7] \wedge B_5[0.5-0.8] \wedge B_6[0-1] \rightarrow S_6[0.9-1]\,.$$

The application of a Fuzzy Model (FM) to gas-dynamic image interpretation and processing was to be preferred for the following reasons:

– Methane concentration received from the working face was stochastic;
– Complex gas-dynamic situations were incompletely identifiable in records of methane concentration;
– Records of hindrances combined with records of methane concentration created difficulties in identification and processing of the gas-dynamic images;
– Difficulties in interpretation of the gas-dynamic situations caused by multiple combinations of occurrences;
– Expert knowledge provided the ability to estimate model parameters based on partial measurements [3].

The development of traditional FMs for gas-dynamic image interpretation and processing took several directions:

– A vector of gas-dynamic images and a vector of attributes were introduced to the model: S_i, $i = [1,m]$, B_j, $j = [1,n]$, $B_j = [0;1]$;
– A matrix of masking of attributes was introduced to the model:
$$v(S_i \rightarrow B_j^*) = R_{ij}^*\,;$$
– Matrices of minimum and maximum gas-dynamic images influence into attributes were introduced instead of the influence- and relations matrices:
$$v(S_i \rightarrow B_j) = R_{ij}\,;$$
– Prior gas-dynamic situations were added to the list of gas-dynamic images, if they were considered to be reasons for attributes appearance;
– Advanced expert information was considered;

The fuzzy identification system was based on processing of gas-dynamic images and attributes; matrices of minimum and maximum influence, and masking.

Auxiliary fuzzy axioms of gas-dynamic image interpretation and processing were the following:

1. If there is reason to appear, the attribute does not appear in the model.
$$\neg \vee (S_i \wedge (S_i \rightarrow B_j)) \supset (\neg B_j \wedge \neg T B_j)\,, \quad 1 \le i \le m\,, \quad 1 \le j \le n\,.$$
2. If there are reasons for the attribute to appear, and no grounds to be masked, the attribute appears in the model.
$$\vee (S_i \wedge (S_i \rightarrow B_j)) \wedge \neg \vee (S_i \wedge (S_i \rightarrow B_j^*)) \supset (B_j \vee \neg T B_j)\,, \quad 1 \le i \le m\,,\ 1 \le j \le n\,.$$
3. The implications chains between reasons are the result of the correlations between reasons.
$$(S_i \rightarrow S_k)) \supset (S_i(S_k)\,, \quad 1 \le i \le m\,,\ 1 \le k \le m\,.$$

A global axiom was created by the intersection of the system of the above-mentioned axioms.
$$G \equiv \wedge (E_j \wedge F_j)\,, 1 \le j \le n\,.$$
The belief function in this FM is a function of the inter-logical distribution between the gas-dynamic images

and the attributes, and is an analogue of the maximum likelihood function in statistics.

$$v(G) = \varphi(s, b, r)\,,$$

where $v(S_i) = s_i$, $v(B_j) = b_j$, $v(S_i \to B_j) = R_{ij}$.

So, the basic fuzzy model of gas-dynamic image interpretation and processing was developed to get solutions for the following extremes:

$$d(b) = \max \varphi(s, b, r)$$

$$s_i(b) = \max\{s_i \colon \varphi(s, b, r) = d(b)\}\,,$$

$$s_i(b) = \min\{s_i \colon \varphi(s, b, r) = d(b)\}\,.$$

Or, in other words, for a given vector $b = (b_1, \ldots, b_n)$, $0 \le b_j \le 1$, $1 \le j \le n$, it was necessary:

1. To define such a maximum belief function value d, $0 \le d \le 1$, for which the system of max-min equations (1-2) had at least one decision $s = (s_1, \ldots, s_m)$, $r = [r_{ij}]$ in interval $0 \le s_i \le 1$, $r'_{ij} \le r_{ij} \le r''_{ij}$, $1 \le i \le m$;

$$\begin{gathered} b_j - (1 - d) \le \max\min(s_i, r_{ij})\,, \\ 1 \le j \le n\,,\ \ 1 \le i \le m\,, \end{gathered} \tag{1}$$

$$\begin{gathered} \min\{\max\min(s_i, r_{ij})\,,\, 1 - \max\min(s_i, r^*_{ij})\} \\ \le b_j + (1 - d)\,,\ \ 1 \le i \le m\,. \end{gathered} \tag{2}$$

2. To define exact minimum and maximum limit values of coordinates of the system, which corresponded to a maximum belief function value $d = d\max$.

In the developed DSS, the forward-chained (*ie* , from attributes to gas-dynamic images) and the backward-chained (*ie* , from the interpretation results to primary gas-dynamic data) inference engines were used.

The DSS's algorithms were quite different from traditional ones, in which the result could be received based on attributes using only single reasons. The advantage of the developed fuzzy algorithms was accomplished by using composite, not single, processing rules. [1, 3]

4 FINDINGS AND CONCLUSIONS

1. The quantitative and qualitative information used by a ventilation operator for decision-making was analyzed. This analysis proved the effectiveness of applying fuzzy models and algorithms to gas-dynamic image interpretation and processing.
2. Fuzzy models and algorithms for gas-dynamic image interpretation and processing were developed.
3. DSS for a ventilation operator was constructed. Programs were written in C++ for Windows environment.
4. The effectiveness of the DSS for a ventilation operator was confirmed by positive results. Laboratory tests included multiple expert gas-dynamic image estimation and processing for the purpose of identifying the reasons for the considerable fluctuations in observed gas-dynamic parameters in coal mine atmospheres.

References

[1] ZADE, L. A.: Outline of a New Approach to the Analysis of Complex Systems and Decision Process, IEEE Transactions on Systems, Man and Cybernetics, vol. SMC-2, 1973.

[2] PUCHKOV, L. A..—TEMKIN, I.. O.: Mining Ventilation: Expert System based operative control 23-rd International Symposium APCOM. Tucson, Canada, 1992.

[3] LOKSHINA, I. V.: Application of Fuzzy Models for Decision Support Systems, in Proceedings of 5th International Symposium on Environmental Issues and Waste Management in Energy and Mineral Production, May 5–8 1998, Ankara, Turkey.

[4] LOKSHINA, I. V.: Expert System Based on the Fuzzy Diagnostic Model to Support Coal Ventilation Operator's Decisions, in Advances in Intelligent Systems, Fuzzy Systems, Evolutionary Computation. Artificial Intelligence. A series of Reference Books and Textbooks. WSEAS Press, 2002. ISBN: 960-8052-49-1.

Received 10 July 2003

Izabella V. Lokshina is an Assistant Professor of Management Information Systems at SUNY Oneonta. She has 20 years of experience, including 15 years in industry, consulting, and academia in Russia, and the 5 last years in industry and academia in the United States. Her positions include Senior Scientific Researcher at the Moscow Central Research Institute of Complex Automation; Project Expert at the Obninsk State Center of Information Research, Project Consultant at the Ministry of the Coal Industry in Moscow, and Associate Professor of Automated Control Systems at Moscow State Mining University. She received her doctorate in Computer Science from Moscow State Mining University, and an MS and BS in computer science from the Moscow Oil and Gas Institute. She is a member of Russian Academy of Information and a member of World Scientific and Engineering Academy and Society.

Richard C. Insinga is an Associate Professor of Operations Management at SUNY Oneonta. He has over 30 years of experience in industry, government, consulting, and academia. His positions include Corporate Director of Technology Development at Avco Corporation, director of strategic planning at United Technologies Research Center, and Senior Consultant with Booz, Allen & Hamilton Inc. He received his doctorate in Management from the Lubin School of Business at Pace University, an MBA from Stanford University, and a MS and BS in Mechanical Engineering from Columbia University. In 2001, he received an honorary doctorate from the Siberian Aerospace Academy (Krasnoyarsk, Russia) in recognition of his achievements in creating a business school there.