EXPERT SYSTEM UTILIZATION FOR MODELING THE DECISION MAKING PROCESSES UPON INDETERMINATION

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ABSTRACT

Computer aided modeling of the decision making processes requires the availability of a system, enabling to gather the knowledge of numerous experts. That is why the subject matter concerns first the simulation of the decision making processes, as well as the methods and procedures of knowledge acquisition from the above experts.

Keywords: *Expert system, fuzzy sets, modeling new technologies.*

Generally, the human mental behavior may be featured as the decision making, planning, coordination and communication activities, respectively, being based on all the data acquisition, data storage, evaluation, and classification of the information. So that any system may substitute a human in some of the above mentioned activities and/or “support” them, such a system must be ready at least to communicate well with the superior human as well as to offer him/her tools, which would contribute/support the activities. The following features belong to the most important:

- possibility to apply the heuristics (together with formally expressed/determined knowledge) to solving decision making problems,
- capability to provide explanations concerning derivations-in-progress as well as concerning the applied knowledge,
- possibility to integrate simply a new accrual knowledge into existing sum of system knowledge.

1. FEATURES OF DECISION MAKING PROCESSES SIMULATION UPON INDETERMINATION

The simulation of decision making processes is featured as follows:

- Decision making is not based on analytic information only, but predominantly on the knowledge, represented by both cognitive and abstraction processes (which are the privilege of brain activities);
- Decision making can be done through various approaches, depending on the number of judging persons;
- It is very difficult to formulate an algorithm of making decision procedure;
- A Lot of information used during decision making is of external origin with respect to already implemented data base of the decision making issue.

Decision making process can be defined as an organic unity of three phases:

- information one (acquiring the knowledge),
- planning one (considering the alternatives),
- selection one (choice of a variant).

To identify the structure of decision making process and to establish the prerequisites for finding effective procedures for its algorithmization, we have to deal with the decision making processes from a wider, especially methodological point of view. One of characteristic features of the decision making processes is the fact that we often work with indeterminate and non-metrical information. This often follows from the fact that inputs to these processes are entered by a human using his/her experience, opinion, etc.

Indetermination, pertinently insufficient defining these processes, has also its own structure, which enables the use of respective tools for working with a certain type of incompleteness. Basic structure of the incompleteness in the sphere of information (we are interested predominantly in this sphere), may be depicted by the following scheme (see Fig. 1).

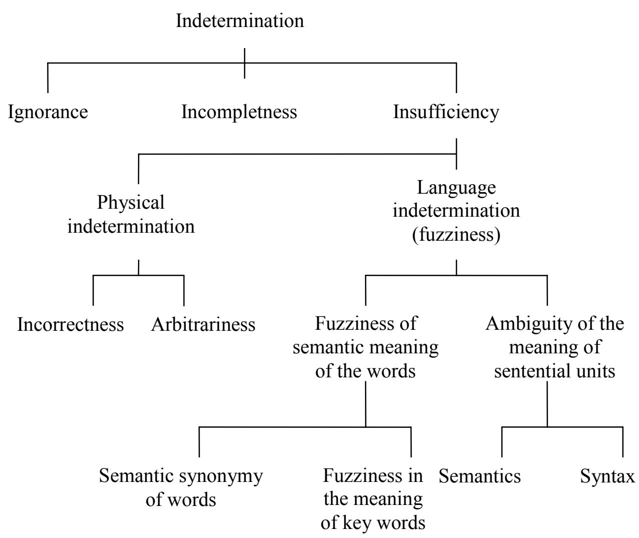

Fig. 1. Structure of indetermination

While analyzing indeterminations during the solving a given decision making process, we often used to find that the indetermination is represented in fact by insufficient information caused either by external factors (physical indetermination) or by a language, by means of which a human factor enters the solving process. The insufficiency itself is in its principle represented especially by a physical indetermination, resulted either from inaccuracies from measuring of given quantities and their quantitative expression or in the existence of physical possibilities, the occurrence of which is more or less accidental, and it is impossible to predict it in advance with sufficient accuracy. Another type of insufficient information is the use of natural language, which is brought to the decision making process by a human, and through which he/she describes the decision making process itself and its functioning. Insufficiency of this information predicts in fact that the human factor is enforced to describe situations using a finite number of words; for finite time period, this number may be infinite during a limited time period. This fact necessarily results in situations, when most of words and also most of sentential units have a considerable diffusion of their own meaning. These indeterminations (fuzziness) of the semantic field of words are caused both through semantic synonymies of the words, and (this in the first place) certain fuzziness in the meaning of key words. Then, this fuzziness becomes the key causation for the fact that classical mathematics as well as exact sciences were not capable to work with linguistically defined situations with a sufficient adequacy. A change took place in the last period, when so called fuzzy mathematics was created, enabling work efficiently just with such verbally described situations.

In this paper we will be focused especially to application of fuzzy mathematics for modeling the decision making processes.

In spite of the fact that the decision making process involves numerous indeterminations, we are capable to define its structure relatively well. Especially, the elements of this decision making process can be divided into the following groups:

S – set of situations,

D – set of all possible solutions,

G – set of targets (admissible) for further functioning of a given system,

F– set of all the degrees of the existence (probabilities) of given object,

K – set of all evaluations for given solution,

T – time interval.

The making decision process itself is represented by various mappings among these sets. Subject matter concerns especially the following mappings:

1. The mapping to amend the information with situations as well as its evaluations, i.e. selection of these information only, which are of significance for final solution:

$$M_1 : S \times T \times F \rightarrow S \times T \times F$$

2. The mapping for creating a set of admissible solutions, which consists of two partial mappings

$M_2 = M_{22} \circ M_{21}$, where

M_{21} – formulating management targets based on description of given situation,

M_{22} – formulating admissible solutions:

$$M_{21}\text{: } S \times T \times F \rightarrow G \times S \times T \times F$$

$$M_{22}\text{: } G \times S \times T \times F \rightarrow D \times S \times T \times F$$

3. The mapping for modeling the effects of admissible solutions

$$M_3 : D \times S \times T \times F \rightarrow D \times S \times T \times (S \times T)^* \times F,$$

where a set of situations is allocated to any and each admissible solution including their time courses, resulting from given decision.

4. The mapping for acceptance of the solution itself, which consists of two partial mappings

$M_4 = M_{42} \circ M_{41}$, where

M_{41} – evaluating the behavior of admissible solution effects,

M_{42} – selection of best variants:

$$M_{41} : D \times S \times T \times (S \times T)^* \times F \rightarrow D \times K \times T \times F$$
$$M_{42} : D \times K \times T \times F \rightarrow D \times T$$

The overall mapping is created through step-by-step composition of these partial mappings

$$M = M_4 \circ M_3 \circ M_2 \circ M_1 .$$

We can depict it at the following diagram (see Fig. 2).

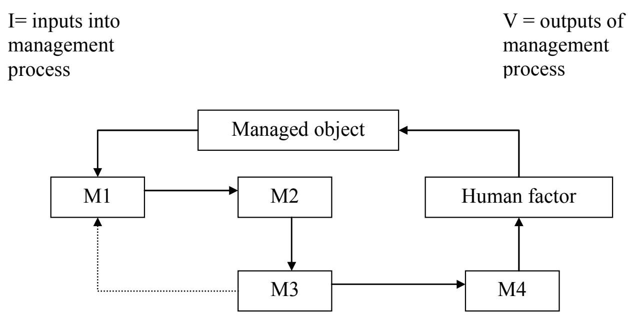

Fig. 2 Making decision process

Let us note that the inherent performance of particular mappings M_1 – M_4 can be ensured by means of so called fuzzy algorithms using the results of fuzzy sets theory [1].

Particular mappings M_1 – M_4 differ one from another by the character of both input and output quantities as well as by relations being performed with the framework of these mappings.

Generally speaking, each process can be featured by the following scenario $(T_i, T_v, X_{ch}, T_p, T_k, T_{kk})$
where

T_i – type of inputs,

T_v – type of outputs,

X_{ch} - character of outputs,

T_p – type of indetermination,

T_k – type of selection criterion,

T_{kk} – type of particular elements of the criterion.

The particular types may take the values given in the following diagram (see Fig. 3)

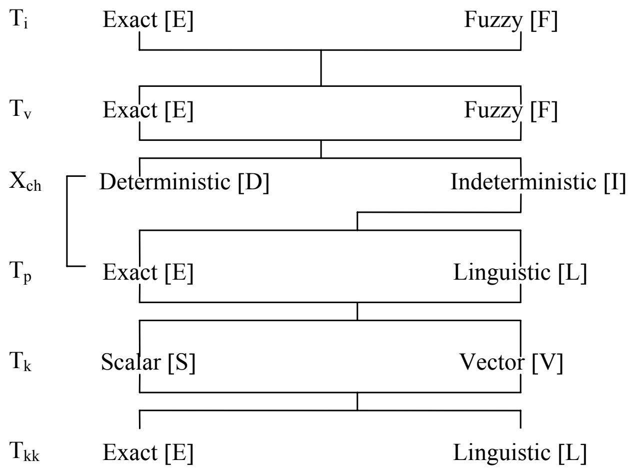

Fig. 3 Types of processes

2. DECISION MAKING SYSTEM FOR SIMULATING COMPLEX EFFECTS OF NEW TECHNOLOGIES IN COAL MINING

Having created the simulation system, we reached a view that it would not be necessary to consider all mappings $M_1, ..., M_{42}$, because some of them are evident.

First, we can assume that the mapping of making information on a given situation and its evaluation M_1 complete, was already a part of acquisition the input evaluation on the situation, that is why it is not necessary to labor it furthermore.

The mapping M_{21} formulating the solution targets based on given situation may be considered to be another one, because the set of all targets G is unambiguously determined through economic criteria.

That is why M_{22}, M_3, M_{41}, M_{42} mappings can be considered to be the key for the making decision process.

Input information to the decision making processes concerning the efficiency of new technologies within the coal mining, can be divided into the following groups:

- social conditions,
- coal reserves,
- mine geological conditions,
- technical means including safety devices;
- economic features (material costs, capital investment means, material reserves, required costs, coal price, etc.).

Set of all possible solutions D should be the output of the entire system represented by the following characteristics:

- Efficiency of coal field exploitation expressed e.g. by means of:
  - real quantity of exploited coal (coal yield, exploitation quantity),
  - achieved outputs (profit, rentability, etc.),
  - exploitation costs and other costs (including research, pertinently including new technologies, environmental protection, ensuring the social welfare, etc.).
- Recommendations concerning the application of exploitation technology and its incorporation into the complex of technologies of the entire mine.

Subsequently, we would try to indicate, how to perform the particular processes, whereas we would presume that some parts of these processes, being specific for conditions of coal field underground mining, were already processed. This concerns especially the processes connected with M_3 – simulating the impacts of particular decisions.

Based on this specification, we can define the general structure of the decision making system, solving this issue (see Fig. 4).

First, let us consider the M_{42} process. From the classification point of view, as depicted on the Fig. 3, the process of selecting the optimum variant belongs into the following two key categories:

I. category = (E, E, D, E, V, E)

II. category = (F, F, I, L, I, L)

The two categories correspond to the fact that during selection of the optimum variant the input quantities are entered either exactly or verbally, while the output quantity is either exact (detailed analysis of the technology) or (on the contrary) verbally described suitability of a given technology. A vector criterion resulting from the technology selection process can be also entered either exactly and/or defined verbally.

It is evident that the performance of both processes M_{42}^{I} and M_{42}^{II} is quite different. Whereas in case of M_{42}^{I} process a classic vector optimization is concerned, in case of M_{42}^{II} process the situation is quite different.

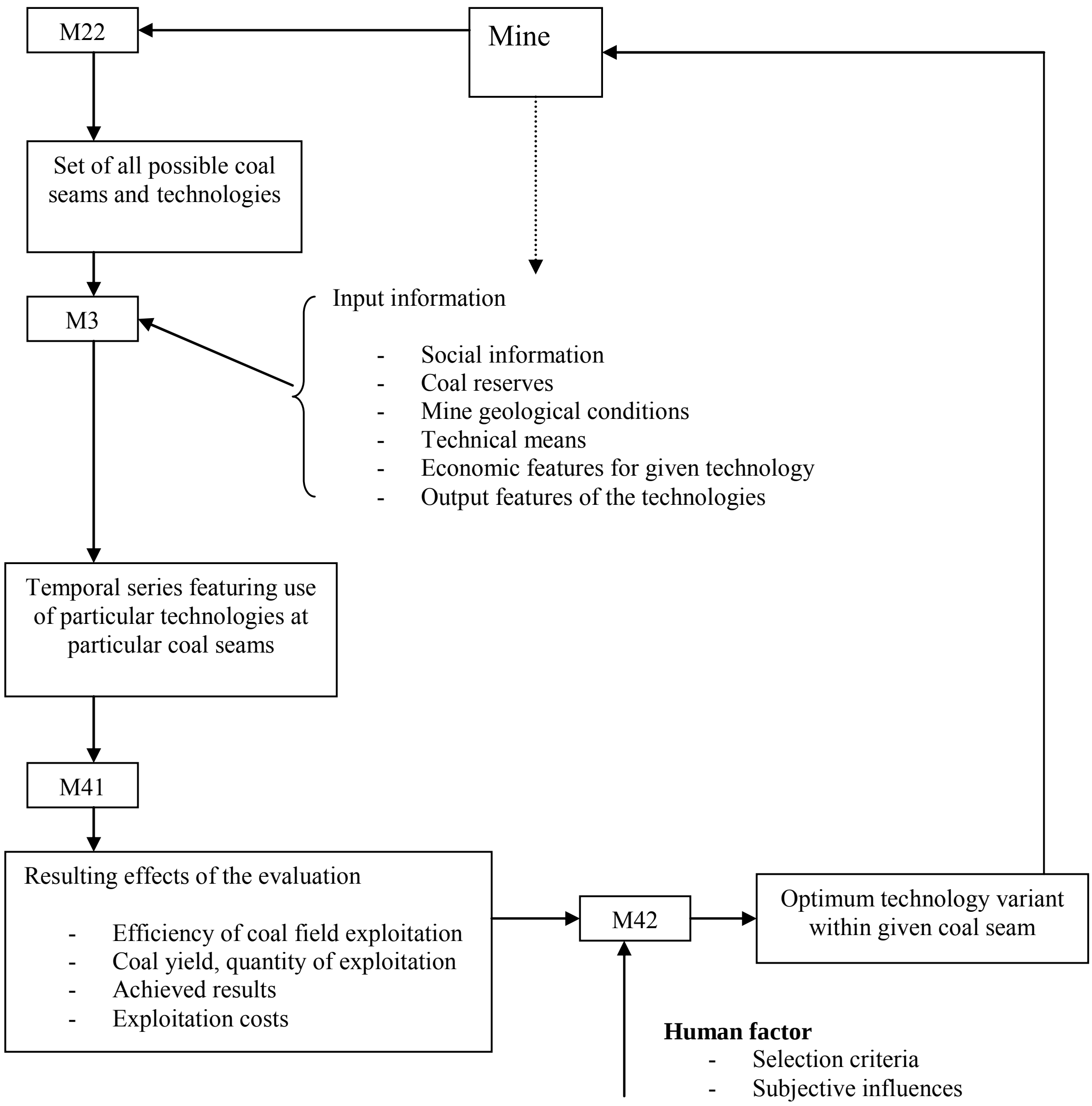

Fig. 4 Structure of decision making system

Let us suppose that both inputs of the M_{42} decision making process and the decision making algorithm itself can be described in a nondeterministic way, mostly by means of linguistic notions characterizing the size of given quantities, eventually the relations among given quantities. However, to make computerized performance of such inputs and algorithms possible, it is necessary to use suitable mathematical tools. Fuzzy set theory, established approximately in 60ties, represents one of possibilities to describe these quantities. Here we would like to explain briefly some descriptions based on the above mentioned theory, which can be used in decision making process immediately.

Let us suppose that U represents a set of objects, to which our decision making process relates (e.g. U is a time interval or an interval representing average coal exploitation costs or costs for operation of given technology, etc.). The fuzzy set A in U could be defined as

$$A : U \to [0,1],$$

where $A(x)$, $x \in U$, is the membership function giving the degree of membership of the element x in fuzzy set A. For example, if $U= [2000, 10\ 000]$ is the universe representing the quantity of exploitation, then the fuzzy set A in U defined by a diagram in Fig. 5

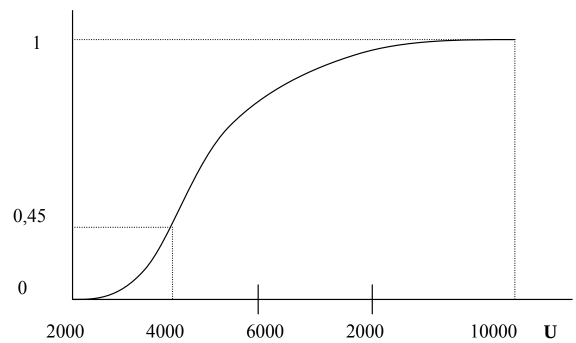

Fig. 5 Fuzzy set diagram

represents the verbal expression *A = HIGH EXPLOITATION LEVEL*. The fact that A is a fuzzy set in U we can write $A \subseteq U$. Furthermore, the term "fuzzy relation" is important for our purposes. If U_1, U_2 are two universes, then fuzzy relation is a fuzzy set in their Cartesian product, i.e. $R \subseteq U_1 \times U_2$. If, e.g. $U_1 = U_2 = U$ in the previous example, then we can define the fuzzy relation
R=NEARLY EQUAL to $\subseteq U \times U$ by means of functional prescription

$$R(x,y) = e^{-|x-y|}, x, y \in [2000,10000]. \qquad (1)$$

Within the class of fuzzy sets we can define analog operations like for classical sets. Particularly, if U is an universe, $A, B \subseteq U$, then we define

$$(A \cup B)(x) = \max\{A(x), B(x)\}, \qquad (2)$$

$$(A \cap B)(x) = \min\{A(x), B(x)\}, \qquad (3)$$

$$\neg A(x) = 1 - A(x), \qquad (4)$$

$$(A \times B)(x,y) = \min\{A(x), B(y)\}. \qquad (5)$$

For our next targets, it is important to introduce the notion of linguistic variable, i.e. the variable χ represented by the following structure

$$\chi = \langle X, \tau, M \rangle, \qquad (6)$$

where X is a domain of values, τ is a set of terms (i.e. particular words) and M is the semantics, i.e. representation assigning a fuzzy set $M(t) \subseteq X$ to each term t. For example, we consider the linguistic variable

$$\chi = SIZES. \qquad (7)$$

Set of terms τ of this variable can be created e.g. as follows

$$\tau = \{ \text{SMALL, MEDIUM, BIG, VERY BIG, ...} \}. \qquad (8)$$

Then we can define as a domain X e.g. interval
$X = <0, 700>$ (e.g. t of exploitation level).
Finally, the function M for particular terms can be defined e.g. through the following diagrams and relations

And furthermore

$$M(\text{VERY } t)(x) = [M(t)(x)]^2 ; x \in X, \qquad (9)$$

$$M(\text{NON-}t)(x) = 1 - M(t)(x), \qquad (10)$$

$$M(t_1 \text{ AND } t_2)(x) = \min\{M(t_1)(x), M(t_2)(x)\}, \qquad (11)$$

$$M(t_1 \text{ OR } t_2)(x) = \max\{M(t_1)(x), M(t_2)(x)\}. \qquad (12)$$

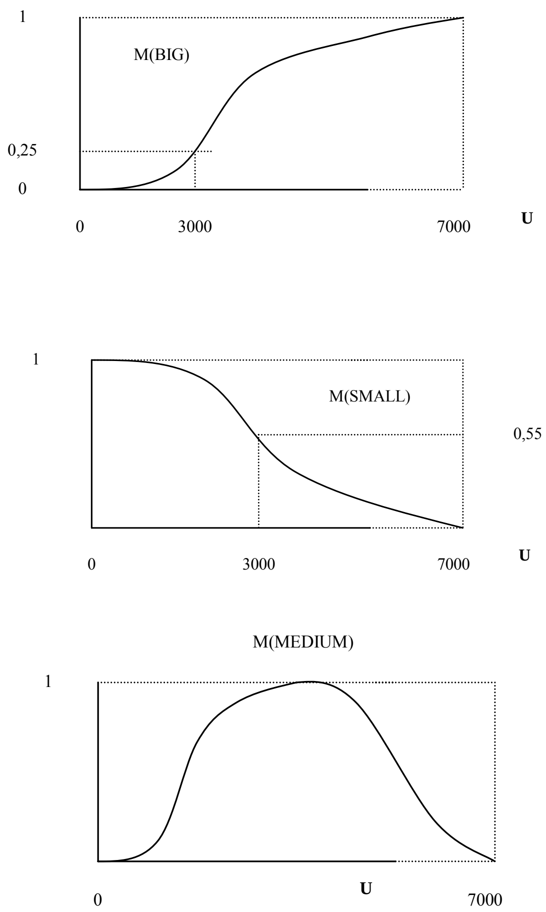

Fig. 6 Diagrams of fuzzy sets

Then for example, the exploitation level of
$x = 3000\ t$ corresponds to the verbal expression

$$t = \text{NON VERY BIG AND NON VERY SMALL} \qquad (13)$$

with the membership degree

$$\begin{aligned} M(t)(x) &= \min\{M(\text{NON VERY BIG})(x), M(\text{NON SMALL})(x)\} = \\ &= \min\{1-M(\text{VERY BIG})(x), 1-M(\text{SMALL})(x)\} = \\ &= \min\{1-(M(\text{BIG})(x))^2, 1-M(\text{SMALL})(x)\} = \\ &= \min\{1-0.25^2, 1-0.55\} = \min\{0.9375, 0.45\} = \\ &= 0.45, \end{aligned} \qquad (14)$$

i.e. with the degree approximately one-half.

Using linguistic variables, we are able to set up the fuzzy algorithms of certain processes.

If the input quantities of given system are $x=(x_1 .. x_n)$ and output ones $y=(y_1..y_m)$, then fuzzy algorithm means the expression:

If $\varphi(x_1..x_n)$, **then** $\sigma(y_1..y_m)$, **or** $\psi(y_1..y_m)$,

where $\varphi(x_1..x_n)$, $\sigma(y_1..y_m)$ $\psi(y_1..y_m)$,

are the linguistic expressions corresponding to the particular quantities.

For example, in process M_{42}^{II} we consider the following situation. One of the particular decision making rules in this process can concern e.g. the relations among the efficiency (e), exploitation yield (v), unit costs for coal exploitation (j), and the choice of given technology (t). Let us suppose that $e \in \langle a_1, b_1 \rangle, v \in \langle 0,\ 100 \rangle$ %. Then the verbal expression of one of decision making rules can be as follows:

R_1: **if** e = MEDIUM, v = BIG, j = MEDIUM,
then t = HIGH SUITABILITY
or
R_2: **if** e = BIG, v = BIG, j = BIG,
then t = MEDIUM SUITABILITY.

That is why we consider the relation among 4 linguistic variables

E = <{SMALL, MEDIUM, BIG, VERY, AND, NON, OR}, <a_1,b_1>,M_e> (15)

V = <{SMALL, MEDIUM, BIG, VERY, AND, NON, OR}, <0, 100 %>,M_v> (16)

J = <{SMALL, MEDIUM, BIG, VERY, AND, NON, OR}, <a_2,b_2>,M_{1j}> (17)

T = <{LOW SUITABILITY, MEDIUM SUITABILITY, HIGH SUITABILITY, VERY, AND, NON, OR}, <0,100%>, M_t>, (18)

some fuzzy sets of which can be, e.g., as follows:

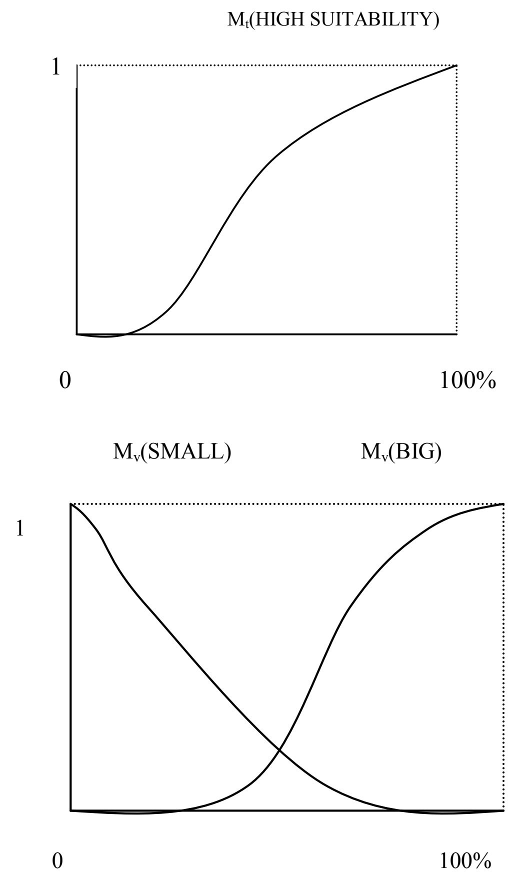

Fig. 7 Diagrams of fuzzy sets

Therefore, we have the following available rules

R_1: **if** e = A_1, v = B_1, j = C_1, **then** t = D_1
.
.
.
R_k: **if** e = A_k, v = B_k, j = C_k, **then** t = D_k.

In case we have a specified input vector (e,v,j), we can determine the corresponding value of technology t.
Let d_i be an x-coordinate of the gravity center of surface laying above the graph of function D_i, i.e.

$$d_i = \int_0^{100} xD_i(x)dx \Big/ \int_0^{100} D_i(x)dx;\ i = 1, ..., k\,. \tag{19}$$

Let furthermore

$$s_i = \min\{A_i(e), B_i(v), C_i(j)\} \in <0,1>. \tag{20}$$

Then we can put

$$\text{SUITABILITY}\ V(t) = \frac{\sum_{i=1}^{k} d_i . s_i}{\sum_{i=1}^{k} s_i} 100 \in \langle 0{,}100\% \rangle \tag{21}$$

The set of rules R_i,...R_k can be obtained preferably by using the expert assessments.

One of the problems connected with the application of fuzzy sets in process M_{42} is the problem of constructing the corresponding fuzzy sets *M(t)*, where *t* denotes terms of the particular linguistic variables. We will show here several possible approaches to solving the problems.

Let us consider e.g. a linguistic variable V=EXPLOITATION YIELD and its term t = BIG. We need to define functions
M_v (BIG) : [0,100] → [0,1].

(1) We have *m* available experts. For any value x ∈ [0,100], the experts answer the question whether the value corresponds to the expression BIG or not. Let *n* of these experts confirm that it corresponds, then

$$M_v(BIG)(x) = \frac{n}{m} \in [0{,}1]. \tag{22}$$

(2) Le us assume again that we have *m* experts and only values *x = 0, 1, 2, . ,.. 100* are tested. Each of experts then defines the values m_{ij} in such a way that

M_{ij} = 1, if he/she considers M_v (BIG)(i) approximately equal to M_v (BIG)(j),

M_{ij} = 3, if he/she considers M_v (BIG)(i) is little bigger than M_v (BIG)(j),

M_{ij} = 5, if he/she cosiders M_v (BIG)(i) is bigger than M_v (BIG)(j),

$M_{ij} = 7$, if he/she cosiders M_v (BIG)(i) is bigger enough than M_v (BIG)(j),

$M_{ij} = 9$, if he/she cosiders M_v (BIG)(i) is much bigger than M_v (BIG)(j).

If it was defined already m_{ij}, i<j, it is put $m_{ji} = 1/ m_{ij}$.

If the maximum inherent number of the matrix $A = \left\| m_{ij} \right\|$, we can find the solution x = ($x_1..x_{100}$) of the matrix equation

$$(A - \alpha.E).X = 0\,. \tag{23}$$

Then we have

$$M_v(BIG)(i) = \frac{x_i}{\sum_{j=1}^{100} x_j} \tag{24}$$

The same situation is also in case of process M_{41}, which can be decomposed as well into two parts M_{41}^{I}, M_{41}^{II}. For the deterministic part of M_{41} we can use classical methods for analyzing time series, which are usually available.

3. CONCLUSION

Working with the decision making modeling system might be divided into two separate parts as follows:
a) creating the model, i.e. constructing the appropriate fuzzy sets and establishment the decision making rules. This stage is relatively demanding as of the analytic activities, requiring close co-operation with experts.

b) applying the model and its recovery, i.e. based on specific input parameters pursuing the calculations of input values. This stage is demanding as of simple mathematic operations, being mostly done by computers.

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