METHODS AND MODELS FOR SELECTION OF RATIONAL SOLUTIONS IN DECISION-MAKING SYSTEMS

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Abstract: *The problems of analysis and synthesis of the intelligent systems for decision-making under conditions of uncertainty and multi-objectiveness are considered. The models and methods for the multi-objective presentation of emergencies are developed taking into account the micro situation concepts and knowledge quanta under conditions of uncertainty.*

Keywords: *decision-making, extreme situations, solution models, micro situations, knowledge engineering.*

Introduction

Analysis of development of natural catastrophic phenomena on the Earth shows that despite scientific and technological progress protection of people and techno sphere against naturally occurring dangers doesn't rise. Annually the number of victims of destructive natural phenomena in the world increases by 4,3% and preys – by 8,6%. Economic losses increase on the average about 6% per year. At present there is an understanding in the world that natural catastrophes represent the global problem being the source of the most profound humanitarian shocks and it remains one of the most important factors defining the stable development of economy. The chief causes for retaining and aggravating of natural dangers are as follows: the increase in anthropogenic action on the environment; irrational placement of the economy objects; settling of people in the zones of potential natural danger; insufficient efficiency and lack of development of the environment monitoring system: weakening of the state system of observation over the natural processes and phenomena; absence or a poor state of hydro technical, anti mudflow and other protective engineer constructions as well as protective afforestation; insufficient volumes and low rates of seismological construction, strengthening of buildings and structures in seismically dangerous areas; lack or insufficiency of cadasters of potentially dangerous areas (regularly flooded, particularly seismically dangerous, sill dangerous, avalanche dangerous, tsunami dangerous etc.).

An extremely complicated decision-making (DM) problem before and after extreme situations (ES) emergence has to be solved under uncertainty and multi-objectiveness conditions. Artificial intelligence (AI) methods are used in solution models and methods [1, 2, 3].

But the hope to receive efficient solutions requires additional investigations in many applications.

It is pertinent to note that the information collected from different sources and at different time is aging [4]. To increase the reliability the rate of inquiry into the date transducers and sources is associated with some delay. Moreover, change in the situation during the period of the ES prediction often represents a random process and collection of the precedent and ontological information is always associated with a time factor and variations in the information quality and quantity. This is, by no means, incomplete enumeration of the factors acting on the information aging [4].

The information aging, development of rational knowledge base for making decisions with minimal expenditures of time and material resources when preventing ES and eliminating their results should be taken into account when developing the quantum approach to the knowledge engineering [3] the concept of algorithmic structures of k – knowledge [1,2] and concepts of micro situations $\{Sit_i\}$, $i=\overline{1,n}$ [3]. In this case using data and knowledge systems analysis one should estimate the micro situation taking into account the information aging, its reliability and value of knowledge quanta, revisions or additions of quantitative and qualitative data during estimation and overcoming of the ES results, which act on changing the ES development scenario, machine algebras needed for quantitative and qualitative estimation of the ES. The number and numerical sequence described by the knowledge quanta of the 0th level; the vector or function described by the quantum of the 1st level; the matrix or composition of functions described by the quantum of the 2nd level etc. [1] are needed to reveal micro situations [2, 3] according to the theorems of Godel and Gabor [5, 6]. In this case it is necessary to realize the principles of self-organization of the model, of the outer addition, Godel approach at self-organization of the models, to take into account the outer criteria of models selection, to carry out partitioning of the data table into parts, to use the hypothesis of selection and principle of conservation of freedom in choosing, to apply heuristic methods, to realize simultaneous simulation at different levels of generality of the language of the mathematical description of objects [6].Optimal complexity of the ES prediction models is defined by the uncertainty and multi criteria conditions.

Setting of the problem

The problem – it is necessary to develop models for prediction of natural emergency situations which will give the possibility to raise reliability and safety of the quantitative data of the situations analysis, knowledge base and provide efficiency of prevention and elimination of the natural emergency situations results.

Solution of the problem. The problem of control and prediction of the natural environment Sit. To solve the problem stated above it is offered to introduce the optimal procedures of prediction $\Pr_p$ and search for $\Pr_r$ solution.

The procedures $\Pr_p$ are carried out using the models – $\{Mod\}$, which represent the properties of the natural environment in the ES zone of control and give the possibility to predict the ES coming with a sufficient degree of precision as soon as possible. In so doing the $\Pr_p$ procedures should be realized as best as possible the requirements and characteristics of the statistical model $\{Mod\}$ for defining the set of micro situations for precedent data

$$\{Sit_i\},\ i=\overline{1,I}$$

Notation of the micro situations has the following form presented in fig.1

In this case it is possible to separate a set of the knowledge quanta $\{kz_j\}$, $j=\overline{1,J}$ of the best ontological solutions. Besides the geo information context G_n, $n=\overline{1,N}$, the already obtained ontological experience for the knowledge quanta is singled out in the form of the best rational solutions from the set of resources $\{Res\}$, which can be or must be at the disposal of the decision-making person (DMP).

In the general form the ES class pattern for modeling of the object-oriented mode can be defined as follows:

Emergency situation (ES):=

Group microsituations |for several points of control declaration-concepts of a group –microsituations|

declaration-concepts of a property-properties -notions

group-of microsituations

group-of microsituations :=

Precedent microsituations: ;

microsituations :=

microsituation 1;

microcituation 2

…

microcituation N.

microsituation i:=

central-concept. |

central-concept, geo information context.

secondary-concept, making decisions.

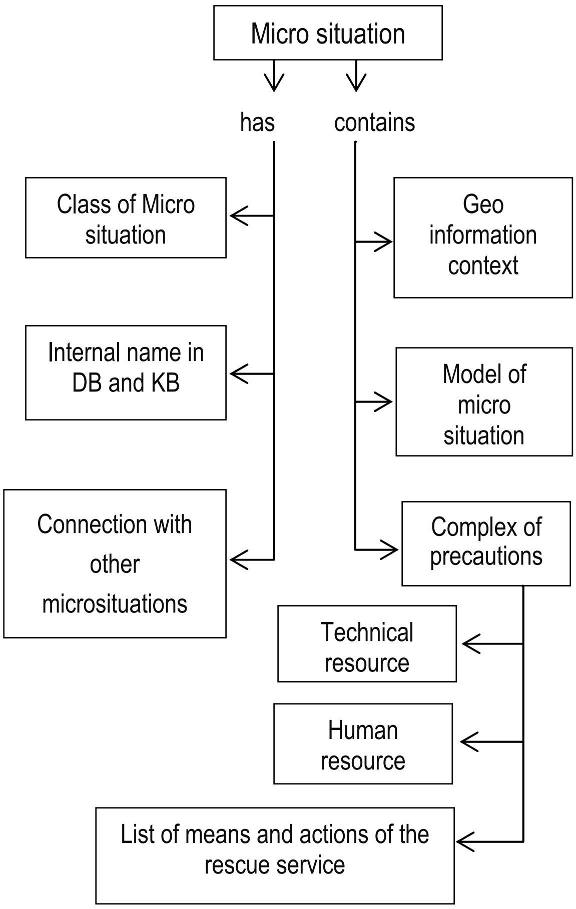

Figure 1. Micro situation notation

Precedent knowledge kz_j quanta are defined for the corresponding geoinformation context in the ontological areas of ES. Procedures Pr_r should ensure making of rational decisions on the basis of the systems analysis of the precedent data and knowledge base with the best ontological decisions. The Pr_r procedures in the rational decision search methods use switching of the controlled and precedent microcituations models built on the data and knowledge bases.

As a whole the problem of simulation under uncertainty conditions can be specified formally by a set of the following form

$$\mathrm{SS} = \left\langle \mathrm{Mod}, \mathrm{R}\left(\mathrm{Mod}, \mathrm{F}\left(\mathrm{Mod}\right), \mathrm{F}\left(\mathrm{SS}\right)\right)\right\rangle,$$

where $\mathrm{Mod} = \left\{\mathrm{Mod}_1, \ldots, \mathrm{Mod}_m\right\}$ – is a set of formal or logical-linguistic models based on the precedent data and knowledge of the situation which realize definite intelligent situation functions;

$\mathrm{R}\left(\mathrm{Mod}\right)$ – is a set of rules for selection of the microsituations representing the data acting the most strongly on the origin of ES, on the needed model or a totality of models in the current situation, i.e. the rules for realization of the mapping $\mathrm{R}\left(\mathrm{Mod}\right): \mathrm{Sit} \to \mathrm{Mod}$, where Sit – is a set of the possible situations (states) which can be either an open one, or $\mathrm{Sit}' \to \mathrm{M}$, where Sit' – is some set of the generalized microsituations (states), for example, normal (standard), anomalous or emergency, the model change takes place when falling within them;

$\mathrm{F}\left(\mathrm{Mod}\right) = \left\{\mathrm{F}\left(\mathrm{Mod}_1\right), \ldots, \mathrm{F}\left(\mathrm{Mod}_m\right)\right\}$ – is a set of the modification rules of the models $\mathrm{Mod}_m, m = \overline{1, M}.$.

Each rule $\mathrm{F}\left(\mathrm{Mod}_m\right)$ realizes the mapping

$$\mathrm{F}\left(\mathrm{Mod}_m\right): \mathrm{Sit}'' \times \mathrm{Mod}_m \to \mathrm{Mod}',$$

where $\mathrm{Sit}'' \subseteq \mathrm{Sit}, \mathrm{Mod}_m'$ – is some modification of the model Mod_m;

Mod_m – is the modification rule of the proper model system SS – of its base constructions $\mathrm{Mod}, \mathrm{R}\left(\mathrm{Mod}\right), \mathrm{F}\left(\mathrm{Mod}\right)$ and, probably, of the rule $\mathrm{F}\left(\mathrm{SS}\right)$ itself, i.e. $\mathrm{F}\left(\mathrm{SS}\right)$ realizes a diversity of mappings (or a complex mapping)

$$\mathrm{F}\left(\mathrm{SS}\right): \mathrm{Sit}''' \times \mathrm{Mod} \to \mathrm{Mod}',$$

$$\mathrm{Sit}''' \times \mathrm{R}\left(\mathrm{Mod}\right) \to \mathrm{R}'\left(\mathrm{Mod}\right),$$

$$\mathrm{Sit}''' \times \mathrm{F}\left(\mathrm{Mod}\right) \to \mathrm{F}'\left(\mathrm{Mod}\right),$$

$$\mathrm{Sit}''' \times \mathrm{F}\left(\mathrm{SS}\right) \to \mathrm{F}'\left(\mathrm{SS}\right),$$

where $\mathrm{Sit}''' \subseteq, \ \mathrm{Sit}''' \cap \mathrm{Sit}' = \varnothing, \ \mathrm{Sit}''' \cap \mathrm{Sit}'' = \varnothing$ i. e. the given type modification rules are used in the situations when the available sets of models, selection rules and modification rules are insufficient for searching for a decision (decisions) in the problematic situation at hand. In this case both the internal means for models and rules (hypotheses) generation, and the external meta knowledge representing the pragmatic aspect of the problematic situation can be used for modification of $F\left(SS\right)$.

The particularity of the ES appearance is associated with variations in the environment, the decision-making is accompanied by limitations or insufficient resources which are available to a DMP. The decision which has been made is generally called a rational one. Such a decision is made in the course of a very limited moment

$t_m \in [t_n, t_k]$, where t_n – is the interval low boundary, t_k – is the interval upper boundary, but sometimes even this time is insufficient. Thus it is offered to use the data and knowledge precedents ontological experience in the given work to solve this complicated problem.

Ontological quantitative and qualitative precedents distinguished for successful and qualitative solution should be used in the constructive solution to prevention or eliminate the ES results, as it was mentioned above.

In this case it is necessary to strive for the optimal decision using the allowable resource set $\{Res_c\}$, $c = \overline{1, C}$

$$Res^0 = \arg \underset{Res_c}{\text{extr}}\, Q(Res_c),\ c = \overline{1, C},$$

where the symbol $\arg\text{extr}Q(Res_c)$ makes it possible to define Res_c – quantitative and qualitative means of evacuation, announcement, building-assembly means for elimination of the ES results or its prevention, communication means etc.

So, to eliminate results or prevent the ES it is important that the decisions made by the DMP should be timely in the specified time interval and solve the problem in a sufficiently complete and complex form. That is why it is necessary to solve the multicriteria problem of optimization taking into account the local criteria presented by the criteria finite sequence

$$Q^{\Sigma} = \arg \underset{Res_i \in \{Res\}}{\text{extr}} \langle Q(Res) \rangle,\ \forall i = \overline{1, K},$$

where K – is the number of local criteria;

Q^{Σ} – is the local criteria finite sequence presentation, among them there can be: minimization of a risk, material resources for prevention or elimination of the ES results, minimization of time expenditures for searching rational solutions, time for announcement of population about the ES threat, maximization of protective constructions reliability etc.

In this case the valid decision of the set problem can be presented in the following form:

$$\{X_k, X_q, Mod, Sit, kz, Q\} \xrightarrow{\{Pr_p, Pr_r\}} Res^0.$$

Mod – is the model of the ENS presentation should reflect the connection between natural situations with the search of the managerial, organizational solutions and will require the necessary resources – Res, directed to prevention or elimination of the emergencies consequences which ensure the minimum risk for a human being vital activity $\Re$.

In other words, to solve the problem set above for the controlled situation of the environment in the specified controlled region it is necessary to develop the model of the ENS in the following form:

$$Mod_m = \underset{r_i^m \in \Re}{\text{extr}}\, Mod\{X_k, X_q, \Re, Res\}.$$

Integration of the indicated elements in one model can exist if the following regularities are taken into account: A – associations; Π – sequences; K – classifications; KL – clusterizations; Pr – predictions.

Association occurs in the case if the current problematic natural situation Sit_t, where t – is current time and preceding or the precedent situation occurred earlier Sit_i were related. There is a communication $A : \mathrm{Sit}_t \to \mathrm{Sit}_i$.

For Π it is true $\Pi : \mathrm{Sit}_i^{t-1} \to \mathrm{Sit}_i^t$ as there is a sequence of situations connected in time.

Using the classifications $\mathrm{Sit}_i = \mathrm{Kl}\left\{\left(\mathrm{Sit}_i \in \mathrm{Kl}_{kr}\right) \vee \left(\mathrm{Sit}_i \in \mathrm{Kl}_{\neg kr}\right)\right\}$, where K_{kr} – is a class of emergencies, and $K_{\neg kr}$ – is a class of not emergency situations, the features are revealed through the introduced microsituations [1, 2, 4], which characterize the group of situations, one or other situation belongs to this group [2, 3]. This is performed through the analysis of the already classified situations and formulation of some set of rules [3, 4].

Clusterization of differs from the classification in that the groups themselves are not set in advance $\mathrm{Sit}_i = \mathrm{Kl}\left\{\left(\mathrm{Sit}_i \in \mathrm{Kl}_{kr}\right) \vee \left(\mathrm{Sit}_i \in \mathrm{Kl}_{\neg kr}\right)\right\}$. The Data Mining means separate independently different similar data groups using the clusterization.

Under conditions of uncertainty and multicriteriality the informative core of the offered knowledge-oriented microsituation approach to prediction of the ES and decision-making before and after the ES rise is solution of the following problems decision:

1. Formalization of different level k – knowledge, estimation of sets of microsituations for these levels, taking into account the information aging and self-organization of the ES mathematical models corresponding to the principles of the non-final decisions of D. Gabor, external addition of Godel and mass selection of A.G. Ivakhnenko.
2. Identification (recognition), proximity to the standard situation.
3. Prediction of ES.

The standard microsituation is defined on the basis of systems analysis of a set of microsituations of knowledge quanta of $\alpha -, \beta -, \lambda -$ uncertainty for presentation of cluster of each level using models and methods for the models self-organization. The proximity of the standard microsituation makes it possible to group together the knowledge quanta for every level by the most influencing factors for the specified geoinformational context. The generalized standard microsituation is defined for all precedents and ontologies. The current controlled situation is compared to the generalized standard microsituation. The comparison results are based the on the self-organizing models of knowledge quanta of $\alpha -, \beta -, \lambda -$ uncertainty.

1. Estimation of the standard microsituation of the set of microsituations of knowledge quanta of $\alpha -, \beta -, \lambda -$ uncertainty for the geoinformation context situation being analyzed.

1.1. Estimation of the knowledge quanta microsituations.

Statement 1. The principle of the non-ultimate solutions offered by D. Gabor, 1971: "…each uniserial procedure can be changed for a multiserial one on retention of the sufficient freedom in choosing several best solutions in every step of self-organization" is valid at systems analysis of the precedent data on ES.

Statement 2. Selection of solutions is impossible on the basis of the precedent data coincidence with current indices of the situation in the region being controlled and should correspond to the principle of the external addition which is associated with indispensable fulfillment of Godel theorem (Naguel, Newman, 1970): "...only the external criteria based on a new information make it possible to synthesize the object true model hidden in the noised experimental data".

None axioms system can be logically closed: one can always find such a theorem for the proof of which the external addition will be required – extension of the initial axioms system.

1.2. Base of data and precedent knowledge accumulation

Statement 3. Data and knowledge are aging. Digital representation of the continuous signal (temperature, pressure, humidity of environment etc.) in the form of the readings totality hampers further reconstruction of the continuous form of the signal, moreover, it is necessary to take into account the information "aging" factor (Efimov A.N.) in the system of control with a closed circuit stipulated by its delay in the feedback circuit. The action of the information delay and the signal continuous form restoration method on the system error is growing proportional to the frequency of the signals being converted and processed. Moreover, the concepts, statements and knowledge also are "aging" and require a regular renewal.

2. Models self-organization.

Statement 4. Long-term weather forecast is possible on the basis of use of the heuristic principle of mass selection at the cost of detection of factors acting the most on ES emergence with the help of microsituations and introduction of the models quality criteria. Such a principle of models self-organization was proposed by A.G. Ivakhnenko (1982): "...the model of the optimal complexity results in the course of the most expedient gradual complication of the self-organizing model at reaching the minimum of the external criterion of its quality".

Each of the system models is oriented to processing of some type of uncertainty. In particular, models and methods, using the approximate set apparatus for operating with incomplete and contradictory information, are effective in the situations of maximal uncertainty when there is no additional information on the ES identification problem.

As an additional information becomes available, for example, in the form of probabilities for the rules, the integrated approach combining methods of the approximate sets and probability theory can be applied, this increases the degree of probability of recommendations produced by the system for a decision-making person (DMP). With the complete information about a problematic situation at hand the solutions can be reliable and received as a result of the multicriteria optimization problem solution.

It should be noted that ES characterize the data and knowledge of the environment state $\{X_k, X_q\}$, $k = \overline{1,K}$, $q = \overline{1,Q}$, and the decision making is associated with the resource parameters $\{\mathrm{Res}_f\}$, $f = \overline{1,F}$, DMP can use them or influence on them. As a whole the state in the ES region can be presented as $\{Sit_n\}$, $n = \overline{1,N}$ in simulation.

For ES simulation it is possible to use the method of Kolmogorov-Gabor, where the ideas of self-organization and mechanisms of the living nature crossing (hybridization) and selection (choosing) are applied. It is possible to describe the model F(x) by the results of environment observations for the zone of the ES control. In this case the structure of the F(x) model is unknown.

Traditionally there is a sampling of N observations in the database to estimate the precedent information about ES:

$$\begin{array}{ll} \{X(1) & Sit(1)\} \\ \{X(2) & Sit(2)\} \\ & \dots \\ \{X(N) & Sit(N)\} \end{array}$$

The most complete dependence between the inputs X(i) and outputs $\{Sit_n\},\ n=\overline{1,N}$ can be presented with the generalized polynomial of Kolmogorov-Gabor.

For $X=\{x_1,x_2,...,x_i,...,x_j,...,x_N\}$ the polynomial has the form:

$$Sit = a_0 + \sum_{i=1}^{N} a_i x_i + \sum_{j=1}^{N}\sum_{i\le j} a_{ij} x_i x_j + \sum_{i=1}^{N}\sum_{j\le i}\sum_{k\le j} a_{ijk} x_i x_j x_k + \dots$$

where all coefficients a are unknown.

When constructing the model (when defining the coefficients values) the criterion of regularity (precision) can be used as the criterion:

$$\overline{\varepsilon^2} = \frac{1}{N}\sum_{i=1}^{N}(Sit_i - f(x_i))^2 .$$

It is necessary that

$$\overline{\varepsilon^2} \to \min .$$

To ensure the raise the zero error can be ensured in the given sampling if to rise the degree of the model polynomial. If as a result of this there are N nodes of interpolation then it is possible to built a whole family models, each of them will give a zero error when passing through the experimental points

$$\overline{\varepsilon^2} = 0.$$

Generally nonlinearity degree is taken no higher than $n-1$, if n – is the number of the sampling points. Let us symbolize by Sl – the complexity of the model (it is defined by the number of Kolmogorov-Gabor polynomial members). The value of the error $\overline{\varepsilon^2}$ depends on the model complexity.

At the first stage of simulation the complexity of the ES model will be raised at the expense of the generalized estimate of the microsituations $\{Sit_i\},\quad i=\overline{1,n}$ for the values $X=\{x_1,x_2,...,x_i,...,x_j,...,x_N\}$ at different time for the precedent values of such ES. For such an ES the standard value of the precedent microsituation is defined

$$\{Sit_h^{et}\},\quad h=\overline{1,H}$$

where H – is the general number of ES which are used for accumulation of the precedent data from the ontological sources for ES close to the ES type being considered. An expert defines the proximity by the type.

The knowledge quantum is defined at the next simulation stage using Euclidian metric. Therewith as the complexity increases it will decline first and it will rise then. But we need to choose such an optimal complexity at which the error will be a minimal one. Furthermore, the following moments can be singled out if the errors action is taken into account:

With different level of errors the dependence $\overline{\varepsilon^2}$ on the complexity Sl will be changed preserving the general direction (it should be kept in mind that initially it will show a decrease with the increase in complexity, but then it will grow).

With the increase in the errors level the value of $\min\limits_{Sl}\overline{\varepsilon^2}$ will grow.

With the increase in the level of errors $Sl = \arg\min \overline{\varepsilon^2}$ will decrease. In this case $\overline{\varepsilon^2}(Sl_0) > 0$, if the noise level is not zero.

Godel incompleteness theorem:

Each formal logical system contains a number of statements and theorems which can be neither disprove, nor prove remaining in the frameworks of this system of axioms.

In this case this theorem means that the sampling is always incomplete.

One of the ways to overcome this incompleteness is the principle of the external addition. An additional sampling (control) is used as an external addition, the points of this sampling were not use when training the system (i.e. when searching for the evaluating values of Kolmogorov-Gabor polynomial coefficients).

The search for the best model is realized in the following manner:

The whole sampling falls into the training sampling and the control one: $N_{vyb} = N_{obuch} + N_{pruf}$.

The values $\hat{a}_0, \hat{a}_i, \hat{a}_{ij}$ are defined from the training sampling N_{obuch}.

The best models are chosen from the control sampling N_{pruf}.

The input vector has the dimensionality $N \ (X = \{x_1, x_2, ..., x_N\})$.

The principle of freedom in choosing (inconclusiveness of the intermediate solution):

For each pair x_i and x_j the partial descriptions (of the whole C_N^2) type are constructed:

or $\hat{Sit}^{(Sl)} = \varphi(x_i, x_j) = a_0 + a_i x_i + a_j x_j, \quad Sl = 1 \ldots C_N^2$ (linear);

or

$$\hat{Sit}^{(Sl)} = \varphi(x_i, x_j) = a_0 + x_i + a_j x_j + a_{ii} x_i^2 + a_{ij} x_i x_j + a_{jj} x_j^2, \quad Sl = 1 \ldots C_N^2$$

(quadratic).

1. We define coefficients of these models using the method of least squares (MLS) making use of the learning sampling. I.e. we find $\hat{a}_0, \hat{a}_1, \ldots, \hat{a}_j, \ldots, \hat{a}_N, \hat{a}_{11}, \ldots, \hat{a}_{ij}, \ldots, \hat{a}_{NN}$.

2. Further on we find an estimate for every of these models using the control sampling

$$\overline{\varepsilon_{Sl}^2} = \frac{1}{N_{pruf}} \sum_{i=1}^{Npruf} \left[Sit(k) - \hat{Sit}_k^{(Sl)} \right]^2,$$

where $Y(k)$ – is the real output value in the k-th control point of the control sampling;

$\hat{Y}_k^{(Sl)}$ – is the output value in the k – th point of the control sampling according to the s – th model) and then we define F of the best models.

$$z_I = \varphi^{(2)}\left(x_i, x_j\right) = a_0^{(2)} + a_1^{(2)} x_i + a_2^{(2)} x_j + a_3^{(2)} x_i^2 + a_4^{(2)} x_i x_j + a_5^{(2)} x_j^2 .$$

The estimate here is the same as in the first series. Selection of the best ones is realized again in the same way, but $F_2 < F_1$. The process of the series construction is repeated so long as the error mean square will fall. When the increase in the error $\overline{\varepsilon^2}$ is obtained, then the process is stopped.

If the partial descriptions are quadratic ones and the number of the polynomial series is Sl, then we receive the polynomial degree $k = 2^{Sl}$.

As opposed to the conventional methods of statistical analysis it is possible to receive sufficiently complicated dependence with such approach even having such a short sampling.

There is a problem: some variables x_i and x_j, not acting on the output data, can be thrown away.

In this connection the following modification is offered: to feed y_i and x_j at the second layer, i.e.:

$$z_I = a_0^{(2)} + a_1^{(2)} y_i + a_2^{(2)} x_j + a_3^{(2)} y_i^2 + a_4^{(2)} y_i x_j + a_5^{(2)} x_j^2 .$$

This is important in the presence of a high level of noise to ensure nonbiasedness.

Two methods emerge for choosing the best candidates of partial description fed at a definite layer.

1. Criterion of regularity (precision) $\overline{\varepsilon_{pr}^2}$.

$$\overline{\varepsilon^2} = \frac{1}{N_{pruf}} \sum_{i=1}^{N_{pruf}} \left(Sit_i - Sit_i^*\right)^2 ,$$

$$\overline{\Delta_{pruf}^2} = \frac{\sum_{i=1}^{N_{pruf}} \left(Sit_i - Sit_i^*(x)\right)}{\sum_{i=1}^{N_{pruf}} \left(Sit_i - \overline{Sit}\right)^2} .$$

Criterion of nonbiasedness. Let us take the whole sampling and divide it into two parts $R = R_1 + R_2$. The first experiment: R_1 – is the learning sampling, R_2 – is the control sampling; define the model outputs $y_i^*, i = 1 \ldots R$. The second experiment: R_2 – is the learning sampling, R_1 – is the control sampling; define the model outputs $y_i^{**}, i = 1 \ldots R$, and compare. Criterion of nonbiasedness:

$$n_{sm} = \frac{1}{N} \sum_{i=1}^{R} \left(Sit_i^* - Sit_i^{**}\right)^2$$

The less is n_{sm}, the greater is nonbiased the model.

Such a criterion is defined for each partial description of the first level and then n_{sm} is found for the level as a whole

$$n_{sm} = \frac{1}{F}\sum_{i=1}^{F} n_{sm,i}^{(1)}$$

for F of the best models. In a number of versions $F = 1$. The same is observed at the second layer $n_{sm}^{(2)}$.

The selection process lasts till this criterion stops decreasing, i.e. till meeting the condition

$$n_{sm}^{(2)} \to \min .$$

Conclusion

The intelligent model of the multi-objective presentation of an emergency taking into account separation of knowledge quanta and precedent micro situations based on data of successful or rational decisions has been developed. The model of the situation, which features a priori indefinability taking into account the information aging, has been developed; random phenomena are joined by the cause and effect relations in this model.

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Bibliography

Efimov A.N. Information: value, aging, distance M,. "Znanie",1978. P.- 64. (Novelty in life, science and engineering, Series "Mathematics for Cybernetic Engineers" published monthly since 1967) (Rus)

Kuzemin A, Fastova D, Yanchevsky I. Methods of adaptive extraction and analysis of knowledge for knowledge-base construction and fast decision making // International Journal on Information Theories&Applicatios.– Bulgaria. – 2005. – Vol. 12, №1.– P. 93 – 99

Kuzemin A., Sorochan M., Y.anchevskiy I., Torojev A. The use of situation representation when searching for solutions in computer aided design systems International Journal // Information Theories & Applications. – 2005. – Vol.11, №1 .– P. 101 – 107.

Martin Davis, "The Incompleteness Theorem", in Notices of the AMS vol. 53 no. 4 (April 2006), p. 414.

Olivier Bousquet, Stéphane Boucheron, Gábor Lugosi «Introduction to Statistical Learning Theory» Advanced Lectures on Machine Learningю Lecture Notes in Computer Science Volume 3176, 2004, pp 169-207.

Sirodzha IB Quantum models and artificial intelligence for decision-making and management. - Kiev, Naukova Dumka, 2002, P.- 490.(Rus)

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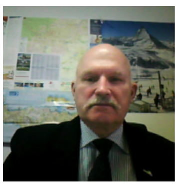

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