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SCENARIO-COGNITIVE MODELING OF COMPLEX SYSTEMS BASED ON EVENT-DRIVEN IDENTIFICATION OF FACTOR DYNAMICS

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Abstract. This paper is devoted to methodological problems of increasing the effectiveness of scenario analysis and modeling of development processes in socio-economic systems. The corresponding results can be used in management decision support systems for proactive evaluation of their effectiveness. Several limitations of the traditional approach to scenario-cognitive modeling are considered; due to these limitations, the resulting scenario neglects key events directly affecting the assessment of the current situation and decision-making. A novel approach is proposed to identify and analyze the dynamics of factor values when studying the model as well as to form additional scenario-event interrelations between the factors in order to increase the adequacy of the model to the situation. A computational algorithm is developed to analyze the dynamics of factor values of the model. This algorithm is implemented and tested within the program-analytical complex of scenario modeling. Finally, an example of using the algorithm is given.

Keywords: control, scenario approach, graph models, simulation modeling, event identification, factors, verification.

INTRODUCTION

The preparation and proactive evaluation of the effectiveness of management decisions, especially on a long horizon, require a sufficiently clear understanding of possible alternatives in situation development both at the controlled object and in its environment. The scenario approach is an effective tool for proactive analysis of such alternatives. This approach involves the mathematical apparatus of sign digraphs and has recently become a key structural element of decision support systems. Its potential lies in the broad functionality of simulation models for the comprehensive proactive analysis of various-nature interrelated and interdependent processes and phenomena that reflect possible development trends for the controlled object and its environment [1].

Nowadays, there is rich experience in solving a wide range of practical problems in the scenario analysis of organizational control processes [2]. At the same time, the results of the practical application of the scenario approach have been generalized and several technological limitations have been identified. Due to some limitations, it is impossible to completely analyze the influence of the dynamics of the key model factors and (or) the moments of change in these dynamics on the properties and characteristics of the development processes of complex controlled objects under study (socio-economic, sociopolitical, information, and other systems). This inevitably affects the quality of generated scenarios.

1. PROBLEMS OF THE TRADITIONAL APPROACH TO SCENARIO-COGNITIVE MODELING

The scenario analysis technology is methodologically based on the mathematical model of signed, weighted signed, and functional signed digraphs. This model is an extension of the classical graph counterpart. Besides a digraph $G(X, E)$, where X and E are finite sets of vertices and arcs, respectively, the model includes other components. First, a set of parameters $V=\{v_i, i \le N=\|X\|\}$ is introduced for vertices: a parameter $v_i \in V$ is assigned to each vertex x_i. Second, an arc transformation functional is defined: a sign ("+" or "–"), a weight ($+W_{ij}$ or $-W_{ij}$), or a function $f_{ij}(v_i, v_j)$ is assigned to each arc (v_i, v_j) [2].

In a practical interpretation, the parameters of graph vertices are key quantitative or qualitative indicators (factors), and the structure of the signed graph reflects their causal relations. An aggregate of values of the vertex parameters in the graph model describes a particular state of the situation at a given time. A change in the values of vertex parameters generates a pulse and is treated as the transition of the system from one state to another.

For a long time, modeling technologies based on this mathematical apparatus mainly evolved through the creation and analysis of fuzzy cognitive models of weakly structured systems [3, 4] and the use of complex functional interrelations between the factors [1, 2] in scenario investigation.

Despite the obvious advantages of the scenario modeling methodology in increasing the effectiveness of management decisions, the traditional approach imposes serious limitations on the models (see the discussion above) as follows:

- Only a limited number of factor characteristics can be used to calculate modeling results.
- It is impossible to reconfigure the model structure flexibly depending on the current (intermediate) modeling results, which determine the need to change the model within the goals of study.
- It is difficult to implement inter-model (especially, hierarchical) relations.
- There are problems with the practical interpretation of modeling results and, accordingly, their comprehension by decision-makers.
- There are problems with organizing interconnections with external data sources, information systems, etc.

The limited number of characteristics of the factors used to calculate modeling results and form interrelations in the model structure significantly narrows the possibilities to generate and analyze the obtained scenarios. Also, it narrows the set of processes and phenomena that make up these scenarios. Modeling involves only three types of components (the values of factors, the values of pulses, and simulation steps); as a result, the generated scenarios may neglect key events for analyzing the situation and making management decisions. Such events can be connected with the type and pattern of factor dynamics, the time step of dynamics change (e.g., from increase to decrease), the absolute or relative period of preserving the pattern of factor dynamics, etc. (The relative period is the ratio of the time interval when the dynamics of a certain factor have a particular pattern to the scenario simulation horizon, expressed in percentage terms.)

Fixed causal relations between model factors far from always match the properties of the modeled object or situation. Often, the model structure should be flexibly changed depending on the dynamics of significant factors obtained during simulation. For example, an increased value of a significant factor and a decreased value of another one on a certain time interval (in simulation steps) may require additional managerial actions to respond to the changes in the situation. These actions will be modeled by modifying the properties of certain causal relations (in the elementary case, reducing or increasing the mutual influence of relevant factors of the model), activating or deactivating some factor or group of factors, introducing additional external pulses into the selected substructures of the model, etc. Thus, in order to improve the adequacy of the model to the controlled object or the situation, it is necessary to reconfigure flexibly the structure and composition of model factors depending on the assessment of the current model results.

For a complex object or situation under study, it may be necessary to combine several models of controlled objects, related subject domains, or processes and systems into one multimodel. In such cases, scenario modeling technologies based on the apparatus of signed functional graphs involve three main types of interrelations as follows:

- direct causal relations between factors within each subsystem;
- mediated (indirect) relations between individual subsystems (in contrast to the first type, an unambiguous and almost instantaneous response of one subsystem to any change in the factor values of another subsystem may be absent in such relations: they are determined through the analysis of this change);
- mediated hierarchical relations between the subsystems of different levels (e.g., "government—region—the sphere of activity"); they are determined through the analysis and evaluation of the response of each higher level to situation trends at lower levels, considering the independence, autonomy, and co-subordination of these subsystems.

2. EXPANDING THE FUNCTIONALITY OF SIMULATION MODELING BY ANALYZING FACTOR DYNAMICS

Let the pattern of dynamics be revealed for a certain factor during simulation. If it requires establishing (correcting) a mediated relation in the simulation process, it will be considered an *event*, and the corresponding relation will be called a *scenario-event* relation. For brevity, *factor dynamics* will refer to the pattern of the temporal dependence of factor values during simulation.

According to this definition, events are formed by changes in the characteristics of factors significant for the analysis of the behavior of the modeled object. If a subset of significant factors is selected from the set of model factors, then a change in the dynamics of at least one significant factor (e.g., from increase to decrease) should automatically lead to a new event in the scenario. Of course, this is only the simplest example of the criterion to form a new event. Generally, an event may include aggregates of characteristics of factor dynamics with complex logical expressions.

Consider the basic types of factor dynamics, assigning to each *i*th factor a corresponding identifier SC_i of the current dynamics (Table 1).

Table 1

The identifiers of elementary factor dynamics

Scenario identifier, *SC*	The type of factor dynamics
0	Not defined (not calculated)
1	Increase
2	Decrease
3	Constant value
4	Fluctuations with bounded amplitude
5	Divergent fluctuations
6	Convergent fluctuations

As an example, Fig. 1 shows the simplified hierarchical multimodel structure.

Often, the upper-level subsystem in a hierarchical structure responds only to certain long-term dynamics of the factors included in the lower-level subsystem. For example, let V_{1i} be the *i*th factor (vertex) of the first-level subsystem, V_{2j} be the *j*th factor (vertex) of the second-level subsystem, and I_{2j} be the pulse coming from the *2j*th factor. Then the weight of the arc D_{2j1i} can be defined asD_{2j1i} = iif (SC_{2j} = 1, 2I_{2j}, 0) with the following meaning: if the parameter of the 2*j*th vertex has increased for some period, the pulse 2I_{2j} will pass along the arc D_{2j1i} at each subsequent time step. Otherwise (no increase in the dynamics), this arc will disappear (its weight will be 0).

In addition, the two subsystems may have the following relation. Let V_{1i} and V_{1j} be the *i*th and *j*th factors (vertices) of the first-level subsystem, respectively. Then the weight of the arc D_{1j1i} can be defined as

$$D_{1j1i} = \text{iif } (SC_{2j} = 2, -2I_{1j}, I_{1j}).$$

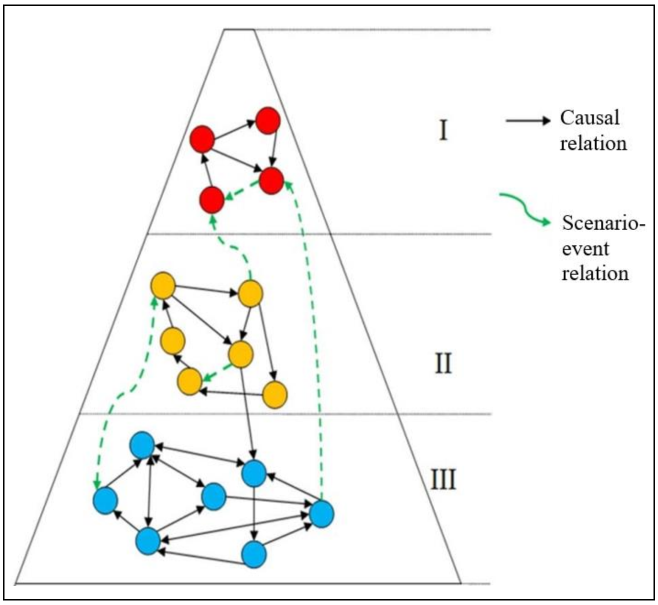


Fig. 1. Scenario model hierarchy.

In other words, if the factor of the 2*j*th vertex has decreased, the pulse -2I_{2j} will pass along the arc D_{1j1i} at each subsequent time step. Otherwise (no decrease in the dynamics), the weight of this arc will be 1. (There may be no direct arc between the two subsystems.) Note that generally, the factor dynamics of one subsystem may influence the weight of an arc between some factors of the other subsystem. Of course, more complex conditions can be specified using the logical operations of negation (NOT), disjunction (OR), conjunction (AND), and exclusive disjunction (XOR). For example, the following construction is possible: several factors grouped by a certain attribute (model layer) will be activated (or deactivated) if the value of the factor v_k has increased during the last ten steps, or if the value of the factor v_m has decreased during 40% of the past simulation interval, or if a positive pulse has arrived from the factor v_r.

To expand modeling functionality for complex systems and processes, we modify the process of forming analytical data to create scenario-event interrelations between factors and introduce the following parameters:

- *P*, the frequency of calculating factor dynamics (the frequency of monitoring for the modeled system);
- *K*, the number of simulation steps used to analyze factor dynamics (the depth of monitoring for the modeled system);
- *Z*, the number of simulation steps used to reflect the time delay in the situation analysis and decision-making process.

The general modeling scheme with the identification of scenario events is presented in Fig. 2.

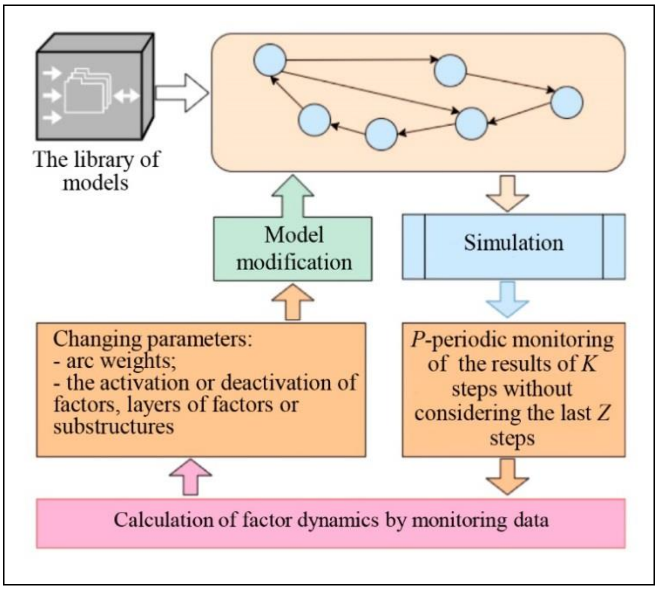


Fig. 2. The general scheme of event identification in scenario modeling.

For example, let P = 20, K = 10, and Z = 2. Then the data on the factor dynamics of given vertices will be updated every 20 simulation steps; the values obtained for the last 10 steps will be used for the calculation without considering the last 2 steps (e.g., due to the delayed response of the control action to the situation monitoring data). For example, at the 40th simulation step, the recalculation procedure of the indicators is launched at steps from the 28th to 38th. Between runs of the recalculation procedure, the factor dynamics are assumed to have the same pattern.

The analytical component of the model structure can be further expanded by extending the use of scenario parameters in the functional conditions to activate or deactivate factors (or their layers).

Scenario-event identification algorithm

The algorithm is developed to use the results of factor dynamics analysis in the simulation process. The results of calculations are the variables characterizing the type of factor dynamics. Let an elementary scenario of a factor be the type of its dynamics at a given time step.

The identifiers of the elementary scenario types are combined in Table 1. Obviously, the entire set of possible factor dynamics can be characterized by two regression lines [5, 6]. The points of local maxima and minima are used as the initial data of the analysis for the chosen range of factor values; the upper and lower regression lines are constructed accordingly (Table 2). This approach refines the more general method of dummy variables for inflection points: the points of local maxima and minima are separated into two samples for independent trend assessment and further comparison. Note that assessing the rest of the sample is not required in such calculations.

In the case of a linear change of a factor, the two regression lines coincide.

Let f_i denote the logarithmic value of the ith factor of the model. The algorithm for analyzing the dynamics of f_i on the time interval between steps t_k and t_n includes the following stages.

Stage 1. Determine the sets of local minimum $f_i^{\min}$ and maximum $f_i^{\max}$ values (inflection points) of the model factor and the corresponding simulation steps $t_i^{\min}$ and $t_i^{\max}$ for the chosen range. Discard the "false" (insignificant) inflection points.

Stage 2. Calculate the cardinalities $\mathrm{col}_i^{\min} = \left| f_i^{\min} \right|$ and $\mathrm{col}_i^{\max} = \left| f_i^{\max} \right|$ of these sets.

Stage 3. If $\mathrm{col}_i^{\min} < 2$ or $\mathrm{col}_i^{\max} < 2$, proceed to Stage 4; otherwise, to Stage 8.

Stage 4. Determine the average values of two variables (time and factor value) for the chosen time range of the factor dynamics:

$$t_i^{\mathrm{avg}} = \frac{(t_n - t_k)}{n-k},$$

$$t_i^{\mathrm{avg}} = \sum_{j=k}^{n} \frac{t_i(j)}{n-k+1},$$

$$f_i^{\mathrm{avg}} = \sum_{j=k}^{n} \frac{f_i(j)}{n-k+1}.$$

Stage 5. Calculate the sample covariances and variances for these variables:

$$S(f_i) = \mathrm{cov}(f_i, f_{i,}) = \sum_{j=k}^{n} \frac{(f_i(j) - f_i^{\mathrm{avg}})^2}{n-k+1},$$

$$\mathrm{cov}(f_i, t_i) = \sum_{j=k}^{n} \frac{(f_i(j) - f_i^{\mathrm{avg}})\,(t(j) - t_i^{\mathrm{avg}})}{n-k+1},$$

$$S(t_i) = \mathrm{cov}(t_i, t_i) = \sum_{j=k}^{n} \frac{\left(t(j) - t_i^{\mathrm{avg}}\right)^2}{n-k+1}.$$

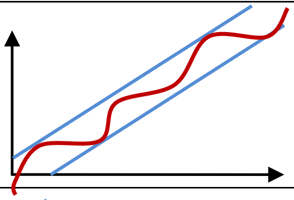
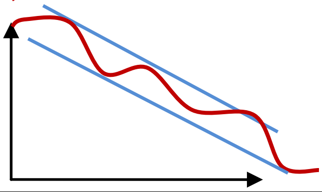
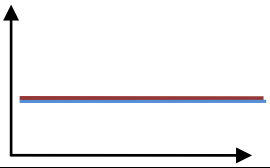
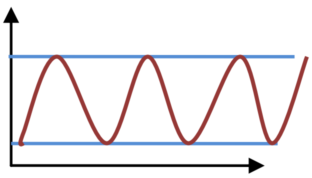
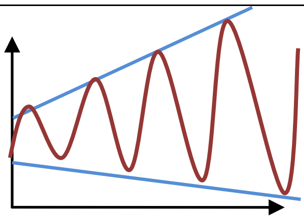
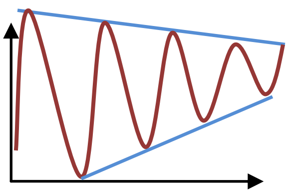
Stage 6. Calculate the slope of the regression lines:

$$\theta_i = \mathrm{cov}(f_i, t_i) / \mathrm{cov}(t_i, t_i).$$

(It shows how much the minimum or maximum value of the factor will change with increasing the step.)

Table 2

The regression characteristics of elementary scenarios

Id	The description of factor dynamics	Factor dynamics and regression lines	The slopes of regression lines	
			Upper	Lower
1	Increase		> 0	> 0
2	Decrease		< 0	< 0
3	Constant value		= 0	= 0
4	Fluctuations with bounded amplitude		= 0	= 0
5	Divergent fluctuations		> 0	< 0
6	Convergent fluctuations		< 0	> 0

Stage 7. Calculate the coefficient of determination R^2 (a measure of the linear relation between the variables—the trend and the values—in the observation data and the quality of the regression):

$$\text{if } \operatorname{cov}(f_i, t_i) = 0(t_i, t_i) = 0, \text{ then } R^2 = 0;$$

$$\text{otherwise, } R^2 = \left(\frac{\operatorname{cov}(f_i, t_i)}{\sqrt{\operatorname{cov}(t_i, t_i)} \times \sqrt{\operatorname{cov}(f_i, f_{i,})}} \right)^2 .$$

The minimum value of the coefficient of determination is 0. In this case, the trend of the linear relation between the variables is not detected: the model does not explain the dynamics of the variable f_i.

The maximum value of the coefficient of determination is 1. In this case, the trend of the linear relation between the variables has the greatest extent: all the values of f_i are on the same straight line $f_i = \alpha_i + \theta_i * t$. This means that the model fully explains the dynamics of the variable f_i.

Thus, the coefficient of determination satisfies the inequality $0 \le R^2 \le 1$. For empirical data in classical econometric calculations, the extreme values of R^2 are unattainable. However, the simulated results are not random variables, and regression analysis is used to classify scenarios as a machine learning method. Therefore, the coefficient of determination can be 1, e.g., if the dynamics of the variable strictly increase or decrease according to the simulations.

Pass to Stage 12.

Stage 8. Determine the average values for each set $f_i^{\min}$, $f_i^{\max}$, $t_i^{\min}$, and $t_i^{\max}$:

$$f_i^{\min\,avg} = \sum_{j=1}^{col_i^{\min}} \frac{f_i^{\min}(j)}{col_i^{\min}},$$

$$t_i^{\min\,avg} = \sum_{j=1}^{col_i^{\min}} \frac{t_i^{\min}(j)}{col_i^{\min}},$$

$$f_i^{\max\,avg} = \sum_{j=1}^{col_i^{\max}} \frac{f_i^{\max}(j)}{col_i^{\max}},$$

$$t_i^{\max\,avg} = \sum_{j=1}^{col_i^{\max}} \frac{t_i^{\max}(j)}{col_i^{\max}}.$$

Stage 9. Calculate the sample covariances and variances for these sets:

$$\mathrm{cov}\left(f_i^{\max}, f_i^{\max}\right) = \sum_{j=1}^{col_i^{\max}} \frac{(f_i^{\max}(j) - f_i^{\max\,avg})^2}{col_i^{\max}},$$

$$\mathrm{cov}\left(t_i^{\max}, t_i^{\max}\right) = \sum_{j=1}^{col_i^{\max}} \frac{(t_i^{\max}(j) - t_i^{\max\,avg})^2}{col_i^{\max}},$$

$$\mathrm{cov}\left(f_i^{\max}, t_i^{\max}\right) = \sum_{j=1}^{col_i^{\max}} \frac{(f_i^{\max}(j) - f_i^{\max\,avg})\,(t_i^{\max}(j) - t_i^{\max\,avg})}{col_i^{\max}},$$

$$\mathrm{cov}\left(f_i^{\min}, f_i^{\min}\right) = \sum_{j=1}^{col_i^{\min}} \frac{(f_i^{\min}(j) - f_i^{\min\,avg})^2}{col_i^{\min}},$$

$$\mathrm{cov}\left(t_i^{\min}, t_i^{\min}\right) = \sum_{j=1}^{col_i^{\min}} \frac{(t_i^{\min}(j) - t_i^{\min\,avg})^2}{col_i^{\min}},$$

$$\mathrm{cov}\left(f_i^{\min}, t_i^{\min}\right) = \sum_{j=1}^{col_i^{\min}} \frac{(f_i^{\min}(j) - f_i^{\min\,avg})(t_i^{\min}(j) - t_i^{\min\,avg})}{col_i^{\min}}.$$

Stage 10. Calculate the coefficient of determination R^2 by analogy to Stage 7.

Stage 11. Calculate the slope of the regression lines for the two sets of inflection points:

$$\theta_i^{\max} = \mathrm{cov}\left(f_i^{\max}, t_i^{\max}\right) / \mathrm{cov}\left(t_i^{\max}, t_i^{\max}\right),$$

$$\theta_i^{\min} = \mathrm{cov}\left(f_i^{\min}, t_i^{\min}\right) / \mathrm{cov}\left(t_i^{\min}, t_i^{\min}\right).$$

Stage 12. Typify the elementary scenario based on the calculated regression parameters.

Stage 13. Determine the other parameters of the regression lines to visualize the simulation results. The regression line has the form $y = \propto + \theta x$. The parameters for the upper and lower regression lines are calculated by the formulas:

$$\propto_i^{\max} = f_i^{\max\,avg} - \theta_i^{\max} t_i^{\max\,avg},$$

$$\propto_i^{\min} = f_i^{\min\,avg} - \theta_i^{\min} t_i^{\min\,avg}.$$

(Recall that they are constructed by the inflection points of the local maxima and minima.)

Stage 14. Obtain the regression lines

$$f_i^{\max}(t) = \propto_i^{\max} + \theta_i^{\max} t,$$

$$f_i^{\min}(t) = \propto_i^{\min} + \theta_i^{\min} t,$$

and plot their graphs to visualize the results.

3. THE SCENARIO-EVENT IDENTIFICATION ALGORITHM: AN EXAMPLE OF APPLICATION

As an example to illustrate the algorithm, we present the results of studying a well-known ecological control model for a region; for details, see [2]. The structure of this model is shown in Fig. 3.

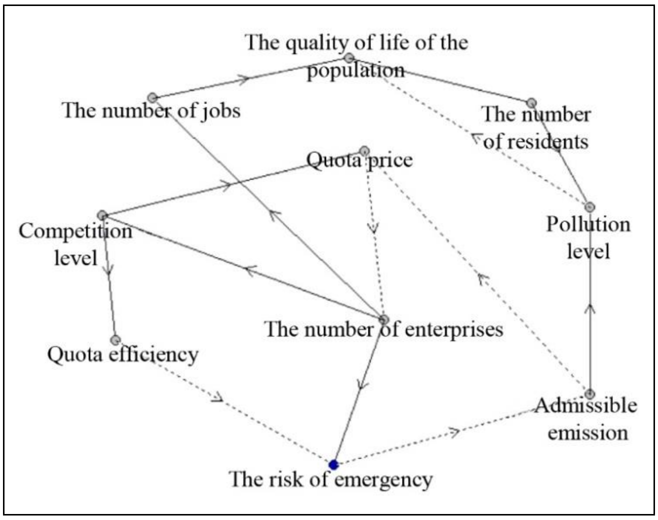


Fig. 3. The structure of the regional ecological control model.

The graphs in Fig. 4 demonstrate the dynamics of two factors of the emergency control model with regression lines (left) and their regression lines separately (right). The scenario automatically generated according to the analysis results is described in Table 3; the calculated values of the regression parameters are combined in Table 4. Capital letters indicate the factors whose dynamics formed a new event in the scenario.

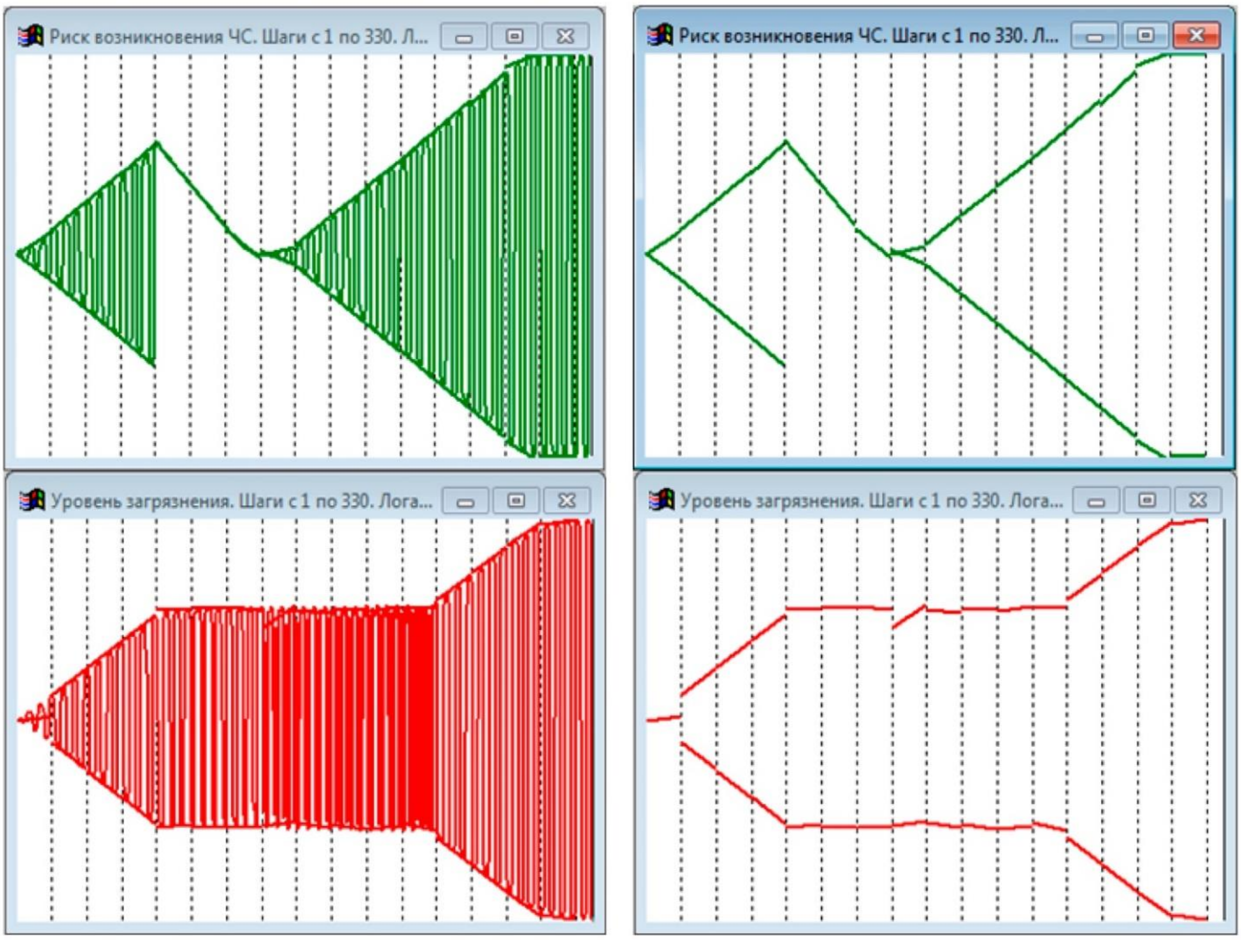


Fig. 4. The dynamics of model factors on steps 1–330 (logarithmic values): the risk of emergency (top) and pollution level (bottom); the graphs with regression lines (left) and the regression lines separately (right).

Table 3

Text description of the scenario

Stage	Steps		The dynamics of factors forming the events (stages) of the scenario
	from	to	
1	1	20	“The risk of emergency” – Constant value
			“Pollution level” – Constant value
2	21	40	“THE RISK OF EMERGENCY” – UNSTABLE
			“POLLUTION LEVEL” – INCREASE
3	41	100	“The risk of emergency” – Unstable
			“POLLUTION LEVEL” – UNSTABLE
4	101	120	“THE RISK OF EMERGENCY” – DECREASE
			“POLLUTION LEVEL” – INCREASE
5	121	140	“The risk of emergency” – Decrease
			“POLLUTION LEVEL” – UNSTABLE
6	141	160	“The risk of emergency” – Decrease
			“POLLUTION LEVEL” – DECREASE

Table 3 (continued)

Stage	Steps		The dynamics of factors forming the events (stages) of the scenario
	from	to	
7	161	180	"THE RISK OF EMERGENCY" – UNSTABLE
			"POLLUTION LEVEL" – INCREASE
8	181	220	"The risk of emergency" – Unstable
			"POLLUTION LEVEL" – DECREASE
9	221	240	"The risk of emergency" – Unstable
			"POLLUTION LEVEL" – INCREASE
10	241	260	"The risk of emergency" – Unstable
			"POLLUTION LEVEL" – DECREASE
11	261	320	"The risk of emergency" – Unstable
			"POLLUTION LEVEL" – UNSTABLE
12	321	340	"THE RISK OF EMERGENCY" – STABLE STATE
			"Pollution level" – Unstable

Table 4

The calculated regression parameters

Steps		Vertex name	Id	Scenario description	R^2_{max}	R^2_{min}	θ_{max}	θ_{min}
from	to							
1	2	3	4	5	6	7	8	9
		...						
20	40	The risk of emergency	5	Unstable	0.9997	0.9965	0.230	–0.235
20	40	Pollution level	5	Unstable	1.0000	0.9932	0.247	–0.235
40	60	The risk of emergency	5	Unstable	0.9925	0.9990	0.232	–0.231
40	60	Pollution level	5	Unstable	1.0000	0.9970	0.230	–0.232
60	80	The risk of emergency	5	Unstable	0.9966	0.9999	0.235	–0.234
60	80	Pollution level	5	Unstable	0.9947	0.9991	0.232	–0.234
80	100	The risk of emergency	2	Decrease	0.9994	0.9994	–0.344	–0.344
80	100	Pollution level	1	Increase	0.9356	0.7590	0.013	0.033
100	120	The risk of emergency	2	Decrease	1.0000	1.0000	–0.339	–0.339
100	120	Pollution level	5	Unstable	0.9999	0.9997	0.005	–0.010
120	140	The risk of emergency	2	Decrease	0.9601	0.9601	–0.235	–0.235
320	340	Pollution level	5	Unstable	0.9965	0.9975	0.034	–0.029
		...						

Thus, analytical results are used to form functional dependences in the model structure; moreover, it is possible to automatically generate the resulting scenario, graphically and in the form of event-driven text of the scenario. Typical descriptions of factor dynamics significant for the formation of events ("Decrease," "Increase," etc.) can be replaced with the terms of the subject domain. Such a representation of the scenario is familiar to the decision-maker. For example, the term "Favorable" can be assigned to the factor "Political situation" in the case of "Increase." For each factor in the program-analytical complex, the user can specify a particular set of terms to describe its dynamics. These terms—the vocabulary of the subject domain—are stored in a single file of the model structure.

This example can also serve to illustrate the hierarchy of relations. Assume that there is a hierarchy of models (Fig. 5): the regional ecological control model (Model *B*) is linked to the social stability model (Model *A*). That is, both

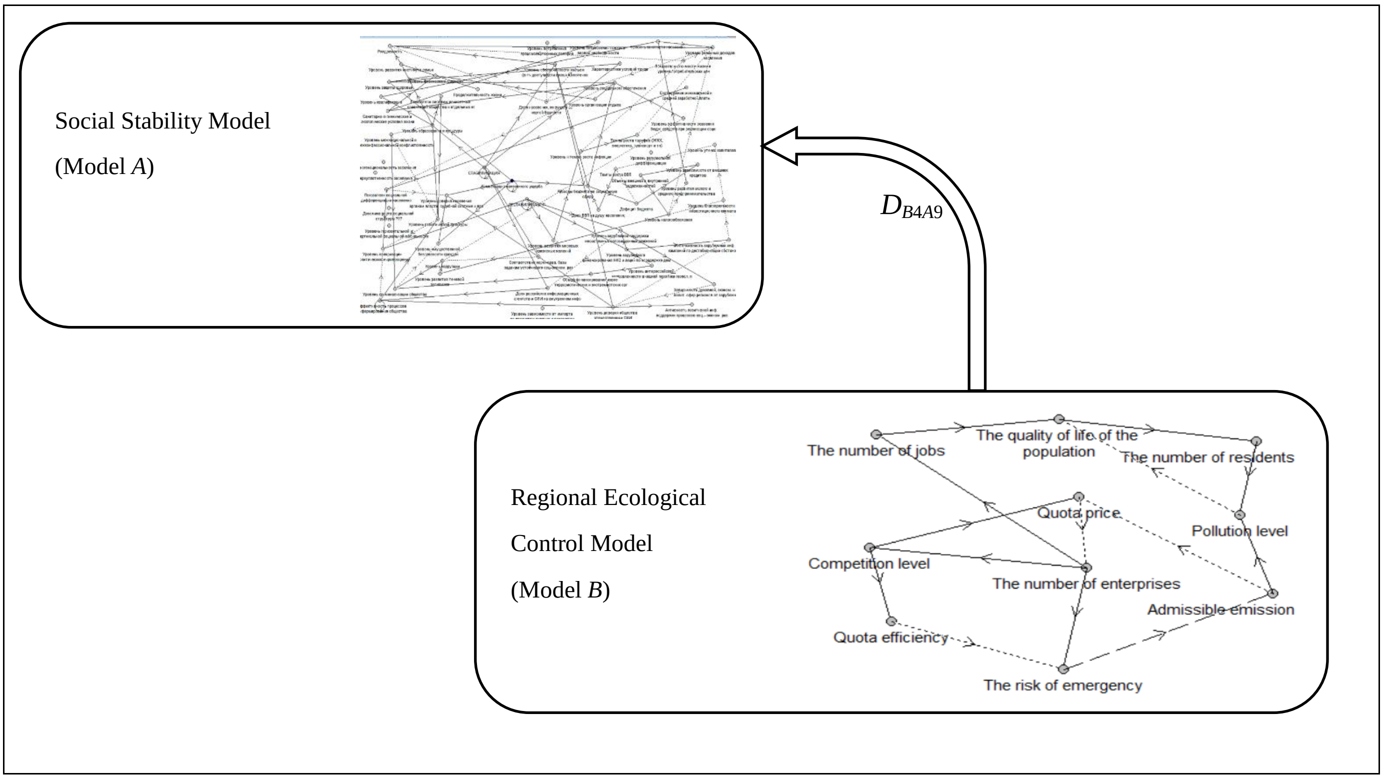


Fig. 5. An example of a scenario model hierarchy.

models have the factor "Quality of life of the population" in their structure (identifiers $A9$ and $B4$). Models A and B have a relation, i.e., the arc D_{B4A9}.

Social tension may be due to the decreased quality of life of the population: not one-time fluctuations of this factor but long-term trends with a negative history. This situation agrees well with reality. In addition, suppose that strictly negative trends have a much stronger influence on social tension than other trends. Therefore, it seems reasonable to form the relation between Models A and B based on scenario-event identification. The weight of the arc D_{B4A9} can be defined as

$$D_{B4A9} = \text{iif}\,(SC_{B4} = 2 \text{ and } TS_{B4} = 10 \text{ and } \text{dol}_{B4}(2) = 25,\ 2I_{B4},\ 0).$$

This means the following: if the parameter of the vertex $B4$ has "Decrease" ($SC_{B4} = 2$) and such dynamics persist for 10 simulation steps ($TS_{B4} = 10$) and on 25% of the entire simulation horizon in aggregate ($\text{dol}_{B4}(2) = 25$), the arc D_{2j1i} will be equal to $2I_{B4}$ at each subsequent time instant. If the dynamics of the parameter differ, the influence is negligible. In this simplified example, the situation under consideration means the disconnection of the arc. (Of course, the model may alternatively include nested logical expressions reflecting such situations.)

CONCLUSIONS

The scenario modeling technology presented in this paper has been implemented in the pilot version of the program-analytical complex of scenario modeling to computerize the processes of scenario investigation of socio-economic systems [2]. This complex is used in decision support systems for proactive evaluation of their effectiveness based on the analysis of generated alternative scenarios of the development of situations, processes, and phenomena under study.

The proposed approach to expanding modeling functionality has been validated in practice, showing high effectiveness in the scenario investigation of complex models of socio-economic systems. This approach and the scenario-event identification algorithm have been applied to implement the mechanism of event-driven functional relations between model factors, in particular the multilayer (hierarchical) representation of the multimodel structure. Within this mechanism, expert knowledge in various subject domains can be effectively used to plan and analyze development processes for socio-economic and political systems.

The algorithm has been implemented to improve the visualization of simulation results through scenario description in terms of the subject domain. In addition, it has become possible to transfer the current analytical data in real time to external software complexes. In particular, such an interface has been recently implemented for the Panorama geoinformation system and information space monitoring systems.

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