Fuzzy dynamic models of situation analysis, decision support, and control in complex systems

Armen Bagdasaryan and Dubravka Gavric
Department of Mathematics, College of Engineering and Technology, American University of the Middle East, Kuwait
E-mail: armen.bagdasaryan@aum.edu.kw; dubravka.gavric@aum.edu.kw

Abstract. In this work we consider the theoretical foundations of building fuzzy models of system dynamics, analysis of situations, their development, and control in complex weakly-structured systems based on knowledge modeling and expert preferences. The proposed fuzzy models can serve as mathematical tool for analyzing the behavior of a system in various situations, as well as to serve as the basis of specialized computer simulation systems of decision support in unstructured fuzzy situations. As is known, decision making problems under uncertainty can be divided into two groups: decision making in static situations and decision making in dynamic situations. For decision making in static situations, the methods and models of decision support based on the theory of choice are developed. For decision-making in dynamic situations, the dynamic models, including those based on expert knowledge, are used. To build a dynamic model of a situation, the expert knowledge about physical, economic, or social processes occurring in a system, which are represented as a cognitive map, is employed. The models of analysis of static situations are focused on evaluation and ordering of alternatives, and models of analysis of dynamic situations are focused on generating of strategies (alternatives) to achieve the targets of control, that is, the desired target state of the situation. Thus, one of the aims of this paper is to develop mathematical methods for constructing integrated decision support models based on fuzzy models of hierarchical estimation, control, and fuzzy cognitive modeling.

1. Introduction
The methods of cognitive analysis and modeling of weakly structured and fuzzy systems, fuzzy processes, and situations have been actively developed in the last decades. These methods, that in addition facilitate decision making processes, are mostly based on different types of fuzzy cognitive models, such as fuzzy cognitive maps [1] and their modifications [2], rule-based fuzzy cognitive maps [6, 7, 8] and generalized models of rule-based fuzzy cognitive maps [9], fuzzy relational cognitive maps [12].

Using these models, one has the tools for qualitative and quantitative analysis and modeling of fuzzy systems and situations under stochastic and non-stochastic uncertainty, thus solving a wide class of analytic problems, e.g. stability analysis, detection of unwanted cycles, analysis and estimation of system characteristics, analysis of mutual influence of system factors – both direct and indirect, scenario analysis under various actions, analysis of reachability of target goals and situations, prognosis of system parameters development, etc., as well as solving the system modeling problems, such as modeling of system dynamics with and without control actions, modeling of system state dynamics under restricted resources, and the others [3].
The decision making problems under uncertainty can be divided into two groups: decision making in static situations and decision making in dynamic situations. For decision making in static situations, the methods and models of decision support based on the theory of choice are developed. The meaning of these methods is to order the set of possible solutions to the problem (alternatives) and then select the best alternative using the subjective utility function of the expert. The construction of the utility function is based on the extraction of an individual system of preferences, assessments and expert knowledge. For decision-making in dynamic situations, the dynamic models, including those based on expert knowledge, are used. To build a dynamic model of a situation, the expert knowledge about physical, economic, or social processes occurring in a system, which are represented as a cognitive map, is employed. The decision making in this case is to predict the development of situations and to find a strategy for steering the situation from the current state to the desired target state.

The decision-making process includes the following steps: (1) analysis of the situation, (2) generation of solutions — alternatives, (3) evaluation of alternatives, (4) selection of the best alternative. The methods discussed above provide decision support at different stages of the decision process: models of analysis of static situations are focused on evaluation and ordering of alternatives, and models of analysis of dynamic situations are focused on generating of control strategies (alternatives) to achieve the targets of control, that is, the desired target state of the situation [3, 13]. Obviously, these models complement each other.

In this work we consider the theoretical foundations of building fuzzy models of system dynamics, situations analysis, and control in complex weakly-structured systems based on knowledge modeling and expert preferences. One of the main aims of this paper is to propose the mathematical methods for constructing integrated decision support models based on fuzzy models of hierarchical estimation, control, and fuzzy cognitive modeling. The proposed models can serve as mathematical tool for analyzing the behavior of a system in various situations, as well as to serve as the basis of specialized computer simulation systems of decision support in unstructured fuzzy situations.

2. The model of cognitive analysis and modeling

The methodology of cognitive modeling is relied upon the construction of subjective model of situation that reflects the knowledge about the situation evolution. The cognitive model is represented in the form of a signed digraph in which the vertices are the factors of the situation, and weighted arcs represent the cause-effect relations – the strength of influence between the factors of the situation; the weights can take on the values from the interval $w_{ij} \in [-1, 1]$. The value $w_{ij} = -1$ characterizes the most negative influence, $w_{ij} = 1$ corresponds to the most positive influence of the factor $f_i$ on the factor $f_j$, and the value $w_{ij} = 0$ means the absence of direct influence of $f_i$ on $f_j$. The positive influence of the factor $f_i$ on the factor $f_j$, $w_{ij} > 0$, means that the increase of the value of $f_i$ implies the increase of the value of $f_j$, and the decrease of $f_i$ implies the decrease of $f_j$. However, when $w_{ij} < 0$, the increase of the value of $f_i$ leads to the decrease of the value of $f_j$, and vice versa. At the same time, the simultaneous influence of factors on each other is also considered with the different values of $w_{ij}$ and $w_{ji}$.

One of the problems that can be solved by fuzzy cognitive maps is the prediction of situation development. To get a prognosis about the situation development, we need the following: a set of factors of a situation under study, $F = \{f_j\}, j = 1, 2, \ldots, m$; the scales $X_i$ for all factors; a cognitive map $(F, W)$, where $F$ is a set of vertices – factors of a situation, $W = |w_{ij}|$ is the adjacency matrix, $w_{ij}$ are weights; the initial state of the situation given by the vector $X(0) = (x_1^0, x_2^0, \ldots, x_m^0)$ of the values of all factors of the situation; and the initial vector $P(t) = (p_1, p_2, \ldots, p_m)$ of increments of the factors.

It is required to find the state vector $X(t), X(t + 1), \ldots, X(t + n)$ of the situation and the vector of increments $P(t), P(t + 1), \ldots, P(t + n)$ of the state of the situation at the consecutive
discrete time moments \( t, t + 1, \ldots, t + n \), where \( n \) is the modeling tact. 

The prognosis of situation development is defined by the matrix equation 
\[
P(t + 1) = P(t) \circ W,
\]
where the symbol \( \circ \) means the max-product rule:
\[
p_i(t + 1) = \max_j (p_j(t) \cdot w_{ij}).
\]

The \( i \)-component of the vector of situation development prognosis \( p_i(t + 1) \in P(t + 1) \) is represented by the pair
\[
\langle p_i(t + 1), c_i(t + 1) \rangle,
\]
where \( p_i(t + 1) \) is the value of the increment of a factor, and \( c_i(t + 1) \) is the consonance of the value of a factor. The cognitive consonance of the value of a factor is used to characterize the subjective confidence in the results of modeling. When \( c_i(t) = 1 \) the subjective confidence in the factor increment \( p_i(t) \) is considered to be maximal; when \( c_i(t) = 0 \) the subjective confidence in the factor increment \( p_i(t) \) is considered to be minimal.

The state of a situation is defined by the pair
\[
\langle X(t + 1), C(t + 1) \rangle,
\]
where
\[
X(t + 1) = X(t) + P(t + 1)
\]
is the state vector of the situation; the component of this vector is \( x_i(t + 1) = x_i(t) + p_i(t + 1) \); the cognitive consonance \( c_i(t + 1) \in C(t + 1) \).

In this case, the plausible prognosis of situation development is given by the pair
\[
\langle X(m), C(m) \rangle,
\]
where \( X(m) = (x_1(m), x_2(m), \ldots, x_m(m)) \) is the vector of the values of situation factors, and \( C(m) = (c_1(m), c_2(m), \ldots, c_m(m)) \) is the vector of consonance of the factors values at \( t = m \).

3. The hierarchical model of situation analysis

The hierarchical decomposition of the global control goal in a complex system is quite natural technique to cope with the complexity [3, 10]. The control goal in weakly structured systems can be represented as a hierarchical structure, in the form of criteria tree. The global goal is decomposed into criteria that characterize the control goal, and the criteria are divided into more specific subcriteria. The hierarchy is built by "top-down" structural decomposition technique. The process of structural decomposition of control goal comes to the end when it reaches the non-decomposable further criteria \( k_1, k_2, \ldots, k_n \) called the leaf criteria. We assume the positive connection (feedback) between criteria at different levels of hierarchy, that is, the implementation of lower-level criteria does not lead to the decrease in the possibility to implement the upper-level criteria. Moreover, it is assumed that the functional dependence between criteria at the adjacent levels of the hierarchy is linear. The above principles lead to the hierarchical structure which is represented by an acyclic digraph \( G = (V, E) \), with a set of vertices \( V \) that correspond to the set of criteria, and a set of arcs \( E \). The arc \( (i, j) \in E \) means that the criterion (vertex) \( i \) directly depends on the criterion \( j \) in the graph. The level of leaf criteria is followed by the level of alternatives \( A = \{K^J\}, J = 1, 2, \ldots, M \). Each alternative determines the decision characterized by certain properties that coincide with the leaf criteria \( k_i \). The problem is to find the best alternative \( K^J \in A \) with respect to the global control goal located at the highest level of the
hierrarchy. The best alternative is found by the method of analysis of fuzzy hierarchies that allows one to define the expert preferences in the form of interval or fuzzy estimates.

Using the expert knowledge we obtain a weighted binary relation \( \rho \left\{ \left( k_m, k_l \right), r_{ml}^i \right\} \), where the number \( r_{ml}^i > 0 \) defines the preference degree of criterion \( k_m \) compared to criterion \( k_l \). By the pairwise comparison of estimates we get the weights \( y_{ij}, y_{ij} \in (0, 1) \), of all arcs \((i, j)\) in the hierarchy coming out of \( i \) vertex.

To define the weights of vertices (criteria) we set the weight of the global goal at the highest level of hierarchy to be maximal, \( \nu_0 = 1 \). Then the weights of vertices-criteria at the lower level are determined by the top-down recurrent recount of all the vertex weights (criteria weights):

\[
\nu_i = \sum_{j \in \Gamma_i^{-1}} y_{ij} \nu_j, \quad i \in L_1, \quad \nu_i = \sum_{j \in \Gamma_i^{-1}} y_{ij} \nu_j, \quad i \in L_2, \ldots \quad \nu_i = \sum_{j \in \Gamma_i^{-1}} y_{ij} \nu_j, \quad i \in L_N,
\]

where \( \Gamma_i^{-1} = \{ j \mid (j, i) \} \); \((j, i)\) is an arc in the graph; \( L_1, L_2, \ldots, L_N \) are the criteria levels in the hierarchical model; \( \nu_i \) are the weights of leaf criteria.

The weights of alternatives \( K^J \in A \) are determined by means of the pairwise comparison of alternatives over the set of all the leaf criteria. Solving the problem of ordering, using the binary relation \( \rho \) and taking into account the preferences, we get a vector of values that the given alternative can take on the set of values of each leaf criterion, that is, \( K^J = (y_{k_1}^J, y_{k_2}^J, \ldots, y_{k_n}^J) \), where \( y_{k_i}^J \in [0, 1] \) is the value from a set of values of \( i \)-th leaf criterion which can be assigned to this criterion in the alternative \( K^J \), and \( n \) is the number of leaf criteria.

To evaluate the goal reachability by different alternatives we define a function

\[
F : (K^J, \nu_i) \to \mathbb{R}, \quad i = 1, 2, \ldots, n
\]

where \( \nu_i \) are the weights of leaf criteria in the hierarchical model; \( K^J \in A \) are alternatives; \( j = 1, 2, \ldots, M \).

Since the functional dependence between criteria in the hierarchical model is linear, then the goal reachability is given by

\[
F (K^J, \nu_i) = \sum_{i=1}^{n} y_{k_i}^J \nu_i, \quad i = 1, 2, \ldots, n
\]

which is a linear convolution.

4. Compatibility of factors in fuzzy cognitive model and hierarchical model

The integration of the hierarchical model and the dynamic cognitive model of situation requires the development of a compatibility scheme of situation factors described in both models, and constructing of a mapping of values of situation factors of the cognitive model into the values of leaf criteria of the hierarchical model. To solve this problem, we utilize the structural-functional decomposition of a situation and consider the situation separately in structural and functional aspects. Using the structural decomposition we describe a situation in the form of a "whole-part" hierarchy \( \langle S, \chi \rangle \) and determine the basic factors \( F = \{ f_{ij} \} \) of constituents of the situation \( s_i \), where \( s_i \) is an element of a set \( S = \{ s_i \} \) that characterize the "whole-part" relation \( \chi \) given on the set \( S \) and that reflect the whole part of the situation and its constituents. Using the functional decomposition we construct the cognitive maps for each element of a situation \( s_i \in S \) represented by the pair \( (F_i, W_i) \), where \( F_i = \{ f_{ij} \} \) are the factors of the element \( s_i \) and \( W_i = \{ w_{ij} \} \) is the adjacency (weights) matrix of mutual influence of factors – the laws of functioning of the element of the situation \( s_i \). The collection of cognitive maps \( (F_i, W_i) \) represent the hierarchical cognitive
map of a complex situation \((F, W)\), where \(F = \cup F_i\) is a set of situation factors for each element \(s_i\), and \(W\) is the adjacency matrix of the digraph that describe the complex situation and that includes all the matrices \(W_i\) of element of the situation and relations between them. Then among all the factors of the cognitive model, we find the factors that are compatible with the leaf criteria of the hierarchical model, thus defining the subset \(\Phi \subset F\) of factors of the cognitive model that correspond to the leaf criteria \(k_i, i = 1, n\).

Formally, the fuzzy hierarchical cognitive map is defined by

\[
FHC\text{M} = (F, W, \chi, \tau),
\]

where \(F, W,\) and \(\chi\) are as defined above, and \(\tau = \{\tau_{ij}\}\) is a set of compatibility degrees between the factors \(\Phi \subset F\) and the leaf criteria \(k_i\) in the hierarchical model.

For each leaf criterion \(k_i\) in the hierarchical model we have defined a set of possible values in the form of a vector \(\left(y_{1i}^k, y_{2i}^k, \ldots, y_{Mi}^k\right)\) of the arc \((i, j), j = 1, 2, \ldots, M\), that connects the alternative \(K^j\) with the leaf criterion \(k_i\). In other words, to each component of the vector \(\left(y_{1i}^k, y_{2i}^k, \ldots, y_{Mi}^k\right)\) corresponds the alternative \(K^j\). We order the set of all the values of the leaf criterion \(k_i\) and the corresponding alternatives and thus get the scale for the criterion \(k_i\)

\[
k_i : Y_{ki} = \{y_{1i}^k, \ldots, y_{Mi}^k\}, \quad y_{ij}^k \in [0, 1], \quad J \in \{1, 2, \ldots, M\}.
\]

Then we define the alternative that we are going to estimate as the vector of values of leaf criteria \(K^J = (y_{kJ1}, y_{kJ2}, \ldots, y_{kJn})\), where \(y_{kJi} \in [0, 1]\) is the value from the set of values of the scale \(Y_{ki}\) of \(i\)-th leaf criterion, and \(n\) is the number of leaf criteria.

Upon integration of the hierarchical model with cognitive modeling, the alternatives are not determined a priori but are being constructed in the process of situation modeling. Hence, it is required to construct the scale for leaf criteria based on the scales of the corresponding factors of the cognitive model. In general case, one has to build the mapping

\[
\Psi_{km} : \{x_{ij}\} \rightarrow \{y_{km}^j\},
\]

where \(\{x_{ij}\}\) is a set of values of a factor \(f_i\) of the cognitive model, given on the interval \([0, 1]\); \(\{y_{km}^j\}\) is a set of values of the corresponding leaf criterion \(k_m\) of the hierarchy: \(y_{kmi} \in [0, 1]\).

The rules of constructing the mapping \(\Psi_{km}\) that we consider are the following.

(i) an expert (decision maker) determines a one-to-one correspondence between a leaf criterion \(k_m\) of the hierarchical model and a factor \(f_i\) of the cognitive model. The mapping \(\Psi_{km}\) in this case is the identity function, which means that every scale value of the factor is equal to the scale value of the criterion. Thus, \(\Psi_{km} : y_{km}^j = x_{ij}\), where \(j\) is the number of grades in the scale of the factor \(f_i\).

(ii) an expert determines the correspondence between a leaf criterion and a factor of the cognitive model in the form of a correlation, but the rule of positive connection (feedback) for the hierarchical model is not satisfied. In fact, this means that the implementation of lower-level criteria does not lead to the impossibility of implementation of upper-level criteria in the hierarchy. At the same time, there might exist factors in the cognitive model that have the same meaning (close correlation) but decreasing the possibility to implement the criteria at the upper levels. For example, in the hierarchical model the leaf criterion \(k_{m}\) could be quality of control, and the close factor \(f_i\) in the cognitive model could be efficiency of control. To find the compatibility between them in such cases, the mapping \(\Psi_{km}\) has the following form: \(\Psi_{km} : y_{km}^j = 1 - x_{ij}, i = 1, 2, \ldots, j\), where \(j\) is the number of grades in the scale of the factor \(f_i\).

(iii) an expert has found the correlation between a criterion \(k_{m}\) and a factor \(f_i\), but the mapping \(\Psi_{km}\) cannot be defined as above. In this case, the scale of the criterion \(k_{m}\) is constructed and then each value \(x_{ij}\) on the scale of the factor \(f_i\) is put in correspondence the value on the scale of the criterion \(k_{m}\) by the rule: \(\Psi_{km} : \{x_{ij}\} \rightarrow \{y_{km}^j\}\).
5. Evaluation functions in the cognitive model

The prognosis of situation development in the system of cognitive modeling is represented by the pair \( (X(m), C(m)) \), where \( X(m) \) is a state vector of the situation at \( t = m \), and \( C(m) \) is a consonance vector of factor values at \( t = m \). This representation may result in the case when different situation development predictions can be characterized by the same state vector \( X(m) \) but different consonance vector \( C(m) \), say \( C_1(m) \neq C_2(m) \). The evaluation of such states should lead to different results. For this reason, the hierarchical model of evaluation should be able to order the situation estimates based on their preferences, taking into account both factor values and its consonance.

In order to use the hierarchical model and the cognitive model together, an evaluation function for each factor of a situation can be defined. The evaluation function is a two-variable function whose arguments are the factor increment and the factor consonance, that is, \( \phi_{x_i} = \sigma_i(p_i, c_i) \). The construction of such a function can be based on expert knowledge with independent expert procedures. However, the process of construction of the evaluation function is a tedious process, especially, for a large number of factors. For this reason, as the evaluation functions we use the monotonic, increasing, functions with parameters

\[
\begin{align*}
\sigma_{x_i}(p_i) &= \text{sgn}(p_i) |p_i^\alpha| \\
\sigma_{c_i}(c_i) &= c_i^\beta, 
\end{align*}
\]

where \( \alpha \) and \( \beta \) are function parameters, \( \alpha > 0, \beta > 0; p_i \) is the increment of \( i \)th factor.

Then the evaluation function has the form:

\[
\phi_{x_i} = \text{sgn}(p_i) |p_i^\alpha| \cdot c_i^\beta.
\]

The different values of parameters \( \alpha \) and \( \beta \) for factor increment and consonance allows one to model various expert preferences and their characteristics.

Thus, the evaluation vector of factor increments is defined as follows

\[
\Theta : (P(m), C(m)) \rightarrow (\phi_{x_1}, \phi_{x_2}, \ldots, \phi_{x_m}),
\]

where \( \Theta = (\sigma_1(p_1, c_1), \sigma_2(p_2, c_2), \ldots, \sigma_m(p_m, c_m)) \) is a vector of evaluation functions; \( (P(m), C(m)) \) is the prognostic increment of factor values and their consonances in the cognitive model; \( (\phi_{x_1}, \phi_{x_2}, \ldots, \phi_{x_m}) \) is the evaluation vector of prognostic increments of factor values in the cognitive model.

Then, the component of the state vector of a situation \( X(m) = (x_1(m), x_2(m), \ldots, x_m(m)) \) is defined as

\[
x_i(m) = x_i^0 + \phi_{x_i},
\]

where \( x_i^0 \) is the initial state of \( i \)th factor of the cognitive model.

6. Integrated decision support model

The hierarchical model of estimation of situation control alternatives and the dynamical cognitive model of the situation describe the same situation but from different viewpoints and in different aspects. The hierarchical model describes the situation form the viewpoint of situation control goal which is expressed in terms of expert preferences, their weights, and the values of leaf criteria in a certain scale. The dynamic cognitive model describe a qualitative dynamics of situation development that can be defined with the use of qualitative scales of situation factors.

The integrated decision support model for weakly structured fuzzy situation is represented by the following 7-tuple

\[
DSM = \langle FCM, HM, \Phi, \Psi, \Theta, P, F (X^0_K(m), \nu_i) \rangle.
\]

The components of \( DCM \) are defined as follows.
• FCM is a fuzzy cognitive model defined as
  
  (i) \( FCM = (\langle F, W \rangle, X, X(0)) \), where \( (F, W) \) is a cognitive map of a situation: \( F \) is a set of factors of the situation, \( W \) is the incidence matrix of a digraph;
  
  (ii) \( X = \{ X_i \} \) is a set of scales of factors;
  
  (iii) \( X(0) \) is the initial state of the situation, the vector of initial values of all factors of a cognitive model.

• \( HM = (\langle Z, E \rangle, K, Y, \{ \nu_i \}) \) is a hierarchical model of evaluation, where \( (Z, E) \) is a hierarchical acyclic digraph of evaluation: \( Z \) is a set of criteria of different levels of hierarchy, \( E \) is a set of arcs that connect criteria at different levels of hierarchy; \( K = \{ k_i \} \) is a set of leaf criteria located at the lowest level of the hierarchy, \( K \subset Z \); \( Y = \{ Y_i \} \) is a set of scales of leaf criteria; \( \{ \nu_i \} \) is a set of weights of leaf criteria \( K \).

• \( \Phi \) is a set of factors of a cognitive model, \( \Phi \subset F \), similar (compatible) to the leaf criteria \( K \) of the hierarchical model, that is, \( \Phi = \{ f_i \in F, k_j \in K, f_i \approx k_j, j = 1, 2, \ldots, n \} \), where the symbol \( \approx \) means the similarity of factors from the sets \( F \) and \( K \).

• \( \Psi = \{ \psi_i \} \) is a set of mappings from the set of scales of factors \( X \) of a cognitive model to the set of scales of leaf criteria \( Y \) of the hierarchical model, that is, \( \psi_i: X_i \rightarrow Y_i \).

• \( \Theta = (\sigma_1(p_1, c_1), \sigma_2(p_2, c_2), \ldots, \sigma_m(p_m, c_m)) \) is a vector of estimation functions.

• \( P = \{ P^K \} \) is a set of alternatives of the integrated decision support model.

• \( F(X^\Phi_K(m), \nu_i) \) is a function estimating the reachability of the global goal by the alternative of the integrated decision support model.

Now let us define the concept of alternative in the integrated decision support model. Let a set of possible control actions \( P = \{ P^K \} \) is determined, where \( P^K = \{ p_1^K, p_2^K, \ldots, p_m^K \} \) is a vector of increments of factors of a situation at the initial time moment. Then for every control action \( P^K \in P \) we can get the prognosis of the situation development at the consecutive discrete time moments \( X_K(0), X_K(1), \ldots, X_K(T) \), where \( X_K(t) = (x^K_1(t), x^K_2(t), \ldots, x^K_m(t)) \) is a vector of values of all factors of the cognitive model at time moment \( t \). The values of the factors from the set \( \Phi \), directly related with the leaf criteria of the hierarchical model, will also vary. Then the hierarchical model will evaluate the state vector \( \langle X^\Phi_K(0), X^\Phi_K(1), \ldots, X^\Phi_K(T) \rangle \), which means that we obtain the estimates for all consecutive prognosis states \( F(X^\Phi_K(T), \nu_i) \).

Hence, a control action \( P^K \in P \) is referred to as alternative in the integrated decision support model. The estimate of the global goal reachability by the alternative \( P^K \) is the estimation of situation development prognosis \( F(X^\Phi_K(m), \nu_i) \) for this alternative \( P^K \), where \( m \) is the number of factors in the cognitive model.

7. Conclusion

The proposed fuzzy models and the integrated decision support model allows one to implement the following. First of all, the integrated model supports:

• the analysis of situations is based on the global goal decomposition defined by the expert, and on the structural-functional decomposition of situation, which result in the description of behavior – dynamics – of weakly structured situation from general systemic viewpoints.

• generation of (control) solutions, alternatives, by means of the cognitive model.

• the selection of the best solution is based on the evaluation of situation development prognosis obtained by the cognitive model in the hierarchical model of estimation.

Second, a set of alternatives in the integrated model is not fixed and the alternative can be generated, and its evaluation with respect to the reachability of the global goal can be obtained. Third, the integrated model can evaluate the changes in the current state of the situation, which allows using the model in monitoring systems.
The presented fuzzy models and integrated decision support model can serve as the basis for specialized computer simulation systems of decision support in unstructured fuzzy situations, based on knowledge modeling and expert information. More elaborated mathematical models and theoretical details, as well as simulation results and its analysis will be published elsewhere.

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