Fuzzy cognitive modeling of socio-economic systems taking into account the time factor

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Abstract. Analysis and identification of trends in the development of socio-economic and socio-technical systems is a complex problem, the solution of which is an important direction in the development of scientific approaches to management. The use of a cognitive approach based on the construction, structural-parametric identification, and research of fuzzy cognitive maps (FCM) for these purposes is constrained by the complexity of time factor accounting. A review of domestic and foreign sources based on a systematic approach revealed the key areas of time series data Mining, which currently combines statistical, neural network and fuzzy models and technologies for time series analysis (TS), including cognitive approaches. Indirect expert methods used for parametric identification are based on dividing the problem of determining the weights of interaction of factors into simpler subtasks (Saati Method, Jager level method, Churchman-Ackoff method, etc. The elements of the FCM adjacency matrix, which characterizes the mutual influence of concepts, are proposed to be represented as two components – (1) a constant that is indistinctly set by experts; (2) a time-dependent one, the parameters of which are estimated from the analysis of the dynamics of statistical data over a certain period. The use of time-dependent parabolic dependence for setting the elements of the adjacency matrix FCM is proposed. In the further research strict methods for parameterizing dynamic functions that define the level of interaction between NCC concepts can be developed to construct fuzzy cognitive models that explicitly take into account the time factor.

1. Introduction
Analysis and identification of trends in the development of various socio-technical systems is a complex problem, the solution of which is an important direction in the development of scientific approaches to management [1, 11]. For these purposes, the use of a cognitive approach based on the construction, structural-parametric identification, and research of fuzzy cognitive maps (FCM) is constrained by the complexity of time factor accounting [2, 7, 12]. A review of domestic and foreign sources based on a systematic approach allowed us to identify the key areas of intellectual time series...
analysis (Time Series Data Mining), which currently combines statistical, neural network and fuzzy models and technologies for analyzing multidimensional time series (MTS), including cognitive ones [2, 12]. The latter allow us to analyze unclear trends, predict not only the numerical values of the MVR, but also the direction of their change, and even generate a brief description of the behavior of the time series in linguistic form [12].

In general, cognitive modeling refers to the study of the structure, functioning, and development of a system by analyzing its cognitive model based on a cognitive map [4-6]. The cognitive model is an effective tool for evaluating the development of the system, but it does not allow us to obtain quantitative characteristics of the system under study. The cognitive model allows us to assess trends related to the functioning and development of the simulated system, and identify key factors that affect these processes. The model provides search and development of effective solutions for system management, as well as scenario modeling that allows you to identify risks and develop strategies to reduce them [3]. Scenario modeling allows you to predict the state of the simulated system under various control actions and search for alternative solutions that bring the system to the target state.

The main tasks that can be effectively solved using cognitive modeling can be divided into two groups [4]: (1) structural-target analysis tasks; (2) dynamic analysis tasks (o direct problem (“what if”); o inverse problem (“how”). The mathematical apparatus underlying the methods of analyzing cognitive models in the form of fuzzy cognitive maps is fuzzy logic. The fuzzy cognitive model takes into account that the intensity of influences between factors can be constant or variable over time [2, 4, 7]. A cognitive map with an odd W ratio is called a fuzzy cognitive map (FCM).

In the process of constructing and identifying fuzzy cognitive models, there are stages of structural identification (definition of a set of concepts E and a clear relation W over this set); parametric identification (transition from a clear relation W to a fuzzy one with determination of the intensity of influence between factors.

In the process of building FCM, experts are the key source of information. Expert methods used for parametric identification can be direct or indirect. Indirect methods are based on splitting the problem of determining the weights of the interaction of factors into simpler subtasks (the Saati method, the Jager level method, the Churchman-Akoff method, etc.) [5, 9]. If there is statistical information about the values of factors, it can be used to identify the weight coefficients of the relationship between such concepts instead of expert evaluation. However, there are a number of methodological problems associated with the identification of fuzzy cognitive models based on statistical data.

Since the modeled systems are dynamic, statistical information about them is presented in the form of an IMR. Hence, it is necessary to determine the relationship weights based on the analysis of such series [10]. A promising problem is the development of methods for structural identification of FCM based on statistical data using time series analysis methods [5]. In this paper, we propose applying the Granger causality criterion to the structural identification of FCM, where the decision to add a relationship between two factors is made on the basis of an expert representation of the simulated system. If there are statistical data on some concepts of X and Y in the form of MBR, then the Granger criterion can be used to check whether it is appropriate to add a link between them: if X affects Y, then the change in X must precede the change in Y. In addition, the following conditions must be met: X must make a significant contribution to the prediction of Y; but Y must not make a significant contribution to the prediction of X. The Granger causal relationship between time-based MVS is an essential, but not sufficient, condition for a causal relationship between the relevant factors. The final decision on whether to add a link to FCM is up to the experts.
2. Materials and methods
The study uses fundamental methods of system analysis - systems theory, cognitive analysis, algorithm theory, and the theory of multidimensional time series.

To describe the FS support system, based on domain analysis, the NCC was constructed in the form of a weighted directed graph, the structure and parameters of which were set by the adjacency matrix \( A_{ij} \) [5].

The result of formalization of systems in the form of a causal network, has the form:

\[
G = \langle E, W, t \rangle,
\]

where \( E = (e_1, e_2, \ldots, e_k) \) is the set of factors of the simulated system; \( W \) is a binary relation on the set \( E \) that defines the set of cause-and-effect relationships between its elements, \(-1 \leq w_{ij} \leq 1\); \( t \) is the dimensionless time.

Graphically, FCM can be represented as a weighted oriented graph, whose points correspond to the elements of the set, and whose du-GI correspond to the non-zero elements of the relation \( W \). The relation \( W \) can be represented as a matrix of dimension \( n \times n \) (where \( n \) is the number of factors), which can be considered as the adjacency matrix of the graph.

Software implementation of preliminary cognitive modeling was provided using the Strategist computer system developed at the Volgograd state technical University [16]. The system has a user-friendly interface that provides interactive construction, visualization, and research of a fuzzy cognitive model. A special software system was developed to simulate the influence of the time factor on changing relationships between concepts.

3. Results and discussion
Elements of the NCC adjacency matrix, which characterizes the mutual influence of concepts, include two components:
- a constant, vaguely defined by experts,
- a time-dependent, whose parameters are estimated from the analysis of the dynamics of statistical data for a known period.

\[
A = \| a_{ij}(t) \|	ag{2}
\]

where \( A \) is the adjacency matrix of the modeling FCM, \( a_{ij} \) is an element of the matrix \( A \), and \( t \) is dimensionless time.

Then you can write an expression for elements of matrix \( A \):

\[
a_{ij} = \alpha w_{ij,e} + \varphi(t)(1 - \alpha)
\]

\[
a_{ij} = \alpha w_{ij,e} + (1 - \alpha)(A_{ij}t^2 + B_{ij}t + C_{ij})
\]

where \( a_{ij} \) is the element of matrix \( A \); \( w_{ij,e} \) - expert (fuzzy) coefficient of influence of concept \( i \) on concept \( j \); \( \alpha \) - is a dimensionless parameter that takes into account the fraction of time influence on an element of the matrix \( A \); \( A, B, C \) - parameters of the parabolic function;

\[
\varphi(t) = A_{ij}t^2 + B_{ij}t + C_{ij},
\]

specifying the time change of the coefficients of influence of concepts; \( E \) – dimensionless time.

The value of parameters \( A, B \) and \( C \) is chosen from a priori considerations, taking into account the opinions of experts.

For the case of symmetric arrangement of branches of a quadratic parabola (5), we have:

\[
B = 0; \varphi(0)= C; A < 0; \varphi(t_{end}) = 0, \tag{6}
\]

where \( t_{end} \) is the dimensionless completion time of the steady-state simulation process.

In this case, we have a monotonically decreasing function \( \varphi(t) \), which can be used to smoothly change the values of the elements \( a_{ij} \) of the matrix \( A \). The value of parameter \( A \) can be determined from conditions (6) by solving equation (7):

\[
A_{ij}t^2 + C_{ij} = 0,
\]

for \( t = t_{end} \).
In the case when $A \neq 0$ and $B \neq 0$, it is possible to obtain a non-monotonic dependence for $\varphi(t)$. The Interface of the developed program for fuzzy cognitive modeling is shown in Fig. 1-a.

![Interface of the developed program for fuzzy cognitive modeling](image)

Figure 1. Developed programs for fuzzy cognitive modeling with dynamic weights:
- a-input of parameters $A$, $B$, $C$;
- b - FCM graph.

The developed system allows you to set the values of elements of the adjacency matrix in the form of functional dependencies on time, which ensures that the time factor is taken into account in cognitive modeling.

4. Conclusion

The study of the possibilities and problems of fuzzy cognitive modeling allowed us to obtain the following conclusions:

1. The considered problems of constructing and parametric identification of fuzzy cognitive models, including existing expert and well-known statistical methods, revealed the need to develop new or modified methods to solve this problem.

2. The use of time-dependent parabolic dependence for setting the elements of the adjacency matrix FCM is proposed.

3. In the course of further research, strict methods for parameterizing dynamic functions that define the level of interaction between FCM concepts can be developed to construct fuzzy cognitive models that explicitly take into account the time factor.

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