Combined approach to the complex objects control and stability analysis of management decisions

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Abstract: The main problems and features of combined approach to the complex objects control and management stability analysis are investigated in the paper. Analytical-simulation scenarios and scenarios of intelligent models and systems execution for complex objects control and management stability analysis are given. The paper describes a particular group of models and modelling systems – hybrid intelligent models and systems that allow in conditions of uncertainty, incomplete initial data and complex interdependence between elements of complex objects to evaluate the implications of realization of various scenarios and risk evaluation. The investigations have shown successful possibility of risks evaluation by the combined implementation of the analytical-simulation models and algorithms, and ANFIS method – the method of hybrid neural-fuzzy modelling.

Keywords: stability analysis; risk management; management decision; combined approach; complex objects; coordination of models; simulation systems; fuzzy logic; neural networks; hybrid modelling; ANFIS method.

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1 Introduction

The main subjects of our investigation are complex objects (CO). By CO we mean objects that should be studied through polytypic models and combined methods. In some instances investigations of complex systems require multiple methodological approaches, many theories and disciplines, as well as to carry out interdisciplinary researches. Different aspects of complexity can be considered to distinguish between a complex system and a simple one, for example: structure complexity, operational complexity,

complexity of behaviour choice, complexity of development (Ashby, 1956; Avramchuk et al., 1980; Casti, 1979; Okhtilev et al., 2006). Classic examples of CO are: control systems for various classes of moving objects such as surface and air transport, ships, space and launch vehicles, etc., geographically distributed heterogeneous networks, flexible computerised manufacturing. One of the main features of modern CO is the changeability of their parameters and structures due to objective and subjective causes at different stages of the CO life cycle. In other words, we always come across the CO structure dynamics in practice. Under these conditions in order to increase (stabilise) CO potentialities and capacity for work structure control is to be performed (Ivanov et al., 2016a, 2016b; Kalinin and Sokolov, 1996; Okhtilev et al., 2006).

The traditional understanding of the analysis of classical dynamic objects (CDO) control stability (stability control?) consists of proving system's stability with regard to small perturbation impacts (Lyapunov, 1966). This approach has limitations regarding the CO domain. In this case, we should distinguish different levels of CO control and management. CO control processes are realised in the low levels of CO control and management systems and CO management processes are executed in the high levels. So, CO as management systems evolve from state to state not only through perturbation influences (Ivanov et al., 2016a, 2016b; Kalinin and Sokolov, 1996; Moiseev, 1974) but through control managerial actions of both a planned and regulative (as a reaction to mitigate negative perturbation influences) nature. In CO, unlike in mechanical systems, there is usually no need to ensure 100% stability. The nature of management systems lies in taking entrepreneurship risks (Ivanov et al., 2016a, 2016b). Additionally, these risks are perceived individually by different CO managers. Hence the essence of CO stability is, in our opinion, to ensure such a CO functioning so that the CO control and management goals (e.g., service level) can be achieved at a level that would be acceptable to managers (or that these goals' values would lie within some predetermined intervals).

At present, the limited capabilities of existing tools for CO control and management stability analysis have contributed for the joint application of traditional and new (intelligent) models and relevant modelling technologies, i.e., the transition to the concept of integrated modelling (Avramchuk et al., 1980; Kalinin and Sokolov, 1996; Moiseev, 1974; Motta and Rampazzo, 2000; Okhtilev et al., 2006; Sirotin and Formalskii, 2003).

In this case, integrated modelling for CO control and management stability analysis should include the following phases (Okhtilev et al., 2006):

a determination of scenarios for CO environment, particularly determination of extreme situations and impacts that can have catastrophic results

b analysis of CO operation in a normal mode on the basis of a priori probability information (if any), simulation, and processing of expert information through the theory of subjective probabilities and theory of fuzzy sets

c repetition of item b for the main extreme situations and estimation of guaranteed results of CO operation in these situations

d computing of general (integral) CO efficiency and stability measures.

At present the key concepts and technologies of CO integrated modelling are best implemented within the so-called simulation systems (SiS), which are characterised by a deep combination of simulation, intelligent and analytical approaches to modelling, as well as the full use of the mathematical apparatus, computers and human creative thinking (Moiseev, 1974; Okhtilev et al., 2006).

Currently, the term SiS is disclosed as a specially organised modelling complex consisting of the following elements:

a simulation model (SM) (hierarchy of classical and intelligent SMs), reflecting a certain problem area

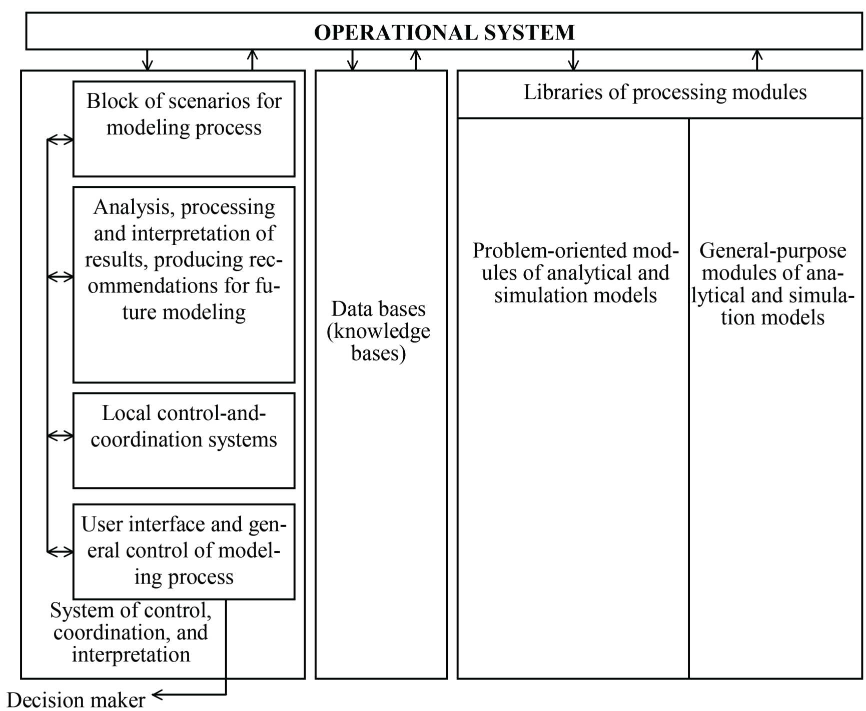
b analytical models (AM) (hierarchy of AMs), giving a simplified (aggregated) description of the various aspects of the simulated phenomena

c information subsystem, including the database of data (data bank), and in the future – knowledge base, relying on the ideas of artificial intelligence

d control and interface system, which provides interaction of all components of the system and work with the user (decision maker) in the interactive dialogue mode (Moiseev, 1974).

A general structure of SIS is shown in Figure 1.

Figure 1 General structure of SIS



Let us consider the main features of the organisation and implementation of integrated modelling scenarios for CO control and management stability analysis.

2 Analytical-simulation scenarios for CO control and management stability analysis

Multi-model and multi-criteria description of CO control and management problems necessitates the interaction between analytical-simulation SIS components and decision makers while searching for solutions.

$$\boldsymbol{J}\left(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{x}(t), t\right) \rightarrow \underset{\boldsymbol{u}\in\Delta}{\text{extr}} \tag{1}$$

$$\begin{aligned}\Delta = \Big\{\boldsymbol{u} \,|\, \boldsymbol{x}(t) = \boldsymbol{\varphi}\left(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\xi}(t), \boldsymbol{\beta}(t)\right), \boldsymbol{t}(t) = \boldsymbol{\psi}\left(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\xi}(t), \boldsymbol{\beta}, t\right),\\ \boldsymbol{x}(T_0) \in \boldsymbol{X}_0(\beta), \boldsymbol{x}\left(T_f\right) \in X_f(\beta), \boldsymbol{u}(t) \in Q\left(\boldsymbol{x}(t), t\right), \boldsymbol{\xi}(t) \in \Xi\left(\boldsymbol{x}(t), t\right),\\ \boldsymbol{\beta} \in \mathbf{B}, \boldsymbol{x}(t) \in \tilde{X}(t)n, \boldsymbol{u}(t) = \left\|\boldsymbol{u}_{np}(t), \boldsymbol{v}\left(\boldsymbol{x}(t), t\right)\right\|^{\mathrm{T}},\\ Q\left(\boldsymbol{x}(t), t\right) = Q^{(np)}\left(\boldsymbol{x}(t), t\right) \times V\left(\boldsymbol{x}(t), t\right)\Big\},\end{aligned} \tag{2}$$

$$\boldsymbol{x}(t) = \left\|\boldsymbol{x}^{(g)\mathrm{T}}, \boldsymbol{x}^{(o)\mathrm{T}}, \boldsymbol{x}^{(k)\mathrm{T}}, \boldsymbol{x}^{(p)\mathrm{T}}, \boldsymbol{x}^{(n)\mathrm{T}}, \boldsymbol{x}^{(e)\mathrm{T}}, \boldsymbol{x}^{(c)\mathrm{T}}, \boldsymbol{x}^{(v)\mathrm{T}}\right\|^{\mathrm{T}},$$

$$\boldsymbol{y}(t) = \left\|\boldsymbol{y}^{(g)\mathrm{T}}, \boldsymbol{y}^{(o)\mathrm{T}}, \boldsymbol{y}^{(k)\mathrm{T}}, \boldsymbol{y}^{(p)\mathrm{T}}, \boldsymbol{y}^{(n)\mathrm{T}}, \boldsymbol{y}^{(e)\mathrm{T}}, \boldsymbol{y}^{(c)\mathrm{T}}, \boldsymbol{y}^{(v)\mathrm{T}}\right\|^{\mathrm{T}},$$

$$\boldsymbol{u}_{np}(t) = \left\|\boldsymbol{u}_{np}^{(g)\mathrm{T}}, \boldsymbol{u}_{np}^{(o)\mathrm{T}}, \boldsymbol{u}_{np}^{(k)\mathrm{T}}, \boldsymbol{u}_{np}^{(p)\mathrm{T}}, \boldsymbol{u}_{np}^{(n)\mathrm{T}}, \boldsymbol{yu}_{np}^{(e)\mathrm{T}}, \boldsymbol{u}_{np}^{(c)\mathrm{T}}, \boldsymbol{u}_{np}^{(v)\mathrm{T}}\right\|^{\mathrm{T}},$$

$$\begin{aligned}\boldsymbol{v}\left(\boldsymbol{x}(t), t\right) = \Big\|\boldsymbol{v}^{(g)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(o)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(k)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(p)\mathrm{T}}\left(\boldsymbol{x}(t), t\right),\\ \boldsymbol{v}^{(n)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(e)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(c)\mathrm{T}}\left(\boldsymbol{x}(t), t\right), \boldsymbol{v}^{(v)\mathrm{T}}\left(\boldsymbol{x}(t), t\right)\Big\|\end{aligned}$$

$$\boldsymbol{\xi}(t) = \left\|\boldsymbol{\xi}^{(g)\mathrm{T}}, \boldsymbol{\xi}^{(o)\mathrm{T}}, \boldsymbol{\xi}^{(k\kappa)\mathrm{T}}, \boldsymbol{\xi}^{(p)\mathrm{T}}, \boldsymbol{\xi}^{(n)\mathrm{T}}, \boldsymbol{\xi}^{(e)\mathrm{T}}, \boldsymbol{\xi}^{(c)\mathrm{T}}, \boldsymbol{\xi}^{(v)\mathrm{T}}\right\|$$

$$\boldsymbol{\beta}(t) = \left\|\boldsymbol{\beta}^{(g)\mathrm{T}}, \boldsymbol{\beta}^{(o)\mathrm{T}}, \boldsymbol{\beta}^{(k)\mathrm{T}}, \boldsymbol{\beta}^{(p)\mathrm{T}}, \boldsymbol{\beta}^{(n)\mathrm{T}}, \boldsymbol{\beta}^{(e)\mathrm{T}}, \boldsymbol{\beta}^{(c)\mathrm{T}}, \boldsymbol{\beta}^{(v)\mathrm{T}}\right\|$$

where $\boldsymbol{x}(t)$, $\boldsymbol{y}(t)$ are generalised vectors of state and output characteristics, correspondingly; $\boldsymbol{u}_{\text{пр}}(t)$ is a generalised vector of CO program control (such vectors represent functioning plans for CO elements and subsystems); $\boldsymbol{v}(\boldsymbol{x}(t), t)$ is a generalised vector of control at operating period [implementation of plans under conditions of perturbation actions at operating period $\boldsymbol{\xi}(t)$]; $\boldsymbol{\xi}$(t) is a vector of perturbation actions (systematic and random); $\boldsymbol{\beta}$ is a vector of CO structure parameters (characteristics) defining CO layout. The components of all introduced vectors are particular vectors belonging to models of different type. The types of models are defined by the subscripts: '*g*' (motion), '*o*' (operations of interaction), '*k*' (channel, data links), '*p*' (resources), '*n*' (flows), '*e*' (parameters of operations), '*c*' (structures), 'v' (auxiliary operations) (see components of the generalised conceptual model in (Kalinin and Sokolov, 1996; Okhtilev et al., 2006).

All described vectors should meet space-time, technical, and technological limitations, in other words, the vectors should belong to given sets:

$$\boldsymbol{u}_{np}(t) \in Q^{(np)}\left(\boldsymbol{x}(t), t\right), \quad \boldsymbol{v}\left(\boldsymbol{x}(t), t\right) \in V\left(\boldsymbol{x}(t), t\right) \tag{3}$$

$$\boldsymbol{\xi}(t) \in \Xi\left(\boldsymbol{x}(t), t\right), \quad \boldsymbol{\beta} \in \mathbf{B} \tag{4}$$

$$\boldsymbol{x}(t) \in \tilde{\boldsymbol{X}}(t), \tag{5}$$

where $Q^{(np)}(\boldsymbol{x}(t))$ is a given set of permissible program control; $V(\boldsymbol{x}(t), t)$ is a given set of permissible control inputs for real-time mode; Ξ $(\boldsymbol{x}(t), t)$ is a set of possible perturbation actions; **B** is a set of permissible values of structure parameters $X\sim(t)$ – is a set of current values of the CO structure dynamics of the state vector.

The dynamics of state and output vectors can be described by the transition function and by the output one:

$$\boldsymbol{x}(t) = \boldsymbol{\varphi}\left(\boldsymbol{x}(t), \boldsymbol{u}_{np}(t), \boldsymbol{v}\left(\boldsymbol{x}(t), t\right), \boldsymbol{\xi}(t), \boldsymbol{\beta}, t\right), \tag{6}$$

$$\boldsymbol{y}(t) = \boldsymbol{\psi}\left(\boldsymbol{x}(t), \boldsymbol{u}_{np}(t), \boldsymbol{v}\left(\boldsymbol{x}(t), t\right), \boldsymbol{\xi}(t), \boldsymbol{\beta}, t\right). \tag{7}$$

There are additional constraints for the initial state and the final state:

$$\boldsymbol{x}\left(T_0\right) \in X_0(\boldsymbol{\beta}), \quad \boldsymbol{x}\left(T_f\right) \in X_f(\boldsymbol{\beta}), \tag{8}$$

where T_0 is the beginning, T_f is the end of a time interval under consideration.

To evaluate effectiveness of control processes of CO structure dynamics at the operation period let us introduce the following vector of quality functionals:

$$\boldsymbol{J}\left(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{\xi}(t), t\right) = \left\| \boldsymbol{J}^{(g)\mathrm{T}}, \boldsymbol{J}^{(o)\mathrm{T}}, \boldsymbol{J}^{(k)\mathrm{T}}, \boldsymbol{J}^{(p)\mathrm{T}}, \boldsymbol{J}^{(n)\mathrm{T}}, \boldsymbol{J}^{(e)\mathrm{T}}, \boldsymbol{J}^{(c)\mathrm{T}}, \boldsymbol{J}^{(v)\mathrm{T}} \right\|^{\mathrm{T}}, \tag{9}$$

where $\boldsymbol{J}^{(g)}$, $\boldsymbol{J}^{(o)}$, $\boldsymbol{J}^{(k)}$, $\boldsymbol{J}^{(p)}$, $\boldsymbol{J}^{(n)}$, $\boldsymbol{J}^{(e)}$, $\boldsymbol{J}^{(c)}$, $\boldsymbol{J}^{(v)}$ are vectors of control effectiveness measures for motion, operations of interaction, channels, resources, flows, parameters of operations, structures, and auxiliary operations correspondingly.

In (2) transition and output functions are, in general, algorithmically implemented in SiS. Procedures of structure-dynamics problem solving depend on the variants of transition and output functions (operators) implementation.

Various approaches, methods, algorithms and procedures of coordinated choice through the complexes of heterogeneous models have been developed by now (Casti, 1979; Chernousko, 1994; Clarke et al., 1995; Guseinov, 2009; Ivanov et al., 2016a, 2016b; Kalinin and Sokolov, 1996; Lou, 2004; Moiseev, 1974; Motta and Rampazzo, 2000; Okhtilev et al., 2006).

Table 1 describes different types of the above-mentioned procedures. The following notations were used: AOM (analytical optimisation model); AN [analysis (automatic or decision maker-assisted) of received results]; C (correction of obtained solutions); $\Delta^{(a)}$, $\Delta^{(u)}$ are sets (subsets) of allowable alternatives (2) analytically ($\Delta^{(a)}$) or algorithmically ($\Delta^{(u)}$ described; $f_0^{(a)}$, $f_0^{(u)}$ are general measures of CO stability and effectiveness calculated trough the solving of multi-objective problems (1) and analytically ($f_0^{(a)}$) or algorithmically ($f_0^{(u)}$) described.

The schemes of coordination for models and measures of effectiveness can differ in:

- methods of solution generation in CO control and management tasks
- rules of constraints verification for analytical and algorithmic constraints
- variants of interactive elimination of allowable alternatives.

Table 1 Analytical-simulation scenarios for CO integrated modelling

Procedures of CO integrated modelling \ Models of CO	$f_0^{(a)} \to \underset{\Delta^{(a)}}{extr}$	$f_0^{(a)} \to \underset{\Delta^{(u)}}{extr}$	$f_0^{(a)} \to \underset{\Delta^{(a)} \cap \Delta^{(u)}}{extr}$	$f_0^{(a)} \to \underset{\Delta^{(a)}}{extr}$	$f_0^{(a)} \to \underset{\Delta^{(u)}}{extr}$	$f_0^{(a)} \to \underset{\Delta^{(a)} \cap \Delta^{(u)}}{extr}$
$\mathrm{AOM} \to \mathrm{AN} \to \mathrm{C}$	+					
$\mathrm{SOM} \to \mathrm{AN} \to \mathrm{C}$				+	+	+
$\mathrm{AOM} \to \mathrm{SOM} \to \mathrm{AN} \to \mathrm{C}$		+	+			
$(\mathrm{AOM} \subset \mathrm{SOM}) \to \mathrm{AN} \to \mathrm{C}$			+			
$(\mathrm{SOM} \subset \mathrm{AOM}) \to \mathrm{AN} \to \mathrm{C}$			+		+	+
$\begin{pmatrix} \mathrm{AOM}_1 \\ \cup \\ \mathrm{SOM} \\ \cap \\ \mathrm{AOM}_2 \end{pmatrix} \to \mathrm{AN} \to \mathrm{C}$				+	+	+

For stochastic input data general measures of CO stability and effectiveness should be calculated by providing statistical significance of stability estimations of the multiple simulation experiments. Here the methods of variance lowering can be applied to reduce the number of the experiments. If we use the stochastic input data, then the stability can be often expressed as a probability of some event. The most appropriate event for this purpose is the completion of a given mission in accordance with the plan. For certain cases, the necessary level of stability can be defined in the form of equality (Avramchuk et al., 1980; Guseinov, 2009; Ivanov et al., 2016a, 2016b; Kalinin and Sokolov, 1996):

$$P\{\hat{z}_h \geq z_\alpha\} = \alpha^{(\xi)}, \tag{10}$$

where z_α, $\boldsymbol{\alpha}$ are given values, $\hat{z}_{\bar{\boldsymbol{h}}} = \rho(\hat{\mathbf{x}}_{\bar{\boldsymbol{h}}}^{(\xi)}(T_f), \hat{\mathbf{x}}_{\bar{\boldsymbol{h}}}^{(pl)}(T_f))$ is the estimation of the difference between the planed CO state and the perturbed one.

The stability of CO plan can be indirectly estimated by means of the following objective function:

$$\hat{\boldsymbol{M}}_{es}\left(\boldsymbol{J}_{\bar{\boldsymbol{h}}}^{(pl)} - \boldsymbol{J}_{\bar{\boldsymbol{h}}}^{(\xi)}\right), \tag{11}$$

where $\hat{\boldsymbol{M}}_{es}$ is the expectation sign, $\boldsymbol{J}_{\bar{\boldsymbol{h}}}^{(pl)}$ is a general measure of CO effectiveness (a convolution $\boldsymbol{J}_{1\tilde{h}}^{(pl)}, \ldots, \boldsymbol{J}_{1_M \tilde{h}}^{(pl)}; \boldsymbol{J}_{\tilde{h}}^{(pl)}$ is a measure of losses caused by perturbation influences and resources consumption for adjustment managerial actions. The probability of the situation is such that the correction of the plan is not necessary until the given time point; the mean value of a time point is such that the correction of the plan becomes necessary; mean value of plan’s corrections during a given time period.

Let us consider a particular example of model coordination. In the example given below the coordination of SiS models is performed for schedule and plan stability and efficiency analysis of the functioning of active moving objects of the control system (AMO CS) (Kalinin and Sokolov, 1996; Okhtilev et al., 2006). The tasks of planning are interrelated with different problems of analysis, observation and selection. Thus, a complex of tasks should be considered.

Step 1 For a given state of the environment and given constant input data the additional data are received through the models of AMO CS functioning. To receive data necessary for planning, the numerous computation experiments are performed with the models of AMO motion, models of telecommunication system, and models of computing systems. The following information should be obtained: the possible variants of AMO motion and possible rates of data transmission and processing in AMO CS.

Step 2 In accordance with the computation resources the schedule of modelling is worked out.

Step 3 The existence of a solution for the planning tasks is analysed. Here the end conditions in the planning problem are verified through examination of the previously constructed attainability set.

Step 4 If the solution exists, the allowable plan of AMO CS functioning is worked out in an automatic mode or through the interaction with a decision maker.

Step 5 The optimal plan of AMO CS functioning is obtained as a result of a multi-stage iterative search process on the basis of models (1)–(9).

Step 6 The stability of the plan obtained at the Step 5 is verified via the simulation models of AMO CS goal-directed applications under conditions of environmental impact. The input data for the SMs can have different forms: deterministic, stochastic, fuzzy, and interval forms. The principles of reflexive control are implemented in the AMO CS SMs. This is the main distinctive feature of the proposed models.

Step 7 The parametric and structure adaptation of the plans to the perturbation inputs is performed.

Step 8 The final (optimal) plan is being chosen via the interaction with decision makers.

3 Scenarios of intelligent models and systems execution for complex objects control and management stability analysis

Intelligent models and systems, which describe CO, allow one to evaluate the implications of realisation of various management scenarios in conditions of uncertainty, incomplete initial data and complex interdependence between elements of investigated complex control system, including risk management system. Building these types of models, as a rule, is a time-consuming process from a calculating point of view. This requires the involvement of the potential of modern information and communication technologies both when building models and carrying out model experiments. The class of intelligent models includes system-dynamics and agent-based models as well as models and methods of 'soft computing (SC)' — fuzzy logic, neural networks and evolutionary computation.

Soft computing is a set of computational methodologies that collectively provide a basis for understanding, designing, and development of intelligent systems for use in various fields of science, including management. In contrast to traditional modelling methods, the essence of soft computing is that it aims at adapting to the inaccuracies of the real world.

The scientific traditions, as a rule, give preference to the quantitative, formal, and precise theories and concepts. However, nowadays, this tradition has been changed by appearance of new problems for which finding of exact solutions was impossible, but the approximate solution methods of SC were quite acceptable. The main components of soft computing concept are fuzzy logic (FL), neural networks (NN), evolutionary computation (EC), and probabilistic inference (PE). Each of the above four methodologies has its strengths and weaknesses. Although they have some common characteristics, they can be considered to be complementing each other, because one part of the required attributes can be missing from one technology, but appear in the other (Krichevsky and Serova, 2016). Table 2 shows the comparative analysis of possibilities of intelligent technologies using certain criteria for major components of soft computing. Graduations of fuzzy logic are used as estimates of criteria.

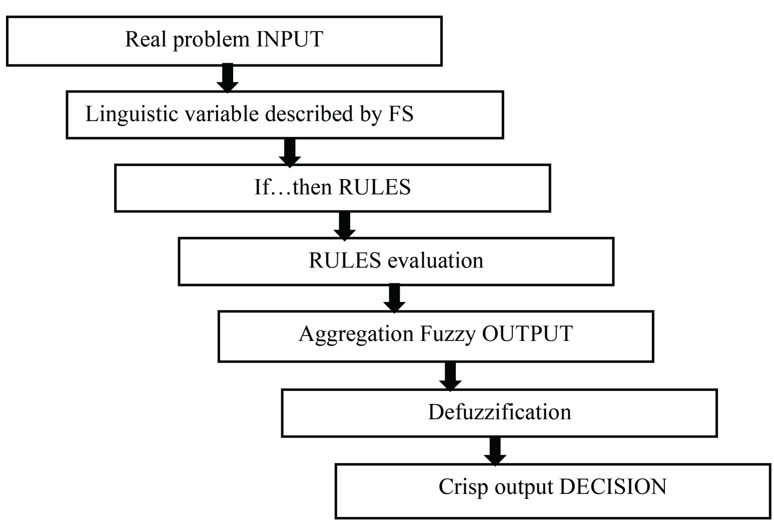
Table 2 Comparison of intelligent systems

Evaluation criteria	*Neural networks*	*Fuzzy logic*	*Evolutionary computation*
Mathematical model	Slightly good	Bad	Bad
Learning ability	Bad	Good	Slightly good
Knowledge representation	Good	Bad	Slightly good
Expert knowledge	Good	Bad	Bad
Nonlinearity	Good	Good	Good
Capability of optimisation	Bad	Slightly good	Good
Tolerance of uncertainty	Good	Good	Good
Operating time	Good	Slightly good	Slightly bad

Source: Krichevsky (2015)

It is noteworthy that fuzzy logic is now considered as essential feature of decision making in companies that actively employ modern risk management systems. Application of the information and communication technologies, which are used in soft computing, allows achieving the quantitative results, which is very important for a manager to make a decision. Fuzzy set was introduced by Zadeh (1994) as a means of representing data that was neither precise nor complete. There are two main characteristics of fuzzy systems that give better performance for specific applications: the first is that fuzzy systems are suitable for uncertain or approximate reasoning and the second is that fuzzy logic allows for problem solving and decision making on the basis of incomplete or uncertain information. Fuzzy technologies as technologies of artificial intelligence are now having a significant influence on information systems design and analysis (Kecman, 2001; McNelis, 2005). Fuzzy logic models employ fuzzy sets to handle and describe imprecise and complex phenomena and use logic operations to find a solution. A block diagram of a fuzzy logic model is represented in Figure 2.

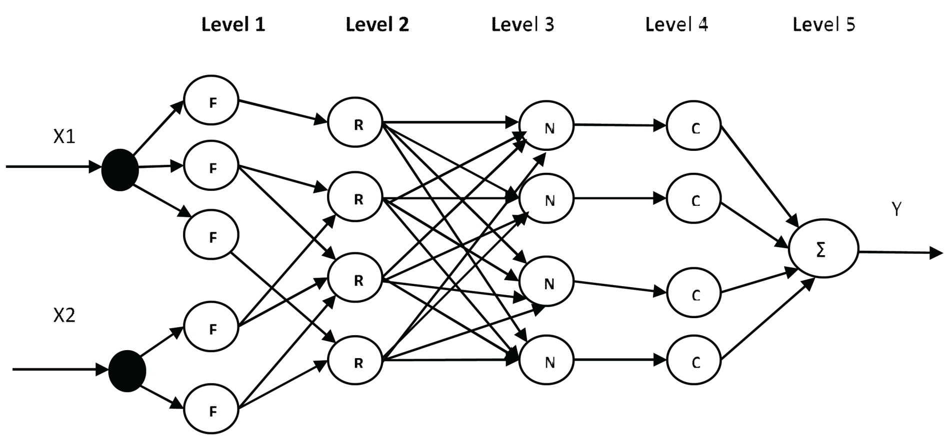
Figure 2 FL model block diagram



Nowadays, the combination of different approaches, styles, and paradigms to build the most appropriate and efficient single hybrid model is one of the effective methods to use intellectual tools for risk minimisation. ANFIS is a hybrid technique, which combines the best features of fuzzy logic and parallel processing neural networks. It possesses fast convergence and has more accuracy than a back propagation neural network. Using a given input/output dataset, the toolbox function ANFIS constructs a Fuzzy Inference System (FIS) whose membership function parameters are tuned (adjusted) by using either a backpropagation algorithm alone or in combination with a least squares type of method. This adjustment allows fuzzy systems to learn from the data they are modelling. The modelling approach used by ANFIS is similar to many system identification techniques. The main steps of ANFIS creation are:

- to hypothesise a parameterised model structure (relating inputs to membership functions, to rules, to outputs, to membership functions, and so on)
- to collect input/output data in a form that will be usable by ANFIS for training
- to use ANFIS for training the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion (Martínez et al., 2010).

Figure 3 Architecture of ANFIS hybrid model



ANFIS architecture consists of five layers as shown in Figure 3. Each layer contains several nodes described by the node function (Jang et al., 1997; Kaynak, 2015).

a Layer 1

Each node in the first layer of ANFIS architecture processes the coming inputs by using node functions.

b Layer 2

This is a layer of rules. The outputs of the first layer constitute the inputs of this one.

c Layer 3

This is a layer of normalisation. All the outputs of the nodes in the layer of rules are used as input. The proportion of the ignition power of the node i in the layer of rules to the sum of the ignition power of all the nodes gives the normalised ignition rate of node I.

d Layer 4

This is the clarification layer. Node i in this layer computes the contribution of the i^{th} rule toward the overall output.

e Layer 5

There is one node in this layer. This node sums the output values of each node in the layer 4. This summation is the output value of the ANFIS system.

The major advantage of intelligent models and systems is their ability for multidimensional representation of complex systems. Thus, the possibility of risks evaluation can be successfully realised (Thus, risks can be successfully evaluated by implementing the ANFIS) by the implementation of the ANFIS method – a method of hybrid neural-fuzzy modelling.

4 Conclusions

The conducted research has shown that the required level of CO control and management stability and efficiency analysis demands the use of modern methods and technologies of complex modelling. The main advantage of this type of modelling is that due to the multi-model description of each specific subject area under study and the corresponding coordination of different types of models, methods and algorithms of analysis and synthesis of CO at the formalised (deep) level of description, it is possible, firstly, to compensate for the shortcomings and limitations inherent in each particular class of models, methods and algorithms, and, secondly, to obtain a synergetic effect from their integrative use, expressed in the formation of new knowledge about CO and its behaviour. Moreover, the investigations have shown a successful possibility of risks evaluation by the combined implementation of the analytical-SMs and algorithms, and the ANFIS method – a method of hybrid neural-fuzzy modelling.

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References

Ashby, W.R. (1956) *An Introduction to Cybernetics*, Chapman & Hall, London.

Avramchuk, E.F., Vavilov, A.A., Emel'yanov, S.V. et al. (1988) *Technology of System Modeling*, in Russian, edited by Emel'yanova, S.V., Ihevsk, Mashinostroenie.

Casti, J.L. (1979) *Connectivity, Complexity and Catastrophe in Large-Scale Systems*, Wiley-Interscience, New York; London.

Chernousko, F.L. (1994) *State Estimation of Dynamic Systems*. SRC Press, Boca Raton, Florida.

Clarke, F.H., Ledyaev, Yu, S., Stern, R.J. and Wolenskii, P.R. (1995) 'Qualitative properties of trajectories of control systems: a survey', *Journal of Dynamic Control Systems*, Vol. 1, No. 1, pp.1–48.

Guseinov, K.G. (2009) 'Approximation of the attainable sets of the nonlinear control systems with integral constraint on controls', *Nonlinear Anal*, Vol. 71, Nos. 1–2, pp.622–645.

Ivanov, D., Dolgui, A. and Sokolov, B. (2016a) 'Robust dynamic schedule coordination control in the supply chain', *Computers and Industrial Engineering*, Vol. 94, No. 1, pp.18–31.

Ivanov, D., Dolgui, A., Sokolov, B. and Werner, F. (2016b) 'Schedule robustness analysis with the help of attainable sets in continuous flow problem under capacity disruptions', *International Journal of Production Research*, Vol. 54, No. 1, pp.3397–3413.

Jang, J-S.R., Sun, C-T. and Mizutani, E. (1997) *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence*, Prentice-Hall, Englewood Cliffs, NJ.

Kalinin, V.N. and Sokolov, B.V. (1996) 'Multiple-model description of control processes for airspace crafts', *Journal Computer System Science International*, Vol. 34, No.6, pp.192–199.

Kaynak, S., Evirgen, H. and Kaynak, B. (2015) 'Adaptive neuro-fuzzy inference system in predicting the success of student's in a particular course', *International Journal of Computer Theory and Engineering*, Vol. 7, No. 1, pp.34–39.

Kecman, V. (2001) *Learning and Soft Computing – Support Vector Machines, Neural Networks, and Fuzzy Logic Models*, The MIT Press, London.

Krichevsky, M. and Serova, E. (2016) *Business Analysis and Decision Making Based on Data and Models. Theory, Practice, and Tools*, Professional Literature, St., Petersburg.

Krichevsky, M.L. (2015) *Research Methods in Management*, KNORUS, Moscow.

Lou, H.W. (2004) 'On the attainable sets of control systems with p-integrable controls', *Journal of Optimal Theory and Applications*, Vol. 123, No. 1, pp.123–147.

Lyapunov, A.M. (1966) *Stability of Motion*, Academic Press, New York; London.

Martínez, L.G. et al. (2010) 'Big five patterns for software engineering roles using an ANFIS learning approach with RAMSET', *Proceedings of the 10th Mexican International Conference, MICAI 2010, Part II, LNAI 6438*, pp.428–439.

McNelis, P.D. (2005) *Neural Networks in Finance: Gaining Predictive Edge in the Market*, Elsevier Academic Press, Amsterdam.

Moiseev, N.N. (1974) *Element of the Optimal Systems Theory*, in Russian, Nauka, Moscow.

Motta, M. and Rampazzo, F. (2000) 'Multivalued dynamics on a closed domain with absorbing boundary, applications to optimal control problems with integral constraints', *Journal of Nonlinear Analysis TMA*, Vol. 41, Nos. 5–6, pp.631–647.

Okhtilev, M., Sokolov, B. and Yusupov, R. (2006) *Intelligent Technologies of Complex Systems Monitoring and Structure Dynamics Control*, in Russian, Nauka, Moscow.

Sirotin, A.N. and Formalskii, A.M. (2003) 'Reachability and controllability of discrete-time systems under control actions bounded in magnitude and norm', *Journal Automation and Remote Control*, Vol. 64, No. 12, pp.1844–1857.

Zadeh, L. (1994) 'Neural network, and soft computing', *Fuzzy Logic, Communication of the ACM*, Vol. 37, No. 3, pp.77–84.