The Technology for Determining the Level of Process Control in Complex Systems

Volodymyr Polishchuk[a], Mykola Malyar [a], Miroslav Kelemen[b] and Andriy Polishchuk[a]

[a] *Uzhhorod National University, Narodna Square, 3, Uzhhorod, 88000, Ukraine*
[b] *Technical University of Kosice, Rampova 7, Kosice, 04121, Slovak republic*

Abstract
A study of the current problem of developing technology for determining the level of process controllability in complex systems, with different modes of operation was done. In this investigation for the first time was proposed a fuzzy mathematical model based on expert hybrid data, using linguistic and quantitative variables. Based on the obtained result, can be determined the level of safe operation of the system to prevent negative consequences or confidence in achieving the goals of the system. An experimental approbation of the research on the problem of determining the level of process controllability in airport management information systems, with data security threats, taking into account different modes of operation was done. A web application was created for the developed model, with which is possible to configure models and conduct experimental research for various application tasks.

Keywords [1]
Process controllability, fuzzy set, decision-making, modes of system operation

1. Introduction

Information systems and technologies are increasingly replacing intellectual ones, but the desire to represent the future does not disappear. At the present stage of human development, there is an increasing desire to control the processes in the world. Tools for analyzing massive data sets, today allow you to get new, high-quality knowledge from various information. The amount of data is growing rapidly in all areas, with them there is a need for processing, which is reduced to obtaining knowledge, on the basis of which further decisions are made. Such technologies make life more comfortable, more stable, smarter, and most importantly safer.

Today, decision support systems are increasingly using data mining tools. But most of them are designed to make decisions in the safe mode of operation of systems. For conditions where the system is rapidly changing modes from safe operation, emergency to disaster, most decision support models are not able to adequately assess the situation. Proof of this is the work of the municipality, region, state in the conditions of, for example, a pandemic of coronavirus infection (COVID-19).

Every day, due to various circumstances, extraordinary situations occur that lead to material destruction, threat to health or life. Often through the fault of decision-maker, making the wrong management decisions. Management decisions directly affect the safe state of the system environment. Sometimes decision-maker try to control processes in complex systems without suspecting that process control is very low or non-existent. There are circumstances that do not depend on people. However, there is our desire to know whether we can influence certain processes. There are events that we cannot change, but we must work to anticipate them.

At a time when a complex system is moving from a safe mode of operation to a catastrophe, the situation is changing rapidly, the controllability of processes is declining, the data influencing

VII International conference "Information Technology and Interactions" (IT&I-2020), December 2–3, 2020, Kyiv, Ukraine
EMAIL: volodymyr.polishchuk@uzhnu.edu.ua (V. Polishchuk); mykola.malyar@uzhnu.edu.ua (M. Malyar); miroslav.kelemen@tuke.sk (M. Kelemen); andriy.v.polishchuk@gmail.com (A. Polishchuk)
ORCID: 0000-0003-4586-1333 (V. Polishchuk); 0000-0002-2544-1959 (M. Malyar); 0000-0001-7459-927X (M. Kelemen); 0000-0003-3093-8393 (A. Polishchuk)

decision-making are becoming increasingly vague. Any emergency or catastrophe is the end result of a consistent transition of the normal mode of operation of the system, respectively, in an emergency or catastrophic situation [1].

Confirmation of the above is illustrated by the following example. The investigation of the plane crash shows what factors and influences accompanied the events of the crash. The conclusion of the causes of the crash indicates whether the accident situation depended on the pilots, the technical condition of the vessel, weather conditions and the possibility of avoiding the accident. The factors of the internal condition of the aircraft, the influence of the external environment, the actions of pilots in an emergency situation and human factors in the management of air traffic are indicated. In other words, the assessment of process controllability in a complex ship piloting system is indicated. And most importantly, the International Civil Aviation Organization [2] is taking clear steps to prevent similar situations in the future.

In connection with the above, there is a topical study of the development of technology to determine the level of process control in complex (weakly structured) systems, taking into account different modes of operation.

The logic of the study is as follows: if the overall assessment of the system is high, the factors influencing the control processes for the appropriate mode of operation, then we can talk about a high level of process control in the system, and competent management decisions will achieve the goals of the system. ensure the appropriate level of security of the system operation environment.

2. Overview of Domestic and Foreign Research Studies

The level of process control in complex systems depends on many factors, for example: management's views on the concept of danger, its risk appetite, emotional state, risk-oriented factors, external and internal factors, and others. The choice of behavior is the result of the interaction of external factors, features and opinions of decision-maker. This choice is a prerequisite in the system of personal qualities of decision-maker, which include his worldview, experience, knowledge, as well as features of the internal system of moral and social control, including legal awareness [3]. Therefore, when considering alternative solutions for decision management, in any system of operation, it is necessary to consider at least optimistic, cautious, average and pessimistic scenarios. Thus, the subjective reason for the level of process control in complex systems is the decision of decision-maker. In addition, there are some circumstances that during the system of operation lead to unusual, risky situations [1].

The issue of process control is raised in the theoretical and sociological study [4] and substantiates that without control the normal functioning and development of society is impossible. In [5] the methods of controllability assessment and methodologies of their integration into the design process for some modes of operation are considered, the conclusions of controllability assessment problems for nonlinear processes are made. A number of world publications consider the processes of controllability for applied tasks, for example: controllability of the process of pulp processing with low consistency [6]; controllability of business processes by means of time variables [7]; resource management of work processes in conditions of uncertainty [8-9]; use of controlled and explained interfaces for the task of searching for social information [10], and others. In [11] the concept of controllability of reaction systems is introduced, as the ability to transition between any two states through the appropriate choice of context sequences. To date, there is no common methodology for assessing the level of process control in any complex systems given the different modes of operation.

In addition, our study uses expert information that reflects the substantive features of the studied systems of functioning and is set in natural language. The description in this case is vague, and to reflect the knowledge about the object of study and to reduce the risk, it is advisable to use the theory of fuzzy sets [12-13]. To properly assess the level of process control in complex systems, it is necessary to learn to scientifically model information uncertainty, drawing formally described boundaries between reliable knowledge, knowledge with a certain level of reliability and what we do not know. To do this, in order to model the uncertainty in the work used fuzzy-multiple descriptions [14-15]. For example, [16-17] discusses the general ideas and benefits on which modern views on the use of fuzzy logic in decision support systems are based. In [18-19] the use of fuzzy logic in different areas of application is presented, which allows to determine the optimal parameters under conditions of uncertainty of the input data. For example [20] presents fuzzy decision support systems in maritime practice; [21] considers an intelligent system for measuring customer loyalty and decision-making based on fuzzy logic; [22] investigated product rankings using online reviews using fuzzy sets and others. And in the works [23-24] the advantages of research of complex objects of functioning in different modes and system analysis are scientifically substantiated.

The above, argues and confirms the relevance of our study on the application of intelligent analysis, systems approach, processing fuzzy data to develop technology to assess the level of process control in complex systems from normal to disaster. The relevance of this study proves the need to understand the controllability of processes in different objects of study and different modes of operation, for sustainable operation of systems, achieving its goals, formalization of such processes, especially in a pandemic COVID-19.

3. Fuzzy model for determining the level of process control in a complex system, with a different modes of operation

3.1. Formal problem statement and input data

Let it be known some object of study that we will consider as a complex poorly structured system S. There are many known system goals and many factors that affect the controllability of complex systems. Also known are the indicators of the system that allow to quantify or qualitatively assess the property of the system. Fuzzy models of system evaluation are built on the basis of known indicators. Within this, it is necessary to assess the controllability of processes in the object of study for quality decision-making depending on the modes *C*: regular situation, out of the regular mode, critical situation, emergency, accident situation, accident, catastrophic situation, catastrophe.

Suppose we have a set of indicators $K = (K_1, K_2, \dots, K_m)$, according to which we will assess the level of process control in a complex system *S*. Indicators can be a whole system of criteria, factors and models, based on which a single aggregate assessment is derived. For example: the level of control of the aircraft is influenced by indicators that depend on the factors of the technical condition of the aircraft, external conditions, human factors and risk-oriented situations; the level of safe financing of innovative projects is influenced by factors of the microenvironment of the project (strength of the idea), environmental factors (competitors, market, policy), factors of risk management and anticipation, and the main level of project developers.

Suppose we have eight modes of operation of the system $= (C_1, C_2, \dots, C_8)$, where: C_1 – regular mode, C_2 – out of the regular mode, C_3 – critical situation, C_4 – emergency, C_5 – accident situation, C_6 – accident, C_7 – catastrophic situation, C_8 – disaster. Decision-maker has the ability to obtain estimates for four scenarios $M = \{M_1; M_2; M_3; M_4\}$, where: M_1 – pessimistic scenario; M_2 – cautious scenario; M_3 – average scenario; M_4 – optimistic scenario.

Formally, we can present a fuzzy model for determining the level of process control in complex systems, taking into account the different modes of operation as follows:

$$A(I; M; C) \to R(\mu), \qquad (1)$$

A – an operator that matches a set of output values *R*, with input variables *I;M;C*. The input data of the model are: *I* – expert indicator or quantitative assessment of the level of process control in the system, or a combination thereof; *M* – taking into account the reasoning of the decision-maker on the scenario of unfolding events; *C* – system operation mode. At the output of the evaluation model we have: μ – assessment of process control in complex systems taking into account different modes of operation on the basis of which the level is determined *R*.

The solution of this problem can be clearly demonstrated in the form of a block diagram, fig. 1. Since this study focuses on various complex systems, we consider the following input data.

1. All indicators are evaluated by an expert using a linguistic variable. To do this, based on experience and knowledge about the object of study *S*, a group of experts (or an expert) analyzes

it, draws conclusions and makes one linguistic assessment for each indicator K, from some term set $T = \{T_1; T_2; \dots; T_l\}$. Presenting the term set of linguistic variables as the level of the situation in the system described by the indicator K.

2. All indicators have a quantitative normalized assessment of the factors influencing the level of process control in the system. Each indicator can be an aggregated quantitative estimate obtained by fuzzy knowledge modeling or within the framework of big data mining. As a result, for each indicator we obtain a quantitative estimate of q from the interval [0; 1].

3. Indicators are evaluated in a hybrid manner, based on expert experience and methods of intellectual analysis of quantitative data. As a result, for each indicator we obtain a quantitative estimate q from the interval [0; 1] and linguistic evaluation from some term set T.

At the first stage, it is necessary to carry out fuzzification of input data of the complex systems. Here is a block diagram of the choice of the method of processing input data for their fuzzyfication, fig. 2.

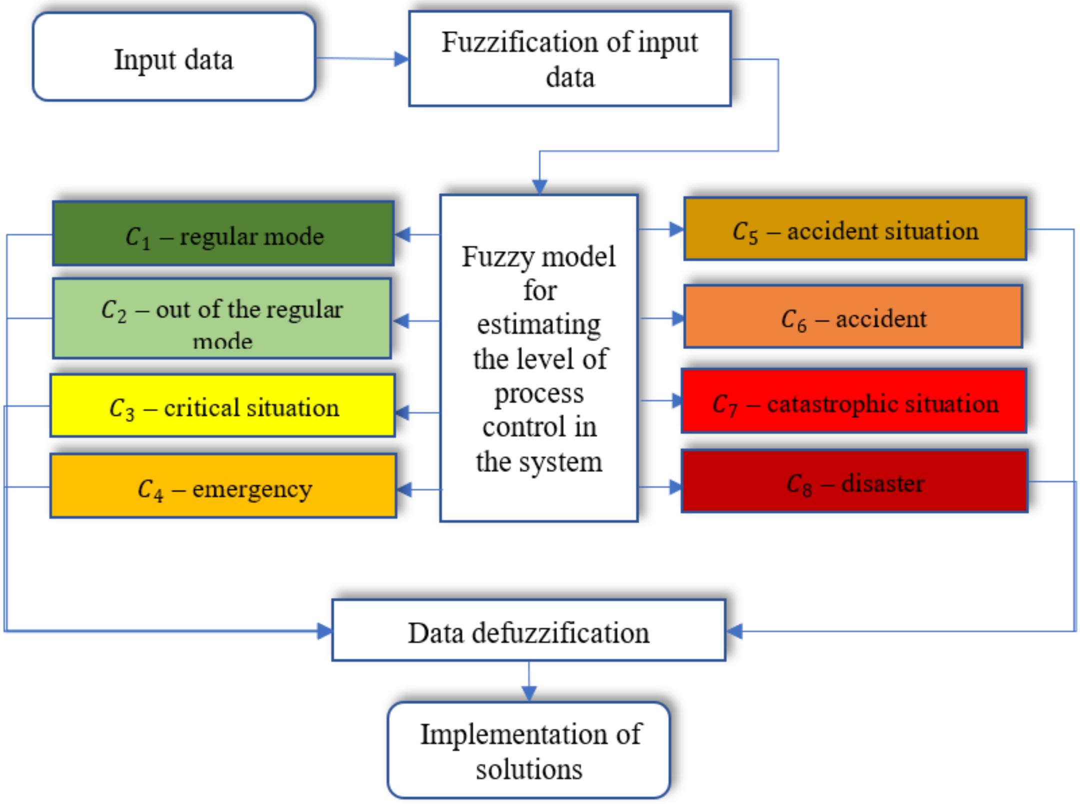

Figure 1: Block diagram of the solution of the researched problem

The neuro-fuzzy model of multicriteria evaluation [25] makes it possible to combine the quantitative characteristics of the object with expert opinions in the form of qualitative assessments. On the one hand, the model uses different characteristics of the object, which are evaluated by quantitative indicators and on the basis of different models of knowledge about the object, and on the other hand uses the experience, knowledge, and competencies of experts in the relevant subject area. In addition, this model is based on a neural-fuzzy network, which has the ability to change the settings of synaptic weights; you can conduct network training and adjust decision-making levels; according to the proposed "interval representation" of scales, the model can be used to solve those problems where there is no data for the training of the neural-fuzzy network.

Information modeling of fuzzy knowledge [12] on the basis of functions of belonging of estimations on criteria, gives the chance to apply for various applied problems. The methodology of application of this approach makes it possible to obtain interpretations for the gained expert scores of a weakly structured or unstructured task, revealing the subjectivity of experts and to have a quantitative assessment of informal information tasks.

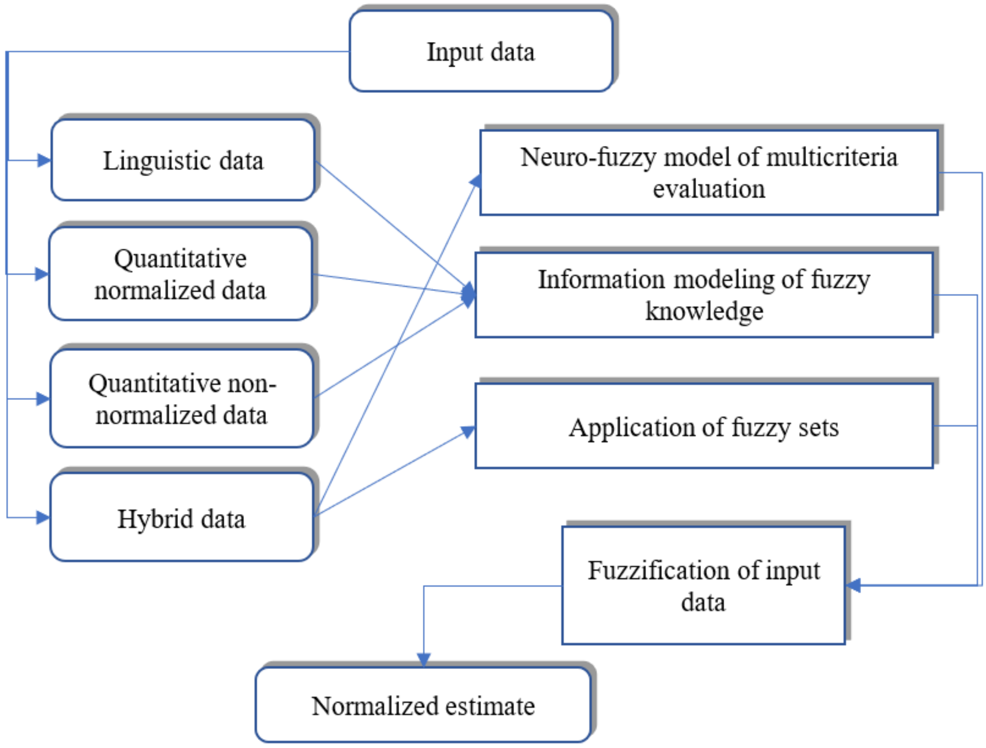

Figure 2: Block diagram of the choice of input data processing method for their fuzzification

3.2. Fuzzy mathematical model

Consider in more detail the method of data fuzzification using fuzzy sets. Input data to determine the level of process control in complex systems, taking into account the different modes of operation are as follows: t_i – variable from the term set T for i criterion; q_i – quantitative assessment from the interval [0; 1], I criterion, $i = \overline{1, m}$.

For each input value $(t_i; q_i)$ is matched to the value of the membership function $\mu(t_i)$. To obtain a normalized estimate of the input data, we construct membership rules.

Let the term set of linguistic variables T be represented on some numerical interval, to distinguish the terms $[a_0; a_l]$, where $T_1 \in [a_0; a_1]$, $T_2 \in [a_1; a_2]$, …, $T_l \in [a_{l-1}; a_l]$. The values of the partitioning of the intervals can be adjusted and changed in the process of using real data of a complex system of operation.

Next, we calculate criterion assessments O_i, using linguistic variables T, quantitative estimates q and the value of partitioning $[a_0; a_l]$, for example, with the following characteristic function:

$$O_i = \begin{cases} a_1 \cdot q_i, & \text{якщо} \quad t_i \in T_1; \\ a_2 \cdot q_i, & \text{якщо} \quad t_i \in T_2; \\ \ldots & \ldots \quad \ldots; \\ a_l \cdot q_i, & \text{якщо} \quad t_i \in T_l. \end{cases} \quad i = \overline{1, m}. \tag{2}$$

Depending on the applied problem, without reducing the generality, the systems analyst can use other known methods of fuzzy inference systems to aggregate qualitative and quantitative data [26].

To compare the data it is necessary to normalize the obtained estimates. We offer to do this with the help of membership functions. The type of uncertainty depends on the applied problem, the estimated complex system or subsystem, for example: approximately equal, average value, small value, high level, etc. Given the type of uncertainty, analysts choose the membership function. For example, such a choice for uncertainty of the type "high level", the type of *S*-shaped membership function will look like [1]:

$$\mu(O_i) = \begin{cases} 0, & O_i \le a_0 \\ 2\left(\frac{O_i - a_0}{a_l - a_0}\right)^2, & a_0 < O_i \le \frac{a_0 + a_l}{2} \\ 1 - 2\left(\frac{a_l - O_i}{a_l - a_0}\right)^2, & \frac{a_0 + a_l}{2} < O_i < a_l \\ 1, & O_i \ge a_l \end{cases}. \quad i = \overline{1,m}. \qquad (3)$$

The membership function constructed in this way indicates that the value obtained $\mu(O_i)$ will go to 1, if the high level of the *i-th* performance of the system.

Thus, based on the use of fuzzy sets, the subjectivity of expert opinions is revealed and the transition from fuzzy expert linguistic and quantitative assessments to normalized and comparable ones is made.

In the second stage, we will aggregate the estimates of the system indicators taking into account the considerations of decision-maker. Let the decision-maker for each indicator of the system can set the weights v_i, $i = \overline{1,m}$, from interval [1; 10]. Otherwise, the criteria may be equally important and the correspondingly normalized weights are determined [25]:

$$w_i = \frac{v_i}{\sum_{i=1}^{m} v_i}, i = \overline{1,m}. \qquad (4)$$

Next, the membership function is built, as one of the proposed convolutions, depending on the considerations of decision-maker, on the development of events [1]:

$$M_1(S) = \frac{1}{\sum_{i=1}^{m} \frac{w_i}{\mu(O_i)}} \text{ – pessimistic scenario;} \qquad (5)$$

$$M_2(S) = \prod_{i=1}^{m} (\mu(O_i))^{w_i} \text{ – cautious scenario;} \qquad (6)$$

$$M_3(S) = \sum_{i=1}^{m} w_i \cdot \mu(O_i) \text{ – average scenario;} \qquad (7)$$

$$M_4(S) = \sqrt{\sum_{i=1}^{m} w_i (\mu(O_i))^2} \text{ – optimistic scenario.} \qquad (8)$$

Where w_i ($i = \overline{1,m}$) normalized weights for each criterion.

There is the following subordination between them [1]: $M_1(S) \le M_2(S) \le M_3(S) \le M_4(S)$.

Next, at first, let's design a scenario for the development of events on the «trend of the level of process control in the system».

Here you need to build a membership function, which forms the following dependence: the greater the aggregate assessment of the system, the higher the level of controllability of processes in the system. With this in mind, consider the dependence in the form of an *S*-linear membership function [1], which we call the «trend of the level of process control in the system»:

$$M_g(S) = \begin{cases} 0, & R_g < a; \\ \frac{R_g - a}{b - a}, & a \le R_g \le b; \\ 1, & R_g > b. \end{cases} \qquad (9)$$

Where a, b numerical values.

As the values of the membership function $M_g(S)$ ($g = \overline{1,4}$) are known, then from the formula (9) calculate R_g . The obtained values R_g – this is an assessment of the projection of the «trend of the level of process control in the system» on the aggregate assessment of the functioning of the system, taking into account the considerations of decision-maker.

Next, we assess the level of process control in different modes of system operation. Graphically, we can interpret this as fig. 3.

Let's have modes of operation of the system $C = (C_1, C_2, \ldots, C_8)$. With the rise of the emergency, rapidly changing values that affect the stability of any system, and hence to reduce the level of process control in the system. For this, let's input the concept of some a priori gave, acceptable values – «the threshold of the possibility of functioning of the system».

To interpret the dependence of the aggregate assessment and the level of process control in the system relative to the modes of operation of the system, the following function is proposed [1]:

$$\mu_C(R_g) = 1 - \begin{cases} 0, & R_g < a; \\ \left(\frac{R_g - a}{b - a}\right)^k, & a \le R_g \le b; \\ 1, & R_g > b. \end{cases} \quad (10)$$

Where κ – threshold of the possibility of system operation. The value of this threshold varies depending on the modes in which the decision-maker needs to make a decision. For example, experimentally put: k= 2 for regular mode C_1; k= $\frac{7}{4}$ for out of regular mode C_2; k= $\frac{3}{2}$ for a critical situation C_3; k= $\frac{5}{4}$ for an emergency C_4; k= $\frac{3}{4}$ for accident situation C_5; k= $\frac{1}{2}$ for an accident C_6; k= $\frac{1}{4}$ for a catastrophic situation C_7; k= $\frac{1}{8}$ for disaster C_8. Then by the formula (10) get an estimate process control in complex systems taking into account different modes of operation $\mu_{C_1}(R_g)$, $\mu_{C_2}(R_g)$,…,$\mu_{C_8}(R_g)$, $g = \overline{1,4}$.

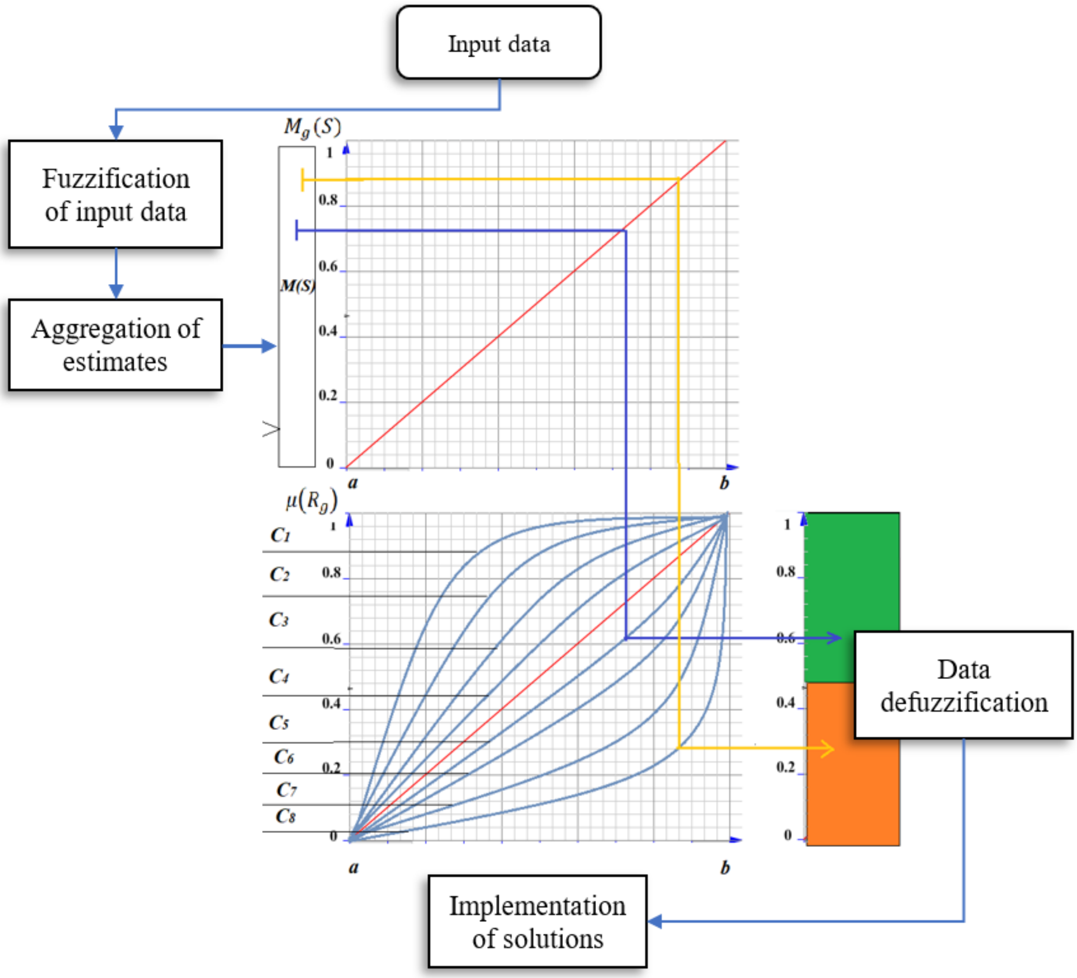

Figure 3: Graphical interpretation of fuzzy model

Thus, the obtained values are estimates of process control in complex systems according to the *g*-th reasoning of decision-maker on the scenario of events in the appropriate mode of operation of the system. At the last stage, we carry out the defuzzification of data. Based on the obtained assessment of process control in complex systems, taking into account the mode of operation, we draw conclusions for further selection and implementation of solutions. For example, we can determine the level of safe state of the system, to prevent negative consequences or confidence in achieving the goals by the system. The decision-maker sets a threshold for this $\alpha \in (0; 1)$. For example: $\mu_C(R_g) \in [0; \alpha)$ – unsafe state of system operation and low level of achievement of goals by the system in the appropriate mode of system operation C and according to the scenario of unfolding events g; $\mu_C(R_g) \in [\alpha; 1]$ – safe state of system operation and high level of achievement of system goals in the appropriate mode of system C operation and in relation to the scenario of events g.

4. Results

Consider the example of the developed fuzzy model for determining the level of process control in airport management information systems [27], with data security threats, given the different modes of operation [28]. Within, the continuation of the preliminary study Educational Model for Evaluation of Airport NIS Security for Safe and Sustainable Air Transport [29], consider six indicators of airport's assets: K_1 – intelligent surveillance systems; K_2 – meteorological information systems; K_3 – departure control information systems; K_4 – runway monitoring system; K_5 – Software; K_6 – flight information display system [30-31].

A group of security experts, based on experience and knowledge of the object of study, analyzed and inserted one linguistic assessment for each indicator K. The term set is proposed as following $T = \{T_1; T_2; T_3; T_4; T_5\}$, where: T_1 – «low level of protection»; T_2 – «the level of protection is below average»; T_3 – «average level of protection»; T_4 – «the level of protection is above average»; T_5 – «high level of protection». In addition, each asset has a quantitative level q, from the interval [0; 1], system security against data security threats obtained by modeling fuzzy knowledge. Represented training test input data and weight coefficients (interval [1; 10]) fig. 4. Let's evaluate the level of process control in airport management systems according to the developed fuzzy model.

In the first stage, we will fuzzyfication the input data using fuzzy sets. Since the indicators characterize the level of security of the system, then the term set of linguistic variables T is presented on a percentage numerical interval, to distinguish the terms $[0; 100]$, where $T_1 \in [0; 20]$, $T_2 \in (20; 40]$, $T_3 \in (40; 60]$, $T_4 \in (60; 80]$, $T_5 \in (80; 100]$. Let's calculate the criterion estimates by the formula (2): *O=(60; 48; 56; 48; 90; 56).* Since the higher the estimate, the higher the level of security of the system, then we introduce the *S*-shaped membership function and calculate the value by the formula (3): $\mu(O)$*=(0,68; 0,47; 0,61; 0,46; 0,98; 0,61).*

Next, calculate the normalized weights by the formula (6): *w=(0,13; 0,148; 0,185; 0,185; 0,167; 0,185).* Let the decision-maker estimate the average scenario, then calculate the convolution of airport assets by the formula (7): $M_3(S)$=0,632.

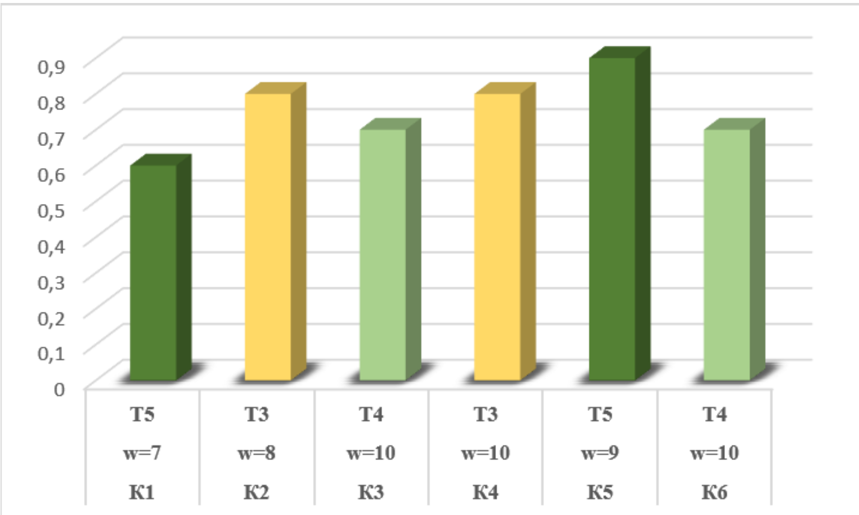

Figure 4: Visualization of input data

In the next step, we calculate the estimate of the projection of the «trend of the level of process control in the system» on the aggregate assessment of the system, according to the formula (9), putting *a=0, b=100*: $R_3 = 63{,}204$.

Calculate the assessment of the level of process control in airport management information systems, with data security threats, by formula (10) for three modes: for regular mode (k= 2) – $\mu_{C_1}(R_3)$ =0,6; for a critical situation (k= $\frac{3}{2}$) – $\mu_{C_3}(R_3)$ =0,49; for accident situation (k= $\frac{3}{4}$) – $\mu_{C_5}(R_3)$ =0,29.

Based on the obtained estimates, we draw the following conclusions. With the threshold $\alpha = 0{,}5$ in critical and accident situations not safe state of the system and low level of achievement of goals by the system, and in regular mode, the airport management information system, in case of data security threats, has a secure state. As part of the study, was developed innovative software in the form of a web application, which called "Assessment of the level of process control in systems taking into account different modes", based on the fuzzy model, Fig. 5. In this web application, can be made all the settings of the developed fuzzy model.

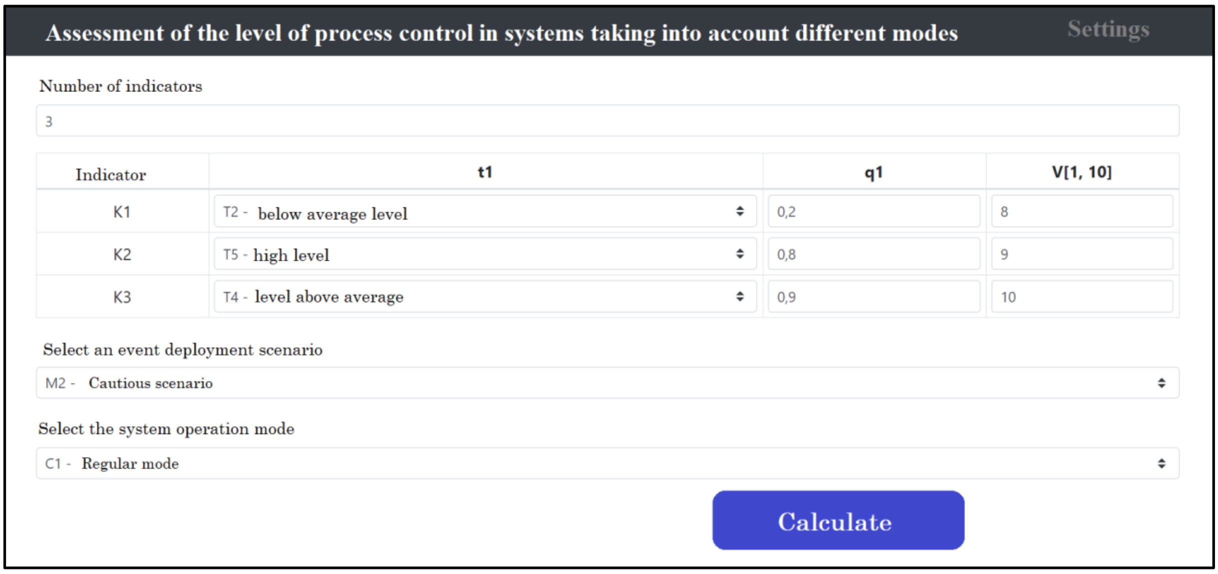

Figure 5: The main window of the developed software

5. Discussion

To apply the developed technology to applied tasks, it is necessary to adequately determine the set of evaluation indicators, create models of intellectual analysis of knowledge, adjust the fuzzification of input data, experimentally investigate the threshold of the system in different modes, and the threshold of safe operation to prevent negative consequences or confidence achievement of goals by the system. All these tasks are assigned to system analysts who develop an information system within the application problem. Thus, for qualitative comparison of data, delimitation of terms, it is necessary to carry out separately for each indicator as various indicators carry in themselves the numerical sense. If the system S consists of many subsystems $S_1, S_2, \dots, S_n$ then we evaluate each subsystem separately, and to aggregate the resulting data we can use one of the methods [12]. To qualitatively obtain input quantitative estimates and data mining (knowledge) using fuzzy set theory, membership functions, and a systems approach, you can use the models described in [12, 19].

6. Conclusions

A study of the current problem of developing technology for determining the level of process control in complex (weakly structured) systems, taking into account different modes of operation was done. For the first time the following results were obtained:

- a fuzzy mathematical model for determining the level of process control in complex (weakly structured) systems taking into account different modes of operation, based on expert hybrid data, using linguistic and quantitative variables has been proposed. The estimates of the indicators of a complex system are aggregated in relation to the decision-maker reasoning about the scenario of events. One aggregate estimate of the level of process control in a complex system with respect to different modes of operation is derived. Based on the obtained result, can be determined the level of safe operation of the system to prevent negative consequences or confidence in achieving the goals of the system. All this allows to reveal the uncertainties of expert opinions and data obtained, justifying the degree of decision-making and to draw adequate conclusions, taking into account the different modes of operation;

- experimental testing of the conducted research in the task of determining the level of process control in the airport management's information systems, with data security threats, taking into account different modes of operation was done. A web application was created for the developed model, with the help of which you can configure models and conduct experimental research for various application tasks.

The rationality of the obtained aggregate estimates, the level of safe state to prevent negative consequences of the system, or the confidence of achieving the goals of the system in different modes of operation, proves the advantages of the developed model. The reliability of the obtained results is ensured by the correct use of intellectual analysis of knowledge, system approach, fuzzy set theory, which is confirmed by research results.

Further research of the problem is as follows: to develop methodologies for assessing the level of process control in complex systems using risk-oriented factors. This investigation will be a useful tool to support decision-making on the creation and management of decisions in different modes of operation of the system.

7. References

[1] V. Polishchuk, and M. Malyar. “Modeling of risk level of the socioeconomic systems functioning”. Scientific Bulletin of Uzhhorod University, Mathematics and Informatics 1 (36) (2020): 92-104. doi: 10.24144/2616-7700.2020.1(36).92-104.

[2] International Civil Aviation Organization, 2020. URL: https://www.icao.int/Pages/default.aspx

[3] V. Kudryavtsev, Pravo i povedeniye, [Law and conduct]. Moskva, Yuridicheskaya literatura, 1978. (In Russian).

[4] M. Rubtcova. “Manageability: Sociological Theoretical Analysis of Notions”. Sotsiologicheskiye issledovaniya, 12, (2007).

[5] P. Kurt, S. B. Jørgensen, and S. Skogestad. “A review on process controllability”. Unpublished internal paper, (1999). doi: http://130.203. 133.150/viewdoc/download .

[6] K. Olejnik, A. Fabijanska, P. Pelczynski, and A. Stanislawska. “Controllability of low-consistency chemical pulp refining process”. Computers & Chemical Engineering, 128, (2019). doi: 10.1016/j.compchemeng.2019.06.024.

[7] E. Johann, M. Franceschetti, and J. Köpke. “Controllability of business processes with temporal variables”. 34th. ACM/SIGAPP Symposium on Applied Computing, 2019, 40–47.

[8] M. Zavatteri, C. Combi, and L. Viganò. “Resource controllability of workflows under conditional uncertainty”. In: C. Di Francescomarino, R. Dijkman, U. Zdun (Ed.), Business Process Management Workshops, Springer, Cham, 2019, pp. 68-80. doi: 10.1007/978-3-030-37453-2_7

[9] C. Cabanillas, M. Resinas, A. del-Río-Ortega, and A.R Cortés. “Specification and automated design-time analysis of the business process human resource perspective”. Inf. Syst. 52, (2015): 55–82.

[10] C. H. Tsai, and P. Brusilovsky. “User Feedback in Controllable and Explainable Social Recommender Systems: a Linguistic Analysis”. In CEUR Workshop Proceedings, CEUR-WS, Vol. 2682, (2020): 1-13.

[11] S. Ivanov, and I. Petre. “Controllability of reaction systems”. J Membr Comput, 2, (2020): 290–302. doi: https://doi.org/10.1007/s41965-020-00055-x

[12] O. Voloshyn, M. Malyar, V. Polishchuk, and M. Sharkadi. “Informatsiyne modelyuvannya nechitkykh znan”. [Information modeling of fuzzy knowledge]. Radioelektronika, informatyka, upravlinnya, 2018/4 (2018). (In Ukranian). doi: 10.15588/1607-3274-2018-4-8

[13] G. Korshunov, V. Smirnov, E. Frolova, and S. Nazarevich. “Fuzzy models and system technical condition estimation criteria”. In Fourth International Congress on Information and Communication Technology, Springer, Singapore, 2020, 179-189.
[14] G.J. Klir, and B. Yuan, Fuzzy Sets and Fuzzy Logic: Theory and Applications, NJ, USA, Prentice Hall, Englewood Cliffs, 1995.
[15] Y. Zaychenko, Nechetkiye modeli i metody v intellektualnykh sistemakh: navchalny posibnyk, Kiev, Slovo, 2008.
[16] V. Snityuk, Evolyutsionnyye tekhnologii prinyatiya resheniy v usloviyakh neopredelennosti, Kiev, MP Lesya, 2015.
[17] O. Buchelnikov, A. Grishkov, F. Malchinskiy, L. Medyanikova, and S. Nekrasov. “Modelirovaniye sistemy otbora letchikov-istruktorov” [Modeling of the system of selection of pilots-instructors], Yuzhno-Rossiyskiy zhurnal sotsialnykh nauk, Vol. 19, №4, (2018). (In Russian).
[18] V. Polishchuk, M. Kelemen, B. Gavurová, C. Varotsos, R. Andoga, M. Gera, J. Christodoulakis, R. Soušek, J. Kozuba, P. Blišťan, S. and Szabo Jr. “A Fuzzy Model of Risk Assessment for Environmental Start-up Projects in the Air Transport Sector”. Int. J. Environ. Res. Public Health, Vol. 16, 3573 (2019). doi: 10.3390/ijerph16193573.
[19] M. Kelemen, V. Polishchuk, B. Gavurová, S. Szabo, R. Rozenberg, M. Gera, J. Kozuba, J. Hospodka, R. Andoga, A. Divoková, P. Blišt’an. “Fuzzy Model for Quantitative Assessment of Environmental Start-up Projects in Air Transport”. Int. J. Environ. Res. Public Health, Vol. 16, 3585 (2019). doi: 10.3390/ijerph16193585
[20] M. Solesvik, Y. Kondratenko, G. Kondratenko, I. Sidenko, V. Kharchenko and A. Boyarchuk. “Fuzzy decision support systems in marine practice”. 2017 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), Naples, (2017): 1-6. doi: 10.1109/FUZZ-IEEE.2017.8015471.
[21] U. Ghani, IS. Bajwa, and A. Ashfaq. “A Fuzzy Logic Based Intelligent System for Measuring Customer Loyalty and Decision Making”. Symmetry. Vol. 10(12), (2018): 761.
[22] Y Liu, J.W. Bi, and Z.P. Fan. “Ranking products through online reviews: A method based on sentiment analysis technique and intuitionistic fuzzy set theory”. Inf. Fusion, Vol. 36, (2017): 149–161. doi: https://doi.org/10.1016/j.inffus.2016.11.012
[23] M. Zgurovsky, and N. Pankratova, Osnovy systemnoho analizu, [Fundamentals of systems analysis]. Kiev, VNV, 2007. (In Ukranian).
[24] M. Zhurovsky. “Stsenarnyy analiz yak systemna metodolohiya peredbachennya”, [Scenario analysis as a systemic methodology of prediction]. Systemni doslidzhennya ta informatsiyni tekhnolohiyi, Vol. 1, (2002): 7-38. (In Ukranian).
[25] M. Malyar, A. Polishchuk, V. Polishchuk, and M. Sharkadi. “Neuro-fuzzy multicriteria assessment model”. Radio Electronics, Computer Science, Control, Vol. 2019/4, (2019). doi: 10.15588/1607-3274-2019-4-8.
[26] V. Snytyuk, Prohnozuvannya. Modeli. Metody. Alhorytmy: navch. posib. [Prognostication. Models. Methods. Algorithms: Tutorial]. Kiev, Maklaut, 2008. (In Ukranian).
[27] J. Skorupski, and P. Uchroński. “A fuzzy model for evaluating airport security screeners’ work”. J. Air Transp. Manag, 48, (2015), 42–51. doi: https://doi.org/10.1016/j.jairtraman.2015.06.011
[28] S. Szabo, M. Pilát, A. Tobisová, and S. Makó. “Operational statistics of Košice airport”. In Scientific Journal of Silesian University of Technology, Series Transport, Vol. 102, (2019). doi: 10.20858/sjsutst.2019.102.16.
[29] M. Kelemen, V. Polishchuk, B. Gavurová, R. Andoga, S. Szabo, W. Yang, J. Christodoulakis, M. Gera, J. Kozuba, P. Kaľavský, and M. Antoško. “Educational Model for Evaluation of Airport NIS Security for Safe and Sustainable Air Transport”. Sustainability, Vol. 12, (2020): 6352. doi: 10.3390/su12166352.
[30] Cyber-Security Application for SESAR OFA 05.01.01-D3, Final Report, 2016. URL: https://www.sesarju.eu/sites/default/files/documents/news/Addressing_airport_cyber-security_Full_0.pdf
[31] V. Dragos, J. Ziegler, and J.P. Villiers. “Application of URREF Criteria to Assess Knowledge Representation in Cyber Threat Models”. 21st International Conference on Information Fusion (FUSION), Cambridge, UK, July 2018, 664–671.