Fuzzy model for assessing the organizational effect of an intelligent process control system

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Abstract. The article considers the problem of assessing the organizational effect of the functioning of an intelligent decision support system for controlling complex technical systems at the level of a technological control system. The level of organization of activity is used as an indicator of the organizational effect of an intellectual system. To obtain the numerical values of individual indicators of organizational effects, a system of mathematical models is presented that takes into account the specifics of the subject area. Aggregation of heterogeneous indicators to obtain generalized and complex indicators, which are measured on different scales and have a different range of values, is based on a fuzzy classification of parameter values and a fuzzy inference model using the Takagi-Sugeno algorithm. The obtained quantitative assessment of the organizational effect is complemented by a qualitative assessment containing a linguistic description of the level of organization of activities and the degree of expert's confidence in the result. The considered system of mathematical models for calculating the indicators of the organizational effect can be supplemented depending on the goals, the degree of detail and the depth of analysis and used in the analysis of the effectiveness of existing and future decision support systems and automated information systems at all stages of the life cycle.

1. Introduction

Each enterprise that manufactures high-tech, science-intensive and innovative products and pays great attention to the quality of its development and implementation should have a system of methods, models and procedures that gives a complete picture of all the benefits of its use and allows assessing the quality, various effects and effectiveness. Without belittling the merits of existing developments and approaches to solving the problem of obtaining adequate estimates in the analysis of efficiency [1-9], it should be noted that in practice difficulties arise when choosing a procedure for forming a system of criteria and performance indicators that can be measured, monitored and manageable, models of aggregation of indicators and methodologies for their assessment. The proposed study is in line with the further development of the theory and practice of assessing efficiency in relation to intelligent decision support systems (IDSS) for technological control of complex technical systems (CTS), which emphasizes its relevance. This work is a continuation of the study devoted to assessing the quality characteristics of IDSS, in which the issues of fuzzy assessment of the quality of IDSS were considered [10], a Bayesian model for assessing pragmatic efficiency [11] and an approach to assessing organizational effect were
developed. The aim of this study is to develop a fuzzy model for assessing the organizational effect of the functioning of the IDSS for the control of the CTS [12-14] at the level of the technological control system (TCS). This goal is achieved by developing a system of mathematical models for calculating indicators of the organizational effect of IDSS, taking into account the specifics of the technological control of CTS and the presence of uncertainty in the initial data.

2. Main part

To determine the organizational effect of the functioning of an intelligent system, a comparative assessment method was used, which is actively used in evaluating innovative projects and solutions for the development and implementation of new equipment or technology. It allows you to evaluate options for solutions that are alternative to ensure the production of specific products with certain characteristics in a given volume. Using a comparative approach, a quantitative assessment of the indicator of the organizational effect of IDSS, which is the level of organization of activities $E_{AO}$, can be obtained by the following formula:

$$E_{AO} = U_{AO}^1 - U_{AO}^2,$$

where $U_{AO}^1$, $U_{AO}^2$ – generalized indicators of the level of organization of the activity of the TSC with and without the use of IDSS.

It is proposed to supplement the obtained quantitative assessment with a qualitative assessment in the form of a linguistic description of the level of organization of activities and the degree of expert's confidence in the result. Such an assessment is understandable and convenient for information consumers and is aimed at facilitating their perception of numerical values and, consequently, at increasing the efficiency of the process of developing control decisions. To determine the qualitative assessment of the indicator, it is proposed to use a fuzzy classifier, a graphic representation of which is shown in figure 1. The description of the classifier is given in table 1.

![Figure 1. Five-level fuzzy classifier $E_{AO}$](image)

As the maximum value of the indicator, the target value of the indicator is used, which is determined at the stage of analysis of the pre-design stage of the life cycle by expert means based on the trend of technical progress in the industry for the future period. Since the unit segment of the real axis [0,1] is selected as the carrier of the linguistic variable, the classified indicator is normalized.

To calculate the generalized indicator of the level of organization of the activity of the TSC ($U_{AO}$), a multi-level system of quantitative indicators and a complex of mathematical models for their assessment are formed, shown in tables 2, 3, 4.
Table 1. Fuzzy presentation of organizational performance indicator IDSS.

| Classified parameter | Linguistic variable | Term set | The function of fuzzy set |
|----------------------|---------------------|----------|---------------------------|
| $E_{AO}$            | Indicator level     | $VL$ – very low | $\mu_2 (E_{AO}; 0.15, 0.25)$ |
|                     |                     | $L$ – low    | $\mu_T (E_{AO}; 0.15, 0.25, 0.35, 0.45)$ |
|                     |                     | $A$ – average | $\mu_T (E_{AO}; 0.35, 0.45, 0.55, 0.65)$ |
|                     |                     | $H$ – high   | $\mu_T (E_{AO}; 0.55, 0.65, 0.75, 0.85)$ |
|                     |                     | $VH$ – very high | $\mu_S (E_{AO}; 0.75, 0.85)$ |

Table 2. A complex of mathematical models for calculating the indicators of the organizational effect of TSC.

| Indicator (designation) | Mathematical model for calculation |
|------------------------|-----------------------------------|
| Efficiency of updating information objects ($O_A$) | $O_A = \frac{1}{n} \sum_{i=1}^{n} (t_2 - t_1)_i$, where $t_1$ – information object creation time, $t_2$ – time of appearance of the information object in the TSC, $n$ – the number of changes made during the observation period |
| Prompt access to information resources ($O_{IR}$) | $O_{IR} = \frac{1}{n} \sum_{i=1}^{n} (t_1 - t_2)_i$, where $t_1$ – time of occurrence of operational needs (familiarization, modification, destruction, etc.) of the end user, $t_2$ – time of appearance of access to information resources, $n$ – the number of needs that arose during the observation period |
| Efficiency of analytical information processing ($O_{PI}$) | $O_{PI} = \frac{1}{n} \sum_{i=1}^{n} (t_1 + t_2 + t_3 + t_4)_i$, where $t_1$ – time spent on selecting, organizing and structuring data from heterogeneous sources, $t_2$ – the time spent on determining the criteria for choosing an alternative, $t_3$ – time spent on mathematical calculations and logical reasoning, $t_4$ – time spent on forming alternatives and choosing the best alternative, $n$ – number of measurements during the observation period |
| Controllability of access to information resources for persons without authority ($I_{AC}$) | $I_{AC} = \frac{n_1}{n_2}$, where $n_1$ – the number of detected prohibited actions of various types during the observed period, $n_2$ – the total number of prohibited actions established in the regulatory documents |
| Preventing loss of documents ($I_{PLD}$) | $I_{PLD} = \frac{n}{t}$, where $n$ – the number of cases of loss of documents, $t$ – monitored period |
| Preventing corruption of data and information ($I_{PD}$) | $I_{PD} = \frac{n}{t}$, where $n$ – number of cases of data and information corruption, $t$ – monitored period |
| Security of information resources ($I_{SIR}$) | $I_{SIR} = f(I_{AC},I_{PLD},I_{PD})$ |
| Process control organization level ($U_{MO}$) | Fuzzy evaluation model for $I_{SIR}$ based on the Takagi-Sugeno algorithm $U_{MO} = f(O_A, O_{IR}, O_{PI}, I_{SIR})$ |
### Table 3. Complex of mathematical models for calculating organizational effect indicators.

| Indicator (designation)                                           | Mathematical model for calculation                                                                 |
|------------------------------------------------------------------|---------------------------------------------------------------------------------------------------|
| Automation factor for analytical information processing ($K_A$) | $K_A = \frac{1}{n} \sum_{i=1}^{n} \frac{t_i}{t_i + t_{ij}}$,                                       |
|                                                                  | where $t_1$ – laboriousness of performing automated operations, $t_2$ – laboriousness of performing |
|                                                                  | manual operations, $n$ – number of measurements during the monitored period.                        |
| Equipment automation factor ($K_{EA}$)                           | $K_{EA} = \frac{n_1}{n_2}$,                                                                        |
|                                                                  | where $n_1$ – number of units of automatic and automated equipment for the monitored period, $n_2$ – |
|                                                                  | total number of TSC equipment units for the monitored period                                        |
| Preventing loss of organizational knowledge ($I_{plK}$)          | $I_{plK} = 1 - \frac{n}{n}$,                                                                        |
|                                                                  | where $n$ – the number of cases of loss of organizational knowledge due to the departure of highly |
|                                                                  | qualified specialists (retirement age, dismissal, etc.), loss of a physical carrier of knowledge, |
|                                                                  | lack of formal knowledge, loss during transmission (distortion during fixation, misunderstanding |
|                                                                  | during training, etc.), $t$ – monitored period                                                      |
| Coefficient of provision of TSC with the necessary technical means ($K_{ST}$) | $K_{ST} = \frac{n_1}{n_2}$,                                                                         |
|                                                                  | where $n_1$ – the number of technical means used in the TSC for the monitored period, $n_2$ – number |
|                                                                  | of required technical means                                                                        |
| Personnel technical equipment level ($U_T$)                      | $U_T = \frac{n_1}{n_2}$,                                                                            |
|                                                                  | where $n_1$ – the number of technical means used in the TSC for the monitored period, $n_2$ – number |
|                                                                  | of staff for the monitored period                                                                   |
| Labor automation coefficient ($K_{AW}$)                          | $K_{AW} = \frac{n_1}{n_1 + n_2}$,                                                                   |
|                                                                  | where $n_1$ – the number of workers employed in automated work during the monitored period, $n_2$ – |
|                                                                  | number of workers performing manual operations during the monitored period                           |
| Coefficient of losses of working time due to organizational reasons ($K_{LWT}$) | $K_{LWT} = \frac{t_1}{t_2}$,                                                                   |
|                                                                  | where $t_1$ – total working time of TSC personnel for the monitored period spent on performing |
|                                                                  | routine operations, as well as lost due to insufficient qualifications, $t_2$ – total working |
|                                                                  | hours of the TSK personnel for the monitored period                                                 |
| Freelance utilization rate ($K_{UPS}$)                           | $K_{UPS} = 1 - \frac{n_1}{n_1 + n_2}$,                                                            |
|                                                                  | where $n_1$ – the number of cases of attracting freelance specialists (highly qualified employees of |
|                                                                  | the organization, developers, external consultants) and part-time workers when performing analytical |
|                                                                  | processing operations for the monitored period, $n_2$ – the number of cases of independent |
|                                                                  | performance of these operations by the TSC personnel during the monitored period                   |
| Information utilization rate ($K_{IU}$)                          | $K_{IU} = \frac{n_1}{n_2}$,                                                                        |
|                                                                  | where $n_1$ – number of cases of document use during the monitored period, $n_2$ – total number of |
|                                                                  | documents                                                                                           |
| Indicator (designation)                                      | Mathematical model for calculation                                                                 |
|-----------------------------------------------------------|-----------------------------------------------------------------------------------------------------|
| Personnel recruitment, training and utilization level     | \( U_S = f(K_{AW}, K_{LWT}, K_{IFS}, K_{R}) \)                                                     |
| Level of automation coverage of inspection tasks          | \( U_{OA} = \frac{n_1}{n_2} \) \hspace{1cm} \text{where} \ n_1 \ - \ \text{number of control tasks solved in an automated way}, \ n_2 \ - \ \text{the number of control tasks that can in principle be automated} |
| Activity uncertainty coefficient \( (K_{UA}) \)           | \( I_{UA} = 1 - \frac{n_1}{n_2} \) \hspace{1cm} \text{where} \ n_1 \ - \ \text{the number of operations requiring highly qualified personnel and the possible involvement of freelance specialists}, \ n_2 \ - \ \text{total number of operations performed by TSC} |
| The level of rationalization of labor processes \( (U_R) \)| \( U_R = f(U_{OA}, K_{UA}) \)                                                                         |
| Labor organization level \( (U_{OW}) \)                   | \( U_{OW} = f(K_{A}, K_{EA}, I_{PLK}, K_{ST}, U_T, U_7, U_5, U_R) \)                                |
| Correspondence ratio of personnel qualifications to the work performed \( (K_{QC}) \) | \( K_{QC} = \frac{n_1}{n_2} \) \hspace{1cm} \text{where} \ n_1 \ - \ \text{number of TSK employees with qualifications corresponding to the work performed}, \ n_2 \ - \ \text{total number of TSC employees} |
| External training cost ratio \( (K_{CE}) \)               | \( K_{CE} = \frac{c}{n} \) \hspace{1cm} \text{where} \ c \ - \ \text{costs of external training of TSC personnel for the observed period}, \ n \ - \ \text{total number of TSC employees} |
| Personnel qualification level \( (U_{PQ}) \)              | \( U_{PQ} = f(K_{QC}, K_{CE}) \)                                                                     |
| The level of organization of the TSC activity \( (U_{OA}) \)| \( U_{OA} = f(U_{MO}, U_{OW}, U_{PQ}) \)                                                              |

The table shows that to calculate generalized and complex indicators, a fuzzy assessment model is used, based on a fuzzy classification [16-18] of the output and input parameters of the model and the Takagi-Sugeno fuzzy inference algorithm of the 1st order, which is widely used in practice and has a high expert assessment [19-23].

The estimation model is based on the use of four fuzzy classifiers and fuzzy inference using the Takagi-Sugeno algorithm. The input parameters of the model are the numerical values of the indicators of the lower level \( U_{MO}, U_{OW}, U_{PQ} \), obtained at the previous stage of the assessment. Using the fuzzy inference algorithm and the fuzzy classifier of the output parameter (indicator \( U_{OA} \)), both quantitative and qualitative assessment of \( U_{OA} \) are determined.

The choice of the type and parameters of the used membership functions, the number of terms of linguistic variables is made by an expert, taking into account the results of the analysis of published works and recommendations in [24, 25]. All four classifiers are constructed as shown in figure 1. As the maximum values of indicators, their target values are used, which are set on the basis of expert assessments, taking into account the trends of technological progress in the industry for the future period. The classified indicators are normalized, because the unit segment of the real axis \([0,1]\) is chosen as the carrier of the linguistic variable. The description of the classifiers is given in table 5.
The recognition algorithm that allows you to obtain a quantitative and qualitative assessment of \( U_{OA} \) consists of the following stages:

Stage 1. Input of initial data:
- \( U_{MO}^* , U_{OW}^* , U_{PO}^* \) and \( U_{OA}^* \) - numerical values of classified parameters;
- \( U_1 , U_2 , U_3 \) and \( U \) - linguistic variables;
- \( T(U_i) = \{VL_i, L_i, A_i, H_i, VH_i\} , \ldots , T(U) = \{VL_4, L_4, A_4, H_4, VH_4\} \) - basic term sets;
- base of fuzzy production rules with the following structure:

RULE 1: IF «\( U_1 \) is \( VL_1 \)» AND «\( U_2 \) is \( VL_2 \)» AND «\( U_3 \) is \( VL_3 \)», THAN « \( U = w_1^0 + w_1^1 U_1 + w_2^2 U_2 + w_3^3 U_3 \) »; …; RULE \( n \): IF «\( U_1 \) is \( VH_1 \)» AND «\( U_2 \) is \( VH_2 \)» AND «\( U_3 \) is \( VH_3 \)», THAN « \( U_n = w_n^0 + w_n^1 U_1 + w_n^2 U_2 + w_n^3 U_3 \) »,

where \( w_1^0 , w_1^1 , w_1^2 , w_1^3 \) - weight coefficients, the values of which are determined by expert methods, are refined when training the model.

Stage 2. Fuzzification of input parameters. Determination of the set of values of membership functions for each \( i \)-th of the rule base subconditions and for all input parameters.

Stage 3. Aggregation of subconditions. The min-conjunction operation is used as an aggregation method.

Stage 4. Activation of conclusions of each rule from the base of active rules. Calculating the numerical values of the output variables \( U_{OA} \) of each rule using formulas for conclusions of the rule base into which instead of \( U_1 , U_2 , U_3 \) values \( U_{MO}^* , U_{OW}^* , U_{PO}^* \) are substituted (2).

### Table 5. Fuzzy presentation of indicators \( U_{MO}, U_{OW}, U_{PO}, U_{OA} \).

| Classified parameter | Linguistic variable | Term set | The function of fuzzy set |
|----------------------|---------------------|----------|--------------------------|
| \( U_{MO} \)         | \( U_1 \) - level \( U_{MO} \) | \( VL_1 \) | \( \mu_2 \ (U_{MO} ; 0.15, 0.25) \) |
|                      |                     | \( L_1 \) | \( \mu_1 \ (U_{MO} ; 0.15, 0.25, 0.35, 0.45) \) |
|                      |                     | \( A_1 \) | \( \mu_1 \ (U_{MO} ; 0.35, 0.45, 0.55, 0.65) \) |
|                      |                     | \( H_1 \) | \( \mu_1 \ (U_{MO} ; 0.55, 0.65, 0.75, 0.85) \) |
|                      |                     | \( VH_1 \) | \( \mu_8 \ (U_{MO} ; 0.75, 0.85) \) |
| \( U_{OW} \)         | \( U_2 \) - level \( U_{OW} \) | \( VL_2 \) | \( \mu_2 \ (U_{OW} ; 0.15, 0.25) \) |
|                      |                     | \( L_2 \) | \( \mu_1 \ (U_{OW} ; 0.15, 0.25, 0.35, 0.45) \) |
|                      |                     | \( A_2 \) | \( \mu_1 \ (U_{OW} ; 0.35, 0.45, 0.55, 0.65) \) |
|                      |                     | \( H_2 \) | \( \mu_1 \ (U_{OW} ; 0.55, 0.65, 0.75, 0.85) \) |
|                      |                     | \( VH_2 \) | \( \mu_8 \ (U_{OW} ; 0.75, 0.85) \) |
| \( U_{PO} \)         | \( U_3 \) - level \( U_{PO} \) | \( VL_3 \) | \( \mu_2 \ (U_{PO} ; 0.15, 0.25) \) |
|                      |                     | \( L_3 \) | \( \mu_1 \ (U_{PO} ; 0.15, 0.25, 0.35, 0.45) \) |
|                      |                     | \( A_3 \) | \( \mu_1 \ (U_{PO} ; 0.35, 0.45, 0.55, 0.65) \) |
|                      |                     | \( H_3 \) | \( \mu_1 \ (U_{PO} ; 0.55, 0.65, 0.75, 0.85) \) |
|                      |                     | \( VH_3 \) | \( \mu_8 \ (U_{PO} ; 0.75, 0.85) \) |
| \( U_{OA} \)         | \( U \) - level \( U_{OA} \) | \( VL_4 \) | \( \mu_2 \ (U_{OA} ; 0.15, 0.25) \) |
|                      |                     | \( L_4 \) | \( \mu_1 \ (U_{OA} ; 0.15, 0.25, 0.35, 0.45) \) |
|                      |                     | \( A_4 \) | \( \mu_1 \ (U_{OA} ; 0.35, 0.45, 0.55, 0.65) \) |
|                      |                     | \( H_4 \) | \( \mu_1 \ (U_{OA} ; 0.55, 0.65, 0.75, 0.85) \) |
|                      |                     | \( VH_4 \) | \( \mu_8 \ (U_{OA} ; 0.75, 0.85) \) |
\[ U_{OA}^* = w_1 U_{OA}^{w_1} + w_2 U_{OA}^{w_2} + w_3 U_{FQ}^{w_3}. \] (2)

Stage 5. Defuzzification of output variables. To calculate \( U_{OA}^* \) the method of the center of gravity for single-point sets is used and the following formula:

\[ U_{OA}^* = \frac{\sum_{i=1}^{n} \alpha_i U_{OA}^*}{\sum_{i=1}^{n} \alpha_i}. \] (3)

Stage 6. Classification of \( U_{OA}^* \). Obtaining a qualitative assessment of the generalized indicator \( U_{OA}^* \) in the form of a linguistic description of the level of organization of the TSC activity and the degree of expert confidence in the result is carried out on the basis of the obtained numerical value, table 3 and formulas describing the trapezoidal membership functions [4-6].

Thus, having calculated the numerical values \( U_{AO}^1 \) and \( U_{AO}^2 \), according to formula (1), one can obtain a quantitative estimate of the indicator of the organizational effect of IDSS.

It should be noted that the proposed system of indicators and mathematical models for their calculation can be supplemented and adapted depending on the goals, degree of detail and depth of analysis and used in analyzing the effectiveness of existing and future decision support systems and automated information systems at all stages of the life cycle.

3. Conclusion

The article discusses a fuzzy model for assessing the organizational effect of the functioning of the IDSS for the control of the CTS at the TSC level. A feature of the considered model is the combined use of a comparative approach to assessing the effect, a system of mathematical models for calculating a generalized indicator of the level of organization of the activity of a TSC, taking into account the specifics of the subject area, and a fuzzy classification of the numerical value of the indicator of the level of organization of activity to obtain its qualitative assessment. To aggregate the indicators of the hierarchical system, a fuzzy inference model is used according to the Takagi-Sugeno algorithm, which makes it possible to take into account the presence of uncertainty in the initial data.

The theoretical significance of the study lies in the development of methodological foundations for assessing the effectiveness of the functioning of intelligent systems in the field of technological control of complex systems. The results obtained can be used in the aerospace, nuclear, transport industry and shipbuilding in the development and implementation of IDSS.

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