Intelligent decision support system for the control of complex technical systems

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Abstract. This article discusses the design of the control system of complex technical objects. A model of the system for intelligent decision support in the performance of control tasks, characterized by multi-criteria and the presence of various kinds of uncertainties in the source information and expertise. The description of criteria, models and algorithms allowing to expand functionality of hardware of process of parametric admission control of a condition of technical systems is given.

1. Introduction
The urgency of the problem of improving the control and verification equipment for complex technical systems (CTS) increases with the complexity of the objects of control, the conditions of their functioning, increasing the responsibility of the functions performed and the increase in the price of failure. The key direction of development of control systems (SC) is the development of intelligent decision support systems (IDSS), which improve the quality of decision-making, which determines the effectiveness of the SC at all stages of the life cycle (LC) in the overall system to ensure the reliability of technical facilities. We can distinguish the following main functional tasks that require solutions at the present stage of development of the theory and practice of technical control:

- improving the accuracy of estimations of the state of the object of control. A deeper estimation of the state of workable products will allow for the timely detection of prefault states and the detection of susceptibility to the instability of a up state in the early stages of defect development;
- Increasing the resolution of diagnostic tools to locate the fault at the level of the component parts (CP) of the technical system in the presence of uncertainty in the estimation of the results of parametric control;
- prediction of the technical condition of the object of control, taking into account the lack of a priori information associated with the lack of the necessary mathematical description, small sample size of parameter values, lack of information about the laws of degradation processes in electronic components, the nature of the relationship between the set of destabilizing factors and the behavior of parameters, with limited experimental research processes to obtain sufficient statistical information, etc. Predictive estimates will allow for individual planning of maintenance and repair work, to make adjustments to the composition of a set of spare parts, tools and accessories, etc.;
• ensuring prompt access to information about the product, resources, processes and results obtained at various stages of the LC.

In this paper, the subject of research is the development of an IDSS model, which provides information and analytical support for the person making the decisions (PMD) in the automated mode for solving control problems characterized by multi-criteria and uncertainty.

2. IDSS model for control of the CTS

The use of IDSS (Figure 1) to expand the functionality of the SC is a justified solution, since it solves the most important task of ensuring and maintaining the quality of the processes of creating and operating the product at a given level, taking into account the interaction and interaction of the subjects of the LC.

![Figure 1](attachment://model.png)

**Figure 1.** Model IDSS for control of the CTS.

The application of the methods of the theory of artificial intelligence is due to the emergence of an increasing number of semi-structured tasks during control. They are characterized by the absence of a clear relationship between causes and effects, a general universal solution algorithm applicable for
each specific case, the impossibility of directly measuring the values of parameters of interest to the researcher, the predominance of qualitative parameters over quantitative ones. To support decision-making processes, it is proposed to use an IDSS, a hardware-software complex that uses and integrates elements of artificial intelligence technologies and information systems to process significant amounts of objective and subjective information, allowing to form a set of reporting forms containing information for decision-making and (or) variants of decisions. The results of the IDSS are the initial data for the subsequent analysis of PMD. They are supplemented by a description of the set of diagnostic features obtained using visual and organoleptic methods of control (noise, vibration, overheating, etc.), as well as information obtained in the process of coordinating decisions within the LC of the product, and information from the database and knowledge base IDSS.

When developing knowledge base blocks that allow copying, modeling, and replicating with the help of IDSS, reasoning, experience, and knowledge of highly qualified specialists, promising approaches to the theory of artificial intelligence were chosen. These include: the theory of fuzzy sets, methods of fuzzy logic [1-3], methods for modeling reasoning based on cases and Bayesian trust networks (BTN) [4-6], models and algorithms of artificial immune systems (AIS) [7-9].

3. The block finding of the faults
The block finding of the faults is designed to solve the problem of localizing faults at the level of the CP of a CTS in the presence of uncertainty in the estimation of the results of parametric control. The proposed model allows you to create a ranked list of CP, which sets the order of their dismantling and testing at specialized stands. Consider a fuzzy algorithm for determining the sequence of diagnostic operations. At the preparatory stage, the numerical values of the preliminary estimations of the down state of the CP of a CTS are calculated using two diagnostic models, case and Bayesian.

Input variables for the case model are a set of estimations of the values of parameters 0 (“fit”) and 1 (“not fit”) and the results of test checks 0 (“normal”) and 1 (“not normal”). To ensure the effectiveness of the process of extracting cases, it is proposed to use a three-tier model for finding suitable cases. The search begins with an analysis of the results of test checks, then the totality of a certain part of the Boolean estimates of the parameters and groups of parameters is analyzed. The search ends with an analysis of parameter value estimates.

To calculate the metric distance at each hierarchical search level, modified Hamming formulas are used:

\[ d(X, X') = \sum_{i=1}^{k} w_{X_i} |x_i - x_i'| \]  

(1)

where \( X \) is a set of CTS parameters describing this case in Boolean format, \( X' \) is a set of CTS parameters characterizing the incident, i.e. current failure state; \( w_{X_i} \) are the weight coefficients of the set \( WX \), taking into account the relative value of each parameter included in \( X \). To improve the accuracy and performance of the solution search, settings are used that limit the number of selected cases, reduce the considered number of cases at the stage of their ranking and take into account the numerical assessment of the applicability of the case. The numerical estimation of the down state of the CP of a CTS is obtained by calculating the metric distance between the case and the incident.

The input variables for the Bayesian diagnostic model are test results. Figure 2 shows an illustrative example of the topology of the BTN for the preliminary estimate of the down state of the CP of a CTS.

BTN is constructed in such a way that unobservable variables (the CP of a CTS) are located in the root nodes of the acyclic graph, and the observed (test checks) are located in the lower level of the network. The values of the variables \( A_1, \ldots, A_5 \), corresponding to the down state, are 1, and the up state, respectively, 0. The values of the variables \( B_1, \ldots, B_7 \), corresponding to the negative result of the test check (“not normal”), are 1, but the positive result (“normal”), respectively, 0. The numerical estimate of the down state of the CP of a CTS is obtained by calculating the a posterior probabilities of the down state \( A_1, \ldots, A_5 \) in accordance with the established values of the variables \( B_1, \ldots, B_7 \).
Coordination of the intermediate results of the estimation and obtaining a comprehensive estimation is based on the use of three fuzzy classifiers and the Takagi-Sugeno first-order fuzzy inference algorithm. Each classified variable corresponds to a linguistic variable characterized by a basic term set with a set of membership functions of fuzzy sets. The combination of linguistic values $A_1$, $A_2$ and $B$ are presented in Table 1.

**Table 1. Setting term sets for variables $A_1$, $A_2$ and $B$.**

| Classified variable | Linguistic variable | Term set |
|---------------------|---------------------|----------|
| $x_1$               | $A_1$– preliminary estimation of the down state of a CP of a CTS to the particular criterion of the a posteriori probability of failure | very small value ($VSV_1$), small value ($SV_1$), average value ($AV_1$), large value ($LV_1$), very large value ($VLV_1$) |
| $x_2$               | $A_2$– preliminary estimation of the down state of a CP of a CTS to the particular criterion of the metric distance between the use case and the incident | very small value ($VSV_2$), small value ($SV_2$), average value ($AV_2$), large value ($LV_2$), very large value ($VLV_2$) |
| $y$                 | $B$– preliminary estimation of the down state of a CP of a CTS to the complex criterion of the level of down state | very low level ($VLL$), low level ($LL$), medium level ($ML$), high level ($HL$), very high level ($VHL$) |

The proposed classifiers have the same structure, presented graphically in Figure 3.

**Figure 3.** Five-level fuzzy classifier.

The basis of fuzzy inference is the base of rules, which have the following form:

RULE 1: IF “$A_1$ is $VSV_1$” AND “$A_2$ is $VSV_2$”, THEN “$B_1 = w_0^1 + w_1^1 A_1 + w_2^1 A_2$”;

...  

RULE N: IF “$A_1$ is $VLV_1$” AND “$A_2$ is $VLV_2$”, THEN “$B_n = w_0^0 + w_1^0 A_1 + w_2^0 A_2$”.  


where $w_i^j, w_j^j, w_j^k$ are the weighting factors of the $j$-th rule, which are set by an expert and are refined when experimental data are received in the process of learning the model. To aggregate the sub-conditions of active rules, the operation of min-conjunction is used. The numerical value of the output variable $y^*$ is determined by the center of gravity method for single-point sets using the formula:

$$y^* = \frac{\sum_{i=1}^{n} \alpha_i y_i^*}{\sum_{i=1}^{n} \alpha_i},$$

where $\alpha_i$ is the numerical value of the cut-off level according to the $i$-th rule base rule. The resulting numerical estimates are ranked in the direction of decreasing their values. The solution of the task is a ranked list of CP with their description. The description contains a numerical estimation and a linguistic description of the level of down state, as well as the degree of evaluative confidence in the recognition result.

4. The block of estimation of the parameters of the up state

In the existing practice of automated control to estimation the up state of the product is used tolerance method. It is not focused on the estimation of up states of products with different levels of performance in accordance with a specific set of parameter values. However, such an estimation is necessary because the proximity of the parameter values to the boundaries of the tolerance fields and their abnormal change in time within the tolerance zone are signs of instability of the up state, the prerequisites for the onset of the down state. The proposed approach to estimating the “fit” parameters, based on the theory of fuzzy sets and the theory of time series analysis, allows you to more accurately control the influence of multifactorial influences and provides new opportunities for managing the LC processes of the CTS. It is based on the use of seven fuzzy classifiers and the Mamdani fuzzy inference algorithm. The structure of classifiers, the designation and name of linguistic variables and their meanings are presented in Figure 3 and in Table 2.

To calculate the numerical values of the variables $x_1, \ldots, x_6$, historical data from the database is used, namely, the time series of parameter values measured during various control tests at the stages of manufacture and operation. Formulas for calculating the variables $x_1, \ldots, x_6$ can be found in [3]. Fuzzy inference is carried out using the system of production rules: The basis of fuzzy inference is the rule base, which has the following form:

RULE 1: IF “$A_1$ is $EC_1$” AND “$A_2$ is $EC_2$” AND “$A_3$ is $EC_3$” AND “$A_4$ is $EC_4$” AND “$A_5$ is $EC_5$” AND “$A_6$ is $EC_6$”, THEN “$B$=EC”; 

... 

RULE N: IF “$A_1$ is $PS_1$” AND “$A_2$ is $PS_2$” AND “$A_3$ is $PS_3$” AND “$A_4$ is $PS_4$” AND “$A_5$ is $PS_5$” AND “$A_6$ is $PS_6$”, THEN “$B$=PS”.

At the aggregation stage, it is proposed to apply the min-conjunction operation, at the activation stage – the min-activation method, at the accumulation stage – the max-disjunction operation, at the defuzzification stage – the left modal value method. The obtained quantitative estimation of the level of up state is complemented by a qualitative estimation using a fuzzy five-level classifier of the parameter $y$. Qualitative estimation in the form of a linguistic description of the level of up state and the degree of estimated confidence in the result of recognition is a convenient form of presenting the result when making management decisions and making recommendations. It should be added that it is expedient to apply the considered procedure to estimate a part of the monitored parameters from the entire available population. As a criterion for choosing such parameters, it is proposed to use an acceptable level of significance of possible consequences.
### Table 2. Setting term sets for variables $A_1$, $A_2$, $A_3$, $A_4$, $A_5$, $A_6$ and $B$.

| Classified variable | Linguistic variable | Term set                        |
|---------------------|---------------------|---------------------------------|
| $x_1$               | $A_1$ – estimation of the state of the parameter according to the criterion of the workability margin by the parameter tolerance | excellent condition $(EC_1)$, good condition $(GC_1)$, satisfactory condition $(SC_1)$, hazardous state $(HS_1)$, prefault state $(PS_1)$ |
| $x_2$               | $A_2$ – estimation of the state of the parameter according to the stability criterion of the dynamics tendency steadiness | excellent condition $(EC_2)$, good condition $(GC_2)$, satisfactory condition $(SC_2)$, hazardous state $(HS_2)$, prefault state $(PS_2)$ |
| $x_3$               | $A_3$ – estimation of the state of the parameter according to the criterion of the value of the progressive change of the parameter | excellent condition $(EC_3)$, good condition $(GC_3)$, satisfactory condition $(SC_3)$, hazardous state $(HS_3)$, prefault state $(PS_3)$ |
| $x_4$               | $A_4$ – estimation of the state of the parameter according to the criterion of the value of the reverse parameter change | excellent condition $(EC_4)$, good condition $(GC_4)$, satisfactory condition $(SC_4)$, hazardous state $(HS_4)$, prefault state $(PS_4)$ |
| $x_5$               | $A_5$ – estimation of the parameter state by the criterion of the rate of change of the parameter | excellent condition $(EC_5)$, good condition $(GC_5)$, satisfactory condition $(SC_5)$, hazardous state $(HS_5)$, prefault state $(PS_5)$ |
| $x_6$               | $A_6$ – estimation of the state of the parameter according to the criterion of acceleration of the parameter change | excellent condition $(EC_6)$, good condition $(GC_6)$, satisfactory condition $(SC_6)$, hazardous state $(HS_6)$, prefault state $(PS_6)$ |
| $y$                 | $B$ – estimation of the parameter state by the criterion of the level of up state | prefault state $(PS)$, hazardous state $(HS)$, satisfactory condition $(SC)$, good condition $(GC)$, excellent condition $(EC)$ |

5. **The block prediction of the drift parameters**

The main difficulties in solving the problem of prediction the technical state of the CTS are associated with a high degree of uncertainty of the time series of parameter values. Traditional prediction methods, due to a number of restrictions on their use, do not provide an adequate estimation of upcoming changes in the behavior of parameters. To solve the problem of predicting the drift of parameters, it is proposed to use an AIS based on a combination of promising approaches: a method of modeling reasoning based on cases, an immune model of clonal selection and a method of approximation by cubic splines (Figure 4).

Prediction of the drift of the CTS parameter is reduced to the formation of a prediction consisting of two parts: a dot and an interval prediction. A dot prediction is an estimate of the value of the predicted variable – the time from the moment the prediction was made to the moment when the parameter reaches the limit of a predetermined field of warning within its acceptable range. The interval prediction is a pessimistic $t_p$ and optimistic $t_o$ estimate of the values of the predicted variable, setting the boundaries of the interval in which the actual value of the predicted variable can be expected. The parameter of the field of warning for each monitored parameter is selected by a classifier built on the basis of the mathematical apparatus of fuzzy sets. The division of the zone of the
allowed parameter values with linguistic estimation "fit", on a subzones, which characterize the intensity of this properties ("dangerously low", "satisfactorily low", "dangerously large", etc.) produced using $\alpha$-levels of fuzzy variable "fit" obtained by means of expertise.

Figure 4. Structure of AIS prediction.

The strategy of prediction is to build a prediction on analytical expressions describing the possible behavior of a parameter in the field of warning. To obtain analytical dependencies, an initial set of competing antibodies is used (precedents, potential solutions presented in a format for processing by the search algorithm operators) containing a formalized description of a time series of parameter values and an analytical trend expression describing the behavior of the parameter. The selection, adaptation and generation of antibodies for the immune response to an antigen, i.e. to solve the current problem of prediction is carried out by a modified clonal selection algorithm, based on the principles of the immune system. To obtain trend dependencies and calculate the missing values of the time series, the experimental data approximation method by cubic splines is used. Cubic spline of defect 1 with nodes coinciding with nodes of the table function $f(t)$ is described by the equation:

$$Spl(t) = \begin{cases} Spl_i(t), & t \in [t_{n-i}, t_n] \\ \ldots \\ Spl_n(t), & t \in [t_{n-i}, t_n] \end{cases}.$$ (3)

Piecewise functions of a spline are polynomials of the third degree:

$$Spl_i(t) = a_i + b_i \cdot (t - t_{i-1}) + c_i \cdot (t - t_{i-1})^2 + d_i \cdot (t - t_{i-1})^3,$$ (4)

where $a_i, b_i, c_i, d_i$ are the coefficients of the polynomials of the $i$-th piecewise function of the spline.

The result of the execution of the procedure of building prediction is a two-part prediction or prediction variants in accordance with the initial values of the settings of the solution search procedure. The procedure for the formation of training information is performed when the actual values of the predicted values are received. If the accuracy of the dot prediction corresponds to the selected criterion for estimation the quality of the prediction, then two antibodies form two memory cells (cases presented in the format for long-term storage in AIS), which are added to the library of immunological memory. To estimation the quality of prediction, it is proposed to use a combination of the following indicators: $AE$ (absolute error), $MAE$ (mean absolute error), $MPE$ (mean percentage error), $MSE$ (mean squared error), $U$ (Theil mismatch coefficient), $K_{ip}$ – quality coefficient of the
interval prediction, $K_{dp}$ – quality coefficient of the dot prediction. The coefficients $K_{ip}$ and $K_{dp}$ are calculated by formulas (5) and (6).

$$K_{ip} = \frac{Y_{ip}}{Y_{ip} + N_{ip}},$$

(5)

where $Y_{ip}$ is the number of confirmed ($t_p \leq t^* \leq t_u$) interval predictions, $N_{ip}$ is the number of unconfirmed ($t_p > t^*$ or $t^* > t_u$) interval predictions, $t_a$ is the actual value of the predicted value.

$$K_{dp} = \frac{Y_{dp}}{Y_{dp} + N_{dp}},$$

(6)

where $Y_{dp}$ is the number of confirmed ($AE \leq \Delta_{AE}$) dot predictions, $N_{dp}$ is the number of unconfirmed ($AE > \Delta_{AE}$) dot predictions, $\Delta_{AE}$ – given error $AE$.

A detailed description of the operation of the modified clonal selection immune algorithm is given in [9].

6. Conclusion

The paper proposes an IDSS model for controlling CTS, expanding the functionality of the SC through integration and rational use of data, knowledge, and intellectual models for analyzing and solving problems characterized by multi-criteria and various kinds of uncertainties in the initial information and expert knowledge. It differs from the known models by the functional components of the knowledge base and the composition of the database, taking into account the specifics of the subject area. The fault finding model based on three fuzzy classifiers and the Takagi-Sugeno first-order fuzzy inference algorithm is used to localize faults under uncertainty conditions. A deeper estimation of the monitored parameters is provided by an additional estimation procedure using seven fuzzy classifiers and the Mamdani fuzzy inference model. Prediction of the parameters drift is performed using the AIS prediction based on a combination of a case-based modeling method, an clonal selection immune algorithm and a cubic spline approximation method.

The considered structure and intellectual components of the ISPR knowledge base have the prospect of successful application in designing equipment for monitoring automation systems for airborne, energy, transport and other critical facilities.

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