Data Mining Information System for Complex Technical Systems Failure Risk Evaluation

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Abstract

The article presents the results of the development of a data mining information system for complex technical systems failure risk evaluation and modelling, which allows taking into account the probabilities of system elements failure with the analysis of the numerical values of damage to interelement connections. The proposed system implements a risk assessment method, as well as intelligent models for assessing and analyzing the risk of elements failures and components of complex technical systems of various topologies and hierarchies based on simulation modeling, soft computing theory and data mining models. For the holistic storage of the obtained and revealed knowledge from the data in the system, a distributed data warehouse module configuration has been developed, based on the use of trained decision tree models, which makes it possible to automate the processes of generating and analyzing brief metadata on the key parameters of the system elements in dynamics when assessing the risks of their failure. The use of the proposed method and models within the framework of the developed system makes it possible analysis process automating, assessing the performance and reliability of complex technical systems elements and interelement connections in heterogeneous emergency scenarios for various target risk management programs. The use of the developed data mining information system for complex technical systems failure risk evaluation has made it possible to increase the efficiency and effectiveness of managerial decision-making by 10% compared to the existing cognitive-simulation approach without intelligent models.

Keywords

Complex technical system, imitational modeling, data mining system, cognitive and fuzzy models, expert systems, knowledge base.

1. Introduction

The efficiency of functioning of complex technical systems (CTS) largely depends on the reliability of their interconnected, interacting elements, inter-element connections (IEC). Examples of CTS are telecommunications, energy, transport systems, oil and gas production, mining and processing industries. Ensuring reliability is possible by using methods, diagnostic tools and predicting the technical state of systems at the stages of CTS design and operation [1,2]. Assessment of the technical state of elements and IEC is based on the analysis of the CTS failure risk, which combines the probabilities and possible damage from failures [3-6]. The problems arising in assessing the risk of CTS failures are associated [2] with: a variety of equipment with structural and functional features, differing in physical principles and modes of operation, making it difficult to use universal methods, means of diagnosing the technical state of systems; a composition of numerous interconnected, interacting subsystems, blocks and nodes, with non-trivial IEC, between which there is a mutual exchange of energy, matter and information (EMI); incompleteness and vagueness of information, accounting complexity and interaction of interrelated subsystems and their elements.

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To ensure high indicators of efficiency, reliability, environmental performance, it is required to use methods of diagnostics and forecasting the technical state of CTS [7], which allow timely identification of the presence and location of failed components, determine the degree of operability under changes in operating conditions and predict possible system failure.

Taking into account the described specifics of the CTS, one should take into account the heterogeneity and large amount of diagnostic data obtained for various subsystems and elements [4]. This increases the relevance of automating the search and identifying hidden patterns in the identified failures and violations of the operating modes of the components of technical systems, which becomes possible through the use of modern methods and technologies of data mining built into the process of analyzing and evaluating data.

2. Description of Problem

Analysis of publications showed the predominant use of deterministic, probabilistic, expert, combined methods for assessing the failure risk of various types of CTS [8]. The methods based on probabilistic safety analyzes consider only individual sequences of events during the operation of the equipment. Many methods are based on the assumption that all elements of the system are operating normally. Often, methods for assessing the risk of CTS failures are based on engineering, model, expert and other approaches that have a narrow industry focus, which limits the possibility of their widespread use. However, the significant advantages of the probabilistic method of Bayesian networks and its further development make it promising to use the method for assessing the structural and functional risk of failures of interconnected, interacting CTS components. Bayesian networks combine empirical frequencies of occurrence of various values of variables, subjective estimates of expectations and theoretical ideas about the mathematical probabilities of certain consequences from a priori information [8].

The use of information, analytical and intellectual capabilities in the systems of diagnostics and forecasting with the determination of reliability level allows for high-quality design and maintenance CTS equipment [2,9,10]. The use of a data mining information system (DMIS) of the risk of CTS failures, based on knowledge, fast processing and analysis of large volumes of heterogeneous information provides an adequate approach to design, reliable operation, and high-quality diagnostics of systems [11]. The basis for the intelligent solution of the problems CTS state diagnostics and forecasting are traditional for the class of unstructured and poorly formalized problems [11, 12]: the lack of the possibility of obtaining complete and reliable information for making informed decisions; the presence of uncertainty in the data used, as well as multivariance in the search for a solution. Such problems lead to an increase in the labor intensity and financial costs of diagnostics, forecasting at the stages of CTS operation and design. The solution of problems within the framework of the DMIS is possible by using methods and models that use the results of simulation and fuzzy modeling [2,9,10]. The successful implementation of diagnostics and forecasting CTS risk of failures is achieved by the use of achievements in the ISDF, in particular, the technologies of expert systems (ES) using knowledge bases (KB) [2].

The analysis of publications [27,28] showed also that the development of information technologies allows solving the problem of assessing the failure risk of CTS with a large elements number, with the display of systems in the directed graphs form with structural and functional relationships and interactions of elements [2,13,14]. To study the CTS model, among the many existing methods of reliability modeling, it is recommended to use a relatively developed technology of cognitive simulation (CS) of the CTS failure risk [15,16]. Each element of the CTS corresponds to the vertex of the digraph, to each IEC, a directed arc that coincides with the direction of transmission of the EMI. The vertex of the directed graph and the branch connecting the vertices of the model graph can have certain characteristics expressed in numerical values (branch weights, branch transformation coefficients, and so on).

Within the framework of the cognitive approach, the basis of the model is a cognitive map in the form of a directed graph, which includes the elements of the CTS [17-19]. The advantage of CS over analytical methods for studying the risk assessments of CTS failures is the use of partially reliable and incomplete data about the object of research in modeling.

The developed theoretical base and the availability of a large range of simulation software with AnyLogic, Extend, Arena and other famous systems [20] contributes to the use of CS. Considering the existing uncertainty, incompleteness and vagueness of the information received by the systems for diagnostics and forecasting CTS technical state, it is advisable in the ISDF, in addition to cognitive model (CM), to use fuzzy-probabilistic models (Fig. 1) [20-23], which will allow the joint use of heterogeneous data for obtaining a reliable assessment failure risk.

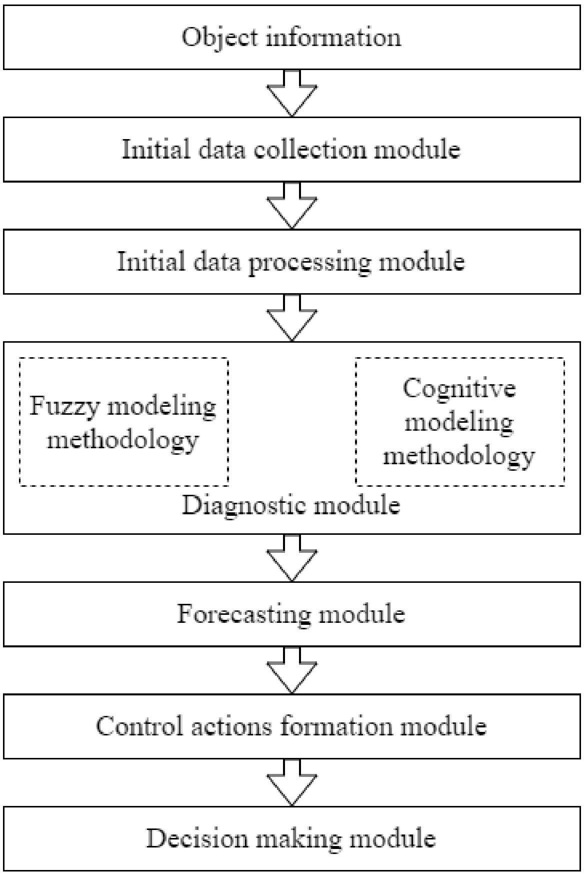

Figure 1: DMIS Structure

The initial data processing module (Fig. 1) in DMIS will allow processing data for further clear cognitive and fuzzy modeling. The diagnostics module will provide the construction of clear cognitive and fuzzy models for diagnostics and predicting in the design and operation CTS failures risk.

There are various approaches to the formation of fuzzy probabilistic models for assessing the risk of failures of functionally interconnected and interacting CTS. To construct such models, it is recommended to use the probabilities of loss of performance as input parameters, as well as damage from the consequences of a risk event in the event of failures of elements and IEC of the CTS [24]. The paper [25] describes the use of fuzzy-probabilistic models for assessing the risk of CTS failures, which allow early identification of a possible transition of a particular process to an emergency mode to prevent and risk unacceptable scales. In [26], a model for identifying pre-emergency situations of a technological process based on a fuzzy logic apparatus with additions by elements is used as a similar model, which allows taking into account the probability of CTS equipment failure. The use of fuzzy logic for the construction of fuzzy-probabilistic models for assessing the risk of failure of interconnected and interacting elements and CTS IEC in various operating conditions allows to reduce the time spent on researching systems [15].

When assessing the risks of failure of CTS elements as a component of the analysis of the overall level of its reliability [29], it is important to take into account that ehe effectiveness of DMIS largely depends on the results of using the technologies of expert systems using knowledge bases [2]. A typical diagram of an ES with a knowledge base (KB) and a database (DB) is shown in Fig. 2. When constructing a knowledge base, the choice of knowledge representation models is essential [24]. Such models for the representation of knowledge: production, based on the rules, allowing to represent knowledge in a sentence: if a condition, then an action (the disadvantage of the model is that products contradict each other when a large number of them accumulate); frame (a frame contains a finite number of slots); ontological - conceptual constructions based on the global categories of space, time and quality. Currently, machine learning methods are being actively developed, which make it possible to automate data analysis processes with the support of making control decisions. For example, methods for constructing models of decision trees (DT), used in addition to typical problems of classification and regression to describe key ontological information about heterogeneous datasets of large volumes. This provides a more compact form of their presentation with subsequent processing and analysis.

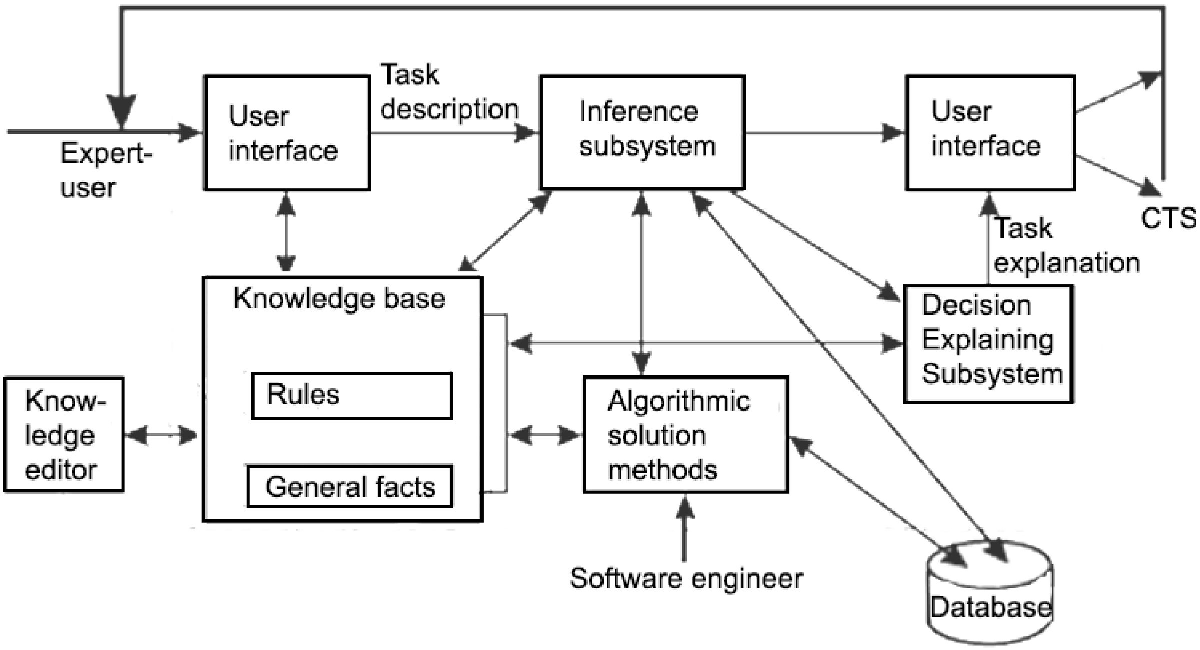

Figure 2: Typical ES scheme

DT visualization can be done by displaying a connected directed acyclic graph. The branches of the graph of the constructed decision tree DT can store the values of attributes, which are functional parameters of the elements of the studied CTS, on which its reliability depends, and the values of the failure risk are displayed on the leaves of DT [23,24]. Consisting in the fact that the structure of the DT partition can be expressed as a set of logical rules in production form, the peculiarities of constructing DT models makes it possible to use such models as the basis for KB. There are known works in which the following are proposed: an approach to constructing a fuzzy KB, which is the basis for constructing fuzzy inference systems for operational control; architectural, multi-level KB model for storing information in a subject-oriented intelligent system [26].

Thus, the further development of methods of cognitive-imitation and fuzzy-probabilistic modeling, the use of DT models as the basis for KB, is relevant when constructing the DMIS of the CTS risk failure of interrelated and interacting elements and EMI.

3. Method for diagnostics and prediction CTS risk failures in an data mining system

The method of diagnostics and forecasting involves the determination of an assessment of the risk of CTS failures based on heterogeneous information of different volume and content. The method is implemented in the DMIS scheme (Fig. 3), which includes cognitive and fuzzy models for assessing the failure risk of CTS, KB and DB elements. In the proposed DMIS, the knowledge base uses the results of fuzzy and cognitive modeling, as well as scenarios for the development of the risk of CTS failures arising during system designing and portioning. CM is based on Bayesian analysis and Bayesian networks. A Bayesian network is a directed graph. The nodes of the network are many random variables. The vertices are connected in pairs by oriented edges. The complex indicator of the reliability of CTS elements is the risk of failure (R) - a combination of the probabilities of failures (P) and losses from failures (D), Conseq, means consequence.

$$R\left(\frac{Conseq.}{Time}\right) = P\left(\frac{Event}{Time}\right) \cdot D\left(\frac{Conseq.}{Time}\right) \tag{1}$$

$$R = \{ < P_{i(j)}, D_{i(j)}, q_{i(j)}, P_{ij}, D_{ij}, q_{ij} > \},\ i,j = 1,2,...,N \ , \tag{2}$$

where i – the number of the vertex from which the edge CM emerges; j - the number of the vertex that contains the edge CM; $P_{i(ij)}$ - element failure risk probability (IEC) CTS; $D_{i(ij)}$ - damage from the consequences of the risk of failure of an element (IEC) CTS; $q_{i(ij)}$ - weight $i(j)$ for each element failure risk (IEC) CTS within 0 ... 1 under the conditions $\sum_{i=1,j=1}^{N} q_{i(j)} = 1(i, j = 1, N)$ and $\sum_{ij=1}^{M} q_{ij} = 1(ij = 1, M)$; N - amount of elements CTS, M – amount of IEC.

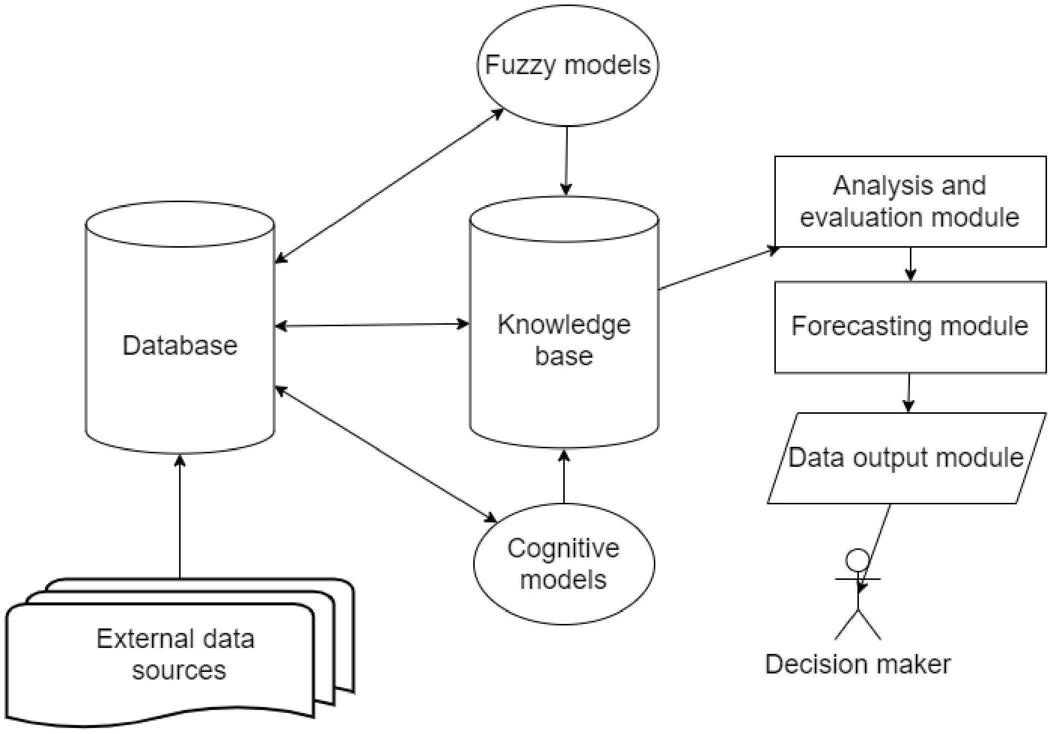

Figure 3: DMIS structural scheme

Cumulative estimates of the risk of failures, taking into account the relationships and interactions of elements and IEC CTS

$$\mathrm{R} = \sum_{i=1}^{N} R_i \cdot q_i + \sum_{j=1}^{M} R_j \cdot q_j + \sum_{i,j=1}^{N,M} R_{i,j} \cdot q_{i,j} \ . \tag{3}$$

The model is based on the structural representation of the CTS in the form of a directed graph, which is negatively influenced by external impulses. Each directed graph is reflected using an incidence matrix, the columns of which are the edges of the directed graph CM CTS, and the rows are the vertices. The construction of a model for assessing the structural and functional risk of failures by elements and IEC for CTS is carried out in 3 stages. The first stage of CS is the development of a CM, taking into account the type of the EMI resource in the form of a cognitive map and an oriented graph with N vertices and M edges [2,15]. In the second stage, the structural and functional damages from the failure of the vertices and edges of the model are researched. At the third stage, structural and functional risk assessments of failures by elements and IEC CTS are made. If it is possible to single out the structural or functional elements of the CTS, then the vertices of the directed graph correspond to the structural elements of the system, the edges of the directed graph correspond to the IEC. If it is difficult to select the elements, the vertices of the directed graph correspond to the parameters of the system, and the edges of the directed graph correspond to the cause-and-effect relationships between the parameters. Several edges can enter (exit) each vertex. Each edge is incident with two vertices located at its ends.

To assess the structural performance of the CTS and the associated damage, CM uses striking simulation impulses (SSI). The proposed SSI propagation procedure is close to the approach considered in [15], but it is simpler, there are no nonlinear operations. The procedure is easily formalized and transformed into a computational algorithm, which is important for CTS with numerous elements.

Uncertainty, incompleteness and fuzziness of information in assessing the structural and functional risk of failure of interrelated and interacting components designed and operated by CTS requires the ISDF to use the apparatus of a fuzzy probabilistic model. The developed structure of the fuzzy-probabilistic model includes input linguistic variables: D - damage, P - probability of failure and the output value R - risk of failure. The Takagi-Sugeno model is used to assess the risk of CTS failures based on a fuzzy probabilistic model. This allows us to obtain the final fuzzy set for the output variable of the failure risk assessment with a membership function of the form

$$\mu_{x_i}(f_{R_i}, q_i) = \max_{Y_R} [\mu_{xP_i}(f_R), \mu_{xD_i}(f_R), \mu_{xq_i}(f_R)] \ , \tag{4}$$

where $\mu_{xP_i}(f_R)$ - fuzzy set of element failure probabilities CTS; $\mu_{xD_i}(f_R)$ - fuzzy set of damage from failures of CTS elements; $\mu_{xq_i}(f_R)$ - fuzzy set of weights of the failure risks of CTS elements.

The production rules were entered on the basis of the Harrington generalized desirability function in accordance with the method of assessing the structural and functional risk of CTS failures. As a membership function, the Gauss distribution function was used, implemented in Matlab in the form of gaussmf to set smooth symmetric membership functions. At the fuzzification stage, the input variables of the fuzzy-probabilistic model for assessing the failure risk of designed and operated CTS are set in the form of the probabilities of failures and damages from failures of elements and EMI. To describe the key ontological information about heterogeneous datasets of large volumes, as well as to provide a more compact form of their presentation with subsequent processing and analysis, the structure of partitioning decision trees can be expressed as a set of logical rules in production form. This makes it possible to use such models as the basis for KB in ISDF. It is proposed to formalize the structure of the DT model using the CART algorithm. The use of the algorithm is due to its focus on building binary DTs, each individual node of which, in the process of logical partitioning, forms only two descendants. CART is implemented by splitting a lot of data by gender at each step. On one branch of the tree there are examples where the logical rule is executed successfully, and on the other it is not successful [1]. In the process of increasing the KB structure, at each DT node, an enumeration of all possible attributes is performed, separating only the one that maximizes the target indicator.

4. Experiments and results analysis

The process of conducting experiments was carried out on the basis of several stages:

- collection and extraction of data on the studied CTS structure, which is a transport engine cooling system [2] from the OREDA database [6];
- estimation of the probability distribution of CTS failure components based on normal distribution and failover statistics;
- allocation of individual categories of failures by priority (low, medium, high);
- data structuring, preparing and computer simulation with data visualization.

To study the DMIS of the risk of CTS failures in emergency scenarios, as an example, we studied a system consisting of 12 elements and 26 IEC (Fig. 4), 17 of which are energy carriers (indicated by solid lines), 9 are carriers of matter (indicated by dashed lines). To determine the damage to the edges and vertices of the directed graph CM DMIS of the failure risk CTS, we set the weight values S_{vi} - for vertices (Table 1) and S_{aj} - for edges (Table 2). Values of the probabilities of failure of vertices and edges of the directed graph CM CTS $p_{vi}(t)$ and $p_{aj}(t)$ are presented in tables 1,2.

The results of the impact of the SSI on the CM CTS were established by research in the developed software package based on the cross-platform Python language. The structure of the CTS in the form of a directed graph is represented using the dot language. The technical state of the CTS elements in CM is reflected in the JSON format. Graphviz is used to visualize graphs. Analysis of the simulation results was carried out in MS Office and Open Office.

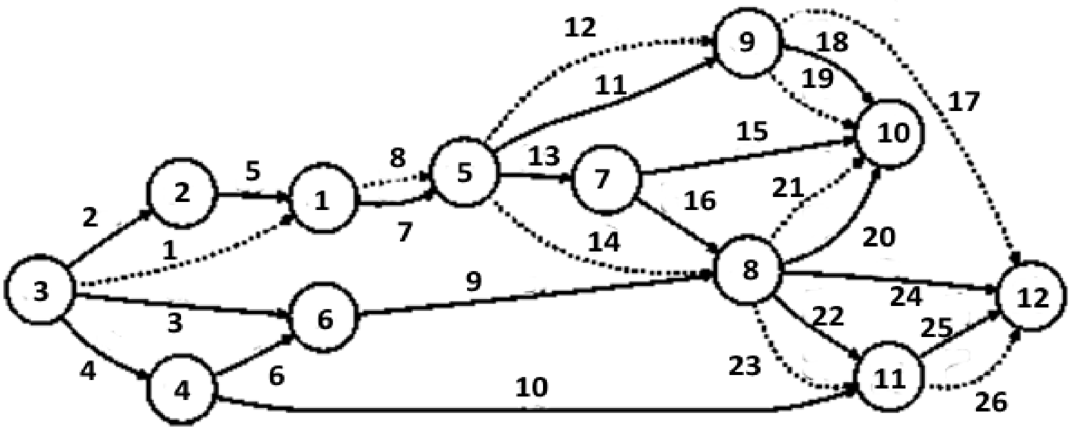

Figure 4: Oriented graph of CM elements and EMI CTS

Table 1
Values of the probabilities of failure of the vertices of the directed graph CM CTS

No. of the i-th verticle	$p_{vi}(t)$	No. of the i-th verticle	$p_{vi}(t)$
1	0,07	7	0,11
2	0,09	8	0,16
3	0,17	9	0,13
4	0,03	10	0,2
5	0,12	11	0,21
6	0,05	12	0,26

Table 2
The values of the probabilities of failure of the edges of the directed graph CM CTS

No. of the j-th edge	$p_{aj}(t)$	No. of the j-th edge	$p_{aj}(t)$	No. of the j-th edge	$p_{aj}(t)$
1	0,12	10	0,18	19	0,21
2	0,2	11	0,25	20	0,16
3	0,15	12	0,35	21	0,17
4	0,17	13	0,14	22	0,11
5	0,11	14	0,17	23	0,06
6	0,41	15	0,09	24	0,23
7	0,32	16	0,29	25	0,38
8	0,21	17	0,23	26	0,26
9	0,29	18	0,19		

From the results of the research it follows that the place of application of the SSI has a significant impact on the process of distribution of the SSI along the directed graph CM CTS. Taking into account such structural features of a directed graph as connectivity, the presence of contours, the vulnerability of its vertices and the type of EMI resource, the most connected components of a directed graph, which are affected by a number of EMI of various resource types, have been identified.

The values of estimates of the structural risk of failures established by modeling for the vertices of the CM CTS and their ranking are shown in Fig. 5. In the course of research, it has been confirmed that if the place of application of the SSI does not belong to the structural component of strong connectivity, then the passage of the SSI is less associated with the risk of CTS failure. In the studied CTS, the components of strong connectivity are elements 3, 8 and IEC 2, 5, the performance of which determines the risk of failures of adjacent elements and IEC. If IEC 2 is damaged, risks arise during the operation of elements 1, 5, 7-12, and if element 3 is damaged, risks arise for all CTS elements.

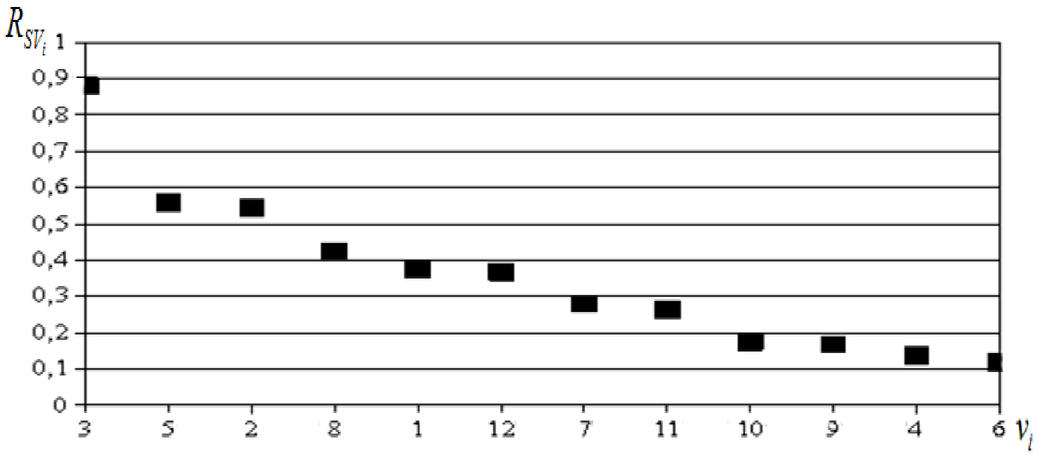

Figure 5: Ranking of the values of the structural risk of failures R_{SV_i} by elements v_i CTS

To effectively store data for different types of system elements, an add-on was created for distributed data warehouse based on the use of Microsoft Azure Data Lake Storage Service, which will allow scaling the system's capabilities.

The developed CM reflects the direct dependence of the risk of failures of elements and IEC on their positions in the system structure, as well as the dependence of the entire CTS on the selected topology at the design stage. The advantage of the method is its simplicity, clarity and applicability for assessing the risk of failures of a wide class of CTS. The procedures of the method implementation are easily formalized and transformed into a computational algorithm and model for assessing the risk of failure, which is important for CTS with a large number of elements and IEC. Considering that the objects of technical condition diagnostics often consist of various CTS, for some of which the use of CM for assessing the risk of element failures and IEC is difficult due to the uncertainty, incompleteness and fuzziness of information received by the diagnostic systems and predicting their technical condition, it is advisable in DMIS additionally in addition to cognitive modeling, use fuzzy probabilistic models. An example of such a CTS can be a ship power plant (SPP), the diagnostic information from which is characterized by uncertainty, incompleteness and indistinctness [30]. As a fuzzy model, the Takagi-Sugeno model is used, the advantages of which include a more compact size of the rules repository compared to the Mamdani fuzzy inference models, as well as lower computational complexity due to a simpler defuzzification procedure [24,37]. Fuzzy rules have the structure “If damage or probability then risk”, where damage and probability are the linguistic value of the antecedent, determined by the fuzzy membership function, which is a consequent stochastic variable equal to one of the values in the range from 0 to 1.

The result of the fuzzification stage is the establishment of a correspondence between the specific value of a separate input variable of the fuzzy inference system and the value of the membership function of the corresponding term of the input linguistic variable.

The aggregation operation is based on the maximization method implemented in Matlab as max. The weight values for all input variables of the fuzzy-probabilistic model were taken equal to one.

During accumulation, the max-disjunction method was used to combine all degrees of truth of the conclusions of the rules. The developed fuzzy-probabilistic model contains 25 logical rules. Defuzzification was carried out using the center of gravity method implemented in Matlab.

The damage to the elements and IEC of the SPP was set using the linguistic variables Not significant (0-0.25), Low (0.12-0.36), Medium (0.3-0.6), High (0.55-0.8), Critical (0.7-1). On the basis of the developed fuzzy-probabilistic model, it is possible to minimize the time of assessing the risk of failures of the designed and operated SPP. This is achieved due to the mechanism of fuzzy rules incorporated into the developed model for assessing the risk of failure of the SPP using the Matlab Rule Viewer module. Such a mechanism makes it possible to identify and quantitatively reflect the degree of influence of specific values of damage and the elements and IEC probabilities failure on the risk of failure of the SPP as a whole. In particular, with the value of damage equal to 0.234 and the value of the probability of failure equal to 0.5, the value of the output variable of the risk of failure was 0.157, i.e. about 16%, which testifies to the low degree of danger of the SPP efficiency loss.

The probability of SPP elements and IEC failure was set using the linguistic variables: Not significant (0-0.15), Low (0.1-0.31), Average (0.22-0.6), High (0.45-0.75), Critical (0.6-1). The terms Minimum risk (0-0.2), Acceptable risk (0.1-0.35), Significant risk (0, 3-0.65), Critical Risk (0.63-1). In the course of modeling, a three-dimensional visualization model's surface for assessing the risk of failure of elements and IEC of the SPP was obtained (Fig. 6).

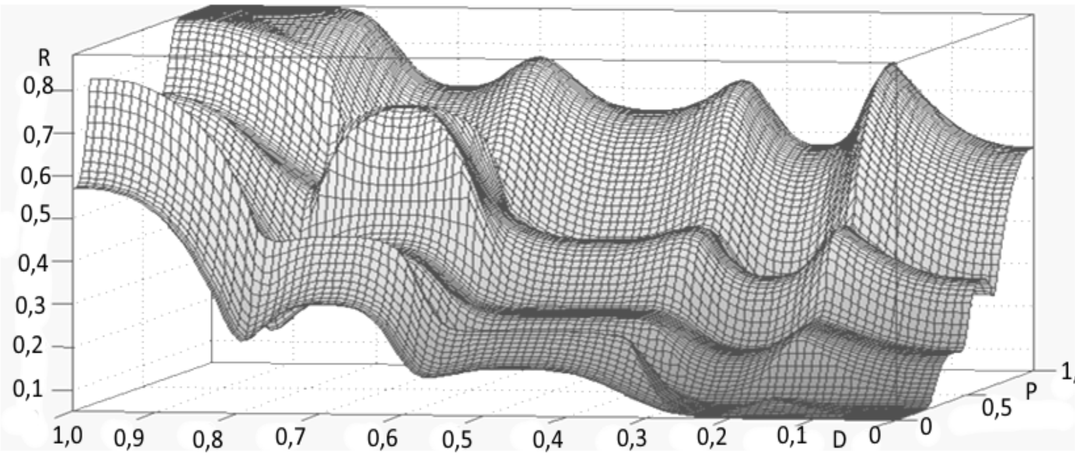

Figure 6: Visualization of the results of the fuzzy-probabilistic model of risk assessments

The results fuzzy-probabilistic model studying make it possible to establish that the probability of failure of elements and EMI has a more significant effect on the assessment of the risk of failure of the EMI.

According to the obtained three-dimensional visualization fuzzy-probabilistic assessment model's surface the greatest increase in the level of risk of EEC is observed with values of the probability of failures in the range from 0.455 to 1. In order to use KB for possible scenarios of actions when making control decisions and forming a visual structure for a data set from CTS, the DT graph is used (Fig. 7).

The composition of the logical rules records for KB based on the interpretation of this model can be expressed as: IF StructRisk> 0.435 AND Average cost <= 1600 AND Maintainability = "High" THEN Damage is Middle. Additional clarification of this rule is possible by using the priorities of features or weight values (degree of significance) for each of them. An example of a selection of options for the values of input and output parameters obtained from the results of cognitive and fuzzy-probabilistic modeling is shown in table. 3.

Table 3 is supplemented with a column of logical inference obtained based on the use of KB for possible target alternatives (action scenarios) when making management decisions out of 4 possible options: prevention, repair, replacement, no action). The received recommendations can be assessed by a decision-maker to make changes to the KB structure both in manual and automatic mode, which provides feedback to the model and its adaptability

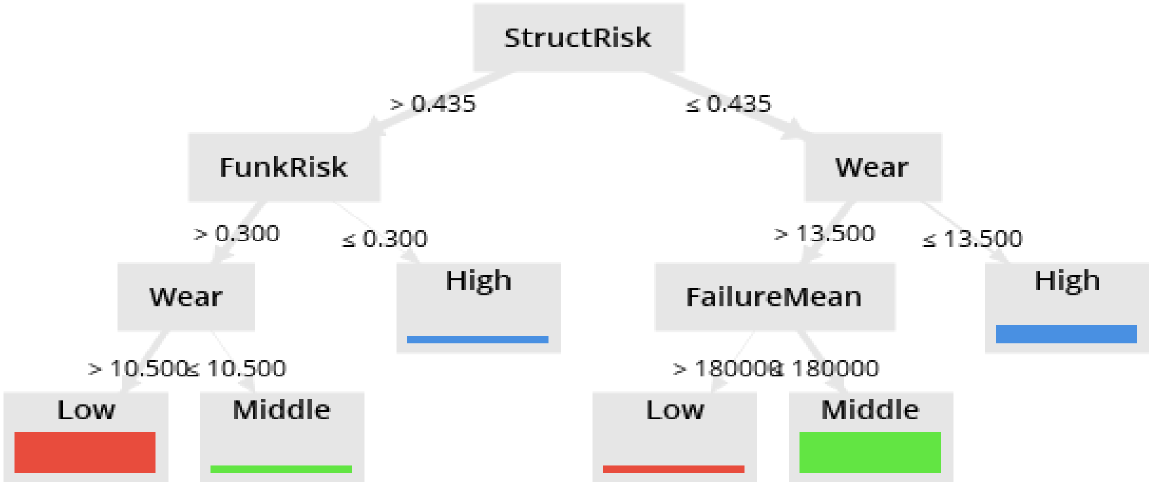

Figure 7: DT model visualization based on logical rules

Table 3
Selections of options for values of input and output parameters

No	Probability of failure	Damage	Risk	Most Priority Action Scenario
1	0,078	0,21	0,016	no action
2	0,194	0,3	0,058	prevention
3	0,29	0,31	0,09	prevention
4	0,354	0,37	0,13	prevention
5	0,398	0,08	0,032	no action
6	0,462	0,21	0,1	prevention
7	0,107	0,64	0,07	prevention
8	0,106	0,23	0,025	no action
9	0,634	0,63	0,4	replacement
10	0,794	0,43	0,34	repair

5. Conclusion

A data mining system has been developed for diagnostics, predicting failure risk assessments of designed and operated interconnected and interacting elements, inter-element connections of complex technical systems, based on the application of the method and cognitive-imitation, fuzzy-probabilistic models of failure risk assessments.

The knowledge base of the proposed system is based on the methodology of cognitive and fuzzy-probabilistic modeling, the decision tree model, which makes it possible to take into account the scenarios of the development of the risk of failure of elements and inter-element connections of systems.

The use of the developed methods and models in the intellectual system makes it possible to assess the reliability of systems based on the results of the effects of the damaging effect of each element in emergency scenarios on the structure of the system, as well as to predict the consequences of failure of elements and inter-element connections of systems. The practical application of the developed system can be performed by automating the tasks of collecting and processing data from various CTS, especially in the transport sector.

The use of machine learning algorithms in the created system makes it possible to form linked and structured metadata sets based on risk assessments of failure of elements and interelement links in various scenarios.

Application of the developed method and models will make it possible to make effective management decisions to ensure the reliability of systems, both in the design and in the operation of complex technical systems.

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