Complex Technical System Condition Diagnostics and Prediction Computerization

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Abstract. Based on the analysis of literary sources, the article sets the goal of forming a methodological application of information technology in diagnostics, as well as in predicting the state of complex technical systems. It is advisable to carry out a diagnostic assessment of the system failures risk based on modeling their components interaction. To achieve this goal, an informational cognitive model has been developed that allows for diagnosis to assess complex technical systems components failure risk. In order to provide a search for the failures causes of a complex technical system diagnosed subsystems components, a decision support model has been developed and researched. Using the developed informational cognitive model for diagnosing complex technical systems, the method and decision support model allows us to: diagnose the risk values of system component failures when information about component failures is received; to predict system components failure risk value in order to select a strategy for their recovery; support decision making when searching for the causes of system component failures. The developed methods and models, the proposed solutions for informatization of diagnostics and prediction of the complex system technical condition provide flexibility and adaptability.

Keywords: complex technical system, diagnostics, simulation, cognitive model, decision support

1 Introduction

Designed complex technical systems (CTS) are characterized by multicomponent structural and functional complexity. The increasing complexity of CTS requires the development of new methods to ensure such systems reliability. Reliable CTS operation isn't possible without diagnostic tools and predicting the technical condition of systems. Diagnosis and prediction CTS's state with an assessment components failure risk needs information support based on modern advances in information technology.

2 Description of Problem

Currently, it remains relevant to develop new methods based on information technology applications in the CTS diagnosis with an assessment of their components failure risk [1-3]. A widely used method for predicting system's technical condition based on modeling using time series CTS parameters characterizing [4]. Advantages and disadvantages of such methods are described in several publications [5,6]. When forecasting based on retrospective data, machine learning systems based on artificial neural networks are used [7]. For monitoring, diagnosing the causes of CTS failures, forecasting, deep learning methods are also used [8-10]. Intelligent methods used in CTS diagnostics and prediction systems include evolutionary programming. Modifications to the Bayesian approach and Bayesian networks can be used to predict CTS accidents and failures occurrence. In [11], a dynamic Bayesian trust network is presented, which allows predicting the values of failure probabilities and searching for defects and malfunctions in decision support systems.

At present, simulation modeling (SM) is widely used, which makes it possible to experiment with the analytic-probabilistic model, exploring various situations and simplifying the decision-making process. Simulation software in particular, SM products, such as Arena, AutoMod, AnyLogic, Extend, GPSS World and others, contributes to the widespread are widely used for research tasks. However, software tools facilitate the process of diagnosing and predicting CTS components failures risk, but do not facilitate the solution of the time-consuming task of collecting initial information, its interpretation, formalization, and an adequate ratio with a specific CTS. A promising SM method for studying systems reliability during their transitions between different state variants is cognitive simulation (CIM) based on models in the form of oriented graphs that reflect the CTS components interaction [12-17].

The analysis CTS cognitive models for both diagnosis and prediction system components failures risk showed the need to develop an informational cognitive model for diagnosing CTS components failures risk as a whole, a forecasting model and decision support when searching for the causes diagnosed systems components failures. Prospects for the further development of CIM methods for diagnosing and predicting CTS components failures risk with interpretation, formalization and an adequate ratio of incoming information about the technical condition of the system. In order to interpret, formalize and adequately correlate the incoming information during the study of the reliability of systems during their transitions between different state options, further improvement of the software for diagnostics and prediction CTS components failures risk is necessary. It is necessary to develop methods and models, new solutions for informatization of diagnostics and predicting the technical condition of a complex system to ensure: flexibility - the ability to use methods at any level to assess CTS subsystems components failure risk with their various configurations; adaptability - methods must have the ability to adapt when changing the configuration of CTS subsystems.

3 Information software for the diagnostics, forecasting and decision support CTS subsystem failures risk assessment

3.1 System concept

The concept of the CTS risk failures assessing in emergency scenarios is based on combining heterogeneous CTS components into a single model [18-20]. The model should provide an CTS failures risk assessment taking into account the interconnectedness and interaction of their components in regard to significance and criticality for the entire system functioning as a whole, and also ensure the identification of structural threats and vulnerabilities in the CTS.

The cognitive model can be represented as a functional graph

$$F_{gr}(G, X, F, Q) \tag{1}$$

where $G = \langle V, T, E \rangle$, G- sign oriented graph; $V = \{v_i\}$, i=1,2,…k - cognitive map vertices; $E = \{e_{ij}\}$ - many arcs connecting the vertices v_i and v_j; T – time; $X = \{x_i\}$ - vertex parameters; $F = f\{v_i, v_j, e_{ij}\}$ - connection function between vertices; Q – vertex parameter space.

As a measure of damage to an undesirable event, it is proposed to determine the structural damage of components and inter-component communications (IC) in accordance with the method for assessing the CTS structural failure risk. Performing diagnostics to assess the components failures risk and the IC of the ICE with the subsystems, failures probabilities for the system's components and IC are preliminarily determined. For this, statistical data obtained for a fixed time, containing information on the number of component and IC outages, is used. The components and IC failure probabilities CTS sub-systems are determined as

$$P_{v_i} = \frac{n_{v_i}}{\tau}, \quad P_{a_j} = \frac{n_{a_j}}{\tau}, \tag{2}$$

where p_{v_i} – the i-th component failure probability; p_{a_j}– the i-th IC failure probability; n_{v_i}– the i-th component number of failures; n_{a_j} – the i-th IC number of failures ; $\tau = 10^6$ ч. – statistical testing period.

3.2 Modelling CTS diagnosis software development

When implementing CIM, it is proposed to use developed application software for modeling is based on the client-server architecture. A striking modeling impulse on the system effect was applied for the CTS diagnosis. For this, the distribution of the operating system Debian GNU / Linux 8.0 (stable) is used. Python was used as the programming language. Data on the CTS components is hosted in the NoSQL MongoDB. Data exchange between the client and server side is carried out using the Restfull API. The initial data of the models are presented in JSON format. Automation of the system was carried out on the basis of GNU make tools. Analysis of the results was carried out by Calc Libre Office means. The diagrams of use cases are used to determine the general boundaries and context of the simulated domain at the developing software initial stages for assessing the risk of CTS failures, damage from loss of system operability and formulating general requirements for its behavior (Fig. 1). Software use cases diagram allows us to develop project main entities models by building class diagrams. A software class diagram fragment is shown in Fig. 2.

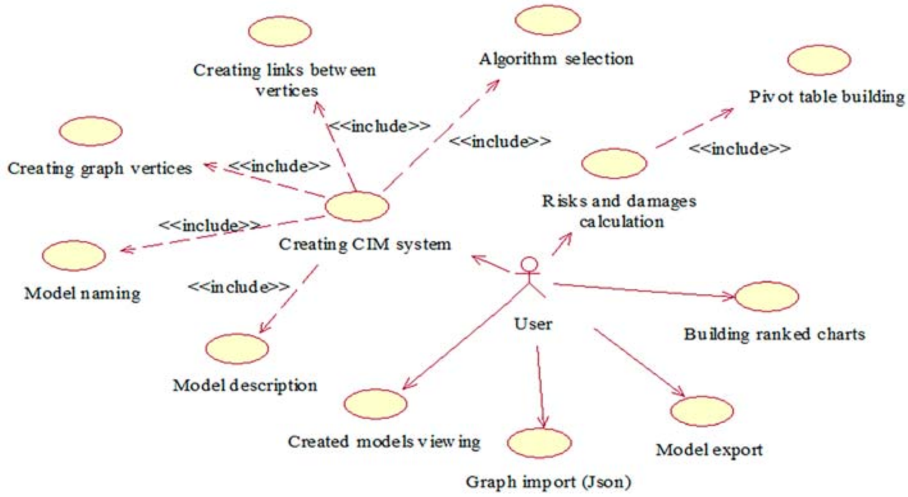

Fig. 1. Diagnosis software use case diagram

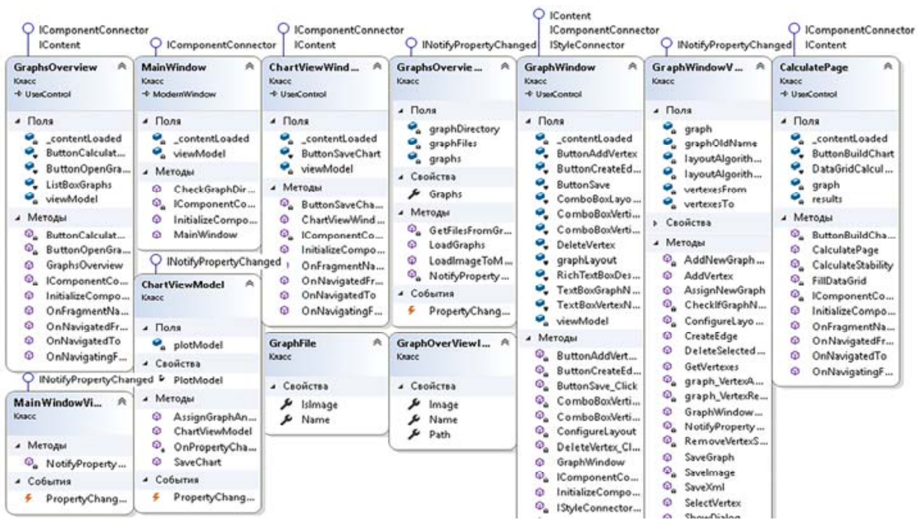

Fig. 2. Diagnosis software class diagram

The classes GraphsOverview, MainWindow, ChartViewWindow, GraphsOverviewWindow, GraphWindow, GraphWindowView, CalcutePage, MainWindowView, and ChartViewModel implement a number of interfaces to provide the necessary visualization functions for the processed and calculated data. To implement the indicated logic, the following interfaces for CIM were used and involved in the form of a graph: IComponentConnector (to ensure the connection of element objects among themselves); IContent (for displaying and implementing functions of dynamic linking and drawing objects of a working graphic container on the corresponding form); INotifyPropertyChanged (for handling events created graphic objects properties changing); IStyleConnector (to change the type of communication between components).The features of the system's physical representation are described in the relationship between system basic components form formalization. To do this, use the component diagram (Fig. 3) allows us to determine system architecture, taking into account the relationship between software components, which may be the source, binary and executable code. The main module (MainApp) carries out the functions of calling the appropriate modules to process user requests for: constructing a graph model (GraphBuilder) based on the use of external dependencies Graph # and OxyPlot, as well as the WPF GraphLay-out module to ensure the interactive visualization container operation with received models calculation system failures damage and risk; viewing the results in tabular form to evaluate their values; construction and viewing a graph showing calculations results in a ranked form..

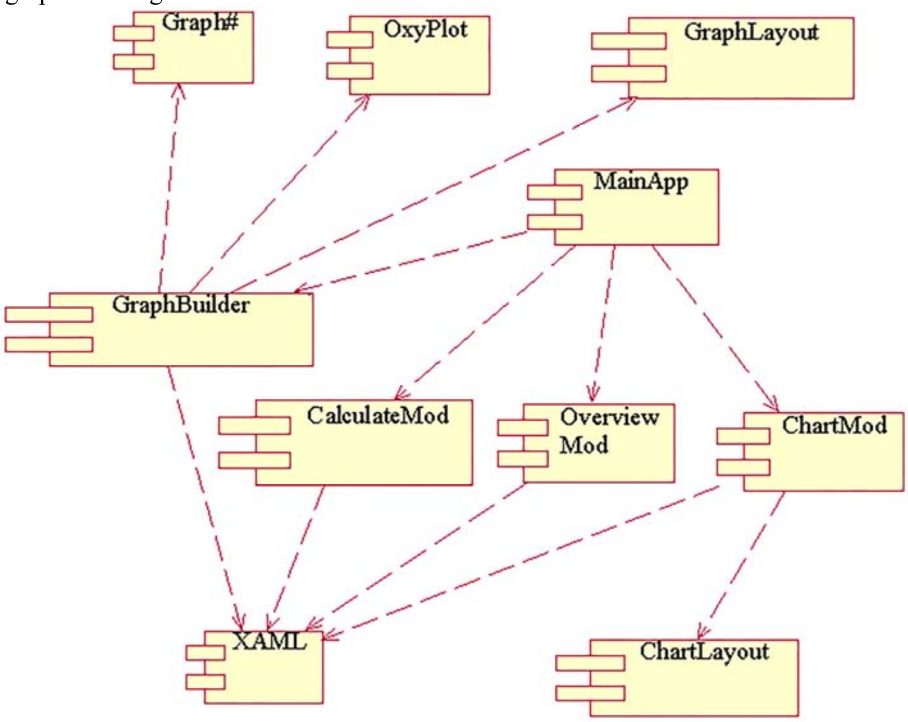

Fig. 3. Diagnosis software component diagram

As graphic libraries connected in external dependencies mode, Graph # and OxyPlot were used. Graph # library for graph visualization, containing some layout algorithms, as well as for controlling GraphLayout WPF applications. Supported build and delete algorithms: Fruchterman - Reingold; Kamada - Kawai; ISOM LinLog; simple tree layout; Sugiyama; Force-Scan allocation algorithm. In order to simulate the interaction of objects in the designed software over time, as well as messages exchange between them, a sequence diagram (Fig. 4) is used Each of the above forms (except the main one) is a separate fragment dynamically loaded in a single space in the new tab form (TabPane object), located at the main form. The basic component of the graph structure construction method is the Sugiyama algorithm.

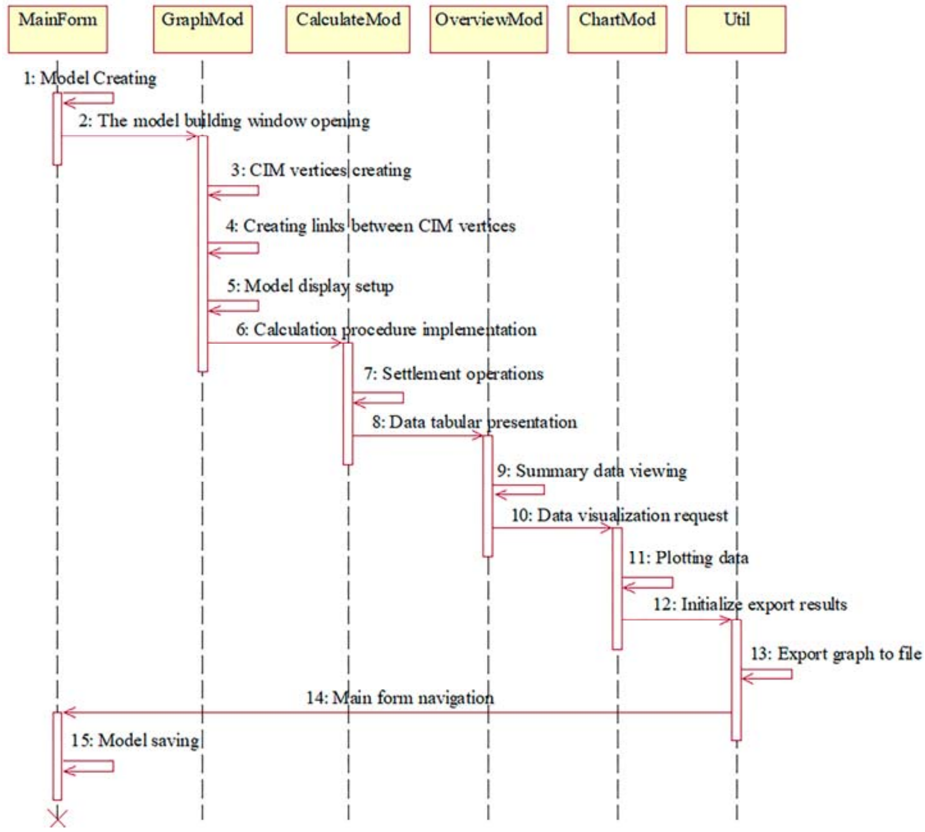

Fig. 4. Diagnosis software flow chart

In order to describe the CTS diagnosis software functionality, we denote the key classes that implement created software's business logic:

1. Calculations class CalculatePage: UserControl, IContent, IComponentConnector. It interprets and uses the obtained results of constructing a system model in the graph form to assess damage and the failures risk.
2. A class for constructing and displaying a ranked graph of calculated failure risk values ChartViewModel: INotifyPropertyChanged.
3. The CIM construction class in the graph form GraphWindowViewModel: INotifyPropertyChanged.

The system resulting graph model display class Graphs Overview: UserControl, IContent, IComponentConnector.The developed CTS diagnosis software used for research allows the user to:

- create a CTS CIM in the graph form, with support for the model name functions, setting a brief description, creating a new vertex and its image on the panel, creating a connection between the vertices, choosing an algorithm for positioning and displaying the structure in a graphic container;
- view the structure of the previously created CIM in the form of a graph with the vertices and edges total number display, supporting the loading operation into the program workspace;
- import a graph in *.json format for its visualization in the system;
- export CIM as a graph to a separate graphic file in *.jpg format;
- calculate the damage from failures values and the simulated CTS components failures risks and display the results in a summary table;
- build graphs obtained results visualization in a ranked form.

CTS subsystems are a dynamic structure, because their components have a different wear degree and change their characteristics at different speeds. All this leads to the following requirements for the decision-making support method (DSM) used [11,20] when searching diagnosed CTS subsystems components failures causes: flexibility - the ability to use the method at any level to assess the ICE components failure risk with their various configurations; adaptability - the method should have the ability to adapt to changes in the CTS subsystems configuration. To support decision-making on failure ICE subsystems risk assessments as well as when searching for failed system components, a method based on dynamic Bayesian trust networks (DBTN) is used [21]. The method has several advantages over other methods in assessing the likelihood of a CTS failure-free operation. The use of DBTN allows us to: assess the risk of CTS failures upon receipt of a new information about element failures; to predict the value of the risk of CTS failures in order to choose a system recovery strategy; support decision making when searching for the cause of component failure and the CTS as a whole. The proposed approach, regardless of the structure of the CTS, is based on the fact that the objective function of assessing the health of the objective function CTS components efficiency assessing through DBTN is

$$F(P_b) = \{G, M\}, \tag{3}$$

where G – acyclic directed network graph; M – ICE subsystems DBTN components.

The graph vertices are CTS's subsystems, which, taking into account the hierarchy, are determined as

$$v = \left\{ v_i^j \middle| \overline{1,n},\ j = \overline{1,m} \right\}, \tag{4}$$

where v – CTS element name; i – network block number, n – number of blocks in the network; j – network level number; m –levels number in the network.

Based on the component location in the DBTN structure, two types of graph elements (vertices) are possible: parents $(v_i^j = parent(v_i^{j+1}))$ variety vertex v_i^j, vertex v_i^{j+1}, providing parent connections v_i^j to child element v_i^{j+1}; child element $(v_i^{j+1} = children\ (v_i^j))$ variety vertex v_i^{j+1}, vertex - v_i^j, providing relationships between a child v_i^{j+1} and parent v_i^j.

CTS subsystems diagnosed DSM model implementation is carried out in accordance with the decision support algorithm for assessing CTS subsystems failure risk and consists in constructing the CTS DBTN using the following databases: design and regulatory documentation; expert evaluations of decision support for typical failure risk scenarios; decision support criteria; statistics of diagnosed data on the static and dynamic CTS subsystems elements characteristics.

A data sample is formed for a specific scenario CTS subsystems components data failure risk occurrence during analyzing procedure. Data is then interpreted and processed using blocks for acquiring knowledge, supporting decision making, and managing rules. As a result, they are replenished with new bases and knowledge data, data and rules, which then enter the analysis decisions unit.

4 Experiments and results analysis

4.1 Developed simulation model research

An automobile internal combustion engine system was chosen as an example of the diagnostic method practical implementation for assessing the CTS subsystems failure risk. Automobile internal combustion engine (ICE) as a directed graph diagram with subsystems is shown in Fig. 5.

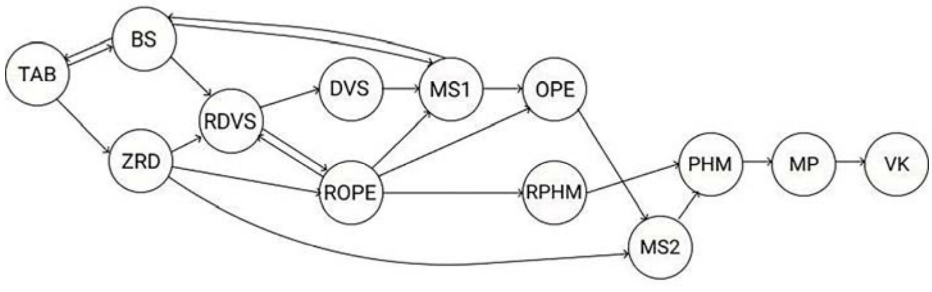

Fig. 5. Internal combustion engine directed graph diagram

The scheme of an internal combustion engine with subsystems (Fig. 5) consists of: TAB – traction battery; DVS – internal combustion engine; ZRD – drive mode dial; BS – unit for summing voltages and powers; OPE – reversible energy converter; PHM – speed and torque converter; MP – mechanical transmission; VK – driving wheels; MSI – clutch between DVS and OPE shafts; MS2 – clutch between OPE and MP shafts; ROPE – OPE knob; RPHM – regulator PHM; RDVS – DVS controller.

CIM modeling results let us to evaluate failures risk for all internal combustion engine's elements with subsystems and rank the calculation results (Fig. 6). From the internal combustion engine elements structural damages results it follows that the most critical elements are the elements TAB, BS and RDVS. This is due to the high values of their structural damage (1.0, 0.85 and 0.75). Less critical elements are elements MP, VK, namely mechanical transmission, drive wheels; having slightly lower structural damage values (0.15 and 0.05).

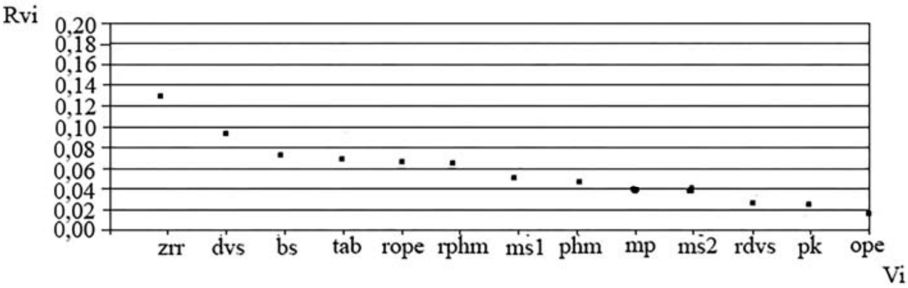

Fig. 6. Structural risk results ranking of CTS elements with sub-systems

It also follows that the engine itself belongs to the most ICE vulnerable elements with subsystems, based on the obtained values of the element failure risk (0,089). Less vulnerable ICE elements with subsystems include the OPE regulator (0.02).

The construction and study of the CTS subsystems component failure risk assessment DBTN was carried out using the GiNIe software product [22].

4.2 Decision support method CTS subsystems failure risk assessing research

Simulating ICE subsystems DBTN (Fig. 7) for different values of the subsystem failure probability (risk) at the CTS model input the risk values for 20,000 hours of ICE operation was determined (Fig. 8).

Research results let us define that with an increase subsystem's failure risk at the CTS model input from 0.09 to 0.26, the daughter CTS failures risk values increase notably.

Simulation model for assessing the failure risk during the ICE subsystems operation study showed that even a relatively small number of the subsystems considered components generate a large possible scenarios number and options leads to extreme situation when any component might be damaged. When models are supplemented with indicators of real subsystems criticality and spatial arrangement, models scale increases several times. The studied subsystems scale enlargement leads to a further increase in sub-systems emergency conditions.

The practical implementation of the proposed method for diagnosing the risk of failure of ICE subsystems can easily apply to any CTS structure, which has any complexity degree, any relationships between CTS components and subsystems.

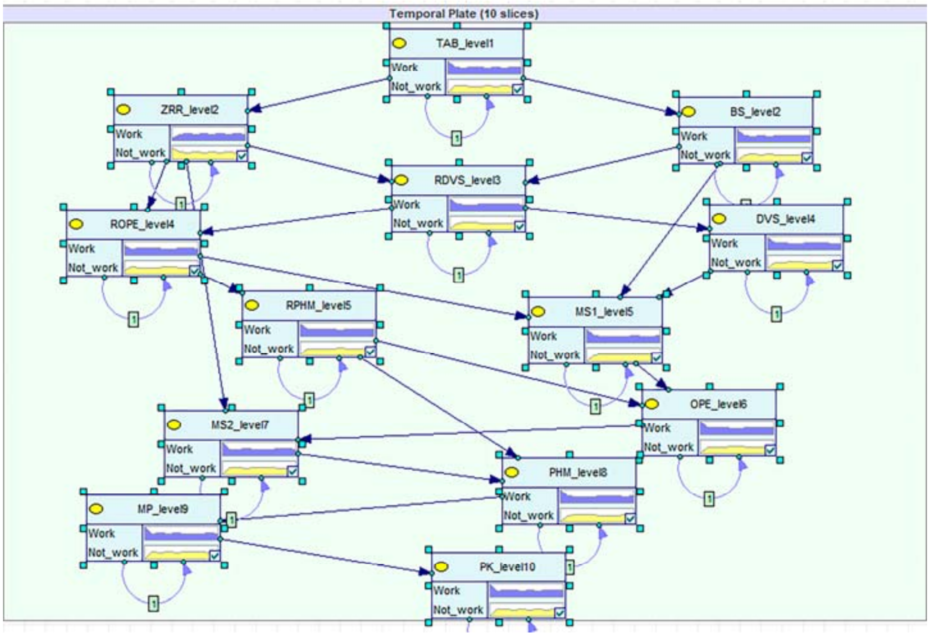

Fig. 7. DBTN for ICE subsystems in the GeNIe environment when determining CTS subsystem failures risk (subsystem failure risk at the model 0.26 input)

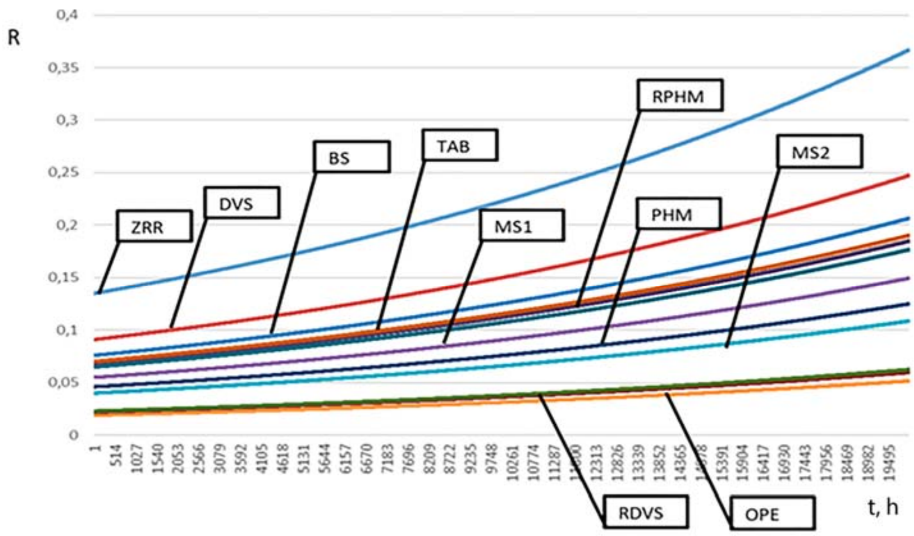

Fig. 8. ICE subsystems failure risk with the subsystem operability loss probability at the system input 0.26

4.3 Practical implementation and research of the decision support forecasting method and model in CTS subsystems finding failures causes

Practical implementation and research of the decision support forecasting method and model in CTS subsystems finding failures causes are provided on ICE example. When conducting studies diagnosed ICE subsystems DSM model each subsystem influence degree on the probability of performance loss the both subsystems and CTS failures risk as a whole was determined.

From a retrospective research results analysis the subsystems were installed to the greatest extent, affecting the overall system performance.

Emergency situations studying and CTS events analysis has the main goal to determine the cause of the system performance loss. From the research results it follows that the maximum failure risk during the subsystems operation is 20,000 hours for the ZRR subsystem. The ZRR subsystem is interdependent in operation from other ICE subsystems. Therefore, it is necessary to check the subsystem in order to find the failure cause. To identify the possible cause of the ZRR failure, relevant research processes were carried out using the search scheme for the ZRR subsystem failure cause, shown in Fig. 9.

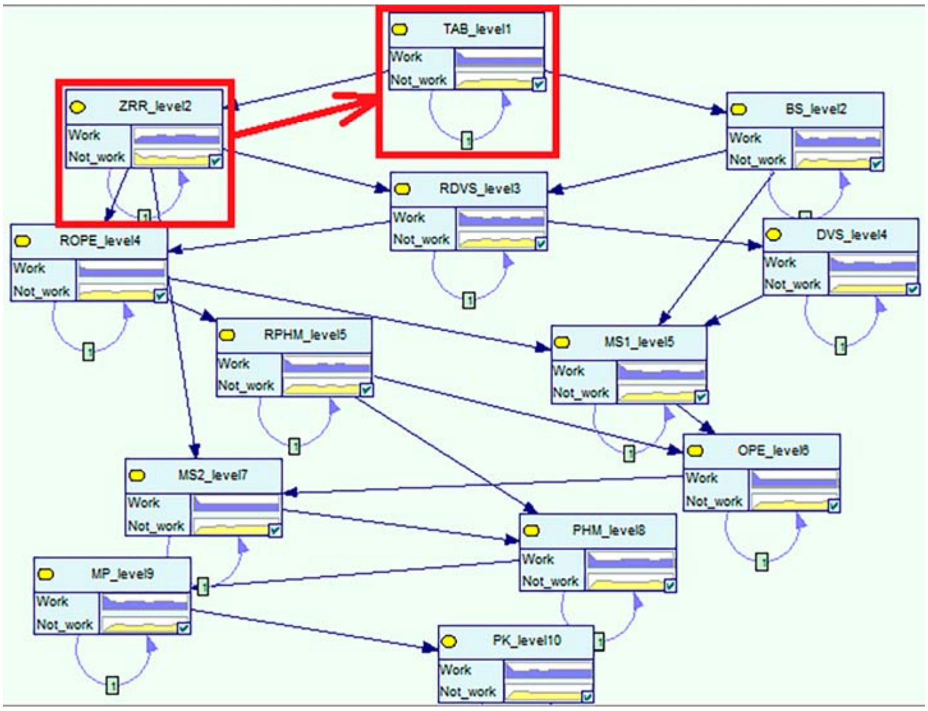

Fig. 9. ZRR subsystem cause failure search scheme

The ZRR subsystem failure cause search was performed in accordance with the algorithm shown in Fig. 10.

The purpose of the use of DBTN in assessing both the performance loss probability and the subsystems failure risk is an a posteriori conclusion. It consists in the fact that upon information receipt about subsystems failures, a priori failures probability (risk) that is incompatible with the evidence and is equal to zero.

A priori data are listed and form in a posteriori failures probability (risk) estimate, which is a priori data for processing new information. The posterior conclusion is based on data analysis procedures resulting from the DBTN usage.

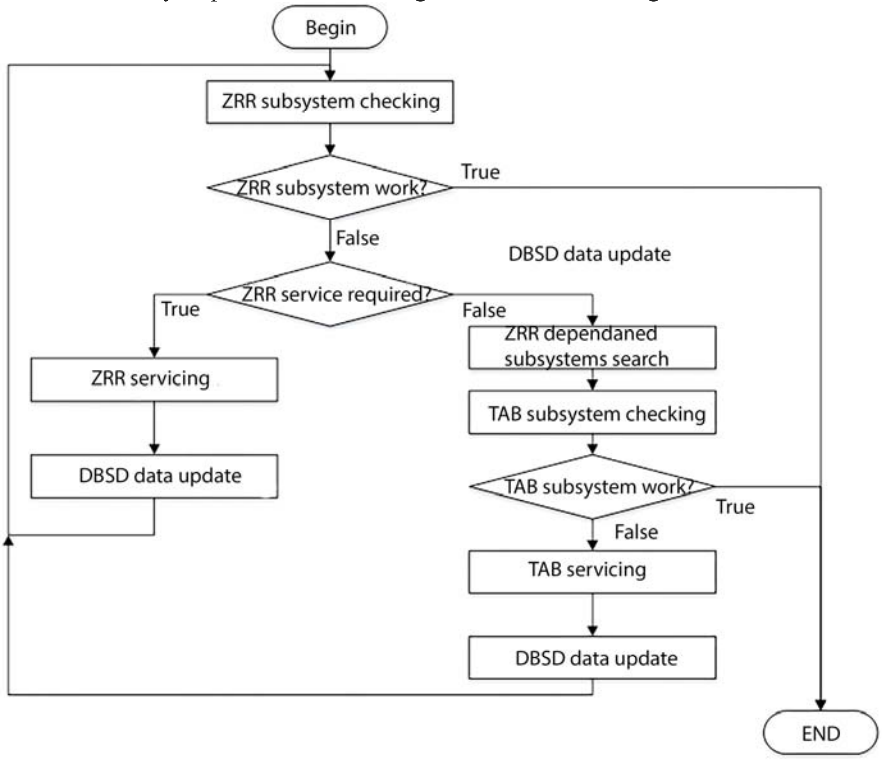

Fig. 10. ZRR subsystem failure cause search algorithm

When this approach is implemented, studies based on a priori and posterior data modeling have determined CTS subsystems for various time intervals that have the vastly impact on the CTS performance. It has been established that BS and ZRR belong to such subsystems (Fig. 11, 12).

The performed researches allow us to obtain algorithmic and methodological support for making informed decisions at the stage CTS subsystems operation ща any complexity. The used troubleshooting algorithm in CTS provides: finding technically critical subsystems at all system levels, which maintenance must be performed immediately; troubleshooting time optimization.

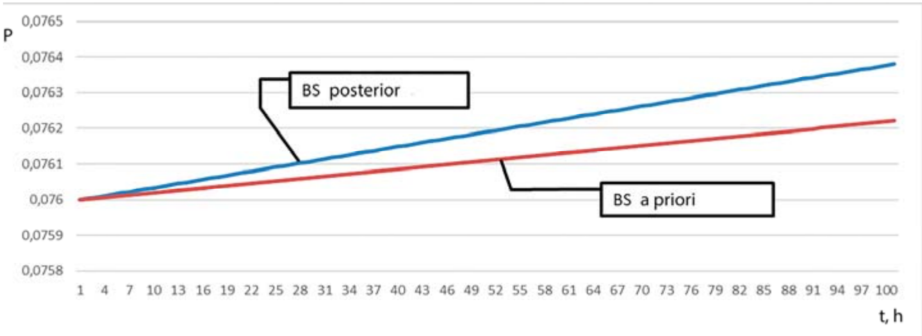

Fig. 11. A priori and a posteriori probability BS performance loss upon receipt of information about failures in ICE subsystems

Developed models research results application for the CTS emergency situations retrospective analysis purpose allows us to solve the determining their causes problem.

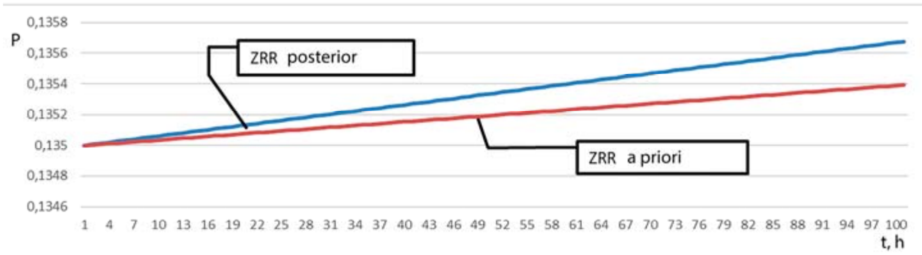

Fig. 12. A priori and a posteriori ZRR performance loss probability upon receipt of information about failures in ICE subsystems

This becomes especially relevant when the accident analysis the identification of its root cause and appropriate measures adoption eliminates or reduces the adverse events recurrence likelihood, which means that it will fulfill the task and increase the CTS components operation reliability.

5 Conclusion

Using the developed methods and models of diagnostics, forecasting and decision support when searching CTS diagnosed subsystems components failures causes allows you to: diagnose the system components risk failures values upon receipt of information about failures in subsystems; to predict the risk of system components failure in order to select a strategy for their recovery; support decision making when searching for the causes of system components failures; increase the efficiency of the operation of the CTS as a result of subsystems elements prone to failure early identification.

The application of the developed software for the CTS diagnostic processes with an assessment system failures risk makes it possible to identify the least efficient components and inter-component communications, the functioning of which significantly affects the operability and reliability of the entire system.

The developed methods and models, the proposed solutions for informatization of diagnostics, as well as forecasting the technical condition of a complex system, unlike existing approaches, provide: flexibility - the ability to use methods and models at any level to assess CTS subsystems components failure risk with their various configurations; adaptability - methods and models have the ability to adapt when changing the configuration CTS subsystems.

Reference

1. Vychuzhanin, V.V., Rudnichenko N.D.: Metody informatsionnykh tekhnologiy v diagnostike sostoyaniya slozhnykh tekhnicheskikh sistem. Monografiya, Odessa (2019).
2. Tsvetkov, V.YA.: Slozhnyye tekhnicheskiye sistemy. Obrazovatel'nyye resursy i tekhnologii, №3(20), pp. 86-92 (2017).
3. Vychuzhanin, V.V., Rudnichenko N.D.: Assessment of risks structurally and functionally complex technical systems. Eastern-European Journal of Enterprise Technologies, Vol.1, №2, pp. 18-22 (2014).
4. Shevtsov, YU.D. Dudnik, L.N., Aref'yeva, S.A., Fadeyev, Ye.D.: Prognozirovaniye parametrov tekhnicheskogo sostoyaniya dvigateley energeticheskikh ustanovok. Politematicheskiy setevoy elektronnyy nauchnyy zhurnal Kubanskogo gosudarstvennogo agrarnogo universiteta, № 132, pp. 508-517 (2017).
5. Bukreyev, V.G., Kolesnikova, S.I., Yankovskaya A.Ye.: Vyyavleniye zakonomernostey vo vremennykh ryadakh v zadachakh raspoznavaniya sostoyaniy dinamicheskikh ob"yektov: monografiya,, Tomsk (2010).
6. Vychuzhanin, V.: Evaluation model of marine engineering systems survivability. NUS Journal. Electronic Edition, №3, pp. 62-67 (2012).
7. Shin, S.J., Meilanitasari, P.: Developing a big data analytics platform for manufacturing systems: architecture, method, and implementation. International Journal of Advanced Manufacturing Technology, pp.1-42 (2018).
8. Wang, J., Ma, Y., Zhang, L., Gao R.X.: Deep learning for smart manufacturing: Methods and applications. Journal of Manufacturing Systems,Vol. 48, pp. 144-156 (2018).
9. Park, J.K., Kwon, B.K., Park, J.H., Kang D.J.: Machine learning-based imaging system for surface defect inspection. International Journal of Precision Engineering and Manufacturing-Green Technologies, Vol. 3, No. 3, pp. 303–310 (2016).
10. Zhao, R., Yan, Z., Chen, Z, Mao, K., Wang, P.: Deep learning and its applications to machine health monitoring: a survey: https://arxiv. org/pdf/1612.07640.pdf.
11. Vychuzhanin, V. Shibaeva, N.: Informatization of prognostication of risk structurally of the difficult technical systems by means of models of the bayes networks of trust. Informatics and mathematical methods in simulation, Vol. 6, №. 3, pp. 205-214 (2016).
12. Rudnichenko, N. Vichuzhanin, V.: Information cognitive model of technological interdependence of marine technical recourses. Informatics and mathematical methods in simulation, Vol.3, №3, pp. 240-247 (2013).

13. Zenkin, E., Vychuzhanin, V. Rudnichenko, N.: Cognitive Model of the Internal Combustion Engine. SAE International, 2018-01-1738, pp. 1-10 (2018).
14. Frank, A. Bittner, S., Raubal, M.: Spatial and cognitive simulation with multi-agent systems. Spatial Information Theory, pp. 124–139 (2001).
15. Buss, M., Beetz, M. Wollherr D.: CoTeSys – cognition for technical systems. inProceedings of the 4th COE Workshop on Human Adaptive Mechatronics (HAM) (2007).
16. Schwenk, C.R.: The cognitive perspective on strategic decision making. Journal of Management Studies, Vol.25, №1, pp. 41–55 (2007).
17. Vose, D.: Risk analysis: a quantitative quide. John Wiley Sons (2008).
18. Vychuzhanin, V., Rudnichenko, N., Shibaeva, N., Konovalov, S.: Devising a method for the estimation and prediction of technical condition of ship complex systems. Eastern-European Journal of Enterprise Technologies, Vol. 84, № 6/9, pp. 4 -11 (2016).
19. Beetz, M. Buss, M., Wollherr D.: Cognitive technical systems - what is the role of artificial intelligence. Advances in Artificial Intelligence, 30th Annual German Conference on AI, pp. 19 – 42 (2007).
20. Vichuzhanin, V., Rudnichenko, N.: Development of the neural network model for prediction failure risk's of complex technical systems components. Informatics and mathematical methods in simulation, Vol. 6, №4, pp. 333-338 (2016).
21. Dorozhko, I. V., Tarasov, A. G., Baranovskiy A. M.: Otsenka nadezhnosti strukturno slozhnykh tekhnicheskikh kompleksov s pomoshch'yu modeley bayyesovskikh setey doveriya v srede GeNIe. Intellectual Technologies on Transport, № 3, pp. 36-45 (2015).
22. Pohorletskyi, D., Gritsuk I., Zenkin, E., Bulgakov, N., Golovan, A.: The Complex Application of Monitoring and Express Diagnosing for Searching Failures on Common Rail System Units. SAE International, 2018-01-1773, pp. 1-10 (2018).