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INTELLIGENT SYSTEM FOR ASSESSING AND FORECASTING THE RISK OF FAILURE OF COMPONENTS OF A COMPLEX TECHNICAL SYSTEM

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The complexity of the composition and the increase in the number of technical systems lead to an increase in the intensity of their failures. As a result, there is a need to repair the equipment of complex technical systems, leading to system downtime. The search for failed components and the elimination of their failures contributes to an increase in the safety level of operation of complex technical systems. Diagnostics and prediction of failures of components of automated systems and mechanisms (subsystems, elements, intersystem and interelement connections) in real operation to find and eliminate the causes of failures remains an urgent task. The operational reliability of restored complex technical systems and their components is effectively achieved by the strategy of operating systems with technical condition monitoring based on technical diagnostic systems. Reducing failures and man-made risks in the operation of complex technical systems is facilitated by predicting their technical condition based on diagnostics. The article presents an intelligent system that operates using the developed model for assessing and predicting the risk of failure of components of a complex technical system using the example of a ship power plant. Building a model taking into account the hierarchical levels of subsystems (components), intersystem (interelement) connections of an intelligent system is based on the use of a priori information about failures of components of complex technical systems. The model connects the types of technical condition of components and diagnostic features of systems in the form of the risk of their failures. The use of a posteriori inference in Bayesian belief networks makes it possible to determine the risk of system component failures, taking into account the incoming diagnostic information and information about component failures. In order to build and research a diagnostic Bayesian network model of an intelligent system for assessing the risk of failures for a system for diagnosing and predicting the technical condition of the components of a complex technical system consisting of numerous variables, the software product GeNIe was used. The results of studies of the model for assessing and predicting the risk of failure of components of a complex technical system confirmed the possibility of predicting the risk of failure of components and the system as a whole.

Keywords: complex technical system, components, diagnostics, prediction, failure risk assessment, intelligent system, Bayesian belief network

Introduction

The complexity of the composition and the increase in the number of technical systems installed at various facilities lead to an increase in the intensity of their failures. As a result, there is a need to repair the equipment of the systems, which leads to its downtime.

When designing, manufacturing and operating complex technical systems (CTS), reliability is ensured by methods and means specific to each stage of the "life cycle" of systems. The operational reliability of the restored CTS and their components is effectively achieved by the strategy of operating systems with technical condition monitoring based on technical diagnostic systems [1-5]. The reduction of failures and man-made risks during the operation of CTS is facilitated by the prediction of their technical condition based on diagnostics.

Currently, the volume of implementation of automation, digitalization and artificial intelligence technologies in various industries continues to grow. For example, in accordance with the requirements of the Register of Maritime Navigation, all modern ships must be equipped with automation systems for technical means using digital technologies, as well as artificial intelligence technologies [2,6-10]. Such systems should constantly monitor the components of the ship's CTS, analyze trends in changing the operating modes of the equipment of the systems, perform emergency transfers and provide decision support. To implement such a technology, appropriate algorithmic and software tools are needed to provide diagnostics, forecasting the technical state of systems, and support for decision-making that is adequate to the goal. The diagnostic algorithms used, as a rule, are based on the tolerance control of individual diagnostic parameters. At the same time, the volume of measuring and diagnostic information, the number of connections, dependencies of diagnostic features and types of technical states of systems can be significant. In theory, engineering practice, various methods are used to assess the risk of failure of CTS components.

An example of the application of risk theory is the logical development of a probabilistic approach for assessing the risk of failures [11,12]. With a probabilistic approach, the level of reliability is selected depending on the possible consequences of damage (failure) of system components. In this regard, the assessment of the risk of CTS failures lies in the unacceptable probability of their damage. However, the negative consequences of a failure in systems are often taken into account intuitively, implicitly, by taking certain values of the probability of failure-free operation or the safety factor of system components.

In artificial intelligence, various models of knowledge representation are actively developing. Bayesian belief networks (BBN) are a promising mathematical tool that can be used, in relation to diagnostic tasks, to take into account both the causal relationship between the types of CTS technical condition and diagnostic features, and the arrival of new information in the form of statistical data or predictive estimates. Bayesian networks allow combining a priori (initial) knowledge about an object with experimental data to obtain an a posteriori estimate [13,14].

Forecasting the state of CTS plays an important role in planning their operation. It is assumed that the actual technical condition of an object can be assessed by the results of monitoring its parameters, and predicting their changes allows the object to be operated until signs of a dangerous decrease in reliability appear. There are efficient algorithms and forecasting methods. Artificial intelligence models, in particular, neural networks, are being actively developed to solve forecasting problems [15,16]. However, the main problem for the productive operation of a neural network is the need for a significant amount of statistical data, which is difficult to obtain in real conditions due to a number of reasons (high cost of the systems under study, high costs for testing, limited time, etc.). The lack of a clear understanding in the choice of neural network architecture for solving various types of problems (pattern recognition, approximation, prediction, etc.) and areas of application also complicates their application.

The conceptual basis for the intellectualization of the solution of interrelated problems of diagnostics, forecasting and decision support is traditional for the class of unstructured and poorly formalized tasks: the impossibility of obtaining complete and objective information for making adequate decisions and the resulting need to involve informal (subjective, heuristic) information; the presence of uncertainty in the initial data, as well as the presence of ambiguity (multiple options) in the process of finding a solution; the need to develop and justify the desired solutions to the problem inconditions of strict time constraints, which are determined by the course of controlled processes; the need to correct and introduce additional information into the process of finding solutions, the interactive (dialogue, human-machine) nature of the logical inference of solutions. Taking these factors into account forces us to abandon traditional algorithmic methods and models of decision-making and management and move on to intelligent technologies. Combined with the tasks of diagnosing and predicting, the task of modeling the behavior of the CTS acts as a source of data on the state of the object at the stages of system testing.

Thus, during the operation of CTS, an urgent task remains the improvement of methods and models aimed at accurate and prompt assessments, management of the risk of failures of CTS components.

Objective

The aim of the work is to improve the reliability of CTS operation based on the use of an intelligent system for assessing and predicting the risk of failures of components and systems as a whole.

Main part

Currently, Bayesian belief networks are actively developing in the field of modeling and knowledge representation [13,14]. When solving the problems of diagnosing CTS, BBN allow taking into account both the dependence between the types of technical systems and diagnostic features, taking into account the reliability of their checks, and the results of checking diagnostic features, data on failures of CTS components.

The model of an intelligent syste m for assessing and predicting the risk of failure of components of a complex technical system in the form of a BBN can be written as:

$$<M,S,R,L> \quad (1)$$

where *M* - is the set of subsystems (elements) of the CTS; *S* - a set of intersystem (interelement) links of CTS; *R* - a set of diagnostic assessments of the risk of failures of subsystems (elements), intersystem (interelement) links of CTS; *L* - mapping of connections between the sets *M, S* and *R*, based on the CTS diagnostic model.

The set of subsystems (elements) of ship CTS, taking into account the hierarchical levels of subsystems (elements), is determined by:

$$M = \{\upsilon_{i_{S(E)}}^{<j_{S(E)}>} \mid i_{S(E)} = \overline{1, I_{S(E)}}; j_{S(E)} = \overline{0, J_{S(E)}}\}, \quad (2)$$

where $\upsilon_{i_{S(E)}}^{<j_{S(E)}>}$ - is the state of each subsystem (element) of the CTS; $i_{S(E)}$ - number of subsystem (element) of CTS; $j_{S(E)}$ - number of the hierarchical level of the subsystem (element) of the CTS; $I_{S(E)}$ - number of subsystems (elements) of CTS; $J_{S(E)}$ - number of hierarchical levels of subsystems (elements) of CTS

The state of each subsystem (element) of the CTS:

$$\upsilon_{i_{S(E)}}^{<j_{S(E)}>} = \{F_{\upsilon_{n_{S(E)}}}, F_{\upsilon_{i_{S(E)}}}, a_{\upsilon_{in_{S(E)}}}, a_{\upsilon_{on_{S(E)}}}\}, \quad (3)$$

where $F_{\upsilon_{n_{S(E)}}}$ - is the nominal performance of the subsystem (element) of the STS; $F_{\upsilon_{i_{S(E)}}}$ - operability of a subsystem (element) in case of its partial loss; $a_{\upsilon_{in_{S(E)}}}, a_{\upsilon_{on_{S(E)}}}$ - intersystem (interelement) connections incoming and outgoing to subsystems (elements), *in, on* – sequence number of incoming and outgoing intersystem (interelement) connections.

A set of intersystem (interelement) links of CTS:

$$S = \{\omega_{c,h}^{<b,q>} \mid c = \overline{1, C}; h = \overline{1, H}; b = \overline{1, B}; q = \overline{1, Q}\}, \quad (4)$$

where $\omega_{c,h}^{<b,q>}$ - is the state of each intersystem (interelement) connection; *c* – number of intersystem communication; *h* - is the number of the interelement bond; b is the number of the hierarchical level of intersystem communication; *q* - is the number of the hierarchical level of the interelement connection; *C* - is the number of intersystem connections; *H* - is the number of interelement bonds; *B* - is the number of hierarchical levels of intersystem links; *Q* - is the number of hierarchical levels of interelement connections

The state of each intersystem (interelement) connection

$$\omega_{c,h}^{<b,q>} = \{F_{\omega_{cn}}; F_{\omega_{cp}}; F_{\omega_{hn}}; F_{\omega_{hp}}\}, \tag{5}$$

where $F_{\omega_{cn}}$ - is the nominal performance of intersystem connections; $F_{\omega_{cp}}$ - operability of intersystem communication in case of its partial loss; $F_{\omega_{hn}}$ - nominal performance of the interelement connection; $F_{\omega_{hp}}$ - operability of intersystem communication in case of its partial loss.

A set of diagnostic assessments of the risk of failures of subsystems (elements), intersystem (interelement) links of CTS:

$$\begin{gathered} R < P, Y > \\ R_m = \{r_m \mid m = \overline{1, M}\}, \\ R_s = \{r_s \mid s = \overline{1, S}\}, \end{gathered} \tag{6}$$

where *M, S* - are determined based on the failure trees, presented as a set of risk of failures of subsystems (elements) and intersystem (interelement) links, taking into account their failure probabilities (*P*) and damages from failures (*Y*); r_m - risk of failures of subsystems (elements) of CTS; r_s - risk of failures of intersystem (interelement) connections.

The initial data for constructing a model of an intelligent system for assessing and predicting the risk of failures of components of a complex technical system on the example of a ship power plant (SPP) [17], based on a dynamic BBN, are: SPP scheme; the principle of operation of the SPP; probability of failures of CTS components.

The construction and study of the BBN of the probability of loss of working capacity, assessments of the risk of failures of CTS components was carried out using the GenNIe software product [18]. It is a fully portable C++ class library that implements graphical decision theory methods such as the Bayesian network. jobs and impact diagrams that are directly amenable to inclusion in intelligent systems. Its Windows user interface, Genie is a versatile and user-friendly development environment for graphical decision theory models. modeling tools into intelligent systems. The use of the GenNIe environment allows diagnosing each component of the CTS. Perform a regression analysis of the influence of each parent element of the network on its corresponding child element. Implement a graphical display of the results of predicting the risk assessment of failures of CTS components. Calculate the value of the probability of loss of performance, damage and risk assessments of failures of CTS components. When modeling the BBN of the SPP (Fig. 1), for various values of the probability (risk) of failure of the input element, the values of the probability (risk) of failures, the performance of the components of the SPP for 20,000 hours of its operation are determined. Symbols of the elements of the SPP are given in Table 1. The operating state and failure, for example, of the SSV subsystem for the risk of failure at the input element of the SPP 0.014 is shown in Fig.2.

Table 1

Symbols of the components of the SPP

Component name	Symbol	Failure risk value
Input element	VHOD	0,26
Manual control of the main engine	RUGD	0,035
Compressed air system	SSV	0,047
Control system for propulsion and steering complex (PSC)	SUDRK	0,081
Boiler plant	KU	0,13
Ship power plant	SE	0,09
Fire fighting system	PS	0,01
Main engine	GD	0,16
Remote automated control system of the main engine	DAU	0,01
Ballast drainage system	BOS	0,019
Transfer of power from the main engine to the propeller	PM	0,003
Emergency drive PSC	AP	0,01

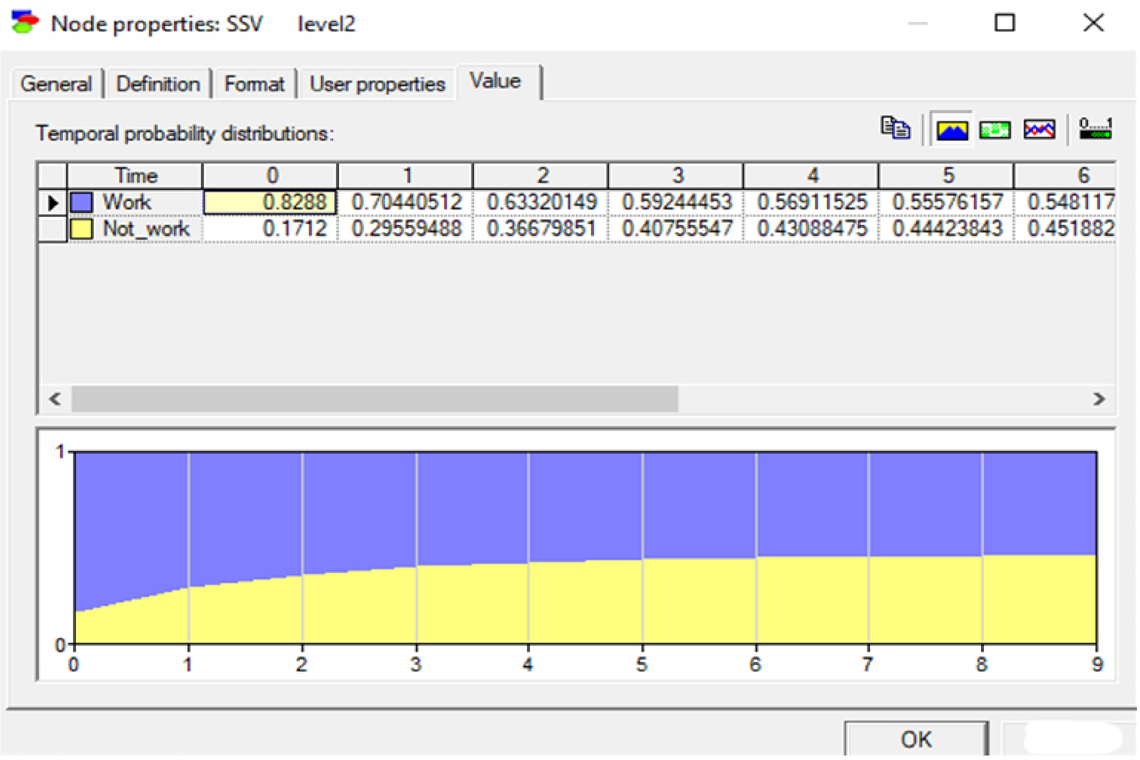

Fig.1. Operating state and failure of the SSV subsystem for the risk of failure at the input element of the SPP 0.014

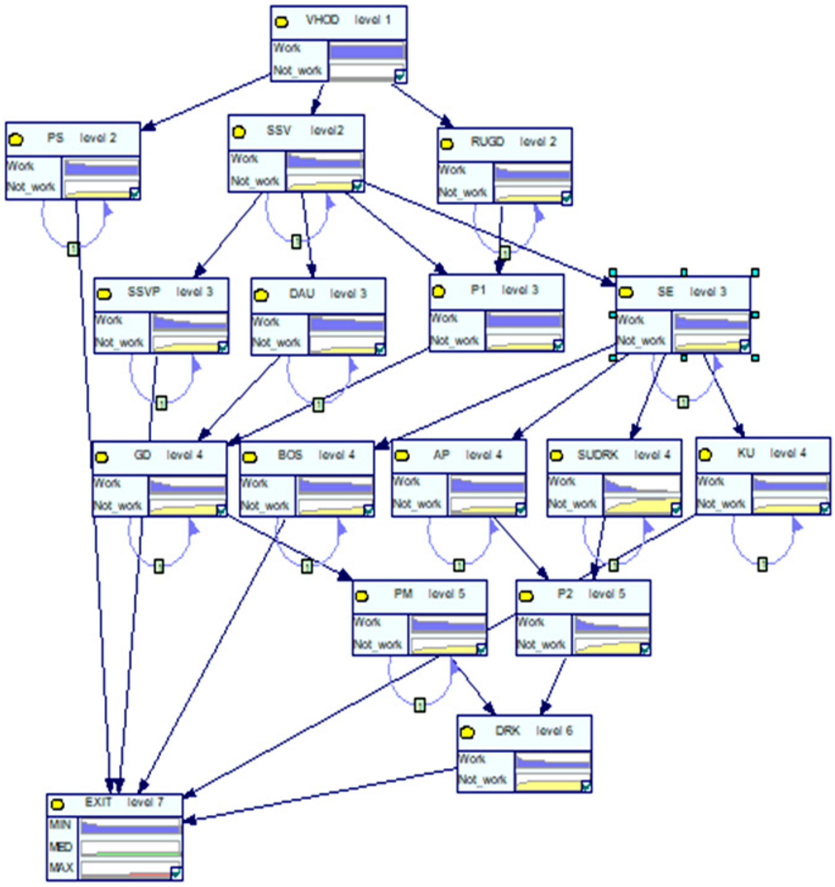

Fig.2. BBN SPP in the GeNIe environment when searching for the causes of failures at the risk of failure of the input component

From the retrospective analysis of the research results in the simulation of the SPP, the components that affect the overall performance of the system are identified. In the study of emergency situations, the analysis of incidents in the CTS, the main goal is to determine the cause of the accident. It follows from the research results that the maximum non-operating state during the operation of the SPP is 20,000 hours. corresponds to the SUDRK complex (Fig. 2). Because Since the SUDRK complex is dependent at the level of the hierarchical structure of the SPP, it is necessary to check the complex in order to find the cause of its failure.

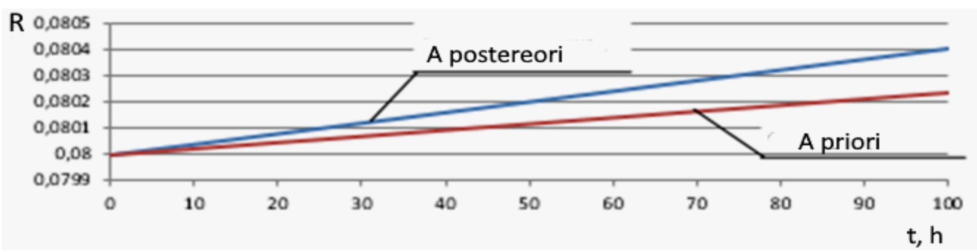

Fig.3. A posteriori and a priori estimates of the risk of failure power plant compressed air systems

The purpose of using the BBN in assessing both the probability of loss of performance and the risk of failure of the elements of the CTS components is an a posteriori conclusion. The a priori data are dynamically recalculated and form a posterior failure risk estimate, which is a priori information, to process the new information. The a posteriori conclusion is based on the procedures for analyzing the data obtained as a result of using the BBN. When implementing this approach in research, modeling using a priori and a posteriori data, the subsystems of the power plant are determined that have the greatest impact on the performance of the main engine and the operation of the entire system for various periods of time. Figure 3 shows a priori and a posteriori data and studies of the compressed air system for 100 hours of SPP operation. The risk of system failure increased slightly, changing from 0.08 to 0.085.

Conclusions

Application of the research results of the developed model for the purpose of a retrospective analysis of emergency situations at CTS makes it possible to improve the reliability of systems operation by solving the problem of determining their causes. The application of the developed model, taking into account the hierarchical levels of subsystems (components), intersystem (interelement) connections for an intelligent system for assessing and predicting the risk of failures of components of a complex technical system when searching for the causes of failures of CTS components, allows:

• control the values of the risk of failures of the system components upon receipt of information about failures;

• predict trends in the risk of failures of CTS components, taking into account changes in the risk of failures of individual components in order to select a strategy for their recovery.

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ІНТЕЛЕКТУАЛЬНА СИСТЕМА ОЦІНКИ І ПРОГНОЗУВАННЯ РИЗИКУ ВІДМОВ КОМПОНЕНТІВ СКЛАДНОЇ ТЕХНІЧНОЇ СИСТЕМИ

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Складність складу та збільшення кількості технічних систем призводять до зростання інтенсивності їх відмов. В результаті виникає необхідність ремонту обладнання складних технічних систем, що веде до простоїв систем. Пошук компонентів, що відмовили, та усунення їх відмов сприяє підвищенню рівня безпеки експлуатації складних технічних систем. Діагностика та прогнозування відмов компонентів автоматизованих систем та механізмів (підсистем, елементів, міжсистемних та міжелементних зв'язків) у реальних експлуатації для пошуку та усунення причин відмов залишається актуальним завданням. Експлуатаційна надійність складних технічних систем, що відновлюються, та їх компонентів ефективно досягається стратегією експлуатації систем з контролем технічного стану на основі систем технічної діагностики. Зменшенню відмов та техногенних ризиків під час експлуатації складних технічних систем сприяє прогнозування їх технічного стану на основі діагностики. У статті наведено інтелектуальну систему, що функціонує з використанням розробленої моделі оцінки та прогнозування ризику відмов компонентів складної технічної системи на прикладі суднової енергетичної установки. Побудова моделі з урахуванням ієрархічних рівнів підсистем (компонентів), міжсистемних (міжелементних) зв'язків інтелектуальної системи ґрунтується на використанні апріорної інформації про відмови компонентів складних технічних систем. Модель пов'язує види технічного стану компонентів та діагностичні ознаки систем у вигляді ризику їх відмов. Використання апостеріорного висновку в байєсівських мережах довіри дозволяє визначати ризик відмов компонентів системи з урахуванням діагностичної інформації, що надходить, та інформації про відмови компонентів. З метою побудови та досліджень діагностичної байєсівської мережевої моделі інтелектуальної системи оцінки ризику відмов для системи діагностики та прогнозування технічного стану компонентів складної технічної системи, що складається з численних змінних, застосовано програмний продукт GeNIe. Отримані результати досліджень моделі оцінки та прогнозування ризику відмов компонентів складної технічної системи підтвердили можливість прогнозувати значення ризику відмов компонентів та системи загалом.

Ключові слова: складна технічна система, компоненти, оцінка ризику відмови, інтелектуальна система, байєсовська мережа довіри, діагностика, прогнозування.