Diagnosis Intellectualization of Complex Technical Systems

Vladimir Vychuzhanin[a], Nickolay Rudnichenko[a], Alexey Vychuzhanin[a], Andrzej Rychlik[b]

[a] *Odessa Polytechnic National University, Shevchenko Avenue 1, Odessa, 65001, Ukraine*
[b] *Lodz University of Technology, Wólczańska str., 215, Łódź, 90-924, Poland*

Abstract

The article presents the results of developing a model for diagnosing a ship complex technical system with incomplete data and its implementation in an intelligent system for assessing the risk of failures of subsystems, components, intercomponent links, which allows obtaining a priori information about the technical condition of a complex system. Types of technical condition of subsystems, components, intercomponent connections are determined on the basis of diagnostic features of a complex system using the example of a ship power plant to assess the risk of their failures. Predicting the type of technical state of a complex technical system was carried out using a posteriori inference in Bayesian belief networks. The studies presented in the article assessed the risk of failures as a result of the use of an intelligent system for diagnosing and predicting the risk of failures of a ship complex technical system. The model for diagnosing and predicting the risk of failures of subsystems, components, interconnections can be considered as a conceptual model of an intelligent system for diagnosing and predicting the risk of failures of complex technical systems on network infrastructures, which has a relative insensitivity to incomplete technological data.

Keywords

Technical condition, complex technical system, risk of failure, diagnostics, forecasting, intelligent system, Bayesian belief network, insensitivity to incomplete data.

1. Introduction

Complex technical systems (CTS), having structural and functional diversity, differ in the principles of operation and consist of numerous interconnected and interdependent subsystems, components with complex intersystem, intercomponent links [1,2]. The increase in the complexity of the composition of ship CTS affects the growth of system failures, which in turn is accompanied by an increase in repair work or CTS components replacement. Intellectualization of diagnostics and forecasting of the technical condition (TC) of ship complex systems makes it possible to extend the operation time of such CTS. This article is devoted to the development and application of artificial intelligence methods for evaluating the TC of subsystems (TS), components (CM), intersystem (IS) and CTS intercomponent communications (ICC) in order to prevent their possible failures.

2. Description of Problem

Diagnostics and prediction of TC helps to reduce the CTS risk of failures of subsystems, components, intersystem and intercomponent connections at their operation stage [3,4,5,6]. Diagnosis (evaluation) and prediction of the technical state of the CTS should take into account the specifics of systems that are often operated under uncertain conditions of the external and internal environment, with unspecified CTS regulatory parameters values and have relative insensitivity to incomplete system components technological data [7].

ICST-2023: Information Control Systems & Technologies, September 21-23, 2023, Odesa, Ukraine.
EMAIL: v.v.vychuzhanin@op.edu.ua (V.Vychuzhanin); nickolay.rud@gmail.com (N.Rudnichenko); vychuzhanin.o.v@op.edu.ua (A. Vychuzhanin); andrzej.rychlik@p.lodz.pl (A. Rychlik).
ORCID: 0000-0002-6302-1832 (V.Vychuzhanin); 0000-0002-7343-8076 (N.Rudnichenko); 0000-0001-8779-2503 (A. Vychuzhanin); 0000-0003-2068-9274 (A. Rychlik).

The CTS reliability can be assessed by the results of diagnosing the TC, and the prediction of changes in the TC makes it possible to operate the systems until signs of a dangerous decrease in reliability appear, while excluding premature dismantling of components and assemblies, as well as performing other labor-intensive work that is often of dubious usefulness for the CTS reliable operation.

To successfully solve the problem of ensuring the ship CTS reliability it is necessary to remove a number of uncertainties. Such uncertainties include incomplete data on external, internal impacts on systems and on the state of such systems. The removal of uncertainties can be based on solving problems of assessing the risk of CTS failures and its prediction with relative insensitivity to incomplete technological data FS, FC, FIC and FI [8,9,10].

Traditional automation of ship equipment includes, in addition to monitoring parameters and controlling installations and mechanisms, also equipping them with complexes that allow us to create hierarchical distributed integrated systems for diagnosing and predicting complex systems TC [1,11,12].

Diagnostic and forecasting systems should: constantly carry out diagnostics of the ship CTS TC of functional FS, FC, FIC and FI; analyze trends in changes in the technical equipment of systems; perform failover and provide TS prediction. To implement such a technology, appropriate algorithmic and software tools are required. The diagnostic algorithms used, as a rule, are based on the tolerance control of individual diagnostic parameters. However, the analysis and integral assessment of FS, FC, FIC and FI TC, the development of control actions in most cases is carried out by ship operators based on heuristic rules. At the same time, the volume of measuring and diagnostic information, the number of connections, dependencies of systems diagnostic TC features and types can be significant.

In theory, engineering practice, various methods are used to assess the risk of failures FS, FC, FIC and FI CTC. An example of the application of risk theory is the logical development of probabilistic analysis to assess CTS failures risk [13]. Advantages of probabilistic analysis: the full range of accident scenarios and consequences of FS, FC, FIC and FI failures is analyzed, and not only design basis accidents; balanced approach; an objective assessment of the accident rate is used; accounting for the interdependence between CTS subsystems and components in an explicit form. With a probabilistic approach, the reliability level is selected depending on the possible consequences in case of damage (failure) of FS, FC, FIC and FI systems. In this regard, the assessment of the risk of ship CTS failures lies in their damage unacceptable probability. However, the negative consequences of a failure in systems are often taken into account intuitively, implicitly, by taking certain failure-free operation probability values or system components safety factor.

Intellectualization of automated diagnostic systems involves solving a number of interrelated tasks of a structural, functional, informational and organizational nature, which should be provided at the stage of designing diagnostic systems for TC CTS [6]. Expert systems are widely used to automatically analyze data and issue recommendations to prevent possible failures. These systems can be integrated with control and monitoring systems, which allows us to quickly respond to changes in the parameters of the CTS operation and take measures to ensure its safety and reliability.

In artificial intelligence, knowledge representation models are actively developing - Bayesian Belief Networks (BBN), used to diagnose the TC of complex systems [14,15,16]. One of the BBNs advantages for vehicle diagnostics is their ability to work with uncertain and incomplete CTS process data. BBN can be applied to assess the risk of failures in CTS, providing data and knowledge integration to assess the likelihood of various failure scenarios and their consequences. By identifying critical components, evaluating maintenance strategies, and supporting regulatory compliance, BBNs can help ensure safe and reliable CTS operations.

Thus, the problems associated with ensuring the reliable operation of ship CTS require further improvement and the search for new methods, models and algorithms aimed at promptly detecting emergency conditions of equipment, at solving the problems of diagnosing and predicting system failures risk under conditions of relative insensitivity to incomplete data on FS, FC, FIC and FI. Since all modern ships must be equipped with automation systems for technical means using artificial intelligence technologies, the introduction of approaches based on such methods, models and algorithms should help ensure ship's CTS reliable operation.

That is, taking into account the existing problems in ensuring reliability during the operation of CTS, the intellectualization of diagnostics and predicting ship's CTS failures risk by diagnostic features is a significant direction that allows us to influence the safety and reliability of systems and is an urgent task.

Statement of the problem: to substantiate the forecast failures risk of FS, FC, FIC and FI by intellectualizing the assessment ship complex systems TC by diagnostic features.

The purpose of the work: ensuring the reliability and safety of ship CTS by reducing the risk of failures FS, FC, FIC and FI.

3. Model diagnostics technical condition intellectualization and prediction ship complex systems failures risk

In a formalized form, BBN for diagnosing the TC and predicting the risk of ship CTS failures contains an acyclic directed graph G, a set of vertex variables and directed links between them. A formalized generalized model for the intellectualization of TC diagnostics and predicting failures risk of FS, FC, FIC and FI by diagnostic features can be described as follows:

$$< G, S(C), I_S(I_C), R_{S(C)}, R_{I_S(I_C)}, L >, \tag{1}$$

where: $S(C)$,set FS (FC);

$I_S(I_C)$, set FIC (FI);

$R_{S(C)}, R_{I_S(I_C)}$, set of failures risk diagnostic assessments FS (FC) и FIC (FI) CTS;

L - mapping relationships between sets $S(C), I_S(I_C)$ и $R_{S(C)}, R_{I_S(I_C)}$, based on the fault tree of the CTS diagnostic mode.

TC FS (FC) and FIC (FI) sets with $S(C), I_S(I_C)$ is determined based on the failure tree (Failure Tree), presented as a set failures risk of FS, FC, FIC and FI. The tree consists of failure risk sequences, which are a multi-level graphological structure diagnostic model causal relationships, obtained by tracking failures in the reverse order of the structure, in order to find occurrence their possible causes. The advantage of a fault tree over other failure scoring models is that failure analysis is limited to identifying only those FS, FC, FIC, and FI of the system and the events that lead to a particular system failure or crash. The fault tree allows us to identify all the paths leading to the failure of the CTS, and provides the determination of the minimum number of combinations of events that cause the system to fail [17].

The set FS (FC) of the CTS, taking into account their hierarchical levels, is determined

$$S(C) = \{\upsilon_{n_{s(c)}}^{<m_{s(c)}>} \mid n_{s(c)} = \overline{1, N_{S(C)}}; m_{s(c)} = \overline{1, M_{S(C)}}\}, \tag{2}$$

where $\upsilon_{n_{s(c)}}^{<m_{s(c)}>}$, each FS (FC) condition;

$n_{s(c)}$, FS (FC) number;

$m_{s(c)}$, hierarchical level number FS (FC);

$N_{S(C)}$, FS (FC) value;

$M_{S(C)}$, hierarchical level number value FS (FC).

The state of each FS and FC CTC is expressed as:

$$\upsilon_{n_{S(C)}}^{<m_{S(C)}>} = \{W^0_{\upsilon_{S(C)n(m)}}, W^f_{\upsilon_{S(C)n(m)}}, a_{\upsilon_{in_{S(C)n(m)}}}, a_{\upsilon_{on_{S(C)n(m)}}}\}, \tag{3}$$

where $W^0_{\upsilon_{S(C)\,n(m)}}$, full working capacity FS (FC);

$W^{f}_{\upsilon_{S(C)_{n(m)}}}$, performance FS (FC) at different degrees of their losses;

$a_{\upsilon_{in_{S(C)_{n(m)}}}}, a_{\upsilon_{on_{S(C)_{n(m)}}}}$, incoming and outgoing FS (FC);

in, on, sequence number of incoming and outgoing FIC, FI.

Operability of FS and FC at different degrees of their losses:

$$W^{f}_{\upsilon_{S(C)_{n(m)}}} = \{W_{f}^{<n_{s(c)}, m_{s(c)}>} \mid f = \overline{0,1}; n_{s(c)} = \overline{1, N_{S(C)}}; m_{s(c)} = \overline{1, M_{S(C)}}\}, \tag{4}$$

In (4) f =0 is the correct state of the STS, f=1 is the failure of the CTS

The set of FIC and FI CTS is determined by:

$$I_{S(C)} = \{\omega^{<a,b,z,q>}_{I_{S(C)}} \mid a = \overline{1,A}; b = \overline{1,B}; z = \overline{1,Z}; q = \overline{1,Q}\}, \tag{5}$$

where $\omega^{<a,b,z,q>}_{I_{S(C)}}$, state of each FIC (FI);

a, FIC number;

z, FI number;

b, hierarchical level number FIC;

q, hierarchical level number FI;

A, FIC value;

Z, FI value;

B, hierarchical level value FIC;

Q, hierarchical level value FI.

State of each FIC and FI:

$$\omega^{<a,b,z,q>}_{I_{S(C)}} = \{W^{0}_{\omega_{I_{S(C)_{a(z)}}}}; W^{f}_{\omega_{I_{S(C)_{a(z)}}}}\}, \tag{6}$$

where $W^{0}_{\omega_{I_{S(C)_{a(z)}}}}$, full working capacity FIC (FI);

$W^{f}_{\omega_{I_{S(C)_{a(z)}}}}$, operability FIC (FI) at different degrees of their loss.

Operability of FIC and FI at different degrees of their loss:

$$W^{f}_{\omega_{I_{S(C)_{a(z)}}}} = \{W_{f}^{<a,z>} \mid f = \overline{0,1}; a = \overline{1,A}; z = \overline{1,Z};\} \tag{7}$$

$n(m)$ FS (FC) failure risk:

$$R_{S(C)_{n(m)}} = D_{S(C)_{n(m)}} \cdot P_{S(C)_{n(m)}}(t) \tag{8}$$

$a(z)$ FIC (FI) failure risk:

$$R_{I_{S(C)_{a(z)}}} = D_{I_{S(C)_{a(z)}}} \cdot P_{I_{S(C)_{a(z)}}}(t) \tag{9}$$

Modeling assumptions and limitations are that FS and FC CTSs can have a failure risk level distributed based on the Harrington desirability function [18]: 0 - 0.2 - minimal (the consequences of failure are minimal); 0.2 - 0.37 acceptable (consequences of failure are insignificant); 0.37 - 0.63 - maximum (consequences of failure are significant); 0.63 - 1 - critical.

An available source for the reliability statistics FS, FC, FIC and FI of ship CTS when choosing the values of the conditional probabilities of their failures to determine failures risk is the OREDA offshore database [19]. In the database, conditional probabilities correspond to the exponential distribution law for the time between failures FS, FC, FIC and FI, whose resource is installed before the end of the normal operation period. CTS with a set of FS, FC, FIC and FI can be classified as "non-aging" systems, since they operate only in the area with the failure rate λ(t)=λ=const. The failure rate is determined:

$$\lambda(t) = \frac{\alpha \cdot \exp(-\alpha T_0)}{\exp(-\alpha T_0)} = \alpha \tag{10}$$

where α – distribution parameter, taken according to the test results equal to $\alpha \approx 1/\widehat{T_o}$, $\widehat{T_o}$ – mean time to failure estimate.

Mean time to failure:

$$T_0 = \int_0^\infty P(t)dt = 1/\lambda \tag{11}$$

The failure probability FS and FC CTS, taking into account the number of failures of a certain subsystem (component), can also be determined:

$$P_{S(C)_{n(m)}} = \frac{v_{S(C)_{n(m)}}}{\tau} \tag{12}$$

where $P_{S(C)_{n(m)}}$, failure probability $n(m)$ FS (FC);

$v_{S(C)_{n(m)}}$, number of failures $n(m)$ FS (FC);

$\tau = 10^6$ hours - the period of statistical testing.

The probability of failure FIC and FI CTS, taking into account the number of failures of a certain intersystem (intercomponent) connection, can be determined:

$$P_{I_{S(C)_{a(z)}}} = \frac{v_{I_{S(C)_{a(z)}}}}{\tau} \tag{13}$$

where $P_{I_{S(C)_{a(z)}}}$, conditional failure probability $a(z)$ FIC and FI;

$v_{I_{S(C)_{a(z)}}}$, number of failures $a(z)$ FIC and FI.

Quantitative assessment of damage FS, FC from failure of a subsystem (component) to determine the risk of failure:

$$D_{S(C)_{n(m)}} = \frac{Nu_{n(m)} \cdot (C_{n(m)} + Ci_{n(m)} + Cd_{n(m)})}{Nf_{n(m)}}; \tag{14}$$

where $Nu_{n(m)}$, number of unrecoverable failures FS (FC);

$C_{n(m)}$, FS (FC) price;

$Ci_{n(m)}$, FS (FC) installation cost;

$Cd_{n(m)}$, FS (FC) disposal cost;

$Nf_{n(m)}$, number of failures FS (FC);

$d_{s(c)_{n(m)}}$, damage from abandonment FS (FC).

Quantification of FIC and FI damage from failure $a(z)$ FIC and FI:

$$D_{I_{S(C)_{a(z)}}} = \frac{Nu_{a(z)} \cdot (C_{a(z)} + Ci_{a(z)} + Cd_{a(z)})}{Nf_{a(z)}}; \tag{15}$$

where $Nu_{a(z)}$, number of unrecoverable failures FIC (FI); $C_{a(z)}$, price FIC (FI); $Ci_{n(m)}$, installation cost FIC (FI); $Cd_{a(z)}$, disposal cost FIC (FI); $Nf_{a(z)}$, number of failures FIC (FI); $d_{i_{s(c)_{a(z)}}}$, damage from abandonment FIC (FI). The verbal form is used to describe the category of damage from refusal FS (FC). To compare numerical estimates for different classes of damage, the Harrington scale is used [18]: “Insignificant damage” - 0.1· Dcrit; "Damage is insignificant" - 0.29· Dcrit; "Damage of medium significance" - 0.51· Dcrit; “Significant damage” – 0.72· Dcrit; "Damage Critical" –1· Dcrit. According to the established conditional failure probabilities and damages from failures FS, FC, FIC and FI according to (8), (9), their risk of failures is determined. The initial data for constructing an intellectualization model for assessing the technical condition and predicting the risk of failures of complex systems on the example of a ship power plant (SPP) based on dynamic are: PPS principle operation scheme; failure probabilities FS, FC, FIC and FI CTS. The set of TS FS, FC, FIC and FI CTS is determined based on the failure tree, presented as a set of their failure risk (Fig. 1). R represents the risk of failure of the system, S1-S6 different combinations of sequences of failure of the elements of the system F1-F14 types of events for failures of the elements of the systems.

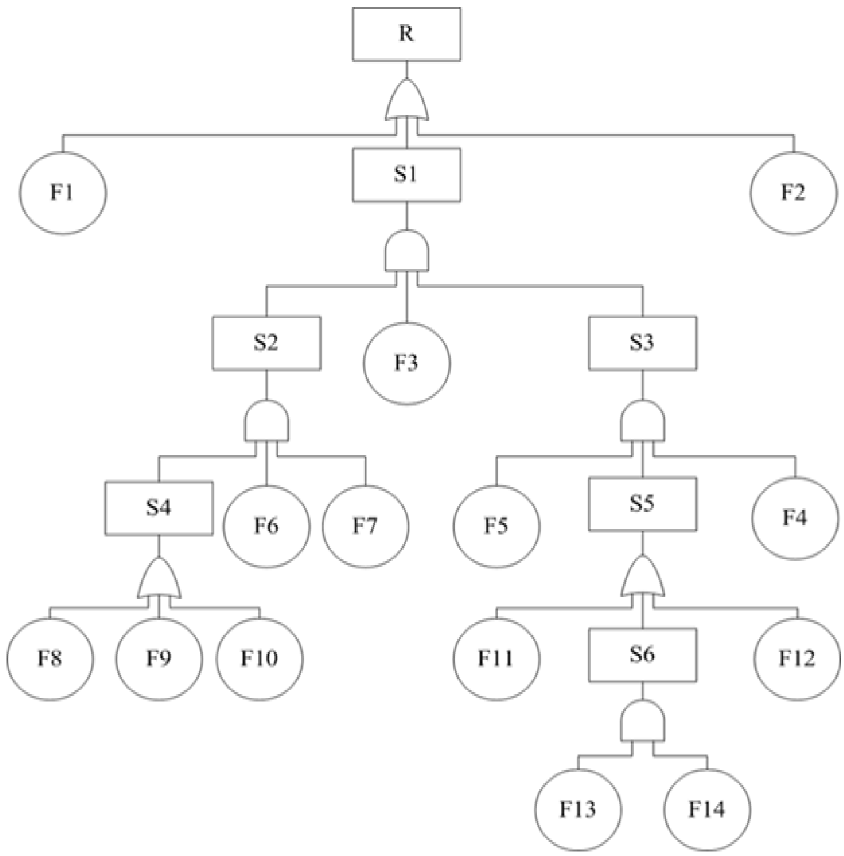

Figure 1: Fault tree of subsystems (components), intersystem (intercomponent) connections of the SPP

Based on the generated fault tree, the general structure of the SPP is formed, which makes it possible to formalize the model for diagnostics. Symbols of subsystems, components of the SPP in

BBN: Input element - IE; Fire fighting system - FFS; Compressed air system - CAS; Manual control of the main engine - MCME; Control system - CS; Remote automated control system of the main engine - RACSME; Intermediate component - P1; Ship power plant - SPP; Main engine - ME; Ballast drainage system - BDS; Emergency drive propulsion and steering complex - ED PSC; Control system for propulsion and steering complex -CSPSC; Boiler plant - BP; Transfer of power from the main engine to the propeller - TPMEP; Intermediate component - P2; Propulsion and steering complex - PSC; Output component - EXIT. Tab. 1 reflects the correspondence of symbols on the fault tree S and FS, FC BBN.

Table 1
Correspondence table S and subsystems (components) BBN

Designation	Event characteristics
S1	Violation of the IE element
S2	Violation of the FFS, CAS, MCME elements
S3	Violation of the RACSME, P1, SPP elements
S4	Violation of the CS, BDS, BP elements
S5	Violation of the ME, ED_PSC, CSPSC elements
S6	Violation of the TPMEP, P2, PSC elements

The structure of the BBN SPP, shown in Fig. 2, is a multi-level subsystem location system, consisting of 13 subsystems, 7 levels with the addition of specialized intermediate nodes P1 and P2, providing the implementation of a multi-level network structure.

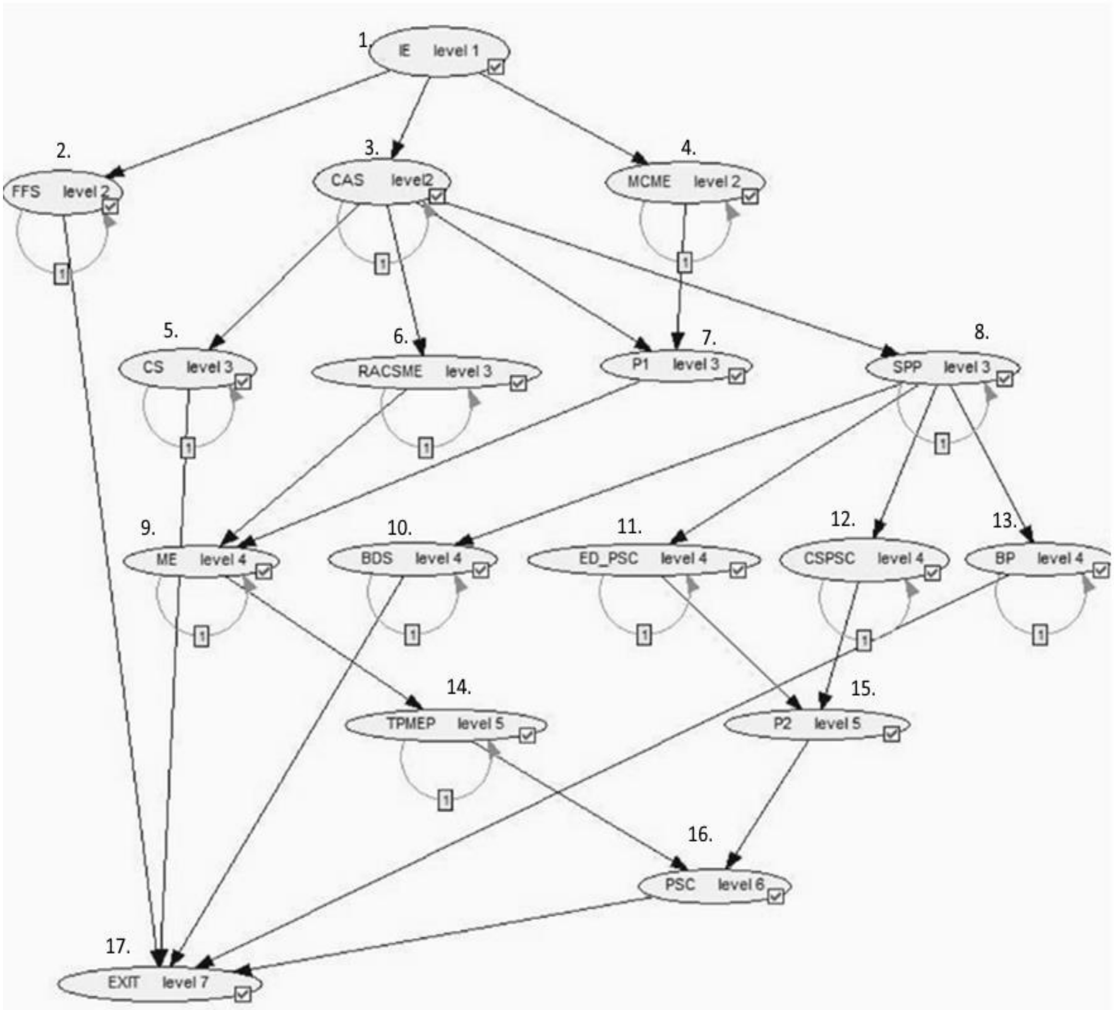

Figure 2: Structure of BBN SPP

For the subsystems of the upper level SPP BBN structure, conditional failure probabilities are specified, taking into account the influence of subsystems of a lower hierarchical level on subsystems of a higher level.

As an BBN example for interconnected power plant units (Fig. 2) IE, CAS, SPP and interconnections IE-CAS, CAS - SPP, sets of failure risk at the initial time and taking into account the dynamics of technical conditions over time based on a priori data on intensities bounce

$$
\begin{gathered}
R(Work_{1,3,8}^{1,2,3})_{t=0} = 0\,; \\
R(Not\_work_{1,3,8}^{1,2,3})_{t=0} = 1\,; \\
R(Work_{IE-CAS,CAS-SPP}^{2,3})_{t=0} = 0\,; \\
R(Not\_work_{IE-CAS,CAS-SPP}^{2,3})_{t=0} = 1\,; \\
R((Work_{1,3,8}^{1,2,3})_t /(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}1\,; \\
R((Work_{IE\_CAS,CAS\_SPP}^{2,3})_t /(Work_{IE\_CAS,CAS-SPP}^{2,3})_{t-1}) = 0{,}1
\end{gathered} \tag{16}
$$

Sets of risk of failures at the current moment of time, taking into account the previous state of subsystems and intersystem communications, can be within:

- the level of risk of failure is estimated as minimal, the consequences of an accident are minimal at:

$$
\begin{gathered}
R((Not\_work_{1,3,8}^{1,2,3})_t /(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}1 - 0{,}2\,; \\
R((Not\_work_{IE\_CAS,CAS\_SPP}^{2,3})_t /(Work_{IE\_CAS,CAS-SPP}^{1,3})_{t-1}) = 0{,}1 - 0{,}2\,;
\end{gathered} \tag{17}
$$

- the risk failure level is assessed as acceptable, the consequences of the accident are insignificant at:

$$
\begin{gathered}
R((Not\_work_{1,3,8}^{1,2,3})_t /(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}2 - 0{,}37\,; \\
R((Not\_work_{IE\_CAS,CAS\_SPP}^{2,3})_t /(Work_{IE\_CAS,CAS-SPP}^{1,3})_{t-1}) = 0{,}2 - 0{,}37\,;
\end{gathered} \tag{18}
$$

- the risk failure level is estimated as maximum, the consequences of the accident are significant at:

$$
\begin{gathered}
R((Not\_work_{1,3,8}^{1,2,3})_t /(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}37 - 0{,}63\,; \\
R((Not\_work_{IE\_CAS,CAS\_SPP}^{2,3})_t /(Work_{IE\_CAS,CAS-SPP}^{2,3})_{t-1}) = 0{,}37 - 0{,}63\,;
\end{gathered} \tag{19}
$$

- the failure risk level is assessed as critical at:

$$
\begin{gathered}
R((Not\_work_{1,3,8}^{1,2,3})_t /(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}63 - 1\,; \\
R((Not\_work_{IE\_CAS,CAS\_SPP}^{2,3})_t /(Work_{IE\_CAS,CAS-SPP}^{2,3})_{t-1}) = 0{,}63 - 1
\end{gathered} \tag{20}
$$

The construction and study of BBN failure risk assessments FS, FC, FIC and FI CTS was carried out using the software product GeNIe [20].

The use of the GeNIe environment makes it possible to diagnose the TC of each FS, FC, FIC and FI CTS. Perform a regression analysis of the influence of network each parent element on its corresponding child element. Implement a graphical display of the failures risk assessment predicting results FS, FC, FIC and FI CTC. Calculate the values of the working capacity loss probability, damage from failures and assessments of failures risk FS, FC, FIC and FI CTC.

When modeling the SPP's BBN (Fig. 2), for various failure risk values the input component, the failures risk values of functionally interconnected and interacting FS for 20,000 hours SPP operation were determined (Fig. 3).

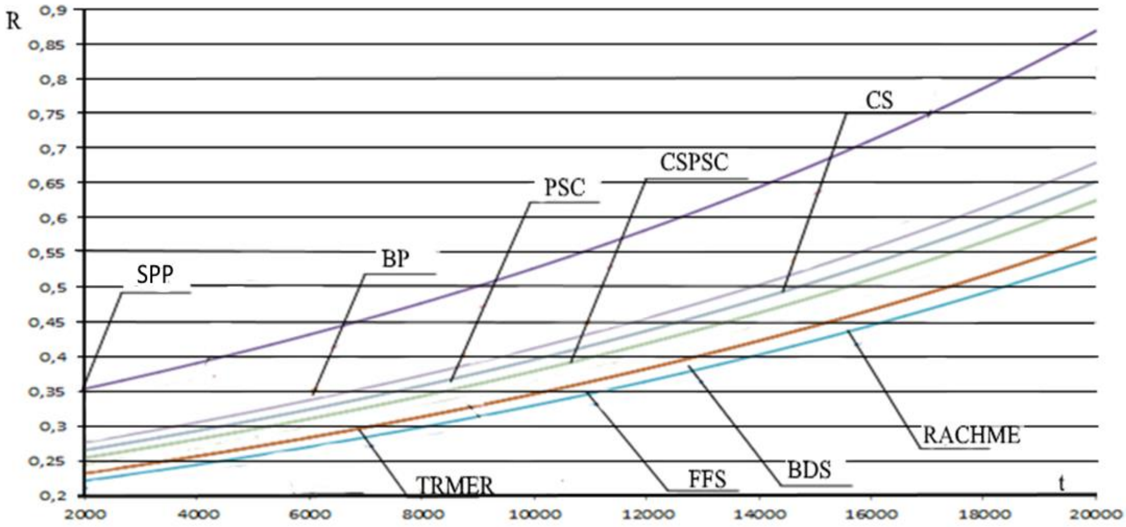

Figure 3: SPP subsystems predictable risk

The operating state and failure, for example, of the CS subsystem for the risk of failure at the input element of the SPP 0.26 when simulating the BBN of the SPP is shown in Fig. 4.

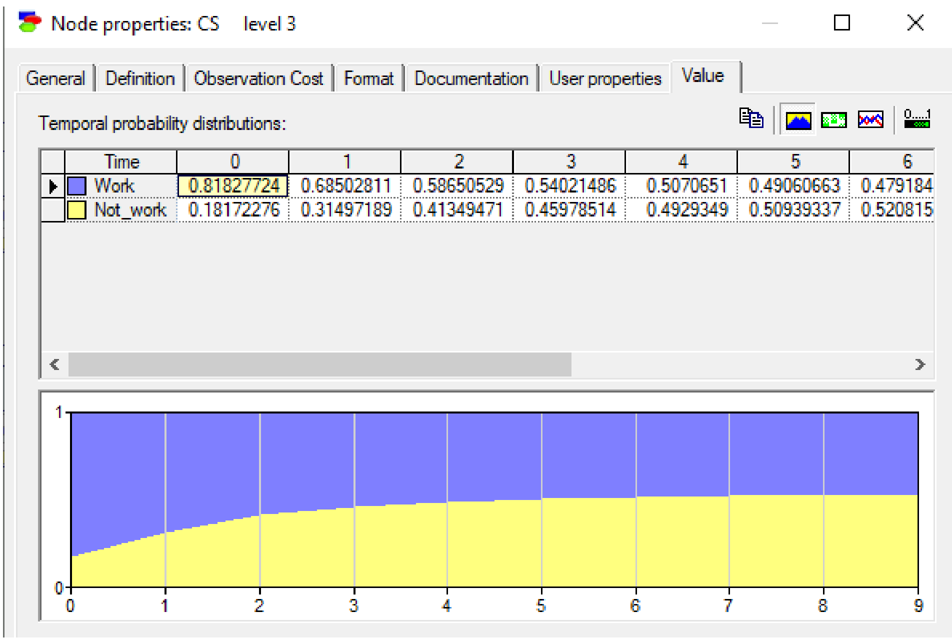

Figure 4: Operating state and failure of the CS subsystem for failure risk the input component of the SPP 0.26

The purpose of using BBN in assessing the risk of failures FS, FC CTC is 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.

Post hoc inference is based on procedures for analyzing data obtained from the use of BBN.

When implementing this approach in research, modeling on a priori and a posteriori data, the predicted TC FS, FC of the power plant are determined, which have the greatest impact on the performance of the main engine and the operation of the entire system for various time periods. It follows from the research results that the predicted maximum non-operating state during the operation of the SPP is 20,000 hours. Corresponds to the most vulnerable subsystems ME, VR (Fig. 2).

Because subsystems ME, VR are dependent at the level of the hierarchical structure of the SPP, therefore, in the future, it is necessary to regularly check the subsystems in order to find possible causes of their failure, thereby increasing operation reliability of ME, VR, and hence the whole SPP at all.

Thus, based on the intellectualization TC assessment FS, FC, FIC and FI of the CTS by diagnostic features, it is possible to substantiate the forecast failures risk FS, FC, FIC and FI of the SPP.

The considered principle intelligent system functioning, its structure, in terms of the technical and technological foundations of construction on the example of SPP, reflected in the method and model for assessing and predicting FS, FC, FIC and FI CTS failures risk can be considered as conceptual task.

The described method, the developed model of an intelligent system for assessing and predicting the risk of CTS failures on network infrastructures, as a research result, confirmed the relative insensitivity to incomplete technological data FS, FC, FIC and FI.

Application of research results allows providing:

- formation of principles for the intelligent system for diagnosing and predicting the CTS failures risk construction and operation;
- intellectualization model of TC estimation and forecasting ship CTS failures risk by diagnostic features, which has a relative insensitivity to incomplete technological data FS, FC, FIC and FI CTS creation;
- intellectualization model for ES evaluation based on the use of a priori information about failures, linking the types of TC FS, FC, FIC and FI of complex systems and their diagnostic features in the failure risk form creation;
- identifying the most vulnerable FS, FC, FIC and FI CTS and solving the problem of determining the failures causes depending on failures risk in the TC diagnostics.

4. Conclusion

The results of the development of a diagnostic model for a complex technical system with incomplete technological data and its implementation in an intelligent system for assessing and predicting FS, FC, FIC and FI ship CTS failures risk made it possible to obtain a priori information about the technical condition of a complex system.

The types of technical condition FS, FC, FIC and FI are determined on the basis of diagnostic features of a complex system using ship power plant example.

Predicting complex technical system technical state type was carried out using a posteriori inference in Bayesian belief networks.

The conducted studies presented in the article evaluated the results of functioning of an intelligent system for diagnosing and predicting complex technical system failures risk, which makes it possible to identify the most vulnerable FS, FC, FIC and FI CTS and predict their TC.

The model for diagnosing and predicting the risk of failures of subsystems, components, interconnections can be considered as an intelligent system conceptual model for diagnosing and predicting complex technical systems failures risk on network infrastructures, which has a relative insensitivity to incomplete technological data.

The use of the developed method and model, taking into account the hierarchical levels FS, FC, FIC and FI, when searching for the causes of failures in complex technical systems, allows us to control failures risk in systems when information about failures in their structures is received according to TC. The application of the method and model allows predicting trends in the risk of system failures, taking into account changes in individual FS failures risk of FC, FIC and FI in order to further choose a strategy for their restoration or replacement.

5. References

[1] V.Vychuzhanin, N. Rudnichenko, Metody informatsionnykh tekhnologiy v diagnostike sostoyaniya slozhnykh tekhnicheskikh sistem, monografiya, 2019.

[2] V. Vychuzhanin, N. Rudnichenko, Devising a method for the estimation and prediction of technical condition of ship complex systems, Eastern-European Journal of Enterprise Technologies, 84 (2016) 4-11. DOI:10.15587/1729-4061.2016.85605.

[3] V. Vyuzhuzhanin, N. Rudnichenko, N. Shibaeva, Data Control in the Diagnostics and Forecasting the State of Complex Technical Systems, Herald of Advanced Information Technology, 2 (2019) 183-196. DOI:10.15276/hait.03.2019.2.

[4] V. Vychuzhanin, N. Rudnichenko, Complex Technical System Condition Diagnostics and Prediction Computerization, in: CMIS-2020 Computer Modeling and Intelligent Systems / Ceur-ws.org. 2608.2020. pp.1-15. DOI:10.32782/cmis/2608-4

[5] J. Sшrensen, Marine Control Systems Propulsion and Motion Control of Ships and Ocean Structures, 2013.

[6] I. Lazakis, Advanced ship systems condition monitoring for enhanced inspection, maintenance and decision making in ship operations, Transportation Research Procedia, (14) 2016 1679 – 1688. DOI:10.1016/j.trpro.2016.05.133

[7] P. Zhang, Z. GaoCao, L. Dong, Marine Systems and Equipment Prognostics and Health Management. Systematic Review from Health Condition Monitoring to Maintenance Strategy, Machines, 10 (2022) 72-79. DOI:10.3390/machines10020072.

[8] F. Lan, Y. Jiang, Performance Prediction Method of Prognostics and Health Management of Marine Diesel Engine, in: Proceedings of the 2020 3rd International Conference on Applied Mathematics, Modeling and Simulation, Shanghai, China, 20–21 September 2020, 2020 vol 1670. pp.1-8. DOI:10.1088/1742-6596/1670/1/012014.

[9] D. Boullosa-Falces, J. Barrena, Monitoring of fuel oil process of marine diesel engine, Appl. Therm. Eng, 127 (2017) 517–526.

[10] P. Compton, Troubleshooting Marine Diesels, International Marine, 2017. DOI:10.1016/j.applthermaleng.2017.08.036

[11] Z. Jin, L. Meng, J.M. Guerrero, R. Han, Hierarchical Control Design for Shipboard Power System with DC Distribution and Energy Storage aboard Future More-Electric Ships, IEEE Transactions on Industrial Informatics, 14 (2018) 703-714. DOI:10.1109/TII.2017.2772343

[12] V.V. Vychuzhanin, N.D. Rudnichenko, A.V. Vychuzhanin, A.Ye. Kozlov Programnoye obespecheniye avtomatizatsii otsenki riska otkazov slozhnykh tekhnicheskikh system, Informatics and Mathematical Methods in Simulation, 4 (2019) 315-323.

[13] P.C. Lucienne An Introduction to Probabilistic Risk Analysis for Engineered Systems, 2011. DOI:10.1002/9780470400531.eorms0680

[14] R. Wang Chen, C. Guan, A Bayesian inference-based approach for performance prognostics towards uncertainty quantification and its applications on the marine diesel engine, ISA Trans, 118 (2021) 159–173. DOI: 10.1016/j.isatra.2021.02.024

[15] F.V. Jensen, Bayesian Networks and Decision Graphs, 2007.

[16] D. Handayani, W. Sediono. Anomaly Detection in Vessel Tracking: A Bayesian Networks (Bns) Approach, International Journal of Maritime Engineering (RINA Transactions Part A) 157 (2015) 145–152. DOI:10.3940/rina.ijme.2015.a3.316

[17] R. Ferdous, F. Khan, R. Sadiq, P. Amyotte, B. Veitch, Fault and Event Tree Analyses for Process Systems Risk Analysis: Uncertainty Handling Formulations, Risk Analysis 31 1 (2011) 86–107. DOI: 10.1111/j.1539-6924.2010.01475.x

[18] E.C. Harrington, The desirable function. Industrial Quality Control, 2110 (1965) 494-498.

[19] OREDA. OREDA-Offshore Reliability Data Handbook, 2015.

[20] Genie9: Making Local Backup Easy and Affordable - Genie9, 2022. URL: https://www.zoolz.com/genie9/(date of access: 19.04.2023).