Intellectualization Method and Model of Complex Technical System's Failures Risk Estimation and Prediction

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Abstract

The article describes the developed intellectualization method and model of the complex system failures risk technical condition assessment and prediction by diagnostic features. The developed model has a relative insensitivity to incomplete data about the system and is considered as a conceptual one for an intelligent system for assessing and predicting the complex technical systems failures risk on network infrastructures. Developed method and model can take into account the hierarchical levels of subsystems (components), intersystem (interelement) links when searching for the failures causes. Proposed method and model allow us to control the risk of failures in complex technical systems when information about failures in their structures is received. In addition, the application of the method and model makes it possible to predict trends in the risk of system failures, taking into account changes in the risk of failures, in order to further choose a strategy for their recovery.

Keywords

Complex technical system, diagnostics, forecasting, model, intelligent system, Bayesian belief network, performance, failure risk assessment.

1. Introduction

The diversity of the composition and the increase in the number of complex technical systems (CTS), for example, installed on ships, is accompanied by an increase in the failure rate of such systems. This leads to the need to repair CTS equipment, which means to ship downtime, so probably losses associated with the time spent on repairs and the resources used might be increased significantly. The use of intelligent systems for assessing and predicting the technical condition (TC) of complex systems can significantly extend the life cycle of CTS, including ships [1]. Estimation, prediction of the risk of CTS failures involves the development of methods and technologies of artificial intelligence in order to identify and prevent possible failures in the operation of CTS [2]. This article is devoted to this problem solution.

2. Description of Problem

The operational reliability of recoverable CTSs is effectively achieved by the strategy of operating systems with TC control based on technical diagnostic systems [3,4]. When designing, manufacturing and operating CTS for various purposes, the following hierarchical structure of the CTS diagnostic model is used system (consisting of subsystems); subsystem (functional devices consisting of components); component (concentrated structure containing elements); intercomponent communication or links (distributed structure containing links between components).

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Subsystems and components are referred to as functional elements (FE). Intersystem and intercomponent links form a group of functional inner-connections (FI) or links.

In design, manufacture and operation, the reliability of CTS is ensured by methods and means specific to each stage of the systems "life cycle". Reliability of ship CTS is estimated based on the results of FE and FI TC diagnosing and can be assessed in the failures risk form [5,6,7].

During CTS operation, prediction of their TC based on diagnostics helps to reduce the risk of system failures [8]. At the same time, the CTS shipboard FE and FI failures risk assessment should take into account their structure (hierarchy and topology of systems), functional states (operability, failure) of their subsystems (components), intersystem (intercomponent) connections, as well as systems data incompleteness.

Studies of ship CTS (energy, electric power, etc.) reliability models show us that the defeat of any subsystems, components in systems generates a significant number of possible scenarios and options for the development of such systems emergency states, as a result, it leads to possible marine accidents.

Available statistics of marine accidents and incidents related to CTS failures are reflected in the well-known databases Global Integrated Shipping Information System - Marine Casualties and Incidents [9], Marine Accident Investigation Branch reports [10], Marine Accident Reporting Scheme reports [11], National Transportation Safety Board NTSB [12], Casualty and Events [13]. Moreover, according to statistics, one of the main CTS - ship power plant (SPP) accounts for 60-80% of all failures of ship systems [14].

Improving the strategy for the operation and maintenance of ship equipment can be achieved by solving the problems of choosing: a rational strategy for servicing CTS equipment; the level of diagnosis and structural parameters characterizing its TC; diagnostic methods and diagnostic parameters; algorithms for extracting diagnostic information; forecasting methods.

Currently, the volume of implementation of automation, digitalization and artificial intelligence (AI) technologies in various industries continues to grow. Intellectualization of estimation and prediction in complex systems failures risk is a task related to the development of methods and technologies that allow automatically determining the risk (probability) of failures in CTS and predicting their possible consequences.

Assessing and predicting the risk of CTS failures is a task that requires the ability to process large amounts of data, analyze them and find patterns and relationships between various system operation parameters. In this case, the use of intelligent technologies can greatly simplify and speed up the process of data analysis.

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 AI technologies [15,16]. So, for example, an AI system for power plants should monitor the state and control of engines and their systems, auxiliary mechanisms, power supply systems in accordance with the plan for their maintenance and inspection.

The conceptual basis for the intellectualization of the solution of interrelated problems of CTS TC diagnostics and prediction are traditional for the class of unstructured and poorly formalized tasks, such as the impossibility of obtaining complete and objective information for making adequate decisions and, due to this circumstance, the 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 necessity to develop and justify the desired solutions to the problem under severe time constraints determined by the course of controlled processes; the necessity 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 decision-making models and move on to intelligent system technologies [17].

To successfully solve the problem of ensuring the reliability of ship CTS, it is necessary to remove a number of uncertainties, each of which is quite complex and significant. Such uncertainties include: incomplete data on external, internal impacts on systems and on the state of such systems; uncertainty in the behavior of systems.

The removal of the listed uncertainties can be based on solving the problems of assessing the risk of CTS failures and its prediction with relative insensitivity to incomplete data on systems [18].

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 design stage of TC CTS diagnostic systems [17].

There are various algorithms, models and methods for predicting TC CTS. AI models are actively developing, in particular, neural networks. To solve the problem of classifying TC based on diagnostic results, for example, a probabilistic neural network (PNN network - Probabilistic Neural Network [19]) is used.

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 of testing, limited time, etc.).

Lack of a clear understanding in the choice of neural network architecture for solving various types of problems (pattern recognition, approximation, forecasting, etc.) and areas of application also complicates their application.

In AI, knowledge representation models are actively developing - Bayesian networks [20]. Bayesian networks allow us to combine a priori (initial) knowledge about an object with new (experimental) data to obtain aposteriori (after experimental) estimates. One of the advantages of using Bayesian belief networks (BBN) for TC diagnostics is their ability to work with uncertain and incomplete data.

Instead of using rigid rules and thresholds, which may be ineffective in case of complex and ambiguous situations, the BBN might be useful to provide the possible technique for estimation of the probability (risk of failures) of various system states based on the available data.

Using BNN for CTS implementation let us to reduce the probability (risk of failures) of false reactions and improves diagnostics accuracy. In addition, the BBN can be used to analyze not only individual components of the system with different performance, but also their interactions, connections, which allows us to identify both individual faults and their interactions, which can be useful in solving complex problems associated with failures in systems.

To assess the risk of CTS failures based on the BBN, modern and available software technologies are used (Microsoft Bayesian Network Editor, Bayes Net Toolbox for Matlab, GeNIe, Smile, AgenaRisk, Analytica, Bayes Server, Hugin Expert). In addition, there are ready-made libraries and modules for Python, C++, C#, MatLab, R, VB.NET on various operating systems (Windows, Linux, macOS).

Thus, the problems associated with ensuring the reliable operation of the CTS require improvement and the search for new methods, models and algorithms implemented in the form of problem-oriented programs.

They should be aimed at prompt detection of emergency conditions of equipment, at solving problems of system failures risk assessing and predicting under conditions of relative insensitivity to incomplete data on FE and FI, which have different operability.

Since all modern ships must be equipped with AI-based technology automation systems, the implementation of approaches based on such methods, models and algorithms should be aimed at ensuring the reliable operation of shipboard CTS.

So, taking into account the specifics and existing problems in ensuring reliability during the CTS shipboard operation, the development and development intellectualization methods, models for estimating and predicting the risk of failures of complex systems by diagnostic features are important for the new technologies development performance aimed at ensuring complex systems safety and reliability.

Statement of the problem: intellectualization of the CTS TC assessment by diagnostic features, to substantiate the forecast failures risk in subsystems (components), intersystem (intercomponent) connections of systems with different performance.

Purpose of the work:

- ensuring the reliability and safety of work, as well as reducing the risk of CTS failures by solving causes determining problem of their failures;
- formation of principles for the construction and intelligent system operation for assessing and predicting the risk of CTS failures with different performance, their constituent FE and FI;

- intellectualization method and model for the TC estimation and predicting complex systems failures risk by diagnostic features development. The results might be used relatively insensitive to incomplete data about systems based the priori information about failures that connects the types of technical condition FE and FI of complex systems and their diagnostic features.

3. Intellectualization method and model of complex systems failures risk technical state estimation and prediction by diagnostic features

The proposed method is based on a formalized generalized intellectualization model of TC failures risk estimation and prediction of complex systems FE and FI by diagnostic features, which can be described in the following form:

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

where: $S(C)$ set FE CTS;

$I_S(I_C)$ set FI CTS;

$R_{S(C)}, R_{I_S(I_C)}$ set of diagnostic failure risk assessments FE and FI CTS;

G acyclic directed graph;

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

A failures risk diagnostic assessment set of FE and FI CTS

$$R\left\{R_{S(C)_{n(m)}}, R_{I_{S(C)_{a(z)}}}\right\}, \tag{2}$$

$$R_{s(c)_{n(m)}} = \{r_{s(c)_{n(m)}} \mid s(c) = \overline{1, S(C)}, n_{s(c)} = \overline{1, N_{S(C)}}, m_{s(c)} = \overline{1, M_{S(C)}}\},$$

$$R_{I_{s(c)_{a(z)}}} = \{r_{i_{s(c)_{a(z)}}} \mid i_{s(c)} = \overline{1, I_{S(C)}}, a = \overline{1, A}, z = \overline{1, Z}\},$$

where $r_{s(c)_{n(m)}}$ FE CTS failure risk;

$r_{i_{s(c)_{a(z)}}}$ FI CTS failure risk;

$n_{s(c)}$ FE CTS number;

$m_{s(c)}$ FE CTS hierarchical level number;

$N_{S(C)}$ FE CTS quantity;

$M_{S(C)}$ FE CTS hierarchical level quantity;

a intersystem link number;
z interconnect number;
A number of interconnections;
Z number of intercomponent bonds.

Created model for FE, FI failures risk determining:

$$< P_{S(C)_{n(m)}}, P_{I_{S(C)_{a(z)}}}, D_{S(C)_{n(m)}}, D_{I_{S(C)_{a(z)}}}, e_{s(c)_{n(m)}}, e_{I_{s(c)_{a(z)}}} >, \tag{3}$$

where $P_{S(C)_{n(m)}}, P_{I_{S(C)_{a(z)}}}$ conditional failure probabilities FE and FI respectively;

$D_{S(C)_{n(m)}}, D_{I_{S(C)_{a(z)}}}$ failure damage FE and FI respectively;

$e_{s(c)_{n(m)}}, e_{I_{s(c)_{a(z)}}}$ FE and FI weight given their hierarchy in CTS respectively.

Failure risk for $n(m)$ FE CTS:

$$R_{S(C)_{n(m)}} = D_{S(C)_{n(m)}} \cdot P_{S(C)_{n(m)}}(t). \tag{4}$$

Failure risk for $a(z)$ FI CTS

$$R_{I_{S(C)_{a(z)}}} = D_{I_{S(C)_{a(z)}}} \cdot P_{I_{S(C)_{a(z)}}}(t). \tag{5}$$

The total failure risk assessment CTS, taking into account the failures risk assessment of FE, FI is determined

$$\mathrm{R} = \sum_{s(c)=1}^{\mathrm{S(C)}} \sum_{n(m)=1}^{N(M)} (\mathrm{R}_{\mathrm{s(c)_{n(m)}}} \cdot e_{s(c)_{n(m)}}) + \sum_{i_{s(c)}=1,}^{I_{S(C)}} \sum_{a(z)=1}^{A(Z)} (R_{i_{s(c)_{a(z)}}} \cdot e_{I_{s(c)_{a(z)}}}). \tag{6}$$

The failure probability of FE and FI is determined by the formulas:

$$P_{S(C)_{n(m)}} \cdot \lambda(t)_{S(C)_{n(m)}} = \frac{\alpha_{S(C)_{n(m)}} \cdot \exp(-\alpha_{S(C)_{n(m)}} \cdot T_{S(C)_{n(m)}})}{\exp(-\alpha_{S(C)_{n(m)}} \cdot T_{S(C)_{n(m)}})} = \alpha_{S(C)_{n(m)}}, \tag{7}$$

$$P_{I_{S(C)_{a(z)}}} \cdot \lambda_{I_{S(C)_{a(z)}}}(t) = \frac{\alpha_{I_{S(C)_{a(z)}}} \cdot \exp(-\alpha_{I_{S(C)_{a(z)}}} \cdot T_{I_{S(C)_{a(z)}}})}{\exp(-\alpha_{I_{S(C)_{a(z)}}} \cdot T_{(I_{S(C)_{a(z)}}})} = \alpha_{I_{S(C)_{a(z)}}} \tag{8}$$

where λ failure rate;

α distribution parameter, taken according to the test results equal to $\alpha \approx 1/\hat{T}_0$, $\hat{T}_0$ mean time to failure estimate.

Quantifying damage to FE from failure $n(m)$ subsystem (component) to determine the risk of failure

$$D_{S(C)_{n(m)}} = \{d_{s(c)_{n(m)}} \mid s(c) = \overline{1, S(C)}, n = \overline{1, N}, m = \overline{1, M}\}, \tag{9}$$

where $d_{s(c)_{n(m)}}$ damage from subsystem (component) failure CTS.

Quantifying damage FI from failure $a(z)$ intersystem (intercomponent) communication:

$$D_{I_{s(c)_{a(z)}}} = \{d_{I_{s(c)_{a(z)}}} \mid i_{s(c)} = \overline{1, I_{S(C)}}, a = \overline{1, A}, z = \overline{1, Z}\}, \tag{10}$$

where $d_{i_{s(c)_{a(z)}}}$ damage from failure of intersystem (intercomponent) communication.

According to the established conditional failure probabilities and damages from failures FE and FI according to (4), (5), their risk of failures is determined.

The intellectualization model of complex systems TC failures risk estimation and prediction by diagnostic features using the BBN apparatus is a synthesis of reliability and diagnostic models. In the technical condition diagnostics model, the BBN is used to assess the risk of system failure (probability).

To create a diagnostic TC model, it is necessary to determine the risk of failure (conditional probabilities) for each node in the network. This data is derived from expert knowledge and analysis of historical data.

After determining the risk of failure (conditional probabilities), the model can be used to estimate (predict) the CTS state.

To do this, the model determines the risk of failure for system's each state using information about the current values of the system's state and the failures risk determined for each node in the network.

The technique for building a model based on BBN can be represented as follows:

1. Building a BBN:

1.1 Vertices and intersystem (intercomponent) Bayesian networks are created, denote subsystems (components) of CTS, according to their TC:

1.1.1 Each subsystem (component) can be in the following technical condition:

$Work_{n_{S(C)}}^{<m_{S(C)}>}$ operational state $n_{S(C)}$ subsystem (component) $m_{S(C)}$ level;

$Not\_work_{n_{S(C)}}^{<m_{S(C)}>}$ failure partial (complete) $n_{S(C)}$ subsystem (component) $m_{S(C)}$ level.

1.1.2. Each intersystem (intercomponent) connection is in the states:

$Work_{a(z)_{I_{S(C)}}}^{<b,q>}$ operational state $a(z)_{I_{S(C)}}$ intersystem (intercomponent) communication $b(q)$ level;

$Not\_work_{a(z)_{I_{S(C)}}}^{<b,q>}$ failure partial (complete) $a(z)_{I_{S(C)}}$ intersystem (intercomponent) communication $b(q)$ level, where b number of hierarchical level of system interconnection; q number of hierarchical level of component interconnection.

1.2. The connections between the nodes of the Bayesian network are indicated, denoting subsystems (components), intersystem (interelement) CTS connections and diagnostic appropriate assessments R.

2. BBN parameters are specified:

2.1. Initial failure risk for FE and FI CTS, assuming that they are all operational before the start of the CTS

$$R(Work_{n_{S(C)}}^{<m_{S(C)}>})_{t=0} = F(P(Work_{n_{S(C)}}^{<m_{S(C)}>})_{t=0}) = 0\ ; \qquad (11)$$

$$R(Work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t=0} = F(P(Work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t=0}) = 0\ .$$

2.2. Initial failure risk for FE and FI CTS, assuming that they are all inoperable before the start of the CTS

$$R(Not\_work_{n_{S(C)}}^{<m_{S(C)}>})_{t=0} = F(P(Not\_work_{n_{S(C)}}^{<m_{S(C)}>})_{t=0}) = 1\ ; \qquad (12)$$

$$R(Not\_work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t=0} = F(P(Not\_work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t=0}) = 1\ .$$

2.3. Risk of failure of FE and FI CTS at the current moment of time, provided that some FE and FI failed at the previous moment of time

$$R((Not\_work_{n_{S(C)}}^{<m_{S(C)}>})_t /(Not\_work_{n_{S(C)}}^{<m_{S(C)}>})_{t-1}) = 1\,; \quad (13)$$

$$R((Not\_work_{a(z)_{I_{S(C)}}}^{<,b,q>})_t /(Not\_work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t-1})) = 1\,.$$

2.4. FE and FI CTS failure risk at the current moment of time, while they are in a working state at the current moment of time, which also were operable at the previous moment of time

$$R((Work_{n_{S(C)}}^{<m_{S(C)}>})_t /(Work_{n_{S(C)}}^{<m_{S(C)}>})_{t-1}) = \frac{e^{-\lambda_{n_{S(C)}}^{<m_{S(C)}>} t}}{e^{-\lambda_{n_{S(C)}}^{<m_{S(C)}>} (t-1)}} = e^{-\lambda_{n_{S(C)}}^{<jm_{S(C)}}} = 0\,; \quad (14)$$

$$R((Work_{a(z)_{I_{S(C)}}}^{<b,q>})_t /(Work_{a(z)_{I_{S9C0}}}^{<b,q>})_{t-1}) = \frac{e^{-\lambda_{a(z)_{I_{S(C)}}}^{<b,q>} t}}{e^{-\lambda_{a(z)_{I_{S(C)}}}^{<b,q>} (t-1)}} = e^{-\lambda_{a(z)_{I_{S(C)}}}^{<b,q>}} = 0\,.$$

2.5. FE and FI CTS failure risk at the current moment of time, subject to failure of FE and FI at the current moment of time, provided that it were operational at the previous moment of time

$$R((Not\_work_{n_{S(C)}}^{<m_{S(C)}>})_t /(Work_{n_{S(C)}}^{<m_{S(C)}>})_{t-1}) = (1 - e^{-\lambda_{n_{S(C)}}^{<m_{S(C)}>}}) \cdot D_{S(C)_{n(m)}}\,; \quad (15)$$

$$R((Not\_work_{a(z)_{I_{S(C)}}}^{<b,q>})_t /(Work_{a(z)_{I_{S(C)}}}^{<b,q>})_{t-1}) = (1 - e^{-\lambda_{a(z)_{I_{S(C)}}}^{<<b,q>}}) \cdot D_{I_{S(C)_{a(z)}}}$$

4. Experiments and results analysis

As an example, when modeling the BBN SPP, various failure risk values input element were selected and the predicted failures risk values and operability of the FE and FI of the power plant for 20,000 hours of installation operation were determined. Symbols of subsystems, components of the ECS are given in Table 1.

The purpose of using BBN in assessing how the risk of loss of performance due to the risk of failures FE and FI CTS is posteriori.

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.

Failure risk value predicted distributions for blocks and links of the multilevel structure diagnostic model (shown in Fig. 1) in BBN with a serial connection, for example, SPP subsystems IE - CAS - SPP and interconnections IE-CAS, CAS - SPP and SPP operation for 20,000 hours for SPP shown in Fig.2.

From the given a priori and a posteriori data based on the SPP study results included in the SPP multi-level structure, for 20,000 hours of operation for a conditionally accepted SPP failure risk value input component of 0.26 and possible failures of IE, CAS and interconnections IE - CAS, CAS - SPP according to posterior data, the predicted risk of SPP failure will change from 0.25 to 0.68.

Table 1
Symbols of subsystems, components of the SPP

Subsystem (component) number $n_{s(c)}$	Hierarchical number subsystem (component) level ($m_{s(c)}$)	Subsystem (component) name	Symbol	Subsystem (component) weight $e_{s(c)n(m)}$
1	1	Input element	IE	0,26
2	2	Firefighting system	FFS	0,01
3	2	Compressed air system	CAS	0,047
4	2	Main engine manual control	MCME	0,035
5	3	Control system	CS	0,081
6	3	Main engine remote automated control system	RACSME	0,01
7	3	Intermediate component	P1	0,01
8	3	Ship power plant	SPP	0,09
9	4	Main engine	ME	0,16
10	4	Ballast drainage system	BDS	0,019
11	4	Emergency drive propulsion and steering complex	ED PSC	0,01
12	4	Propulsion and steering complex control system	CSPSC	0,081
13	4	Boiler plant	BP	0,13
14	5	Power transfer from main engine to propeller	TPMEP	0,003
15	5	Intermediate component	P2	0,01
16	6	Propulsion and steering complex	PSC	0,01
17	7	Output component	EXIT	0,26

Similarly, from a retrospective results analysis obtained by modeling SPP, FE and FI are identified that affect the overall system performance.

From the research results, as reflected in the diagnostic model, it follows that the maximum non-operating state during the operation of the SPP 20000 hours corresponds to the CSPSC subsystem directly.

Since the CSPSC subsystem is dependent in the level of the SPP layered structure, then in the future it is necessary to check the subsystem in order to find its failure cause.

The implementation of the intellectualization method and model for estimation and prediction CTS failures risk in the conducted studies, carried out by modeling on a priori and a posteriori data, determines the FE and FI SPP that have the greatest impact on the performance of the main engine and the operation of the entire system at various points in time.

Carrying out studies of emergency situations, analysis of incidents in the CTS will determine the causes of the accident FE and FI SPP.

Thus, based on the intellectualization of FE and FI CTS TC estimation by diagnostic features, it is possible to substantiate the failure risk prediction for FE and FI systems with a large number of variable parameters and with different operability.

The considered principle of intelligent system functioning (due to its structure) in terms of the technical and technological foundations of construction on the SPP example reflected in the method and model for assessing and predicting the FE and FI CTS risk failures.

Method and model implementation with different operability and incomplete data let us to assess and predict the risk of CTS failures on network infrastructures with relative insensitivity to incomplete data.

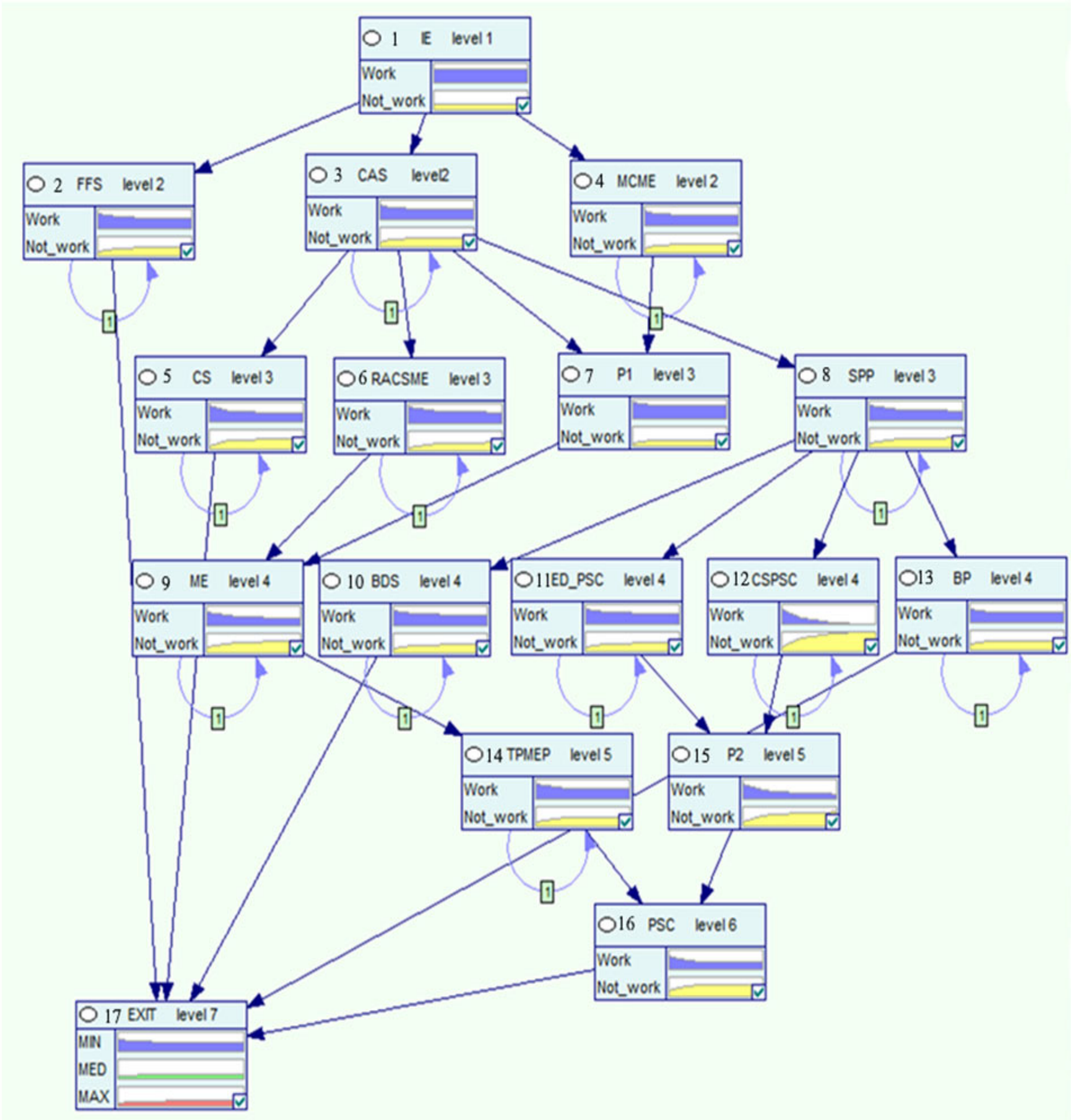

Figure 1: Diagnostic model of the technical condition of the SPP using the BBN in the GeNIe environment

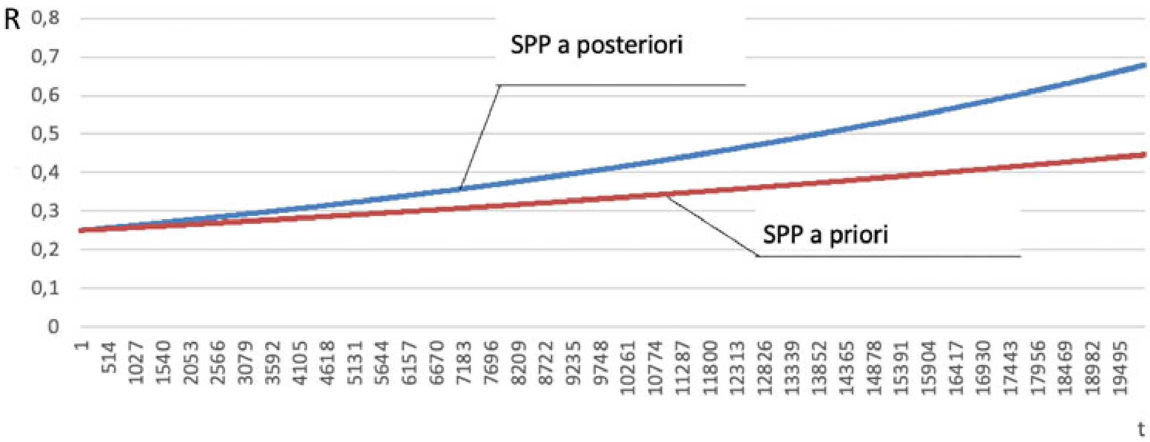

Figure 2: A posteriori and a priori estimates of the risk SPP for the input component failure risk of the ECS 0.26

5. Conclusion

Intellectualization of the CTS TC assessment by diagnostic features, the failures risk predicted values in subsystems (components), intersystem (intercomponent) connections of systems with different operability and incomplete data are substantiated.

In order to ensure the reliability and safety of work, as well as reduce CTS failures risk the all our main tasks were solved. It was determining the causes of their failures, we formated of principles for the construction and operation of an intelligent system for assessing and predicting CTS risk failures with different performance, their constituent FE and FI; development of a method and model for the intellectualization TC estimation and predicting complex systems failures risk by diagnostic features that are relatively insensitive to incomplete data about systems, based on the use of a priori information about failures, linking the types of technical condition FE and FI of complex systems and their diagnostic features in the bounce risk form.

The use of the developed method and model, which takes into account the hierarchical levels of subsystems (components), intersystem (interelement) links when searching for the causes of failures in complex technical systems, allows us to control the risk of failures in systems when information about failures in their structures is received. The application of the method and model makes it possible to predict trends in the risk of system failures, with updated changes in the risk of failures of individual subsystems (components), intersystem (interelement) links in order to further choose a strategy for their recovery.

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