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Stochastic Models and Methods for Diagnostics, Assessment, and Prediction of the Technical Condition of Complex Critical Systems

Monograph

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The monograph highlights the following: the specifics of using complex technical systems under uncertainty during operation; decision-making strategies for failure detection based on assessments of the technical condition of complex systems' equipment; and the development of an intelligent information system for diagnosing, evaluating, and forecasting the technical condition of complex systems.

The materials of this monograph will be valuable for postgraduate students, master's students, and university instructors specializing in the field of IT technologies..

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CONTENTS

LIST OF ABBREVIATIONS AND SYMBOLS

AI - Artificial Intelligence
BD - Database
BZ - Knowledge Base
BBN - Bayesian Belief Networks
CA - Critical Application
CBR - Case-Based Reasoning
CCS - Complex Critical Systems
CSM - Cognitive Simulation Model
CTS - Complex Technical System
DM - Decision Maker
DTRS - Data Transmission and Reception System
FC - Set of Intercomponent, Interelement Connections
FE - Set of Subsystems, Components, Elements
IIS - Intelligent Information System
OLAP - Online Analytical Processing
SW – Software
SPP - Ship's Power Plant
TC - Technical Condition
TS – Technical System

INTRODUCTION

One of the main causes of technogenic accidents involving CTS used in transportation, aviation, energy, and other fields remains operational equipment failures. An analysis of the results of ship operations shows that despite measures taken to ensure maritime safety, the number of accidents at sea remains high. A primary reason for many of these accidents is the failure of CTS. As a result, such systems are classified as critical application systems.

Complex technical systems of critical application are hierarchical structures with non-trivial internal organization, multifunctional subsystems, components, and elements, interconnected with complex links and subject to various failure states. A characteristic feature of CTS operation is uncertainty, as well as incomplete information about the technical condition of the systems.

Due to increasing demands for safety and reliability of expensive maritime CTS, their efficiency depends significantly on extending operational life and resource use. Enhanced efficiency can be achieved by applying models and methods for diagnosing, assessing, and forecasting the TC of complex systems and integrating them into intelligent information systems. These IIS enable the evaluation and prediction of TC based on diagnostic results. Existing diagnostic models and methods are widely used in practice, but they do not always ensure comprehensive operational efficiency of CTS. Additionally, current TC diagnostic models often account only for full functional failures but overlook partial ones. Partial failures are more diverse in their types and locations of manifestation compared to full failures. Advanced diagnostic algorithms are required to meet efficiency demands in decision-making while considering the continuation of CTS operation.

Promising modeling methods for TC diagnostics include Bayesian belief networks, which account for uncertainties and incomplete data of modeled CTS, and cognitive simulation modeling methods, which additionally evaluate the structural and functional vulnerabilities of system equipment. However, cognitive simulation modeling requires improvements due to its limitations: lack of universality regarding structural threats and vulnerabilities in CTS, and insufficient consideration of the significance and criticality of equipment for overall system functionality.

Known methods for assessing and predicting TC in complex systems implemented in IIS include case-based reasoning; analogies; systematic and heuristic methods for optimization tasks (e.g., genetic algorithms, artificial immune networks, annealing methods, swarm intelligence methods including ant algorithms); and structural representation methods based on OWL ontology precedents. Some of these methods face challenges such as high algorithmic and computational complexity, the necessity of intricate preliminary data processing stages, and limited visualization capabilities for interpreting results. A general drawback is the high dimensionality of possible tasks during decision-making.

Improving the efficiency of CTS operation by applying diagnostic, assessment, and forecasting models and methods that consider both partial and full equipment failures is a critical scientific problem.

Research Aim.

The aim of this research is to enhance the operational efficiency of CTS by developing models and methods for diagnosing, assessing, and forecasting the TC of critical application complex systems.

Research Objectives.

To achieve this aim, the following tasks were identified and resolved:

Analysis of models, methods, and information systems for diagnosing, assessing, and forecasting the TC of critical application CTS.

Development of stochastic models and a method for diagnosing the TC of critical application CTS.

Research and analysis of stochastic models and the diagnostic method for CTS.

Development of a method for assessing and forecasting the TC of CTS.

Creation of an IIS for diagnosing, assessing, and forecasting the TC of CTS.

Research Object.

The processes of diagnosing, assessing, and forecasting the TC of critical application CTS.

Research Subject.

The models and methods for diagnosing, assessing, and forecasting the TC of critical application CTS.

Research Methods.

To achieve the research goals, mathematical, simulation, and computer modeling methods were used, along with expert evaluation and theories of information, control, decision-making, graphs, artificial intelligence, cognitive analysis, literature content analysis, data processing, diagnostics, and forecasting. Methods of theoretical, applied, and object-oriented programming were employed in developing conceptual stochastic diagnostic models for CTS. Optimization theory methods were applied in data transmission modeling, as well as in diagnosing, assessing, and forecasting CTS.

Scientific Novelty.

The scientific novelty of the obtained results includes:

For the first time:

A stochastic diagnostic model for CTS was proposed, which simultaneously accounts for the presence of subsystems, components, and elements, their interconnections, and the probabilities of partial or complete functional failure. This led to the development of a diagnostic method based on a Bayesian belief network for critical application CTS.

A data transmission and reception model for diagnosing, assessing, and forecasting the TC of CTS was developed. It considers conflicting requirements and competing criteria, enabling the identification of Pareto-optimal solutions for effective data transmission and reception.

Further development was achieved in:

The diagnostic method for CTS based on a Bayesian belief network, enabling the timely identification and visualization of structural and functional vulnerabilities, thus enhancing the operational efficiency of critical application systems.

The case-based reasoning method, ensuring TC assessment and prediction to improve the performance of CTS.

Improvements were made to:

The cognitive simulation model, incorporating simulation-impact impulses, which allows for diagnosing equipment TC with consideration of interdependencies and mutual influences.

Practical Significance.

The practical significance lies in the development of an IIS that automates the processes of assessing and predicting the TC of critical application CTS in various states of functionality.

An algorithm was created to detect failures in subsystems, components, and elements, including their interconnections, based on risk assessments of these failures.

This algorithm enables the implementation of a targeted IIS operation strategy. A user interface for the knowledge base was developed, allowing experts to review formalized data and make final risk assessments for equipment failures in CTS.

CHAPTER 1
ANALYSIS OF MODELS, METHODS, AND INFORMATION SYSTEMS FOR DIAGNOSTICS, ASSESSMENT, AND FORECASTING OF THE TECHNICAL CONDITION OF COMPLEX SYSTEMS FOR CRITICAL APPLICATIONS

1.1 Analysis of Operational Challenges in Complex Technical Systems for Critical Applications

1.1.1 Principles of Design and Characteristics of Complex Technical Systems for Critical Applications

Modern CTS used in transportation, aviation, energy, and other fields are hierarchical structures comprising multi-functional subsystems, components, and elements with nontrivial interconnections. These systems operate in states of partial or complete functional failure.

The structure of CTS reflects the overall picture of cause-and-effect interactions among the system's subsystems, components, and elements [1, 2].

The operation of CTS involves uncertainties that are challenging to fully describe, understand, or predict. CTS exhibit properties such as nonlinearity, adaptability, self-organization, and integrity [1, 2]. Adaptability refers to the system's ability to exist in multiple states. Information components of CTS [1, 3, 4], equipped with artificial intelligence elements, enable system adaptability.

The property of self-organization is demonstrated by the system’s ability to modify its characteristics and return to its initial state when displaced. The integrity of the system is expressed in its ability to maintain systemic qualities.

CTS can be classified as probabilistic or deterministic (based on the degree of functional predictability) and as well-organized or poorly organized. Based on interaction with the environment, CTS can be categorized as open or closed systems [1, 2].

Each component of a CTS is characterized by a set of attributes whose values determine its condition. Changes in the properties of individual subsystems, components, elements, and their interconnections lead to changes in the properties of other subsystems, components, and elements. The functioning of CTS is based on systemic principles [1, 2]:

Functional alignment of elements within components, components within subsystems, and subsystems within the CTS.

The system's properties are not reducible to the sum of the properties of its constituent subsystems, components, and elements.

Typical examples of CTS include marine systems—complexes comprising dozens of interdependent technical systems (mechanisms, assemblies, devices, pipelines, etc.) designed to ensure the operation of ships [3, 5]. An example of a CTS is a ship's power plant (SPP), consisting of interrelated subsystems, components, and elements with various functionalities. Figure 1.1 shows a graph representing the structure of an SPP.

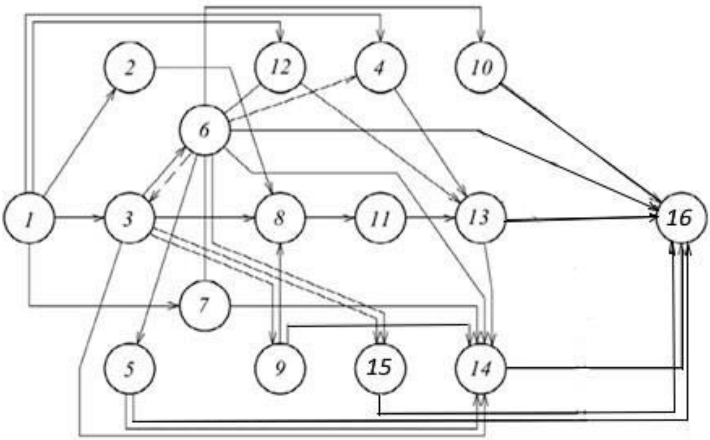

Figure 1.1 – Structure of the Marine Power Plant

The graph vertices include: input component 1; manual control of the main engine 2; subsystems for compressed air 3 and propulsion-rudder complex (PRC) control 4; boiler plant 5; power station 6; fire protection system 7; main engine 8; subsystems for remote-automated control 9 and ballast-drainage 10; power transmission from the main engine to the propeller 11; emergency PRC drive 12; PRC 13; subsystems for measuring instruments 14 and sanitary water treatment 15; output component 16.

Thus, complex technical systems represent an organized set of numerous functionally interconnected and interacting subsystems, components, and elements, linked by nontrivial connections. These connections often involve uncertainties in input data, making them difficult or impossible to predict, and they exist in various states of failure.

1.1.2 Analysis of Technogenic Accidents Caused by Failures in Complex Technical Systems of Critical Application

One of the main causes of technogenic accidents associated with the operation of CTS used in transport, aviation, energy, and other fields remains the failure of their subsystems, components, and elements [6]. This categorizes such CTS as systems of critical application.

Theoretically, the reliability of the TC of complex systems is a fundamental concept linked to the properties of systems recorded under specific external environmental conditions at a particular moment in time.

Changes in the TC during the operation of CTS (Figure 1.2) necessitate the evaluation of system TC.

Reliability [7, 8, 9] is the property of maintaining parameter values that characterize the functioning of CTS over a specific period.

The key reliability indicators include: the probability (risk) of failure-free operation, the distribution frequency and intensity of failures, and the mean time between failures. The probability of failure and the criticality level of CTS can be represented in the form of a criticality matrix (Figure 1.3) [7].

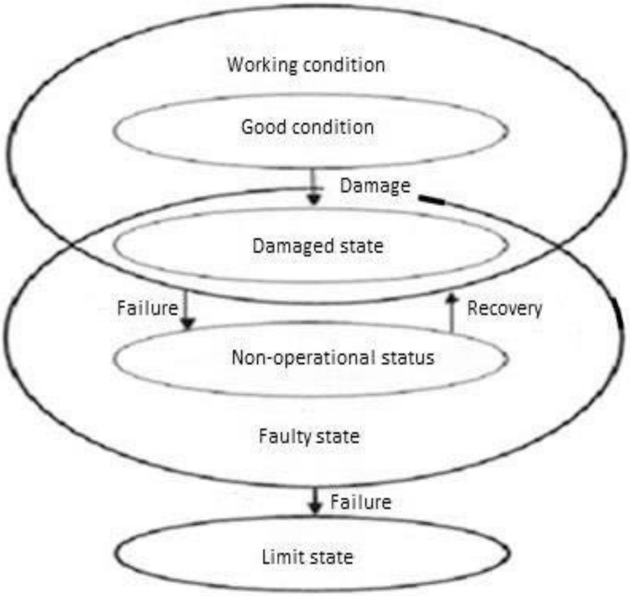

Figure 1.2 - Diagram of the Technical State and Events During the Operation of CTS

Confidence	significance of inheritances: catastrophic	great	middle	insignificant
Visoka	X	X	1	2
Serednya	X	X	1	2
Low	X	X	1	2
Very low	X	1	1	2
The edge is low	1	2	2	3

Figure 1.3 - Qualitative Criticality Matrix for CTS Operation (categories of failure risk: X – unacceptable; 1 – undesirable; 2 – acceptable; 3 – insignificant)

Failure in reliability theory is a random event involving partial or total loss of functionality. The concept of partial failure is used as a transitional state between functionality and complete failure. Partial failure of the CTS refers to the inability to perform some functions due to a partial loss of system performance efficiency. Such CTS are considered systems with multiple states.

External influences increase the load on an individual subsystem, component, or element of the CTS, which affects their ability to perform their functions, decreases efficiency and reliability, and leads to technological accidents. The causes of such accidents also include: CTS failures due to manufacturing defects and violations of operational modes; operator errors.

Among the sectors of the economy where higher requirements for efficiency and reliability of critical application CTS are imposed, maritime and river transport are included. Dozens of CTS installed on ships affect their survivability, which is not ensured by compliance with regulatory requirements at the design and construction stages, as well as during ship operation [10, 11, 12].

The databases [13] provide information on maritime accidents and incidents at sea. The Global Integrated Shipping Information System (GISIS), maintained by the IMO, contains full similar information [14] (Figures 1.4, 1.5).

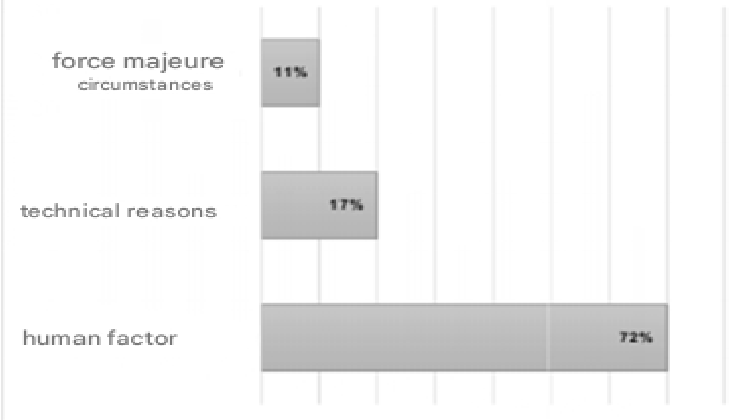

Figure 1.4 - Analysis of accident factors

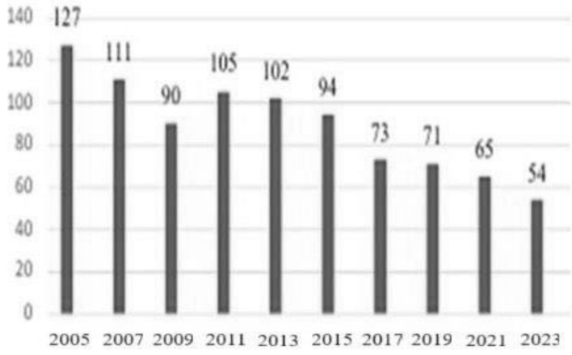

Figure 1.5 - Vessel losses

Systematized statistical data on maritime incidents are also presented by the European Maritime Safety Agency (EMSA) [15]. Statistics registered, for example, in the JTSB database within the Japanese shipping zone for the period 2008–2023 indicate [16] that the number of incidents shows a slight downward trend (Figures 1.6–1.8). The issue of ensuring reliability remains relevant for both older and newer vessels, particularly for large-tonnage ships equipped with advanced control and communication systems, which consequently have more vulnerable subsystems [17, 18, 19].

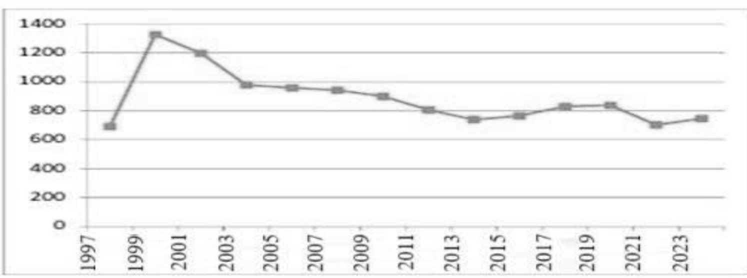

Figure 1.6 - Trends in the overall accident rate of ships

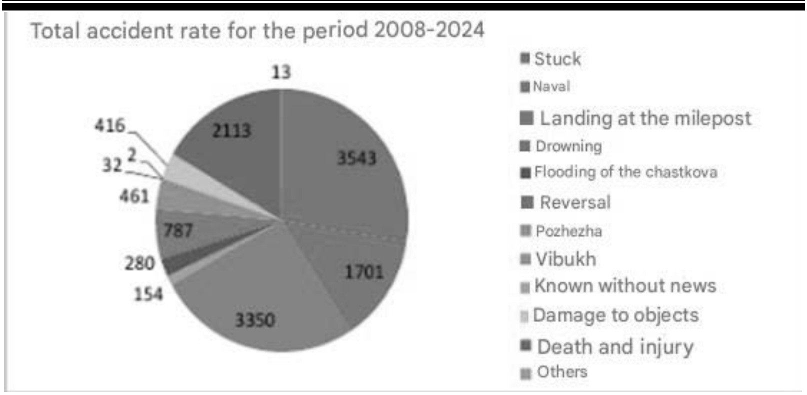

Figure 1.7 - Breakdown of accidents by type of accident

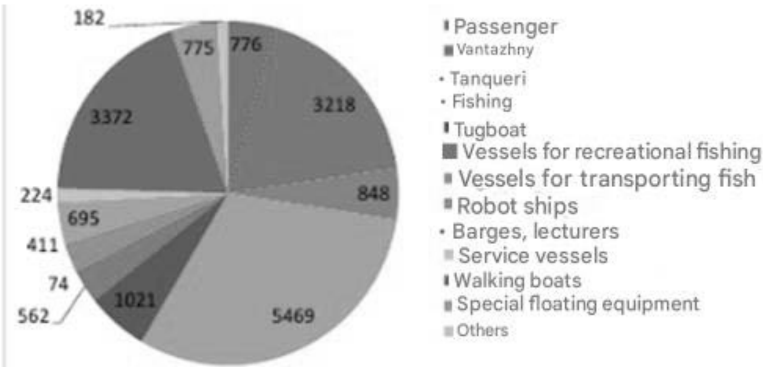

Figure 1.8 - Breakdown of accidents by vessel type

The analysis of vessel operation results indicates that despite measures taken to ensure maritime safety, the number of maritime accidents remains high. One of the most frequent causes of ship accidents is the failure of CTS.

Maritime accidents pose a serious threat to human life, vessels, the environment, or coastal infrastructure [20, 21, 22]. For example, the failure of the a SPP on a container ship led to a technogenic accident in Baltimore in 2024 (Figure 1.9).

According to the United Nations, the damages caused by man-made disasters over the past 30 years have reached $200 billion per year.

Figure 1.9 - A man-made accident in Baltimore in 2024

As a result, maritime organizations, such as flag states, port authorities, and classification societies, have intensified their joint efforts to ensure the reliability and safety of ships and their systems. Currently, international requirements for maritime safety are becoming stricter. The operation of SPPs highlights the critical need to prioritize the safe functioning of such CTS.

Thus, the analysis of vessel operation results indicates that, despite measures to enhance maritime safety, the number of maritime accidents remains high.

An analysis of the distribution of accidents based on ship tonnage and age shows that the failure of CTS is one of the most frequent causes of ship accidents.

With increasing safety requirements for expensive CTS, the demands for their efficiency, which depends on time and resources during their operation, are also growing. Ensuring the safe and efficient operation of ship CTS remains a pressing scientific and technical challenge.

1.2 Analysis of Models and Methods for the Intelligent Diagnosis, Assessment, and Prediction of the Technical Condition of Complex Critical Systems

1.2.1 Comparative Analysis of Models and Methods for Intelligent Diagnosis of the Technical Condition of Complex Critical Systems

The effective operation of critical CTS largely depends on the performance of their subsystems, components, elements, and their interconnections. Regulatory documents establish [23] that ensuring the uninterrupted operation of CTS requires monitoring the systems' TC, including diagnostics, assessment, and prediction of the performance of their equipment.

The methods and tools for TC diagnostics, implemented during the design and operation of CTS, aim to ensure system efficiency and reliability [1, 23, 24, 25, 26]. These measures allow for the timely detection of equipment faults and their interconnections in CTS, determining the degree of functionality under changing operating conditions, reducing downtime and repair costs, and obtaining necessary information for evaluating and predicting the system's TC. Diagnostics should be performed without taking equipment out of operation, avoiding its disassembly.

Diagnostics of TC is based on the theories of pattern recognition and testability [6]. The first involves developing algorithms for recognizing TC under limited information conditions, decision-making rules, and diagnostic system models. The second includes developing tools and methods for obtaining diagnostic information and identifying faults. In TC recognition tasks, probabilistic and deterministic approaches are used. The probabilistic approach considers the system in one of its random states, while the deterministic approach matches the TC diagnosis with a specific domain in the feature space. Probabilistic methods are most commonly applied but require a large amount of prior information.

A pressing issue for the safe operation of CTS is determining their TC based on non-invasive diagnostics and non-destructive testing.

Diagnostic theory relies on the relationship between the TC of a complex system and its representation in diagnostic parameters. Since diagnostics are performed under conditions of limited information during operation, diagnostic models are critical in fault recognition. Modeling CTS diagnostics is challenging due to the complex interconnections between subsystems, components, and elements, as well as interactions between the system and its environment.

The numerical values of component parameters in diagnostic models depend on numerous factors that are difficult to account for during analysis. Additionally, since such models describe random processes, researchers classify them as stochastic models. It is assumed that the randomness of certain phenomena is expressed in terms of probability. Diagnostic models of CTS are also conceptual, defining the structure and properties of the modeled CTS under conditions of uncertainty. In this case, the mathematical model of CTS takes the following form [24, 25]:

$$Y(t)=F(X(t),U(t),V(t)), \qquad (1.1)$$

where X – vector of the system model's current state;
U – vector of control inputs;
V – vector of external influences;
Y – vector of model output signals.

The diversity of models and methods for diagnosing TC is determined by their dependence on the informativeness of the system's behavior, its complexity, and the variety of diagnostic tasks. The more complex a system, the more complicated its TC diagnosis, and the greater the risks of failures and emergencies during the operation of CTS [8, 28, 29, 30, 31].

TC diagnosis includes: anomaly detection, fault localization, and fault classification. To achieve these tasks, machine learning and artificial intelligence methods are applied, such as support vector machines [32], nearest neighbors [33], and decision trees [34]. During the design and operation of CTS, specialized diagnostic methods and models are also used for TC diagnosis (Table 1.1)

[35–45]. Standards [46, 47] recommend fault trees and Petri nets for modeling TC diagnosis. However, fault trees cannot account for common equipment failures in CTS. Petri nets are used, for instance, in Monte Carlo simulation modeling, but these models are difficult to use, especially for large systems.

From the analysis of literature sources, it is evident that existing methods for modeling TC diagnostics of complex systems do not provide reliable data that can be used for assessing and mitigating the consequences of failures in systems or making necessary management decisions. In this context, Bayesian belief networks (BBNs), as artificial intelligence models, are a valuable tool for TC diagnosis due to the following advantages [27, 48–51]:

High efficiency in solving problems for CTS with numerous subsystems, components, and elements;

Simplicity of interpretation and visualization;

Logical explanation of fault propagation.

Table 1.1 Methods and models of TC diagnostics of folding systems

Method	Name	Description and Application	Advantages	Disadvantages
Deterministic	Failure Mode and Effects Analysis (FMEA/FMECA) [5]	Used to identify failure modes of components or systems that lead to loss of functionality.	Identifies failure types, causes, and consequences. Provides input for monitoring program development.	Suitable only for identifying individual failures, not combinations. Time-consuming for complex systems.
	Monte Carlo [23]	Evaluates result ranges and frequency distributions.	Adaptable to any data distribution. Simpler models.	Cannot adequately model rare events with very high or low probabilities.
	Markov Analysis [24]	For repairable systems where the next state depends only on the current state.	Calculates probabilities when analytical methods fail. Handles degradation and recovery states.	Assumes constant transition probabilities and event independence. Difficult to model large systems.
Probabilistic	Event Tree Analysis (ETA) [5]	Models, calculates, and ranks incident scenarios.	Graphically represents event progression. Analyzes system responses and evaluates mitigation strategies.	Applicable only for binary system states (functional/failure).

	Fault Tree Analysis (FTA) [5]	Identifies causes and paths leading to failure. Quantifies failure probabilities.	Considers various factors and their impact on final outcomes.	Static model; does not account for time dependence. Limited to binary system states.
	Cause-and-Effect Analysis [5]	Combines fault and event tree methods to analyze critical events and subsystem responses.	Combines the strengths of ETA and FTA methods.	More complex than FTA and ETA for scheme building and dependency analysis.
	Bayesian Networks [25,26,27]	Uses observable variables to infer inaccessible ones. Suitable for risk prediction and assessment.	Requires only prior knowledge. Supports classification and prediction.	Difficult to identify interactions in complex systems. Requires extensive conditional probability data.
	Logic-Probability Method [5]	Solves problems by representing systems as directed graphs of events with known probabilities.	Provides weighted values for elements, helping assess their significance to the system.	Challenging to determine precise probabilities due to static assumptions.
Expert Assessment	Fuzzy Sets [28]	For scenarios with uncertain quantitative descriptions or risk factor interactions.	Simplifies mathematical models.	Limited parameter distribution data. Simplified models reduce risk estimate accuracy.
	Hazard and Operability Study (HAZOP) [5]	Structured analysis of processes or systems.	Applicable to a wide range of systems and processes.	Time-intensive. Limited by project scope and objectives.
	Decision Tree Analysis [5]	Sequentially compares alternatives with uncertainties.	Clearly represents decision details. Supports optimal solution identification.	May oversimplify complex situations.
	Neural Network Technologies [5]	Enables systems to compare sensor data with reference values.	Analyzes system parameters comprehensively for failure prediction.	Time-intensive. High training accuracy may lead to unstable results.

BBN theory is based on probability and graph theories. Bayesian rules rely on expert assessments as well as prior and posterior observation data for solving diagnostic problems.

When diagnosing the TC of complex critical systems (CCS), incomplete data are available for each subsystem, component, or element at any given time. This indicates uncertainty, which is addressed using probabilistic reasoning in BBN methods and cognitive simulation models for diagnosing the TC of complex systems [52].

BBNs leverage modern software technologies (Microsoft Bayesian Network Editor, Bayes Net Toolbox for Matlab, GeNIe, Smile, AgenaRisk, Analytica, Bayes Server, Hugin Expert). There are also ready-made libraries and modules for Python, C++, C#, Matlab, R, and VB.NET, compatible with various operating systems (Windows, Linux, macOS) [53–60]. A key product is GeNIe Modeler, which allows for the creation of models of any size and complexity [28, 61, 62]. Well-known software packages for Matlab (BNT – Bayes Net Toolbox) and R (gRain package) further expand the capabilities of BBNs [63–65].

The content and methods of simulation modeling aim to create cognitive simulation models (CSMs) for TC diagnosis by exploring a wide range of potential alternatives. A simulation model can be viewed as a set of rules that facilitate TS diagnosis [66], considering their significance and criticality for the overall CTS operation. The advantages of CSMs over analytical methods for TC diagnosis include the ability to construct models of complex systems without relying on analytical methods, using partially reliable and incomplete data about the object being modeled. Theoretical foundations and a wide range of software products, such as Arena, AutoMod, AnyLogic, Extend, and GPSS World, facilitate the application of CSMs.

Given the inherent uncertainty, incompleteness, and vagueness of information about CTS, fuzzy logic is often used for TC diagnosis [45]. This approach enables the diagnosis of the TC of complex systems under extreme scenarios while minimizing computation time. Both functional interconnections and equipment interactions within CTS are taken into account.

Combining CSMs with fuzzy modeling is particularly effective for diagnosing the TC of complex systems, as it is supported by algorithms and methods that accurately reflect system features [40, 67]. However, this approach requires further development for diagnosing the TC of complex systems.

From the analysis of typical models and methods, it is evident that there is no universal methodology for diagnosing the TC of CTS. Existing methods have the following limitations:

They are applied only within narrow scopes due to the "rigidity" of information processing schemes;

They do not account for the history of the TC;

They require significant modifications when the composition or logic of CTS operation changes;

They fail to consider partial failures in the functionality of system equipment and their interconnections.

From the analysis of literature sources related to partial failures of functionality, it follows [36, 37, 38]:

The spectrum of possible partial failures in almost any technical device is significantly broader than that of complete failures.

Detection and identification of partial failures involve more complex recognition algorithms.

At present, there are no tools for a theoretical approach to the development of diagnostic models for TC that account for partial failures. This is due to the infrequent collection of statistics related to such failures. The identification algorithms used do not distinguish failures based on the criterion of partial or complete failure.

From the analysis of models and diagnostic methods for CS, it follows that the operational strategy for CS should be preventive. Enhancing the operational and maintenance strategies of CS is achieved through a comprehensive approach to developing and implementing appropriate diagnostic support.

When addressing tasks related to improving the efficiency of CS operation, the role of methods based on modern diagnostic software increases.

Thus, for the effective operation of CS in critical systems, timely diagnostics of both partial and complete equipment failures based on conceptual stochastic models and diagnostic methods is crucial.

Diagnostics must consider incomplete data from CS equipment, providing knowledge under uncertainty while ensuring the highest accuracy of results.

1.2.2 Comparative Analysis of Models and Methods for Intellectualizing the Evaluation and Prediction of the Technical Condition of Complex Critical Systems

The development of conceptual models and methods for assessing the TC of complex CS requires considering the possibility of continued operation under partial failures with multiple scenarios for their evolution [68, 69, 70, 71, 72, 73].

Such an approach improves CS efficiency by extending productive operation until scheduled maintenance and recovery activities.

The extent of technogenic accidents is measured by the risk of equipment failure, with consequences determined by the level and duration of CS operation [74, 75, 76].

Risk assessment involves identifying hazards and evaluating them against acceptable failure risk criteria, producing qualitative and quantitative results, and converting hazards into measurable categories [77, 78, 79].

When assessing the risk of CS failures, the following should be considered:

The hierarchy, topology, and diversity of equipment differing in physical principles, parameters, and operational modes.

Functional state and operating conditions under uncertainties.

Diagnostic results for TC.

Challenges in obtaining statistical and expert data on failures [28, 29, 30, 78, 80, 81].

Available sources for failure risk statistics, such as for marine CS, include the OREDA database [82] and maintenance methods with safety assessments of CS [83, 84].

Known methods for assessing CS failure risks differ in how probabilities and losses from failures are obtained [85, 86, 87, 88, 89].

Risk assessments within the technocratic concept are performed using methods classified as deterministic, probabilistic, expert-based under uncertainty, or combined, based on TC diagnostics of complex systems.

Advantages of the probabilistic method include:

Analysis of failure scenarios and consequences.

Explicit consideration of interdependencies between CS equipment regarding failures.

Quantitative assessment of uncertainty impact on risk evaluations.

Ranking deficiencies and safety problems.

However, as noted in the literature [90], models based on probabilistic approaches for assessing failure risks in marine CS are used to a limited extent. They provide approximate failure risk estimates without sufficient objective information.

Expert methods are the most widely used for evaluating failure risk indicators [91]. However, these methods face limitations due to the high complexity of selecting experts with the required qualifications and the subjectivity of their assessments. The significant advantages of Bayesian network methods (BNM) make them promising for evaluating failure risks in CS. Risk assessment models of equipment, considering its importance and criticality for CS functionality, also employ cognitive simulation modeling technology [67, 92, 93, 94, 95, 96].

To establish the relationship between the actual resource and the probability of failure of CS, the fuzzy-probabilistic modeling method is used [97, 98]. However, the existence of standards for fuzzy logic does not resolve the issue of numerical risk assessment of CS failures. This is because the standards provide criteria without the models required for comparative analysis of CS failure risk assessment options.

Failure risk rankings are performed using risk indices, but these lack reliable models and input data. For example, a matrix of failure consequences and probabilities is used, which requires expert assessments.

To rank failure risk assessments of CS, Harrington's generalized desirability function [99] is recommended with risk levels and consequences defined as follows:

0–0.2: Minimal (minimal impact that does not affect CS operation).

0.2–0.37: Acceptable (minor impacts allowing CS operation without repairs).

0.37–0.63: Maximum (significant impacts, CS operation is possible with repairs).

0.63–1.0: Critical (catastrophic impacts, CS operation is not allowed).

From the conducted analysis of models and methods, it follows that despite their advantages, they cannot be applied in their original form as conceptual models or methods for CS failure risk assessments due to their narrow industry-specific focus. Most models and methods are based on the assumption that CS equipment operates under normal conditions, without considering partial failures of functionality. However, leveraging advancements in information technology can address many of the aforementioned challenges in CS failure risk assessment [1, 100, 101].

The safety level of systems, such as marine CS, is largely determined by the quality of TC forecasting based on failure risk assessments of their equipment [102, 103, 104]. Forecasting, like TC diagnostics, must consider the specifics of CS operating under uncertain and extreme influences, with insensitivity to incomplete equipment data, interconnections, and partial or complete failures [25, 80, 97, 102, 105, 106].

A list of forecasting methods suitable for use depending on the level of CS formalization is shown in Figure 1.10 [107]. TC forecasting can be performed using machine learning methods based on predefined CS performance indicators [108, 109, 110, 111, 112]. However, this approach is applicable only when considering binary TS.

For calculating the remaining operational life of CS, the PHM (Prognostic Health Management) method is a promising forecasting approach [113, 114].

The analysis of models and forecasting methods revealed that changes in the TC of marine CS are highly challenging to predict. This difficulty arises from the following factors: a lack of qualitative and quantitative expert data on system reliability, the dynamic nature of operational conditions, and the human factor [115].

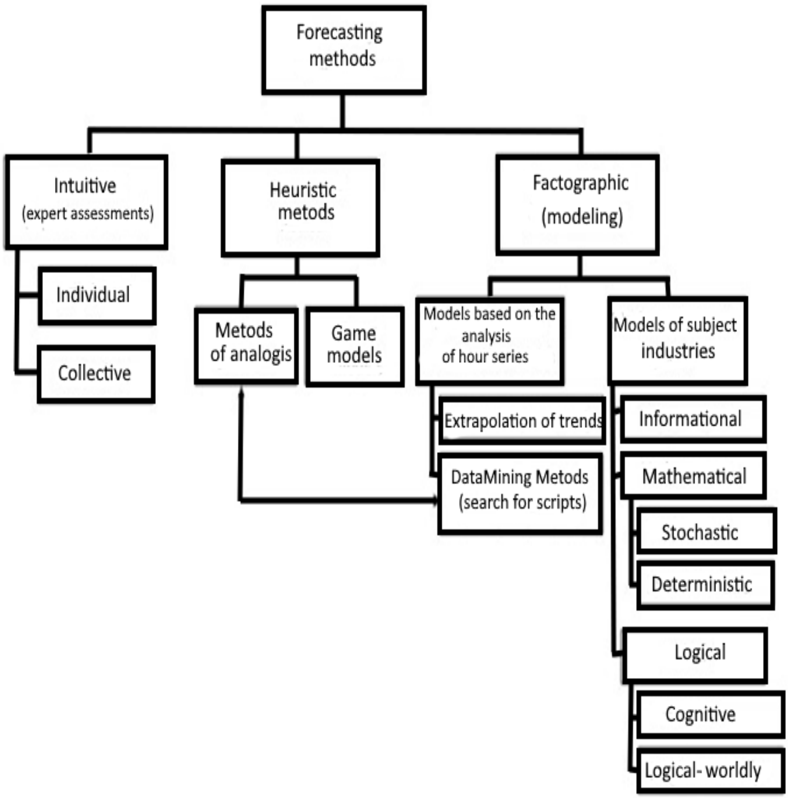

Figure 1.10 - Classification of forecasting methods

Existing TC forecasting models and methods, which rely on deterministic and formalized statistical models, are not universal. They do not fully account for the specific operating conditions of system equipment, especially under uncertain influences of various external or internal factors on CS.

A significant drawback of such models and methods is that they are not recommended for marine CS because they fail to meet the requirements of the International Convention for the Safety of Life at Sea (SOLAS-74) and the provisions of the International Safety Management Code [116, 117]. Another major shortcoming is that these models and methods have not undergone long-term practical validation. A notable advantage in achieving adequate forecasting of CS failure risk assessments is provided by structural models based on artificial intelligence mechanisms and methods [118, 119, 120]. Such models enable the prediction of CS failure risks by identifying implicit dependencies between input and output data samples and supporting various learning algorithms.

This capability is particularly beneficial for CS in evaluating and forecasting scenarios of functionality loss that involve hundreds of criteria and indicators. Addressing these issues is also linked to the development and enhancement of problem-oriented software packages [100, 121, 122]. Consequently, the role of modern software-based TC assessment and forecasting methods for complex systems is increasing.

Ensuring the guaranteed safe operation of CS by timely and proactive prevention of normal situations transitioning into critical, emergency, or accident scenarios is the foundation of the failure risk management strategy [23, 73, 123, 124]. This strategy is based on a systematic analysis of multifactorial failure risks, their reliable assessment under various CS operating conditions, and TC forecasting throughout their operational lifecycle [28, 125]. An analysis of publications and regulatory materials on failure risk assessment and forecasting for various types of CS revealed that the existing diversity of models and methods requires addressing significant uncertainties and improving the accuracy of assessments and forecasts.

Many models and methods focus on the operation of CS equipment under normal conditions, without accounting for partial functionality failures. They are often based on engineering, expert, and other approaches, involving complex and expensive calculations, which limit their widespread use and highlight the narrow specialization of these models and methods.

Therefore, to ensure the effective operation of CS, the development of new models, methods, and their algorithms—implemented as problem-oriented software packages for TC assessment and forecasting—remains a relevant task.

1.3 Comparative Analysis of Information and Intelligent Systems for Diagnosing, Assessing, and Forecasting the Technical State of Complex Critical Systems

Traditionally, information and intelligent systems (IIS) are understood as interactive computer systems that assist decision-makers in using information, as well as a set of mathematical and heuristic models and methods for solving poorly structured or hard-to-formalize tasks [126, 127, 128, 129, 130, 131]. The effectiveness of IIS functionality directly impacts the operational efficiency of CS throughout their lifecycle.

IIS are unified by a general methodology for generating alternative management decisions in CS, determining the consequences of their implementation, and substantiating the choice of an acceptable management decision [132, 133]. IIS components include data sources and models, a model database, and a software subsystem comprising a database management system (DBMS), a model base management system (MBMS), and a user interface (Figure 1.11).

The primary tasks solved by IIS [128, 129] include data input, storage, and analysis.

Main functionalities of IIS:

Collecting necessary information from various data sources.

Converting the collected information into a unified data format.

Generating queries to the data warehouse, processing them, searching for information, and presenting it in a format suitable for analysis and decision-making.

An Intelligent Information System should feature a web-based client interface or be fully web-oriented [134]. The IIC data repository can be built using various types of DBMS; however, given the web orientation and the growing adoption of cloud technologies, it is preferable to rely on web-based DBMS like MySQL and PostgreSQL, as well as specialized cloud DBMS such as MS Azure. Data sources originate from operational-level information systems, special databases, and include engineering data along with information from external sources.

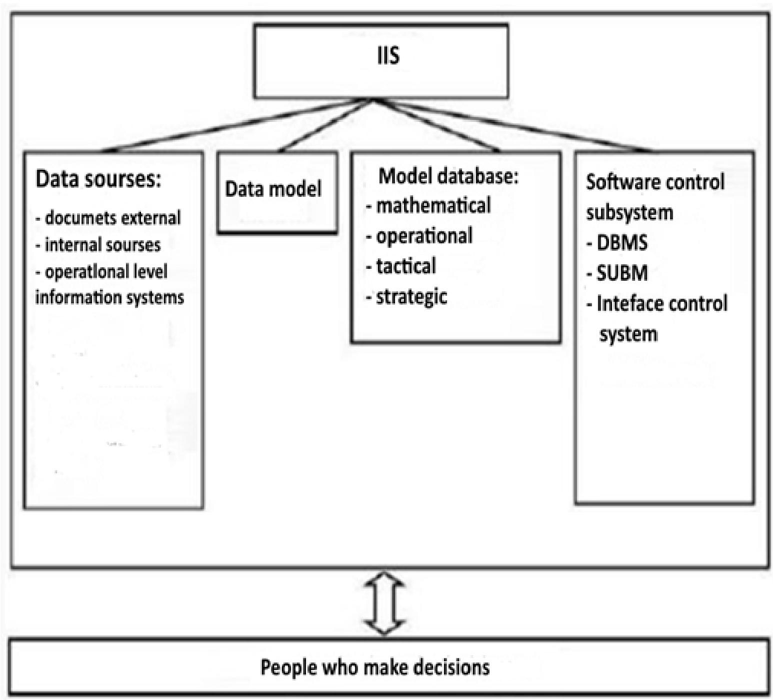

Figure 1.11 - IIS structure

The data model is constructed based on the following components:

Data sources and repositories,
Operational data storage and data marts,
Metadata.

The model database enables analysis within the IIS. Most DBMS solutions include OLAP extensions in one form or another, so the operational-analytical component of the IIS is considered ready once a DBMS type is selected for the data repository. When designing the data repository, it is crucial to implement a mechanism for metadata handling to describe the structure of the data within the database. Developers of the IIS design and build the metadata tree structure.

At a conceptual level, IISs are classified as follows:

Communication-Driven DSS (focused on messaging),
Data-Driven DSS (focused on data),
Document-Driven DSS (focused on documents),
Knowledge-Driven DSS (focused on knowledge),
Model-Driven DSS (focused on models).

Architecturally, IISs can be categorized as functional, independent data marts, or two-tier and three-tier data warehouses. Depending on the type of data these systems process, IISs can be classified into operational and strategic categories.

OLAP and Data Mining represent two essential components of the decision-making support process. Data operations are performed by the OLAP engine, which implements the concept of online analytical processing. Depending on the storage type, OLAP systems are classified into MOLAP, ROLAP, and HOLAP. Based on the location of the OLAP engine, systems are divided into OLAP clients and OLAP servers.

An OLAP client constructs a multidimensional cube based on source data (to generate the required reports and cross-sections) and performs calculations on the client-side PC.

An OLAP server processes requests, performs computations, and stores aggregated data on the server, providing results upon request.

Cubes and other analytical reports must be configured [135]. IICs are also classified by levels (basic, intermediate, advanced) and by distribution levels (centralized, distributed) [136].

To perform analysis and generate recommendations, IICs employ various methods (Table 1.2 [137]):

Information retrieval,
Data mining,
Knowledge discovery in databases (KDD),
Case-based reasoning,
Simulation modeling,
Evolutionary computations and genetic algorithms,
Neural networks,
Situational analysis,
Cognitive modeling, and others.

The application of artificial intelligence in IICs enables the system to expand its functionality, enhance operational efficiency, and improve the reliability of CS.

Table 1.2 - IIS methods and models

Methods of Organizing IIS	Model of Presenting Data and Knowledge	Problem-Solving Tasks
The formation of a solution with the coordination of the collections of data	Online Analytical Processing (OLAP) Models	Organization of the environment for data accumulation. Collecting and combining data. Intelligent data analysis.
Formation of solutions in an expert system based on rules	Product models, Logical models, Semantic measures, Frames	Searching for solutions based on rules. Explanation of decisions. Learning the basics and understanding new rules.
Formation of decisions based on precedents (CBR systems)	Piece neural networks, Precedents of problematic situations	Accumulation of precedents. Searching for solutions in the base of precedents. Adapting solutions to new problem situations.
Formation of solutions based on ontologies	Semantic frameworks that describe concepts in the subject area and their connections	Formation of distinctions between concepts. Development of logical ontology models.

One of the most crucial functions of IIS software is the evaluation of potential outcomes of decisions and the forecasting of the TC of CS [138, 139, 140]. The choice of the specific forecasting method for a particular IIS is left to the system developers.

Factographic methods, which are the least dependent on subjective factors, are commonly used in software. For poorly formalized input data, expert methods are utilized, though they come with limitations related to the availability of a sufficient number of experts.

As noted in [28, 80], during the operation of CTS, adverse influencing factors (AIFs) can disable individual subsystems, components, or affect overall system functionality. AIFs are typically unpredictable or difficult to forecast (e.g., human errors, natural disasters). Their impact can range in severity up to the complete destruction of the CTS [141].

Developing intelligent information complexes (IISs) for managing equipment failure risks to ensure the survivability of marine CTS under the influence of AIFs is a promising area in enhancing CTS safety [124].

Such IISs can be implemented as standalone solutions or as modules that complement general-purpose control and decision-making systems with additional functionality. They enable rapid decision-making in addressing the consequences of AIFs, ensuring CTS reliability by identifying, analyzing, and assessing existing equipment failure risks [107, 124, 141].

Most IICs are designed to address specific tasks or general classes of problems, targeting various types of users. Developing IISs for managing failure risks to ensure CTS survivability under incomplete and uncertain information, combined with the presence of unforeseen AIFs, is a forward-looking direction for effective and reliable operation of subsystems, components, and CTS as a whole.

The primary concept of IISs is to address classical problems arising in unstructured and poorly formalized CTS [142, 143].

These challenges include the inability to obtain complete and objective information for rational decision-making, as well as the need to utilize subjective and heuristic information. Additional issues include uncertainties in input data and ambiguities in the search for optimal solutions. Moreover, solutions in such cases must interact with the user through dialogue or other forms of human-machine communication.

Given these factors, traditional algorithmic methods and decision-making models need to be abandoned in favor of using intelligent system technologies [144].

Theoretical substantiation and implementation of information technologies based on AI for designing, modeling, and solving practical problems in IICs have been explored by scientists such as V.M. Glushkov, A.N. Kolmogorov, N.J. Wiener, W.R. Ashby, F. Wassermann, S. Haykin, F. Rosenblatt, T. Kohonen, G.S. Tesler, N.G., V.P. Bespalko, V.V. Davydov, M.M. Potashnik, G.V. Skok, among others [145, 146, 147, 148, 149, 150, 151, 152, 153].

IISs should implement the following scheme: assessment – forecasting – decision-making – action. IICs provide decision-makers with analysis of the problem being solved. Key IIS functions include assessment, event forecasting, self-learning and adaptation, working with knowledge bases (including creation, structuring, storage, and database content), decision-making, and implementation.

Known methods implemented in IISs include [144, 154, 155, 156, 157, 158]:

Analog and systemic methods;

Heuristic methods for optimization tasks (genetic algorithms, artificial immune networks, simulated annealing, swarm intelligence methods, including ant colony algorithms);

Case-based reasoning (nearest neighbor, decision tree-based case extraction, knowledge-based cases, and cases considering application scenarios);

Structural mapping based on OWL ontologies.

IISs are often created by combining AI systems, expert system technologies, machine learning, and agent-based systems [154, 159, 160].

Machine learning is widely used to automate risk assessment and predict potential failures (e.g., analyzing large datasets, identifying patterns and trends, system modeling and simulation).

However, the use of large datasets involves limitations, such as potential errors in risk assessment and inaccurate predictions.

The structural mapping method offers advantages, including the ability to formalize complex hierarchical interactions among CTS equipment functioning under stochastic conditions; flexibility in implementing a production-based approach for knowledge base creation within IISs; and convenient software implementation using an object-oriented approach.

Most models enabling new knowledge acquisition based on existing data can be reduced to production models.

A drawback of these models is the limited representation of the problem domain, affecting flexibility in user-expert system dialogues [154].

Bayesian networks can be used for modeling relationships between various factors and their uncertainties in IISs for CTS with numerous equipment components, providing a structured foundation for failure risk assessment under uncertainty and assisting decision-makers in prioritizing decisions [48, 58].

In IISs, methods based on case-based reasoning (CBR) can be employed for assessing and forecasting the technical state of CTS to generalize and apply accumulated experience [161, 162, 163].

When operating CTS under conditions of uncertainty, the case-based approach simplifies the decision-making process. The advantages of this method include:

The ability to learn from experience;
Versatility;
The capability to work with incomplete or unstructured data;
Flexibility in adapting to new situations.

Stages of the Case-Based Reasoning (CBR) cycle (Fig. 1.12):

Capture cases from the case library (CL).
Indexing (for quick retrieval of similar cases).
Search for the most suitable cases for the new task.
Review and adaptation (modification for the current task).
Evaluation for suitability, storage, and implementation.

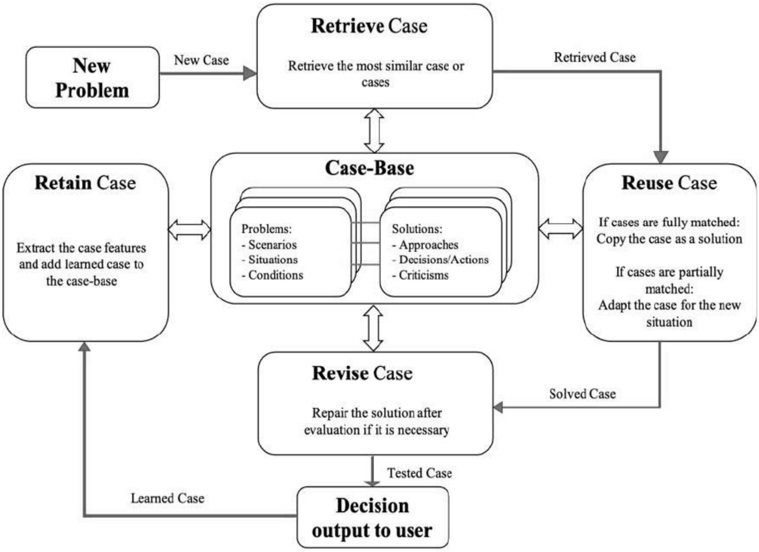

Figure 1.12 - Case-based Reasoning cycle [162].

The classical architecture of IIS (Fig. 1.13):

Provides justification for alternatives based on models and methods utilizing expert evaluations by specialists.

Includes decision-making methods under uncertainty with the modeling of problematic decision-making scenarios.

Contains a knowledge base (KB) – a set of rules for selecting appropriate models and decision-making methods to justify alternatives depending on the specific implementation of task elements.

Incorporates a database (DB) for storing information.

Performs multidimensional task analysis and generates analytical reports using an OLAP server.

The use of problem-oriented KB in the form of knowledge models enables the identification of new heuristic knowledge under uncertainty [164, 165] (Fig. 1.14).

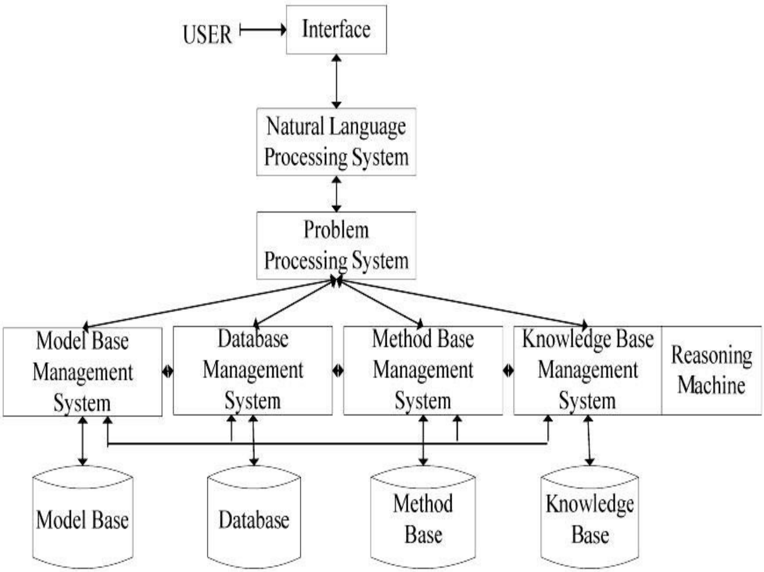

Figure 1.13 - IIS architecture

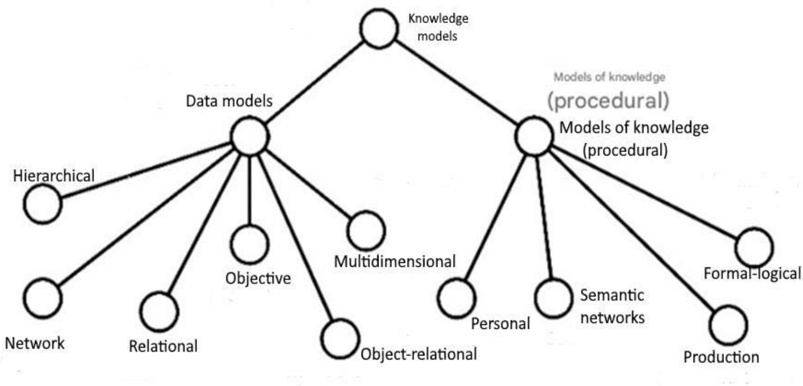

Figure 1.14 – Knowledge Representation Model Scheme

Currently, technologies of AI are being increasingly implemented to enhance the operational efficiency of CTS.

For example, according to the requirements of the Maritime Register, all vessels must be equipped with AI-based systems [25, 102].

This requires algorithmic and software tools capable of assessing and predicting the technical state of systems in alignment with the defined objectives [1, 166, 167].

An example of using an IIS is the PHM method, which encompasses the entire process from data collection to utilizing decision-making results.

Real-time information about the state of ITS is used to assess the technical condition within the IIC framework. For modeling technical states, the following can be employed: fault tree analysis, event tree analysis, and Bayesian belief networks.

Bayesian belief networks are preferred as a tool for assessing the risk of ITS failures.

Among software solutions addressing decision-making tasks, Crystal Info (Seagate Info) is utilized—an IIS based on flexible data access and processing technology.

Open OLAP technology allows the integration of multidimensional OLAP data from heterogeneous sources (Crystal Info, Crystal Holos, Hyperion Essbase, OLE DB for OLAP providers (Microsoft SQL Server OLAP Services, Applix TM 1, IBM DB2 OLAP Services, and Informix MetaCube)). All OLAP sources can be represented within a unified interface.

For many years, researchers have been developing IISs for various purposes; however, certain challenges regarding the efficiency and formalization of knowledge in ITS remain unresolved [168]:

Enhancing the objectivity and reliability of decisions made under uncertainty in evaluation and failure risk forecasting tasks;

Accounting for factors of incompleteness, ambiguity, and contradictions in initial information (data and knowledge) and rules;

Ensuring the representation and processing of diverse types of knowledge, data, and models, as well as the development of corresponding databases, knowledge bases, and models;

Collecting, storing, and accumulating declarative and expert information about the problem domain in databases, knowledge bases, and case libraries;

Improving the accuracy of ITS assessments based on new models, methods, algorithms, and software invariant to the subject area for evaluation and failure risk forecasting, aiming to detect early signs of pre-failure states in equipment;

Applying adequate and technically feasible formal models for solving tasks, considering structural, functional, informational, and subject-specific features of ITS.

To successfully address the issue of efficient and accident-free operation of ITS under emergency operating modes, it is necessary to use information technologies with software and hardware modules for receiving and transmitting diagnostics, assessment, and forecasting results for complex systems [1, 169, 170].

The quality of data reception and transmission systems (DRTS) is determined by a set of characteristics affecting their efficiency: topology, bandwidth, speed, permissible error magnitude in data transmission and reception, information security efficiency, and the risk of device failures in DRTS.

From the conducted analysis of literary sources, it follows that to ensure effective ITS operation, the IIS must implement the following scheme: evaluation – forecast – decision – action, based on the results of diagnosing the technical state of subsystems, components, elements, and their interconnections within ITS.

Utilizing the results of the structural scheme implementation shown in Figure 1.15 is essential.

Thus, solving the challenges of effective and reliable operation of critical application CCS requires improvement and the development of new models, methods, and algorithms, as well as problem-oriented software complexes.

These should be aimed at identifying pre-failure and failure states of equipment systems, addressing tasks of assessment and failure risk forecasting under conditions of uncertainty, and ensuring relative insensitivity to incomplete equipment data, taking into account both partial and complete failures.

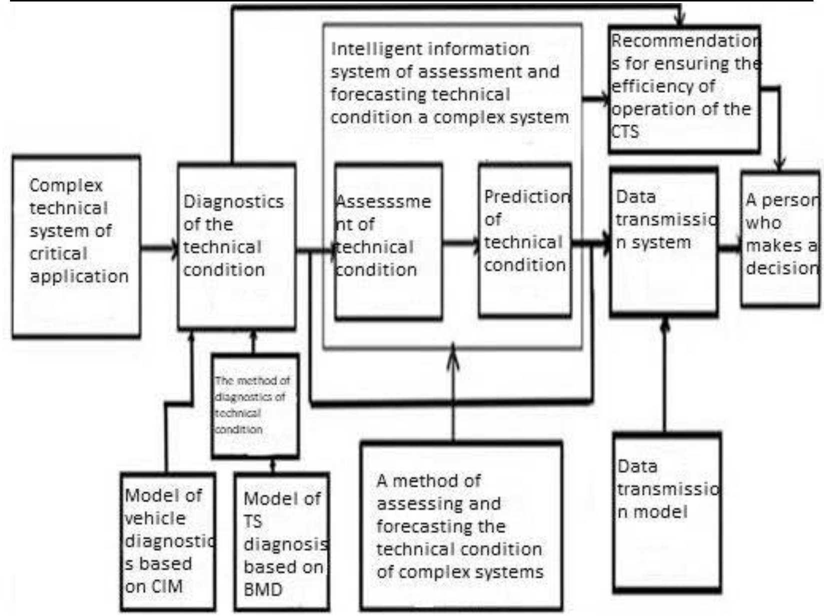

Figure 1.15 - Structural Diagram of Diagnostics, Assessment, and Forecasting of Technical States in CCS

The informatization of assessment and forecasting of technical states should be based on artificial intelligence methods.

The intellectualization of evaluating and forecasting the technical states of systems with reasoning based on cases and diagnostic features remains a necessary direction for the development of modern technologies.

This approach ensures operational efficiency of CCS at different stages of their lifecycle and is a pressing issue.

1.4 Conclusions for Chapter One

The conducted analysis of existing models, methods, and information systems for diagnostics, assessment, and forecasting of technical states in complex CCS demonstrates that known structural models and methods only consider complete failures of operability while ignoring partial failures. They are also constrained by increased algorithmic and computational complexity, as well as the need for complex preprocessing of diverse data, which reduces the effectiveness of CCS operation.

Promising modeling methods for diagnosing technical states include Bayesian belief networks, which account for uncertainties, stochastic processes, and incomplete CCS data.

Additionally, cognitive simulation modeling methods can assess structural and functional vulnerabilities of system equipment. Within IISs, case-based reasoning methods are identified as prospective approaches for evaluating and forecasting technical states of complex systems.

Hence, there is an urgent scientific and practical task to enhance the efficiency of CCS operations through the intellectualization of diagnostics, assessment, and forecasting of technical states under conditions of uncertainty and relative insensitivity to incomplete equipment data, considering both partial and complete failures.

Research Objective

The goal of this study is to improve the operational efficiency of critical application CCS through the development of models and methods for diagnostics, assessment, and forecasting of technical states in such systems.

Research Tasks

To achieve this objective, the following tasks must be addressed:

Analyze models, methods, and information systems for diagnostics, assessment, and forecasting of technical states in critical application CCS.

Develop stochastic models and a diagnostic method for the technical states of critical application CCS.

Conduct research and analysis of the stochastic models and diagnostic method for the technical states of critical application CCS.

Develop a method for assessing and forecasting the technical states of critical application CCS.

Design an intelligent information system for diagnostics, assessment, and forecasting of the technical states of critical application CCS.

CHAPTER 2
DEVELOPMENT OF STOCHASTIC MODELS AND METHODS FOR DIAGNOSTICS OF THE TECHNICAL CONDITION OF COMPLEX CRITICAL APPLICATION SYSTEMS

2.1 Development of a Stochastic Structural Model and Method for Diagnosing the Technical Condition of Complex Critical Application Systems

2.1.1 Problem Statement for Developing a Stochastic Structural Model and Method for Diagnosing the Technical Condition of Complex Critical Application Systems

The operational efficiency of ship-based CTSs can be assessed based on reliability in the form of the risk of equipment failures. In this regard, the evaluation of equipment failure risk must account for the CTS structure (hierarchy and topology), functional states (partial or total loss of functionality), as well as incomplete system data. Operating CTSs involves uncertainties (incomplete information about external and internal factors affecting systems and their technical condition, and uncertainty in system behavior). Based on this and as noted in Section 1.2, models and methods for diagnosing the technical condition of complex systems fall under stochastic and conceptual approaches.

As derived from the analysis in Section 1.2.1, the most promising approach for diagnosing the technical condition of complex systems is the intelligent Bayesian Network Method, which simplifies and accelerates the development of corresponding models. In the development of diagnostic models for the technical condition of ship-based critical complex systems, the following considerations are made:

- A hierarchical structure is adopted.
- Interactions between equipment are modeled using GeNIeRate [61].

This approach enables aggregated information about equipment to provide insights into the overall system. Variants of object status in terms of equipment failure risk are highlighted based on Harrington's desirability function. For describing loss categories resulting from failures, a verbal form may be used, allowing numerical assessments to be matched with various damage classes based on Harrington's scale. On this scale, critical damage is denoted as Dcrit, with the following classifications:

- 0.1·Dcrit: minor damage.
- 0.29·Dcrit: insignificant damage.
- 0.51·Dcrit: moderate damage.
- 0.72·Dcrit: significant damage.
- 1.0·Dcrit: critical damage.

Thus, for the effective operation of CTS equipment in various failure states, the conceptual stochastic diagnostic models being developed should demonstrate robustness to incomplete data and link types of technical conditions of complex systems with their diagnostic indicators in the form of failure risks. Results obtained using diagnostic models should facilitate intelligent assessment and prediction of the technical condition of complex systems.

2.1.2 Development of a Stochastic Structural Model and Method for Diagnosing the Technical Condition of Complex Critical Application Systems

The foundation for developing a conceptual stochastic model and an intelligent diagnostic method for technical condition in the form of a dynamic Bayesian network involves using diagnostic features of CTS, along with a model for describing the intellectualization of failure risk diagnostics, encompassing:

- Subsystems (S),
- Components (C),
- Elements (E),
- Inter-system connections (IS),
- Inter-component connections (IC)
- Inter-element connections (IE).

The model includes sets of functional elements and connections of complex systems based on diagnostic features.

The proposed conceptual stochastic diagnostic model for the technical condition of ship-based complex systems, presented in graphical and probabilistic form, appears as follows:

$$\mathrm{CCM} =< G, \{x_i\}, F, Q, \{FE\}, \{FC\}, \{R_{FE}\}, \{R_{FC}\}, L >, \qquad (2.1)$$

where G - is a cyclic directed graph ($G = \langle V, T, E \rangle$, $V = \{v_i\}$ – the sets of vertices and edges of the digraph; T – time; $E = \{e_{ij}\}$ – the set of edges connecting the vertices of the digraph; i – the sequential number of the graph vertex, $i=1,2,...,k$, ij – the sequential numbers of the incoming and outgoing functional connections);

$X = \{x_i\}$ – the set of parameters of the digraph vertices;

$F = f\{v_i, e_{ij}\}$ – the function representing connections between the digraph vertices;

Q – the domain of parameters for the digraph vertices;

FE, FC – functional equipment (subsystems, components, elements) and connections included in the CTS structure;

$\{R_{FE}\}, \{R_{FC}\}$ – sets of diagnostic risk assessments of failures for *FE* and *FC*;

L – the mapping of connections between the sets $\{FE\}, \{FC\}, \{R_{FE}\}, \{R_{FC}\}$, based on the fault tree of the CTS diagnostic model.

The sets of *FE* in CTS, considering hierarchical levels, are defined as:

$$\{FE\} = \{\upsilon_{n_{fe}}^{<m_{fe}>} \mid i = \overline{1, I_{FE}}; m_{fe} = \overline{1, M_{FE}}\}. \qquad (2.2)$$

where: $\upsilon_{n_{fe}}^{<m_{fe}>}$ – the TS of each *FE*;

i – the index of *FE*;

m_{fe} – the index of the hierarchical level of FE;

I_{FE} – the total number of FE;

M_{FE} – the number of hierarchical levels of FE.

The technical state of each FE in CTS is determined by:

$$\upsilon_i^{<m_{fe}>} = \{W^{0}_{\upsilon_{FE}}, W^{f}_{\upsilon_{FE}}, a_{\upsilon_{in_{FE_i}}}, a_{\upsilon_{on_{FE_j}}}\}, \qquad (2.3)$$

where: $W^{0}_{\upsilon_{FE}}$, $W^{f}_{\upsilon_{FE}}$ – full and partial functionality of FE;

$a_{\upsilon_{in_{FE_i}}}, a_{\upsilon_{on_{FE_j}}}$ – the technical states of the incoming and outgoing FC in FE;

m_{fe} – the hierarchical level of FE;

in,out – indices of incoming and outgoing FC in FE.

Partial functionality of FE under various degrees of loss is determined by:

$$W^{f}_{\upsilon_{FE}} = \{W_f^{<i,m_{fe}>} \mid f = \overline{0,1}; i = \overline{1, I_{FE}}; m_{fe} = \overline{1, M_{FE}}\} \qquad (2.4)$$

In (2.4), *f=0* indicates the functional state of CTS, and *f=1* represents the complete failure of CTS.

The sets of FC in CTS are defined as:

$$\{FC\} = \{\omega_{FC}^{<a,b,z,s>} \mid a = \overline{1,A}; b = \overline{1,B}; z = \overline{1,Z}; s = \overline{1,S}\}, \qquad (2.5)$$

where: $\omega_{FC}^{<a,b,z,q>}$ – the technical state of each FC;

a – the index of inter-component connection;

z – the index of inter-system connection;

b – the hierarchical level index for inter-component connections;

s – the hierarchical level index for inter-system connections;

A – the number of inter-component connections;

Z – the number of inter-system connections;

B – the number of hierarchical levels for inter-component connections;

S – the number of hierarchical levels for inter-system connections.

The technical condition of each inter-component and inter-system connection:

$$\omega_{FC}^{<a,b,z,s>} = \{W^{0}_{\omega_{FC_{a(b),z(s)}}}; W^{f}_{\omega_{FC_{a(b),z(s)}}}; \upsilon_i^{<m_{fe}>}\}, \qquad (2.6)$$

where: $W^{0}_{\omega_{FC_{a(b),z(s)}}}$, $W^{f}_{\omega_{FC_{a(b),z(s)}}}$ - full and partial working capacity of the FC

Partial performance of the FC at different degrees of its loss:

$$W^{f}_{\omega_{FC_{a(b),z(q)}}} = \{W_f^{<a(b),z(q)>} \mid f = \overline{0,1}; a = \overline{1,A}; b = \overline{1=B}; z = \overline{1,Z}; s = \overline{1,S}\} \qquad (2.7)$$

Sets of diagnostic assessments of the risk of failure of FE and FC CTS:

$$R\{R_{FE}, R_{FC}\}, \qquad (2.8)$$

$$R_{FE} = \{r_{fe_{n(m)}} \mid fe = \overline{1,FE}, n_{fe} = \overline{1,N_{FE}}, m_{fe} = \overline{1,M_{FE}}\},$$

$$R_{FC} = \{r_{fc_{a(b),z(s)}} \mid i_{fc} = \overline{1,FC}, a = \overline{1,A}, b = \overline{1,B}, z = \overline{1,Z}, s = \overline{1,S}\},$$

where: $r_{fe_{n(m)}}$, $r_{fc_{a(b),z(s)}}$ - risk of failure of each FE and FC of the CTS

A generalised model for determining the risk of FE and FC failures:

$$KR = < P_{FE_{n(m)}}, P_{FC_{a(b),z(q)}}, D_{FE)_{n(m)}}, D_{FC_{a(b),z(q)}}, e_{FE\,n(m)}, e_{FC_{a(b),z(q)}} >, \qquad (2.9)$$

where: $P_{FE_{n(m)}}, P_{FC_{a(b),z(q)}}$ - are the conditional probabilities of failure FE and FC, respectively;

$D_{FE)_{n(m)}}, D_{FC_{a(b),z(q)}}$ - respectively, failure losses FE and FC;

$e_{FE\,n(m)}, e_{FC_{a(b),z(q)}}$ - is the weight of FE and FC, respectively, taking into account the hierarchy in the CTS

The risk of failure $n(m)$ is the FE of the CTS:

$$R_{FE_{n(m)}} = D_{FE_{n(m)}} \cdot P_{FE_{n(m)}}(t) \qquad (2.10)$$

The risk of failure $a(b), z(q)$ is the FC CTS:

$$R_{FC_{a(b),z(q)}} = D_{FC_{a(b),z(q)}} \cdot P_{FC_{a(b),z(q)}}(t) \qquad (2.11)$$

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

$$\mathrm{R} = \sum_{\mathrm{fe}=1}^{\mathrm{FE}} \sum_{n(m)=1}^{N(M)} (\mathrm{R}_{fe_{\mathrm{n(m)}}} \cdot e_{fe_{n(m)}}) + \sum_{fc=1}^{FC} \sum_{a(b),z(q)=1}^{A(B),Z(Q)} (R_{fc_{a(b),z(q)}} \cdot e_{fc_{a(b),z(q)}}) \qquad (2.12)$$

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

$$P_{FE_{n(m)}} \cdot \lambda(t)_{FE_{n(m)}} = \frac{\alpha_{FE_{n(m)}} \cdot \exp(-\alpha_{FE_{n(m)}} \cdot T_{FE_{n(m)}})}{\exp(-\alpha_{FE_{n(m)}} \cdot T_{FE_{n(m)}})} = \alpha_{FE_{n(m)}}, \qquad (2.13)$$

$$P_{FC_{a(b),z(q)}} \cdot \lambda(t)_{FC_{a(b),z(q)}} = \frac{\alpha_{FC_{a(b),z(q)}} \cdot \exp(-\alpha_{FC_{a(b),z(q)}} \cdot T_{FC_{a(b).z(q)}})}{\exp(-\alpha_{FC_{a(b),z(q)}} \cdot T_{FC_{a(b),z(q)}})} = \alpha_{FC_{a(b),z(q)}} \qquad (2.14)$$

where λ is the failure rate;

α is the distribution parameter, which is taken equal to рівним

$\alpha \approx 1/\widehat{T}_o$, based on the test results, рівним $\widehat{T}_o$ is the estimate of the average time to failure.

Quantification of FE losses from failure $n(m)$ of the subsystem (component, element) to determine the risk of failure:

$$D_{FE_{n(m)}} = \{d_{fe_{n(m)}} \mid fe = \overline{1, FE}, n = \overline{1, N}, m = \overline{1, M}\}, \qquad (2.15)$$

where $d_{FE_{n(m)}}$ - losses from the failure of a subsystem (component) of the CTS

Quantification of losses incurred by FC from the failure $a(b), z(q)$ of intersystem (intercomponent) communication:

$$D_{FC_{a(b),z(q)}} = \{d_{fc_{a(b),z(q)}} \mid fc = \overline{1, FC}, a = \overline{1, A}, b = \overline{1, B}, z = \overline{1.Z}, q = \overline{1, Q}\}, \quad (2.16)$$

where $d_{fc_{a(b),z(q)}}$ - losses from failure of intersystem (intercomponent) communication

To describe the category of losses from failures of inter-system (inter-component) connections, a verbal form is used.

Based on the established conditional probabilities of failures and the associated losses for FE and FC (2.10), (2.11), their risk of failure is determined. The assumptions and constraints adopted during modeling include that FE and FC in CTS have a level of failure risk distributed according to Harrington's desirability function.

The model for the intellectualized evaluation of the technical state of complex systems based on diagnostic features using BBN is a synthesis of reliability and diagnostic models. In the diagnostic model, BBN is used to assess the risk of failure (probability) in the system.

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

After defining the failure risk (conditional probabilities), the model can be used to assess and predict the TS. In the model, the risk of failure for each state of the system is determined using information about the system's TS and the risk of failure for each node in the network.

The development of a stochastic diagnostic model for the TS of complex systems, which simultaneously accounts for the presence of equipment, their interconnections, and the risk of partial or complete failure, enabled the proposal of a diagnostic method for the TS of critical application complex systems based on BBN.

The development of the diagnostic method for the TS of critical application complex systems based on BBN includes the following stages:

1. Construction of a BBN based on a stochastic diagnostic model of the TS of complex systems.
2. Initialization of the model by extracting failure risk data for equipment and their interconnections from the OREDA database.
3. Conducting research by simulating emergency situations.
4. Identifying and visualizing structural and functional vulnerabilities of the equipment, and analyzing the simulation results.
5. Transferring the diagnostic data of the TS of the critical application complex system to an intelligent information system for assessment and prediction of the TS of the complex system.

The construction of a BBN based on a stochastic diagnostic model of the TS of complex systems includes the following steps:

1. Construction of the BBN:

1.1. Nodes and inter-system (inter-component) BBNs representing the subsystems (components) of the CTS are created, taking into account the TS:

1.1.1. Each subsystem (component, element) can exist in the following technical states:

$Work_{n_{fe}}^{<m_{fe}>}$ - operable state n_{fe}- of the nfe subsystem (component, element) m_{fe} of the mfe level;

$Not\_work_{nfe}^{<m_{fef}>}$ - partial (complete) failure of the n_{fe} - th subsystem (component, element) of the m_{fe} - th level.

1.1.2. Each intersystem (intercomponent) link is in states:

$Work_{a(z)_{fc}}^{<b,q>}$ - is the operable state $a(z)_{fc}$ of the *b(q)* level intersystem (intercomponent) link;

$Not\_work_{a(z)_{fc}}^{<b,q>}$ - partial (complete) failure $a(z)_{fc}$ of the *b(q)* level intersystem (intercomponent) link

1.2. The connections between the BBN nodes, representing subsystems (components, elements), inter-system (inter-component) connections of the CTS, and diagnostic values *R*, are specified.

2. The parameters of the BBN are specified:

2.1. The risk of failure at the initial moment of time for FE and FC of the CTS, assuming that all of them are operational before the CTS begins operation:

$$R(Work_{n_{fe)}}^{<m_{fe)}>})_{t=0} = F(P(Work_{n_{fe}}^{<m_{fe}>})_{t=0}) = 0 ; \quad (2.17)$$

$$R(Work_{a(z)_{fc}}^{<b,q>})_{t=0} = F(P(Work_{a(z)_{fc}}^{<b,q>})_{t=0}) = 0$$

2.2. Risk of failure at the initial time point for the FE and FC of the CTS, assuming that all of them are inoperable before the CTS starts:

$$R(Not\_work_{n_{fe}}^{<m_{fe)}>})_{t=0} = F(P(Not\_work_{n_{fe}}^{<m_{fe}>})_{t=0}) = 1 ; \quad (2.18)$$

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

2.3. The risk of failure of the FEs and FCs of the CTS at the current time point, provided that some FEs and FCs failed at a previous time point:

$$R((Not\_work_{n_{fe)}}^{<mfe>})_t /(Not\_work_{n_{fe}}^{<m_{fe}>})_{t-1}) = 1 ; \quad (2.19)$$

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

2.4. The risk of failure of the FE and FC of the CTS at the current time point, provided they are in a serviceable condition, and at the current time point, provided they were in a serviceable condition and at the previous time point:

$$R((Work_{n_{fe}}^{<m_{fe}>})_t/(Work_{n_{fe}}^{<m_{fe}>})_{t-1}) = \frac{e^{-\lambda_{n_{fe}}^{<m_{fe}>}t}}{e^{-\lambda_{nfe}^{<m_{fe}>}(t-1)}} = e^{-\lambda_{n_{fe})}^{<jm_{fe})}} = 0; \quad (2.20)$$

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

2.5. The risk of failure of the FE and FC of the CTS at the current time point, provided that the FE and FC fail at the current time point and are operable at the previous time point:

$$R((Not\_work_{n_{fe}}^{<m_{fe}>})_t/(Work_{n_{fe}}^{<m_{fe}>})_{t-1}) = (1-e^{-\lambda_{n_{fe})}^{<m_{fe}>}})\cdot D_{FE}; \quad (2.21)$$

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

When developing the model and method of intelligence for diagnosing the TS of complex systems, such as the SPP, based on the BBN, the input data include:

1. The schematic diagram and operating principles of the SPP, which detail the system's structure and functional capabilities.
2. The probabilities of failure for FE and FC, which allow formalizing variations of scenarios in which a specific element or system cannot perform its intended function.
3. A fault tree, representing a structured set of possible scenarios for the cessation of FE and FC TS functioning, along with the corresponding levels of failure risk.

The number of FE and FC TS in the CTS can be determined based on the analysis of fault tree models and the associated failure risk values (Figure 2.1).

The synthesis and analysis of the fault tree are performed from a structural perspective, based on the logical schemes of equipment interactions within the CTS in terms of maintaining its operability. Structural analysis employs statistical data on the reliability of CTS equipment.

In Figure 2.1, *R* represents the system failure risk; *S1-S6* denote various combinations of failure sequences; *F1-F14* represent system elements, event types, and their failures.

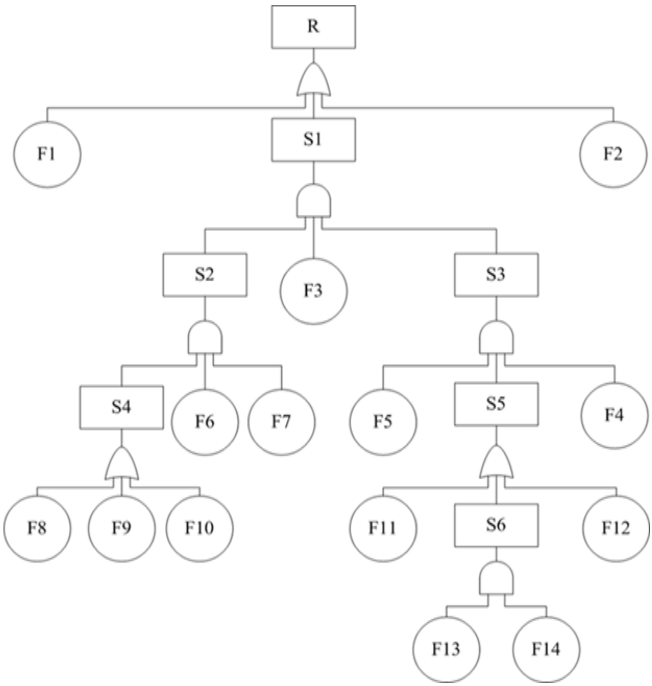

Figure 2.1 - Fault Tree of Subsystems (Components, Elements) and Inter-System (Inter-Component) Connections of the SPP

Table 2.1 illustrates the correspondence between the designations *S* in the fault tree and FE in the BBN.

Table 2.1 - Correspondence Between S and Subsystems (Components) in the BBN

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

The developed structure of the BBN for the SPP (Figure 2.2) is a multi-level system comprising thirteen subsystems distributed across seven levels. *P1* and *P2* are specialized intermediate nodes designed to implement the multi-level structure of the BBN.

Legend of subsystems and components in the SPP BBN:

- Input Element – IE;
- Firefighting System and Compressed Air System – FFS, CAS;
- Manual Control of the Main Engine – MCME;
- Control Systems and Remote Automated Control of the Main Engine – CS, RACSME;
- Intermediate Component – P1;
- Ship Power Plant – SPP;
- Main Engine – ME;
- Ballast Drainage System – BDS;
- Emergency Drive for the Propulsion and Steering Complex – EDPSC;
- Control System for the Propulsion and Steering Complex – CSPSC;
- Boiler Room – BR;
- Power Transmission from the Main Engine to the Propeller – TPMEP;
- Intermediate Component – P2;

- Propulsion and Steering Complex – PSC;
- Output Component – EXIT

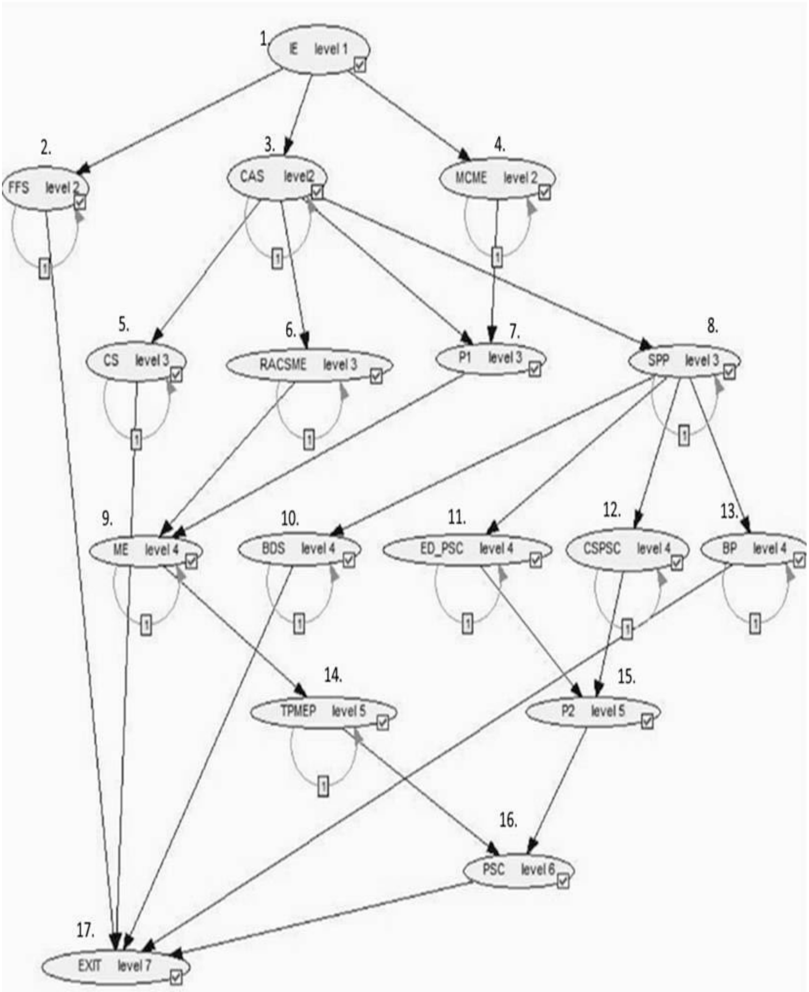

Figure 2.2 - Structure of the BBN for the SPP

For the subsystems of the top-level structure of the BBN for the SPP, conditional failures are determined based on the impact of subsystems from the lower hierarchical levels.

An example of applying the BBN to interconnected SPP blocks IE, CAS, SPP, and their connections IE – CAS, CAS – SPP (Figure 2.2), using failure rate data, can be presented as follows:

$$
\begin{gathered}
R(Work^{1,2,3}_{1,3,8})_{t=0} = 0\,; \\
R(Not\_work^{1,2,3}_{1,3,8})_{t=0} = 1\,; \\
R(Work^{2,3}_{IE-CAS,CAS-SPP})_{t=0} = 0\,; \\
R(Not\_work^{2,3}_{IE-CAS,CAS-SPP})_{t=0} = 1\,; \\
R((Work^{1,2,3}_{1,3,8})_t /(Work^{1,2,3}_{1,3,8})_{t-1}) = 0{,}1\,; \\
R((Work^{2,3}_{IE\_CAS,CAS\_SPP})_t /(Work^{2,3}_{IE\_CAS,CAS-SPP})_{t-1}) = 0{,}1
\end{gathered}
\tag{2.22}
$$

The sets of failure risk at the current time, considering the previous state of subsystems (components, elements) and intersystem (intercomponent) connections, can be within the following ranges:

- The expected level of failure risk is assessed as minimal, and the consequences of the accident are minimal under the following conditions:

$$R((Not\_work^{1,2,3}_{1,3,8})_t /(Work^{1,2,3}_{1,3,8})_{t-1}) = 0{,}1 - 0{,}2\,; \tag{2.23}$$

$$R((Not\_work^{2,3}_{IE\_CAS,CAS\_SPP})_t /(Work^{1,3}_{IE\_CAS,CAS-SPP})_{t-1}) = 0{,}1 - 0{,}2$$

The expected level of failure risk is assessed as acceptable, and the consequences of the accident are minor under the following conditions:

$$R((Not\_work^{1,2,3}_{1,3,8})_t /(Work^{1,2,3}_{1,3,8})_{t-1}) = 0{,}2 - 0{,}37\,; \tag{2.24}$$

$$R((Not\_work^{2,3}_{IE\_CAS,CAS\_SPP})_t /(Work^{1,3}_{IE\_CAS,CAS-SPP})_{t-1}) = 0{,}2 - 0{,}37$$

- The expected level of failure risk is assessed as maximal, and the consequences of the accident are significant under the following conditions:

$$R((Not\_work_{1,3,8}^{1,2,3})_t\,/(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}37 - 0{,}63; \quad (2.25)$$

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

- The expected level of failure risk is assessed as critical under the following conditions:

$$R((Not\_work_{1,3,8}^{1,2,3})_t\,/(Work_{1,3,8}^{1,2,3})_{t-1}) = 0{,}63 - 1; \quad (2.26)$$

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

Based on the retrospective analysis conducted, it is possible to identify the most probable causes of failures and investigate the reasons for subsystem, component, and element failures in CTS. The use of a BNT for analyzing subsystem and component failure risks in CTS is considered adequate.

Accounting for partial failures of CTS equipment enables the identification of failure causes. Conducting preventive maintenance before failures occur will enhance system reliability and improve operational efficiency.

The first novelty point is formulated as follows: a stochastic diagnostic model for complex systems has been proposed for the first time. This model simultaneously considers the presence of subsystems, components, and elements, their interconnections, and the probability of partial or complete functionality loss, enabling the development of a diagnostic method for complex critical systems using a Bayesian Network of Trust.

The presented BBN structure, which supports implementing the diagnostic method based on a graph-probabilistic model, reflects the essence of the second novelty point: the diagnostic method for complex systems based on BBN has been further developed. This method facilitates timely detection and visualization of structural and functional vulnerabilities, enhancing the operational efficiency of critical complex systems.

2.2 Development of a Cognitive Simulation Modeling Approach for Diagnosing the Technical Condition of Critical Complex Systems

From the perspective of technical safety, diagnosing the risk of CTS failures is a necessary yet complex task that requires the development and application of specialized mathematical tools. Solutions to such problems often rely on failure tree analysis.

A promising simulation modeling method for studying CTS reliability during system transitions between different states is Cognitive Simulation Modeling.

This approach utilizes directed graph models to represent the interactions of FE and FC within CTS.

Based on an analysis of transition graphs for determining the states of FE and FC across all hierarchy levels, algorithms for decision-making in corresponding software functions were developed and implemented.

In modeling the structural and functional properties of subsystems and their connections, the directed graph serves as a structural model of FE and FC within CTS.

The goal of developing a conceptual approach to CSM-based methods is to establish methodological foundations for diagnosing CTS failure risks under the influence of unpredictable external and internal factors.

The concept of diagnosing CTS failure risks under emergency scenarios is based on integrating FE and FC into a unified model.

This model must ensure failure risk diagnosis for FE and FC, considering their interconnections and mutual influences, based on their significance and criticality for overall system functionality. It must also identify structural vulnerabilities within CTS.

The transition from a cognitive map to a cognitive model is achieved by applying CSM, where structural vulnerabilities in CTS equipment are diagnosed via simulation modeling using diagnostic impulses.

During model testing, a diagnostic impulse (DI) is generated, applied to a conditional node (edge) of the CSM, and propagates to subsequent nodes (edges), inducing failure states in interconnected FE of the CTS.

The conceptual stochastic CSM for diagnosing complex system conditions includes an impulse vector $imp_k(t), k \in 1,2,...,l$ for discrete time.

This is determined by the change in weights of the nodes and edges in the directed graph, defining the dynamics of impact propagation across the CTS.

For an impact of *imp = 0*, the element remains unaffected, while an impact of *imp = 1* disables the element with 100% probability.

The proposed conceptual stochastic CSM for diagnosing critical ship complex systems is structured as follows:

CCM=<G,{x_i},F,Q,{FE},{FC},⟦R_FE},{R_FC },L,⟦imp⟧_k(t)⟧> (2.27)

$$imp_k(T) = (x_1, x_2, \dots, x_{V(E)}), \qquad (2.28)$$

where $x_1, x_2, x_{V(E)}$ – state of FE та FC CTC

To test the developed software, a CSM of a CTS was created in the form of a directed graph, using an internal combustion engine (ICE) as an example (Fig. 2.3).

The directed graph diagram of the ICE example with subsystems is shown in Fig. 2.4.

As a measure of damage, it is proposed to determine the structural losses from FE and FC failures in accordance with the method for diagnosing structural failure risk in CTS.

For diagnosing the failure risk of FE and FC in the ICE, it is necessary to determine the probabilities of failure for each FE and FC.

Statistical data tied to a specific time τ are used, containing information about the number of failures *n* for FE and FC.

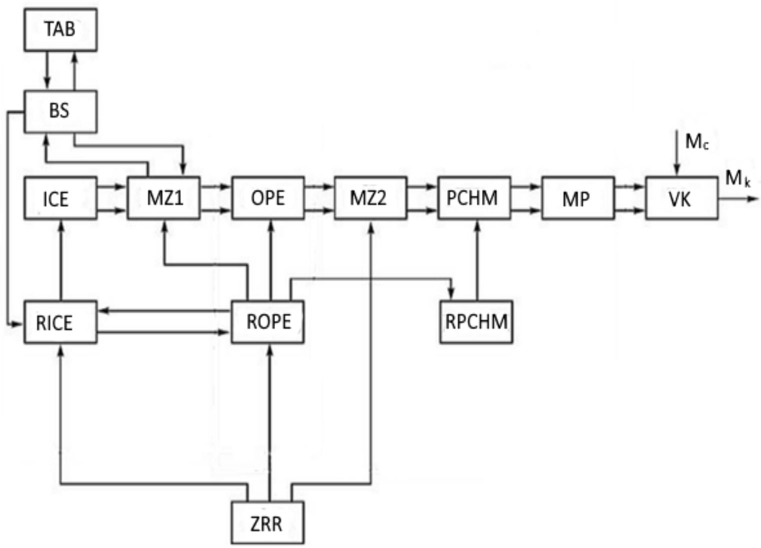

Figure 2.3 - Structural diagram of the internal combustion engine with subsystems (TAB - traction accumulator battery; ICE - internal combustion engine; ZRR - motion mode controller; BS - block for summing up voltages and power; OPE - energy converter; PCHM - rotation speed and torque converter; MP - mechanical transmission; VK - driving wheels; MZI - clutch coupling between the ICE and OPE shafts; MZ2 - clutch coupling between the OPE and PCHM shafts; ROPE - OPE regulator; RPCHM - PCHM regulator; RICE - ICE regulator; Mc - resistance torque on the shaft; Mk - torque on the shaft).

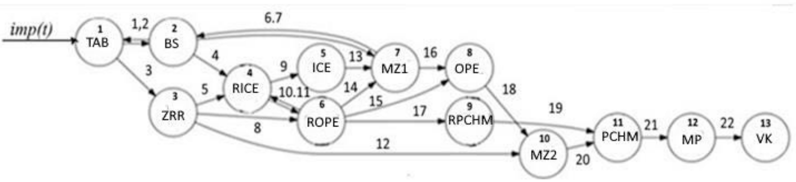

Figure 2.4 - Schematic of the orientated graph of the ICE

The probability of failure of FE and FS of the ICE is determined:

$$P_{v_i} = \frac{n_{v_i}}{\tau}, \quad P_{a_j} = \frac{n_{a_j}}{\tau}, \qquad (2.29)$$

where p_{v_i} is the probability of failure of the i-th FE;

p_{a_j} - is the probability of failure of the j-th FC;

n_{v_i} - is the number of failures of the i-th FE;

n_{a_j} - is the number of failures of the j-th FC;

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

Based on the method of diagnosing the risk of failures during the operation of FE and FC of a CTS, an algorithm for diagnosing the risk of failures of FE and FC depending on the degree of their mutual influence was developed (Fig. 2.5).

The existing theoretical foundation and the availability of a wide range of simulation software, such as Arena, AutoMod, AnyLogic, Extend, GPSS World, and others, contribute to the active application of CSM for diagnosing the risk of CTS failures [171, 172]. However, the known software tools only facilitate the testing process itself and do not address the most challenging task of collecting the initial information, its interpretation, formalization, and adequate correlation with the specific object. Mastering such software environments requires significant effort. Based on the concept of failure risk diagnosis of FE and FC CTS described in [93], it becomes possible to develop software that enables automated risk diagnosis of FE and FC CTS failures, taking into account their TC [8]. To determine the general boundaries and context of the subject area being modeled, at the initial stages of developing failure risk diagnosis software for partial and complete loss of CTS operability, as well as formulating general requirements for its behavior, a diagram of the created software has been developed (Figure 2.6).

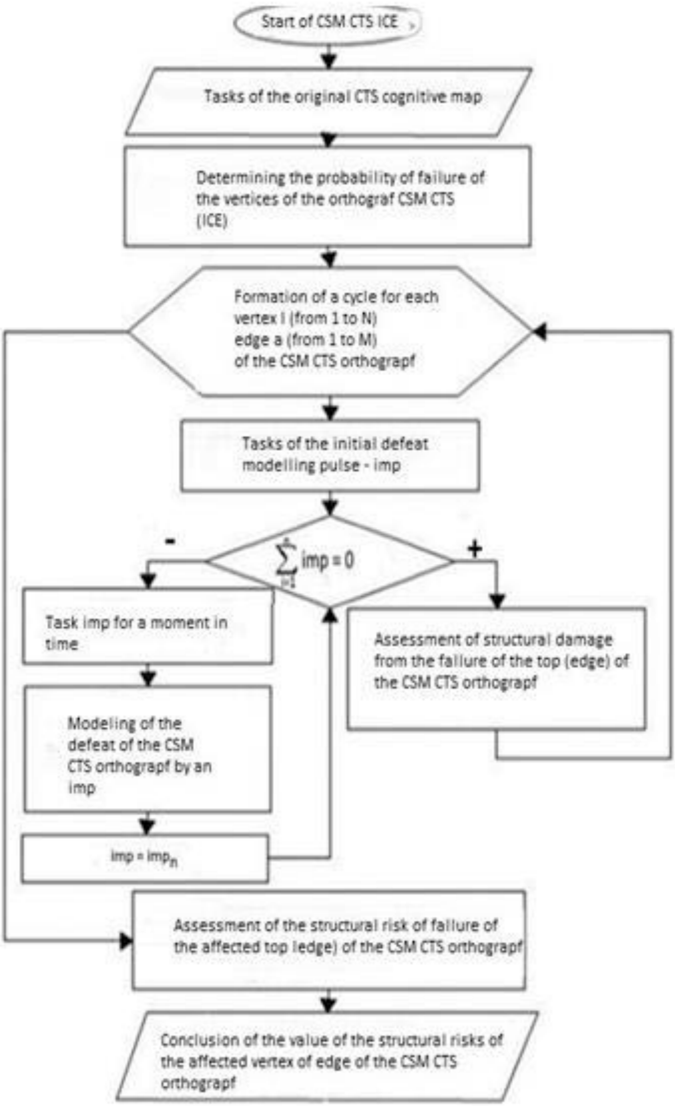

Figure 2.5 - Algorithm for Diagnosing Failure Risk Based on the Impact Degree of CSM CTS Components

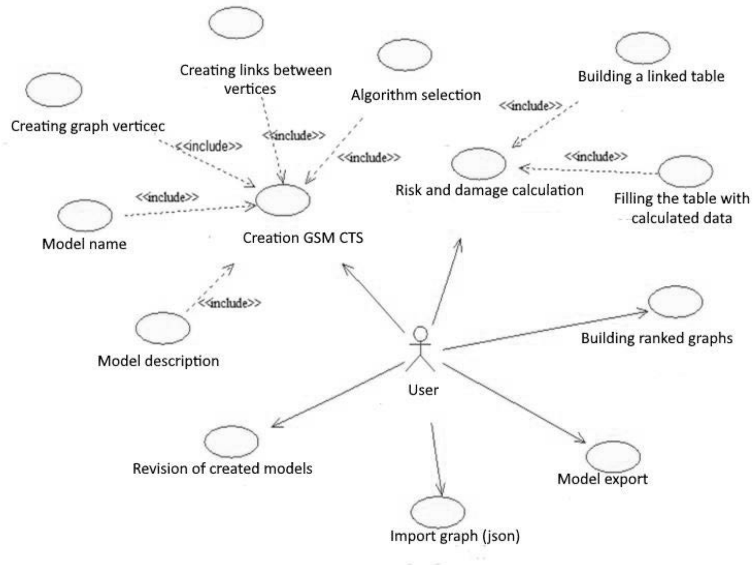

Figure 2.6 – Use Case Diagram of the Created Software Variants

The developed software allows the user to:

- Create a CTS model in the form of a digraph, supporting features such as specifying the model name, entering a brief textual description, setting a new vertex in the digraph and visualizing it on the model display panel, building connections between selected vertices of the model, activating the current model layout algorithm on the panel, and visualizing the resulting structure in the created graphical container;
- Display the previously obtained structure of the developed CSM in the form of a digraph with visualization of all edges and vertices, providing the possibility of direct import into the program;
- Add a model to the system serialized in JSON format for parsing and display;
- Perform the procedure for exporting the CSM in the form of the created digraph to a graphic file in PNG or JPG format;

- Execute the procedure for calculating the numerical values of failure risks for FE and FC CTS and visualize the results by generating a table format;
- Display the results graphically, applying value ranking in descending order.

The built use case diagram of the software allows for the design of the logical entities of the software implementation through the development of corresponding class diagrams.

The key developed classes of the software are shown in Figure 2.7.

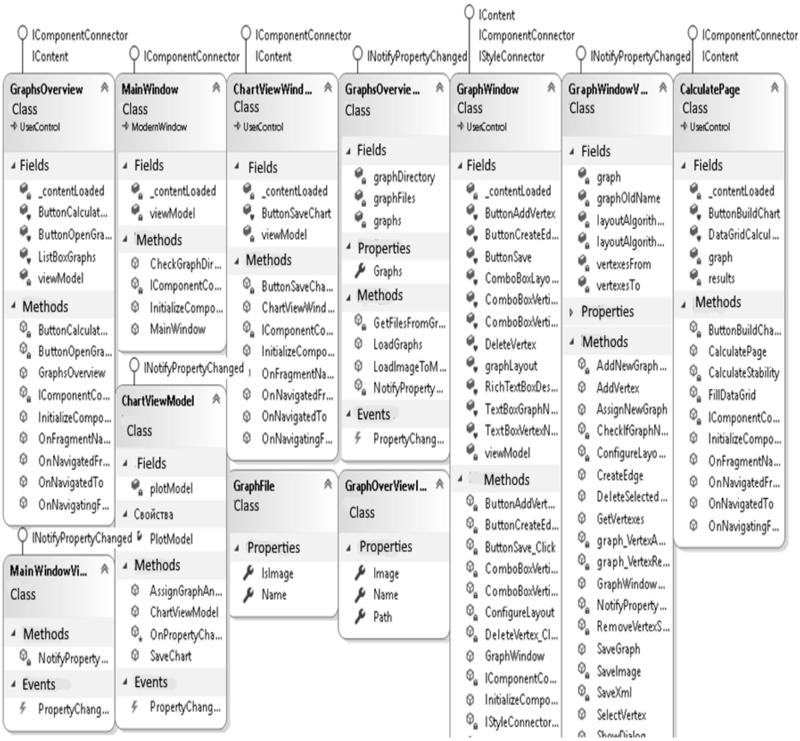

Figure 2.7 – Class Diagram of the Developed Software

The classes GraphsOverview, MainWindow, ChartViewWindow, GraphsOverviewWindow, GraphWindow, GraphWindowView, CalcutePage, MainWindowView, and ChartViewModel implement functional interfaces for the flexible adaptation of logic to introduce specified functional capabilities for displaying data processing results and performing computational operations.

To implement the described software logic, interfaces for the CSM in the form of a digraph are used:

- IComponentConnector (for ensuring the connection of FE components);
- IContent (for displaying and implementing the dynamic combination and description capabilities of the entities in the created graphical container on each system interface form);
- INotifyPropertyChanged (for event binding related to changes in the properties of the implemented CSM objects on the software panel);
- IStyleConnector (for modifying and selecting FE connections).

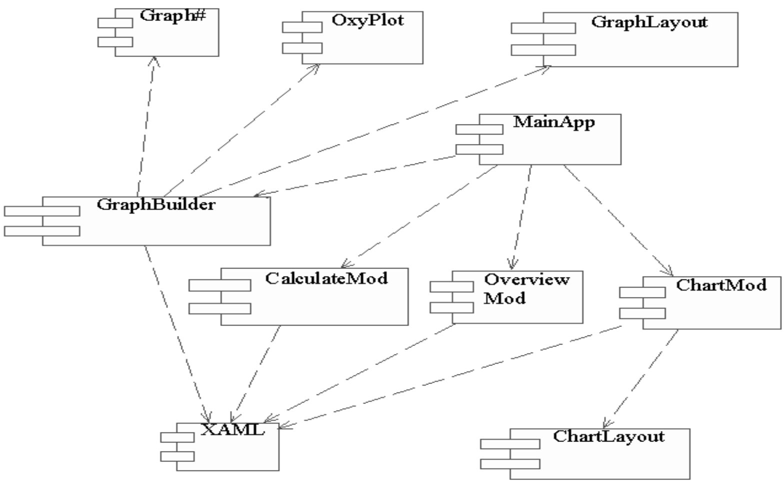

Figure 2.8 – Software Component Diagram

Based on the created diagrams, the characteristics of the physical representation of the system are described in the form of formalizing the order of interconnections between the basic CTS FE components.

To this end, the component diagram (Figure 2.8) should be applied, which defines the software architecture by formalizing all the connections between the created software components.

MainApp is the main module and is designed to invoke other modules to process requests for the following processes: building the CSM digraph model using the GraphBuilder class by applying the Graph# and OxyPlot dependencies, which are external artifacts of the project, as well as the GraphLayout class to construct the container for interactive visualization of the created model; evaluating values of losses and failure risks; displaying calculation results in table form for their visual assessment; building and displaying a graphical object for ranking results.

The Graph# and OxyPlot artifacts were used as libraries for processing graphical primitives.

The first of these dependencies contains a number of algorithms for fast layout of digraph models, including support for: Force-Scan, LinLog, Fruchterman – Reingold, ISOM, Sugiyama, Kamada – Kawai, and a simple tree layout.

To simulate the interaction of objects over time within the developed software and to ensure message exchange processes between them, a sequence diagram of the software actions has been created (Figure 2.9).

All forms, except for the main one, shown in this diagram are independent fragments that dynamically integrate into a single collection within the main form through the generation of new tabs.

The basis of the digraph structure-building method is the Sugiyama algorithm, which is based on the following tasks: distributing the formed vertices of the digraph into levels to achieve minimal length values, while maintaining their direction unchanged; minimizing the total number of dummy vertices; minimizing edge crossings in the digraph by changing the order of assigned model vertices on their respective levels; selecting values for each vertex coordinate to reduce the number of edge bends.

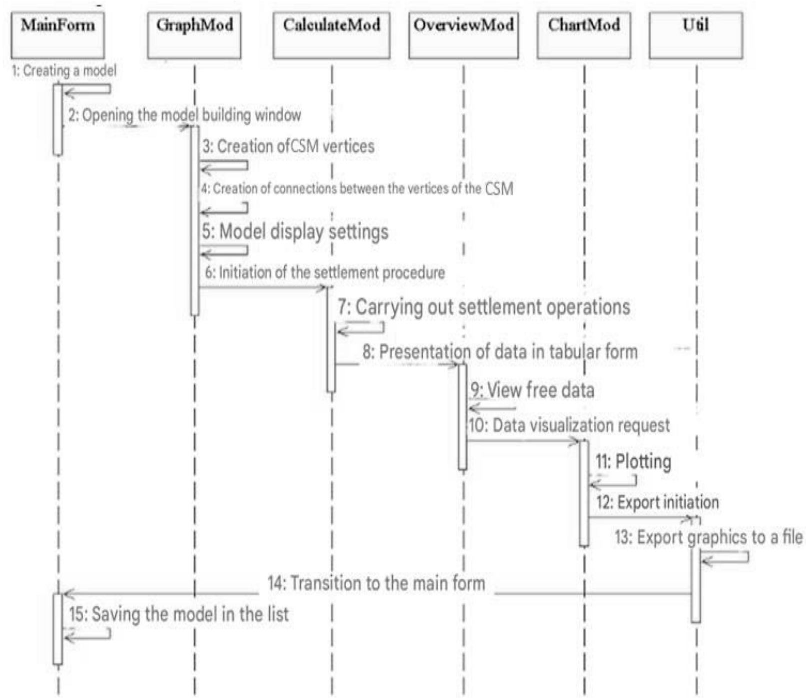

Figure 2.9 – Software Action Sequence Diagram

To formalize the software functionality, the following functional classes have been developed:

1. Public partial class CalculatePage: UserControl, IContent, IComponentConnector for data interpretation and using the results of the developed model in the form of a digraph for quantitative assessment of CTS FE losses and their failure risks.
2. Public class ChartViewModel: INotifyPropertyChanged for building and visualizing the ranked chart of the obtained CTS FE failure risk values.
3. Class GraphWindowViewModel: INotifyPropertyChanged for creating the CSM digraph.

4. Public class GraphsOverview: UserControl, IContent, IComponentConnector for displaying the digraph model to the user interface.

The interface of the CSM digraph creation form for the developed software is shown in Figure 2.10. This form allows selecting one of the supported algorithms for building and displaying the digraph within the container, assigning it a name as a string, entering its textual description, and saving the created model in *.xml format.

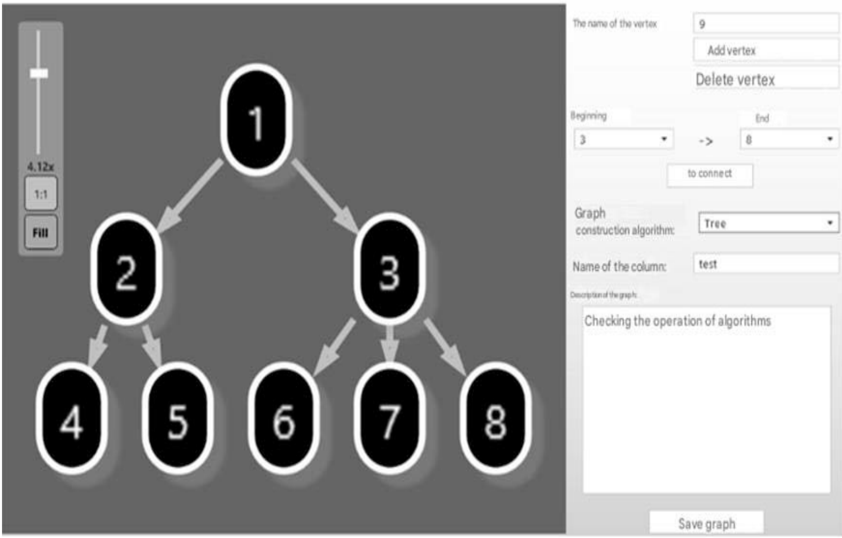

Figure 2.10 – Interface of the CSM Digraph Creation Form for the Developed Software

To test the software, a CSM diagnostic model of the CTS as a digraph was created, based on the example of vector control of the rudder transmission with an electric drive for a ship (Figure 2.11) [124]. It includes the following components: 1 - steering machine; 2 - worm wheel segment and brake; 3 - worm gear; 4 - rudder tiller; 5 - gearbox; 6 - rudder stock; 7 - rudder sector; 8 - semi-axle; 9 - bracket for the tray; 10 - bolt; 11 - bolt with nut; 12 - washer; 13 - locking plate; 14, 15, 16, 24, 25 - gears; 17 - carrier; 18 - free epicycle; 19 - gear wheels; 20 - free carrier; 21, 22 - shafts; 23 - braking epicycle; 26 - engine; 27 - spring; 28 - rudder baler; 29 - profiled rudder; 30 - drive wheel; 31 - propeller shaft; 32, 33 - low-pressure and high-pressure turbine shafts; 34 - turbocharging unit; 35 - drive wheel; 36 - intermediate gears; 37 - crankshaft drive wheel; 38 - camshaft; 39 - connecting rod; 40 - piston; 41 - cylinder sleeve; 42 - cooling water chamber; 43 - crankshaft; 44 - charge air cooler; 45 - exhaust gas pipeline; 46, 47 - charge air and cooling water pipelines; 48, 49 - oil and fuel pipelines; 50 - pushrod; 51 - fuel pump; 52 - oil ring; 53 - cylinder head; 54, 55, 56 - exhaust, intake, and fuel valves; 58 - oil sump; 59 - cylinder block.

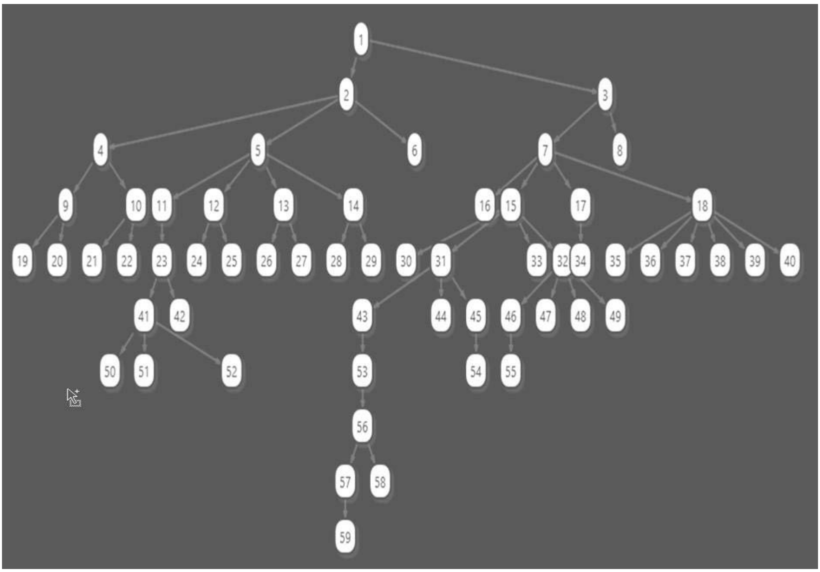

Figure 2.11 – CSM Diagnostic Model of CTS

From the conducted modeling, it is evident that the most vulnerable elements of the system are the steering sector, worm, worm wheel segment, brake, and gearbox.

Their failure poses the greatest threat to the functioning of the entire vector control system of the rudder transmission with an electric drive.

Therefore, constant diagnostics of the CTS is necessary, which will help prevent the loss of functionality of FE and FC CTS, and reduce the risk of failures.

To automate the process of building the CSM for diagnosing the risk of equipment failure in the ship's CTS, a cross-platform program was developed in the Java programming language, using the JavaFX graphical framework and XML markup language. After launching the developed application, the user selects the operating mode (manual – allows step-by-step assessment of parameters by entering the necessary data for the selected system (Figure 2.12), automatic – activates automatic data processing).

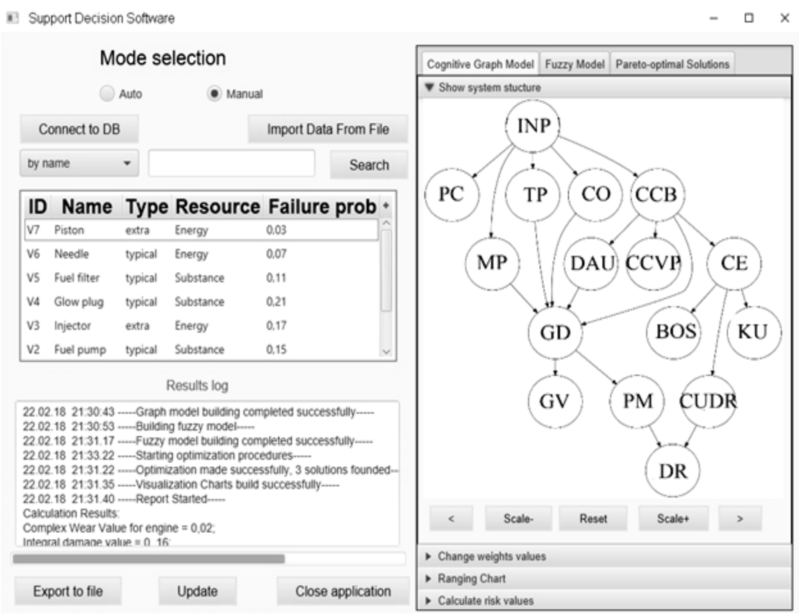

Figure 2.12 – Interface for Viewing CSM Diagnostic of CTS in Manual Mode

The following conditional symbols are used for CTS: input element – INP; oil subsystem – MP; fuel subsystem – TP; cooling, compressed air, and drive-steering complex control systems – CO, CCC, CUDR; ship's power plant – CE; fire protection system – PC; main engine – GD; remote automated control system for the main engine – DAU; ballast-drying system – BOS; boiler room – KU; power transmission from the main engine to the propeller – PM; drive-steering complex – DR; sanitary water preparation system – PC3P; exhaust gas system – GV.

An analysis of technical solutions aimed at improving the reliability of CTS operations has shown that timely and high-quality diagnostics, including remote components for complex technical systems during operation, significantly enhance system reliability and operational efficiency.

Software and hardware wireless data transmission in information systems integrated with smartphones further enables remote control, resource expenditure monitoring, synchronization of CTS equipment operations, and coordination of distributed computational processes.

The relevance of utilizing the open Android operating system as a platform for mobile application (MA) development is particularly noteworthy.

Android offers advantages such as:

- Integration support for third-party services and components.
- Mechanisms for implementing virtualization.
- Flexibility in application development using Java MVC templates and design patterns.
- SSL protocol protection for transmitted data.
- Optimization for mobile traffic data transmission.

The functionality provided by the Android platform allows for the development of mobile applications for remote monitoring and failure risk forecasting of technical system components.

The developed mobile application is designed for use on mobile devices with an Android operating system version, a screen size of 4.5 inches, and a resolution of 800 × 600 pixels or higher. The user interface (UI) flexibility is achieved through:

- Elements for color-coded interaction and dynamic visualization upon activation.
- Options to adjust text block sizes, fonts, and styles via Typekit.
- Support for switching between screen tabs using an event-handling method.
- Preference for flat design elements over skeuomorphic ones.
- Clarity and dynamic animations when rendering statistics in graphical form.
- Partial blurring of background activity upon the appearance of dialog boxes or informational messages.
- Placement of all functional elements on a single screen, eliminating the need for vertical scrolling.
- An integrated intelligent keyboard for text data input.

The choice of a database management system (DBMS) for developing and implementing the mobile application depends on effective interaction with the mobile client application, complicated by the wide array of available solutions. SQLite, with its built-in file server support in Android OS, is advantageous for fully offline operation.

However, the mobile application's operations require continuous connection to an external remote server.

DBMS solutions integrated with standard tools and supported libraries enhance the speed and efficiency of the mobile application.

For long-term scalability based on evolving project requirements, NoSQL databases may be selected.

To achieve the objectives, the mobile application includes tables such as equipment, sensors, parameters, CTS equipment failure probabilities, failure losses, forecast parameters, and log lists.

Data types in the application primarily consist of integers, real numbers, and large registration data entries.

Based on the designed ER model, a concrete physical database model was implemented using MySQL Workbench or SQL Navigator.

Application usage scenarios are designed and illustrated using a mobile application use-case diagram (Figure 2.13).

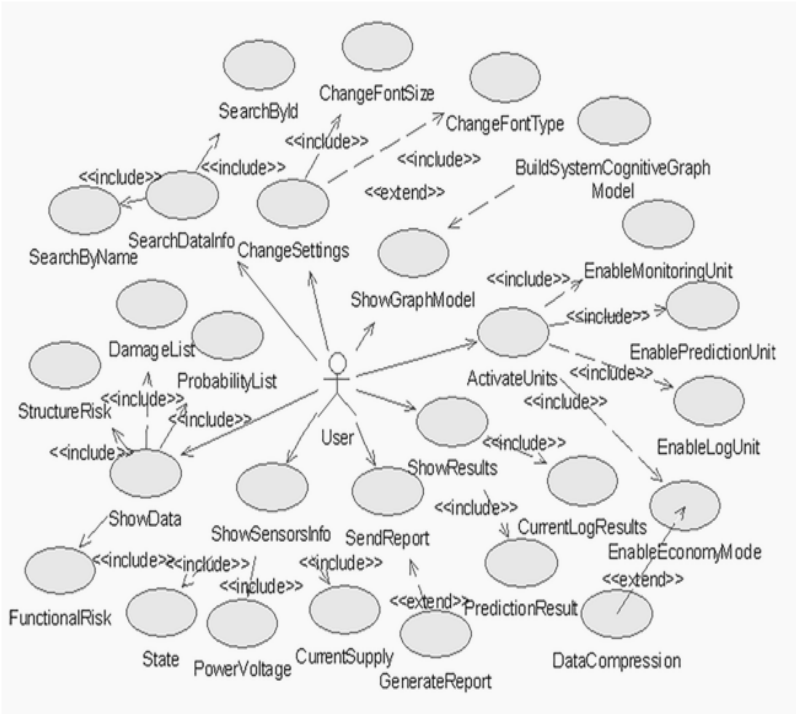

Figure 2.13 – Use Case Diagram for the Mobile Application

The application's functionalities include:

- Viewing information on CTS equipment damage.
- Assessing failure probability and structural/functional failure risks.
- Searching the database by object name or unique ID.
- Local storage and generation of reports in PDF format.
- Building CSM.
- Modifying user interface settings.
- Viewing forecast results for CTS equipment conditions.
- Enabling and disabling monitoring, diagnostics, and forecasting modules for CTS equipment.

- Maintaining a log and providing additional data compression for server-transmitted data.

To formalize the class and object models of the mobile application (MA), a project class diagram was developed, illustrating the relationships between classes and their instances (Figure 2.14).

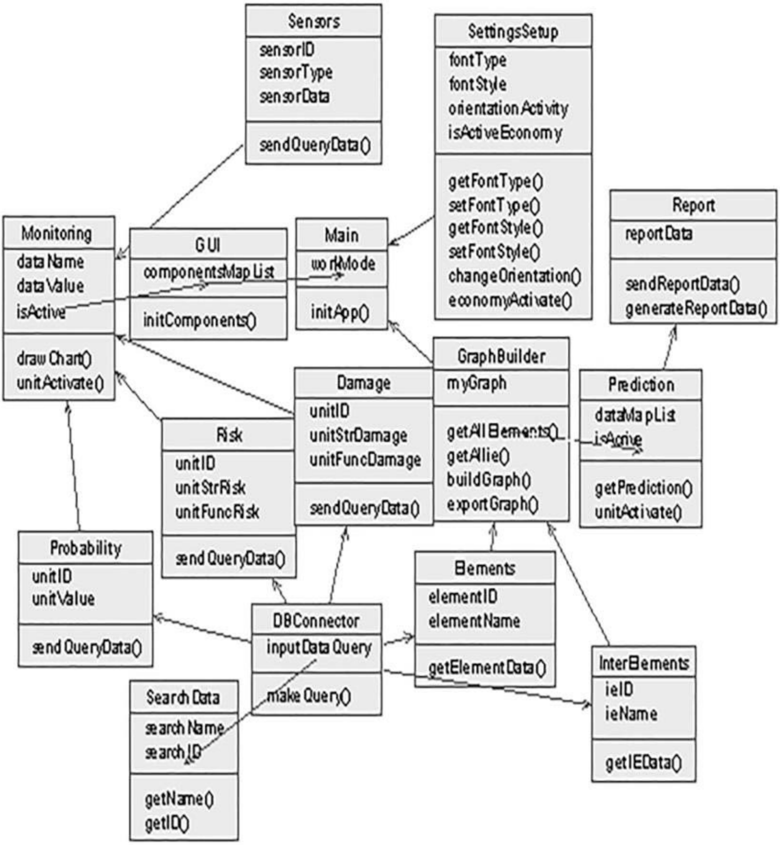

Figure 2.14 – Fragment of the MA Class Diagram

The MA is launched in a separate thread via the initApp method in the Main class. The authorization procedure is handled by the Autoriz class, which generates a graphical user activity interface with login and password fields. Each class implements the following functionalities:

- Monitoring, diagnostics, and forecasting.
- Building CSM graphs.
- Searching and viewing information from sensors monitoring CTS parameters.
- Determining the probability of CTS equipment failures, failure risks, and associated losses.

For a more detailed description of the MA, an activity diagram was developed (Figure 2.15).

The objects in the diagram include:

- Client-Mobile Application: Interfaces with users for system interaction and data visualization.
- External Server: Synchronizes, processes, and verifies statistical data on the performance of CTS components.
- Management Server: Performs tasks related to data storage, processing, backup, and data exchange with the external server and data collection system.
- Data Collection System: Collects data directly from sensors located on individual CTS components and transmits the information to the CTS management server.

The MA is used to verify server activity and establish a connection between the server and the client. It sends a package of requests to check for key active updates in repositories, validate authorization data, and retrieve technical and statistical information about the operation of the CTS.

To implement the prototype interface and develop the program code, formalized through UML functionality, an algorithm for MA operation was developed (Figure 2.16).

The application installation package is downloaded to the mobile device in *.apk format.

As a result, all components and dependencies of the application are initialized, including checks for connectivity to wireless Internet access points using supported technologies (via the android.net package) and operations of the remote server.

Subsequently, the data update visualization component on the server is rendered.

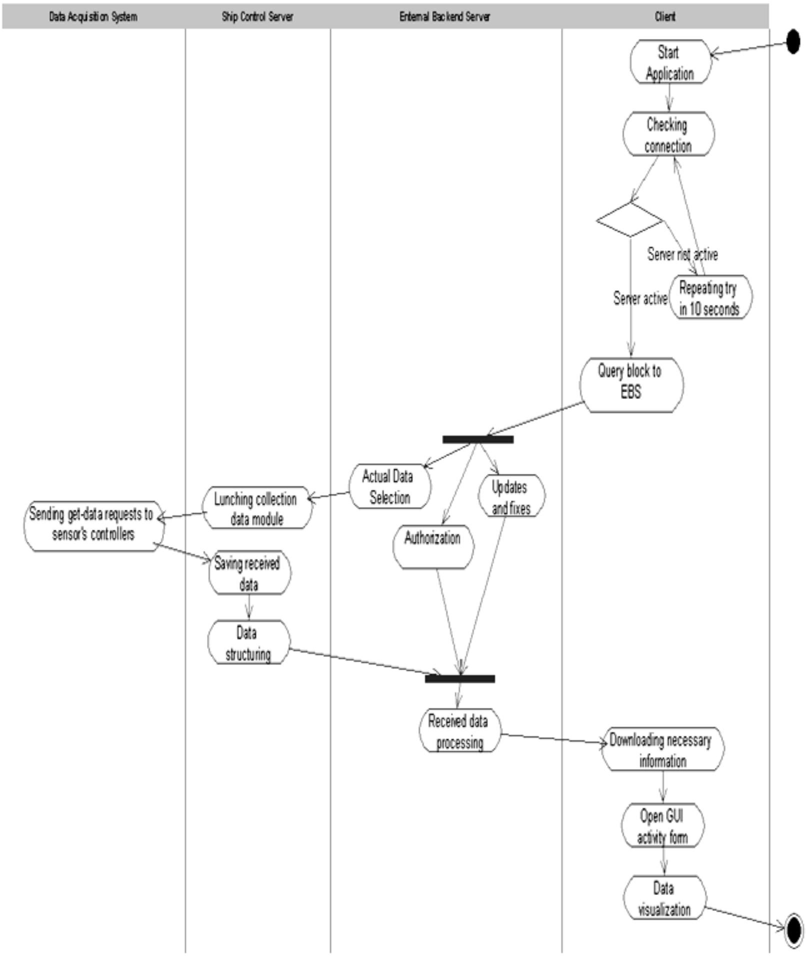

Figure 2.15 – MA Activity Diagram

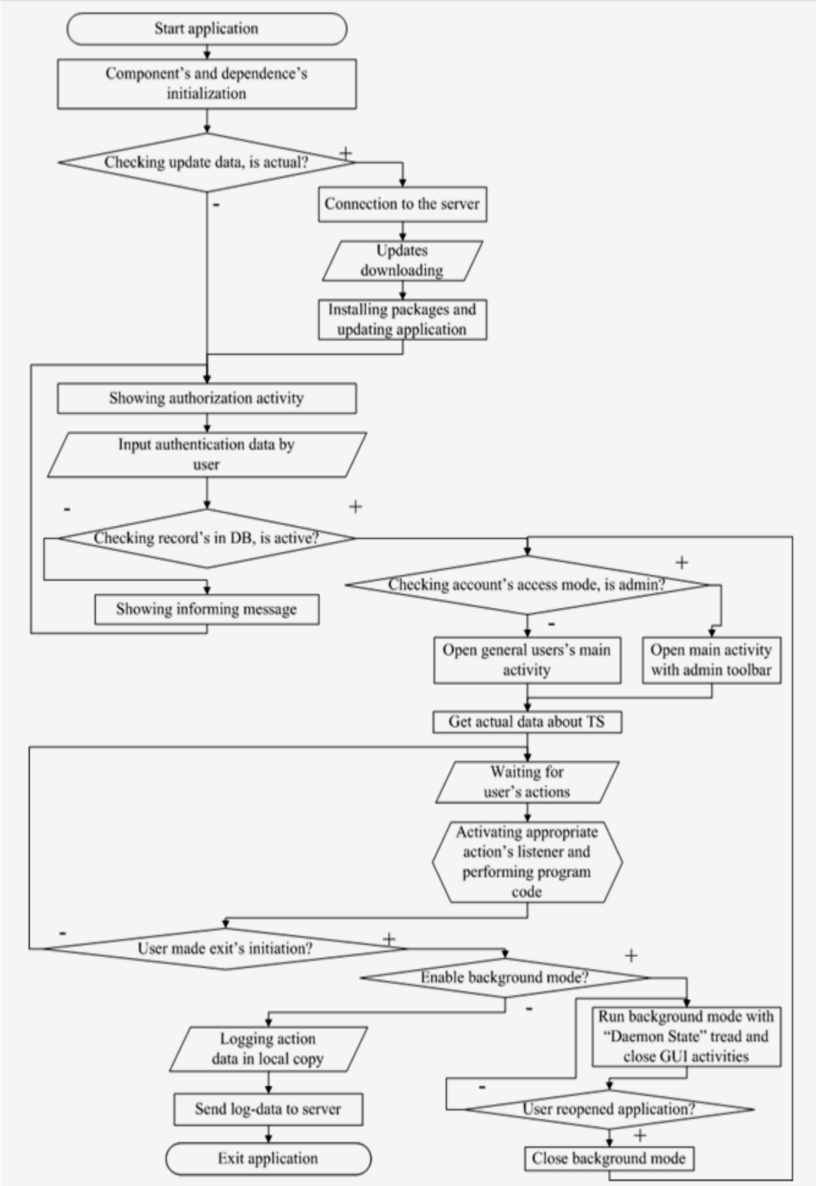

Figure 2.16 – MA Algorithm

When such a procedure is implemented, a new process begins installing the necessary packages and updating programs in the background.

The user accesses the system via the login interface by entering a username and password. Technical and statistical information about the system components is then retrieved.

After this, the application transitions to the main form, entering standby mode and user request mode. In these modes, the execution of the program code is triggered through the respective event handler.

Upon closing the application, an additional dialog box is displayed, offering the option to run the MA in the background. If the user selects this option, the application runs in a separate process and thread, and the GUI is unloaded from the mobile device's RAM.

If the application, already running in the background, is relaunched, the background mode is terminated, and control is passed for access verification to the application mode.

When the user initiates the final closure of the application in the background mode, all actions performed are logged in the local working directory copy of the mobile application.

If the server connection is active, data is sent to the server.

Afterward, the application is fully unloaded from the mobile device’s main memory.

The amount of MA data stored in the corresponding Cache directory must not exceed 2.5 megabytes.

Otherwise, a caching procedure will be initiated.

The developed MA consists of the following modules:

- Initialization of user interface components
- Verification of the current data module for the application version
- Connection to the remote server module
- Building and visualization of the CSM system module
- Reporting module for transformation and export of statistics and graphical data from applications
- Prediction module for creating and training an artificial neural network using the backpropagation method, linear normalization

function, and tangent activation function. The network is trained with error value evaluation

- Visualization of statistical data
- Retrieval of data query implementation from the server database

These modules form the core structure of the MA development project.

They are stored in separate packages, which can be extended. The prototype implementation of the software client interface is shown in Figure 2.17.

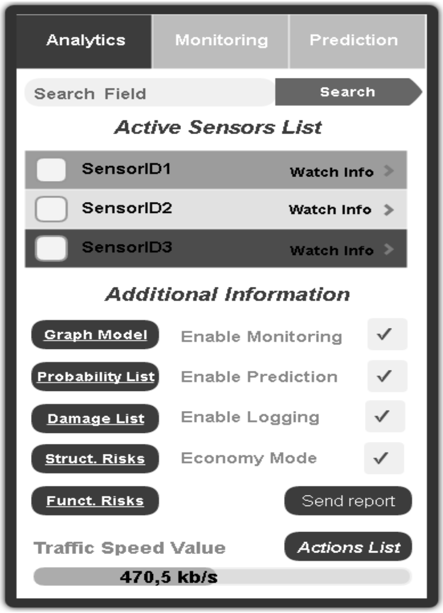

Figure 2.17 – Mobile Client Interface Prototype

The prototype was developed using the SaaS cloud service fluidui.com and consists of three tabs:

- Analytics: Includes components for viewing the list of active sensors, retrieving information, and managing the monitoring, diagnostic, and predictive modules of CTS equipment. It also supports logging.
- Monitoring: Features graphical components for the dynamic visualization of parameters and system characteristics.
- Prediction: Contains a table of predicted risk values based on the selected time period.

The developed MA project for monitoring, diagnosing, and predicting the risk of CTS equipment failures is complete and logically structured. During code development, it is advisable to use Gradle configuration to accelerate the processes of refactoring, profiling, and integration with the GIT version control system.

The developed MA simplifies the process of assessing the risk of CTS equipment failures.

Additional content and functional enhancements to the project are feasible through Android-Core interfaces.

As an alternative to the server side, it is recommended to use modern cloud services and technologies based on IaaS and PaaS models.

The third point of scientific novelty is formulated as follows: an improved cognitive simulation model that uses simulation shock impulses, enabling the diagnosis of CTS equipment systems while considering their interconnection and influence.

2.3 Conclusions to the Second Chapter

In the second chapter, stochastic models and a method for diagnosing the CTS of complex systems were developed.

The models reflect a new approach that takes into account uncertainties and incomplete data of the modeled systems, considering partial and complete failures of equipment operability, the identification and visualization of structural and functional vulnerabilities of subsystems, components, and elements of their interconnections. The method of dynamic BBN was used for modeling.

A stochastic model for diagnosing the CTS of complex systems is proposed for the first time, which simultaneously considers the presence of subsystems, components, and elements, their interconnections, and the probability of partial or complete failure of operability.

This allowed for the introduction of a method for diagnosing CTS based on a Bayesian trust network for complex critical application systems.

The method for diagnosing the CTS of complex systems based on the Bayesian trust network has been further developed, enabling the timely detection and visualization of structural and functional vulnerabilities and improving the efficiency of complex critical application systems.

To detect and visualize vulnerabilities of CTS equipment with consideration for their mutual relationships and influence, uncertainty and data incompleteness, partial and complete equipment failures, as well as tracking the consequences and system responses to failure risks with non-obvious sources, a cognitive simulation model for diagnosing the risk of equipment failure was used. This model employs simulation impact impulses.

An improved cognitive simulation model has been developed, which applies simulation impact impulses, enabling the diagnosis of CTS equipment in systems, considering their mutual connections and influences.

CHAPTER 3
RESEARCH AND ANALYSIS OF STOCHASTIC MODELS AND METHODS FOR DIAGNOSING THE TECHNICAL CONDITION OF COMPLEX CRITICAL SYSTEMS

3.1 Research and Analysis of the Stochastic Structural Model and Method for Diagnosing the Technical Condition of Complex Critical Systems Using the Dynamic Bayesian Network Method

The purpose of studying the developed conceptual stochastic model for risk diagnosis of CTS failures (Section 2.1) is to identify vulnerable FE and FC of the system, considering their partial and complete failures.

Reducing the problem of diagnosing the risk of FE and FC failures in CTS to constructing a Bayesian Network Model (BNM) enables the use of the algorithmic apparatus of BNM theory and software tools like GeNIe.

In this case, the comprehensive monitoring of failure risks (probabilities) of FE and FC in CTS, hidden variable characteristics, and their necessary visualization are addressed using the developed model from Section 2.1.

In the diagnostic model, BNMs are employed to estimate the risk (probability) of failure for FE and FC of the system.

This is based on its operating principles and expert data (sourced from the OREDA database).

The model determines the failure risk for each CTS component, considering the current and previous technical states related to the risk of failure identified for each interconnected FE in the system.

The research focuses on a ship's critical CTS—its propulsion plant (PP). The structure of the dynamic BNM was developed with consideration of the layout and operating principles of the PP, consisting of seven levels and seventeen nodes.

Table 3.1 presents the designations for PP equipment, the hierarchical level numbers, and the weight of each subsystem (component, element) within the dynamic BNM of the PP modeled in the GeNIe environment.

Таблиця 3.1 Symbols of subsystems, components of the SPP

Subsystem (Component) Number	Hierarchical Level Number	Subsystem (Component) Name	Symbol	Subsystem (Component) Weight
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

The modeling was conducted using the traditional "top-down" and "bottom-up" approaches, based on the model's prior characteristics.

The following assumptions and constraints were adopted during the modeling process:

- The FE and FC of the CTS are in either partial or complete failure states;
- At the initial time, the FE and FC of the CTS are in a functional state;
- The current technical state of each FE and FC of the CTS depends on their current and previous technical states;
- Time is discrete, with a step size of one hour.

When modeling the DBN of the SPP (Fig. 3.1), for various values of the probability (risk) of failure of the input subsystem, the probability (risk) values for the failure and operability of the FE and FC of the SPP were determined over 20,000 hours of operation.

Figure 3.1 shows the BNM of the SPP for modeling and diagnosing the failures of FE and FC at an input element failure risk of 0.26, displaying the operational state and failure risk level of each FE and FC of the SPP.

Fragments of operational states and failures, for example, subsystems CS and SPP, located on the third level of the BNM and at the output of the model, are shown in Fig. 3.1.

Similar studies were conducted for an input element failure risk of 0.49, showing the operational state and failure risk level of each FE and FC of the SPP (Fig. 3.2).

Figures 3.3 and 3.4 present the calculated values of conditional probability and failure risk for the FE and FC obtained from modeling results for 2,863, 8,616, 13,079, 16,726, 19,809, and 20,000 hours of SPP operation, respectively.

Figures 3.5 and 3.6 present the calculated values of the probability and risk of failure for the FE and FC obtained from modeling the operation of the SPP over 20,000 hours in the GeNIe environment.

Retrospective analysis of the study results identifies FEs that are in partial or complete failure states.

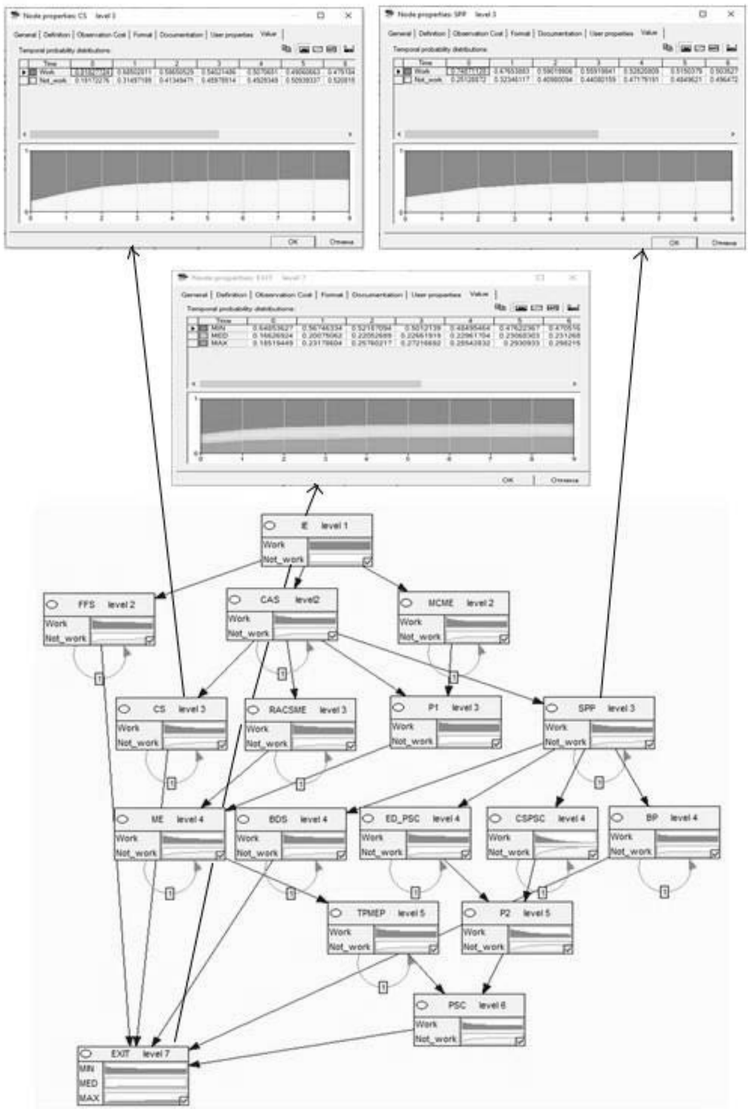

Figure 3.1 - BNM of SPP in GeNIe environment for modelling FE and FC failures at the risk of input element failure of 0.26

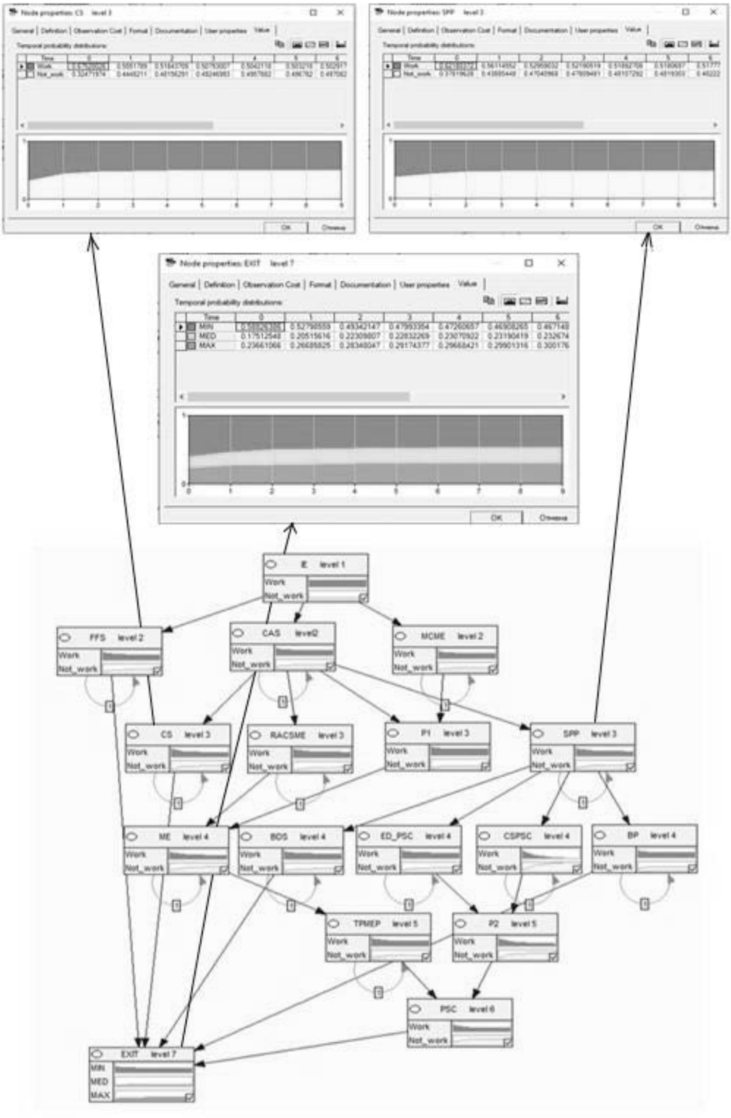

Figure 3.2 - BNM of SPP in the GeNIe environment for modelling FE and FS failures at the risk of input element failure of 0.49

In studying emergency situations and analyzing CTS events, the primary objective is to determine the causes of FE and FC failures.

t	IE	MCME	CS	CSPSC	BP	SPP	FFS	ME	RACSME	BDS	TPMEP	ED PSC
	0,26	0,07	0,05	0,19	0,34	0,14	0,02	0,36	0,02	0,05	0,003	0,02
0	0,26	0,07	0,05	0,19	0,34	0,14	0,02	0,36	0,02	0,05	0,003	0,02
2863	0,300015	0,080773201	0,057695144	0,219242	0,392326977	0,161546	0,023078	0,415405	0,023078	0,057695	0,003462	0,023078057
8616	0,400007	0,107694148	0,076924391	0,292313	0,523085859	0,215388	0,03077	0,553856	0,03077	0,076924	0,004615	0,030769756
13079	0,500012	0,134618553	0,096156109	0,365393	0,653861541	0,269237	0,038462	0,692324	0,038462	0,096156	0,005769	0,038462444
16726	0,600031	0,161546858	0,115390613	0,438484	0,784656167	0,323094	0,046156	0,830812	0,046156	0,115391	0,006923	0,046156245
19809	0,700036	0,188471206	0,13462229	0,511565	0,915431572	0,376942	0,053849	0,96928	0,053849	0,134622	0,008077	0,053848916
20000	0,706753	0,190279728	0,135914091	0,516474	0,924215822	0,380559	0,054366	0,978581	0,054366	0,135914	0,008155	0,054365637

Figure 3.3 - Conditional probabilities of failure of FE and FC of SPP

t	IE	MCME	CS	CSPSC	BP	SPP	FFS	ME	RACSME	BDS	TPMEP	ED PSC
	0,26	0,035	0,047	0,081	0,13	0,09	0,01	0,16	0,01	0,019	0,003	0,01
0	0,26	0,035	0,047	0,081	0,13	0,09	0,01	0,16	0,01	0,019	0,003	0,01
2863	0,300014747	0,040386601	0,054233435	0,093466133	0,150007	0,103851	0,011539	0,184624	0,011539	0,021924	0,003462	0,011539
8616	0,400006834	0,053847074	0,072308928	0,124617514	0,200003	0,138464	0,015385	0,246158	0,015385	0,029231	0,004615	0,015385
13079	0,500011766	0,067309276	0,090386742	0,155772896	0,250006	0,173081	0,019231	0,3077	0,019231	0,036539	0,005769	0,019231
16725	0,600001185	0,08076939	0,108461753	0,186923446	0,300001	0,207693	0,023077	0,369231	0,023077	0,043846	0,006923	0,023077
19808	0,700000907	0,094230891	0,126538626	0,218077206	0,35	0,242308	0,026923	0,43077	0,026923	0,051154	0,008077	0,026923
20000	0,706753275	0,095139864	0,127759246	0,220180828	0,353377	0,244645	0,027183	0,434925	0,027183	0,051647	0,008155	0,027183

Figure 3.4 - Failure risk of FE and FC of SPP

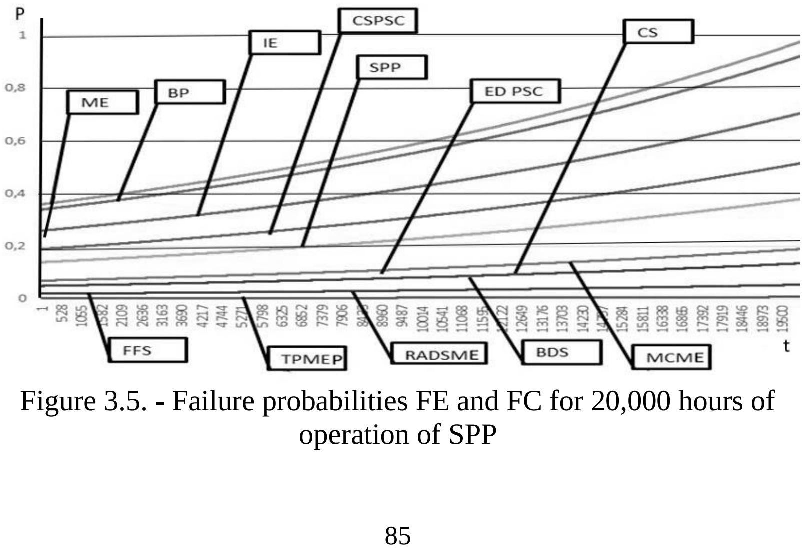

Figure 3.5. - Failure probabilities FE and FC for 20,000 hours of operation of SPP

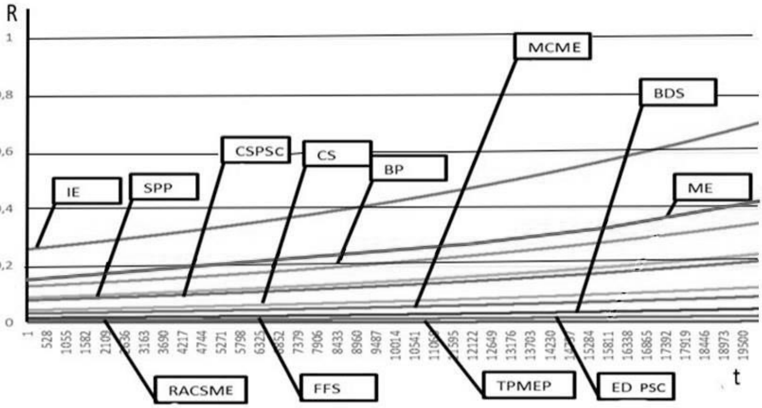

Figure 3.6 - Failure risk of FE and FC for 20,000 hours of operation of the SPP

The research results indicate that one of the highest failure risk values, 0.35, occurs when the input element failure risk varies from 0.26 to 0.70 over 20,000 hours of subsystem operation in the BP subsystem (Fig. 3.6).

This subsystem is interdependent on the functioning of other SPP subsystems (IE, CAS, SPP).

The maximum failure risk value of 0.43 was recorded when the input element failure risk varied from 0.26 to 0.70 over 20,000 hours of operation in the ME subsystem. This is explained by the significant influence on the ME's technical state by its interconnected subsystems: IE – CAS – RACSME, IE – MCME – P1, and IE – CAS – P1.

To identify the potential causes of BP failures, a study was conducted using the BP subsystem failure cause investigation scheme shown in Fig. 3.7. The factors influencing the technical state of the BP subsystem are indicated in Fig. 3.8.

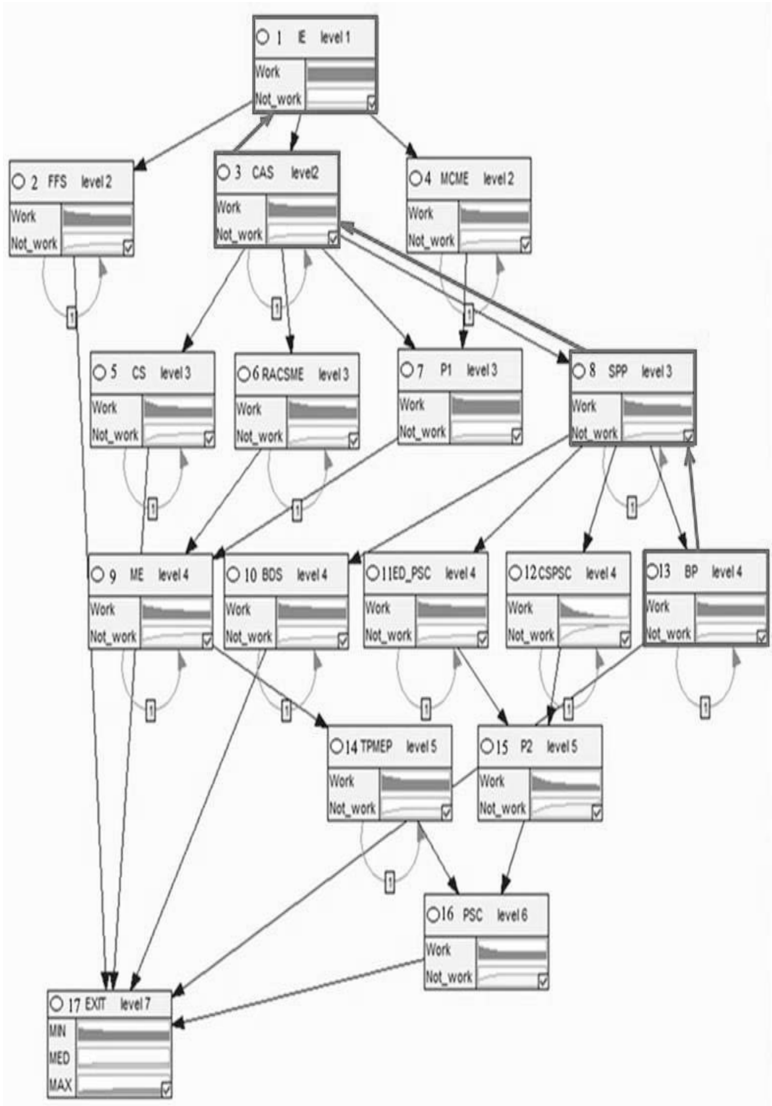

Figure 3.7 - Scheme of searching for the causes of failure of the BP subsystem

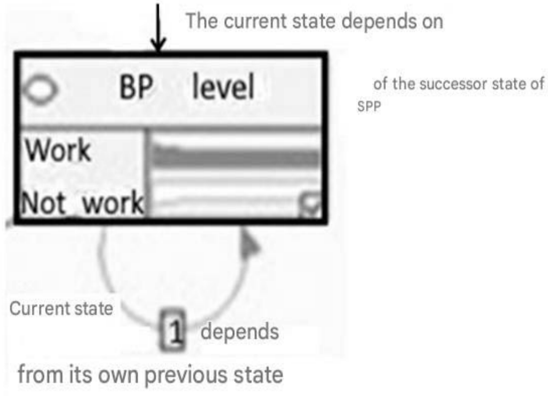

Figure 3.8 - Factors affecting the BP vehicle

The search for the causes of failures of the BP subsystem of the dynamic BNM was performed in accordance with the algorithm shown in Fig. 3.9.

When searching for the causes of failures of the BP subsystem for FE of the SPP BNM (Fig. 3.9), IE, CAS, SPP, BP: IE - CAS, CAS - SPP, SPP - BP are sets of failure risk at the initial time point and taking into account the dynamics of the TC in time based on a priori data on the intensity of failures:

$$R(Work^{1,2,3,4}_{1,3,8,13})_{t=0} = 0;\ R(Not\_work^{1,2,3,4}_{1,3,8,13})_{t=0} = 1;$$

$$R(Work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t=0} = 0;$$

$$R(Not\_work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t=0} = 1; \qquad (3.1)$$

$$R((Work^{1,2,3,4}_{1,3,8,13})_t\ /(Work^{1,2,3,4}_{1,3,8,13})_{t-1}) = 0{,}1;$$

$$R((Work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_t\ /(Work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t-1}) = 0{,}1$$

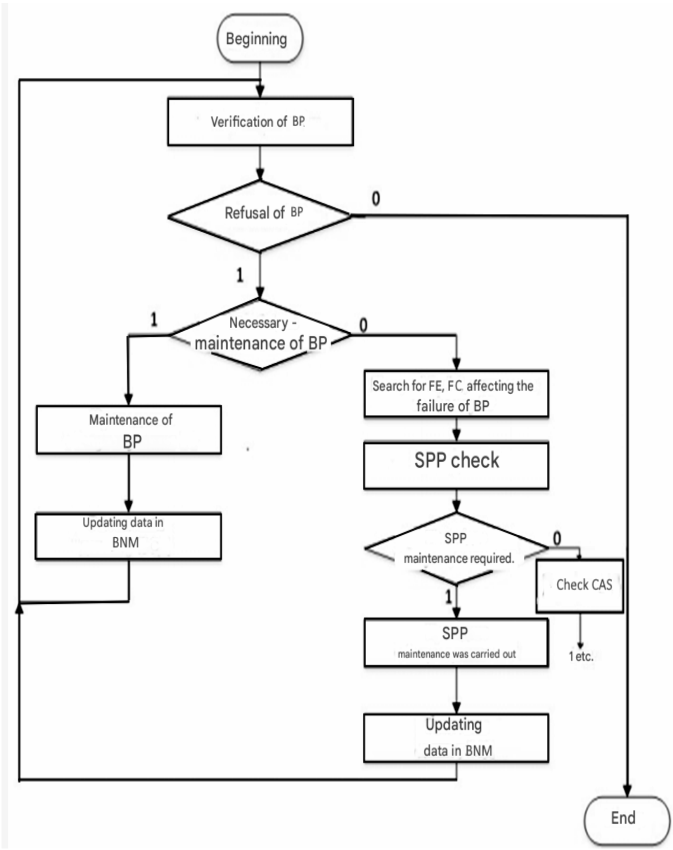

Figure 3.9 - Algorithm for finding a fault in the BP subsystem

Failure risk sets at the current moment of time, taking into account the previous FE and FC, may be within the limits:

- the level of failure risk is assessed as minimal, the consequences of an accident are minimal for:

$$R((Not\_work^{1,2,3,4}_{1,3,8,13})_t\ /(Work^{1,2,3,4}_{1,3,8,13})_{t-1}) = 0{,}1 - 0{,}2\,; \tag{3.2}$$

$$R((Not\_work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_t\ /(Work^{1,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t-1}) = 0{,}1 - 0{,}2$$

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

$$R((Not\_work^{1,2,3,4}_{1,3,8,13})_t\ /(Work^{1,2,3,4}_{1,3,8,13})_{t-1}) = 0{,}2 - 0{,}37; \quad (3.3)$$

$$R((Not\_work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_t\ /(Work^{1,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t-1}) = 0{,}2 - 0{,}37$$

- the risk of failure is assessed as maximum, the consequences of an accident are significant at:

$$R((Not\_work^{1,2,3,4}_{1,3,8,13})_t\ /(Work^{1,2,3,4}_{1,3,8,13})_{t-1}) = 0{,}37 - 0{,}63; \quad (3.4)$$

$$R((Not\_work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_t\ /(Work^{1,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t-1}) = 0{,}37 - 0{,}63$$

- the risk of failure is assessed as critical at:

$$R((Not\_work^{1,2,3,4}_{1,3,8,13})_t\ /(Work^{1,2,3,4}_{1,3,8,13})_{t-1}) = 0{,}63 - 1; \quad (3.5)$$

$$R((Not\_work^{2,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_t\ /(Work^{1,3,4}_{IE-CAS,CAS-SPP,SPP-BP})_{t-1}) = 0{,}63 - 1$$

ailure risk allocation of FE and FC in a dynamic failure-adjusted BNM is as follows:

- for the distribution of the risk of failure of the BP of the SPP:

$$\begin{aligned}
&R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Not_work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Not_work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Not_work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Not_work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Not_work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \quad (3.6) \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Not_work^2_{IE-CAS})_{t-1} \cdot R(Work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} + \\
&+ R(Work^4_{13})_t = R((Work^4_{13})_t\ /(Work^4_{13})_{t-1}) \cdot R(Work^1_1)_{t-1} \cdot R(Work^2_3)_{t-1} \cdot R(Work^3_8)_{t-1} \times \\
&\times R(Work^4_{13})_{t-1} \cdot R(Work^2_{IE-CAS})_{t-1} \cdot R(Not_work^3_{CAS-SPP})_{t-1} \cdot R(Work^4_{SPP-BP})_{t-1} +
\end{aligned}$$

$$+R(Work_{13}^{4})_{t}=R((Work_{13}^{4})_{t}/(Work_{13}^{4})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\cdot R(Work_{8}^{3})_{t-1}\times$$
$$\times R(Work_{13}^{4})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}\cdot R(Not\_work_{SPP-BP}^{4})_{t-1}$$

- o distribute the risk of failure of the SPP:

$$R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Work_{8}^{3})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\times$$
$$\times R(Work_{8}^{3})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}+$$
$$+R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Not\_work_{8}^{3})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\times \quad (3.7)$$
$$\times R(Not\_work_{8}^{3})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}+$$
$$+R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Work_{8}^{3})_{t-1})\cdot R(Not-work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\times$$
$$\times R(Work_{8}^{3})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}+$$
$$+R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Work_{8}^{3})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Not\_work_{3}^{2})_{t-1}\times$$
$$\times R(Work_{8}^{3})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}+$$
$$+R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Work_{8}^{3})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\times$$
$$\times R(Work_{8}^{3})_{t-1}\cdot R(Not\_work_{IE-CAS}^{2})_{t-1}\cdot R(Work_{CAS-SPP}^{3})_{t-1}+$$
$$+R(Work_{8}^{3})_{t}=R((Work_{8}^{3})_{t}/(Work_{8}^{3})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\times$$
$$\times R(Work_{8}^{3})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}\cdot R(Not\_work_{CAS-SPP}^{3})_{t-1}$$

- to distribute the risk of CAS failure of the SPP:

$$R(Work_{3}^{2})_{t}=R((Work_{3}^{2})_{t}/(Work_{3}^{2})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}+ \quad (3.8)$$
$$+R((Work_{3}^{2})_{t}/(Not\_work_{3}^{2})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Not\_work_{3}^{2})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}+$$
$$+R((Work_{3}^{2})_{t}/(Work_{3}^{2})_{t-1})\cdot R(Not\_work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\cdot R(Work_{IE-CAS}^{2})_{t-1}+$$
$$+R((Work_{3}^{2})_{t}/(Work_{3}^{2})_{t-1})\cdot R(Work_{1}^{1})_{t-1}\cdot R(Work_{3}^{2})_{t-1}\cdot R(Not\_work_{IE-CAS}^{2})_{t-1}$$

- to distribute the risk of failure of the SPP input component:

$$R(Work_{1}^{1})_{t}=R((Work_{1}^{1})_{t}/(Work_{1}^{1})_{t-1})\cdot R(Work_{1}^{1})_{t-1}+ \quad (3.9)$$
$$+R((Work_{1}^{1})/(Not\_work_{1}^{1})_{t-1})\cdot R(Not\_work_{1}^{1})_{t-1}$$

The use of BNM in the process of diagnosing the risk (probability) of FE and FC failures aims to obtain posterior conclusions.

This is achieved by recalculating prior data to assess the risk or failure probability values, which serve as the initial information for analyzing new data.

Posterior conclusions are based on the results of data analysis processes obtained through the application of BNM.

Following modeling with prior and posterior data, the probabilities (risks) of FE and FC failures in the SPP, which affect the main engine's operability and the overall system performance over various time intervals within 20,000 hours, are determined (Figs. 3.10–3.32).

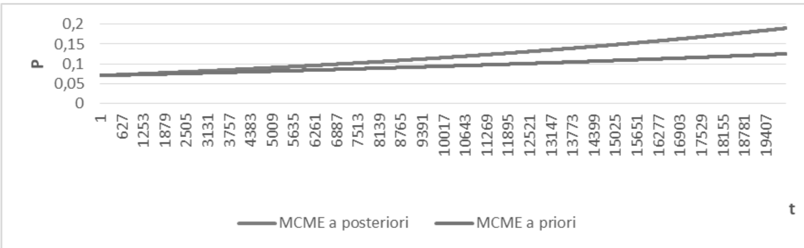

Figure 3.10 - A posteriori and a priori estimates of the probability of failure of the MCME subsystem

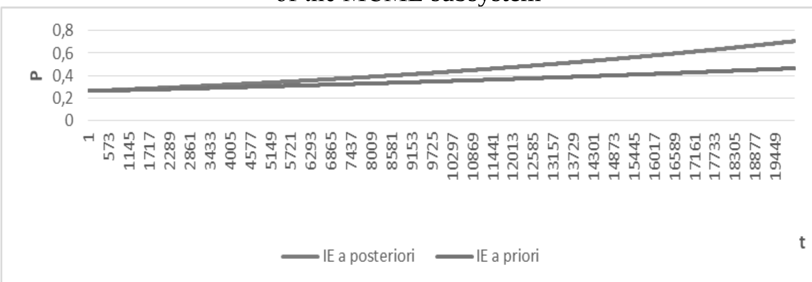

Figure 3.11 - Posterior and a priori estimates of the probability of failure of the IE subsystem

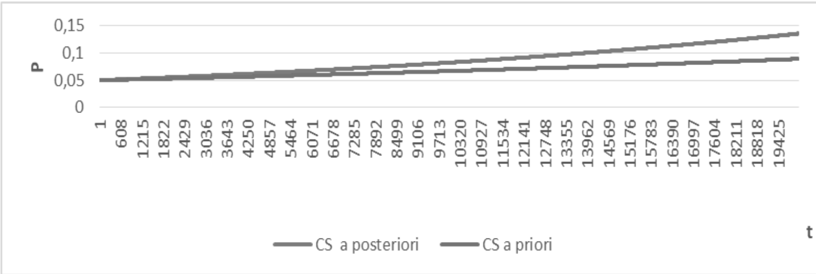

Figure 3.12 - A posteriori and a priori estimates of the probability of failure of the CS subsystem

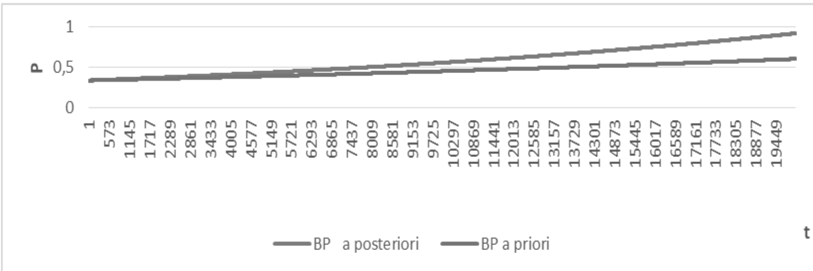

Figure 3.13 - A posteriori and a priori estimates of the probability of failure of the BP subsystem

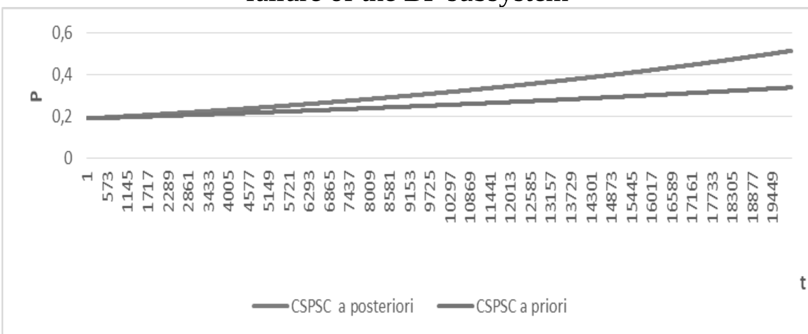

Figure 3.14 - A posteriori and a priori estimates of the probability of failure of the CSPSC subsystem

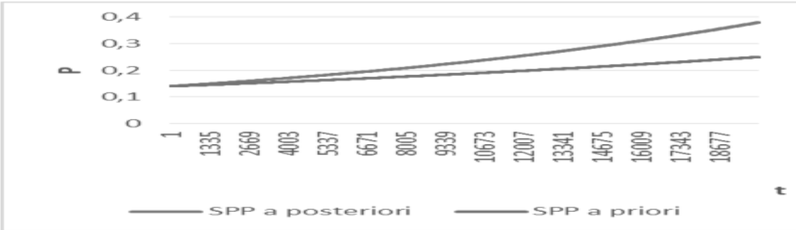

Figure 3.15 - Posterior and a priori estimates of the probability of failure of the SPP subsystem

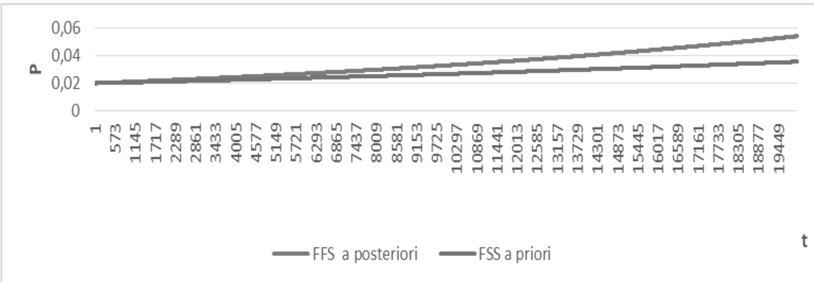

Figure 3.16 - A posteriori and a priori estimates of the probability of failure of the FFS subsystem

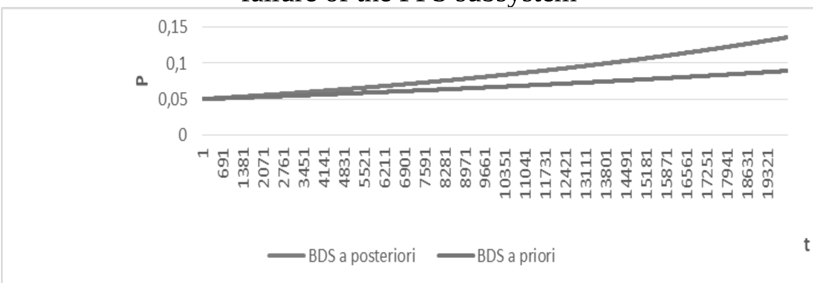

Figure 3.17 - Posterior and a priori estimates of the probability of failure of the BDS subsystem

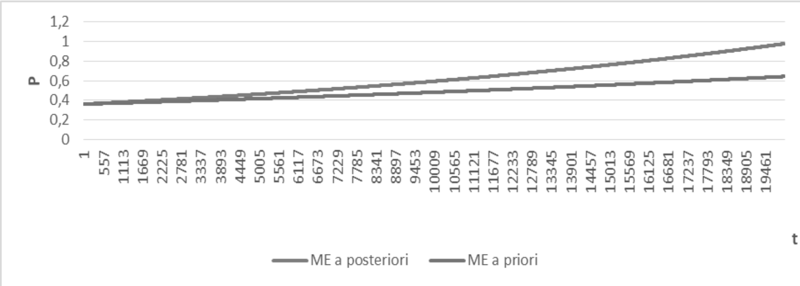

Figure 3.18 - A posteriori and a priori estimates of the probability of failure of the ME subsystem

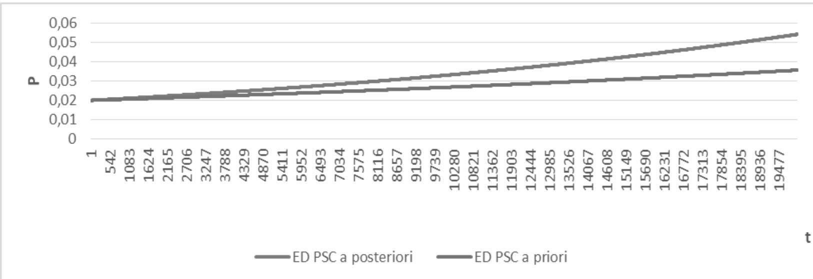

Figure 3.19 - A posteriori and a priori estimates of the probability of failure of the ED PSC subsystem

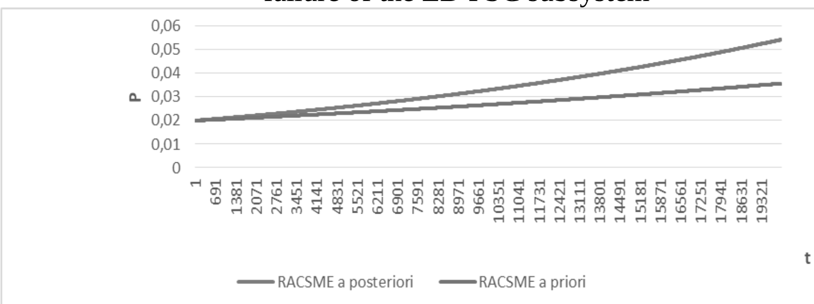

Figure 3.20 - Posterior and a priori estimates of the probability of failure of the RACSME subsystem

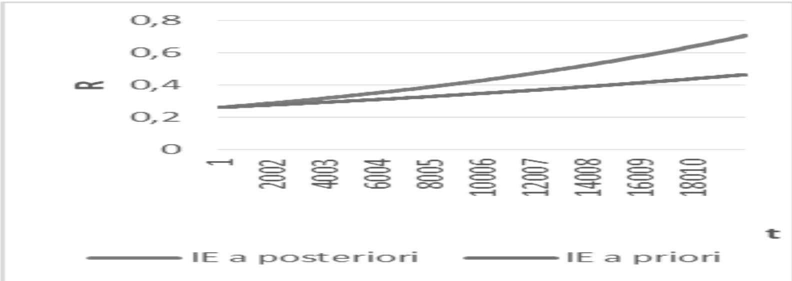

Figure 3.21 - A posteriori and a priori estimates of the risk of failure of the SPP input component

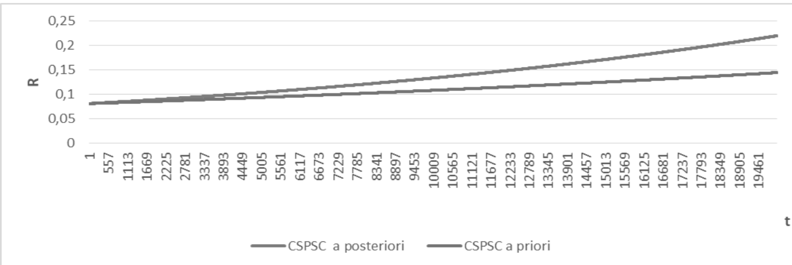

Figure 3.22 - A posteriori and a priori estimates of CSPSC subsystem failure risk

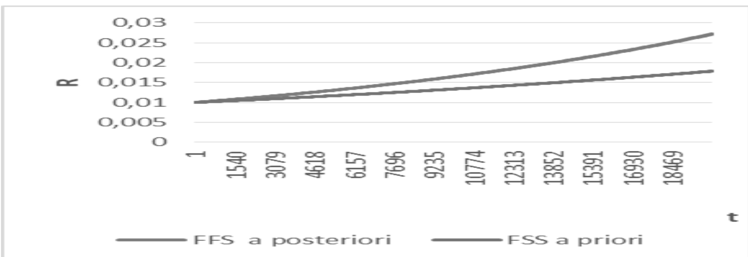

Figure 3.23 - A posteriori and a priori risk assessments of FSS subsystem failure

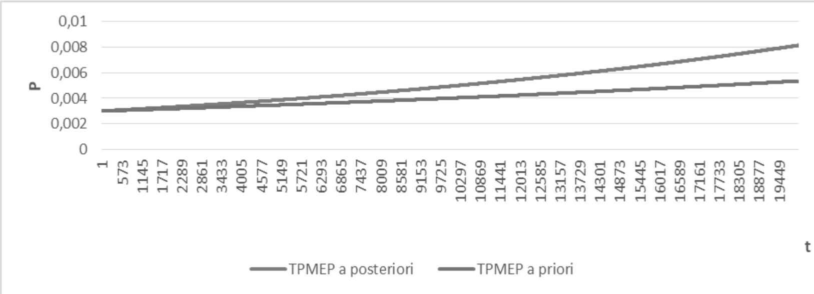

Figure 3.24 - Posterior and a priori estimates of the probability of failure of the TPMEP subsystem

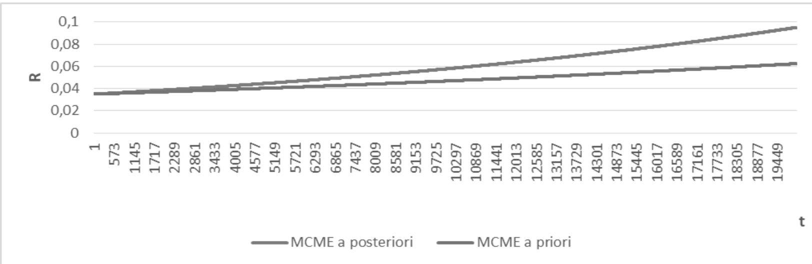

Figure 3.25 - A posteriori and a priori estimates of the risk of failure of the MCME subsystem

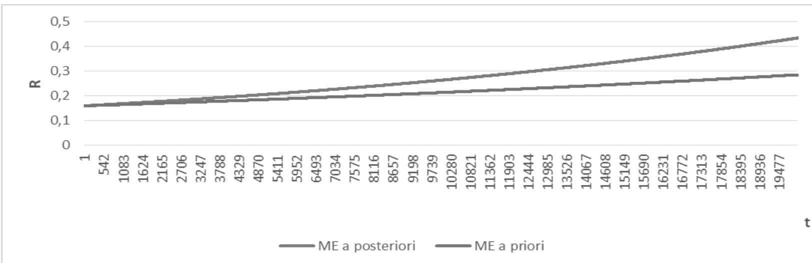

Figure 3.26 - A posteriori and a priori risk assessments of ME subsystem failure

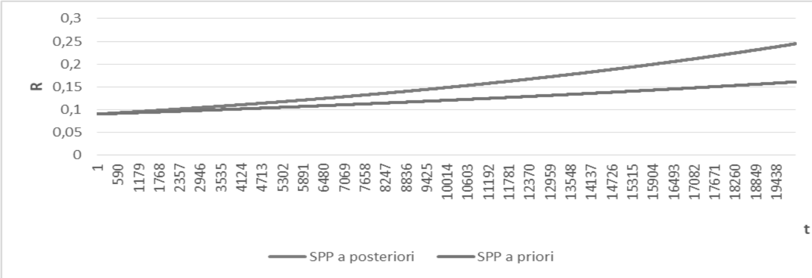

Figure 3.27 - A posteriori and a priori risk assessments of SPP subsystem failure

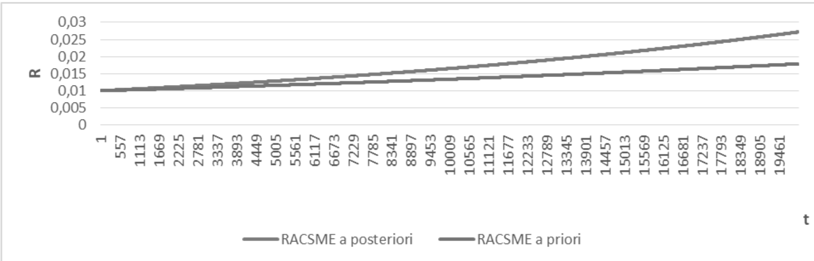

Figure 3.28 - A posteriori and a priori risk assessments of the RACSME subsystem failure

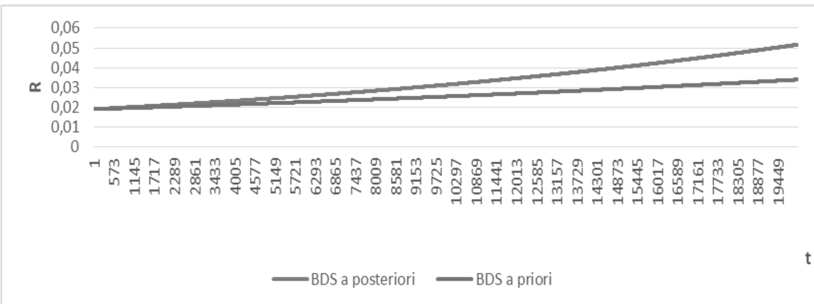

Figure 3.29 - A posteriori and a priori risk assessments of the BDS subsystem failure

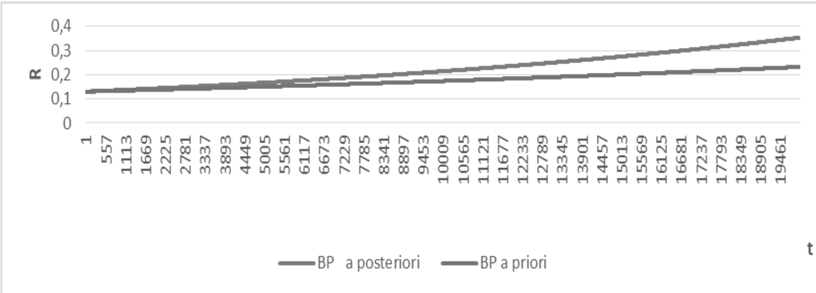

Figure 3.30 - A posteriori and a priori estimates of the risk of failure of the BP subsystem

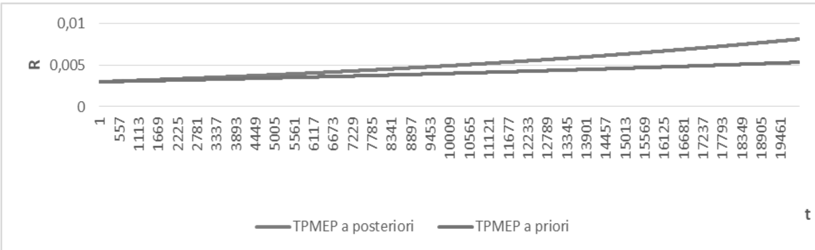

Figure 3.31 - A posteriori and a priori risk assessments of the TPMEP subsystem failure

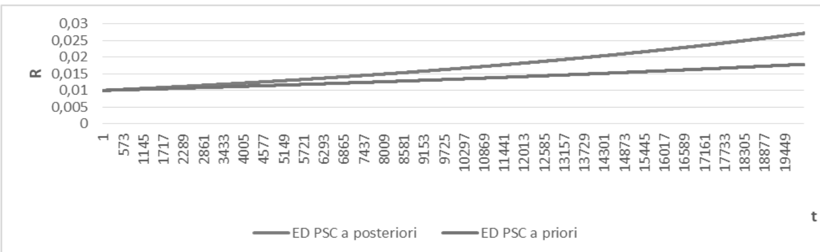

Figure 3.32 - A posteriori and a priori risk assessments of ED PSC subsystem failure

It has been confirmed that the most critical FE and FC with the highest predicted probabilities and risks of failure are BP and ME. Since the BP and ME subsystems are interdependent within the hierarchical structure of the SPP, a thorough examination of the CTS was conducted to identify the causes of the high risk (probability) values for their failures.

The use of dynamic BNM enabled the diagnosis of the probability (risk) of CTS failures during the modeling of interdependencies between different failure probability (risk) values.

The results of developing the CTS diagnostic model with incomplete technological data and its implementation in an intelligent system for diagnosing the risk of FE and FC failures in critical MPP applications provided prior information about the technical state of each subsystem (component) of the complex system.

Posterior characteristics obtained from the study results during the diagnosis of the TS of the SPP over 20,000 hours of operation show that the risk values of FE and FC failures vary slightly from the prior characteristics. This does not contradict the expert failure risk values for FE and FC of the ship's CTS recorded in the OREDA database. The TS indicator for the CTS and its FE and FC—posterior failure risk—is focused on making a reliable conclusion about system failures and their FE and FC.

The calculation of the posterior distribution of variables provided reliability assessments for the CTS to minimize losses from subsystem (component) failures and reduce the probability of erroneous decisions. The studies confirmed that the developed model and method, considering the hierarchical levels of FE and FC for intelligent diagnostics of CTS failure risks and identifying the causes of failures, allow for monitoring the risk (probability) of failures as new information becomes available about FE and FC failure risks in the current and future periods over 20,000 hours.

An intelligent diagnostic method for FE and FC failure risks in CTS with varying degrees of operability loss and incomplete system data was developed using the CPP as an example. This method relies on prior information about failures linking the types of TS of FE and FC.

The diagnostic results reflecting the failure risks of FE and FC confirmed that the model can be considered conceptual. Thus, the studies demonstrated that the developed stochastic model and diagnostic method of TS, which account for partial and complete operability losses with retrospective analysis of their causes, identification of the most vulnerable FE and FC, and implementation of appropriate measures, enable the exclusion or reduction of repeat failures. This approach fulfills the task of improving the efficiency and reliability of FE and FC operation in CTS.

The practical implementation of the proposed method for assessing FE and FC failure risks in SPP can be extended to any CTS structure of any complexity with varying interdependencies between FE and FC.

3.2 Research and Analysis of the Cognitive Simulation Model for Diagnosing the Technical State of Complex Critical Systems

The studies in Section 3.1 enabled the diagnosis of FE and FC failure risks in CTS but did not address the functioning of systems in extreme emergency situations. To diagnose the TS of equipment systems considering their interconnections and interactions, as well as to track system responses to failure risks with non-obvious causes, a cognitive simulation model was developed.

Cognitive simulation modeling complements the results obtained in Section 3.1 by studying models and methods for diagnosing FE and FC failure risks under simulated impacts in unpredictable external conditions and internal damaging factors in extreme emergency situations.

The goal of cognitive simulation modeling is to generate and test hypotheses about CTS failure risks and derive FE and FC failure risks that explain the causes of CTS failures. One advantage of the CSM-based information system for CTS is its ability to process scenarios with varying probabilities of failure, addressing "What if?" questions.

The studies consider both the position and role of FE and FC in CTS and the risk (probability) of their failures under defeat modelling pulse (DMI) impacts. The influence of DMI on the system is modeled as closely as possible to reality. This allows for evaluating possible scenarios of development and consequences of FE and FC failures in CTS. DMI propagates from the affected FE (a node in the digraph) to adjacent FE (nodes), transitioning them to a failed state. Each node and edge in the CTS digraph in CSM has a failure indicator ranging from 0 (failed) to 1 (operational). DMI is modeled as an impulse vector containing DMI values, indicating the degree of impact on the respective node in the digraph, ranging from 0 (node remains unaffected) to 1 (node completely fails). It is assumed that DMI propagates along the edge between two nodes in the digraph within a discrete time period.

To achieve the research objective of diagnosing CTS failure risks and identifying causes of FE and FC failures using the method implemented in CSM, software was developed. The listing is provided in Appendix G.

The studies utilized a digraph of an ICE as an example, as shown in Section 2.2 (Fig. 2.4). The model was activated using GNU Make tools, and visualizations were generated with Graphviz. The modeling process has the following structure (Fig. 3.33): the initial model is defined as a JSON file, which is processed by a Python program to generate a set of tables in CSV format and diagrams in DOT format. The Make utility processes DOT files using Graphviz to produce a set of TS diagrams for the complex system in PNG format.

For the analysis of obtained results, Calc LibreOffice is used. Utilizing the JSON format allows for conveniently and efficiently defining the structure and configuration of available equipment.

One of the advantages of working with the JSON format is the ability to formalize the complete system specification (with numerical characteristics of nodes, configuration, and the digraph of inter-node connections) within a single file.

The JSON file can be edited manually using text editors or via automated tools for data collection and processing.

The propagation of diagnostic impulses through the system can be represented graphically or as CSV-based scenarios.

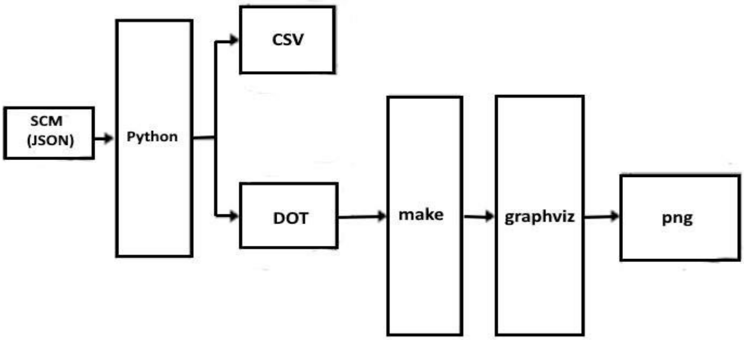

Figure 3.33 - Modelling process in the Debian GNU/Linux environment

This process generates a separate intermediate protocol file for step-by-step DMI propagation, as well as a final CSV file summarizing the protocols and calculating numerical failure risk metrics for various system changes.

The generated CSV files contain calculated characteristics for any FE of the CTS based on the specified topology.

These CSV files can be used in various analytical software tools, such as spreadsheet editors (e.g., Microsoft Excel or LibreOffice) or advanced visualization systems like Gnuplot, R, Statistica, or Seaborn.

By combining JSON, CSV, and DOT formats, the system manages configuration and analyzes the CTS considering different aspects, including visual, automated, and their combinations. Preliminary analysis of the obtained characteristics can be performed visually using DMI propagation diagrams.

Methods employing automated behavior utilize CSV files to numerically analyze system characteristics and generate and evaluate solutions.

Thus, the method for diagnosing FE failure risks under various operating conditions within the CTS framework is based on describing the state functionalities and the CSM of the system's structural FEs.

This enables an assessment of the operational level of CTS FEs based on DMI impacts on the CSM, as well as the influence of corresponding FEs on the overall system structure under different emergency scenarios.

The values of the DMI vector are determined sequentially before each iteration of its propagation across all vertices and edges of the MTS CSM digraph.

If the DMI does not reach the terminal vertices of the digraph, the next computational iteration is performed.

In such cases, the obtained DMI vector values are recorded in a text file and can later be used to assess the structural failure of the CSM TS along the edges or vertices of the constructed digraph.

After completing the cycle for evaluating the structural failure risk of the CTS CSM, the text file is analyzed.

Based on the obtained DMI vector values, calculations are performed to determine the coefficients of structural threats and failure risks, which are displayed in the program window and added to the text file.

The simulation results in the CSM form values for structural loss assessments and failure risks based on the probabilities of FE and FC failures in the ICE. These results are used for ranking the calculations (Figs. 3.34–3.37).

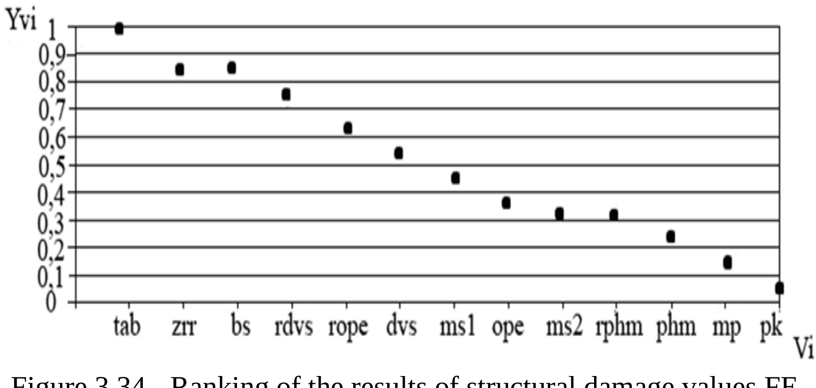

Figure 3.34 - Ranking of the results of structural damage values FE

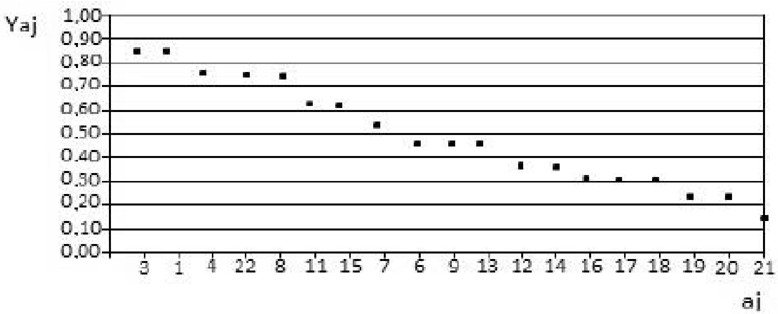

Figure 3.35 - Ranking of the results of structural damage values FS

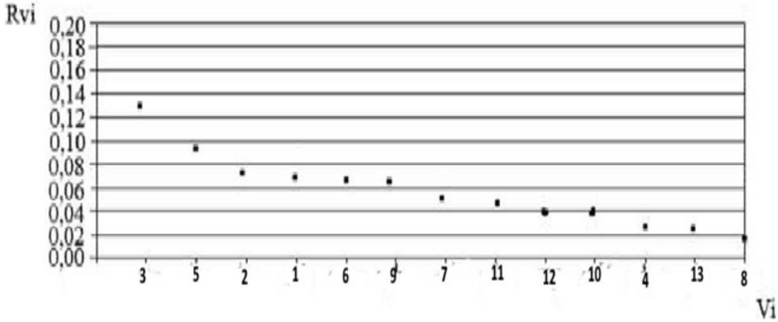

Figure 3.36 - Ranking of the results of the structural risk of failure FE

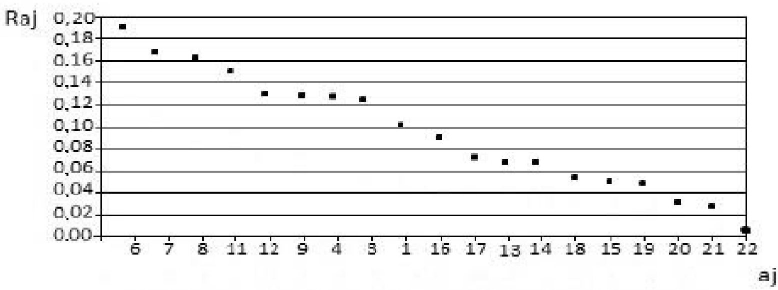

Figure 3.37 - Ranking of the results of the structural risk of failure FS

The research results demonstrate that the application of DMI significantly influences the process of its propagation across the CTS CSM digraph.

Taking into account such structural features of the digraph as connectivity, the presence of loops, vertex vulnerability, and the type of FC resource, the most connected FEs of the digraph affected by the FCs were identified.

The findings on structural losses of ICE FEs indicate that the most critical FEs are the battery, ignition system, and combustion chamber, with high structural damage values resulting from failures (1.0, 0.85, and 0.75, respectively).

Less critical elements include the transmission system and the driving wheels, which show slightly lower structural damage values from failures (0.15 and 0.05).

Among the least vulnerable ICE FEs and subsystems is the fuel injection regulator (0.02). Comparatively low structural failure risk values for CTS FEs are attributed to minor structural damage caused by equipment failures.

This confirms the correctness of the topology design for the arrangement of ICE FEs and FCs during the system's development.

The developed CTS CSM substantiates the feasibility of using DMI for diagnosing the failure risk of FEs and FCs in CTS.

The advantages of the developed CSM include its simplicity, clarity, and applicability for diagnosing the failure risk of a wide range of CTS.

The CSM procedures are easily formalized and transformed into computational algorithms and models for diagnosing failure risk, which is particularly important for CTS with a large number of FEs and FCs.

Thus, the conducted research revealed that the developed CSM reflects a direct relationship between the failure risk of CTS FEs and FCs and the system's topology. It also enables the identification of the least functional FEs and FCs, whose operation significantly impacts the system's performance, efficiency, and reliability.

3.3 Conclusions for Chapter three

In Chapter three, the results of research and analysis of stochastic models and the method for diagnosing complex CTS systems were presented.

The goal of the research on the developed models is to diagnose CTS vulnerabilities, including subsystems, components, elements, and their interconnections over time, considering partial and complete functionality failures. The chosen object for the study was the ICE.

The input data for modeling failure risk (probability) diagnostics based on the CTS CSM include the object's schematic and operating principles, as well as expert evaluations. Cognitive simulation modeling was conducted to simulate the impacts on CTS equipment under unpredictable external influences, internal damaging factors, and extreme emergency scenarios. During the modeling process, a damaging impulse was applied to the system in conditions as close as possible to real-world CTS operating environments. The cognitive simulation modeling was implemented through the development of specialized software.

The procedures of the method are easily transformed into a model for diagnosing failure risk (probability), which is crucial for CTS with a large amount of equipment.

This approach enabled the tracking of consequences and CTS responses to failure risk (probability) from less apparent sources and causes. Using the method for diagnosing failure risk (probability) in CTS equipment allows for the identification and visualization of structural and functional vulnerabilities.

Methods for intelligent failure risk diagnostics of subsystems, components, and elements under various CTS conditions and incomplete data, using technical and technological foundations, were confirmed through the example of ICE.

The developed models can be considered conceptual. Applying the research results of the developed models, along with retrospective analysis of emergency scenarios, enhances the effectiveness of CTS diagnostics and, consequently, the efficiency of CTS operation.

CHAPTER 4
DEVELOPMENT OF A METHOD FOR ASSESSING AND PREDICTING THE TECHNICAL CONDITION OF COMPLEX CRITICAL APPLICATION SYSTEMS

4.1 Development of an assessment and prediction method based on the case-based reasoning method for the technical condition of complex critical application systems

The growing complexity of technical systems, the diversity of their parameters, and the inadequacy of system descriptions require the improvement of management decisions under conditions of uncertainty to ensure the efficiency and reliability of FE and FC systems, based on the results of assessing and predicting their TC.

In order to improve the operation of shipboard critical application systems (CAS), decision-making becomes more complex due to the need to account for a significant number of various factors.

Primarily, this includes the need for a large volume of information about the system; accounting for the mutual influence of FE and its parameters on one another; partial and total failures.

When operating CAS, an important task remains the development and improvement of methods aimed not only at diagnosing the system but also at assessing and predicting the system’s technical condition.

That is, the development of IIS for assessing and predicting the technical condition of FE and FC of shipboard CAS under adverse impacts and disturbing factors is one of the promising directions for ensuring the efficiency and safety of such technical systems.

Based on the analysis of methods for assessing and predicting the technical condition of FE and FC of CAS, the method of structural representation was selected due to its advantages, including: the ability to formalize the nature of interconnected hierarchical interactions between FE systems; effective application for CAS operating under stochastic conditions; flexibility in implementing a production approach for the formation of knowledge bases in IIS; ease of software implementation based on an object-oriented approach; and the support for integrating automation tools to ensure interactive interpretation of results.

For the practical implementation and operation of the IIS, it is necessary to link the proposed models and methods (Sections 2 and 3) with heterogeneous a priori information, which includes indicators for diagnosing the technical condition of complex systems, along with an expert system containing computational, experimental, and expert data obtained during the operation of the CAS.

The development of a case-based reasoning method for the technical condition of complex critical application systems includes the following stages:

1. Representation of a case with a set of parameters with specific values and decisions.
2. Input of diagnostic data for the technical condition of a complex critical system into the IIS for assessing and predicting the technical condition of the system.
3. Obtaining assessment and prediction data for the technical condition of the complex critical system.
4. Transmitting assessment and prediction data for the technical condition of the system to the decision-making process.

IIS can be implemented either as standalone solutions or as modules that complement ready-made general-purpose management and decision-making systems with the necessary functionality.

These systems will enable the operational decision-making process during the removal of consequences from adverse impacts and disturbing factors, ensuring the effective operation of shipboard CAS through the ability to assess and predict their technical condition [155, 157].

The implementation of the strategy in the IIS for assessing and predicting the TC of complex systems (Fig. 4.1) is ensured by targeted actions in accordance with the IIS algorithm (Fig. 4.2) to find failures in FE and FC based on failure risk assessments.

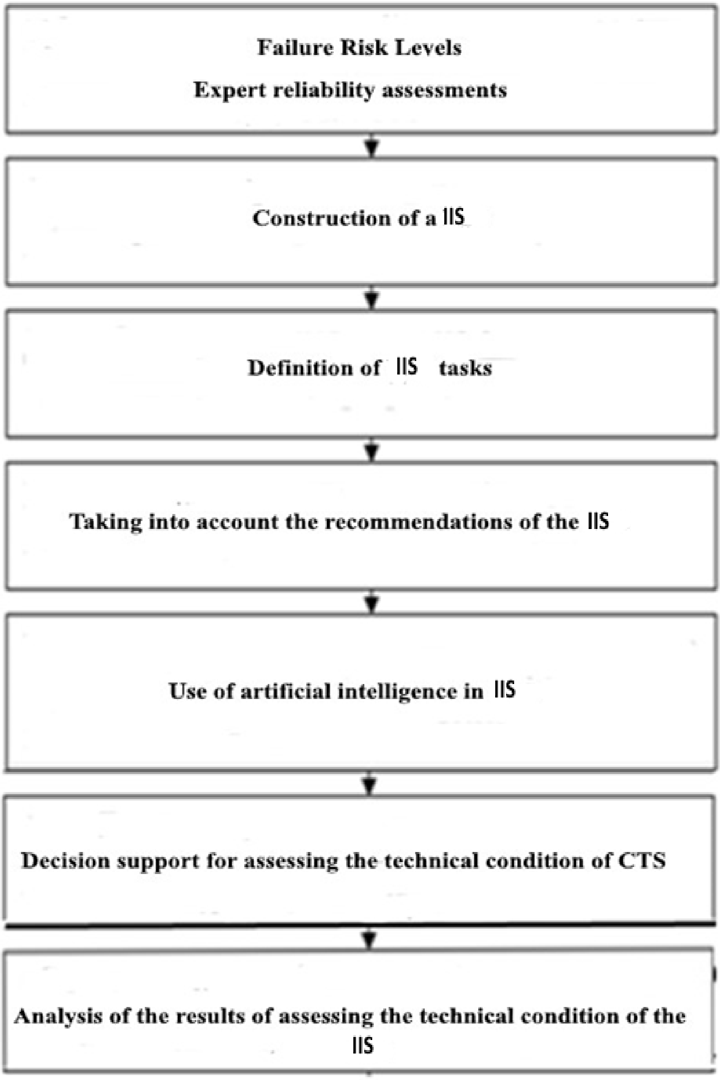

Figure 4.1 - The strategy of the IIS in assessing and predicting the TC of complex systems

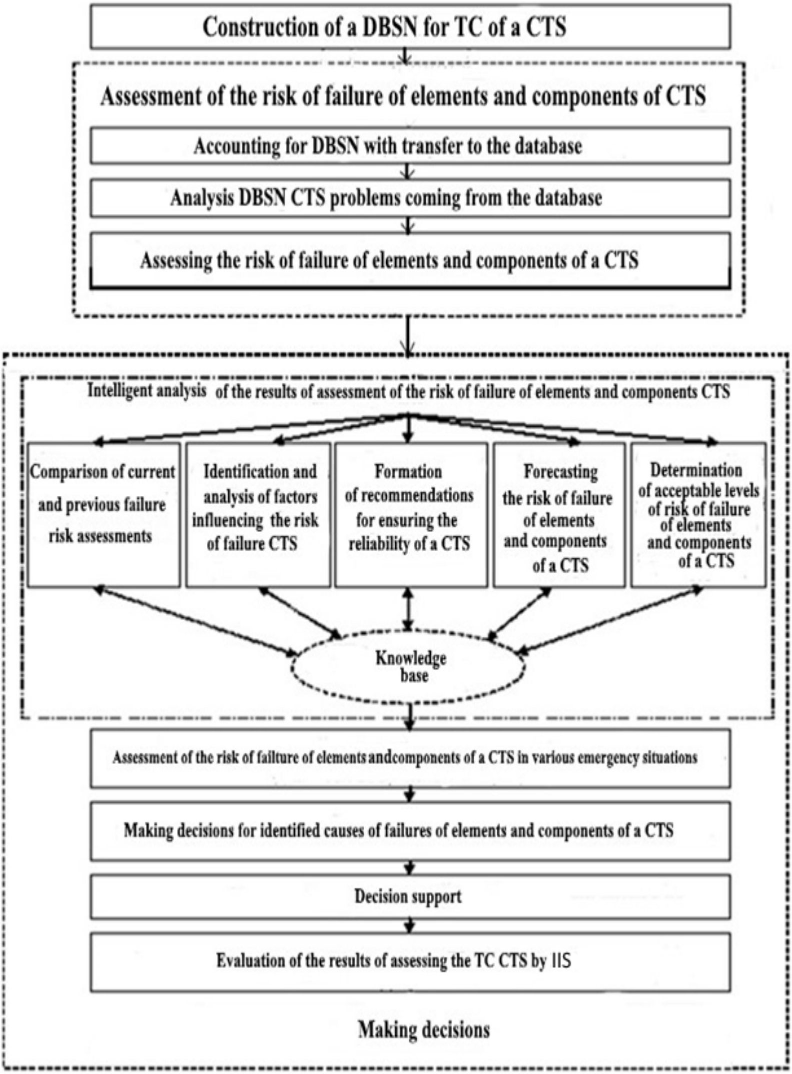

Figure 4.2 – IIS Algorithm for Failure Detection in CAS

The foundation for constructing the IIS is the formulation of the decision-making task in general terms:

$$N = f(F, G, A, FR, SG, P, C, PC, NS), \qquad (4.1)$$

where: F – the number of failures in the FE and FC of the CAS;

G – the set of set goals;

A – the set of possible alternatives;

FR – the set of failure rates in the FE and FC of the CAS;

SG,P,C – the set of characteristics, advantages, and criteria for ensuring the reliability of FE and FC of the CAS;

PC – the set of coordination principles for evaluating alternatives, taking into account individual criteria;

NS – the required solution to the problem.

The priority F represents the evaluation of the utility of the method for achieving the goal.

This is specified without distinguishing the features on which it was made or without the characteristics SG. The characteristics include the degree of achievement of the goal. To make the final choice of the method for achieving the goal, it is necessary to formulate criteria, the number of which is determined by the number of features. If the IIS uses multiple criteria, it is necessary to apply the coordination principles PC to harmonize the evaluation of alternatives for each criterion.

The problem-oriented knowledge base model in IIS is based on the following lists:

FE and FC that affect the failure-free operation of the CAS;

The state of the CAS during failure-free operation of the FE and FC systems;

Factors that can change the current reliability of the CAS;

Problem states that the CAS may enter under the influence of equipment failures.

The knowledge base is represented as a five-level hierarchical tree (Figure 4.3). Considering the hierarchical structure of the knowledge base allows for the quick localization of the cause of a defect or failure and reduces the time for assessing the technical condition of the complex system.

Knowledge acquisition and addition occur automatically during the training and implementation of the expert system. Knowledge is provided by an expert and is also adapted to changes in the subject area and its operational conditions.

This is achieved by replacing the rules or information in the KB within the IIS.

The main limitations of the methods and technologies currently used in the IIS relate to solving complex formalized problems due to the insufficient effectiveness of: solving training tasks, tuning, and adapting to the problem domain; processing incomplete and inaccurate input information; data interpretation; and accumulation of expert knowledge. These limitations in the IIS are eliminated by using the case-based reasoning (CBR) method [162].

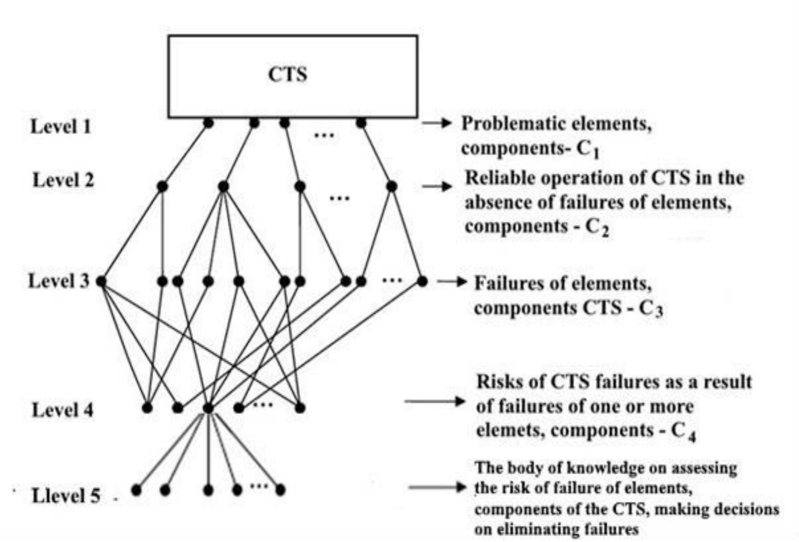

Figure 4.3 - Multi-level hierarchical structure of the knowledge base tree

The development and research of IIS using CBR, with the aim of increasing the effectiveness of the implementation of learning mechanisms and adaptation to the specifics of the problem environment for the relevant specific applications, as well as increasing the effectiveness of decision-making in DM based on the results of evaluation, forecasting of TC of complex systems is relevant.

Such development and research was carried out taking into account: partial and complete failures of FE and FS performance; a precedent model of knowledge based on a vehicle dynamics model from a serviceable state to complete failure. The TC dynamics model takes into account cause-and-effect relationships and the hierarchical structure of the TC, which consists of: elements (E); components (C); subsystems (S).

The description of the problematic situation during the operation of the CTS consists in the consequences of partial or complete loss of FE and FS of a complex system.

When using the method of reasoning based on precedents for the representation of precedents, a fairly simple parametric representation, i.e. presentation of a precedent in the form of a set of parameters with specific values and decisions (estimates, TC forecasts and recommendations to the person making the decision):

$$CASE = \left(R, P, D, W^{f}_{\theta_{S(C,E)_{n(m)}}}, W^{f}_{\omega_{I_{S(C)_{a(z)}}}}, RE, SS, RF, FF, DR\right), \quad (4.2)$$

where R,P,D are parameters (risk, probability, loss) describing the precedent;

$R\left\{R_{S(C,E)_{n(m)}}, R_{I_{S(C)_{a(z)}}}\right\}$ - sets of FE and FS CTS failure risk assessments and a decision maker recommendations;

$P\left\{P_{S(C,E)_{n(m)}}, P_{I_{S(C)_{a(z)}}}\right\}$ - sets of FE and FS CTS failure probability estimates and a decision maker recommendations;

$D\{D_{S(C,E)_{n(m)}}, D_{I_{S(C)_{a(z)}}}\}$ - sets of estimates of losses from failures of FE and FS CTS and recommendations of a decision maker;

$W^{f}_{\upsilon_{S(C,E)_{n(m)}}}$ - assessments of working capacity (partial or full) of FE and recommendations of a decision maker;

$W^{f}_{\omega_{I_{S(C)_{a(z)}}}}$ - evaluations of the operational capacity (partial or full) of the FS and recommendations of the OPR:

RE – sets of refined specific estimates of parameters of TC FE and FS CTS, decision-making ($re_1,\ldots re_N \in RE$);

S*S* - saving a set of refined estimates of parameters of TC FE and FS STS, adopted decisions;

RF - sets of refined certain predicted values of parameters of TC FE and FS of CTS, decision-making ($rf_1,\ldots rf_N \in RF$);

FF - preservation of a set of refined forecasted values of TC parameters FE and FS of TC, adopted decisions;

DR - diagnosis and recommendations of a decision maker [38]

$$R_{s(c,e)_{n(m)}} = \{r_{s(c,e)_{n(m)}} \mid s(c,e) = \overline{1, S(C,E)}, n_{s(c,e)} = \overline{1, N_{S(C,E)}}, m_{s(c)} = \overline{1, M_{S(C)}}\}, \quad (4.3)$$

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

where $r_{s(c,e)_{n(m)}}$ - is the risk of failures of FE CTS;

$r_{i_{s(c)_{a(z)}}}$ - the risk of FC CTS failures;

$n_{s(c,e)}$ - FE number in CTS;

$m_{s(c)}$ - the number of the hierarchical level of FC CTS;

$N_{S(C,E)}$ - number of FE CTS;

$M_{S(C)}$ - the number of hierarchical levels of FC CTS;

S, C, E – FE CTS;

I_S, I_C – FC CTS;

n, m – number, hierarchical level in the CTS;

a – number of intercomponent communication;
z - is the number of intersystem communication.
A - the number of intercomponent connections;
Z - is the number of intersystem connections

$$P_{S(C,E)_{n(m)}} \cdot \lambda(t)_{S(C,E)_{n(m)}} = \frac{\alpha_{S(C,E)_{n(m)}} \cdot \exp(-\alpha_{S(C,E)_{n(m)}} \cdot T_{S(C,E)_{n(m)}})}{\exp(-\alpha_{S(C,E)_{n(m)}} \cdot T_{S(C,E)_{n(m)}})} = \alpha_{S(C,E)_{n(m)}}, \quad (4.4)$$

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

where λ - is the intensity of failures;

α – distribution parameter, $\alpha \approx 1/(T_o)\hat{}$, (T*o*) – estimate of average service life before failure

Quantitative assessment of damage from failure $n(m,e)$ - subsystem, component, element to determine the risk of failure:

$$D_{S(C,E)_{n(m)}} = \{d_{s(c,e)_{n(m)}} \mid s(c,e) = \overline{1, S(C,E)}, n = \overline{1,N}, m = \overline{1,M}\}, \quad (4.5)$$

where $d_{s(c)_{n(m)}}$ - losses from failure of FE CTS

Quantitative assessment of losses from failure $a(z)$ - FC determination of the risk of failure:

$$D_{I_{S(C)_{a(z)}}} = \{d_{I_{s(c)_{a(z)}}} \mid i_{s(c)} = \overline{1, I_{S(C)}}, a = \overline{1, A}, z = \overline{1, Z}\}, \quad (4.6)$$

where $d_{i_{s(c)_{a(z)}}}$ - is the loss from failure FC

Performance of FE at different degrees of its loss:

$$W^{f}_{\upsilon_{S(C,E)_{n(m)}}} = \{W_f^{<n_{s(c)}, m_{s(c)}>} \mid f = \overline{0,1}; n_{s(c,e)} = \overline{1, N_{S(C,E)}}; m_{s(c)} = \overline{1, M_{S(C)}}\} \quad (4.7)$$

Functional capacity of FC at different degrees of its loss:

$$W^{f}_{\omega_{I_{S(C)_{a(z)}}}} = \{W_f^{<a,z>} \mid f = \overline{0,1}; a = \overline{1, A}; z = \overline{1, Z};\} \quad (4.8)$$

In the process of functioning of FE CTS in emergency scenarios, taking into account Harrington's generalized desirability function, they can be in one of the following TC [38]: 0 - 0.2 - the level of risk and consequences are minimal, which do not affect the operation of CTS (RMi); 0.2 - 0.37 - the level of risk is acceptable and the consequences are insignificant, allowing the operation of the CTS without repair (RA); 0.37 – 0.63 – the level of risk is maximum, the consequences are significant, but allowing the operation of the CTS during repair work (RMa); 0.63 - 1.0 - the level of risk is critical, the consequences are catastrophic, preventing the operation of the CTS (RC).

Taking into account [39] for the hierarchical structure of CTS, TC transitions are possible in the form of a TC matrix (Fig. 3). In Fig. 3, k_e, k_c, k_s are the weight (significance) coefficients of an element, component, subsystem in the structures of the CTS.

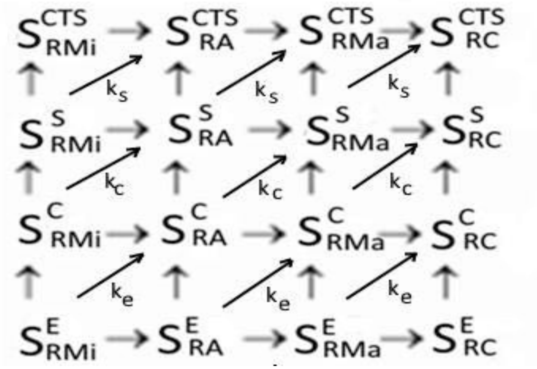

Figure 4.4 - CTS TC matrix

4.2 Development of the Data Reception and Transmission Model for Diagnosis, Assessment, and Prediction of the Technical Condition of Complex Critical Application Systems

To successfully address the issue of effective, failure-free operation of CAS in emergency operating modes, it is necessary to utilize information technologies with software and hardware modules for receiving and transmitting the results of diagnostics, assessment, and prediction of the TC of complex systems [1, 174, 175].

The quality of the data reception and transmission system (DRTS) is determined by a set of characteristics that influence its operational efficiency: topology; bandwidth; performance; acceptable error margin in data reception and transmission; effectiveness of information protection in the system; risk of failure of DRTS devices.

When developing the data reception and transmission model for diagnosing, assessing, and predicting the TC of complex critical systems, it is necessary to consider the presence of multiple conflicting requirements and competing criteria.

To justify the choice of the DRTS topology, it is necessary to solve the task of multi-parameter, multi-criteria optimization of information parameters aimed at increasing performance, minimizing errors and failure risks in subsystems, components, and elements of CAS, and maximizing the protection of the received and transmitted information.

The application of optimization methods to solve practical multi-criteria, multi-parameter optimization problems [176, 177] must account for: large problem dimensions (tens and hundreds of variables and constraints); topological complexity of the optimized function; significant computational costs; the need to solve the problem in a multi-criteria context, using unrelated models.

The operation of an open platform for DRTS may rely on ISO standards in the field of Condition Monitoring and Diagnostics of Machines [178].

Using a standard base ensures the unification of approaches to receiving and transmitting information.

The reception and transmission of information are carried out based on one of the standards for digital DRTS, such as IEEE 802.15, WiMax, IEEE 802.22, UMTS, LTE.

The quality of the DRTS model's operation is determined by a set of characteristics influencing its performance: topology $\{F_o\}$; bandwidth $\{B\}$; performance $\{T_\Sigma\}$; acceptable error margin in data reception and transmission $\{\sigma\}$; effectiveness of information protection in the system $\{Z_\Sigma\}$; risk of failure of DRTS devices $\{R_\Sigma\}$.

It is assumed that the model describing the DRTS is linear, with both deterministic and concentrated stochastic parameters.

The set of quality indicators of the model can be represented as a vector, whose coordinates are the individual indicators, and their given values need to be improved to the required level.

A model for data reception and transmission during the diagnosis, assessment, and prediction of the TC of complex critical systems is proposed as a function of its functionality:

$$< MPP >= f(H), \tag{4.9}$$

$$H = \{\{F_0\},\{T_\Sigma\},\{B\},\{\delta\},\{R_\Sigma\},\{Z_\Sigma\}\}$$

The generalized quality indicator of the DRTS operation is determined based on the results of optimizing the information parameters and its reliability characteristics. The objective function for optimizing the information parameters of the model is a multi-parameter optimization of variables that affect the performance of the DRTS:

$$\varphi(F) = \max\, \varphi(F_o) = \max\, \varphi(L, C, S)\,, \tag{4.10}$$

$$L = \left\{L_o \in L \middle| L_{\min} \angle L \angle L_{\max}\right\}, C = \left\{C_o \in C \middle| C_{\min} \angle C \angle C_{\max}\right\},$$

$S = \left\{S_o \in S \middle| 0 \angle C \angle C_o\right\}$,where L – the length of the data transmission and reception paths;

C – the compactness of the system structure;

S – the degree of centralization of the system structure;

D_0, K_0, C_0 – normalized individual criteria of the system topology performance, obtained by converting the indicators into dimensionless form.

The objective function for optimizing the DRTS operating time:

$$\varphi(T) = \max \varphi(T_\Sigma) = \max \varphi\left(\sum_{l=1}^{p} T_{S_{no_i}}, T_{KO}, T_{C1}, T_C, T_{DC}, T_{PT}, T_{RP}, T_{TG}, T_{LN}, T_{C2}\right), \tag{4.11}$$

$$T=\left\{T_{S_{no_i}}\in T\left|T_{So_{\min}}\angle T_{So}\angle T_{So_{\max}}\right.\right\},T=\left\{T_{KO}\in T\left|T_{KO_{\min}}\angle T_{KO}\angle T_{KO_{\max}}\right.\right\},$$

$$T=\left\{T_{C1}\in T\left|T_{C1_{\min}}\angle T_{C1}\angle T_{C1_{\max}}\right.\right\},T=\left\{T_{RP}\in T\left|T_{RP_{\min}}\angle T_{RP}\angle T_{RP_{\max}}\right.\right\},$$

$$T=\left\{T_{DC}\in T\left|T_{DC_{\min}}\angle T_{DC}\angle T_{DC_{\max}}\right.\right\},T=\left\{T_{C2}\in T\left|T_{C2_{\min}}\angle T_{C2}\angle T_{C2_{\max}}\right.\right\},$$

$$T=\left\{T_{C}\in T\left|T_{C_{\min}}\angle T_{C}\angle T_{C_{\max}}\right.\right\},\ T=\left\{T_{LN}\in T\left|T_{LN_{\min}}\angle T_{LN}\angle T_{LN_{\max}}\right.\right\},$$

$$T=\left\{T_{TG}\in T\left|T_{TG_{\min}}\angle T_{TG}\angle T_{TG_{\max}}\right.\right\},T=\left\{T_{PT}\in T\left|T_{PT_{\min}}\angle T_{PT}\angle T_{PT_{\max}}\right.\right\},$$

$$T=\left\{T_{3}\in T\left|T_{3_{\min}}\angle T_{3}\angle T_{3_{\max}}\right.\right\},T=\left\{T_{L}\in T\left|T_{L_{\min}}\angle T_{L}\angle T_{L_{\max}}\right.\right\}$$

$$\varphi(T)=\min\ \varphi(T_D),\ \varphi(T_K)=\max\ \varphi(n,T_L),$$

$$\varphi(T_{LN})=\max\ \varphi(B_{LN},f),\qquad \varphi(T_{TG})=\max\ \varphi(B_{TG},f),$$

$$\varphi(T_{KC})=\max\ \varphi(B_{KC},f),\ \ \varphi(B)=\max\ \varphi(B_{LN},B_{TG},B_{KC}),$$

$$B=\left\{B_{LN}\in B\left|B_{LN_{\min}}\angle B_{LN}\angle B_{LN_{\max}}\right.\right\},\ B=\left\{B_{TG}\in B\left|B_{TG_{\min}}\angle B_{TG}\angle B_{TG_{\max}}\right.\right\},$$

$$B=\left\{B_{KC}\in B\left|B_{KC_{\min}}\angle B_{KC}\angle B_{KC_{\max}}\right.\right\},$$

where T_{Soi} – the performance of the CAS equipment;

T_{KO} – the performance of the switching device;

T_{C_1}, T_{C_2} – the performance of the servers on the transmission and reception sides of the DRTS;

T_C, T_{DC} – the performance of the coder and decoder;

T_{PT} – the performance of the transmission path;

T_{RP} – the performance of the reception path;

T_{LN} – the performance of processing network flows in the local network;

T_{TG} – the performance of processing network packets in the transit gateway;

T_D - the delay of signals in redundant nodes;

f – the size of network packets;

B_{LN} – the bandwidth of the local network;

B_{TG} – the bandwidth of the transit gateway;

B_{KC} - the bandwidth of the communication channel;

n – the length of the code combination;

T_L – the time required for receiving and transmitting the code combination.

The objective function for the error in data reception and transmission:

$$\varphi(\delta) = \min \varphi(\delta_{S_{n0}}, \delta_{СПД}), \tag{4.12}$$

where $\delta_{S_{n0}}$ - data errors;

δ_{DRTS} - data errors during reception and transmission;

The optimization task for protection is to ensure the maximum level of security with the minimum risk of potential breaches of the DRTS, i.e.

$$\varphi(Z_\Sigma) = \min \varphi(R_{MR,} T_a),\ \varphi(Z_\Sigma) = \max \varphi(N_f) \tag{4.13}$$

$$N_f \geq N_{fo}\ ,\ T_a \leq T_{ao}\ ,\ R_{MR} = p_{MR} \cdot H\ ,$$

$$p_{MR} = p_i \cdot p_a \cdot p_b \cdot p_c \cdot p_d\ ,$$

where R_{MR} – multiplicative risk criterion for the probability of a DRTS breach;

p_{MR} – the probability of a breach of the information system, determined based on expert data;

p_i – the probability that a given information system is on the list of potential targets;

p_a - the probability that the system will be selected from the list and attacked;

p_b – the probability that the bordering technologies will be breached;

p_c –the probability that attacks will intensify;

p_d – the probability that the DRTS will be damaged;

H – potential losses from information security breaches;

N_f – the number of functions characterizing the functionality of the DRTS;

T_a - – average access time to DRTS protection objects;;

N_{f0}, T_{a0} - limitations on functionality and performance.

The objective function for the risk of device failure in the DRTS:

$$\varphi(R) = \min \varphi(R_{S_{n0}}, R_{DRTS},\ p_{S_{n0}}, H_{S_{no}},\ R_i, P(S_i)), \quad (4.14)$$

where $R_{S_{n0}}$ – risk of device failure in the DRTS;

R_{DRTS} – average risk of failure in the DRTS;

$p_{S_{n0}}$ – probability of device failure in the DRTS;

$H_{S_{n0}}$ – losses from device failure in the DRTS;

R_i – conditional risk during data reception and transmission in the TC;

$P(S_i)$ – conditional probability of error during data reception and transmission

The developed model is designed to optimize the information parameters of the DRTS to ensure its effectiveness.

The method used, which allows for the investigation of the developed model and optimization of the information parameters of the DRTS in the TC state, is based on considering the presence of a set of conflicting requirements for such a system.

The complexity of solving multi-criteria optimization problems lies in the fact that the criteria compete with each other.

The problem can be solved using the Pareto optimality principle [179, 180].

A characteristic of the Pareto optimal set is the ability to "discard" consciously unsuccessful alternatives that are inferior to others on all criteria.

As a result of solving the optimization problem, a set of alternative solutions is determined that satisfy the Pareto optimality principle and meet the imposed constraints.

This strategy for solving optimization problems significantly differs from known nonlinear programming approaches, offering higher efficiency and substantially broader capabilities.

The sequence of optimization of the information parameters of the DRTS includes the following stages:

- determination of the set of independent parameters, as well as the conditions that define the acceptable values that the variables can take;
- obtaining the objective function as a measure of ensuring the quality of the optimization object with the given variables;
- selection of the method and solution to the optimization problem.

To investigate the model of multi-criteria and multi-parameter optimization of the information parameters of the DRTS, algorithms implemented in freely distributed software [181], based on response surface technology, were used.

A distinguishing feature of this technology is the efficiency of finding an optimal solution when investigating DRTS models, which are simulated at high levels of complexity and hierarchy, including achieving mathematical modeling (2D and 3D problems) and the possibility of rapid integration.

The program is designed for the numerical solution of multi-criteria parametric optimization problems of complex functional dependencies under functional constraints and operates with target functions (4.10) – (4.14).

The ranges of numerical values for the quality indicators of the DRTS are given in Table 4.1.

The solution to the optimization problem of the DRTS information parameters lies in finding the maximum efficiency of the system under certain conditions of its indicators.

To optimize the information parameters of the DRTS for the ship's TC, a software structure for its operation has been developed (Fig. 4.5).

As an example, the results of solving the bandwidth optimization problem for the DRTS are presented.

The bandwidth of the DRTS is determined by the maximum transmission capacities of the communication channels of the system, which receive and transmit data from the local networks and the transport gateway of the DRTS.

Table 4.1 - Ranges of numerical values of DRTS quality indicators

Quality Indicator	Constraint	Min	Max
Bandwidth (B)	10 MB/s	10 MB/s	100 MB/s
Information Protection Efficiency $(Z)_\Sigma$	0.95	0.95	1.0
Structure Risks $(R)_\Sigma$	0.2	0.2	0.37
Acceptable Data Transmission Error (σ)	0.5 byte	0.5 byte	1.0 byte

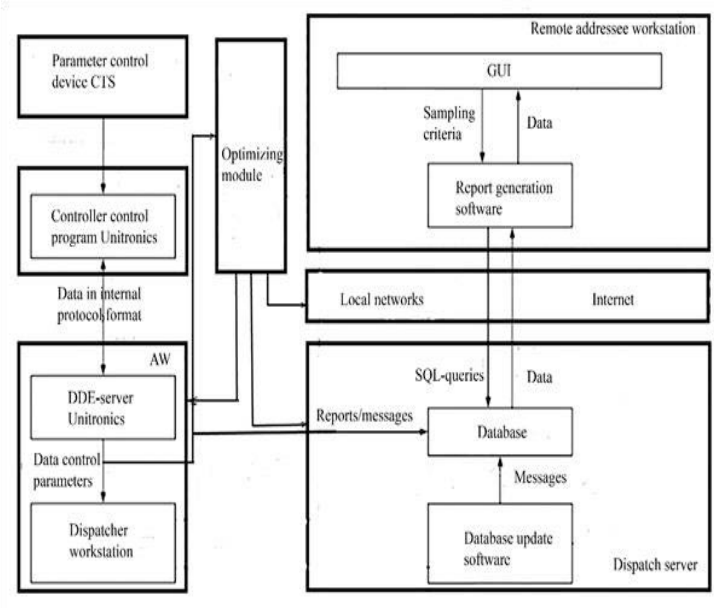

Figure 4.5 - The structure of the DTS in RD software

The maximum capacity of a communication channel with additive noise is determined by Shannon:

$$B = W \cdot \log_2 (1 + \frac{S}{W \cdot N}) , \qquad (4.15)$$

where W – is the bandwidth of the communication channel, kHz;

S/N – signal-to-noise ratio in the recipient's receiver, dB

The target function of the DRTS throughput::

$$\varphi(B) = \max \varphi(W, S/N) \qquad (4.16)$$

As shown in Fig. 4.6, the solution to the optimization problem of the DRTS information parameters based on the developed model allows finding several Pareto-optimal solutions for the quality indicator (criterion) – bandwidth.

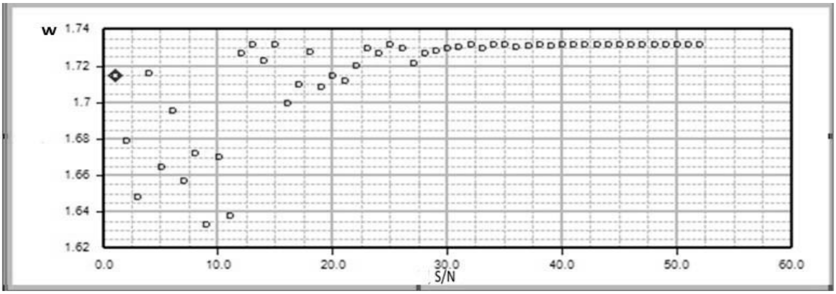

Figure 4.6 – Scatter diagram of the set of Pareto-optimal solutions for bandwidth with respect to the set i and j.

Since all points in the non-dominated set in the criteria space are equivalent according to the Pareto set of the solution space, the main role in supporting decision-making based on the results of multi-criteria optimization is played by the Decision Support System (DSS).

Based on the consideration of preferences, the DSS determines the unique Pareto-optimal solution, which is considered the final result of the selection procedure. By performing linear convolution for the two criteria iii and jjj, and taking into account equation (4.16), the best optimal solution is determined – the bandwidth of 1.735 kHz, with a signal-to-noise ratio of 42.5–52.5 dB.

When formulating and solving the optimization problem for the information parameters of the DRTS TC, a set of independent parameters, conditions defining their permissible values, obtained objective functions, and a method for solving optimization problems were defined. The developed model for optimizing the information characteristics of the DRTS TC allows:

- Monitoring the DSS state of the TC in real-time, which will help avoid accidents during its operation;
- Reducing the risk of failure of the DRTS equipment.

The fifth point of scientific novelty is formulated: for the first time, a model for data reception and transmission during the diagnosis, assessment, and forecasting of the technical condition of complex systems for critical applications has been developed, which takes into account the presence of conflicting requirements and competing criteria, allowing the identification of Pareto-optimal solutions to ensure the efficiency of data reception and transmission.

4.3. Conclusions to Chapter Four

In Chapter Four, a method for assessing and forecasting the TC of complex systems for critical applications was developed.

The method is based on: presenting a precedent with a set of parameters with specific values and decisions; obtaining evaluation data and forecasting TC of a complex system; and forming recommendations to ensure the effective operation of the equipment in the system.

The method of reasoning based on precedents was further developed, which allowed for the evaluation and forecasting of the technical condition and improved the operational efficiency of complex critical systems.

When receiving and transmitting various diagnostic, evaluation, and forecasting data for the TC of complex KA systems, their effective reception and transmission must be ensured while reducing the redundancy of the information during processing, maximizing its protection, and minimizing errors.

To solve this issue, a model for receiving and transmitting diagnostic, evaluation, and forecasting data was developed, along with the solution to the multi-parameter, multi-criteria optimization of information parameters affecting its performance, using the Pareto optimality principle.

For the first time, a model for receiving and transmitting data during the diagnosis, evaluation, and forecasting of the TC of complex critical application systems has been developed, which accounts for the presence of conflicting requirements and competing criteria, enabling the identification of Pareto-optimal solutions for ensuring the efficiency of data reception and transmission.

Chapter 5
DEVELOPMENT OF AN INTELLIGENT INFORMATION SYSTEM FOR DIAGNOSTICS, ASSESSMENT, AND PREDICTION OF THE TECHNICAL CONDITION OF COMPLEX CRITICAL SYSTEMS

5.1 Design of an Intelligent Information System for Diagnostics, Assessment, and Prediction of the Technical Condition of Complex Critical Systems

Decision-making methods in an intelligent information system (IIS) based on precedents involve using analogies with previously solved problems to find and adapt solutions to new situations. Such methods include the stages that form the CBR (Case-Based Reasoning) cycle:

1. Capturing cases from the case library (CL).
2. Indexing (organizing cases for finding similar instances).
3. Searching for the most relevant cases for the new task.
4. Adapting (modifying the retrieved case to fit the current task).
5. Evaluating and implementing (verifying the adapted solution for suitability and implementing it if necessary).

Advantages of case-based reasoning: adaptability; the ability to work with incomplete information; versatility; and learning capability. Cases can be represented in various forms, including textual descriptions, diagrams, tables, prototypes, usage scenarios, and UML-based modeling. Each method can be effective depending on the context and project goals.

The representation of cases is implemented as follows. In the proposed CBR cycle (Fig. 5.1), to support knowledge exchange, the initial task formulation block receives a set of input parameters of the diagnosed TS and an ontology array representing a structured description of the domain of marine CTS.

As a result, the structure of the new case object is generated, and its content is extracted using the nearest neighbor method based on the similarity (proximity) evaluation of the analyzed scenario with the TS and considering data in the knowledge base.

Based on this procedure, a solution object is formed, which can be modified for its targeted adaptation, taking into account all aspects of partial and complete failure scenarios (FE and FC) of the CTS by applying a transformational method [181].

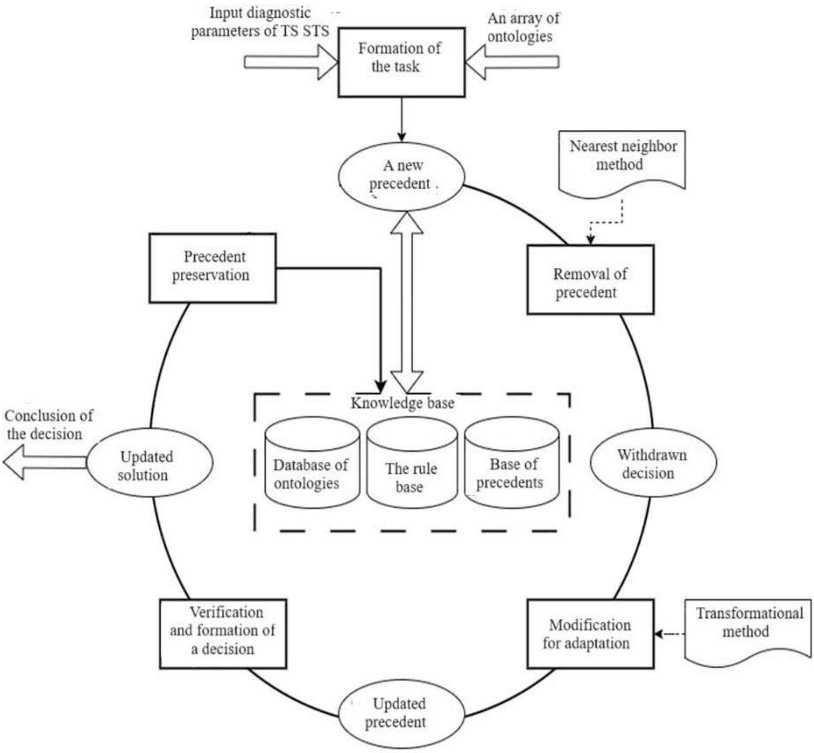

Figure 5.1 - CBR Cycle Structure

The updated precedent is verified for logical consistency, considering the use of predicate productions and applying the ontological reasoning approach via the Hermit reasoning system [181]. The resulting solution is exported as a separate object containing recommendations for the decision-maker (DM) and metadata.

Subsequently, the precedent is stored in the case base, which is a component of the knowledge base (see Fig. 5.1).

The decision-making sequence (Fig. 5.2) using the proposed CBR cycle, with consideration of operations for processing and structuring precedent data within the framework of the applied software system, is carried out as follows:

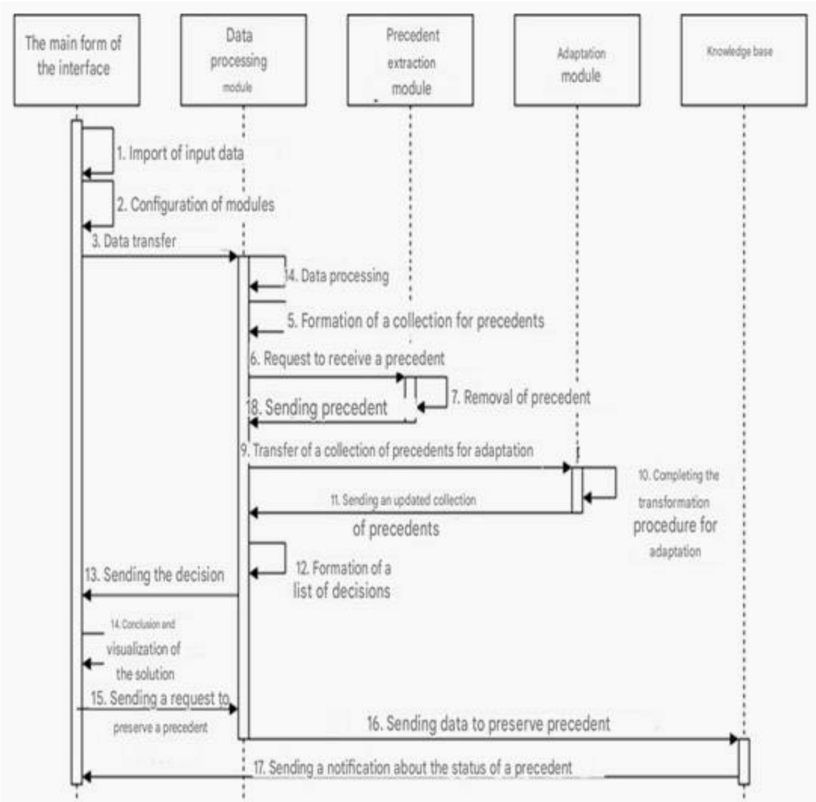

Figure 5.2 - Decision-Making Sequence Diagram

When the software system is launched, the main user interface form is initialized, providing the ability to import input data for task formulation. Next, control parameters and configuration options for the operation of all modules involved in the information processing cycle are set, including the Data Processing Module (DPMod), Precedent Extraction Module (PEMod), and Adaptation Module (AMod).

A request is then made to transfer the generated data arrays to the DPMod, where data processing procedures are conducted step by step (including consistency checks and fragmentation). A collection for storing precedents is created, taking into account metadata (such as a brief textual description of the target purpose, its identifier, creation date, and some statistical indicators).

After this, a request is made to retrieve a specific precedent via the PEMod, where actions for metric evaluation are performed using the nearest neighbor method. The result is sent to the DPMod as a collection based on an associative array. After verification and validation, the DPMod sends the processed collection to the AMod for adaptation procedures.

Adaptation uses a transformation method, aligning the precedent with a set of rules and considering logical productions of correspondence. As a result, the updated precedent collection is returned to the DPMod for generating a list of final decisions and validating them.

The results are output as text records and graphical representations. The serialized solution (in JSON format) is sent to the main interface form for further initiation of precedent data transmission, storage in the knowledge base, and providing the user with a notification about the transaction results.

For creating precedents, simple parametric representation suffices, i.e., presenting the precedent as a set of parameters with specific values and a solution (diagnosis and recommendations for the decision-maker).

Various methods are known for extracting and modifying precedents. The most common include:

- Nearest Neighbor (NN) method [182];

- Precedent extraction based on decision trees;
- Precedent retrieval based on knowledge [157, 183];
- Precedent extraction considering their application.

These methods utilize diverse metrics. Among the primary metrics, the nearest neighbor method is applied, enabling easy calculation of the similarity between the current problem situation and precedents in the case library. The nearest neighbor method uses simple coordinate-wise comparison of the current situation with the precedent, where each parameter describing the precedent is considered as one of the coordinates.

The distance DCTD_{CT}DCT between the point corresponding to the current situation and the point corresponding to the precedent is calculated.

The effectiveness of the nearest neighbor method depends on the choice of metric. If precedent CCC and current problem situation TTT are defined in an n-dimensional property space, the similarity or proximity S(C,T)S(C, T)S(C,T) between precedent CCC and situation TTT can be determined using one of the metrics for calculating the distance between two points xiCx_i^CxiC and xiTx_i^TxiT, such as the Euclidean distance:

$$D_{CT} = \sqrt{\sum_{i=1}^{n}(x_i^C - x_i^T)^2} \qquad (5.1)$$

To determine the similarity degree value (SIM), the maximum distance DmaxD_{max}Dmax is calculated within the chosen metric using the parameter range limits for describing the precedents. Subsequently, the similarity degree value is determined using the parameter range limits for describing the initial and final precedents, i=1,…,ni = 1, \dots, ni=1,…,n.

The similarity degree value can be calculated as follows:

$$SIM = 1 - D_{CT} / D_{max} \qquad (5.2)$$

5.2 Implementation of the Intelligent Information System for Diagnostics, Evaluation, and Forecasting of the Technical Condition of Complex Critical Systems

The implementation of the intelligent information system with CBR (Fig. 5.3) integrates the developed models and the diagnostic method for TS with a database (DB), a knowledge base (KB), and an expert system. The expert system contains computational, experimental, and expert-provided data obtained during the operation of the CTS.

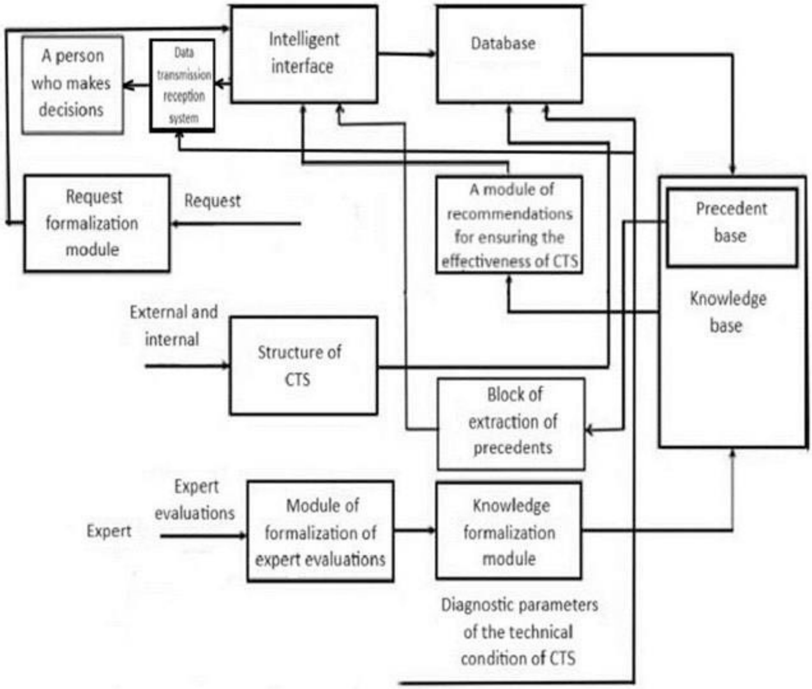

Figure 5.3 - Structural diagram of the implementation of the method of reasoning based on precedents for evaluating and forecasting the TC of a complex short-circuit system

The software structure development began with a schematic representation of the primary interacting modules of the IIS. The structural diagram of the modules and their interconnections (Fig. 5.3) visually represents the interaction of FE and FC within the IIS.

During the development of the IIS, the control and executive unit (CEU) was selected as the object for TS evaluation and forecasting. When assessing the reliability of the SPP, it was taken into account that CTS is characterized by a large number of diagnosable parameters. These parameters differ in informativeness and accessibility, particularly under conditions of insufficient information for TS assessments, as well as by specific and diverse operating conditions under uncertainty.

The Core Components of the Intelligent Information System (IIS):

The cores of the IIS are:

- DB: A structured storage of all system-related data.
- KB: Includes methods for calculating reliability indicators (risks and probabilities of failures) and a set of decision rules for selecting appropriate decision-making methods.
- Model for the Intellectual Evaluation of TC of FE and (FC in CTS.

The IIS includes:

- User Interface Module: Facilitates interaction between the user and the system.
- KB with a Precedent Library and DB: Supports decision-making.
- Query Formalization Module: Structures and processes user requests.
- Recommendations Module for Ensuring CTS Efficiency: Provides actionable suggestions based on evaluations.
- Libraries of Structural Schemes for Marine CTS: Contains predefined structural templates.
- Expert Evaluation Formalization Module: Standardizes expert input into actionable data.
- Knowledge Formalization Module: Structures and organizes the knowledge base.

The implementation of the developed strategy in the IIS ensures targeted actions in support of decision-making to identify FE and FC failures based on established TC evaluations.

Knowledge Base:

The KB model is production-based, while its software functionality is object-oriented. The developed KB is represented by rules derived from:

- Intelligent data analysis (a multi-level hierarchical structure of the knowledge base tree).
- Expert evaluations.
- Results from applying diagnostic models for the technical condition of complex systems.

The KB operates according to the developed decision-making sequence (Fig. 5.2) and considers the CTS TC matrix (Fig. 4.4). All data and expert evaluations are retrieved from the database based on queries. As a result, the KB generates evaluations of TC for subsystems, components, elements, and their interconnections.

These evaluations are passed to the Recommendations Module for ensuring effective CTS operation and subsequently to the Decision Maker (DM) for managing the technical condition of the complex system.

Database:

The DB contains:

- CTS Structure Database: Stores structural information.
- Failure Risk Criteria Database: Contains risk evaluation metrics.
- Complex Systems TC Database: Records conditions of technical systems.
- Degradation Processes Database: Tracks wear and aging patterns.
- Risk Mitigation Measures Database: Details actions to reduce failure risks.

The precedent library consists of:

- Incident Precedent Library: Documents cases of minor issues.
- Emergency Situation Precedent Library: Contains data on critical failures.

Diagnostics of Problematic Situations:

Diagnostics of full or partial equipment failures and their interconnections in CTS is performed by simulating diagnostics based on risk (probability) of failure and failure-related losses. Using the diagnostic data, the KB and precedent library provide established TC evaluations of the complex system and form recommendations for DM decision-making.

Forecasting and Recommendations:

Based on these evaluations, the system forecasts the TC of the complex system. The results may include a list of actions performed, additional comments, and links to other precedents.

Hierarchical Structure and Logic Implementation (Fig. 5.4): The hierarchical structure of the program logic for data processing modules by precedents and reasoning includes the following interfaces for abstraction levels and object behavior polymorphism:

- IData: Manages the path to the location of input data sets, initializes data structures and collections, normalizes data, checks for missing rows, and defines structures.
- IOntology: Stores attributes, classes, and relationships, assembles ontology structures, and validates them.
- IPrecedent: Handles properties of situation scenarios, problems, and solutions, and manages the process of precedent creation, storage, serialization, and logical consistency checks.

Each class implements a different version of the logger() method to ensure the logging of intermediate results during the execution of computational operations over time.

- The DataLoader class implements the IData interface, handling data loading into the system and performing operations such as creating collections of precedents, verifying data integrity, executing necessary transformations, filtering, aggregating, setting up structures, and issuing status messages based on the outcomes of these actions.
- The OntologyMaker class implements the IOntology interface, working with a partial collection of ontologies in a dynamic array to aggregate individual ontology elements. This class is designed to construct the logical base structure of the system for each precedent. It also provides visualization of the ontology in a graph-oriented form.
- The PrecedentExtractor and PrecedentAdapter classes implement the IPrecedent interface, overriding methods for managing

precedent data. These methods are utilized in the processes of extraction and adaptation performed by the extractPrecedent() and adaptPrecedent() methods, respectively. The result of these processes is a Precedent object.

• A separate KnowledgeBase class is implemented to manage CRUD operations with rules.

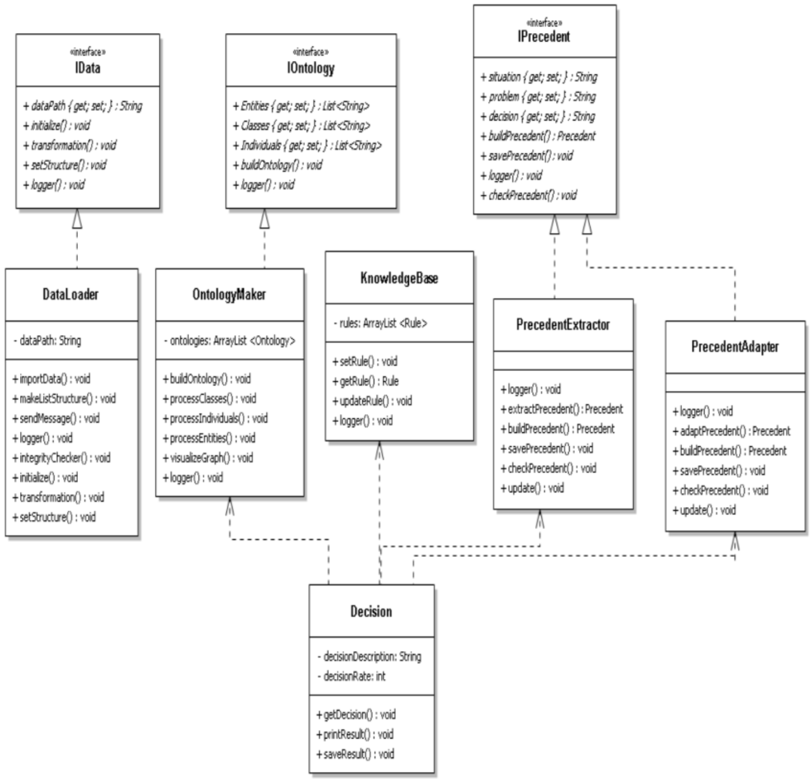

Figure 5.4 - Hierarchical structure of the key program logic of fragments of data processing modules regarding precedents and considerations

Using instances of these classes, a Decision object is created. The state of the Decision object is described by private properties decisionDescription and decisionRate, while its behavior is expressed through public methods for creating, displaying, and saving the decision results.

The IIS with the CBR cycle was implemented using the Visual Studio development environment, the .NET 4.7 framework, WinForms technology for creating graphical user interfaces, and functional libraries such as Hermit for ontology support and JSON handling [170].

An interface of the main form of the software system, featuring a tab for managing the precedent creation process within the proposed CBR cycle for assessing and forecasting the technical condition of systems (demonstrated using the example of a marine CTS), is shown in Fig. 5.5.

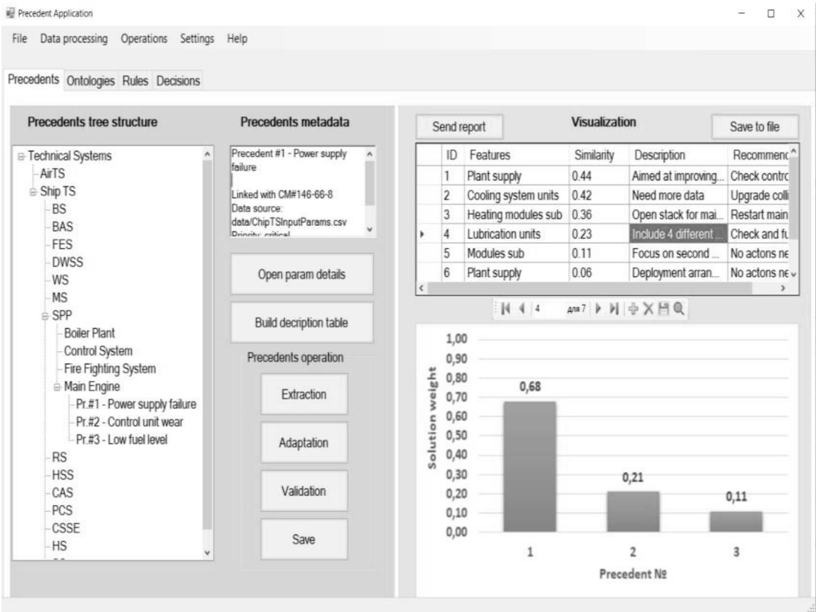

Figure 5.5 - The interface of the main form of the software system with the tab for managing the process of creating precedents

The system includes a main menu for navigating between processes such as connecting data sources and the knowledge base (File menu), managing and processing data (Data Processing menu), selecting and executing computational operations (Operations menu), configuring system modules and settings (Settings menu), and accessing reference information about the system's functionality (Help menu).

The functionality supports working with data from precedents, ontologies, rules, and decisions. For the hierarchical representation of the structure of marine CTS, as well as their FE and FC, a dedicated graphical widget is provided in the form of a tree of nodes.

Data entry for precedents is carried out through a corresponding text field.

Options are available for providing a detailed description of parameters, constructing a summary crosstab for all values of marine CTS and their equipment, as well as forms for extracting, adapting, and validating the created precedents.

A table is implemented to display the results obtained from precedents, including similarity evaluations, descriptions, and a brief set of typical recommendations.

For easier management, a quick navigation component is provided for performing CRUD operations and search functionality within the table.

Visualization tools are introduced to highlight the most suitable options for adapting precedents to specific CTS operational scenarios after completing all analytical procedures. The system supports local saving of visualization results in PDF and CSV formats.

The results of risk evaluations for subsystem failures of the studied SEU, formulated considering the created precedents, are presented in Figure 5.6.

The results of failure risk prediction for the FE and FC of the SEU—for instance, for the Main Engine subsystem—can be viewed in the interface block for risk prediction review by navigating to the web page labeled Predictions (Figure 5.7).

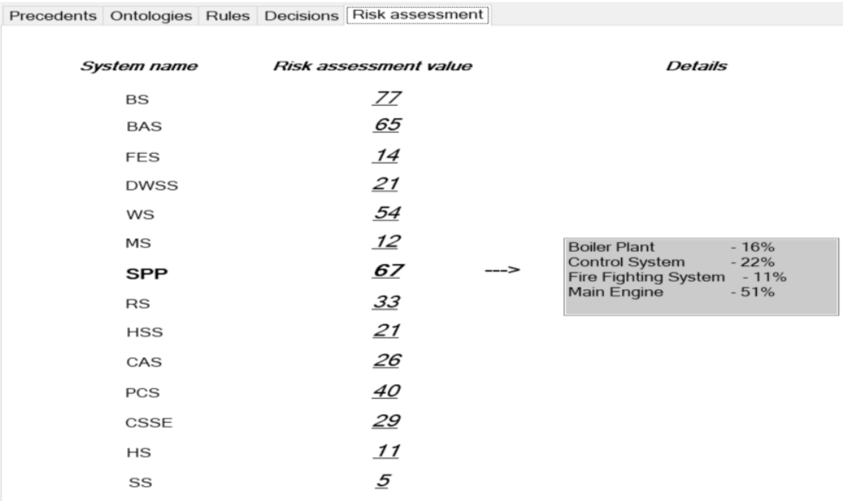

Figure 5.6 - The interface of the risk assessment form for the analyzed subsystems of the ship's power plant

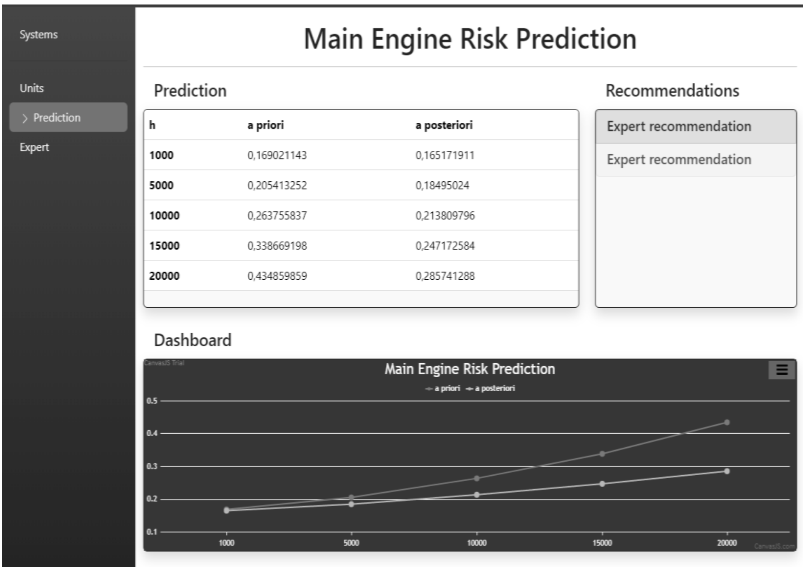

Figure 5.7 - Main Engine subsystem failure risk prediction block

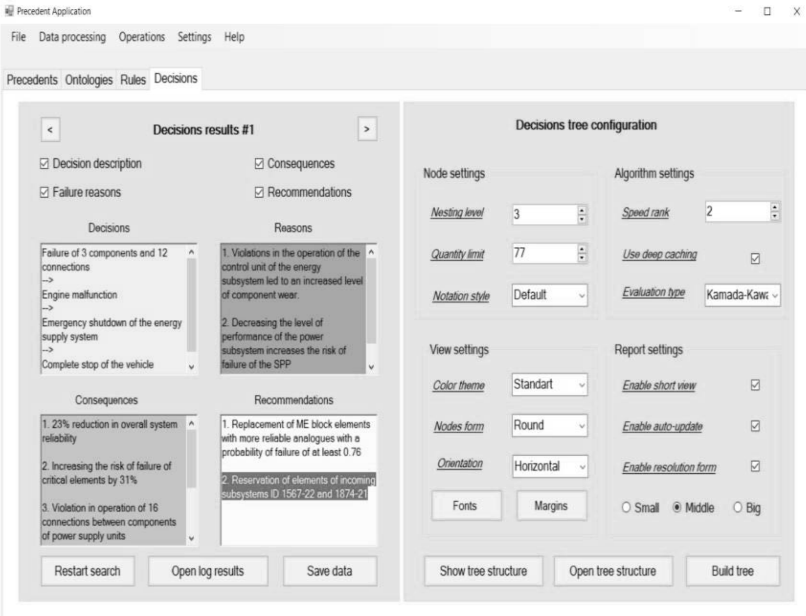

Figure 5.8 - User interface

A block is provided for displaying the prior and posterior failure risk values for the Main Engine, as well as a widget for showing the dependence of the predicted prior and posterior failure risk values for the Main Engine.

The user interface for the view form of the module displaying the results of the system's generated decisions is shown in Figure 5.8.

The system supports navigation through decision scenarios, as well as components for displaying data regarding decisions, causes of violations, consequences of scenarios for further system operation, and a list of recommended actions for improving the performance of the ITS.

Options for opening log files to view intermediate stages of computational operations and calculations are provided, along with options for saving results to the database.

For managing the process of constructing a failure tree model, components have been developed to configure the parameters for node construction methods, graph visualization algorithms, graphical representations, and report generation. Functionality is provided for building decision trees, viewing their structure, and editing the model in editor mode.

A drawback of the precedent-based method with the CBR cycle is the increased time for finding the closest precedent.

Therefore, a comparative analysis of the time required to find the nearest precedent was conducted, depending on the size of the precedent database, considering data caching during the initialization of the data structure as a collection of an associative array.

The graph showing the time required to determine the complex system's state as a function of the number of precedents is shown in Figure 5.9.

The time spent on finding the closest precedent for 10,000 precedents in the knowledge base was about 370 ms.

The first closest precedent from 5,000 precedents was found in approximately 50 ms.

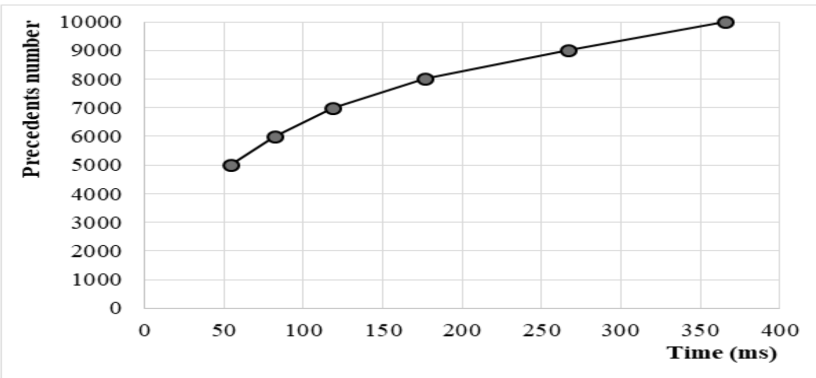

Figure 5.9 - Time to determine the TS of a complex system depending on the size of the precedent base

As the number of precedents in the precedent library increases, the time required to determine the state of a complex system increases as well, but it does not significantly affect the overall time spent on assessing the subsystems of the investigated marine power plant.

Despite this drawback, the study showed the potential application of the CBR-based reasoning method and its appropriate use for decision-making in real operational conditions.

The developed IIS demonstrates high performance.

In order to assess the time costs for constructing the knowledge base within the implementation of the proposed method, a comparison of the execution time of computational processes was conducted using the developed IIS under the following system modes: single-threaded, dual-threaded, and quad-threaded (Figure 5.10). It is important to note the overall exponential nature of the dependency between the execution time of computational processes for the assessment and forecasting of the state of the complex energy system (CES) and the number of precedents in the KB.

Thanks to the distributed computing mode, it becomes possible to reduce the time costs by up to 28% when using two isolated data threads, and by up to 42% when the computational load is divided into four separate data threads.

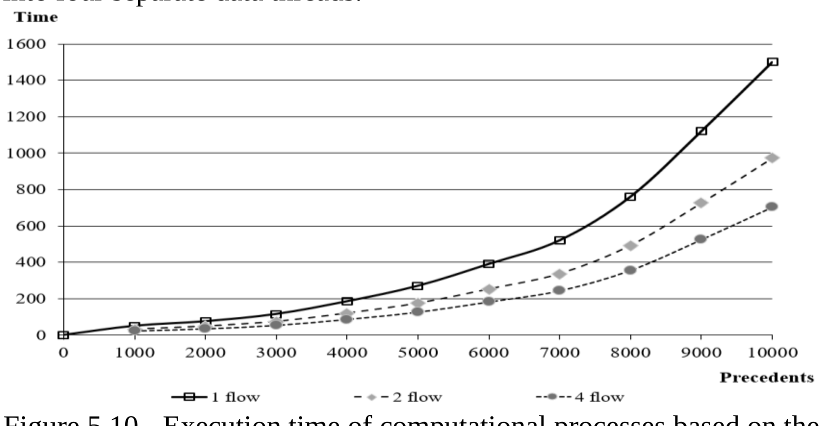

Figure 5.10 - Execution time of computational processes based on the number of formed precedents

The interface of the main form of the software system, with the tab for managing the process of creating precedents, implements the functionality for determining the operability of the IIS with the CBR cycle and the implementation of its embedded functions.

Considering partial and complete equipment failures of the ship's CKS in the IIS will allow the OPR to make decisions aimed at pre-failure maintenance of complex systems, thereby extending the operational life of systems and increasing their operational efficiency.

Thus, the development and research of the IIS with CBR, designed for effective assessment and forecasting of TS of complex systems, was conducted by ensuring the IIS's performance.

The effective operation of the IIS with CBR is based on the use of the precedent-based reasoning method. The IIS with CBR consists of: an interface module; a knowledge base with a precedent library and database; a query formalization module; a recommendations module for ensuring the efficiency of the CKS; a library of structural diagrams for the CKS; expert evaluation formalization modules and knowledge formalization modules.

Experimental studies of the IIS for TS assessment and forecasting of complex systems showed that the time spent to retrieve the nearest precedent with 10,000 precedents in the knowledge base was about 370 ms.

The decision-making process, using the proposed IIS with the CBR cycle system, which considers operations for processing and structuring data according to precedents within the functioning of the developed software system, demonstrates high performance, facilitates operation with incomplete information, and supports learning for decision-making.

Thanks to the distributed computing mode, it becomes possible, when using two isolated data threads, to reduce time costs by up to 28%, and up to 42% when the computational load is divided into four separate data threads.

When the proposed IIS is operational, partial and complete failures of the operability of subsystems, components, elements, and their interconnections in the CKS are taken into account.

The increased efficiency of CKS operation is ensured by the fast evaluation and forecasting of TS, as well as the OPR's actions aimed at making decisions regarding pre-failure maintenance of complex systems at the early stages of failure development.

5.3 Efficiency of Complex Technical System Operation Based on Diagnostics, Assessment, and Forecasting of Equipment Technical Condition

As a result of the conducted research based on diagnostic data of the TS equipment of the complex system, the IIS has performed an assessment and determined the predicted values of failure risk (probabilities) for FE, FC. Table 5.1 shows the obtained probabilities of failure and the probability of maintaining the operability of the CKS upon detection of partial equipment failures during 20,000 hours of system operation.

Table 5.1 - Probability Characteristics for Partial Equipment Failures in the CKS

Time, hours	1000	2500	5000	7500	10000	12500	15000	20000
Probability of failure	0.133	0.144	0.163	0.185	0.209	0.237	0.269	0.304
Probability of maintaining operability	0.867	0.856	0.837	0.815	0.791	0.763	0.731	0.696

The operational efficiency of the CTS is determined by a scalar value (E), which depends on the effectiveness of its functional subsystems, components, elements, and their interconnections:

$$E = E[FE, FC] \tag{5.3}$$

The operational efficiency of the CTS is determined by the probability of maintaining system functionality, which does not exceed the threshold probability value P0P_0P0, at which a complete system failure occurs:

$$P\{E > E_0\} < P_0 \tag{5.4}$$

The threshold failure probability P0P_0P0 is determined from Harrington's generalized desirability function [99], and the range of 0.63 - 1.0 represents the critical probability (system operation becomes impossible).

The failure probability is calculated using the well-known formula from reliability theory:

$$P(t) = 1 - \exp\left[-\int_0^T \lambda(t)dt\right], \tag{5.5}$$

where - λ The failure intensity, which depends on the operating time of the system,

For n partial failures, the probability of maintaining the operability of the system, which determines the effectiveness of the system's operation:

$$P(t) = (P(t)_1 + P(t)_2 + \cdots P(t)_{n-1} + P(t)_n)/n < P_0 \tag{5.6}$$

When equipment with partial failure is detected and preventive maintenance is carried out, its failure intensity decreases (λ(t)−Δλ(t)). The probability of maintaining the system in an operational state increases (Table 5.2).

Table 5.2 - Probability characteristics for partial failures during preventive maintenance of the system's equipment.

Time, hours	1000	2500	5000	7500	10000	12500	15000	20000
Probability of failure	0.110	0.121	0.140	0.162	0.186	0.214	0.246	0.289
Probability of maintaining operational capability	0.890	0.879	0.860	0.838	0.814	0.786	0.754	0.711

Figure 5.11 shows the results of the obtained probabilities of the operational capability of the system in the case of detected partial failures and detected partial failures with preventive measures.

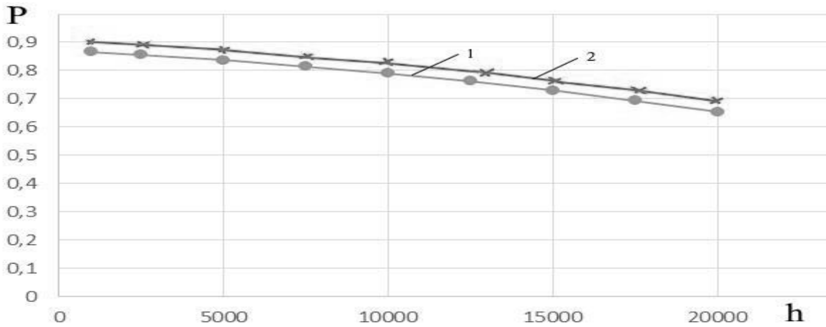

Figure 5.11 - Probabilities of the operational capability of the system in the case of: detected partial failures - 1; detected partial failures with preventive measures - 2.

The operational efficiency of the equipment in the system, with partial failures and preventive maintenance, is determined by:

$$P_E = P(t)P_{cf}(t)P_{ei}(t)P_{dm}(t)P_{er}(t), \qquad (5.7)$$

where $P_{cf}(t)$ is the probability of no complete failure;

$P_{ei}(t)$ is the probability of no external influences leading to complete failure of the system equipment;

$P_{dm}(t)$ is the probability of errors by the operator;

$P_{er}(t)$ is the probability of error-free expert assessments.

The results of the calculation of the operational efficiency of the CTS, determined by the probability of maintaining operability, considering partial equipment failures and preventive maintenance, do not exceed the threshold probability at which a complete failure of the CTS occurs, as defined by the generalized desirability function of Harrington.

The probability of maintaining the system in working condition increases by 3%.

Thus, when partial failures are detected and preventive measures are taken for the CTS, the probability of maintaining operability increases, which, in turn, extends the system equipment's operational lifespan and improves the operational efficiency of the FE and FC.

5.4 Conclusions to Chapter Five

In Chapter Five, the development of an IIS for the diagnosis, evaluation, and forecasting of complex systems of the complex technical systems was carried out. The design of the IIS focused on ensuring the operational efficiency of the CTS using a method of CBR.

The design of the IIS with CBR links the developed models and methods for diagnosing, evaluating, and forecasting the CTS of complex systems with an expert system that includes computational, experimental, and expert-derived data obtained during the operation of the CTS.

The cores of the IIS are: a database;

- a knowledge base with a library of precedents, methods for calculating probability indicators, failure risks, and a set of decision-making rules; a query formalization module;
- a recommendation module for ensuring CTS effectiveness; libraries of structural schemes of the CTS;
- a module for formalizing expert assessments; and a knowledge formalization module.

The implementation of the developed strategy within the IIS is supported by targeted actions according to decision-making processes aimed at identifying equipment failures based on the established evaluations of their CTS.

To test its functionality, the full cycle of the IIS's operation, including the evaluation and forecasting of the failure risk (probability) of the CTS, was simulated using the developed knowledge base, applied to a ship's energy installation.

The obtained risk (probability) assessments of subsystem, component, and element failures, which do not contradict expert evaluations, indicate the effectiveness of the diagnostics, evaluation, and forecasting of complex systems, accounting for both partial and complete failures.

The results of the operational efficiency calculations of the complex technical system, determined by the probability of maintaining operability, taking into account partial equipment failures and preventive maintenance, do not exceed the threshold probability at which complete failure of the CTS occurs, as defined by the generalized desirability function of Harrington.

The probability of maintaining the CTS in operational condition increased by 3%.

GENERAL CONCLUSIONS

The research is dedicated to solving an important scientific and technical problem: increasing the operational efficiency of complex technical systems through the use of results from the development of stochastic models and methods for diagnosing, evaluating, and forecasting system equipment failures, taking into account partial and complete failures.

1. An analysis of existing models, methods, and information systems for diagnosing, evaluating, and forecasting CTS showed that the known structural models and diagnostic methods only account for complete system failures but do not consider partial failures. These models have limitations (increased algorithmic and computational complexity, the need for complex preprocessing of diverse data), which reduces their effectiveness in improving the operational efficiency of CTS.

2. Stochastic models and methods for diagnosing CTS were developed that simultaneously account for subsystems, components, elements, their interconnections, and the risk (probability) of partial or complete failure, as well as uncertainties and incomplete data. This led to the development of a diagnostic method for complex CTS based on BBN. The improvement of the cognitive simulation model, which applies simulation impulse effects, allows for diagnosing system equipment with consideration of their interrelations and influence. Further development of this method enables timely identification and visualization of structural and functional vulnerabilities, enhancing the operational efficiency of complex systems.

3. Research and analysis of stochastic models and diagnostic methods for vulnerable subsystems, components, elements, and their interconnections in CTS, considering partial and complete failures, were conducted. The simulation used a ship's energy installation (SPP) as an object. The input data for the risk (probability) failure modeling based on BBN included the system's scheme, operational principles, and expert assessments. Cognitive simulation modeling was used to simulate internal and external impacts and to track

responses to risks (probabilities) of equipment failures with unclear sources and causes. The application of this diagnostic method using incomplete data revealed and visualized structural and functional vulnerabilities, confirming that the developed stochastic models can be considered conceptual.

4. A method for evaluating and forecasting complex CTS was developed, based on the further development of the reasoning method based on precedents. This method ensures the evaluation and forecasting of CTS and improves the operational efficiency of complex systems.

5. An information intelligent system for diagnosing, evaluating, and forecasting complex CTS was developed. The IIS, using CBR, links the developed models and methods for diagnosing, evaluating, and forecasting with an expert system containing computational, experimental, and expert data. The IIS's implementation supports targeted decision-making to identify equipment failures based on CTS evaluations. The obtained risk assessments of subsystem, component, and element failures, which align with expert evaluations, confirm the effectiveness of the diagnostics and forecasting of complex systems, considering partial and complete failures. The results of the efficiency calculation for the IIS, using CBR and considering preventive maintenance, show that the probability of maintaining operability increases by 3%.

6. The scientific results of this research in the form of information and software have been implemented in the operations of the Maersk shipping company (Denmark) and have been reflected in the scientific activities and educational processes at the Department of Information Technology at the National University "Odessa Polytechnic."

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