renewable energy infrastructure for maritime transport. The results of the survey conducted as part of this study serve to inform policy makers on the extent to which policy can or should attempt to provide guidelines and incentives in shaping industry attitudes or behavior towards the use of renewable energy sources. There is a high degree of preference for renewables over fossil fuels for both ship power plants and households. While solar energy is the most favored type of energy for households, hydrogen combustion (80%) is the most supported alternative for commercial shipping power. Fuel cells are the next most popular (64%) alternative energy used on board ships, according to the maritime industry. The result also indicates that the preference for a particular type of energy on board is also based on other factors, such as feasibility, rather than personal preference.

Keywords: *sea vessel, alternative energy, renewable energy, fuel cell.*

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Nosov P.S.

SYSTEMIC APPROACHES TO RATIONAL MANAGEMENT OF FUNCTIONAL MARINE TECHNICAL SYSTEMS AND COMPLEXES

Наразі набуває особливої актуальності питання розвитку ефективних та безпечних методів управління суднові технічними системами та комплексами (СТСК). У статті, враховуючи безперервний прогрес науки та технологій, пропонується розробка комплексного підходу до раціонального управління функціональними СТСК, який інтегрує наукові стратегії, автоматизацію та інтелектуальні системи.

Основна мета дослідження полягає у формуванні рамкової структури комплексних заходів для управління СТСК в умовах часткової внутрішньої та зовнішньої невизначеності, з особливим акцентом на людський фактор та ергономіку в управлінні. Пропонуєтья глибокий аналіз ризиків, що включає перегляд еволюції методів оцінки ризиків, від інтуїтивних до науково обґрунтованих стратегій, та розглядається впровадження автоматизованих та інтелектуальних систем у процеси управління ризиками СТСК. Робота зосереджується на важливості створення структурної моделі інформаційної підтримки СТСК, включаючи ідентифікацію ключових компонентів зосереджених на ризиках, вивчення внутрішніх і зовнішніх факторів, що впливають на СТСК, та розробку механізмів для їх моніторингу та аналізу. Значну увагу приділено розробці схеми для забезпечення раціонального управління СТСК в умовах часткової невизначеності, з акцентом на створенні адаптивних стратегій управління.

Наголошується на важливості розробки інтелектуальної моделі прийняття рішень для СТСК, яка включає детальний аналіз методів інтелектуального аналізу даних, специфічних для суднових технічних систем, імплементацію машинного навчання для динамічного управління судном та розробку критеріїв раціональності управління. Нарешті, стаття підкреслює необхідність удосконалення методу виведення коефіцієнта раціонального управління СТСК, включаючи розробку моделей взаємодії між операторами та технічними засобами для оптимізації інтерфейсів та підготовки операторів.

Отже запропоновано комплексний підхід до управління СТСК, який інтегрує наукові стратегії, автоматизацію, інтелектуальні системи, ергономіку та розглядає важливість врахування людського фактору. Такий підхід має на меті підвищення ефективності, *швидкості, точності та безпеки управління СТСК, особливо враховуючи важливість моніторингу дій операторів суден.*

Ключові слова: *раціональне управління; суднові технічні системи; автоматизація та інтелектуальні системи; управління ризиками; ергатичні аспекти; людський фактор.*

Problem Statement. The current state of maritime transportation has encountered challenges in managing MTSC, which include the need for adaptation to changing conditions and potential uncertainty, as well as the necessity of integrating intelligent and automated systems to optimize MTSC management processes. In particular, the efficiency of MTSC technical operations can be significantly enhanced through the integration of ergatic and automated management systems. Automated control modules can play a crucial role in maintaining a high level of readiness of functional installations and the vessel itself, as well as in adapting the crew to changing operational conditions in real-time. The use of intelligent decision-making systems can be a key factor in addressing these challenges, ensuring a high level of reliability, optimizing operational processes, and adapting them to dynamic changes in MTSC operational conditions.

The growth in globalization and the intensification of international freight forwarding contribute to the expansion of maritime routes, underscoring the need for modern, effective, and safe methods of managing vessels and their MTSC. This need is shaped by the continuous development of science and technology. With the rapid evolution of these technologies, new methods emerge to optimize the management and operational processes of MTSC, including automated and intelligent systems. Considering the criticality level in maritime transportation due to accidents caused by human operator errors, there arises a necessity to utilize modern technologies for rational MTSC management models in risk conditions.

Analysis of Recent Research and Publications. Marine and inland waterway transport play a pivotal role in the global movement of goods and passengers. With the rise of globalization, intensification of international trade, and expansion of maritime routes, there emerges a need for modern, efficient, and safe vessel management methods [1]. Such a requirement is shaped not only by geopolitical factors but also by the relentless advancement of science and technology [2].

The contemporary world is marked by the rapid development of information technologies, leading to the emergence of novel methods for optimizing operational processes [3]. Intelligent and automated systems find their applications across various industrial sectors, including maritime transport.

The efficiency of vessel technical operations can be significantly enhanced through the synergistic integration of ergatic and automated systems [4]. Automated control modules can play a crucial role in maintaining a high level of readiness of the power installations and the vessel as a whole, as well as in adapting the crew to changing operational conditions in real-time [5].

Employing intelligent decision-making systems can be a key factor in addressing this challenge, ensuring a high level of reliability, optimizing workflows, and adapting to the dynamic shifts in operational conditions.

Thus, there is an urgent need to develop a framework of comprehensive measures for the rational management of functional maritime technical systems and complexes under conditions of partial internal and external ambiguity.

The aim of the study is to develop a framework structure of comprehensive measures for the rational management of functional Marine Technical Systems and Complexes (MTSC) in conditions of partial internal and external uncertainty, as well as to improve the interaction between the systems and the human factor of MTSC operators.

To achieve the set goal, it is necessary to resolve a series of the following research tasks:

1. Propose principles for analyzing the current state in the field of MTSC management, aiming to consider risks and determine potential management strategies for them.

2. Define the structural model of information support for managing complex technical and MTSC.

3. Formulate a scheme to ensure rational management of functional MTSC in conditions of partial uncertainty.

4. Describe the structure of an intelligent decision-making model for the rational management of functional MTSC.

5. Provide suggestions for refining the method of deriving the coefficient of rational management for functional MTSC.

1. Analysis of the current state in the field of managing complex technical and transport functional of MTSC.

To achieve a higher quality level of risk management in the realm of functional MTSC control, a comprehensive analysis of contemporary approaches is imperative [6]. Firstly, this encompasses the evolution of risk assessment and management methods, which transitions from intuitive methodologies towards scientifically substantiated strategies. An exploration of this progression underscores the significance of implementing research-based strategies in practice, rather than relying on informal techniques.

Subsequently, the focus shifts to the incorporation of automated and intelligent systems into MTSC risk management processes. The integration of such systems can lead to the optimization of functional MTSC management. Specifically, automation holds the potential to enhance accuracy, speed, and efficacy of control. It is crucial to consider how different automation strategies can contribute to the mitigation of operational risks of vessels [7]. The application of intelligent control systems within MTSC also warrants attention. Such systems offer innovative prospects, like real-time risk forecasting and monitoring. However, alongside these benefits, there are inherent risks associated with the dependence on these systems, necessitating strategies for their mitigation.

It's worth noting that the ergatic aspects of MTSC play a pivotal role in risk management. The interfaces of information systems can influence operator errors, and consequently, safety risks. Thus, strategies optimizing human-machine interaction demand development and implementation in MTSC management.

Lastly, the human operator factor remains fundamental and pivotal in MTSC risk management. To comprehend and manage these risks, a focus on the psychophysiological analysis of typical operator errors is essential. Recommendations for monitoring operator actions, both in off-line and on-line modes, can aid in minimizing risks in functional MTSC management.

In conclusion, for optimal risk management in MTSC, a synergy of scientific approaches, automation, intelligent systems, ergatic strategies, and consideration of the human operator factor is necessary (Fig. 1).

We shall analyze formal approaches that will allow for the necessary calculations to implement the proposed ideas and solutions.

a. Analysis of contemporary sources [8]:

Statistical Analysis:

The coefficient of determination R^2, which indicates the proportion of variability in variable y explained by the model:

$$R^2 = 1 - \frac{\sum_i \left(y_i - \hat{y}_i\right)^2}{\sum_i \left(y_i - \bar{y}\right)^2}.$$

It will be used to measure the quality of the regression model and will be applied to assess the effectiveness of risk models in MTSC.

The standard error of regression for estimating the accuracy of regression coefficients:

$$SE(\beta) = \sqrt{\frac{\sum_i \left(y_i - \hat{y}_i\right)^2}{n-2}}.$$

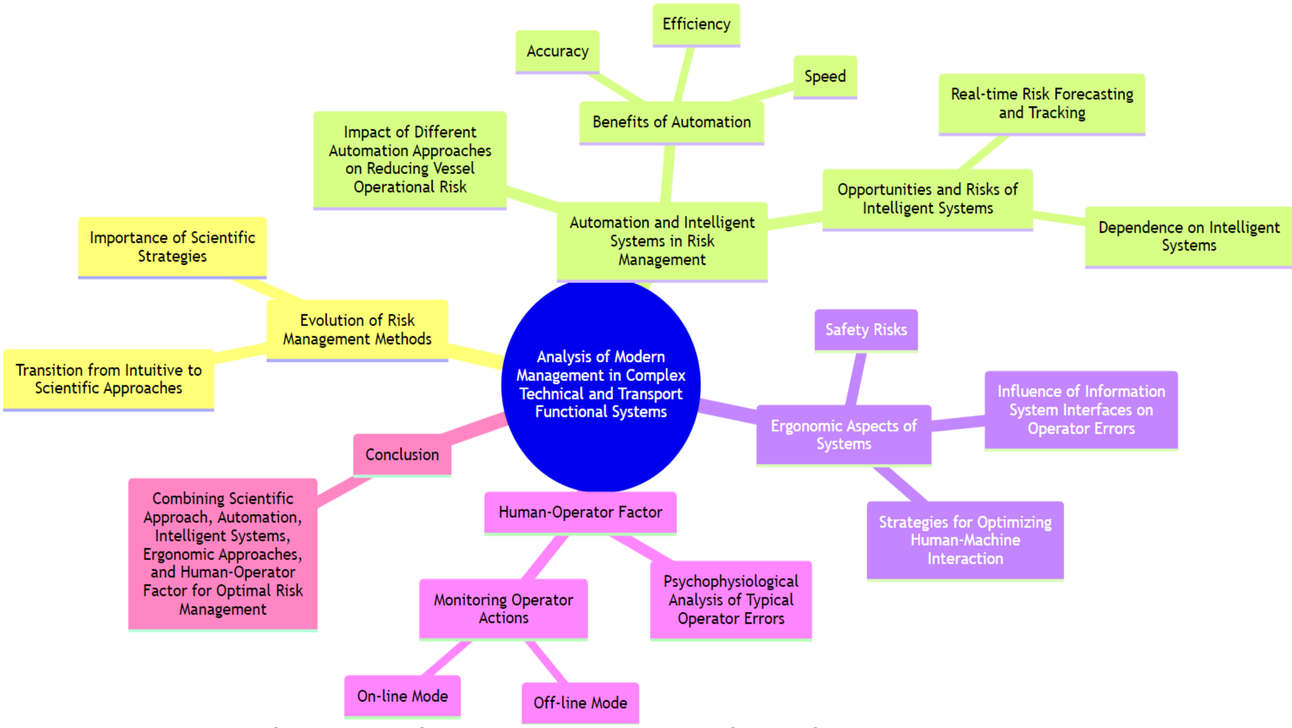

Fig. 1. Structure of analysis of the current state in the field of managing complex technical and transport functional MTSC

This will help determine the reliability of forecasts made by the model, crucial for risk management in MTSC.

Time-Series and Forecasting [9]:

The complex ARIMA (*p*, *d*, *q*) model, including differencing for stationarity:

$$\left(1-\sum_{i=1}^{p}\phi_i L^i\right)(1-L)^d\, y_t=\left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t,$$

where L is the lag operator, d is the order of differencing.

This model is used for forecasting and understanding time patterns in MTSC risk management, such as trends and cyclical variations in risk factors.

b. Implementation of automated and intelligent systems:

1. Modeling and Simulation [10]:

The dynamic system model in state space:

$$\begin{cases}\dot{x}(t)=Ax(t)+Bu(t)\\ y(t)=Cx(t)+Du(t)\end{cases},$$

where A, B, C, D are system matrices, $\dot{x}(t)$ is the derivative of the state vector $x(t)$ over time, $y(t)$ is the output vector.

In MTSC, this model will be used to simulate various scenarios and assess the impact of different risk factors.

1. Optimization [11]:

Quadratic programming for optimization with a quadratic objective function and linear constraints:

$\min_x \frac{1}{2}x^T Qx + c^T x$, $Ax \le b$, where Q is a symmetric positive definite matrix.

Used for optimizing with a quadratic objective function and linear constraints. In MTSC, this can aid in optimizing resource allocation and operational strategies to minimize risks.

1. Machine Learning:

Support Vector Machine (SVM) for classification [12]:

$$\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \xi_i \,,\ y_i \left(w^T \phi(x_i) + b \right) \geq 1 - \xi_i ,\ \xi \geq 0 ,$$

where w is the weight vector, b is the bias, ξ_i are slack variables, ϕ is the mapping function to a higher-dimensional space, C is the regularization parameter.

SVMs are used for classification and can assist in identifying patterns in data indicative of high-risk scenarios in MTSC.

The indicated models should provide a scientific basis for the analysis and management of risks in MTSC. They will enable the development of more accurate and reliable risk management strategies, which are vital for ensuring the safety and efficiency of these complex systems.

2. Structural model of information support for the management of complex technical and MTSC.

To ensure effective risk management of functional MTSC, it's crucial to focus on creating a comprehensive structural model for information support. This process initiates with the identification of pivotal components of information support centered on risks. Recognizing data sources is an essential step since they serve as a foundation for a detailed risk evaluation and monitoring. Concurrently, determining the most effective tools for risk analysis, prediction, and tracking is imperative, allowing for prompt responses to potential threats [13].

In the subsequent phase, establishing connections between components within the context of risk management becomes paramount. Understanding how different data sources and tools can collaborate is critical for holistic risk management. In this regard, identifying potential vulnerabilities in information flows to devise strategies for their mitigation and ensure continuous monitoring is vital.

Modeling potential MTSC operational scenarios is the ensuing step in this research. Developing predictive models allows for risk analysis under various operational conditions and evaluating potential deviations from the system's standard functioning and their probable impact on MTSC safety and reliability.

In conclusion, integrating ergonomics principles into the structural model plays a significant role. Scientific analysis of the influence of information interface design on operators' decision-making can assist in formulating recommendations for interface optimization [14]. Such an approach aims to enhance risk management efficiency, reduce operator errors, and ensure greater stability and safety of functional MTSC during real-time operations (Fig. 2).

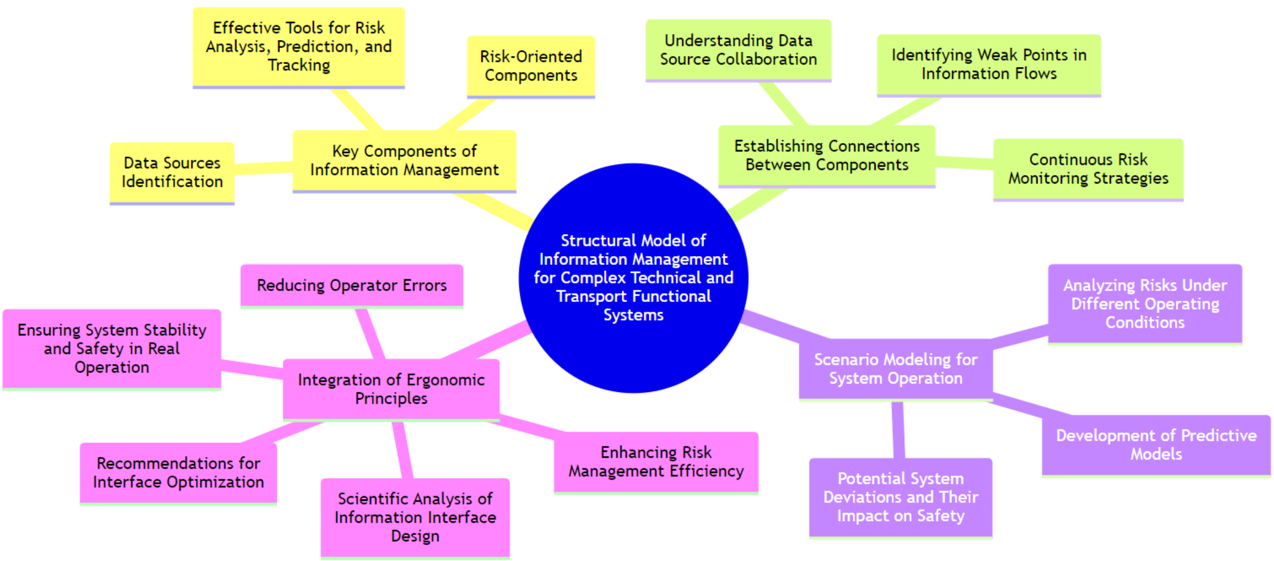

Fig. 2. Structural model of information support for the management of complex technical and marine functional systems and complexes

Let's examine mathematical methods aimed at improving MTSC risk management.

a. Identifying key components of risk-oriented information support:

Data Source Identification [15]:

Utilizing a weighted sum of similarity indices to assess the similarity between data (signals, documents, etc.):

$$S = \sum_{i=1}^{n} w_i J\left(A_i, B_i\right),$$

w_i is the importance weight of each data source, $J(A, B)$ is the Jaccard index of similarity between data A and B.

This method is crucial for identifying relevant data sources for risk assessment in MTSC.

Defining Tools for Analysis [16]:

Advanced Principal Component Analysis (PCA) using spectral decomposition for large data:

$Y = U\Sigma V^T$, where U and V are the left and right singular vectors, and Σ is the diagonal matrix of singular values.

PCA will reduce data dimensions and extract significant features critical for risk analysis and forecasting in MTSC.

b. Establishing connections between components:

Data Source Interaction [17]:

Determining the degree of interaction between components using correlation matrices and network analysis:

$$Corr\left(X_i, X_j\right) = \frac{Cov\left(X_i, X_j\right)}{\sigma_{X_i}\sigma_{X_j}},$$

Where Cov is the covariance, σ is the standard deviation.

This tool will help determine how different data sources are interconnected and affect risk management in MTSC.

2. Vulnerability Detection [18]:

Utilizing community-risk detection algorithms in networks to identify potential vulnerabilities in information flows. Essential for reducing risks and ensuring continuous monitoring in MTSC's lifecycle processes.

c. Modeling Potential Scenarios:

Predictive Models [19]:

Developing stochastic models based on Markov processes for predicting system states:

$P\left(X_{t+1} = x \mid X_t = x_t, ..., X_0 = x_0\right) = P\left(X_{t+1} = x \mid X_t = x_t\right).$

This will allow for analyzing risks under various operational conditions in MTSC.

2. More Complex Models, such as Integrated Differential Equations for modeling systems with limited resources:

$\frac{dx_i}{dt} = f\left(x_i, r_i, K_i\right) - g\left(x_i\right)$, where $g\left(x_i\right)$ represents the resource expenditure function.

This approach will determine resource constraints and their impact on risk management in MTSC.

d. Integrating Ergatic Principles:

Decision Cost Analysis [20]:

Developing mathematical models for optimizing costs:

$\min_x \ f\left(x\right) + \lambda R\left(x\right)$ where $R(x)$ is the risk or cost function, λ is the balance parameter between risk and cost.

This will balance risks and costs in decision-making in MTSC.

2. Optimization Recommendations [21]:

Developing factorial experiments to determine optimal interface parameters:

Experiment

$$Y = \beta_0 + \sum \beta_i X_i + \sum \beta_{ij} X_i X_j + \varepsilon .$$

Experiment (factors,levels)

Such methods are crucial for enhancing risk management efficiency and reducing operator errors in MTSC.

Overall, these models provide a comprehensive approach to risk management in MTSC. They will enable the analysis of data sources, interactions, and vulnerabilities, assist in predictive modeling and ergonomic optimization, thereby increasing overall safety and stability of operations in MTSC.

3. Method of ensuring rational management of functional MTSC in conditions of partial uncertainty.

To secure rational management of functional MTSC under conditions of partial uncertainty, it's imperative to meticulously study and consider a number of pivotal aspects. Firstly, a profound analysis and identification of factors potentially inducing partial uncertainty is essential. Investigating internal and external factors, such as equipment instability or signal interference, will facilitate the determination of their impact on MTSC management effectiveness and allow for forecasting potential consequences.

While scrutinizing the influence of uncertainty factors, the aim should be towards developing adaptive management strategies. Modeling will enable the dynamic adjustment of management parameters, reflecting the current degree of uncertainty. In this context, it's crucial to focus on devising tactics oriented towards minimizing risks associated with uncertainty.

To assist in the implementation of these adaptive strategies, automated analysis and selection of optimal management parameters become indispensable. Employing intelligent systems for system state prediction will allow operators to swiftly respond to changing conditions and adeptly adapt to novel situations (Fig. 3).

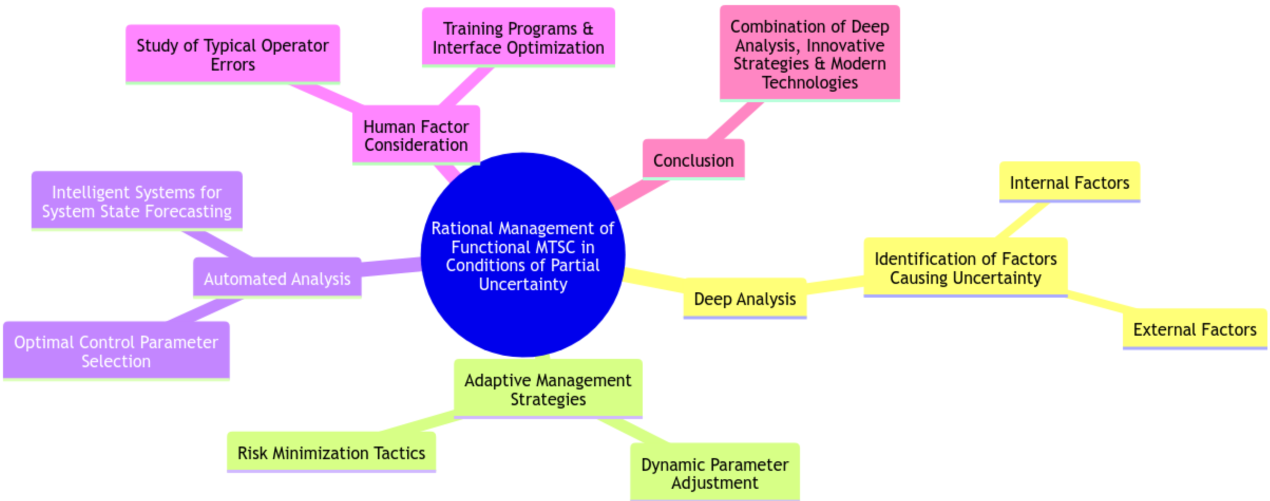

Fig. 3. Method of ensuring rational management of functional MTSC in conditions of partial uncertainty

The last, but by no means least, consideration is the human factor. Even with the finest systems and strategies, management errors may arise due to the human element, especially under heightened uncertainty. Hence, emphasis should be placed on studying typical operator errors and devising training programs and interfaces that utmostly facilitate operators' making judicious decisions under complex conditions.

Rational management of functional MTSC in instances of uncertainty necessitates a combination of profound analysis, innovative strategies, and the integration of contemporary technologies, collectively ensuring the system's reliability, safety, and efficacy.

Let us consider the mathematical apparatus that is crucial for managing MTSC in conditions of partial uncertainty. Here is a brief analysis of the main parts and application methods of the formal research component:

a. Identification and Analysis of Factors Causing Partial Uncertainty:

1. Statistical Method [22]:

Multidimensional regression analysis using interactions between variables:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_{ij} X_i X_j + \ldots + \varepsilon .$$

This is necessary for a quantitative assessment of the influence of both internal and external factors, such as equipment instability, signal obstructions, operator actions, etc.

The partial correlation coefficient, considering the influence of third variables:

$$r_{x_1x_2x_3} = \frac{r_{x_1x_2} - r_{x_1x_3} r_{x_2x_3}}{\sqrt{\left(1 - r_{x_1x_3}^2\right)\left(1 - r_{x_2x_3}^2\right)}} .$$

This approach helps understand the unique impact of each variable, isolating its effect from other factors. It is important for identifying the most significant factors contributing to uncertainty manifestations in MTSC.

Forecasting Methods [23]:

Smoothing using the Holt-Winters method for seasonal time series:

$$S_t = \alpha\left(y_t - I_{t-L}\right) + \left(1-\alpha\right)\left(S_{t-1} + b_{t-1}\right),$$
$$b_t = \beta\left(S_t - S_{t-1}\right) + \left(1-\beta\right) b_{t-1},$$
$$I_t = \gamma \frac{y_t}{S_t} + \left(1-\gamma\right) I_{t-L}.$$

The use of multidimensional regression analysis considering variable interactions will allow assessing the impact of various factors on MTSC management.

b. Creation of Adaptive Management Strategies:

1. Control Theory [24]:

Optimal control using Pontryagin's maximum principle:

$$H\left(x,u,\lambda\right) = f\left(x,u\right) + \lambda^T g\left(x,u\right), \ \frac{\partial H}{\partial u} = 0 .$$

This approach aids in forming strategies that dynamically adapt to changing conditions, optimizing a certain efficiency criterion, essential in unpredictable conditions.

Optimization:

Stochastic programming for optimization under uncertainty:

$$\min\nolimits_{x \in X} \mathrm{E}\left[f\left(x,\omega\right)\right].$$

This method is used for decision-making in implicit scenarios, crucial for managing MTSC in unpredictable conditions.

c. Automated Analysis and Selection of Optimal Management Parameters:

1. Intelligent Systems:

Deep neural networks for big data [25]:

$$y = \phi\left(\sum\nolimits_{i=1}^{n} W_{ij} \phi\left(\sum\nolimits_{k=1}^{m} W_{ki} x_k + b_i\right) + b_j\right).$$

These networks will help process large volumes of data and detect patterns, aiding in predicting system states and making rapid decisions.

2. Rapid Response Algorithms:

Reinforcement learning algorithms for optimal real-time management:

$$Q\left(s,a\right) = Q\left(s,a\right) + a\left[r + \gamma \max\nolimits_{a'} Q\left(s',a'\right) - Q\left(s,a\right)\right].$$

These algorithms help continuously learn and adapt strategies based on real-time data, crucial for dynamic management of MTSC.

d. Creation of Methods to Detect and Minimize the Negative Impacts of the Human Factor:

1. Cognitive Methods:

Cognitive modeling for evaluating decision-making errors:

$$P(error) = \frac{1}{1+e^{-(a+bX)}} .$$

These methods allow for estimating the probability of decision-making errors, key to identifying and reducing human errors in MTSC management.

2. Ergonomic Methods [26]:

Load modeling based on NASA-TLX criteria for task perception assessment:

$$TLX = \sum_{i=1}^{n} w_i r_i .$$

This method will assess perceived load under stress conditions, helping design operator interfaces and training programs that reduce operator errors in real MTSC management conditions.

Overall, these models and methods will provide a comprehensive approach to managing functional MTSC in conditions of uncertainty. They enable the analysis and mitigation of uncertainty factors, the development of adaptive management strategies, the optimization of management parameters, and the reduction of human operator errors, ensuring the reliability, safety, and efficiency of the system.

4. Intelligent decision-making model for the rational management of functional MTSC.

In the contemporary maritime industry context, particular emphasis is placed on intelligent decision-making systems for managing functional MTSC. To achieve optimal system control, and responses, a series of sequential actions must be undertaken.

The initial step should be a thorough analysis of intelligent data analysis methods that are specific to shipborne systems. Modern approaches to processing data from various sensors and systems are not always directly applicable without adaptation. Hence, there's a need to tailor these methods to the peculiarities of functional MTSC, especially considering the dynamic nature of the data and the imperative for rapid responses.

The subsequent phase focuses on implementing machine learning algorithms for dynamic management. Developing neural networks and other machine learning models capable of learning from operational data will be key to creating adaptive systems. Critical at this juncture is the real-data testing and tuning of algorithms, ensuring an optimal level of adaptability.

Given the specificities of ship operation, the next step involves establishing rational management criteria. It's essential to identify standard and unconventional operational situations that require a certain management approach, as well as to develop metrics that clearly reflect management efficiency under various conditions.

The concluding stage is dedicated to modeling the human-machine interaction system. Studying the primary behavioral patterns of operators when working with shipborne systems will facilitate the development of interfaces that optimize the decision-making process. The objective is to present information to the operator in the most accessible form, promoting swift and well-considered decision-making.

Together, these stages constitute a comprehensive approach to developing an intelligent decision-making model for managing functional MTSC, addressing the contemporary challenges of the maritime industry (Fig. 4).

Fig. 4. Scheme of intelligent decision-making model for the rational management of functional MTSC

Let us examine the formal methods and approaches that are key to managing MTSC using intelligent decision-making systems.

a. Detailed Analysis of Data Mining Methods Specific to Ship Systems:

1. Data Processing Method:

Advanced cluster analysis using the *k*-means method:

$\min \sum_{i=1}^{k} \sum_{x \in C_i} \left\| x - \mu_i \right\|^2$, where C_i is the cluster, μ_i is the cluster center, x is the data point.

This will aid in grouping and analyzing data from various sensors and systems, crucial for identifying informational patterns in MTSC.

Adapting to Dynamic Data [27]:

Autoregressive Moving Average Model (ARMA):

$$X_t = \sum_{i=1}^{p} \phi_i X_{t-1} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-1} + \varepsilon_t .$$

The model will be apt for adapting and forecasting dynamic data, facilitating rapid response in MTSC management.

b. Implementing Machine Learning Algorithms for Dynamic Management:

1. Neural Networks:

Deep learning using Convolutional Neural Networks (CNN):

$f(x) = \max(0, x * W + b)$, where $*$ - is the convolution operation, W - is the weight matrix, b is the bias.

This will assist in developing adaptive systems learning from operational data.

2. Testing and Tuning on Real Data:

Utilizing cross-validation for model assessment. This is crucial for ensuring an optimal level of adaptability of algorithms, using cross-validation.

c. Creating Criteria for Rational Management:

1. Risk Level Assessment [28]:

Bayesian networks for risk assessment:

$P(S \mid E) = \dfrac{P(E \mid S) P(S)}{P(E)}$, where E is the evidence, S is the system state.

Necessary for analyzing standard and atypical operational situations in MTSC.

Efficiency Metrics:

Using entropy to assess uncertainty:

$$H(X) = -\sum_i p(x_i) \log p(x_i).$$

The approach of applying entropy to assess uncertainty will aid in developing metrics reflecting management efficiency under various operational conditions of MTSC.

d. Modeling Human-Machine Interaction System:

1. Operator Behavior Analysis:

Stochastic models for operator behavior considering uncertainty:

$P(O \mid S,I) = \dfrac{P(S \mid O,I)P(O \mid I)}{P(S \mid I)}$, I is the information available to the operator.

Necessary for using stochastic models to assess operator behavior in uncertain conditions.

2. Interface Optimization [29]:

Adaptive interfaces using recommendation systems:

$U(u,i) = r_{ui} + k \cdot \sum_{s\in S} sim(i,s)(r_{us} - \overline{r}_u)$, where r_{ui} is the rating of operator u for item i, $i, sim(i,s)$ is the similarity between items.

Adaptive interfaces, developed based on recommendation systems, will help optimize the decision-making process in complex operational and management conditions of MTSC.

5. Refinement of the method for deriving the coefficient of rational control for functional MTSC.

To ensure reliable and efficient management of functional MTSC, it is paramount not only to develop and implement new systems but also to refine existing methods. In this context, studying and enhancing the method of deriving the coefficient of rational control becomes a pertinent task.

Firstly, a profound analysis of operational factors that directly influence the management of maritime systems must be conducted. Understanding factors such as weather conditions, the technical condition of the ship, sea state, among others, will facilitate better adaptation to external conditions and appropriate response strategies [30]. Assessing the degree of uncertainty of these factors and their interactions in real-world conditions is vital for devising response strategies.

Subsequently, with the obtained information in hand, it is crucial to perform dynamic modeling of the interaction between external and internal system factors. Developing mathematical models will not only allow for predicting potential risks but will also optimize the management process, ensuring maximum adaptability to various operational scenarios.

Nonetheless, managing maritime systems also has its nuances associated with marine operation. Thus, the next phase will involve adapting management strategies to these specific constraints and optimizing management methods to ensure efficiency in conditions of limited resources.

Lastly, the human-machine interaction aspect cannot be understated. Analyzing the behavior of operators in managing maritime systems will help identify bottlenecks and problematic areas. This, in turn, will enable the development of corrective measures for operators' actions [31], ensuring high efficiency and safety in management, edging us closer to the creation of an optimal control system for functional MTSC (Fig. 5).

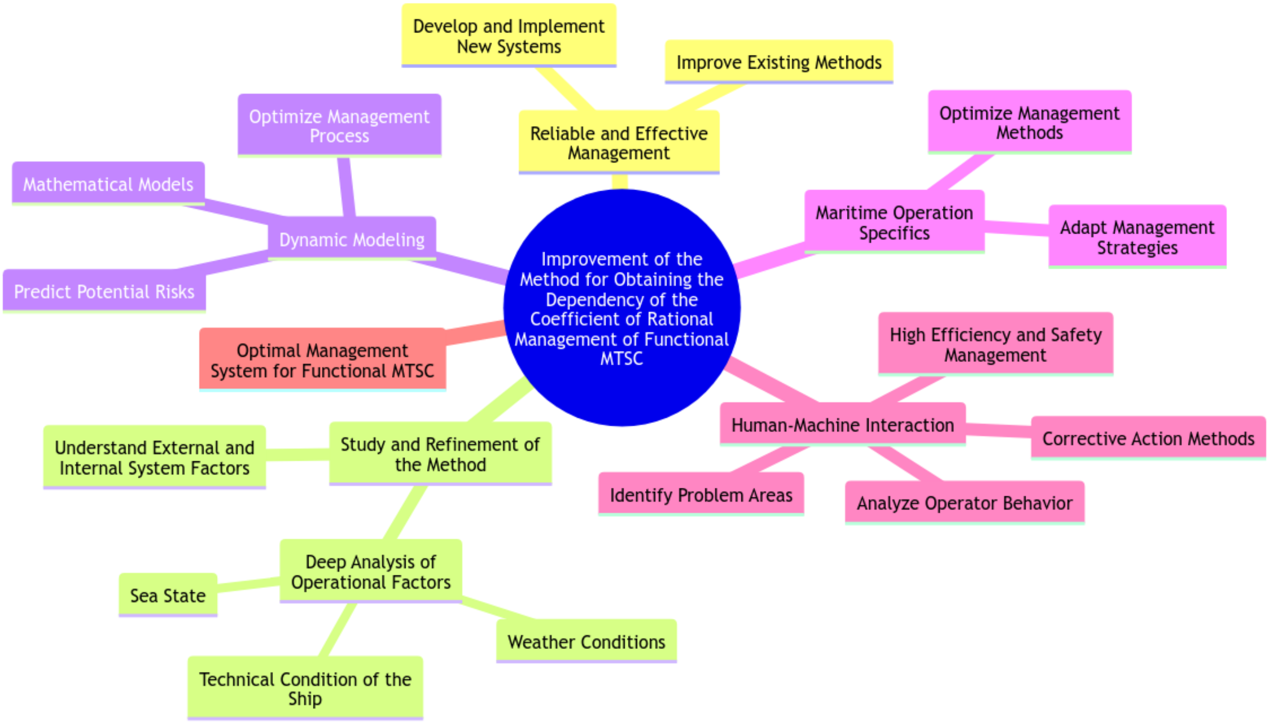

Fig. 5. Refinement of the Method for Deriving the Coefficient of Rational Control for Functional MTSC

In accordance with the outlined structure, it is necessary to identify the appropriate mathematical approaches and formulas aimed at improving the management of MTSC.

a. In-depth Analysis of Operational Factors:

1. Statistical Analysis [32]:

Advanced dispersion analysis for variability assessment:

$$S^2 = \frac{1}{n-1}\sum_{i=1}^{n}\left(x_i - \bar{x}\right)^2 .$$

This method should be used to assess the variability of factors affecting MTSC. It will assist in quantitatively measuring the degree of uncertainty in operational factors.

2. Modified Pearson correlation index for non-standard distributions:

$$r_{xy} = \frac{\sum\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum\left(x_i - \bar{x}\right)^2 \sum\left(y_i - \bar{y}\right)^2}} \cdot adjustment\ factor .$$

This method is critically important for assessing the correlation between operational factors and MTSC management efficiency, especially when data distribution is non-standard.

Risk Assessment Methods:

Use of integrated risk metrics combining different types of risks:

$R = \sum w_i \cdot R_i$, where R_i is the individual risk, w_i is the weight of importance.

b. Dynamic Modeling of Interaction between External and Internal Factors:

1. Mathematical Modeling:

Extension of the system of differential equations incorporating stochastic elements:

$dX_t = f\left(X_t, Y_t, Z_t\right)dt + g\left(X_t, Y_t, Z_t\right)dW_t$, where dW_t is the Wiener process for modeling random shocks.

These models are intended for dynamic representation of the interaction of various elements within MTSC, including randomness.

2. Computational Modeling:

Use of agent-based dynamic equation systems for modeling the behavior of individual components:

$\frac{dX_i}{dt} = h\left(X_i, \{X_j\}_{j \neq i}, U\right)$, where U is the control signal from the management system.

This approach models the behavior of individual components within MTSC, considering control signals from the management system to corresponding functional systems.

c. Development of Methods to Account for Constraints Characteristic of Maritime Transport:

1. Optimization [33]:

Application of multi-criteria linear programming to determine the optimal resource allocation:

$\min_x \; Z = c^T x$, $Ax \le b$, $x \ge 0$, $\min_x \; \sum_i w_i \cdot C_i(x)$, where $C_i(x)$ - is the objective function for the *i*-th criterion, w_i is the weight of the criterion.

This technique is used to determine the optimal resource allocation under constraints characteristic of maritime operations.

d. Modeling the Human-Machine Interaction System:

1. Operator Behavior Analysis:

Modeling operator decisions using multi-level hierarchical models:

$P_{decision}(O_t \mid S_t, I_t) = \frac{e^{u(O_t, S_t, I_t)}}{\sum_O e^{u(O_t, S_t, I_t)}}$, where u is the utility of making decision O_t in state S_t with information I_t.

The specified mathematical models will help forecast decision-making patterns of operators in various operational scenarios.

2. Interface Optimization:

Optimization of interface ergonomics using covariance analysis:

$\min_x Var(x) + \lambda \cdot Cov(x, u)$, where $Var(x)$ is the variance of interface parameters, $Cov(x, u)$ - is the covariance of interface parameters with user preferences, λ - is the penalty coefficient.

This method is used to optimize the ergonomics of the adaptive operator interface, balancing variations in interface parameters with individual characteristics and the level of risk.

Overall, these mathematical models and methods contribute to refining the process of deriving the coefficient of rational management for MTSC. Through the analysis of operational factors, dynamic modeling of interactions, optimization of resources, and considering the interaction of the human operator and the technical system, these approaches aim to enhance the efficiency and reliability of MTSC management under various risk conditions.

Conclusion. Thus, for rational risk management within the MTSC system, it is crucial to integrate scientific strategies, automation, and intelligent systems. Efficiency, speed, and accuracy are paramount, with a special emphasis on considering the role of the human operator factor, particularly in terms of ergonomics and monitoring their actions. Informational support necessitates the development of a comprehensive model, continuous monitoring of data sources, and effective design of control system interfaces. Given the inherent uncertainties, it is essential to devise adaptive management strategies, employ automation and intelligent systems for rapid response to changes, and consider various factors to minimize risks.

In line with the research objectives, the following tasks have been accomplished:

1. Principles for analyzing the current state in the field of MTSC management have been formulated. A comprehensive risk analysis and potential management strategies for MTSC have been proposed. This includes examining the evolution of risk assessment methods, transitioning from intuitive to scientifically based strategies, and implementing automated and intelligent systems in MTSC risk management processes.

2. A structural model for MTSC informational support has been defined, encompassing the identification of key components focused on risks. The model involves studying internal and external factors affecting MTSC and developing mechanisms for their monitoring and analysis.

3. A scheme for ensuring rational MTSC management has been proposed. The necessity of creating adaptive management strategies has been demonstrated, allowing dynamic adaptation to changing operational conditions, including the development of models for dynamically adjusting MTSC optimal management parameters.

4. A structure for an intelligent decision-making model for MTSC has been developed. The strategy for developing an intelligent decision-making model is described, including a thorough analysis of data mining methods specific to maritime systems and the implementation of machine learning for dynamic MTSC management.

5. Principles for refining the method of deriving the coefficient of rational MTSC management have been outlined. Techniques have been proposed, particularly through modeling the interaction between operators and MTSC functional systems, aiming at optimizing interfaces and operator training.

Overall, the study proposes a comprehensive approach to MTSC management, integrating scientific strategies, automation, and intelligent systems. Efficiency, speed, and precision are key, with a special focus on the role of the human operator factor in MTSC, particularly in aspects of ergonomics and monitoring operator actions.

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Nosov P.S.

SYSTEMIC APPROACHES TO RATIONAL MANAGEMENT OF FUNCTIONAL MARINE TECHNICAL SYSTEMS AND COMPLEXES

In the present era, the development of effective and safe management methods for marine technical systems and complexes (MTSC) is gaining particular importance. The article, considering the continuous progress of science and technology, proposes the development of a comprehensive approach to the rational management of functional MTSC, integrating scientific strategies, automation, and intelligent systems.

The main goal of the research is to create a framework structure of comprehensive measures for managing MTSC in conditions of partial internal and external uncertainty, with a special emphasis on the human factor and ergonomics in management. A deep risk analysis is proposed, including a review of the evolution of risk assessment methods, from intuitive to scientifically substantiated strategies, and the implementation of automated and intelligent systems in the processes of managing MTSC risks.

The work focuses on the importance of creating a structural model of information support for MTSC, including the identification of key components focused on risks, studying internal and external factors affecting MTSC, and developing mechanisms for their monitoring and analysis. Significant attention is paid to the development of a scheme for ensuring rational management of MTSC in conditions of partial uncertainty, with an emphasis on creating adaptive management strategies.

The importance of developing an intelligent decision-making model for MTSC is emphasized, which includes a detailed analysis of methods for intelligent data analysis specific to ship technical systems, the implementation of machine learning for dynamic ship management, and the development of criteria for management rationality.

Finally, the article highlights the need to refine the method for deriving the coefficient of rational management of MTSC, including the development of models of interaction between operators and technical means to optimize interfaces and train operators.

Thus, a comprehensive approach to managing MTSC is proposed, integrating scientific strategies, automation, intelligent systems, ergonomics, and considering the importance of the human factor. This approach aims to increase the efficiency, speed, accuracy, and safety of managing MTSC, especially considering the importance of monitoring the actions of ship operators.

Keywords: *rational management; ship technical systems; automation and intelligent systems; risk management; ergatic aspects; human factor.*