*Adv Syst Sci Appl* 2025; **4**; 29-43
Published online at https://ijassa.ipu.ru.

# A Method for Analyzing Causal Relationships to Ensure the Reliability and Safety of Complex Human-Machine Systems

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**Abstract**: The article presents a method for analyzing causal relationships aimed at ensuring the reliability and safety of complex human-machine systems (HMS). The developed approach combines system decomposition with modeling of dynamic interactions, considering the influence of human, technical, and organizational factors. A model based on Markov processes with variable transition intensities dependent on subsystem states is proposed, which allows for identifying cascade failures and reducing the dimensionality of tasks without loss of informativeness. In the literature review, we performed an analysis of modern methods, including dynamic Bayesian networks, fuzzy cognitive maps with genetic tuning, and system-theoretic process analysis. The effectiveness of hybrid algorithms in identifying critical risks is demonstrated. As a result, we have conducted numerical experiments on aviation systems, such as Airbus A-320, Bombardier CRJ-200, Boeing 747, and Sukhoi Superjet 100 (RRJ-95). These experiments illustrate the calculation of stationary state probabilities and risk dynamics. Conclusions are formulated regarding the methodological flexibility of the approach, its advantages in overcoming the "curse of dimensionality," and prospects for application in other industries.

***Keywords***: Human-machine systems, causal relationships, reliability, safety, Markov processes, decomposition, cascade failures

## 1. INTRODUCTION

Due to the accelerated development of complex human-machine systems (HMS), integrating technical, human, and organizational components in critically important sectors, such as aviation, transportation [16], energy, and industry, ensuring their reliability and safety comes to the forefront [15]. Emergency incidents in such systems arise not from isolated component failures but from cascading combinations of events. Individual events in such chains often pose minimal threat in isolation; however, their sequential or concurrent interaction produces catastrophic consequences. Nevertheless, the computational complexity increases significantly with the accumulation of such events. The combination of these factors necessitates a shift from traditional statistical techniques to methods capable of decomposing the system, modeling dynamic causal relationships, and managing task dimensionality without loss of prognostic accuracy.

Despite advancements in HMS analysis, existing tools often encounter limitations in accounting for nonlinear interactions and the "curse of dimensionality," which reduces their effectiveness for high-dimensional systems. The proposed method overcomes these barriers through the integration of a decomposition principle with Markov modeling, introducing variable transition intensities and influence coefficients to describe cascade effects.

The objective of the study is to develop and apply an approach to analyzing causal relationships for enhancing the reliability and safety of HMS.

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This study addresses the following tasks to achieve the stated objective:

- Conducting a comparative analysis of modern methods for analyzing causal relationships, with an evaluation of their advantages and limitations in the context of HMS.
- Formalizing a mathematical model based on Markov chains with variable intensities $\lambda$ (failures) and $\mu$ (recoveries), accounting for subsystem state dependencies through influence coefficients $\beta$, as well as procedures for dimensionality reduction to decrease computational complexity.
- Performing numerical experiments using real parameters of aviation systems (A-320, CRJ-200, B-747, RRJ-95), including solving the system of Kolmogorov-Chapman differential equations for 27 states and constructing graphs of probability dynamics.
- Quantitative assessment of stationary probabilities of functional states, partial failures, and risks of catastrophic failures, with calculation of measures of factor influence on overall reliability.
- Formulating practical recommendations for minimizing identified vulnerabilities, including improving personnel training, optimizing regulations, implementing redundant systems, and measures to reduce cascade effects.

The structure of the article includes a literature review on approaches (Section 1), problem statement (Section 2), model description (Section 3), experimental results (Section 4), and conclusion.

## 2. APPROACHES TO ENSURING RELIABILITY AND SAFETY OF COMPLEX HUMAN-MACHINE SYSTEMS: LITERATURE REVIEW

In connection with the increasing complexity of human-machine systems and their widespread dissemination, ensuring their reliability and safety becomes a key factor in the design and operation of such systems.

In such systems, emergency situations most often arise not due to a single "major" failure, but as a consequence of critical combinations of events, each of which individually may appear acceptable, but whose joint realization forms an emergency scenario. Under these conditions, it is necessary not only to expand the set of statistical models but also to structure causal relationships between heterogeneous processes and stages of system functioning using controlled dimensionality reduction of models without loss of prognostic informativeness. The foundation of the considered research lies in the focus on decomposition and causality.

A range of modern methods for analyzing causal relationships currently enhances the reliability and safety of complex human-machine systems (HMS). These methods identify critical risk factors, model dynamic interactions, and quantitatively assess failure probabilities. Among these methods, dynamic Bayesian networks (DBN) integrated with dynamic fault trees (DFT) [7] stand out, providing the capability to model complex logical and temporal dependencies between components of the "human-machine" system. This approach allows for identifying critical risk nodes and conducting quantitative safety analysis while accounting for the system's evolution over time. For example, researchers successfully apply this method to assess risks during operations at spaceports, particularly in the rocket fueling process.

Hybrid algorithms also demonstrate significant potential, combining causal models with data obtained from simulators. These algorithms integrate information on system operation, cognitive models of human behavior, and Bayesian network apparatus, enabling a more accurate quantitative assessment of the human factor in failure analysis within engineering HMS. Another promising direction is the combination of system-theoretic process analysis (STPA) with methods of cognitive error evaluation. This hybrid approach, aimed at identifying potentially hazardous control actions and constructing formal models for quantitative risk assessment, finds application in aviation, marine systems, and the design of integrated interfaces.

For systems with fuzzily defined structures, such as the "driver-vehicle-road" system, researchers effectively employ fuzzy cognitive maps with genetic tuning. This approach ranks factors that influence reliability. In turn, for a comprehensive reliability assessment that accounts for both technical and human stochastic factors, researchers integrate classical methods [4]. This integration proves particularly relevant for highly mobile transportation systems. No less important is the quantitative evaluation of the contribution of organizational factors (e.g., training quality and procedures) to overall system reliability, for which causal Bayesian networks are successfully employed, assessed in the chemical and process industries.

Modern methods for analyzing causal relationships, including dynamic Bayesian networks and system-theoretic process analysis [1], enable comprehensive consideration of organizational and stochastic factors in complex interactions between humans and machines. Hybrid approaches that combine formal models, expert evaluations, and simulator data demonstrate the greatest effectiveness. Among the critically important factors for HMS reliability are personnel training quality, clarity of regulations and procedures, timely identification of hazardous control actions, and adequate accounting of organizational aspects.

The analysis of human-machine system reliability using fuzzy cognitive maps (FCM), modified by genetic tuning methods, represents a modern, promising approach that allows accounting for complex, nonlinear, and weakly formalized interrelationships between factors influencing system safety [13]. The essence of this method lies in the synthesis of qualitative expert knowledge and quantitative observational data. At the first stage, researchers construct a cognitive map, a cognitive map, the nodes of which represent key reliability factors (human, technical, and organizational), and directed arcs between them represent causal relationships. Experts assign fuzzy weight coefficients to these links to account for the inherent uncertainty and subjectivity of expert evaluations.

To minimize the subjectivity of the initial model and enhance its predictive accuracy, a genetic tuning procedure is applied. The genetic algorithm uses sets of FCM link weight coefficients as chromosomes, taken from permissible value intervals [14]. The fitness criterion (fitness function) is the measure of discrepancy between the output data obtained from simulation modeling based on the FCM and real observational data or high-precision simulations. The iterative process of selection, crossover, and mutation of "chromosomes" allows for an evolutionary search for a weight configuration that ensures the minimum specified discrepancy, thereby adapting the model to objective data.

The key advantages of the hybrid FCM method with genetic tuning are, firstly, the ability to adequately model systems with fuzzily defined structures and incomplete input data, which is characteristic of many complex HMS [12]. Secondly, the automated optimization process significantly reduces the degree of subjectivity inherent in traditional expert procedures for setting weights. Thirdly, adaptive tuning substantially increases the accuracy of predictive estimates. Empirical studies demonstrate that the prediction error can be reduced by nearly half compared to untuned models. This approach demonstrates both effectiveness and universality through successful validation in the analysis and forecasting of reliability for heterogeneous systems.

Thus, the use of fuzzy cognitive maps in combination with genetic algorithms forms an effective toolkit for analyzing the reliability of human-machine systems. This method allows not only for identifying and ranking key risk factors based on modeling their complex interinfluences but also for enhancing the reliability of forecasts through automatic model calibration based on empirical data.

The decomposition method for analyzing complex systems possesses significant methodological advantages compared to alternative approaches, as confirmed by research in systems analysis and control theory. Unlike rigid holistic methods that require a priori specification of all system parameters, this approach applies the principle of adaptive detailing. This principle enables iterative adjustment of analysis depth for individual subsystems as researchers obtain intermediate results. This feature ensures the methodological flexibility necessary for investigating systems with high degrees of uncertainty and dynamic variability.

When comparing with holistic analysis methods, it is important to note the decomposition approach's ability to effectively overcome the "curse of dimensionality"–a fundamental problem arising from attempts to simultaneously account for all factors in a complex system. As demonstrated by studies in systems engineering, breaking down the system into interconnected subsystems transforms a multidimensional task into a set of lower-dimensional tasks while preserving the ability to account for specific characteristics of individual components. This is particularly significant in the analysis of human-machine systems, where technical, ergonomic, and psychological aspects require the application of diverse methodological tools.

In comparison with statistical methods, the decomposition approach provides a deeper understanding of the causal mechanisms of system functioning. Statistical methods primarily identify correlational dependencies between observed parameters. In contrast, this type of analysis reconstructs causal relationships and interaction mechanisms between system elements. Researchers achieve this through the construction of structural-functional models that reflect not only statistical patterns but also the substantive logic of subsystem functioning.

The decomposition method also demonstrates a significant advantage in comparison with simulation modeling. Despite the high diagnostic value of simulation models, their creation and verification require substantial computational resources and time expenditures. In contrast, the decomposition approach enables analysis of the system structure without the need to build a full-scale simulation model, focusing on key interrelationships and providing a deeper understanding of the system architecture. This is particularly important at the initial stages of research when it is necessary to identify critical points and determining factors of system functioning.

The methodological strength of this approach also lies in its ability to integrate qualitative and quantitative analysis methods, ensuring a multilevel understanding of complex systems. This synthetic nature allows for overcoming limitations inherent in individual methods and creating comprehensive research strategies adequate to the complexity of the studied objects.

Early works [10, 9] formed the methodological foundation: systems thinking, multilevel hierarchical organization, and the principle of decomposition of complex objects. Such a paradigm sets the normative framework for analyzing human-machine systems. It also justifies the necessity of stepwise structuring of processes and rational limitation of the factor space, which is fundamentally important for subsequent quantitative analysis of reliability and safety.

In [6], authors proposed a cybernetic approach to modeling heterogeneous processes in complex mechatronic human-machine systems and formalized the causal complex (CC) as a language for composing links that incorporate conditions for realization both before and after the effect. This apparatus reduces the share of subjectivity in reconstructing critical chains and allows for a consistent description of the interaction between "human" and "technical" factors. The CC concept serves as a direct prerequisite for distributing partial reliability and safety indicators across classes of heterogeneous processes and life cycle stages.

This topic received further development in applied works on aviation system management, which demonstrate the transition from qualitative causal schemes to quantitative risk assessment. In work [11], it is proposed to build event trees, calculate probabilities of accidents and catastrophes under unfavorable combinations of factors, and formulate optimization problems for selecting control actions in stochastic state dynamics using tools such as Kolmogorov-Chapman differential equation systems and non-Markov schemes with neural networks or fuzzy logic. These models demonstrate the aforementioned transition from qualitative causal schemes to quantitative "risk-based management," but they have a limitation in the form of high dimensionality and labor-intensive parameterization, which intensifies the need for preliminary structural filtering of factors.

 

Modern interpretations of risk [2] emphasize its dual nature: they consider risk simultaneously as an event measure and as a processual characteristic of functioning quality over time. Such risk interpretations for the complex HMS methodologically justify the exclusion of causal links that do not influence the system's trajectory toward a dangerous combination of events at preliminary stages of structural analysis, thereby supporting model simplification without loss of prognostic value.

The conclusions of the work [3] support the methodology used in our article. In [3], the authors implemented a “relevance filter” before labor-intensive optimization calculations, which aligns with the stepwise causal decomposition and selection of essential processes used in this article. This also allows for simplifying the model without loss of prognostic informativeness and reducing the load required for obtaining expert evaluations.

In related tasks of managing damage from atmospheric emissions under uncertainties [8], researchers demonstrate the necessity of approximations, decomposition, and explicit separation of controls/disturbances for ensured solvability and interpretability of the formulation. They transfer these methods to human-machine system safety: structuring causal relationships serves as a relevance filter that reduces dimensionality without sacrificing substantive accuracy.

The primary contribution of this work, relative to existing causal methods, lies in shifting causal analysis from post-event investigation to predictive modelling. By conducting structural filtering prior to quantitative evaluation, the approach substantially decreases the effort and cost required for expert assessments. In comparison with risk-based management models, where dimensionality grows sharply due to event combinations [11], the proposed mechanism acts as a relevance filter, ensuring computational feasibility without detriment to substantive completeness, thereby alleviating computational complexity while preserving the accuracy and reliability of subsequent assessments.

In contrast with our previous study [5], we refine the Markov model by adopting three states per subsystem (functional, partial failure, complete failure), yielding $3^3 = 27$ states for three components (crew, engines, avionics), versus the binary $2^5 = 32$ states across five components. Also, we introduce influence coefficients $\beta$ to simulate transition intensities, capturing interdependencies and cascade failures for granular nonlinear analysis.

This study demonstrates the application of the method to an ATS. This example confirms the method’s practical applicability in scenarios that demand coordinated integration of human, technical, and environmental factors. The work logically bridges the gap between descriptive causal schemes and computationally intensive quantitative formulations in aviation transport system safety management. In this framework, critical states emerge as combinations of unfavorable factors, while analysts assess risk through event trees and stochastic models. This formalized selection of essential causal links at the system’s life-cycle stages achieves the stated objective. Thereby, the work integrates into the existing line of research on aviation safety management and simultaneously offers a practical mechanism for dimensionality reduction through stepwise decomposition of factors before probabilistic-optimization calculations.

## 3. PROBLEM STATEMENT

Let the complex human-machine system function over the time interval $t \in [0, T]$.

The system evolves through a sequence of distinct stages:

$$E = \{ e_1, e_2, \dots, e_k \},$$

where $e_j$ – is a stage of system functioning (for example, “taxiing,” “acceleration and run-up,” “takeoff,” “climb,” etc.).

Let us introduce the matrix of system parameters:

$$X(t) = \left[ x_{ij}(t) \right]_{i=1,\dots,n}^{j=1,\dots,k},$$

where $i = 1, \dots, n$ are system parameters, $j = 1, \dots, k$ are stages.

Each element $x_{ij}(t)$ describes the influence of parameter $i$ on stage $e_j$ at time moment $t$:

$$x_{ij}(t) \in [0,1], \quad \begin{cases} x_{ij}(t) = 1, & \text{heterogeneous influence of the parameter on stage } e_j \text{ in the time interval } t, \\ x_{ij}(t) = 0, & \text{absence of influence of the parameter on stage } e_j \text{ in the time interval } t, \\ 0 < x_{ij}(t) < 1, & \text{partial influence of the parameter on stage } e_j \text{ in the time interval } t. \end{cases}$$

At the same time, part of the parameters is controllable (those on which the aircraft crew can influence in flight), and part is uncontrollable (those on which the crew cannot influence):

$$x_{aj}(t), \quad a = 1, \dots, h \ - \ \text{controllable parameters},$$
$$x_{bj}(t), \quad b = h+1, \dots, n \ - \ \text{uncontrollable parameters},$$

For each stage $e_j$, a subset of actually influencing parameters is selected:

$$P_j = \{x_i \in P \mid x_{ij}(t) > 0\}, \quad |P_j| = m_j \le n,$$

and only these parameters participate in the computation of the accident probability criterion on stage $e_j$:

$$f_j\left(\{x_{ij}(t) \mid x_i \in P_j, t \in [t_j^{\text{start}}, t_j^{\text{end}}]\}\right) : [0,1]^{m_j} \to [0,1].$$

The overall system criterion accounts for all stages and integrates the influence of parameters over time:

$$P_{\text{fail}} = \int_0^T F\left(x_{11}(t), \dots, x_{nk}(t)\right) dt,$$

where $F$ aggregates the accident probability over all stages at time moment $t$.

If all parameters $P$ are considered for each stage, and the time interval is discretized into $L$ points (where $L$ corresponds to the number of time samples on the interval $[0, T]$), then the total number of computations for evaluating the integral over time grows exponentially with the number of parameters and stages:

$$\text{G} \sim L \cdot \prod_{j=1}^{k} d^{|P|} = L \cdot d^{n \cdot k},$$

where $d$ is the number of discretization levels for each parameter (for example, if the value $x_{ij}(t)$ is taken not as continuous, but approximated by a grid of $d$ values on the segment $[0,1]$).

Discarding insignificant parameters at each stage (leaving only $m_j$ actually influencing parameters) allows for a substantial reduction in computational load:

$$\text{G} \sim L \cdot \prod_{j=1}^{k} d^{m_j} \ll L \cdot d^{n \cdot k}.$$

Within the framework of the problem statement, the objective is to reduce the computational power of the model by selecting the minimum number of parameters for each stage $e_j$.

## 4. DESCRIPTION OF THE MODEL

Within the framework of reliability theory for complex technical systems, each technological process exhibits a discrete set of states that constitute the state space of possible operating modes. The state of process $i$ is formally given by the variable $S_i \in \{0, 1, 2\}$, where:

- 0 corresponds to the functional state.
- 1 represents the state of partial failure.
- 2 identifies the state of complete failure.

Thus, the complete state of the entire system is described by the vector $s = (S_1, S_2, S_3)$, where $S_i \in \{0,1,2\}$, forming a state space consisting of $3^n = 3^3 = 27$ possible combinations.

State numbering follows the formula:

$$k = s_1 \cdot 9 + s_2 \cdot 3 + s_3 \cdot 1, k \in \{0, 1, \dots, 26\}, \quad (1)$$

where $k$ is the state number.

Intensity parameters with probabilistic interpretation govern transitions between these states. The parameter $\lambda_i$ characterizes the failure intensity of the component $i$ and represents the limiting probability of transition from the functional state to the failure state per unit time, assuming continuous operation at the initial moment. The statistical estimation of this parameter is performed using the formula: $\lambda_i = \frac{k_i}{T_{obs}}$, where $k_i$ is the number of failures of the component $i$ over the observation time $T_{obs}$. Similarly, the parameter $\mu_i$ represents the recovery intensity and is calculated as $\mu_i = \frac{1}{T_{r,i}}$, where $T_{r,i}$ is the mean recovery time of component $i$, determined from operational statistical data.

The system evolves according to a continuous-time homogeneous Markov process. For each component $i$ basic transition intensities between its internal states are defined according to the definitions of $\lambda$ and $\mu$:

$\lambda_i^{(p)}$ – intensity of transition from the functional state to the partial failure state $(p)$ (0→1).

$\lambda_i^{(f)}$ – intensity of transition from the partial failure state to the complete failure $(f)$ (1→2).

$\mu_i^{(p)}$ – recovery intensity from the partial failure state to the functional state $(p)$ to the functional state (1→0).

$\mu_i^{(f)}$ – recovery intensity from the complete failure state $(f)$ to the functional state (2→0).

A key feature of complex systems is the presence of interdependencies between components, manifested in correlated failures and cascade effects. To formalize these interrelationships, a system of influence coefficients $\beta_{j\to i}$, is introduced, quantitatively expressing the degree of impact of the state of the component $j$ on the failure intensity of the component $i$. The physical interpretation of these coefficients is that when the component $j$ is in a failure state, the failure intensity of the component $i$ increases by a factor of $(1 + \beta_{j\to i})$.

Mathematically, this is expressed through the effective failure intensity:

$$\lambda_i^{eff} = \lambda_i \cdot \left[1 + \Sigma_{j\neq i}\, \beta_{j\to i} \cdot I_j\right], \tag{2}$$

Here $I_j$ is the indicator function of the state of the component $j$, taking the value 1 if $S_j > 0$ and 0 otherwise.

Let us introduce coefficients $\beta_{j\to i}^{(p)}$ and $\beta_{j\to i}^{(f)}$, which indicate how a partial or complete failure of component $j$ increases the intensity of partial or complete failure of component $i$, respectively. To formalize this, indicator functions $I_{\{s_j=1\}} = \begin{cases} 1, s_j = 1 \\ 0, \ otherwise \end{cases}$, $I_{\{s_j=2\}} = \begin{cases} 1, s_j = 2 \\ 0, \ otherwise \end{cases}$, taking the value 1 if component $j$ is in the state of partial or complete failure, respectively, and 0 otherwise. The effective transition intensities associated with failures for component $i$ in the global state $j$, are calculated as follows:

Intensity of partial failure occurrence: $q_i^{0\to 1}(s) = \lambda_i^{(p)}(1 + \sum_{j\neq i}(\beta_{j\to i}^{(p)} I_{\{s_j=1\}} + \beta_{j\to i}^{(f)} I_{\{s_j=2\}}))$;

Intensity of escalation from partial to complete failure: $q_i^{1\to 2}(s) = \lambda_i^{(f)}(1 + \sum_{j\neq i}(\beta_{j\to i}^{(p)} I_{\{s_j=1\}} + \beta_{j\to i}^{(f)} I_{\{s_j=2\}}))$.

Let us describe the methodology for calculating the influence coefficients β. The coefficients $\beta_{\{j\to i\}}$ are estimated based on statistical data on joint component failures obtained from operational statistics of aviation systems. The primary approach involves using conditional failure intensities: $\beta_{\{j\to i\}} = \left(\frac{\lambda_{\{i|j\}}}{\lambda_i}\right) - 1$, where $\lambda_{\{i|j\}}$ is the failure intensity of the component $i$ conditional on the failure of the component $j$, and $\lambda_i$ is the baseline independent failure intensity.

Due to the introduction of such coefficients, $\lambda$ and $\mu$ are no longer fixed but can vary depending on the states of other processes.

 

An important assumption of the model is that recovery processes are considered independent of the states of other components. Thus, the recovery intensities remain constant:

$q_i^{1\to 0}(s) = \mu_i^{(p)}$;

$q_i^{2\to 0}(s) = \mu_i^{(f)}$.

The dynamics of the probabilities of the system being in each of the 27 states is described by the Kolmogorov system of differential equations. For an arbitrary state $x = (s_1, s_2, s_3)$, the equation has the form:

$$\frac{dP_{s_1s_2s_3}}{dt} = \sum_{i=1}^{3}\sum_{r\neq s_i} q_i^{r\to s_i}(s^{(i,r)})P_{s_1\ldots r\ldots s_3} - (\sum_{i=1}^{3}\sum_{r\neq s_i} q_i^{s_i\to r}(s)P_{s_1s_2s_3};$$

Where $s^{(i,r)}$ denotes a state identical to $x$, except that component $i$ is in state $r$. The first sum (inflow) accounts for all transitions from any other states leading to state $x$. The second sum (outflow) represents the total intensity of all possible transitions from state $x$ to any other states and determines the rate of decrease of the probability $P_{s_1s_2s_3}$.

For illustration, the equation for the fully functional state (0,0,0) is as follows:

$$\dot{P}_{000} = -\left(q_1^{0\to 1}(0{,}0{,}0) + q_2^{0\to 1}(0{,}0{,}0) + q_3^{0\to 1}(0{,}0{,}0)\right)P_{000} + \mu_1^{(p)}P_{100} + \mu_2^{(p)}P_{010} + \mu_3^{(p)}P_{001};$$

In this equation, the outflow is due to the risk of partial failure of any of the three components, and the inflow is due to the recovery of any component from the partial failure state to the fully functional state, provided that the other two components are functional.

Similarly, the equation for state (0,0,1), where avionics has a partial failure, accounts for more complex interactions:

$$\dot{P}_{001} = q_3^{0\to 1}(0{,}0{,}0)P_{000} - \left(q_1^{0\to 1}(0{,}0{,}1) + q_2^{0\to 1}(0{,}0{,}1) + q_3^{1\to 2}(0{,}0{,}1) + \mu_3^{(p)}\right)P_{001} + \mu_1^{(p)}P_{101} + \mu_2^{(p)}P_{011} + \mu_3^{(f)}P_{002};$$

Here, the failure intensities of the crew and engines ($q_1^{0\to 1}$ may be influenced by the state of avionics through the coefficients $\beta$.

Similarly, the equation for state (0,0,2):

$$\dot{P}_{002} = q_3^{1\to 2}(0{,}0{,}1)P_{001} - \left(q_1^{0\to 1}(0{,}0{,}2) + q_2^{0\to 1}(0{,}0{,}2) + \mu_3^{(f)}\right)P_{002} + \mu_1^{(p)}P_{102} + \mu_2^{(p)}P_{012};$$

Similarly, the equation for state (0,1,0):

$$\dot{P}_{002} = q_3^{1\to 2}(0{,}0{,}1)P_{001} - \left(q_1^{0\to 1}(0{,}0{,}2) + q_2^{0\to 1}(0{,}0{,}2) + \mu_3^{(f)}\right)P_{002} + \mu_1^{(p)}P_{102} + \mu_2^{(p)}P_{012};$$

This model enables an adequate assessment of the reliability of a complex system, accounting for cascade and dependent failures, providing a tool for predicting the probabilities of critical states and analyzing system vulnerabilities. Solving the resulting system of 27 differential equations requires the application of numerical methods but provides a complete picture of the temporal evolution of the system's reliability.

The system evolves as a continuous-time Markov process, with transition probabilities governed by the intensity transition matrix $Q$. Each element $q_{S\to S'}$ of this matrix represents the intensity of transition from state $S$ to state $S'$ and is calculated based on the effective failure and recovery intensities of the components.

Direct solution of the Kolmogorov system of differential equations for state probabilities $dp(t)/dt = p(t)Q$ becomes computationally intensive with increasing system dimensionality. To mitigate the curse of dimensionality, the model employs reduction techniques, including:

- Exclusion of low-influence components based on sensitivity analysis.
- Aggregation of states with similar reliability characteristics.

The practical implementation of the methodology includes the following steps:

- Statistical estimation of baseline intensities $\lambda_i$ and $\mu_i$ from operational data.

 

- Expert determination of the influence coefficient matrix $\beta_{j\to i}$ based on analysis of functional linkages.
- Construction of a reduced state space accounting for dominant influence factors.
- Numerical solution of the system of differential equations for state probabilities.
- Verification of the model against failure statistics and parameter adjustment.

The proposed approach allows for adequate modeling of cascade failures in complex systems and evaluation of comprehensive reliability indicators, accounting for mutual component influences, as confirmed by the results of computational experiments for various classes of technical systems.

## 5. THE RESULTS

This section presents the results of numerical simulations that apply the proposed approach to aviation human-machine systems. The analysis employs operational parameters from four aircraft types: A-320, CRJ-200, B-747, and RRJ-95. The parameters include intensities of partial ($\lambda_p$) and complete ($\lambda_f$) failures, recovery intensities ($\mu_p$, $\mu_f$), as well as matrices of influence coefficients ($\beta_p$ for partial failures and $\beta_f$ for complete failures). These data are based on statistical observations and expert assessments and are reflected in the Table 5.1 below.

**Table 5.1.** The parameters for every aircraft type

| **Aircraft** | $\lambda^{(f)}$ | $\mu^{(f)}$ | $\lambda^{(p)}$ | $\mu^{(p)}$ | $\beta^{(p)}$ | $\beta^{(f)}$ |
|---|---|---|---|---|---|---|
| A-320 | [3, 10, 1] | [57, 190, 19] | [20, 10, 15] | [280, 190, 250] | $\begin{pmatrix} 0 & 0.03 & 0.1 \\ 0.08 & 0 & 0.05 \\ 0.06 & 0.04 & 0 \end{pmatrix}$ | $\begin{pmatrix} 0 & 0.25 & 0.4 \\ 0.3 & 0 & 0.2 \\ 0.2 & 0.1 & 0 \end{pmatrix}$ |
| CRJ-200 | [1, 2, 1] | [19, 38, 19] | [2, 3, 1] | [365, 365, 300] | $\begin{pmatrix} 0 & 0.03 & 0.06 \\ 0.05 & 0 & 0.04 \\ 0.04 & 0.03 & 0 \end{pmatrix}$ | $\begin{pmatrix} 0 & 0.15 & 0.25 \\ 0.2 & 0 & 0.12 \\ 0.12 & 0.08 & 0 \end{pmatrix}$ |
| B-747 | [0, 1, 0] | [0, 19, 0] | [0.5, 2, 0.2] | [365, 190, 365] | $\begin{pmatrix} 0 & 0.02 & 0.03 \\ 0.04 & 0 & 0.03 \\ 0.02 & 0.02 & 0 \end{pmatrix}$ | $\begin{pmatrix} 0 & 0.12 & 0.08 \\ 0.2 & 0 & 0.1 \\ 0.05 & 0.04 & 0 \end{pmatrix}$ |
| RRJ-95 | [0, 18, 3] | [0, 342, 57] | [10, 31, 22] | [365, 400, 250] | $\begin{pmatrix} 0 & 0.04 & 0.06 \\ 0.08 & 0 & 0.06 \\ 0.05 & 0.04 & 0 \end{pmatrix}$ | $\begin{pmatrix} 0 & 0.3 & 0.35 \\ 0.35 & 0 & 0.25 \\ 0.2 & 0.15 & 0 \end{pmatrix}$ |

Perform calculations for each aircraft type based on the obtained failure and recovery flow intensities, along with the previously presented system of differential equations and coefficients.

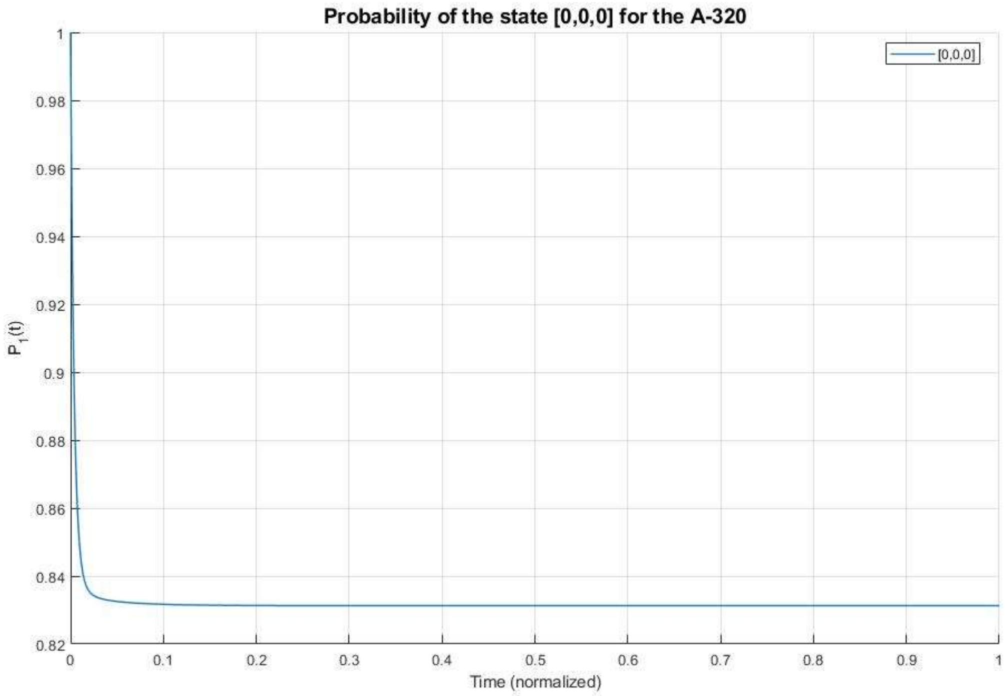


**Fig. 5.1.** Probabilistic safety characteristics for the A-320 ($P_{000}(t)$)

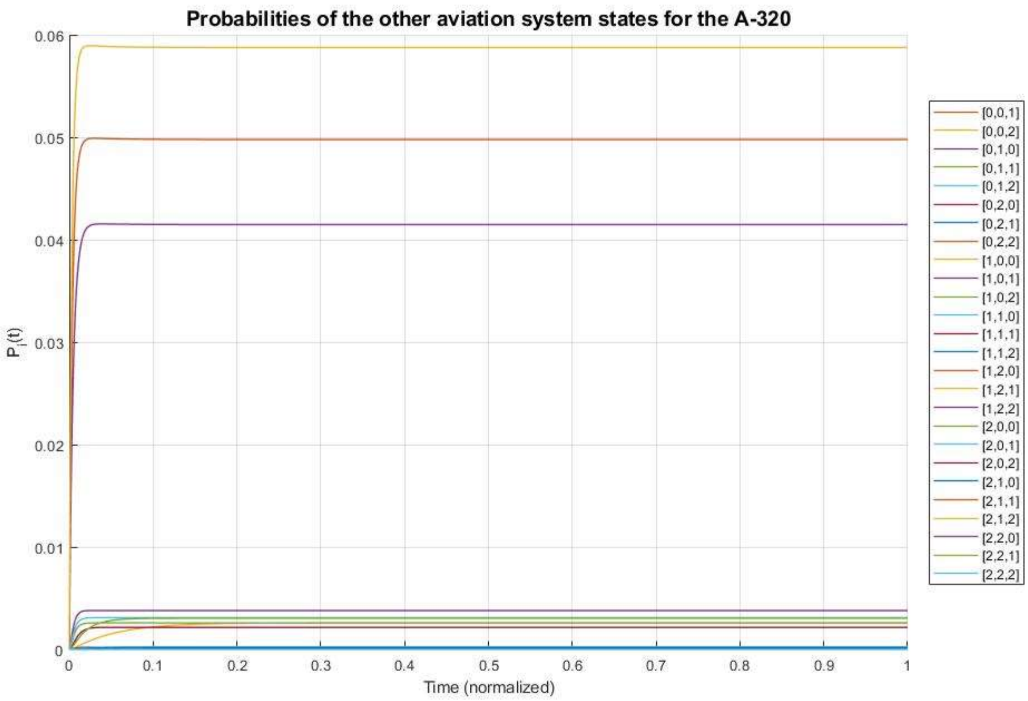


**Fig. 5.2.** Probabilistic safety characteristics for the A-320 (the other 26 states)

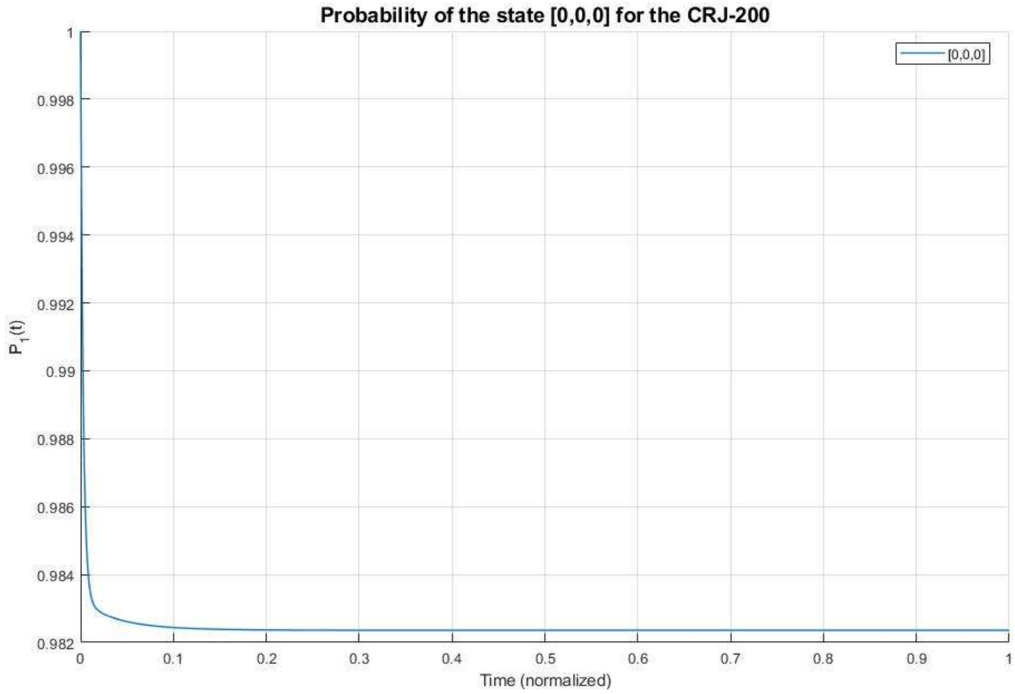


**Fig. 5.3.** Probabilistic safety characteristics for the CRJ-200 ($P_{000}(t)$)

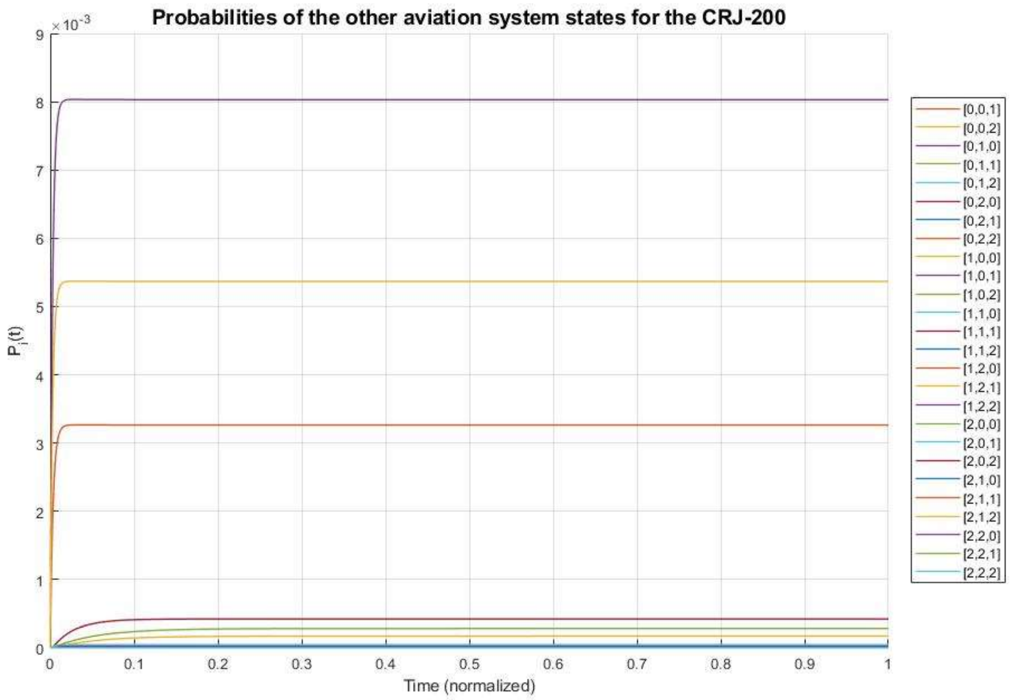


**Fig. 5.4.** Probabilistic safety characteristics for the CRJ-200 (the other 26 states)

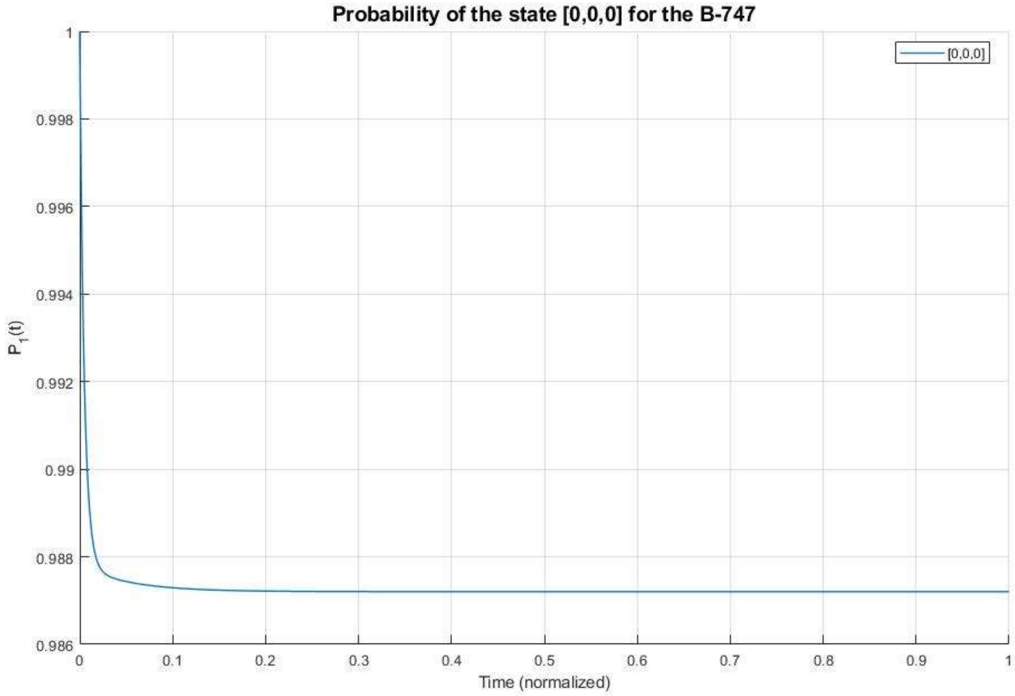


**Fig. 5.5.** Probabilistic safety characteristics for the B-747 ($P_{000}(t)$)

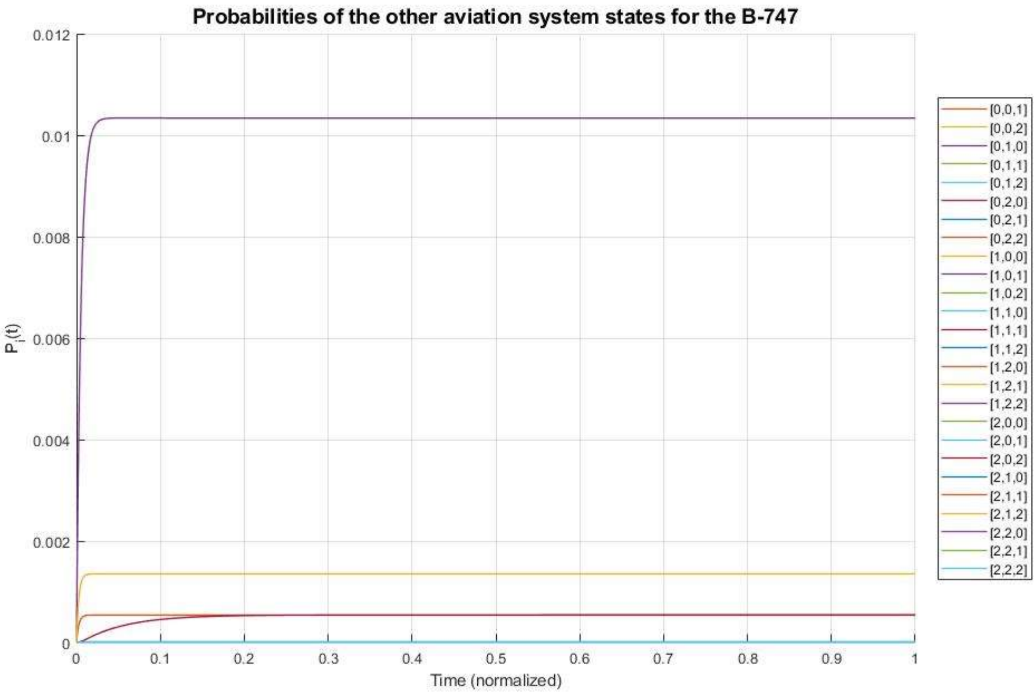


**Fig. 5.6.** Probabilistic safety characteristics for the B-747 (the other 26 states)

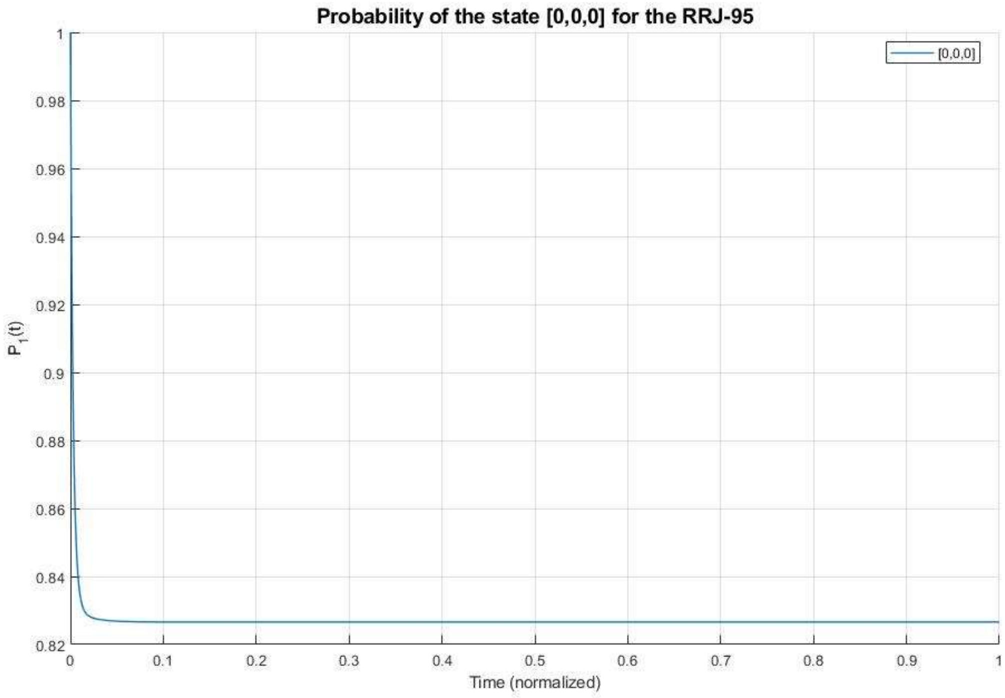


**Fig. 5.7.** Probabilistic safety characteristics for the RRJ-95 ($P_{000}(t)$)

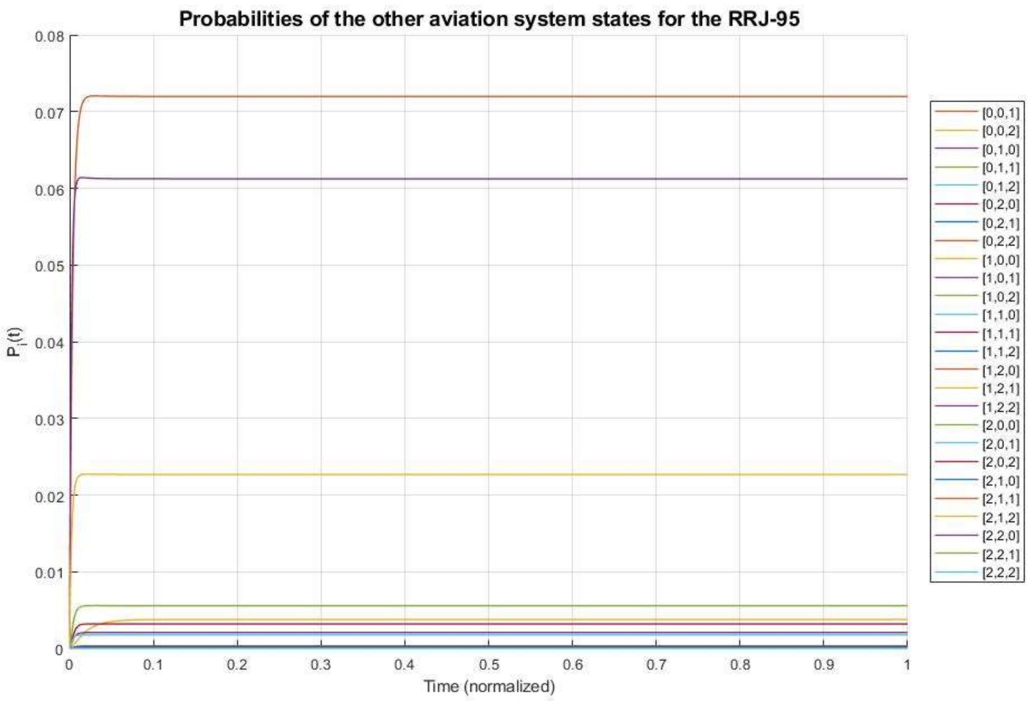


**Fig. 5.8.** Probabilistic safety characteristics for the RRJ-95 (the other 26 states)

Figures 5.1–5.8 demonstrate that the state in which all elementary components of the system remain fully operational serves as the primary indicator for safety evaluation. This probabilistic characteristic remains high, while the values associated with other combinations of functional or failed elementary states $S_i$, appear significantly lower, often approaching zero or remaining around 0.05.

The analysis of failure and recovery parameters presented in the article shows that, among the considered aircraft types, the B-747 possesses the lowest failure intensities, leading to the highest safety level with a stationary probability of the fully operational state $P_{000}(t) \approx 0.99$.

In contrast, the A-320, with higher intensities, demonstrates the lowest safety estimate with $P_{000}(t) \approx 0.83$. For the CRJ-200 $P_{000}(t) \approx 0.98$, and for the RRJ-95 $P_{000}(t) \approx 0.83$, which confirms the influence of human, technical, and organizational factors on cascade failures and the overall reliability of the systems.

## 6. CONCLUSION

The developed method for analyzing causal relationships to ensure the reliability and safety of complex human-machine systems demonstrates high effectiveness in addressing system modeling tasks. The integration of the decomposition principle with Markov processes featuring variable transition intensities, accounting for subsystem state dependencies through influence coefficients $\beta$, enables the identification of cascade failures and a substantial reduction in computational complexity while preserving prognostic informativeness. Numerical experiments on examples of aviation systems (A-320, CRJ-200, B-747, RRJ-95) confirm the predominance of functional states in the stationary regime and limited risks of catastrophic scenarios, despite nonlinear interactions.

The quantitative assessment of factor contributions to overall reliability revealed the dominant role of technical subsystems (engines), the human factor, and organizational aspects. Sensitivity analysis showed that increasing the $\beta$ coefficients lead to a significant rise in the probability of catastrophic failures, emphasizing the necessity of managing causal relationships.

The proposed approach surpasses traditional methods in flexibility and scalability, successfully overcoming the "curse of dimensionality" and providing adaptive detailing of the analysis. Practical recommendations, including enhanced personnel training, optimization of regulations, implementation of redundant systems, and monitoring of critical $\beta$, hold applied value for improving safety in aviation, transportation, and industry.

Prospects for further research are associated with integrating the method with artificial intelligence for real-time forecasting, expanding to systems with fuzzy structures, and verification on operational data from other human-machine complexes, including autonomous vehicles and energy systems. Thus, the developed toolkit forms the basis for creating adaptive risk management systems in highly dependable human-machine interactions.

ACKNOWLEDGEMENTS

The research is partly supported by the Russian science foundation, project № 24-19-00430.

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