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MODELING OF INTELIGENT SOFTWARE FOR THE DIAGNOSIS AND MONITORING OF SHIP POWER PLANT COMPONENTS USING MARKOV CHAINS

Introduction

The cost of maritime vessels reaches tens of millions of US dollars. Ship power plant systems (SPPs) account for 10 to 30% of this cost. The construction period of a single vessel lasts over a year, with a normative service life of 20 to 25 years. Throughout the entire service life, the power plant is usually not replaced but undergoes continuous maintenance and periodic repairs.

The reliability and operational suitability of metal structures depend on the quality of monitoring the technical condition and mechanical properties of materials in accordance with international standards. However, during operation, deviations from the normative values of material properties occur due to the uncertain nature and magnitude of loads, necessitating periodic equipment shutdowns for diagnostic purposes.

The execution of diagnostic work in transportation is determined by technical conditions and regulations. To forecast diagnostic results in the short term, regression models, discriminant models, cluster analysis, and taxonomy are used. These methods require prior knowledge of past situations and operating parameters, which are practically impossible to determine in transportation conditions. Simultaneously, during the intervals between diagnostic processes, there may be emergency peak loads on the turbocharger material during operation.

In all four-stroke internal combustion engines, air compression is achieved using a compressor v_2, which is powered by a gas turbine. The combination of the compressor and gas turbine is called a turbocharger. The gas section of the turbocharger consists of a radial-axial wheel located in a housing. Sealing along the gas section aims to prevent gas leakage from the working chamber of the gas section. The structural properties of turbocharger components deteriorate not only with increasing operating time but also with intensified power loads.

The smooth operation of marine vessel power equipment elements depends on the quality of monitoring their technical condition through physical diagnostic methods. The most effective method to reduce operational costs and enhance equipment reliability is to conduct maintenance based on interactive monitoring of its condition, detection of malfunctions, and prediction of power equipment parameters. This makes the tasks of control, diagnostics, and prediction of power equipment parameters particularly relevant.

In the operating conditions of ship power plant (SPP) elements, the effects of unpredictable and often extreme loads are probabilistic in nature. Since there is no historical record of the reasons for changes in mechanical properties, their magnitude, and duration, the diagnostic process starts without considering or making any adjustments based on the current situation. It consists of a sequential determination of structural properties according to existing regulations. After obtaining information related to the quantitative assessment of one of the factors at the start of the diagnostic process, the reference point for the beginning of the diagnosis shifts towards shortening the diagnostic process. Thus, the process of changing the position of the reference point is random, characterized by the arbitrary selection of the initial adjustable factor with discrete time characteristics for the duration of the first and subsequent steps and a finite or countable set of states. Such a process will be Markovian since subsequent states of the initial point in the diagnostic process are independent of past states.

The objective of this work is to mathematically model the diagnostic processes during the monitoring of the technical condition of turbocharger elements in ship power plant systems (SPPs) using Markov chains.

The purpose of the work is the practical use of Markov chains to assess the quality of diagnostics of elements of ship power plants during their operation

Problem Statement

Methods for assessing the reliability of equipment in the absence of information about peak and extreme loads during the period between repair cycles during the operation of products, when used, have a number of limitations and inaccurate assessments caused by dynamic changes in the external environment and stochasticity of processes, i.e., there is a situation of uncertainty and risk. Broad prospects open up when using probabilistic methods, including Markov chains.

Analysis of recent research and publications

Markov chains characterize a stochastic process in which the conditional probability distribution of future states depends only on the current state of the process.

Markov chains make it possible to improve the mechanism for making decisions and diagnosing the situation at various levels of processes [1, 2]. The use of information technologies for assessing the suitability of enterprises for innovative transformations using Markov chains is presented in [3]. Information support for managing complex organizational and technical objects based on Markov chains is presented in [4]. Models of Markov processes of logical transitions, taking into account probabilistic estimates of the states of methods, are presented in [5, 6]. In [7], the main methodological provisions for constructing a homogeneous Markov network with a fixed number of states and a discontinuous period are presented in detail. Markov chains with discrete time are used [8, 9]. An intelligent forecasting model for a hydrological water system is described in [10]. The connection between control and the human factor in mathematical models of complex systems based on the Markov chain is presented in [11]. In [12], the possibility of checking the asymptotic distribution of transition probabilities of the Markov sequence of a parametric family was studied. In [13], stochastic interception using filtering and smoothing is described, in [14] stochastic estimation of the efficiency of transport materials. The scenario-based stochastic optimization model is described in [15]. The information-entropy model of the basis for making managerial decisions under conditions of uncertainty is presented in [16], the analysis of delay in constructing the hierarchy of Bayesian networks in [17]. The use of information technology to identify uncertainty parameters in statistical estimates is presented in [18, 19]. Mathematical support for excluding the human factor's influence on navigation equipment systems under uncertainty and risk is presented in [20-22]. A quantitative assessment the uncertainty forecasts is presented in [23], in [24] a review of the fate of the characteristics of mechanical tests is given. The origin and destination matrix based on Markov chains is presented in [25]. Intelligent charging of connecting electric vehicles under driving behavior uncertainty is shown in [26]. Evolutionary trends in building a business management system are presented in [27, 28]. The application of the Monte Carlo method in the construction of Markov chains is described in [29–31]. This review shows that the practical applications of Markov chains are wide and varied. Separate fragments of the presented experience were used to develop the research methodology.

As evident from the provided overview, Markov chains have specific applications characterized by a general methodology for changing the dynamics of probabilities within their respective domains. However, the characteristic features of the diagnostic modeling process for elements of SPP do not allow for the complete utilization and transfer of accumulated experience in solving loosely-structured problems. This is due to the need to transition from discrete time of operation for SPP to a continuous sequence of states characterized by diagnostic intervals during the monitoring process. The construction of transition probability matrices and corresponding directed graphs aimed at ranking the elements of the SPP in terms of their failures during operation is also essential in this context.

Materials and methods

The study utilized diagnostic parameters of turbocharger elements such as the casing, compressor, turbine, seals, rotor, bearings, oil pumps, and probabilistic estimates of their failures. These estimates were obtained based on a larger statistical dataset of ship operation in conditions of uncertain external influences. Markov chains were employed as the research method.

In the context of diagnosing in conditions of uncertain external influences characterized by elements of randomness, the goal of Markov chains is to search for a combination of characteristics and parameters that improve the mechanisms of diagnosis and decision-making in a visual form. If the system transitions from one state to another at predetermined time intervals with the accumulation of corresponding informational resources, it represents a discrete-time sequential Markov process.

Input information about failures of turbocharger elements in terms of conditional probabilities is presented in Table 1.

Table 1

Current State of Turbocharger Element Diagnostic System

№	Controlled parameter	Weight ratio	Designation
1	Frame	0.090	v_1
2	Compressor	0.005	v_2
3	Turbine	0.048	v_3
4	Seal	0.167	v_4
5	Rotor	0.152	v_5
6	Bearing	0.438	v_6
7	Oil pumps	0.1	v_7

Markov chains enable the generation of events. Technical solutions for evaluating the sequence of using diagnostic procedures for specific turbocharger elements in shipboard power systems within the framework of Markov theory postulate the selection of the best alternative, which can be facilitated by the apparatus of probability theory.

Methodology

Reliability of equipment is a comprehensive property that refers to its ability to perform the assigned functions while maintaining its characteristics under specific operating conditions within defined limits or for a required period of time. Markov chains are used as a mathematical model to study the behavior of certain stochastic systems.

When modeling complex technical objects or organizational-technical systems, an essential aspect is representing the structure of interactions and transitions. Independent trials are a special case of Markov chains. Events are considered as the states of the system, and the trials themselves represent changes in the system's state.

Transition probabilities P_{ji} do not depend on the moment of time, but depend only on *j* and *i*

$$P = \begin{vmatrix} P_{11} & P_{12}\ldots & P_{1n} \\ P_{21} & P_{22}\ldots & P_{2n} \\ P_{1n} & P_{n2}\ldots & P_{nn} \end{vmatrix} \qquad (1)$$

where $0 \le P_{ji} \le 1 \ldots \sum_{i=1}^{n} P_{ji} = 1$.

Here *n* – is the number of system components.

A Markov chain is said to be homogeneous when the transition probability P_{ji} of the system moving from state *i* to state *j* does not depend on the trial number. The probability P_{ji} is referred to as the transitional probability.

The probability $P_{ji}(n)$ can be found using the formula known as the Markov equality:

$$P_{ji}(n) = \sum P(m)P(n-m), \qquad (2)$$

where *m* – the number of steps in which the diagnostic system can go from state *i* to state *j*.

Any state S_j can be reached from any other state within a finite number of transitions.

The probability of transitioning from one state to another is the same regardless of the number of intermediate states that need to be passed through to reach the intended target.

A characteristic feature of modeling the intelligent support for diagnostics and monitoring of ship power plant elements is that the conditional probability $P_{ji}(S)$ does not depend on the current state, i.e., $P_{ji}(S) = P_{ji}$. Here, i represents the previous state number, and j represents the subsequent state number.

The transition probabilities can be represented by the following equation

$$P(x_0 = S) = q_0(S)\forall_{S \in E}, \qquad (3)$$

where $\forall$ – is the universal quantifier, *S* – represents discrete states, q_0 – is the probability of finding the system at time $t_0 = 0$, is the reference point.

The variable E represents a finite number of states

$$E = \{e_1, e_2, \ldots, e_n\}. \qquad (4)$$

The probability of the system transition is expressed through the stages of diagnosing the elements of the SPP turbochargers

$$P(x_{n+1} = S_{n+1} \| x_n = S_n) = P(S_n, S_{n+1})\forall(S_{n+1}, S_n). \qquad (5)$$

The use of Markov chains for determining the processes of intelligent diagnosis and monitoring of turbocharger elements in shipboard power plants (SPP) is based on the following principles. The diagnostic system operates in states $S_1, S_2 \ldots S_n$. Transitions are only possible at the time points that correspond to monitoring stages, which are considered as steps. The argument of the Markov chain is the step number.

At any given time, the Markov chain can be characterized by row vectors of the transition probability matrix (1). By multiplying the row vector that describes the probability distribution at a certain diagnostic stage by the transition probability matrix, we obtain the probability distribution at the next stage in a visual form and at different monitoring levels. The conceptual model of intelligent diagnosis and monitoring of SPP elements using Markov chains can be represented as fig. 1.

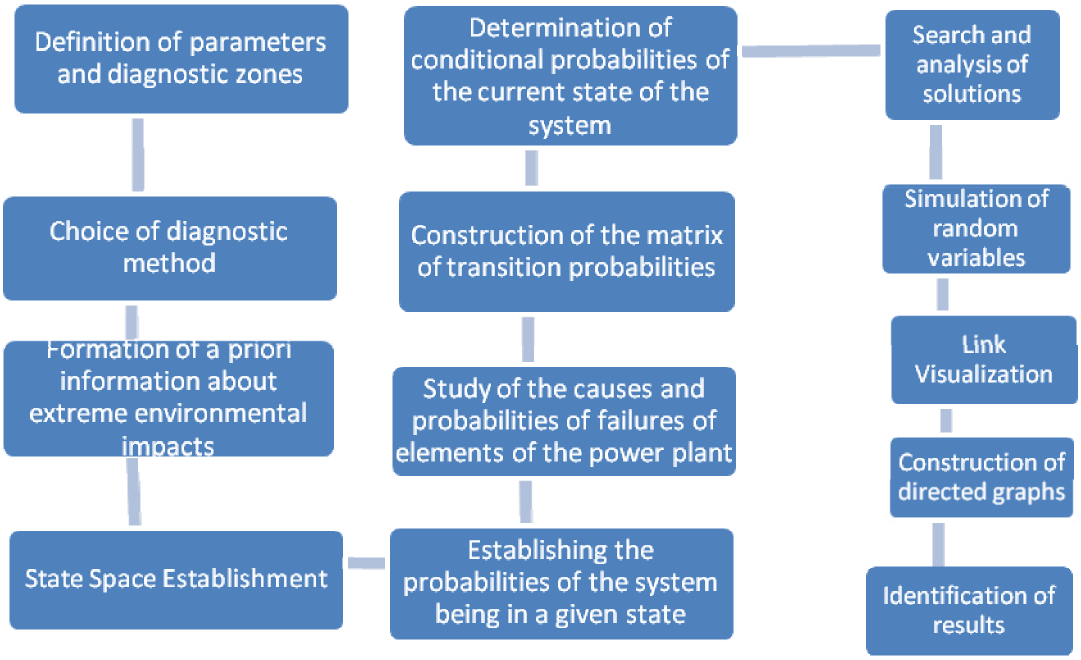

Fig. 1. Conceptual model of diagnostics and monitoring of transportation equipment elements using Markov chains

Experiment

By selecting reliability and fitness for operation as the primary parameters for diagnosing the turbocharger elements in shipboard power plants (SPP) in terms of their failure probabilities, we construct a transition probability matrix (Table 2).

According to Tables 1 and 2, the diagnostic system can be in one of the seven states. If the SPP elements are operating under extreme load conditions, the probability of turbocharger housing failure, as per Table 2, will be 0.09. The probability of compressor v_2 failure is 0.005, turbine failure is 0.048, seal failure is 0.167, rotor failure is 0.152, bearing failure is 0.438, and oil pump failure is 0.1.

If there are emergency changes in equipment operation during the service, the state of the diagnostic system will be characterized by the second row of the transition matrix. Therefore, the probability of housing failure remains at the same level of 0.09. However, the probability of compressor v_2 failure increases to 0.008, turbine failure increases to 0.051, seal failure increases to 0.18, and bearing failure increases to 0.431. The probability of oil pump failure decreases to 0.09.

Similar transformations of conditional probabilities can occur in the monitoring process through other rows of the transition matrix in subsequent stages of priority use of diagnostic parameters.

Table 2

Conditional probabilities of the monitoring process for turbocharger elements in SPP

	Frame	Compressor	Turbine	Seal	Rotor	Bearing	Oil pumps
Frame	0.09	0.005	0.048	0.167	0.152	0.438	0.1
Compressor	0.09	0.008	0.051	0.15	0.18	0.431	0.09
Turbine	0.08	0.006	0.068	0.169	0.151	0.446	0.08
Seal	0.08	0.007	0.054	0.152	0.163	0.474	0.07

End of table 2

	Frame	Compressor	Turbine	Seal	Rotor	Bearing	Oil pumps
Rotor	0.07	0.005	0.062	0.141	0.172	0.44	0.11
Bearing	0.09	0.007	0.056	0.15	0.166	0.421	0.11
Oil pumps	0.08	0.006	0.064	0.159	0.161	0.43	0.1

If we multiply the initial state probability distribution vector by the transition probability matrix, we will obtain the probability distribution for the next diagnostic step. The probability of the diagnostic system transitioning from state S_0 to state S_1 on the first step will be equal to

$$P(1)=(0.09\ 0.005\ 0.048\ 0.167\ 0.152\ 0.438\ 0.1)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

$$=(0.076115\ 0.005932\ 0.0530915\ 0.138106\ 0.150879\ 0.3990015\ 0.091375)$$

The probability that at the second step the system will switch to the state S_2 under the influence of ongoing changes in operating conditions and the influence of the environment will be equal to

$$P(2)=(0.076\ 0.0059\ 0.0531\ 0.138\ 0.151\ 0.399\ 0.091)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

$$=(0.07646161\ 0.005808971\ 0.052570518\ 0.13921821\ 0.150061988\ 0.398693323\ 0.09168438)$$

In conditions of unstable operation of turbochargers in ship energy installations (SEU), experimental environmental influences, and alternating loads, the probability of the diagnostic system transitioning from state S_2 to state S_3 is equal to

$$P(3)=(0.076\ 0.0058\ 0.0525\ 0.139\ 0.1501\ 0.398\ 0.0916)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

= (0.07646861 0.005809975 0.052557234 0.13922596 0.15005277 0.398729431 0.09165102)

The probability of transition from state S_2 to state S_4 is

$$P(4)=(0.0765\ 0.0058\ 0.0525\ 0.1392\ 0.15005\ 0.3987\ 0.0916)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

= (0.07646882 0.005809998 0.052556461 0.13922503 0.150052307 0.398727454 0.09165093)

The probability of transition from state S_4 to state S_5 is

$$P(5)=(0.0765\ 0.00581\ 0.0525\ 0.1392\ 0.15005\ 0.3987\ 0.0916)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

= (0.07646857 0.00580998 0.052556268 0.139224552 0.150051843 0.398726167 0.09165062)

The probability of transition from state S_5 to state S_6 is

$$P(6)=(0.0765\ 0.0058\ 0.0525\ 0.1392\ 0.15005\ 0.3987\ 0.0916)\times\begin{vmatrix} 0.09 & 0.005 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.09 & 0.008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0.08 & 0.006 & 0.068 & 0.169 & 0.151 & 0.446 & 0.08 \\ 0.08 & 0.007 & 0.054 & 0.152 & 0.163 & 0.474 & 0.07 \\ 0.07 & 0.005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0.09 & 0.007 & 0.056 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0.08 & 0.006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

= (0.07646824 0.005809953 0.052556045 0.139223959 0.150051162 0.398724401 0.09165024)

The probability of transition from state S_6 to state S_7 is

$$P(7)=(0.076\ 0.0058\ 0.0525\ 0.1392\ 0.15005\ 0.3987\ 0.0916)\times\begin{vmatrix} 0.09 & 0,05 & 0.048 & 0.167 & 0.152 & 0.438 & 0.1 \\ 0.05 & 0,008 & 0.051 & 0.15 & 0.18 & 0.431 & 0.09 \\ 0,08 & 0,006 & 0.068 & 0.0169 & 0.161 & 0.436 & 0.08 \\ 0,08 & 0,007 & 0.054 & 0.0152 & 0.153 & 0.421 & 0.07 \\ 0,07 & 0,005 & 0.062 & 0.141 & 0.172 & 0.44 & 0.11 \\ 0,09 & 0,007 & 0.052 & 0.15 & 0.166 & 0.421 & 0.11 \\ 0,08 & 0,006 & 0.064 & 0.159 & 0.161 & 0.43 & 0.1 \end{vmatrix}=$$

= (0.07646798 0.005809932 0.052555879 0.139223507 0.150050667 0.398723085 0.09164995).

The overall probability of the diagnostic and monitoring system for turbochargers in ship energy installations can be represented as a system of inequalities, which shows that the probability of failures and the system's failure to detect them decreases at each step: P(1) > P(2) > P(3) > P(4) > P(5) > P(6) > P(7).

Results and Discussion

The formalization of the main activities for the development of intelligent diagnostic and monitoring software for ship energy installation elements, as presented in Figure 1, has allowed establishing the degree of reliability of the interconnections between individual diagnostic system characteristics. This serves as the basis for predicting failures of the ship energy installation elements before and after the diagnostic process.

A key feature of the presented model is the consideration of possible deviations from normal functioning of the turbocharger elements in ship energy installations and a consistent level of risk in making management decisions regarding their further operation under challenging conditions.

When making management decisions regarding the implementation or abandonment of intelligent diagnostic and monitoring software for ship energy installation elements, the only error-free assessment lies in evaluating the current situation regarding the condition of the turbocharger elements in the ship energy installation. The monitoring results are influenced by numerous factors, some of which are difficult to account for and can be represented as associative probabilities.

The probability of a selected state in the subsequent time interval, denoted as P_{ij}, will be determined based on the existing situation without their simultaneity. By combining all the transition probabilities from these states, we obtain a probability matrix, the visualization of which can be reflected in a directed graph or a network diagram.

Each transition from state i to state j is characterized by a transition probability, which indicates how often the system will transition from state i to state j. If we measure the transition frequencies over a sufficiently long period of time, they will coincide with the transition probabilities.

To implement the proposed conceptual model of intelligent diagnostic and monitoring software for ship energy installation elements using Markov chains, a simulation model in the form of a directed graph or a network diagram has been created.

In the directed graph, the vertices represent the states of the process, while the edges represent the transitions between them. The flexibility of the simulation model implemented using the directed graph lies in its adaptability to the external environment in which diagnostic volumes are operated. The key factors of simulation models are the input variables, which are determined by reactions to external stimuli.

Since the graph is directed, it is not possible to transition to another state from every state when each state has its own probability. The transition from one node to another can occur after a random time interval. It is proposed to consider the step number as the argument that determines the process, rather than time. In this case, the random process will be characterized by a sequence of states.

When the initial probability distribution and the transition probability matrix are known, the overall probabilistic dynamics of the process can be determined and calculated cyclically.

As an example of constructing a Markov chain graph that reflects the modeling of intelligent diagnostic and monitoring systems for marine power plants using Markov chains, states were selected based on the priority of parameter placement, characterized by the most significant probabilities of failure. These parameters include bearings, seals, rotor, oil pumps, casing, turbine, and compressor v_2. Transitions between these states are represented as edges or arcs of the graph components.

The weights of the edges, expressed in terms of empirically determined probabilities, are based on the synthesis of information published in statistical compilations. Based on the calculations performed, the priority, main content, methodologies, and level of the diagnostic process are determined. A step-by-step plan is developed, strategies are formulated, and necessary resources are mobilized.

The goal of using Markov chains in this study is to find a combination of diagnostic system characteristics and parameters that enables the improvement of the monitoring mechanism and decision-making process in a visual form. The visualization of Markov chains in a finite-dimensional state space for modeling the intelligent diagnosis and monitoring of ship power plant turbocharger elements using Markov chains is presented in Fig. 2.

An advantage of the information management system for intelligent diagnosis and monitoring of SPP using Markov chains is the ability to customize the system for any information situation. It is possible to change the priority of the first monitored element, which in our scheme is the bearing, and the sequence of subsequent steps.

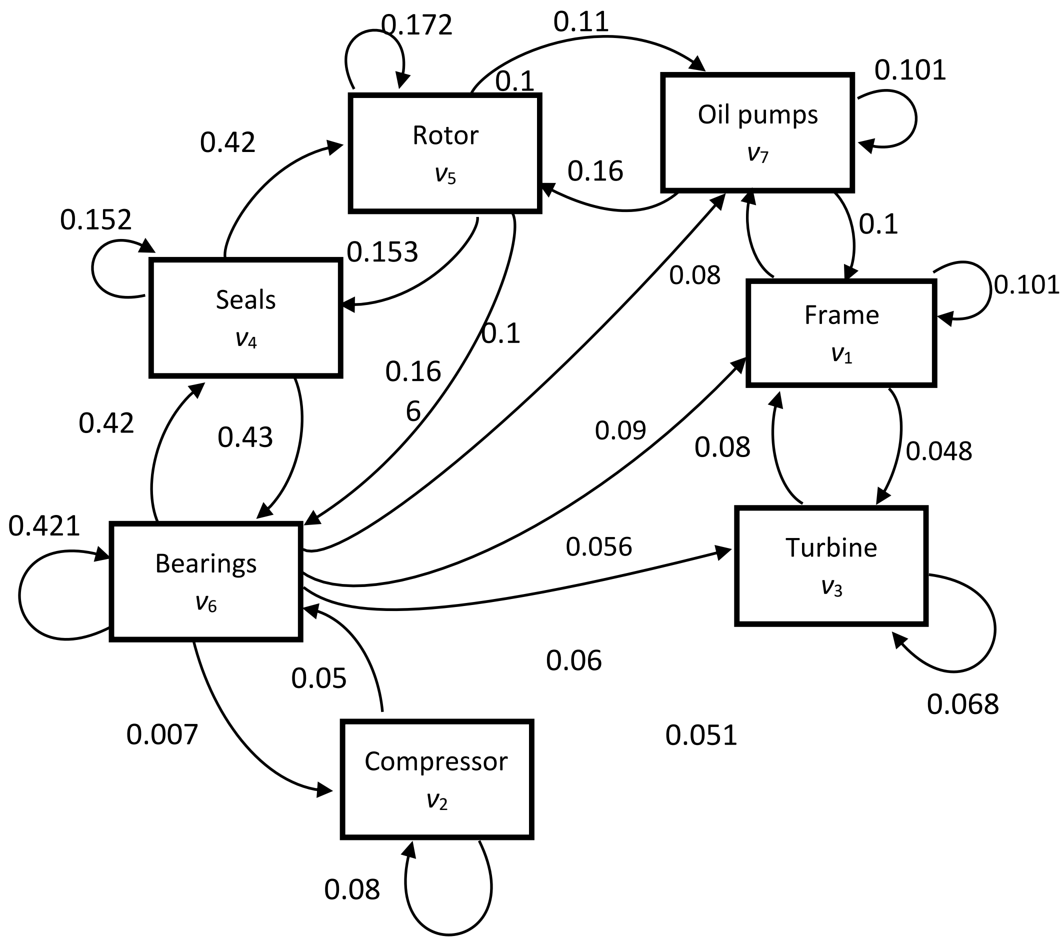

Fig. 2. Directed graph of Markov chains for the diagnosis and monitoring of turbocharger elements

Conclusions

A conceptual model of intelligent monitoring support for turbocharger elements in SPP has been developed, aimed at improving the mechanisms of diagnosis and decision-making based on Markov chains. An imitation model in the form of a directed graph (orgaph) has been created, where the nodes represent the process states and the edges represent the transitions between them. The novelty of the model lies in using the diagnostic sequence of states and the step number, reflecting the discretization intervals of turbocharger element monitoring in complex operating conditions, as the diagnostic parameter instead of time. An distinguishing feature of the presented orgaph is its adaptability to external influences.

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МОДЕЛЮВАННЯ ІНТЕЛЕКТУАЛЬНОГО ПРОГРАМНОГО ЗАБЕЗПЕЧЕННЯ ДЛЯ ДІАГНОСТИКИ ТА МОНІТОРИНГУ КОМПОНЕНТІВ СУДНОВОЇ ЕЛЕКТРОННОЇ УСТАНОВКИ ЗА ДОПОМОГОЮ ЛАНЦЮГІВ МАРКОВА

Надійність і експлуатаційна придатність металоконструкцій залежить від якості контролю за технічним станом і механічними властивостями матеріалів відповідно до міжнародних стандартів. Проте в процесі експлуатації виникають відхилення від нормативних значень властивостей матеріалів через невизначений характер і величину навантажень, що зумовлює необхідність періодичних відключень обладнання з метою діагностики. Безперебійна робота елементів енергетичного обладнання морських суден залежить від якості контролю їх технічного стану фізичними методами діагностики. Найбільш ефективним методом зниження експлуатаційних витрат і підвищення надійності обладнання є проведення технічного обслуговування на основі інтерактивного моніторингу його стану, виявлення несправностей і прогнозування параметрів енергетичного обладнання. Це робить особливо актуальними завдання контролю, діагностики та прогнозування параметрів енергетичного обладнання. У той же час використання різних методів діагностики не дозволяє врахувати всіх особливостей реальних умов експлуатації. Особливо гостро ця проблема постає в умовах різних екстремальних ситуацій та пікових навантажень, які врахувати неможливо. Перспективним напрямом досліджень є імовірнісні методи, зокрема ланцюги Маркова.

Представлена система інтелектуальної діагностики та моніторингу турбокомпресорів суднової енергетичної установки з використанням ланцюгів Маркова. Новизна розробленої методики полягає в заміні дискретних інтервалів часу діагностичного процесу послідовністю станів технічних об'єктів. У цьому формулюванні ланцюги Маркова являють собою синтетичну властивість, яка акумулює різноманітні фактори. Рандомізація процесів стохастичної діагностики та моніторингу компонентів суднової енергетичної установки дозволяє підвищити надійність обладнання у важких умовах експлуатації. Наведено результати розрахунків оцифровки експериментальних даних, розрахунків матриць переходів і побудови орграфа, що дозволяє досліджувати кінетику накопичення ушкоджень в реальному часі.

Ключові слова: моделювання; ланцюги Маркова; суднові енергетичні установки; діагностика; моніторинг.

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MODELING OF INTELIGENT SOFTWARE FOR THE DIAGNOSIS AND MONITORING OF SHIP POWER PLANT COMPONENTS USING MARKOV CHAINS

The reliability and serviceability of metal structures depends on the quality of control over the technical condition and mechanical properties of materials in accordance with international standards. However, in the course of operation, deviations from the normative values of material properties occur due to the uncertain nature and magnitude of the loads, which necessitates periodic shutdowns of the equipment for the purpose of diagnostics. Uninterrupted operation of elements of power equipment of marine vessels depends on the quality of control of their technical condition by physical diagnostic methods. The most effective method of reducing operating costs and increasing the reliability of equipment is maintenance based on interactive monitoring of its condition, detection of malfunctions and forecasting of energy equipment parameters. This makes the tasks of control, diagnosis and forecasting of energy equipment parameters particularly relevant. At the same time, the use of various diagnostic methods does not allow *taking into account all the features of real operating conditions. This problem is especially acute in conditions of various extreme situations and peak loads, which cannot be taken into account. Probabilistic methods, in particular Markov chains, are a promising area of research. The system of intelligent diagnostics and monitoring of ship power plant turbochargers using Markov chains is presented. The novelty of the developed methodology lies in replacing discrete time intervals of the diagnostic process with a sequence of states of technical objects. In this formulation, Markov chains represent a synthetic property that accumulates diverse factors. Randomization of stochastic diagnostic and monitoring processes of ship power plant components enables an increase in reliability of equipment under severe operating conditions. The results of calculations of digitalization of experimental data, calculations of transition matrices and construction of an orgraph allowing to study the kinetics of damage accumulation in real time are presented.*

Keywords: Modeling; Markov chains; ship power plants; diagnostics; monitoring.

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