Intelligent systems of optimisation maritime transport development management under conditions of multicriteria and uncertainty of input information

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Abstract
A solution to an important scientific and practical problem is presented optimisation of maritime transport development management under conditions of multicriteria and uncertainty of input information. The paper presents a methodology for selecting optimal diagnostic and operational parameters under multicriteriality conditions and input information uncertainty. The novelty of the methodology is the compilation of an efficiency matrix, the rows of which are represented by statistical characteristics of vibration signals, columns by criteria of statistical solutions of Laplace, Wald, Hurwitz, additive, multiplicative and additive multiplicative convolutions, and its elements by practical results. Three cornerstones of the proposed methodology implementation that play a decisive role in the development of marine transport technologies are considered. The first is optimization of diagnostic parameters during operation of marine plain bearings under variable loads, selection of the optimal one. The second is selection of the optimal formulation for construction of port infrastructure facilities with optimization of physical, mechanical and thermodynamic properties of materials. The third is optimization of transport logistics parameters under uncertainty and unpredictability of route conditions at transitions through global transport corridors. The following features of the main characteristics of the analyzed information were used as optimization parameters: monotony, rate of change, sensitivity, deviation from adaptability, energy. Each discrete characteristic was approximated by a nonlinear function in the form of a cubic spline in the pre-destruction section. Optimization of the presented tasks makes it possible to manage diagnostic information under uncertainty and risk.

Keywords
information technology, multicriteriality, uncertainty, diagnostic parameters, sea transportation

1. Introduction

The active development of world trade is characterized by the emergence of new forms of interaction – global transport systems and the emergence of global logistics initiatives. The process of globalization is characterized by high complexity and nonlinearity of the configuration of logistics systems. The specifics of transportation require a constant exchange of information. The functioning of marine transport logistics and transportation is carried out in complex conditions of the external environment and multicriteriality and uncertainty of input information. The nature of such uncertainty is that the optimization parameters are unclear. Only their external manifestations are recorded, and making control decisions under risk conditions is necessary.

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Normal operation of marine power plants (MPP) depends on the correct functioning of their main elements: cylinder-piston group, fuel equipment, gas turbochargers, bearings, etc. The main task of identifying and determining the residual life of vehicles during operation is to monitor changes in the mechanical properties of materials with the accumulation of damage and to determine the parameters of precursors of the occurrence of information signals during equipment destruction. Vibration diagnostics is the most effective method for determining the technical condition of various rotor-type mechanisms. In diagnostic analytical models, monitoring the condition of bearings becomes possible when a database and modern expert diagnostic systems use complex algorithms for processing and filtering signals. When monitoring, it is necessary to use mathematical models to ensure the accuracy of calculations of the resource of diagnostic objects and to establish the date of repair based on the condition of the object. Vibration signals are multicomponent, i.e. they are a finite additive set of multi-scale components localized by frequency bands of different types of vibrations. Optimization of the management of the development of marine transport in conditions of multicriteriality and uncertainty of input information is one of the unsolved problems of information theory, solid state mechanics, and physical acoustics.

The aim work is to develop intelligent maritime transport management systems, new approaches to assessing the diagnostic and operational parameters of transportation.

2. Literature review

In [1-4], computational algorithms for vibration signal parameters estimated in the frequency domain are presented, which characterize potentially dangerous phenomena based on Fourier transforms. It is noted that vibration signals of the equipment in operation are subject to the influence of complex and variable operating conditions and can be estimated considering the frequency-time analysis.

In [5,6], a mechanism for multimode sampling of vibration signals is presented. The presence of equipment malfunctions can be considered as a non-stationary signal, the propagation of which in [7] is considered using the Markov model. It is noted that the presented methodologies allow for finding the points of initial degradation of the equipment condition earlier. Extraction of features and characteristics of rolling bearing vibration signals based on combining and screening multiparameter information is described in [8]. The method uses wavelet packet decomposition of the rolling bearing vibration signal to combine the asymmetry, kurtosis and permutation values to identify information about the nature of the fault. Similar works on merging data from contrast learning [9], statistical and nonlinear signal processing methods [10] and forecasting the condition of bearings using the principal component method [11] use the correlation of signals from several sources to monitor mechanical equipment.

The [12-15] section presents multifunctional diagnostics of navigation equipment, while the [16-19] section presents innovative transformations.

The presented analysis of publications confirmed the topic's relevance and showed the direction of research associated with the search for new information-diagnostic and operational parameters.

3. Materials and methods

The materials used were the effectiveness of diagnostics and monitoring of the equipment in operation. The methods used were multicriterial analysis, game theory and statistical decisions.

4. Methodology

The effectiveness of monitoring directly depends on the rate of defect development and can be determined by optimization parameters based on the change in the trajectory of the main diagnostic parameter.

These parameters can be used as rows of the efficiency matrix. The efficiency matrix R has the form:

$$R = \begin{pmatrix} & \Pi_1 & \Pi_2 & \dots & \Pi_j \\ q_1 & \delta y_{11} & \delta y_{12} & \dots & \delta y_{1j} \\ q_2 & \delta y_{21} & \delta y_{22} & \dots & \delta y_{2j} \\ \dots & \dots & \dots & \dots & \dots \\ q_i & \delta y_{i1} & \delta y_{i2} & \dots & \delta y_{ij} \end{pmatrix} \quad (1)$$

where $q_1 \dots q_i$ – vibration signal characteristics,
$\Pi_1 \dots \Pi_j$ – optimization parameters,
i – line number,
j – column number.

Relative deviation δy_{ij} j-th feature from the optimal value is determined as follows.

$$\delta y_{ij} = \begin{cases} \dfrac{|y_{ij} - c_j|}{y_{j,\max} - c_j}; & y_{ij} > c_j \\ \dfrac{|y_{ij} - c_j|}{c_j - y_{j,\min}}; & y_{ij} < c_j \end{cases} \quad (2)$$

As c_j it is necessary to choose the best values of the analyzed parameters from the point of view of the problem being solved - these can be the maximum or minimum from the experimental sample. With this approach, formula (2) will convert dimensional quantities into relative ones within the scale (0.1). However, with such a choice c_j there will necessarily be observed elements of matrix (1) coinciding with the value c_j, which will lead to $\delta y_{ij}=0$. When using additive convolution, this leads to the corresponding feature falling out of the overall assessment of the object, and when using multiplicative convolution, to its zeroing. One way to eliminate such situations is to expand the upper (for the maximum) or lower (for the minimum) limit of each feature c_j in the same percentage ratio. Below, the maximum (minimum) values of each of the analyzed parameters c_j were increased (decreased) by 1%.

The criteria of statistical decision theory can be used as columns of the efficiency matrix (Table 1).

In the presented formulas of Table 1 ρ – pessimism index, which in conventional calculations is taken to be equal to 0.5, ω_j – weighting coefficient of the j-th optimization parameter.

The main stages of constructing a multi-criteria approach to selecting optimal diagnostic characteristics for monitoring ship bearings are working with quantitative experimental information, mathematical calculations, storing and exchanging information, and interpreting the results.

Table 1
Criteria of statistical decision theory

Optimization criterion name	Principles of organization	Calculation formulas	Behavior strategy
Laplace	Orientation to optimistic development of the situation	$L = \max\limits_{1 \le i \le m} \max\limits_{1 \le j \le n} \delta y_{ij}$	Offensive, ignoring risk
Wald	Orientation to pessimistic development of the situation	$W = \max\limits_{1 \le i \le m} \min\limits_{1 \le j \le n} \delta y_{ij}$	Strategy of inevitability and fatalism

Hurwitz	Pessimism-optimism	$H_z = \max\limits_{1\le i\le m}\left\{\rho \min\limits_{1\le j\le n} \delta y_{ij} + (1-\rho)\max\limits_{1\le o\le m} \delta y_{ij}\right\}$	Reinsurance in the worst case
Additive convolution	The total value of individual characteristics taking into account their importance	$y_a = \delta y_i = \sum_{j=1}^{n} \omega_j \delta y_{ij}$	Minimization of the sum of deviations
Multiplicative convolution	Agreed assessments of all characteristics	$y_{ms} = \delta y_i = \prod_{j=1}^{n} \left(\delta y_{ij}\right)^{\omega_j}$	Minimization of products of deviations
Complementary multiplicative convolution	Exclusion of zero values	$y_{md} = \delta y_i = 1 - \prod_{j=1}^{n} \left(1 - \omega_j \delta y_{ij}\right)$	Minimization of deviations

5. Experiment

The measurements are taken on the bearing unit housing, namely in its lower part, since the loads on the unit are maximum here. The signals from the sensors can be digitized and recorded for trend analysis. An accelerometer is used to record vibration levels. A vibration signal lasting 6 s was received daily for 50 days in a row. A bearing malfunction occurred, which led to its failure.

6. Results and discussion

During post-processing, statistical characteristics of vibration signals in the time and frequency domains were determined. In the time domain, 11 statistical characteristics were determined: mean value (Mean), standard deviation (Std), skewness, excess (Kurtosis), full swing of oscillations (Peak2Peak), root mean square (RMS), crest factor (CrestFactor), shape factor (ShapeFactor), impulse factor (ImpulseFactor), marginal factor (MarginFactor), energy (Energy). In the frequency domain, 4 statistical characteristics were determined: mean spectral value (SKMean), standard spectral deviation (SKStd), spectral skewness (SKSkewness) and spectral excess (SKKurtosis). All of the listed statistical characteristics of vibration signals can serve as potential indicators of bearing condition degradation (Fig. 1). The filtering and smoothing procedure was applied to the extracted statistical characteristics.
In order to determine the most optimal characteristic for monitoring the condition of a sliding bearing, a multi-criteria optimization was carried out using five parameters with different weighting factors ω:

1. monotony (ω = 0.25)
2. sensitivity (ω = 0.25)
3. rate of linear change (ω = 0.20)
4. deviation from additivity (ω = 0.15)
5. area under the curve (ω = 0.15).

To quantitatively assess the monotonicity of statistical characteristics, the formula was used

$$\text{Monotonicity}(x_i) = \frac{1}{m}\sum_{j=1}^{m}\frac{\left|\text{number of positive diff}\left(x_i^j\right) - \text{number of negative diff}\left(x_i^j\right)\right|}{n-1} \tag{3}$$

where n – number of measurement points, in our case n = 50. m – the number of controlled samples, in our case m = 1, x_i^j – i-th characteristic measured on j-th sample, $\text{diff}\left(x_i^j\right) = x_i^j(t) - x_i^j(t-1)$.

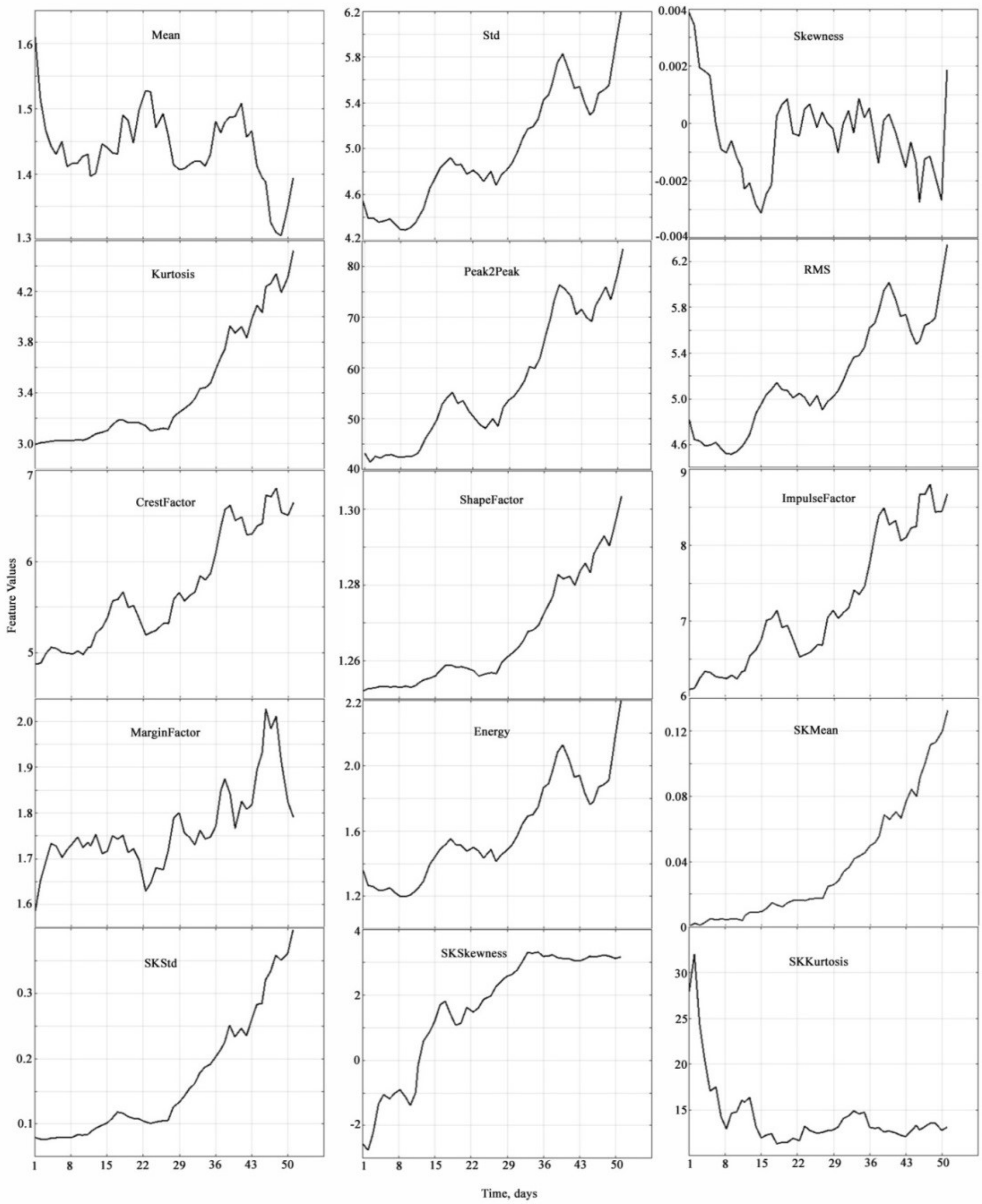

Figure 1: Evolution of dimensionless statistical characteristics of vibration signals during operation of a plain bearing

To determine the remaining optimization parameters, each discrete statistical characteristic of the vibration signal was approximated by a continuous nonlinear function f_1 in the form of a cubic spline, a linear function f_2 obtained by the least squares method, and a linear function f_3 on the final pre-destruction interval of 40-50 days, also obtained by the least squares method. Fig. 2 shows an example of such approximations for excess. The choice of a linear trend for functions f_2 and f_3 is explained by its greatest optimality for monitoring plain bearings.

After the approximations were carried out, the corresponding optimization parameters were determined as follows:

Sensitivity

$$\Delta = \frac{df_3}{dt} \tag{4}$$

rate of linear change

$$\upsilon = \frac{df_2}{dt} \tag{5}$$

deviation from additivity

$$\varepsilon = \frac{n\sum_{i=1}^{n} t_i f_{1i} - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} f_{1i}}{\sqrt{\left[n\sum_{i=1}^{n} f_{1i}^2 - \left(\sum_{i=1}^{n} f_{1i}\right)^2\right]\left[n\sum_{i=1}^{n} t_i^2 - \left(\sum_{i=1}^{n} t_i\right)^2\right]}} \tag{6}$$

area under the curve

$$S = \int_1^n f_1 dt \tag{7}$$

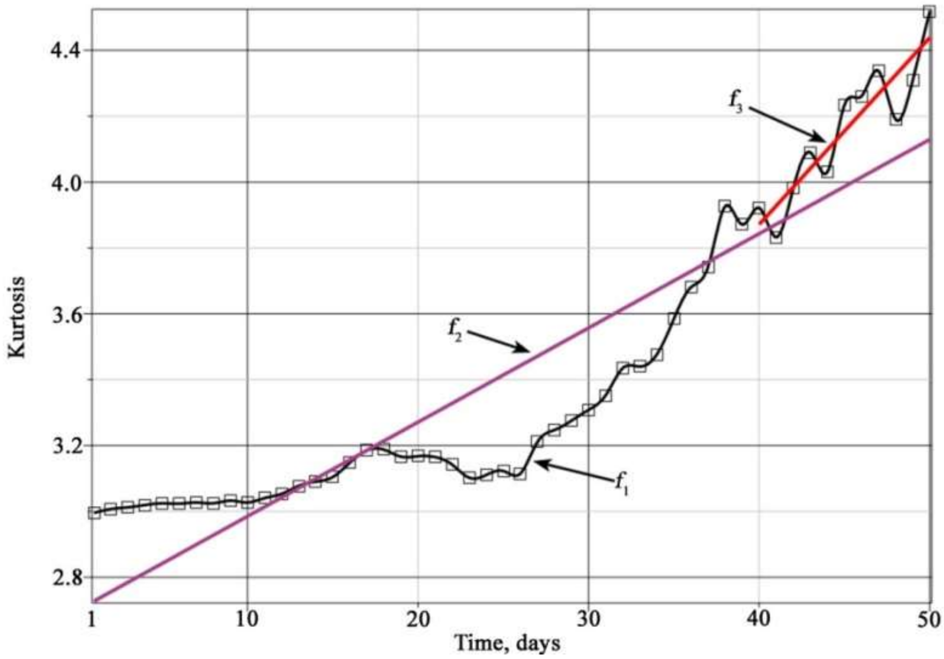

Figure 2: Approximation of the statistical characteristic of the vibration signal: f_1 is a continuous nonlinear function in the form of a cubic spline, f_2 is a continuous linear function, f_3 is a continuous linear function in the pre-destruction zone, the dots show the experimental discrete values of the statistical characteristic

The results of calculating the optimization parameters for each statistical characteristic of vibration signals are presented in Table 2.

Table 2.
Values of optimization parameters for statistical characteristics of vibration signals

	monotone	sensitivity	rate of linear change	deviation from additivity	area under the curve
Mean (Mean)	0.1600	0.0159	0.0015	0.4103	46.6570
Standard deviation (Std)	0.3600	0.0416	0.0319	0.9250	243.3900
Skewness (Skewness)	0.2600	0.0001	0.0002	0.2798	0.0219
Kurtosis (Kurtosis)	0.5800	0.0567	0.0286	0.9152	167.6600
Peak2peak (Peak2Peak)	0.4650	0.9143	0.8115	0.9431	2788.1000
Root mean square (RMS)	0.1600	0.0387	0.0313	0.9220	246.5500
Crest factor (crestfactor)	0.3600	0.0289	0.0392	0.9389	280.7100
Shape factor (shapefactor)	0.5800	0.0020	0.0009	0.8700	62.1400
Impulse factor (impulsefactor)	0.3600	0.0503	0.0558	0.9408	356.5100
Marginal factor (marginfactor)	0.2600	0.0023	0.0042	0.6639	90.0130
Energy (Energy)	0.1600	0.0282	0.0190	0.9132	73.6190
Mean spectral value (skmean)	0.1600	0.0064	0.0023	0.9255	1.8038
Standard spectral deviation (skstd)	0.3600	0.0157	0.0059	0.9239	5.5387
Spectral skewness (skskewness)	0.2600	0.0099	0.0840	0.9197	97.7310
Spectral kurtosis (skkurtosis)	0.0450	0.0986	0.1847	0.8270	531.9900

Relative deviations calculated using formula (2) δy_{ij} parameters of statistical characteristics of vibration signals from the optimal value, as well as the values of convolutions and criteria are presented in Table 3.

For a final conclusion regarding the optimal statistical characteristic for monitoring, it is necessary to take into account the coincidences in different generalizing functions, the degree of adequacy of each generalizing function to the problem being solved. The analysis of the results presented in Table 4 shows that the additive convolution, multiplicative convolution, additional multiplicative convolution, Laplace and Wald criteria clearly indicate the peak factor (Peak2Peak) as the most optimal characteristic for monitoring the state of a sliding bearing.

The most important characteristics of monitoring are:

- continuity and stability of indicators and parameters.
- frequency of receiving information,
- processing and aggregation of collected information,
- integration of the monitoring function into the system without emergency operation of the equipment.

Vibration monitoring of plain bearings of power plants makes it possible to know their condition at any given time and to determine possible problems of further operation in advance. The advantages of the considered methodology are the possibility of detecting hidden defects, obtaining information about the condition of equipment located in hard-to-reach places, monitoring and obtaining information about a defect at the stage of its origin, reducing the risk of emergency situations due to untimely detection of defects. In addition, it reduces the time for scheduled diagnostics and repairs while increasing the service life of the equipment. The introduction of a vibration diagnostics system increases the reliability and trouble-free operation of the equipment, creates the ability to predict the condition and plan routine maintenance.

Table 3
Matrix of dimensionless values of optimization parameters of statistical characteristics of vibration signals, as well as values of convolutions and criteria

Statistical characteristics	**monotone**	**sensitivity Δ**	**rate of linear change υ**	**deviation from additivity ε**	**area under the curve S**	**min**	**max**	y_a	y_{ms}	y_{md}
Mean	0.787	0.982	0.998	0.806	0.983	0.787	0.998	0.910	0.905	0.636
Std	0.417	0.955	0.961	0.040	0.913	0.040	0.961	0.678	0.481	0.527
Skewness	0.602	1.000	1.000	1.000	1.000	0.602	1.000	0.900	0.881	0.631
Kurtosis	0.010	0.938	0.965	0.055	0.940	0.010	0.965	0.579	0.201	0.475
Peak2Peak	0.223	0.009	0.009	0.014	0.009	**0.009**	**0.223**	**0.063**	**0.022**	**0.063**
RMS	0.787	0.958	0.962	0.045	0.912	0.045	0.962	0.772	0.573	0.577
CrestFactor	0.417	0.968	0.952	0.020	0.900	0.020	0.968	0.675	0.433	0.526
ShapeFactor	0.010	0.997	0.999	0.122	0.977	0.010	0.999	0.617	0.233	0.498
ImpulseFactor	0.417	0.945	0.932	0.017	0.873	0.017	0.945	0.660	0.417	0.517
MarginFactor	0.602	0.997	0.995	0.429	0.968	0.429	0.997	0.808	0.770	0.591
Energy	0.787	0.969	0.977	0.058	0.973	0.058	0.977	0.789	0.605	0.585
SKMean	0.787	0.993	0.997	0.040	0.999	0.040	0.999	0.800	0.580	0.591
SKStd	0.417	0.983	0.993	0.042	0.998	0.042	0.998	0.704	0.497	0.542
SKSkewness	0.602	0.989	0.897	0.048	0.965	0.048	0.989	0.729	0.543	0.554
SKKurtosis	1.000	0.893	0.774	0.186	0.811	0.186	1.000	0.777	0.695	0.579
		Vald	*Laplas*	*Bayes*						
		0.223	**0.009**	**0.504**						

Another practical example of the developed methodology for optimizing the management of maritime transport in the context of multicriteriality and uncertainty of input information is the use of multicriterial analysis in the study of thermodynamic processes in ship repair and transport infrastructure [20, 21]. Maritime transport logistics includes not only the processes of cargo movement, but also the infrastructure involved: roads, warehouses, loading and unloading terminals, berth walls, mooring devices, landing stages and engineering structures. Together, they form a single mechanism for carrying out transportation. This paper solves the problem of finding a recipe for concrete structures for maritime transport infrastructure a multi-criteria analysis system for determining the main characteristics of concrete mixtures for ship repair and transport infrastructure in real time has been proposed. Its advantages are scalability and adaptability to workloads. The computational basis for the calculations was the digitalization of the technology for research and analysis of physical and mechanical properties of concrete mixtures. An algorithm for multi-criteria analysis in the study of thermodynamic processes in ship repair has been developed. The presented system for applying multi-criteria analysis in the study of thermodynamic processes in ship repair and transport infrastructure is a set of statistical expert information, in which the qualitative weakly structured side is determined through the weight content of the analyzed thermodynamic properties subject to expert assessment, and criterion methods are used to obtain a final conclusion.

The third practical example of optimization of management decisions in conditions of multi-criteriality and uncertainty of input information is the solution of problems of transport logistics aimed at ensuring transportation within the established timeframe with fixed costs. Reasons for deviations from the agreed modes of transportation:

- weather conditions
- equipment failures
- operational factors
- organizational factors

The optimization parameters of sea transportation are:

1. vessel loading
2. delivery duration
3. transit speed
4. development of optimal routes taking into account the specifics of cargo
5. easonal weather conditions

Conclusions

1. Optimisation of sea transport development management under multicriteria conditions and uncertainty of input information is used in constructing a diagnostic method. A methodology has been developed; optimisation parameters have been proposed and studied in detail based on changing the trajectory of the main diagnostic feature when it approaches the state of degradation. The creation of vibration diagnostic methods involves the initial construction of a physical model, followed by diagnostic models, which use deterministic and probabilistic methods. In diagnostic analytical models, monitoring the condition of bearings becomes possible when a database and modern expert diagnostic systems use complex algorithms for processing and filtering signals. The monitoring efficiency depends on the rate of defect development and is determined by optimisation parameters based on changing the trajectory of the main diagnostic parameter.
2. The requirements for using the developed multicriteria analysis methodology to optimise the management of sea transport development under multicriteria conditions and the uncertainty of input information are formulated and used to construct a diagnostic method. The method of developing the parameters of goal functions is based on a rich criterion analysis with the vitalistic criteria of Laplace, Hurwitz, and Wald, emphasising the successive vigour and finding of experimental values in the form of priority development of goals. The use of multicriteria analysis in modelling the parameters of the objective function for ship repair and transport infrastructure has demonstrated the advantage of digitalisation of technologies in the analysis of the performance of concrete systems, where the final result best combines the results of experimental studies and their mathematical operations.
3. The areas of application of the developed multicriteria analysis methodology are determined. As a prospect for further research, the use of multicriteria analysis in optimising the parameters of maritime transport logistics is proposed. Taking into account the variations and justification of the ranges of change and the reasons for the need to optimise these values, the transportation parameters are determined. Using this information makes it possible to compile an efficiency matrix and perform the corresponding calculations.

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Declaration on Generative AI

The authors have not employed any Generative AI tools.

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