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DEVELOPMENT OF AN INTELLIGENT SYSTEM FOR ENHANCING MARINE ENGINEER READINESS FOR THE OPERATION AND REPAIR OF INJECTORS WITH VISUALIZATION OF THEIR 3D MODELS

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The problem of enhancing the readiness of marine engineers for the operation and repair of ship technical systems is relevant due to the difficulty of detecting faults and the need for timely diagnostics. The aim of this research is to develop and implement an intelligent system that improves marine engineer readiness by visualizing 3D models of injectors and using fuzzy diagnostic methods. The research includes the formation of a conceptual system description, the creation of a formal-logical structure of injector diagnostic rules based on symptoms, the development of 3D injector models, and decision-support software.

The research employed methods of machine learning, automation, and fuzzy logic to improve diagnostic accuracy. The main functional elements of the system include: data input, where symptoms of injector faults are entered as a set of parameters; rule evaluation, which assesses the input data based on threshold values to determine the severity levels of symptoms; recommendation generation, where the system automatically generates recommendations based on rule evaluation; visualization of membership functions through the construction of graphs for each diagnostic rule; and 3D modeling, which involves creating 3D models of injectors for visualizing damaged components and facilitating the diagnostic process.

Experiments have shown that the developed system reduces the risk of errors and increases the efficiency of injector repairs. Testing demonstrated that the speed of operations in injector repairs increased by 22.5%. The system automatically evaluates symptoms and generates recommendations for the marine engineer, ensuring timely fault detection.

The practical significance of the system lies in its ability to reduce the impact of human factors on the operation of ship technical systems, enhancing overall reliability and safety. The system ensures operational flexibility, allowing the marine engineer to visually identify damaged injector components. The implementation of the intelligent system contributes to reducing the risk of emergency situations and optimizing the repair process.

The theoretical significance lies in the introduction of new approaches to injector diagnostics using machine learning, automation, and 3D visualization. The use of fuzzy logic for symptom evaluation and recommendation generation ensures more accurate and reliable fault detection. The proposed methods can be adapted for diagnosing other components of ship technical systems, opening new prospects for further research.

Bibliography: 33 sources, 5 figures.

Key words: *intelligent system; readiness enhancement; automation; injector repair; 3D modeling; machine learning; fault diagnostics; maritime safety; risks; uncertainty.*

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Introduction. The development of means to enhance the readiness of ship crews for the operation of ship technical systems and complexes is an important task that requires control from shipping companies and qualification centers for the training of seafarers [1]. Special attention should be paid to the complexity of feedback during the monitoring of crew actions, particularly marine engineers on the ship during the operation and repair of ship engine components and other power units, considering the human factor [2]. Additionally, the decline in qualification levels, their fragmented heterogeneity considering operational and repair experience, and the influence of fatigue factors can pose problems [3]. Monitoring such manifestations of the human factor – marine engineerin real-time is quite difficult because although crew members may notice deviations in the work of an individual specialist, they cannot help or, moreover, replace them. At the same time, there are unfortunately many cases where specialists have documentary proof of their qualifications but make mistakes under real conditions [4, 5].

In some cases, researchers actively use automated reinforcement learning methods to optimize the management of digital flow processes in ship networks [6]. Furthermore, during the operation of ship technical systems and complexes, difficulties may arise, particularly when installing ship system bearings, which can significantly reduce lubrication efficiency, leading to wear and failure of the bearings [7]. Installing stern bearings requires special attention due to their sensitivity to vertical and horizontal errors. Implementing intelligent monitoring and correction systems using 3D models can improve service quality and reduce the risk of errors, enhancing the overall readiness of marine engineers for the operation and repair of ship systems.

Problems arising from human errors and electrical failures have shown that a significant portion of accidents is associated with the human factor [8]. The use of the SHEL method to assess human error in the ship's power supply system revealed that non-compliance with standard operating procedures (SOP) and lack of proper experience lead to failures in the electrical system, accounting for 12.7% and 17.2%, respectively. Moreover, the implementation of condition monitoring and fault diagnosis (CMFD) technologies can significantly increase the reliability and safety of ship systems, reducing the impact of the human factor [9]. Current fault detection and diagnosis methods are often outdated and rely on manual inspections and regular maintenance, which can be subjective and inaccurate.

Thus, the development and implementation of intelligent monitoring systems that use machine learning algorithms and big data allow real-time assessment of equipment condition, prediction of potential faults, and optimization of operational parameters. This is particularly important for ensuring the stable operation of the crew and extending the service life of ship technical systems.

Problem Statement. Many researches have shown a positive trend in both the application and development of new intelligent systems and tools aimed at improving operational quality, reducing risks, and ensuring the safety of ship technical systems and the vessel as a whole. For example, in the research [10], the importance of monitoring the technical condition of materials of metal structures according to international standards to ensure the reliability of marine equipment is highlighted. The authors propose an innovative diagnostic system for ship power plant turbochargers based on Markov chains, which replaces discrete time intervals of diagnostics with a sequence of states of technical objects. This allows for consideration of various operational factors and enhances equipment reliability under harsh operating conditions. The practical significance of the methodology is confirmed by the results of data digitization, calculation of transition matrices, and construction of an orgraph for studying the kinetics of damage in real-time. However, there is a lack of detailed information on the application of the methodology in specific diagnostic tasks, making the research relevant and promising but requiring additional details for a fuller understanding.

In another research [11], the main methods include the integration of machine and deep learning for automatic extraction of key fault features, early warning, and precise identification of potential faults. Using advanced big data processing technologies such as stream computing and distributed storage, the system significantly improves the accuracy and speed of diagnostics. The combination of neural networks with genetic search algorithms ensures higher efficiency in fault detection and prediction in real-time, which is confirmed by experimental results where the BP-GA model showed the best results in accuracy, precision, and F1 score. However, although the article demonstrates significant potential in improving diagnostics and reducing costs, it lacks details on specific methods and their application, limiting the understanding of the full value of the proposed methodology.

Other researchers in their work [12] have improved the traditional genetic algorithm by adding an interpolation test function to avoid obstacle crossing and introducing a concentration value to evaluate the probability of individuals transitioning to the next generation. The A* algorithm is used to search for sub-paths during crossover and mutation, significantly enhancing problem-solving efficiency. In simulation experiments, the improved A*-genetic algorithm showed better results in six indicators, including pipeline length, number of bends, energy value, fitness value, number of optimal solutions, and average number of iterations to convergence, compared to other algorithms. Thus, the proposed algorithm provides higher quality of pipeline layout and problem-solving efficiency. However, the lack of real-life application examples limits the understanding of its practical value, and the complexity of the algorithm may require significant computational resources.

Additionally, developments are underway regarding the use of artificial intelligence technologies for vulnerability analysis in information management intrusions [13]. The proposed AFL-VA-ISN (Adaptive Fuzzy Logic-assisted Vulnerability Analysis of Intelligent Ship Networks) model combines fuzzy logic and artificial intelligence for effective management of uncertainty and fuzziness in intelligent ship networks. The model uses multi-sensor nodes to assess data on malicious attacks and self-executing protective nodes to prevent attacks. Experimental results showed that the model increases data transmission speed by 99.2%, attack detection rate by 98.5%, risk assessment rate by 97.5%, and access control rate by 96.3%, while reducing network latency by 11.4% compared to existing models. However, for more guaranteed results when applying this approach, additional research is needed to optimize the system and adapt it to different real-time usage scenarios.

Researchers in their work [14] also conceptually identified the necessary intelligent functions for inland vessels by 2030, 2035, and 2050, focusing on artificial intelligence technologies, the Internet of Things, cloud computing, and big data to enhance safety, reliability, and energy efficiency. The main methods include sensors for data collection, communication technologies for information exchange, and evaluation and decision-making technologies for navigation, energy efficiency management, and vessel maintenance. Although the lack of practical examples and implementation complexity may limit technology adoption, the proposed approaches provide clear guidelines for the development of intelligent vessels and improved energy efficiency management.

Another research examines a wide range of intelligent tools that will enhance the operational level of the engine room [15]. Specifically, it describes the use of intelligent engine room systems on ships, including artificial intelligence technologies such as neural networks, support vector machines, and genetic algorithms for fault diagnostics and equipment condition monitoring. The use of big data, cloud computing, and industrial Internet increases the efficiency and safety of engine room operations, although existing automation systems remain closed and isolated, limiting their integration and real-time data exchange. Despite theoretical advantages, the lack of practical examples and implementation complexity raise doubts about the effectiveness and feasibility of widespread application of the proposed technologies.

Thus, the productivity of approaches to creating intelligent tools should also be considered. In the research [16], the development of a database for an intelligent ship management system using MySQL and distributed software MYCAT is described to ensure high performance and management flexibility. The main methods include data flow analysis, database structuring, and table design for storing information about the ship, user management, equipment, and signaling points, ensuring system stability and reliability. Although the proposed architecture is effective, it requires further optimization to handle highly competitive events and adaptation to real usage conditions, particularly in the engine room.

The approaches discussed in the section and their critical analysis indicate the necessity and importance of both developing and applying intelligent systems for ship process management, ensuring safety, improving operational efficiency, and diagnosing faults in the engine room. The current situation requires more flexible human-machine interaction systems when using intelligent decision support systems for the marine engineer, which will enhance their operational readiness, especially under conditions of implicit fault detection. One of the means to improve adaptive feedback between the operator-marine engineer and the intelligent system could be higher-quality 3D visualization of parts that require maintenance and repair, their components, and elements of fuzzy determination using appropriate methods. All the above requires the development of separate diagnostic modules for individual elements of ship technical systems and complexes, which process symptoms and obtain the most effective operational solutions using fuzzy conclusions.

Research Purpose and Objectives. The aim of this research is to enhance the operational readiness level of the engine room crew by developing and applying an intelligent decision support system for marine engineesr, accompanied by 3D visualization of parts, using the example of injector repair. To achieve this goal, a series of sequential tasks must be addressed, namely:

1. Formulate a conceptual description of the intelligent decision support system for marine engineers.
2. Describe the formal-logical structure of rules for identifying injector faults based on symptoms.
3. Develop a 3D measurable model of the injector to improve the visualization of faults in its components.
4. Develop a software tool with inference functions to support the decision-making process of the marine engineer-operator.

Primary Research Material. To address ***the first task*** of the research, a description of the intelligent decision support system for marine engineers during the operation of the ship's engine in relation to injector replacement and repair was formulated. Structurally, the system comprises the following component blocks:

1. Data input - (input data on symptoms).

Symptoms: power_loss, rpm_fluctuation, acceleration_delay, fuel_leakage, pressure_drop, fuel_smell, corrosion_level, fuel_consumption_increase, startup_delay, visible_cracks, black_smoke, misfire_frequency, oil_consumption_increase, deposits, vibrations, white_smoke.

2. Rule evaluation (Rules 1–15)

Each rule (from evaluate_rule_1 to evaluate_rule_15) has its inputs (specific symptoms) and outputs (severity levels and recommendations).

– Rule 1:

Input: power_loss, rpm_fluctuation, acceleration_delay

Output: severity levels of symptoms, recommendation

– Rule 2:

Input: fuel_leakage, pressure_drop, fuel_smell

Output: severity levels of symptoms, recommendation

And so on for each rule from 1 to 15.

3. Recommendation determination

4. Combining rule results and determining best match

5. Visualization of membership functions

6. Plotting membership function graphs for each rule

To facilitate the most favorable understanding of the system's operation, a graphical diagram of the system was constructed (Figure 1).

To accomplish the second task, relevant literature was analyzed, providing a formal-logical framework for defining and refining rules that allow the identification of injector faults in real-time.

Rule 1: Nozzle Valve Clogging

If there is a decrease in engine power, uneven engine operation, or loss of power during acceleration, this may be due to nozzle valve clogging [17, 18].

Solution: Cleaning or replacing the nozzle

Symptoms: Decrease in engine power, uneven engine operation, loss of power during acceleration.

Equation for Mass Flow Rate (1)

$$Q = C_d A \sqrt{\frac{2\Delta P}{\rho}} \tag{1}$$

Q – mass flow rate (kg/s)

C_d – discharge coefficient
A – cross-sectional area (m²)
ΔP – pressure difference (Pa)
ρ – fluid density (kg/m³)

Purpose: This formula is used to determine the mass flow rate through the nozzle. It helps to establish whether there is nozzle clogging, which may cause a decrease in engine power and other symptoms.

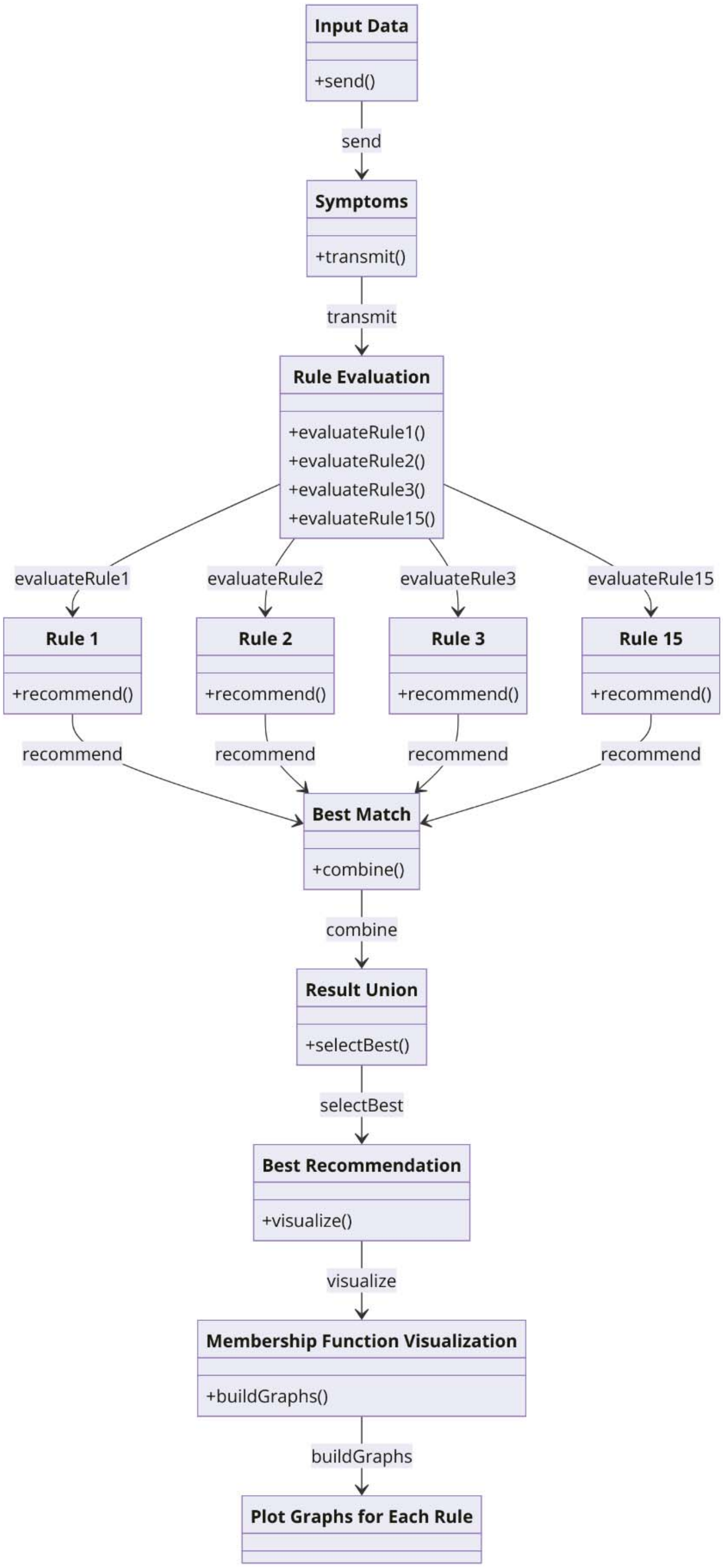


Figure 1 – Structural-Logical Diagram of the System's Functionality

Fuel Flow Rate (2)

$$Q = k \cdot \Delta P \tag{2}$$

Q – fuel flow rate
ΔP – pressure drop
k – discharge coefficient

Purpose: This formula allows the determination of fuel flow rate through the pressure drop. It helps to assess the efficiency of the nozzle operation and detect potential clogging.

Evaporation Constant (3)

$$b_{ev} = Y \cdot \frac{p_c}{d^2} \tag{3}$$

b_{ev} – evaporation constant
Y – correction factor
p_c – final pressure of the compression process
d – average diameter of fuel droplets

Purpose: This formula is used to assess the evaporation of fuel, which helps to determine the efficiency of the combustion process in case of a clogged nozzle.

Rule 2: Seal Wear (Nozzle Cap Nut, Cap Nut) [19]

Symptoms: Fuel leakage, pressure drop in the fuel system, fuel smell in the cabin.

Solution: Seal replacement.

Leakage Flow Rate (1)

Purpose: Used to determine the leakage flow rate through the seals. It helps identify worn seals that may lead to fuel leakage.

Fuel Leakage (4)

$$L = \frac{Q}{A \cdot 2g \cdot h} \tag{4}$$

L – fuel leakage
Q – fuel flow rate
A – cross-sectional area
g – acceleration due to gravity
h – height of the fuel level

Purpose: Helps determine the amount of fuel lost through leakage. This is important for assessing the effectiveness of the seals.

Fuel Evaporation Correction (5)

$$Y = \left(\frac{1000}{n_{crank}}\right)^{m_Y} \tag{5}$$

Y – correction coefficient
n_{crank} – crankshaft rotational frequency
m_Y – exponent of the evaporation correction function (0.65–1.00)

Purpose: Used to correct the fuel evaporation process, which helps assess the quality of the sealing and the impact of its wear.

Rule 3: Nozzle Corrosion (Nozzle Body) [20]

Symptoms: Corrosion on the nozzle, increased fuel consumption, difficulty starting the engine.

Solution: Cleaning the nozzle, using high-quality fuel.

Corrosion Rate (6)

$$\dot{m}_{corrosion} = k \cdot A_{corrosion} \tag{6}$$

$\dot{m}$ – швидкість корозії (кг/с)
k – корозійний коефіцієнт
$A_{corrosion}$ – площа корозії (м²)

Purpose: Used to determine the corrosion rate on the nozzle. It helps assess the extent of corrosion and the need for cleaning or replacing the nozzle.

Corrosion Stress (7)

$$\sigma_c = \frac{F}{A} \tag{7}$$

σ_c – corrosion stress

F – force due to corrosion impact

A – surface area of the nozzle

Purpose: Helps evaluate the mechanical impact of corrosion on the nozzle, which can lead to damage.

Pressure Before and After Seal (8)

$$\Delta P_{seal} = P_{before} - P_{after} \tag{8}$$

ΔP_{seal} – pressure difference before and after the seal

P_{before} – pressure before the seal

P_{after} – pressure after the seal

Purpose: Used to assess the pressure difference before and after the seal, which can be an indicator of corrosion or wear.

Rule 4: Incorrect Nozzle Calibration (Valve Spring) [21, 22]

Symptoms: Increased fuel consumption, uneven engine idling, black smoke from the exhaust pipe.

Solution: Nozzle calibration.

Injection Pressure (9)

$$P_{inj} = \frac{m_{fuel} \cdot R \cdot T_{fuel}}{V_{chamber}} \tag{9}$$

P_{inj} – injection pressure

m_{fuelm} – mass of fuel

R – gas constant

T_{fuel} – fuel temperature

$V_{chamber}$ – combustion chamber volume

Purpose: Used to determine the injection pressure. It helps identify incorrect nozzle calibration that affects combustion efficiency.

Ignition Delay Time (10)

$$\tau_i = B_0 \left(1 - k_n n_{crank}\right) \frac{p_{cyl.in.start} T_{cyl.in.start} e^{E_a / RT_{cyl.in.start}}}{\left(25 + CN\right) / 70} \tag{10}$$

τ_i – ignition delay time

B_0 – coefficient

k_n – coefficient

n_{crankn} – crankshaft rotational frequency

$p_{cyl.in.j.startp}$ – pressure at the start of compression

$T_{cyl.in.j.start}$ – temperature at the start of compression

E_a – activation energy

R – universal gas constant

CN – cetane number of the fuel

Purpose: Helps determine the ignition delay time, which may be influenced by incorrect nozzle calibration.

Rule 5: Mechanical Damage to Nozzle (Nozzle Body, Spindle) [23]

Symptoms: Fuel leakage, visible cracks on the nozzle body, constant pressure drop in the fuel system.

Solution: Nozzle replacement.

Leakage Flow Rate (1)

Purpose: Used to determine the leakage flow rate through cracks. It helps identify mechanical damage to the nozzle.

Mechanical Stress (11)

$$\sigma_m = \frac{K \cdot P_{fuel}}{A} \tag{11}$$

σ_m – mechanical stress

K – impact coefficient

P_{fuel} – fuel pressure

A – crack area

Purpose: Helps evaluate the mechanical stress on the nozzle due to fuel pressure, which can lead to cracks.

Impact Stress (12)

$$\sigma_b = \frac{F_{impact}}{A_{crack}} \tag{12}$$

σ_b – impact stress

F_{impact} – impact force

A_{crack} – crack area

Purpose: Used to assess the stress arising from impacts, which can cause mechanical damage to the nozzle.

Rule 6: Clogged Injector Filters (Fuel Inlet) [24, 18]

Symptoms: Uneven engine operation, white smoke from the exhaust pipe, difficulty starting the engine in cold conditions.

Solution: Cleaning or replacing the filters.

Equation for Mass Flow Rate (1)

Purpose: Used to determine the mass flow rate through the filter. It helps identify clogged filters.

Filter Resistance (13)

$$R_{filter} = \frac{\Delta P}{Q} \tag{13}$$

ΔP – pressure drop across the filter

Q – fuel flow rate

Purpose: Helps evaluate the filter resistance, which can indicate clogging.

NO Concentration (14)

$$[NO] = K_1 [O][N_2] \tag{14}$$

$[NO]$ – NO concentration

K_1 – reaction constant

$[O]$ – oxygen concentration

$[N_2]$ – nitrogen concentration

Purpose: Used to assess the NO concentration, which helps evaluate the combustion quality of the fuel with clogged filters.

Rule 7: Damage to Connecting Elements (Lock Nut, Spring Cap Nut) [25]

Symptoms: Fuel leakage, corrosion on joints, fuel smell around the engine.

Solution: Replacement of connecting elements.

Shear Stress (15)

$$\tau = \frac{F_{tight}}{A_{joint}} \tag{15}$$

τ – shear stress

F_{tight} – tightening force

A_{joint} – joint area

Purpose: Used to evaluate the shear stress in the connecting elements. It helps identify damage that can lead to fuel leakage.

Correlation and Sensitivity Coefficient (16)

$$v = \frac{m_0 m_4}{m_2^2} \tag{16}$$

v – correlation and sensitivity coefficient

m_0, m_2, m_4 – spectral moments

Purpose: Helps evaluate the correlation and sensitivity of the system to damage in the connecting elements.

Multivariate Correlation Model (17)

$$H\left(x_1, x_2, \ldots, x_k\right) = \phi_{0,0,\ldots,0} + \sum_{i=1}^{k} \phi_{i,0,\ldots,0} x_i + \sum_{i=1}^{k} \phi_{i,j,0,\ldots,0} x_i x_j + \ldots + \phi_{r,0,\ldots,0} x^r{}_i \tag{17}$$

$H(x_1, x_2, \ldots, x_k)$ – overall multivariate model

x_i – variables

k – number of variables

r – model order

ϕ – model coefficients

Purpose: Used to assess the relationships between different system parameters, which helps identify problems in the connecting elements.

Rule 8: Wear of the Spring Inside the Injector (Valve Spring) [26]

Symptoms: Increased fuel consumption, loss of power at high RPM, black smoke from the exhaust pipe.

Solution: Spring replacement.

Spring Stiffness (18)

$$k_s = \frac{F}{\Delta x} \tag{18}$$

k_s – spring stiffness

F – force

Δx – spring deformation

Purpose: Used to determine the stiffness of the spring. It helps identify spring wear, which affects the efficiency of fuel injection.

Gas Linear Velocity (19)

$$w = \mu \sqrt{\frac{2\left(p_1 - p_2\right)}{\rho}} \tag{19}$$

w – gas linear velocity

μ – discharge coefficient

p_1 – pressure before the valve

p_2 – pressure after the valve

ρ – gas density

Purpose: Used to determine the linear velocity of the gas, which helps evaluate the efficiency of the spring's operation.

Period of Angular Velocity Oscillation (20)

$$T = \frac{N_{cyl}}{n} \tag{20}$$

T – period of oscillations (s)

N_{cyl} – number of engine cylinders

n – crankshaft rotational frequency (revolutions per second)

Purpose: Used to evaluate the period of angular velocity oscillations of the crankshaft, which may be influenced by a worn spring.

Rule 9: Wear of the Injector Valve (Nozzle Valve) [27, 28]
Symptoms: Uneven engine operation, black smoke from the exhaust pipe, frequent misfires.
Solution: Valve replacement.
Valve Flow Coefficient (21)

$$C_v = \frac{Q}{\sqrt{\Delta P / \rho}} \tag{21}$$

C_v – valve flow coefficient
Q – flow rate
ΔP – pressure drop across the valve
ρ – fuel density
Purpose: Used to evaluate the flow rate through the valve. It helps identify valve wear, which affects the uniformity of engine operation.
Root Mean Square Error (22)

$$\sigma_s = \frac{1}{n(n-1)} \sum_{i=1}^{n} \left(a_i - a_{aver}\right)^2 \tag{22}$$

σ_s – root mean square error
n – number of measurements
a_i – value of the diagnostic parameter
a_{aver} – average value of the parameter
Purpose: Used to evaluate the accuracy of measurements, which helps identify problems with the valve.
Rule 10: Damage to the Nozzle Body (Nozzle Body) [23–25]
Symptoms: Fuel leakage, increased oil consumption, black smoke from the exhaust pipe.
Solution: Nozzle replacement.
Leakage Flow Rate (1)
Purpose: Used to determine the leakage flow rate through cracks. It helps identify damage to the nozzle body.
Mechanical Ship Dynamics (23)

$$m_{ship} \frac{dv_{ship}}{d\tau} = (1-t) T_{prop} - R_{ship} \tag{23}$$

m_{ship} – ship displacement (kg)
v_{ship} – ship speed (m/s)
τ – dynamic time (s)
T_{prop} – propeller torque (N·m)
R_{ship} – hull resistance (N)
Purpose: Used to evaluate the ship's dynamics and intensity, which can impact the damage to the nozzle body.
Vibroacoustic Signals (24)

$$a_p(\theta,\tau) = O\left[a_o(\theta,\tau)\right] = O\left[g_o\left(F, E_s, Z, Y\right), \tau\right] \tag{24}$$

$a_p(\theta,\tau)$ – vibroacoustic signals
$a_o(\theta,\tau)$ – output signal
$g_o(F,Es,Z,Y)$ – signal generation function
F – force
E_s – energy
Z – resistance
Y – mechanical properties of the material
Purpose: Used to analyze vibroacoustic signals, which helps identify issues with the nozzle body.
Rule 11: Corrosion of the Injector from Aggressive Environment (Nozzle Body) [29]

Symptoms: Corrosion on the nozzle, difficulty starting the engine, power loss under increased loads.

Solution: Cleaning the nozzle, checking operating conditions.

Corrosion Rate (6)

Purpose: Used to determine the corrosion rate on the nozzle. It helps assess the extent of corrosion and the need for cleaning or replacing the nozzle.

Mass Loss Due to Corrosion (25)

$$k_c = \frac{M_{loss}}{t} \tag{25}$$

Purpose: Helps evaluate the mass loss due to corrosion, which can affect the efficiency of the nozzle's operation.

Rule 12: Incorrect Pressure in the Fuel System (Fuel Inlet) [30]

Symptoms: Increased fuel consumption, unstable engine operation when shifting gears, black smoke from the exhaust pipe.

Solution: Adjusting the pressure in the fuel system.

System Pressure (26)

$$P_{system} = P_{set} + \Delta P_{loss} \tag{26}$$

P_{system} – system pressure

P_{set} – set pressure

ΔP_{loss} – pressure losses

Purpose: Used to evaluate the pressure in the system. It helps identify incorrect pressure in the fuel system.

Indicated Thermal Efficiency (27)

$$ITE = \frac{W_c}{Q_{in}} \tag{27}$$

ITE – indicated thermal efficiency

W_c – indicated work

Q_{in} – heat input

Purpose: Used to assess the combustion efficiency under incorrect pressure in the fuel system.

Rule 13: Use of Low-Quality Fuel (Fuel Inlet, Nozzle Valve) [31]

Symptoms: Increased fuel consumption, uneven engine operation, black smoke from the exhaust pipe.

Solution: Use of high-quality fuel.

Combustion Efficiency (28)

$$\eta_f = \frac{Q_{combustion}}{Q_{fuel}} \tag{28}$$

η_f – combustion efficiency

$Q_{combustion}$ – amount of heat obtained from combustion

Q_{fuel} – amount of heat contained in the fuel

Purpose: Used to evaluate the combustion efficiency of the fuel. It helps identify the use of low-quality fuel.

CO Concentration (29)

$$\frac{d[CO]}{d\tau} = K_1 C[CO][OH] \tag{29}$$

$\frac{d[CO]}{d\tau}$ – rate of change in CO concentration over time

K_1 – reaction constant

C – CO concentration

$[OH]$ – concentration of hydroxyl groups

Purpose: Used to evaluate the kinetics of reactions affecting CO concentration when using low-quality fuel.

Rule 14: Clogging of Fuel Supply Channels (Fuel Inlet, Spindle) [32]

Symptoms: Uneven engine operation, idling vibrations, white smoke from the exhaust pipe.

Solution: Cleaning the fuel supply channels.

Equation for Mass Flow Rate (1)

Purpose: Used to determine the mass flow rate through the channels. It helps identify clogging in the fuel supply channels.

Rule 15: Improper Storage or Transportation of the Nozzle (Nozzle Body) [33]

Symptoms: Corrosion on the nozzle, fuel leakage, power loss at high RPM.

Solution: Nozzle replacement, adherence to storage rules.

Transport Stress (30)

$$\sigma_h = \frac{F_{transport}}{A_{surface}} \tag{30}$$

σ_h – transport stress

$F_{transport}$ – transport force

$A_{surface}$ – surface area

Purpose: Used to evaluate the stress during transportation, which can cause corrosion or damage to the nozzle.

The next task, ***the third one***, is the development of a 3D measurable model of the nozzle to enhance the visualization of faults in its components. For this purpose, a drawing of the nozzle was created, followed by a step-by-step construction of its three-dimensional model. This model will enable the marine engineer to quickly navigate during the operation of the program, which will indicate specific elements of the nozzle for replacement or repair (Figure 2).

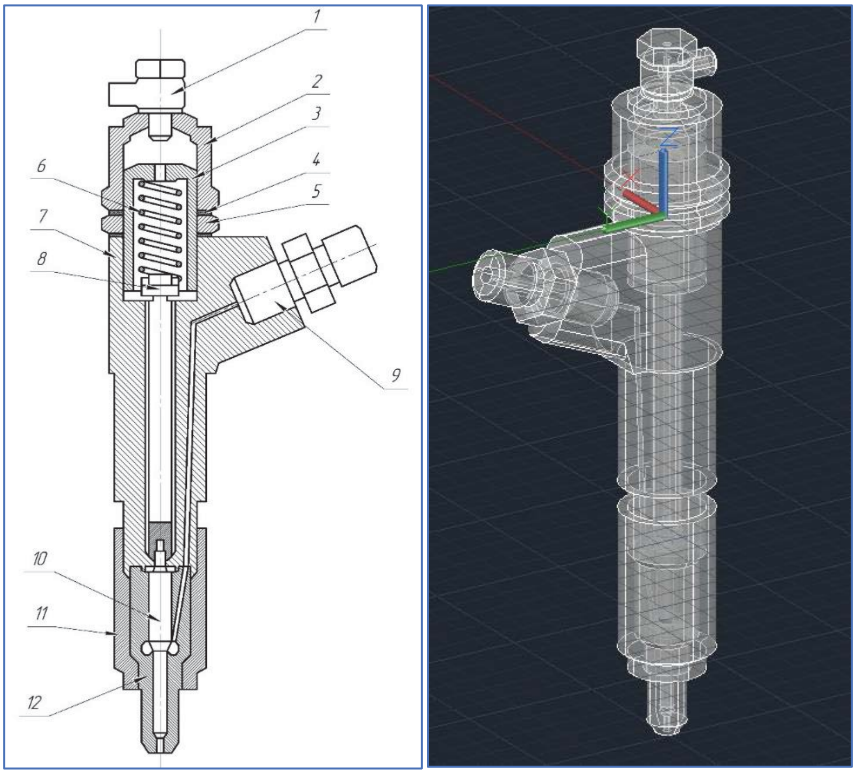


Figure 2 – 3D Modeling of the Nozzle as an Assembly Unit

The ***fourth task*** of the research involved the development of a specialized software tool with inference functionality to support the marine engineer-operator's decision-making process. To create this system, whose primary function is automated expert assessment and the generation of appropriate advice, the Anaconda programming environment and the Python programming language were used.

Main functional elements of the system:

1. Object Initialization (init method): The init method accepts input data in the form of a dictionary and stores it as object attributes.

2. Symptom Evaluation (evaluate_rule_X methods): Each evaluate_rule_X method evaluates a specific diagnostic rule (from 1 to 15). The input data is checked against various threshold values to determine the severity of symptoms (minor, moderate, significant, critical). The method returns the evaluation results and a match score.

3. Evaluate_all Method: This method calls all rule evaluation methods (evaluate_rule_1 ... evaluate_rule_15) and collects the results into a dictionary. It also collects match scores for each rule.

4. Determine_best_match Method: This method analyzes the match scores and determines the rule with the highest match score as the best match.

5. Plot_membership_functions Method: This method plots the membership functions for all diagnostic rules (Figure 3). It uses the matplotlib library for visualization.

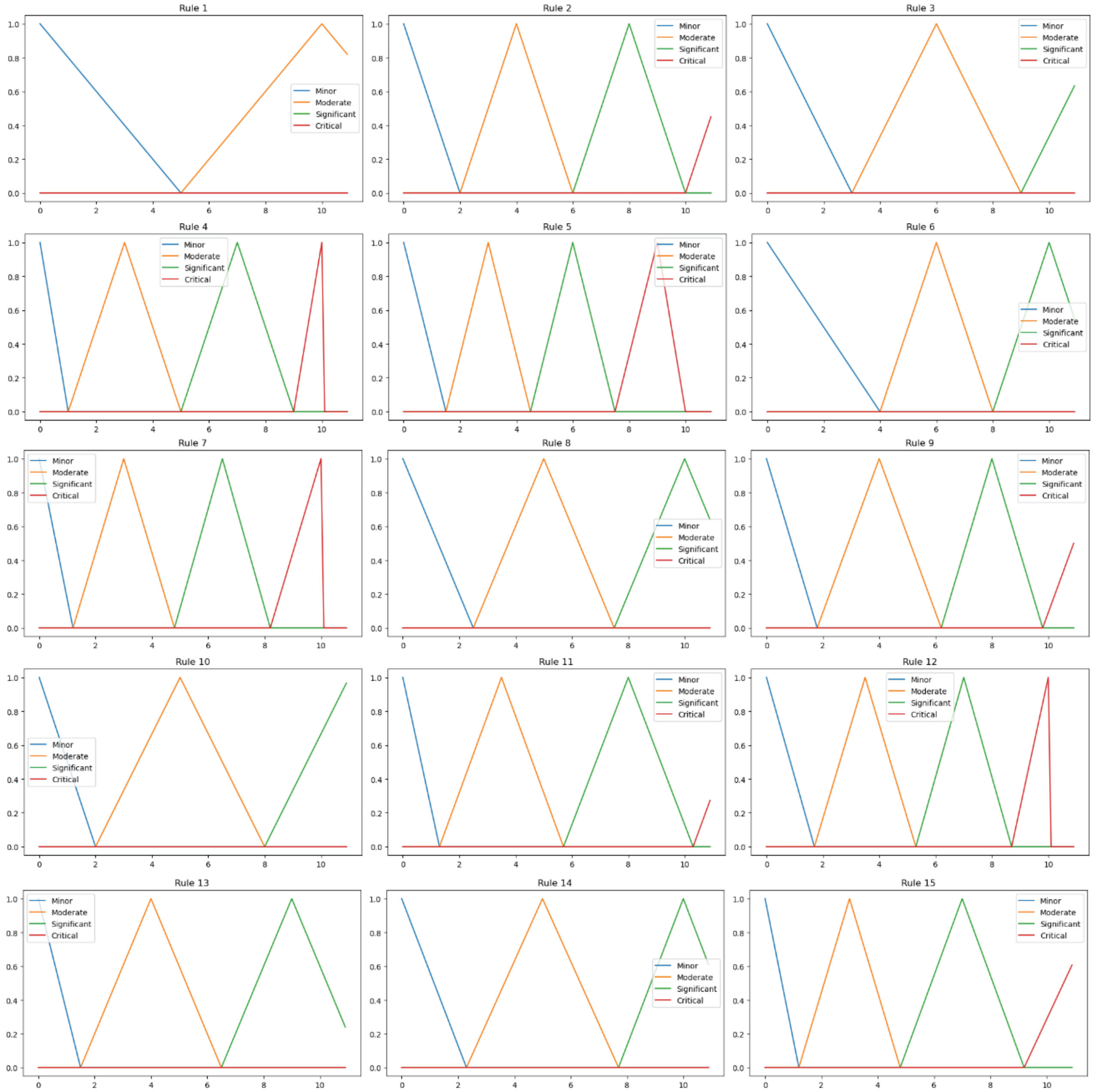
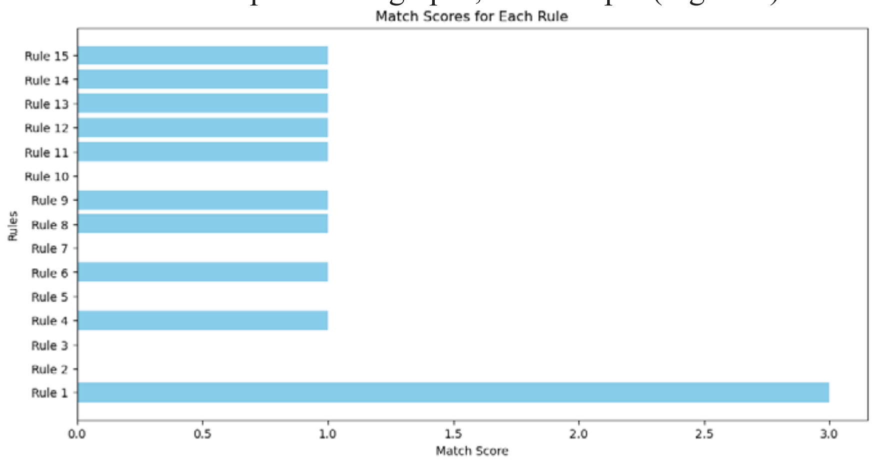


Figure 3 – Visualization of Membership Functions

Obtaining Membership Functions (get_membership_functions method): Returns the membership functions for a specific diagnostic rule based on triangular membership functions. As a result of testing the program, 5 situations were analyzed, and the corresponding results were obtained in the form of membership function graphs, for example (Figure 4).



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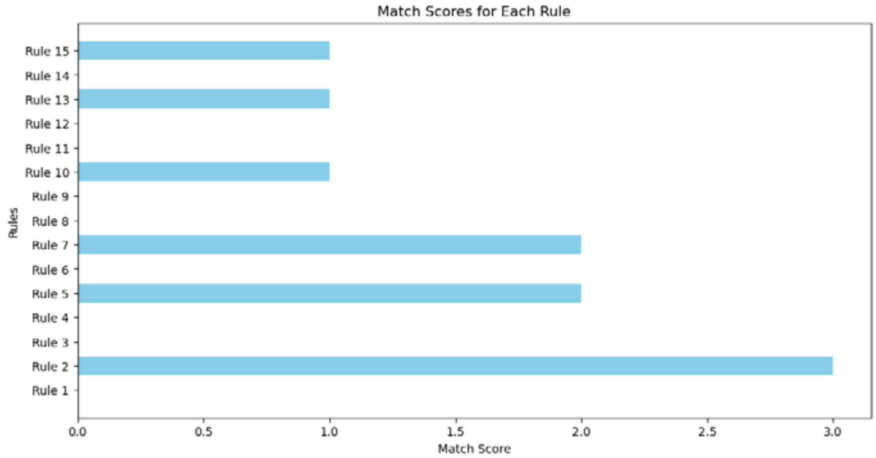
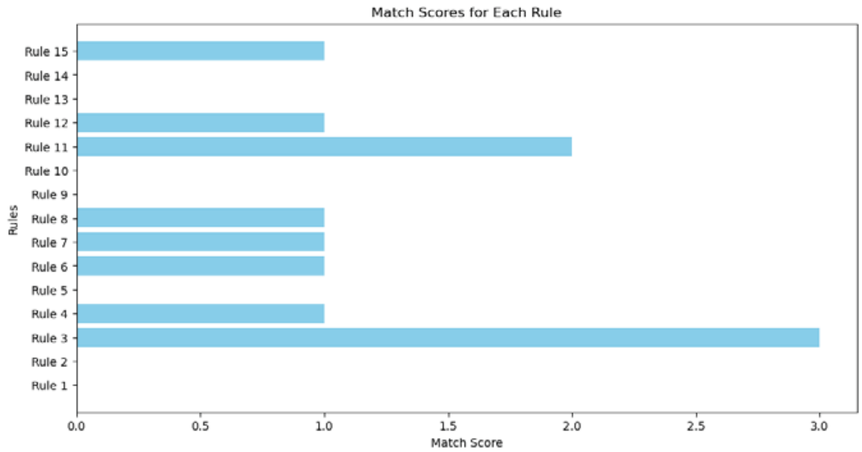


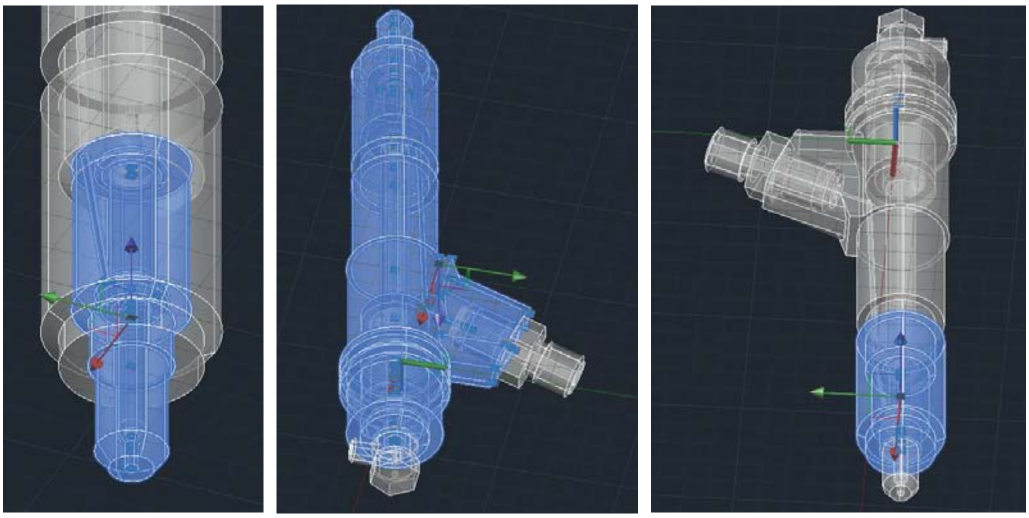
b



c

Figure 4 – Visualization of Membership for Situations No. 1, 2, 3 with Input Parameters
data_samples = [{'power_loss': 10, 'rpm_fluctuation': 3, 'acceleration_delay': 1.0},
{'fuel_leakage': 1.5, 'pressure_drop': 10, 'fuel_smell': 2},
{'corrosion_level': 2, 'fuel_consumption_increase': 12, 'startup_delay': 4},]

Additionally, the program provides recommendations in the form of visual advice.
For Situation No. 1, the applicable rule is (Figure 5a): Nozzle replacement.
For Situation No. 2, the most effective advice is: Complete seal replacement (Figure 5b).
For Situation No. 3: Injector replacement (Figure 5c).



a *b* *c*

Figure 5 – Visualizations of Damaged Nozzle Elements Requiring Replacement

The proposed approach will allow for quick operations in the maintenance and repair of injectors, as it enables the marine engineer to promptly identify the corresponding damaged elements and parts that require replacement or repair.

Conclusion. The research objective of developing an intelligent system to enhance the marine engineer's readiness for the operation and repair of injectors has been achieved through a series of tasks that ensured the implementation of a comprehensive approach:

1. A conceptual structure of the intelligent system was developed, which includes several key components such as data input, symptom evaluation, recommendation determination, and visualization of membership functions. This allows for a comprehensive approach to diagnostics. In terms of implementation, a user interface has been provided, ensuring ease of use for marine engineers.

2. A formal-logical structure of rules for diagnosing injector faults was described. For example, symptoms such as power loss, uneven engine operation, and fuel leakage are classified by severity levels. Each of the 15 rules evaluates symptoms based on specified threshold values. If a symptom meets certain criteria, the system generates the corresponding severity level and recommendation.

3. 3D models of the injector were designed, allowing the marine engineer to visually locate damaged components. This significantly improves diagnostic accuracy and fault identification because the 3D model enables the user to interact with different parts of the injector, facilitating the learning and diagnostic process.

4. A software tool with a fuzzy inference function was developed to support the marine engineer-operator's decision-making process. The Python-based software tool automatically evaluates symptoms and generates recommendations. Additionally, membership functions for each diagnostic rule were visualized, making the results easier to understand and allowing developers to improve and flexibly adjust the system.

Overall, testing of the developed system showed that the speed of operationalization during injector repair increased by 22.5%, significantly improving the maintenance processes and enhancing their overall safety and reliability.

Prospects for further research. Despite the fact that the developed system improves the accuracy of diagnosing and identifying injector faults by reducing the impact of the marine engineer human factor on the operation and repair of ship technical systems, future tasks should focus on its enhancement, namely:

• Improve the effectiveness of marine engineer training through visualization and intelligent support by adding dynamic display functions of repair processes and virtual augmented reality tools.

• Optimize the system for real-time operation, ensuring timely detection and elimination of faults.

• Expand the system's functionality to diagnose other components of ship technical systems.
• Explore possibilities for integration with other monitoring and ship management systems, which will allow for the creation of a comprehensive decision support system for the entire ship crew.

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Носов Павло, Гудзь Артем, Пономарьова Вікторія РОЗРОБКА ІНТЕЛЕКТУАЛЬНОЇ СИСТЕМИ ПІДВИЩЕННЯ ГОТОВНОСТІ МЕХАНІКА ДО ЕКСПЛУАТАЦІЇ ТА РЕМОНТУ ФОРСУНОК З ВІЗУАЛІЗАЦІЄЮ ЇХ 3D МОДЕЛЕЙ

Проблема підвищення готовності механіка до експлуатації та ремонту суднових технічних систем є актуальною через складність виявлення несправностей та необхідність своєчасної діагностики. Метою цього дослідження є розробка та впровадження інтелектуальної системи, що підвищує готовність механіка шляхом візуалізації 3D моделей форсунок і використання нечітких методів діагностики.

Для вирішення поставлених завдань дослідження було проведено кілька ключових етапів. Спочатку було сформовано концептуальний опис інтелектуальної системи підтримки прийняття рішень механіка, який включає введення даних про симптоми несправностей, оцінку цих симптомів на основі заданих правил, генерацію рекомендацій та візуалізацію функцій належності. Основні елементи функціоналу системи включають: введення даних, де симптоми несправностей форсунок вводяться у вигляді набору параметрів; оцінка правил, які оцінюють вхідні дані на основі порогових значень для визначення рівнів серйозності симптомів; визначення рекомендацій, де система автоматично генерує рекомендації на основі оцінки правил; візуалізація функцій належності через побудову графіків функцій належності для кожного правила діагностики; 3D моделювання, що включає створення 3D моделей форсунок для візуалізації пошкоджених компонентів та полегшення процесу діагностики.

Наступним етапом було створення формально-логічної структури правил для ідентифікації несправностей форсунок на основі симптомів. Кожне з 15 правил оцінює симптоми на основі заданих порогових значень.

На завершальному етапі було розроблено програмний засіб із функцією нечіткого висновку для підтримки прийняття рішень оператора-механіка. Програмний засіб автоматично оцінює симптоми та генерує рекомендації. Крім того, було візуалізовано функції належності для кожного правила діагностики, що полегшує розуміння результатів та дозволяє розробникам покращувати та гнучко налаштовувати систему.

Експерименти показали, що розроблена система дозволяє знизити ризик помилок та підвищити ефективність ремонту форсунок. Тестування показало, що швидкість операцій при ремонті форсунок зросла на 22,5%. Система автоматично оцінює симптоми та генерує рекомендації для механіка, забезпечуючи своєчасне виявлення несправностей.

Система забезпечує оперативність та гнучкість у використанні, дозволяючи механіку візуально ідентифікувати пошкоджені компоненти форсунок. Впровадження інтелектуальної системи сприяє зниженню ризику аварійних ситуацій та оптимізації процесу ремонту.

Запропоновані методи можуть бути адаптовані для діагностики інших компонентів суднових технічних систем, що відкриває нові перспективи для подальших досліджень. Подальші дослідження передбачають інтеграцію з іншими системами моніторингу та управління судном, а також розширення функціоналу для діагностики інших компонентів суднових технічних систем. Планується впровадження динамічного відображення процесів ремонту та віртуальних засобів доповненої реальності для підвищення ефективності підготовки механіків.

Бібл. 33, рис. 5.

Ключові слова: *інтелектуальна система; підвищення готовності; автоматизація; ремонт форсунок; 3D моделювання; машинне навчання; діагностика несправностей; безпека мореплавства; ризики; невизначеність.*

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