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METHOD OF THE SHIP MAIN ENGINE CONDITION OPERATIONAL DIAGNOSTICS

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The article is devoted to solving the problem of improving the quality of operational diagnostics of the ship main engine in real time. Modern technical diagnostic systems must perform quick and high-quality identification of increasing malfunctions for the most effective use of monitoring results when solving operational tasks with the issuance of recommendations, which will allow expanding the competence of technical personnel in the decision-making process. Therefore, an important task is the development of mathematical models of time series of measured values of controlled parameters, which will allow to improve the procedure of operational diagnostics due to the detection of the probability of failure of ship engine units before the area of the most intense wear or destruction. In order to improve the existing methods of technical diagnostics of technological equipment, effective operational diagnostics algorithms have been developed, which are implemented in software modules and fully take into account technical and economic requirements, stochastic nature of external influences. When building the operational diagnostics algorithms, the specifics of the processes taking place in the ship main engine were taken into account, modern techniques and methods of mathematical modeling and information theory were used. On the basis of the values obtained as a result of measurements of the controlled parameters of the ship main engine, autoregressive models of the moving average were selected, which describe the obtained time series as accurately as possible. The parameters of the autoregression models were identified using the method of least squares. A method of operational diagnostics based on the determination of spectral entropy and the procedure of logical-time processing is proposed. On the basis of the developed mathematical models and the proposed diagnostic method, an automated system of operational diagnostics of the state of the ship main engine has been developed, which allows timely detection of critical modes of operation of technological equipment in real time.

Key words: *ship main engine; diagnostics; monitoring; identification.*

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Introduction. In the process of developing ship diagnostic and monitoring systems, complex automation of equipment is increasingly being used with an increase in the degree of operational computer processing of information [1]. The improvement of information processing methods in systems for monitoring and diagnosing the condition of technical equipment is caused by an increase in the number of monitored parameters, stricter requirements for maintaining optimal operating modes, and the development of methods for operational diagnostics and forecasting of equipment condition. Since the ship main engine, as a complex control object, consists of a certain set of components and systems, the technical condition of each component is determined by a group of diagnostic parameters [2].

Statement of the problem. The fundamental task of the ship main engine condition operational diagnostics is to compare the current technical condition with some reference (completely normal, corresponding to the nominal passport characteristics) condition to support decision-making [3] by technical personnel about the admissibility of further operation of the object.

Operational technical diagnostics are carried out without any dismantling (disassembly) of the object and consist in the systematic determination of all parameters characterizing the operating mode, external conditions, fuel and oils used, the flow of the work process, the technical condition of working components and parts as well as the functioning of service systems [4]. Therefore, an important task is the development of methods, models, algorithms and software modules of operational diagnostics, versatile and applicable to any complex technical object, which will allow to detect a malfunction in a minimum time interval. Considering the above, the mathematical formulation of the problem of technical diagnostics can be written in the form

$$\Delta t = t_f - t_d \to \min, \tag{1}$$

where Δt – the time interval required to identify a malfunction of a technical object, t_f – fault occurrence timestamp, t_d – fault detection timestamp.

Analysis of the recent research and publications. A modern monitoring system for the ship main engine is designed as a single hardware and software complex that analyzes parameters and partially calculates the work process in real time. The most well-known modern systems of this type are:

1. KONGSBERG Engine monitoring systems [5]. KONGSBERG Engine Monitoring Systems consist of bearing monitoring components covering Bearing Wear, Water in Oil, Temperature of all bearings and additional measuring points such as Cylinder liner and exhaust gas temperature. Software & system components are common with the K-Chief 600 marine automation system and the AutoChief 600 propulsion control system, allowing integration and joined support.

2. MAN Energy Solutions SaCoS 5000 engine control system [6] – is the evolution of the well-known SaCoSone control system with proven reliability, robustness, tailored functionality for the demands of MAN Energy Solutions engines and extended safety features.

3. Praxis Automation Technology B. V. engine control system Mega-Guard ECS [7]. This Monitoring & Control system is an independent programmable system that monitors the operational parameters of the diesel engine and automates the diesel engine operations. The Monitoring & Control System main functions are: backup safety shutdown; monitoring and alarming of potential harmful or dangerous engine parameters; load (rpm) reduction request in case of engine overload or deviation from normal running conditions; low temperature cooling water thermostat control; self-diagnostics and sensor diagnostics; pre-lube oil pump control.

4. Wärtsilä Engine Control System WECS–9520 has been specially designed for two-stroke engines with Wärtsilä Common Rail technology, covering all engine-related and cylinder-related control functions [8]. Fig. 1 is a schematic representation of the related components and their interconnections. Main components of WECS–9520:

– Control box E90 (SIB) as communication to the external systems, containing a FCM–20 module as 'Online Spare'.

– Per cylinder a control box E95.xx, containing a FCM–20 module each for engine and cylinder-related control functions.

All modules are connected by the system bus. All control boxes (E90, E95.xx) are arranged on the rail unit, and power supply box (E85) is placed nearby the engine.

Engine-related control functions:

– Fuel rail pressure

– Servo oil pressure for exhaust valve drive.

All engine-related control functions are distributed within six FCM–20 modules (cylinders 1–6). For safety reasons all important functions, input and output signals of the modules are redundant. The engine remains in operation if one module fails. The power supply is also redundant. A defective module could be replaced with the 'Online Spare' module. The control box E90 must subsequently be completed with a new module as 'Online Spare' which will receive a download of all application data.

Cylinder-related control functions:

– Volumetric injection control

– Exhaust valve control

– Starting valve control

– Crank angle sensor.

Every cylinder is equipped with an FCM–20 module. A redundant CANopen bus provides communication between the FCM–20 modules (system bus). The FCM–20 modules receive the crank angle signal via a redundant SSI bus. If a FCM–20 module breaks down, the respective cylinder is cut out. The other FCM–20 modules remain in operation.

The 'Common Function' to the external systems is ensured by data buses to the propulsion control system and to the ship alarm and monitoring system. They serve as interface between operator and engine control.

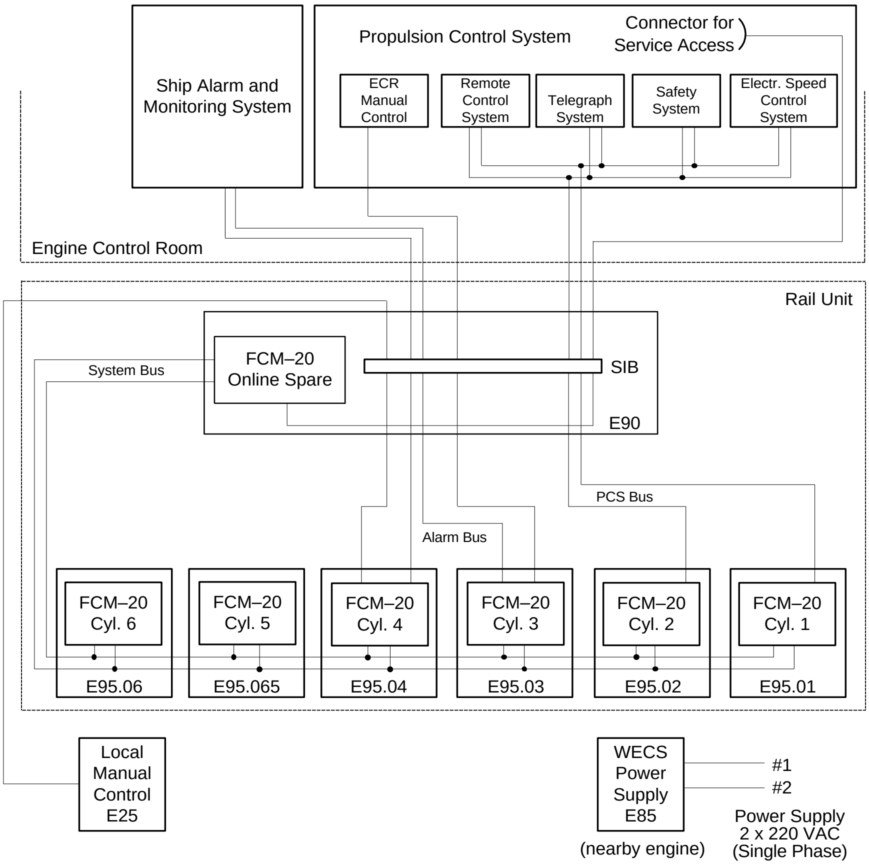


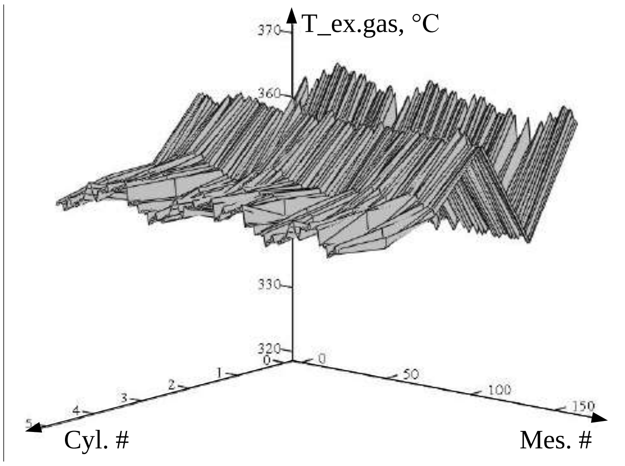
Figure 1 – Wärtsilä Engine Control System WECS–9520 structural scheme

The disadvantages of the considered systems are the averaging of the measurement results of the operating parameters of the ship main engine, which leads to the loss of the most informative part of the diagnostic information that must be used in the decision-making process by technical personnel.

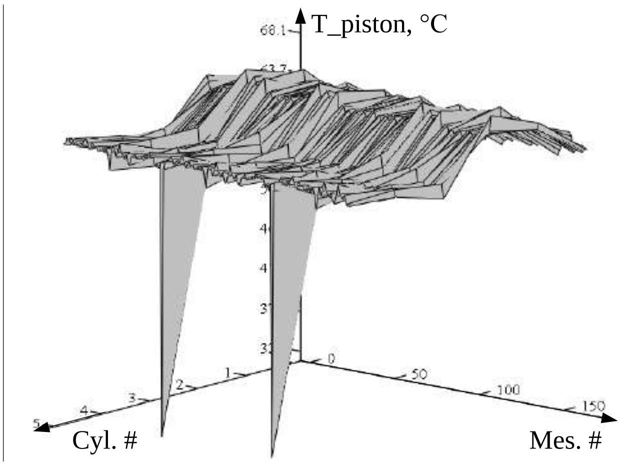
The aim of the research is to develop a method of the ship main engine condition operational diagnostics using the logic-time processing of the measurement signals of the controlled parameters based on the entropy approach for high-quality identification of increasing faults in real time and the most effective use of monitoring results to solve operational problems with the production of recommendations, which will expand the competence of technical personnel in the decision-making process.

Main part. To improve the method of operational diagnostics, an analysis of the operating parameters of the Wärtsilä RT-flex50-B ship main engine was carried out, characterizing the operating mode, external conditions, fuel and oils used, and the flow of the working process.

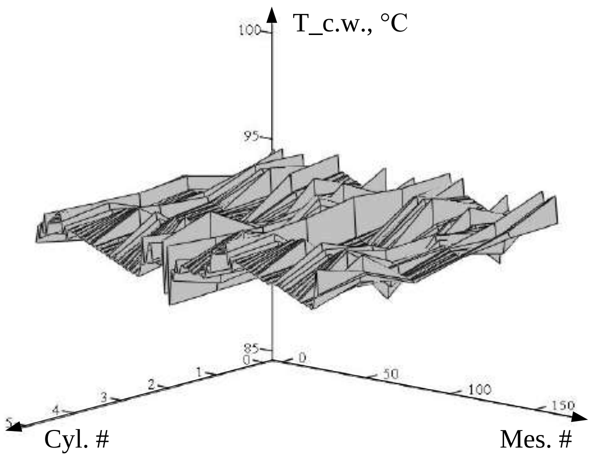
The ship main engine was considered as a complex technical system. Its working processes in each cylinder are subject to random disturbances, which requires the use of time series processing methods, mathematical statistics, information theory and the theory of random processes to describe them. Figure 2 shows the surfaces of the measured cylinder-related controlled parameters depending on the cylinder number (Cyl. #) and the measured value number (Mes. #) in the time series.



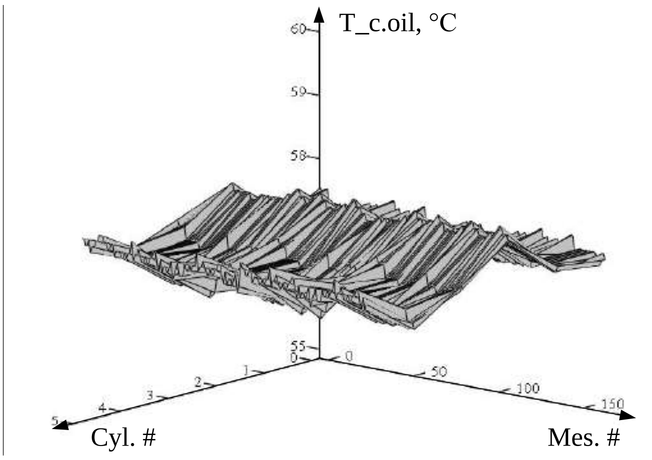
a) Exhaust gas temperature (T_ex.gas)



b) Under piston temperature (T_piston)



c) HT cooling water temperature (T_c.w.)



d) Piston cooling oil temperature (T_c.oil)

Figure 2 – Surfaces of cylinder-related controlled parameters

It is advisable to construct mathematical models of the controlled parameters dynamics for use in the process of technical object condition diagnostics with help of time series regression analysis methods [9].

The autoregressive model is based on the assumption that the value of a process $y[k]$ depends linearly on a certain number of previous values of the same process $y[k-1],..., y[k-n]$.

To achieve greater accuracy in identifying the controlled parameter, it is advisable to combine autoregression and moving average in one model [10]. Then the analyzed time series of controlled parameters can be presented in the form of a model:

$$y[k] = a_0 y[k-1] + a_1 y[k-2] + a_2 y[k-3] + ... + a_{n-1} y[k-n]. \qquad (2)$$

To identify the parameters of model (2), the least squares method can be used. From the experimentally measured data it was obtained:

$$\vec{Y} = x\vec{a}\,, \qquad (3)$$

where $\vec{Y} = [y[n+1] \quad y[n+2] \quad \dots \quad y[N]]^T$ are the elements of the time series starting from $n+1$ order.

The vector of model parameters is determined according to:

$$\vec{a} = \left[X^T X\right]^{-1} X^T \vec{Y}\,, \qquad (4)$$

where matrix X is a matrix of input factors, which is formed from elements of a time series:

$$X = \begin{bmatrix} y[n] & y[n-1] & \dots & y[1] \\ y[n+1] & y[n] & \dots & y[2] \\ \dots & \dots & \dots & \dots \\ y[N] & y[N-1] & \dots & y[N-n] \end{bmatrix}. \quad (5)$$

As a result of calculations according to formulas (2) – (5), mathematical models of the controlled parameters for each of the 6 cylinders were obtained. For example, in Fig. 3 shows a graphical representation of the measured parameters (dots) and the predicted parameters according to the obtained mathematical models (solid line) for cylinder #1.

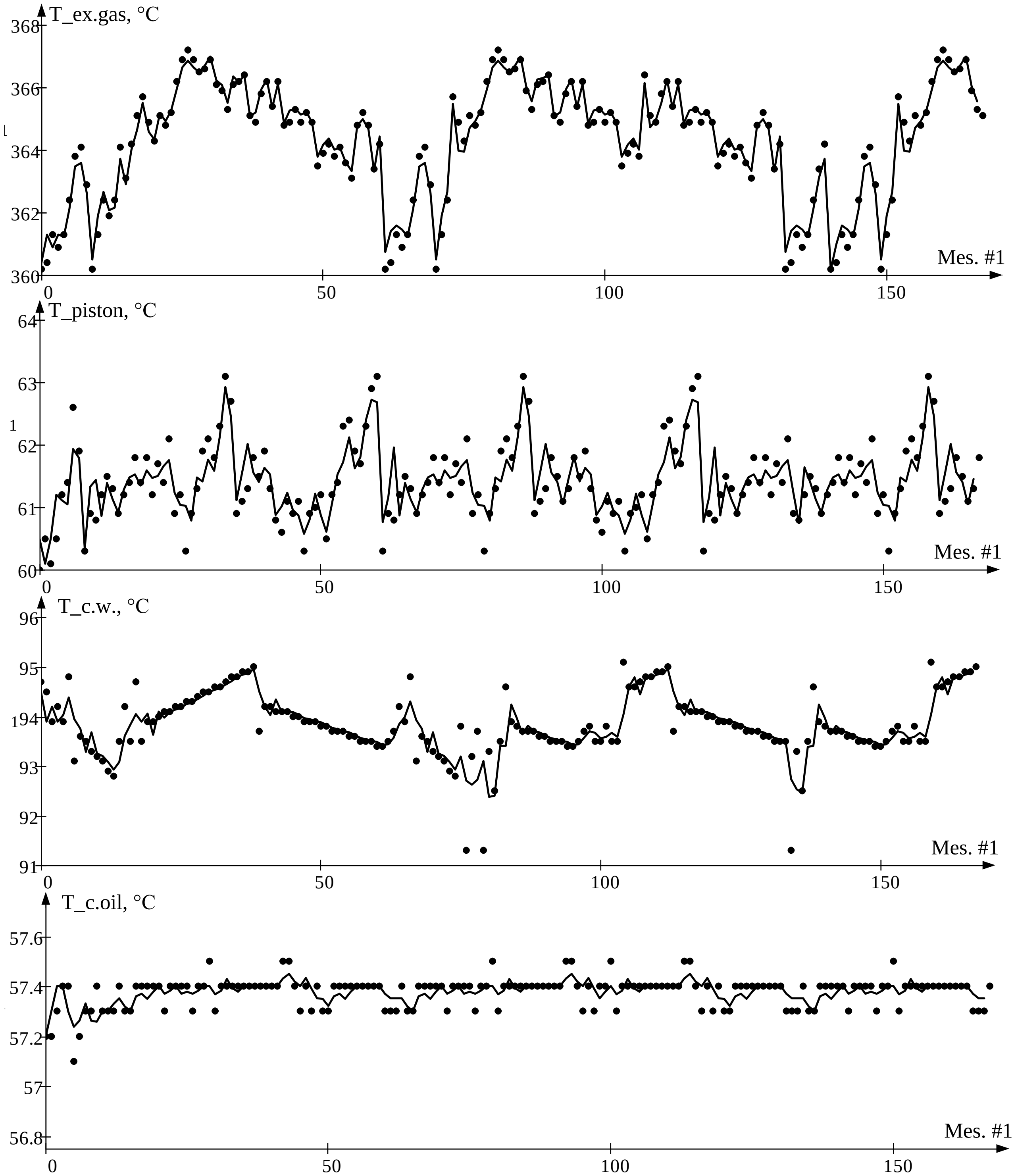


Figure 3 – The measured parameters (dots) and the predicted parameters (solid line) for cylinder #1.

As a result of processing the values of controlled parameters, model coefficients of 5th order were obtained. On the basis of the obtained parameter vectors $\vec{a}$ for each of the 6 cylinders, matrices of mathematical models of the corresponding controlled parameters were formed: $A_{\text{T\_ex.gas}}$ – for exhaust gas temperature, $A_{\text{T\_piston}}$ for under piston temperature, $A_{\text{T\_c.w.}}$ – for HT cooling water temperature, $A_{\text{T\_c.oil}}$ – for piston cooling oil temperature. The obtained matrices have the form:

$$A_{\text{T\_ex.gas}} = \begin{bmatrix} 0.895 & 0.533 & 0.645 & 0.631 & 0.724 & 0.784 \\ -0.11 & 0.1 & 0.178 & 0.256 & 0.233 & 0.124 \\ 0.08 & 0.1 & -0.028 & 0.142 & 0.162 & 0.015 \\ -0.04 & 0.026 & 0.139 & -0.05 & -0.169 & -0.117 \\ 0.174 & 0.241 & 0.067 & 0.022 & 0.05 & 0.194 \end{bmatrix},$$

$$A_{\text{T\_piston}} = \begin{bmatrix} 0.725 & 0.516 & 0.325 & 0.679 & 0.462 & 0.235 \\ 0.092 & 0.275 & 0.14 & 0.064 & 0.134 & 0.209 \\ -0.256 & -0.042 & 0.016 & 0.063 & 0.054 & 0.191 \\ 0.433 & 0.094 & 0.383 & 0.298 & 0.17 & 0.211 \\ 0.007 & 0.158 & 0.137 & -0.105 & 0.18 & 0.154 \end{bmatrix},$$

(6)

$$A_{\text{T\_c.w.}} = \begin{bmatrix} 0.358 & 0.364 & 0.43 & 0.127 & 0.49 & 0.336 \\ 0.41 & 0.474 & 0.345 & 0.411 & 0.301 & 0.306 \\ 0.274 & 0.137 & 0.153 & 0.329 & 0.198 & 0.392 \\ -0.157 & -0.06 & -0.077 & 0.085 & -0.007 & -0.081 \\ 0.116 & 0.084 & 0.149 & 0.048 & 0.018 & 0.047 \end{bmatrix},$$

$$A_{\text{T\_c.oil}} = \begin{bmatrix} 0.455 & 0.301 & 0.647 & 0.836 & 0.741 & 0.356 \\ 0.008 & 0.187 & -0.137 & -0.088 & -0.099 & 0.138 \\ 0.123 & 0.002 & 0.319 & 0.257 & 0.36 & 0.179 \\ 0.172 & 0.298 & -0.003 & -0.077 & 0.015 & 0.308 \\ 0.243 & 0.211 & 0.174 & 0.072 & -0.017 & 0.019 \end{bmatrix}.$$

The adequacy validation check of the obtained mathematical models was carried out using the root mean square error of recovery of the predicted time series according to the formula

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(y_{oi} - y_{mi})^2}{\sum_{i=1}^{N} y_{oi}^{\,2}}}, \qquad (7)$$

where N is the number of readings, y_{oi} are the actual normalized values of the time series, and y_{mi} are predicted values, $i = \overline{1, N}$.

The values obtained as a result of sigma calculations according to formula (7) belong to the range $(3...5) \cdot 10^{-3}$, which satisfies the accuracy requirements.

The next important task is the development of an algorithm for the diagnosis of the ship main engine based on the assessment of the normalized energy spectrum of the measured signals and spectral entropy. Diagnostics based on spectral entropy consists of a sequence of the following stages [11–13].

A spectrum is calculated for each s -th segment of length ΔN as

$$Y_s(k) = \sum_{n=0}^{\Delta N-1} y_s(n) e^{-j(2\pi/\Delta N)nk}, \; k \in \overline{0, \Delta N-1}, \; s \in \overline{1, N/\Delta N}. \tag{8}$$

The normalized energy spectrum is calculated according to the formula

$$\|W_s(k)\| = \frac{W_s(k)}{\sum_{m=0}^{\Delta N-1} W_s(m)}, \text{ where } W_s(k) = |Y_s(k)|^2. \tag{9}$$

A rule is used to suppress narrow-band noise and wide-band white noise

$$\|W_s(k)\| = 0, \text{ if } \delta_1 < \|W_s(k)\| < \delta_2. \tag{10}$$

Then the spectral entropy is calculated:

$$H_S = \sum_{k=0}^{\Delta N-1} \|W_s(k)\| \lg \|W_s(k)\|. \tag{11}$$

Filtering is carried out according to the algorithm of median smoothing of the sequence $H_1,...,H_L$, $L = N/\Delta N$, and the sequence of entropy estimates $\tilde{H}_1,...,\tilde{H}_L$ is obtained.

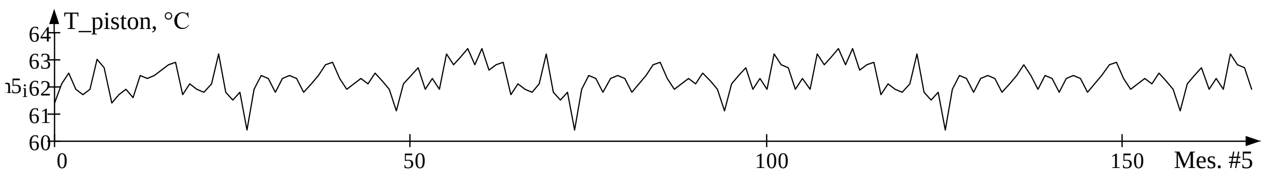
An adaptive threshold is calculated in the form

$$\gamma = \left(\frac{\max \tilde{H}_S + \min \tilde{H}_S}{2} \right) \mu, \tag{12}$$

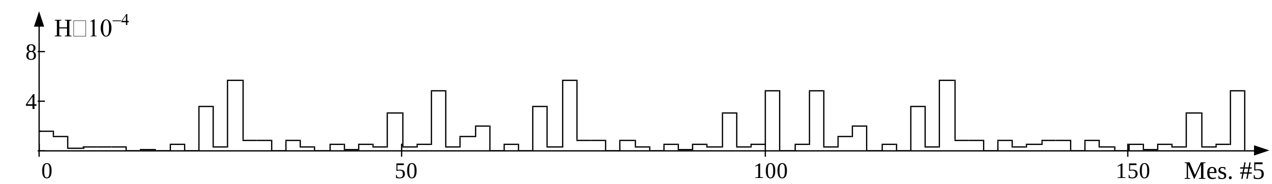
where μ is a parameter determined experimentally.

If $\gamma > \tilde{H}_S$, then the segment of the signal is considered normal, where there are no deviations of the controlled parameters from the nominal values ($P = 1$). If $\gamma < \tilde{H}_S$, then the segment of the signal is considered abnormal, where there are deviations of the controlled parameters from the nominal values ($P = 0$).

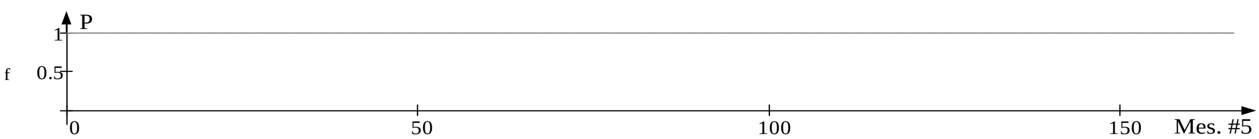
The results of the proposed diagnostic method without deviations from the nominal values of the controlled parameters are shown in Fig. 4, and in the case of deviations – in Fig. 5.



a) Under piston temperature dynamics in the cylinder #5

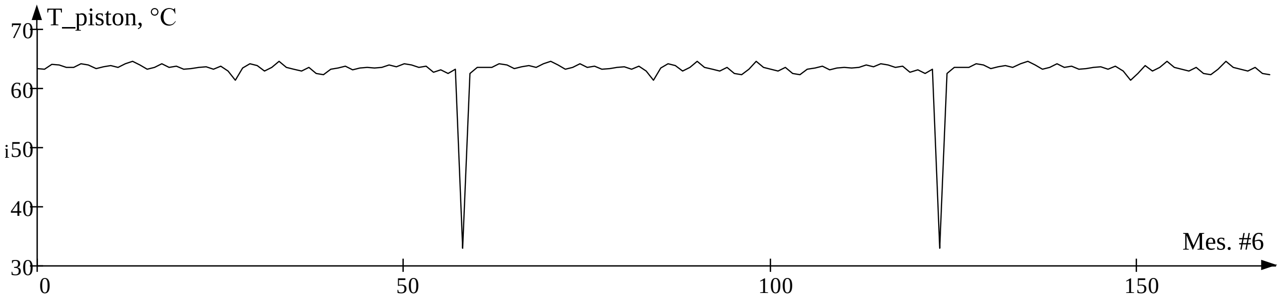


b) Result of entropy calculation

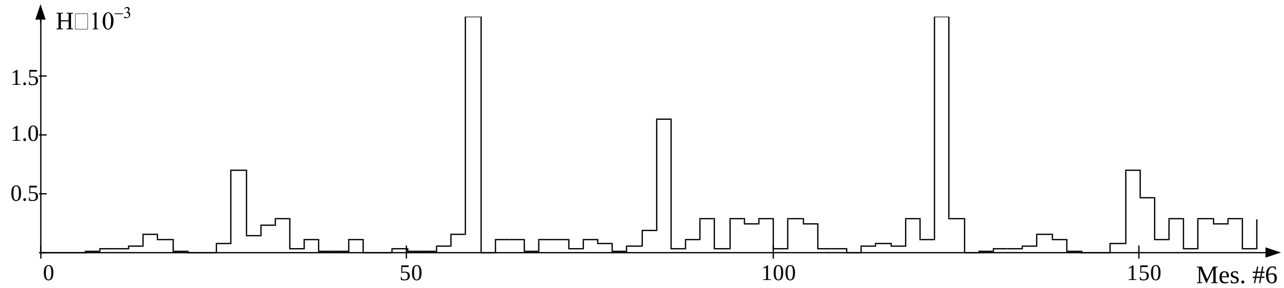


c) Result of logic-time processing

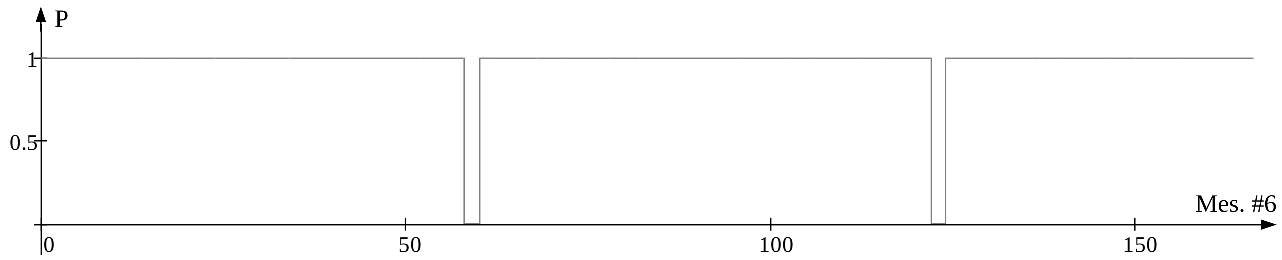
Figure 4 – The results of the diagnostic method without deviations



a) Under piston temperature dynamics in the cylinder #6



b) Result of entropy calculation



c) Result of logic-time processing

Figure 5 – The results of the diagnostic method with deviations

On the basis of the developed mathematical models and the proposed diagnostic method, a structural diagram of the automated system of operational diagnostics of the condition of the ship main engine was designed, shown in fig. 6. The technical condition of each node of the ship main engine is determined by a group of diagnostic parameters. The structure of the operational diagnostics system includes: a database, modules for building mathematical models of monitored parameters with adequacy verification, an interactive interface for interaction with the technical personnel. The database [14] is formed from arrays of numerous values of controlled parameters. The Problem Symptoms Identification Subsystem estimates the current state of the monitored parameters. The result of the analysis is issued by the device in the form of a signal about the normal or abnormal technical condition of the engine.

The implementation of the operational diagnostics system based on the developed mathematical models and the proposed diagnostic algorithm, based on the methods of determining spectral entropy and logical-time processing, allows to formalize the procedures of information support of the technical personnel (Decision Maker) in the assessment of the technical condition of the ship main engine according to controlled parameters.

The implementation of the diagnostic algorithm assumes the following conditions: the process of changing the technical state of the object is monotonous; the limit value of the diagnostic parameter should be known; the trend model of the diagnostic parameter should allow extrapolation that is satisfactory in terms of accuracy.

Similar methods and procedures should be applied to all groups of controlled parameters: cooling water, lubricating oil, fuel oil, scavenge air, air, exhaust gas [15].

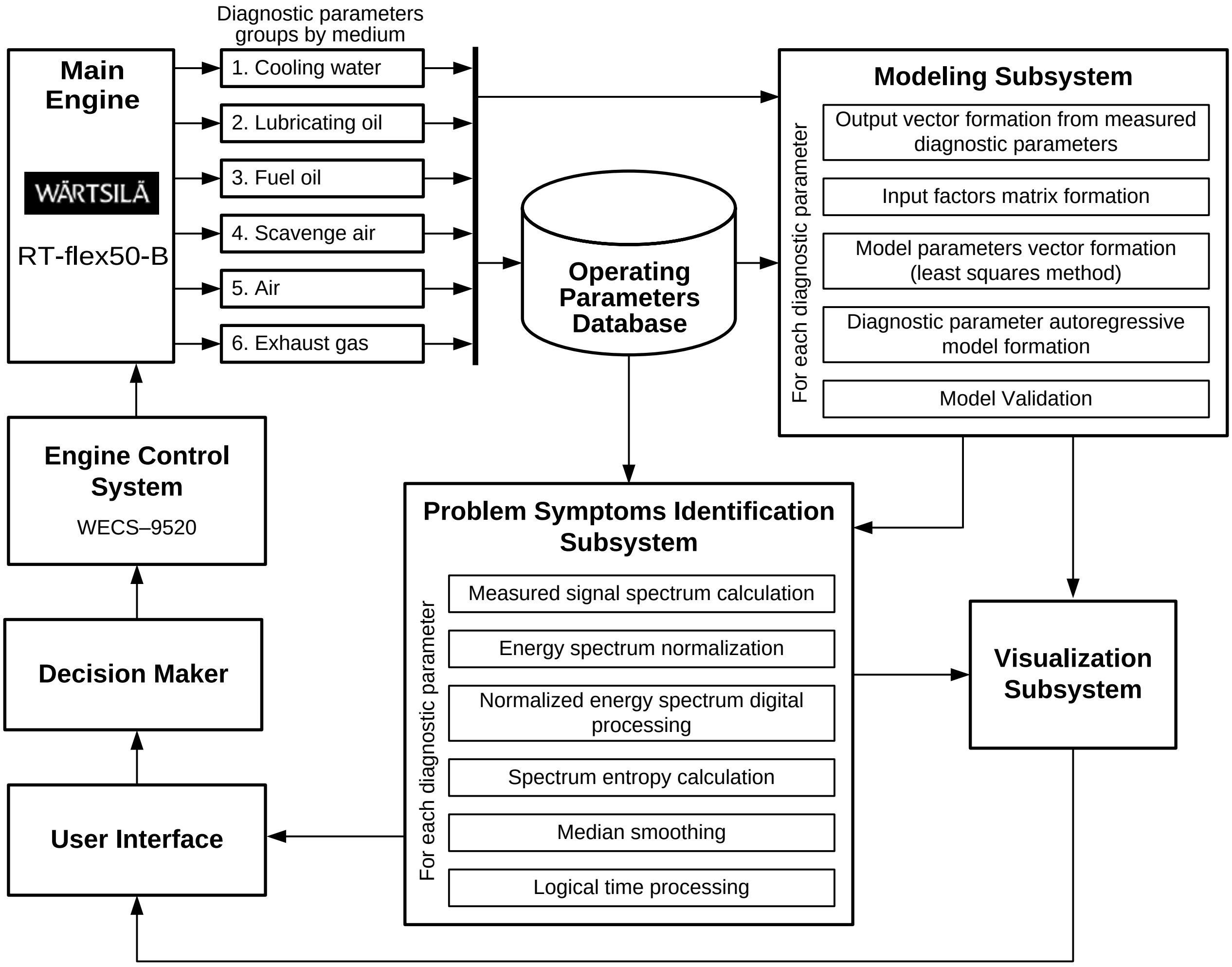


Figure 6 – Structural diagram of the automated system of operational diagnostics

Discussion of results. The resulting autoregression models of the moving average adequately describe the time series corresponding to the measured signals of the controlled parameters for various parts of the ship main engine in various operating modes. The application of the method of digital processing of registered signals opens up the possibility of finding malfunctions in the operation of the equipment and makes it possible to evaluate non-nominal and pre-emergency modes of operation of the engine. Visualization of the values of the controlled parameters in the form of continuous surfaces enables the technical personnel to perform an initial assessment of the operation of the equipment. The conducted studies showed that models of the 4th–5th order adequately describe the dynamics of the controlled parameters.

For further use of the obtained models for processing in software modules of the diagnostics subsystem, it is advisable to present the calculated parameters of the models in the form of matrices for individual parts of the equipment.

The proposed diagnostic method using the entropy approach makes it possible to determine malfunctions of parts of the ship main engine in a time of no more than $2T$, i.e. $\Delta t \le 2T$, where T is the time interval between measurements of the values of controlled parameters. The monitoring data used in the study were obtained at an average interval of $T = 8$ minutes.

Conducted studies of the application of the entropy approach to the analysis of the characteristic signals of the equipment showed the dependence of the obtained results on the adjustment of signal processing parameters, such as: frame length, the value of the adaptive threshold. For different signals of the controlled parameters of the same group, the optimal settings of the parameters retain their values.

Conclusions. In the research, the method of the ship main engine condition operational diagnostics was developed using the logic-time processing of the measurement signals of the controlled parameters based on the entropy approach. The proposed method of signal analysis using autoregressive moving average for identification of model parameters. On the basis of the developed mathematical models and the proposed diagnostic method, the automated system of operational diagnostics of the condition of the ship main engine was designed, which allows timely detection of critical modes of operation of technological equipment in real time.

Directions for further research. Further research is being expediently carried out in the direction of the implementation of diagnostic and prognostic procedures, which allows to use optimization methods and reserves of the actual technical condition at a qualitatively new level to prevent failures and increase the inter-repair period.

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Поливода О. В., Поливода В. В., Сіманенков А. Л. МЕТОД ОПЕРАТИВНОЇ ДІАГНОСТИКИ СТАНУ ГОЛОВНОГО СУДНОВОГО ДВИГУНА

Стаття присвячена вирішенню проблеми підвищення якості оперативної діагностики головного суднового двигуна в режимі реального часу. Сучасні системи технічної діагностики повинні виконувати швидку та якісну ідентифікацію наростаючих несправностей для найбільш ефективного використання результатів моніторингу при вирішенні експлуатаційних завдань з видачею рекомендацій, що дозволить розширити компетентність технічного персоналу у процесі прийняття рішень. Тому актуальною задачею є розробка математичних моделей часових рядів виміряних значень контрольованих параметрів, які дозволять вдосконалити процедуру оперативної діагностики завдяки виявленню ймовірності відмови вузлів суднового двигуна раніше області найбільш інтенсивного зносу або руйнування. З метою покращення існуючих методів технічної діагностики технологічного обладнання розроблено ефективні алгоритми оперативного діагностування, що реалізовані у програмних модулях і в повній мірі враховують технічні та економічні вимоги, стохастичний характер зовнішніх впливів. При побудові алгоритмів оперативної діагностики враховано специфіку процесів, що відбуваються в головному судновому двигуні, використано сучасні прийоми і методи математичного моделювання та теорії інформації. На базі значень, отриманих у результаті вимірювань контрольованих параметрів головного суднового двигуна були обрані авторегресійні моделі ковзного середнього, які максимально точно описують отримані часові ряди. Параметри моделей авторегресії були ідентифіковані за допомогою методу найменших квадратів. Запропоновано метод оперативної діагностики, що заснований на визначенні спектральної ентропії і процедурі логіко-часової обробки. На основі розроблених математичних моделей і запропонованого методу діагностики розроблено автоматизовану систему оперативної діагностики стану головного суднового двигуна, яка дозволяє здійснювати своєчасне виявлення критичних режимів роботи технологічного обладнання в режимі реального часу.

Ключові слова: *головний судновий двигун; діагностика; моніторинг; ідентифікація.*

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