networks, as applied to a complex dynamic system of SPP-shipMarine intelligent technologies. 2020. No. 4-4 (50). pp. 18-22.
6. Kondratiev S.I. Methods for calculating characteristic polynomials in problems of control of moving objects. Textbook / S. I. Kondratiev, G. A. Zelenkov // Federal state. educational institution of higher education prof. education "Marine State Academician named after Admiral F.F. Ushakov". Novorossiysk, 2007.
7. Engovatova V.V., Dmitrenko E.V., Shkoda V.V., Solonnikova N.V., Modina M.A. Life safety and labor protection of workers of industrial enterprises. Part 2. Study guide / Krasnodar, 2020.
8. Studenikin D.E., Bovan S.D., Hekert E.V., Modina M.A.Using neural networks to organize visual observation//Marine intelligent technologies. 2019. No. 4-3 (46). pp. 91-95.
9. Studenikin D. E., Kondratiev S. I., Hekert E. V., Modina M. A. Dynamic formation of a safety corridor when planning a ship's route // Marine Intelligent Technologies. - 2021. - T. 4. - No. 2 (53). - S. 128-131. – DOI 10.37220/MIT.2021.52.2.081.
10. Studenikin, D. E. Some aspects of vessel's movement in congested waters analysis for preliminary route planning / D. E. Studenikin, S. I. Kondratev, M. L. Javuktsyan // Marine transport operation. - 2019. - No. 3 (92). – P. 30-34. – DOI 10.34046/aumsuomt92/5.
11. Boran-Keshishyan, A.L., Astrein, V.V., Kondratiev, S.I. Formalization of the general decision-making strategy to achieve the ship's integrated safety, Marine Intelligent Technologies. - 2019. - No. 1-2 (43). - S. 127-131.

УДК 621.431.7
DOI: 10.34046/aumsuomt102/21

DEVELOPMENT OF NEURAL NETWORKS FOR PREDICTING THE RISK OF FAILURE OF COMPONENTS OF SHIP MACHINES AND MECHANISMS OF MARINE AUTONOMOUS SURFACE VESSELS

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The article discusses the possibilities of applying neurocybernetics approaches for the implementation of intelligent prediction of the risk of failure of components of ship technical means of autonomous sea surface ships. In the course of the research, a method was proposed that allows one to build a formal model of the observed units and equipment of ship installations based on the tasks of classification and pattern recognition. An algorithm for the initialization of a neural network is also proposed, which makes it possible to achieve a given accuracy of determining the parameters of the operation of technical means, which makes it possible to provide flexibility in setting up management of emerging risks based on predetermined criteria.
Key words: risks, units, equipment, vessel, forecasting, management.

РАЗРАБОТКА НЕЙРОННЫХ СЕТЕЙ ДЛЯ ПРОГНОЗИРОВАНИЯ РИСКА ВЫХОДА ИЗ СТРОЯ КОМПОНЕНТОВ СУДОВЫХ ТЕХНИЧЕСКИХ СРЕДСТВ МОРСКИХ АВТОНОМНЫХ НАДВОДНЫХ СУДОВ

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В статье рассмотрены возможности применения подходов нейрокибернетики для осуществления интеллектуального прогнозирования риска выхода из строя компонентов судовых технических средств морских автономных надводных судов. В процессе исследования предложен алгоритм, который позволяет построить формальную модель рисков отказа наблюдаемых узлов и оборудования судовых установок на основании задач классификации и распознавания образов. Также предложен алгоритм инициализации нейронной сети, благодаря которому может быть достигнута заданная точность определения параметров работы технических средств, что дает возможность обеспечить гибкость настройки управления возникающими рисками на основании заранее определенных критериев.
Ключевые слова: риски, узлы, оборудование, судно, прогнозирование.

The current level of organization and management of ship technical facilities, which are a complex dynamic system consisting of many interacting elements and subsystems, puts forward increased requirements for the development of new approaches based on the use of advanced information technologies and intelligent support and decision-making tools [1, 4, 5, 14].

A wide range of instrumental methods and approaches to monitoring, analyzing, diagnosing and predicting the technical condition of ship equipment, as well as the risks of its failure, has a significant drawback, which lies in the fact that their use is possible only with a certain frequency, in accordance with a given technical program maintenance of a particular type of installation, which may not be sufficient to prevent malfunctions that could lead to serious consequences and accidents.

Therefore, at present, artificial intelligence technologies, which form the basis of neurocontrol, are widely used to solve complex and large-scale nonlinear problems without any statistical assumptions about the data.

Today, with the help of neurocontrol, thanks to the useful properties of neural networks common to various types of nonlinear dynamic objects, the problems of identification, analysis, synthesis and machines and mechanisms implementation of control over complex technical systems in conditions of non-stationarity, uncertainty, incompleteness and fuzziness of information are solved [2, 11, 12, 13]. Thanks to neurocontrol, the problem of predicting the risk of failure of ship machines and mechanisms components, which belongs to the problems of classification and pattern recognition, can be effectively solved.

Formalization of the problem of pattern recognition implies the need to use an axiomatic approach, which involves the construction of a formal model of the subject area within the framework of a constructive system. The formalized axiomatic theory makes it possible to consider ship machines and mechanisms as a complex dynamic system consisting of objects of different nature, which are subject to various kinds of risks leading to equipment failure.

Despite the active development of neurocontrol systems, the development of new methods for diagnosing and predicting the risks of failure of the element base of technical means based on fuzzy neural networks, deep learning networks and extreme learning machines, not all tasks in this area can be considered solved, so the need for their deeper study predetermines the choice of the topic of this article.

The issues of developing digital control systems and predicting the operation of equipment on modern ships are discussed in the publications of Darshana Godaliyadde; Nilo de Moura Jorge; Chang, Chia-Hsun; Kontovas, Christos; Bordyuga A.S.; Turkin V.A., Davydov D.A., Styazhkin A.A.

The development of the theoretical foundations of fuzzy logic, the improvement of the methodology of modeling and solving problems of managing complex systems are carried out by such scientists as: Shcherbatov I.A., Popov V.V., Sorokin K.N., Pestryakov E.V., Dai, Shi Lu; Wang, Min; Wang, Kong; Li, Liejun.

Highly appreciating the achievements to date, it should be noted that the published articles on the diagnostics of ship technical equipment have a limited scope. Basically, the authors focus on extracting signs of equipment defects.

Thus, the above circumstances make it possible to formulate the purpose of the article as follows - to consider the possibilities of applying neurocybernetics approaches for the implementation of intelligent prediction of the risk of failure of the components of the ship's technical means of marine autonomous surface vessels [9, 10].

The decision-making process in the control of ship technical means of marine autonomous surface vessels is inextricably linked with the solution of the problem of recognizing risky and non-standard situations. But the high complexity of recognition problems does not allow us to consider the issues of their formalization completely resolved. Therefore, the main goal of risk prediction is to build efficient computational models and methods for assigning formalized descriptions of situations to the appropriate classes. When a correspondence is established between the classes specified on the set of decisions and the set of recognized risk situations, the automation of equipment failure prediction procedures becomes an element of decision-making automation.

In view of the foregoing, the following algorithm is proposed for predicting the risk of failure of the components of the ship's technical means of marine autonomous surface vessels using neural network structures [6, 7, 8].

1. Statement of the problem of forecasting. Observed parameters of the equipment are determined (power, effective torque, pressure, fuel and oil consumption, etc.), the type of neural network (NN) model (dynamic or static) is selected, requirements for the accuracy of the NN model are set, the sampling frequency and implementation method are determined. (machines and mechanisms, software).

2. Formalization of the risks of failure of various types of ship machines and mechanisms components.

3. Development of a knowledge representation model and rules for logical inference from situation recognition.

4. Planning of the experiment. The main task of this stage is to obtain a lot of data on the functioning of the ship's technical means, which are necessary for the subsequent parametric optimization of the NS model.

5. Data pre-processing (filtering, removal of redundant data and signal spikes).

6. Choice of model structure. A static NN model of technical means is created on the basis of a

multilayer neural network without feedback; the dynamic model is based on a recurrent multilayer NN.

7. Optimization of the NS-model parameters. The NN model training procedure involves a combination of fast and back propagation algorithms. This will allow to achieve the required accuracy of the learning process, rapid convergence to the minimum point of the objective function.

8. Deciding on the adequacy of the model. The viability of the model is confirmed by an estimate of the average learning error $\varepsilon_{зад}$.

9. Implementation of the NS-model.

In general, the scheme for solving the problem of predicting the risks of equipment failure has the following form: the output vector of the observed object y and the output vector of the NS y_{HM} are compared with the same vector of input actions u. The NN training procedure consists in changing the weight of its connections in such a way as to reduce the sum of squared residuals to an acceptable (sufficiently small) value:

$$E = \Sigma_{ij}^{\varepsilon_i^2 < E_d}$$

where $E_i = y_i - y_{ii}$ - discrepancy at the i-th step;

E_d - is the allowable value of the training error.

Let the set M of possible risks s be given. Moreover, the set has a breakdown into a finite number of subsets (classes) $\Omega, i = \overline{1,m};\ M = \cup_{i=1}^{m} \Omega_i$. Only some information about the classes Ω_i is given. Risks s are given by the values of some features $x, j = \overline{J,N}$. The set of feature values determines the risk description s. Each of the signs can take values from different sets of allowable values, for example: $\{0,1,\Delta\}$, 0 - the equipment failure risk sign is not confirmed, 1 - the failure risk sign is confirmed, Δ - there is no information about the sign; $\{a_1, \ldots, a_d\}$ – the attribute has a finite number of values d.

The task of recognizing risk situations is to determine the value of the predicate $P(s \in \Omega_m)$ for a given risk s and a set of classes $\Omega_i, \ldots, \Omega_m$ using information $I_0(\Omega_i, \ldots, \Omega_m)$ about classes and description of risk.

In accordance with the guiding documents for the operation of autonomous marine vessels, two main emerging situations can be distinguished - “normal” and “emergency”. The “regular” situation provides for minor events that can be eliminated by the repair duty units closest to the autonomous ship within the specified territorial restrictions (Z_k), loss volumes (ΔV_z), repair duration (ΔH_z), a certain technical work progress vector ($\Delta \Psi_z$), interval time (Δt_z) and emerging non-standard situations (K_j).

The emergency situation implies the need to remove the autonomous vessel from the route with its subsequent delivery to the repair shipyard.

Sources of operational parametric control and current regime information can be selected as sources of data on the operation of ship machines and mechanisms. Messages from these sources will be considered the initial data for solving the problem of recognizing the risks of equipment failure. Sources of information include coordinate signs of a possible breakdown and time data. They should be formed based on the results of processing the received information and have a minimum time delay [3, 4, 6, 9].

Therefore, messages, for example, from control sensors, will be considered current data, then information about the risk of failure j - technical means can be represented by the following relationship:

$$I_j^m = \{\vec{A}_j, \vec{\Pi}_j, \vec{t}_j,\}$$

where $\vec{A}_j$, $\vec{\Pi}_j$ are vectors of coordinates and signs of failure of the j-th technical facility at time t, which contain the following data:

$$\vec{A}_j = \{X_j, Y_j, H_j, V_j, \psi_j\}$$

where X_j, Y_j are the coordinates of the risk of a breakdown of the j-th technical means;

H_j - is the duration of the predicted situation;

V_j – predicted volumes of breakdowns,

ψ_j – is the trajectory of the development of the situation.

$$\vec{\Pi}_j = \{P_j, K_j, t_j\}$$

where P_j – is a sign that the ship's technical facility belongs to a certain equipment;

K_j – is an information feature (the number of failed nodes, the amount of damage, destruction, etc. - a statistical classifier);

t_j – is the time of obtaining information about the emergency j-th situation.

In general, the initial data for the forecast can be represented as follows:

$$I_k^p = \{N_k, \vec{A}_k^p, \vec{\Pi}_k^p, t_k^p\}$$

where k – predicted risks;

N_k – the possibility of belonging to one of the emergency situations;

$\vec{A}_k^p, \vec{\Pi}_k^p$ – are vectors of coordinate and information data of the k-th risk containing the following data:

$$\vec{A}_k^p = \{X_k^p, Y_k^p, H_k^p, V_k^p, \Psi_k^p,\}\ \vec{\Pi}_k^p = \left\{K_k^p, O_{K_k^p}\right\}$$

Using the above approach in practice, consider the following test problem:

1. Construction of an NN model for predicting risks in the operation of the fuel supply control channel for a dual-circuit gas turbine engine of an

autonomous marine vessel with an afterburner and an electronic regulator in accordance with a full authority digital engine control system (FADEC).

The input values of the channel for regulating the fuel supply to the main combustion chamber are: α - mode of operation; n_1 – is the low pressure compressor rotor speed; n_2 – is the high pressure compressor rotor speed; $\pi_к$ – is the degree of pressure increase in the compressor; T^* - is the temperature of the stagnant gas flow through the turbine, G_p – is the amount of working fuel supplied to the main combustion chamber.

The neural network model for predicting the risk of failure of the fuel supply control channel is shown in fig. 1.

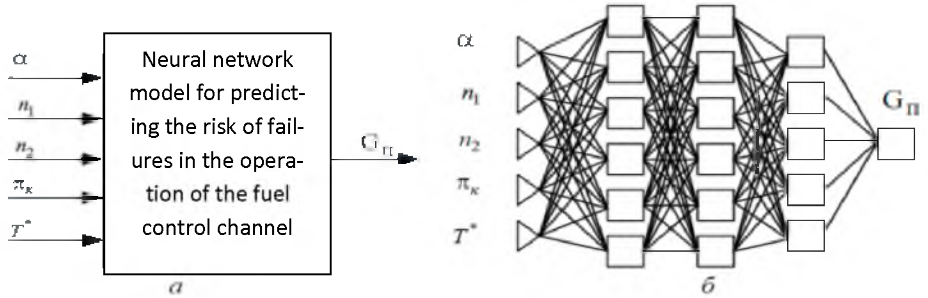

Fig. 1 Neural network model for predicting the risk of failures in the operation of the fuel control channel (a) and its topology (b)

The next step in the development of the NN model is the identification of weight coefficients and their optimization.

The presented model is a dynamic (recurrent) NN based on a perceptron. It includes $(p+q+1)$ neurons in the input layer, σ neurons in the hidden layer, and one neuron in the output layer, the connections between which are carried out using adjustable (training) weights $W_{\alpha\beta}$:

$$W_\beta(\alpha = 1,2, \dots, p+q+1;\ \beta = 1,2, \dots, \sigma)$$

The dynamics of this network is described by the difference equation:

$$u[k] = F(u[k-1], \dots, u[k-q], v\,[k], \dots, v[k-p])$$

where F(…) is a non-linear function with respect to the specified arguments (p+q+1)

$$u[k-1], \dots, u[k-q], v\,[k], \dots, v[k-p]$$

The training of the NN model is carried out as follows. The model inputs are segments of the time series: $y_1(t), \dots, y_N(t), t \subset (t_i, t_{i+1})$, belonging to pre-known classes (modes of operation) of the fuel control channel S_α, $(\alpha = 1, 2, \dots, k)$.

The expected response of the neural network to risk prediction in each case will be a value equal to one at one of the outputs of the neural network, corresponding to the recognized risk. For example, the class of steady modes corresponds to output number 1, the class of transient modes corresponds to output number 2, the class of unstable modes corresponds to output number 3. The minimum error corresponds to a trained network that solves the problem of predicting the risks of failure of the fuel supply control channel work and basic elements [10, 11, 12, 13].

Then, depending on the response of the NN model, one or another strategy for managing the identified risk is selected. According to the general goal of controlling the operating modes of technical systems of autonomous marine vessels, we express the target requirements for their efficiency indicator $TE_d = \{C_\Sigma(t), K_r(t), W(t)\}$ as follows:

$$\Theta_{K_r} = \{K_r(t_n) \geq \hat{K}_r\}$$

$$\Theta_w = \{W(t_n) \geq \hat{W}\}$$

$$\Theta_c = \{C_\Sigma(t_n)/t_n \leq (1 - a_n) C_\Sigma(t_{n-1})/t_{n-1}\}$$

where TE_d – is the technical efficiency of ship installations;

C_Σ – total cost of repairing a damaged unit during operation in normal mode or in emergency mode;

K_r - coefficient characterizing the reliability of the technical means during operation;

W(t) – determines the degree of efficiency in eliminating the identified risks when using various control modes.

As a result of training the neural network, the resulting distance values (time intervals) are formed, at which an acceptable level of risk of failure of the fuel supply control channel for a bypass gas turbine engine is reached. Thus, conclusions can be drawn and input parameters that have little effect on the result can be identified [12, 13, 14].

The article proposes an algorithm for predicting the risk of failure of components of marine autonomous surface vessels using a neural network (on the example of a gas turbine engine element). This method makes it possible to carry out calculations based on multivalued logic for processing knowledge containing elements of uncertainty. The use of this algorithm allows solving both computational and logical-analytical problems, which is due to the use of artificial intelligence methods.

Литература:

1. Brezhnev V.I. Flexible complexes for the control of a ship power plant // Modern Science: Actual Problems of Theory and Practice. Series: Natural and technical sciences. 2020. No. 8-2. pp. 42-46.
2. Faruque, Md Omar Fuzzy Logic Based Energy Storage Management System for MVDC Power System of All Electric Ship // IEEE transactions on energy conversion. 2017. Volume 32: Number 2; pp 798-809.
3. Tang, Ruoli Optimal operation of hybrid energy system for intelligent ship: An ultrahigh-dimensional model and control method // Energy: the international journal. 2020. Volume 211.
4. Epikhin, A. I. Integrated system for ensuring safe operation of technical means of ships carrying liquefied gases / A. I. Epikhin // Scientific, technical, economic and legal aspects of the development of the transport complex : Materials of the III (XVII) National Scientific and practical Conference, Novorossiysk, November 14-15, 2019. Novorossiysk: Admiral F.F. Ushakov State Maritime University, 2019. - pp. 165-167.
5. Epikhin, A. I. Building a decision support system for integrated security of gas tankers / A. I. Epikhin // Bulletin of the Admiral S.O. Makarov State University of Marine and River Fleet. - 2017. - Vol. 9. - No. 3. - pp. 481-488. - DOI 10.21821/2309-5180-2017-9-3-481-488.
6. Kondratyev, S. I. A diagnostic system of an intelligent component based on Bayesian accurate inference networks / S. I. Kondratyev, A. I. Epikhin, S. O. Malakhov // Journal of Physics: Conference Series, Novosibirsk, May 12-14, 2021. – Novosibirsk, 2021. – P. 012022. – DOI 10.1088/1742-6596/2032/1/012022.
7. Epikhin, A. I. Method for synthesis of an intelligent automatic system for diagnosing combustion engine vibration of the power supply system of an unmanned vessel / A. I. Epikhin // Journal of Physics: Conference Series, Novorossiysk, Virtual, June 15-16, 2021. – Novorossiysk, Virtual, 2021. – P. 012023. – DOI 10.1088/1742-6596/2061/1/012023.
8. Khekert, E.V. Analysis of methods to optimize control systems for power supply of marine vessels using fuzzy logic and fractal analysis / E. V. Khekert, A. I. Epikhin // Journal of Physics: Conference Series, Novorossiysk, Virtual, June 15-16, 2021. – Novorossiysk, Virtual, 2021. – P. 012088. – DOI 10.1088/1742-6596/2061/1/012088.
9. Epikhin, A. I. Neurocontrol methods in the context of development of technical solutions for transition to unmanned navigation / A. I. Epikhin // Journal of Physics: Conference Series, Novorossiysk, Virtual, June 15-16, 2021. - Novorossiysk, Virtual, 2021. - P. 012115– - DOI 10.1088/1742-6596/2061/1/012115.
10. The main trends in the introduction of artificial intelligence technologies in the management of marine autonomous surface vessels / A. I. Epikhin, A.V. Ignatenko, D. E. Studenikin, E. V. Heckert // Operation of sea transport. – 2021. – № 1(98). – Pp. 88-96– - DOI 10.34046/aumsuomt98/14.
11. Patent No. 2737457 C1 Russian Federation, IPC B63H 21/22, G06F 17/00, G05B 17/02. Automatic system with a neuro-fuzzy network for complex technical diagnostics and control of a ship's power plant : No. 2020121876 : application 26.06.2020 : publ. 30.11.2020 / A. I. Epikhin ; applicant Federal State Budgetary Educational Institution of Higher Education "Admiral F.F. Ushakov State Maritime University".
12. Epikhin, A. I. Application of neural networks based on a multilayer perceptron using fuzzy logic for technical diagnostics of ship technical means / A. I. Epikhin, S. I. Kondratiev, E. V. Heckert // Operation of sea transport. – 2020. – № 3(96). – Pp. 111-119– - DOI 10.34046/aumsuomt96/15.
13. Epikhin, A. I. Principles of neuro-management and variants of neural network architecture, applied to a complex dynamic system of SEU-VESSEL / A. I. Epikhin, E. V. Heckert, M. A. Modina // Marine intelligent technologies. – 2020. – № 4-4(50). – Pp. 18-22– - DOI 10.37220/MIT.2020.50.4.091.
14. Patent No. 2713077 C1 Russian Federation, IPC B63H 21/22, G06F 17/00, G05B 17/02. Decision support system with modular structure for operators of double-acting vessels: No. 2019114000: application 06.05.2019: publ. 03.02.2020 / A.I. Epikhin, E. V. Heckert; applicant Federal State Budgetary Educational Institution of Higher Education "Admiral F.F. Ushakov State Maritime University".

УДК 548.312.2; 53.082.7
DOI: 10.34046/aumsuomt102/22

ДИАГНОСТИКА КРИСТАЛЛОГРАФИЧЕСКОЙ СТРУКТУРЫ МАТЕРИАЛОВ ПРИ ИХ ТРАНСПОРТИРОВКЕ ПРИ ПОМОЩИ ТЕРМОСТИМУЛИРОВАННЫХ ТОКОВ

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Одной из технических проблем при транспортировке кристаллических сыпучих грузов является изменение их структуры при высокой влажности или высокой температуре. При этом может изменяется количество молекул воды в формульной единице кристаллов, что приводит к изменению физических