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EMERGENCY CONTROL SYSTEM BASED ON NEURAL NETWORKS AND FUZZY LOGIC

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СИСТЕМА ПРОТИВОАВАРІЙНОГО УПРАВЛІННЯ НА ОСНОВІ НЕЙРОННОЇ МЕРЕЖІ ТА НЕЧІТКОЇ ЛОГІКИ

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СИСТЕМА ПРОТИВОАВАРИЙНОГО УПРАВЛЕНИЯ НА ОСНОВЕ НЕЙРОННОЙ СЕТИ И НЕЧЕТКОЙ ЛОГИКИ

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Abstract. The presented paper investigates the problem of ensuring the safety of modern vessels, represented as complex organizational and technical systems. This study solves the task of diagnosing and predicting the level of ships' operational reliability using a hybrid expert system based on a combination of a neural network and fuzzy logic. Trends in modern control systems show that they must be adaptive and intelligent. However, these requirements cannot be met by expert systems based only on fuzzy logic. This work explores the possibility of combining neural network modules with fuzzy logic and considers the features of emergency management stages based on the offered hybrid expert system. The input information arrives in a knowledge base through gauges, where it is structured and distributed in the form of performance indicators. Emergency recommendations for the operator are formed as a result of a combination of performance indicators available in the knowledge base. Modules of the neural network and fuzzy logic form a system for assessing a complex technical system's health based on calculated estimates of the health of technical nodes. In addition, the authors formed a hierarchy of factors affecting the reliability of the system. While developing the knowledge base, critical values for each variable influencing the system performance are set, and when the values are reached, the operation mode becomes an emergency. The authors chose a multilayer perceptron with a layer of recurrent neurons and inputs as fed factors and criteria for performance; one output displays the value of system performance. Prediction of the technical state of the system is made based on time series analysis. The system with six variables was used as a test set, three of which are non-linguistic (efficiency coefficient, temperature, and pressure). The standard linguistic variable, calculated by the neural network, includes speed, fuel consumption, and wear of the node. The fuzzy logic module was used to form recommendations for the prevention or elimination of an emergency.

Key words: hybrid expert system, neural network, fuzzy logic, emergency control, complex technical system, diagnostics, operability, forecasting.

Анотація. У статті розглядається проблема забезпечення безпеки сучасних суден, наданих у вигляді складних організаційно-технічних систем. Дане дослідження вирішує завдання діагностування і прогнозування рівня експлуатаційної надійності суден за допомогою гібридної експертної системи на основі поєднання нейронної мережі і нечіткої логіки. Тенденції розвитку сучасних систем управління показують, що вони повинні бути адаптивними й інтелектуальними. Проте забезпечення цих вимог неможливо для експертних систем на основі лише нечіткої логіки. У даній статті вивчається можливість комбінації модулів нейронної мережі і нечіткої логіки. Розглянуто особливості етапів протиаварійного керування на основі запропонованої гібридної експертної системи. Вхідна інформація надходить в базу знань через давачі, де структурується і розподіляється у вигляді показників працездатності. Протиаварійні рекомендації для оператора формуються в результаті комбінації показників працездатності за їх наявності в базі знань. Модулі нейронної мережі і нечіткої логіки формують систему оцінки працездатності складної технічної системи на основі розрахункових оцінок працездатності технічних вузлів. Крім того, сформовано ієрархію факторів, що впливають на надійність системи. При розробці бази знань встановлені критичні значення для кожної змінної, яка впливає на працездатність системи, при досягненні значень яких режим роботи стає аварійним. Блок нейронної мережі, що використовується, являє собою багатошаровий персептрон з шаром рекурентних нейронів, на входи якого подаються фактори і критерії працездатності, а на виході відображається значення працездатності системи. Прогнозування технічного стану системи виконано на основі аналізу часових рядів. В якості тестового прикладу використовувалася система з шістьма змінними, три з яких нелінгвістичні (коефіцієнт корисної дії, температура і тиск). Загальна лінгвістична змінна, яка розраховується нейронною мережею, включає три складові: швидкість роботи, витрату палива і ступінь зношеності вузла. Формування рекомендацій щодо запобігання або ліквідації аварійної ситуації виконано за допомогою модуля нечіткої логіки.

Ключові слова: гібридна експертна система, нейронна мережа, нечітка логіка, протиаварійне управління, складна технічна система, діагностика, працездатність, прогнозування.

Аннотация. В статье рассматривается проблема обеспечения безопасности современных судов, представленных в виде сложных организационно-технических систем. Представленное исследование решает задачу диагностирования и прогнозирования уровня эксплуатационной надежности судов с помощью гибридной экспертной системы на основе сочетания нейронной сети и нечеткой логики. Тенденции развития современных систем управления показывают, что они должны быть адаптивными и интеллектуальными. Тем не менее, обеспечение этих требований невозможно для экспертных систем на основе лишь нечеткой логики. В данной статье изучается возможность комбинации модулей нейронной сети и нечеткой логики. Рассмотрены особенности этапов противоаварийного управления на основе предложенной гибридной экспертной системы. Входная информация поступает в базу знаний через датчики, где структурируется и распределяется в виде показателей работоспособности. Противоаварийные рекомендации для оператора формируются в результате комбинации показателей работоспособности при их наличии в базе знаний. Модули нейронной сети и нечеткой логики формируют систему оценки работоспособности сложной технической системы на основе расчётных оценок работоспособности технических узлов. Кроме того, сформирована иерархия факторов, влияющих на надёжность системы. При разработке базы знаний установлены критические значения для каждой переменной, влияющей на работоспособность системы, при достижении значений которых режим работы становится аварийным. Используемый блок нейронной сети представляет собой многослойный персептрон со слоем рекуррентных нейронов, на входы которого подаются факторы и критерии работоспособности, а на выходе отображается значение работоспособности системы. Прогнозирование технического состояния системы выполнено на основе анализа временных рядов. В качестве тестового набора использовалась система с шестью переменными, три из которых нелингвистические (коэффициент полезного действия, температура и давление). Общая лингвистическая переменная, рассчитываемая нейронной сетью, включает три компонента: скорость работы, расход топлива и степень изношенности узла. Формирование рекомендаций по предотвращению или ликвидации аварийной ситуации выполнено с помощью модуля нечеткой логики.

Ключевые слова: гибридная экспертная система, нейронная сеть, нечёткая логика, противоаварийное управление, сложная техническая система, диагностика, работоспособность, прогнозирование.

Introduction. In recent decades, modern ships contain various complex technical systems (CTS) which are able to affect the efficiency of operation of ships. Features of the operation of the CTS are the cause of a decrease in the operability of systems, as well as an increase in the likelihood of failures of both systems in general and their elements [1, 2].

To solve this problem, the best method is the use of emergency control systems (ESC) CTS [3].

The most common emergency control, which is based on hybrid expert systems (HES). Inside such systems, various models of knowledge representation are integrated, as well as the mechanisms of functioning of systems. In an HES, it is difficult to combine knowledge even within a single information space due to the various forms of knowledge representation (frames, semantic networks, databases (DB), knowledge bases (KB), neural networks (NN), fuzzy logic (FL), genetic algorithms).

Traditional HES have several disadvantages [4, 5]:

– the difficulty and unnaturalness of the implementation of certain conditions of automation and telemechanics, and

– difficulties in conditions of uncertainty, lack of knowledge.

It is possible to reduce the effect of deficiencies in the ECS of the CTS based on the HES using an HES, which include NN and FL. The NN, however, is based on a mathematical model that reproduces the activity of the nervous system of a living organism.

Problem statement. The main disadvantage of systems with FL is the inability to adapt and learn. However, this is replaced by the merit of methods with NN - fast learning and adaptation. In a changing external environment, and with emergency control, the ability of the NN to learn is a significant advantage, as well as: wide possibilities and ease of use. Their main drawback is the need for a training sample, the size and reliability of the elements of which affect the quality of the forecast and the accuracy of the calculations as a result of the operation of the HES. The knowledge accumulated by the NN is distributed among all its elements, which makes them practically inaccessible to the observer. Moreover, such is a lack of a control system with FL.

It follows from this that the development of the ECS CTS method on the basis of hydroelectric power stations, one of the main components of which are NN and FL, capable of avoiding difficulties at the stage of creation, and at the same time qualitatively process information, has recently been a fairly urgent task.

The main goal of the work is to develop a hydroelectric power station emergency control system capable of all of the above, avoiding possible disadvantages, while it should do all this faster and more reliable compared to other similar systems.

Data processing. All emergency control can be divided into certain stages: receipt and processing of data, operability diagnostics, forecasting and actions for decision makers.

Information from the CTS through the sensors enters the knowledge bases (KB), where it is structured and distributed in the form of operability indicators. The NN and FL form an operability assessment system [6]. Based on the operability values of the CTS elements, the overall operability of the CTS is calculated. In the NN, the state of the CTS is forecast based on the data received in the NN at various time intervals. In the FL block, the technical condition of the CTS is predicted based on the forecast of the data of the NN block taking into account data from the KB and NN blocks according to the results of the analysis of the state of the CTS. The HES with the help of the FL unit and the multi-agent control system forms recommendations on the prevention or elimination of accidents for decision-makers.

The HES processes the information it receives at regular intervals, in the form of variables from CTS sensors (linguistic and non-linguistic) and variable external factors that affect the value of the error in the system. Also, based on the critical values of these variables, abnormal (emergency) situations occurring in the operation of the CTS can occur (1):

$$W(t_i) = \langle X(t), Y(t), F(t) \rangle, \tag{1}$$

where $X(t) = \{x_1(t_i), x_2(t_i), ..., x_n(t_i)\}, i \in [1;T]$ – a lot of non-linguistic variables at a time t_i; n – number of non-linguistic variables; T – number of time points; $Y(t) = \{y_1(t_i), y_2(t_i), ..., y_m(t_i)\}, i \in [1;T]$ – a lot of linguistic variables at a time t_i; m – number of linguistic variables; $F(t) = \{f_1(t_i), f_2(t_i), ..., f_h(t_i)\}, i \in [1;T]$ – many external factors affecting the operation of the system at a point in time t_i (error); h – number of factors; $W(t_i), i \in [1;T]$ – value of operability at the moment of time t_i.

The reliability of the CTS is affected by the value of its operability of technical nodes, consisting of calculated estimates of operability, a common linguistic variable, and operational error.

Based on this, it is possible to compose a hierarchy of factors affecting the reliability of the system (Fig. 1).

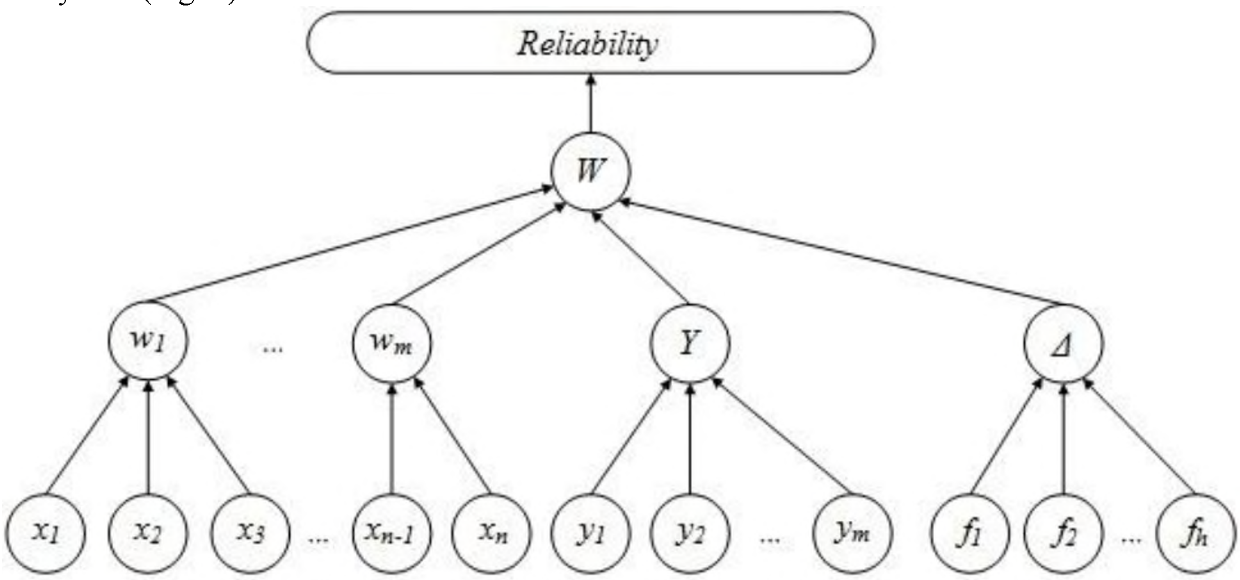

Figure 1 – The hierarchy of factors affecting the reliability of the CTS

During the development of the KB HES, critical values are established for each variable, which directly affects the operability of the CTS, taking into account their individual parameters, upon reaching which, the operation mode of the CTS becomes emergency.

For each variable, as well as for operability, the value at which the CTS enters emergency mode is set individually (Table 1) [7].

Table 1 – Values of the parameters of the CTS variables

Variable	Parameter Value	
	Non-emergency mode	Emergency mode
w_1	$[a_1...b_1]$	$(< a_1) \vee (> b_1)$
w_2	$[a_2...b_2]$	$(< a_2) \vee (> b_2)$
...	...	...
w_m	$[a_m...b_m]$	$(< a_m) \vee (> b_m)$
W	$[a_W...b_W]$	$(< a_W) \vee (> b_W)$

In Table 1 $w_1 - w_m$ – variables affecting the operability of the CTS; W – operability of CTS; $a_1 - a_m$, $b_1 - b_m$ – boundary values of the parameters of these variables; a_W, b_W – boundary values of the operability parameters.

Neural network module. The presented NN consists of neurons, each of which has one input and several outputs. The operation of these neurons depends on several factors: the values of the input signals, synapse weights, the probability of the neuron triggering, etc. The condition or potential of a neuron P is determined by the formula (2) [8]:

$$P = \sum_{i=1}^{n} q_i x_i p_i, \quad (2)$$

where n – the number of inputs of the neuron; q_i – weight coefficient of the i-th neuron; x_i – input signal of the i-th neuron; p_i – probability of triggering of the i-th neuron.

The sum of the received signals, which is transmitted to the neuron, is converted into the output signal of the neuron $f(P)$ using the transfer function (3):

$$y = f(P). \quad (3)$$

The network is trained by combining the back propagation methods of the error [8] and the recursive method. The back propagation method is convenient if there is not enough data for the recursive method.

In general terms, the neural network for a HES is a multilayer perceptron with several hidden layers, as well as a layer of recurrent neurons. Each layer contains N_d elements, $d = 1,\dots,M$, as well as a recurrence layer R. The ANN has an output showing the value of the CTS operability, the layer before the output contains the health values of the CTS elements, and factors and criteria of operability are fed to the inputs (Fig. 2).

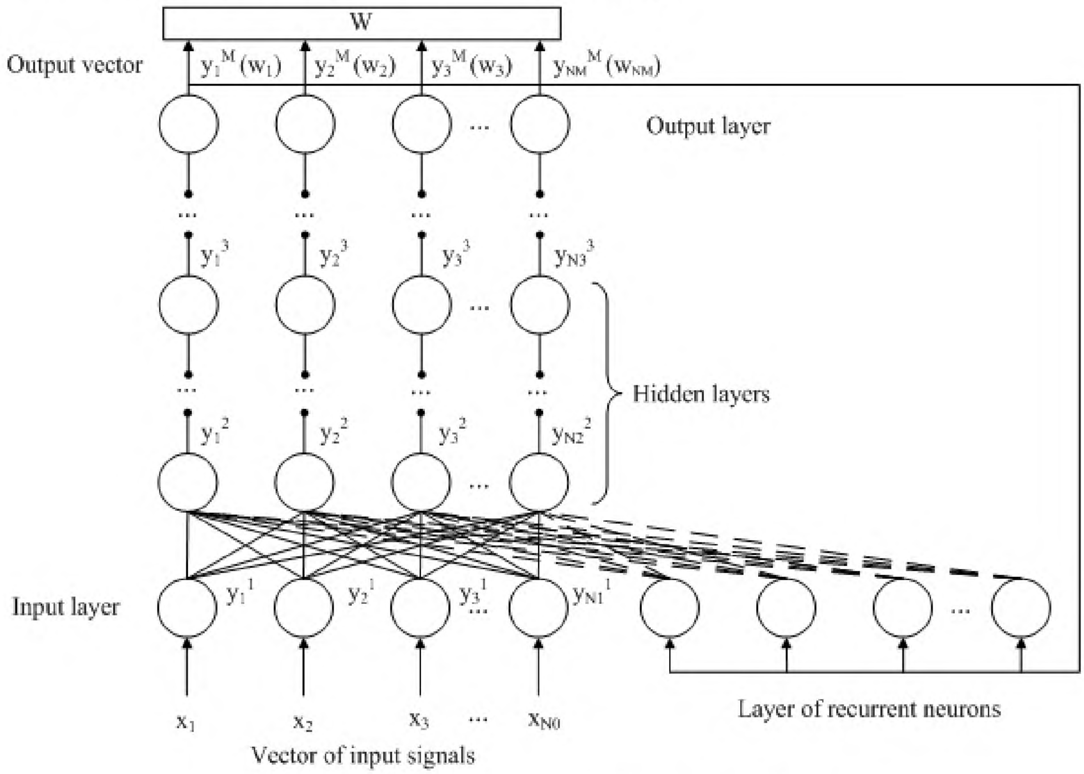

Figure 2 – Multilayer recurrent artificial NN

The developed artificial NN allows calculations for a HES with a large data range. At the same time, she avoids mistakes and failures due to multifunctionality in calculations, as well as during training.

Fuzzy logic block. Blocks NN and FL form a performance assessment system. The results of all calculations, together with the data from the DB and NN, are sent to the FL block. There is feedback between the FL and DB blocks so that data on emergency recommendations are received in the DB. In the FL block, the CTS health data is compared with the subsequent identification of the causes of a particular result based on the calculation of the CTS health indicators.

In the FL block, the technical condition of the CTS is predicted based on the forecast of the data of the NN block taking into account data from the DB and NN blocks according to the results of the analysis of the state of the CTS. A hydroelectric station, with the help of an FL unit, makes recommendations on the prevention or elimination of accidents for decision-makers. In general, the FL unit has a control function, and also affects the quality of forecasting the state of the CTS.

Prediction. The generalized mathematical model of the CTS is described by the functional dependence between the variable states of the system, the control actions, the observed parameters of the system and the environment (4) [7]:

$$W(t) = F(X(t), U(t), V(t)), \tag{4}$$

where X – is the vector of the current state of the system model; U – vector of control actions; V – vector of external influences; W – is the vector of the model output signals.

Forecasting of the technical condition of the CTS is carried out by analyzing time series with established time intervals.

The time series uses two time intervals (windows) I_J and I_O, which, upon the onset of the subsequent time series, move with a certain step along the elements responsible for operability, collecting data on the operation of the CTS at certain points in time. Having received the data, the first window I_J transmits them to the input of the NN, and the second I_O – to the output. At each step, a pair of time intervals is formed (5):

$$I_J \to I_O. \tag{5}$$

In this case, the NN is supplemented with new data from the results of pairs of time intervals for the CTS variables for each new time interval and derives the patterns by which the forecast is based.

Thus, the forecast value $W(t)$ depends on the values of the CTS variables, and is found using the NN of HES.

The accuracy of the forecast depends on the training of the NN, which, in turn, depends on the architecture of the NN: the number of layers and elements in the layers of the NN, as well as on the initialization of the weight coefficients of the NN (6):

$$I_J \approx \frac{1}{\sqrt{n(j)}}, \tag{6}$$

where $n(j)$ the number of neural elements in the layer j.

Experiments. As a test set, we used data from a system with six variables, three of which are non-linguistic (efficiency - S1, temperature - S2 and pressure - S3).

The value of the general linguistic variable Y (%) is found using the same NN unit and is a composition of three linguistic variables such as operating speed (S4), fuel consumption (S5), and degree of deterioration (S6). The resulting value is distributed in one of the following categories: High (H), Above Average (AA), Average (A), Below Average (BA) and Low (L).

Matlab Simulink was used as a modeling environment. The scheme of the model used is presented in the Figure 3.

Signals S4, S5, S6 are sent to the Fuzzy Logic Controller Y block, where the common linguistic score Y is formed based on the rules of the controller P_y.fis. Then this score Y, together with signals S1, S2, S3, goes to the Fuzzy Logic Controller P block , where, based on the rules of the controller P_p.fis, the P health is formed, the value of which displays the Display element. The experimental results showed a direct relationship between the parameters S1…S6 and the value of operability P.

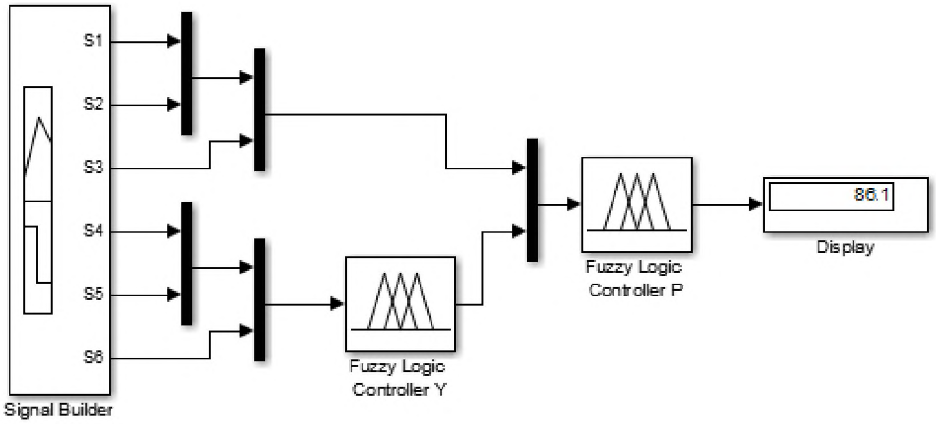

Figure 3 – Model in Matlab Simulink environment

Experimentals were carried out on three test data set. Data sets parameters (S1…S6), obtained value of the operability Ptest (model), expert value of the operability P are shown in Table 2.

Table 2 – Values of the CTS test cases

Test case	S1	S2	S3	S4	S5	S6	P	Ptest	The percentage of errors
1	1	45	98	18	6	1	88,78	86,1	0,03
2	0,2	30	15	6	3	0,1	76,4	68,62	0,10
3	0,5	35	20	8	4	0,2	78,3	71,92	0,08

The smallest error value (0.03) is observed in the first set, in which values of all three linguistic variables belong to the same category (High), which corresponds to the real operating conditions of the system. The error increased by a factor of 3.4 (0.1) in the second test set due to the fact that values of three linguistic variables were taken from different categories (Below Average, Average, Low). In the case when two of the three linguistic variables belong to one category (Average) and one variable belongs to another category (Low), the error increased by a factor of 2.6.

Conclusion. Due to the constant modernization of existing and commissioning of new equipment, as well as regular maintenance, the task of ensuring the safety of modern ships, which are complex organizational and technical systems, is relevant. Timely identification of the degree of danger, assessment of the adequacy of resources, forces and means, for the localization and elimination of possible emergency situations, which can be provided by predicting the technical condition of the system based on an assessment of the operability of its nodes, is required. The proposed combination of neural network modules and fuzzy logic within the framework of a hybrid expert system allows us to solve the problem of diagnosing and predicting the level of operational reliability.

REFERENCES:

1. Konovalov, S.N., V.V. Vychuzhanin. "Method for antifault control of complex technical systems." Development of transport, collection of scientific works, no. 1 (1), 2017. p. 45-49.

2. Vychuzhanin, V., et al. "Devising a method for the estimation and prediction of technical condition of ship complex systems." Eastern-European Journal of Enterprise Technologies, vol. 84, no. 6/9, 2016. p. 4-11.

3. Nourian, R., et al. "A fuzzy expert system for mitigation of risks and effective control of gas pressure reduction stations with a real application." Journal of loss prevention in the process industries, no. 59, 2019. p. 77-90.

4. Lopez, C., A. Ishizaka. “A scenario-based modeling method for controlling ECM performance.” Expert systems with applications, no. 97, 2018. p. 253-265.

5. Ручкин, В.Н., В.А. Фулин. Универсальный искусственный интеллект и экспертные системы, БХВ-Петербург, 2009.

6. Коновалов, С.Н., А.А. Егошина. “Особенности разработки искусственной нейронной сети гибридной экспертной системы.” Штучний інтелект, № 2 (80), Наука і освіта, 2018, с.139-143.

7. Коновалов, С.М., Г.А. Єгошина. “Діагностика ризиків аварійних ситуацій за допомогою гібридних експертних систем.” Информационные управляющие системы и технологии. Проблемы и решения: монография, Экология, 2019, с.162–174.

8. Кацуба, Ю.Н., Л.В. Григорьева. “Применение искусственных нейронных сетей для прогнозирования технического состояния изделий.” <http://research-journal.org/technical/primenenie-iskusstvennyx-nejronnyx-setej-dlya-prognozirovaniya-texnicheskogo-sostoyaniya-izdelij/> accessed Jun 29 2020.

ЛІТЕРАТУРА:

1. Konovalov S.N. Method for antifault control of complex technical systems / S.N. Коновалов, V.V. Vychuzhanin // Development of transport, collection of scientific works. – Odessa: ONMU, 2017. – № 1 (1). – P. 45–59.

2. Devising a method for the estimation and prediction of technical condition of ship complex systems / [V. Vychuzhanin, N. Rudnichenko, V. Boyko et al.] // Eastern-European Journal of Enterprise Technologies. – 2016. – V. 84. – № 6/9. – P. 4–11.

3. Nourian R. A fuzzy expert system for mitigation of risks and effective control of gas pressure reduction stations with a real application / R. Nourian, S.M. Mousavi, S. Raissi // Journal of loss prevention in the process industries. – 2019. – № 59. – p. 77–90.

4. Lopez C. A scenario-based modeling method for controlling ECM performance / C. Lopez, Ishizaka // Expert systems with applications. – 2018. – № 97. – p. 253–265.

5. Ручкин В.Н. Универсальный искусственный интеллект и экспертные системы / В.Н. Ручкин, В.А. Фулин. – СПб: БХВ-Петербург, 2009. – 240 с.

6. Коновалов С.Н. Особенности разработки искусственной нейронной сети гибридной экспертной системы / С.Н. Коновалов, А.А. Егошина // Штучний інтелект. Київ: ІПШІ Наука і освіта, 2018. – № 2 (80). – С. 139–143.

7. Коновалов С.М. Діагностика ризиків аварійних ситуацій за допомогою гібридних експертних систем / С.М. Коновалов, Г.А. Єгошина // Информационные управляющие системы и технологии. Проблемы и решения: монография / С.М. Коновалов, Г.А. Єгошина. – Одесса: Экология, 2019. – С. 162–174. ISBN 978-617-7046-88-1

8. Кацуба Ю.Н. Применение искусственных нейронных сетей для прогнозирования технического состояния изделий: веб-сайт. URL:http://research-journal.org/technical/primenenie-iskusstvennyx-nejronnyx-setej-dlya-prognozirovaniya-texnicheskogo-sostoyaniya-izdelij/
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