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MODEL OF DECISION MAKING USING ARTIFICIAL NEURAL NETWORKS

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Abstract—*The article makes theoretical generalizations and provides promising solutions to the scientific and theoretical problem of human factor assessment in the safety management system based on predicting the occurrence of an adverse event that may involve risks in aviation activities. The current state and prospects of developing a proactive approach to the safety risk management system and the place of the human factor in identifying sources of danger are analyzed. Generalization and current prospects for the use of artificial neural networks for forecasting tasks and their place in the decision-making system, which allowed to identify unresolved issues, justify appropriate approaches to its solution, in particular to assess the possibility of adverse events of the cardiovascular system . A method for constructing an artificial neural network for forecasting biological risk objects based on a theoretical approach using a decision-making model has been developed. The use of artificial neural networks allowed to develop a model for predicting the occurrence of a negative event of sudden disruption of the functional state of the cardiovascular system of the operator.*

Index Terms—Neural networks; human factor; flight safety; risk management; forecasting; functional state; model for predicting; adaptive potential; factors of destabilization.

I. INTRODUCTION

According to the order of the Cabinet of Ministers of Ukraine of June 16, 2021 № 656-r. "On approval of the State Aviation Safety Program" civil aviation is an integral part of the economy and society, integrated into the transport system of Ukraine. Ensuring flight safety is a priority of air transport and an integral part of national security. Ukraine, as an acceding state to the Convention on International Civil Aviation, is responsible for fulfilling its international obligations under the Convention, including the implementation of the State Aviation Safety Program, which is an integral basis for effective and efficient safety management. Safety management is based on a systematic approach to identifying and eliminating hazards and controlling risks to ensure safety in order to minimize human losses, material, financial, environmental and social damage. Implementing an effective safety management system at the state level by implementing the provisions of the European Regional Safety Plan and in accordance with ICAO Doc 10131 Guidelines for the development of regional and national safety plans is impossible without adequate assessment of the level of risk associated with aviation work. Management of risk factors for flight safety at the state level is necessary to maintain a high level of flight safety and aviation security [1].

II. PROBLEM STATEMENT

A systematic and comprehensive approach to safety risk management is needed to increase safety in today's challenges. System safety management is based on risks and predictability, which combines elements of quality management and risk management into an integrated system, and helps aviation entities to: identify threats and related risks that affect the entire organization; monitor, monitor, report and review such risks; ensure the quality of products and services in accordance with standards; constantly improve products and services [2]. In an aviation safety management system, aviation operators must establish acceptable risk management and risk management processes, safety and reporting objectives, procedures for auditing, investigations, corrective actions and training in order to comply with the acceptable level of safety performance (ALoSP) on security issues [3]. Currently, the problem of developing models and algorithms of the subsystem for forecasting and preventing adverse aviation events in flight is determined by the level of development of mathematical methods and the needs of the applied area, the development of which is constantly accelerating and leading to qualitative and structural complexity.

At the ICAO symposium on December 18, 2020. Much attention is paid to the introduction of safety The urgency of the work is aimed at analyzing the problem of assessing the impact of the human factor and determining its place in the safety management system.

Normative regulation of the process of safety oversight in the air traffic management system as one of the main subsystems of civil aviation of Ukraine is provided by the Regulations on flight safety oversight in the air traffic management system, approved by the order of the Ministry of Transport and Communications of Ukraine from 31.05.2010 № 320 and registered by the Ministry of Justice of Ukraine on June 30, 2010 under №446 / 17741.

Requirements the provisions of the regulation meet the Aviation Safety Regulatory Requirements (ESARR 1) of the European Air Navigation Safety Organization [4] of which Ukraine is a member and create the conditions for the implementation of the Implementing Regulation in Ukraine. EU Regulation 2016/1377 of 04.08.2016 on the basic requirements for providers and organization of safety oversight in air traffic management and air navigation services and the EU Implementing Regulation 1034/2011 of 17.10.2011 on flight safety oversight in air traffic management and air navigation maintenance. culture and the human factor in the safety management system [5].

Analysis "мethodology for assessing management systems" used to assess compliance and the effectiveness of the safety management system through an appropriate set of components based on the second edition of ICAO Annex 19, EASA requirements for management systems organizations and approved by the State Aviation Service of Ukraine allows to identify the human factor as a source of danger, which must be timely analyzed, assessed and taken into account. The difficulty of assessing the impact of the human factor lies in the skeletal relationship of this factor with all other components of the aviation system. The feature of the pro-active approach is to predict the occurrence of a dangerous event and minimize aviation accidents due to human guilt related to aviation. Given the pro-active approach to identifying the impact of human factors in assessing the current functional state of the operator and predicting the violation of its functional stability will reduce the development of adverse events involving humans. In the offered work the model of decision-making concerning possibility of occurrence of a risk event of disturbance of a current functional condition of the operator is developed.

III. Problem Solution

Today, the Safety risk management (SRM) process includes five successive stages in a closed cycle:

1) identification of safety issues (safety issue);
2) assess the safety risks associated with the identified problems;
3) development and / or implementation of safety risk management measures;
4) control over flight safety measures;
5) analysis and determination of the existing level of security.

Today, the SRM uses the European Risk Classification Scheme (ERCS), a methodology developed by a group of experts set up by the European Commission to implement the requirements of Regulation (EC) 376/2014 [6].

The European Plan for Aviation Safety (EPAS) – Safety Management at European Level The purpose of the EPAS is to ensure that the principles of safety management are applied within the European Aviation Community so as to continually improve safety performance. It is driven by Regulation (EU) 2018/1139, known as the European Union Aviation Safety Agency (EASA) Basic Regulation, to ensure the application of ICAO safety management principles that are fundamental to the continuous improvement of civil aviation safety. The EPAS seeks to anticipate emerging industry safety risks and make best use of technical resources through a common framework for prioritising, planning and implementing safety improvement actions. EASA develops the EPAS in close collaboration with the Member States and other relevant stakeholders. The EPAS is produced annually and looks ahead to the following four years. It examines relevant safety information sources (notably occurrences), prioritisation of issues and evaluates options to address them. It identifies the main areas of concern affecting the European aviation safety system. It then sets out the strategic actions necessary to mitigate those concerns and return safety risk back to an acceptable level.

In the stages of the SRM cycle, the following are identified: key risk areas (KRAs), in the circumstances that lead to aviation events prevented by EPAS measures and safety issues (SI), ie causal and concomitant factors that lead to KRA (which causes aviation events) [7]. Examples of SI are icing in flight, untimely or incorrect actions of pilots, etc.

Risk assessment in the ERCS methodology is based on the ERCS matrix, which consists of two axes (Fig. 1).

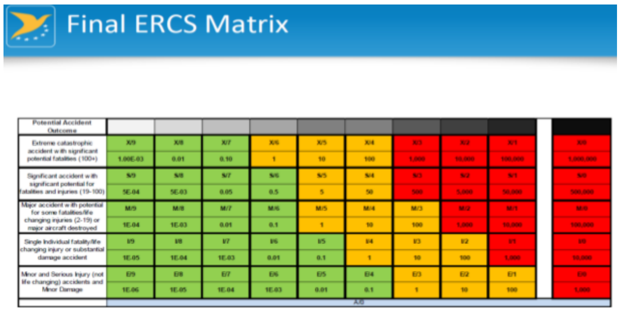

Fig. 1. ERCS matrix

The vertical axis determines the severity of the consequences in the event of a safety event to a high-level event. This is done by considering both the size of the aircraft and how serious the consequences could be. The horizontal axis, based on the barrier assessment model, measures how close the event was to evolving into a high-level event.

Risk safety risk assessment for the period from 2016 to 2020 (Fig. 2). Based on the results of statistical and analytical processing of flight safety data using the web portal https://rmd.avia.gov.ua/, the Safety Risk Portfolio (SRP) was created and risk assessment for the defined period from 2016 to 2020 [8].

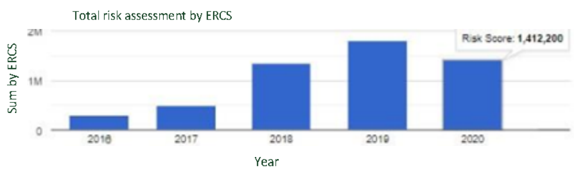

Fig. 2. Risk assessment on the ERCS scale in Ukraine from 2016 to 2020

Safety Risk Portfolio has two levels.

The first level is the key area of risk (KRA), which is the most likely circumstance of potential aviation events by area of activity and is aggregated according to their risk levels established using the ERCS methodology.

The second level includes safety issues (SI), which are causal and concomitant factors that lead to KRA (which causes aviation accidents).

Experience in investigating the causes of aviation accidents has shown that each of them is due to the impact of several simple hazards, which in the period before the aviation accident, were hidden in the form of shortcomings. Given the hidden nature of the dangers, they were not only not actively detected, but also did not attach much importance to accidental detection. However, practice has convincingly shown that the presence of a hidden flaw in the system can, under certain conditions, lead to its potential transformation into a trigger (cause, trigger), which triggers further negative developments. That is why the content of preventive work is fundamentally changing [9]. In other words, real preventive work should be carried out on the far approaches to possible aviation events, not after they occur. One of these hidden dangers is the current functional state of the decision-maker, which can be due to both a sudden deterioration in health and the inability of the body's current adaptive capacity to withstand the current external factors of destabilization. And since the main place in such a proactive approach is the identification and development of corrective measures to reduce the impact of the human factor in the safety management system, it requires a systematic approach to identifying possible methods for assessing the current state of the operator.

The ability of a person to make erroneous or illogical decisions in specific situations, which is referred to as a human factor is associated with limitations or errors that are characteristic of any person. Psychological and psychophysiological characteristics of a person do not always correspond to the level of complexity of the tasks or problems to be solved. The resolution adopted by the ICAO Assembly on flight safety and the role of the human factor in interaction with machines (H), procedures (S), environment (E) and interaction with each other (L) makes it possible to identify features of human factor assessment as a source of risk. This assessment should be based on a practical solution to safety problems, based on the analysis of erroneous actions of all participants in the human-machine system, which led or could lead to accidents [10]. The goal of a pro-active approach to the human factor is to minimize aviation accidents due to human aviation. Methods for studying the role of human and organizational factors are discussed in Parts III and IV of ICAO Document Doc 9756, where both of these aspects are given special attention. According to the ICAO guidance material contained in Part IV, it is proposed that a separate section of the final report be devoted to human factors. In addition, Section IV contains a list of human-related terms that may be used in the investigation. A good understanding of these terms will contribute to the successful study of the impact of the human factor. In this regard, the ideology of risk management has been developed, which directs the search for ways and determines the early detection of hazards and dangerous factors that occur in the form of certain events, predictors.

The analysis allows to determine the need to identify the human factor as one of the sources of risks in the methodology of flight safety management.

Among the ways to quantify the magnitude of risk requires the use of two main approaches: theoretical and empirical. The theoretical approach characterizes the requirements for the results of the decision, subject to the calculation of risk by logical reasoning, rather than based on past experience. The empirical approach extrapolates the risk calculated on the basis of past events using the statistical method. The statistical method is to study the statistics of risks that occurred in a given person and determine the frequency of certain levels of losses.

To calculate the risk based on a theoretical approach, it is proposed to use artificial neural networks as artificial intelligence, which allows to predict the occurrence of an adverse event based on a test sample. The advantage of the theoretical approach is the development of an artificial neural network with minimal error on the test set of data, which allows its use as a prediction tool for subsequent study participants.

The transition to continuous focused work on forecasting and eliminating hidden dangers and their factors within the theoretical approach makes it necessary to develop forecasting models for the overall decision-making system on the probability of an adverse event.

Predicting the occurrence of an adverse event (trigger) in the construction of a model for predicting future risks, based on already known data and forecasting future data before they become the cause of risk [11]. Artificial neural networks are widely used in solving the problem of forecasting. But for the effective use of artificial neural networks for forecasting tasks, it is necessary to perform the steps of the following method.

1) According to the task of forecasting to choose the structure or architecture of the neural network. The following architectures of neural networks were chosen as an example in the work: radial-base, linear, multilayer perceptron, general regression neural network. The choice of a certain number of network architectures is associated with the ability to choose the most efficient networks after its training on a certain criterion of efficiency. This criterion is the error that occurs on each source element on the training set of data, namely: the error of a single source element, which is necessary to implement the procedure of backpropagation of the error; the error of the whole network at a particular input signal, which gives us information about how correct the network's response at a given time; the average error of the network, calculated after the presentation of the entire set of training data, which shows how well the network has mastered the laws of the set of training data. The last error is the average of the second type of training data error value of the second type.

2) To reduce these errors, it is necessary to prepare the next stage of the methodology

3) Preparation of a set of training and test data. The amount of training data should exceed 100 data [11]. It is necessary to check that the examples of the training set are not repeated in the test, because in this case the network will simply remember the result and reproduce it.

4) Choice of the number of input and output neurons, hidden layers. At the beginning of the work you need to clearly determine the number of input parameters - this will be the number of input neurons, and the output parameters will determine the number of output neurons. The number of hidden layers of the neural network can be adjusted, and in this process it is necessary to conduct a series of experiments to determine the best option [12].

5) The current sample (initially the first) is taken from the training sample and its input parameters (representing in total the vector of input signals) are fed to the input synapses of the student's neural network. Typically, each input parameter of the example is fed to one corresponding input synapse.

6) The neural network performs a given number of clock cycles, while the vector of input signals propagates through the connections between neurons (direct functioning).

7) Measure signals issued by those neurons that are considered output.

8) The interpretation of the issued signals is carried out, and the estimation characterizing a difference between the issued network of the answer and the necessary answer available in an example is calculated. The score is calculated using the appropriate score function.

9) If the estimate of the example is not equal to zero on its basis, the correction factors are calculated for each synaptic weight of the matrix of connections, followed by the adjustment of synaptic weights (reverse operation). It is the correction of synapse weights that carries out the learning process [13].

10) The transition to the next example and the above operations are repeated, which can be considered one cycle of training.

As an example, the model of decision-making on the occurrence of an adverse event of violation of the functional state of the aviation industry operator is considered. The structure of this model is shown in Fig. 3.

Central to this model is the unit for predicting the occurrence of an adverse event based on an artificial neural network. The parameter Y is the probability of an adverse event – i.e. a violation of the cardiovascular system of the operator. As measured parameters on the basis of which the forecast is carried out indicators $X_1... .X_{17}$, which determine the state of the cardiovascular system and which are related:

$$M[Y] = F(M[X_1],\ \dots M[X_k]).$$

The general block diagram of the decision-making model presented in Fig. 1 determines the process of measuring and converting information about the value of the predicted parameter Y, namely the time of occurrence of an adverse event.

The first unit converts the values of the primary information $X_1, .., X_k$ into an estimate of the measured values $X_1{*},.\ X_k{*}$ in the assessment $Y{*}$ parameter value Y,

$$Y{*} = F \quad X_1\ X_k \,\big|\, a_1, \dots a_p$$

The coefficients $a_1, \dots, a_p$ are estimated at the stage of studying the object of diagnosis by sampling volume n for each of the fixed quantities $Y_j,\ j=\overline{1,m}$ levels of parameter Y (training stage artificial neural network). The decision-making unit makes the choice $y_j \quad \{a_l, b_c\}_1^m$ of one $\{y_j\}_1^m$ of many $\{y_1\}_1^m$ decisions about the value of Y after comparing $Y{*}$ in accordance with the rule of learning the neural network:

$$\forall Y{*}[Y{*} \in (\alpha_j, b_j) \rightarrow Y{*} \in Y_j].$$

The set $\{\psi\}$ are factors that influence the correctness of the choice of the model of transformation $\hat{F}(\cdot)$ and the accuracy of the estimation of the coefficients $a_1, \dots a_p$ of this model.

Medico-biological indicators of the survey of 110 study participants were used as a test sample, which allowed to fulfill the condition for improving the reliability of the network forecast based on a sufficient amount of initial data of the test set. Data characterizing the state of the cardiovascular system on 17 indicators were processed, the time parameters from the examination to the occurrence of a sudden violation of the functional state of the cardiovascular system (t) and the probability of death of the subject (r) were determined as initial parameters. The input data includes 17 diagnostic indicators that reflect the condition of 110 study participants. This amount of data allowed to increase the reliability of the forecast, because the creation of the neural network is preceded by the stage of data collection on their quality will depend on the result. The test sample contains diagnostic data of study participants and the time of occurrence or absence of negative event in this group.

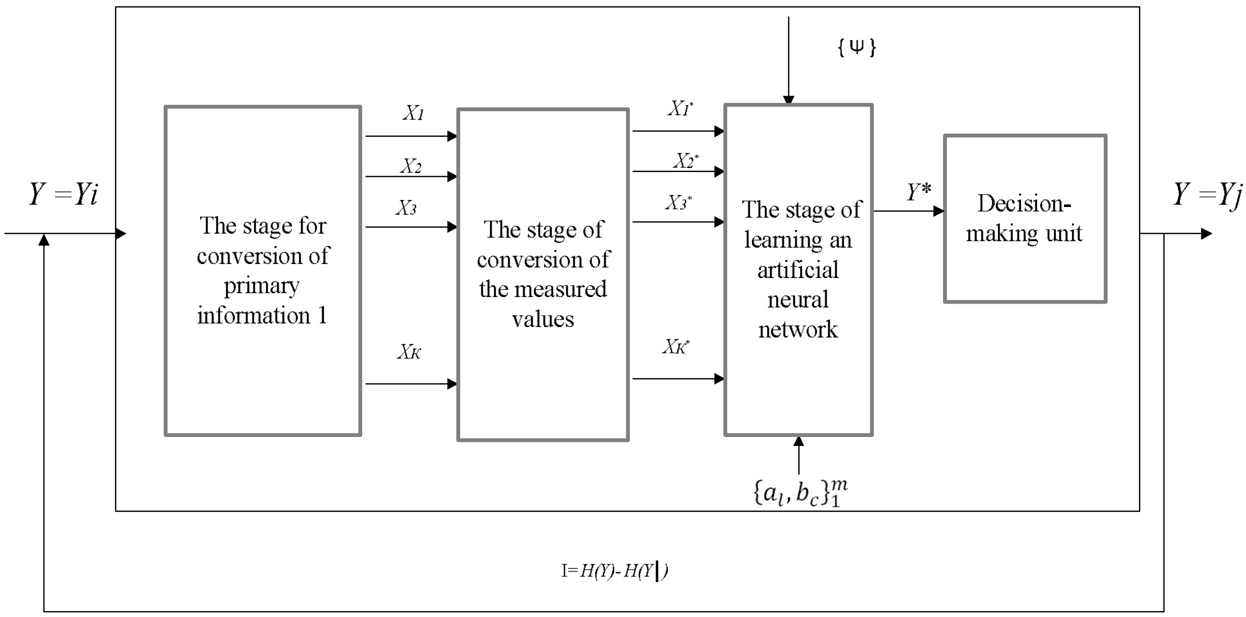

Fig. 3. Model of decision-making based on artificial neural networks

The following neural network architectures were constructed: a is the radial-base network (number of input neurons 17, number of neurons in the first hidden layer – 3, number of neurons in the second hidden layer – 0); b is the linear network (number of input neurons 1, number of neurons in the first hidden layer – 0, number of neurons in the second hidden layer – 0); c is the multilayer perceptron (number of input neurons 1, number of neurons in the first hidden layer – 5, number of neurons in the second hidden layer – 0); d is the multilayer perceptron (number of input neurons 2, number of neurons in the first hidden layer – 4, number of neurons in the second hidden layer – 0); e is the neural network of general regression (number of input neurons 17, number of neurons in the first hidden layer – 6, number of neurons in the second hidden layer – 3). Visual representation of these neural network developed in program STATISICA are presented in Fig.4. The learning results of these networks are presented in Table. I.

The criterion of regularity was used to evaluate the learning outcomes of the network and its generalizing properties. Table II shows the result of verification of the developed 5 neural networks using a test sample.

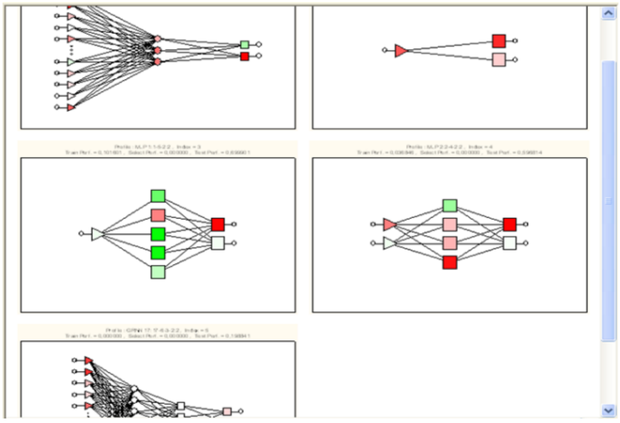

Fig. 4. Visual representation of artificial neural networks for model of decision-making

TABLE I. GENERAL DESCRIPTION OF 5 NEURAL NETWORKS

No	Net-work type	Selective error	Learning error	Test error
1	RBF 17:17-3-2:2	0.21899	0.27335	0.782
2	Linear 1:1-2:2	0.39975	0.16659	0.276
3	MLP 1:1-5-2:2	0.11409	0.03548	0.301
4	MLP 2:2-4-2:2	0.01313	0.01585	0.542
5	GRNN 17:17-6-3-2:2	0.00247	0.001	0.044

TABLE II. THE RESULT OF CHECKING 5 NEURAL NETWORKS IN A TEST SAMPLE

No	The time of occurrence of the adverse event (fact)	The presence of an adverse event (fact)	Projected indicators t i k each of the 5 developed neural networks									
	t_f *(month)*	r_f	t_n^1	r_n^1	t_n^2	r_n^2	t_n^3	r_n^3	t_n^4	r_n^4	t_n^5	r_n^5
1	12	0	12.15	0.06	8.94	0.41	11.79	-0.04	12.09	-0.02	12.00	0.00
2	12	0	10.54	0.12	10.84	0.13	12.02	-0.03	11.97	0.01	12.00	0.00
3	12	0	12.77	-0.009	10.37	0.20	11.65	-0.043	12.01	0.001	12.00	0.00
4	12	0	11.44	0.12	7.99	0.55	12.31	0.001	12.04	-0.009	11.99	0.001
5	12	0	11.37	0.03	11.84	-0.007	12.32	0.019	11.99	0.002	12.00	0.00
6	3	1	3.46	1.05	8.99	0.40	3.26	1.17	2.61	1.61	3.00	1.00
7	6	1	5.60	0.90	8.28	0.51	1.59	1.34	6.09	1.01	4.80	1.00
8	8	1	5.02	0.59	6.47	0.77	7.47	0.71	10.60	0.22	8.00	1.00
9	12	0	7.77	0.08	10.94	0.12	11.59	0.18	11.82	0.018	12.00	0.00
10	12	0	12.34	-0.10	9.27	0.36	12.32	0.019	12.03	-0.009	12.00	0.00

We find an estimate of the amount of information about the parameter Y: the amount of information is determined by the difference between the original $H(Y)$ and the conditional $H(Y|Y_j)$ entropy [14]: $I = H(Y) - H(Y|Y_j)$, where:

$$H(Y) = -\sum_{i=1}^{k}\left[\int_{a_j}^{b_j} f(y)dy\right]\ln\left[\int_{a_j}^{b_j} f(y)dy\right],$$

$f(y)$ is the density distribution of the value Y in the range A_y [7].

We find the conditional entropy by the conditional probability $P(Y_i | Y_j)$ that the true value of $M[Y] = Y_j$, while the result of the solution $Y = Y_j$, gives the value

$$Y = Y_j : H(Y | Y_j) = -\sum_{i=1}^{k} P(Y_i | Y_j) \ln P(Y_i | Y_j) .$$

If the law of distribution of deviations of Y* from the actual value of $M[Y]$ = const, if the variance of this deviation is σ_y^2, we have:

$$H\ (Y) = \ln \frac{A_y}{\Delta} \quad \to H(Y | Y_i) = \ln \frac{\sigma_y \sqrt{2\pi e}}{\Delta}.$$

Estimation of the amount of information, taking into account expressions will take the form:

$$I = \ln \frac{A_y}{\sigma_y \sqrt{2\pi e}}. \qquad (1)$$

According to table 1, the smallest error in testing on the test set showed the network "*c*" which belongs to the type of neural networks of general regression contains 17 input neurons, 6 and 3 neurons in the hidden layers. Such a network has an error of 0.043 when learning on a test set, and an error of 0.001 when testing on a test set. Comparison of the results of forecasting neural networks, the data of which are shown in table 1, using a test sample is shown in Table II.

These data reflect the ability of the constructed neural network to make a forecast based on data not used in network training, so these results are quite informative in the study of the quality of the created neural networks [13].

Expression (1) can be considered as the number of expected received measuring information about the controlled value *Y* with irremovable dispersion. Due to the fact that the state of the cardiovascular system can be assessed by a large amount of measuring information, by increasing *k* of these values. However, in this case, the ratio of the size of training samples n to the number k of input values should be either remain constant or also increase.

This means that the volume of the training sample should grow as new input values are attracted for control. In fact, the condition

$$n / k = \text{const} .$$

Presence in the denominator, under the sign of the logarithm in expression (1), the offset indicates that that the training phase of the forecasting system plays important role. It determines the magnitude of unremovable systematicical shifts in estimating the coefficients of the measuring model transformation *F*.

Reduce these offsets, and, consequently, consequently, improve the reliability of forecasting by increasing amount of information, it is possible only by increasing the volume training sample n. Increasing only the number of N multiples measurements does not eliminate the negative effects of factors $\{\psi\}$.

Completing the analysis of the information properties of the forecasting system of objects with random parameters, should say that the values k, n, N, as well as the number of levels m control parameter to be adjusted cannot be selected individually. They are mutual are connected within the framework of model (1) and their choice is an optimization a task in which the quality criterion is the number of possibilities no expected information.

The values of these coefficients are obtained from the results of retrospective data, taking into account the individual characteristics of the organism.

The solution of the proposed mathematical model makes it possible to quantify the level of equilibrium of the response of the body's adaptive potential to destabilizing factors and can be used to calculate the risk load based on an empirical approach.

IV. Conclusions

Using an empirical and theoretical approach allows you to develop methods for quantifying risks and predict their occurrence, which corresponds to a proactive approach in risk management and provide a mathematically sound basis for preventing the development of hazards, risks to flight safety, including those that can lead to accidents. number of possibilities no expected information.

The implementation of a proactive approach aims to identify and assess dangerous factors that can lead to the occurrence of a dangerous event before its occurrence.

The use of a theoretical approach to develop a decision-making model to assess the occurrence of a risk event makes it necessary to use methods and tools that allow you to predict triggers. Artificial neural networks are an effective method for solving forecasting problems. In the offered work the model of decision-making on occurrence of a risk event with use of artificial neural networks is offered. A comparative analysis of five neural networks of different architecture. The method of using artificial non-uniform networks for the tasks of predicting the occurrence of a negative event is proposed.

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Р. В. Хращевський, О. Б. Іванець, К. С. Нестеренко, О. М. Горський, О. Г. Байбуз. Модель прийняття рішень з використанням штучних нейронних мереж

У роботі зроблено теоретичні узагальнення та отримано перспективні рішення науково-теоретичних проблем оцінки людського фактора в системі керування безпекою польотів на основі прогнозування виникнення небезпечної подій, що може отримати за собою ризики в авіаційній діяльності. Проаналізовано сучасний стан і перспективи розвитку активного підходу до системи керування ризиками безпеки польотів і місця людського фактора у виявленні джерел небезпеки. Загальні положення та сучасні перспективи розвитку штучних нейронних мереж для прогнозування завдань та їх місце в системі прийняття рішень, що дозволить визначити невирішені питання, обґрунтувати відповідні підходи до її вирішення, зокрема оцінити можливість виникнення небезпечної події порушення стану серцево-судинної системи оператора авіаційної діяльності. Розроблено методику побудови штучної нейронної мережі для задач прогнозування біологічних об'єктів ризику, засновано на теоретичному підході для використанням в моделі прийняття рішень. Використання штучних нейронних мереж дозволило розробити модель прогнозування настання негативної події раптового порушення стану серцево-судинної системи оператора авіаційної діяльності.

Ключові слова: людський фактор; безпека польотів; управління ризиками; нейронні мережі; прогнозування; функціональний стан; модель прогнозування; модель прийняття рішень; фактори дестабілізації.

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Р. В. Хращевський, О. Б. Иванец, К. С. Нестеренко, О. Н. Горський, О. Г. Байбуз. Модель принятия решений с использованием искусственных нейронных сетей

В работе сделаны теоретические обобщения и получены перспективные решения научно-теоретической проблемы оценки человеческого фактора в системе управления безопасностью полетов на основе прогнозирования возникновения неблагоприятного события, что может повлечь за собой риски в авиационной деятельности. Анализируются современное состояние и перспективы развития проактивного подхода к системе управления рисками безопасности полетов и место человеческого фактора в выявлении источников опасности. Обобщение и современные перспективы развития использования искусственных нейронных сетей для задач прогнозирования и их место в системе принятия решений, что позволило очертить нерешенные вопросы, обосновать соответствующие подходы к ее решению, в частности оценить возможность появления неблагоприятного события резкого ухудшения состояния сердечнососудистой системы оператора авиационной деятельности. Разработана методика построения искусственной нейронной сети для задач прогнозирования биологических объектов, основанная на теоретическом подходе для использования в модели принятия решений. Использование искусственных нейронных сетей позволило разработать модель прогнозирования наступления негативного события внезапного нарушения функциональное состояние сердечно-сосудистой системы оператора, работающего в авиационной сфере.

Ключевые слова: человеческий фактор; безопасность полетов; управление рисками; нейронные сети; прогнозирование; функциональное состояние; модель прогнозирования; модель принятия решений; факторы дестабилизации.

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