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On the use of fuzzy neural networks in the framework of a risk-based approach in control and supervisory activities in civil aviation

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Abstract: A risk-oriented approach implemented in conducting control and supervisory activities in Civil Aviation organizations makes it possible to increase the effectiveness of such activities, the objectivity of assessments, to reduce costs and the additional burden on business. The main provisions, regulating the activities of control and supervision bodies, including the issues of risk assessment, are generally specified in regulatory documents. However, uncertainty remains regarding the use of so-called risk indicators, which are designed to forecast risks for flight safety. Currently, there are no guidelines on the number and composition of such indicators, there are no methods to use them for the intended purpose. The article proposes a solution to this problem using elements of artificial intelligence. Based on the example of risk indicators distinctive for air traffic service organizations, the feasibility of forecasting the level of risk through a fuzzy (hybrid) neural network is shown. As is well known, such hybrid structures, combining neural networks and fuzzy logic, collect the best properties of both methods. The formation of a set of risk indicators and initial data for network training is carried out with the involvement of qualified experts with extensive experience in flight safety management and control and supervisory activities. The trained network allows us to quantify a forecasted level of risk in an airline based on the identified risk indicators considering the degree of their manifestation. All the stages of building and using the network in the ANFIS editor of the MATLAB software package are shown. The proposed method can also be used in the flight safety management systems for various providers of aviation services.

Key words: safety risk, air traffic service, risk-oriented approach, risk indicator, fuzzy neural network.

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О применении нечетких нейронных сетей в рамках рискориентированного подхода к контрольно-надзорной деятельности в гражданской авиации

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Аннотация: Рискориентированный подход, реализуемый при проведении контрольно-надзорных мероприятий в организациях гражданской авиации, позволяет повысить эффективность таких мероприятий, объективность оценок, снизить расходы и дополнительную нагрузку на бизнес. Основные положения, регулирующие деятельность органов контроля и надзора, в том числе и в вопросах оценки рисков, в целом указаны в нормативных документах. Однако остается неопределенность в части использования так называемых индикаторов риска, которые предназначены для прогнозирования рисков для безопасности полетов. В настоящее время нет каких-либо указаний по количеству и составу таких индикаторов, отсутствуют методики их использования по назначению. В статье предлагается решение этого вопроса с использованием элементов искусственного интеллекта. На примере индикаторов риска, характерных для организаций обслуживания воздушного движения, показана возможность прогнозировать уровень риска посредством нечеткой (гибридной) нейронной сети. Как известно, такие гибридные структуры, объединяющие в себе нейронные сети и нечеткую логику, собирают наилучшие свойства обоих методов. Формирование набора индикаторов риска и исходных данных для обучения сети проводится с привлечением квалифицированных экспертов с большим опытом управления безопасностью полетов и контрольно-надзорной работы. Обученная сеть позволяет количественно оценить прогнозируемый уровень риска на авиапредприятии на основании выявленных индикаторов риска с учетом степени их проявления. Показаны все этапы построения и использования сети в редакторе ANFIS программного пакета Matlab. Предлагаемый метод может использоваться также и в системах управления безопасностью полетов различных поставщиков авиационных услуг.

Ключевые слова: риск для безопасности полетов, обслуживание воздушного движения, рискориентированный подход, индикатор риска, нечеткая нейронная сеть.

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Introduction

Currently, the supervising activity is based on a risk-oriented approach which can be considered generally and properly [1, 2].

By reference to Civil Aviation (CA), its application generally assumes including the proactive management of risks into a state program (system) of flight safety. This long-term objective was delegated by the ICAO to states in the long run up to 2027[1]. Mitigating operational risks was announced as a top priority in the current ICAO conception over a period of 2020–2022[2]. This state activity is aimed at ensuring the fulfillment of the Standard from the ICAO Appendix 19[3] according to critical element 8 of the National Civil Aviation Safety Program and refers to the implementation of the requirements of the Russian Federation Government Resolution № 1215[4] (void) and later-issued Resolution № 642[5] in accordance with data acquisition and processing about the hazard factors (HF) and risks associated with major providers of aviation services.

The risk-oriented approach towards the state-regulated CA activity is, in narrow sense, based on the provisions of the FL-248[6], construing the risk management as “the implementation of preventive actions and control (supervising) activities, based on the risk assessment of the damaging event, for the purpose of ensuring the permissible level of damage risk in the respective sphere of activity” (p. 22, p. 4). The frequency, volume, and scale of actions depend on a risk category to which a specific object of central or local government oversight is attributed.

The law formulates the general recommendations with respect to identifying a risk category for various objects of oversight. Some details of the procedure with respect to the activity of the CA oversight body (State Aviation Safety Inspectorate) is encapsulated in the Russian Feder-

[1] Doc. 10004. (2014). ICAO global aviation safety. ICAO 2014–2016. ICAO, 76 p.

[2] Doc. 10004. (2020). ICAO global aviation safety. ICAO 2020–2022. ICAO, 162 p.

[3] Flight safety management. Appendix 19 to the Convention about the International Civil Aviation. (2016). 2nd ed. ICAO, 48 p.

[4] The Russian Federation Resolution № 1215 of 18.11.2014, 6 p. Available at: http://www.consultant.ru/document/cons_doc_LAW_171133/92d969e26a4326c5d02fa79b8f9cf4994ee5633b/ (accessed: 15.08.2022).

[5] The Russian Federation Resolution № 642 of 12.04.2022, 7 p. Available at: http://www.consultant.ru/document/cons_doc_LAW_414577/92d969e26a4326c5d02fa79b8f9cf4994ee5633b/ (accessed: 15.08.2022).

[6] The FL-248. About the Central control (oversight) and Local Government oversight in the Russian Federation. (2020). 78 p. Available at: https://base.garant.ru/74449814/ (accessed: 15.08.2022).

ation Government Resolution № 1064[7] of 30.06.2021. However, while conducting inspections and developing preventive actions, it is always advisable for an oversight body to have quantitative assessments (indicators) of risk.

Currently, guidelines regarding the description, composition, and the number of such indicators to make a risk forecast are not available while conducting inspections in those cases when HF have not manifested themselves yet in the form of events. It means that the "pro-activity" of risk management in the ICAO conception[8] while conducting inspections is not sufficiently implemented. Scientifically valid methods to fulfill these forecasts are not provided as well.

It is obvious that a variety of indicators will be different for various providers of aviation services but approaches to forecast risks can be general.

For the solution to the given problem, the use of artificial intellect elements in the form of neural networks, specifically, fuzzy (hybrid) as the most relevant to the distinctive nature of solvable problems, seems perspective.

1. Basic provisions of a risk-oriented approach and their applicability to supervising and control activities in Civil Aviation

The risk-oriented approach is the technique of arranging for oversight which assumes reducing the number of state inspections of business where the risk of violations is lower. Such an approach is used for the optimal use of organization assets, reduction of entity costs and the enhancement of activity efficiency of the state regulatory authorities.

The risk-oriented approach concept originally rose to view in 2015 with the enforcement of the FL-246, Article 8.1. The list of types of government control, using the risk-oriented approach and the rules for assigning activity to a category of risk, were formalized by Government Resolutions № 806[9] and № 245[10] in 2016–2017. Nevertheless, as [3] notes, the similar system of the risk management has been used much earlier-since 2003 in the customs and tax control. It stems from the domination of the fiscal managerial functions of the State over the specified time and from the necessity of tightening the financial discipline of regulated subjects when their activity is simultaneously boosted.

The risk-oriented approach is based on widely and long-discussed ideas of *Responsive regulation* [4–6] involved in search of the optimal ratio between the strict government control of business activity and the independent enterprise and entity performance.

The approach relies on the research results and the international practice which proved its efficiency. The article [7] provides several examples. For example, in Denmark, the control over the food market is exercised by five groups of hazards, and a normative frequency of inspections occurs twice a year. If there were not penal sanctions in the last four reports on inspections, a company is granted a top-class status, and the number of inspections reduces from five to three in the highest group of risk and from three to one in the lowest one.

The document[11] illustrates how the risk-oriented approach contributes to countering money laundering and corruption.

In the FL-248, Chapter 5 is dedicated to the risk-oriented approach issues. A concept is not given but it is stated that a probability of event occurrence, the consequence of which can be damage of different scale and severity to assets protected by law, is interpreted as the damage risk within the framework of the present Federal

[7] The Russian Federation Resolution № 1064 of 21.06.2021, 20 p. Available at: https://base.garant.ru/401423120/ (accessed: 15.08.2022).

[8] Doc. 9859. (2018). Safety Management Manual. 4th ed. ICAO, 218 p.

[9] The Russian Federation Resolution № 806 of 17.08.2016, 14 p. Available at: https://base.garant.ru/71473944/ (accessed: 15.08.2022).

[10] The Russian Federation Resolution №245 of 2.03.2017, 6 p. Available at: https://base.garant.ru/71625910/ (accessed: 15.08.2022).

[11] Manual of the risk-oriented approach in the supervisory activity application. FATF. Paris. Convenience translation by ANCO ITMCFM // FATF. Paris. March 2021, 124 p. Available at: https://www.fedsfm.ru/content/files/documents/fatf/2021/nadzor_web.pdf (accessed: 15.08.2022).

Law. This definition complies with a “technocratic concept of risk” [8] and the interpretation of risk for flight safety in conformity with the ICAO Standard from Appendix 19.

Six categories of risk, varying from low to exceptionally high, are established, a concept of the risk criterion as an assessing factor for the probability of negative event occurrence and its severity is defined. The determination of probability and severity criteria is carried out considering information about preceding events, caused by specified causes, as well as their observed frequency and the severity of consequences. While defining the criteria, the relevance of assessing inspectors’ fair practices, taking into consideration the accomplishment of their actions to mitigate risk, availability of control systems, providing information access, undergoing voluntary certification, and procuring agreements of insurance, is highlighted.

Under the government control, the federal body of executive authority, exercising the functions regarding the legal and regulatory framework in the stated sphere, categorizes an object in terms of risk. In CA, the State Aviation Safety Inspectorate, which has been implementing the transition for a risk-oriented model since 2017, is engaged in the activity, as the article [9] indicates. Concurrently, among others, the following summarized tasks have been posed:

- categorizing subjects of control by risk categories in accordance with the methodology approved by the Russian Federation Government Resolution № 806 of 17.08.2016;
- formulating requirements to develop a “dynamic model” of categorizing subjects of control based on statistics data and performance indices of activity for control subjects;
- developing the methodology of performance evaluation of final publicly significant results for the branches of activity under control.

It is necessary to note that the methodology of Government Resolution № 806 along with the FL-248 stipulated six categories of risk or hazard classes. Hence, special aspects of conducting supervisory activities were specified. However, later-enacted Resolution № 1064 reduced the number of risk categories up to four: high, high/medium, medium, low.

Categorizing an object is carried out depending on the combination of risk components – the probability of a negative event and its severity according to the Table of Appendix 1 of this Resolution. This Table can be easily transformed into a matrix (fig. 1) corresponding to the method of “consequences and probabilities” under GOST P-58771-2019[12], often called the “ICAO matrix” in aviation, since this method of risk management is recommended by the ICAO Safety Management Manual.

Группа вероятности

Группа тяжести	1	2	3	4
А	Высокий	Значительный	Средний	Средний
Б	Высокий	Значительный	Средний	Средний
В	Значительный	Значительный	Средний	Средний
Г	Средний	Средний	Низкий	Низкий

Fig. 1. Matrix of risk categories for control (oversight) of objects in CA

In addition, to take a decision concerning the type of unannounced control activity, a regulatory body establishes risk indices of violating the compulsory requirements. The indices are discrepancies or deviations from the parameters of object under control according to which we can assess a risk level. Such an approach is close to the “proactive methodology” of identifying HF in the ICAO Safety Management System.

An emphasis [9] is given to the supervising activity in the air traffic management sphere which encompasses air traffic organization and service, radio-technical support of flights and aeronautical telecommunication service, providing aeronautical and meteorological information, aerospace search and rescue in all the flight phases.

[12] GOST R 58771-2019 (ISO 3110–2019 NEQ). (2020). Risk Management. Technologies of Risk Assessment. Moscow: Standartinform, 85 p.

Table 1

Risk indicators and their characteristics

№	Indicator	Possible consequences	Regulation
1	Lack of radar control	1.Risks of collisions between A/C and A/C collisions with obstacles are increased. 2. Control of air traffic is complicated. 3. Control to follow the use of air space regulations is reduced	The Air Code of the Russian Federation regarding the control to follow the use of air space regulations. FAR №216, non-compliance with the Certificate concerning available observation facilities
2	Violation of the requirements during the probational period and personnel inspection	1. Systemic failures during the air traffic service. 2. Conducting the specific procedures with failures	The Order of the Russian Federation Ministry of Transport № 93[13] of 14.04.2010 with respect to functioning the system of training, certifying, period of probation
3	Flight Safety Management does not comply with the Air Laws and Regulations requirements	Risks of information lack regarding actual or potentially hazardous situations for Flight Safety or ATM-related drawbacks are increased	FR-642 and FAR-293 concerning the analysis on a regular and systematic basis by qualified specialists and ensuring flight safety while servicing air traffic
4	Drawbacks in maintaining the performance capabilities of flight radio-engineering support and aeronautical telecommunication facilities	Partial and/or incomplete issuance of information to a controller, aeronautical telecommunication facilities and equipment failures are possible	FAR-297 concerning maintenance of objects and flight radio-engineering support and aeronautical telecommunication facilities

Within the framework of the present study by experts of territorial bodies of the Federal Air Transport Agency and the Federal Transportation Inspection Service, four risk indicators were proposed for ATM organizations which are stated in Table 1.

The use of a fuzzy neural network is proposed for developing the method of forecasting risk, provided, manifestation of the given indicators is established during an inspection.

2. Building a fuzzy neural network to forecast risks

2.1. Features of fuzzy neural networks

For solving risk-related problems, including the aviation sphere, due to a high degree of uncertainty, the applications of the fuzzy-set theory are used which is expressed in a variety of academic papers on the given subject [10–12].

However, there are problems, the basic of which, emerge due to the necessity of determining a priori components of models (membership functions (MF) of fuzzy rule base). It makes the adaptation and training of the system impossible [13].

Neural networks have training and adaptation properties and can be trained how to control an object without possessing complete data about it such as a mathematical model. They comprise a big number of interrelated elements (neurons), each of which performs signal processing which allows for immense computation power and fault tolerance. At the same time, there is no definite algorithm to compute the required amount of network layers and the number of neurons in

[13] The Russian Federation Order of the Ministry of Transport № 93 of 14.04.2010 “About the Approval of the Procedure of functioning the continuous system of the professional training, including the issues of the certification, internship, the order of permit-to-work system, periodicity of upgrading skills of managerial and traffic control personnel”. System GARANT. 2010. 15 p. Available at: https://base.garant.ru/199197/ (accessed: 15.08.2022).

each layer which results in designing a network intuitively. Moreover, knowledge, accumulated by a network, is distributed among all its elements which makes it difficult to present a functional dependence between the object input and output in an explicit form [14, 15].

The Adaptive Network-based Fuzzy Inference System – ANFIS was proposed by J-S. R. Jang in 1992 to combine the advantages and counterbalance the disadvantages of these two methods. The system is described in detail in his work [16]. This is an artificial neural network based on the fuzzy inference system by Sugeno.

Such hybrid structures, integrating neural networks and fuzzy logic, acquire the best properties of both methods, and at the same time, they are released from their problems. On the one hand, they activate the computation power and the capacity of neural networks for training, on the other hand, the intellectual capacity of neural networks is intensified with fuzzy rules of making solutions appropriate for a "human" manner of thought. In fuzzy neural networks, the inference is made based on the apparatus of fuzzy logic, and MF settings are configured using algorithms of the neural network training.

Let us briefly consider the features of building the network under [15–17]. It is common knowledge that in an "ordinary" network (fig. 2) input signals x_i "interface" with weights w_i, and the sum of their products p_i forms input *net* of neuron:

$$P_i = x_i w_i;\ net = p_1 + p_2;\ i = 1, 2.$$

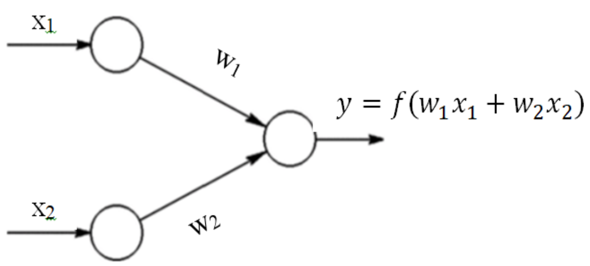

Fig. 2. The simplest single-layer neural network

The output neural signal is the transformation of input *net* with some activation function *f*.

$$y = f(net) = f(w_1x_1 + w_2x_2).$$

The fuzzy (hybrid) neural network is that one in which settings *x, w, p* are connected using not the ordinary addition and multiplication but by means of t-norm, t-co-norm[14] or other continuous operations. The fuzzy neural network is usually built on a multilayer one using AND, OR neurons.

For the fuzzy neuron AND (fig. 3), signals x_i and weights w_i are combined by means of t-conorm $p_i = S(x_i w_i),\ i = 1, 2$. Input is formed using a t-norm:

$$y = (p_1.p_2) = T(p_1.p_2) =$$
$$= T\big(S(w_1.x_1), S(w_{2.}x_2)\big).$$

If to assign T = min, S = max, the fuzzy neuron AND realizes the composition min-max:

$$y = min(w_1 \vee x_1, w_2 \vee x_2).$$

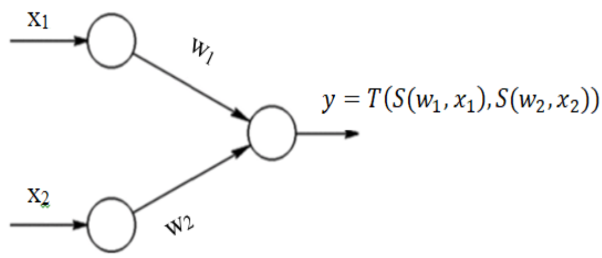

Fig. 3. The structure of the fuzzy neuron AND

In the fuzzy neuron "OR" (fig. 4), signals are also combined using t-norm $p_i = T$, $i = 1, 2$, and output is formed using t-co-norm.

$$y = (p_1.p_2) = S(p_1.p_2) =$$
$$= S\big(T(w_1.x_1), T(w_2x_2)\big).$$

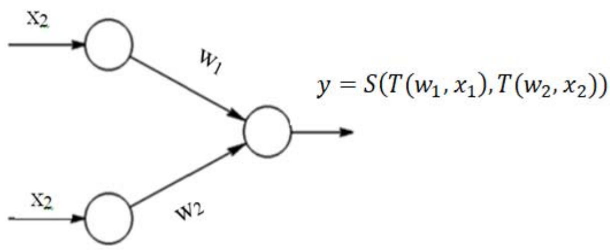

Fig. 4. The structure of the fuzzy neuron OR

[14] Determination of concepts "t-norm", and "t-co-norm". Available at: https://science.fandom.com/ru/wiki/Т-нормы,t-конормы_и_порядковые_суммы (accessed: 15.08.2022).

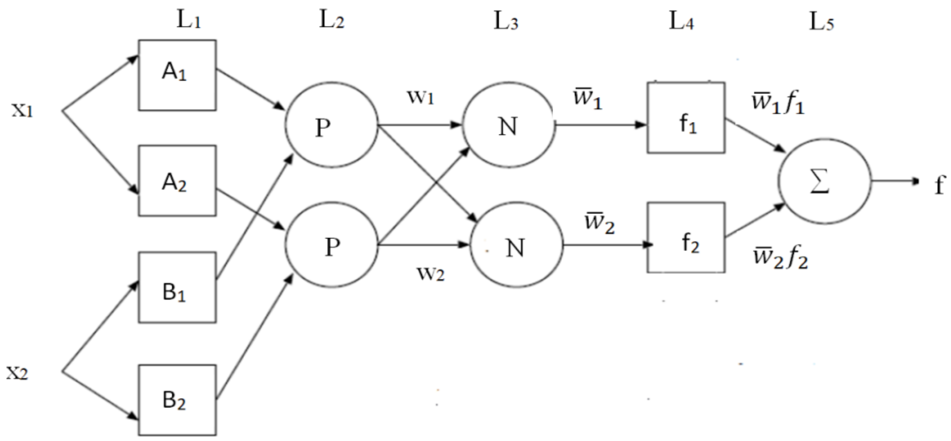

Fig. 5. Fuzzy (hybrid) neural network architecture

If to assign T = min, S = max, then the fuzzy neuron OR realizes the composition of max-min type.

Let us explain the network structure on the example of the system with two inputs x_1, x_2 and one output. The model of fuzzy inference by Sugeno uses the following rule:

– if x_1 is A_1 and x_2 is B_1, we have $y = f_1 = p_1x_1 + q_1x_{12} + r_1$,

– if x_1 is A_2 and x_2 is B_2, we have $y = f_2 = p_2x_1 + q_2x_{12} + r_2$.

ANFIS, realizing the given model, is presented in Figure 5.

Typically, the fuzzy network consists of five layers (L_1–L_5). Neurons in the network have the various structure and purpose. Let us denote $V_{L,\,I}$ as output of i-neuron of layer L.

The neurons of the first layer calculate Membership Function (MF) of fuzzy terms:

$$V_{1,i} = \mu_{A_i}(x_1), \text{ for } i = 1, 2; \; V_{1,i} = \\ = \mu_{B_{i-2}}(x_2), \text{ for } i = 3, 4.$$

Each neuron of the second layer calculates the product:

$$V_{2,i} = w_i = \mu_{A_i}(x|1) \quad \mu_{B_i}(x|2) \text{ for } i = 1, 2.$$

Neuron output presents the rule activation level.

Layer 3 normalizes the levels of rule activation:

$$V_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2} \text{ for } i = 1, 2.$$

Layer 4 calculates the conclusion of rules:

$$V_{4,i} = \overline{w_i}f_i = w_i(p_ix_1 + q_ix_2 + r_i) \\ \text{for } i = 1, 2,$$

where p_i, q_i, r_i are parameters of the node.

Layer 5 calculates the result of fuzzy inference as a sum of arguments:

$$V_{5,1} = \sum_i \overline{w_i}\, f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}.$$

Layers 1 and 4 are adaptive and provide the network training, the rest of the layers are fixed.

2.2. Methodology of building ANFIS network to solve the formulated problem

The network ANFIS can be built by means of the package Matlab. The purpose is to obtain a tool of forecasting organization risk under identified signs of one or several available indicators with different severity levels of their manifestation during inspections.

In order to organize a training data set, experts were proposed to assess the probable level of organization risk with various combinations of indicators manifestation from Table 1. For this purpose, a table was drawn up, four columns of which were corresponding to indictors, in

Table 2

Fragment of the expert survey table

№	INDICATORS				Risk level
	1. Lack of radar control	**2. Violation of the probation period and inspection requirements**	**3. Flight Safety Management does not comply with the requirements**	**4. Drawbacks in maintaining the condition of flight radio-engineering support, communication**	
1	Yes	No	Yes	Yes	
2	No	No	Yes	Yes	
3	No	Yes	No	No	

Table 3

Fragment of a data matrix for training a neural network

INDICATORS				RISK
1	**2**	**3**	**4**	
1	0	1	1	4
0	0	1	1	2
0	1	0	0	2

each line, one of combinations of their manifestations was assigned: "Yes" means that an indicator became apparent, "No" means an indicator is not available.

The expert task was copying an anticipated risk level appropriate for the combination of indicators manifestations in the given line, using the cells of column 5.

The risk level should be denoted according to the Russian Federation Government Resolution № 1064: "High", "High/Medium", "Medium"," Low".

The survey fragment is provided in Table 2.

The general number of combinations "Yes-No" with four indicators equals $2^4 = 16$. Five qualified specialist experts participated in the survey, thus, $16 \times 5 = 80$ risk assessments were obtained depending on the indicators under observation.

While building the network in Matlab, the manual [18] was used. For downloading into the ANFIS editor, the acquired data were transformed into the matrix 80×5, the fragment of which is given in Table 3. In the matrix, one unit corresponds to the version "Yes" (indicator available), null does the version "No" (indicator not available).

The indicators were enumerated in conformity with Table 1, experts-assigned risk levels were given numeric values: 'High" – 4, "High/Medium" – 3, "Medium" – 2, "Low" – 1.

The set of databases for training is assigned by the command *edit* and saved by expanding *.dat.* The editor window of hybrid systems is called using the command *anfisedit* (fig. 5) and, we download the matrix of the training kit. Furthermore, we generate the structure of fuzzy inference FIS of Sugeno type by selecting the number of MF for the terms of input variables equal 2 and the type of Gauss's MF.

We assign settings of network training. Default Error Tolerance is 0 and changing is not advised. Let us determine the number of training cycles (*Epochs*) 20.

A hybrid method of training is selected, which presents a combination of the least-squares method and the method of gradient decreasing. We conduct the network training (fig. 6).

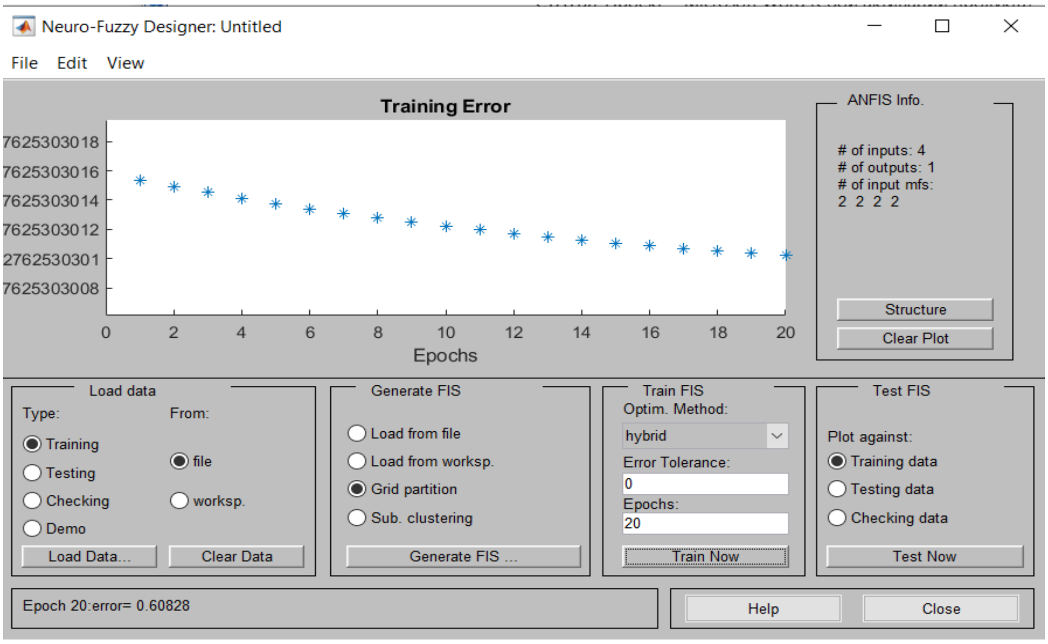

Fig. 6. Results of the network training in the Hybrid Systems Editor window

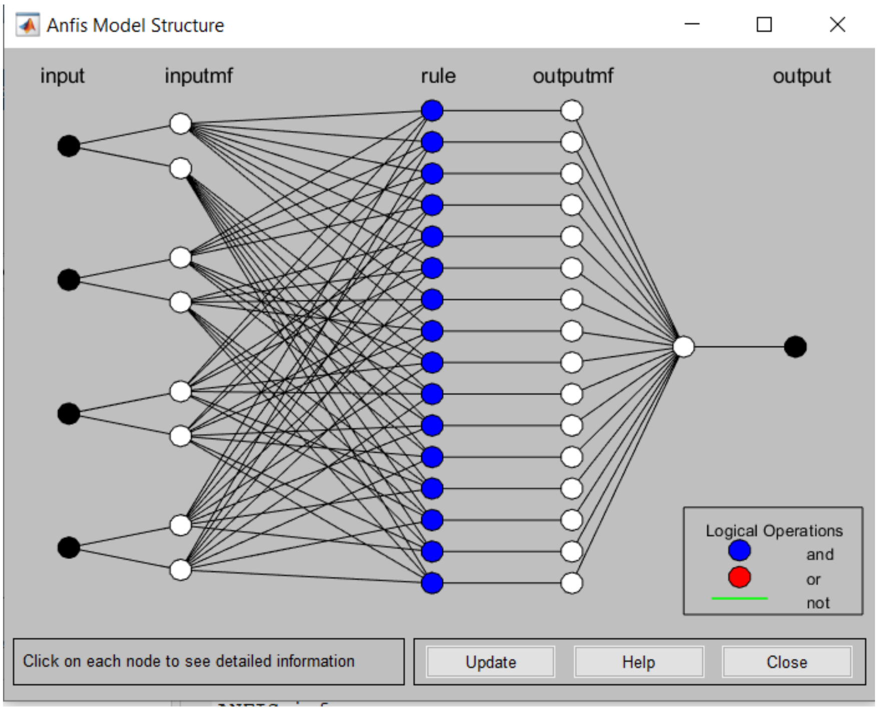

Fig. 7. The structure of the generated fuzzy neural network

The structure of the built network (fig. 7) is called by a key *Structure*.

The Figure shows the number of neurons in each layer, the neural type (in this case, neurons AND not available), and neurons and layers links are visible.

The use of interface to view the rules of the generated system of fuzzy inference, which is shown in Figure 8, allows for the solution to the formulated problem of risk forecasting with any combinations of indicators and any degree of their manifestation.

Fig. 8. Output of the results of forecasting risks for the object based on the identified manifestations of risk indicators

Let us introduce an exponent "Degree of risk indicator X manifestation" as a real number from 0 to 1, which shows the degree of the given indicator manifestation based on the control results. For example, if indicator 1 is clearly and uniquely observed, we reckon $X_1 = 1$. If the availability of indicator 2 can be considered as manifesting to the extent of 50%, then $X_2 = 0.5$, etc. The indicator X value for each observed risk indicator is established by an inspector. The different degree of manifestation, frequently available in practice, therefore, the different hazard degree of defective features and discrepancies, their "fuzziness" is also taken into consideration.

The generated and trained fuzzy neural network allows us, assigning values of all $X_i = 1–4$, to obtain a quantitative assessment of R risk forecast varying from 1 to 4, i.e., from low up to high. To complete this task, it is necessary to assign values X_i for indicators from 1 to 4 in succession, using white space, in the window *Input* in the lower left-hand side of the configuration *Rule Viewer* or relocate red cursors to the respective positions in the MF columns.

For example, $X_1 = 1$; $X_2 = 0.5$; $X_3 = 0$; $X_4 = 0.25$ are assigned in Figure 8. These values (Input 1, 2, 3, 4) can be viewed over the respective MF columns. We have the system-computed risk assessment R = 3.11 over the rightmost column of results (*Output*). It means that in the given case, a forecasted risk is slightly greater than high/medium, however, substantially less than high.

In general, the interpretation of the result obtained is an expert task carrying out control and supervisory functions. It is obviously essential to take into consideration a system fault in this context.

Matlab makes it possible to obtain a graphic interface to view the surface of the generated

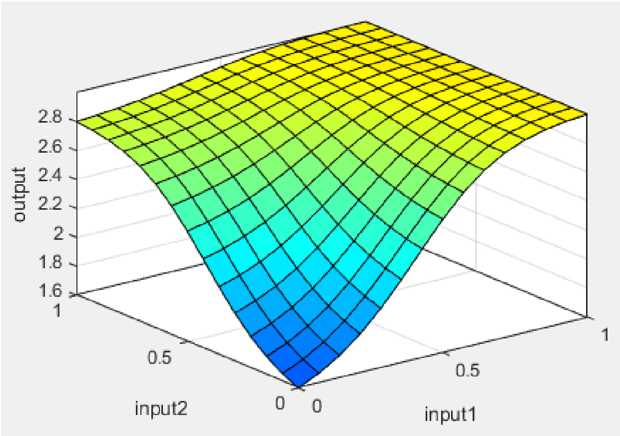

Fig. 9. The surface of the risk level in coordinates X_1/X_2 if $X_3 = X_4 = 0$

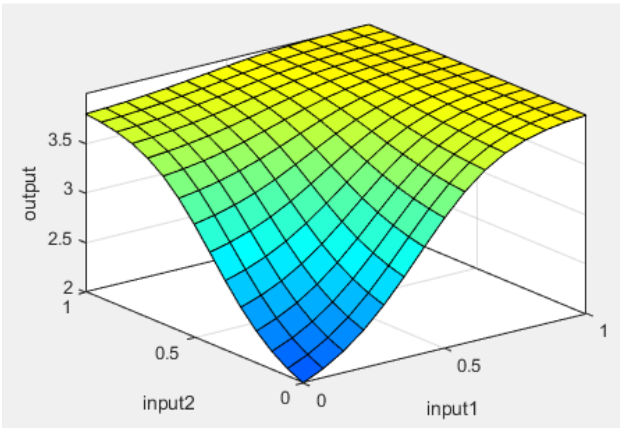

Fig. 10. The surface of the risk level in coordinates X_1/X_2 if $X_3 = X_4 = 1$

system as an additional option. Figures 9 and 10 illustrate the surfaces of the risk forecast result in coordinates X_1/X_2 under different fixed values X_3 и X_4.

Conclusion

While conducting control and supervisory activities in airlines to assess a risk level of an object, it is necessary to take into consideration manifestations of risk indicators. It will boost the “proactive” (in ICAO conception) component of the risk-oriented approach towards inspections of organizations.

The neural networks can be the tool of forecasting. The feasibility of using the adaptive neural fuzzy inference system (ANFIS), possessing the advantages to solve the given task compared to other networks, is shown. The method allows us to obtain substantiated quantitative risk assessments depending on “the degree of risk indicator manifestation”. The network training can be conducted based on expert survey data similar to the stated study, also on actual results of inspections and investigations of aviation events as they accumulate.

The applicability of the network is shown as an example of risk indicators for the air traffic management organization, but the methodology can be used in any entity of Civil Aviation not only during an inspection but also during the self-control within the framework of the valid Flight Safety Management System.

The generation and applicability of the network in the software package Matlab can be conducted by specialists of control authorities and inspections (departments) on flight safety of airlines which do not have specialized mathematical knowledge and skills in the software domain.

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