Intelligent System for Supporting Collaborative Decision Making by the Pilot/Air Traffic Controller in Flight Emergencies

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Abstract

For comprehensive accounting of the factors influencing the collaborative decision making (CDM) process by the pilot/air traffic controller in the flight emergency (FE), a conceptual model of the adaptive Intelligent System for Supporting Collaborative Decision Making (ISSCDM), which considers dynamic, static and expert information about the state of the control object (aircraft), environment (characteristics of air traffic control zone and aerodromes) and Air Navigation System operators (characteristics of the pilot/air traffic controller), was built. ISSCDM by the pilot/air traffic controller in the FE uses CDM models based on an artificial neural network.

For assessing the risk of CDM by the pilot and air traffic controller in the FE, a four-layer recurrent neural network with additional inputs – biases was developed: the first layer (input) – the losses in the FE depending on the flight situation; the second layer (hidden) – the normative time of technological procedures for FE parrying; the third layer (hidden) – the normative sequence of technological procedures for FE parrying; the fourth layer (output) – the risk assessment in FE. The developed neural network model due to the biases makes it possible to take into account the interaction between the pilot and air traffic controller when performing technological procedures on FE parrying and with the help of feedback to correct the predicted CDM risk assessment based on dynamic data about compliance by the operators' coordinated standards of time and normative sequences of actions.

With the help of NeuroSolutions neuroemulator (version 7.1.1.1) on the example of FE "Failure and fire of the engine on the aircraft when climbing after take-off" the multilayer feedforward perceptron with biases was built and trained with the teacher by the procedure of the error backpropagation.

Keywords

Artificial neural network, bias, coordinated actions, interaction, neuroemulator, risk assessment, technological procedures

1. Introduction

Flight safety in the aviation industry is very important. Despite the significant amount of passengers in previous years, statistics show that flights have never been safer. From 1959 to 2017 years, in 500 aviation accidents with commercial passenger aircraft (ACFT) 29 298 people died. However, between 2008 and 2017 years, 2 199 people (less than 8% of the total) was killed as a result

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of 37 accidents. In 2017 year, for the first time in at least 60 years of aviation's existence, there were no fatalities on commercial ACFT. Even 2018 year, which saw a total of 15 catastrophes, ranks third in flight safety in history. The probability of a passenger dying in an aviation accident is much low compared to other modes of transport, such as a car or bicycle accident, as well as other more unexpected cases, such as a random shot from a pistol or a dog attack [1]. The continuous rise of the flight safety level can be explained by many factors. ACFT have become more reliable. Safety systems and protocols have improved significantly. A number of design decisions have had a substantive impact on accidence, including improvements in the aerodynamic characteristics and design of the ACFT, construction failure criteria, improvement of cockpit instruments, and an increase in the number of operated ACFT with automatically controlled flight [2–3]. Scientific advances have also allowed the aviation industry to better understand how the human factor influences flight safety. At the same time, important enhancements in production processes, ACFT operation, and regulation have also been achieved [4]. Despite improvements of ACFT and air traffic control (ATC) systems, the human factor still has an appreciable impact on flight safety [5–6].

2. Analysis of the latest research and publications

In the reports on the state of flight safety in civil aviation of the members of the Agreement on Civil Aviation and on the Use of Airspace [7], statistics show a certain dynamics of aviation accidents due to the human factor (Table 1, Figure 1).

As is clear from Table 1 and Figure 1, in the period from 2012 to 2014, the indicator of aviation accidents due to the human factor has remained at the level 80-83%, in 2015 has decreased to 70%, in 2016 has sharply increased to 94%, and in 2017-2018 has declined again. Every three of the four incidents occur due to communication disorders and difficulties in understanding between the pilot and the air traffic controller (ATCO) [8].

During the flight, the pilot and the ATCO are in constant interaction, in the process of which there is a coordination of actions, planning of joint activities, division of functions, etc. [9].

The process of interaction is classically considered as one that includes three components (Table 2). The interaction between the pilot and the ATCO can be defined as a professionally determined, dynamic form of streamlining the activity of Air Navigation System (ANS) operators, which regulates their functions and responsibilities and is manifested in purposeful interconnection, interaction, understanding, and cooperation. Interaction can be carried out in the form of collaborative decision making (CDM) by ANS operators based on the mutual exchange of useful information [10].

In the course of research of the errors arising during the interaction of ATCO with pilots ten typical types of errors are allocated and the frequency of their occurrence is defined [11]. The most common errors are violations of the radio communications rules (26%) and contradictory flight information (22%). Next are: wrong ATCO commands (10%); violation of interaction between ATCO of adjacent zones (8%); lack of radio communication (8%); lack of radar control of the aircraft (6%); failure of the crew to communicate with serviceable radio equipment (6%); no report about aviation accident (6%); non-execution of ATCO commands (4%); fuzzy ATCO commands (4%) (Figure 2).

One of the approaches to increase the efficiency of CDM by ANS operators, especially in extreme situations, is the introduction of Intelligent Decision Support Systems (IDSS) [12–13].

The purpose of the article is a presentation of the Intelligent System for Supporting Collaborative Decision Making (ISSCDM) by the pilot/ATCO in the flight emergency (FE), which uses CDM models based on an artificial neural network (ANN).

3. Conceptual model of Intelligent System for Supporting Collaborative Decision Making by the pilot/air traffic controller in the flight emergency

In general, IDSS can be defined as an interactive computer system, designed to support various activities of a specialist during decision making in poorly structured and unstructured problems, based on the use of models and procedures for data and knowledge processing based on artificial intelligence technologies [12–13].

Table 1
Data of flight safety reports for 2012-2018 years.

Reporting year	Human factor, %	Failures and malfunctions of aircraft, %	Adverse external influences, %
2012	80	20	-
2013	83	15	2
2014	82	16	2
2015	70	24	6
2016	94	6	-
2017	82	17	3
2018	75	25	-
In average	81	17	2

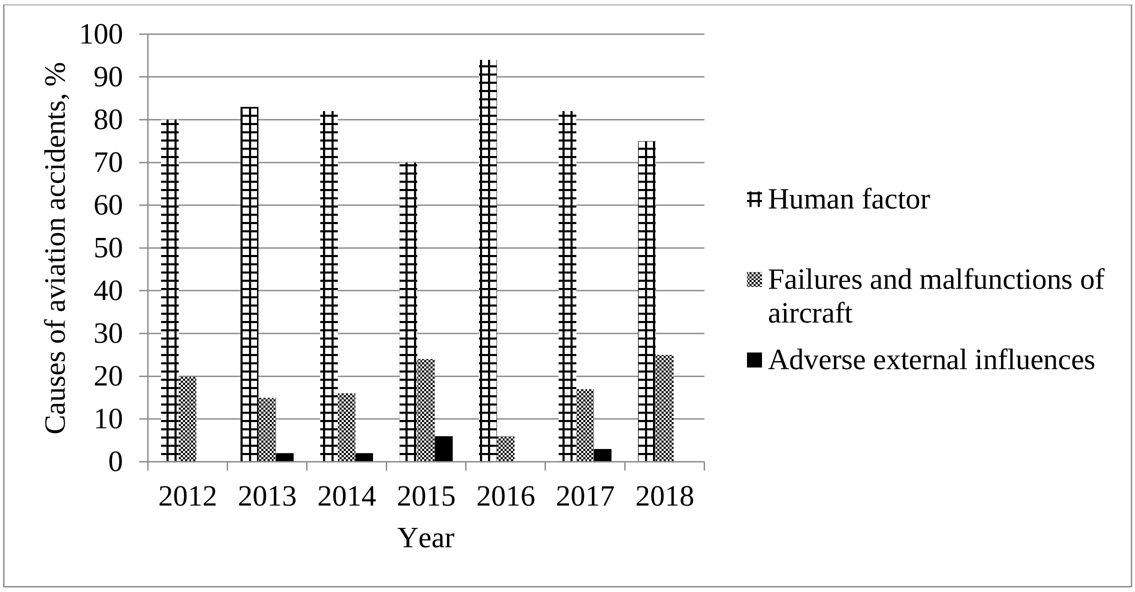

Figure 1: Graphical interpretation of flight safety report data for 2012-2018 years

Table 2
Components of the interaction process

Component	The essence of the component
Communicative (Latin communico – connect, communicate)	Active exchange of information between those who report it (communicator) and those who perceive it (recipient)
Socio-perceptual (Latin socialis – public + perception – perception)	The process of perception by communication partners of each other and the establishment of mutual understanding on this basis
Interactive (Latin inter – between + activus – active)	Different phenomena of interaction

The main characteristics of modern IDSS are given in Figure 3.

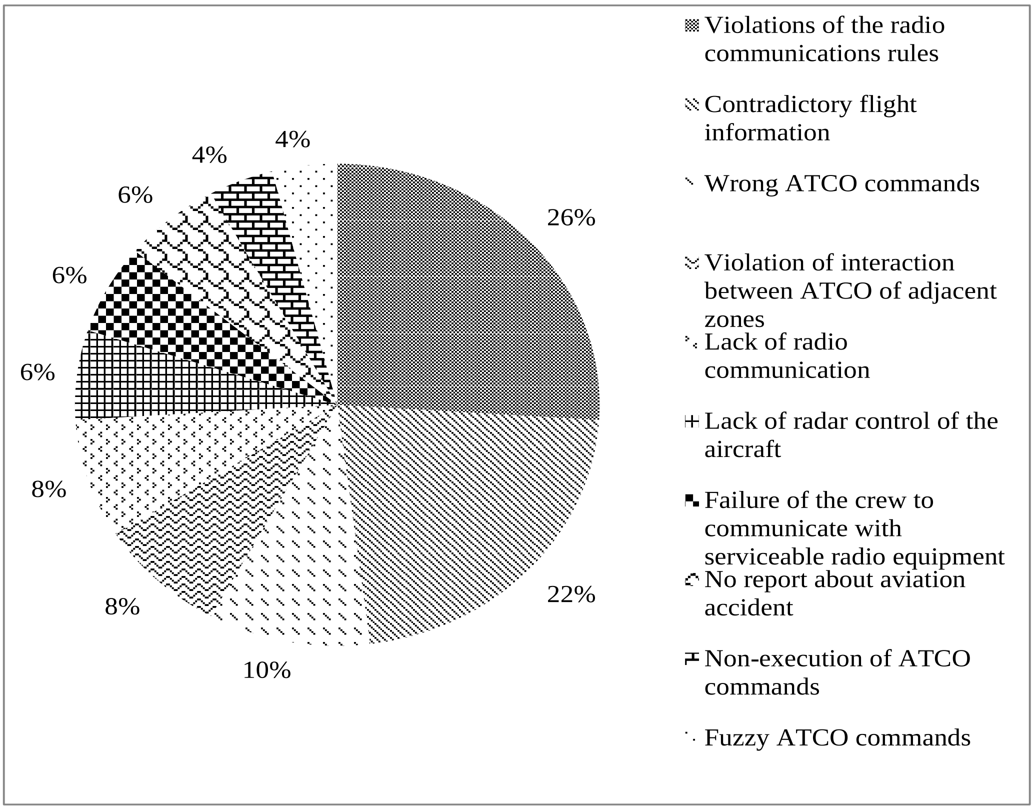

Figure 2: Distribution of errors that occur in the process of interaction between ATCO and pilots

Research has shown, that CDM by the pilot/ATCO in the FE requires ANS operators to analyze significant amounts of diverse information. To comprehensively take into account the factors influencing the CDM process in the FE, it is necessary to build an adaptive ISSCDM, which considers static, dynamic, and expert information about the state of the control object (ACFT), the external environment (characteristics of the ATC zone and aerodromes), and ANS operators (characteristics of the pilot/ATCO).

The main tasks of ISSCDM by pilot/ATCO in the FE are:

1. Collection of data about the state of the control object (ACFT), the external environment (characteristics of the ATC zone and aerodromes), and ANS operators (characteristics of the pilot/ATCO).
2. Forecasting the development of the flight situation.
3. Formation of a set of alternative actions (for example, the continuation of the flight to the aerodrome of destination (alternative) or performance of forced landing).
4. Evaluation of the effectiveness of possible alternatives and formation of recommendations for determining the optimal variant of action.

The tasks of ISSCDM are related to the necessary data, which can be divided into three categories: static, dynamic (operational), and expert.

The static information about the aircraft includes:

a) planning data that the system receives from the flight plan:

- ACFT identification index;
- flight rules and flight type;
- type of aircraft and category of turbulence;
- aircraft equipment;
- departure airport;
- estimated time of departure;
- ACFT take-off/landing minima;
- cruising speed;
- cruising echelon;
- flight route;

- destination aerodrome and the total estimated elapsed time;
- alternate aerodromes;
- fuel supply;
- total number of people on board;
- emergency rescue equipment, etc.;

b) tactical and technical characteristics of the ACFT, describing its operational properties:

- wingspan;
- length of the ACFT;
- ACFT height;
- wing area;
- maximum roll angle;
- aerodynamic quality;
- mass of empty ACFT, normal take-off, maximum take-off;
- internal fuel;
- number and type of engines, power;
- maximum speed;
- cruising speed;
- vertical speed;
- flight range;
- practical flight ceiling;
- the runway length required for landing under standard conditions;
- the number of crew members, etc.

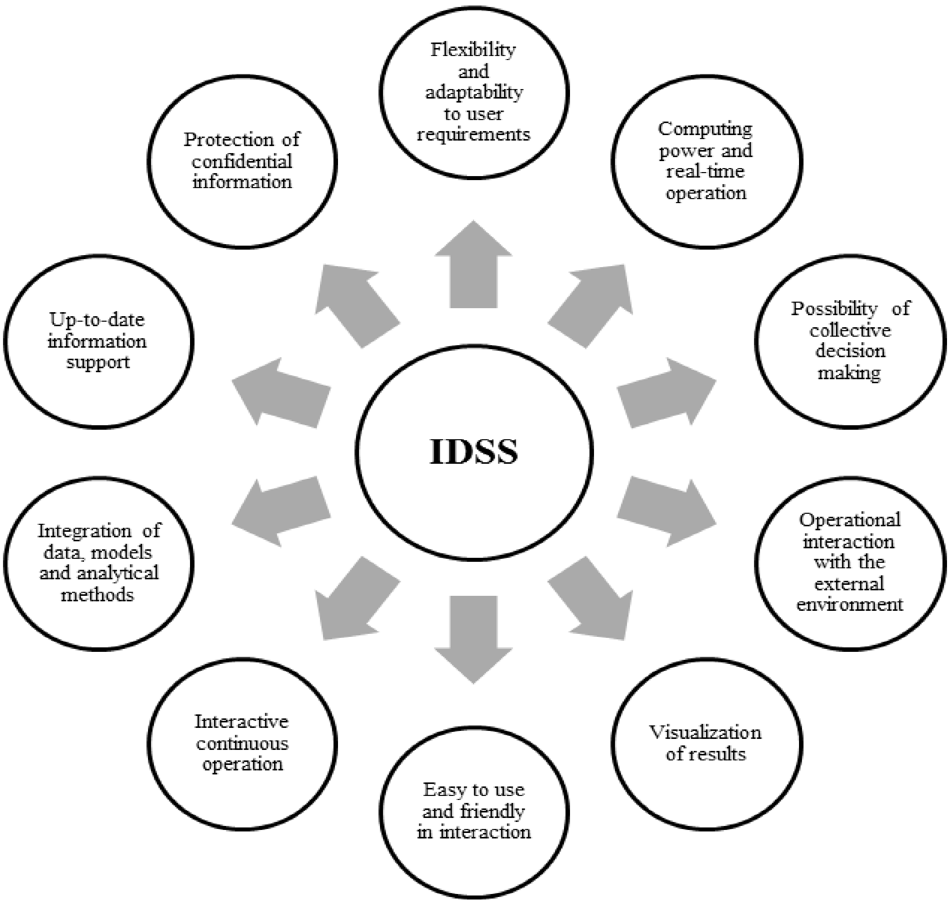

Figure 3: The main characteristics of modern IDSS

Dynamic information about the ACFT includes monitoring data, obtained in the process of direct observation of the ACFT:

- type of flight situation;
- state of the ACFT;
- height of the ACFT;
- coordinates of the ACFT;
- flight course of the ACFT;
- actual landing mass of the ACFT.

The static information about the ATC zone and aerodromes includes the following data:

- scheme of air routes and location of navigation means;
- limits of reception-transfer of ATC;
- air navigation and airport fees;
- coordinates of aerodromes;
- heights of aerodromes;
- minimum of aerodromes for take-off/landing;
- landing approach schemes at aerodromes;
- number and type of runways at aerodromes (artificial or ground);
- runway length;
- runway landing angle;
- the slope of the runway;
- radio navigation, lighting, and emergency rescue equipment of aerodromes;
- availability of a handling service, customs service, border and migration control service at aerodromes, etc.

Dynamic information about the ATC area and aerodromes includes:

- air situation;
- prohibitions and restrictions on the airspace use;
- condition of radio navigation and lighting equipment (capacity or incapacity);
- condition of the runway (repair works, time of the release of the runway, coefficient of adhesion, presence of snow, slush, water, ice, soil moisture and strength, snow strength);
- meteorological conditions on the route and at aerodromes (dangerous weather phenomena, clouds, and visibility, atmospheric pressure, wind direction and strength, actual temperature);
- the readiness of emergency services at aerodromes.

The static information about ANS operators (pilot/ATCO) includes the following data:

- educational level;
- work experience in the specialty;
- specialist class, which is determined by the knowledge, skills, and abilities acquired during training and professional activities;
- minimum of pilot-in-command for take-off/landing;
- experience of action in FE;
- individual-psychological characteristics (temperament, attention, perception, thinking, imagination, nature, will, health, experience, memory);
- psychophysiological characteristics (time delay of reaction, neuromuscular delay, time for decision making, emotional type, sociotype);
- socio-psychological characteristics (system of benefits under the influence of social, economic, legal, political, moral factors).

Dynamic information about ANS operators (pilot/ATCO) includes:

- composition of the ACFT crew;
- composition of the ATCO team.

A conceptual model of ISSCDM by pilot/ATCO in the FE, which uses CDM models based on ANN, was constructed (Figure 4).

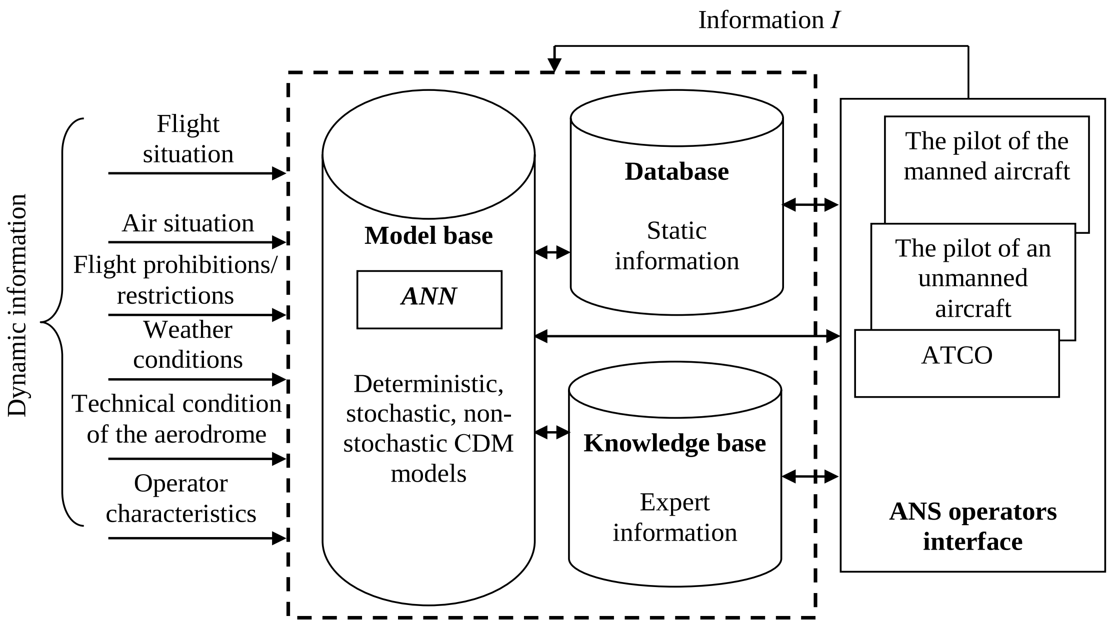

Figure 4: Conceptual model of ISSCDM by ANS operators in the FE

Analysis of Figure 4 allows drawing concluding the need to create databases of two types. The first group includes databases, which are a stationary source of data – they are created before the start of ISSCDM; to the second – a dynamic data source – databases, which are built by the system itself in the processing of dynamic information about the ATCO, ATC zone and aerodromes, ANS operators and further used by it.

The first grope will include the following databases:

- static information on the ACFT;
- static information on the ATC zone and aerodromes;
- static information on ANS operators.

The basis of the second group will be:

- dynamic information on the ACFT;
- dynamic information on the ATC zone and aerodromes;
- dynamic information on ANS operators.

Based on the information received from ANS operators, it is possible to adjust the bases of data, models, and knowledge.

When creating a database, it is important to adhere to the principle of development, which is caused by the specifics of the control object and external conditions – their dynamics. This should affect both the choice of the software platform and the database structure.

The algorithm of functioning of the ISSCDM prototype is given in Figure 5. When building ISSCDM it is necessary to implement the basic concepts of information systems, such as interactivity, power, accessibility, flexibility, reliability, robustness, and manageability [14–15].

4. Method of intelligent data processing in risk assessment of collaborative decision making by the pilot and the air traffic controller in the flight emergency based on an artificial neural network

The main directions of Decision Support Systems intellectualization are the creation of expert and neural network systems [16–17].

The main disadvantage of expert systems is the possibility of their non-deterministic response when small changes in the input data can lead to output results that differ significantly. Additional complexity – even with similar input signals, the search for a solution can take place on different branches of the decision tree, as a result of which the response time may vary depending on the depth of the search.

Expert systems can give only those results for which they have the appropriate logic. A wide variety of symptoms leads to a "combinatorial explosion" [16]. Therefore, in tasks with a large number of factors influencing decision making, all of which are actually impossible to cover by the rules, it is advisable to use artificial neural network (ANN).

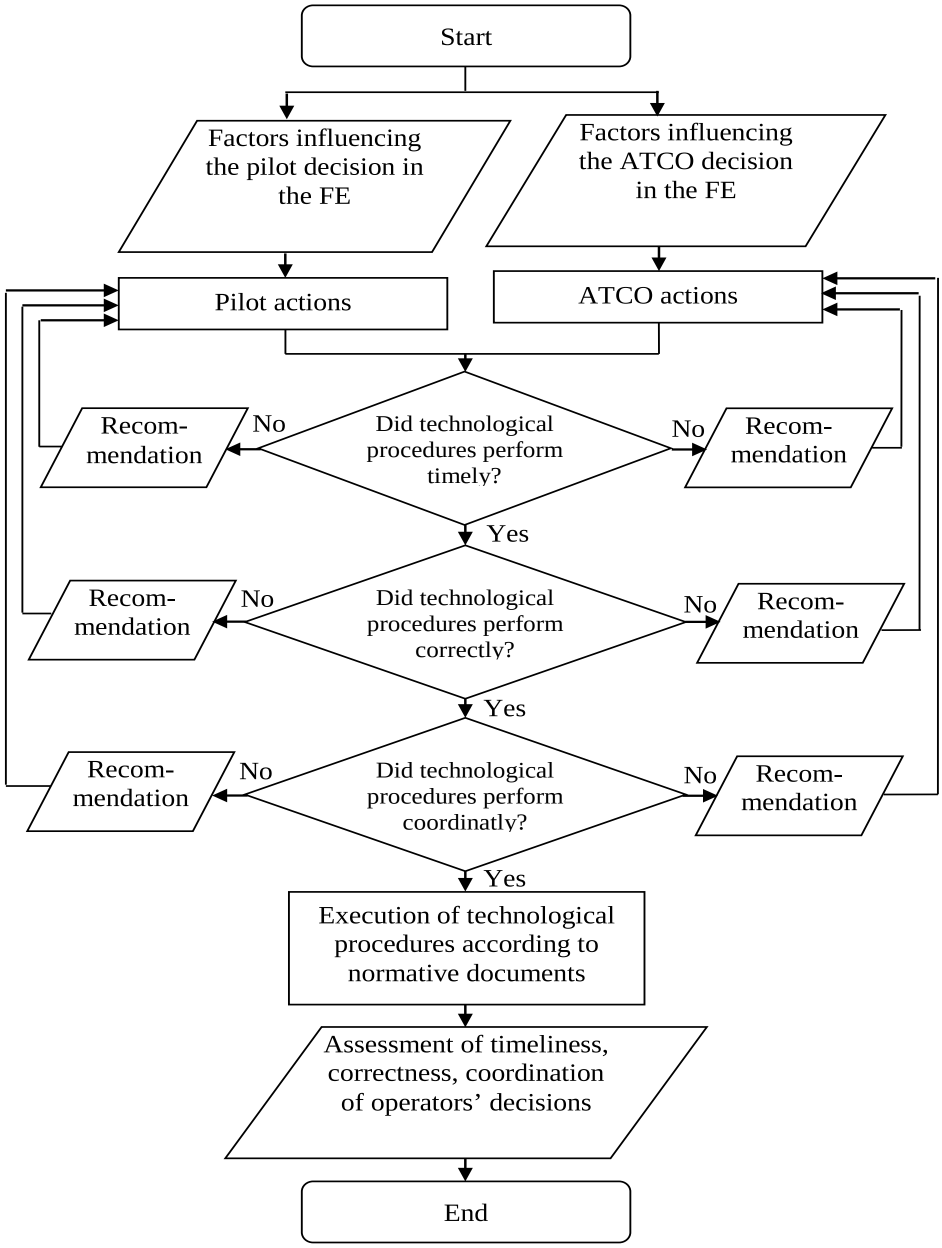

Figure 5: The algorithm of functioning of the ISSCDM prototype

Thus, the advantages of neural networks are their ability to train on examples, work in real-time, deterministic behavior in time (the ability to work with data that were not included in the training sample) and robustness (the ability to work with incomplete input data) [18–19], which determines the choice of the ANN device to solve the problem of optimizing the interaction of the pilot and the ATCO in the process of CDM in the FE.

The structure of the method of intelligent data processing in the risk assessment of CDM by the pilot and the ATCO in the FE based on ANN is presented in Figure 6.

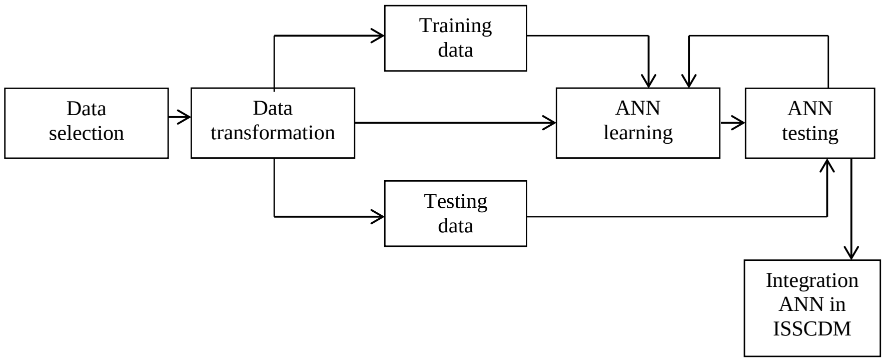

Figure 6: The structure of the method of intelligent data processing in the risk assessment of CDM by the pilot and the ATCO in the FE based on ANN

During operation, the ANN generates an output signal Y in accordance with the input signal X, implementing some function z: $Y = z(X)$. If the network architecture is specified, then the type of function z is determined by the values of synaptic weights w and network biases θ. Take for Z the set of all possible functions z, that corresponds to given network architecture.

Let a function r be the solution to some task. $Y = r(X)$, specified by pairs of inputs and *outputs* $(X^1, Y^1), \ldots, (X^k, Y^k)$, for which $Y^k = r(X^k)$, $k = 1, \ldots, N$. E is an error function (quality functional), which shows for each function z the degree of approximation to r.

To solve the task with the help of ANN of the given architecture means to construct a function $z \in Z$, selecting the parameters of neurons (synaptic weights w and biases θ) so that the quality functionality becomes the optimum for all pairs (X^k, Y^k).

Thus, the task of learning a neural network is determined by a set of five components: $<X, Y, r, Z, E>$. Learning is to find the function z that is optimal for E. It looks like an iterative procedure, at each step of which there is a reduction of error.

Function E can look arbitrary. If a set of examples for learning and a means of calculating the error function are selected, then learning ANN is reduced to the problem of multidimensional optimization, to solve which the following methods can be used [17–19]:

- local optimization with the calculation of partial derivatives of the first order (gradient descent method, methods with one- and two- dimensional optimization in the anti-gradient direction, gradient approximation method);
- local optimization with the calculation of partial derivatives of the first and second order (Newton, Gauss-Newton, Levenberg-Marquardt method, Quasi-Newton methods);
- stochastic optimization (random search, annealing simulation, Monte Carlo method);
- global optimization (search of values of variables on which the objective function depends).

Preference is given to the methods that can teach ANN in a small number of steps and require a small number of additional variables, due to the limitation of computing resources (algorithms for calculating partial derivatives and one-dimensional optimization).

The training of ANN, in this case, is the result of its operation, rather than the prior filling of human knowledge, as in the case of the use of expert systems.

For learning ANN with the teacher the procedure of error backpropagation was chosen [17], the essence of which is to propagate the error from the network outputs to the inputs in the direction opposite to the propagation of signals.

A nonlinear sigmoid activation function was used for ANN training (1):

$$f(x) = \frac{1}{1 + e^{-ax}}, \tag{1}$$

where $a > 0$.

The output fields for network learning were estimated by the method of the least squares with backlash when the minimizing objective function of the ANN error is the value (2):

$$\delta = \sum_i P\left(\frac{Y_i^{'} - Y_i}{\varepsilon}\right), \qquad (2)$$

where $P(\Delta) = \begin{cases} (|\Delta| - 1)^2, \text{if } |\Delta| \geq 1, \\ 0, \text{if } |\Delta| < 1; \end{cases}$

Y_i’ and Y_i – respectively, are the output according to the training sample (desired) and the actual output ANN;

ε – is a backlash, which can vary from zero to the limit of the range of changes in the values of the output field. The network has learned to predict the values of this field with an accuracy of ±5% of the range of risk value changes, which fully satisfies the task statement.

To learn ANN the gradient descent algorithm with perturbation was used, which allows to overcome local inequalities of the error surface and not to stop at local minima. ANN learning algorithm:

Step 1. Initialization of weights.

Weights $w^{(k)}_{ij}$ in all layers are set randomly in the interval [0-1].

Step 2. Representation of the new input vector X and the corresponding desired output vector Y’.

Step 3. Direct passage: calculation of the actual output.

Output $Y^{(k)}_i$ for the i-th neuron in the k-th hidden layer, $k = 1, \ldots, K$ та Y_i in the output layer is calculated by formulas (3)-(4):

$$Y_i^{(k)} = f_\delta\left(w_{i0}^{(k)} + \sum_{j=1}^{H_{k-1}} w_{ij}^{(k)} Y_j^{(k-1)}\right), k = 1, \ldots, K, \text{ where } Y_j^{(0)} = X_j; \qquad (3)$$

$$Y_i = f_\delta\left(w_{i0} + \sum_{j=1}^{H_k} w_{ij}^{(k+1)} Y_j^{(k)}\right), k = 1, \ldots, K, \text{ where } Y_j^{(0)} = X_j, \qquad (4)$$

where H_k – is the number of neurons in the k-th hidden layer.

Step 4. Feed passage: adaptation weights and thresholds.

Use a recursive algorithm that starts at the input layer and returns to the first hidden layer (5):

$$w_{ij}^{(k)}(t+1) = w_{ij}^{(k)}(t) + \eta \delta_i^{(k)} Y_j^{(k-1)}, k = 1, \ldots, K, \qquad (5)$$

where η – is the rate of speed training, $0<\eta<1$.

For $k = k + 1$ member δ_i^k is known, it describes error (6) and can be calculated for all other cases (7):

$$\delta_i^{(k+1)} = (Y_i^{'} - Y_i) Y_i (1 - Y_i); \qquad (6)$$

$$\delta_i^{(k)} = Y_i^{(k)}(1 - Y_i^{(k)}) \sum_j \delta_j^{(k+1)} w_{ji}^{(k+1)}, k = 1, \ldots, K, \qquad (7)$$

where $Y_i^{(k)}(1 - Y_i^{(k)})$ – is the derivative of the sigmoidal function relative to its argument.

Step 5. Repetition from step 2.

The output vector (result) will depend on the type of flight situation, as well as on the coherency of the actions of the pilot and the ATCO during performing the technological procedures for parrying the FE. The best variant of CDM by ANS operators in the FE is selected based on minimizing the potential risk (8):

$$Y_{opt} = min\{r_l\}. \qquad (8)$$

To assess the risk of CDM by the pilot and the ATCO in the FE a four-layer (two layers are hidden) recurrent neural network with biases was developed [20–21] (Figure 7). Multilayer ANN can approximate any functional dependence due to hidden layers of neurons and is capable of learning. The dynamics of recurrent networks is a very important property for a complex socio-technical ANS, as feedback changes the inputs of neurons, which leads to a change in the state of ANN [20–21].

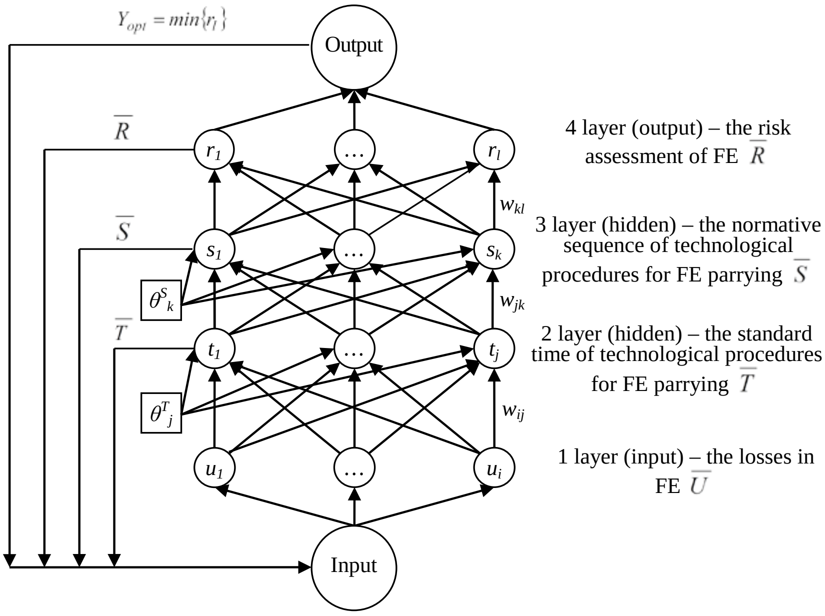

Figure 7: Neural network model for risk assessment of CDM by the pilot and the ATCO in the FE

Consider the ANN model in Figure 7.

The first layer (input) – corresponds to the losses in the FE depending on the type of flight situation ($\overline{U}$). The second layer (hidden) – the standard time to perform technological procedures for FE parrying ($\overline{T}$). The third layer (hidden) – the normative sequence of technological procedures for FE parrying ($\overline{S}$). The fourth layer (output) – the risk assessment of FE ($\overline{R}$). Additional input bias $\overline{\theta}$ characterizes the interaction of ANS operators.

Output vectors of the second, third, fourth layers (9)-(11):

$$\overline{T} = f(\overline{W}_1, \overline{U} - \overline{\theta}^T), \qquad (9)$$

$$\overline{S} = f(\overline{W}_2, \overline{T} - \overline{\theta}^S), \qquad (10)$$

$$\overline{R} = f(\overline{W}_3, \overline{S}), \qquad (11)$$

where $\overline{W}_1$ – are the weights that take into account the probability of violation of the standard time of technological procedures for FE parrying: $\overline{W}_1 = \{w_{ij}\}$;

$\overline{W}_2$ – are the weights that take into account the probability of violation of the normative sequence of technological procedures for FE parrying: $\overline{W}_2 = \{w_{jk}\}$;

$\overline{W}_3$ – are the weights that take into account the probability of complicating the flight situation (for example, engine failure can lead to a fire): $\overline{W}_3 = \{w_{kl}\}$;

$\overline{\theta}^T$, $\overline{\theta}^S$ – are the biases of indicators of timeliness and correctness of technological procedures for FE parrying at joint coordinated actions of ANS operators: $\overline{\theta}^T = \{\theta_j^T\}$; $\overline{\theta}^S = \{\theta_k^S\}$.

The following output signals of vectors of ANN layers are set $\overline{T}$, $\overline{S}$, $\overline{R}$ (12):

$$T,S,R = \begin{cases} 1; \text{ if } \; f(w_{ij}u_i - \theta_j), f(w_{jk}t_j - \theta_k), f(w_{kl}s_k) > 0 \\ 0; \text{ if } \; f(w_{ij}u_i - \theta_j), f(w_{jk}t_j - \theta_k), f(w_{kl}s_k) \le 0 \end{cases}, \qquad (12)$$

where f – is a nonlinear activation function.

Using the neuroemulator NeuroSolutions version 7.1.1.1 (development of NeuroDimension, Inc.) on the example of FE "Failure and fire of the engine on the aircraft when climbing after take-off" the multilayer feedforward perceptron with biases was built and trained with the teacher by the procedure of the error backpropagation (Figure 8).

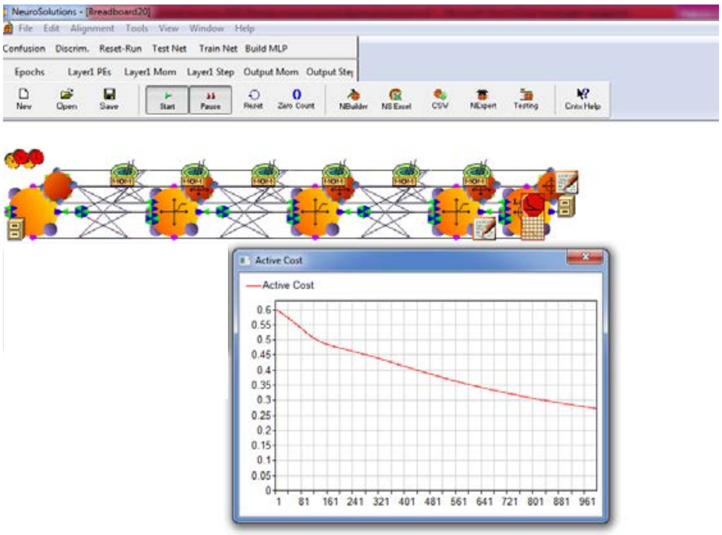

Figure 8: Example of ANN for FE "Failure and fire of the engine on the aircraft when climbing after take-off", which was built in the neuropackage NeuroSolutions

NeuroSolutions 7 is an easy-to-use software package for designing and modeling neural networks in a Windows environment. It combines a modular icon-based network design interface with the implementation of advanced artificial intelligence and learning algorithms using intuitive wizards or an easy-to-use Excel interface. Neuroemulator NeuroSolutions has shown the greatest flexibility in the synthesis and reconfiguration of complex control systems according to the following criteria: ease of creating and learning ANN, intuitive interface; ease of preparation of the training sample; clarity and completeness of information presentation in the process of creating and training ANN; the number of standard neural paradigms, criteria, and algorithms for learning ANN; the ability to create original neural structures; the possibility of using original optimization criteria and algorithms for learning neural networks; the possibility of software extensions of the neuropackage; the cost of the license.

Input vector-matrix ANN $\overline{U}$:

$$\overline{U} = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix} = \left\| \begin{bmatrix} 10 & 0 & 0 & 0 & 0 \\ 0 & 30 & 0 & 0 & 0 \\ 0 & 0 & 50 & 0 & 0 \\ 0 & 0 & 0 & 80 & 0 \\ 0 & 0 & 0 & 0 & 100 \end{bmatrix} \right\| = \left\| \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \right\|.$$

Weights of the first layer ANN $\overline{W}_1$:

$$\overline{W}_1 = \left\| \begin{bmatrix} w_{11} & w_{1j} & \dots & w_{i21} & w_{122} \\ w_{21} & w_{2j} & \dots & w_{i21} & w_{222} \\ w_{31} & w_{3j} & w_{ij} & w_{i21} & w_{322} \\ w_{41} & w_{4j} & \dots & w_{i21} & w_{422} \\ w_{51} & w_{5j} & \dots & w_{i21} & w_{522} \end{bmatrix} \right\|, \ i = \overline{1{,}5};\ j = \overline{1{,}22}.$$

The output vector of the second layer ANN $\overline{T}$:

$$\overline{T} = f\left(\begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix} \times \left\| \begin{bmatrix} w_{11} & w_{1j} & \dots & w_{i21} & w_{122} \\ w_{21} & w_{2j} & \dots & w_{i21} & w_{222} \\ w_{31} & w_{3j} & w_{ij} & w_{i21} & w_{322} \\ w_{41} & w_{4j} & \dots & w_{i21} & w_{422} \\ w_{51} & w_{5j} & \dots & w_{i21} & w_{522} \end{bmatrix} \right\| \times \left[-\theta_1 - \theta_2 \dots - \theta_j \dots - \theta_{22} \right] \right).$$

The weights of the second layer ANN $\overline{W}_2$:

$$\overline{W}_2 = \left\| \begin{bmatrix} w_{11} & w_{1j} & \dots & w_{j21} & w_{122} \\ w_{21} & w_{2j} & \dots & w_{j21} & w_{222} \\ \dots & \dots & w_{jk} & w_{j21} & \dots \\ w_{211} & w_{21j} & \dots & w_{j21} & w_{2122} \\ w_{221} & w_{22j} & \dots & w_{j21} & w_{2222} \end{bmatrix} \right\|, \; j = \overline{1{,}22}; k = \overline{1{,}22}.$$

The output vector of the third layer ANN $\overline{S}$:

$$\overline{S} = f\left(\begin{bmatrix} t_1 \\ \dots \\ t_j \\ \dots \\ t_{22} \end{bmatrix} \times \left\| \begin{bmatrix} w_{11} & w_{1j} & \dots & w_{j21} & w_{122} \\ w_{21} & w_{2j} & \dots & w_{j21} & w_{222} \\ \dots & \dots & w_{jk} & w_{j21} & \dots \\ w_{211} & w_{21j} & \dots & w_{j21} & w_{2122} \\ w_{221} & w_{22j} & \dots & w_{j21} & w_{2222} \end{bmatrix} \right\| \times \left[-\theta_1 - \theta_2 \dots - \theta_k \dots - \theta_{22} \right] \right).$$

Weights of the third layer ANN $\overline{W}_3$:

$$\overline{W}_3 = \left\| \begin{bmatrix} w_{11} & w_{1l} & \dots & w_{k4} & w_{15} \\ w_{21} & w_{2l} & \dots & w_{k4} & w_{25} \\ \dots & \dots & w_{kl} & w_{k4} & \dots \\ w_{211} & w_{21l} & \dots & w_{k4} & w_{215} \\ w_{221} & w_{22l} & \dots & w_{k4} & w_{225} \end{bmatrix} \right\|, \; k = \overline{1{,}22}; l = \overline{1{,}5}.$$

Output vector-matrix ANN $\overline{R}$:

$$\overline{R} = f\left(\begin{bmatrix} s_1 \\ \dots \\ s_k \\ \dots \\ s_{22} \end{bmatrix} \times \left\| \begin{bmatrix} w_{11} & w_{1l} & \dots & w_{k4} & w_{15} \\ w_{21} & w_{2l} & \dots & w_{k4} & w_{25} \\ \dots & \dots & w_{kl} & w_{k4} & \dots \\ w_{211} & w_{21l} & \dots & w_{k4} & w_{215} \\ w_{221} & w_{22l} & \dots & w_{k4} & w_{225} \end{bmatrix} \right\| \right) =$$

$$= \begin{bmatrix} r_1 \\ r_2 \\ r_3 \\ r_4 \\ r_5 \end{bmatrix} = \left\| \begin{bmatrix} 20 & 0 & 0 & 0 & 0 \\ 0 & 40 & 0 & 0 & 0 \\ 0 & 0 & 60 & 0 & 0 \\ 0 & 0 & 0 & 80 & 0 \\ 0 & 0 & 0 & 0 & 100 \end{bmatrix} \right\| = \left\| \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \right\|.$$

The amount of potential loss u_i, which depends on the type of flight situation, was obtained using fuzzy set theory [22–24]: very small loss (the consequence of a normal flight situation) u_1=10 points; small loss (the consequence of a complicated flight situation) u_2=30 points; average loss (the consequence of a difficult flight situation) u_3=50 points; large loss (the consequence of an emergency flight situation) u_4=80 points; very large loss (the consequence of a catastrophic flight situation) u_5=100 points.

According to the matrix of risk indicators ICAO [25], which takes into account the severity and probability of possible consequences, based on the theory of fuzzy sets with the use of linguistic variables, the scale of acceptability (acceptability) of risk r_l was determined [26]: negligible risk r_1=20 points; minor risk r_2=40 points; major risk r_3=60 points; hazardous risk r_4=80 points and catastrophic risk r_5=100 points. To ensure a sufficient level of flight safety, the risk indicators must not exceed 60 points, which is taken as the maximum allowable value of the level of danger.

5. Results

The input, intermediate, and output components of the ANN are set according to statistics for the previous 10-year period [7], additional inputs – biases are conditionally accepted as equal to one at the coordinated actions of ANS operators according to a certain technological procedure and equal to zero – at their uncoordinated actions. Since the number of samples for training must be at least 10 times the number of connections in ANN [17–19], then to assess the risk of CDM by the pilot/ATCO in the FE were prepared 5x22x10 = 1100 samples. ANN learning was performed by modifying the weights between neurons until the error reached a minimum and ceased to decrease. In our case, 1000 cycles of training were sufficient; ANN training time was 5.56 minutes (about 3 sec for each epoch).

Testing of ANN on examples that were not included in the training sample showed high accuracy in the risk determining (error Δ between the actual and obtained through the neural network assessment of the potential risk is not more than 3% from the range of changes in its values), which confirms the reliability of the proposed model.

6. Conclusion

Research has shown, that CDM by the pilot/ATCO in the FE requires from ANS operators the analysis of significant amounts of diverse information. For comprehensive accounting of the factors influencing the CDM process by the pilot/ATCO in the FE, a conceptual model of the adaptive ISSCDM, which considers dynamic, static, and expert information about the state of the control object (ACFT), environment (characteristics of ATC zone and aerodromes), and ANS operators (characteristics of the pilot/ATCO), was built. ISSCDM by the pilot/ATCO in the FE uses CDM models based on ANN.

For assessing the risk of CDM by the pilot and air traffic controller in the FE, a four-layer recurrent neural network with additional inputs – biases was developed: the first layer (input) – the losses in the FE depending on the flight situation; the second layer (hidden) – the normative time of technological procedures for FE parrying; the third layer (hidden) – the normative sequence of technological procedures for FE parrying; the fourth layer (output) – the risk assessment in FE. The developed neural network model due to the biases makes it possible to take into account the interaction between the pilot and air traffic controller when performing technological procedures on FE parrying and with the help of feedback to correct the predicted CDM risk assessment based on dynamic data about compliance by the operators' coordinated standards of time and normative sequences of actions.

With the help of NeuroSolutions neuroemulator (version 7.1.1.1) on the example of FE "Failure and fire of the engine on the aircraft when climbing after take-off" the multilayer feedforward perceptron with biases was built and trained with the teacher by the procedure of the error backpropagation. To learn ANN the gradient descent algorithm with perturbation was used, which allows to overcome local inequalities of the error surface and not to stop at local minima. The reliability of the proposed ANN model was confirmed by testing on examples that were not included in the training sample: error between the actual and obtained through the neural network assessment of the potential risk is not more than 3% from the range of changes in its values.

It is recommended to use ISSCDM in the process of joint training of the pilots and ATCO for CDM in FE, which will increase situational awareness of ANS operators, create a unified flight image to develop skills of active air surveillance, predict the development of the flight situation and timely warning flight situation deterioration due to the improvement of the pilot-ATCO technological interaction.

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