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INTERPRETATION OF NEURAL NETWORK TECHNOLOGIES FOR PREDICTION AND MANAGEMENT OF RISK FACTORS

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Abstract. The analysis carried out, as well as the systematisation and generalisation of flight safety problems, has allowed us to propose a model for a flight safety management system and to define directions for priority research. To solve flight safety problems, it is suggested to use the integrated methods of flight safety management on the basis of basic and partial criteria totality, where it is possible to take into account simultaneously the probabilistic indices of the system and informative indices, which are connected by means of using neural networks.

Keywords: flight safety, neural network, probabilistic method, risk factors, management decisions, diagnosis, automated systems, analysis.

1. Introduction

Civil aviation is a strategic priority for the geopolitical, social and economic development of Ukraine, as well as an important element of manufacture and social infrastructure, and its continuous and effective functioning is a necessary condition for the provision of national safety, gradual economic growth, and a rise in living standards.

Differential diagnosis of risk factors (RF) involved in the occurrence of air incidents (AI) is associated with considerable difficulties having a probabilistic character; the lack of *a priori* information leads to a situation when decision making at all stages is carried out in conditions of uncertainty, and the characteristics of every air

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operator have individual features.

Local activities concerning the prediction, authentic-cation and management of RF are the focus of considerable scientific work performed by key scientists in the aviation industry. The basic methodological issues relating to the creation and application of mathematical models of flight safety management systems (SMS) are also described there. However, the lack of materials containing a complex integrated solution of the SMS problem and its automation should be mentioned (Safety… 2006).

2. Conceptual model of safety management system (SMS)

In the formation of the strategy of a SMS (H_i), special attention is given to factors and decision makers (DM) with the highest levels of priority. The processes of formation, decrease and recovery of the flight safety level (FSL) for actions classified as potentially dangerous are determined by the following matrix:

$$Y = \begin{vmatrix} y_1(1) & y_1(2) & \dots & y_1(i) & \dots & y_1(k) \\ y_2(1) & y_2(2) & \dots & y_2(i) & \dots & y_2(k) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ y_i(1) & y_i(2) & \dots & y_i(i) & \dots & y_i(k) \\ \dots & \dots & \dots & \dots & \dots & \dots \\ y_n(1) & y_n(2) & \dots & y_n(i) & \dots & y_n(k) \end{vmatrix}.$$

On the stage of periodic control during realisation of automated SMS algorithm, the following requirement to periodicity of measures is taken into account: the interval between two successive verifications must be less than the normative time interval for which FSL will decrease to the minimum acceptable value of SMS: Thus, during the period between measures it is necessary to provide the assured maintenance of the flight safety level within the range of standard operation. Implementation of this condition is provided by specifying individual verification periodicity for each air operator with the purpose of detecting and timely eliminating risk factors (Kharchenko *et al.* 2008).

The formalised general model of the system ($S^{(ST)}_{Tren}$) follows:

$$S^{(ST)}_{Tren} = \left\langle \begin{matrix} \sum_{j=1}^{N} U_j, \sum_{k=1}^{N} Y_k(t), P(S_i, S_i^*, T_i), \\ \sum_{i=1}^{N} P(H_i), B(R^{I(J)}(T), R^M(Y)) \end{matrix} \right\rangle$$

In this model, the main elements of system implementation are:

$\sum_{j=1}^{N} U_j$ is the totality of recommendations based on j generalised analyses of AI, $j = \overline{(1, N)}$ used as the basic components.

$\sum_{k=1}^{N} Y_k(t)$ is the totality based on k models of operators $k \in \overline{(1, N)}$. $Y_k(t)$ changes over time (t) in the course of professional training (PT) and professional activity (PA).

$P(S_i, S_i^*, T_i)$ is an inspector's activity model; ($P(S_i)$ is for automated procedure of diagnosis, $P(S_i^*)$ is for partially automated procedure of diagnosis, and $P(T_i)$ is used at analysis of AI investigation.

$\sum_{i=1}^{N} P(H_i)$ is the individual *i*-strategies of preventing the AI (H_i) which represent the totality of decisions made dependently on $Y_k(t)$ and recommendations (standards). $B(R^{I(J)}(T), R^M(Y))$ is a database of professional reliability during PA; ($R^{I(J)}(T)$ is the results of professional training (activity of specialists registered over the course of training on a simulator), and $R^M(Y)$ is the secondary results of professional training (after executing the complex analysis and interpretation $R^{I(J)}(T)$). The functional diagram of an integrated Automated Flight Safety Management System (AFSMS) is shown below.

The structure of the system is based on the necessary condition of constant information gain. The system automatically creates abstract objects based on the input signals and forms their adequate pattern. The intellectual system has multiple input channels K_i for receiving external information. Information in NN is distributed according to levels. In case of level rise, the information elements enlarge. Let us mark out three NN levels with sublevels in each of them:

1. $E_{1i} = KL_i$; $S_1(t_k) = \sum_i KL_i(t_k)$ $P_1 = \sum_{t=t_1}^{i2} S_1(t)$;

2. $E_{2i} = OBr_i^{ob} = E_1$; $S_2(t_k) = \sum OBr_i^{ob}(t_k)$;

$$P_2 = \sum_{t=t_1}^{t_2} S_2(t) = OBr_i^{pr} = \lim_{n\to\infty} \sum_i P_{1i}(t_n) = P_1^{pr};$$

3. $E_{3i} = M_i^{ob} = E_2^{pr}$; $S_3(t_k) = \sum_i M_i^{ob}(t_k)$;

$$P_3 = \sum_{t=t_1}^{t_2} S_3(t) = M_i^{pr} = \lim_{n\to\infty} \sum_i P_{2i}(t_n) = P_2^{pr};$$

Every level of information is characterised by information elements E_{ij}, which are saved in information matrices of MI_i level. The first level elements are represented by the clusters $E_{1i} = KL_i$ (properties of external objects; information about these objects is supplied via the input channels). The second level elements are represented by the images of objects $E_{2i} = OBr_i$ as a combination of clusters (properties of objects). The third level elements are represented by the models of object images $E_{3i}=M_i$ as static frames $S_i(t_k)$ being a totality of information elements activated in information matrices of this level at time t_k.

Information contained in these frames is analysed by the intellectual system. This analysis is accompanied by the creation of information elements on high levels: processes P_{ij} being the totality of static frames from beginning to finish of process action and stored in the matrices of the processes of this level MP_i. On the first level, the process represents the totality of objects' properties, on the second it represents objects' images, on the third it represents objects' models. Each element of high level of information representation in the system is assigned a specified totality of the lower level information elements, i.e. the limit to which any localized totality of information elements tries to reach if the condition number of frames goes to infinity. In the display system, the principle of the hierarchical saving of information is used. Activation of any element of the system causes activation of all elements of the lower levels associated with the primary element. Activation of any element in combination with other elements of the same level causes activation of the higher-level elements for which this combination is the basic one.

3. Administrative decisions and diagnosis

Decision made with the help of the aforementioned models and algorithms may not always satisfy the decision makers. Furthermore, cases can occur when the situation cannot be described or related to a certain class by means of these tools. To avoid such deadlock situations, a mathematical tool in the form of a network model and based on representation of knowledge by the rules was developed. This tool allows creating the decision making plan and determining the cause-and-effect relation which is described using a structure similar to that of a Petri net (Berger 1993; Daubechies 1992). The nodes of such a network are the classes of conditions (sets of determined classification identifiers of RF) and decision making, respectively the positions and transitions of the grid.

The modification of Petri nets developed, rules for their functioning, and algorithmic support of the simulation of the functioning of the diagnostic process allow one to carry out the creation of a functional model of the diagnostic process, to keep track of the current state of the diagnostic system, and to execute decision making option generation by means of simulation.

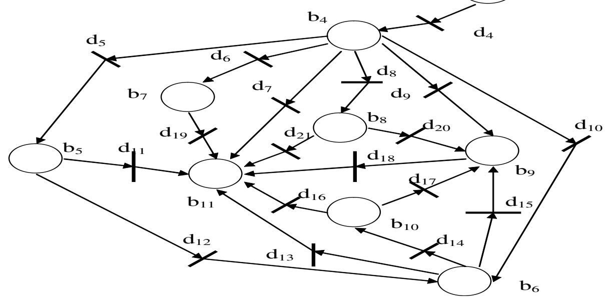

Fig 1. Modification of Petri networks

A description of the settings follows: b0 – identification of probable risk factors based on initial information; b1 – evaluation of the flight safety level based on quantitative estimations of the totality of the risk factors identified and factors preventing the occurrence of special situations; b2 – diagnosis of 'thin places' (factors which jeopardize the flight safety level in the greatest degree) using partial indicators of risk; b3 – synthesis of recommendations (options of control actions) to enhance the flight safety level; b4 – evaluation of costs which are necessary to implement the synthesized recommendations during the established time interval; b5 – preliminary evaluation of the efficiency of the recommendations executed; b6 – analysis and diagnosis; and b7 – on-line and periodical (resultant) monitoring and evaluation of flight safety management efficiency using the probability indices system for air incidents preventing (Kharchenko *et al.* 2008; Berger 1993; Cheeseman *et al.* 1988).

4. Neural network approach

At the stage of the pre-arranged processing of flow of information, the classification of events and processes depends on the factors that influence safety, and it is necessary to determine the risks that bring in different data in the case of these decisions. Mathematic statistics may be used, but many of these methods cannot be effective with a large volume of information. In our case, this could take place for many phenomena due to factors influencing BP and usually to a shortage of information. In this case, statistical methods cannot guarantee a successful result. In such cases, neural network (NN) technologies should be used to solve the problems.

The task of automating the processes of UBP and prediction and creating consulting models will require the application of the NN theory that is considered in section 1 in detail. To solve this task, it is suggested to use the NN structure shown in figure 2.

The network consists of two layers. The first and the second layers have ***m*** neurons, where ***m*** is the number of samples defined by the aggregate of possible 'risks'.

The neurons of the first layer have ***p*** synapses connecting with the network entrances. At the network entrance, an unknown vector is given, and the dimension of this vector is determined by the information flow about phenomena, events, actions and processes that influence safety.

The NN model described in section 1 generally performs the following conversions:

$S: X \Rightarrow A, \quad H: A \Rightarrow A', \quad P: A' \Rightarrow y,$

where X-N is the measuring space of continuous input signals; A-n is the measuring space of associations; A is the space of associations converted by means of a hashing algorithm; and y is the output signals vector.

Conversion corresponds to information encoding:

$a = S(x)$,

hashing: $a' = H(a)$,

output signal calculation:

$y = P(a') = (a')^T \omega = (H)a))^T \omega$. The selection of a base function is an important item during the implementation of the network.

This expression describes the conversion carried out in conventional NN using information hashing while selecting rectangular base functions. If neurons with activation functions different from rectangular ones are used in the network, the conversions will have the form (Narenda *et al.* 1990; Child 2005; Daubechies 1992):

$$y = H(a^T \Phi(x))\omega,$$

$$\Phi(x) = \begin{bmatrix} \Phi_1(x) & 0 & \dots & 0 \\ 0 & \Phi_2(x) & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & \Phi_n(x) \end{bmatrix},$$

$$\Phi_i(x) = \prod_{j=1}^{N} \oint_{ij}(x_j); \oint_{ij}(x_j)$$

values of selected base function in point.

In the NN, the rectangular base functions that allow executing permanent approximation are used. In this case, the calculation time will be minimal, ensuring a considerable decrease in the network reaction time after input signal appearance. In this case, the association vector components can have the value 0 or 1. Rate of network adaptation at the selection of rectangular base functions will have maximum value.

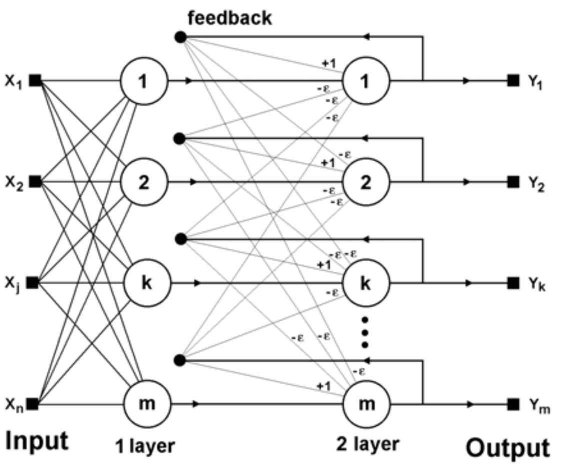

Fig 2. Neural networks

Base functions are represented by Gauss functions, which have the property of local exciting (Daubechies 1992; FSF… 1996). It is possible to specify the boundaries of their exciting sufficiently clearly, which is important for encoding the information in NN. The Gauss function shown below is free of this disadvantage.

$$\Phi_i(x_j) = \exp\left\{ -\frac{(x_j - \mu_i)^2}{\sigma_i^2} \right\}.$$

$$\Phi_i(x) = \begin{cases} \exp\left\{ -\dfrac{(\lambda_2 - \lambda_1)^2 / 4}{(x - \lambda_1)(\lambda 2 - x)} \right\} \\ 0 \end{cases}$$

and trigonometric (cosine)

$$\Phi_i(x_j) = \begin{cases} \cos\left(\dfrac{\pi}{\rho r_j}(x_j - \lambda_i) \right) & x_j \in (\lambda_i - \dfrac{\rho r_j}{2}, \lambda_1 + \dfrac{\rho r_j}{2}) \\ 0 \end{cases}$$

where - is the centre of the quantization domain.

Neurons of the second layer are interconnected by inhibitory (prohibiting) synaptic links. A single synapse with a positive reverse link for every neuron is connected with an axon of the same neuron.

The idea of network operation consists in the determination of the Hamming distance from the tested image to all samples.

For binary strings a and b, the Hamming distance is equal to the number of ones in a XOR b. The metric space of length-n binary strings with the Hamming distance is known as the Hamming cube; it is equivalent as a metric space to the set of distances between vertices in a hypercube graph. One can also view a binary string of length n as a vector in R^n by treating each symbol in the string as a real coordinate; with this embedding, the strings form the vertices of an n-dimensional hypercube, and the Hamming distance of the strings is equivalent to the Manhattan distance between the vertices. (Distance of Hamming is the number of separate bits in two binary vectors.)

The network must select the sample with minimum Hamming distance to unknown input signal resulting in activation of only one network output which corresponds to this sample (Carlin *et al.* 2000; Child 2005). In other words, the NN will select (predict) the risk levels according to input vector X and offer the proposition on decision making in the form of output vector (Child 2005; Artificial… 1994; Lane *et al.* 1992; FSF… 1996; 56th International… 2003; Carlin *et al.* 2000).

5. Conclusions

This multifactor model for the risk of the occurrence of AI allows:

– Monitoring risk for every type of aircraft, taking into account the number of flights performed in the estimation period;

– Quantitatively evaluating the degree of change in the risk of AI according to results of flight operation or after every investigation of AI;

– Predicting the risk of the occurrence of AI (either according to AI statistics or according to the results of the expert prediction of AI for the next period of flight operation);

– Periodically correcting AI risk prediction results during the process of operation on the basis of newly collected statistic data or after every AI. A neural network model of the automated management of flight safety will allow effectively solving the task of the risk synthesis of the occurrence of AI and provide the network control signals vector using partial and distorted information on phenomena and incidents and processes impacting flight safety.

It is necessary only to provide a list of factors, which influence the predictable index and perform a selection of a sufficient amount of examples, which describe the behaviour of this index previously. The NN will adapt itself to specified totality of examples, minimizing the total error of prediction. Analysis of set NN allows determining the hidden correlations between input and output data that is impossible to carry out using conventional methods.

Foreseeing that the character of correlation between the specified parameters will not change during some time period, the expert can use the adapted NN for short-term/long-term prediction and decision-making development.

The primary application of the method consists in use for an information system of a municipal air transport arrangement in megalopolis with large relief loading per area unit, maintaining a high level of requirements for route limitations and advanced level of flight safety with a maximum level of protection against damage to population and objects in the municipal zone.

The implementation of method covers:

– acquisition and statistic processing of information using the declared methods with the complex evaluation of risks being the primary condition of the arrangement automated decision-making system, issue of flight clearance;

– monitoring the values of parameters characterizing the state of the flight safety system for operation within municipal boundaries;

– providing the necessary flight information on board aircraft;

– advisory control of moving objects with estimating the situation and defining recommended solutions;

– automatic external lock on aircraft operator malfunction in case of a critical situation.

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NEURONINIŲ TINKLŲ TECHNOLOGIJŲ, SKIRTŲ RIZIKOS VEIKSNIŲ NUMATYMUI IR JŲ VALDYMUI, AIŠKINIMAS

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S a n t r a u k a

Atliktas tyrimas, taip pat skrydžio saugumo problemų susisteminimas bei apibendrinimas leido numatyti skrydžių saugumo valdymo sistemos tobulinimo kelius, nustatyti prioritetines jų tyrimo kryptis.
Siekiant užtikrinti skrydžių saugumą, siūloma taikyti integruotus skrydžių saugumo valdymo metodus, kurie remiasi bazinių bei dalinių kriterijų visuma; čia galima kartu įvertinti sistemos tikimybinius bei informacinius duomenis, kurių jungiamąja grandimi yra neuroniniai tinklai.

Reikšminiai žodžiai: skrydžio sauga, neuroniniai tinklai, tikimybių metodas, rizikos faktoriai**,** vadybos sprendimai, diagnozė, automatizuotos sistemos, analizė.