Emergency probability for aircraft vehicle

A Nekhrest-Bobkova* and A Burdina

Institute of Engineering Economics and Humanities, Moscow Aviation Institute (National Research University), 4 Volokolamskoe Highway, 125993, Moscow, Russian Federation

*E-mail: AANekhrest@mai.education

Abstract. The probability of an emergency assessment is one of the most important problems in the aviation sector. Timely identification of possible equipment failure can be a solution of this problem, that saves people’s lives. The article considers existing methods for risk assessment. The comparison of these methods is carried out. As a result of this paper, the artificial neural network was designed. The set of vital input parameters was determined during the neural network development. All the input variables are divided into groups. The most promising and accurate approach for probability of an emergency assessing the was determined, which forms the basis of the mechanism for engineering accidents.

1. Introduction

According to statistics about 22% of all the aircraft emergency occur by the reason of equipment failure, despite of the fact that they have to pass technical control. During its life cycle an aircraft vehicle passes different types of controlling events, such as transit check, daily check, weekly check, A-check, B-check, C-check, D-check and shop visit. But despite tough technical control accidents by the reason of equipment failure occur. Its highly important to identify possible equipment malfunction before an aircraft takes off.

Taking into account systems approach, an aircraft is an extremely complicated system. Nether the less three main subsystems, such as fuselage, aviation equipment and engine system, can be distinguished and considered as objects for study. The probability of emergency by the reason of equipment failure is the corner stone of this paper.

To calculate probability artificial networks can be used. Feedforward networks are possible to solve the classification problem and as output they give probability value of the sample belonging to some class. In terms of this paper these classes describe current state of the aviation equipment of an aircraft.

The application neural network technology to aircraft diagnostics makes up the novelty of the study. Reviewing foreign studies in this area we can say that there’s a lack of information about neural networks application in aviation sector in terms of diagnostics. Mostly neural networks are used in systems of autopilot and in photosystems to perform image recognition [1-4].

The aim of this paper is to develop an artificial neural network for forecasting the emergency by reason of equipment failure, to describe and group its input parameters. Another purpose is to review existing approaches to accident prediction and to compare them with developed neural network performance. As a result, the most accurate method for emergency prediction will be named.
2. Methodology

According to the generalized dynamic technogenic risk model of the Ostreikovsky [5], the quantitative value of the risk is expressed by the formula (1):

\[ R = \sum_{i=1}^{n} R_i = \sum_{i=1}^{n} Q_i C_i \]  

(1)

\( Q_i \) - the probability of the initial event, \( C_i \) – the consequences (damage) from the initial event (failure, accident, disaster).

Figure 1 shows the Farmer curve that represents this approach. In this case, the risk value is understood as the value of possible damage with the corresponding probability value, and the initial events should be considered according to the system event tree.

![Farmer's curve](image)

**Figure 1.** Farmer's curve that characterizes the dynamic technogenic risk model.

This model considers the set of possible probabilities of initial events \( Q = \{q_1 \ldots q_n\} \), the set of possible consequences (damage) \( C = \{c_1 \ldots c_n\} \) from the occurrence of the \( i \)-th event, the finite set of time points \( T = \{t_i\}, i = 1, n \) and the set of possible risks \( R = \{R_i\}, i = 1, n \).

The probability values of the initial events \( q_i \) and damage \( c_i \) are independent random variables that generally have their own distribution functions \( f_q(q/c_i) \) and \( f_c(c/q_i) \). Then the risk value can generally be expressed as an image of some \( H_2 \) operator as follows: \( R = H_2(q, c) \), and the risk distribution function will be calculated using the following formula (2):

\[ F_r(r) = \int_{W_i} f_{qc}(q, c) dq dc = \int_{W_i} f_q(q) f_c(c) dq dc \]  

(2)

\( W_i \) – the scope defined in the following way (3):

\[ W_i = \left\{ \begin{array}{l} q_i \in [0,1] \\ c_i \in [0, c_{max}] \end{array} \right\} \]  

(3)

Using such an approach in [5], a table of analytical dependencies was constructed for the function of the distribution density of technogenic risk. Considering various distributions of random variables, we can organize table 1 as follows:
Table 1. Analytical expressions of the risk distribution density.

|                         | Initial events density | Damage density | Risk density |
|-------------------------|------------------------|----------------|--------------|
| **Gauss**               |                        |                |              |
| \( f_{eq}(q) = \frac{m_q}{\sqrt{2\pi}\sigma_q} \exp\left(-\frac{(q-m_q)^2}{2\sigma_q^2}\right) \) | \( f_{ec}(c) = \frac{m_c}{\sqrt{2\pi}\sigma_c} \exp\left(-\frac{(c-m_c)^2}{2\sigma_c^2}\right) \) | \( f_{e}(r) = \frac{1}{\sqrt{2\pi}\sigma_q\sigma_c} \exp\left(-\frac{(q-m_q)^2}{2\sigma_q^2}\right) \) \( \times \exp\left(-\frac{(r-m_r)^2}{2\sigma_r^2}\right) \) dq |
| **Relay**               |                        |                |              |
| \( f_{eq}(q) = \frac{q}{\sigma_q^2} \exp\left(-\frac{q^2}{2\sigma_q^2}\right) \) | \( f_{ec}(c) = \frac{c}{\sigma_c^2} \exp\left(-\frac{c^2}{2\sigma_c^2}\right) \) | \( f_{e}(r) = \frac{r}{\sigma_q^2\sigma_c^2} \exp\left(-\frac{r^2}{2\sigma_q^2}\right) \) dq |
| **Weibull**             |                        |                |              |
| \( f_{eq}(q) = a_q \lambda q^{a_q-1} \exp\left(-\lambda q^{a_q}\right) \) | \( f_{ec}(c) = a_c \lambda c^{a_c-1} \exp\left(-\lambda c^{a_c}\right) \) | \( f_{e}(r) = a_q \lambda q^{a_q-1} \exp\left(-\frac{r}{q}\right) \) dq |
| **Lognormal**           |                        |                |              |
| \( f_{eq}(q) = \frac{1}{\sqrt{2\pi}\sigma_q} \exp\left(-\frac{(\ln q-m_q)^2}{2\sigma_q^2}\right) \) | \( f_{ec}(c) = \frac{1}{\sqrt{2\pi}\sigma_c} \exp\left(-\frac{(\ln c-m_c)^2}{2\sigma_c^2}\right) \) | \( f_{e}(r) = \frac{1}{\sqrt{2\pi}\sigma_q\sigma_c} \exp\left(-\frac{(\ln q-m_q)^2}{2\sigma_q^2}\right) \) \( \times \exp\left(-\frac{(\ln r/m_r)^2}{2\sigma_r^2}\right) \) dq |
| **Student**             |                        |                |              |
| \( f_{eq}(q,n) = \frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{n\pi} \Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{q^2}{n}\right)^{-\frac{n+1}{2}} \) | \( f_{ec}(c,n) = \frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{n\pi} \Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{c^2}{n}\right)^{-\frac{n+1}{2}} \) | \( f_{e}(r,n) = \frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{n\pi} \Gamma\left(\frac{n}{2}\right)} \left(1 + \frac{r^2}{n}\right)^{-\frac{n+1}{2}} \) \( \times \left(1 + \frac{q^2}{n}\right)^{-\frac{n+1}{2}} \) dq |

Thus, in Ostreikovsky works [5], calculating the probability of emergency occurrence situations and associated risks methods are described.

2.1. Erlang Distribution

However, the random processes of initial emergency events and their damage functions differ from the simplest random processes approximated by Gauss, Weibull, Rayleigh, and other distributions. In reality, they are stochastically dependent, hence the need to consider rare events with limited consequences. In [5], we consider the application of the Erlang distribution to assess the risks of an accident.

The K-th order Erlang distribution is a distribution describing a continuous random variable \( x \) that takes positive values in the range \((0; +\infty)\) and is the sum of \( k \) independent random variables distributed according to the same exponential distribution law with the parameter \( \lambda \). The function (4) and density (5) of the K-th order Erlang distribution have the form:

\[
F_k(x) = 1 - e^{-\lambda x} \sum_{i=0}^{k-1} \frac{(\lambda x)^i}{i!} \quad (4)
\]

\[
f_k(x) = \sum_{i=1}^{k} \frac{\lambda (\lambda x)^i}{(i-1)!} e^{-\lambda x} \quad (5)
\]

\( \lambda \) and \( k \) – positive distribution parameters \((\lambda \geq 0; \ k = 1, 2, ..., K)\); \( x \geq 0 \) – continuous random variable. Average \( M = k/\lambda \), dispersion \( D = k/\lambda^2 \).

In the case when the random variables \( q \) and \( c \) are independent, the density (6) and the risk distribution function (7) have the form:

\[
f_r(r) = \frac{\lambda q^k c^k e^{-\lambda q - \lambda c}}{(k_q-1)(k_c-1)!} \int_0^1 q^{k_q-k} \exp\left(-\lambda q - \lambda_c \frac{c}{q}\right) dq \quad (6)
\]
For dependent random variables, it is also possible to obtain analytical expressions for the density and risk distribution function, taking into account the correlation between them.

According to [5], to obtain a close to true risk assessment, the following algorithm must be performed:

1. Based on an experiment or a known functional relationship to determine the relationship between the random variables of the initial events \( q \) and the damage from them \( c \);
2. determine the \( q \) and \( c \) distributions Experimentally or based on a priori knowledge and determine the risk distribution;
3. On the basis of the requirements for the security level system to determine the maximum deviation of the damage \( A_c = \sigma_c/m_c \) and probabilities \( A_q = \sigma_q/m_q \).

### 2.2. Calculating the probability based on the frequency of emergency

According to [6] the process of aviation systems reliability assessment contains the step of empirical reliability characteristics calculation with the frequency of emergency among them.

The considering time interval with duration \( n \) divides into \( k \) ranks under Sturgeon’s rule (8):

\[
k = 1 + 3.3 \log n
\]

For each rank the calculation of empirical values for density, failure intensity and probability of failure-free operation is carried out by expressions (8), (9), (10) accordingly:

\[
f_i = \frac{\Delta n_i}{N \Delta \tau_i} \tag{9}
\]

\[
\lambda_i = \frac{\Delta n_i}{N \tau_i} \tag{10}
\]

\[
P_i = \frac{f_i}{\lambda_i} \tag{11}
\]

Than the theoretical distribution law is to be chosen, unknown parameters of the distribution law are to be identified, the correctness of the accepted hypothesis about the distribution law is to be checked. The result of this procedure is the estimation of equipment failure frequency.

Work of aviation equipment during the flight of an aircraft can be considered as a Poisson random process. It is an ordinary stream of homogeneous events, for which the number of events in the interval \( A \) does not depend on the number of events in any intervals that do not intersect with \( A \), and obeys the Poisson distribution. In the theory of random processes, it describes the number of random events that occur with constant intensity.

Thus, to determine the probability of an emergency, you can use the Poisson distribution (12) with an intensity \( \lambda \), equal to the frequency of equipment failure.

\[
F_R(r) = \frac{e^{-\lambda r} \lambda^r}{r!} \tag{12}
\]

The known distribution function makes it possible to calculate the emergency probability.

### 2.3. Artificial neural networks application

Artificial neural networks are also applicable to the emergency probability calculation. The advantage of their application is the fact that neural networks can take a large number of variables as input parameters, the relationships between which are not only nonlinear, but even implicit.

To determine the probability of an emergency [7,8].

To identify input parameters, the analysis of influencing factors has to be conducted. In general, an emergency can occur by the internal and external reasons. Internal reasons correspond to the state of all equipment subsystems, that are depicted in the figure 2. As a quantitative measure of these

\[
F_R(r) = \frac{\Gamma(r+1, \lambda \tau)}{r!} \tag{12}
\]

The known distribution function makes it possible to calculate the emergency probability.
parameters a corresponding indicator is taken. It is in range $(0; 1)$ and can be calculated by an expert, or as a result of A, B, C or D-check or even using other neural networks.

To take into account external influence on aviation equipment, another set of indicators was designed. Such parameters as temperature, humidity, pressure, vibration, radiation etc. also affect aviation equipment. These parameters form the second group of input parameters for developed neural network.

So developed neural network takes as input vector $X$ based on both internal and external factors, which describes the current state of an aircraft vehicle.

As output, the neural network gives the probability $q_i$, with which it belongs to the $Y_i$ class. Classes $\{Y_i\}$ present the degree of emergency risks that correspond to condition of the equipment [8] (table 2). The topology of this neural network is shown in figure 2.

**Table 2.** Classification of aviation equipment states.

| Status class | The assessment transcript |
|--------------|---------------------------|
| $y_1$       | The equipment is not suitable for use, high probability of an accident. |
| $y_2$       | Significant equipment repairs are required. |
| $y_3$       | The equipment is in a satisfactory condition and will last the predicted period. |
| $y_4$       | The equipment is in good condition and requires minor repairs on some of its sections. |
| $y_5$       | The equipment is in excellent condition, no repairs are required. |

Thus, the use of neural networks also makes it possible to determine the probability of an emergency. The main requirement is the ability to quantify the space of input parameters.

Another advantage of this approach is the fact that the input data vector contains information about the aviation equipment itself: parameters of the technical condition of each system according to diagnostic [9-11].
3. Results and discussion

For a comparative analysis of these probability calculation methods, an aircraft with the following technical characteristics was considered. This open source data was provided by the aircraft, which in reality had equipment failure.

The developed neural network was learnt on the similar data. The A-check of this aircraft vehicle gave the result in table 3.

| Name of the group | Name of the system                        | Value |
|-------------------|-------------------------------------------|-------|
| Equipment         | Lighting equipment                        | 0.735 |
|                   | Power plant control system                | 0.643 |
|                   | Electrical equipment                      | 0.379 |
|                   | Air conditioning system                   | 0.954 |
|                   | Fire-fighting information                 | 0.765 |
|                   | De-icing systems                          | 0.677 |
|                   | Instrumentation equipment                 | 0.521 |
|                   | High-altitude and oxygen equipment        | 1     |
|                   | Flight recorders and recorders            | 0.691 |
|                   | Automatic control systems                 | 0.354 |
|                   | Navigation systems                        | 0.764 |
|                   | Fuel automation                           | 0.842 |

| External parameters | Temperature | Humidity | Pressure, linear and angular acceleration | Vibration and shock | Precipitation (snow, hail, dust, sand) | Radiation and electromagnetic radiation | Biological factors (mold, germs) |
|---------------------|-------------|----------|-------------------------------------------|--------------------|----------------------------------------|----------------------------------|---------------------------------|
|                     | 27          | 0.81     | 761; 0.51; 0.765                          | 0.31; 0            | 0.1                                   | 0.05; 0.03                       | 0                               |

Table 3. Values of the input parameters for an experiment.

Determination of parameters of distributions laws can be obtained in two ways: the first one is based on statistical data of the actual operation of a particular object or its analogues, and the second one is based on mathematical modeling on a computer.

For the numerical experiment, the AnyLogic simulation system was used. When calculating the probability, we assume the maximum allowable risk equal to the value $\alpha$. The results of modeling the probability of an emergency are presented in table 4.

| Gauss distribution (0.24; 0.09) | Erlang distribution | Poisson distribution | Artificial neural networks |
|--------------------------------|---------------------|----------------------|----------------------------|
| 0.6451                         | 0.7122              | 0.0067               | 0.8715                     |

Table 4. The numerical experiment results.

Based on the simulation results, it can be seen that the probability calculation using a neural network more accurately describes the state of considering aviation equipment.

4. Conclusion

In the course of the work, various methods for calculating the emergency probability were considered, and their comparison was made. The event of an emergency situation was simulated by using Poisson and Erlang distributions. A neural network has been developed for calculating the emergency
occurrence by the reason of equipment failure. As a result, the calculation of probability using a neural network gave the most accurate results. We consider this method to be the most promising, since the neural network can be retrained and redesigned. So the goals of this paper are reached. Such an approach to system diagnostics is a novelty in aviation sector. To improve the accuracy of this method more specific parameters of diagnostics should be added to the model.

References
[1] Doğru A, Bouarfa S, Arizar R and Aydoğan R 2020 Using convolutional neural networks to automate aircraft maintenance visual inspection. Aerospace 7(12) 171 https://doi.org/10.3390/aerospace7120171
[2] Bleu-Laine M, Puranik T, Mavris D and Matthews B 2021 Predicting adverse events and their precursors in aviation using multi-class multiple-instance learning. AIAA J. 2021-0776 https://doi.org/10.2514/6.2021-0776
[3] Qiang Chen M, Ming Zhang G and Feng J 2013 The research of aircraft landing problems based on neural network. Adv. Mat. Res. 651 891 https://doi.org/10.4028/www.scientific.net/AMR.651.891
[4] Cheng T, Wen P and Li Y 2016 Research Status of Artificial Neural Network and Its Application Assumption in Aviation. Proc. 12th Int. Conf. on Computational Intelligence and Security (December 16-19, Wuxi, China: Institute of Electrical and Electronics Engineers) p 706
[5] Ostreykovsky V A and Pavlov A S 2016 Mathematical models of anthropogenic risk estimation for complex systems on the basis of the erlang distribution. Reliability and Quality of Complex Systems 1(13) 99 [In Russian]
[6] Li J, Wei Dong Q, Zhan Y and Bin Yu 2014 Reliability study of aviation equipment. Adv. Mat. Res. 933 428 https://doi.org/10.4028/www.scientific.net/AMR.933.428
[7] Burdina A A, Nekhrest-Bobkova A A, Gorelov B A and Burdin S S 2020 Accident damage technology sciences publication. IJRTE. 8(6) 4260 https://doi.org/10.35940/ijrte.F8312.038620
[8] Nikolsky O, Vorobyev N, Kulikova L and Khomutov S 2016 Analysis of technogenic risks hazard production facilities using soft computing. Matec Web. Conf. 106 07023 https://doi.org/10.1051/matecconf/201710607023
[9] Van Deventer D R, Imai K and Mesler M 2013 Advanced Financial Risk Management: Tools and Techniques for Integrated Credit Risk and Interest Rate Risk Management (New York: John Wiley & Sons Singapore Pte. Ltd.) p 112
[10] Chatterjee R 2014 Practical Methods of Financial Engineering and Risk Management: Tools for Modern Financial Professionals (New York: Apress Media, LLC) p 388
[11] Dash Wu D 2011 Quantitative Financial Risk Management (Berlin: Springer Berlin Heidelberg) p 338