Mathematical Method of Artificial Neural Networks in Aircraft Maintenance, Repair and Overhaul

Marina M. Gyazova, Igor D. Vlaznev

Moscow Aviation Institute (MAI), 125993, Volokolamskoe highway, 4, Moscow, Russia

***Abstract* – Aircraft Maintenance, Repair and Overhaul (MRO) is one of the major components of the Aircraft Life Cycle Cost (LCC). Increasing the efficiency of MRO, as well as reducing MRO cost, is one of the main ways to reduce LCC. In modern aviation technology complexity of Avionics and its maintenance increase. Traditional methods of failure prediction are difficult to apply in complex technical systems which make it necessary to reduce MRO interval. This research proposed the mathematical method of Artificial Neural Networks (ANN) as a possible solution to this problem. The avionics of Unmanned Aerial Vehicle (UAV) is the research object. The reliability and forecasting of failures by traditional and ANN methods have been analyzed, and results comparison are received. The study suggests that the method used is suitable for solving this problem. The obtained results show a high degree of reliability. Further research is proposed to scale to more complex avionics aircraft. The introduction of ANN in the MRO system entails many advantages, including the possibility of increasing the avionics service intervals and failure prediction, taking into account external factors of operation. This will inevitably lead to LCC reduction and increase safety.**

***Keywords* – Life Cycle Cost (LCC), Maintenance, Repair and Overhaul (MRO), Artificial Neural Networks (ANN), Unmanned Aerial Vehicle (UAV).**

DOI: 10.18421/TEM94-08
https://doi.org/10.18421/TEM94-08

Corresponding author: Marina M. Gyazova,
Moscow Aviation Institute (MAI), Moscow, Russia.
Email: mmgyazova@mail.ru

Received: 30 June 2020.
Revised: 23 October 2020.
Accepted: 28 October 2020.
Published: 27 November 2020.

© 2020 Marina M. Gyazova & Igor D. Vlazne; published by UIKTEN. This work is licensed under the Creative Commons Attribution-NonCommercial-NoDerivs 4.0 License.

The article is published with Open Access at www.temjournal.com

1. Introduction

With the rapid increasing competitiveness in the aviation market, product life cycle cost (LCC) has become the most important criteria of the air vehicle. One of the objective criteria for LCC evaluation is direct operation cost (DOC). Its dominant components are depreciation, fuel and maintenance, repair and overhaul (MRO) costs. Because of increasing complexity of aircraft avionics, MRO cost share in DOC grows up [1], [2].

Traditionally, modern aircraft maintenance is a hierarchical structure, consisting of 3-5 levels, including, maintenance, repairs and modifications [1]. Some of the procedures are carried out by the operator independently, but now outsourcing become widely distributed, especially for in complicated systems maintenance [2]. The largest operators have the ability to quickly replace the problem unit with another, without waiting for repair, but even in this case the aircraft gets out from service for some time. The inventory creation and forecasting is also a problem [3].

Modern avionics units are usually created within non-maintenance during the inter-service period conception. However, integrated diagnostic systems implemented in such units cover only up to 95% of possible failures [4]. Classical failure analysis methods such as failure mode, effects and critical analysis (FMECA) and failure tree analysis (FTA) do not give a full guarantee of failures prediction [5]. Fault tolerant systems have a high degree of redundancy, allowing most failures not to lead to accidents, but can still adversely affect the DOC. One of the key indicators describing the reliability of electronics is mean time between failure (MTBF). It is usually given by original equipment manufacturers (OEMs) as a constant, but actually, it depends on the operating conditions [6]. These conditions are described by vibration modes, power supply parameters (current and voltage), climatic conditions (temperature, humidity, radiation) and human factors [7]. This implies that for accurate MTBF estimation required the collection, storage and analysis of large number of onboard parameters during operation.

The aviation industry is very conservative. The introduction of innovation in the aircraft maintenance system is limited to very complex bureaucratic procedures. The risks are also very high. The best solution for testing innovative solutions is the field of unmanned aircraft. The absence of people on board reduces the requirements for aircraft, making all procedures easier to implement. However, in the future, all proofed solutions can be shifted to the traditional aviation industry. The consequence of softer requirements to unmanned aerial vehicles (UAV), is their higher accident rate. On average, accidents per flight hour of occur 100 times more often than with manned aircraft. The main factors of high accident rate are frequent assembly and disassembly of systems, ignoring collection and analysis of information about the nature of component failures, low level of service and personnel qualification [8]. Low requirements level for UAV reliability allow manufacturers not to reserve some components and systems, so some failures, which in classical aviation lead only to partial performance degradation ("soft failure"), lead to emergency situations ("hard failure") [9]. Also, the lack of stringent UAV design requirements leads to the widespread use of commercial non-specialized components, without detailed safety specifications and special requirements [10].

However, the widespread use of commercial components has some advantage – the possibility of obtaining big data on their use under different operating conditions and its further analysis. This study proposes the use of mathematical method of artificial neural networks for aircraft maintenance. Statistics on the operation of individual components will be used to neural networks learning, and the predicted reliability analysis based on operational and maintenance history data are used as a decision support system (DSS), to provide recommendations for detailed inspections and, if necessary, further repair or maintenance.

Artificial Neural Networks (ANN) are used for machine learning and artificial intelligence tasks. With the help of this method, problems that are difficult to maintain in algorithmic mode can be solved. They are particularly useful in statistical problems, one of which is essentially the task of predicting the reliability of aircraft electronics based on historical data [11].

The problem of using ANN to detect various failures in the aircraft was investigated by Alfredo Arcos Jimenez in the article Machine Learning and Neural Network for Maintenance Management [12]. Data from ultrasonic sensors are used for machine learning. The known problem sites are used as a target data. This is a classic example showing the possibility of solving complex algorithmized problems of reliability using ANN. Researcher Alberto Pliego Marugan have studied possibility of reliability evaluation using the supervisory control and data acquisition (SCADA) control and monitoring system data as an ANN input in the paper SCADA and Artificial Neural Networks for Maintenance Management [13]. The author argues that due to the different operating conditions, the thresholds used for alarms vary. The possibility of the ANN LCC evaluating showed in a thesis on Whole Life Cost Methods for Aero-Engine Design by James Stephen Wong [14]. The researcher considers the possibility of identifying implicit links between the input data on the product and the life cycle cost. This demonstrates the ability of the method to identify implicit patterns, which requires much less effort than the analytical work on the conclusion of empirical formulas.

In the paper Probabilistic Risk Assessment Tool AMETA (Aircraft Maintenance Event Tree Analysis) for Aircraft Structural Integrity and Fatigue, Michael Shiao, and Tzi-Kang (John) Chen present Aircraft Maintenance Event Tree Analysis (AMETA) - damage tolerance (DT)-based probabilistic method [15]. They argue that the traditional assessment of the reliability of aircraft systems is based on not taking into account the remaining service life after initiating damage. The complexity of the reliability assessment lies in the uncertain behavior of the system and the complexity of its modeling.

According Clive Dyer and David Rodgers, Effects on Spacecraft & Aircraft Electronics, Space Radiation makes impact on Aerospace Electronics reliability [16]. The research demonstrates that the effects are nonlinear. Analysis of the effect of the accumulated dose of radiation by traditional methods is difficult, which opens up opportunities for an attempt at an effective analysis by ANN. In Thermal Phenomena Modeling on Aircraft Electronic Unit, authors Zdenek Ancik and Radek Vlach describe the influence of environmental temperature factors on the reliability of aircraft electronics. The study demonstrates that in some cases, modern software for thermal modeling of electronics sometimes give significant errors. Using number of thermal sensors directly integrated into the chips and chips, and sensors that provide information about the temperature inside the electronic units, is a significantly reliable tool for reliability analysis [17]. Luis F. F. M. Santos and R. Melicio investigate the influence of the human factor on the maintenance of aircraft in the research Stress, Pressure and Fatigue on Aircraft Maintenance Personal. Results indicates that the urgency of repairs and the number of working hours directly depend on the number of errors during inspections [18].

These recent researches clearly have considerable potential of possibility using mathematical method of ANN in the aircraft maintenance. It demonstrates several non-linear factors in electronic reliability. The literature shows importance of consideration these factors to final reliability model. But they still have a gap. These papers do not present the possibility of developing a concept based on ANN, DSS to focus the attention of staff on possible problem blocks. Studying the literature, it was found that the possibility of studying nonlinear factors on the reliability of aviation electronics using ANN was also not evaluated.

This study was design to develop a concept of the DSS for the maintenance the electronic components of UAV. The future-proof system will reduce the impact of the human factor on the reliability of the UAV. Analysis of the components' reliability using the ANN method will enable us to include the influence of factors based on historical data, which are difficult to predict. The place of ANN DSS system implementation in the traditional service model is also proposed.

The analysis of the reliability with regard to the communication electronic unit UAV includes mathematical method ANN. Detailed big data reliability of aviation electronic components is confidential and is not laid out in open access. For this reason, training data will be generated and based on traditional reliability assessment methods. Conclusions of empirical formulas correspond to conservative estimates of reliability of electronics. Part of the generated data is used for training, part of the data – to validate the results and assess the accuracy of prediction. A comparison of the use of raw data serves as a training sample, and smoothed with the help of mathematical transformations. The accuracy of the results is compared with the traditional method of mathematical interpolation.

Also, the evaluation of the analysis of the nonlinear factors, the introduction of additional perturbations starts at a specific time. This simulates cumulative factors such as cosmic radiation.

This work is a contribution to the promising UAV service models. If the model is implemented and shows its effectiveness, in the future it can be extended to traditional aviation. The conducted research should improve safety – the DSS developed has the task of reducing the human factor during inspections. The reduction of unscheduled repairs leads to lower MRO costs. The result will be a reduction in DOC and whole LCC.

The paper is structured as follows. Section II presents a proposal to modify the current MRO information flow structure using the proposed ANN DSS. ANN DSS structure is provided in Section III. Section IV shows a conservative electronic unit reliability estimation. Section V presents the process of generating the source data, based on a conservative assessment of the reliability of their mathematical transformation. Section VI shows ANN's learning process. Section VII assesses the result of the work of the trained ANN and the evaluation of the accuracy of the results. Section VIII demonstrates ANN DSS example. Section IX is a discussion part. Finally, Section X outlines the conclusion.

2. ANN DSS in MRO Structure

Figure 1 shows the traditional aircraft maintenance model. Each product's supplier provides information about the characteristics of its product. The next-tier supplier uses this information as part of the higher-tier component, and ultimately the OEM of the aircraft component. Information on all components and systems is included in the aircraft information. This data, together with the MRO schedule, forms the final data on the aircraft MRO, which is transmitted to the technical personnel.

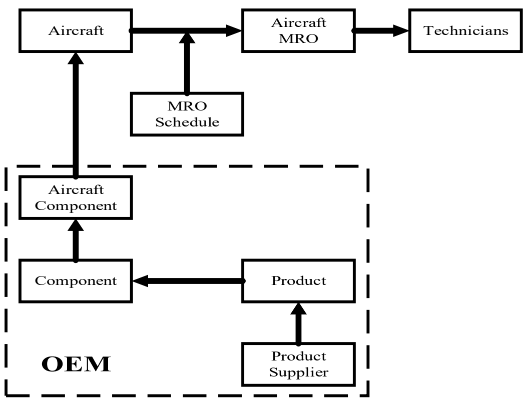

Figure 1. Current MRO information flow

Figure 2 displays the proposed MRO information flow. The main difference is the implementation of ANN DSS. The system is pre-trained. The input data is a large historical data. It consists of information from suppliers and OEM, MRO results and operating conditions. The results of the analysis are given to technicians as inspection recommendations and, if necessary, they are used to make changes to the MRO schedule.

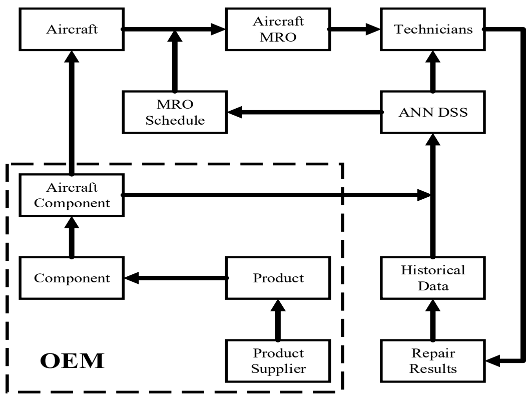

Figure 2. Proposal MRO information flow

DSS is a system capable of analyzing and making recommendations based on a set of input data. In this example, three types of recommendations are issued:

- Changing the schedule for inspection, maintenance, and repair / replacement;
- Alarm to reduce the reliability level to a critical level.

The expected changes lead to the optimization of service and reducing the number of unplanned failures. The consequence is a decrease in DOC and LCC, as well as an increase in the safety level.

3. ANN DSS Structure

The ANN DSS structure is presented in Figure 3. It is a classic black box. Input parameters are information such as failure history, repair and maintenance, and operating mode data. The output is recommendations for inspection, repair and maintenance.

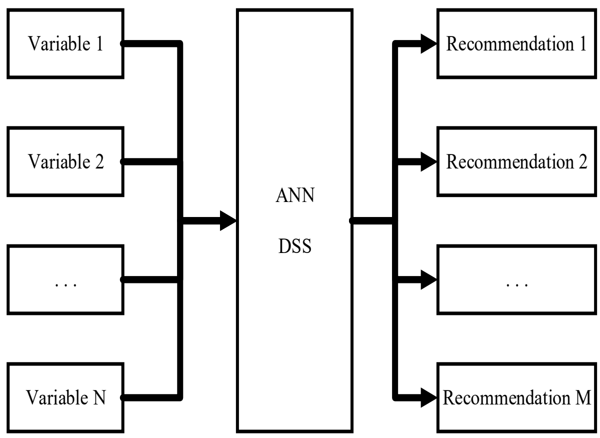

Figure 3. ANN DSS structure

The functioning of this system requires a pre-trained ANN. Figure 4 provides the training scheme. Part of historical data is used as input data. The output is compared with real historical data and the ANN parameters are adjusted using feedback. This process is iterative. It is repeated until the difference between the output parameters and historical data is reduced to the required accuracy.

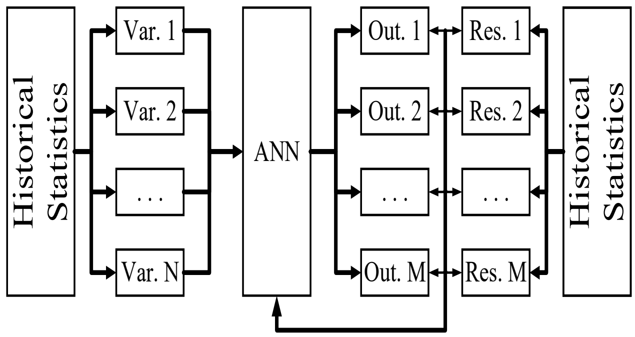

Figure 4. ANN training scheme

4. Conservative Reliability Estimation

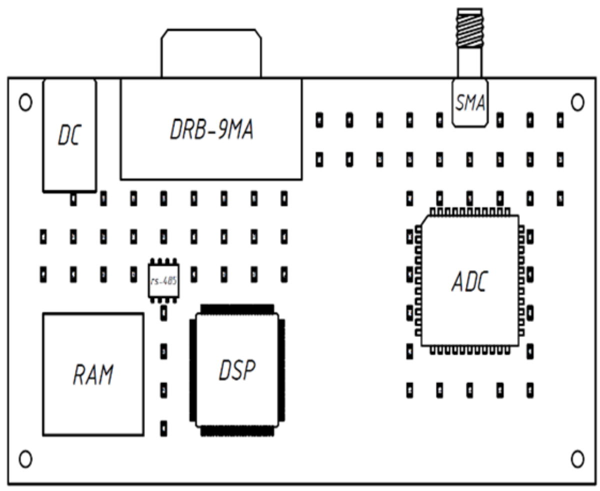

Figure 5. UAV communication unit

The communication unit of the unmanned aerial vehicle is illustrated in Figure 5. It is considered as the researched electronic unit. Conservative estimation of reliability consists of following stages:

1. Unit decomposition into separate elements;
2. Separate elements conservative reliability estimation;
3. Unit conservative reliability estimation.

The result of communication unit decomposition:

- Digital Signal Processor (DSP);
- Analog-to-Digital Processor (ADP);
- Random Access Memory (RAM);
- Interface Controller;
- 20 x Ceramic Capacitors (0.1mkF);
- 20 x Ceramic Capacitors (0.01mkF);
- 25 x Ceramic Resistors;
- Coaxial Connector;
- Interface Connector;
- Power Connector;
- Printed Circuit Board (PCB);
- PCB contact tracks.

Conservative assessment of the components of the communication unit:

All of the components follow exponential distribution:

$$P_i = e^{-\lambda_{\text{э}_i} \cdot t} \qquad (1)$$

DSP reliability estimation:

$$\lambda_{DSP} = (\lambda_0 \cdot K_t \cdot K_c + \lambda_f \cdot K_u \cdot K_q \cdot K_i) \cdot 10^{-6} \tag{2}$$

$$K_t = 0.1 \cdot exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c + 273} - \frac{1}{N_t}\right)\right) \tag{3}$$

$$T_c = T_e + R \cdot P \tag{4}$$

$$P_{DSP} = \exp\left(-\left(1.9799 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 277.4} - \frac{1}{298}\right)\right) + 0.7978\right) \cdot 10^{-6} \cdot t\right) \tag{5}$$

ADP reliability estimation:

$$\lambda_{ADP} = (\lambda_0 \cdot K_t + \lambda_f \cdot K_u) \cdot K_q \cdot 10^{-6} \tag{6}$$

$$K_t = 0.1 \cdot exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c + 273} - \frac{1}{N_t}\right)\right) \tag{7}$$

$$T_c = T_e + R \cdot P \tag{8}$$

$$P_{ADP} = \exp\left(-\left(0.004 \cdot exp\left((-7543.2) \cdot \left(\frac{1}{T_e + 273.2} - \frac{1}{298}\right)\right) + 0.0668\right) \cdot 10^{-6} \cdot t\right) \tag{9}$$

RAM reliability estimation:

$$\lambda_{RAM} = (\lambda_0 \cdot K_t + \lambda_f \cdot K_u) \cdot K_q \cdot 10^{-6} \tag{10}$$

$$K_t = 0.1 \cdot exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c + 273} - \frac{1}{N_t}\right)\right) \tag{11}$$

$$T_c = T_e + R \cdot P \tag{12}$$

$$P_{RAM} = \exp\left(-\left(0.024 \cdot exp\left((-6963) \cdot \left(\frac{1}{T_e + 278} - \frac{1}{298}\right)\right) + 0.278\right) \cdot 10^{-6} \cdot t\right) \tag{13}$$

Interface Controller reliability estimation:

$$\lambda_{con} = (\lambda_0 \cdot K_t + \lambda_f \cdot K_u) \cdot K_q \cdot 10^{-6} \tag{14}$$

$$K_t = 0.1 \cdot exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c + 273} - \frac{1}{N_t}\right)\right) \tag{15}$$

$$T_c = T_e + R \cdot P \tag{16}$$

$$P_{con} = \exp\left(-\left(0.006 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 277.5} - \frac{1}{298}\right)\right) + 0.0106\right) \cdot 10^{-6} \cdot t\right) \tag{17}$$

0.1mkF ceramic capacitors set reliability estimation:

$$\lambda_{cap_1} = \left(\lambda_0 \cdot K_t \cdot K_e \cdot K_h \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{18}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c + 273} - \frac{1}{N_t}\right)\right) \tag{19}$$

$$T_c = T_e \tag{20}$$

$$P_{cap_1} = \left(\exp\left(-\left(0.0168 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e+273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{20} \tag{21}$$

0.01mkF ceramic capacitors set reliability estimation:

$$\lambda_{cap_2} = \left(\lambda_0 \cdot K_t \cdot K_e \cdot K_h \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{22}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c+273} - \frac{1}{N_t}\right)\right) \tag{23}$$

$$T_c = T_e \tag{24}$$

$$P_{cap_2} = \left(\exp\left(-\left(0.0136 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e+273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{20} \tag{25}$$

Ceramic resistors set reliability estimation:

$$\lambda_{res} = \left(\lambda_0 \cdot K_t \cdot K_e \cdot K_h \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{26}$$

$$T_c = T_e \tag{27}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c+273} - \frac{1}{N_t}\right)\right) \tag{28}$$

$$P_{res} = \left(\exp\left(-\left(2.2376 \cdot exp\left((-928.4) \cdot \left(\frac{1}{T_e+273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{25} \tag{29}$$

Coaxial connector reliability estimation:

$$\lambda_{con_c} = \left(\lambda_0 \cdot K_t \cdot K_{com} \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{30}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c+273} - \frac{1}{N_t}\right)\right) \tag{31}$$

$$T_{max} = T_e + \Delta T \tag{32}$$

$$P_{con_c} = \exp\left(-\left(60.0022 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e+278} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \tag{33}$$

Interface connector reliability estimation:

$$\lambda_{con_i} = \left(\lambda_0 \cdot K_t \cdot K_{com} \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{34}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c+273} - \frac{1}{N_t}\right)\right) \tag{35}$$

$$T_{max} = T_e + A \cdot I^{0,85} \tag{36}$$

$$P_{con_i} = \exp\left(-\left(4.8 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e+273.49} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \tag{37}$$

Power connector reliability estimation:

$$\lambda_{con_p} = \left(\lambda_0 \cdot K_t \cdot K_{com} \cdot K_u \cdot K_q\right) \cdot 10^{-6} \tag{38}$$

$$K_t = exp\left(\frac{-E_a}{8.617 \cdot 10^{-5}} \cdot \left(\frac{1}{T_c+273} - \frac{1}{N_t}\right)\right) \tag{39}$$

$$T_{max} = T_e + A \cdot I^{0,85} \tag{40}$$

$$P_{con_p} = \exp\left(-\left(4.8 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e+273.32} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \tag{41}$$

PCB reliability estimation:

$$\lambda_{PCB} = K_э \cdot \sum_{i=1}^{n} N_i \cdot \lambda_{0_i} \tag{42}$$

$$P_{PCB} = \exp(-2{,}1675 \cdot 10^{-8} \cdot t) \tag{43}$$

Contact tracks reliability estimation:

$$\lambda_{con_{pcb}} = K_э \cdot \sum_{i=1}^{n} N_i \cdot \lambda_{0_i} \tag{44}$$

$$P_{con_{pcb}} = \exp(-0{,}1861 \cdot 10^{-6} \cdot t) \tag{45}$$

The final calculation of the reliability of the communication unit:

Reliability scheme is demonstrated in Figure 6. System is serial.

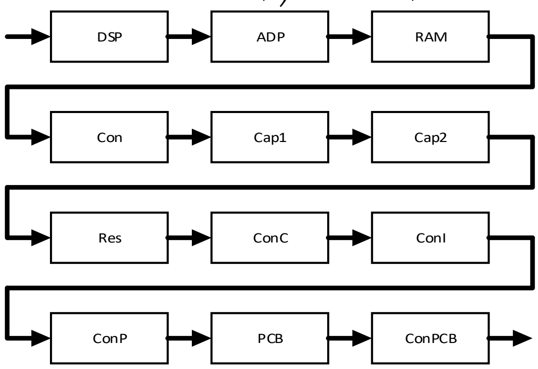

Figure 6. UAV communication unit reliability scheme

Completely conservative estimation of UAV Communication Unit:

$$P_{unit} = \exp\left(-\left(1.9799 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 277.4} - \frac{1}{298}\right)\right) + 0.7978\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp\left(-\left(0.004 \cdot exp\left((-7543.2) \cdot \left(\frac{1}{T_e + 273.2} - \frac{1}{298}\right)\right) + 0.0668\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp\left(-\left(0.024 \cdot exp\left((-6963) \cdot \left(\frac{1}{T_e + 278} - \frac{1}{298}\right)\right) + 0.278\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp\left(-\left(0.006 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 277.5} - \frac{1}{298}\right)\right) + 0.0106\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \left(\exp\left(-\left(0.0168 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{20} \cdot$$

$$\cdot \left(\exp\left(-\left(0.0136 \cdot exp\left((-4061.7) \cdot \left(\frac{1}{T_e + 273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{20} \cdot$$

$$\cdot \left(\exp\left(-\left(2.2376 \cdot exp\left((-928.4) \cdot \left(\frac{1}{T_e + 273} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right)\right)^{25} \cdot$$

$$\cdot \exp\left(-\left(60.0022 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e + 278} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp\left(-\left(4.8 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e + 273.49} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp\left(-\left(4.8 \cdot exp\left((-1624.7) \cdot \left(\frac{1}{T_e + 273.32} - \frac{1}{298}\right)\right)\right) \cdot 10^{-6} \cdot t\right) \cdot$$

$$\cdot \exp(-2{,}1675 \cdot 10^{-8} \cdot t) \cdot \exp(-0{,}1861 \cdot 10^{-6} \cdot t) \tag{46}$$

A graph of the UAV communication unit reliability is given in Figure 7.

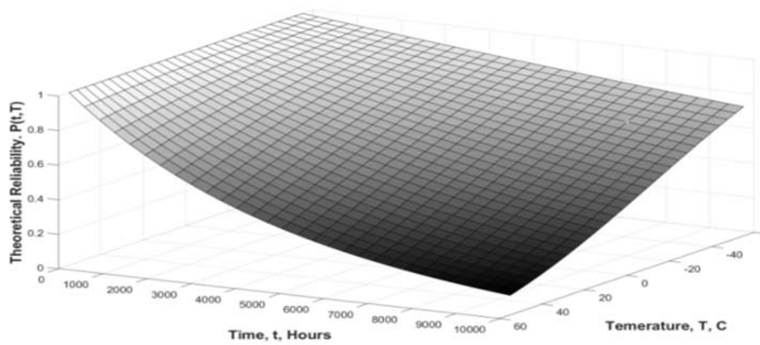

Figure 7. UAV communication unit reliability graph

Time interval equal to 10000 hours. It is enough for this research. Temperature range from -55 to +55 C. It is the most useful range for aviation equipment. It depends on different temperature, reliability on 10000 hours varied from 0.1136 to 0.7483.

5. Source Data Generating

Results of aviation electronic unit's tests are confidential information and cannot be given in this work. Random generation of test data based on conservative reliability assessment was carried out for the study. The Matlab development environment is used for it.

The result of generation with constant temperature (+55 C) for better illustrating is plotted in Figure 8.

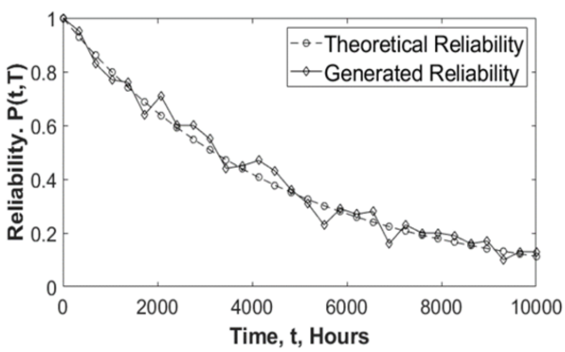

Figure 8. Reliability data generation on +55 C result

The completely results of reliability data generation, based on conservative estimation is displayed in Figure 9.

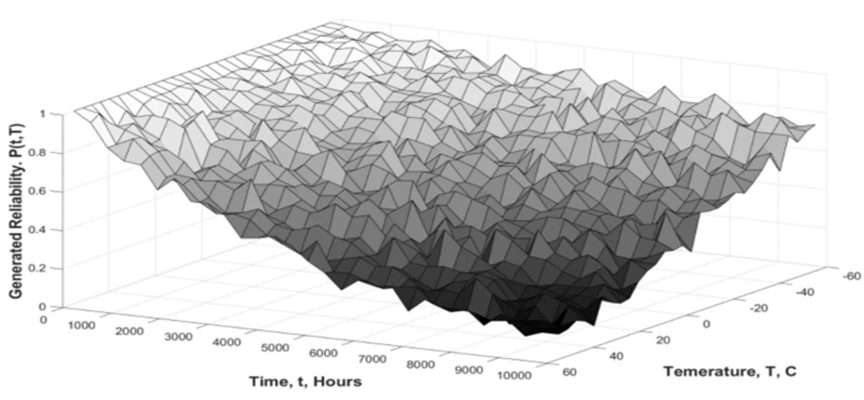

Figure 9. Reliability data generation result

6. ANN Training Process

For this research uses ANN with following parameters:

- Layers number: 3;
- Input neurons number: 2;
- Input neurons number: 7;
- Output neuron number: 1;
- Neuron function: 'tansig'.

Figure 10 shows ANN scheme.

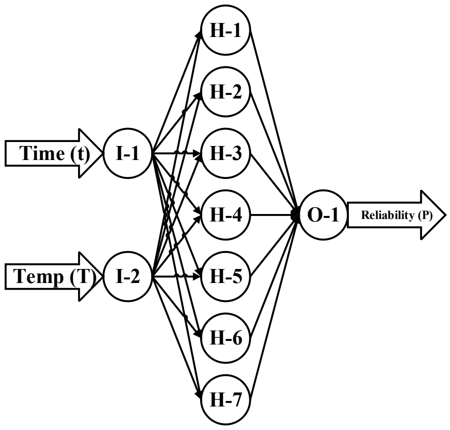

Figure 10. ANN Scheme

25% of the generated data used as input data. The remaining 75% is required to verify the training result. Training data is provided in Figure 11.

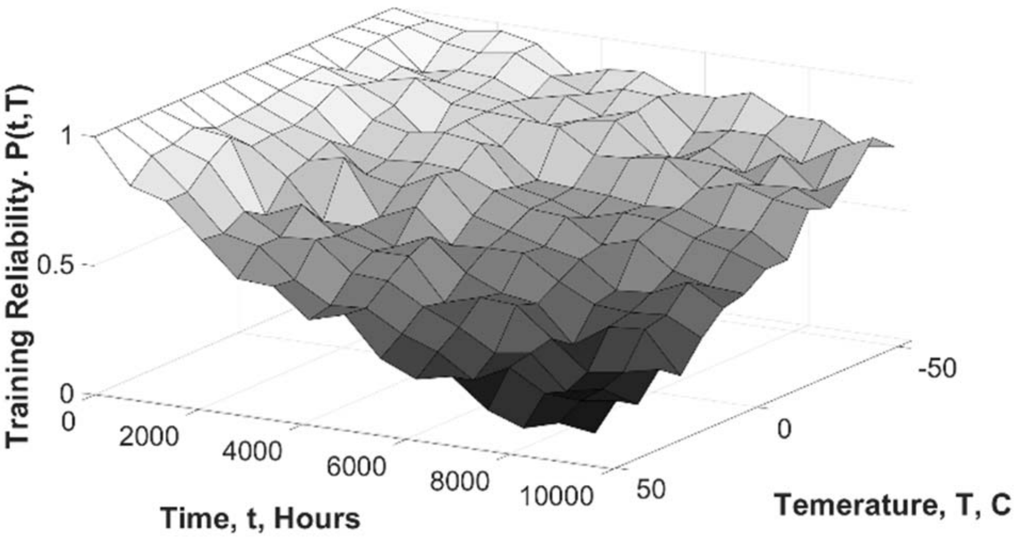

Figure 11. ANN training data

For the ANN establishment and training the Matlab software was chosen due to its simplicity and wide distribution.

ANN training options:

- Training algorithm: Levenberg-Marquardt;
- Performance: Mean Squared Error;
- Iteration limit: 500.

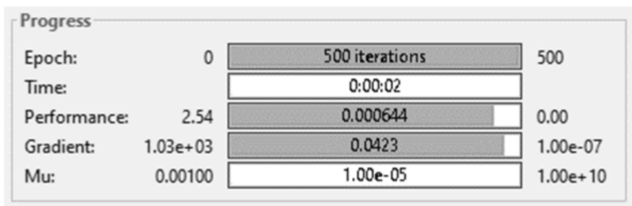

Figure 12. Matlab ANN training results

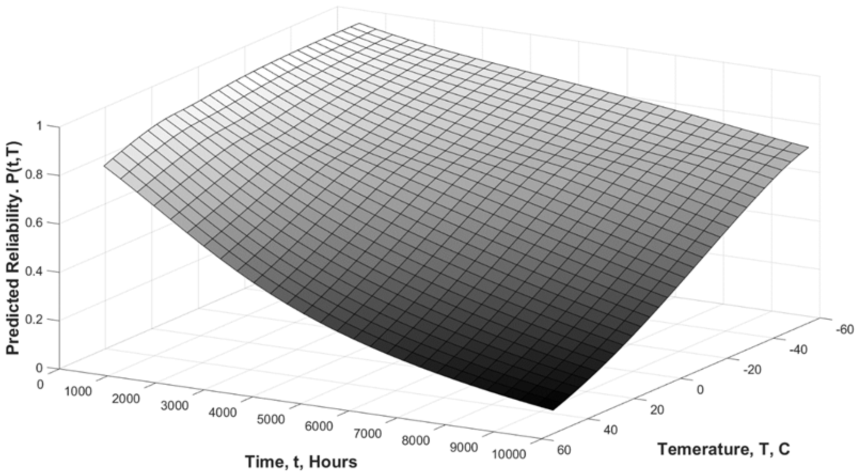

Figure 13. ANN simulation result

7. ANN Accuracy Evaluation

The ANN operation simulation is carried out. Time (up to 10,000 hours) and environment temperature is (from -55 to +55 C) used as input data. Figure 13 displays simulation result.

100% of data used for simulation.

A graph of the absolute errors of the ANN reliability evaluation results with respect to the generated data is shown in Figure 14.

Conservative reliability estimation errors are used as ideal data for comparison. Figure 14 also shows conservative reliability error.

Error averages:

- For ANN method: 0.0693;
- For the conservative method: 0.0323.

The result shows one order of error, which indicates sufficient accuracy of the ANN method.

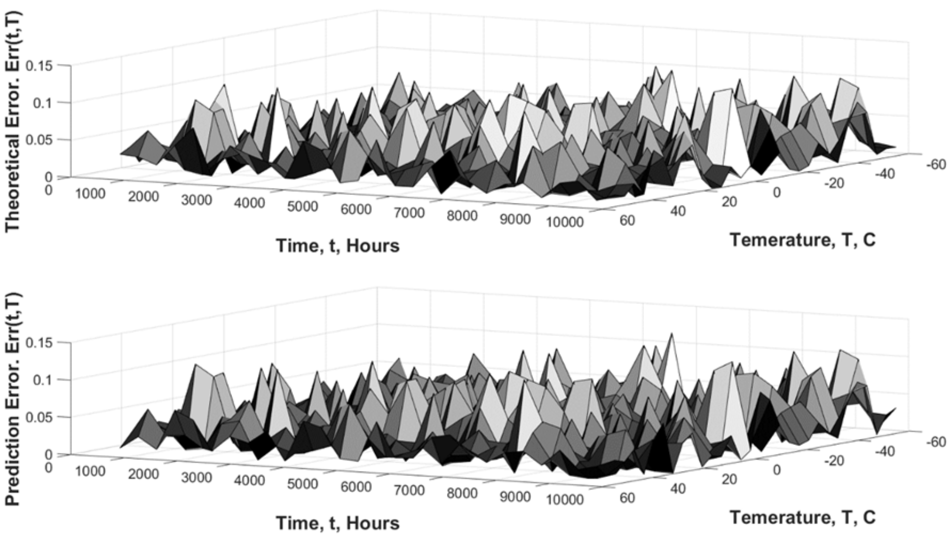

Figure 14. ANN and conservative reliability estimation error graph

8. ANN DSS Example

Training ANN is a core of ANN DSS. Figure 15 demonstrates possible application of this system.

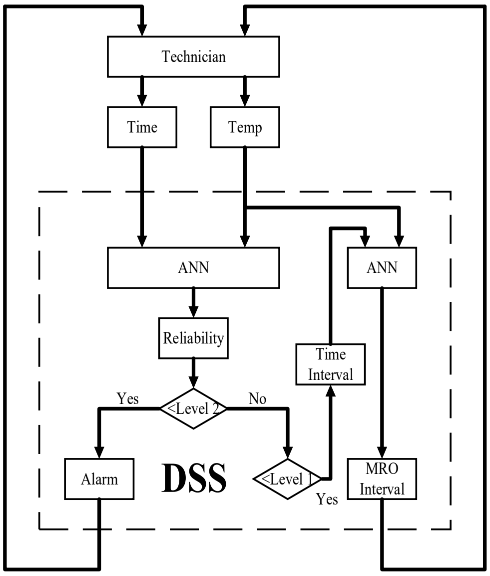

Figure 15. ANN DSS example

Data about environment temperature and total operating time comes from technician. ANN makes simulating and give a recommendation. If reliability is lower than level 1, system estimate optimal maintenance interval, if lower than level 2, send alarm.

9. Discussion

It should be noted that this study has mainly focused on possibility of creating and using ANN DSS in UAV MRO. The traditional aviation industry is extremely conservative, and using of such an innovative system is too radical nowadays. The analysis in the paper has concentrated on demonstrating the capability of ANN in avionic unit reliability predicting based on operation time and environment temperature. The findings are restricted to two input parameters for a visual result displaying in the form of three-dimensional graphs.

The limitations of this study clearly demonstrate the direction of future work. The impact of many other factors such as humidity, radiation, vibration, service history and human factor will be investigated. However, the findings do not imply that ANN training will be as simple a process. It may need to complicate the ANN structure, the selection of the artificial neurons math function, the choice of the optimal learning algorithm, the number of iterations and error measures. Also, the main limitation of this work is the unavailability of the using a real data about the avionic units reliability tests because of their confidentiality. The study was conducted on the randomly generated data, based on conservative reliability analysis.

Despite its preliminary nature, the research does suggest that the results clearly demonstrate the possibility of creating ANN DSS and using it in MRO. The results also show the relevance and prospects of continuing work in this area. However exploratory, this paper may offer some insight into the basic functionality and scope of the proposed system.

10. Conclusion

The aim of this work was to research the possibility of using mathematical method of artificial neural networks (ANN) in aircraft avionic maintenance, repair and overhaul (MRO). The development of ANN decision support system (DSS) was chosen as a possible application.

MRO is one of the three direct operation cost (DOC) within dominant components. Reducing DOC with the proposed system will reduce life cycle cost (LCC) and increase safety level. These two parameters are currently one of the key competitive factors. Companies' operators are increasingly basing their choice on the basis of their evaluation.

The traditional aviation industry is too conservative to directly use the new unprocessed system. For this reason, the UAV industry was chosen to start its implementation. UAV requirements are radically lower, but nowadays, the accident rate of these aircraft is higher by at least an order of magnitude. The proposed system is designed to reduce the accident rate without significantly increasing the MRO cost.

Mathematical method of ANN is based on creating a structure of artificial neurons, similar to the structure of the human brain. To accomplish this task, similar to human, ANN needs training. It is based on input data, which uses a set of influencing factors, and target data - result of the influence. In the case of proper training, ANN is able to produce close to the correct result based on the input data. An indicator of the correctness of training is the errors level.

ANN was trained in this work. Operation time and environment temperature were used as input data. The output parameter was reliability. The generated information is used as a target and verification data on the basis of conservative UAV electronic communication unit regarding reliability estimation. Conservative estimation is also considered in this article. After it, the ANN simulation was provided. The average level of absolute error was 0.0693, which demonstrates a high accuracy comparable to the conservative estimation (0.0323). One of possible solution for this ANN as the core of DSS in the MRO structure was offered.

In this study, only two input parameters are used: operation time and environment temperature for clarity and easy displaying the method and results. In further works, the influence of many other factors such as humidity, radiation, vibration, service history and human factor can be studied. Also, randomly generated information based on conservative reliability assessment is taken as initial data, due to the impossibility of publishing confidential information. However, with the correct conservative estimate of reliability, the real data will be very close to the data used in this work.

The proposed system shows a high degree of accuracy and simplicity of ANN training compared to conservative reliability estimation even for such a simple electronic unit. Scaling work to more complex systems makes the gap even larger.

The use of ANN DSS for MRO UAV will reduce the accident rate without a significant LCC increasing. With the successful implementation of the system will gain confidence and can be further used in traditional aviation. Also, the system can be used not only in the field of avionics, but also transferred to all other aircraft systems, or even to other industries. This will inevitably lead to LCC reduction and increase safety.

Acknowledgments

The author wants to thank his supervisor Professor Yong Chen from Shanghai JiaoTong University for his support, Professor He Ren from COMAC for his maintenance study and Professor V.A. Hachikyan from Moscow Aviation Institute for introduction in Artificial Neural Networks.

References

[1]. Fridlyand, A.A., Gyazova, M.M., & Karapetyan, A.G. (2018). Optimization of the basic requirements of the technical specifications and design and operational characteristics of the aircraft based on the concept of life cycle cost. *Scientific Bulletin of GosNII GA* , (24), 27.

[2]. McFadden, M., & Worrells, D. S. (2012). Global outsourcing of aircraft maintenance. *Journal of Aviation Technology and Engineering*, *1*(2), 4.

[3]. Augustine, B. S. M., Ramesh Bapu, B. R., Narayanan, K. V., & Kolanjiappan, S. (2007). Evaluation of Aircraft Maintainability and Aircraft Maintenance. *Proceedings of International Conference and Exhibition on Emerging Challenges in Design and Manufacturing Technologies (ECHDEM 2007), Sathyabama University, Jeppiaar Nagar, Chennai, India, 2007.*

[4]. Bronnikov, A.M. (2017). Efficiency of technical operation of the aircraft onboard system unattended during the interservice period. *Scientific Bulletin of the Moscow State Technical University of Civil Aviation* , *20*(6), 89-98.

[5]. Bannister, J. A., Adlakha, V., Triyedi, K., & Alspaugh Jr, T. A. (1982). Problems related to the integration of fault tolerant aircraft electronic systems. Retrieved from: https://ntrs.nasa.gov/api/citations/19820021146/downloads/19820021146.pdf [accessed: 20. May 2020].

[6]. Pokorni, S. (2003). Experiences from reliability testing of aircraft electronic equipment. *Vojnotehnički glasnik*, *51*(4-5), 413-419.

[7]. Stamenkovic, Z. (2018). Reliable Electronic Devices, Circuits, and Systems for Communications. *5th International Conference on Electrical, Electronic and Computing Engineering, Palic, Serbia.*

[8]. Hobbs, A. and H. R. Stanley (2005). "Human Factors in the Maintenance of Unmanned Aircraft". Unmanned Aerial Vehicles Human Factors, Program Review, Federal Aviation Administration (FAA), U.S. Department Of Transportation. Washington DC, USA.

[9]. Petritoli, E., Leccese, F., & Ciani, L. (2018). Reliability and maintenance analysis of unmanned aerial vehicles. *Sensors*, *18*(9), 3171.

[10]. Petritoli, E., Leccese, F., & Ciani, L. (2018, June). Reliability degradation, preventive and corrective maintenance of UAV systems. In *2018 5th IEEE International Workshop on Metrology for AeroSpace (MetroAeroSpace)* (pp. 430-434). IEEE.

[11]. Mijwel, M. M., Esen, A., & Shamil, A. (2019). *Overview of Neural Networks.* Jordan: Information Technology Faculty, Middle East University.

[12]. Jiménez, A. A., Muñoz, C. Q. G., & Márquez, F. P. G. (2017, July). Machine learning and neural network for maintenance management. In *International Conference on Management Science and Engineering Management* (pp. 1377-1388). Springer, Cham.

[13]. Marugán, A. P., & Márquez, F. P. G. (2017, July). SCADA and artificial neural networks for maintenance management. In *International conference on management science and engineering management* (pp. 912-919). Springer, Cham.

[14]. Wong, J. S. (2012). *Whole life cost methods for aero-engine design* (Doctoral dissertation, University of Southampton).

[15]. Shiao, M., & Chen, T. K. (2019). Probabilistic Risk Assessment Tool AMETA (Aircraft Maintenance Event Tree Analysis) for Aircraft Structural Integrity and Fatigue Maintenance. In *AIAA Scitech 2019 Forum* (p. 2231).

[16]. Dyer, C., & Rodgers, D. (1998, November). Effects on spacecraft & aircraft electronics. In *Proceedings ESA Workshop on Space Weather, ESA WPP-155* (pp. 17-27).

[17]. Ančík, Z., & Vlach, R. (2011). Thermal Phenomena Modeling of Aircraft Electronic Unit. *Engineering Mechanics*, *18*(5-6), 281-288.

[18]. Santos, L., & Melicio, R. (2019). Stress, pressure and fatigue on aircraft maintenance personal. *Int. Rev.Aerospace Eng., 12*(1), 35-45.