Failure Risk Prediction While Processing Defining Parameters of Telecommunication and Radio-Electronic Systems

Oleksandr Solomentsev[1], Maksym Zaliskyi[1], Oleksiy Zuiev[1], and Alina Osipchuk[1]

[1]National Aviation University, 1, Lubomyr Huzar ave., Kyiv, 03058, Ukraine

Abstract

Effective operation of telecommunications and radio-electronic systems depends on several factors that must be taken into account at all stages of the equipment lifecycle. While using the equipment for its intended purpose, the function of efficiency maintaining is the main task of the operating system. To perform successfully this task, the operating system uses intelligent technologies of statistical data processing. The structure of the data processing is complex and includes procedures of model building, detection, evaluation, prediction, and others. The prediction procedures are very important, as it allows for determining the state of the equipment in the future, in particular, the possibility of failure. The failure risk assessment is usually based on the result of the equipment's defining parameters processing. This paper considers the synthesis of the prediction procedure based on the detection and estimation of changepoint parameters in the observed data trends. This procedure gives the possibility to assess the risk of failure using priori information about the characteristics of the maintenance process. Implementation of the proposed procedure will increase the reliability of telecommunications and radio-electronic systems.

Keywords

Prediction, data processing, risks assessment, operation system, telecommunication system, radio-electronic system.

1. Introduction

To provide the efficiency of telecommunication and radio-electronic systems (TRSs) functioning, operating systems (OSs) are usually used, which have a sophisticated structure of components [1]. These components can change their states over time. Changes can be controlled or uncontrolled [2]. In the general case, these changes are a source of possible risks that can negatively affect both the effectiveness of equipment and the technical and economic characteristics of enterprises [3].

The OS forms corrective actions regarding the state of all components to prevent the occurrence of possible risks [4, 5]. The process of action formation and implementation is based on the results of statistical data processing [6].

The OS can apply various data processing algorithms for diagnostics and technical condition monitoring, estimating the level of reliability, predicting failures, resource consumption, operational conditions deterioration, and others [7, 8]. It is advisable to use extrapolation procedures to predict risks.

The creation of a prediction algorithm includes synthesis and analysis [9, 10]. During the synthesis, the methods of maximum likelihood, moments, ordinary least squares, spline approximation, and others can be used. During the analysis, we can carry out analytical calculations based on the probabilities theory and mathematical statistics, as well as statistical simulation [11–13].

Traditional approaches in the field of prediction are based on the assumption of the stationarity of the analyzed data model trend for the future period [14, 15]. However, the practice of operation shows that the real trend models of the defining parameters and reliable indicators of the TRS can change at a random moment [16]. Therefore, the stationarity disturbance in the flow

CPITS 2023: Workshop on Cybersecurity Providing in Information and Telecommunication Systems, February 28, 2023, Kyiv, Ukraine
EMAIL: avsolomentsev@ukr.net (O. Solomentsev); maximus2812@ukr.net (M. Zaliskyi); 0801zuiev@gmail.com (O. Zuiev); alina.osipchuk2012@gmail.com (A. Osipchuk)
ORCID: 0000-0002-3214-6384 (O. Solomentsev); 0000-0002-1535-4384 (M. Zaliskyi); 0000-0002-4520-3288 (O. Zuiev); 0000-0002-9053-2072 (A. Osipchuk)

of processes is observed. The algorithms for prediction should have a complex structure and include procedures for detecting the fact of changepoint and estimating its parameters (occurrence time and changepoint intensity).

2. Statement of the Problem

Consider the statement of the problem in the general operator form. Operators will display an approach to the formation of events that will be associated with risks during the TRSs operation.

The main organizational element is the operation systems, which functioning is described by the OS($\cdot$) operator. We assume that a specific OS contains *u* elements, i.e. $\overrightarrow{\mathrm{OS}}_u(\cdot)$. Each element over time *T* can be in certain states in the space of phase states that belong to the considered element, therefore $\overrightarrow{\mathrm{St}}_{pj}(T/j=\overline{1,u})$. The number of states p_j is different for each j^{th} element of OS. Suppose that its group of factors $\vec{\Phi}$ determines the state of each element of OS. Then the OS elements can be represented in the following form

$$\overrightarrow{\mathrm{OS}}_u\left(\overrightarrow{\mathrm{St}}_{p_j}(T/j=\overline{1,u})/\vec{\Phi}\right).$$

Based on the OS elements states, it is possible to construct the trajectories of their movement $\overrightarrow{\mathrm{Tr}}$. Thus, it is possible to define functions for each element of the OS

$$\overrightarrow{\mathrm{Tr}}\left(\overrightarrow{\mathrm{OS}}_u\left(\overrightarrow{\mathrm{St}}_{p_j}(T/j=\overline{1,u})/\vec{\Phi}\right)\right).$$

The trajectories of individual elements in the corresponding phase spaces are associated with the occurrence of possible risks $\vec{R}_{p,u}^{(0)}$. Then

$$\vec{R}_{p,u}^{(0)}\left(\overrightarrow{\mathrm{Tr}}\left(\overrightarrow{\mathrm{OS}}_u\left(\overrightarrow{\mathrm{St}}_{p_j}(T/j=\overline{1,u})/\vec{\Phi}\right)\right)\right).$$

We believe that all the states of individual elements of OS are associated with risks, because, resources of various kinds are consumed during the operation process. At the same time, serious events (TRS failures, power supply absence, physical destruction of structures, and others) are more significant. It should be noted that control and preventive actions are formed about certain elements of OS. Data processing algorithms are used to form these actions. Processing and decision-making are performed for each element of OS and the corresponding trajectory in the space of phase states. The relationship between control actions $\vec{\mathrm{C}}$ and processing algorithms $\vec{\mathrm{P}}$ can be represented as

$$\vec{\mathrm{C}}\left(\overrightarrow{\mathrm{Tr}}\left(\overrightarrow{\mathrm{OS}}_u\left(\overrightarrow{\mathrm{St}}_{p_j}(T/j=\overline{1,u})/\vec{\Phi}\right)\right)/\vec{\mathrm{P}}\right).$$

Because of the control actions implementation, potential risks $\vec{R}_{p,u}^{(0)}$ become real $\vec{R}_{p,u}^{(\mathrm{real})}$, then

$$\vec{R}_{p,u}^{(\mathrm{real})}=\vec{R}_{p,u}^{(0)}\left(\vec{\mathrm{C}}\left(\overrightarrow{\mathrm{Tr}}\left(\overrightarrow{\mathrm{OS}}_u\left(\overrightarrow{\mathrm{St}}_p/\vec{\Phi}\right)\right)/\vec{\mathrm{P}}\right)\right).$$

Risks are usually possibilities. Therefore, real cost functions are formed in a separate way using the operator $\Psi(\cdot)$, then

$$\mathrm{Cost}(T)=\Psi\left(\vec{R}_{p,u}^{(\mathrm{real})}/\vec{\mathrm{P}}_{p,u}\right).$$

According to all statements, the problem is to develop such a set of data processing algorithms for each element of the OS so that the OS costs during the observation time T_{obs} will be minimal or will not exceed a certain value, then

$$\min(\mathrm{Cost}(T_{\mathrm{obs}}))=\Psi\left(\vec{R}_{p,u}^{(\mathrm{real})}/\vec{P}_{p,u}^{(\mathrm{opt})}\right),$$

where $\vec{P}_{p,u}^{(\mathrm{opt})}$ is an optimal design solution in terms of data processing algorithms for each trajectory of a certain element of the OS.

3. Materials and Methods

This section presents the synthesis of two procedures for the prediction of possible failure of TRS. To solve this task, we assumed the following limitations:

1. The Defining Parameter (DP) is available for observation. The measurements give the possibility to create a dataset with discrete values and constant sampling time Δ. The information about operating thresholds (upper and lower) $V_{\mathrm{O\,up}}$ and $V_{\mathrm{O\,low}}$ for this DP is known priori.
2. The changepoint occurs randomly. The probability density function of time moment of changepoint $f(t_{\mathrm{ch}})$ can be arbitrary and unknown.
3. The DP trend contains informational and stochastic components. The first component corresponds to DP model. The second component is random Gaussian noise with zero means and known standard deviation σ. According to this limitation, the DP can be presented as follows

$$DP_i=A_0+\xi(i\Delta-t_{\mathrm{ch}})\varphi(i\Delta-t_{\mathrm{ch}})+n_i,$$

where A_0 is a DP value for normal operation conditions, ξ is the changepoint intensity, $\varphi(t)$ is a step function, n_i is the noise. The presented equation corresponds to the most commonly used case of degradation according to a linear model. The changepoint intensity for this case is equal to the tangent of the trend inclination angle after the changepoint occurrence.

4. The probability density function of changepoint intensity $f(\xi)$ is arbitrary and unknown.

5. To prevent the failure of TRS, the corrective maintenance is carried out. The time for maintenance implementation T_{M} is random, but with a known probability density function.

The prediction procedure aims to determine the optimal time moment of maintenance in case of gradual failure prevention. The gradual failure usually occurs in case of one of the inequalities fulfillment

$$DP_i > V_{\mathrm{O\,up}} \text{ or } DP_i < V_{\mathrm{O\,low}}.$$

The operating time to failure, in this case, will be following

$$t_{\mathrm{F}} = \arg(DP_i/(DP_i = V_{\mathrm{O\,up}} \cup DP_i = V_{\mathrm{O\,low}})).$$

If a changepoint is detected, the prediction procedure will estimate the time of failure and form a decision to carry out the maintenance. The corresponding decision is made at the time t_{D}.

According to mentioned assumptions, the risk of failure R can be considered as the probability that time for maintenance implementation is greater than the remaining time to failure, i.e.

$$R = \Pr\,(t_{\mathrm{F}} - t_{\mathrm{D}} < t_{\mathrm{M}}).$$

The prediction procedure is implemented based on data processing in a sliding window with a size of n samples. The processing consists of four steps.

The first step. Observed data approximation using one of two techniques.

The first approach is associated with Simple Linear Regression (SLR) usage for data in sliding windows. For k^{th} iteration of sliding the estimates of DP are determined according to the equation

$$\widehat{DP_{i,k}} = c_{0,k} + c_{1,k} i,$$

where $c_{0,k}$ and $c_{1,k}$ are coefficients of linear regression, $i \in [0; n-1]$ is current number of sample in sliding window. Using the ordinary least squares method we can easily get

$$\begin{pmatrix} c_{0,k} \\ c_{1,k} \end{pmatrix} = \begin{pmatrix} n & \sum_{i=0}^{n-1} i \\ \sum_{i=0}^{n-1} i & \sum_{i=0}^{n-1} i^2 \end{pmatrix}^{-1} \begin{pmatrix} \sum_{i=0}^{n-1} DP_{i+k} \\ \sum_{i=0}^{n-1} i\, DP_{i+k} \end{pmatrix}.$$

The second approach is associated with Linear Two-Segmented Regression (LTSR) usage for data in sliding windows. The point of segment connection is the middle of the sliding window. For k^{th} iteration of sliding the estimates of DP are determined according to the equation

$$\widehat{DP_{i,k}} = c_{0,k} + c_{1,k} i + c_{2,k}\left(i - \frac{n}{2}\right) \varphi\left(i - \frac{n}{2}\right).$$

Using the ordinary least squares method we can easily get

$$\begin{pmatrix} c_{0,k} \\ c_{1,k} \\ c_{2,k} \end{pmatrix} = \mathcal{H}^{-1} \wp,$$

$$\mathcal{H} = \begin{pmatrix} \mathrm{n} & \sum_{i=0}^{n-1} i & \sum_{i=0}^{n-1} \omega_i \\ \sum_{i=0}^{n-1} i & \sum_{i=0}^{n-1} i^2 & \sum_{i=0}^{n-1} i\omega_i \\ \sum_{i=0}^{n-1} \omega_i & \sum_{i=0}^{n-1} i\omega_i & \sum_{i=0}^{n-1} \omega_i^2 \end{pmatrix}, \wp == \begin{pmatrix} \sum_{i=0}^{n-1} DP_{i+k} \\ \sum_{i=0}^{n-1} iDP_{i+k} \\ \sum_{i=0}^{n-1} \omega_i DP_{i+k} \end{pmatrix}, \omega_i = \left(i - \frac{n}{2}\right) \varphi\left(i - \frac{n}{2}\right).$$

To increase the veracity of prediction for the LTSR approach, the optimization technique discussed in [17] can be applied.

The second step. Decision-making about changepoint.

The classical methods of the changepoint study assume complicated calculations associated with the implementation of the statistical procedure of detection. For our research, we tried to use the simple approach; therefore we choose the Fisher test to check the significance of regression coefficients. In case of changepoint absence, the regression coefficients will be insignificant.

To use the Fisher test, it is necessary to calculate the determination coefficient

$$d = 1 - \frac{\sum_{i=0}^{n-1}\left(DP_{i+k} - \widehat{DP_{i,k}}\right)^2}{\sum_{i=0}^{n-1}(DP_{i+k} - \overline{DP_k})^2},$$

where $\overline{DP_k}$ is the mathematical expectation of DP for k^{th} iteration of sliding

$$\overline{DP_k} = \frac{1}{n}\sum_{i=0}^{n-1} DP_{i+k}.$$

The determination coefficient is recalculated into the value of a decisive statistic using the following equation

$$F = \frac{d(n-s-1)}{(1-d)s},$$

where s is the quantity of DP. In our case, we observe only one DP, so $s = 1$.

To decide on changepoint presence, the obtained parameter F should be compared with threshold F_{t}. In the general case, the threshold depends on sample size, DP quantity, and the probability of false alarm α. It should be noted that the prediction procedure finishes only in case of decision-making on changepoint presence. Therefore, one detection procedure contains a big number of decisions about the continuation of data processing and only one decision associated with the break-in case of the changepoint. Because of this, the probability of a false alarm should be close to zero.

It $F < F_{\mathrm{t}}$ for k^{th} iteration, we will go to the next iteration. Otherwise, the decision on the change point is made.

Third step. Estimation of operating time to failure.

In the case of SLR usage, the estimate of operating time to failure can be determined as follows

$$t_{\mathrm{F}} = t_{\mathrm{D}} + \left(\frac{V - c_{0,N}}{c_{1,N}} - n + 1\right)\Delta,$$

where N is the number of final iterations, V is the upper or lower operating threshold.

In the case of LTSR usage, the estimate of operating time to failure can be determined as follows

$$t_{\mathrm{F}} = t_{\mathrm{D}} + \left(\frac{V - c_{0,N} + 0.5nc_{2,N}}{c_{1,N} + c_{2,N}} - n + 1\right)\Delta.$$

Fourth step. Failure risk assessment.

The assessment of the risk is possible based on the information about the probability density function of time for maintenance implementation. In the general case, the risk of failure will be

$$R = \int_{\tau}^{\infty} f(T_{\mathrm{M}}) dT_{\mathrm{M}} \,,$$

where in the case of SLR

$$\tau = \left(\frac{V - c_{0,N}}{c_{1,N}} - n + 1\right)\Delta,$$

and in case of LTSR

$$\tau = \left(\frac{V - c_{0,N} + 0.5nc_{2,N}}{c_{1,N} + c_{2,N}} - n + 1\right)\Delta\,.$$

After the synthesis, it is necessary to analyze the efficiency of the proposed procedure of data processing. It will be discussed in the next section.

4. Results and Discussion

The analysis procedure was carried out based on statistical simulation. For the convenience of presenting the material, we will consider specific examples of the simulation implementation.

The flowchart of data processing procedures for the implementation of the prediction algorithm during simulation is shown in Fig. 1.

The initial parameters for analysis according to the introduced limitations are:

1. The sampling time is 1 minute.
2. The observation time is $T_{\mathrm{obs}} = 1440$ minutes.
3. The sliding window size is $n = 60$ minutes.
4. The DP value for normal operating conditions is $A_0 = 100$ conventional units.
5. The standard deviation of the noise is $\sigma = 8$ conditional units.
6. The operating thresholds are $V_{\mathrm{O\,up}} = 150$ and $V_{\mathrm{O\,low}} = 50$ conditional units.

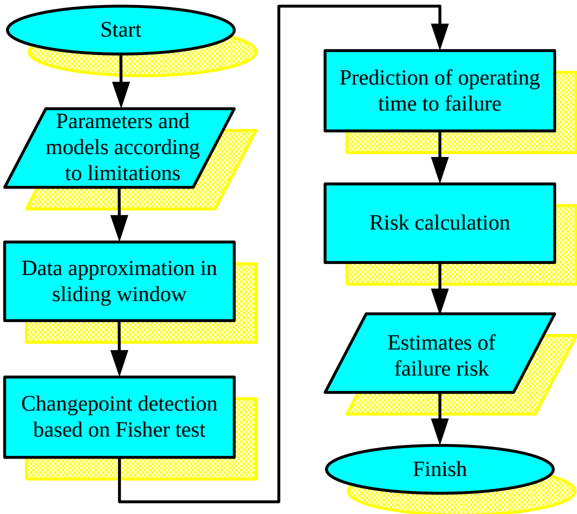

Figure 1: The flowchart of data processing procedures during the simulation

7. The time moment of changepoint occurrence has uniform distribution inside the second half of observation.
8. The changepoint intensity has uniform distribution in the range [0; 1].
9. The probability density function of time for maintenance implementation is normal. The mean value is 60 minutes; the standard deviation is 20 minutes.
10. The number of simulation procedure repetitions is $L = 1000$.

To perform further calculations, we need to form discrete data arrays containing information about DP trends. For given numerical values of initial parameters, such an array will be two-dimensional and have a size $(T_{\mathrm{obs}}/\Delta) \times L$. Such an array will allow future calculations to determine the statistical characteristics of the risk of failure, up to the most complete characteristic—the probability density function.

Fig. 2 shows examples of two possible trends of DP.

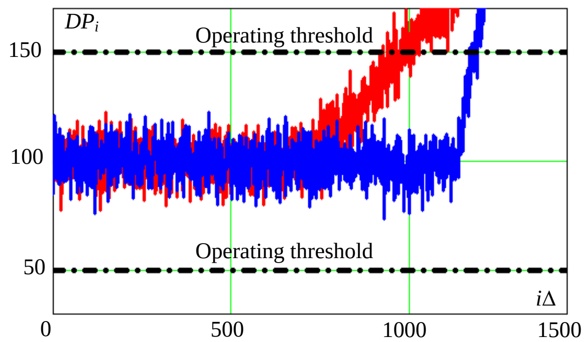

Figure 2: The DP trend examples

To describe the calculations, consider a specific numerical example. The DP trend in the initial dataset is characterized by the following parameters: the time of changepoint occurrence is 960-th minute, and the changepoint intensity is 0.279.

The approximation results using SLR and LTSR in the sliding window for iteration number 930 (this iteration corresponds to the event when the real-time changepoint is located at the middle of the sliding window) can be presented as follows

$$\widehat{DP}_{i,k\,\text{SLR}} = 95.677 + 0.192(i-930),$$

$$\widehat{DP}_{i,k\,\text{LTSR}} = 95.377 + 0.212(i-930) - -0.042(i-960)\varphi(i-960).$$

Fig. 3 presents the results of data approximation.

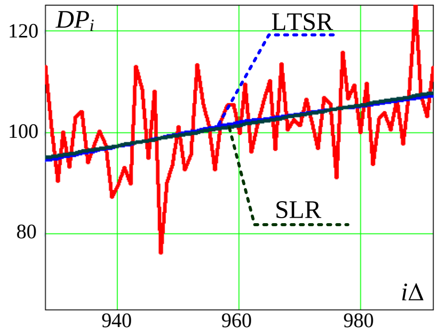

Figure 3: The results of data approximation

To perform calculations according to the Fisher test, the decisive statistics were computed. The corresponding data are shown in Fig. 4. The obtained dependencies for cases of SLR and LTSR almost coincide. The threshold of decision-making is equal to 17.462. This value was obtained for the probability of false alarm equaled to 0.0001. In this particular example, both approximation techniques give the same estimate for the time of changepoint occurrence. This estimate is equal to 966-th minute.

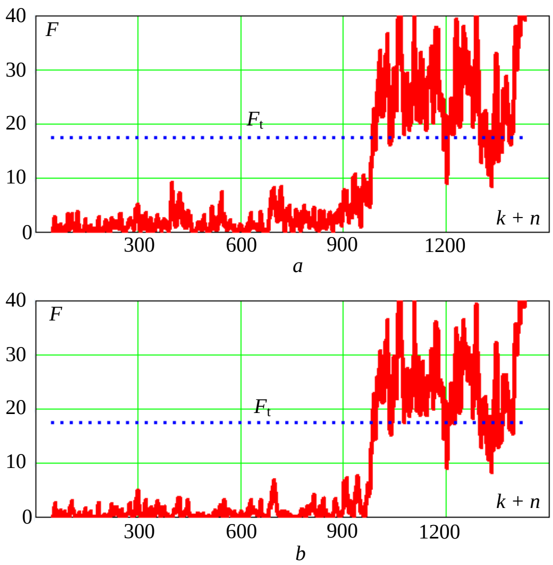

Figure 4: The decisive statistics: a) in the case of LTSR, b) in the case of LSR

The next step is a calculation of the remaining time to failure. For this numerical example, the SLR method predicts 92 minutes to failure, and LTSR predicts 121 minutes to failure. According to the simulation, failure occurs 114 minutes after the changepoint. Therefore, for this example, the LTSR method has a more correct estimate but is slightly greater than the real value.

The risk of failure is $5.35{\cdot}10^{-2}$ and $5.77{\cdot}10^{-4}$ for SLR and LTSR methods, respectively.

The simulation repetition gives the possibility to build the histograms of risk estimates. The corresponding histograms are shown in Fig. 5.

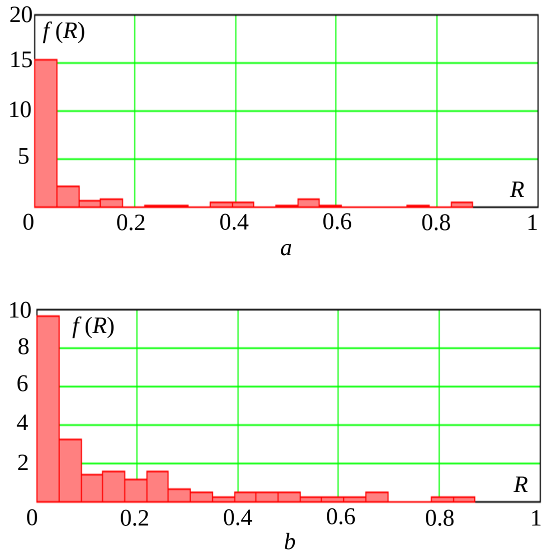

Figure 5: The histograms of risk estimate: a) in case of LTSR, b) in case of LSR

The expected values of risk are equal to 0.148 and 0.098 for SLR and LTSR methods, respectively. It should be noted that shown numerical result reflect only one case for introduced initial parameters. The computed value of risk can be used to improve the maintenance process for TRSs.

5. Conclusions

The obtained results are relevant for the theory and practice of design and improvement of TRS operation systems. The emphasis on statistical data processing algorithms for timely detection and prevention of failures and, accordingly, reducing the risks of possible losses in the TRS OS is justified. The proposed data processing methods make it possible to increase the level of TRS reliability by performing preventive maintenance.

The future scope is associated with several directions. If we assume that the statistical characteristics of the distributions for defining parameters are priori unknown, then it is advisable to develop adaptive algorithms of prediction. Another direction is connected with taking into account a large number of OS elements. Such accounting can allow a more complete assessment of both possible risks and the consequences of their occurrence.

6. References

[1] D.J. Smith, Reliability, Maintainability and Risk. Practical Methods for Engineers, 10th ed., Elsevier, London, 2021.

[2] R. Voliansky, A. Pranolo, Parallel Mathematical Models of Dynamic Objects, Int. J. Adv. Intell. Informs. 4(2) (2018) 120–131. doi:10.26555/ijain.v4i2.229

[3] D. Galar, P. Sandborn, U. Kumar, Maintenance Costs and Life Cycle Cost Analysis, CRC Press, Boca Raton, 2017.

[4] A. Jardine, A.H.C. Tsang, Maintenance, Replacement, and Reliability: Theory and Applications, 2nd ed., CRC Press, Boca Raton, 2017.

[5] O. Solomentsev, M. Zaliskyi, O. Zuiev, Radioelectronic Equipment Availability Factor Models, Signal Processing Symposium (SPS), Serock, Poland, 2013, 1–3. doi:10.1109/SPS.2013.6623616

[6] O. Solomentsev, et al., Data Processing in Exploitation System of Unmanned Aerial Vehicles Radioelectronic Equipment, IEEE 2nd International Conference Actual Problems of Unmanned Air Vehicles Developments (APUAVD), Kyiv, Ukraine, 2013, 77–80. doi:10.1109/APUAVD.2013.6705288

[7] O. Solomentsev, et al., Substantiation of Probability Characteristics for Efficiency Analysis in the Process of Radio Equipment Diagnostics, IEEE 3rd Ukrainian Conference on Electrical and Computer Engineering (UKRCON), Lviv, Ukraine, 2021, 535–540. doi:10.1109/UKRCON53503.2021.9575603

[8] A. Cachada et al., Maintenance 4.0: Intelligent and Predictive Maintenance System Architecture, IEEE 23rd International Conference on Emerging Technologies and Factory Automation (ETFA), Turin, Italy, 2018, 139–146. doi:10.1109/ETFA.2018.8502489

[9] W. Cave, Prediction Theory for Control Systems, PS Inc., New Jersey, 2020.

[10] M. Kuhn, K. Johnson, Applied Predictive Modeling, Springer, New York, 2013.

[11] Y. Sadykov, et al., Technology of Location Hiding by Spoofing the Mobile Operator IP Address, in: IEEE International Conference on Information and Telecommunication Technologies and Radio Electronics (2021) 22–25. doi: 10.1109/UkrMiCo52950.2021.9716700

[12] M. TajDini, V. Sokolov, P. Skladannyi, Performing Sniffing and Spoofing Attack Against ADS-B and Mode S using Software Define Radio, in: IEEE International Conference on Information and Telecommunication Technologies and Radio Electronics (2021) 7–11. doi: 10.1109/UkrMiCo52950.2021.9716665

[13] Z. Hu, et al., Bandwidth Research of Wireless IoT Switches. In 2020 IEEE 15th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (2020). doi: 10.1109/tcset49122.2020.2354922

[14] I. Ostroumov, K. Marais, N. Kuzmenko, Aircraft Positioning Using Multiple Distance Measurements and Spline Prediction, Aviation, 26(1) (2022) 1–10. doi:10.3846/aviation.2022.16589

[15] I. Ostroumov, N. Kuzmenko, Statistical Analysis and Flight Route Extraction from Automatic Dependent Surveillance-Broadcast Data, Integrated Communications Navigation and Surveillance Conference, Dulles, USA, 2022, 1–9. doi:10.1109/ICNS54818.2022.9771515

[16] Z. Cai, et al., Adaptive Prediction of Remaining Useful Lifetime for Single Equipment Based on Accelerated Degradation Modeling, Global Reliability and Prognostics and Health Management Conference, Shanghai, China, 2020, 1–5. doi:10.1109/PHM-Shanghai49105.2020.9280996

[17] J. Al-Azzeh, et al., A Method of Accuracy Increment Using Segmented Regression, Algorithms, 15(10) 378 (2022) 1–24. doi:10.3390/a15100378