Evaluation of Network Reliability and Element Importance Metrics

Aleksandr Moshnikov[a]

[a]ITMO University, 49 Kronverksky Pr., St. Petersburg, Russian Federation

Abstract

The article considers an approach to assessing the importance metrics and reliability of networks. The Monte Carlo method is used to estimate Birnbaum metrics and failure probability with determination of the confidence interval. To conduct a computational experiment, the R software package is used. A description is given of the representation of the control system reliability model in the iGraph package, which provides visualization of the results. The model of a three-level network structure is considered as an example.

Keywords

Monte Carlo method, Reliability estimation, R language, Importance metrics

1. Introduction

Currently, there is a rapid development of information technologies and their implementation in various areas of human activity [1]. Control transmission networks have become an integral part of people's lives, without which information exchange is practically unthinkable. In such a situation, the analysis of the technical characteristics of existing data transmission networks and the design of new networks, taking into account the given characteristics, remains one of the urgent tasks in the field of information technology.

In addition to such technical characteristics of computer networks as: performance, latency, security, scalability, extremely important characteristics are complex reliability indicators: availability factor, average unavailability time per year [2]. The reliability of the network also indirectly depends on the safety of the operation of control systems for any objects in which the untimely response (due to failures and failures in the data transmission network) of the control system to any critical changes in the control object can lead to serious consequences. In this situation, the analysis of reliability indicators of distributed control systems is a particularly relevant problem. Reliability is defined as the probability of a system or a sub-component functioning correctly under certain conditions over a specified interval of time [3].

Issues of reliability of systems with a network structure are still relevant [4, 5].

For instance, the reliability of network nodes, termed as the terminal reliability, is the probability that a set of operational edges provides communication paths between every pair of

Proceedings of the 12th Majorov International Conference on Software Engineering and Computer Systems, December 10–11, 2020, Online & Saint Petersburg, Russia
moshnikov.alex@gmail.com (A. Moshnikov)
0000-0002-3689-2472 (A. Moshnikov)

nodes. Another closely related concept with reliability is availability, which can be defined as the probability that a component will be available when demanded [3].

Importance measures (IMs) are used to evaluate the effect of component reliability on system reliability. IMs are useful tools in reliability engineering [14], risk analysis [15, 17], and system reliability optimization. These measures can help reliability engineers to find a better solution rapidly because they can identify the weakest links of the system, which are the premise and foundation of system design, maintenance, and resource configurations. During the system design period, component importance can help designers determine cost effective design ideas with relatively high system reliability and low cost rapidly.

Note that the significance of a system element according to Birnbaum I_{BIM} reflects the degree of influence of changes in the element's readiness coefficient on changes in the system's readiness coefficient. The significance of a system element according to Barlow-Proshan I_{BP} reflects the probability that a system failure that occurred at a certain point was caused by this element. The significance of a Vesely-Fassel system element reflects the probability that this element is one of the failed elements, provided that the system failed. Vesely-Fassel significance I_{VF} characterizes those elements that are most often involved in system failures.

The cost of increasing the risk for a system element I_{RAW} reflects the importance of maintaining the current level of reliability of this element. The cost of reducing the risk for a system element I_{RRW} reflects the degree to which the system's availability coefficient increases if this element is replaced with a flawless element. The critical significance of a system element I_C reflects the probability that this element is critical for the system at a given time. The potential for improvement of a system element I_{IT} reflects the gain in system reliability if this element is replaced with a completely reliable one [16].

The most widely used importance measures were acquired in the component allocation problem. The optimal component allocation problem arises when a pool of available components exists (in the market or in the company store) for each subsystem and a designer chooses a set of components for each subsystem such that the system reliability is maximized subject to constraints such as weight and cost.

2. Reliability and importance assessment

2.1. Monte-Carlo method for reliability estimation

The easiest way to estimate P is to use Crude Monte-Carlo simulation [19]. Let $X_{(1)}, ..., X_{(N)}$ be independent identically distributor random vectors with the same distribution as $\boldsymbol{X}$. Then

$$P = \frac{1}{N} \cdot \sum_{i=1}^{N} h(X_{(i)}) \tag{1}$$

is an unbiased estimator for P, where $h()$ is reliability function. Its sample variance is given by

$$var(P) = \frac{1}{N} \cdot (p - p^2) \tag{2}$$

An important measure for the "efficiency" of any estimator is its relative error. Relative error for P is given by

$$re(P) = \sqrt{\frac{1-p}{pN}} \tag{3}$$

To achieve acceptable accuracy, we assume an error less 0.01, and the number of iterations is 5143.

2.2. Element importance metrics

It is natural to assume that different elements affect the system's behavior in terms of reliability in different ways. The ability of the researcher to quantify the nature of the elements influence on the behavior of the system is of particular importance in the analysis of systems. This makes it possible to identify system weaknesses, select optimal redundancy, and make a rational impact on the reliability of the system as a whole.

The importance of the element e_i in the system is defined as a private derivative of the availability factor (the probability of) the system availability (the probability of) the element for which an analysis of its significance:

$$I_{BIM}(i,p) = \frac{\partial h(p)}{\partial p_i} \tag{4}$$

This characteristic is called Birnbaum significance (BIM-significance) [6]. The significance is estimated by the number of times the system availability coefficient increases when the element availability coefficient increases. BIM-significance does not depend on the readiness coefficient of the element p, but depends only on p_j for all $i = j$ in satisfies the inequalities $0 \leq I_{BIM}(i) \leq 1$.

Birnbaum importance considers the relationships between the system performance when component i is perfect, the system performance when component i fails, and the current system performance.

For the BIM-significance indicator, you can get an expression in the following form:

$$I_{BIM}(i,p) = h(1_i,p) - h(0_i,p) \tag{5}$$

where $h(i,p)$ is reliability function, $h(1_i,p)$ for absolutely reliable component, $h(0_i,p)$ for absolutely unreliable component.

Other metrics are also used to analyze the significance of elements. The list is presented in table 1.

Birnbaum $I_{BIM}(x_i)$ reflects the degree of influence of the change in the availability factor of the element on the change in the availability factor of the system. Risk Decrease $I_{RD}(x_i)$ reflects the importance of maintaining the current level of reliability of this element. Fussell-Vesely $I_{FV}(x_i)$ reflects the probability that this element is one of the failed elements, provided that the system failed, the Vesely-Fassel significance characterizes those elements that are most often involved in system failures. Risk Increase $I_{RI}(x_i)$ reflects the importance of maintaining the current level of reliability of this element. Criticality Importance $I_{CR}(x_i)$ reflects the probability that this element is critical for the system at a given time.

Table 1
Importance metrics and calculated ratios

Indicator	Equation
Birnbaum $I_{BIM}(x_i)$	$P(x_i = 1) - P(x_i = 0)$
Risk Decrease $I_{RD}(x_i)$	$P(x_{base}) - P(x_i = 0)$
Fussell-Vesely $I_{FV}(x_i)$	$(P(x_{base}) - P(x_i = 0))/P(x_{base})$
Risk Decrease Factor $I_{RDF}(x_i)$	$P(x_{base})/P(x_i = 0)$
Criticality Importance $I_{CR}(x_i)$	$(P(x_i = 1) - P(x_i = 0))/P(x_{base})$
Risk Increase $I_{RI}(x_i)$	$P(x_i = 1) - P(x_{base})$
Risk Increase Factor $I_{RIF}(x_i)$	$P(x_i = 1)/P(x_{base})$

Many researches have been devoted to computational aspects of significance estimation, including [7, 8].

3. Modeling using R

R is a programming language for statistical data processing and working with graphics, as well as a free open-source computing environment for the GNU project. The R language contains tools that allow you to create multiple parallel threads of calculations (due to simultaneous loading of several processor cores) and reduce the time spent on modeling several times. To assess the accuracy of the results obtained, the bootstrap method is proposed. The essence of the method in this case is that on the basis of one available sample (obtained using the graph traversal algorithm), a series of pseudo-samples of the same size is formed, consisting of random combinations of the original set of elements. In this case, the "random selection with return" algorithm is used, i.e. the extracted element is returned to the original set and has a chance to be selected again. For each random sample to estimate the probability of failure (or probability of failure) and thus formed the sample probabilities of system failure (or probability of failure-free operation), which further evaluated the necessary statistical data (standard deviation or confidence limits). To calculate the number of iterations and estimate the confidence interval, a standard approach is used in accordance with [3]. Various techniques can also be used to improve accuracy, with the most widespread sampling by significance [10].

To search the graph for paths between certain vertices, use the width traversal algorithm (an implementation of this algorithm in the iGraph library is used). To generate random numbers with an exponential distribution law, the basic functions of the R language are used [9].

Reliability modeling includes N iterations. At each iteration, a random operating time before failure is generated for each system element (vertex) (this time is generated based on the specified failure rate of the system element). After that, the elements are sorted in ascending order of uptime to failure, and the element (vertex) with the lowest time is selected. This vertex is removed from the graph and the existence of paths between certain vertices of the graph is checked (between which vertices the presence of a path should be checked is listed in the description of system failure criteria). If all necessary vertexes are found, the current iteration continues and the next element in increasing time to failure is selected and the corresponding vertex is removed from the graph. Next, it checks again whether there are paths between certain vertexes. If no paths are found between the specified vertexes, the system is considered to have failed. The failure time T_i is fixed and a new iteration begins.

4. Numerical examples

4.1. The dodecahedron graph

For this experiment, we take the dodecahedron graph (Fig. 1), the model that is widely considered for a network reliability example. The dodecahedron graph with 20 vertices, 30 edges, and fault criteria - loss connection of $\{1, 20\}$.

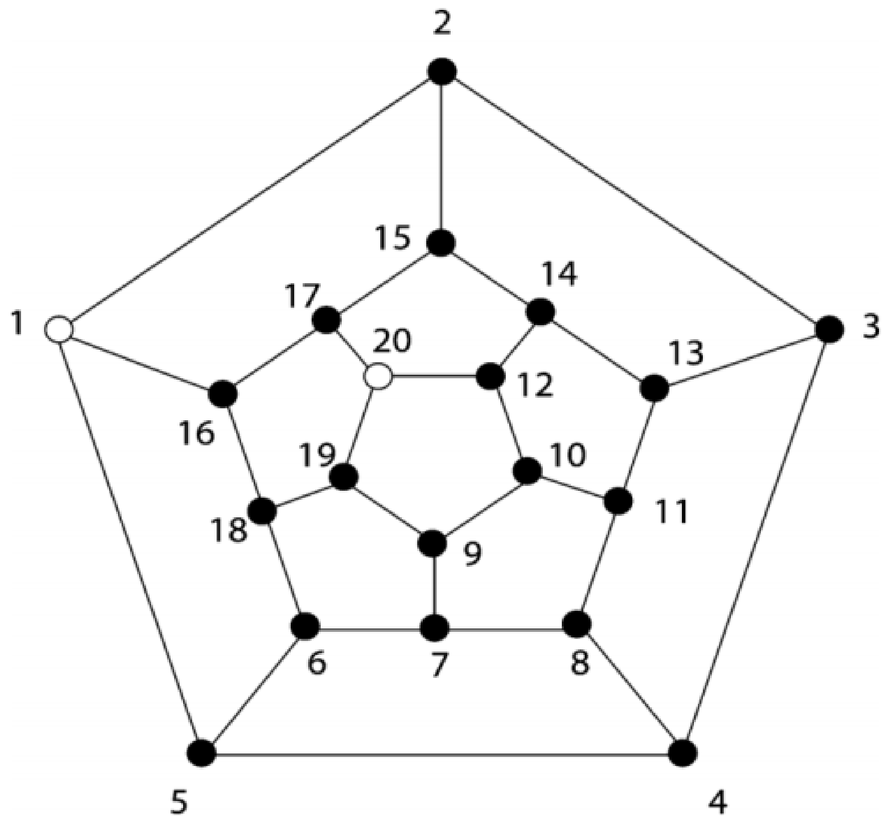

Figure 1: The dodecahedron graph

In this model, it is assumed that the vertexes are reliable, and the edges (communication lines) may fail. The probability of edge failure is constant over time and is equal to q. Using the Monte-Carlo method we estimate the dependence of the probability of failure of the graph on the probability of failure of each edge. The obtained simulation results are in good agreement with the results obtained [11].

The obtained results show a sharp decrease in the probability of connectivity when the probability of edge failure is less than 10^{-1}, which correlates well with the presence of one

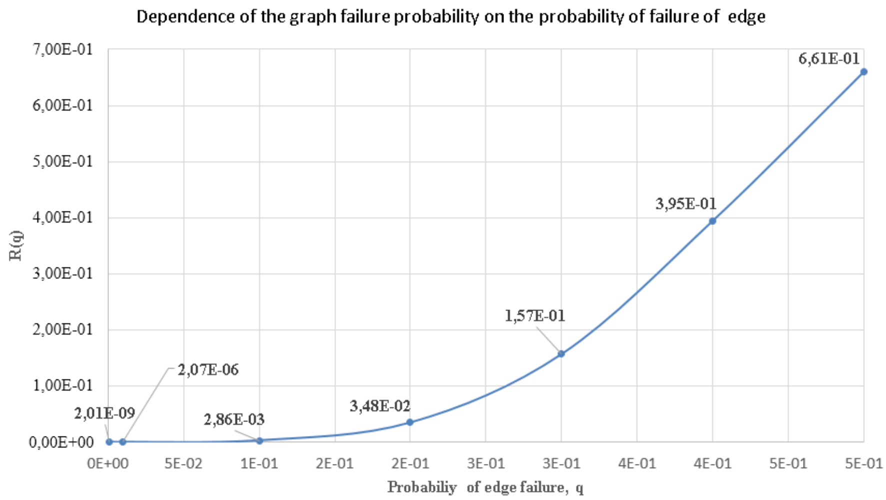

Figure 2: Dependence of the graph failure probability on the probability of failure of edge

path of length 3, and two paths of length 4 (by length is meant the smallest number of edges lying between the vertices $\{1, 20\}$).

4.2. SCADA system

Automated process control system is a group of technical and software solutions designed to automate technological processes in industrial enterprises. As a rule, automatic process control systems are understood as a complete solution that ensures the automated execution of the basic operations of the technological process of production. Components of automatic process control systems can be separate automatic control systems and automated devices connected in a single complex. Such as Supervisory control and data acquisition systems (SCADA), distributed control systems (DCS), emergency protection systems.

SCADA is a complex of equipment, distributed across three levels of the hierarchy, depending on the functional purpose: upper level: process operator panels; mid-level: server racks, central computing server, lower level: remote control terminal [12]. The architecture of the process control system takes into account the requirements for the implementation of the principle of a single failure and has structural redundancy [2], the structure of the process control system is shown in Fig. 3.

The system consists of the following units:

1. The Hardware of the main computing resources (S1, S2);

2. Control servers (CS1, CS2) is designed for collecting, processing and storing information about the operation of system equipment, as well as information interaction.

3. Remote terminal unit (B1-B8) is designed for control field equipment.

4. Four independent Ethernet line;

The representation in SCADA of the system in the form of a graph and its representation in the package R is shown in Fig. 4. The standard reliability data (Failure rate: Central control

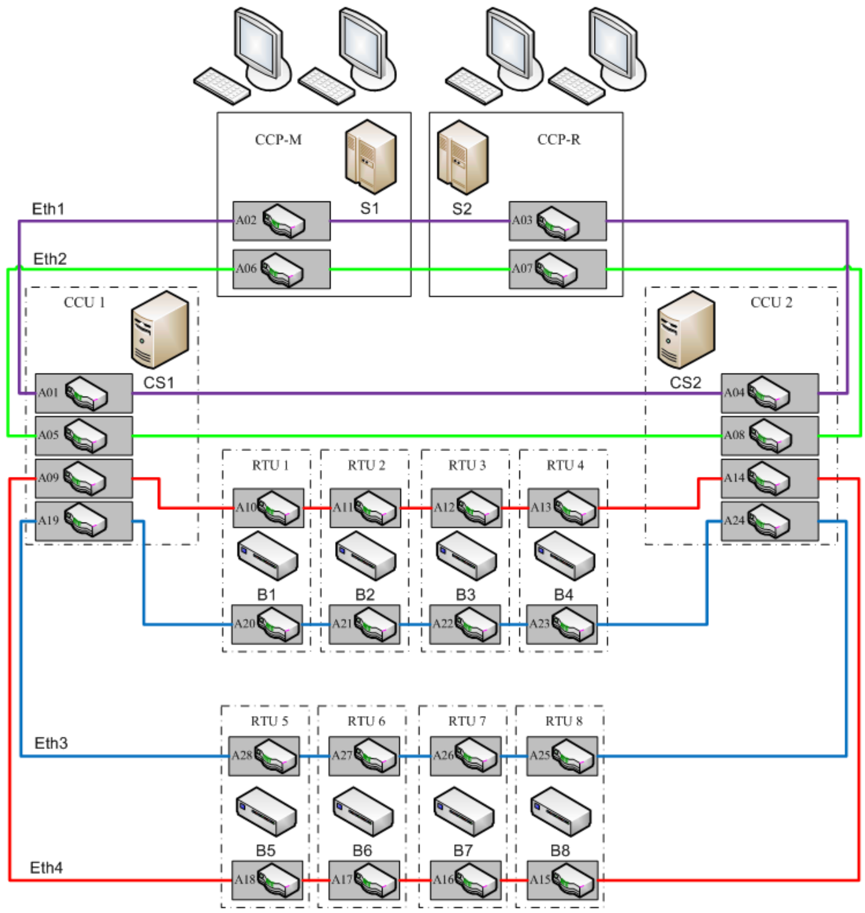

Figure 3: Three-level SCADA, with duplicated data transfer rings

panel main, redundant - $50 \cdot 10^{-6} h^{-1}$, Central control unit - $30 \cdot 10^{-6} h^{-1}$, Remote control terminal - $20 \cdot 10^{-6} h^{-1}$, Commutator - $10 \cdot 10^{-6} h^{-1}$) are considered as initial data [12]. It is assumed that issues related to the process of ensuring computational reliability are provided by the necessary capacities [13].

A system failure is considered to be the loss of communication between the fictitious vertex F1 (SCADA system operator) and the field equipment control subsystems B1-B8.

The simulation results of failure probability are presented in Fig. 5

Table 2 shows the reference reliability importance metrics estimated for the SCADA system.

Increasing the reliability of the elements with the biggest significance will allow achieving the required failure probability. As a result of the BIM assessment, CPUs of CS unit make the greatest contribution to system reliability. If further reliability improvements are needed, these elements should be considered. Possible ways to improve reliability can be considered: the introduction of continuous monitoring, the choice of more reliable components, using the of redundancy by reserving.

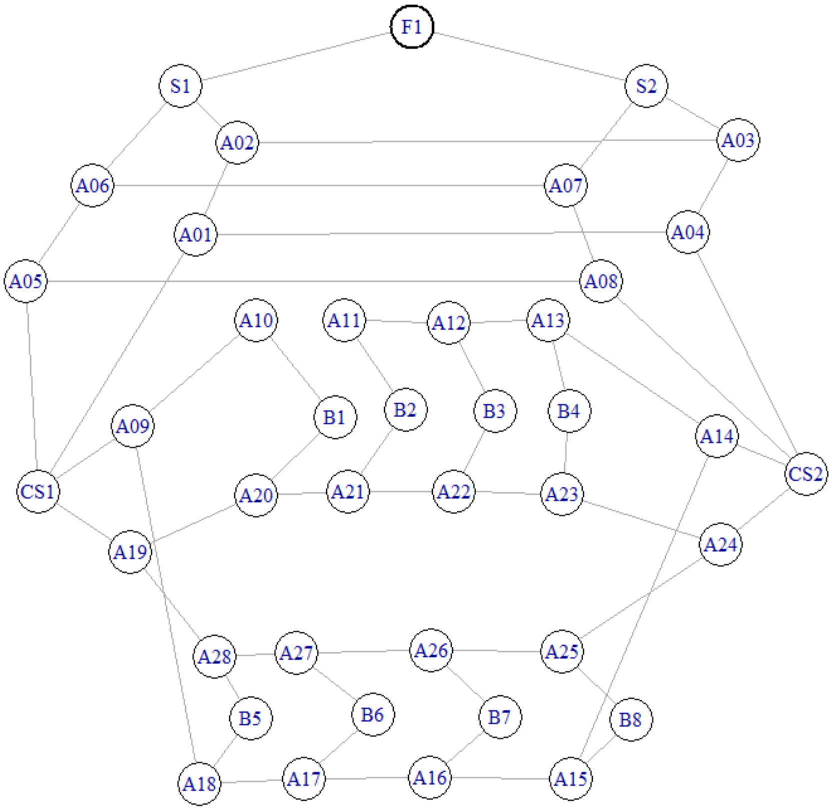

Figure 4: Graph describing the topology of the process control system (representation in the R language)

Table 2
SCADA elements reliability importance

Element	$I_{BIM}(x_i)$	$I_{RD}(x_i)$	$I_{FV}(x_i)$	$I_{RDF}(x_i)$	$I_{CR}(x_i)$	$I_{RI}(x_i)$	$I_{RIF}(x_i)$
Remote control terminal B1-B8	0.994	0.992	1.000	∞	1.002	0.002	1.002
Central control unit CS1, CS2	0.995	0.963	0.022	0.020	0.020	0.002	1.002
Commutator A01-A28	0.004	0.004	0.005	1.004	0.004	0.001	1.001
Central control panel S1, S2	0.995	0.032	0.029	1.030	0.032	0.031	1.002

According to the results of the Monte Carlo simulation (fig. 5), it can be argued that the probability of the SCADA functioning in 5000 hours will be no less than 0.992 with a confidence probability of 0.90. To improve accuracy, methods of reducing the variance of a sample estimate, for example, the Cross-Entropy Monte-Carlo method [11, 18], can be used.

The reliability estimated values and importance metrics can be used for system modernization, in particular when using one of the LKA-LKD algorithms-heuristics [16] for example.

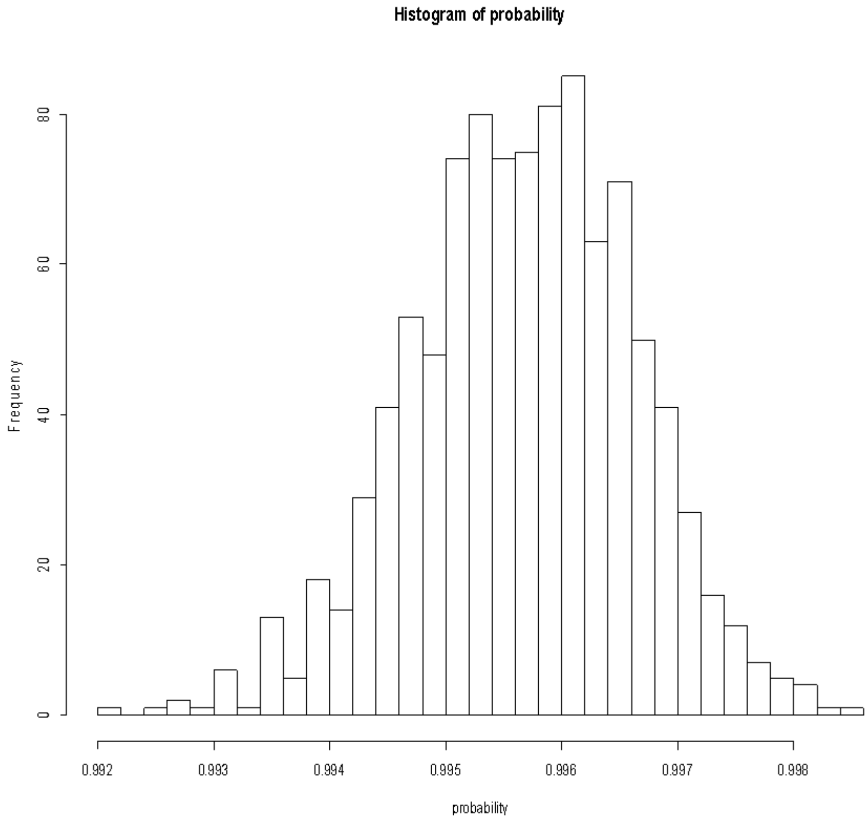

Figure 5: Histogram of the probability uptime distribution of a SCADA over 5000 hours

5. Conclusion

The reliability models of three-level networks based on the model systems with independent elements are also considered, a method for assessing reliability is proposed. The Monte Carlo method is used to estimate failure probability and reliability importance metric with determination of the confidence interval. To conduct a computational experiment, the R software package is used. A description is given of the representation of the control system reliability model in the iGraph package, which provides visualization of the results. R language was primarily created and is continuing to evolve as a statistical data processing tool. The value of the BIM metric is determined for further system improvement.

References

[1] Krieger U.R., Markovich N. Modeling and Reliability Analysis of a Redundant Transport System in a Markovian Environment. Distributed Computer and Communication Networks. DCCN 2019. Lecture Notes in Computer Science, vol 11965. Springer, Cham

[2] Bogatyrev, A.V., Bogatyrev, V.A., Bogatyrev, S.V. Multipath Redundant Transmission with

Packet Segmentation (2019) 2019 Wave Electronics and its Application in Information and Telecommunication Systems, WECONF 2019, art. no. 8840643. doi: 10.1109/WECONF.2019.8840643
[3] Gertsbakh B., Shpungin Y. Models of Network Reliability: Analysis, Combinatorics, and Monte Carlo// Boca Raton, FL, USA: CRC, 2009
[4] Andronov A., Jackiva I., Santalova D. Estimation of the Parameters of Continuous-Time Finite Markov Chain. Distributed Computer and Communication Networks. DCCN 2019. Lecture Notes in Computer Science, vol 11965. Springer, Cham
[5] Nikiforov I. Detection and Detectability of Changes in a Multi-parameter Exponential Distribution. Distributed Computer and Communication Networks. DCCN 2019. Lecture Notes in Computer Science, vol 11965. Springer, Cham
[6] Birnbaum Z. W. "On the importance of different components in a multicomponent system," in Multivariate Analysis II. New York, NY, USA: Academic, 1969, pp. 581–592.
[7] Y. Du, S. Si, T. Jin. Reliability Importance Measures for Network Based on Failure Counting Process. IEEE Transactions on reliability, vol. 65, no. 1, pp. 267-279
[8] Kamalja K. K., Amrutkar K. P. Reliability and Reliability Importance of Weighted-r-Within-Consecutive-k-out-of-n. IEEE Transactions on reliability, vol. 67, no. 3, pp. 951-969
[9] Crawley MJ. The R Book. 2nd ed. Wiley Publishing; 2012.
[10] Blanchet J., Rudoy D. Rare event simulation and counting problems, in Rare Event Simulation Using Monte Carlo Methods. 1st ed. New York, NY, USA: Wiley, 2009
[11] Vaisman R., Kroese D.P., Gertsbakh I.B. Improved Sampling Plans for Combinatorial Invariants of Coherent Systems. IEEE Transactions on reliability, vol. 65, no. 1, pp. 410-424
[12] Moshnikov, Aleksandr and V. S. Kolomoitcev. "Reliability Assessment of Distributed Control Systems with Network Structure." 2020 Wave Electronics and its Application in Information and Telecommunication Systems (WECONF) (2020): 1-4.
[13] Bogatyrev V.A., Bogatyrev S.V., Golubev I.Yu. Optimization and the process of task distribution between computer system clusters. Automatic Control and Computer Sciences 2012, 46(3), pp. 103-111
[14] Compare M, Bellora M, Zio E. Aggregation of importance measures for decision making in reliability engineering. Proceedings of the Institution of Mechanical Engineers 2017, Part O: Journal of Risk and Reliability, 231(3): 242–254
[15] Fang C, Marle F, Xie M. Applying importance measures to risk analysis in engineering project using a risk network model. IEEE Systems Journal 2017, 11(3): 1548–1556
[16] Kuo W, Zhu X (2012). Importance Measures in Reliability, Risk and Optimization: Principles and Applications. Chichester: John Wiley and Sons
[17] Moshnikov, A.; Bogatyrev, V. Risk Reduction Optimization of Process Systems under Cost Constraint Applying Instrumented Safety Measures. Computers 2020, 9, 50. https://doi.org/10.3390/computers9020050
[18] K-P. Hui, N. Bean, M. Kraetz and D.P. Kroese, The Cross-Entropy Method for Network reliability estimation, The Annals of Opereations Research, 134:101-118, 2005.
[19] R.Y. Rubinstein and B. Melamed. Modern Simulation and Modeling. Viley series in probability and Statistics, 1998.