Adv Syst Sci Appl 2022; **02**:11–20
Published online at https://ijassa.ipu.ru.

Investigation of Reliability for Information System for Natural Gas Quality Analysis

Ivan Brokarev[1]*, Sergei Vaskovskii[2]

[1]*National University of Oil and Gas Gubkin University, Moscow, Russia*
E-mail: brokarev.i@gubkin.ru

[2]*V. A. Trapeznikov Institute of Control Sciences of Russian Academy of Sciences, Moscow, Russia*
E-mail: v63v@yandex.ru

Abstract: It is an extremely crucial task for oil and gas industry to assess how reliable gas quality analyzing systems are. The traditional approaches to assess the reliability of this class of systems, due to a number of conditions, do not seem to be applicable. To assess the reliability of such systems, we propose a probabilistic method to determine a distribution function of operating time, a reliability function, and mean time to failure. We build a structural diagram of the system, obtain basic formulae to determine the required functions and reliability indicators. We investigate various scenarios of system failure depending on the number of parameters for which accuracy decreases. For each of the scenarios, we obtain formulae to describe the required functions and reliability indicators.

Keywords: reliability, gas quality analysis system, probabilistic method, distribution function of operating time, reliability function, mean time to failure

1. INTRODUCTION

It is an extremely difficult task to determine and assess the reliability of traditional gas analysis systems to probe the component composition and energy characteristics of gas. One of the problems in full-scale and semi-natural tests of this class of systems is to ensure reliability. In addition, the life cycle of such systems is 25-30 years at a fairly high cost of equipment. When conducting semi-natural tests of gas analysis systems in special heat chambers at high temperature and humidity, it is difficult to obtain a realistic picture of the system's reliability characteristics. In addition, the tests are expensive and time-consuming [15].

However, it is imperative to evaluate how reliable such systems are. Such assessments exist and applicable. However, our system, where the energy characteristics of gas are analyzed, differs in structure and information-computational functionality from those already assessed systems. The existing methods are generally not suitable for our system. To close this gap, this work develops both an adequate model of the system's reliability and a method to obtain the indicators necessary to do the job, for example, up-time, etc. For this purpose, we modify the probabilistic method to assess reliability of the gas analysis system.

The developed method allows us to design specialized structural diagrams of gas analysis systems. The study of such structural schemes makes it possible to evaluate the reliability characteristics of systems by probabilistic methods. Also, the schemes help to detect problem

*Corresponding author: brokarev.i@gubkin.ru

areas of gas analysis systems in terms of reliability and maintenance characteristics. Finally, the method helps to evaluate the developed gas analysis system in terms of the system's reliability.

To assess the reliability of the developed gas-analyzing information and computing system, it is necessary to determine the basic terms and reliability indicators to determine the level of reliability of this class of systems. According to the document [14], reliability is the property of an object to keep in time and within the established time intervals the ability to perform the required functions in specified modes and conditions of use, maintenance, storage, and transportation. The main terms and indicators of the reliability of our system are associated with how we assess its reliability. To assess the reliability of the system, it is necessary to determine the type of failures that occur in the system. In general case, a failure is an event when the system is not functioning. In our task, failures in the system are parametric (leading to the parameters going beyond the permissible time intervals).

The main reliability indicators of a system are:

- the probability of a system failure (the probability of a failure occurring when the system operates);
- average time of failure-free operation of the system; - failure rate;
- the distribution density of failure time.

Methods to assess system reliability make it possible to predict the quality of how systems function, as we take into account the errors that occur, the number and intensity of failures. We can also correct errors in the development and operation of systems [11]. Many methods to assess system reliability are based on probabilistic Markov processes. These methods make it possible to assess how reliable equipment, and devices function in different modes.

Analytical methods are also used to calculate the reliability indicators of technical systems [9]. These include methods of the random process theory, the expert estimate theory (heuristic forecasting), decomposition (equivalence), logical-probabilistic, asymptotic, analytical, and statistical methods. The methods of the random process theory are used to assess how reliable various systems and facilities with continuous technological processes are. Also these methods help us to study the reliability of industrial enterprises systems, including gas complexes.

Usually, at the design stage of distributed systems, reliability calculations are based on failure rate data of the systems' constituent elements; the rates are determined experimentally. But in order to draw a conclusion about the reliability of the system as a whole, it is necessary to take into account the system structure and the possibilities to improve the system. Methods to calculate structural reliability based on failure rate data are investigated. Examples of how to construct and optimize similar models for distributed computing systems and network management systems can be found in [5, 6, 8]. However, in relation to the gas analysis problem, this approach has disadvantages. The concept of structural reliability as ”the ability of a system to perform specified functions within a given time interval” is too general in the problem of gas analysis; it requires specifying what functions are important in this case.

The primary task is to analyze the component composition and energy characteristics of natural gas. It is possible to parameterize how this system functions via a discrete finite state space of the system (for example, ”works” / ”does not work”). However, this does not allow us to construct a practical model of the system, since the concept of accuracy measurement is a characteristic that changes continuously and can vary depending on the application. Therefore, in this chapter, we propose a new approach and an accuracy analysis-based model to determine the gas parameters.

To calculate reliability, a distributed system is usually divided into elements. To calculate reliability indicators, structural - logical reliability schemes are used. These schemes help us to graphically display how the elements are related and included in the system. Also, it helps us to investigate how the elements impact on the system reliability as a whole. Structural logic diagram is a set of elements connected to each other in series and / or in parallel.

Copyright © 2022 ASSA.

Methods to calculate structural reliability are well known and our approach works well under standard assumptions such as, for example, exponential failures, independent elements [2, 7]. The block diagram of our distributed data acquisition system is shown in Fig. 1.1. In this version of the scheme, information enters the analysis system via two independent measuring channels. We use two independent measuring channels to verify the received measuring information. We can add additional measuring channels to increase both the reliability and accuracy characteristics of the distributed system, but in this work we investigate a system with just two. In this version of the system, the measuring devices (MD) are connected in parallel, since it is assumed that if the measuring device fail, the system stay operational, but the system's accuracy decreases.

To calculate the structural reliability according to the structural diagram, we build a state graph. We take into account that all elements have different reliability indicators. The nature of the failure rate, and recovery rate for each element of the system are determined. Based on these data, we determine the probability to find each element in a working or inoperative state at a certain moment of time t.

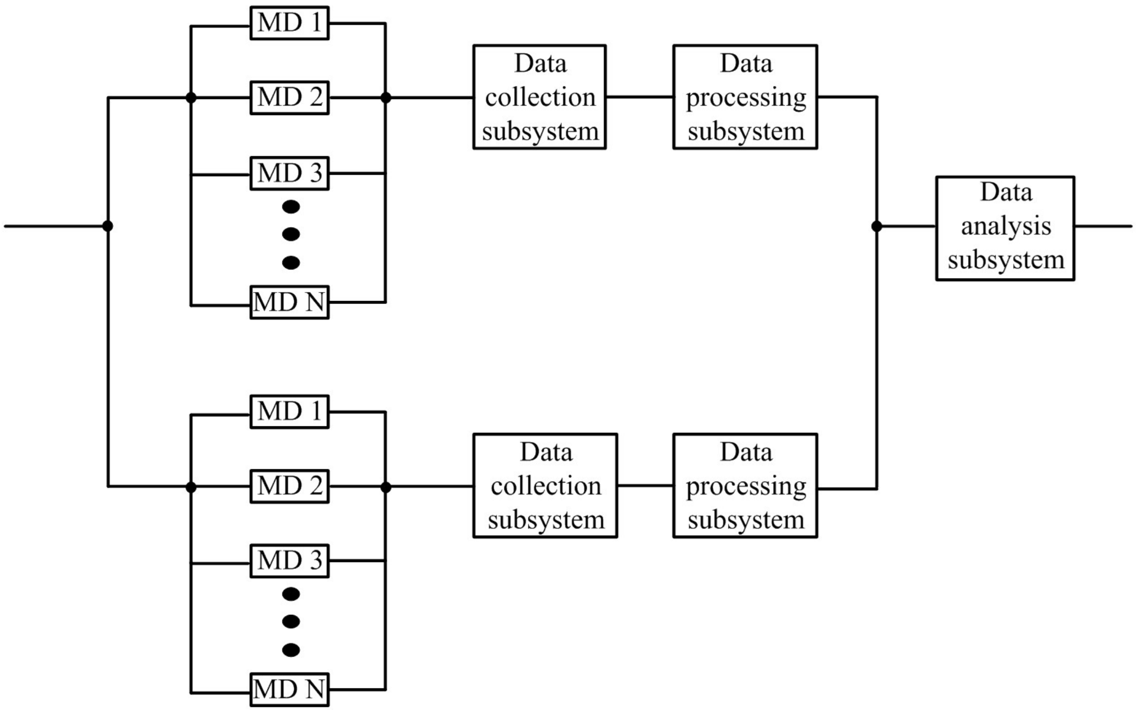

Fig. 1.1. Structural design of our distributed gas analysis system.

The reliability of a redundant system $p_r(t)$, where the system consists of l independent elements, is determined by:

$$p_r(t) = 1 - \prod_{k=1}^{l} \left(\frac{\lambda_k}{\lambda_k + \mu_k} - \frac{\lambda_k}{\lambda_k + \mu_k} e^{-(\lambda_k + \mu_k)t} \right) \tag{1.1}$$

where λ_k and μ_k – are failure and repair rates of element k.

Accordingly, the reliability (the probability of failure-free operation) of a series system with $(n-1)$ redundant m blocks can be calculated by the formula [1]:

$$p_{rm}(t) = \prod_{i=1}^{m} \left(1 - \prod_{j=1}^{n} \left(\frac{\lambda_{ij}}{\lambda_{ij} + \mu_{ij}} - \frac{\lambda_{ij}}{\lambda_{ij} + \mu_{ij}} e^{-(\lambda_{ij} + \mu_{ij})t} \right) \right) \tag{1.2}$$

Copyright © 2022 ASSA.

This scheme is applicable for standard approaches, but does not allow us to ensure the measurement accuracy. The standard scheme to calculate reliability contains drawbacks and is not suitable for our task.

It is impossible to detect faults, if we follow the standard approach and apply formulas (1.1-1.2). Failure to ensure the specified measurement accuracy is essentially a latent failure for an externally operating measuring device to transmit correct data. On the other hand, from the functional point of view, this is a critical failure, because the main function of the system – to determine the energy characteristics of the gas - is not fulfilled. If a system fails to collect, process, and analyze information, this failure can be detected explicitly (failure of the computer). On the other hand, if measuring devices fail, this cannot be detected immediately. If there is a failure of measuring devices, then there may be no obvious external signs of this phenomenon. So, this phenomenon is not observable, and we can judge about it only by the output data: for this, all measuring devices are duplicated (see Fig. 1.1). We will assume that a failure has occurred, if the data transmitted from the measuring devices differs greatly (exceeds some threshold) between the first and second measuring devices. This requires us to develop a new approach to assess the reliability of our measuring device subsystem.

2. STUDY OF A MEASURING DEVICES RELIABILITY MODEL

For our case, we assume that to analyze the composition of natural gas for an N-component mixture, $2N$ measuring devices are needed. For each parameter, two measuring devices are needed - the main and the backup; the two devices operate independently of each other. Measuring devices independently transmit information via two different channels to an information collection system and then to an information processing system - these components together form the measuring channel (MC). The hot standby MC also receives information from measuring devices (standby measuring devices). Thus, the distributed system collects information from $2N$ measuring devices (N main and N backup). Since the main task of the system is to determine the energy characteristics, the system will be considered reliable if it provides a given level of accuracy to determine the required gas characteristics. The reliability of the ”measuring channel - computing system” subsystem is determined according to the standard scheme described, for example, in [7, 8]. And, since all subsystems function independently, the reliability of each of them can be assessed independently.

Let’s consider a model of the measuring device subsystem reliability. We assume that the subsystem to measure one parameter of the gas mixture is in working condition if both measuring devices (main and backup) give approximately the same readings for the same time instant of the same measurement point. If the readings do not differ greatly, then in this case we assume that the system is working. In the other cases, we assume that a failure has occurred. In this case, we can assume that the measuring device designed to determine the corresponding gas parameter is out of order, if at the output we get a large difference in readings (between the main and backup devices). In this situation, a failure of the measuring device subsystem for the corresponding gas parameter is recorded.

Now let’s move on to a more rigorous description of our model. For this, we introduce the following definitions. By the reliability of a measuring system we mean the system’s ability to perform specified functions within a given time interval. In this case, the ”given function of the system” is the system’s ability to measure gas parameters with a given accuracy.

Definition 2.1:
As we measure the $i-th$ gas parameter, we consider the measurement accurate, if the values obtained from the first and second measuring devices differ in a certain pres-elected range $(-\varepsilon_i, \varepsilon_i), \varepsilon_i > 0$.

Copyright © 2022 ASSA.

When it is necessary to determine N parameters, then we will deal with a vector of positive values: $\varepsilon = (\varepsilon_1, ...\varepsilon_N), \varepsilon_i > 0, \forall i = 1, ..., N$, i.e. a certain range of admissible values $(-\varepsilon_i, \varepsilon_i)$ is specified for each measuring device.

Definition 2.2:
By system failure, we mean an accuracy indicator goes beyond the permissible time intervals.

In this case, in practice, what we mean by failure must be clarified each time when we solve a specific problem. For example, in the case of an N-component mixture, the system fails when it goes beyond the specified measurement accuracy for subsystems of k measuring devices from N, where k can take values from 1 up to N (depending on operational conditions and others, for example, economic factors and customer requirements). In case $k = 1$, the most stringent requirements are imposed on the measuring device subsystem, if the system is unable to accurately measure at least one gas parameter, it is already considered a failure. In the case $k = N$, for the device subsystem to work, it is sufficient to be able to measure at least one gas parameter. The essence of the reliability assessment method, where we monitor how the readings of the main and backup measuring devices deviate, is illustrated in Figure 2.2 and in Formula 2.3.

$$
\begin{gathered}
|Y_1^{(1)} - Y_2^{(1)}| = \xi_1 \\
\cdots \\
|Y_1^{(N)} - Y_2^{(N)}| = \xi_N
\end{gathered}
\tag{2.3}
$$

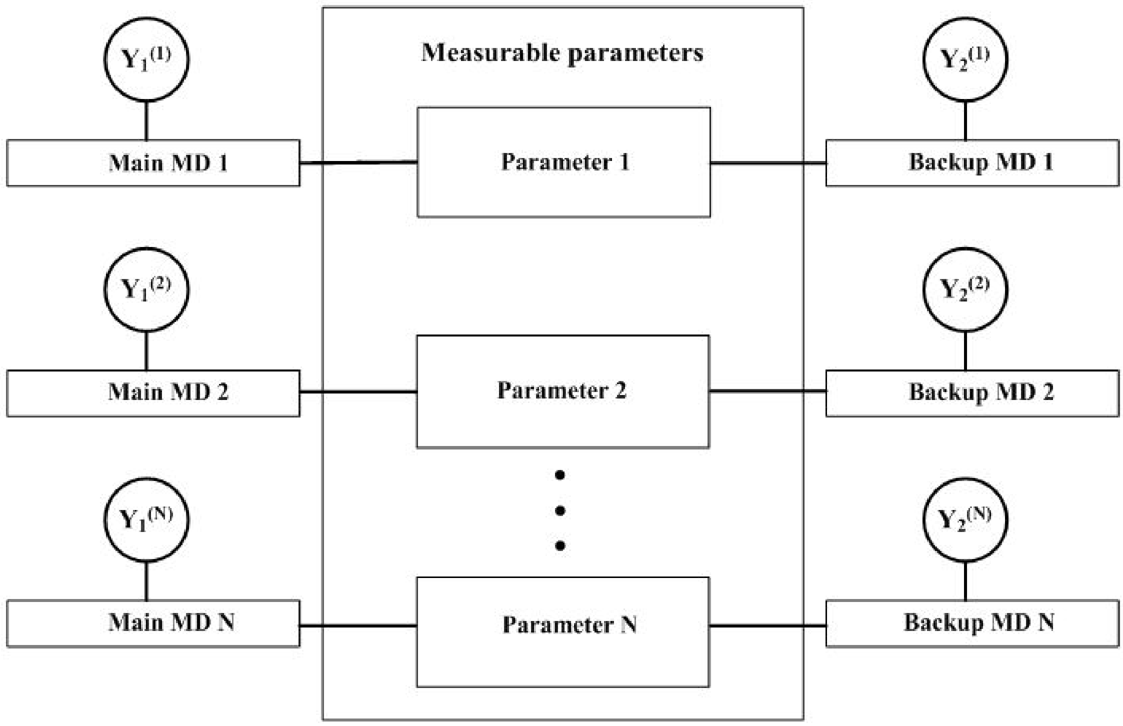

Fig. 2.2. The essence of our reliability estimation method. We monitor how the outputs of the main and the backup devices differ from each other.

3. SUBSYSTEM RELIABILITY MODEL TO MEASURE A SINGLE GAS MIXTURE PARAMETER

Suppose that only one indicator is measured in the system. The readings are received at discrete moments of time from two measuring devices (main and backup). We assume that if the measuring devices operate normally, then the readings from the measuring devices give approximately the same result. We observe a discrete sequence of some random variables: $\xi_i, i = 0, 1, 2...$ which we will interpret as the difference between the readings of measuring devices. It is natural to assume that if the readings of the measuring devices approximately coincide, then the values of this sequence fluctuate around zero. Moreover, if we consider absolute measurements, then the observations would be dependent. But, since we observe the modulus of the difference, then, regardless of fluctuations in the real composition of the gas, we take that $\xi_i, i = 0, 1, 2...$ is an independent and equally distributed random variables. Also, we can interpret ξ_i as some measurement error. Therefore, we assume that the sequence elements of are normal random variables: $\xi_i \sim N(0, \sigma^2), i = 0, 1, 2....$ Without loss of generality, we can assume that $\sigma^2 = 1$, i.e. the elements of the sequence are standard normal random variables.

Let us make the following assumptions regarding measuring devices: as the number of measurements increases, the measuring devices wear off more and more, and accordingly, the error (the difference between the indicators) grows. The growth rate can be considered variable in the general case; the rate depends on time and on the state of the system $m(i, X_i)$. Therefore, as a model of how the system operates, we can consider a random process in discrete time, where the process characterizes the sum of accumulated errors:

$$X_i = m(i, X_i)i + \sum_{k=0}^{i} \xi_k \tag{3.4}$$

where $i = 0, 1, 2 \ldots, m(i, X_i)$ can be interpreted as the error increase rate, where the error is associated with how the measuring device wears off (error accumulation) due to additional factors, and $\xi_i \sim N(0, 1)$.

Without loss of generality, we can assume that measurements are made quite often, therefore, we go from (3.4) to a continuous model. In this case, a natural Brownian motion-based model is relevant [12]. And such a model can be investigated using well-known results from the theory of random processes [10].

4. PRELIMINARY INVESTIGATION. THE RELIABILITY OF A MEASUREMENT DEVICE SUBSYSTEM AS N=1

We observe a random process in continuous time $X(t)$; the process can be described by a simple differential equation [12]:

$$dX(t) = \mu(t, X(t))dt + \sigma(t, X(t))dW(t) \tag{4.5}$$

This approach can also be interpreted as follows: the error (difference) can be modeled as a one-dimensional Brownian motion $X(t) = W(t)$, or, formally, $dX(t) = dW(t)$. Generally, $dX(t) = \sigma(t, X(t))dW(t)$, where the coefficient σ may not be constant in the general case, but depends on the state of the system.

That is, we assume that there is some randomness in our measurements: either the main or the backup measuring device show a higher value, so the error increases and decreases. We also assume that the measuring device wears out over time, so the error grows on average with a certain rate μ.

Copyright © 2022 ASSA.

Intuitively, the model of how the error X changes is described by a random walk. When the time step tends to zero, the process tends to the one defined by equation (4.5). However, in what follows we assume that $\sigma > 0$ and $\mu \geq 0$ are constants:

$$dX(t) = \mu dt + \sigma dW(t) \tag{4.6}$$

Now, suppose that a certain permissible range of values $(-A, A), A > 0$ is specified for the measuring device; the range determines how the system operates normally [2].

Definition 4.1:
The system is workable if $X(t) \in (-A, A)$.

Definition 4.2:
The system fails if the process gets out of the set: $X(t) \notin (-A, A) : X(t) \leq -A$ or $X(t) \geq A$.

Definition 4.3:
$MTTF$ is the first time when the trajectory reaches A: $\tau_A = inf(t \geq 0 : |X(t)| = A)$, (if μ is strictly positive, $P(X(t) = A) \to 0$)

Definition 4.4:
The system reliability function (in general case) is defined as: $R(t) = P(\tau > t)$,

Definition 4.5:
The operating time distribution function of the system (in general case): $F(t) = 1 - R(t) = P(\tau \leq t)$,

Problem 4.1:
For a system described in general case by equation (4.6), estimate the mean time between failures $MTBF = E_\tau$ (in the simplest case, find it analytically).

To select the threshold values A_i for each of the measured parameters, it is necessary to specify how accurately we determine the physical parameters of the gas. Most standards [4] regulate the reduced error of how we determine the required parameters. The values of the thresholds must be the values of the maximum absolute error, where the discrepancy of the device readings does not go beyond the permissible values. We take the value of our measurement repeatability as such values, since there are no regulated values of the absolute error. Threshold values for all input and output parameters are shown in Table 4.1.

Table 4.1. Gas parameters threshold values

Physical gas parameter	Units of measurement	Threshold value A_i
Methane concentration, X_{CH_4}	%	0.1
Propane concentration, $X_{C_3H_8}$	%	0.1
Nitrogen concentration, X_{N_2}	%	0.1
Carbon dioxide concentration, X_{CO_2}	%	0.1
Speed of sound, c	m/s	0.2
Thermal conductivity, χ	W/m*K	0.005

5. RELIABILITY OF THE MEASURING DEVICE SUBSYSTEM

A feature of the model is that if the measuring device fails, the system does not, but the system gets its accuracy characteristics reduced. In our diagram, the measuring devices are connected in parallel. However, if we calculate reliability as the structural reliability of a parallel subsystem, it will not work. Indeed, since if the $N - 1$ subsystem fails, this does not lead to an actual failure of the system, but provides the ability to determine only one gas parameter. Therefore, the reliability model "k out of N" $(k \leq N)$ is correct to take

Copyright © 2022 ASSA.

into account how failures of individual measuring devices influence calculation accuracy; hereinafter, we will assume $N = 5$ everywhere.

Let's consider several scenarios of how the system operates:

Scenario 5.1:
If accuracy indicators of all parameters decrease to a given threshold, we take this as a system failure.

Scenario 5.2:
If the accuracy indicator of at least 1 parameter decreases to a given threshold, we take this as a system failure.

Scenario 5.3:
If accuracy indicators of at least $k(k < 5)$ parameters decrease to a given threshold, we take this as a system failure.

Let's investigate the first scenario.

Let $F_1(t)$ be a distribution function of the system operating time for this scenario.

Theorem 5.1:
The distribution function of the subsystem operating time $F_1(t)$ for Scenario 5.1 is described by the following formula:

$$F_1(t) = \prod_{i=1}^{5} \left(1 - \Phi\left(\frac{A_i - \mu_i t}{\sigma\sqrt{t}}\right) + e^{\frac{-2\mu_i A_i}{\sigma^2}} \Phi\left(\frac{-A_i - \mu_i t}{\sigma\sqrt{t}}\right)\right) \tag{5.7}$$

Demonstration 5.1:
We assume that for each parameter (i = 1, 2, 3, 4, 5) in the gas mixture there is a model of error variation and the parameters A_i, μ_i, σ.

Then the distribution function of the system operating time can be defined as:

$$\begin{aligned} F_1(t) &= P(\tau_1 \leq t, ..., \tau_5 \leq t) = P(\sup_{0\leq s\leq t} X_1(S) \geq A_1, ..., \sup_{0\leq s\leq t} X_5(S) \geq A_5) = \\ &= P(\sup_{0\leq s\leq t} \mu_1 t + \int_0^t \sigma\, dW_1(t) \ \geq A_1, ..., \sup_{0\leq s\leq t} \mu_5 t + \int_0^t \sigma\, dW_5(t) \ \geq A_5) = \\ &= P(\sup_{0\leq s\leq t} W_1(t) \geq \frac{A_1 - \mu_1 t}{\sigma}, ..., \sup_{0\leq s\leq t} W_5(t) \geq \frac{A_5 - \mu_1 t}{\sigma}) \end{aligned} \tag{5.8}$$

Let us use the following well-known result for a Wiener process $W(t)$ to intersect a linear boundary as μ and σ are given [3, 13].

$$P(\sup_{0\leq s\leq t} W(t) \geq A) \approx 1 - \Phi\left(\frac{a - \mu t}{\sigma\sqrt{t}}\right) + e^{\frac{-2\mu a}{\sigma^2}} \Phi\left(\frac{-a - \mu t}{\sigma\sqrt{t}}\right) \tag{5.9}$$

Where Φ is the distribution function for the standard normal distribution.

From the previous formulas it is easy to demonstrate:

$$F_1(t) = \prod_{i=1}^{5} \left(1 - \Phi\left(\frac{A_i - \mu_i t}{\sigma\sqrt{t}}\right) + e^{\frac{-2\mu_i A_i}{\sigma^2}} \Phi\left(\frac{-A_i - \mu_i t}{\sigma\sqrt{t}}\right)\right) \tag{5.10}$$

Corollary 5.1:
As a consequence of the theorem, the reliability function and mean time to failure for Scenario 5.1 are:

Copyright © 2022 ASSA.

$$R_1(t) = 1 - F_1(t) \tag{5.11}$$

$$MTTF_1 = \int_0^{\infty} R_1(t)\, dt \tag{5.12}$$

Corollary 5.2:
The distribution function of the subsystem operating time $F_2(t)$, the reliability function and the mean time to failure for Scenario 5.2 are:

$$F_2(t) = \prod_{i=1}^{n} \left(1 - \Phi\left(\frac{A_i - \mu_i t}{\sigma\sqrt{t}}\right) + e^{\frac{-2\mu_i A_i}{\sigma^2}} \Phi\left(\frac{-A_i - \mu_i t}{\sigma\sqrt{t}}\right)\right) \tag{5.13}$$

$$R_2(t) = 1 - F_2(t) \tag{5.14}$$

$$MTTF_2 = \int_0^{\infty} R_2(t)\, dt \tag{5.15}$$

Theorem 5.2:
The distribution function of the subsystem operating time $F_3(t)$ for Scenario 5.3 is:

$$F_3(t) = \prod_{i=1}^{k} \left(1 - \Phi\left(\frac{A_i - \mu_i t}{\sigma\sqrt{t}}\right) + e^{\frac{-2\mu_i A_i}{\sigma^2}} \Phi\left(\frac{-A_i - \mu_i t}{\sigma\sqrt{t}}\right)\right) \tag{5.16}$$

Demonstration 5.2:
We can find the probabilities that a system of N parameters can determine exactly k (all the parameters of the mixture are considered equivalent, therefore the accuracy is determined only by the number of the working blocks):

$$p_{ffblock} = \sum_{i=k}^{n} p_1(t) \tag{5.17}$$

6. CONCLUSION

Our method to assess the reliability of an information-computing system is based on a probabilistic method to determine a distribution function of operating time, a reliability function and mean time to failure. For the structural diagram of our system, we obtained basic formulas to determine the required functions and reliability indicators. We investigated various scenarios of system failure; the scenarios depend on the number of parameters for which accuracy decreases. For each of the scenarios, we obtained formulae for the required reliability functions. Our method differs from the existing ones as our method takes into account several independent measuring channels and independently operating measuring devices.

Copyright © 2022 ASSA.

REFERENCES

1. Andreev, A.V. (2018) *Theoretical foundations of technical system reliability.* SpB: Izdatelstvo Politekhnicheskogo universiteta, 164 p.
2. Granig, W., Faller, L.-M., Zangl H. (2018) *Sensor system optimization to meet reliability targets.* Microelectronics Reliability 87. DOI: 10.1016/j.microrel.2018.06.005.
3. Ibragimov, I.A., HasminskyR.Z. (1981) *Statistical Estimation. Asymptotic Theory, Applications of Mathematics.* Springer Verlag, New York.
4. ISO 6976: 1995 International Standard. (1995) Natural gas - Calculation of calorific value, density and relative density. 46 p.
5. Kalimulina, E.Y. (2013) A new approach for dependability planning of network systems, *International Journal of System Assurance Engineering,* **4**: 215, https://doi.org/10.1007/s13198-013-0185-2.
6. Kalimulina, E.Y. (2017) Analysis of system reliability with control, dependent failures, and arbitrary repair times, *International Journal of System Assurance Engineering,* **8**: 180, https://doi.org/10.1007/s13198-016-0520-5.
7. Kalimulina, E.Y. (2017) Analysis of Unreliable Open Queueing Network with Dynamic Routing, *Distributed Computer and Communication Networks. DCCN 2017. Communications in Computer and Information Science,* **700**, Springer, Cham.
8. Kalimulina, E.Y. (2018) Math Modeling of the Reliability Control and Monitoring System of Complex Network Platforms, *Intelligent Systems Design and Applications. ISDA-2018 2018. Advances in Intelligent Systems and Computing,* **941**, Springer.
9. Konesev, S.G., Hazieva, R.T. (2015) Methods to estimate reliability of complex systems, *Modern problems of science and education,* **1**, Part 1. [in Russian].
10. Koralov, L., Sinai, Y. G. (2007) Theory of Probability and Random Processes, *Springer Science & Business Media, Mathematics*, 358 p.
11. Lavrisheva, E.M., Pakulin, N.V., Ryzhov, A.G., Zelenov, S.V. (2018) Analysis of methods to estimate equipment reliability. Practical aspects, *Trudy ISP RAN,* 30(3), 99–120.[in Russian].
12. Oksendal, B. (2003) Stochastic Differential Equationsm, *An Introduction with Applications. Fifth Edition, Corrected Printing,* Springer-Verlag, Berlin.
13. Osipov, L.V., Petrov, V.V. On how to estimate the residue of the central limit theorem, *Theory Probab. Appl.,* **12:2**, 281–286. [in Russian].
14. State Standard 27.002–89. (1990) *Reliability of equipment. Basic terminology*. M.: Standard publisher, 40 p. [in Russian].
15. State Standard 52350.29.1-2010 (IEC 60079-29-1:2007) (2010) *Explosive environments, Part 29-1 Gas analyzers. General technical requirements to test gas analyzers of combustible gases.* Standartinfo. [in Russian].

Copyright © 2022 ASSA.