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RESEARCH ARTICLE

Statistical model for assessing the reliability of non-destructive testing systems by solving inverse problems

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Abstract
Objectives. The wear monitoring of metal structural elements of power plants—in particular, pipelines of nuclear power plants—is an essential means of ensuring safety during their operation. Monitoring the state of the pipeline by direct inspection requires a considerable amount of labor, as well as, in some cases, the suspension of power plant operation. In order to reduce costs during monitoring measures, it is proposed to use mathematical modeling. This work aimes to develop a mathematical model of a diagnostic system for assessing the probability of detection of defects by solving inverse problems.
Methods. A binomial model for assessing the reliability of monitoring, comprising the Berens–Hovey parametric model of the probability of detection of defects and a parametric model based on studying test samples, was analyzed. As an alternative to this binomial model, a computational method for assessing the reliability of non-destructive testing systems by solving an inverse problem was proposed. To determine the parameters of the defect detection probability curve, the model uses data obtained by various monitoring teams over a long period of power plant operation. To serve as initial data, the defect distribution density over one or more of the following characteristics can be used: depth, length, and/or cross-sectional area of the defect. Using the proposed mathematical model, a series of test calculations was performed based on nine combinations of initial data. The combinations differed in the confidence coefficient of the initial monitoring system, the parameters of the distribution of defects, and the sensitivity of the monitoring system.
Results. The calculation data were used to construct curves of the probability density of detected defects as a function of the defect size, recover the values of the defect distribution parameters under various test conditions, and estimate the error of recovering the parameters. The degree of imperfection of the system was estimated using the curve of the detection probability of a defect by a certain monitoring system.
Conclusions. Under constraints on the data sample size, the proposed methodology allows the metal monitoring results to be applied with greater confidence than currently used methods at the same time as evaluating the efficiency of monitoring carried out by individual test teams or laboratories. In future, this can be used to form the basis of a recommendation of the involvement of a particular team to perform diagnostic work.

Keywords: non-destructive testing, reliability of power plants, mathematical modeling, statistical analysis, inverse problems

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НАУЧНАЯ СТАТЬЯ

Статистическая модель оценки надежности систем неразрушающего контроля на основе решения обратных задач

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Резюме
Цели. Контроль износа конструктивных элементов энергоустановок, в частности трубопроводов атомных электростанций, является неотъемлемым компонентом обеспечения безопасности при их эксплуатации. Контроль путем непосредственного обследования состояния трубопровода требует, во-первых, достаточно больших трудозатрат, во-вторых, в некоторых случаях, временной остановки работы. Поэтому при проведении контрольных мероприятий предлагается использовать математическое моделирование. Цель статьи – разработка математической модели системы диагностики для оценки вероятности обнаружения дефектов на основе решения обратных задач.
Методы. Анализируются биномиальная модель оценки надежности контроля, параметрическая модель Беренса и Хови вероятности обнаружения дефектов, параметрическая модель на основе исследования тест-образцов. В качестве альтернативы данным моделям предлагается расчетный метод оценки надежности систем неразрушающего контроля на основе решения обратной задачи. Для определения параметров кривой вероятности обнаружения дефектов модель использует данные, полученные различными контролирующими бригадами за длительный период эксплуатации энергоустановки. В качестве исходных данных можно использовать плотности распределения дефектов по одной или нескольким из следующих характеристик: глубине, длине, площади сечения дефекта. С помощью предлагаемой математической модели выполнен набор тестовых расчетов на основе девяти комбинаций исходных данных. Комбинации отличаются между собой коэффициентом достоверности исходной системы контроля, параметром распределения дефектов, чувствительностью системы контроля.
Результаты. По итогам проведенных расчетов построены кривые плотности вероятности обнаруженных дефектов в зависимости от размера дефекта, определены восстановленные значения параметров распределения дефектов при различных условиях испытаний, сделана оценка погрешности восстановления параметров. Для оценки степени несовершенства системы используется кривая вероятности обнаружения дефекта конкретной системой контроля.
Выводы. С учетом ограничений, связанных с размером выборки, предлагаемая методика, во-первых, позволяет применять результаты, полученные по контролю металла, с большей уверенностью, чем методики, используемые в настоящее время, во-вторых, оценивать эффективность контроля, проводимого отдельными бригадами испытателей либо лабораториями. В перспективе это позволит рекомендовать или не рекомендовать привлечение той или иной бригады к выполнению диагностических работ.

Ключевые слова: неразрушающий контроль, надежность энергетических установок, математическое моделирование, статистический анализ, обратные задачи

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INTRODUCTION

One of the most important issues in the operation of large power plants is ensuring the safety of their use. In order to solve this problem, it is necessary to ensure the integrity of the structures of nuclear power plants, including equipment and piping, over the entire working life of the power plant[1]. Regardless of the types of nuclear power plants and operating conditions, damage to the structural elements of nuclear power plants (including cracks) is detected almost every year. The problem can be described in terms of insufficient knowledge of damage models and mechanisms, which corresponds to the impossibility of solving this problem at the design stage.

One approach to solving this problem is to create a system for maintaining a given level of reliability by carrying out periodic diagnostics of the technical state of the most critical objects of the operated power plant, i.e., the organization and performance of works for non-destructive testing of metal of equipment and piping. Based on the current state of the tested objects, the future situation can be predicted and a decision taken to terminate or continue the further operation of the objects.

1. STATISTICAL MODELS FOR ASSESSING THE RELIABILITY OF NON-DESTRUCTIVE TESTING SYSTEMS

In order to assess the current state of the objects being tested, it is necessary to measure the reliability of non-destructive testing. In order to obtain such a metric, the probability-of-detection (*PoD*) curve is used [1, 2] to describe the defect size distribution of the defect detection probability. In practice, this curve can depend on many factors, including the capabilities of the method and monitoring equipment at a selected sensitivity, the location and geometry of the defect, and the properties of the material. Human factors are also taken into account, among which are staff fatigue, stressful situations, and difficult inspection conditions.

For constructing the *PoD* curve, the monitoring results are used as experimental data. These can be obtained using systems similar to those described in the literature [3–5] and materials of the American Society for Nondestructive Testing[2]. The monitoring system used in this case can be used to detect both real defects formed during the operation of equipment and piping of a power plant, and artificially created defects with specified dimensions. Artificially created defects[3] should have the same features as real defects. The most suitable are samples of real objects with real cracks formed during operation. The types of fracture—ductile and brittle—are also taken into account [6].

In general, the assessment test methodology only provides qualitative conclusions about the ability of the non-destructive testing system to detect defects. Most works give results only for the averaged *PoD* curves obtained by testing the same object by different laboratories. An example is the results of interlaboratory comparative non-destructive tests that were conducted in 2018–2019 by nuclear industry organizations[4]. Data obtained by nine laboratories was not suitable for use in the construction of *PoD* curves for individual laboratories due to the small number of measurements for a single defect size. In this case, an averaged *PoD* curve was drawn based on the results

[1] *Requirements for equipment and piping time management in nuclear power plants*. Basic provisions (NP-096-15). http://www.cntr-nrs.gosnadzor.ru/about/AKTS/НП-096-15.pdf. Accessed December 15, 2022 (in Russ.).

[2] Bouis J. NDT to evaluate crevice corrosion initiation sites in alloy pipe and tubing. *The NDT Technician*. 2022;21(1). https://blog.asnt.org/ndt-to-evaluate-crevice-corrosion-initiation-sites-in-alloy-pipe-and-tubing/. Accessed December 15, 2022.

[3] Kanzler D., Müller C., Pitkänen J., Ewert U. Bayesian approach for the evaluation of the reliability of non-destructive testing methods: combination of data from artificial and real defects. *Proceedings: 18th World Conference on Nondestructive Testing WCNDT. Special Issue. e-Journal of Nondestructive Testing* (*eJNDT*). 2012;17(7). http://www.ndt.net/?id=12748. Accessed December 15, 2022.

[4] Analytical report No. 532/789-2019 "*On conducting interlaboratory comparative non-destructive tests in organizations of the nuclear industry under the program P.MSI.NKSS-533/009-2018*," Part 2. Moscow: ROSATOM, VNIINM; 2019 (in Russ.).

of all nine laboratories. This situation is typical for constructing *PoD* curves.

The output characteristic of the monitoring system used is a signal (peak voltage or amplitude), which is compared with a threshold value and can be interpreted as a function of the size of the defect. Comparative analysis between the output signal of the monitoring system and defects of known size a gives estimate $PoD(a)$ of the probability-of-detection curve. The $PoD(a)$ estimate can be found from the number of monitoring events performed by the initial system for a given size a_i as

$$PoD(a_i) = \frac{n_i}{n}, \tag{1}$$

where $PoD(a_i)$ is the probability of detection of a defect of size a_i, n_i is the number of defects of size a_i detected during the monitoring, and n is the total number of defects of size a_i in the test sample.

Repeated use of formula (1) at different sizes of defects a_i gives the defect size distribution of the frequency of detection of defects.

1.1. Binomial model for assessing the reliability of the monitoring system

Let us assume that a given general population contains a fraction of defects of a given size. Then, taking N objects from this population and studying them using the initial monitoring system, it can be hoped that, with an increase in the number N, all defects of a given size will be detected. In this case, each experiment can be considered as an independent trial, while the frequency of occurrence of an event, $\omega = n_i/N$, can be calculated by Bernoulli's formula [7, 8]

$$P\left\{\omega = \frac{n_i}{N}\right\} = \frac{N!}{n_i!(N-n_i)!} p^{n_i}(1-p)^{N-n_i}, \tag{2}$$

where p is the probability of detection of a single defect.

The lower confidence bound on the probability of detection at a given confidence level and a given sample size can be obtained by solving the equation

$$p_{\mathrm{MS}} = \\ = \sup\left\{p : \sum_{n_i=0}^{N-1} \frac{N!}{n_i!\left(N-n_i\right)!} p^{n_i}\left(1-p\right)^{N-n_i} \geq 1-\alpha\right\}, \tag{3}$$

where $(1 - \alpha)$ is the lower confidence bound on a given probability, and MS refers to the monitoring system used.

Having obtained a solution to equation (3), the probability detecting a defect of a given size above 0.9 can be ensured with a given confidence interval of 95% if all 29 defects of 29 given defects are found in 29 trials. Such tests can additionally be used to assess the monitoring system: by setting the number of checks and assuming that all defects will be found by the monitoring system being tested, the detection probability can be determined at a given confidence interval. If the lower confidence interval for a fraction of detected cracks exceeds the specified detection probability value, then the monitoring system is considered to provide the required level of reliability.

However, as already noted [9, 10], the use of a binomial model to assess the reliability of the monitoring system can lead to serious problems. These arise when constructing a *PoD* curve with changing defect sizes. In this case, the confidence bounds on the *PoD* curve have a very unstable behavior, which depends on the chosen analysis method. Moreover, the *PoD* curve throughout the range of defect sizes can be constructed only if the number of defects is sufficiently large due to the need to multiply the defect sample size for one defect size by the number of points required to construct the *PoD* curve.

1.2. Berens–Hovey parametric model for the *PoD* curve

As an alternative to the binomial model, a parametric model was proposed for constructing the *PoD* curve. Berens and Hovey [11, 12] used a different statistical framework to represent the *PoD* curve as a mathematical function. The statistical model proposed by Berens and Hovey [12] is based on a representation of the output signal of the monitoring system as the main component (characterizing the changes in the average signal from one defect to another), together with a random component (describing the changes in the signal when testing the same defect). The properties of the material, the location of the defect, and its orientation, which are represented by the main component, do not change from one test to another. The random component is due to the human factor and the instrumentation used. In turn, the instrumentation depends on the method, methodology, and equipment for monitoring at a selected sensitivity. A possible way to improve the confidence of, e.g., ultrasonic testing was described previously [12]. It is important to note that the human factor is subjective and can change for many reasons, whereas instrumentation factors have objective characteristics, which can be assessed in terms of the error of the method used.

In accordance with the above ideas, Berens and Hovey [13] proposed a statistical model, in which the response signal of the monitoring system is divided into separate components. These components can be written as the following functional relationship

$$\hat{a} = h(a) + \delta + \varepsilon, \tag{4}$$

where $\hat{a}$ is the output signal of the monitoring system; $h(a)$ is the main component, which characterizes the average change in the signal as a function of the defect size; δ is an additional component, which is due to the instrumentation used and is defined as the error of the method used; and ε is an additional component, which is due to the human factor.

According to Berens and Hovey, $h(a)$ is a random variable with its mean value, while δ and ε are random variables with zero means.

1.3. Parametric model of the *PoD* curve based on the results of statistical processing of test samples

The proposed model can only be used in equation (4) for constructing the $PoD(a)$ curve if the sizes of defects and their distribution are known in advance, i.e., if the defects are artificially created as test samples. These data can be obtained from the results of non-destructive tests in organizations of the nuclear industry [14].

This method of constructing the *PoD* curve can be referred to as a direct method. However, organizing and conducting such tests involve significant costs. Since the data obtained from the results of such tests are limited, only data on the average *PoD* are typically presented. In this case, the averaging of the data complicates their further use for solving practical problems and makes it impossible to make an individual assessment of the confidence by different laboratories.

As was noted [9], this is a big drawback because individual assessments by different laboratories allow one to identify more reliable laboratories and use their experience in further work. Additional difficulties arising in the construction of *PoD* curves were described in the literature [15]. The noted shortcomings require the search for alternative methods for estimating the *PoD* curve.

2. STATISTICAL MODEL FOR ASSESSING THE RELIABILITY OF NON-DESTRUCTIVE TESTING SYSTEMS BY SOLVING INVERSE PROBLEMS

As an alternative to direct methods, computational methods based on solving inverse problems [16], as well as computer simulation tools[5], can be used.

[5] Genc K. Simulating reality: Going beyond counting pores and cracks in additive-manufactured parts. *FOCUS The NDT Technician*. 2020;19(2). 3 p. https://www.asnt.org/-/media/Files/Publications/TNT/TNT_19-2.pdf?la=en. Accessed December 15, 2022.

The *PoD* curve is constructed using data on real defects found by testing metal structures. An essential component is the selection of a sample of initial data [18, 19].

Let defects of different sizes a_i be found in a structure operating for time t. After constructing the defect size distribution of the frequency of detection of defects for the obtained sample (Fig. 1), the density distribution of detected defects, $p_f(a)$, can be obtained. A dimensional scale should be chosen as the defect size a_i, e.g., depth, length, or cross-sectional area of the defect. Because of the imperfection of the monitoring system used, some of the defects remain undetected. As mentioned above, the degree of imperfection of the monitoring system is characterized by the probability-of-detection curve $PoD_{\mathrm{MS}}(a)$, where the subscript MS refers to a certain monitoring system.

The set of detected and undetected defects is described by the initial random defect size distribution. Let us call this distribution the real defect density distribution and denote it $p_a(a)$.

In accordance with the introduced definitions, the expression for the density of detected defects has the form

$$p_f(a) = \frac{p_a(a) PoD_{\mathrm{MS}}(a)}{\int\limits_{a_0}^{S} p_a(a) PoD_{\mathrm{MS}}(a) da}, \tag{5}$$

where $p_f(a)$ is the density distribution of detected defects by the initial monitoring system, $p_a(a)$ is the real defect density distribution in the test object, $PoD_{\mathrm{MS}}(a)$ is the probability-of-detection curve for the initial monitoring system MS, S is the maximum size of a defect that can occur in the test object, a_0 is the sensitivity of the initial monitoring system (minimum size of a defect that can be detected by the initial system), and a is the dimensional defect scale.

Considering expression (5), the problem of finding the functions $p_a(a)$ and $PoD_{\mathrm{MS}}(a)$ from the known distribution function $p_f(a)$ can be posed. Such a problem is an inverse problem [19–21]. To solve this problem, it is necessary to know the specific form of the functions $p_a(a)$ and $PoD_{\mathrm{MS}}(a)$.

The distribution function of the real sizes of defects should theoretically be exponential because the number of defects increases with a decrease in the size scale. Under this assumption, let us write the real defect distribution density as

$$p_a(a) = \frac{\exp(-\lambda a)}{\int\limits_{a_0}^{S} \exp(-\lambda a) da}, \tag{6}$$

where λ is the parameter of the real defect distribution.

The form of the function $PoD_{\mathrm{MS}}(a)$ was chosen so that it has few parameters, but takes into account the features of statistical model (4) proposed by Berens and Hovey. With these requirements in mind, the following form was used:

$$PoD_{\mathrm{MS}}(a) = 1 - \exp(-r(a - a_0)), \quad (7)$$

where r is the confidence coefficient of the initial monitoring system.

The confidence coefficient r in formula (7) includes both the main component of the function $PoD_{\mathrm{MS}}(a)$ of the defect size and the additional component due to the human factor [22], which is found from the results of statistical processing of the initial sample. The same is valid for the parameter a_0.

Substitution of formulas (6) and (7) into relation (5) gives

$$p_f(a) = \frac{\exp(-a/\lambda)\left[1 - \exp\left(-r\left(a - a_0\right)\right)\right]}{\int\limits_{a_0}^{S} \exp\left(-a/\lambda\right)\left[1 - \exp\left(-r\left(a - a_0\right)\right)\right] da}. \quad (8)$$

It follows from relation (8) that, knowing the distribution $p_f(a)$, the following three parameters should be obtained: the distribution parameter λ, the confidence coefficient r, and the sensitivity a_0 of the initial monitoring system. The construction of the *PoD* curve of several independent variables was described in the literature [23].

2.1. Calculation procedure

An important feature of the function $p_f(a)$ should be noted. Since this function is defined as the product of the monotonically decreasing function $p_a(a)$ and the monotonically increasing function $PoD_{\mathrm{MS}}(a)$, the function $p_f(a)$ can be assumed to have a maximum. The coordinate of the maximum value should be related to the parameters of the functions $p_a(a)$ and $PoD_{\mathrm{MS}}(a)$. Simple calculations give the abscissa of the point of maximum:

$$a_{\max} = a_0 - \frac{\ln\left(1 + \frac{r}{\lambda}\right)}{r}. \quad (9)$$

Substitution of $a_{\max}$ into relation (8) gives the ordinate of the point of maximum:

$$p_f(a_{\max}) = y_{\max}. \quad (10)$$

These coordinates ($a_{\max}$, $y_{\max}$) can be determined from the experimentally obtained density distribution of detected defects (Fig. 1).

An additional feature of the selected functions should also be noted. Substitution of $a_{\max}$ into formula (6) gives almost the same ordinate of the point of maximum as that in formula (10), i.e.,

$$p_a(a_{\max}) = y_{\max}. \quad (11)$$

The ordinates in formulas (10) and (11) exactly coincide if the used limits of integration in the expressions are 0 and ∞. The difference between the $y_{\max}$ values calculated by formulas (10) and (11) depends on the a_0 value and the chosen value of the maximum defect size S in the region under study. At $S > 20$ mm, the relative error of the difference between these values does not exceed 10^{-4}.

In essence, this means that the probability density distribution function $p_a(a)$ passes through the point of maximum of the density distribution of detected defects $p_f(a)$. Using this property, the nonlinear equation for the unknown parameters a_0 and λ can be written:

$$F(a_0, \lambda) = y_{\max} - \frac{\exp\left(-\lambda a_{\max}\right)}{\int\limits_{a_0}^{S} \exp\left(-\lambda a\right) da} = 0. \quad (12)$$

The unknown parameter a_0 can be found from the experimentally obtained density distribution of detected defects as the intersection of the curve of the distribution of detected defects with the abscissa axis. Knowing the obtained value a_0 and using equation (12), the second unknown parameter, λ, can also be found by considering nonlinear equation (12) in only one parameter λ.

The parameter r was found by the method of successive approximations. Given a set of parameter r values, let us calculate the parameter λ value at each r. Let us divide the initial region of size (a_0, S) into n intervals. The choice of the number of intervals and their sizes is determined by a preliminary analysis of the initial sample. According to formula (6), the probability that real defects of sizes from a to b are in the interval (a, b) has the form

$$p_a(a, b) = \frac{\int\limits_{a}^{b} \exp(-a/\lambda) da}{\int\limits_{a_0}^{S} \exp(-a/\lambda) da}. \quad (13)$$

If the total number $N_{a\Sigma}$ of real defects throughout the region is known, then the number of real defects in the ith interval is

$$N_a^i = p_a\left(a_i, a_{i+1}\right) N_{a\Sigma}. \quad (14)$$

If the number N_f^i of detected defects in each interval is known, then the total number of real defects can be found from the expression

$$N_{a\Sigma} = \sum_{i=1}^{n} N_f^i \frac{1}{1-\exp\left(-r\left(\frac{a_i + a_{i+1}}{2} - a_0\right)\right)}. \quad (15)$$

Thus, by giving the r value and using expression (15), $N_{a\Sigma}$ is found. Then, using formula (14), the number N_a^i of real defects in each (ith) interval is determined. Further, the parameter $\lambda(r)$ is obtained from the known N_a^i values by linear regression.

The $\lambda(r)$ value that is closest to the parameter λ value found from equation (12) is the initial parameter r value.

2.2. Test calculations

The accuracy of the above calculation procedure was checked by test calculations on models. In this case, data modeling offers an important advantage: the results of the calculations can be compared with the known behavior of the general population, which cannot be done by comparing only laboratory data. Some issues of the quality of the recovery procedure were described previously [24, 25].

Let the initial data be a given structure containing a total of $N_{a\Sigma}$ real defects with an exponential defect size distribution with known parameter λ. The current state of the structure is assessed by a non-destructive testing system with known $PoD(a)$ of given form (7) with known characteristics r (confidence coefficient) and a_0 (sensitivity of the initial monitoring system). The monitoring detected $N_{a\Sigma}$ defects of different sizes, which can be sorted by size. The thus-obtained population of $N_{a\Sigma}$ detected defects is the initial sample, which was processed according to the proposed procedure. The obtained values were compared with the initial data. To study the effect of a combination of values of the initial parameters on the recovered characteristics, the initial data were grouped for nine series of calculations (Table 1). For all the selected series, the total number of real defects was assumed to be $N_{a\Sigma}$ = 1000. The pipe wall thickness was chosen to be S = 20 mm.

Table 1. Initial data for modeling

No. of series of calculations	Parameter a_0, mm	Parameter λ, mm^{-1}	Parameter r, mm^{-1}
1	0.5	0.2	0.1
2	0.5	0.2	0.5
3	0.5	0.2	1.0
4	0.5	0.5	0.1
5	0.5	0.5	0.5
6	0.5	0.5	1.0
7	0.5	1.0	0.1
8	0.5	1.0	0.5
9	0.5	1.0	1.0

2.2.1. Determination of parameter a_0

The parameter a_0 was determined by finding the point of intersection of the curve of the density of detected defects with the abscissa axis. The density curve was approximated by a parabola constructed through two points, including the point of maximum of the initial density of detected defects. The following initial parameters of the fourth series were chosen as an example of calculation: λ = 0.5 mm^{-1}, r = 0.1 mm^{-1}, and a_0 = 0.5 mm.

The initial parameters were used to plot the real defect density curve by formula (6). After specifying the number of intervals of division of the initial region (at n = 27), the number of real defects within the obtained intervals is found from formula (14). Knowing the number of real defects within the obtained intervals, the number of detected defects in each interval can be calculated using the dependence

$$N_f^i = N_d^i \int_{a_i}^{a_{i+1}} \left(1-\exp(-r(a-a_0))\right) da. \quad (16)$$

Rounding of the number N_f^i to an integer gives the initial sample of detected defects grouped by their size. The obtained values of detected defects can be rounded down (truncation of the fractional part if it is less than 0.5) and up (increase to the next integer if the fractional part is greater than or equal to 0.5), which leads to two different frequency distributions (Fig. 1, red and blue columns).

For the obtained distribution, let us choose two points (first and third), including the point of maximum of the density, and draw a parabola through them. The point of intersection of the parabola with the abscissa axis gives the parameter a_0 value (Fig. 2). The parameter a_0 can be calculated with the frequency characteristics rounded either down ($a_0^- = 0.365$) or up ($a_0^+ = 0.309$). The average value of the parameter a_0 is $a_0^s = 0.337$. The initial a_0 value is 0.5 mm. The error in calculating the parameter a_0 is δa_0 = 0.326 or 32.6%.

The parameter a_0 values can similarly be calculated at other initial values of the parameters λ and r. Table 2 presents the results of such calculations.

Table 2. Results of the recovery of the parameter a_0^s

Initial value of λ	Confidence coefficient	Recovered value a_0^s	Error δa_0, %
$\lambda = 0.2$	$r = 0.1$	0.189	62.2
	$r = 0.5$	0.303	39.4
	$r = 1.0$	0.321	35.8
$\lambda = 0.5$	$r = 0.1$	0.337	32.6
	$r = 0.5$	0.402	19.6
	$r = 1.0$	0.424	15.2
$\lambda = 1.0$	$r = 0.1$	0.468	6.4
	$r = 0.5$	0.460	8.0
	$r = 1.0$	0.446	10.0

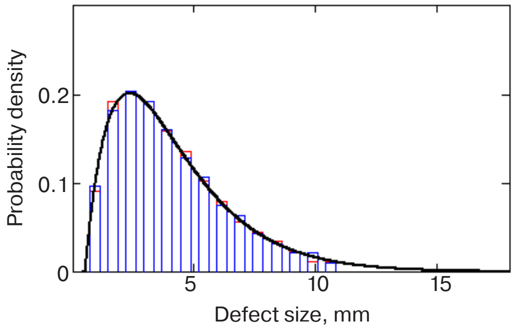

Fig. 1. Defect size distribution of detected defects (all series)

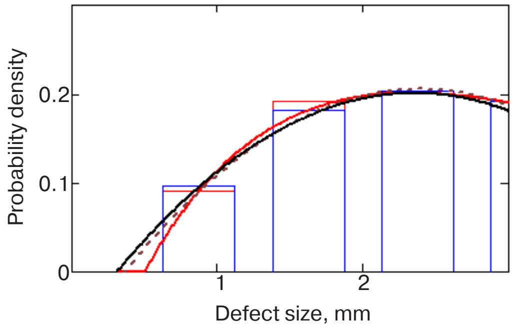

Fig. 2. Two variants of the determination of the parameter a_0 with the frequency characteristics rounded down and up

2.2.2. Determination of the calculated (recovered) value $\tilde{\lambda}$ of the parameter λ

The parameter λ was determined from equation (12). The coordinates of the maximum point of the sample are found using the initial sample of defects (Fig. 1). Knowing these coordinates and using the parameter a_0^s value from Table 2, one can solve nonlinear equation (12) for λ. As a result, the sought-for parameter $\tilde{\lambda}$ is obtained. Table 3 presents the results of these calculations.

2.2.3. Determination of the parameter r

Let us consider an example of calculating the sought-for parameter r at the above initial parameter values of the fifth series: $\lambda = 0.5$ mm^{-1}, $r = 0.5$ mm^{-1}, and $a_0 = 0.5$ mm^{-1}. The number of intervals of division of the

Table 3. Results of the recovery of the parameter $\tilde{\lambda}$

Initial value of λ	Confidence coefficient	Recovered value $\tilde{\lambda}$	Error $\delta\tilde{\lambda}$, %
$\lambda = 0.2$	$r = 0.1$	0.199	0.5
	$r = 0.5$	0.232	16.0
	$r = 1.0$	0.235	12.5
$\lambda = 0.5$	$r = 0.1$	0.529	5.8
	$r = 0.5$	0.594	18.8
	$r = 1.0$	0.574	14.8
$\lambda = 1.0$	$r = 0.1$	0.969	6.4
	$r = 0.5$	1.084	8.4
	$r = 1.0$	1.075	7.5

Note. $\delta\tilde{\lambda}$ is the relative error of calculating the parameter $\tilde{\lambda}$

initial region was specified as $n = 36$. Figure 3 presents the constructed frequency characteristic of detected defects for this series. By setting different values of the parameter r for the initial frequency distribution of detected defects, the corresponding distributions of real defects were obtained. Figure 4 shows one of the obtained distributions of real defects. The real distribution was processed by linear regression, while the parameter λ values were calculated at a given value of r. Table 4 presents the results of such calculations for the fifth series. Comparison of the obtained results with the parameter value (0.954) recovered earlier for this series gave a close value of 0.579; the parameter r values was taken to be 0.27. Note that the initial value of the parameter r was 0.5; i.e., the recovery error of this parameter is 46%.

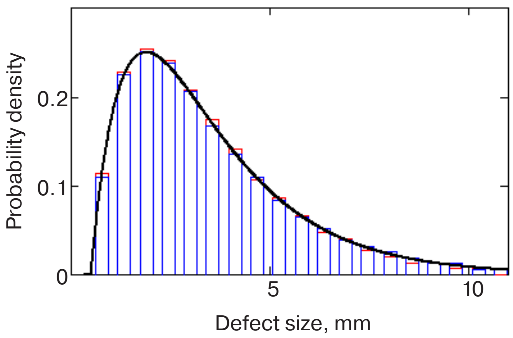

Fig. 3. Defect size distributions of the frequency and density of detected defects for the fifth series

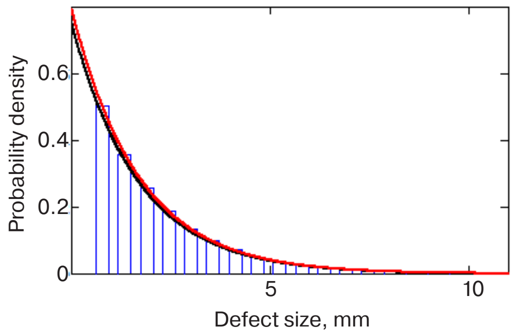

Fig. 4. Defect size distributions of the frequency and density of real defects for the fifth series

The black line in Fig. 4 was constructed by formula (6) at the calculated parameters of the fifth series ($a_0 = 0.402$ from Table 2, $\lambda = 0.594$ from Table 3). The red line was constructed by approximation using formula (17) obtained from the linear regression of the real distribution at $r = 0.27$:

$$p_a^{\exp}(a) = \exp(-0.226 - 0.593a). \tag{17}$$

Similarly, the parameter r values were recovered and the errors for the remaining calculation series were calculated. Table 5 presents he results of the calculations.

The features of the implementation of the developed procedure were described in more detail in the literature [26].

Table 4. Results of the recovery of the parameter $\tilde{\lambda}$ at various confidence coefficients

No. of series	Recovered parameter r, mm^{-1}	Recovered parameter $\tilde{\lambda}$, mm^{-1}	Degree of approximation of recovered parameter $\tilde{\lambda}$ to reference value λ_0 =0.594, $\Delta\lambda = \left\lvert \frac{\lambda_0 - \bar{\lambda}}{\lambda_0} \right\rvert$
1	0.25	0.601	0.012
2	0.26	0.595	$1.7 \cdot 10^{-3}$
3	0.27	0.593	$1.684 \cdot 10^{-3}$
4	0.28	0.588	0.010
5	0.29	0.585	0.015
6	0.30	0.579	0.025
7	0.33	0.568	0.044
8	0.35	0.560	0.057
9	0.4	0.541	0.089
10	0.5	0.502	0.155

Table 5. Results of the recovery of the confidence coefficient

Initial value of parameter λ	Confidence coefficient	Parameter $\tilde{r}$	Error $\delta\tilde{r}$, %
$\lambda = 0.2$	$r = 0.1$	0.095	5.0
	$r = 0.5$	0.4	20.0
	$r = 1.0$	0.9	10.0
$\lambda = 0.5$	$r = 0.1$	0.05	50.0
	$r = 0.5$	0.3	40.0
	$r = 1.0$	0.7	30.0
$\lambda = 1.0$	$r = 0.1$	0.08	20.0
	$r = 0.5$	0.55	10.0
	$r = 1.0$	0.80	20.0

3. ANALYSIS OF THE OBTAINED RESULTS

Comparison of the obtained modeling results and the given initial values of the parameters suggests the following conclusions.

When recovering the parameter a_0, the error was maximum in the series of calculations with the initial value $\lambda = 0.2$ (the maximum error δa_0 was 62.2% at $r = 0.1$). With increasing parameter r from 0.5 to 1.0, the error decreased from 39.4 to 35.8%. With increasing parameter λ from 0.5 to 1.0, the error δa_0 also decreased: the minimum value at $\lambda = 0.5$ was 15.2% at $r = 1.0$; the minimum value at $\lambda = 1.0$ was 6.4% at $r = 0.1$. The error range was 6.4–62.2%.

When recovering the parameter λ, the error in all the series of calculations, which did not exceed 18.8%, ranged from 0.5 to 18.8%.

When recovering the parameter r, the maximum error was 50% at the initial parameter values $\lambda = 0.5$ and $r = 0.1$, while the minimum error was 5% at the initial parameter values $\lambda = 0.2$ and $r = 0.1$. The error range was 5–50%.

The obtained results of numerical modeling showed the fundamental possibility of using the developed procedure to determine both the probability-of-detection curve and the probability distribution of actual defects from the monitoring results.

4. CONCLUSIONS

In this work, the following features of the proposed procedure were identified:

1) The recovery of the probability distribution of real defects is based on statistical processing of only the fraction of the experimental values of the initial sample that determine its extreme value.
2) The obtained extreme value of the initial sample can be used to directly determine the parameter λ of the real defect distribution by solving a nonlinear equation.
3) The recovery of the confidence curve (determination of the parameter r) uses the entire initial sample to solve the inverse problem, which belongs to the class of problems of interpretation of observational or diagnostic data [16–18].

The developed procedure makes it possible to use metal monitoring data both for analyzing the current state of equipment and piping, as well as for predicting their future behavior with greater confidence than currently used methods. This is primarily due to the possibility of using the procedure to assess the reliability (determine the probability-of-detection (*PoD*) curve) for individual test teams directly from the results of experimental tests. An individual assessment of the efficiency of the monitoring carried out by the laboratory also allows the identification of bad and good test teams, whereas the averaging of the results when constructing the *PoD* curve excludes this possibility.

However, it should be noted that the developed methodology only supplements currently existing methods of assessment tests, but does not replace them.

An important application of the developed procedure is to analyze large data arrays obtained by metal monitoring in power plants. In this case, groups of defects can be formed depending on various factors, including types of structural elements, operating conditions, materials used (stainless steel, black steel, composite welded joints), monitoring systems, as well as the quality of work performed by different test teams.

Authors' contributions

A.E. Alexandrov—collecting the results of field measurements, developing a mathematical model, general coordination of the work.

A.P. Titov—developing a mathematical model.

S.P. Borisov and **S.S. Bikovsky**—design of independent software implementations of a mathematical model.

I.V. Stepanova and **L.V. Bunina**—testing and verification of the software model, direct modeling.

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