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ANALYTICAL AND SIMULATION APPROACH TO ESTIMATING THE FAILURE PROBABILITY OF TECHNICAL COMPONENTS USING AN INTERFERENCE MODEL

Summary. This paper presents an analytical and simulation-based approach to estimating the probability of failure of technical components using a stress – strength interference model. The proposed methodology integrates the statistical processing of experimental or operational data with probabilistic modeling and

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simulation implemented within the MATLAB environment. The input variables – operational stress and structural resistance – are described using appropriate probability distributions, enabling the evaluation of their mutual interaction and its impact on system reliability. The developed simulation framework allows for both graphical and numerical assessment of the interference region, which represents critical states in which failure may occur. The influence of variability in input parameters, particularly the standard deviation, is analyzed in order to evaluate the sensitivity and robustness of the model. The results demonstrate that increased dispersion of stress and resistance significantly affects the probability of failure and the system safety margin. The application of the proposed method to a selected technical component revealed a failure probability exceeding the admissible limit, confirming the need for optimization measures. Adjustments to the resistance characteristics led to a partial improvement in reliability; however, additional design or operational modifications were required to meet the prescribed requirements. The main contribution of this work lies in the development of a flexible simulation tool that supports reliability assessment, sensitivity analysis, and decision-making processes in engineering practice. This approach is particularly beneficial under conditions of limited availability of empirical data and can be effectively applied in industries such as automotive engineering, where stochastic loading and material variability play a crucial role in system reliability.

Keywords: reliability, resistance dependability, stress, interference method, failure probability, stress–strength model, risk analysis

1. INTRODUCTION

The interference theory of reliability represents a statistical framework for evaluating system reliability by examining the extent to which the distribution of system demands overlaps with the distribution of its actual performance or durability [1]. This overlap serves as a principal indicator for determining the probability of failure. In reliability assessment, core analytical tools include the examination of failure-free operation and the evaluation of service life, both of which provide essential insights into system performance over time. The theoretical basis of this approach is rooted in the deterministic safe-life concept, which relies on predefined reliability parameters and strict adherence to specified limit values.

Within this deterministic perspective, a failure event is considered to occur when the imposed load exceeds the resistance threshold of the component or system – denoted as R – which represents its capacity to sustain operational stresses. In contrast, the probabilistic (stochastic) formulation of reliability assumes that both the applied stress and resistance to failure are inherently random variables governed by specific probability distribution functions. These quantities may span a wide numerical domain, resulting in scenarios where their distributions either do not intersect at all or exhibit a degree of mutual interference that directly affects the associated reliability estimate [2].

Distribution of random variables:

The first random variable represents the system's operational conditions and the corresponding operating stress, S (system stress). This stress arises from the combined effects of external loads together with the conditions associated with the specific modes in which the system is used.

The second random variable describes the system's resistance, R . Resistance to the acting stress S denotes the capability of the system or its components to withstand physical, chemical, and biological influences which, through their cumulative or instantaneous effects, may induce degradation processes leading to component failures [3].

Both parameters incorporated into the model represent random variables, each defined by stochastic quantities or processes. Their empirical behavior may be illustrated using histograms or – following appropriate statistical evaluation – described through probability distribution functions [4]. Numerous analytical approaches have been proposed in the literature to quantify reliability based on interference, particularly for systems in which the probability density functions of stress, $f_s(S)$, and resistance, $f_r(R)$, follow exponential, normal, Weibull, gamma, or lognormal distributions.

When stress and resistance conform to different probability distributions, the computation of the resulting two-dimensional joint integral becomes mathematically complex, making an analytical determination of reliability difficult. Under such circumstances, it is advantageous to employ mathematical or simulation-based modeling techniques as an alternative to direct analytical evaluation [5]. For this reason, the present paper focuses specifically on the computational methodology associated with the interference theory of reliability.

2. DEFINITION OF THE MODEL

$$P(\text{reliability}) = P(R > S)$$

This is the probability that the system's resistance is greater than the stress.

$$R \sim N(\mu_R, \sigma_R^2) \text{ and } S \sim N(\mu_S, \sigma_S^2) \quad (1)$$

Where:

μ_R , σ_R - mean value and standard deviation of resistance,

μ_S , σ_S - mean value and standard deviation of stress,

Φ - distribution function of standard normal distribution.

The operational stress S and the structural resistance R are represented using their respective probability distribution functions and probability density functions [6]. Let the probability density function associated with the stochastic stress variable S be denoted by $f_s(S)$, and the probability density function corresponding to the random resistance variable R by $f_r(R)$. Similarly, let $F_s(S)$ describe the cumulative distribution function of the stress variable S , while $F_r(R)$ denotes the cumulative distribution function for the resistance variable R . Since both S and R are random quantities, they follow specific probability distribution laws, typically continuous or discrete in nature [7].

These variables may influence one another – an interaction referred to as interference – and this property can be effectively utilized when assessing the reliability of systems or structural elements. The boundary points at which the distributions intersect define the region of mutual interaction between the two variables.

The mathematical formulation of the model can be further described by its fundamental analytical structure, specifically through the following theoretical basis. The interference approach makes it possible to account for the fact that both load and strength are random variables whose mutual interaction directly affects the probability of failure. Analyzing the

overlap of their probability distributions provides a more realistic representation of reliability than traditional deterministic methods.

This approach also helps to identify critical regions in which the probability of failure is highest and enables more accurate modeling of the effects of varying environmental or operational conditions. In practice, this means that a system can be optimized even before its physical implementation by adjusting design parameters or operational strategies to minimize the risk of failure.

Generally, also for other distributions [8]:

$$P(R > S) = \int_{-\infty}^{\infty} f_S(S) \int_{-\infty}^{\infty} (f_R(r) dr) dS \quad (2)$$

Where:

$f_S(S)$ - stress probability density,

$f_R(R)$ - resistance probability density.

For general probability distributions of stress and resistance, this probability is expressed by a double integral of the probability density functions $f_s(S)$ and $f_r(R)$. Mathematically, this represents the integration of the stress probability density over its entire domain, where, for each stress value, the probability that the system resistance exceeds this value is determined. Failure rate (failure probability):

$$F(t) = 1 - R(t) = P(R \leq S) \quad (3)$$

Failure intensity:

The dynamics of the failure process over time are characterized by the failure intensity, $\lambda(t)$, which represents the conditional probability of failure per unit time, assuming failure-free operation up to time t . The failure intensity is defined as the ratio of the probability density function of the time to failure, $f(t)$, to the reliability function, $R(t)$:

$$\lambda(t) = \frac{f(t)}{R(t)} \quad (4)$$

Where:

$f(t)$ - probability density of time to failure,

$R(t)$ - probability of failure-free operation.

These relationships form the basis for the analytical assessment of system reliability using SSI, where the variance and mean values of component stress and resistance are compared. This approach will be utilized in the reliability analysis presented in this paper. The assessed system or object, M_k , which is exposed to loading during the monitored time period, is considered reliable if the given operating stress, L , does not exceed the strength with a specified probability.

$$M_k = \Pr(S > L) \quad (5)$$

Where:

M_k - System or object,

S - Stress [%/MPa],

L - Load Stress [%/MPa].

The presented mathematical framework enables a quantitative assessment of the safe service life of the system and forms the basis for the probabilistic analysis of failures and the lifetime of technical objects.

Figure 1 illustrates the conceptual principle underlying the area that is proportional to the probability of failure. The shaded region represents the domain in which both random variables exert mutual influence [9]. This area corresponds to the probability of failure and reflects the fact that, due to the stochastic nature of the quantities involved – particularly the dispersion of their values – there exists a non-zero likelihood that the applied stress will exceed the available resistance, resulting in a failure event [10].

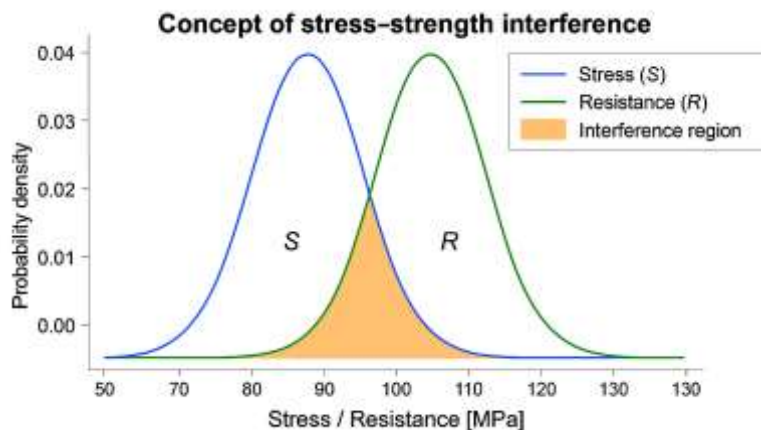


Fig. 1. Illustration of the range of interference

When determining the probability of failure-free operation, R_f , and assuming that the random variables S and R are statistically independent, the calculation can rely on the well-established principle that the probability of the simultaneous occurrence of two independent events is equal to the product of their individual probabilities. These methodological foundations form the basis for constructing analytical and mathematical models of both failure-prone and failure-free elements using the SSI interference method [11].

2. SSI SIMULATION MODEL

The input quantities – stress S and resistance R – are random variables derived from experimental measurements. These measurements produce a non-parametric data distribution that can be further statistically processed, for example, in the form of a histogram, or converted into a suitable parametric distribution [12]. Both approaches allow for the generation of input data that are subsequently used to assess the probability of occurrence of critical events.

On this basis, the probability of failure or failure-free performance of technical components can be evaluated through the interference-based reliability approach. A crucial prerequisite for its correct application is the rigorous statistical processing of input data, which are typically obtained from experimental measurements or operational monitoring. In real engineering systems, both stress S and resistance R are affected by numerous stochastic influences, including variations in material properties, measurement uncertainties, fluctuations in operational conditions, and degradation mechanisms occurring throughout the service life of the component. Consequently, representing these parameters by single deterministic values is generally inadequate and may lead to an underestimated assessment of failure risk.

The expression of random variables S and R by means of relative frequency histograms and corresponding probability density distributions is illustrated in Figure 2.

During the analysis of measured datasets, two methodological strategies may be adopted: non-parametric methods, which rely on empirical probability distributions derived directly from observed data, and parametric methods, in which experimental observations are approximated by selecting an appropriate theoretical distribution model – for example, normal, lognormal, or Weibull distributions. The selection of a suitable distribution depends on several factors, including the physical characteristics of the variable being examined, the size and quality of the available dataset, and the underlying mechanisms governing the behavior of the studied phenomenon.

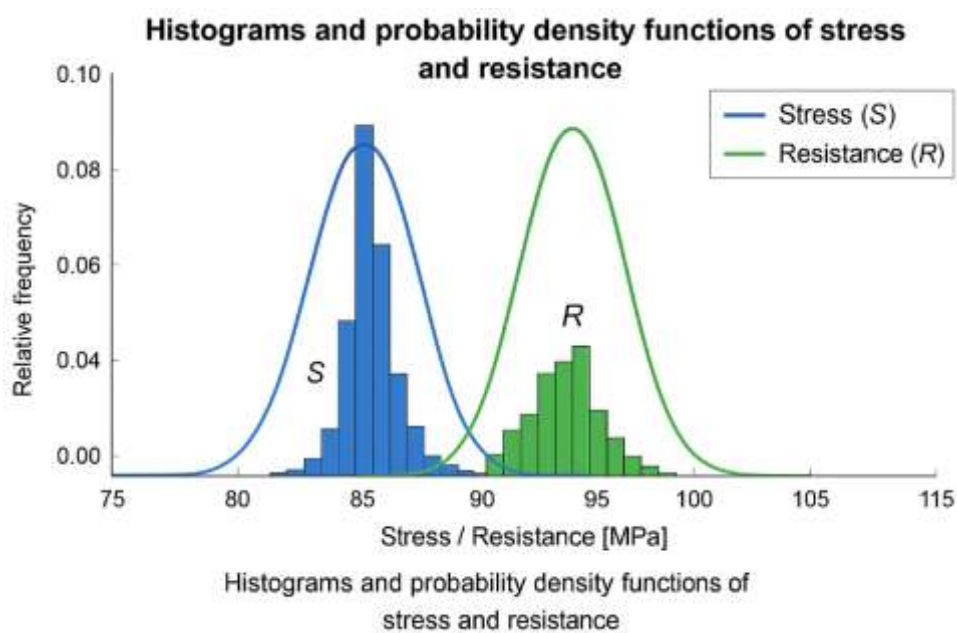


Fig. 2. Expression of random variables S and R by relative frequency histogram and probability density distribution

The procedure for the simulation model operation:

For the range of experimental or generated values, the corresponding values of the distribution functions, $F_r(R)$ and $F_s(S)$, are determined for different values of resistance R [13]. The resulting failure-free performance is influenced by the values of stress S and resistance R across their entire range.

If these two quantities are represented graphically in terms of their mutual dependence, the point of intersection corresponds to a combination of two independent phenomena. The area under the curve in the graph corresponds to the probability of failure-free operation, expressed as a percentage. Conversely, the area above this curve represents the probability of failure.

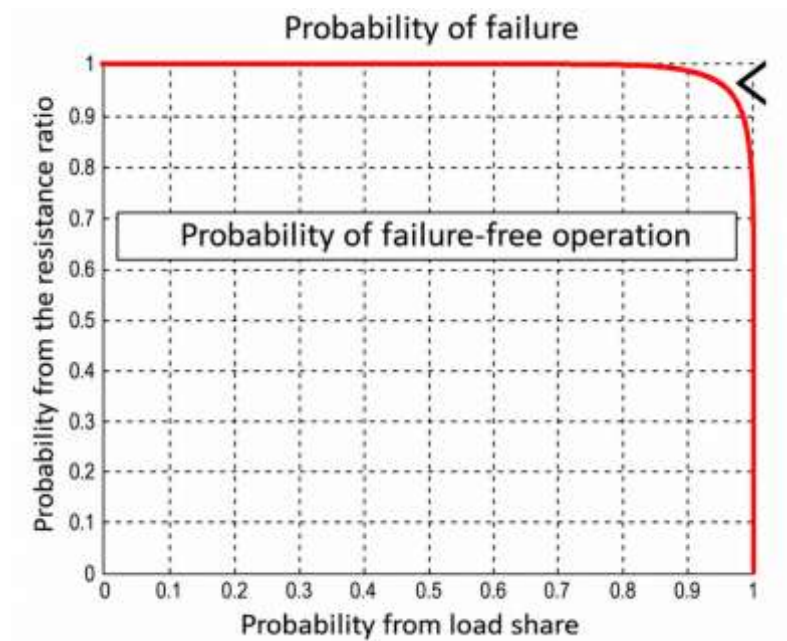


Fig. 3. Probability of failure

The modeling procedure was compiled as follows:

Initially, it is necessary to obtain input data in the form of histograms or probability distributions of the operational stress (S) and resistance (R) of the analyzed element. Subsequently, random values of stress and resistance are generated, thereby creating a specific simulated case [14].

In the present study, a specific analysis is considered, in which resistance represents values obtained from operation, namely the values of selected reliability characteristics within the monitored period: component life (time resistance) and the number of failures over time. The stress associated with the complaint process is represented by the stress parameter.

In the next step, it is determined to which region – failure or failure-free – the given point belongs, and the point is simultaneously recorded graphically. The boundary between these regions is defined by the condition $R \geq S$ and is illustrated in the graph by a red line (see Figure 3). If this condition is not satisfied, the state is classified as a failure.

During the simulation, both the total number of iterations (N) and the number of failure cases (n) are monitored. The generated data are then statistically processed, yielding probability density functions and distribution functions, which are subsequently presented graphically to provide a clearer understanding of the interference between S and R .

The MATLAB software environment is employed for mathematical modeling, providing not only high-quality graphical outputs but also the capability to develop interactive applications. Within this environment, the user can modify the distribution parameters and evaluate which combinations of stress and resistance are appropriate for a given design via a user interface. The program enables the selection of distribution types for stress and resistance, the adjustment of their parameters, and the definition of the number of simulations.

If the results indicate that the required reliability criteria are not satisfied, the user can repeat the simulations with modified input parameters until the desired level of failure-free operation is achieved.

3. SIMULATION MODEL STEPS

It is necessary to determine an appropriate number of simulations and to obtain input data describing the parameters of the probability density distributions for the operational stress and the resistance of the analyzed element. A visualization of the selection of the number of simulations is presented in Figure 4. Determining an appropriate number of simulations for the interference method depends on the desired accuracy of the results, the variability of the input data, and the available computational resources. The objective is to achieve stable and reliable estimates (e.g., of the probability of failure) without resorting to an unnecessarily large number of simulations.

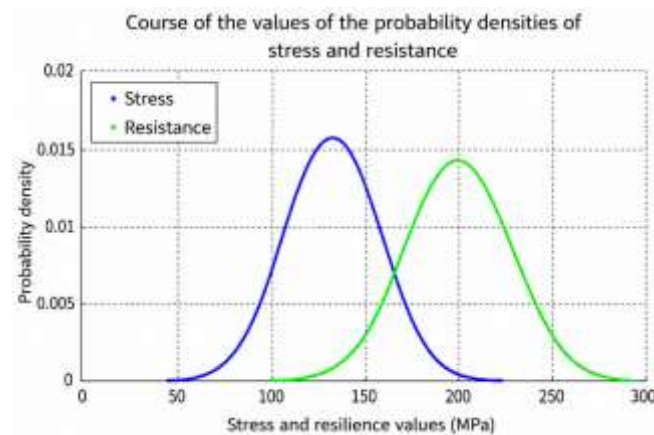


Fig. 4. Determining the number of simulations in a mathematical model

First, the operating stress and resistance values are generated and subsequently statistically processed into probability density functions and distribution functions. The representation of the determination of operating stress is shown in Figure 5. In the next step, the system reliability function is calculated, taking into account the time dependence of the applied stress and the potential reduction of resistance due to degradation processes. Based on the reliability function, the failure intensity can also be determined, which characterizes the instantaneous susceptibility of the system to failure during operation.

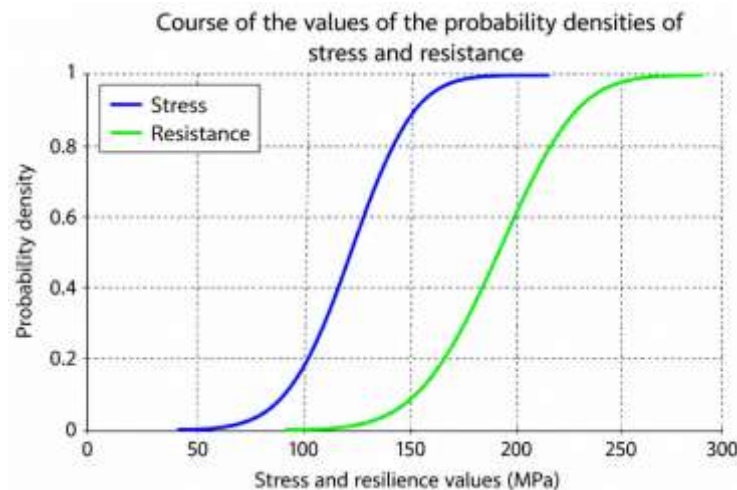


Fig. 5. Determination of operating stress and resistance of a component

The minimum value of the resistance function and the maximum value of the operational stress function are determined. At the same time, the interdependence between the resistance (R) and stress (S) values is illustrated. Finally, the area under the curve is calculated, representing the degree of probability overlap, and this area is shown in Figure 6a and Figure 6b.

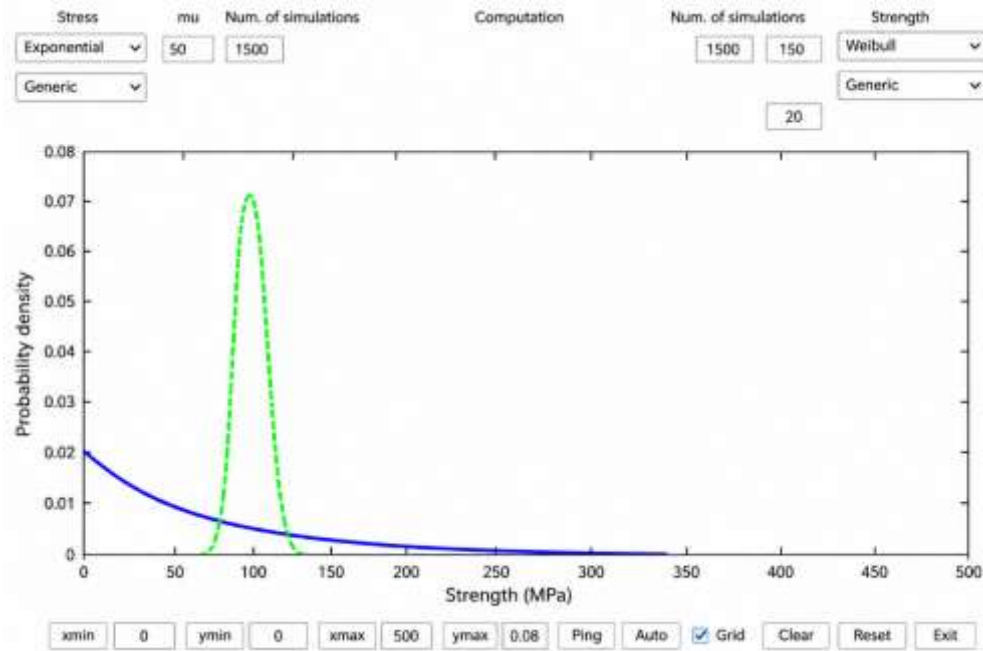


Fig. 6a. Probability density functions and distribution functions

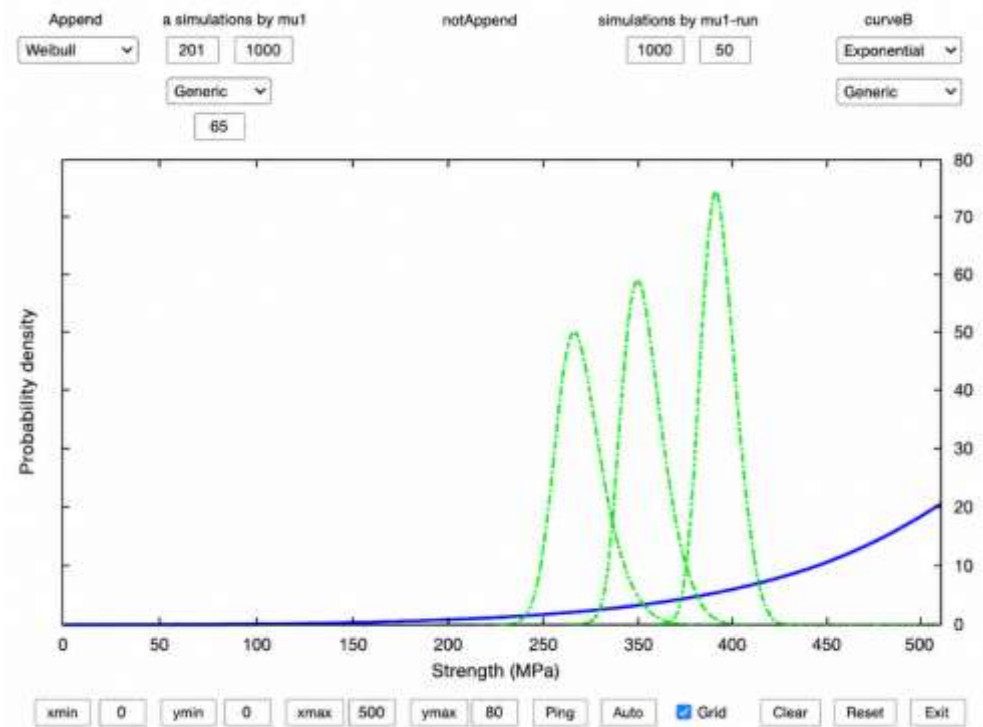


Fig. 6b. Probability density functions and distribution functions

The next step in the experiment is to analyze the impact of variations in standard deviation values. This analysis focuses on how changes in data variability (dispersion) influence the results of statistical evaluations and decision-making processes. The primary objectives of this step are to assess the robustness of the models – for example, how changes in variability affect regression results; to evaluate the reliability of the results – whether conclusions remain valid under higher or lower levels of uncertainty; and to support risk analysis, particularly in fields such as finance, manufacturing, and medicine, where data fluctuations may have significant consequences.

The analysis of the impact of variations in standard deviation within manufacturing systems focuses on assessing how variability in input or output parameters affects the stability and performance of the entire production process. Increased dispersion of technological quantities, such as product life, failure rates, or the number of non-conforming units in production, may lead to a higher probability of defective products, reduced component reliability, or inefficient utilization of production capacity.

For this reason, quantitative analysis of variance represents a key tool in process optimization, quality management, and the reduction of production-related risks.

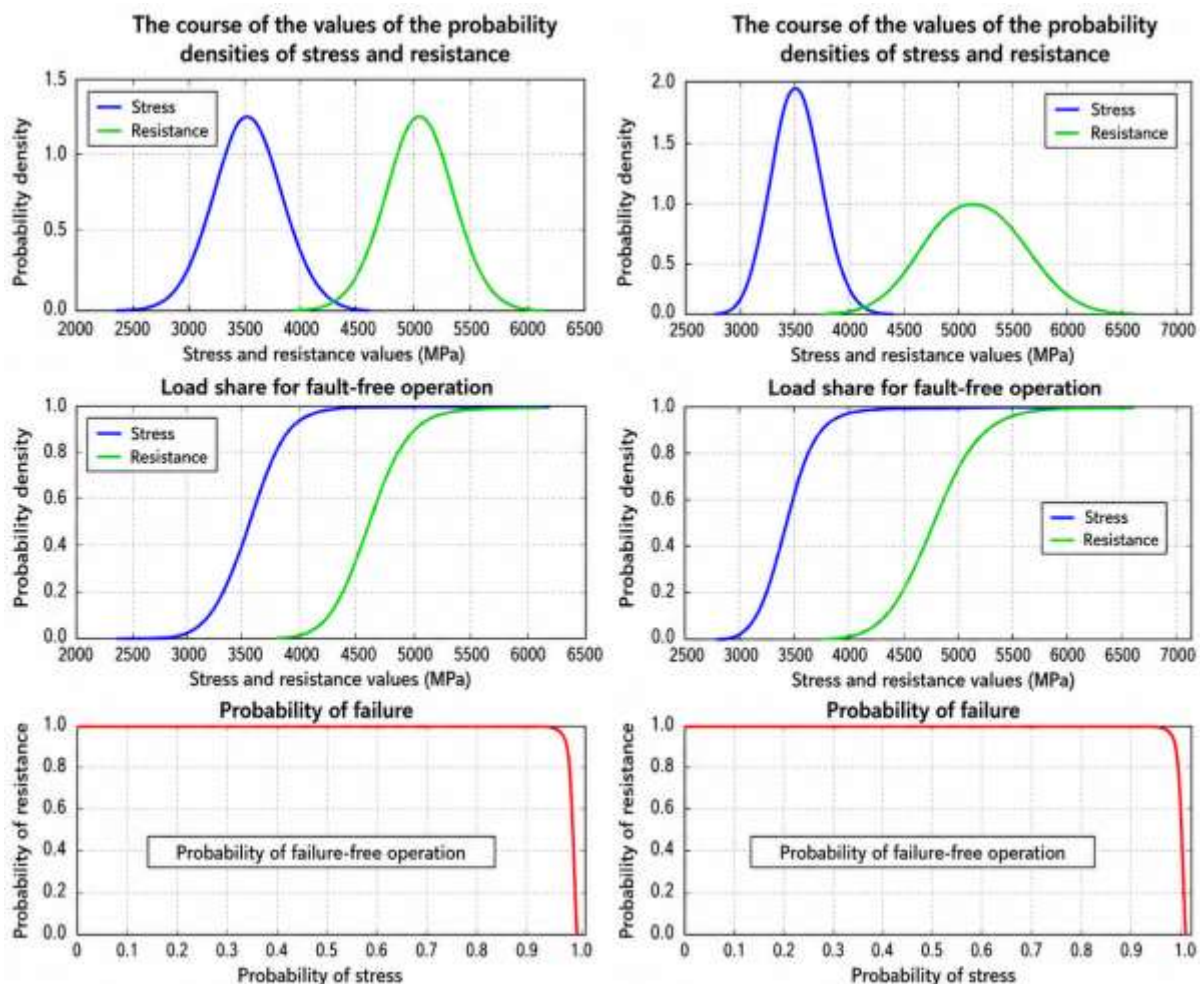


Fig. 7. Principle of impact of changes in the resistance parameter

A statistical probability model can be developed, and the relationship between stress and resistance can be visualized using histograms of randomly generated values through the *scatterhist* function. This function is employed within the MATLAB environment to perform simulations and to provide a combined graphical representation of the data. It integrates a scatter plot with histograms into a single figure (Figure 8).

The central part of the visualization consists of a two-dimensional scatter plot, which illustrates the relationship between two variables (e.g. stress versus resistance). Along the upper edge, a histogram of one variable – stress – is displayed, while the right-hand side presents a histogram of the second variable, namely resistance.

This visualization effectively represents the relationship between randomly generated stress and resistance values. The main plot captures the correlation between the variables, whereas the marginal histograms provide insight into their individual probability distributions. Such a representation enables an efficient assessment of the interrelationship and overlap of the distributions of quantities influencing system reliability.

Based on the resulting graphical output, it is possible to identify regions with a high concentration of stress and resistance values, as well as potentially critical areas of their mutual overlap. These regions correspond to states in which a significant reduction in the system safety margin occurs, leading to an increased probability of failure.

Furthermore, analysis of the scatter plot allows for the assessment of the degree of dependence between stress and resistance. If a correlation exists between the variables, it can be identified from the inclination and shape of the point cloud.

This information is particularly important when refining the probabilistic reliability model, as the assumption of independence between variables may not always be satisfied under real operating conditions. For an indicative assessment, a reduced number of simulation runs is selected. Although increasing the number of iterations would enhance the statistical robustness and precision of the simulation outputs, it would simultaneously reduce the clarity and visual interpretability of the resulting graphical representations. The simulation results, together with their graphical illustrations, clearly demonstrate the significant impact of variability in the individual resistance and stress parameters. The underlying principle of the analytical procedure employed is illustrated in Figure 7, which presents a graphical evaluation of how variations in the resistance parameter influence the resulting reliability characteristics.

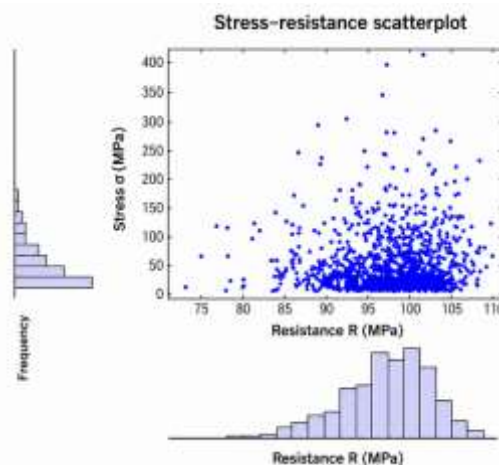


Fig. 8. Relationship between stress and resistance using a scatter–histogram representation

The next step is the analysis of the probability of failure based on a simulation experiment with parameters defined as follows:

Input:

Number of simulations: 1000

Stress parameters: exponential distribution, mean value 50

Resilience parameters: Weibull distribution, standard deviation 20

Output:

Probability of failure-free operation: 0.919

Probability of failure: 0.081

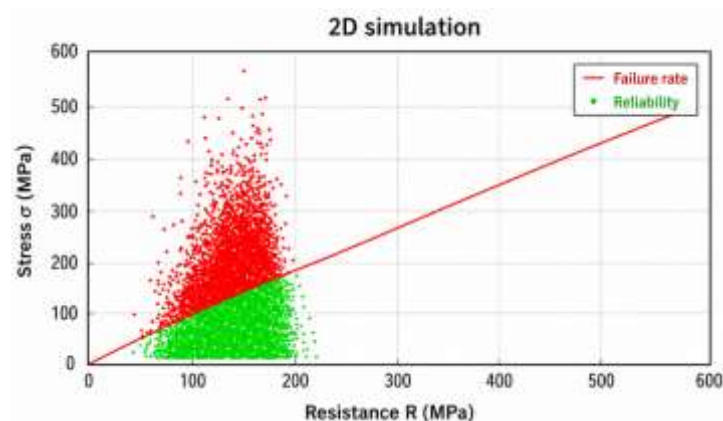


Fig. 9. Graphical representation of 2D faulted and faultless set of realizations at 100,000 simulations

Figure 9 shows the results of a 2D simulation model of the interference of load (stress) and resistance of a technical element. This is a classic stress–strength interference model that allows quantifying the probability of system failure based on the overlap of two random variables – the applied load and the available load capacity of the element.

Interpretation of the graph

The X-axis (Resistance) represents the random variable of the load capacity of the structure or component.

This variable is usually determined by material properties, manufacturing tolerances, and degradation during the life cycle.

The Y-axis (Stress) represents the magnitude of the applied load, which can be deterministic or stochastic, while the model assumes its variability over time or due to operating conditions.

The green points (Reliability region) indicate the states for which:

"Load (Stress)" < "Strength (Resistance)"

In this region, the system is reliable, since the load capacity exceeds the load.

The red points (Failure region) represent situations where:

"Load (Stress)" $\geq$ "Strength (Resistance)"

Failure occurs in this region because the applied load exceeds the load-bearing capacity of the element. To apply this model in practice, an extensive simulation of random values for both

quantities is performed. The resulting scatter plot illustrates the two-dimensional distribution of load and load capacity across a range of operating states. Each simulated state therefore represents one potential configuration of the real system.

The region in which the simulated load values are lower than the corresponding load capacity values represents failure-free operation. These points correspond to cases in which the structure satisfies the required safety and reliability criteria.

Conversely, cases in which the simulated load exceeds the load capacity fall within the failure region. This condition arises as a result of combinations of extreme loads, material degradation, or unfavorable parameter values that lead to the load-bearing capacity of the system being exceeded.

The interference region – the zone in which stress and resistance values overlap – thus represents a critical factor in reliability assessment. It is the density of points within this region that determines the number of simulated cases resulting in failure.

4. CONCLUSION

The simulation results, together with their graphical interpretation, indicate an unacceptably high probability of failure of 0.156, which substantially exceeds the established admissible limit of 0.06. A reduction in this failure probability can be achieved primarily by optimizing manufacturing processes and implementing higher-grade materials, thereby increasing the structural resistance of the examined component. This effect is illustrated in Figure 8, which demonstrates the sensitivity of the resulting failure probability to variations in the resistance parameter. Although increasing the number of simulation iterations generally enhances numerical accuracy, it may also reduce the visual clarity of graphical outputs, which is relevant when interpreting results for design or educational purposes.

The improved failure probability of 0.081 obtained after modifying the resistance distribution reflects partial progress; however, it remains above the required reliability threshold. This indicates that the system, in its current configuration, does not meet the prescribed reliability standards. The presented simulation model proves to be an effective tool for overcoming the limitations inherent in classical analytical approaches, particularly under conditions of limited empirical data availability. The model enables a detailed examination of the interaction between the stochastic characteristics of stress and resistance distributions, thereby supporting a more realistic assessment of reliability in complex technical systems.

Figure 9 provides a combined visualization of safe and unsafe operational regions, where the red region represents the domain of failure and the green region corresponds to failure-free operation. This visual distinction is particularly valuable for both technical diagnostics and pedagogical purposes, as it offers an intuitive understanding of the mathematical relationships underlying the SSI interference method. Moreover, the graphical outputs facilitate comprehension of how different probability distributions of random variables influence system reliability, which is especially beneficial in the teaching of stochastic reliability concepts.

Based on the conducted simulations, it is evident that the current safety margin of the analyzed system is insufficient, highlighting the need for adjustments in either design or operational parameters. Increasing system resistance through the use of higher-quality materials is one possible approach; alternatively, reducing applied stress through optimized operating conditions, load redistribution, or the implementation of additional protective mechanisms may also contribute to achieving the desired reliability level.

A significant advantage of the proposed simulation framework lies in its flexibility and its capability to perform sensitivity analyzes. By modifying the mean values or variances associated with stress and resistance distributions, it becomes possible to identify input parameters that exert the greatest influence on the resulting probability of failure. Such information is highly valuable in engineering decision-making, as it enables designers to determine which measures will yield the most substantial improvements in reliability. Furthermore, the model supports comparative evaluations of alternative design solutions, allowing engineers to assess different configuration scenarios using a unified reliability metric.

When complemented by graphical outputs, the simulation methodology becomes a practical decision-support tool. The results are not only quantitatively measurable but also visually interpretable, thereby significantly enhancing the transparency and clarity of reliability assessments for engineering teams and stakeholders.

From a long-term perspective, the interference-based simulation model offers the capability to predict the time-dependent evolution of system reliability, taking into account gradual material degradation, wear mechanisms, and variations in operational conditions throughout the service life of a component. This predictive potential can improve maintenance planning, optimize inspection intervals, and reduce the likelihood of unexpected failures, thereby contributing to enhanced operational safety and cost-effective asset management.

The findings obtained from the simulation analysis have direct relevance for the automotive industry, where reliability assessment plays a critical role in ensuring vehicle safety, operational robustness, and long-term durability of mechanical, electronic, and structural subsystems. The interference-based simulation approach provides a valuable framework for quantifying the probability that operational loading will exceed the resistance capacity of components, which is essential for identifying failure-critical regions in automotive systems.

In automotive applications, the stochastic nature of stress and resistance parameters is particularly evident due to:

- variability in manufacturing tolerances,
- fluctuations in material properties (e.g., steel grades, aluminum alloys, composites),
- changing environmental and driving conditions,
- ageing processes such as fatigue, corrosion, or thermal degradation,
- uncertainties in driver behavior and real-world loading scenarios.

These factors contribute to an expansion of the interference region and consequently increase the probability of failure, as demonstrated by the simulation results.

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