Fuzzy reliability model of systems for decision support in technical diagnostics

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Abstract. The paper is devoted to the decision support method in technical diagnostics problems. The analysis of two approaches to the determination of the systems technical state: probabilistic and deterministic are carried out. The classical reliability model is considered on the basis of statistical-probabilistic approach, a method for its modification is proposed. A structural-parametric reliability model of complex technical systems (in particular, industrial equipment) is proposed for the purpose of systematizing heterogeneous data using the mathematical apparatus of fuzzy sets. The fuzzy reliability model allows one to process diagnostic information about an object in a unified manner and bring it to a unified form. The problem of reducing the parameters dimension under multifactorial analysis and the problem of objects ordering (ranking) is solved. The technical state concept in terms of fuzzy sets theory is formalized in the paper. The physical meaning of technical state index is described. The presented fuzzy reliability model makes it possible to apply methods of computer information processing for use in problem-oriented control systems and decision-making, allowing to improve equipment reliability and management efficiency. The complex application of the classical reliability model and fuzzy reliability model can improve the decisions foundation made in technical diagnostics problems.

1. Introduction and task statement

The increasing importance of complex and expensive technical systems, especially in hazardous industrial enterprises, safety reliability and durability requirements make it very important to assess the state of the system, its reliability. Technical diagnostics is a field of knowledge which encompasses theory, methods and means of determining the technical state (TS) of objects and systems [1]. Technical diagnostics studies methods of obtaining, processing, evaluating diagnostic information, diagnostic models, and decision-making algorithms. The purpose of technical diagnostics is to increase reliability and lifetime of technical systems.

As is known, the most important reliability indicator is the absence of failures of the technical system during its operation. Due to early detection of defects and malfunctions, technical diagnostics can prevent failures with severe consequences during maintenance. This increases the reliability and efficiency of operation and creates the possibility of operating technical systems in accordance with their TS. This approach also involves the application of the maintenance and repair concept – Reliability-Centered Maintenance, or its particular case – Condition Based Maintenance [2, 3]. In operation, the object is operated up to the limit state in accordance with the recommendations of the technical diagnostics system. Such an approach can bring an economic effect to the enterprise, equivalent to the cost of 30% of the total equipment park [4].

R. Barlow and F. Proshan [5, 6] are experts in the reliability theory, who were among the first to begin research on systems consisting of "ageing" elements. This problem arose because of practical need to make quantitative estimates of the reliability indicators of systems for which only limited statistical information was available. Such systems include, for example, aircraft: there is little failure information due to sufficiently high reliability, but it is known that over time various reliability characteristics are monotonically deteriorating. These studies are based on estimates for the mean values of the time between failures and the fact that the failure intensity function is monotonic.

Technical diagnostics solves a wide range of problems, many of which are adjacent to the tasks of other scientific disciplines. The main task of technical diagnostics is to determine the state of the technical system.

The state of the system is described by a set of parameters (characteristics) which define it. This set can be different. The system state recognition is defined as referring the system state to one of the possible classes (diagnoses). It is often necessary to choose one of two diagnoses (differential diagnosis or dichotomy); for example, "perfect (flawless) state" and "imperfect (flaw) state" [2]. However, in other cases it may be necessary to characterize the imperfect state in more detail. In most cases of technical diagnostics, diagnoses (classes) are established in advance, and in this case the recognition problem is often called the classification problem [4].

The analysis of the state is carried out under operating conditions, in which obtaining information is extremely difficult. Thus, the information is limited, inaccurate or fuzzy. The theoretical foundation for solving the main task of technical diagnostics is the pattern recognition theory. Algorithms for recognition in technical diagnostics are partly based on diagnostic models that establish a connection between the states of a technical system and their mappings in the space of diagnostic signals. An important part of the problem of recognition is the rules of decision-making (decision rules).

The solution of the diagnostic task (referring the object to the perfect or imperfect one) is always associated with the risk of false alarm or defect missing. The false alarm is the case when a decision is made about the presence of a defect, but in reality, the system is in good order. The defect missing is making a decision about a perfect state, while the system contains a defect. To make an informed decision, it is advisable to involve new methods and use an integrated approach. This will reduce the error risk of decision-maker.

Another important area of technical diagnostics is the controllability theory. Controllability refers to the ability of the object to provide a reliable estimate of its technical condition and early detection of malfunctions and failures. A major task of the controllability theory is the study of tools and methods of obtaining diagnostic information.

Thus, technical diagnostics is characterized by two interpenetrating and interrelated directions: the recognition theory and the controllability theory. The recognition theory contains sections related to the construction of recognition algorithms, decision rules and diagnostic models. The controllability theory includes the development of tools and methods for obtaining diagnostic information, automated monitoring and troubleshooting. Technical diagnostics is traditionally considered as a section of the general reliability theory.

Technical diagnostics is sometimes called “without disassembling” diagnostics, i.e. diagnostics, carried out without disassembly of the object and termination of its operation. The task of technical diagnostics is to determine the degree of wear of the object by measurement of indirect parameters. As was mentioned earlier, one of the important features of technical diagnostics is recognition in the situation of limited information, when it is required to be guided by certain methods and rules to make an informed decision. A set of sequential actions in the recognition process is called the recognition algorithm. An essential part of this process is the process of choosing parameters which describe the state of the system.

Since technical diagnostics involves processing of large amounts of information, decision-making (recognition) is often carried out with the help of a computer.

The solution of technical diagnostics problems is always connected with reliability forecasting for the nearest period of operation (until the next technical inspection). The object TS forecast consists of evaluating its possible state at a certain point in time in the future, based on known information about changes in the past and the results of determining the actual state at the present time.

To solve the prediction problem, the time of object operation is divided into two intervals: T_1 - the interval of monitoring the state of the object (past and present) and T_2 - the interval at which forecasting is performed (in the future). The larger the interval T_1 is, the greater the amount of information about the nature of the process of changing the object state of is and the more reliable the forecast is. However, an increase in the observation interval leads to an increase in costs associated with experimental studies and diagnostic results processing. The forecast reliability also depends on the given time in T_2.

The TS change is determined by the nature of the change in the object properties in connection with the constantly occurring processes of internal degradation changes and physicochemical transformations under the environmental influence and operation mode. In this case, a continuous or discrete change in the characteristics characterizing these properties is observed, which leads to the displacement of the state vector of the object in the region of serviceable (perfect) states S_1 to its boundary along a certain trajectory. The task of forecasting in the general case is to predict the type of such trajectory. The nature of change in the properties, and, accordingly, the object state in time, can be described by the dependence:

$$F(Z,t) = A(Z,t) + X(Z,t), \tag{1}$$

where $A(Z, t)$, $X(Z, t)$ – deterministic and probabilistic (random) components of the process, respectively.

If the influence degree of the second component in the expression is negligible $X(Z,t) \rightarrow 0$, the process of object state changing is described as deterministic, otherwise $A(Z,t) \rightarrow 0$ it must be considered as random.

Thus, the recognition of the object TS in technical diagnostics (in particular, technical forecasting) is based on two principles - deterministic (analytical) and probabilistic.

2. Probabilistic method of systems technical state recognition

The problem of probabilistic prediction reduces to an estimate of the object reliability indices at given instants of time in the region T_2. In this case, the procedure for prediction and the reliability of the results obtained are largely determined by the amount of initial information about the reliability of the object and its elements.

With probabilistic prediction it is assumed that malfunctions and failures of elements and systems are random events, then probability theory and mathematical statistics are the main apparatus for investigating reliability. The reliability characteristics are chosen from the number of indicators accepted in probability theory.

The main advantage of statistical recognition methods is the ability to simultaneously take into account the signs of a different physical nature, since they are characterized by dimensionless quantities – the probabilities of their appearance at different states of the system. If the state of the object is changed randomly and, consequently, its diagnostic parameters are, the probabilistic forecast can be calculated only from the results of observations of a group of identical objects operating under the same or similar conditions. The calculation is based on the fact that the characteristics of the position of the random process are non-random functions of time.

Currently, many manufacturers offer operating time to failure as the main technical specification for the prediction of failures. However, this value has an idealized basis, since general statistics are used that do not take into account the specific conditions of operation of the facility. This accuracy in practice is simply not enough for a reliable prediction of equipment failures. As examples of such conditions it is possible to allocate installation, climatic conditions, vibration, noise, electromagnetic field guidance and other. Even from the place that this element will occupy in the common system, the amount of time between failures will depend.

Thus, if for a single case (operation in production 1) an element is influenced by a set of conditions A, then for another case (operation in production 2) the same element will be affected by the set of conditions B.

To increase the reliability of probabilistic prediction, it is necessary for a particular operating company to maintain a particular failure statistics throughout the life cycle of an element to calculate the risk degree – probability of failure. The risk degree should be understood as the expected frequency or likelihood of equipment failure. The application of risk degree concept, thus, allows to translate the danger into a discharge of measured values. The risk degree is actually a measure of danger [7].

Thus, we will receive the magnitude of the risk directly for a specific case, thereby maximally bringing it closer to the true value. The risk degree is a constant value, but for different production conditions it is different. It should be noted that the proposed approach is suitable for enterprises with a geographical extent and a large number of units of unified equipment.

Any transition from one state to another can be gradual with a relatively long duration in time and a sudden one with a relatively short duration in time (figure. 1).

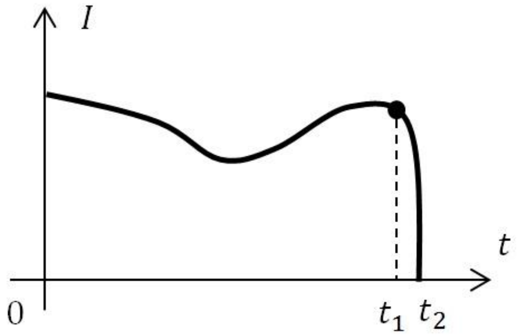


Figure 1. Graphic explanation.

Figure 1 shows the dynamic change in the object TS *I* in time *t*. In the interval from 0 to t_1, the TS changed gradually but in the interval from t_1 to t_2 the TS changed suddenly. The prediction of the moment t_1 has the greatest interest and complexity at the same time. A statistical-probabilistic method is used to determine this sudden moment. It should be noted that a sudden failure means that the reasons for this refusal are not established, that the process of changing the TS of this object has not been studied to the end. Either the set of diagnostic parameters is not determined in due measure, that is the model describing the object TS is incorrectly defined, otherwise there would be no surprise factor at all. In other words, the use of probability theory as a predicting method of objects TS (in particular, failures) should be the last resort.

On the basis of the foregoing, the objective of technical diagnostics can be depicted as the following function (objective function):

$$F(Z,t) \rightarrow A(Z,t), \tag{2}$$

or:

$$A(Z,t) \rightarrow 0, \tag{3}$$

In other words, all occasional failures (and consequently their causes) must be transferred into the category of deterministic ones. Then the failures nature will not be sudden.

Due to the idealized (theorized) nature of the classical reliability theory, the risk of an incorrect decision to classify an object as "perfect" or "imperfect" only on the basis of statistical-probability methods is high. Accordingly, it is necessary to consider the possibility of additional support for decision-making. This problem can be formulated as follows: the development of a method for processing and systematization of various types of diagnostic information (a deterministic approach to the recognition of TS).

3. Deterministic method of systems technical state recognition

When solving the problem of deterministic predicting in direct formulation, the sought-for characteristics are the values of the diagnostic parameters. Since the state recognition of system with a large number of diagnostic parameters is associated with significant difficulties associated with monitoring and systematization of various types of parameters, they are set to minimum for prediction from the condition of ensuring the required reliability of the prediction. In practice, usually one diagnostic parameter is used – critical or integrated. If there is a critical parameter, this greatly simplifies the diagnostic process. A situation is possible where the control of a critical parameter is rather difficult due to various reasons and it is more economical for an enterprise to admit a failure, but to be ready for it than to spend huge resources on diagnosing. The integrated diagnostic parameter requires the application of special mathematical methods of processing and systematization of heterogeneous data - various diagnostic parameters. We can definitely say that to increase the reliability of solutions it is necessary to apply a set of methods.

TS, being a complex property of the object without a definite formalization is difficult for the perception of the decision-maker. Thus, there is an urgent task of developing a mathematical model that systematizes various types of diagnostic data for making decisions in the technical diagnostics tasks.

The object TS can be characterized (estimated) by means of some finite set of parameter values:

$$\boldsymbol{C} = \{ p_1; p_2; p_3; ... p_n \}, \tag{4}$$

where $\boldsymbol{C}$ – TS of object;
p_n – technical parameter value;
n – number of parameters.

In figure 2 on one axis five TS are marked, defined by the standards [2, 3]. If we assume that the TS can be quantitatively expressed by the number I from 0 to 1, where 1 means a perfect TS, then using the numerical representation of the TS instead of discrete values: perfect, imperfect, up state, down state and limiting state, one can observe "Serviceability degree" of the object. This dimensionless quantitative evaluation of the TS is called the Technical State Index (TSI) [8, 9]. The value of TSI characterizes the object state from the point of view of its parameters' compliance with normative values. The parameter is the passport characteristic of the object.

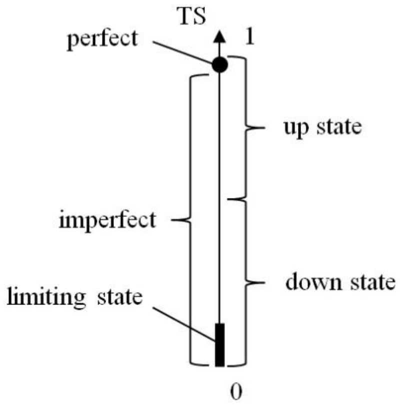


Figure 2. Graphic image of TS.

Thus, any object TS can be expressed using a finite set of TSI:

$$\boldsymbol{C} = \{ I_1; I_2; I_3; ...; I_n \}, \tag{5}$$

where $\boldsymbol{C}$ – TS of object,
I_n – TSI according to parameter n,
n – number of parameters.
Then TSI I_i reflects the degree of correspondence of the i-th parameter to the required (ideal, nominal) value.

It should be noted that in the classical reliability theory [4-6, 10] the system state at time t is described by a random vector:

$$\boldsymbol{X}(t)=\left(X_1(t),...,X_n(t)\right), \tag{6}$$

where $X_i(t)$ – vector components, which can be the values of various system parameters, capable of taking values on the entire real axis. $\boldsymbol{X(t)}$ can be a one-dimensional variable that always takes two values: 1 if the system is operable, and 0 if the system is in a failed state. A random vector $\boldsymbol{X(t)}$ is characterized by probability distribution:

$$\boldsymbol{F}=\left(x_1,...,x_n,t\right), \tag{7}$$

that is, the probability that

$$X_1(t)\le x_1,...,X_n(t)\le x_n. \tag{8}$$

The state of the system can be described in various ways. The fuzzy sets theory [11] will be used as a theoretical basis in this paper.

Assume that the TS is characterized by a single parameter x, then in the view of set theory we can write:

$$x\in\boldsymbol{E}, \tag{9}$$

where $\boldsymbol{E}$ – set of values (range) of this parameter.

If $\boldsymbol{E}$ is the set of all possible values of the parameter, then it necessarily contains some subset of the required (admissible) values of the parameter; denoting this subset as $\boldsymbol{A}$, we get:

$$A\subset\boldsymbol{E}, \tag{10}$$

If the element x of set $\boldsymbol{E}$ is the element of subset $\boldsymbol{A}$ (in other words, the value of the parameter x is in the required (admissible) range of values), then:

$$x\in\boldsymbol{A}. \tag{11}$$

To express this membership in set theory, use the notion – the characteristic function whose value indicates whether (yes or no) x is an element of $\boldsymbol{A}$:

$$\mu_A(x)=\begin{cases}1, & \text{if } x\in\boldsymbol{A},\\ 0, & \text{if } x\notin\boldsymbol{A}.\end{cases} \tag{12}$$

The peculiarity of this function is in the binary nature of its values (figure 3).

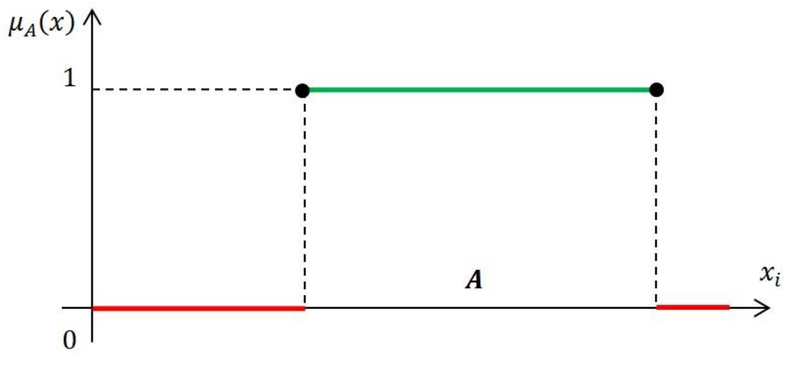


Figure 3. The characteristic function for the set $\boldsymbol{A}$.

In the production application, the characteristic function indicates whether the given technical parameter of an element satisfies the required values. That is, TSI is a dimensionless estimate. The characteristic function shows TSI dependence on specific values of the parameter. Figure 4 provides a graphic explanation of the above.

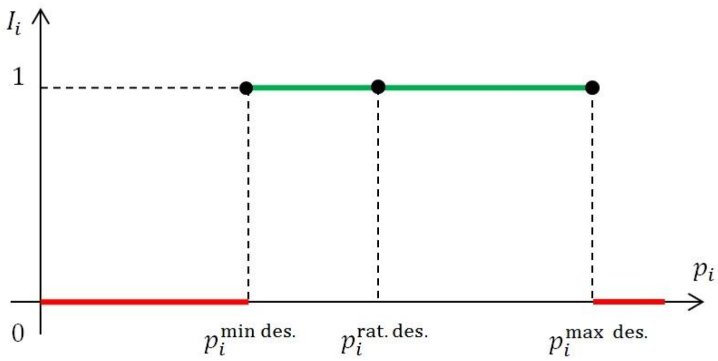


Figure 4. Graphic explanation of TSI.

Figure 4 uses the following notation: I_i – ITS of the i-th parameter, p_i – value of the i-th parameter, $p_i^{\text{min des.}}$, $p_i^{\text{rat. des.}}$, $p_i^{\text{max des.}}$ – minimum, rated and maximum desired (admissible) value accordingly.

However, in practice, the boundary between admissible and inadmissible values of the parameter may not have a clear character, which is why it is rational to consider the solution of the problem of evaluating the TS in the view of the fuzzy sets theory. Then the characteristic function can take any value in the interval [0; 1]. In accordance with this, the element x_i of the set $\boldsymbol{E}$ can belong to $\boldsymbol{A}$ to a certain degree $\mu_{\boldsymbol{A}}(x)$.

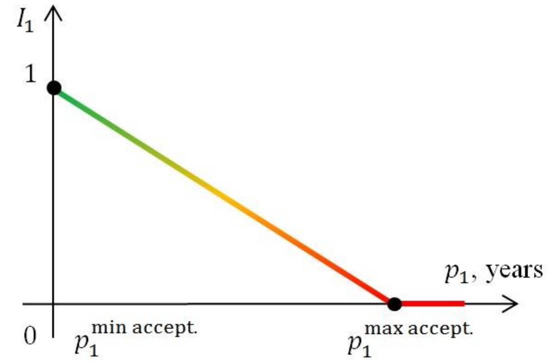
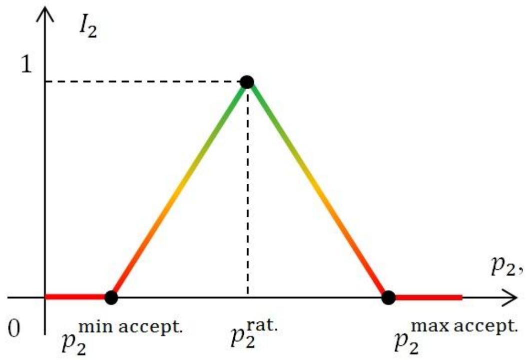
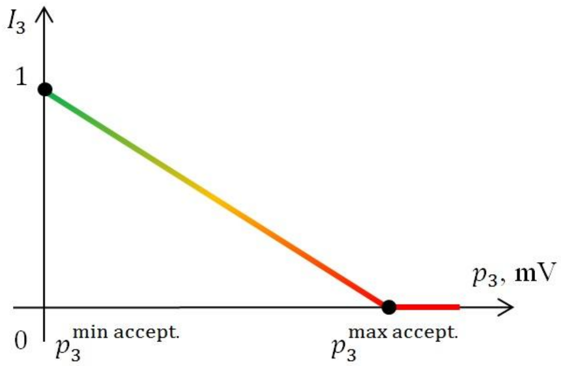
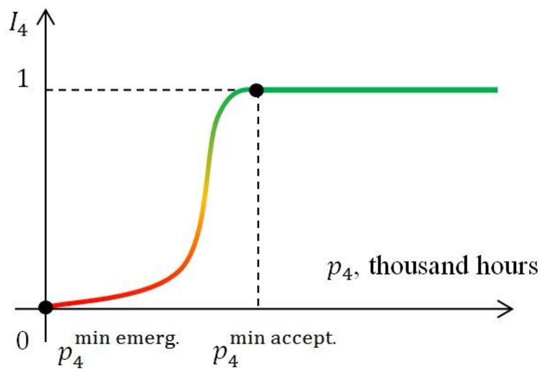
Thus, according to [11], with the help of the notion of fuzzy subset it is possible to study nonrigorous defined concepts (such as TS) using mathematical structures. Then the estimation of the object TS will take its values in the set $\boldsymbol{M}$ = [0; 1] by means of a certain characteristic membership function. And TSI is the current value of the characteristic membership function.

Since each parameter is unique (the set of all possible values, a subset of the required values, the dimension, etc.), then a different membership function is constructed for each parameter. The basis for constructing the membership function is the object manufacturer documentation. Let's consider examples of membership functions of belonging of physical parameters of a technical object – power unit (tables 1, 2).

Table 1. Diagnostic parameters of the power unit**.**

№	Diagnostic parameter	Current value	Minimum acceptable value	Maximum acceptable value
1	Operation life, years	6	0	10
2	Output voltage, V	23.5	23.0	24.0
3	Output voltage ripple, mV	400	0	1000
4	Average failure time, thousand hours	9.5	10	-

Table 2. Membership functions and TSIs of the power unit.

<table>
<tr><th>№</th><th>Membership function</th><th>Current TSI</th></tr>
<tr><td>1</td><td>
</td><td>I_1 = 0,40</td></tr>
<tr><td>2</td><td>
</td><td>I_2 = 1,00</td></tr>
<tr><td>3</td><td>
</td><td>I_3 = 0,60</td></tr>
<tr><td>4</td><td>
</td><td>$I_4 \approx$ 0,46</td></tr>
</table>

I_1 – TSI of power unit by parameter p_1 – «Operation life ». Minimum acceptable value of parameter $p_1^{\min accept.}=0$ years, maximum acceptable value of parameter $p_1^{\max accept.}=10$ years – this value is emergency, that is, the excess of the operation life declared by the manufacturer in the documentation for the object increases the risk of failure.

I_2 – TSI of power unit by parameter p_2 – «Output voltage». Minimum acceptable value of parameter $p_2^{\min accept.} = 23{,}0$ V, maximum acceptable value of parameter $p_2^{\max accept.} = 24{,}0$ V. In this case $p_2^{\min accept.}$ and $p_2^{\max accept.}$ are emergency. The rated (ideal) value in this case is equal to $p_2^{rat.} = 0{,}5 \cdot (p_2^{\min accept.} + p_2^{\max accept.})$.

I_3 – TSI of power unit by parameter p_3 – «Output voltage ripple». Minimum acceptable value of parameter $p_3^{\min accept.} = 0$ mV, maximum acceptable value of parameter $p_3^{\max accept.} = 1000$ mV.

I_4 – TSI of power unit by parameter p_4 – «Average failure time». Minimum acceptable value of parameter $p_4^{\min accept.} = 10$ thousand hours, minimum emergency value of parameter $p_4^{\min emerg.} = 0$ thousand hours. The normal Gauss distribution is chosen as the dependence $I_4(p_4)$, where the mean-square distance of the distribution is assumed to be σ = 0.4.

In this example, one of the parameters for evaluating TS is "Average failure time". This parameter refers to statistical parameters of the classical reliability theory. It should be noted that authors of the paper intentionally included it in a number of parameters for TS estimating to show the possibility of using different types of data in the TS estimating. However, this issue requires further research. There may be a situation where the object TSI will be close to 1, but the object life cycle at the stage of its operation shows that it often fails. Against this background, it is quite difficult to work out a decision regarding the attribution of the object to "serviceable" or "faulty". But, nevertheless, it can be stated that, either a lot of parameters, by which the object is diagnosed, are not sufficient to determine the exact diagnosis, or the object does not have the property of controllability. In this situation, many parameters (deterministic component) should be reviewed, or the deterministic component in (1) should be neglected in order to optimize the diagnostic process. In any case, the fact of a large frequency of object failures when finding all diagnosed parameters in the acceptable zone should be taken into account when evaluating its TS.

Thus, the TS of object A in terms of the fuzzy sets theory can be described (formalized) as follows [12]:

$$\tilde{A} = \begin{array}{|c|c|c|c|} \hline x_1 & x_2 & \dots & x_n \\ \hline \mu_{\tilde{A}_1}(x_1) & \mu_{\tilde{A}_2}(x_2) & \dots & \mu_{\tilde{A}_n}(x_n) \\ \hline \end{array}, \tag{13}$$

where x_i – parameters for evaluating of TS of object A;
n – number of parameters;
$\mu_{\tilde{A}_i}(x_i)$ – membership function (each parameter has the required values subset $\tilde{A}_i$, and accordingly, has its own membership function).

This structure forms the fuzzy reliability model of technical object.

If all current values of the parameters are aligned in the proposed model, the set $\tilde{A}$ will characterize the current TS of the object:

$$\tilde{A}^{curr.} = \begin{array}{|c|c|c|c|} \hline x_1 & x_2 & \dots & x_n \\ \hline \mu_{\tilde{A}_1}(x_{1\,\text{curr.}}) & \mu_{\tilde{A}_2}(x_{2\,\text{curr.}}) & \dots & \mu_{\tilde{A}_n}(x_{n\,\text{curr.}}) \\ \hline \end{array}, \tag{14}$$

where $x_{i\,\text{curr.}}$ – current values of object parameters.
If the object TS is ideal (rated) for all parameters, then its state can be described as follows:

$$\tilde{A} = \begin{array}{|c|c|c|c|} \hline x_1 & x_2 & \dots & x_n \\ \hline 1 & 1 & \dots & 1 \\ \hline \end{array} = \bar{A}^{rat.}. \tag{15}$$

That is, the ideal state of the object can be described in the form of a crisp set, the elements of which are *n* ones.

To determine the integrated TS, we use two estimates – the relative linear distance (Hamming distance) and the relative quadratic distance (Euclidean distance) between set $\tilde{A}^{curr.}$ and set $\bar{A}^{rat.}$. As is known, these two concepts give two estimates of the distance between fuzzy sets.

The relative linear distance between the above sets is determined by the formula:

$$\delta(\tilde{A}^{curr.}, \bar{A}^{rat.}) = n^{-1} \cdot \sum_{i=1}^{n} \left| \mu_{\bar{A}^{rat.}}(x_i) - \mu_{\tilde{A}^{curr.}}(x_i) \right| = n^{-1} \cdot \sum_{i=1}^{n} \left(1 - \mu_{\tilde{A}^{curr.}}(x_i)\right). \quad (16)$$

Formula (16) can be transformed:

$$\delta(\tilde{A}^{curr.}, \bar{A}^{rat.}) = 1 - n^{-1} \cdot \sum_{i=1}^{n} \mu_{\tilde{A}^{curr.}}(x_i) = 1 - \mu_{\tilde{A}^{curr.}}^{arithm.av.}(x_i), \quad (17)$$

where $\mu_{\tilde{A}^{curr.}}^{arithm.av.}(x_i)$ – arithmetic average of all values $\mu_{\tilde{A}^{curr.}}(x_i)$.

The relative quadratic distance between the above sets is determined by the formula:

$$\varepsilon(\tilde{A}^{curr.}, \bar{A}^{rat.}) = \left(n^{-1} \sum_{i=1}^{n} \left(\mu_{\bar{A}^{rat.}}(x_i) - \mu_{\tilde{A}^{curr.}}(x_i) \right)^2 \right)^{1/2} = \left(n^{-1} \cdot \sum_{i=1}^{n} \left(1 - \mu_{\tilde{A}^{curr.}}(x_i)\right)^2 \right)^{1/2} \quad (18)$$

Both relative distances satisfy the conditions:

$$0 \le \delta(\tilde{A}^{curr.}, \bar{A}^{rat.}) \le 1, \quad (19)$$

$$0 \le \varepsilon(\tilde{A}^{curr.}, \bar{A}^{rat.}) \le 1. \quad (20)$$

Thus, using relative distances $\delta(\tilde{A}^{curr.}, \bar{A}^{rat.})$ and $\varepsilon(\tilde{A}^{curr.}, \bar{A}^{rat.})$, we can not only assess the integrated state of the object, but also compare objects with each other (ranking).

Here is an example of calculating the integrated TSI of power unit, discussed above. The current TS of the power unit is described using the reliability fuzzy model:

$$\boldsymbol{C} = \{0,40; 1,00; 0,60; 0,46\}. \quad (21)$$

The reliability model for a given power unit with ideal TS:

$$\boldsymbol{C} = \{1,00; 1,00; 1,00; 1,00\}. \quad (22)$$

Then integrated TSI of the power unit is I = 0,62.

The presented model of object TS description (estimation) allows to solve a problem of "incomparability" of objects among themselves. Even under the condition of different number of parameters, according to which the TS of objects is evaluated, the possibility of comparing (ranking) objects is opened up with the help of reliability fuzzy model. The ranking of objects occurs on a unifying basis – the TS.

To construct the reliability model of a complex system (figure 5), a structurally-parametric method for analyzing hierarchies – hierarchical decomposition is used [13].

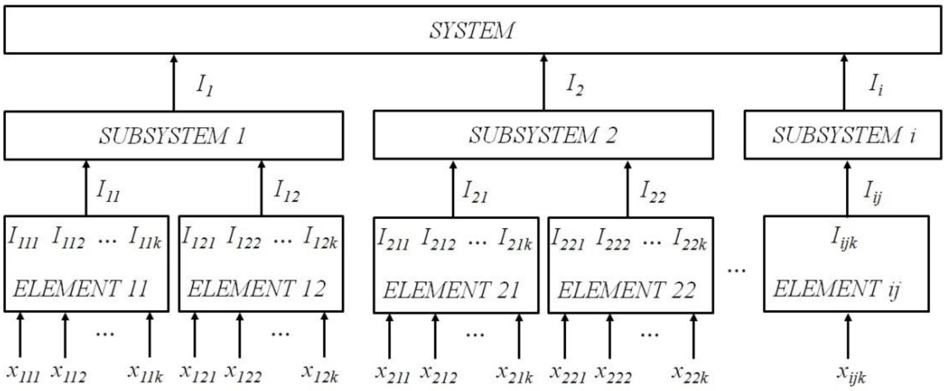


Figure 5. Fuzzy reliability model of system.

The following notations are used in figure 5: I_i –TSI of the *i*-th subsystem, I_{ij} – TSI of the *j*-th element of the *i*-th subsystem, I_{ilk} – TSI by the *k*-th parameter of the *j*-th element of the *i*-th subsystem, x_{ijk} – the *k*-th parameter of the *j*-th element of the *i*-th subsystem.

Thus, in order to carry out an evaluation of the TS of a complex system consisting of set of elements, it is necessary to estimate the TS of each element of the system separately by the parameters established for each element, then calculate the integrated TSI of hierarchical structures of the system.

It is modified in accordance with the evaluation of the manifestation of additivity and integrity properties in the proposed model, (figure 6).

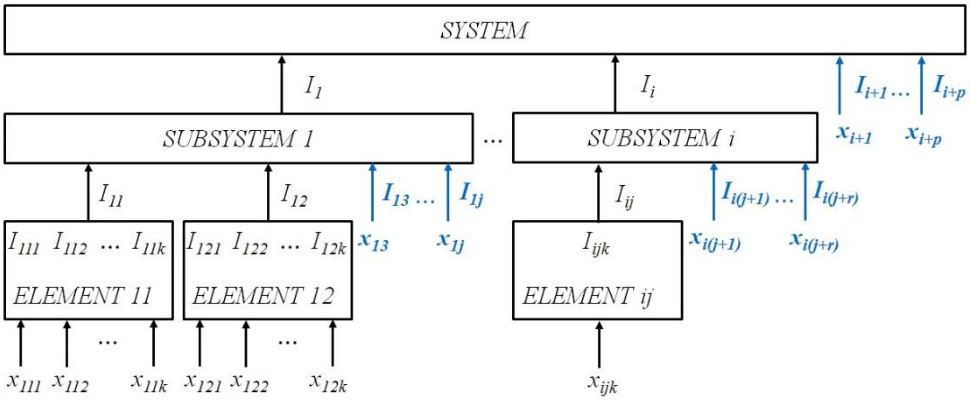


Figure 6. Modified fuzzy reliability model of system.

In figure 6 the system parameters and places that they occupy in the general hierarchical structure are highlighted in color. The presented model makes it possible to take into account both the parameters of the elements and the system parameters, which allows to balance the additivity and integrity in the integrated TS system evaluation (including industrial equipment).

The fuzzy reliability model is a model of system analysis for technical diagnostics tasks to the full extent. Various information management systems (MIS) and decision support systems (DSS) can be developed on its basis.

MIS and DSS, built on the basis of a reliability fuzzy model, can provide a decision-maker with organized information on the equipment condition. As a result, it will allow to perform coordinated work, to make grounded administrative decisions and to increase management process efficiency on the whole.

4. Summary and conclusion

TSI is an integrated indicator of system reliability, which systematizes heterogeneous diagnostic parameters. TSI, like probabilistic characteristics, is a dimensionless value with a range of values from 0 to 1, which introduces an additional advantage when used together.

It is possible to increase accuracy in engineering diagnostics tasks only by means of the combined use of any and all methods. The TS should be evaluated on the basis of both a deterministic approach and a probabilistic approach (table 3) in order to reduce the risk of equipment failures.

Table 3. Comparative features of deterministic and probabilistic principles of systems technical state recognition.

	Deterministic component	**Probabilistic component**
Failure causes	determined	does not matter
Failure frequency	relatively high	relatively low
Predicted (evaluated) result	immediate values of diagnostic parameters, TSI	probabilistic assessments
Obtaining information methods	diagnosis	statistical-probabilistic
Mathematical apparatus	fuzzy sets theory	probability theory
Theoretical basis	reliability theory	

Thus, the fuzzy reliability model and the classical reliability model (statistical-probabilistic method of TS recognition) are complementary. Their integrated application increases the accuracy of the decisions made, as well as the reliability of the systems.

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