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METHODS AND MODELS OF SELF-TRAINED AUTOMATED SYSTEMS DETECTING THE STATE OF HIGH-SPEED RAILWAY TRANSPORT NODES

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ABSTRACT

The article contains the results of researches aimed at the further development of methods and models for self-trained automated detection systems (SADS) of nodes and aggregates of high-speed railway transport (HSRT) based on the clustering of failure signs. There has been developed SADS model of nodes and aggregates of HSRT and a method for its training, in which the procedure of fuzzy clustering of failure signs realization is applied. The procedure for decision rules correction is also considered, that will allow the creation of adaptive self-trained mechanisms for automated systems for detecting HSRT nodes and aggregates. It is proposed to use the modified information condition of functional effectiveness (ICFE) as an evaluation indicator of the training effectiveness of SADS. This condition is based on Kullback-Leibler information-distance criteria. There is considered the method of space fragmentation of failure signs realization of the HSRT nodes and aggregates into clusters during the implementation of the failure recognition procedure. Also there is considered the method of initial training of SADS. The method is an iterative procedure for finding the global maximum of ICFE.

There were substantiated perspectives of decisions on the integrated evaluation of the detection results of the nodes and aggregates of the HSRT rolling stock based on the use in similar automated complexes for detecting models with fuzzy clustering algorithms of hundreds of the HSRT failure signs systems.

***Keywords**: Non-Destructive Control Methods, Railway Rolling Stock, Feature Clustering, Kullback-Leibler Criterion*

1. INTRODUCTION

Reliability, safety and durability in the operation of key nodes and aggregates of railway rolling stock and, in particular, high-speed railway transport (HSRT) is largely associated with continuous control of the working properties state of individual nodes and aggregates. With the development of digital technologies on transport, the methods of control or detection the state of rolling stock nodes and aggregates without equipment dismantling or taking it out of work are becoming more widespread. These technologies are called non-destructive control [1, 2].

As was shown by a number of authors [2–5] a maintenance of rolling stock nodes and aggregates of railway transport based on indicators of the actual state of the equipment, which can be obtained by non-destructive control (NDC), requires precise and reliable results of the measurements analysis and the application of intellectualized automated technologies for the various data processing from control means and measurement tools [3-5].

With the development of computerized methods of machine learning the methods and models associated with the analysis of large data amounts (data mining), there is arisen the task of adaptation and development of these methods and models for solving the tasks of NDC of nodes and aggregates of various technical systems. On the one hand, this is caused by the occurrence of universal mathematical methods, models, and algorithms, for example, such as convolutional neural networks or cluster analysis methods [6, 7]. On the other hand, in the already formed industry and business there is a tendency to maximize income from the use of various applied automated information technologies, in particular, in tasks related to the

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diagnostics of the state of nodes and aggregates of railway transport [7, 8]. It should be noted that this tendency was formed both by miniaturization and reduction the cost of computerized systems and data storage and processing devices, and by introducing new digital technologies into technical tools for diagnostics and detection the state of technically complex systems and nodes, for example, in railway transport [9].

The above mentioned reasons make the topic of our research relevant.

2. LITERATURE REVIEW AND ANALYSIS

As it was shown in [3 - 5] with the development of digital technologies the methods of technical non-destructive control and technical diagnostics of nodes and aggregates of the railway transport (including HSRT) have become very popular in the maintenance of high-tech equipment on transport. In recent years, there have been developed relevant regulatory documents, in particular, standards for the implementation of such control, and have been written numerous articles on this issue. However, with the development of digital technology, these researches need to be developed.

In works [3–5] there was carried out a review and analysis of most of the technical aspects of railway transport systems diagnostics, including using such methods as vibration, heat and acoustic non-destructive control (NDC). In works [5, 6] there was emphasized that NDC becomes an integral part of the technical maintenance of the railway transport RS. As with traditional approaches to the organization of technical diagnostics (TechD), the use of non-destructive control and diagnostics are aimed at ensuring the safety, functional reliability and efficiency of operation of the RS as a whole, as well as of individual nodes and aggregates. In addition, the use of RS NDC and TehD systems of the railway transport, and, in particular, HSRT, contributes to reducing the cost of its maintenance. As a result, losses are reduced as a result of failures or withdrawal of the railway transport RS. However, as the authors themselves [5] note, these researches are still ongoing.

Many researches [6, 8] in the segment of improving the reliability and dependability of HSRT systems are aimed at the creation and implementation of mobile diagnostics complexes for evaluation the state of both the HSRT rolling stock and technical infrastructure facilities. As shown in [7, 9], the priority directions of researches remain the tasks of creating: systems for control and evaluation the geometrical parameters of railway for HSRT; non-contact visual detection of defects of railway for HSRT; non-contact visual detection of defects in HSRT rolling stock and others. For the technical implementation of NDC means many methods are currently used [3, 5, 8, 10], for example, vibration, acoustic and heat of NDC nodes and aggregates.

All these methods give to the side conducting the diagnostics and detection of nodes and aggregates large amounts of very different information, which often may not be the same or may be stored in different formats. And in this situation, it seems promising to use self-trained systems of automated or automatic diagnostics of nodes and aggregates based on machine learning.

Even a preliminary review of researches in the field of automation of non-contact detection of the state of HSRT systems showed that there is an actual scientific problem in the development of mathematical methods and models for automation tools of non-contact detection of the HSRT systems state [4-7]. In particular, a promising seems a solution based on the use in similar automated complexes for detecting models with fuzzy clustering algorithms of hundreds of the HSRT failure signs systems. Therefore, the task of selecting an evaluation indicator of the SADS learning effectiveness seems relevant.

3. PURPOSE OF THE ARTICLE

The article solves the following problems:

1. To justify the need for the use of intelligent technologies in the tasks of non-destructive control and technical diagnostics of nodes and aggregates of railway transport rolling stock. Consider the possibilities of machine learning for the detection the HSRT state based on the clustering of failure signs realizations that can be detected by various non-destructive means of detection and diagnosis.

2. To develop a method for training the system for detecting HSRT nodes and aggregates using the procedure for fuzzy clustering of failure signs realizations and the possibility of decision rules correction, which will allow the creation of adaptive self-trained mechanisms for the diagnostics and detection of HSRT nodes and aggregates.

4. MODELS AND METHODS

For diagnostics (detection) of anomalies in operation or malfunctions of railway transport nodes and aggregates there are used modern digital systems of non-destructive control (NDC), see fig.

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1. However, the data of these systems are rather scattered. For their ordering, it is possible to apply cluster analysis methods, in particular, for training the system for detecting HSRT nodes and aggregates using the fuzzy clustering procedure of failure signs realizations and the possibility of decision rules correction. This will allow the creation of adaptive mechanisms of self-trained systems for diagnostics and detection of nodes and aggregates, for example, for HSRT.

a) small-sized devices for non-destructive vibration control and diagnostics of nodes and aggregates

b) Scheme of box node scanning by the infrared radiation receiver

Figure 1: Remote non-destructive control systems used on the railway transport

Strict regulation of the technical maintenance and repair processes of the rolling stock (in the first place, diesel locomotives and electric locomotives) leads to the need to use methods of non- contact diagnostics and detection of many nodes and aggregates. This reduces the time to perform such work. For example, in the depot, diagnosing nodes of diesel locomotives and electric locomotives there are actively applied methods of thermal (or thermal imaging) control.

For these purposes there are used hand thermal imagers (for example, with uncooled matrix), which have high sensitivity. The result of thermal control will be thermograms. With the recognition of failures according to the results of ash non-contact diagnostics, you can get quite reliable information.

For example, the Figure shows the results of weak contact and overheating detection (Fig. 2) of one of the knife switch, of electrical locomotive nodes.

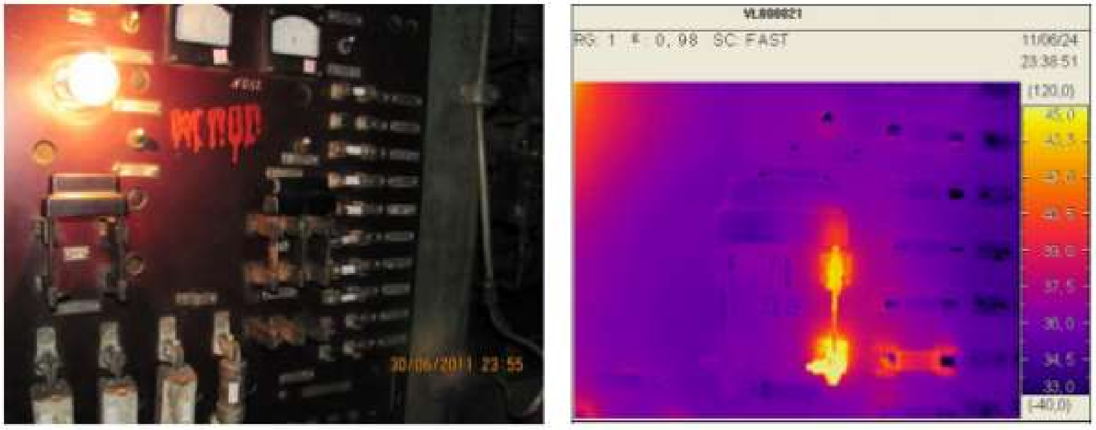
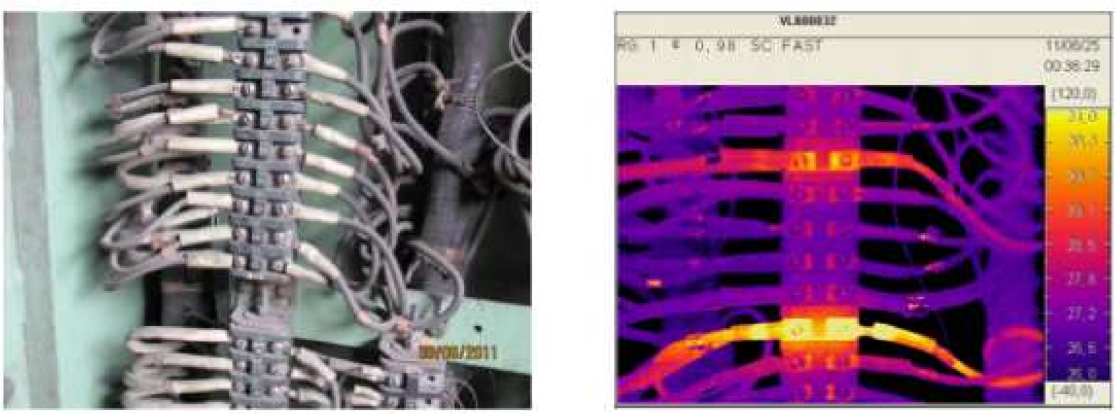


Figure 2. Weak contact and overheating of the knife switch and the corresponding thermogram

During the automated failure analysis, the thermogram displays a so-called thermal wedge or a table of correspondence of brightness (or color) to a specific temperature on the surface of the diagnosed object. The fig. 3, for comparison, shows thermograms of bolted nodes connections of the locomotive crew parts for different tightening. During the analysis, there was found that at weakening of the tightening there are occurred vibrations. This, in turn, leads to a sharp increase of the connection temperature. a) normal bolt connection tightening b) weak bolt connection tightening. The Figure. 3. Thermograms of contact connection of VL80s electric locomotive tires.

We should note that the accuracy of the obtained data depends on the parameters of the object under research and on the conditions of its operation. We believe that the analysis of thermograms as well as in the previous examples can be carried out not only with the help of thermal imaging tools, but also on a computer using the developed automated analysis tools by failure and anomalies parameter in the operation of nodes and aggregates of locomotives.



a) b)

Figure. 3. Overheating of individual contacts due to the increased load current

The creation of a model of data mining during the process of identifying anomalies or failures in the operation of rolling stock is a part of a large-scale data processing process. The complexity of the implementation of the existing models of the systems for diagnostics and detection anomalies and failures of the rolling stock of a formalized recognition theory apparatus lies in the fact that a specific information complex for diagnostics often includes unique software and the corresponding information arrays. On the basis on preliminary conclusions obtained during the process of literature analysis, within the framework of the

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research there is considered an automated system based on the multi-stage detection of anomalies and failures of the rolling stock, see figure. 4.

Let consider the process of a priori fuzzy classified learning matrix formation in order to build decision rules in the process of initial SADS training. Let suppose that the a priori classified multidimensional learning matrix for SADS is known:

$$\left\| z_i^{(j)} \right\|, i = \overline{1, N},\ j = \overline{1, n} \qquad (1)$$

where N, n – accordingly, the amount of anomalies detection signs (recognition in SADS) in operation or malfunctions of nodes and aggregates of railway transport.

Problem statement:

1) in the cluster analysis mode it is necessary to convert the input matrix of signs, which is used in the process of initial SADS training, into a classified one;

2) in the training mode it is necessary to build a clear division of the space of realizations of signs of anomalies or failures recognition of nodes and aggregates into classes $\left\{ R_c^0 \middle| c = \overline{1, C} \right\}$ that respectively characterize the functional states of the controlled process of automatic detection of anomalies or failures by optimizing the coordinates of the vector of SADS functioning parameters:

$$h = \left\langle C, s, \delta, r_{c1}, r_{c2}, O_b, a_c \right\rangle, \qquad (2)$$

where C – the amount of clusters or the alphabet capacity for anomalies or malfunctions recognition (detection) in the operation of nodes or aggregates of railway

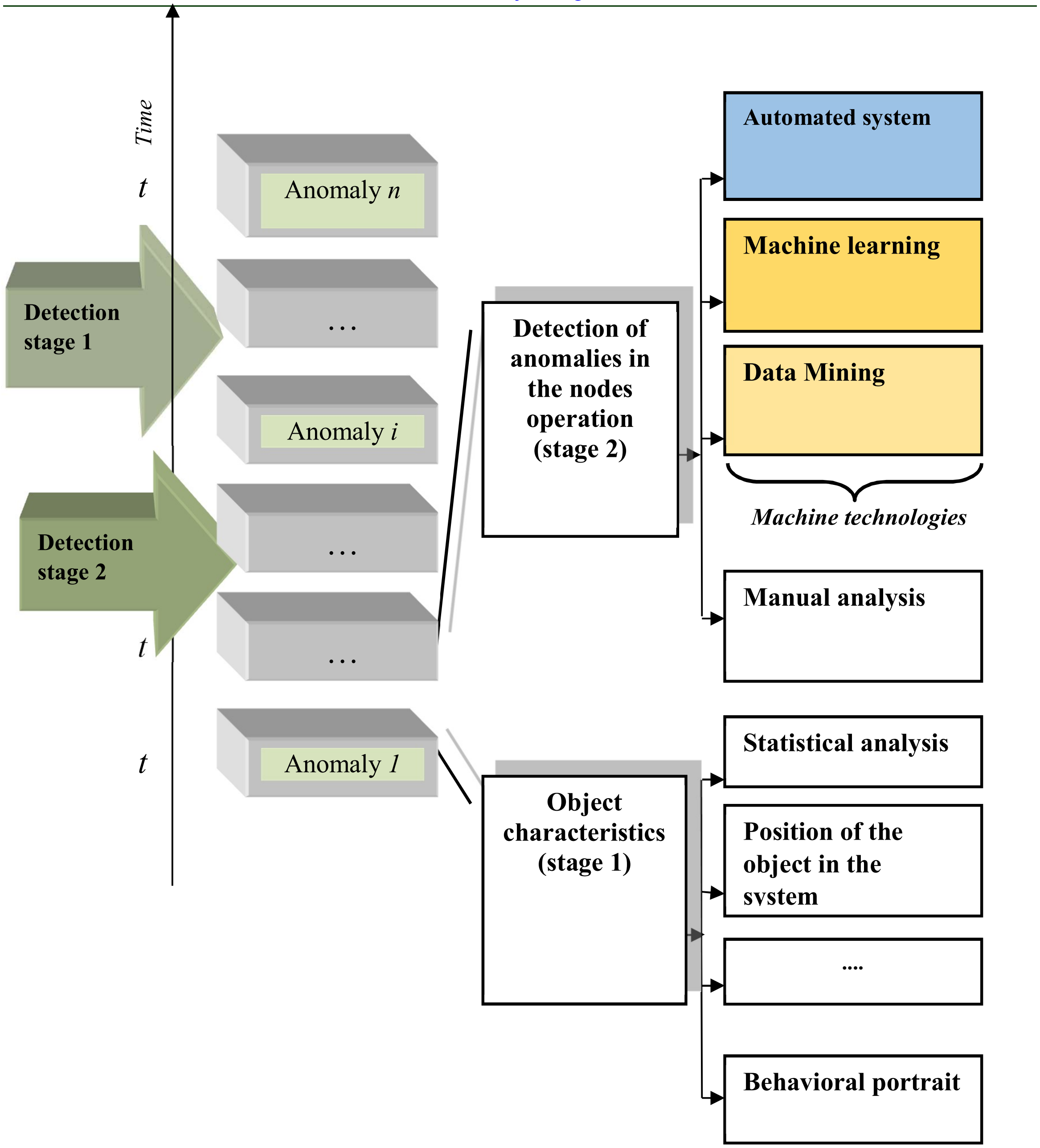

Figure. 4. The scheme of multi-stage detection of anomalies and failures in the operation of nodes and aggregates of the rolling stock

transport; s - a parameter that determines the signs of fuzziness of the algorithm [11–14]; δ - tolerance fields on the detection signs realizations of anomalies or failures; r_{c1}, r_{c2} - binary vectors that determine the coordinates of the first and second focuses of containers for a class of anomalies or failures in the binary signs space; O_b; a_c - the semi-axis of the container class in the space of O_b signs realizations.

Let introduce such restrictions:

$$\begin{cases} 2 \le C \le n / n_{\min}; n_c \ge n_{\min}; s > 1; \\ a_c > d_c; d_c \le N/2; \\ a(r_{d1} \oplus r) + a(r_{d2} \oplus r) - d_d > 0, \\ \forall r \in \{r : a(r_{c1} \oplus r) + a(r_{c2} \oplus r) = 2a_c\}; \\ \delta \in [0, \delta_n / 2], \end{cases} \quad (3)$$

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where $n_{\min}$ − the minimum sample size used to train the system for diagnostics and detection failures for each class of anomalies or failures (the sample must be representative); n_c - the amount of signs realizations within

the class R_c^0; d_c - distance to the center of the container within the boundaries of the class R_C^0; $a(r_{d1} \oplus r)$, $a(r_{d2} \oplus r)$ - respectively, code distances from the first and second container focuses of the next class of anomalies or failures R_c^0; r - vector-realization of the binary space, describing signs of anomalies or failures of nodes and aggregates O_b; d_d - the distance to the center of the container within the class R_c^0 in the space of signs realizations O_b; $a(r_{c1} \oplus r)$, $a(r_{c2} \oplus r)$ - respectively, code distances from the first and second container classes R_c^0; δ_n - normalized tolerance field for the anomalies or failure signs.

During the process of SADS training there are determined the coordinates of the term parameters vector (2) under the constraints (3). This, in turn, allows to ensure the maximum value of the informational condition of functional effectiveness (ICFE) averaged in alphabetical order for recognizing anomalies or failures in the operation of nodes and aggregates, respectively:

$$\overline{E}^* = (1/C) \cdot \sum_{c=1}^{C} \max_{\{w\}} E_c \,, \qquad (4)$$

where E_c – value of ICFE for SADS of anomalies and failures of railway transport for class realizations – R_c^0; $\{w\}$ – many steps for SADS training.

In the SADS test mode, there is decided whether the realization signs of standard images, which characterize the current functional state of a node or aggregate, belong to the corresponding class. That is, at this stage there is performed a defuzzification of the fuzzy data according to the signs realizations - $\{R_c^0 \mid c = \overline{1,C}\}$.

Initialization of non-clustered input data on the anomalies signs in operation or failures of nodes and aggregates of railway transport, including HSRT, is defined as a (vector) matrix:

$$\{z_i^{(j)}, \mid i = \overline{1,N},\ j = \overline{1,n}\} \qquad (5)$$

At the next stage of the algorithm there are generated matrices for observations fragmentation about anomalies signs in operation or failures of nodes and aggregates:

$$V = \begin{bmatrix} v_{11}\ v_{12} \ldots v_{1n} \\ v_{21}\ v_{22} \ldots v_{2n} \\ \ldots \\ v_{C1}\ v_{C2} \ldots v_{Cn} \end{bmatrix} \qquad (6)$$

under condition

$$v_{cj} \in \{0,1\}; \sum_{c=1}^{C} v_{cj} = 1; 0 < \sum_{j=1}^{n} v_{cj} < n,$$

where v_{cj} – degree of belonging of j observation object to the cluster – c.

The centers of clusters of anomalies and failures signs are calculated using the following formula (this condition is based on the Kullback-Leibler information-distance criterion):

$$z_c = \sum_{j=1}^{n} (v_{cj}^{(l-1)})^s \cdot z^{(j)} \Big/ \sum_{j=1}^{n} (v_{cj}^{(l-1)})^s \,, \qquad (7)$$

where l – iteration amount count.

As a result of the algorithm operation there is minimized the following objective function:

$$J = \sum_{c=1}^{C} \sum_{j=1}^{n} v_{cj}^s \cdot a_{K^{(c)}}^2 (z^{(j)}, z_c), \qquad (8)$$

where

$$K^{(c)} = \frac{\sum_{j=1}^{n} (v_{cj}^{(l-1)})^s \cdot (z^{(j)} - z_c)^T \cdot (z^{(j)} - z_c)}{\sum_{j=1}^{n} (v_{cj}^{(l-1)})^s}$$

– covariance for the cluster – c; T – set of moments of time withdrawing information about the NDC means.

If necessary, the elements of the fuzzy fragmentation of the dictionary of anomalies and failures signs, used for SADS training, are recalculated. The calculation is performed using the following formula:

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$$v_{cj}^{(l)} = 1 \Bigg/ \left[\sum_{w=1}^{C} \left(\frac{a_{K^{(c)}}^{2}(z^{(j)}, z_c)}{a_{K^{(c)}}^{2}(z^{(j)}, z_w)} \right)^{\frac{1}{w-1}} \right]. \quad (6)$$

Then the normalized entropy value of the index of the informational component of the self-trained automated system for detection anomalies and failures of nodes and aggregates of the locomotives, based on the failure signs clustering, can be represented as follows:

$$\begin{aligned} CE_m^{(ls)} = 1 + 0{,}5 \cdot \Bigg(& \frac{mis1_m^{(ls)}(cr)}{mis1_m^{(ls)}(cr) + AU_{2,m}^{(ls)}(cr)} \log_2 \frac{mis1_m^{(ls)}(cr)}{mis1_m^{(ls)}(cr) + AU_{2,m}^{(ls)}(cr)} + \\ & + \frac{mis2_m^{(ls)}(cr)}{AU_{1,m}^{(ls)}(cr) + mis2_m^{(ls)}(cr)} \log_2 \frac{mis2_m^{(ls)}(cr)}{AU_{1,m}^{(ls)}(cr) + mis2_m^{(ls)}(cr)} + \\ & + \frac{AU_{1,m}(cr)}{AU_{1,m}^{(ls)}(cr) + mis2_m^{(ls)}(cr)} \log_2 \frac{AU_{1,m}(cr)}{AU_{1,m}^{(ls)}(cr) + mis2_m^{(ls)}(cr)} + \\ & + \frac{AU_{2,m}^{(ls)}(cr)}{mis1_m^{(ls)}(cr) + AU_{2,m}^{(ls)}(cr)} \log_2 \frac{AU_{2,m}^{(ls)}(cr)}{mis1_m^{(ls)}(cr) + AU_{2,m}^{(ls)}(cr)} \Bigg), \end{aligned} \quad (7)$$

where $AU_{1,m}^{(ls)}(cr)$ – first validation procedure; $AU_{2,m}^{(ls)}(cr)$ – second validation procedure; $mis1_m^{(ls)}(cr)$ – errors of the first type confirming a failure decision for ls learning step for the system of detection failures of nodes and aggregates; $mis2_m^{(ls)}(cr)$ – errors of the second type; cr – radius of the containers of the detection system learning classes [13, 14, 19].

Verification of the model effectiveness was carried out in the MATLAB simulation environment.

5. EXPERIMENT

A preliminary model check was carried out for two classes of common failures in railway transport systems, including HSRT - "gearbox failures", "failures in the brake system." The corresponding tables 1 and 2 with failure signs of simulated systems are shown below.

Table 1 – Fragment of the table of the dictionary of anomalies and failures signs of the gearbox for means of non-destructive control and for use of vibration signal tracking methods

№	Type of failure / anomaly in operation	Sign for SADS dictionary
1	Vibrations	Vibration time signal on the gear pairs
2	Cracks	Temporary vibration signal form
3	Tines chipping	Vibration Spectra
4	Others	Vibration signal envelope spectrum, modal analysis

Table 2 – Fragment of the table of the dictionary of anomalies and failures signs in the brake system of a diesel locomotive for non-destructive control means

№	Type of failure / anomaly in operation	Sign for SADS dictionary
1	Extraneous noise in the compressor	Extraneous noise in the compressor
2	Excessive / insufficient line pressure	Excessive / insufficient line pressure
3	The swap process stops quickly	Temporary vibration signal form
4	Others	Vibration signal envelope spectrum, modal analysis, acoustic analysis

The diagrams in MATLAB for simulation are shown in Figures 5 and 6.

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After the formation of binary matrices that are used as objects in the process of learning of the automated system for diagnostics (detection) anomalies and failures in the operation of nodes and aggregates of the rolling stock, there are created binary trees of anomalies or failures signs clustering, see fig. 7, 8.

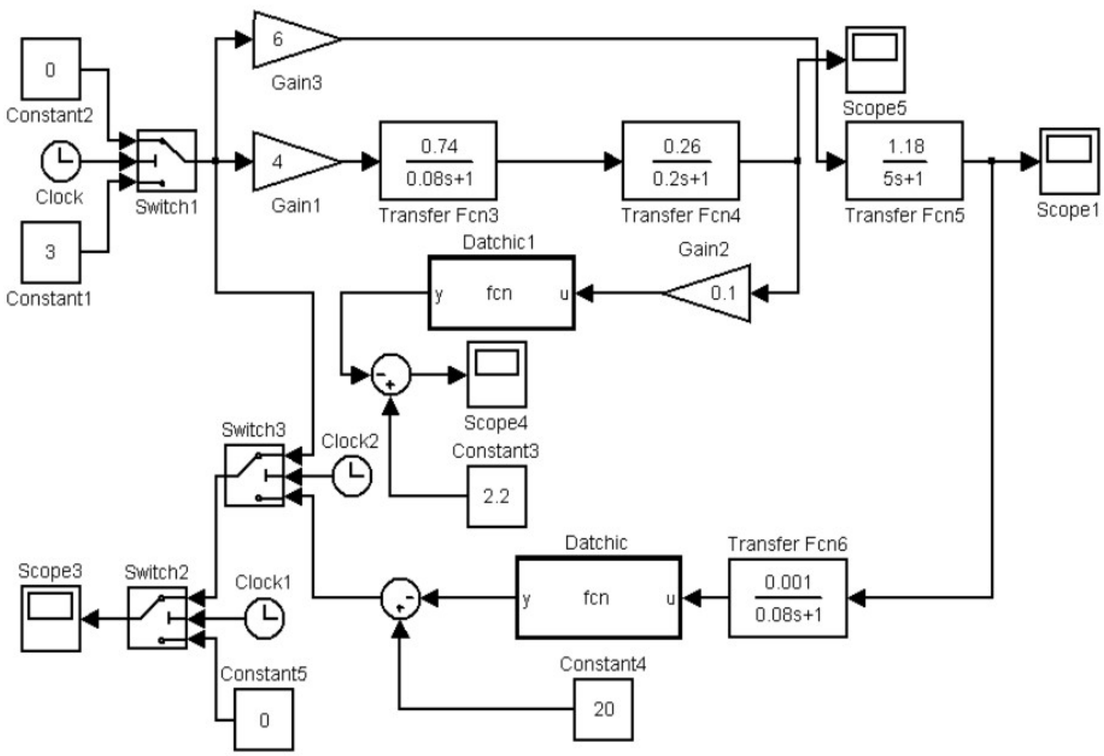

Figure 5: A simulation model for studying the effectiveness of the dictionary of anomalies and failures signs of the gearbox using the NDC methods and with the application of SADS

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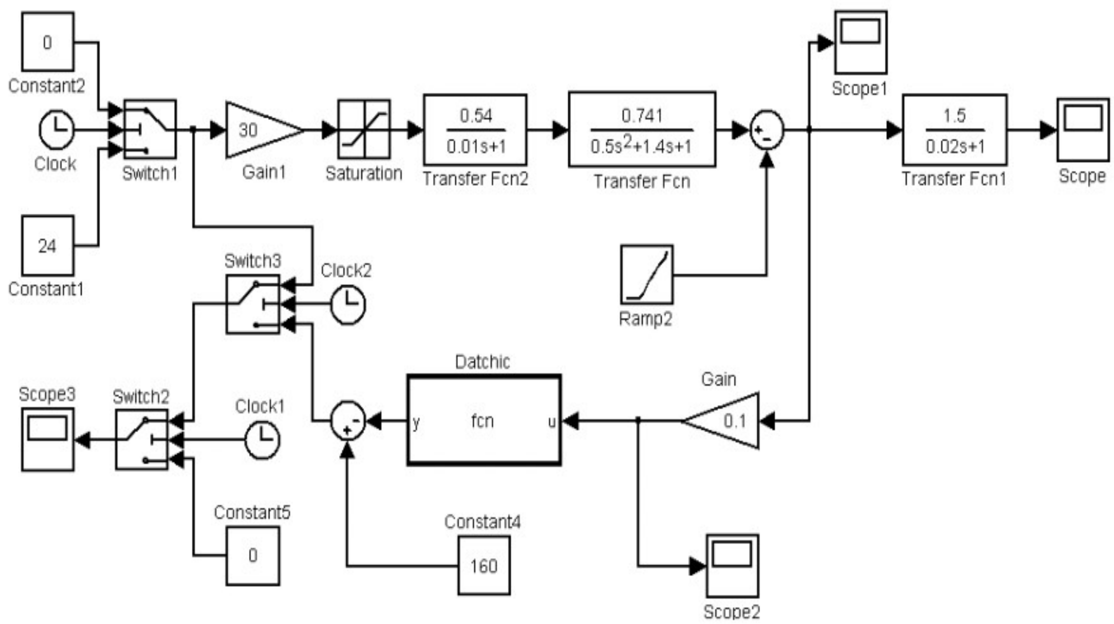

Figure 6: A simulation model for studying the effectiveness of the dictionary of anomalies and failures signs of the brake system using the NDC methods and with the application of SADS

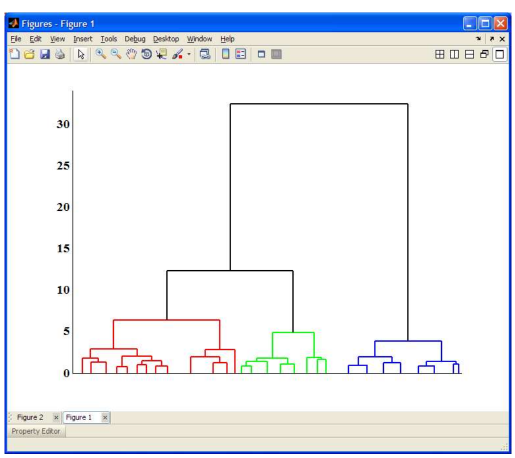

Figure 7. Normal behavior of the detected nodes and aggregates of the railway transport rolling stock

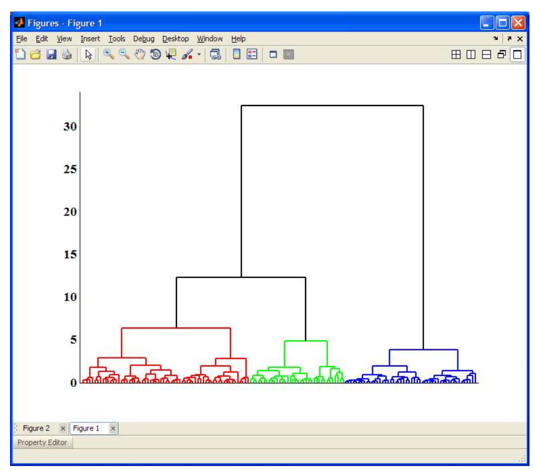

Figure 8. Anomalies or failures signs clustering of the detected nodes and aggregates of the railway transport rolling stock

In this case, the amount of recognition signs varied within $N = 9 - 15$. The optimal amount of clusters was selected at the maximum values of ICFE. As the analysis of the results showed the optimal amount of clusters is equal to $C = 3$.

Figure 4 shows a histogram of the dependence of the ICFE value for variants of the dictionaries of the anomalies and failures signs of nodes and aggregates from the amount of steps of the SADS learning algorithm $\{w\}$, and the Fig. 5 shows the dependence of ICFE from the amount

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of signs used to train the system for failure diagnostics and detection.

Analysis of simulation results showed that the use of an algorithm with 5–10 signs of learning is quite effective in SADS. That is, for this case, the ICFE reaches its maximum value. This, in turn, indicates the possibility of creation error-free decision rules in failure diagnostics and detection.

In the SADS testing mode a sufficient amount of steps $\{w\}$ for accurately determination of anomalies and failures classes were $w = 2500 - 3000$.

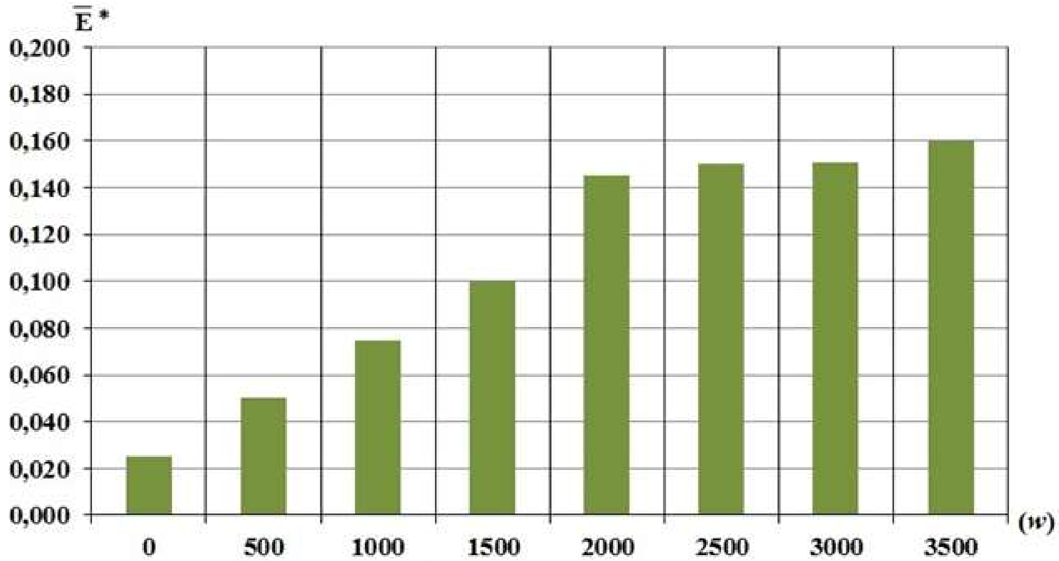

Figure 9: Dependence of the max *ICFE value for variants of the dictionary of anomalies and failures signs of nodes and aggregates of the simulated railways transport systems*

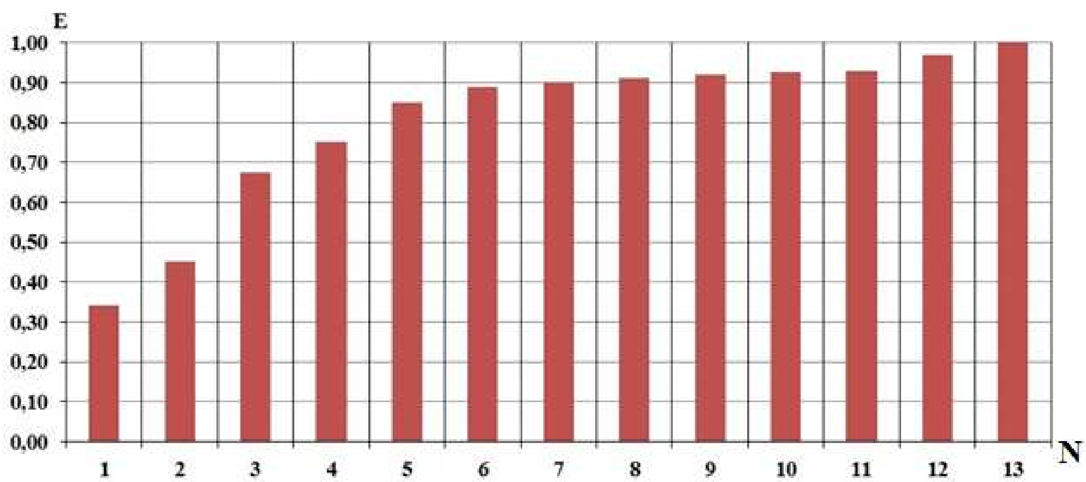

Figure 10: Diagram of the dependence of ICFE from the amount of signs realizations used for SADS

In the situations when during the simulation process and at the creation of an algorithm for recognizing anomalies and failures of nodes and aggregates of railway transport there were added representative sets of greater length, the efficiency of the algorithm was the same. Adding representative sets of shorter length reduced the efficiency of the algorithm.

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6. DISCUSSION OF THE RESEARCH RESULTS

The developed model and algorithm for SADS, in our opinion, not only constitute an independent practical interest, but are an example of a new approach for the creation adaptive NDC systems for diagnostics and detection nodes and aggregates of railway transport, including HSRT.

In particular, compared with the results presented in [3, 4, 13-15], our approach provides a significantly smaller amount of necessary primary signs for the classification of nodes and aggregates. In this case, it is possible to process data obtained from different means of NDC, for example, vibration, heat, sound, etc. This reduces the time spent on self-training of the automated diagnostics and detection system. In our model and in the corresponding algorithms, it is possible to determine automatically the sizes of the training and test matrices of the failures and anomalies signs realizations for nodes and aggregates. This minimizes the participation of service personnel at the stage of identifying the primary signs of failures, which, for example, previously could be detected using manual analysis of the NDC means.

Approbation of the model was implemented only for two classes of failures or anomalies in the operation of nodes and aggregates of the railway transport. This is a definite disadvantage of our research at its current stage. For more complex types of failures and anomalies, obviously, there will be required an increase in the amount of signs realizations, as well as steps of the algorithm, for self-training of an automated diagnostic and detection system that receives data from various means of NDC, which, in turn, will increase the level of requirements for computing resources.

Prospects for further research are to improve the knowledge base for failures and anomalies in the operation of nodes and aggregates, as well as to explore the proposed solutions on a wider class of diagnostic problems for the railway transport.

Now our research is carried out in the following directions: during machine learning it is necessary: 1) to optimize the vector parameters q_h; 2) to determine the criterion of the effectiveness of the system for automated detection of the HSRT systems state; 3) during the process of machine learning to form decision rules for the detection of failures, in particular by optimizing the parameters of the containers of recognition classes.

We believe that the planned researches will improve the reliability of the results of the procedures for the automatic evaluation of failures and defects of the HSRT system components and, accordingly, the degree of reliability of the decisions regarding the organization of technical maintenance and current repair.

7. CONCLUSIONS

The article analyzes the previous researches in the field of non-destructive control and technical diagnostics of nodes and aggregates of railway transport rolling stock. There was substantiated the necessity of using intelligent technologies in the tasks of non-destructive control and technical diagnostics of nodes and aggregates of railway transport rolling stock.

There was considered the possibility of machine learning of the HSRT state detection system based on the clustering of the failure signs realizations that can be detected by various means of detection and diagnostics.

It was shown that the use of NDC and diagnostics methods separately from each other is not always advisable. Simultaneous diagnostics and detection simultaneously by several methods uniquely gives a more complete picture of the object of study. There was substantiated the perspectives of decisions on the complex results evaluation of the detection of nodes and aggregates of the HSRT rolling stock based on the use of models with algorithms of fuzzy clustering of hundreds of failure signs of the HSRT systems.

There are presented the results of researches aimed at the further development of methods and models for self-trained automated detection systems (SADS) of high-speed railway transport (HSRT) nodes and aggregates based on the clustering of failure signs implementations.

There was developed a SADS model of nodes and aggregates of HSRT and a method for its training, in which the procedure of fuzzy clustering of failure signs realizations is applied.

There was considered the procedure for decision rules correction, which will allow the creation of adaptive self-training mechanisms for automated systems for detecting HSRT nodes and aggregates.

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It is proposed to use the modified information condition of functional effectiveness (ICFE) as an evaluation indicator of the SADS learning effectiveness. This condition is based on Kullback-Leibler information-distance criteria.

There was considered the method of space fragmentation for failure signs realizations of the HSRT nodes and aggregates into clusters during the implementation of the failure recognition procedure.

There was considered the method of initial SADS training. The method is an iterative procedure for finding the ICFE global maximum.

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