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CREATION OF A CONCEPTUAL MODEL OF AUTOMATED SELF-LEARNING SYSTEM OF FUNCTIONAL CONTROL AND DETECTION OF RAILWAY TRANSPORT

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Abstract. Ensuring reliable and trouble-free operation of all railway and high-tech systems remains a priority task in the field of scientific developments related to operation and modernization of such complexes. The aim of the study is to develop and refine a machine learning method for the automated detection system (ADS) of functional states of railway transport components and assemblies. The objectives include: creating a glossary of feature realizations for each class of anomalies or faults; determining the minimum size of the training matrix and permissible deviations for feature implementation; developing a binary training matrix (OUFT) and optimizing its structure to improve detection accuracy. Analysis of existing NDC methods and machine learning algorithms (K-means, DBSCAN, FDBSCAN) was performed to build binary matrices and cluster features. The proposed approach optimizes the ADS training process, reduces computational complexity, and improves anomaly and fault detection in railway components and assemblies. Algorithms for parallel optimization of fault detection features and measures to enhance DSS accuracy in automated diagnostics were proposed. The developed machine learning method and ADS structure allow the creation of error-free decision rules for the diagnosis of railway transport components. This approach improves the accuracy and reliability of decision support systems and automated detection systems for functional anomalies.

Keywords: automated detection system, railway transport, machine learning, binary matrix, clustering, component diagnostics, functional states

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ТЕМІРЖОЛ ТРАНСПОРТЫН ФУНКЦИОНАЛДЫ БАҚЫЛАУ МЕН АНЫҚТАУДЫҢ АВТОМАТТАНДЫРЫЛҒАН ӨЗІН-ӨЗІ ОҚЫТУ ЖҮЙЕСІНІҢ ТҰЖЫРЫМДАМАЛЫҚ МОДЕЛІН ҚҰРУ

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Аннотация. Барлық теміржол және жоғары технологиялық жүйелердің сенімді және ақаусыз жұмысын қамтамасыз ету — осы саланың ғылыми зерттеулеріндегі басым міндеттердің бірі. Зерттеудің мақсаты — теміржол көлігінің тораптары мен агрегаттарының функционалды күйін анықтайтын автоматтандырылған жүйенің (ADS) машиналық оқыту әдісін әзірлеу және жетілдіру. Міндеттері: ақаулар немесе аномалиялар классы бойынша белгілер сөздігін жасау; ADS оқыту матрицасының минималды өлшемін және белгілерді жүзеге асыруға рұқсат етілген ауытқуларды анықтау; OUFT бинарлық оқыту матрицасын әзірлеу және оның құрылымын оңтайландыру арқылы анықтау дәлдігін арттыру. NDC әдістері және машиналық оқыту алгоритмдері (K-means, DBSCAN, FDBSCAN) талданды, бинарлық матрицаларды құру және белгілерді кластерлеу жүзеге асырылды. Ұсынылған тәсіл ADS оқыту процесін оңтайландырады, есептеу күрделілігін төмендетеді және ақаулар мен аномалияларды анықтауда тиімділікті арттырады. Сондай-ақ, ақауларды анықтау белгілерін параллель оңтайландыру алгоритмдері ұсынылды. Дайындалған машиналық оқыту әдісі мен ADS құрылымы теміржол көлігінің компоненттерін диагностикалау үшін қателіксіз шешім қабылдау ережелерін жасауға мүмкіндік береді. Ұсынылған тәсіл шешім қабылдау жүйелері мен автоматтандырылған анықтау жүйелерінің дәлдігі мен сенімділігін арттырады.

Түйін сөздер: автоматтандырылған анықтау жүйесі, теміржол көлігі, машиналық оқыту, бинарлық матрица, кластерлеу, компонент диагностикасы, функционалды жағдайлар

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КОНЦЕПТУАЛЬНОЕ ПОСТРОЕНИЕ МОДЕЛИ ДЛЯ АВТОМАТИЗИРОВАННОЙ САМООБУЧАЕМОЙ СИСТЕМЫ ФУНКЦИОНАЛЬНОГО КОНТРОЛЯ И ДЕТЕКТИРОВАНИЯ ЖЕЛЕЗНОДОРОЖНОГО ТРАНСПОРТА

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Аннотация. Обеспечение надежной и безаварийной работы всех железнодорожных и высокотехнологичных систем является одной из приоритетных задач в области научных разработок, связанных с эксплуатацией и модернизацией таких комплексов. Цель исследования — разработка и уточнение метода машинного обучения для автоматизированной системы обнаружения (ADS) функционального состояния узлов и агрегатов железнодорожного транспорта. Основные задачи включают: формирование глоссария признаков для каждого класса аномалий или неисправностей; определение минимального размера матрицы обучения ADS и допустимых отклонений для реализации признаков; разработка бинарной матрицы обучения OUFT и оптимизация её структуры для повышения точности распознавания. Проведен анализ существующих методов NDC и применяемых алгоритмов машинного обучения (K-means, DBSCAN, FDBSCAN) для построения бинарных матриц и кластеризации признаков. Показано, что предложенный подход позволяет оптимизировать процесс обучения ADS, снижая вычислительную сложность и повышая эффективность распознавания аномалий и отказов узлов и агрегатов. Были сформированы алгоритмы параллельной оптимизации контроля признаков неисправностей и предложены меры по повышению точности DSS в автоматизированной диагностике. Разработанный метод машинного обучения и структура ADS обеспечивают возможность создания безошибочных правил принятия решений для диагностики состояния компонентов железнодорожного транспорта. Предложенный подход позволяет улучшить точность и надежность систем поддержки принятия решений и автоматизированных систем обнаружения функциональных нарушений.

Ключевые слова: автоматизированная система обнаружения, железнодорожный транспорт, машинное обучение, бинарная матрица, кластеризация, диагностика узлов, функциональные состояния

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Introduction.

Ensuring reliable and trouble-free operation of all railway and high-tech railway systems remains one of the priority tasks in the segment of scientific developments related to the implementation, operation and modernization of such high-tech complexes. As has been shown by many scientists who have been engaged in research in this direction, in order to increase the operational reliability and service life of the main systems, components and assemblies (SCA) of locomotives, timely identification (detection) of their defects is necessary, even before an emergency occurs. This problem is solved by the functional control system directly during the operation of the control system. In addition, in practice, the recognition classes characterizing the possible functional states of SCA intersect in the feature space, that requires defuzzification of fuzzy data. When using a quantitative scale for measuring detection features, an effective method of such defuzzification is the use of machine learning. This approach makes it possible to transform the a priori fuzzy partition of the space of features for detecting anomalies in operation and faults of SCA into a clear set (Schickert, 2005: 807–815; Aydin, 2012: 1–6; Le Mortellec, 2013: 227–240; Papaelias, 2008: 367–384; Jin, 2009: 8–25).

One of the promising approaches that need further development of the synthesis of a functional control system of SCA of RT is the use of ideas and methods of information-extremal intelligent technology (IEI-technology), based on maximizing the information capacity of the decision support system in the training process of the automated detection system of SCA.

The solution of the problem, in particular, is associated with the need to form on the basis of known and new features (i.e., which were not initially entered into the knowledge base of the automated detection system - ADS) of the so-called object used for training (OUFT). This object is a matrix based on the realizations of the features of anomalies in the operation of SCA.

Materials and methods.

Within the framework of the article, the following tasks are solved:

- to form a glossary of feature implementations for each class of anomalies or faults, as well as an alphabet of classes in terms of fault detection objects (FDO)
- to determine the minimum size of the matrix that is used in the training process of the ADS (OUFT) (subject to the requirements for its representativeness);
- to determine the normalized permissible deviations for the implementation of the features of recognition (detection) of anomalies or faults in the operation of the control system of railway rolling stock.

In order to obtain an input mathematical description of the ADS, it is necessary to study and analyze in detail the features of operation of the primary sources of information, from which the ADS system receives data on the certain realizations of the features of faults. For example, in existing methods and means of NDC, there are used devices as primary sources of information. The mathematical model of ADS in general form as a set-theoretical structure can be represented as follows (Lakhno, 2017: 5778–5786; Dovbish, 2009: 171):

$$\Delta_B = \langle IS, T, RS, SS, OS, \Pi, \Phi \rangle, \quad (1)$$

where IS – a set of input signals that are processed in ADS;

T – moment of time to obtain information about the state of the detected system, node or assembly;

RS – a set of feature implementations that are used in the process of detecting faults;

SS – a space of possible states for a system, node or assembly that are subject to the NDC procedure;

OS – a set of data that is obtained at the output from the module for primary processing of signals (information), for example, from the NDC tools. Or the module of primary data processing – PDPM;

$\Pi : IS \times T \times RS \rightarrow SS$ – transition quantifier (used to record changes in the state of SNA, which are subject to detection during their operation. It is assumed that a change in states can occur under the influence of internal or external factors)

$\Phi : IS \times T \times RS \rightarrow LM$ – formation quantifier of the set LM (learning matrix – *m*).

The Cartesian product of sets IS, T, RS, SS is used as a universe UT of tests during ADS testing

$$UT = IS \times T \times RS \times SS. \quad (2)$$

The ADS scheme, which includes a software module with self-training elements, is shown on Figure 1.

The quantifier $O\Theta : CL^{|2|} \rightarrow RC^{|2|}$ is used to divide the space of realizations of the OR features (faults or anomalies in the operation of SCA or – faults detecting objects – FDO) into two recognition classes.

The classification parameter OC is used to test the statistical assumption (that is, the hypothesis) that the FDO belongs to a certain class of faults or anomalies in the operation of SCA.

After assessing the hypotheses using the quantifier hy, there is formed a set AR^{is} that characterizes the accuracy of detecting the corresponding faults or anomaly in the operation of SCA (i.e., FDO).

It is accepted that ζ - the number of statistical assumptions, $is = \zeta^2$ – the number of characteristics that can be processed in the ADS for SCA of the railway rolling stock.

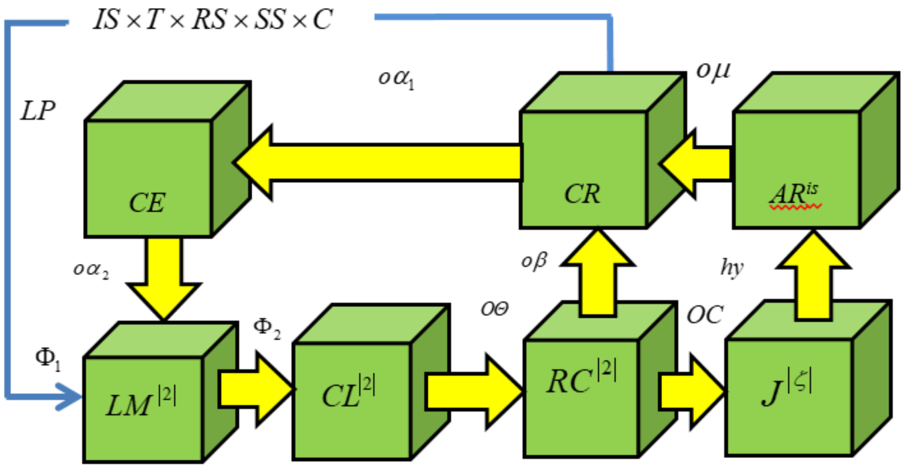

Fig. 1. Schematic diagram of the ADS software module

The quantifier $o\mu$ forms a set CR that allows to implement the procedure for assessing the efficiency of detecting faults or anomalies in the operation of SCA within a class.

The quantifier $o\beta$ closes the detection loop and is used to optimize the system of control deviations from templates (norms) that are stored in the ADS repository.

Quantifiers $\Phi_1 : IS \times T \times RS \times SS \times C \rightarrow LM^{|2|}$ and $\Phi_2 : LM^{|2|} \rightarrow CL^{|2|}$ are used to form the input matrix used in the training process of the ADS (ITM) and in the organization of the binary training matrix (BTM), respectively. Here C - a fragment of data for detection.

The set CE is closed sequentially by quantifiers $o\alpha_1 : CR \rightarrow CE$ and $o\alpha_2 : CE \rightarrow LM^{|2|}$. These quantifiers allow to change the realizations of FDO features for different classes in the process of training ADS.

A quantifier $LP : CR \rightarrow IS \times T \times RS \times SS \times C$ is used to regulate the ADS training process.

Based on the conceptual scheme of the ADS operation, presented on Figure 1, we will formulate the following formalized statement of the problem of information synthesis of the ADS elements. Let the alphabet of FDO classes $\{CL_s^0 | s = \overline{1, S}\}$ and a multidimensional binary matrix used for training (MBMT of FDO) which, accordingly, characterizes the m – th functional state of SCA for a specific recognition class CL_s^o, be known:

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Аннотация. Обеспечение надежной и безаварийной работы всех железнодорожных и высокотехнологичных систем является одной из приоритетных задач в области научных разработок, связанных с эксплуатацией и модернизацией таких комплексов. Цель исследования — разработка и уточнение метода машинного обучения для автоматизированной системы обнаружения (ADS) функционального состояния узлов и агрегатов железнодорожного транспорта. Основные задачи включают: формирование глоссария признаков для каждого класса аномалий или неисправностей; определение минимального размера матрицы обучения ADS и допустимых отклонений для реализации признаков; разработка бинарной матрицы обучения OUFT и оптимизация её структуры для повышения точности распознавания. Проведен анализ существующих методов NDC и применяемых алгоритмов машинного обучения (K-means, DBSCAN, FDBSCAN) для построения бинарных матриц и кластеризации признаков. Показано, что предложенный подход позволяет оптимизировать процесс обучения ADS, снижая вычислительную сложность и повышая эффективность распознавания аномалий и отказов узлов и агрегатов. Были сформированы алгоритмы параллельной оптимизации контроля признаков неисправностей и предложены меры по повышению точности DSS в автоматизированной диагностике. Разработанный метод машинного обучения и структура ADS обеспечивают возможность создания безошибочных правил принятия решений для диагностики состояния компонентов железнодорожного транспорта. Предложенный подход позволяет улучшить точность и надежность систем поддержки принятия решений и автоматизированных систем обнаружения функциональных нарушений.

Ключевые слова: автоматизированная система обнаружения, железнодорожный транспорт, машинное обучение, бинарная матрица, кластеризация, диагностика узлов, функциональные состояния

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Конфликт интересов: авторы заявляют об отсутствии конфликта интересов.

Introduction.

Ensuring reliable and trouble-free operation of all railway and high-tech railway systems remains one of the priority tasks in the segment of scientific developments related to the implementation, operation and modernization of such high-tech complexes. As has been shown by many scientists who have been engaged in research in this direction, in order to increase the operational reliability and service life of the main systems, components and assemblies (SCA) of locomotives, timely identification (detection) of their defects is necessary, even before an emergency occurs. This problem is solved by the functional control system directly during the operation of the control system. In addition, in practice, the recognition classes characterizing the possible functional states of SCA intersect in the feature space, that requires defuzzification of fuzzy data. When using a quantitative scale for measuring detection features, an effective method of such defuzzification is the use of machine learning. This approach makes it possible to transform the a priori fuzzy partition of the space of features for detecting anomalies in operation and faults of SCA into a clear set (Schickert, 2005: 807–815; Aydin, 2012: 1–6; Le Mortellec, 2013: 227–240; Papaelias, 2008: 367–384; Jin, 2009: 8–25).

One of the promising approaches that need further development of the synthesis of a functional control system of SCA of RT is the use of ideas and methods of information-extremal intelligent technology (IEI-technology), based on maximizing the information capacity of the decision support system in the training process of the automated detection system of SCA.

The solution of the problem, in particular, is associated with the need to form on the basis of known and new features (i.e., which were not initially entered into the knowledge base of the automated detection system - ADS) of the so-called object used for training (OUFT). This object is a matrix based on the realizations of the features of anomalies in the operation of SCA.

Materials and methods.

Within the framework of the article, the following tasks are solved:

- to form a glossary of feature implementations for each class of anomalies or faults, as well as an alphabet of classes in terms of fault detection objects (FDO)
- to determine the minimum size of the matrix that is used in the training process of the ADS (OUFT) (subject to the requirements for its representativeness);
- to determine the normalized permissible deviations for the implementation of the features of recognition (detection) of anomalies or faults in the operation of the control system of railway rolling stock.

In order to obtain an input mathematical description of the ADS, it is necessary to study and analyze in detail the features of operation of the primary sources of information, from which the ADS system receives data on the certain realizations of the features of faults. For example, in existing methods and means of NDC, there are used devices as primary sources of information. The mathematical model of ADS in general form as a set-theoretical structure can be represented as follows (Lakhno, 2017: 5778–5786; Dovbish, 2009: 171):

$$\Delta_B = \langle IS, T, RS, SS, OS, \Pi, \Phi \rangle, \tag{1}$$

where IS – a set of input signals that are processed in ADS;

T – moment of time to obtain information about the state of the detected system, node or assembly;

RS – a set of feature implementations that are used in the process of detecting faults;

SS – a space of possible states for a system, node or assembly that are subject to the NDC procedure**;**

OS – a set of data that is obtained at the output from the module for primary processing of signals (information), for example, from the NDC tools. Or the module of primary data processing – PDPM;

$\Pi : IS \times T \times RS \to SS$ – transition quantifier (used to record changes in the state of SNA, which are subject to detection during their operation. It is assumed that a change in states can occur under the influence of internal or external factors)

$\Phi : IS \times T \times RS \to LM$ – formation quantifier of the set LM (learning matrix – *m*).

The Cartesian product of sets IS, T, RS, SS is used as a universe UT of tests during ADS testing of confidence to the generated OUFT matrices. Many works in the field of machine learning systems have been devoted to this issue (Jin, 2009: 8–25; Lakhno, 2016: 18; Dovbish, 2009: 17; Giantomassi, 2015: 1770–1780).

Figure 3 shows the process of forming the structure of the matrix used for training ADS. Moreover, the formation of the structure occurs in stages, including the vectors of realizations $\{cl_1^{(j)}\} \in CL_1^0$ and $\{cl_2^{(j)}\} \in CL_2^0$, respectively (Lakhno, 2017: 5778–5786; Dovbish, 2009: 17; Zhang, 2015: 419–432).

To create such a matrix, only the important characteristics of FDO should be selected. That is, the characteristics that uniquely distinguish some realizations of features of faults or anomalies in the operation of SCA within the class from others.

All possible values of each FDO property can be encoded in binary form (Giantomassi, 2015: 1770–1780), or using non-negative integers (Lakhno, 2017: 5778–5786; Dovbish, 2009: 17; Zhang, 2015: 419–432), where zero corresponds to an undefined value of the FDO property. This, in particular, makes it possible to take into account the missing, new, or not yet provided values of the FDO properties.

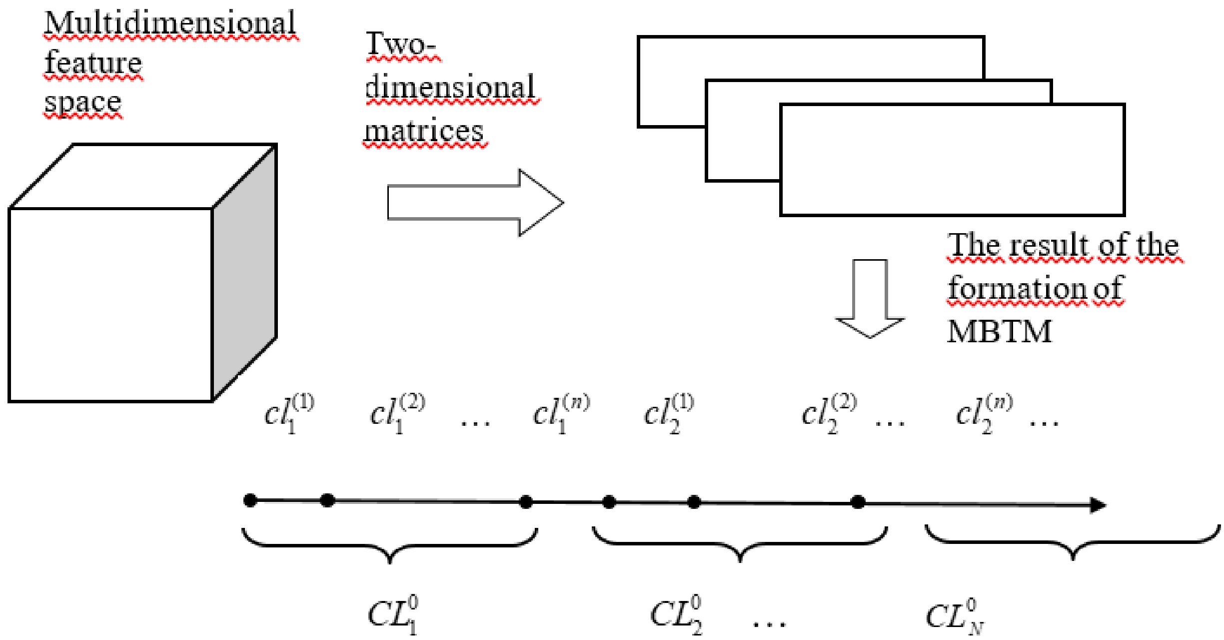
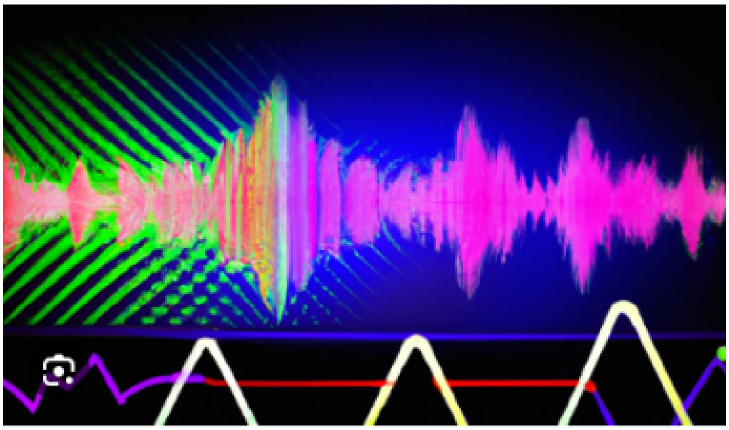
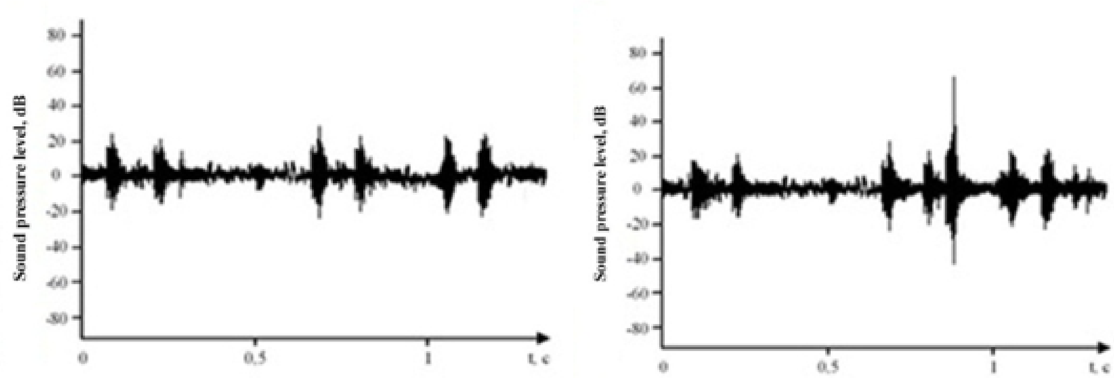


Fig. 3. Scheme of work with the multidimensional information space of the realizations of features of FDO ADS for the railway rolling stock

As an illustration, Table 1 shows an example of the process of forming a binary matrix and, accordingly, clustering the realizations of features in the process of detecting SCA using NDC tools based on the acoustic control of the components of the railway rolling stock (Dovbish, 2009: 17; Zhang, 2015: 419–432; Giantomassi, 2015: 1770–1780).

This effect is used in various devices that make it possible to implement acoustic control of rolling stock components and assemblies, see Figure 4.



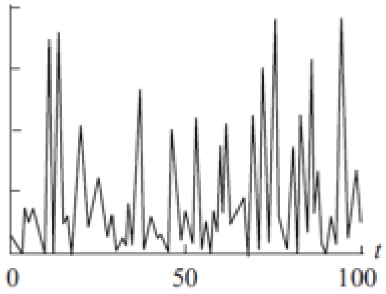
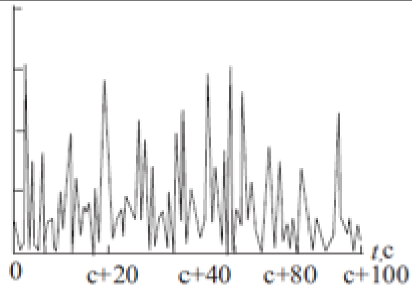
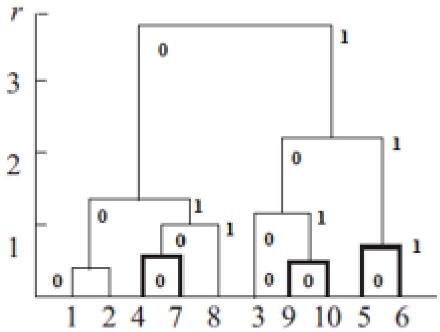
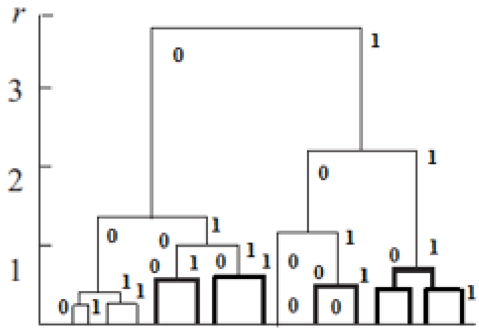


a) b)

Fig. 4. Fragment of the automatic analysis of the sound accompanying the passage of the rolling stock of the undamaged (a) and damaged (b) rolling surface of the wheelset of the railway rolling stock

Eddy current NDC is widely used in various branches of the scientific and industrial complex of Kazakhstan and other countries, due to the high efficiency and reliability of solving problems of flaw detection, quality control of materials and products, determination of parameters and characteristics of objects of control for various purposes (Lakhno, 2016: 32–44; Lakhno, 2016: 18;Lakhno, 2017: 5778–5786; Dovbish, 2009: 17; Zhang, 2015: 419–432).

Table 1. An example of the formation of clusters and a binary matrix for OUFT for detecting the state of the rolling surface of a wheelset of the railway rolling stock (Fig. 4).

No acoustic anomalies	Acoustic anomalies recorded
Diagrams obtained using NDC tools	
	
Formation of clusters	
	
Formation of a binary matrix for OUFT	
Column - sample set for training ADS	**Row - implementation of the FDO representation**
$m=\begin{pmatrix} 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 \end{pmatrix}.$	$m=\begin{pmatrix} 1 & 1 & 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 1 & - & 0 \\ 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 1 & 1 & - & 0 & 0 \end{pmatrix}.$

By combining the data into compact clusters, it is possible to analyze the typical representatives of each cluster and decide whether such data is a realization of a feature of a fault or anomaly in the operation of the SCA or not. Then this solution is transferred to all representatives of the studied cluster. This approach significantly reduces the amount of information required for the successful classification of FDO.

Since clusters can take complex forms in the multidimensional space of feature realizations, some authors have proposed various algorithms for clustering feature realizations. So, for example, in the works listed below, the application of the methods and algorithms K-means, DBSCAN, FDBSCAN (Lakhno, 2017: 5778–5786; Dovbish, 2009: 17; Zhang, 2015: 419–432), etc. is described, see Figure 5.

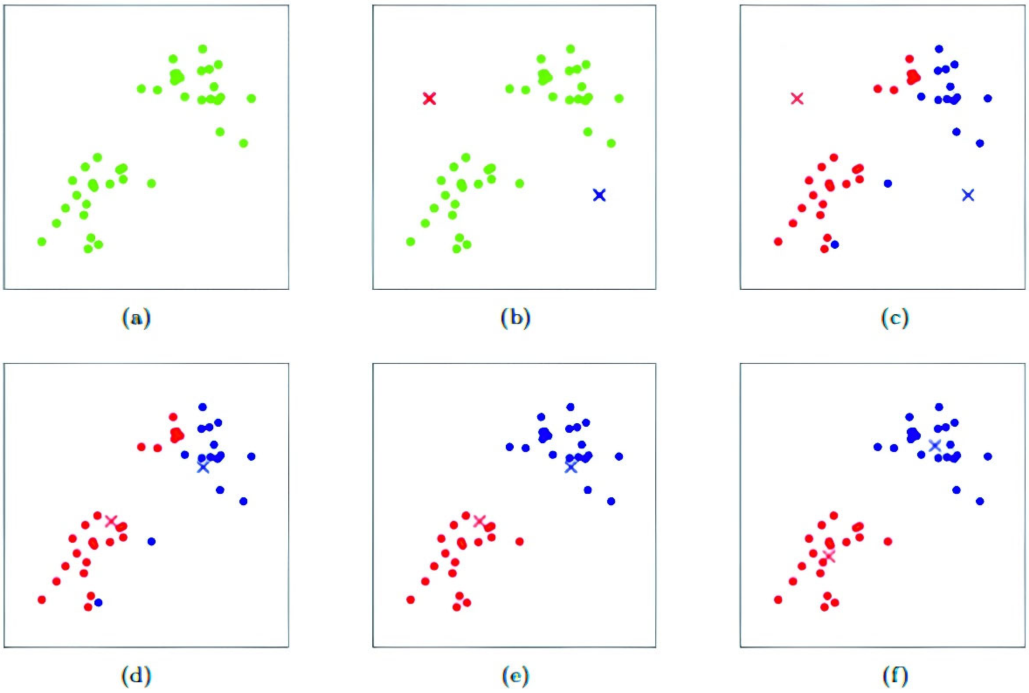


Fig. 5. Examples of data clustering based on DBSCAN and K-means algorithms in diagnostic systems

It was shown that the computational complexity of algorithms used in a binary space for realizations of the detection features of SCA (BSFR) of the corresponding class (classes) depends on the optimal container shape for the corresponding class of the object of detection.

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. 6,7.

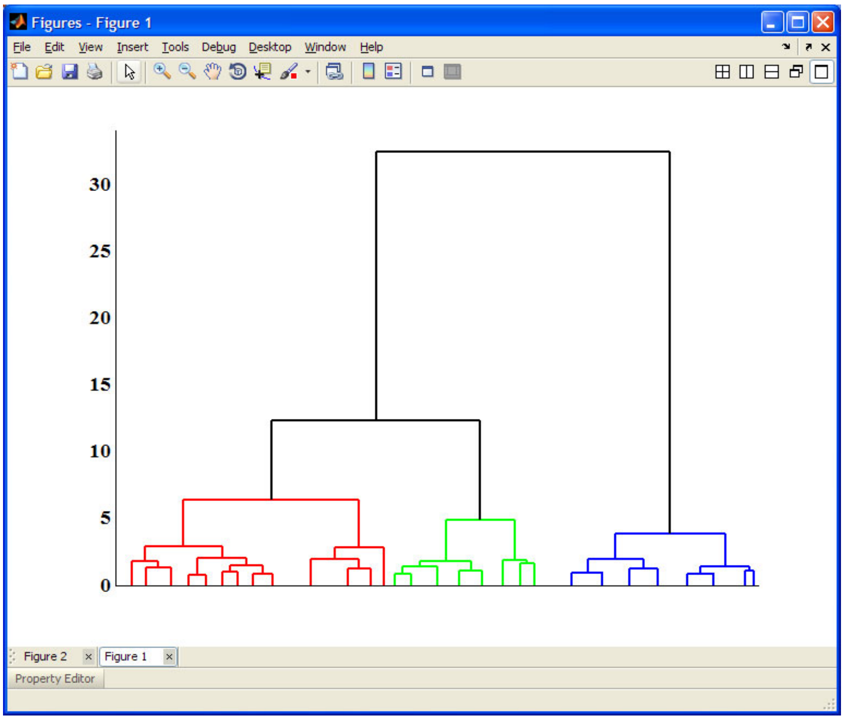


Fig. 6. Normal behavior of the detected nodes and aggregates of the railway transport rolling stock

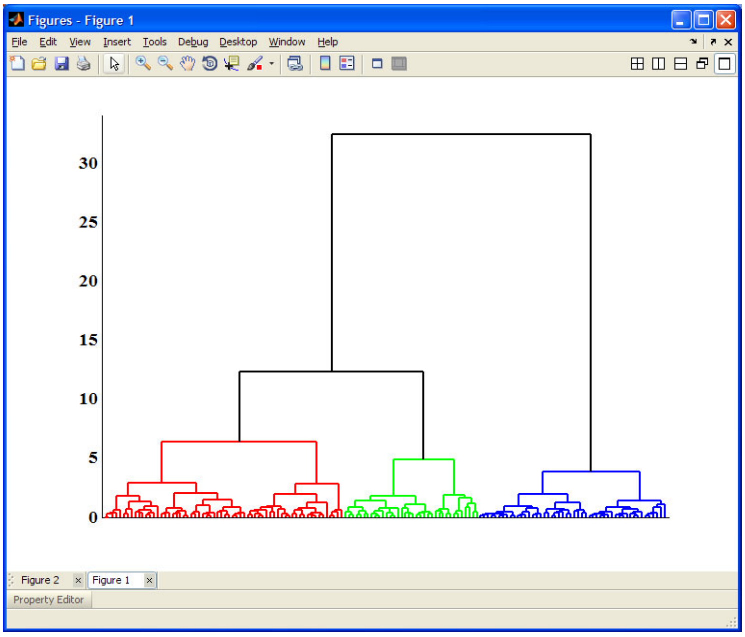


Fig. 7. Anomalies or failures signs clustering of the detected nodes and aggregates of the railway transport rolling stock

Conclusion.

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 $\{w\}$, shows the dependence of ICFE from the amount 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 $w = 2500 - 3000$.

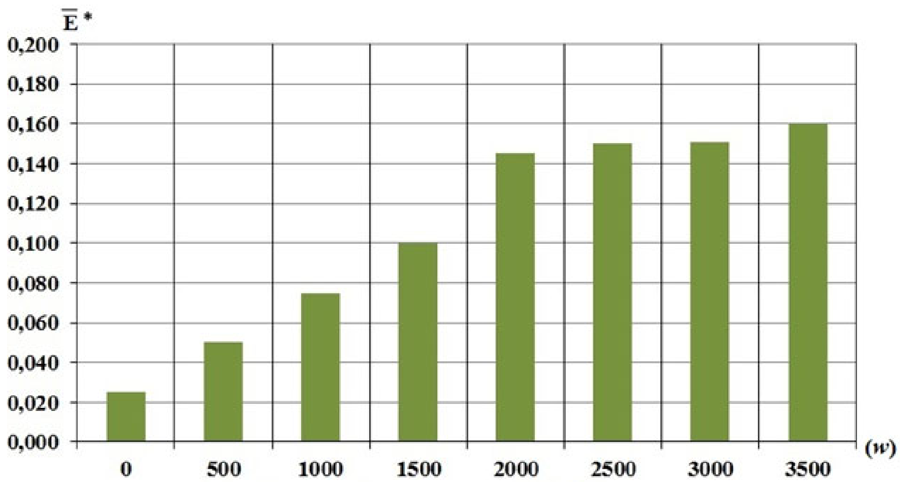


Fig. 8. Dependence of the $\max$ ICFE value for variants of the dictionary of anomalies and failures signs of nodes and aggregates of the simulated railways transport systems

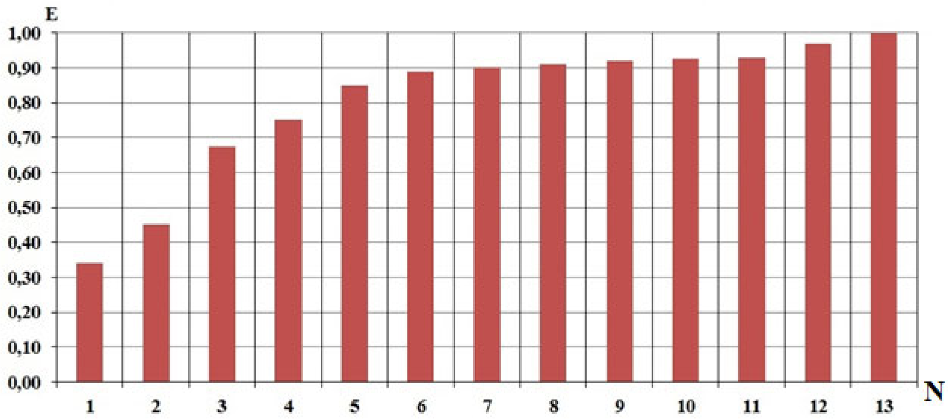


Fig. 9. Diagram of the dependence of ICFE from the amount of signs realizations used for SADS

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.

The article proposes clarifications and additions to the machine learning method of the automatic detection system (ADS) of the functional state of components and assemblies of railway transport. As well as the corresponding model and machine learning algorithm, which, in contrast to existing solutions, are implemented by parallel optimization of control permissions for the features of fault recognition of SCA. Such a solution allows, in the future, to create effective decision rules for intelligent decision support systems (DSS) and ADS of faults and for diagnostics of the state of components and assemblies of railway transport.

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