Automated Self-trained System of Functional Control and State Detection of Railway Transport Nodes

Bakhytzhan Akhmetov, Valeriy Lakhno, Ayaulym Oralbekova, Zhanat Kaskatayev and Gulmira Mussayeva

Abstract—Automation of data processing of contactless diagnostics (detection) of the technical condition of the majority of nodes and aggregates of railway transport (RWT) minimizes the damage from failures of these systems in operating modes. This becomes possible due to the rapid detection of serious defects at the stage of their origin. Basically, in practice, the control of the technical condition of the nodes and aggregates of the RWT is carried out during scheduled repairs. It is not always possible to identify incipient defects. Consequently, it is not always possible to warn personnel (machinists, repairmen, etc.) of significant damage to the RWT systems until their complete failure. The difficulties of obtaining diagnostic information is that there is interdependence between the main nodes of the RWT. This means that if physical damage occurs at any of the RWT nodes, in other nodes there can also occur malfunctions.

As the main way to improve the efficiency of state detection of the nodes and aggregates of RWT, we see the direction of giving the adaptability property for an automated data processing system from various contactless diagnostic information removal systems. The global purpose can be achieved, in particular, through the use of machine learning methods and failure recognition (recognition objects). In order to improve the operational reliability and service life of the main nodes and aggregates of RWT, there are proposed an appropriate model and algorithm of machine learning of the operator control system of nodes and aggregates. It is proposed to use the Shannon normalized entropy measure and the Kullback-Leibler distance information criterion as a criterion of the learning effectiveness of the automated detection system and operator node state control of RWT. The article describes the application of the proposed method on the example of an automatic detection system (ADS) of the state of a traction motor of an electric locomotive. There are given the test data of the model and algorithm in the MATLAB environment.

Keywords—information intellectual technology of failure detection, functional control, learning matrix, learning algorithm, operator effectiveness criterion, nodes and aggregates, railway transport

I. INTRODUCTION

IN order to improve the operational reliability and service life of the main systems, nodes and aggregates (SNA) of railway transport (RWT), the timely detection (diagnosis) of their defects is necessary [1, 2]. This task must be solved before an emergency occurs, which can lead to a significant accident or other serious consequences. It is possible to improve significantly the efficiency of the system for the functional control of the SNA state directly during the operation of RWT. In order to solve the tasks of functional control of SNA of RWT there are widely used data mining methods [3-5].

We should note that most of the known data mining methods have a model character. This is due to the fact that in the considered methods, there are not taken into account random initial conditions, which cause a priori uncertainty in the current state of the SNA of RWT. In addition, in practice, recognition classes that characterize the possible functional states of the SNA intersect in the feature space. In turn, this requires fuzzy data defuzzification. At using the quantitative measurement scale of the defects features recognition in the SNA, the use of machine learning can be an effective method for such defuzzification. This will allow to transform a priori fuzzy splitting of the defect recognition feature space of the SNA of RWT into a clear one.

One of the promising approaches to the synthesis of the functional control system of the SNA is the application of intellectual technology (INTec) methods. This technology is based on maximizing the information ability of an automated decision support system for failure detection during the process of learning [4-6]. This makes the topic of our work relevant.

II. LITERATURE REVIEW

In [2-5] there was shown that the maintenance of nodes and aggregates of rolling stock (RS) of RWT (in particular, promising for Kazakhstan high-speed RWT systems) can be implemented on the basis of indicators of the actual condition of the equipment. In this case, the necessary diagnostic information can be obtained by methods of non-destructive control (NDC). However, we should note that the use of these methods requires accurate and reliable results of the analysis of measurements and the application of intellectualized automated technologies of various data processing obtained from control and measurement means [3-5].

As computerized methods of machine learning, methods and models associated with the analysis of large amounts of data (data mining) are developed, there occurs the task of adaptation and development of these methods and models for solving the tasks of the NDC of the nodes and aggregates of various technical systems [6-8].

For the technical implementation of NDC tools, many methods are currently used [3, 5, 9, 10], for example, vibrating, acoustic and warm NDC of the nodes and aggregates of RWT.

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All these methods give to the party, conducting the diagnosis and detection of the nodes and aggregates, large amounts of different information, which often may not be the same or can be stored in different formats. And in this situation, it seems promising to use self-trained ADS of the nodes and aggregates of RWT based on machine learning.

Even a preliminary research review in the field of automation of contactless RWT systems state detection showed that there is an actual scientific task of mathematical methods and models development for automation tools of contactless detection of the state of SNA of RWT [4-7]. In particular, the promising solution is a solution based on the use in such ADS of the models with parallel optimization algorithms of control limits for failure recognition features [11-13], for example, for electric locomotive traction motors (ETM). Such a solution will allow to create effective decision rules for automated decision support systems during failure detection and diagnostics of the ETM condition and other important systems of RWT.

III. THE PURPOSE OF THE RESEARCH

Development of a model and algorithm for data processing from the systems of contactless diagnostics of systems, nodes and aggregates of HSRT.

The article solves the following problems:

To develop an algorithm for an automated self-trained system of functional control and detection of the state of railway transport nodes using the example of thermal control of a traction motor of an electric locomotive;

To perform a simulation experiment in the MATLAB environment in order to test the proposed models and algorithm.

IV. METHODS AND MODELS

For diagnostics (detection) of anomalies in operation or failures of nodes and aggregates of RWT there are used modern digital systems of non-destructive control (NDC), see (fig. 1). However, the data of these systems are rather scattered. We can use machine learning methods in order to organize them. For example, for training the system of nodes and aggregates detection of RWT using the fuzzy clustering procedure for the implementation of failure signs and the possibility of decision rules correction. This will allow the creation of adaptive self-trained mechanisms for systems of diagnostics and detection of the nodes and aggregates, for example, for electric locomotive ETM.

A. Problem statement

The corresponding states of the electric locomotive SNA, in particular, ETM, are characterized by their functional states. With the help of various sensors, for example, which control thermal states (or others, depending on the purpose of the sensor), it is possible to recognize the initial states of failures at early stages. We believe that for the designed automatic detection system (ADS) of ETM, there is formed the corresponding alphabet of recognition classes - $\{CL_s^0|S = \overline{1,S}\}$. This alphabet characterizes each of the functional state of the system or node. As it was mentioned above, this article
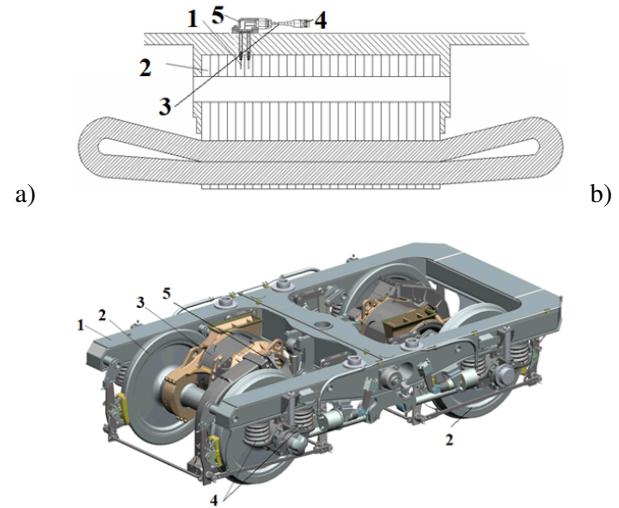

Fig. 1. Systems of distance non-destructive control for ETM of electric 1 - thermistor capsule; 2 - stator core; 3 - cable; 4 - plug connector; 5 - sealing cap a) installation of thermal sensors of electric locomotive ETM 1 - trolley frame; 2 - wheel sets; 3 - ETM; 4 - axle-box suspension springs; 5 - temperature sensors b) placement of ETM on the trolley frame of the electric locomotive 2C10

describes an example of recognition classes for ETM. For example, let consider the following classes: characterizes the normal operating of ETM; CL_2^0 - corresponds to the elevated temperature of ETM bearings; CL_3^0 - increased temperature ETM windings. Of course, the amount of classes may be more. But within the framework of the article, we limit ourselves by the examples for three elements of the classes of the recognition alphabet.

Then for the ADS it is necessary to create a matrix that characterizes the ratio of the corresponding object and its properties.

B. Algorithm for self-trained system of functional control and state detection of locomotive nodes

The matrix, which can be considered as an object used for learning (OUFL), is represented as follows:

$$\|m_{s,i}^j|i = \overline{1,N}; j = \overline{1,n}\|, \tag{1}$$

where N, n - respectively, the amount of implementations of signs of failure recognition for the implementation of the so-called "image" [14-17] of failure, and the amount of implementations, which corresponds to the amount of ETM operation cycles.

Therefore, each column of the matrix (or OUFL) contains values for a training sample of a recognizable feature. A string j is an implementation with N diagnostic signs.

In addition, it is necessary to set the vector of machine learning parameters for ADS, which we write in the following

way:

$$v = \langle cl_s, r_s, \delta \rangle, \qquad (2)$$

where cl_s - average implementation of the class $\{CL_s^0\}$, r_s - class container radius (it is assumed that in the process of machine learning the radius is updated in the radial basis of the field of failure recognition signs); δ - parameter characterizing the field of control limits for each of the classes present in the alphabet.

The following restrictions on machine learning parameters were adopted: cl_s - a vector whose vertex determines the geometric center of the container for the corresponding class:

$$r_s \in [0, (cl_s \oplus cl_c) - 1]$$

where $r(cl_s \oplus cl_c)$ code distance center of the class $\{CL_s^0\}$ from the center of the class closest to it $\{CL_c^0\}$,

$$\delta \in [0, \delta_{norm}/2],$$

where δ_{norm} - normalized field of limits that defines the range of values δ.

In the process of learning ADS of ETM, there must be performed the following stages:

Stage 1. Optimization of the vector parameters (2) using the following information criterion [13-15]:

$$\overline{CR} = 0,5 \cdot S \cdot \sum_{s=1}^{S} \max_{V_{CR \cap \{h\}}} CR_s^{(h)}, \qquad (3)$$

where $CR_s^{(h)}$ - information criterion (INC) for optimization of machine learning parameters, calculated at h step of ADS training; V_{CR} - the allowed range of the INC; (h) - a set of steps of the ADS machine learning of the functional state of ETM.

Stage 2. According to the optimal geometrical parameters, we create decision rules. These rules should ensure that at ADS functioning directly in the operating modes of ETM operation there will be a high overall probability of making the correct classification decisions.

Next, we consider such a task as the optimization of the control limits system for recognition signs. This is important for the subsequent creation of recognition classes containers and, therefore, for accurate classification decisions in the process of failure recognition. As was shown in [14, 15], the specificity of machine learning methods consists in converting of the input Euclidean learning matrix (OUFL) into a working binary matrix. In addition, additional control limits for recognition signs are considered as quantization levels.

The figure 2 shows the limit field for the value of the i - sign.

Let consider the machine learning algorithm of ADS of ETM with parallel optimization of control limits for failure recognition signs.

As it is known, the optimization of control limits in the process of machine learning is carried out by searching at each step of learning the global maximum of INC by the following iterative procedure:

$$\delta_{H,i}^* = arg \max_{V_{\delta,i}} \{ \max_{V_{CR} \cap \{h\}} \overline{CR}^h \}, \qquad (4)$$

where $V_{\delta,i}$ - allowed range of δ_i parameter value for control limits of the i - th recognition sign.
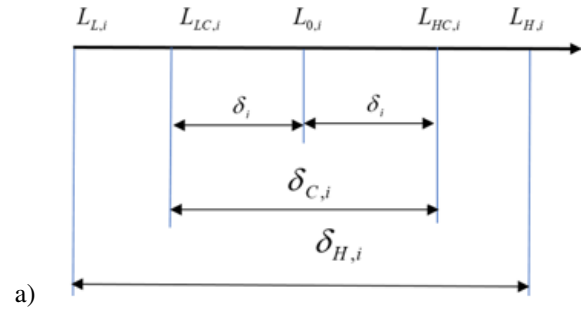

a)

Fig. 2. Field of limits of the i - th sign. The following designations are adopted: $L_{0,i}$ - the nominal value of the sign; $L_{L,i}, L_{H,i}$ - lower and upper normalized limits, respectively; $L_{LC,i}, L_{HC,i}$ - lower and upper control limits, respectively; $\delta_{H,i}$ - normalized field of limits; $\delta_{C,i}$ - control field of limits.

The procedure (4) is implemented in accordance with the scheme of parallel optimization of control limits. Its advantage is the high efficiency of the learning algorithm compared to sequential optimization. This is due to the fact that the control limits at each step of learning change simultaneously for all signs of failure recognition.

An array of OUFL implementations is taken as input data for the parallel optimization algorithm. That is - $\{m_{s,i}^{(j)} | S = \overline{1,S}, i = \overline{1,N}, j = \overline{1,n}\}$. The object used for training is formed for a given alphabet of recognition classes $\{CL_s^0\}$. Normalized limits $\{\delta_{H,i}\}$ will determine the ranges of the control limits values of the corresponding signs for failure recognition, for example, ETM. At the same time, we assume that a basic recognition class is specified, with respect to which the control limits for a specific sign should be calculated. For the practical software implementation, for example, in failure detection tasks, the recognition class that characterizes the normal operation mode of a node should be taken as the basic one.

In the framework of our study, there are described only the basic steps for the implementation of the DSS learning algorithm in the tasks of failure detection in ETM. The main part of the algorithm concerns the stage of parallel optimization δ.

Step 1. After initialization of the recognition classes counters and after steps of change δ, the formation of a binary matrix $\|cl_{s,i}^{(j)}\|$ can occur. We define the elements $\|cl_{s,i}^{(j)}\|$ as follows:

$$\|cl_{s,i}^{(j)}\| = \left\{ 1, if m_{s,i}^j \in \delta_{C,i} \; ; 0, if m_{s,i}^j \notin \delta_{C,i} \right. \quad (5)$$

Step 2. Calculate the average binary implementation for $\{cl_{s,i} | i = \overline{1, N}\}$:

$$cl_{s,i} = \left\{ 1 \; , if (1/n) \cdot \sum_{j-1}^{n} cl_{s,i}^{(j)} > ls_s; 0, if else, \right. \quad (6)$$

where ls_s - sample level for the coordinates of the binary average implementation $cl_s \in CL_s^0$. (accepted value 1/2).

Step 3. The following conditions are checked: if $s \leq S$, there is a transition to the next step. Otherwise, you must return to the step 1.

Step 4. Splitting the set $\{cl_{s,i}\}$ into pairs of averaged realizations of the neighboring classes:

$$\Omega_s \langle cl_m, cl_c \rangle \quad (7)$$

Step 5. The learning step (h) is reset, and then its new initialization.

Step 6. Optimization of the class container radius CL_s^0 is performed. As a criterion of optimization there is accepted the container radius:

$$r_s^* = arg \max_{V_{CR} \cap \{h\}} \overline{CR}^h. \quad (8)$$

Step 7. The following conditions are checked: if $h < r(cl_s \oplus cl_c)$, then the value of the counter increases $(h := h + 1)$. Otherwise, the next step is performed.

Step 8. Calculate the information criterion of the workspace V_{CR}:

$$\overline{CR}^* = \max_{V_{CR} \cap \{h\}} \overline{CR}^h. \quad (9)$$

Step 9. The maximum learning step h^* is determined similar to δ^*. And besides, the control limits fields are determined, in accordance with the scheme 2.

We obtain: $L_{LC,i}^* = m - \delta^*$; $L_{HC,i}^* = m_i + \delta^*$.

After this step, the algorithm is terminated.

As it was mentioned above, the Shannon entropy measure and the Kullback Leibler information-distance criterion can be used as a criterion of the DSS learning effectiveness in the tasks of failure detection [16, 17]. For example, the Kullback-Leibler information-distance criterion will have the following form [14, 15, 17]:

$$CR_s^{(h)} = 0,5 \cdot log_2 \left(\frac{A_{1,s}^{(h)} + A_{2,s}^{(h)}}{\alpha_s^{(h)} + \beta_s^{(h)}} \right) \times \quad (10)$$

$$\times \left[(A_{1,s}^{(h)} + A_{2,s}^{(h)}) - (\alpha_s^{(h)} + \beta_s^{(h)}) \right],$$

where $\alpha_s^{(h)}$, $\beta_s^{(h)}$ - errors of the first and second kind, respectively; $A_{1,s}^{(h)}$, $A_{2,s}^{(h)}$ - first and second failure sign authenticity, respectively. Let note that, depending on the power of the recognition classes alphabet, there may be several working areas for defining a function $\overline{CR}^*$. In this case, h^* is determined in the working area where the global value of $\overline{CR}^*$ will be maximum.

Therefore, the parameters of the DSS machine learning algorithm for failure detection will be optimal: $\{r^*\}$, $\{cl^*\}$ and δ.

These parameters allow the creation of decision rules for DSS in the space of failure recognition signs.

V. EXPERIMENT

The formation of the training matrix should be implemented on different cycles of operation of the detected system (node or aggregate) of RWT. For example, as it was shown above (see clause 4.1 of the article), for classes CL_1^0, CL_2^0, CL_3^0, it is possible to perform the step of OUFL matrix formation by reading information from different sensors (see Fig. 1) with an interval of 200300 ms. As a result, each implementation will be about 3050 structured failure recognition signs of ETM (or another detectable system of RWT).

Since the failure recognition signs for different systems (nodes and aggregates) have different scales and units of measure, it is advisable to carry out the procedure of data normalization which the processed in the DSS. For example, normalization can be performed using the pivot scale method.

In order to assess the influence of the control limits system on the recognition sign in ADS, as well as on the effectiveness of machine learning, there was performed simulation modeling in the MATLAB environment, see fig. 3.

The fig. 3 a) shows a simulation scheme in MATLAB for the study of responses from temperature sensors. The fig. 3 b) shows the dependence of the information criterion of the working area V_{CR} on the recognition classes containers radius. In this article, the results are given only for the class CL_3^0 - increased temperature of the ETM windings. The results were obtained during the implementation of the basic machine learning algorithm.

The central area of the graph shown on Fig. 3b) in blue, is an area of reliable values of signs for a class CL_3^0 - increased temperature of ETM windings. The areas shown on Fig. 3b) in light green color, are located in the temperature sensors random values area. And these values are not entered into the training matrix of the failure detection system and in the DSS knowledge base for the tasks of diagnostics and detection of the states of the nodes and aggregates of the RWT.

Analysis of the data presented on Fig. 3 b shows that the obtained values of the information criterion (9) and (10) are quite sufficient, that allows with a high degree of confidence to speak about the effectiveness of the proposed algorithm for the self-trained system of functional control and detection of
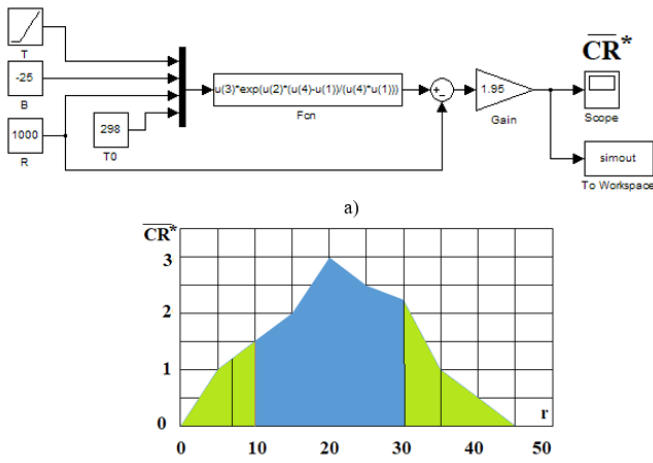
a)

Fig. 3. Simulation research of the algorithm for the self-trained system of functional control and state detection of the railway transport nodes (for example, temperature ETM sensors for electric locomotives, for a class CL_3^0 - increased temperature of ETM windings) a) - Simulation scheme in MATLAB for the study of responses from temperature sensors of the locomotive ETM

the state of railway transport nodes. The average value of $\overline{CR}^*$ is 2.5.

In order to create decision rules for DSS and ADS of failures in nodes and aggregates of RWT, it is necessary to determine additionally the optimal parameters of the recognition class containers. Further research will be devoted to this direction.

It should be noted that the control limits system optimization for ETM failure recognition signs will improve the effectiveness of machine learning of the automatic detection system of nodes and aggregates of RWT.

VI. DISCUSSION OF THE RESEARCH RESULTS

The developed model and algorithm for ADS, in our opinion, not only have an independent practical interest, but is an example of a new approach in the creation of adaptive NDC systems for diagnostics and detection of nodes and aggregates of RWT, including, HSRT.

In particular, in comparison with the results presented in [3, 4, 7, 1719], our approach provides a significantly smaller amount of necessary primary features for the classification of nodes and aggregates failures. In this case, it is possible to process data obtained from different NDC means, for example, vibration, thermal, 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 failure signs and anomalies implementations for the nodes and aggregates. This minimizes the participation of service personnel at the stage of identifying the primary failure signs, which, for example, previously could be detected using manual analysis of the NDC means indications.

Prospects for these researches are to create reliable training matrices and decision rules for other important systems, nodes and aggregates of RWT. This will allow in the future to maximize the data processing automation from the NDC systems

and to increase the degree of reliability of the decisions made at the stage of rolling stock failure detection. Therefore, in order to improve the efficiency of the proposed algorithm, it is advisable to increase the depth of machine learning by optimization of other learning parameters.

VII. CONCLUSION

There are proposed clarifications and additions to the method of machine learning of the automatic detection system (ADS) of the functional state of the electric traction motor (ETM). Additions to the method, as well as the corresponding model and machine learning algorithm, are implemented by parallel optimization of control limits for signs of ETM failures recognition. Such a solution allows in the future to create effective decision rules for intelligent decision support systems (IDSS) and ADS failures and for the state diagnostics of the nodes and aggregates of RWT.

It is shown that in such DSS and ADS there is possible a flexible procedure for correction of decision rules without changing the entire machine learning algorithm for ADS of important nodes of RWT.

The proposed refinements to the ADS learning machine learning method will allow the creation of adaptive self-training mechanisms for ADS nodes and aggregates of RWT, in particular, promising in Kazakhstan high-speed RWT systems.

It has been proposed to use the modified information condition of functional performance (ICFP) as an evaluation indicator of the effectiveness of learning ADS. This condition is based on the Kullback-Leibler information-distance criterion and the Shannon normalized entropy measure.

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