

The Use of Self-Learning Systems to Solve the Problems of Finding Failures on the Railway

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Abstract

The most frequent reason for the violation of the train schedule is the failure of the technical facilities of the infrastructure complex. The number and duration of train downtime and, as a result, the economic losses of Russian Railways depends on the time of search and elimination of failures. Today, failure search is carried out in an intuitive way. In practice, such a path leads to unnecessary time costs. In the study of methods for constructing algorithms, they were classified in terms of the possibility of constructing a model in which each step is a function of all previous steps and the functions cover the entire space of failures. We built these functions and described the generation model of such functions. Such a model for constructing functions can be applied to any technical branch. For the railway infrastructure, 6 functions were obtained. An automatic self-learning system has been developed, which is a multilayer neural network constructed according to a recurrence model. Based on this model, a hardware-software complex was implemented and tested.

1 Introduction

The share of railway freight turnover in the transport system of Russia is 45%, while the growth of freight traffic of Russian Railways continues, in 2018 it amounted to 2596.9 billion ton-kilometers. By order of the government dated March 19, 2019 No. 466-r, a long-term development program for Russian Railways until 2025 was approved, which provides for the transition to a digital railway. In accordance with this, the active development of technical diagnostic and monitoring systems (STDM) continues.

Technical diagnostics is the determination of the technical condition of an object [Efa12]. The object of railway automation and telemechanics can be in one of the following states [Efa12] (Figure 1):

- 1) Intact - this is the state of the facility, during which it meets all the requirements established in the normative and technical documentation for it.
- 2) Faulty - the state of the facility in which it does not meet at least one of the requirements established in the normative and technical documentation for it.
- 3) Workable - the state of an object in which the values of all parameters characterizing the ability to perform specified functions meet the requirements established in the regulatory and technical documentation for this object.

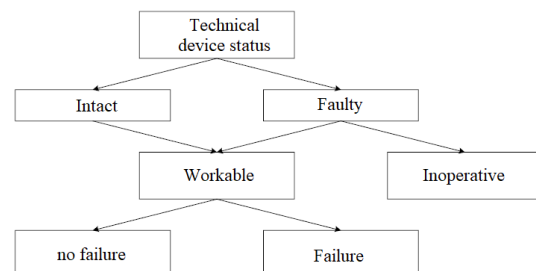


Figure 1. The technical condition of the facilities

4) Inoperative - a state in which the value of at least one of the parameters characterizing the ability to perform specified functions does not meet the requirements in the normative and technical documentation for this object.

5) Failure - the state of the object, characterized by an increased risk of its failure [Efa12, Boc12]. Failure - an event consisting in the violation of the operational state of the object. In the absence of logical analysis and analytical forecasting, a large

number of pre-failure conditions accumulate, since any minor changes in the diagnostic parameters (for example, voltage) are noted by the system [Kal09, Efa12] (Figure 2). The fixation of “false” pre-failure conditions can lead either to a failure, which can cause a violation of the safety and uninterrupted operation of trains, or to a “false” response of service personnel, which will lead to an increase in labor costs.

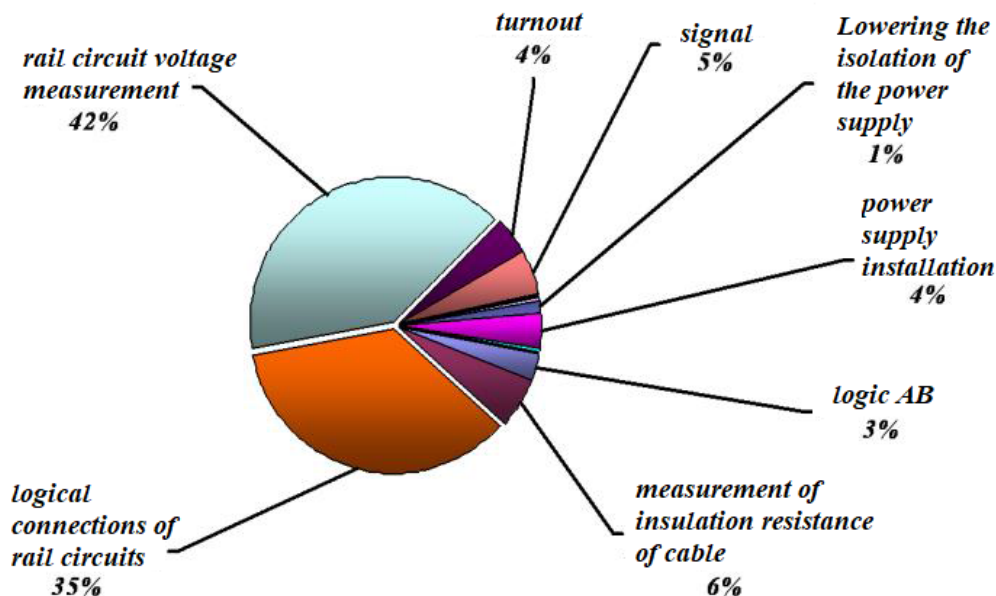


Figure 2. Distribution of pre-cancers resulting from STDM deficiencies

To improve quality and reduce troubleshooting time, monitoring systems for railway automation and telemechanics are being actively developed.

Directions for the development of technical diagnostics and monitoring of HEAT:

- 1) A full range of measurements.
- 2) Analysis of the operation of devices.
- 3) Forecast of changes in the status of devices.
- 4) Issuing service recommendations devices.
- 5) Coverage of all devices with diagnostic tools.

To date, the disadvantages of technical diagnosis include: - “manual” processing of diagnostic information, which leads to an increase in the time for its analysis and decision making; - lack of identification of the reasons for the failure; - lack of evidence-based methods for fixing pre-failure conditions; - lack of troubleshooting algorithms built into STDM; - lack of an optimal set of controlled diagnostic parameters, which leads to low reliability of determining the technical condition.

Therefore, expanding the functionality of systems for identifying the causes of failure, determining the optimal algorithm for troubleshooting and determining the optimal set of monitored parameters is an urgent task.

With an increase in cargo turnover, the throughput of railways should be increased, which requires serious resources. In 2018 alone, about 300 billion rubles were spent on the development of the railway infrastructure of Russian Railways. But all investments are leveled in cases of technical equipment failure.

The most common cause of train schedule disruptions is the failure of infrastructure facilities. The number and duration of train downtime and, as a consequence, the economic losses of Russian Railways depend on the search and elimination of failures.

To date, the search for failures is carried out intuitively. In practice, this way leads to unnecessary time costs.

2 Failure search process

The analysis of the revealed failures shows that their main reason is a violation of the technological process of operation (operational failures). Operational failures account for up to 86% of all failures of railway AT devices [Ana12, Ana09, Sap02]. According to statistics, most of the operational failures cause train delays.

Despite a number of measures to increase the reliability of railway AT devices, which include scheduled preventive maintenance, the organization of new maintenance methods [Aks09], and training of maintenance personnel rules and troubleshooting methods, the time to search for localization and troubleshooting remains relatively large.

The long time to find and eliminate the failure is explained by a number of objective and subjective factors. Objective factors include territorial dispersal, difficult access to some outdoor signaling devices, and sometimes lack of complete technical documentation. Subjective factors include the lack of experience and qualifications of the service personnel of the distance, the inability to read the schematic and wiring diagrams.

Reducing the influence of the human factor on the technological process is a necessary measure to

improve its quality, and this is only possible by increasing the level of its (technological process) automation.

The troubleshooting process takes place in the following sequence: After the failure information appears, preparatory steps for troubleshooting are started: identification of the failed device, collection and analysis of additional information, study of technical documentation, analysis of the train situation to localize the location of the failure and its nature, then collection of necessary tools and materials. Delivery of the employee to the place. Additional checks and elimination of the detected malfunction are carried out on site (Figure 3).

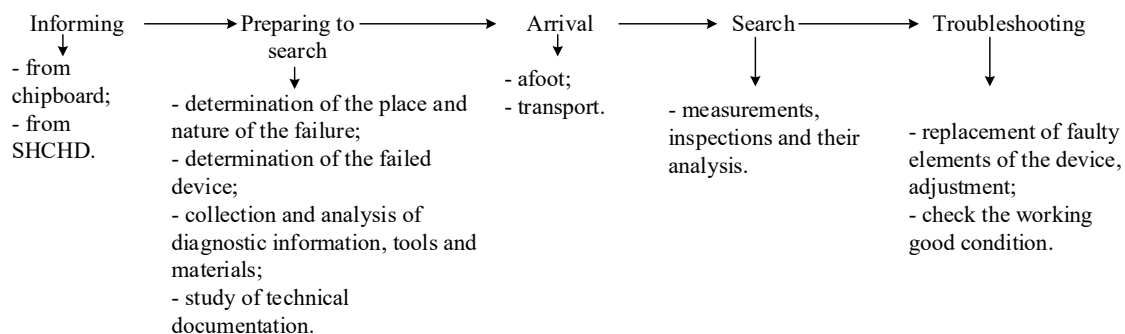


Figure 3. The process of recovering the operability of the device

But there are situations that an electrician has difficulty finding a malfunction, for example, he incorrectly localized the location of a malfunction search: he searches for a malfunction in the field when the malfunction is in the relay room. . In such situations, the role of automated algorithms is increasing, which systematize and structure troubleshooting.

Let us compare the recovery times of the function of operability of devices without and with automated algorithms for troubleshooting.

Average recovery time of TV function of operability of devices of railway automation and telemechanics systems in 1 region on the Moscow Railway:

$$T_v = topv + tav.p + tav.u + ttz = 40 \text{ min.}$$

where topv is the time of notification of a malfunction (1 min);

tav.p - average time for troubleshooting (20 min);

tav.u - average time for troubleshooting (9 min);

ttz - technical delay (10 min).

The development and implementation of automated troubleshooting algorithms minimizes the value of tav.p. when this time tends to a minimum, the ratio will take the following form:

$$T_v = topv + t's \text{ av.p} + tav.u + ttz = 29 \text{ min.}$$

t'av.p - troubleshooting time taking into account STDM (14 min). ttz - technical delay (5 min).

It is worth noting that the preparatory period is the longest from the beginning of the failure to its elimination. The safety and security of the railway transport depend on the knowledge and skills of the employee. Therefore, we have directed efforts to minimize the human factor.

The ideal model for eliminating the problem of Heinrich Saulovich Altshuller suggests that the problem should be eliminated by itself, automatically. To solve the problem in this way, automatic troubleshooting is implemented.

3 Failure search algorithm

There are 2 ways to compile a failure search algorithm [Bla19]:

1) to paint all possible algorithms and depending on the input data to give the optimal search path. Although there are a finite number of such algorithms, from a practical point of view it is large and such a path is not reasonable.

2) The second way is to build a dynamic, recurrent model, where each step will be a function of all previous steps. But to build such an algorithm for all cases is also not optimal. Therefore, we

classified all types of algorithms from the point of view: the possibility of constructing such functions and covering the functions of the entire failure space. We built these functions and described a model for generating such functions. For the railway infrastructure were obtained 6 functions. Such a model for constructing functions can be applied to any technical industry.

In general, classification methods [Dmi86, Zor07] can be attributed to the following types:

1. The linear classifier method.
2. The method of nonlinear classifier.
3. The method of constructing decision trees.

The linear classifier [Kal09] allows one to determine the linear dividing surface. In the case of two classes, such a surface is a hyperplane dividing the space of attributes into two half-spaces. Linear classifiers include the support vector method, Bayesian classifier, and other methods.

In the method of support vectors [Kly87, Par13], a set of training examples is proposed for each state, given as points in multidimensional space. These points form regions in space corresponding to different classes. The extreme points of a class are called reference points, and the distance between the two reference points is the length of the reference vector. It is required to find such a hyperplane that the length of the support vectors is maximal. For the application of this method requires that the classes were linearly separable among themselves. The disadvantage of the method is that it is suitable for solving the classification problem with only two linearly separable classes. To solve a problem with a large number of classes, the division of the problem into subtasks of classification according to the scheme "one-against-the-others" is used. It is necessary to solve the problem of combining the results.

The Bayesian classifier [Sap04] is a method based on the theorem stating that if the density of the distribution of each class is known, then the required algorithm can be written out in an explicit analytic form. For each of the classes, likelihood functions are defined, by which the a posteriori probabilities of the classes are calculated. The object belongs to the class for which the a posteriori probability is maximal. As a rule, in practice, the density of the distribution of classes are unknown, and they have to be collected from the training sample. Recovery is possible only with some sinfulness, and the smaller the training sample, the higher the probability of a retraining effect, when the method loses its generalizing properties and correctly classifies only the examples from the training sample. Also, the efficiency of the method drops sharply when there is an error in the hypotheses about the density of the class distribution.

Linear classifiers are effective for classification problems with two classes. To solve the

classification problem in the case of many classes, it is recommended to use nonlinear classifiers [Kru01], i.e. classifiers that use a nonlinear surface to separate classes. An example of such classifiers is a neural network.

A neural network is a distributed parallel processor consisting of interconnected elementary information processing units (neurons) that accumulate experimental knowledge for their subsequent processing [Kru07, Cal01]. Neurons are implemented by a nonlinear function of one argument-the weighted sum of all input signals. This function is called the activation function. The set of interconnected neurons determines the structure of the network and the tasks that the neural network is able to solve. The weights that characterize the strength of the connection between two neurons are called SYNOPTIC coefficients. The process of selecting SYNOPTIC coefficients is called network learning [Cal01, Hai06]. In the process of training, an array of input values (class attributes) is mapped to each class. Neural networks are able to generalize information obtained during training. Also, the advantage of using neural networks is the absence of the need to adjust the algorithms when changing the number or characteristics of classes. The disadvantage of using neural networks can be a large computational complexity [Sim94] when using complex network structures (for example, convolutional neural networks [Cal01, Hai06, Sim94]).

The method of constructing decision trees allows to construct a visual algorithm of object classification. The decision tree consists of nodes (also called vertices) and branches connecting the nodes. The very first node is called the root of the tree, and the extreme nodes are called leaves. Each vertex is mapped to some characteristic that describes the object, and the branches-the value area of this characteristic. The procedure for constructing a decision tree is an iterative process in which the sign that best satisfies a certain branching criterion is selected for the next vertex of the tree [Hai06]. The branching criterion is selected depending on the algorithm used. Popular algorithms for building a decision tree are ID3 [Hai06, Sim94] (or its improved version C4.5 [Hai06, Sim94]) and CART [Hai06, Sim94]. The difference between these algorithms is in the way the branching feature is selected. The advantage of decision trees is the visibility of the resulting model and the simplicity of its interpretation by a person. The disadvantage of the method is the problem of retraining, i.e. the possibility of constructing an excessively large tree that will not fully represent the data. There is also a need to build a tree from scratch (i.e. a complete change in the diagnostic algorithm) when changing the number of classes and the description of the input data.

Neural networks provide multi-class classification regardless of the linear time-separability of classes. In addition, neural networks are able to determine the presence of the analyzed example features of several classes. The effectiveness of neural networks for classifying the technical condition of devices is shown in [Zue12, Zue13]. Therefore, it was decided to apply the theory of neural networks for the development of methods and algorithms for fault detection.

In order to solve the classification problem with the help of a neural network, the network needs to be taught examples of different images. The training sample should include measures that fully describe the image. In practical problems, to achieve the most complete description of possible images in the training sample, it is necessary to collect a sufficient number of examples. Examples can be located in different parts of the corresponding image area in DK space.

To solve the problem of neural network training, there are many algorithms [Cal01, Hai06]. To train neural networks designed to solve the classification

problem, teacher training is used. The most popular algorithm for learning with a teacher is The backpropagation algorithm [Sim94], based on the gradient descent method on the hyperplane of the error function, and its modified version RProp [Cal01, Hai06, Sim94], which is one of the best first-order learning algorithms.

The process of recovering the operability of the device with an automatic self-learning system, which is a multi-layer neural network based on a recurrent model is presented in Figure 4)

As a result, we changed the Troubleshooting process. There was a unification of information flows, automated process of preparation for Troubleshooting, calculation and issuance of the optimal algorithm of actions.

In the course of elimination of failure there is an adjustment of the optimal algorithm at change of input data (by results of measurements, change of a train situation, the carried-out tests), recommendations are given, after elimination check of operability is carried out.

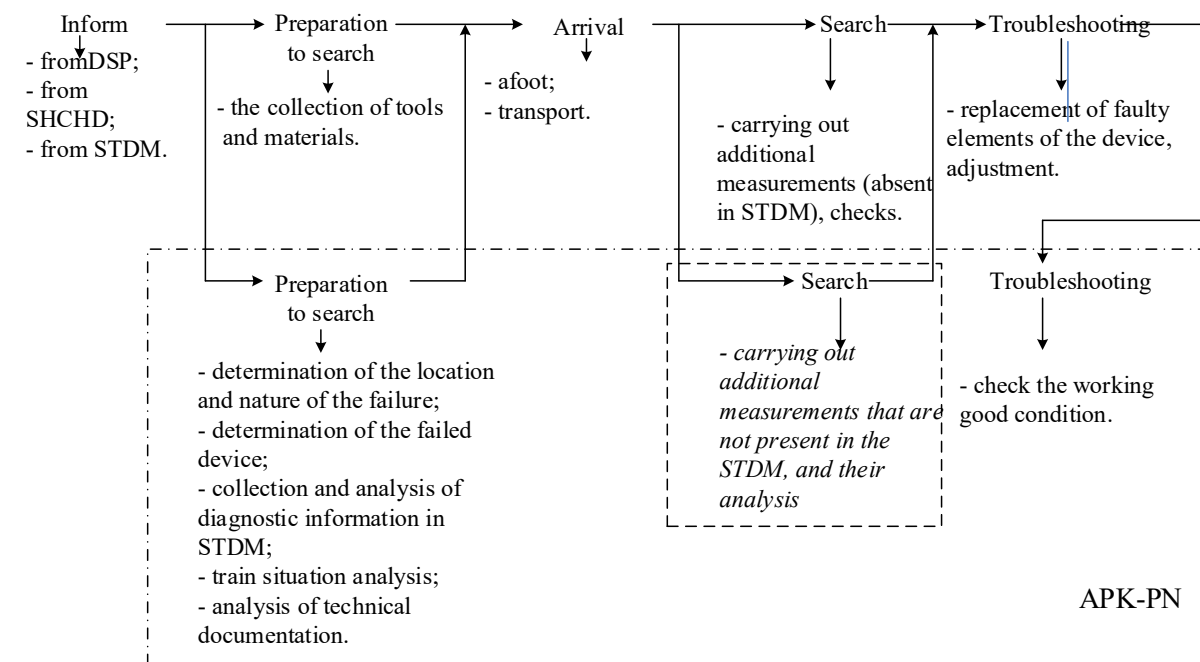


Figure 4. The process of recovering the operability of the device with an automatic self-learning system

4 Description of APK-PN system

The APK-PN system with a mobile measuring and software complex is designed for automatization of fault finding of JAT devices, logging of the fault finding process, checking the device operability after Troubleshooting and providing information to operational personnel. Implementation of APK-PN assumes achievement of the following results:

- reducing the recovery time of the device's working capacity;
- improvement of safety and continuity of trains;

- reduced operating costs;
- development of information exchange between adjacent offices.

The main objectives of creation of APK-PN are:

- reduced Troubleshooting time;
- reducing the number of train delays and their duration;
- reducing the impact of human factors on the Troubleshooting process;
- reducing the complexity of work to restore the operability of railway automation and telemechanics devices;

- reduction of "post-preventive" failures.

To automate the above operations, the APK-PN system provides:

- collection of information from STDM;
- download technical documentation from ARM-VTD;
- display the search algorithm of fault;
- selection of possible faulty elements on circuit diagrams and indication of additional measurement points;
- logging of the process of finding non-rightness;
- integration with existing control systems, interaction with ASU-SH2 databases.

On the basis of the above tasks and goals, we present the structure of the APK-PN system. System APK-PN includes subsystems:

- collection of information in STDM;
- downloads of technical documentation for the railway AT devices;
- analysis of diagnostic information from STDM and technical documentation from ARM-VTD;
- construction and display of the fault finding algorithm of the railway AT device, as well as the image of connection points for additional measurements and selection of the checked elements on the technical documentation (schematic diagram).
- check the operation of the railway AT device after troubleshooting;
- measurement of diagnostic parameters and their analysis.

Devices for which the APC-PN system implements the construction of fault finding algorithms:

- centralization of arrows and signals;
- track blocking;
- moving and barrage centralization;
- the formation and transmission of the signals of ALSN;
- other devices had been controlled by the STDM on the basis of the APK-DK.

On the basis of the General formulated requirements to system APK-PN the hierarchical principle of construction is chosen and two levels are allocated:

- linear data collection point (LPS), which is a mobile measurement and software system (level 1);
- the Central point of construction of algorithms for fault claim in the distances of signaling, centralization and blocking (level 2).

The hierarchical structure of the APC-PN system is shown in Figure 5.

At level 1, there are linear points for collecting additional diagnostic information (LPS), performing additional measurements of diagnostic parameters of the control object and receiving functions from the Central point of the fault finding algorithm.

In case of absence of technical documentation on the failed device, the standard scheme for the corresponding EC or AB system in which the device is operated is loaded.

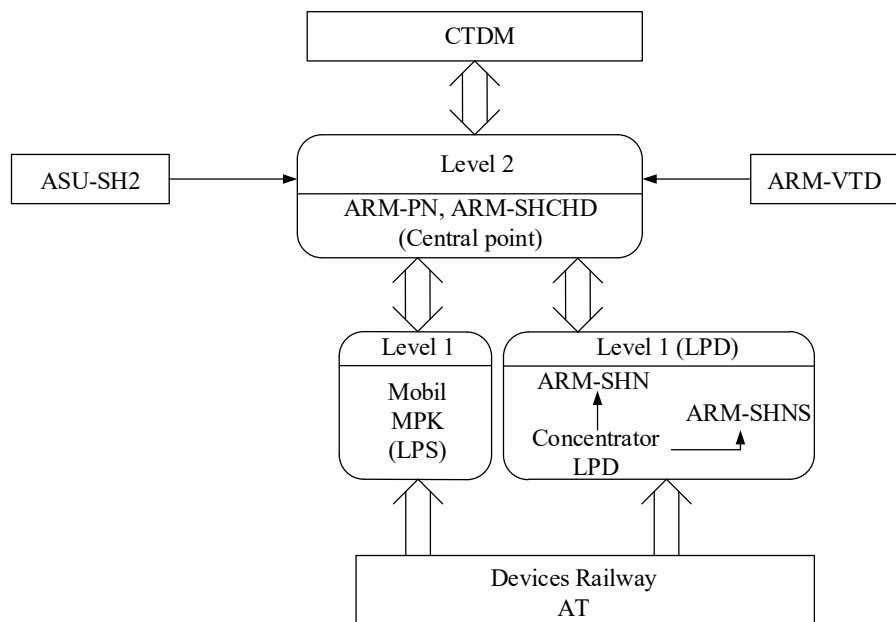


Figure 5. Block diagram of APK-PN

After receiving the full amount of information, the APK-PN begins synthesis of the algorithm for searching for faults on the basis of its knowledge base and a list of the minimum number of possible irregular elements in the sequence in which it is

necessary to carry out checks in order to reduce the search time is issued. In case of insufficient amount of diagnostic information to form a list of the minimum number of possible faulty elements, the APK-PN synthesizes an algorithm for additional

measurements of diagnostic parameters of the device to reduce the search area and identify the faulty element. It also provides for the selection of elements in the schematic diagrams of the device obtained from the ARM-VTD, which must be checked and the points of additional measurements are indicated.

Further, the generated list of the minimum number of possible faulty elements or the synthesized algorithm of additional measurements of diagnostic parameters of the device is transmitted to the linear point of STDM-ARM-SHN and to the linear point of information collection-mobile measuring and software complex. Additional measurements of diagnostic parameters of the device are carried out with the help of mobile measuring and software complex, and the analysis of measurement results is carried out. Based on the analysis of the measurement results, a list of possible faulty elements is formed. The results of the Troubleshooting are transmitted to the network printer, where the final Protocol is printed. Also, the information is transferred back to the workplace of the SHCHD, after which the information is entered into the database of ASU-SH2.

5 Conclusion

This APK is successfully used in the distance of the SCB on the October railway.

We will calculate the economic effect by reducing unplanned breaks in the movement of trains.

Savings by reducing downtime.:

$EP = Tskr \cdot G \cdot x \cdot Spp \cdot g + Tskr \cdot p \cdot x \cdot Spp \cdot p + tskr \cdot PR \cdot x \cdot Spp \cdot PR = 290,764$ rubles.

Calculation of savings by reducing the downtime of trains while reducing the time to search for failures in SCB devices

About 41.9% of all failures led to train delays, the number of failures $Notk / ZP = 255$.

The above costs associated with one stop of the train $SOP = 191$ rubles.

Saving train hours by reducing the time of elimination of failure by 27.5% $\Delta TP = 0.64$.

Reducing the number of delayed trains while reducing the time of elimination of failure by 27.5% $\Delta NP = 165$

Savings by reducing the downtime of trains while reducing the time to search for failures in the STB devices will be (one failure):

$EPO(1) = (Sppp + Sppg + Spppr) \cdot x \cdot T \cdot TP + SOP \cdot x \cdot \Delta NP = 36 \cdot 516$ RUB

For this calculation at $Notk/ZP = 255$ savings will be:

$EPO = Notk/ZP \cdot x \cdot EPO(1) = 9 \cdot 311 \cdot 570$ RUB.

Annual economic benefit:

$Eg = EP + EPO = 290 \cdot 764 + 9 \cdot 311 \cdot 570 = 9 \cdot 602 \cdot 333$ RUB.

References

- [Efa12] Efanov D. V. Bases of construction and principles of functioning of systems of technical diagnostics and monitoring of devices of railway automatics and telemechanics. / Efanov D. V., Lykov A. A. / - SPb.: St. Petersburg state University of Railways, 2012. - 59c.
- [Boc12] Bochkarev S. V. Identification of pre-failure States of railway automatics and telemechanics devices. / Bochkarev S. V., Lykov A. A. // Intellectual technologies at the TRANS-port: materials of the II international scientific and practical conference "Intellect TRANS-2012". - SPb. St. Petersburg state University of means of communication, 2012 - p. 82-88.
- [Kal09] Kalyavin V. p. Reliability and diagnostics of elements of electrical installations / Kalyavin V. P. Ry-Bakov L. M.: Textbook. //Mar.state UN-T.-Yoshkar-Ola-2009-p. 336.
- [Efa12] Efanov D. V. Continuous diagnostics of SCB devices / Efanov D. V., Plekhanov P. A. // Automation, communication, Informatics-2012-No. 7-p. 18-20.
- [Ana13] Analysis of the state of safety of trains, reliability of systems and REAPER devices in the economy of automation and mechanics in 2012. Moscow: JSC "Russian Railways", 2013-156 p.
- [Ana10] Analysis of the state of train safety, reliability of Reaper systems and DEVICES in the automation and telemechanics sector of JSC "Russian Railways" in 2009 to meet the requirements of the quality management system. Moscow: JSC "Russian Railways", 2010-156 p.
- [Sap02] Sapozhnikov V. V. Reliability of systems of self-road automation, telemechanics and communication / Sapozhnikov V. V., Sapozhnikov VL.V., Shamanov V. I. // Textbook for universities railway transport. First edition. Edited by VL.V. Sapozhnikov. - M., UMK Ministry of Railways of the Russian Federation, 2002. - pp. 285.
- [Aks09] Aksamentov N. N. The use of specialized vehicles in the distance. Automation, communication and Informatics. 2009-No. 1-pp. 48-50.
- [Dmi12] Dmitrienko I. E. Technical diagnostics and auto-control of railway automation and telemechanics systems. 2-ed., Rev. and extra M - Transport, 1986 - 144.

- [Zor07] Zorich V. A. "Mathematical analysis". Ed. Mtsnmo 2007.
- [Kal09] Kalyavin V. P. Reliability and diagnostics of elements of electrical installations/ Kalyavin V. P., Ry-Bakov L. M. / Textbook. //Mar.state UN-T.-Yoshkar-Ola-2009-p. 336.
- [Kly87] Klyueva V. V. Technical diagnostics. Volume 9 / Klyueva V. V., Parkhomenko P. P., // ed. - M.: Mashinostroenie, 1987.- 352c.
- [Par81] Parkhomenko P. p. Fundamentals of technical diagnostics: optimization of diagnosis algorithms, hardware / P. p. Parkhomenko, E. S. Soghomonyan. - Moscow: Energo-Atomizdat, 1981. - 320 PP.
- [Bla19] Blagoveshchenskaya E. A. Synthesis of models of automatic Troubleshooting of railway infrastructure./ Blagoveshchenskaya E. A., Bulavsky P. E., Gruzdev N. V. / Proceedings of the XXI International conference on computational mechanics and modern applied software systems' vmspps ' 2019), may 24-31, 2019, Alushta. - Moscow: MAI Publishing house, 2019. — 816 p.: II.
- [Sap04] Sapozhnikov, V. V. Fundamentals of technical diagnostics/ V. V. Sapozhnikov, Vol. V. Sapozhnikov. – M. : The Route, 2004. - 316 p. - ISBN 5-89035-123-0.
- [Kru01] Kruglov V. V. "Fuzzy logic and artificial neural networks" / Kruglov V. V., DLI M. I., Golunov R. Yu. // Ed. FIZMATLIT 2001.
- [Cal01] Callan R. Basic concepts of neural networks. - M.: Williams, 2001. - 288c.
- [Hai06] Haikin S. Neural networks. Full course. - M.: Williams, 2006. - 1104 PP.
- [Hai94] Simon Haykin "Neural Networks: a Comprehensive Foundation". 2-nd Edition. Ed. Mac-millan Coll Div, 1994.
- [Zue12] Zuev D. Solution of the problem of nonin-variance of using connectionist method for image recognition./ Zuev D., Bochkarev S. // Materials of the II international research and practice conference, Vol. I, Munich, December 18-19, 2012; Germany, 2012-650p 257-259 pp.
- [Zue13]. Zuev D. V. Analysis of diagnostic information/ Zuev D. V., Bochkarev S. V., Dmitriev V. V. // Automation, communication, Informatics. - 2013. - No. 9. - pp. 16-17.