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Original Study Article

The procedure for improving the management of the maintenance and repair process using the neural network technology

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ABSTRACT

BACKGROUND: Stable significant degree of wear of on-ground vehicles of transport industry and of agricultural machinery keeps improvement of maintenance management relevant. Development of the procedure for improving the maintenance process using state-of-the-art digital technologies is a relevant technical problem.

AIM: Determination of parameters for development of the procedure of making good managing decisions in the process of maintenance and repair of products in conditions of planned and preventive repair system using the neural network technology.

METHODS: Simulation of operation of the proposed neural network was performed in the Deductor software. The built model of the neural network contains one hidden layer with 10 neurons. A sigmoidal function was used as an activation function in neurons of the neural network model. Tools and definitions of mathematical statistics and algorithms theory were used for solving the given problems.

RESULTS: The cycle variation coefficient is proposed for revealing the necessity of managing impact on the processes of maintenance and repair of products. The proposed values of the coefficient describe stability of product maintenance and repair process. Using these values, the block diagram of the procedure of improving the maintenance process was developed. The tool of the industry 4.0 neural networks was considered. The performed simulation based on the example of vibrational diagnostics of a bearing unit showed that neural networks are capable of defining defects using amplitude-frequency response of a vibration signal that means to interpret the diagnostic information that can be crucial in conditions of expert absence.

The scientific novelty of the study lies in presenting the values of the cycle variation coefficient for making managing decisions in maintenance and repair processes, as well as in obtaining the results of simulation of the neural network operation that confirms potential for their use for interpretation of diagnostic information which is presented in a form of various spectrographs.

CONCLUSIONS: The practical value of the study lies in the potential of using the proposed neural network for development of the system of diagnostic information analysis in condition of expert absence and using the proposed values of the cycle variation coefficient for decision-making in management of maintenance and repair.

Keywords: maintenance; planned and preventive repair system; neural networks.

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Оригинальное исследование

Механизм совершенствования управления процессом технического обслуживания и ремонта с применением нейросетевой технологии

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АННОТАЦИЯ

Обоснование. Все еще остается значимой степень износа на сухопутном транспорте транспортной отрасли и в сельскохозяйственной технике, что подтверждает актуальность дальнейшего совершенствования организации технического сервиса. С этим связана технической задачи разработки механизма совершенствования процесса технического сервиса с использованием современных цифровых технологий.

Цель работы — определение параметров для разработки механизма принятия качественных управленческих решений в процессе технического обслуживания и ремонта изделий в условиях планово-предупредительной системы ремонта с применением технологии нейронных сетей.

Материалы и методы. Моделирование исследуемого процесса с помощью предлагаемой нейронной сети выполнено в программе Deductor. Построенная модель нейронной сети содержит один скрытый слой с 10 нейронами. В качестве функции активации в нейронах модели нейронной сети использовалась сигмоидная функция. Для решения поставленных задач применялись методы и понятия математической статистики и теории алгоритмов.

Результаты. Для выявления необходимости управленческого воздействия на процессы технического обслуживания и ремонта изделия предложен коэффициент вариации цикла. Предлагаются значения коэффициента, которые характеризуют стабильность процесса ремонта и технического обслуживания изделия. На основе этих значений представлена блок-схема механизма совершенствования процесса технического сервиса. Рассмотрен инструмент индустрии 4.0 — нейронные сети. Проведённое на примере вибродиагностики подшипникового узла моделирование показало, что нейронные сети могут распознавать дефекты по амплитудно-частотной характеристики вибросигнала, то есть интерпретировать диагностическую информацию, что может быть критично в условиях отсутствия эксперта. Научная новизна исследования заключается в представлении значений коэффициента вариации цикла для принятия управленческих решений в процессах технического обслуживания и ремонта, а также в получении результатов моделирования работы нейронной сети, которые подтвердили возможность их использования для интерпретации диагностической информации, предоставляющейся в виде различных спектрограмм.

Заключение. Практическая ценность исследования заключается в возможности использования предложенной нейронной сети для разработки системы анализа диагностической информации в условиях отсутствия экспертов и применении предлагаемых значений коэффициента вариации цикла для принятий решений в управлении техническим сервисом и ремонтом.

Ключевые слова: технический сервис; система планово-предупредительного ремонта; нейронные сети.

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BACKGROUND

Machine operability can be ensured by improving the physical and mechanical properties of materials and the design of parts, timely and high-quality technical service, and, which is equally important, through high-quality repairs.

In conditions of high wear of equipment, the maintenance and repair system must be improved. One of the options for ensuring the quality of maintenance and repair is improvement of the organization's technical service management system. Using modern diagnostic systems can also ensure timely detection of defects in components and mechanisms. Not all enterprises with these systems may have qualified specialists who can analyze correctly the diagnostic information, a solution to which may be the use of modern digital technologies.

It is worth noting that in Russia, there are two types of maintenance and repair systems, namely, the traditional system of planned preventive maintenance [1–4] and the system of maintenance based on technical condition [5–8].

This study aimed to determine the parameters for developing a mechanism for making quality management decisions in the process of technical maintenance and repair of products under conditions of a planned preventive repair system using neural network technology.

The research was aimed at solving the following problems:

- determination of the general aspects or principles of implementation of a repair system for technical objects for various purposes;
- identification of a parameter for assessing the impact of management influences on the process of maintenance and repair;
- analysis of the application of neural network technology in technical diagnostics;
- development of a mechanism for improving the technical service process.

ANALYSIS OF THE STATE OF THE ART

The system of planned preventive maintenance involves the implementation of maintenance or repair of transport, technological, and industrial equipment at certain intervals of calendar time or operating time.

The alternation and frequency of technical maintenance and repairs based on the national standard GOST R 20793–2009 "Tractors and Agricultural Machines. Maintenance" are displayed in Fig. 1.

The types of car and tractor maintenance are almost the same. However, the period for routine repairs of tractors is not determined by the frequency of mileage; they are performed when necessary and combined with the next maintenance.

For example, the maintenance of agricultural machinery includes scheduled maintenance and overhaul and daily maintenance, maintenance No. 1 (M-1), maintenance No. 2 (M-2), and maintenance No. 3 (M-3).

Maintenance of agricultural machines is characterized by the fact that due to the short period of use of certain machines, some types of maintenance are not conducted. For example, self-propelled agricultural machines are limited to M-2, complex machines coupled with a tractor are limited to M-1, and simple machines (plows, tooth harrows, cultivators for broadcast tillage) are subject to only monthly maintenance. Meanwhile, all other types of maintenance and repairs are performed during the storage period.

The frequency of vehicle maintenance is determined by mileage and varies depending on operating conditions.

Data from the national standard GOST R 21624–81 "System for maintenance and repair of automotive equipment. Requirements for operational manufacturability

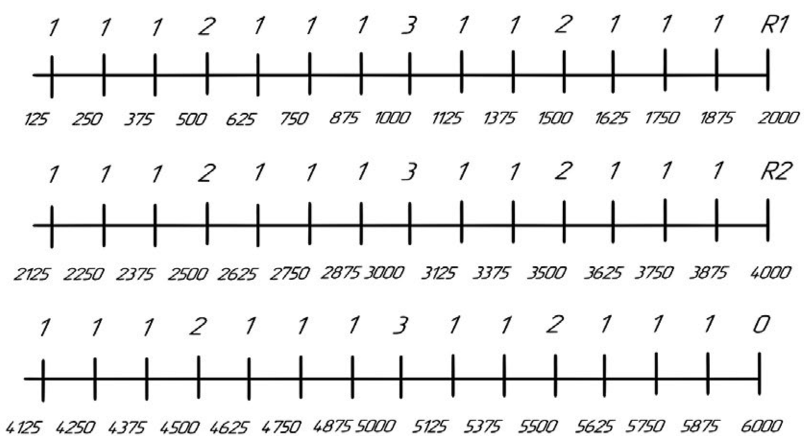

Рис. 1. Шкала периодичности и чередования технического обслуживания и ремонтов тракторов: *1* — ТО-1; *2* — ТО-2; *3* — ТО-3.
Fig. 1. Scale of frequency and sequence of maintenance and repairs of tractors: *1* — TM-1; *2* — TM-2; *3* — TM-3.

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and maintainability of products" for Central Russia and the frequency of maintenance are summarized in Table 1.

Thus, it is typical for a planned preventive repair system to assign equal intervals between maintenance (repairs), which can vary for different objects depending on the intensity and operating conditions.

The Federal State Statistics Service's "Transport of Russia. Information and statistical bulletin" noted the average wear in land transport of the transport industry of the Russian Federation to be 41.9%, while the "Industrial Production in Russia" indicated the wear value for 2021 for fixed assets of manufacturing production to be approximately 51%. These wear values are significant; therefore, improving the organization of technical service currently remains relevant. In addition, a number of factors can influence the technical condition, namely, wear of machinery and equipment [9] and the lack of qualified repair personnel in organizations in various industries [10, 11].

In addition, ensuring the trouble-free performance of products by their functions is especially important for industries such as transport and agricultural machinery. The main tasks of transport include qualitative satisfaction of the needs of the national economy and population for transportation, and agricultural machinery must ensure the timely completion of certain work. For example, for agricultural organizations, there is a risk of crop loss, and to prevent this, the crop must be harvested at a strictly defined time.

Thus, we can highlight the general principles of functioning of the planned preventive repair system for such types of equipment as industrial equipment, transport, and agricultural machines, and there is an appointment of maintenance and repair periods at equal intervals of time or operating time. It is worth noting that improvement of technical service is possible by ensuring the quality of management of this process.

Table 1. Frequency of maintenance types
Таблица 1. Периодичность видов технического обслуживания

Product type	**Maintenance frequency**			
	Daily maintenance	**M-1**	**M-2**	**Maintenance according to vehicle log books**
		km, no less		
Light motor vehicles	Once a working day, regardless of the number of work shifts	5000	20000	10000
Buses		5000	20000	
Trucks, buses based on trucks or using their main units		4000	16000	
Trailers and semitrailers		4000	16000	
All-wheel drive vehicles		4000	16000	

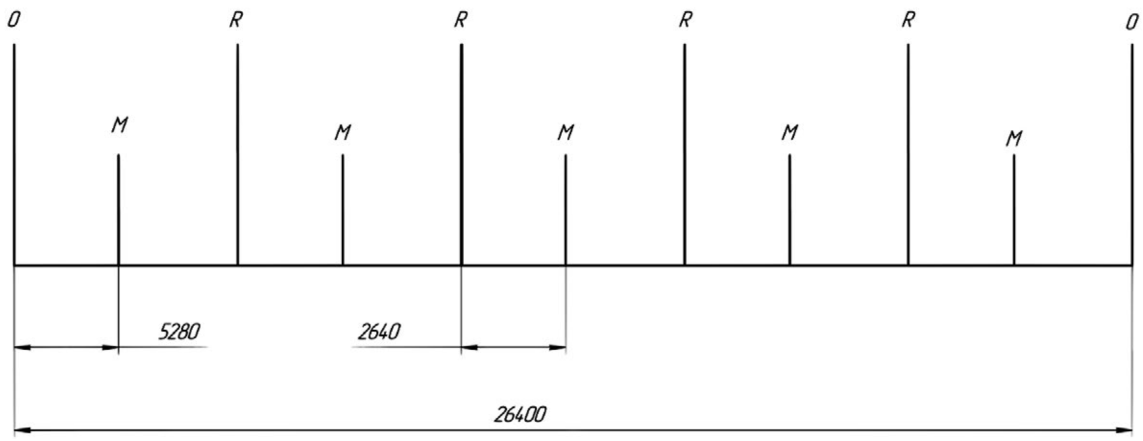

Fig. 2. Diagram of the repair cycle of the 1A616 machine: *R* — repair; *O* — overhaul; *M* — maintenance.
Рис. 2. Диаграмма ремонтного цикла станка 1A616: *R* — ремонт; *O* — капитальный ремонт; *M* — техническое обслуживание.

PROBLEM SOLUTION

The review and analysis of literature sources showed that in the process of maintenance and repair, certain management decisions can be made, namely, searching for a provider of maintenance and repair services, determining the timing of maintenance and repairs, and determining the equipment for repair.

The national standard GOST R 18322–2016 "Equipment maintenance and repair system" adopts the concept of "maintenance (repair) cycle" as the smallest repeating interval of time or running time of an object, during which all established types of periodic maintenance (repair) are performed in a certain sequence based on documentation requirements, and the concept of "frequency of maintenance (repair)" as the time interval, or running time, between a given type of maintenance (repair) and the subsequent one of the same type or another type of greater complexity.

For tractors, their maintenance cycle is assumed to be 125 engine hours and the frequency of M-2 is 500 engine hours; for motor cars, the maintenance cycle is 5000 km and the frequency of M-2 is 20,000 km; for equipment (taking the 1A616 machine as an example), the maintenance (repair) cycle is 2640 h of operation (Fig. 1, 2).

The coefficient of variation of the maintenance (repair) cycle to assess the effect of management influences on the process of maintenance and repair [12]:

$$C_v = \frac{\sigma}{\mu}, \tag{1}$$

where σ is the root-mean-square (standard) deviation of the actual values of the time interval (running time) between stops for maintenance (repairs, including unplanned ones) and μ is the average value of the time interval (running time) between the product outage for maintenance (repairs, including unplanned ones).

According to mathematical statistics and process control theory [13, 14], if the coefficient of variation is less than 10%, then the degree of data diffusion is insignificant and the process under study can be considered stable and controllable; at 10%–25%, the degree of data diffusion is average, the process has some deviations in the parameter(s); at values greater than 25%, the degree of data diffusion is large and the process has a significant scatter in parameters, is unstable, and uncontrollable. In accordance with these judgments, the following ranges of values of the parameter under consideration are proposed (Fig. 3):

- $0 < C_v < 10$ for group of products, %, which is characterized by good technical condition, almost all repairs are performed on schedule, minor fluctuations in the coefficient can be associated with various production tasks and operating conditions;
- $10 < C_v < 25$ for a group of products, %, which is characterized by random failures, if they lead to significant losses in production, performance of the main functions of the product, then an analysis of these causes should be performed, followed by a possible search for other technical service providers;
- $C_v > 25$ for a group of products, %, which is characterized by poor technical condition, which leads to significant losses and the need to analyze the causes of these failures.

Thus, the parameter under consideration in the conditions of a planned preventive repair system allows identifying areas of the maintenance and repair process where management actions are necessary. If the values exceed 10% with significant losses for repairs or exceed 25%, we propose searching for the causes of failures and, on its basis, selecting a technical service provider and improving the personnel competence.

Note that this coefficient may vary slightly due to production needs, but for significant shifts, a large value of the dispersion coefficient will occur during unplanned shutdowns associated with recovery from an unexpected product failure.

MECHANISM FOR IMPROVING THE TECHNICAL SERVICE PROCESS USING NEURAL NETWORK TECHNOLOGY

Let us consider Industry 4.0, i.e., neural networks that can learn based on the data provided and generalize them. Neural network-based software products can replace experts and specialists in their absence in various areas of management and provide decision support.

At certain values of the V_c parameter proposed in this article in technical service management, a decision can be made to "search for a technical service provider."

Previous studies [15, 16] presented the possibility of using neural network-based algorithms to assess the level of reliability of technical service providers and their assessment based on reviews on the internet [16]. These algorithms can be used as an additional tool in making decisions regarding supplier selection. Thus, neural networks can select appropriate suppliers based on indicators such as time of presence on the market, the ratio of positive and negative reviews, etc. To test the ability of neural networks to analyze positive and negative reviews on the internet, a separate study was performed on reviews of car maintenance services organizations with a neural network created using Python. Its training involved using expressions from these reviews. This neural network displayed high-quality work with a large array of data on reviews of car maintenance companies, which is currently one of the ways to obtain characteristics of service providers.

Previous works [18–23] analyzed the operation of neural networks with graphical information aiming

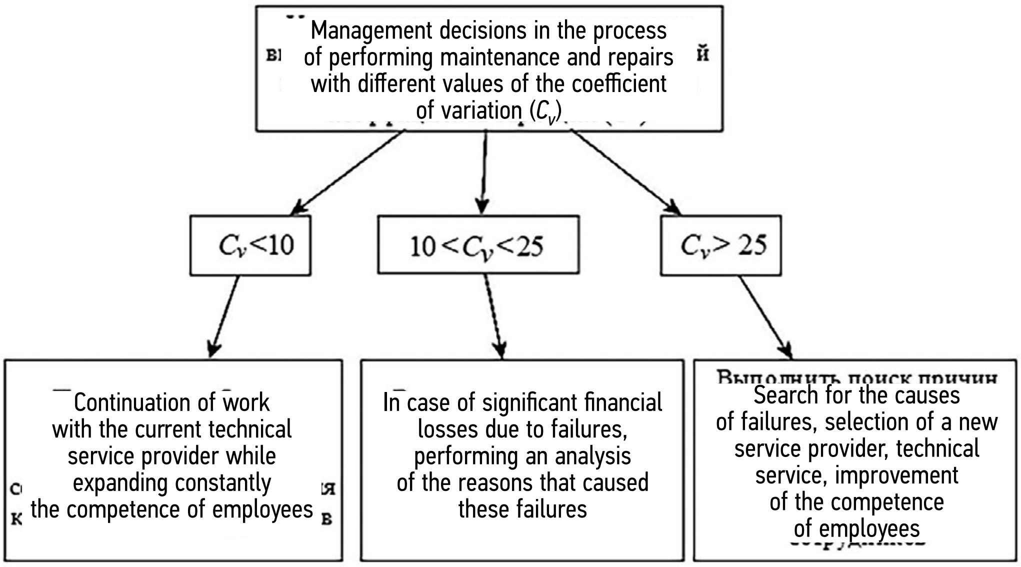

Fig. 3. Block diagram of the application of the maintenance (repair) cycle variation coefficient in process management.
Рис. 3. Блок-схема применения коэффициента вариации цикла технического обслуживания (ремонта) в управлении процессом.

at application in technical diagnostics. For example, when diagnosing an engine using a motor tester, oscillograms are obtained [20], using which a neural network can determine defects [20, 22].

Also, I.V. Karakulov [18] reported the results of vibration diagnostics of pumping equipment obtained in the form of vibration–velocity spectrograms. Their information was stored in graphic files. The author developed and prepared neural networks based on these data. Overall, good accuracy was achieved in recognizing the technical condition using a neural network according to the classification of satisfactory, acceptable, and unacceptable. The neural network in this simulation analyzed graphical information (vibration–velocity spectrograms). A.E. Yablokov [22] conducted an experiment in the Matlab environment to study the ability of neural networks to operate with graphical information that carries data on the technical condition of an object and obtained vibration diagnostic results for various conditions of gear units. He concluded that the neural network recognized the states of gears from images saved in files of 781 × 781 pix with 95% accuracy.

Another group of researchers [23] obtained the results of vibration diagnostics of bearings with various technical conditions and developed a neural network-based algorithm to analyze spectrograms, showing the ability to determine correctly the technical condition of bearings from graphical information with 75%–80% precision.

Research data and many other similar experiments allows drawing a conclusion on the possibility of using neural network technology as a tool for using complex diagnostic equipment, including in the absence of an expert.

Thus, it becomes possible to use expensive, complex equipment in the absence of experts.

To simulate the process of defect recognition, we consider the example of vibration diagnostics of rolling bearings. Bearing defects may include wear on the surface of the outer and inner rings and rolling elements. There may be defects in the installation of rolling bearings and lubrication defects. All of them are diagnosed by vibration diagnostic methods when, depending on the defect, they manifest themselves in the form of increased amplitude at a certain frequency.

Let us consider the 6226-2RS TIMKEN bearing, which is used in various mechanisms and industrial equipment. Using known dependencies [24], we construct a frequency map of the occurrence of defects.

Table 2 summarizes $F_{dnk}(F1)$ (which is the frequency at which the defects in the bearing outer ring appear with increased vibration amplitude), $F_{dvk}(F2)$ (the frequency at which the defects in the bearing inner ring appear with increased vibration amplitude), $F_s(F3)$ (the frequency at which the defects in the bearing separator appear with increased vibration amplitude), and $F_m(F5)$ (the frequency at which an installation defect manifests itself with increased vibration amplitude). For inhomogeneous radial interference, f_p is the rotation speed of the shaft or inner ring of the bearing, z is the number of rolling elements, d is the inner diameter of the bearing, and D is the outer diameter of the bearing.

To create a data set for preparing a neural network, the rotation speed f_p is assumed to be 1200 rpm or 20 Hz. Then the defects from Table 2 will create increased amplitude at the following frequencies for a given bearing (Table 3).

Based on the dependencies presented in Table 2, we will create a data set for preparing a neural network. In this set,

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the highest amplitude values will be at frequencies that correspond to certain defects, if any exists (Table 2). At other frequencies, it will simulate amplitudes with a value of approximately 30% of the peak values.

The data set in this case represents a collection of input vectors, while the output vectors correspond to them. Each input vector *X* is in turn referred to the input of the neural network, and its output is compared with a given output vector *D* paired with an input vector, after which the parameters of the neural network are adjusted in such a way as to reduce the difference between the actual and required output of the network.

The input vector will be formed from the frequencies with the largest amplitudes. The output vector in this case will be a vector with four defects, in which the frequencies from Table 2, corresponding to these defects, will have the largest amplitudes.

A fragment of the input signal matrix is listed in Table 4.

Accordingly, each set (row) of amplitudes at certain frequencies can correspond to a specific defect, and a matrix of output vectors can be obtained (Table 5).

Based on a matrix of input signals containing 200 records, a neural network was prepared in the Deductor software package. Meanwhile, when modeling the neural network, the following designations of types of defects were used: outer ring defect — DNK; inner ring defect — DVK; separator defect — DS; nonuniform radial interference — NRN. Thus, a neural network model was developed, which contains 2 hidden layers of 9 neurons in layer 1 and 10 neurons in layer 2. The graph of this network is illustrated in Fig. 4. The sigmoid function was used as the activation function [12, 15].

The developed neural network recognized correctly the type of defect from the matrix of input signals and was also able to recognize the defect from the new values of the input signals. The simulation confirmed that neural networks can classify or recognize a defect based on the amplitude–frequency characteristics of the vibration signal obtained through vibration diagnostics.

Their ability to recognize defects expands the possibility of using complex diagnostic equipment in the absence of experts. Let us present the mechanism for improving the technical service process in Fig. 5.

In this mechanism, ensuring the quality of management decisions in the process of maintenance and repair is achieved by using the variation parameter of the maintenance (repair) cycle and a software product based on a neural network, as well as neural network technology in technical diagnostics [25, 26].

Table 2. Frequency map of defects of the type 6226-2RS TIMKEN bearing
Таблица 2. Частотная карта дефектов подшипников типа 6226-2RS TIMKEN

Wear defects	Frequency formula (sign of defect)	Value, Hz
Wear defects		
Outer ring defect	$F_{\text{днк}} = \frac{f_{\text{р}} z}{2}\left(1 - \frac{d}{D}\right)$	$F1 = 2.64 f_p$
Inner ring defect	$F_{\text{двк}} = \frac{f_{\text{р}} z}{2}\left(1 + \frac{d}{D}\right)$	$F2 = 9.36 f_p$
Separator defect	$F_{\text{с}} = \frac{f_{\text{р}}}{2}\left(1 - \frac{d}{D}\right)$	$F3 = 0{,}22 f_p$
Installation defects		
Nonuniform radial interference	$F_m = 1{,}5 f_p$	$F_5 = 1{,}5 * f_p$

Table 3. Frequency of appearing of defects at f_p = 20 Hz for the 6226-2RS TIMKEN bearing
Таблица 3. Частоты проявления дефектов при f_p = 20 Гц для подшипника 6226-2RS TIMKEN

Type of defect	Frequency of defect appearance during vibration diagnostics Hz (f_p = 20 Гц)
Wear defects	
Outer ring defect	50
Inner ring defect	200
Separator defect:	5
Installation defects	
Nonuniform radial interference	30

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CONCLUSION

Based on the analysis of planned preventive repair systems for various types of agricultural machinery, vehicles, and industrial equipment, the following conclusions can be drawn:

- For all studied types of equipment, equal intervals of operating time or running time are assigned between the same types of maintenance and repair. To identify the need for managerial influence on the processes of maintenance and repair of a product, a cycle variation coefficient is proposed, which is determined by the values of time intervals (running time) between equipment outage for maintenance (repairs, including unplanned repair). Coefficient values are proposed that characterize the stability of the product repair and maintenance process. In case of instability of the maintenance and repair process, we proposed searching for the causes of failures and, on its basis, selecting a new technical

Table 4. Fragment of the matrix of input signals
Таблица 4. Фрагмент матрицы входных сигналов

	5	30	50	70	90	100	125	150	200
1	10	3	4	2	3	3	4	4	3
2	4	3	11	5	3	4	4	5	3
3	5	15	4	3	5	4	3	4	5
4	5	4	6	5	6	3	5	6	20
5	12	4	5	4	5	3	5	4	3
6	15	5	4	3	3	4	4	5	5
7	4	15	4	4	4	3	5	5	5
8	5	16	5	4	4	3	4	5	3
9	5	4	12	3	5	5	4	4	5
10	4	5	15	3	5	4	5	3	5
11	5	5	3	4	5	4	3	5	15
12	3	3	3	4	2	2	4	3	10

Table 5. Matrix of output vectors of types of defects
Таблица 5. Матрица выходных векторов видов дефектов

	Outer ring defect	Inner ring defect	Separator defect	Nonuniform radial interference
1	0	0	1	0
2	1	0	0	0
3	0	0	0	1
4	0	1	0	0
5	0	0	1	0
6	0	0	1	0
7	0	0	0	1
8	0	0	0	1
9	1	0	0	0
10	1	0	0	0
11	0	1	0	0
12	0	1	0	0

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service provider and improving the competence of the employees.

- It is demonstrated that the ability of neural networks to interpret graphical information allows using them in technical diagnostics at the stage of analyzing diagnostic information, which in turn leads to the use of complex diagnostic equipment in the absence of experts.
- Input signal matrices have been developed to elaborate a neural network model based on the known amplitude–frequency characteristics of vibration of bearings for various defects. The simulation confirmed the ability of the neural network to classify the type of defect based on the amplitude–frequency characteristics of the vibration signal. In our opinion, neural networks can recognize a defect based on the results of other diagnostic methods that provide diagnostic information in the form of various spectrograms. The constructed neural network model comprises 1 hidden layer with 10 neurons, layer 1 with 9 inputs, and an output layer with 4 outputs. The sigmoid function was used as the activation function in the neurons of the neural network model.
- Therefore, a mechanism for improving the technical service process is proposed, which includes assessment of the stability of the maintenance and repair process. Based on this assessment, management decisions are made for the maintenance and repair process. The mechanism also includes the use of neural network technology to conduct technical diagnostics and support decision-making in searching for a supplier providing repair services.

ADDITIONAL INFORMATION

Authors' contribution. A.V. Shimokhin — search for publications on the topic of the article, writing the text of the manuscript, creating images; O.M. Kirasirov — editing the text of the manuscript, expert opinion, approval of the final version. The authors confirm that their authorship complies with the international ICMJE criteria (all authors made a significant contribution to the development of the concept, research and preparation of the article, read and approved the final version before publication).

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ДОПОЛНИТЕЛЬНО

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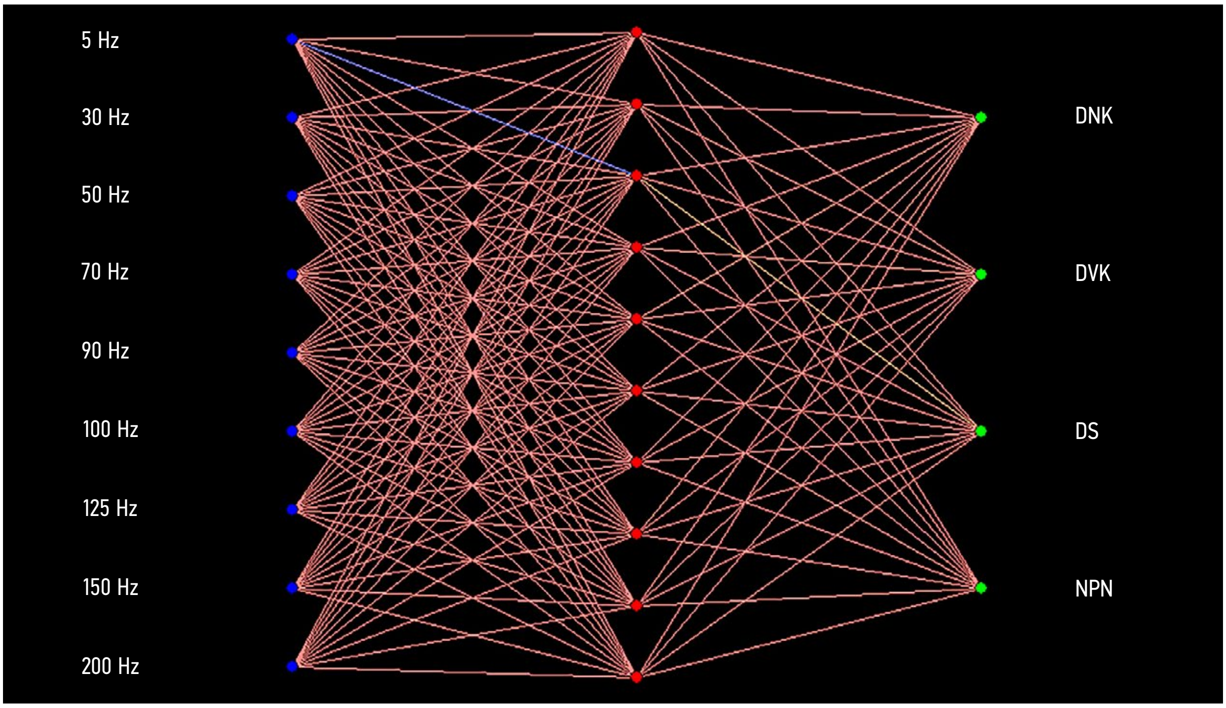

Fig. 4. Graph of the developed neural network.
Рис. 4. Граф разработанной нейронной сети.

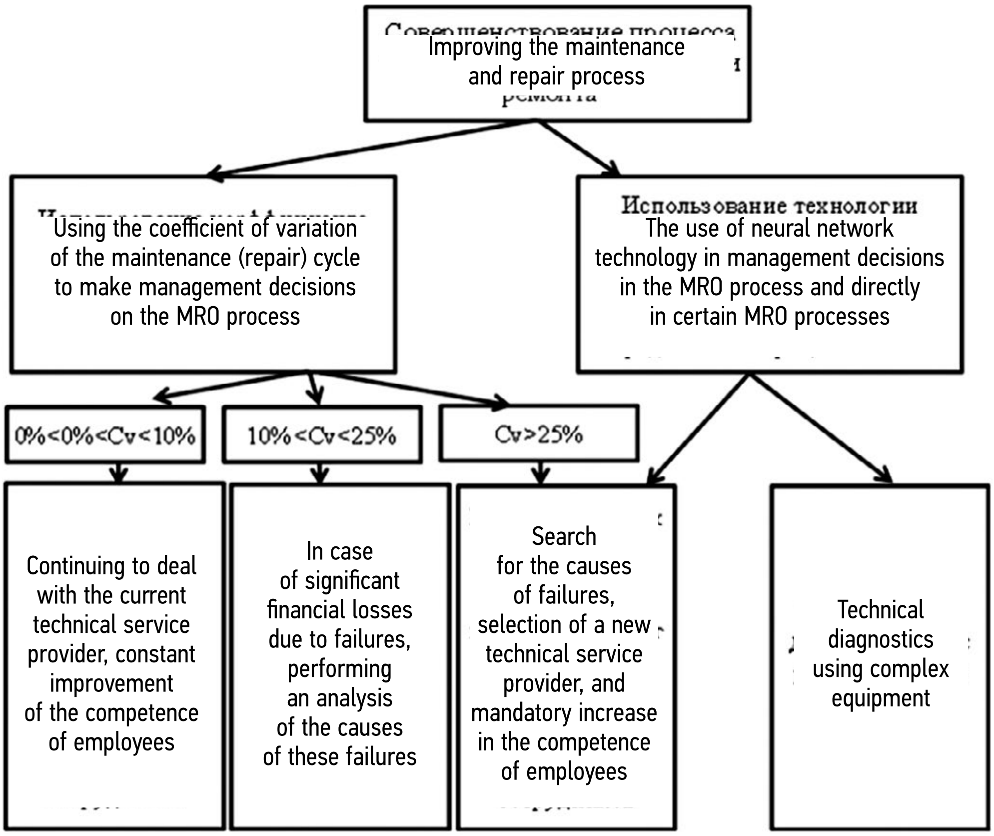

Fig. 5. Block diagram of the procedure for improving the maintenance process.
Рис. 5. Блок-схема механизма совершенствования процесса технического сервиса.

авторства международным критериям *ICMJE* (все авторы внесли существенный вклад в разработку концепции, проведение исследования и подготовку статьи, прочли и одобрили финальную версию перед публикацией).

Конфликт интересов. Авторы декларируют отсутствие явных и потенциальных конфликтов интересов, связанных с публикацией настоящей статьи.
Источник финансирования. Авторы заявляют об отсутствии внешнего финансирования при проведении исследования.

REFERENCES

1. Myalo OV, Myalo VV, Prokopov SP. Theoretical substantiation of machine-tractor fleet technical maintenance system on the example of Omsk region agricultural enterprises. *J. Phys.: Conf. Ser.* 2018;1059:012005. doi: 10.1088/1742-6596/1059/1/012005
2. Myalo OV, Prokopov SP. Material and technical support of the enterprises of the agro-industrial complex of the Omsk region management and certification of the technical component of the production processes in crop production. *J. Phys.: Conf. Ser.* 2019;582(1):012028. doi: 10.1088/1757-899X/582/1/012028
3. Iovlev GA, Pobedinsky VV, Goldina II. Economic justification for the optimal terms of use and frequency of maintenance and repair of machines. *Vestnik NGIEI.* 2021;4(119):105–119. (In Russ.) doi: 10.24412/2227-9407-2021-4-105-119
4. Toygambaev SK, Didmanidze ON. Features of the development of the technological process for maintaining tractors in the farm's machine and tractor fleet. *Vestnik Kurganskoy GSKhA.* 2021;1(37):74–80. (In Russ.) doi: 10.52463/22274227_2021_37_74
5. Kupriyanova TM, Rastimeshin VE. *TRM system: more than a quarter of a century in Russia. Japanese theory. Russian practice. Experience of the TAIR Consulting Community.* Moscow: Buki Vedi; 2019. (In Russ.)
6. Ichikawa A, Takagi I, Takebe Y, et al. *TPM in a simple and accessible presentation.* Moscow: Standarty i kachestvo; 2008. (In Russ.)
7. Akhtulov AL, Ivanova LA, Charushina EB. Measuring the effectiveness of the quality management system as a tool for improving the organization's activities. *IOP Conf. Ser.: Mater. Sci. Eng.* 2019;537:042059. doi: 10.1088/1757-899X/537/4/042059
8. Akhtulov AL, Ivanova LA, Charushina EB. Analysis of the formation and evaluation of performance indicators and efficiency of the organization's management system processes. *J. Phys.: Conf. Ser.* 2020;1515:052032. doi: 10.1088/1742-6596/1515/5/052032

9. Redreev GV, Okunev GA, Voinash SA. Efficiency of Usage of Transport and Technological Machines. In: *Radionov A., Kravchenko O., Guzeev V., et al. (eds) Proceedings of the 5th International Conference on Industrial Engineering (ICIE 2019). ICIE 2019. Lecture Notes in Mechanical Engineering.* Cham: Springer; 2020:625–631. doi: 10.1007/978-3-030-22063-1_6

10. Shaikhov RF. Control of production personnel at a motor transport enterprise. *Transport. Transportnye sooruzheniya. Ekologiya.* 2019;3:89–95. (In Russ.) doi: 10.15593/24111678/2019.03.11

11. Maltsev DV, Repetsky DS. Control of production personnel when performing vehicle maintenance work. *Mir transporta.* 2020;18(6(91)):238–247. (In Russ.) doi: 10.30932/1992-3252-2020-18-6-238-247

12. Shimokhin AV. Mechanism for transferring a business process of an industrial enterprise to outsourcing. *Nauchnyy zhurnal NIU ITMO. Seriya «Ekonomika i ekologicheskiy menedzhment».* 2019;1:45–51. (In Russ.) doi: 10.17586/2310-1172-2019-12-1-45-51

13. Baranova EM, Baranov AN, Borzenkova SYu, et al. Study of information systems efficiency indicators using the STATISTICA program. *Izvestiya Tulskogo gosudarstvennogo universiteta. Tekhnicheskie nauki.* 2022;10:199–205. (In Russ.) doi: 10.24412/2071-6168-2022-10-199-205

14. Karimova VA, Mukhitdinova ML. Modeling processes for managing and forecasting inventories at an enterprise. *Nauka i mir.* 2019;5–2(69):33–36. (In Russ.)

15. Shimokhin AV. Semantic analysis of reviews about suppliers based on the use of neural network technology. *Fundamentalnye issledovaniya.* 2021;5:117–121. (In Russ.) doi: 10.17513/fr.43048

16. Myalo OV. Mathematical Modeling and Information Technologies in the Management of Tractor Maintenance Operations. *IOP Conf. Ser.: Mater. Sci. Eng.* 2019;582:012014. doi: 10.1088/1757-899X/582/1/012014

17. Rubtsova YuV. A neural network model to overcome the degradation of text classification results by sentiment. *Problemy informatiki.* 2018;2(39):4–14. (In Russ.)

18. Karakulov IV. Classification of the technical condition of water pumping equipment using convolutional neural networks. *Prikladnaya matematika i voprosy upravleniya.* 2022;2:37–53. (In Russ.) doi: 10.15593/2499-9873/2022.2.02

19. Katsuba YuN, Grigorieva LV. Application of artificial neural networks to predict the technical condition of products. *Mezhdunarodnyy nauchno-issledovatelskiy zhurnal.* 2016;3–2(45):19–21. (In Russ.) doi: 10.18454/IRJ.2016.45.008

20. Ivanov AI. Using the engine diagnostic technique using a motor tester and a CSS script. *E-Scio.* 2020;5(44):779–787. (In Russ.)

21. Budko SI, Kozarez IV, Kozlov SI, et al. Theoretical research on improving the process of diagnosing diesel engines. *Vestnik Bryanskoy gosudarstvennoy selskokhozyaystvennoy akademii.* 2020;1(77):50–55. (In Russ.)

22. Yablokov AE, Zhila TM. Application of CNN in vibration diagnostics using spectrograms and wavelet scalograms of the signal. *Izvestiya Tulskogo gosudarstvennogo universiteta. Tekhnicheskie nauki.* 2021;12:452–456. (In Russ.) doi: 10.24412/2071-6168-2021-12-452-457

23. Yablokov AE, Zhila TM, Generalov AS. Equipment diagnostics using vibration signal spectrograms using machine learning methods. *Innovatsionnye tekhnologii proizvodstva i khraneniya materialnykh tsennostey dlya gosu-darstvennykh nuzhd.* 2021;15:288–297. (In Russ.)

24. Buynosov AP, Vasilyev VA, Baitov AS, et al. Bench testing of algorithms for diagnosing rolling bearings of an on-board diagnostic system and forecasting the residual life of the main and auxiliary units of the MPVS. *Vestnik Uralskogo gosudarstvennogo universiteta putey soobshcheniya.* 2021;3(51):40–49. (In Russ.) doi: 10.20291/2079-0392-2021-3-40-49

25. Iovlev GA, Goldina II, Zorkov VS. Technical service in agriculture and the digitalization process. *Agrarnoe obrazovanie i nauka.* 2019;2:7. (In Russ.)

26. Tarasenko VE, Rolich OCh, Yakubovich OA, et al. Signal processing algorithms for complex diagnostics of automobile and tractor engines using a multi-channel integrated system. *Trudy NAMI.* 2021;1(284):6–15. (In Russ.) doi: 10.51187/0135-3152-2021-1-6-15

СПИСОК ЛИТЕРАТУРЫ

1. Myalo O.V., Myalo V.V., Prokopov S.P. Theoretical substantiation of machine-tractor fleet technical maintenance system on the example of Omsk region agricultural enterprises // J. Phys.: Conf. Ser. 2018. Vol. 1059. P. 012005. doi: 10.1088/1742-6596/1059/1/012005

2. Myalo O.V., Prokopov S.P. Material and technical support of the enterprises of the agro-industrial complex of the Omsk region management and certification of the technical component of the production processes in crop production // J. Phys.: Conf. Ser. 2019. Vol. 582, N. 1. P. 012028. doi: 10.1088/1757-899X/582/1/012028

3. Иовлев Г.А., Побединский В.В., Голдина И.И. Экономическое обоснование оптимальных сроков использования и периодичности технического обслуживания и ремонта машин // Вестник НГИЭИ. 2021. № 4(119). С. 105–119. doi: 10.24412/2227-9407-2021-4-105-119

4. Тойгамбаев С.К., Дидманидзе О.Н. Особенности разработки технологического процесса технического обслуживания тракторов в машинно-тракторном парке хозяйства // Вестник Курганской ГСХА. 2021. № 1(37). С. 74–80. doi: 10.52463/22274227_2021_37_74

5. Куприянова Т.М., Растимешин В.Е. Система ТРМ: более четверти века в России. Японская теория. Российская практика. Опыт Консультационного сообщества «ТАИР». М.: Буки Веди, 2019.

6. Итикава А., Такаги И., Такэбэ Ю. и др. ТРМ в простом и доступном изложении. М.: Стандарты и качество, 2008.

7. Akhtulov A.L., Ivanova L.A., Charushina E.B. Measuring the effectiveness of the quality management system as a tool for improving the organization's activities // IOP Conf. Ser.: Mater. Sci. Eng. 2019. Vol. 537. P. 042059. doi: 10.1088/1757-899X/537/4/042059

8. Akhtulov A.L., Ivanova L.A., Charushina E.B. Analysis of the formation and evaluation of performance indicators and efficiency of the organization's management system processes // J. Phys.: Conf. Ser. 2020. Vol. 1515. P. 052032. doi: 10.1088/1742-6596/1515/5/052032

9. Redreev G.V., Okunev G.A., Voinash S.A. Efficiency of Usage of Transport and Technological Machines // Radionov A., Kravchenko O., Guzeev V., et al. (eds) Proceedings of the 5th International Conference on Industrial Engineering (ICIE 2019). ICIE 2019. Lecture Notes in Mechanical Engineering. Cham: Springer, 2020. P. 625–631. doi: 10.1007/978-3-030-22063-1_6

10. Шаихов Р.Ф. Контроль производственного персонала на автотранспортном предприятии // Транспорт. Транспортные сооружения. Экология. 2019. № 3. С. 89–95. doi: 10.15593/24111678/2019.03.11

11. Мальцев Д.В., Репецкий Д.С. Контроль производственного персонала при выполнении работ технического обслуживания автомобилей // Мир транспорта. 2020. Т. 18, № 6(91). С. 238–247. doi: 10.30932/1992-3252-2020-18-6-238-247

12. Шимохин А.В. Механизм передачи бизнес-процесса промышленного предприятия на аутсорсинг // Научный журнал НИУ ИТМО. Серия «Экономика и экологический менеджмент». 2019. № 1. С. 45–51. doi: 10.17586/2310-1172-2019-12-1-45-51

13. Баранова Е.М., Баранов А.Н., Борзенкова С.Ю. и др. Исследование показателей эффективности информационных систем с помощью программы STATISTICA // Известия Тульского государственного университета. Технические науки. 2022. № 10. С. 199–205. doi: 10.24412/2071-6168-2022-10-199-205

14. Каримова В.А., Мухитдинова М.Л. Моделирование процессов управления и прогнозирования запасов на предприятии // Наука и мир. 2019. № 5–2(69). С. 33–36.

15. Шимохин А.В. Семантический анализ отзывов о поставщиках на основе применения нейросетевой технологии // Фундаментальные исследования. 2021. № 5. С. 117–121. doi: 10.17513/fr.43048

16. Myalo O.V. Mathematical Modeling and Information Technologies in the Management of Tractor Maintenance Operations // IOP Conf. Ser.: Mater. Sci. Eng. 2019. Vol. 582. P. 012014. doi: 10.1088/1757-899X/582/1/012014

17. Рубцова Ю.В. Модель нейронной сети для преодоления деградации результатов классификации текстов по тональности // Проблемы информатики. 2018. № 2(39). С. 4–14.

18. Каракулов И.В. Классификация технического состояния водонасосного оборудования при помощи сверточных нейронных сетей // Прикладная математика и вопросы управления. 2022. № 2. С. 37–53. doi: 10.15593/2499-9873/2022.2.02

19. Кацуба Ю.Н. Григорьева Л.В. Применение искусственных нейронных сетей для прогнозирования технического состояния изделий // Международный научно-исследовательский журнал. 2016. № 3–2(45). С. 19–21. doi: 10.18454/IRJ.2016.45.008

20. Иванов А.И. Использование методики диагностирования двигателя при помощи мотор-тестера и скрипта CSS // E-Scio. 2020. № 5(44). С. 779–787.

21. Будко С.И., Козарез И.В., Козлов С.И. и др. Теоретические исследования по совершенствованию процесса диагностирования дизелей // Вестник Брянской государственной сельскохозяйственной академии. 2020. № 1(77). С. 50–55.

22. Яблоков А.Е., Жила Т.М. Применение СНС в вибродиагностике по спектрограммам и вейвлет-скалограммам сигнала // Известия Тульского государственного университета. Технические науки. 2021. № 12. С. 452–456. doi: 10.24412/2071-6168-2021-12-452-457

23. Яблоков А.Е., Жила Т.М., Генералов А.С. Диагностика оборудования по спектрограммам вибросигнала методами машинного обучения // Инновационные технологии производства и хранения материальных ценностей для государственных нужд. 2021. № 15. С. 288–297.

24. Буйносов А.П., Васильев В.А., Баитов А.С. и др. Стендовая отработка алгоритмов диагностирования подшипников качения бортовой системы диагностики и прогноза остаточного ресурса основных и вспомогательных узлов МПВС // Вестник Уральского государственного университета путей сообщения. 2021. № 3(51). С. 40–49. doi: 10.20291/2079-0392-2021-3-40-49

25. Иовлев Г.А., Голдина И.И., Зорков В.С. Технический сервис в сельском хозяйстве и процесс цифровизации // Аграрное образование и наука. 2019. № 2. С. 7.

26. Тарасенко В.Е., Ролич О.Ч., Якубович О.А. и др. Алгоритмы обработки сигналов при комплексном диагностировании автотракторных двигателей многоканальной интегрированной системой // Труды НАМИ. 2021. № 1(284). С. 6–15. doi: 10.51187/0135-3152-2021-1-6-15

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