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UDC 621.86
https://doi.org/10.23947/2541-9129-2026-10-2-166-176

Original Empirical Research

EDN: OCLIQI

Intelligent Decision Support System for Comprehensive Diagnostics of Interconnected Vehicle Systems

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Abstract

Introduction. The use of artificial neural networks (ANNs) to diagnose the technical condition of automotive equipment is an active area of research. However, existing work mainly focuses on evaluating individual units, such as the engine, without a comprehensive analysis of the interconnected systems of a car. This creates a gap in the field of the development of intelligent systems that can take into account the state of the chassis, braking, and steering systems at the same time. The aim of this study is to develop an intelligent decision-making support system (IDMSS) based on ANNs that can comprehensively assess the technical condition of a vehicle by combining expert knowledge and data on damage to different components.

Materials and Methods. Defective indicators, determined on the basis of regulatory documents, and manuals on operation, maintenance and repair, were used to defect car parts and assemblies. The research was based on the methodology of neural network modeling. To train the ANN, an array of 100 samples was used, formed on the basis of:

– statistical data;

– expert surveys of specialists from the Automotive Equipment Maintenance and Repair Center at Don State Technical University;

– analysis of big data from online sources.

Defective parameters of 13 main vehicle systems, operational factors and even the psycho-emotional state of the driver were considered. The training array included damage parameters for frame parts, axles, suspension, wheels, brake, and steering systems. To compare the effectiveness, three multilayer perceptrons (MLPs) architectures with different numbers of neurons in hidden layers, activation functions, and the BFGS learning algorithm were created and trained.

Results. The best results were shown by the MLP 8-24-3 neural network (8 input, 24 hidden, 3 output neurons). Its performance on the training sample was 93.75%, on the test sample — 90%. The accuracy of classification by category of technical condition reached 100% for the category “operation permitted”, 94.74% for “operation permitted with restrictions”, and 82.35% for “operation prohibited”. Sensitivity analysis revealed that the parameters of the frame (X1) and axles (X2) had the greatest influence on the classification.

Discussion. The developed ANN has demonstrated high efficiency in a comprehensive assessment of the vehicle's technical condition, going beyond the diagnosis of individual units. It has been established that the weighting coefficients of the neural network can serve as a quantitative measure of the relationship and mutual influence of the details of various systems on the overall safety. The results obtained confirm the practical applicability of the approach for creating flexible IDMSSs in the field of maintenance and diagnostics.

Conclusion. The research contributes to the development of data mining methods for transport systems, offering a new approach to integrating heterogeneous parameters and expertise into a single neural network model. It is an important step towards improving the reliability and safety of automotive equipment. An intelligent system based on expert experience and statistical data is a promising tool for automating assessment and decision-making processes. Further development of the system may include expanding the database and improving learning algorithms, which will increase its accuracy and efficiency.

Keywords: technical condition diagnostics of the chassis, parameters of damage to machine parts, technical condition assessment using MLP 8-24-3, confidence levels for determining the technical condition

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Acknowledgements. The author would like to express his sincere gratitude to the staff of the Automotive Equipment Maintenance and Repair Center at Don State Technical University for the opportunity to use the diagnostic data on automotive equipment, as well as for access to the statistical database of typical damages.

For Citation. Khvan RV. Intelligent Decision Support System for Comprehensive Diagnostics of Interconnected Vehicle Systems. *Safety of Technogenic and Natural Systems*. 2026;10(2):166–176. https://doi.org/10.23947/2541-9129-2026-10-2-166-176

Оригинальное эмпирическое исследование

Интеллектуальная система поддержки принятия решений для комплексной диагностики взаимосвязанных систем автомобиля

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Аннотация

Введение. Применение искусственных нейронных сетей (ИНС) для диагностики технического состояния машин активно исследуется, однако авторы публикаций в основном фокусируются на оценке отдельных агрегатов, например двигателя, без комплексного анализа взаимосвязанных систем автомобиля. Необходимо закрыть этот пробел в области создания интеллектуальных систем, способных одновременно учитывать состояние ходовой, тормозной и рулевой части. Цель исследования — разработка интеллектуальной системы поддержки принятия решений (ИСППР) для комплексной оценки технического состояния автомобиля на основе ИНС, обобщающей опыт экспертов и данные о повреждениях различных узлов.

Материалы и методы. Для дефектации деталей и узлов автомобилей использовались браковочные показатели, определенные по нормативным документам, а также руководствам по эксплуатации, обслуживанию и ремонту. При нейросетевом моделировании для обучения ИНС использовался массив из 100 выборок, сформированных на основе:

– статистических данных,

– экспертных опросов специалистов Центра обслуживания и ремонта машин Донского государственного технического университета,

– анализа больших данных из интернет-источников.

Учитывались браковочные показатели 13 основных систем автомобиля, эксплуатационные факторы и психоэмоциональное состояние водителя. Обучающий массив включал параметры повреждения деталей рамы, мостов, подвески, колес, тормозной и рулевой систем. Для сравнения эффективности были построены и обучены многослойные перцептроны (MLP) с разным количеством нейронов в скрытых слоях, функциями активации и алгоритмом обучения BFGS (три архитектуры).

Результаты исследования. Наилучшие результаты показала нейросеть MLP 8-24-3 (8 входных, 24 скрытых, 3 выходных нейрона). Ее производительность на обучающей выборке составила 93,75 %, на тестовой — 90 %. Точность классификации по категориям технического состояния достигла: 100 % для категории «эксплуатация разрешена», 94,74 % для «эксплуатация разрешена с ограничениями» и 82,35 % для «эксплуатация запрещена». Анализ чувствительности выявил, что наибольшее влияние на классификацию оказывают параметры рамы (X1) и мостов (X2).

Обсуждение. Разработанная ИНС продемонстрировала высокую эффективность в комплексной оценке технического состояния автомобиля. Показатели оказались существенно лучше, чем при диагностике отдельных агрегатов. Установлено, что весовые коэффициенты нейросети могут служить количественной мерой взаимосвязи и взаимного влияния деталей различных систем на общую безопасность. Полученные результаты подтверждают практическую применимость подхода для создания гибких ИСППР в сфере технического обслуживания и диагностики.

Заключение. Исследование вносит вклад в развитие методов интеллектуального анализа данных для транспортных систем. Предлагается новый подход к интеграции разнородных параметров и экспертного опыта в единую нейросетевую модель, что является важным шагом к повышению надежности и безопасности эксплуатации автомобильной техники. Интеллектуальная система, основанная на опыте экспертов и статистических данных, — перспективный инструмент для автоматизации процессов оценки и принятия решений. Дальнейшее развитие, повышение точности и эффективности системы может основываться на расширении базы данных и улучшении алгоритмов обучения.

Ключевые слова: диагностика технического состояния ходовой части, параметры повреждения деталей машин, оценка технического состояния с MLP 8-24-3, доверительные уровни определения технического состояния.

Благодарности. Автор выражает искреннюю благодарность коллективу Центра обслуживания и ремонта автомобильной техники Донского государственного технического университета за возможность использовать данные диагностики автомобильной техники, а также за доступ к статистической базе данных типовых повреждений.

Для цитирования. Хван Р.В. Интеллектуальная система поддержки принятия решений для комплексной диагностики взаимосвязанных систем автомобиля. *Безопасность техногенных и природных систем.* 2026;10(2):166–176. https://doi.org/10.23947/2541-9129-2026-10-2-166-176

Introduction. Artificial intelligence methods, particularly artificial neural networks (ANNs), are widely used in modern research on automotive diagnostics. However, current developments are typically limited to analyzing individual components, primarily the internal combustion engine. For instance, in [1], ANNs are used to detect engine malfunctions without specifying the network architecture. In the following studies, neural network methods have been employed to diagnose specific parameters, such as cylinder shutdown [2], oil chemical composition [3], and cylinder temperature [4], which does not allow a comprehensive assessment of the technical condition of the engine. A significant gap exists in the absence of approaches that can integrate data on the state of interconnected vehicle systems, including the undercarriage, braking, and steering systems. These narrowly focused approaches fail to consider their mutual influence on the overall safety and performance of the vehicle.

Thus, there is a lack of solutions in scientific knowledge that provides a comprehensive assessment of the technical condition of a car based on the integration of diverse data on damage to various components and systems. This gap is also supported by the requirements of regulatory documents, such as GOST R 58197-2018, which mandates a comprehensive examination using an expert method.

The aim of this research was to create an intelligent decision-making support system (IDMSS) for a comprehensive assessment of the technical condition of a car based on an artificial neural network that combines expert experience and statistical data on damage.

To achieve this goal, we have set the following tasks.

1. Generate an array of training data based on indicators of defects, operational factors, and expert assessments of the state of the main vehicle systems.

2. Develop and train multilayer perceptron (MLP) neural networks with various architectures to classify the technical condition.

3. Compare the performance of trained networks and select the optimal architecture through a comparative analysis.

4. Evaluate the sensitivity of the chosen model to changes in input parameters and analyze the results.

Materials and Methods. The research was based on the methodology of neural network modeling. The main stages of the work included data collection, design of neural network architectures, training, and validation of models. To generate an array of training data, we used the experience of the specialists from the Automotive Equipment Maintenance and Repair Center at Don State Technical University (DSTU) and the results of analyzing operational statistics.

Defective indicators were used to defect car parts and assemblies. Their composition was determined taking into account the recommendations of regulatory documents, as well as manuals on the operation, maintenance, and repair of automotive equipment. Artificial neural networks have allowed us to comprehensively consider heterogeneous initial data when assessing the technical condition of automotive equipment. In addition to the defective indicators, operational factors were taken into account:

– service life;

– resource of each component, system, or part under study;

– number of loading cycles.

At the same time, the available source data was sufficient to assess the technical condition of a particular vehicle system. That is, their presence or absence did not limit the performance of the decision support system, but only affected the confidence levels of the assessment [5]. This property of artificial neural systems makes them similar to biological neural networks. When assessing a situation, risks, or technical condition of a machine, a person uses the data and experience that they have. The absence of certain data does not lead to a failure of the thinking system, but only lowers the confidence level of the assessment [6].

Figure 1 demonstrates an intelligent decision-making support system for assessing a vehicle's technical condition. The computational core of this system was an artificial neural network [7]. Each vehicle system added to the IDMSS acted as a subsystem of nodes and parts with its unique architecture.

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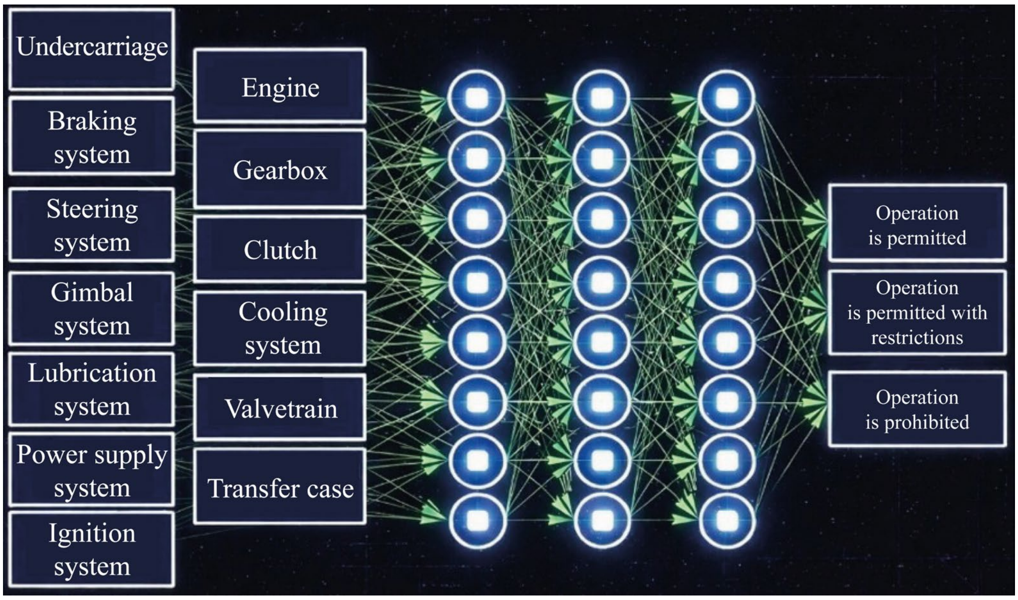

Fig. 1. Intelligent vehicle technical condition assessment system [1]

Thirteen main automotive equipment systems were identified for loading into the input layer of the neural network. To ensure that such an extended ANN model could comprehensively assess the technical condition of the machine, a sufficient number of training samples of experimental operational data were needed [8]. To do this, we needed to know the degree of damage to each part of each system shown in Figure 1. The network performance depended on the number of training samples, which could be used to assess the quality of the ANN. It was difficult to obtain such a volume of experimental data on all automotive systems immediately, so it was decided to use the neural network's ability to retrain. This allowed us to follow the general-to-specific approach. In this case, “specific” meant assessing the technical condition of one or more interconnected systems, while “general” meant a comprehensive assessment of the technical condition of a machine.

Let us emphasize a significant aspect. Figure 1 provides 13 vehicle systems. The theoretical model took into account the psycho-emotional state of the driver. However, at this stage of model development and validation, the training sample contained 8 key parameters related to the chassis (frame, axles, suspension, etc.). This decision was due to two factors. Firstly, according to a preliminary sensitivity analysis, it was the parameters of the chassis (frame X1 and axles X2) that made the greatest contribution to the final safety assessment. Secondly, the amount of labeled and verified data on braking and steering systems was insufficient for full-fledged training. Information about these systems, as well as other components out of the 13 shown in the figure, was reserved for the expansion of the database and was the subject of future scientific research.

Thus, an assessment of the technical condition of the undercarriage was developed (Fig. 2).

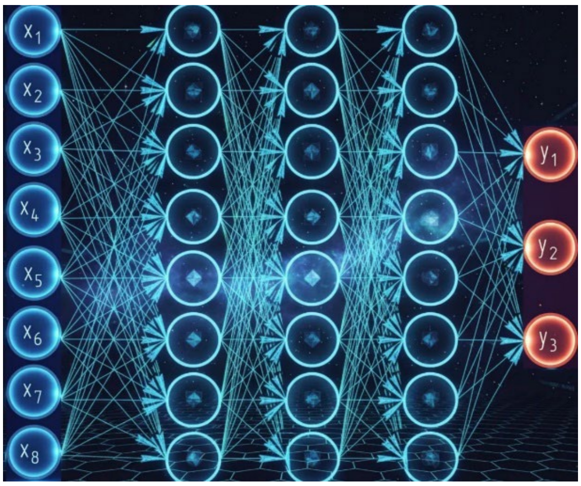

Fig. 2. Undercarriage technical condition assessment ANN model: X1 — frame; X2 — axles; X3 — front suspension; X4 — rear suspension; X5 — wheels and hub; X6 — guiding elements; X7 — fasteners; X8 — additional elements

[1] Gearbox — gear shift box. Valvetrain — gas distribution mechanism.

In the input layer of the artificial neural network, we added indicators reflecting the competence of repair and maintenance specialists, as well as information about the operating conditions and the psycho-emotional state of the driver, or their personal psychological type, to the list of defective indicators and operational factors for a more comprehensive assessment of the technical condition of the vehicle.

Neurons in the ANN's output layer were used to reflect the technical condition of the car and the likelihood of an emergency or failure to complete a task due to a problem [9].

Details from neural network-connected systems are interconnected in real-world operating conditions [10]. For example, damage to the front arm's rubber bushing affects other suspension elements due to gaps and additional dynamic loads during operation. In this regard, the details of certain systems and assemblies were classified according to the degree of impact on the safety of operation and the risk of accidents. The interconnected parts of the suspension, steering, and braking systems were identified (Fig. 3).

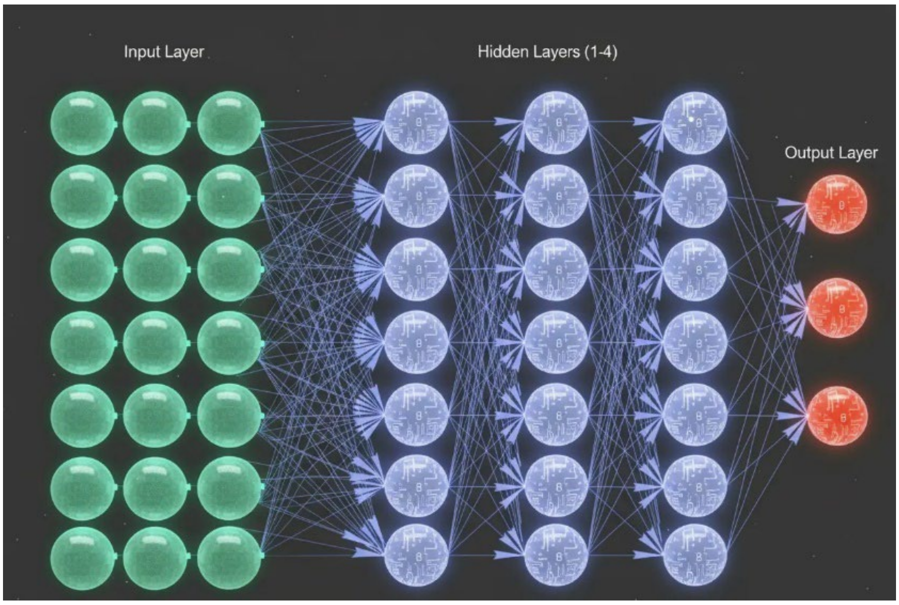

Fig. 3. ANN model with undercarriage, braking, and steering systems a car[2]

Defective parameters of the following systems were considered:

– undercarriage — frame, axles, wheels, levers, shock absorbers, springs, rubber bushings;

– braking system — compressor, receivers, brake chambers, cylinders, energy accumulators, foot brake valve, brake discs (drums), brake pads;

– steering system — column, rack, booster, rods, tips.

Information on typical defects, failure statistics, and causes of failures of parts of the above-mentioned systems was used to train the ANN. Data from other neural networks was also utilized [11]. This allowed us to work with various sources such as car manufacturer websites, car operation manuals, regulatory documents, automotive forums, and scientific literature. The information gathered in this manner was formalized into a format suitable for training the network [12].

A direct propagation neural network, a multilayer perceptron (MLP), was chosen as the basic model. To determine the optimal architecture, three networks with different configurations were built and trained. The following is a description of each of these three networks.

– MLP 8-8-3: 8 input neurons, 8 hidden, neurons 3 output neurons. Learning algorithm: BFGS. The error function was the sum of the squares. The activation function of hidden neurons was hyperbolic, the output function was exponential.

– MLP 8-24-3: 8 input neurons, 24 hidden (distributed over three layers) neurons, 3 output neurons. Learning algorithm: BFGS. The activation function of hidden and output neurons was logistic.

– MLP 8-19-3: 8 input neurons, 19 hidden neurons, 3 output neurons. Learning algorithm: BFGS. The activation function of hidden neurons was logistic, the output function was identity.

[2] Input layer — входной слой, hidden layers — скрытые слои, output layer — выходной слой.

Results. The data set for neural network training consisted of one hundred training samples (Table 1). Each example was obtained from statistical and experimental data collected through questionnaires from experts at the DSTU Automotive Equipment Maintenance and Repair Center. Additionally, artificial neural networks from the Internet were used to work with big data.

Table 1

Neural network training samples

No.	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	Y
1	26	7	18	5	12	22	4	5	2
2	40	23	29	86	5	62	0	87	3
3	0	77	57	5	0	20	0	0	2
4	5	90	10	5	2	20	0	8	2
5	44	0	20	5	73	0	23	0	2
6	33	18	90	15	0	17	0	60	3
7	0	0	0	21	40	0	6	10	1
8	0	2	92	13	0	67	0	16	2
9	85	29	10	3	84	0	10	0	3
10	27	39	25	0	0	32	0	19	2
…	…	…	…	…	…	…	…	…	…
20	0	0	69	49	25	15	0	0	2
30	0	13	0	12	0	54	0	76	3
40	12	11	32	65	34	23	29	1	1
…	…	…	…	…	…	…	…	…	…
100	74	76	1	38	20	33	41	48	3

As in Figure 2, here X1 — frame, X2 — axles, X3 — front suspension, X4 — rear suspension, X5 — wheels and hub, X6 — guiding elements, X7 — fasteners, X8 — additional elements. The frame, spars and crossbars were directly attributed to the frame parts. The axles included front and middle axles, main gear, differential, center differential, locking mechanism, and rear axle. Front suspension parts: springs, shock absorbers, spring shoes with bushings, jet rods. Rear suspension: springs, balancing mechanisms, balancer shoes, shock absorbers. Wheels and hubs: disc wheels with tires, front and rear wheel hubs, wheel nuts. Guiding elements: rotary fists, rotary fist bushings, bolts, bolt bushings, rods. Fasteners: U-bolts, U-bolt screws, U-bolt bushings, mounting bolts, brackets. Additional elements: lateral stability stabilizers, rubber bushings, suspension supports, mounting brackets.

Output parameter Y indicated one of three categories: 1 — operation is permitted, 2 — operation is permitted with restrictions, 3 — operation is prohibited.

We built three artificial neural networks with different architectures. The input and output layers were the same, the number of neurons in the hidden layers was different. Parameters such as the learning algorithm, the error function, the activation function of hidden neurons, and the activation function of output neurons differed [13]. The set parameters and learning outcomes for the three constructed neural networks are summarized in Table 2.

Table 2

Parameters and learning outcomes for three neural networks

No.	Architecture	Performance			Learning algorithm	Error function	Neuron activation function	
		Training	Control	Tests			Hidden	Output
1	MLP 8-8-3	90.00	90.00	80.00	BFGS 20	Sum of squares	Hyperbolic	Exponent
2	MLP 8-24-3	93.75	80.00	90.00	BFGS 14		Logistic	Logistic
3	MLP 8-19-3	91.25	80.00	90.00	BFGS 26		Logistic	Identity

The best network was selected based on three performance criteria: training, control, and tests. The same data sets (training samples) were taken for each network. Table 1 provides a part of the array used. One hundred samples were previously divided into eighty training, ten control and ten test samples.

As can be seen from Table 2, the optimal of these three neural networks was MLP 8-24-3. The 8-24-3 architecture indicated 8 neurons in the input layer, 24 neurons in the hidden layer (8 neurons in each of the three layers) and 3 neurons in the output. Table 3 shows the results of classification by category of vehicle technical condition for MLP 8-24-3 neural network.

Table 3

Classification of the vehicle's technical condition for MLP 8-24-3 neural network

MLP 8-24-3	Category 1	Category 2	Category 3	All
All	25	38	17	80
Correct	25	36	14	75
Wrong	0	2	3	5
Correct (%)	100.00	94.736	82.352	93.750
Wrong (%)	0.0000	5.263	17.647	6.250

Of 25 training samples in the first category, the neural network correctly classified all of them (100% accuracy). For the second category, out of 38 training samples, the neural network incorrectly classified only two (almost 95% accuracy). According to the third category of technical condition, the network achieved 82% accuracy.

The following is a sensitivity analysis of the MLP 8-24-3 model with respect to changes in the network's input parameters. Table 4 provides a ranked list of the neurons in the network's input layer, based on their degree of influence on the final classification of technical condition.

Table 4

Ranking of neurons in the input layer based on their influence on the classification of the technical condition of the car

Rank	1	2	3	4	5	6	7	8
Neurons	X_1	X_2	X_7	X_5	X_8	X_4	X_6	X_3
Sensitivity	2.072	1.603	1.599	1.585	1.533	1.485	1.449	1.280

Table 5 provides the confidence levels for determining the technical condition of a vehicle based on ten control and ten test samples. The last three columns in the table show the activation levels of the three neurons of the output layer of the network during its operation for each data sample. The maximum activation level among the three neurons represents the confidence level.

Table 5

Confidence levels for determining the technical condition of the car

Sample no.	Target	Output	Category 1	Category 2	Category 3
14	1	1	0.531420	0.273081	0.195499
15	1	1	0.386258	0.359916	0.253826
16	1	1	0.576008	0.212090	0.211902
17	3	3	0.179771	0.331566	0.488663
18	2	2	0.278165	0.431201	0.290633
19	3	3	0.198094	0.267284	0.534623
20	2	2	0.241999	0.516263	0.241739
21	2	1	0.568989	0.221012	0.209999
22	1	1	0.574172	0.214602	0.211226

23	2	2	0.269398	0.460988	0.269615
91	2	2	0.208055	0.550675	0.241270
92	3	3	0.157003	0.419964	0.423034
93	2	1	0.493552	0.311828	0.194619
94	3	3	0.200722	0.263546	0.535731
95	2	2	0.211775	0.574774	0.213451
96	3	3	0.245410	0.275353	0.479237
97	2	2	0.260837	0.469146	0.270018
98	3	3	0.174727	0.350631	0.474642
99	3	2	0.253433	0.483170	0.263396
100	3	3	0.241020	0.304389	0.454591

There were control samples from 91 to 100. They were used during training to adjust the parameters of the model. From 14 to 23, there were test samples for final quality control of the neural network. Out of ten control samples, two were misclassified by the neural network:

– In the 93rd sample, instead of being classified as category 2 (operation is permitted with restrictions), it was classified as category 1 (operation is permitted without restrictions);

– In the 99th sample, instead of category 3 (operation is prohibited), it was also classified as category 2.

Of the ten test samples, the neural network misclassified one, the 21st one. Instead of category 2, we got category 1.

These three errors were highlighted in red in the table.

It was necessary to obtain basic descriptive statistics of the confidence levels values for determining the technical condition of the machine for a hundred samples. To this end, the data was processed using the normal distribution law and a histogram and density distribution graph were constructed (Fig. 4).

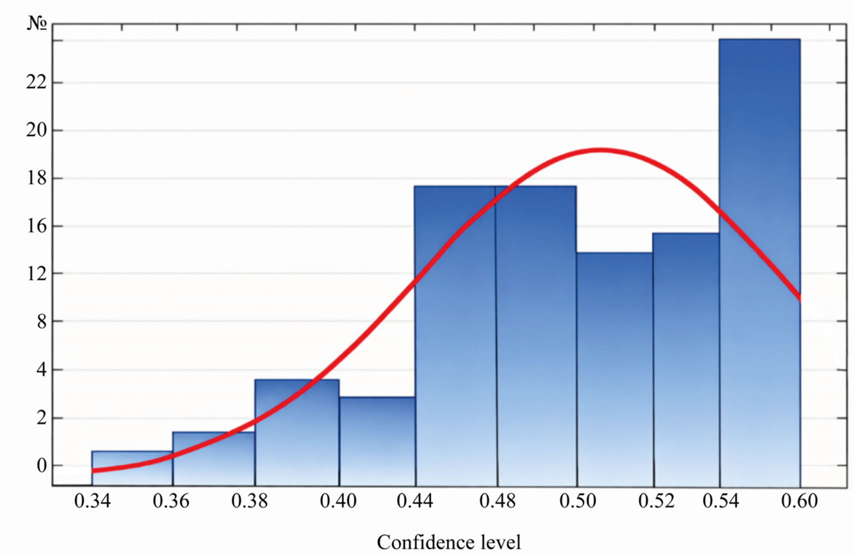

Fig. 4. Histogram of confidence level distribution for assessing the car's technical condition

Discussion. The results of the study confirm the effectiveness of using a multilayer perceptron to solve the problem of a comprehensive assessment of the technical condition of a car. The MLP 8-24-3 model's ability to generalize and provide accurate results was demonstrated by its high classification accuracy, with 93.75% accuracy in training and 90% accuracy on the test set. The accuracy values obtained by category can be logically interpreted in the context of the complexity of the diagnostics: the “operation prohibited” category (82.35%) may include borderline or complex combined damage cases requiring a more detailed analysis.

The BFGS method, the sum-of-squares error function, and various activation functions were used for training. The MLP 8-24-3 network showed the best results with a training performance of 93.75%, control — 80%, and test — 90%. Analysis of the MLP 8-24-3 network classification results:

– for category 1 (“operation permitted”), the accuracy was 100 %;

– for category 2 (“operation permitted with restrictions”), the accuracy was — 94.74 %;

– for category 3 (“operation prohibited”), the accuracy was — 82.35%.

The dominant influence of the frame (X1) and axles (X2) parameters on the final solution of the system, as revealed by sensitivity analysis, is in line with engineering practice. These are components of the load-bearing structure and are crucial for safety. Therefore, the neural network not only effectively classifies states, but also identifies internal, logically justified dependencies between the input data, which brings its work closer to expert reasoning.

The research showed that the weights and synaptic connections of a trained ANN can serve as a quantitative measure of the mutual influence of details of different systems on overall safety [14]. This important theoretical result opens up opportunities for using such models not only as classification tools, but also as tools for analyzing the structural integrity and vulnerabilities of complex technical systems.

The developed system goes beyond existing solutions that focus on individual units and offers an integrated approach. However, it also has limitations. They are related to the size of the training sample (100 examples). Although the method of network retraining used made it possible to compensate for this disadvantage, to increase the stability and accuracy of the model, especially for category 3, it would be necessary to expand the database with a larger number of real diagnostic cases.

Promising areas for future research:

– increasing and diversifying the training array, experimenting with other ANN architectures (for example, convolutional or recurrent networks for analyzing time series of parameters);

– integrating the system into a real diagnostic complex with feedback from experts to continuously improve the model.

Conclusion. The effectiveness of ANN application for the development of an intelligent decision-making support system that comprehensively assesses the technical condition of a vehicle has been confirmed. This work not only achieved high classification accuracy (up to 100% for individual categories) but also demonstrated a fundamentally important result: the neural network model is capable of identifying and quantifying hidden connections between the states of various vehicle systems that directly affect operational safety.

The practical significance of the research lies in the creation of a prototype of an intelligent decision-making support system that allows automating the process of assessing the technical condition of a vehicle.

Modeling has shown that the developed system improves the accuracy of technical condition classification by up to 90% in the test sample and reduces the time for diagnostic decision-making by 30–40% compared to the traditional expert approach. Additionally, the use of the system reduces the influence of subjective factors in assessing the current state, which is particularly important for dealing with complex and interconnected failures. In the future, this could lead to reduced operating costs and increased safety levels of vehicle operation.

The proposed system has potential for implementation in diagnostic complexes at service centers [15], as well as for use in the educational process for training specialists in the field of car maintenance. Further development of this work, aimed at expanding knowledge and optimizing algorithms, will improve the accuracy and reliability of the system, bringing it closer to the level of a highly qualified expert's decision-making.

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Conflict of Interest Statement: **the author declares no conflict of interest.**

The author has read and approved the final version of manuscript.

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***Конфликт интересов*, автор заявляет об отсутствии конфликта интересов.**

Автор прочитал и одобрил окончательный вариант рукописи.

Received / **Поступила в редакцию** 25.01.2026
Reviewed / Поступила после рецензирования 10.03.2026
Accepted / Принята к публикации 17.03.2026