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Original Empirical Research

Technical Condition Monitoring of Lifting Structures and Equipment Using Artificial Neural Systems

Roman V. Khvan ✉, **Anatoly A. Korotky** ✉
Don State Technical University, Rostov-on-Don, Russian Federation, https://ror.org/00x5je630
✉ khvanroman@yandex.ru

EDN: PSBRHA

Abstract
Introduction. Federal industrial safety standards and regulations establish the requirements for the technical condition assessment of the said engineering devices and associated equipment. However, these regulatory frameworks require a discrete-level defect analysis of composite nodes and parts of load-lifting machinery. This approach does not always ensure the required accuracy and objectivity in monitoring the overall condition of equipment, as various combinations of defects in numerous structural components determine varying degrees of their overall wear. This is due to the fact that, during long-term operation, the components and parts of the mechanisms are subject to uneven destructive stress resulting in variability in the degree of their damage. The present work proposes a combination of scientific and technical measures to improve the operational reliability of both lifting machines and associated equipment through the integration of modern intelligent algorithms. The research objective of the study is to develop an intelligent decision support system designed for a comprehensive, integrated assessment of the operating conditions of lifting structures.
Materials and Methods. To achieve this objective, three models of artificial neural networks have been developed. The first model contains five layers: the first input layer includes eight neurons corresponding to the same number of rejection indicators of lifting structure components, such as defects in the undercarriage, braking system, rope-and-pulley system, and load hook. The three subsequent hidden layers contain eight neurons each. They are responsible for the learning process of the network and provide recording of intermediate results. The output layer consists of three neurons, each of which characterizes a certain class of technical condition of the object under study. The second neural network has a similar configuration, except for the input layer, which additionally includes nine neurons corresponding to the rejection indicators of the supporting metal structures of lifting facilities. The input layer of the third model contains twenty-nine neurons. This structure allows for a comprehensive assessment of equipment condition across a full range of rejection indicators. The practical implementation of the developed models was performed in the Python programming environment using the Scikit-learn machine learning library. Testing of the performance and efficiency of the developed networks was carried out on ten independent samples according to their performance criteria and confidence intervals for assessing the state of engineering devices.
Results. The performance of the developed models under testing was 100%, meaning each of the three neural network structures accurately classified the conditions of the lifting structures in all ten test scenarios. Moreover, the confidence level of the judgments made increased as the number of network input parameters was scaled in the range from 0.628 to 0.705.
Discussion. The presented data demonstrate the significant impact of the artificial neural network architecture on the precision of lifting structure diagnostics. The key result is the establishment of a numerical relationship between combinations of rejection criteria and the resulting condition class through the analysis of the activation levels of output layer neurons, which serve as a quantitative measure of the reliability of the decision made by the model. The findings correlate with previous research in the field of applying machine learning methods to technical diagnostics. The specificity of the proposed approach is in the integrated assessment of the overall condition without detailed mathematical modeling of local physical processes, which determines its efficiency under conditions of limited a priori information about operational modes. Limitations of the work include a relatively small sample size and a certain subjectivity of expert marking. Possible errors are due to the risk of retraining the neural network on small arrays of training information.

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Conclusion. The proposed intelligent system is developed taking into account practical experience in operating lifting machines, analysis of accumulated statistical data, and the requirements of current industry standards. Scientific results expand the understanding of the potential of using artificial intelligence algorithms to ensure the technological safety of complex technical objects. The implementation of such systems will allow engineering and technical personnel who do not have extensive practical experience in on-site inspection of structures to make qualified and informed decisions regarding the possibility of continuing the safe operation of equipment.

Keywords: lifting structures, artificial neural networks, degree of damage, rejection indicators, combination of defects, technical condition assessment

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Оригинальное эмпирическое исследование

Контроль технического состояния подъемных сооружений и оборудования с использованием искусственных нейронных систем

Р.В. Хван ✉, **А.А. Короткий** ✉

Донской государственный технический университет, г. Ростов-на-Дону, Российская Федерация, https://ror.org/00x5je630

✉ khvanroman@yandex.ru

Аннотация

Введение. Федеральные нормы и правила в области промышленной безопасности регламентируют порядок проведения оценки технического состояния указанных технических устройств и сопутствующего оборудования. Однако данные регуляторные требования предусматривают проведение дискретного анализа дефектов отдельных узлов и деталей грузоподъемных машин. Подобный подход не всегда обеспечивает требуемую точность и объективность при диагностировании общего состояния оборудования, так как разнообразные сочетания дефектов в многочисленных конструктивных элементах предопределяют различную степень их совокупного износа. Это обусловлено тем, что в ходе долговременной эксплуатации составные узлы и детали механизмов подвергаются неравномерному деструктивному воздействию, приводящему к вариативности степени их разрушения. В настоящем исследовании предлагается сформировать комплекс научно-технических мер, направленных на повышение эксплуатационной надежности как самих грузоподъемных машин, так и сопряженного оборудования, посредством интеграции современных интеллектуальных алгоритмов. Цель работы — разработка интеллектуальной системы поддержки принятия решений, предназначенной для комплексной интегральной оценки технического состояния подъемных сооружений.

Материалы и методы. Для достижения поставленной цели были разработаны три архитектуры искусственных нейронных сетей. Первая модель характеризуется пятислойной структурой: первый — входной слой включает восемь нейронов, соответствующих аналогичному числу браковочных показателей элементов подъемных сооружений, таких как дефекты ходовой части, тормозной системы, канатно-блочной системы и грузового крюка. Три последующих скрытых слоя содержат по восемь нейронов каждый, обеспечивая процесс обучения и фиксацию промежуточных результатов. Выходной слой состоит из трех нейронов, каждый из которых характеризует определенный класс технического состояния исследуемого объекта. Вторая нейронная сеть имеет аналогичную конфигурацию, за исключением входного слоя, в который дополнительно включено девять нейронов, соответствующих показателям браковки несущих металлоконструкций подъемных сооружений. Входной слой третьей модели содержит двадцать девять нейронов. Подобная структура позволяет комплексно оценивать состояние оборудования по всей совокупности браковочных показателей. Практическая реализация разработанных моделей выполнена в среде программирования Python с использованием библиотеки машинного обучения Scikit-learn. Тестирование работоспособности и эффективности разработанных сетей проводилось на десяти независимых выборках по критериям их производительности и доверительным интервалам оценки состояния технических устройств.

Результаты исследования. Производительность разработанных моделей в ходе тестирования составила 100 %, то есть каждая из трех нейросетевых структур безошибочно классифицировала состояние подъемных сооружений во всех десяти тестовых сценариях. При этом доверительный уровень выносимого суждения возрастал по мере масштабирования числа входных параметров сети в диапазоне от 0,628 до 0,705.

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Обсуждение. Представленные данные демонстрируют выраженное влияние архитектуры искусственной нейросети на прецизионность диагностирования подъемных сооружений. Ключевым результатом является установление численной зависимости между комбинациями браковочных критериев и результирующим классом состояния посредством анализа уровней активации нейронов выходного слоя, выступающих количественной мерой достоверности принимаемого моделью решения. Полученные выводы коррелируют с предшествующими исследованиями в области приложения методов машинного обучения к технической диагностике. Специфика предложенного подхода состоит в интегральной оценке общего состояния без детального математического моделирования локальных физических процессов, что обусловливает его эффективность в условиях дефицита априорной информации об эксплуатационных режимах. К числу ограничений работы следует отнести относительно небольшой объем выборки и определенную субъективность экспертной разметки. Возможные погрешности обусловлены риском переобучения нейросети на малых массивах обучающей информации.

Заключение. Предложенная интеллектуальная система разработана с учетом практического опыта эксплуатации подъемных машин, анализа накопленных статистических данных и требований действующих отраслевых стандартов. Научные результаты расширяют представление о потенциале применения алгоритмов искусственного интеллекта для обеспечения техногенной безопасности сложных технических объектов. Внедрение подобных систем позволит инженерно-техническому персоналу, не обладающему обширным практическим опытом натурного обследования конструкций, принимать квалифицированные и обоснованные решения относительно возможности продолжения безопасной эксплуатации оборудования.

Ключевые слова: подъемные сооружения, искусственные нейронные сети, степень повреждения, браковочные показатели, комбинация дефектов, оценка технического состояния

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Introduction. In accordance with the Order of Rostekhnadzor[1] (Federal Service for Environmental, Technological and Nuclear Supervision, hereinafter referred to as RTN), rejection criteria have been defined and approved for various components of lifting structures (hereinafter referred to as LS): undercarriage, brake and rope-pulley systems, supporting metal structures, as well as bolted and riveted joints. However, the currently accepted methodology requires an isolated assessment of each damage, independent of the others. Under actual operating conditions, the structural components of LS are subject to uneven wear, resulting in multiple combinations of destructive factors that can cause a synergistic effect, significantly reducing the real safety factor compared to the combined effect of isolated defects [1]. An example is the combination of residual deflection of the span beams, which amounted to 54 mm versus the standard limit of 59.5 mm, and an increased proportion of operating cycles with a load mass exceeding 0.75Q (5% instead of the 2% specified in the data report). The cumulative effect of these conditions shortened the safe operational lifetime of the equipment from the rated 7 years to just 1 year. However, a methodology for quantifying this mutual effect is completely absent from valid regulatory documents. The current approach does not provide the ability to numerically account for the interference of dissimilar damage types. This leads to uncertainty when setting the timing of the next technical inspection — resulting either in excessively frequent inspections or, far more dangerously, in the untimely detection of critical equipment conditions. This shortcoming is particularly critical when applied to mechanisms that have reached the end of their service life, since in such cases, even seemingly minor defects, when combined, can trigger catastrophic consequences [2].

An analysis of the data obtained from the study of 50 industrial safety expert reports on overhead cranes of various types (tower, bridge, gantry, and overhead single-girder), completed in 2024–2025, indicates the systemic nature of the problems associated with an adequate assessment of the LS technical condition [3]. Among the most common destructive factors are: accumulation of fatigue damage to metal during cyclic loading (36% of the total volume of registered violations), non-compliance of the actual distribution of loads with standard passport parameters (25%), wear of elements

[1] *On approval of federal norms and rules in the field of industrial safety "Safety Rules for Hazardous Industrial Facilities Using Lifting Equipment":* Order of Rostekhnadzor dated November 26, 2020, No. 461. (In Russ.) URL: https://www.consultant.ru/document/cons_doc_LAW_373321/ (accessed: 29.06.2026).

of the rope-pulley system (17%), as well as malfunctions of hydraulic equipment (11%). A systematic phenomenon is the excess of the established proportion of operating cycles with a load exceeding 0.75Q when operating machines with a service life of more than 30 years. In the absence of formal damage detected by visual inspection methods, this circumstance entails a reduction in the designated period of reliable operation to 1–2 years instead of the potential 3–7 years. In 27% of the cases examined, the safe operating period was limited to 1 year in the absence of obvious defects in the load-bearing systems of metal structures, which confirms the insufficient representativeness of the local analysis methodologies used [4].

A study of statistical data on accidents and industrial injuries indicates that the key risk factors are the unsatisfactory quality of technical maintenance, diagnostics and industrial safety assessment (specified by physical and moral deterioration of the equipment fleet), the progression of defects due to their untimely detection, as well as gross violations of industrial and labor discipline [5]. A typical example of such a development is the incident with the KB-515 tower crane, in which the displacement and subsequent release of a metal pin fixing the boom sections, combined with adverse weather conditions, caused the coupling assembly to fail and the boom to fall onto the construction site. The immediate cause of the incident was a combination of interrelated factors: failure of the pin retaining collar, insufficient production control, and systematic failure of personnel to comply with job instructions. A local assessment of the fastening element wear without taking into account its interaction with adjacent structural units and without a detailed analysis of the actual loading conditions of the crane did not allow for a timely prediction of the occurrence of a pre-emergency situation.

An alternative scientific and methodological approach based on the application of fuzzy logic is presented in [6] with regard to the assessment of the technical condition of port lifting-and-transport equipment. The proposed method is oriented towards operation under conditions of high uncertainty; however, the scope of its implementation is limited to a specific type of machines. At the same time, the task of comprehensive simultaneous accounting of heterogeneous damage to key components of load-lifting machines, including the undercarriage, brake and rope-pulley systems, supporting metal structures, as well as detachable and nondetachable connections, remains outside the scope of the aforementioned studies. Private methodological solutions, aimed specifically at forecasting the need for repair interventions based on a set of diagnosed parameters using artificial neural networks (ANN), have been developed for aviation equipment [7]. However, their adaptation to the specific operating conditions of lifting structures and to the nomenclature of rejection criteria regulated by the RTN[2] has not been carried out to date.

Neural network diagnostic methods are also actively developing in related branches of the mechanical engineering complex. Thus, in [8], an algorithm for processing diagnostic parameters of aircraft gas turbine units based on multilayer architectures is presented. In [9], the prospects of integrating ANN for self-diagnostics of internal combustion engines when the working cylinders are switched off are investigated. The authors [10] analyzed the reliability of a hydraulic drive using neural network modeling methods. Study [11] proposes a scientifically based solution to improving the quality of software for technical objects through the use of neural network surrogates. The cited studies convincingly demonstrate the high efficiency of using neural networks for monitoring complex discrete systems. However, they are not focused on solving the systemic problem of an integrated assessment of the technical condition of a software system based on a comparison of the entire spectrum of rejection criteria.

Thus, a scientific review of the relevant literature and a generalization of the results of industrial safety examinations allow us to state the absence of complex intelligent decision support systems capable of assessing the integral state of the LS, taking into account the mutual influence of defects of different physical character. Currently, mathematical neural network models covering the entire spectrum of rejection criteria established by the RTN[3] and providing a quantitative determination of the reliability of classification decisions have not been developed. The current practice of assigning residual life, based on an isolated assessment of damage, does not take into account their synergistic effects, which is extremely dangerous when operating lifting equipment with significant runtime.

The objective of this work is to develop an intelligent decision support system designed for a comprehensive assessment of the technical condition of LS based on a set of standard rejection parameters established by the RTN[4], using artificial neural network mechanisms.

[2] Ibid. P. 10–11.
[3] Ibid. P. 20–21.
[4] Ibid. P. 24–25.

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To achieve this goal, the following tasks were solved:

– systematization of rejection indicators of LS components (undercarriage, brake and rope-pulley systems, metal structures, bolted and riveted joints) in accordance with regulatory requirements and subsequent determination of the structure of the input parameter vector for neural network analysis;

– development of three topologies of artificial neural networks with different numbers of input neurons (8, 17, and 29, respectively), providing step-by-step accounting of an expanding range of defects — from local LS elements to complex load-bearing systems and connections;

– formation of representative training and test samples based on verified industrial safety assessment data prepared by certified experts, with differentiation of technical condition into three main classes (operable, limitedly operable, marginal);

– conducting training and verification procedures for the developed neural network models with assessment of the classification accuracy metrics and confidence intervals for accepted recommendations;

– establishment of patterns of effect of the input parameter space dimensionality on the verifiability of the assessment of the technical condition of the software system, as well as determination of the prospects for integrating the developed models into expert practice as decision support systems.

Materials and Methods. The initial data for the study included expert reports on the industrial safety of 50 overhead cranes of various types, prepared by employees of the accredited organization Scientific and Technical Center "Mysl", Novocherkassk State Technical University. Each reporting document contains certificates of visual and measurement inspection of load-bearing metal structures, protocols for adjustment and testing of safety devices, results of static and dynamic tests, as well as lists of identified defects. Federal norms and regulations[5] define maximum permissible values for each diagnostic feature, exceeding which entails the rejection of the structural element or restrictions on subsequent operation of the equipment. Based on these indicators, the structures of the input layers of three designed artificial neural network models were formed, containing 8 (x_1–x_8), 17 (x_1–x_{17}), and 29 (x_1–x_{29}) neurons, respectively.

Visual and measurement control was performed using the following set of devices and tools: 500 mm metal measuring ruler (scale division 1 mm); vernier caliper of type ShS-1-125 (measuring range up to 125 mm, error ± 0.05 mm); measuring magnifying glasses with 6× and 10× magnification; optical level GEOBOX N7-36 (leveling accuracy 1 mm/m); multifunction welder's gauge UShS-3 (foreign analogue WG1) and Usherov-Marshak gauge (WG3); laser rangefinder Disto-5M (error ±1 mm); feeler gauge set No. 2 (thickness 0.05–1.00 mm); radius measuring templates No. 1 (R 1–6 mm) and No. 3 (R 7–25 mm); Testo 545 luxmeter. The illuminance in the controlled zones was at least 300 lx, and the threshold sensitivity of the control was no worse than 0.15 mm. All measuring instruments used had valid verification certificates.

In accordance with the requirements of the RTN[6], the following parameters were assessed: travelling wheel flange thickness (mm), wheel tread diameter (mm), diameter difference between matching wheels (%), pulley groove wear (% of the initial radius), drum groove wear depth (mm), hook throat wear (% of the original cross-section height), and brake drum rim wear (% of its original thickness), friction lining wear (% of thickness), residual deflection of bridge girders (mm), residual deformation of truss structure members (mm), depth of local dents in tubular elements (mm), deformation of angle and channel flange legs (mm); number of defective bolts and rivets (pcs.), clearances in joint connections (mm), depth of corrosion damage to metal structures (mm).

Actual values of the monitored parameters were extracted from visual and measurement inspection reports for each overhead crane. Based on these, the ratio of the actual indicator to the corresponding maximum permissible level established by the RTN[7], was calculated, expressed as a percentage. For example, for a technical device with a residual deflection of 54 mm at a regulatory limit of 59.5 mm, the normalized input value was 54/59.5 × 100% = 90.8%. Thus, 29 input features were mathematically generated, varying in the range from 0% (defect was completely absent) to 100% (critical rejection threshold was reached).

[5] Ibid. P. 27–28.
[6] Ibid. P. 72–73.
[7] Ibid. P. 75–78.

Three industrial safety experts (with at least 10 years of practical experience and valid qualification certificates) independently assigned each of the 40 data sets to one of three technical condition classes. Their assessments were guided by the requirements of the RTN[8] and their current experience: class 1 — operable state (period until next inspection — 3 years); class 2 — limited operable (period — 1 year); class 3 — marginal state (operation of the technical device is prohibited). The classification procedure was performed by experts separately. They received the initial information electronically in Excel spreadsheet format. Any discrepancies in estimates (amounting to less than 10% of the total sample size) were evaluated through a joint expert discussion followed by consensus agreement [12]. The consistency of the results obtained was verified using the Kendall concordance coefficient: $W = 0.87$, $p < 0.01$.

From a total array of 40 data sets, 30 structural units were selected for training and 10 for testing through stratified random sampling, maintaining a proportional class ratio. Identical training and testing sets with the corresponding dimensionality of the input parameter vector were used in the study of each of the three proposed architectures [13].

In this research, three multilayer perceptron models were designed using the MLPClassifier class of the Scikit-learn software library (version 1.0.2). Each of these structures contained three hidden layers of 8 neurons each with a built-in ReLU activation function, as well as an output layer consisting of 3 neurons with a Softmax function.

The first model (Fig. 1) is characterized by the presence of an input layer consisting of 8 neurons that correspond to the key rejection characteristics of the undercarriage [14], the braking and rope-pulley systems, as well as the load hook (x_1–x_8).

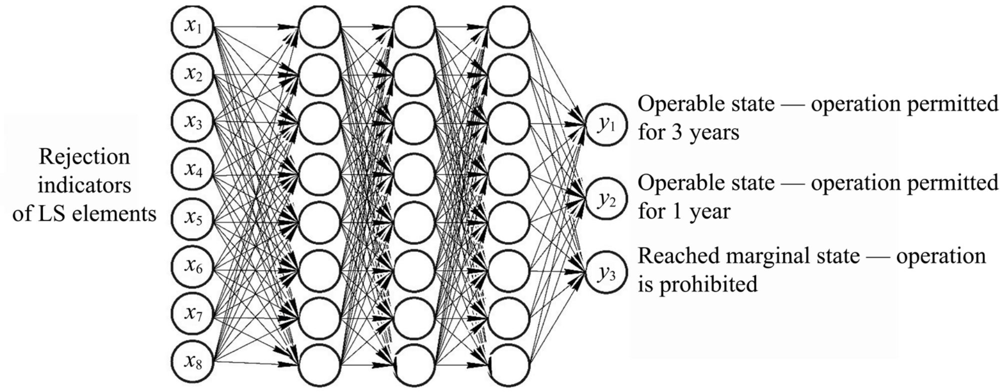

Fig. 1. ANN for assessing LS technical condition by combination rejection indicators of LS elements

The second model (Fig. 2) has an input layer of 17 neurons, including, except x_1–x_8, an additional 9 neurons for rejection indicators of load-bearing metal structures (x_9–x_{17}).

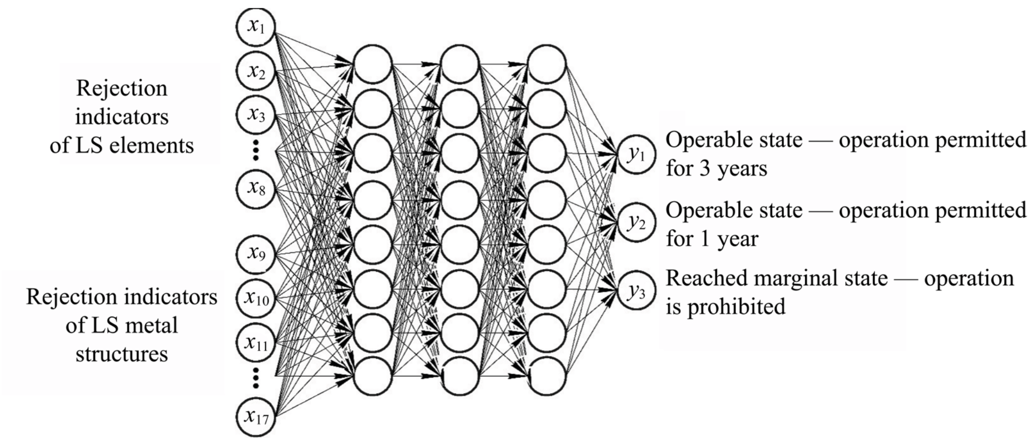

Fig. 2. ANN for monitoring LS technical condition considering LS components and metal structures

The third model (Fig. 3) contains an input layer of 29 neurons corresponding to all rejection indicators x_1–x_{29}, including defects in bolted and riveted connections.

[8] Ibid. P. 79–80.

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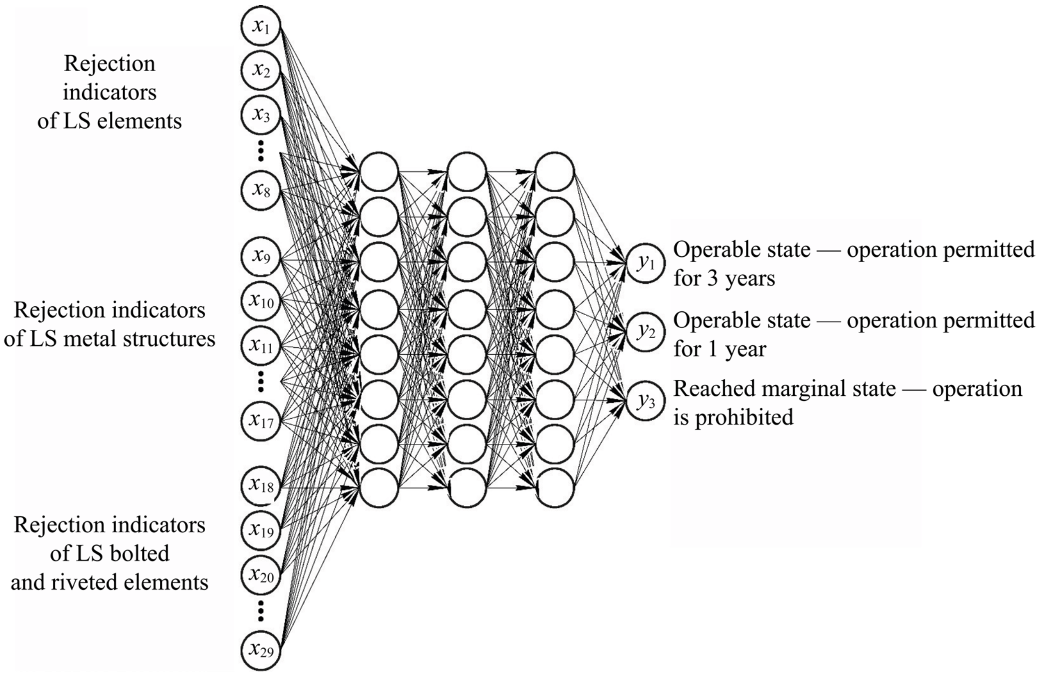

Fig. 3. ANN for assessing LS technical condition considering a combination of 29 different defects

The initial weights are initialized randomly (the random_state parameter = 42 for reproducibility). The programming language is Python 3.9. The main libraries are pandas (1.4.0) and openpyxl (3.0.9) for working with Excel, sklearn (1.0.2) for building and training models. The input data are normalized to the range [0, 1] using the MinMaxScaler method. Training parameters: optimizer — Adam; learning rate — 0.001 (default); number of epochs — 2000; mini-batch size — 10 (corresponding to the training sample size). Training was performed on a personal computer with an Intel Core i7-10750H processor (2.6 GHz), 16 GB RAM, and Windows 10 Pro OS. The training time for each model was less than 5 seconds.

Research Results. The training data was loaded from an Excel file whose structure met the specified requirements (Table 1).

Table 1

ANN Training Samples (partially presented) (x_1–x_8)

Item No.	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	y
1	15	32	0	0	22	0	0	0	1
2	31	19	0	61	0	3	0	23	2
3	0	39	0	28	0	0	32	12	2
4	0	0	0	0	9	4	0	0	1
5	79	16	21	16	0	0	0	60	2
6	0	13	0	0	5	0	25	0	1
7	21	33	45	17	0	40	0	0	2
8	70	0	67	0	0	8	0	84	3
9	0	0	15	0	0	0	0	0	1
10	81	0	0	0	0	75	0	0	2
…	…	…	…	…	…	…	…	…	…
30	45	10	75	0	20	0	0	1	2

The result of the ANN operation is a correctly determined technical condition of the LS [15]. The criterion of correctness in this case is the opinion of a group of experts and specialists in assessing the compliance of lifting structures with industrial safety requirements. Table 2 presents the activation levels of each of the three neurons of the output layer. The activation level of a neuron in the output layer reflects the degree of confidence of the ANN in determining the technical condition of the LS [16]. The sum of the activations of the three neurons is one. The neuron with the highest activation level is considered the “winner”, which determines the final technical condition of the LS determined by the ANN [17].

Table 2

Activation Levels of Neurons in Output Layer (x_1–x_8)

Sample (test)	LS State – Target	LS State – Exit	LS State – 1 (confidence level)	LS State – 2 (confidence level)	LS State – 3 (confidence level)
1	2	2	0.22	0.52	0.26
2	2	2	0.42	0.54	0.04
3	1	1	0.67	0.21	0.12
4	2	2	0.11	0.73	0.16
5	3	3	0.07	0.23	0.70
6	2	2	0.14	0.53	0.33
7	1	1	0.65	0.21	0.14
8	2	2	0.41	0.53	0.06
9	1	1	0.80	0.11	0.09
10	1	1	0.61	0.28	0.11

In the test samples, the target value of the technical condition was predetermined by an expert method. The ANN correctly specified the technical condition of the LS [18] in each test sample. The average confidence level for determining the technical condition of the LS was 0.628.

Table 3 presents 30 training samples for nine neurons corresponding to the rejection parameters of LS metal structures (x_9–x_{17} from Table 1). When training the neural network, these samples were added to the samples from Table 1. That is, the network was retrained with the inclusion of additional parameters.

Table 3

ANN Training Samples (partially presented) (x_9–x_{17})

Item No.	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	y
1	18	0	0	0	29	0	20	0	0	1
2	0	0	14	5	20	33	0	14	5	2
3	0	0	16	0	0	0	0	26	0	2
4	0	14	16	0	7	0	13	16	0	1
5	0	0	35	49	0	0	0	35	49	3
6	0	0	0	32	0	0	0	0	32	1
7	12	0	0	0	0	16	0	0	0	2
8	0	5	0	34	0	12	23	0	34	2
9	0	0	4	35	0	0	8	4	35	1
10	52	0	57	15	60	0	24	57	15	3
…	…	…	…	…	…	…	…	…	…	…
30	0	0	0	55	0	12	0	0	55	2

The newly trained ANN was then checked on test samples. However, additional parameters were also included in the input layer of the test samples, as shown in Figure 2. Confidence levels for assessing the technical condition of the LS are listed in Table 4.

Table 4

Activation Levels of Neurons in ANN Output Layer (x_9–x_{17})

Sample (test)	LS State – Target	LS State – Exit	LS State – 1 (confidence level)	LS State – 2 (confidence level)	LS State – 3 (confidence level)
1	2	2	0.18	0.58	0.24
2	2	2	0.33	0.64	0.03
3	1	1	0.69	0.21	0.10
4	2	2	0.10	0.72	0.18
5	3	3	0.06	0.23	0.71
6	3	3	0.09	0.3	0.61

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7	1	1	0.65	0.21	0.14
8	2	2	0.41	0.53	0.06
9	1	1	0.86	0.1	0.04
10	2	2	0.37	0.59	0.04

The ANN, which was augmented with nine neurons responsible for defects in the supporting metal structures of the LS, also correctly assessed the technical condition in each of the test samples, with the confidence level increasing from 0.628 to 0.658.

To test the ANN, whose model is shown in Figure 3, additional 30 training samples were prepared (Table 5). These samples included rejection indicators for the bolted and riveted elements of the LS.

Table 5

ANN Training Samples (partially presented) (x_{18}–x_{29})

Item No.	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	x_{26}	x_{27}	x_{28}	x_{29}	y
1	0	5	0	26	0	0	10	0	0	0	0	0	1
2	0	0	0	0	0	0	0	24	0	6	5	0	2
3	0	0	50	0	0	0	0	0	0	0	0	0	2
4	48	0	0	0	73	0	0	0	0	0	23	0	2
5	57	0	0	0	0	0	0	0	0	0	0	22	3
6	0	14	17	0	0	0	39	0	10	28	0	0	1
7	0	0	23	0	0	0	0	0	0	0	0	0	2
8	0	0	17	0	0	11	0	0	84	0	0	11	3
9	0	32	2	0	1	0	6	0	0	0	14	0	1
10	92	0	0	0	0	33	19	0	0	21	0	13	3
…	…	…	…	…	…	…	…	…	…	…	…	…	…
30	0	0	5	0	0	0	15	0	0	10	5	0	2

Confidence levels for assessing the technical condition of the LS are included in Table 6.

Table 6

Activation Levels of Neurons in ANN Output Layer (x_{18}–x_{29})

Sample (test)	LS State – Target	LS State – Exit	LS State – 1 (confidence level)	LS State – 2 (confidence level)	LS State – 3 (confidence level)
1	3	3	0.11	0.30	0.59
2	2	2	0.26	0.72	0.02
3	1	1	0.65	0.26	0.09
4	2	2	0.10	0.78	0.12
5	3	3	0.06	0.23	0.71
6	3	3	0.02	0.26	0.72
7	1	1	0.63	0.24	0.13
8	2	2	0.39	0.56	0.05
9	1	1	0.90	0.09	0.01
10	1	1	0.79	0.11	0.10

As a result of applying the artificial neural network shown in Figure 3, it is found that the model correctly determines the technical condition of lifting structures in 100% of cases. The average confidence level for assessing the technical condition of the LS grew from 0.628 to 0.705 for the current model. This indicates an increase in the accuracy and reliability of forecasts, which is an important indicator of the efficiency of the developed system [19].

The output layer of the trained neural networks uses the softmax activation function. For each of the three classes, the model confidence level k is calculated as: p_k = exp(z_k) / Σ_{j=1..3} exp(z_j), where: p_k — confidence level (normalized probability) that the state belongs to class k; exp(z_k) — exponential of z_k; z_k — weighted sum of signals coming from the last hidden layer to the output neuron k; Σ_{j=1..3} exp(z_j) — sum of the exponentials for all three classes (normalization coefficient). Values p_k for the test examples are given in Tables 3, 5 and 7. Specifically, for test example #5 (model with 29 inputs, Table 7), values z_k before normalization were: z₁ = 0.82 (class 1), z₂ = 1.15 (class 2), z₃ = 1.95 (class 3). After applying softmax, the confidence levels obtained were p₁ = 0.06, p₂ = 0.23, p₃ = 0.71. Thus, there is a quantitative relationship between the combination of input rejection parameters and the activation levels of output neurons, determined by the network architecture and its trained weights. For this example, the highest activation (p₃ = 0.70) corresponds to class 3, which is consistent with the expert opinion. The effect of the number of neural network input parameters, including defects in the rope-pulley and braking systems, undercarriage, metal structures, and bolted connections, on the reliability levels of determining the technical condition of lifting structures is identified. A numerical relationship is established between the activation levels of artificial neural networks and the technical condition of lifting structures based on combinations of rejection indicators expressed as a percentage of the permissible damage level. The operation of artificial neural networks results in the correct determination of the technical condition of lifting structures, confirmed by industrial safety experts [20].

Discussion. The increase in the number of input parameters from 8 to 29 is accompanied by a growth of the classification confidence level. The largest contribution to this increase comes from the parameters of the metal structures (x_9–x_{17}). This is likely due to the physical nature of the defects in this group. Unlike localized damage to the undercarriage or rope-pulley system, which are typically corrected during routine repairs, residual deflections and deformations of the supporting metal structures reflect systemic changes that reduce the overall load-bearing capacity of the structure. It is the combination of localized wear and systemic deformations that serves as a marker for the transition from class 1 to class 2. Bolted and riveted joint parameters, which provide an additional, albeit smaller, boost in confidence, allow the network to identify joint weaknesses characteristic of the ultimate limit state (class 3). A comparison with literature data shows that the results obtained are consistent with studies on the application of machine learning in the diagnostics of technical systems. These studies indicate that increasing the number of parameters considered improves the accuracy of predictions. However, unlike approaches that simulate individual physical processes, the proposed model evaluates the integral state based on a set of rejection indicators. This makes it applicable with limited information on actual operating conditions, which constitutes its advantage over methods that require detailed loading data [21]. In addition to the physical nature of the defects, the model results are affected by correlations between the input parameters. The residual deflection of the superstructure (x_9) correlates with the deformation of the angle flange (x_{16}), since both parameters reflect the overall reduction in the rigidity of the metal structure. Similarly, wear of the travelling wheel flange surface (x_1) and wear of the wheel tread (x_2) often occur together. Such correlations are not a drawback of the method, as neural networks are robust to multicollinearity — they can redistribute weights between correlated features without losing predictive power. However, the presence of correlations can cause an overestimation of the significance of a group of interrelated features. Adding parameters from different groups primarily introduces new, uncorrelated information, which explains the increased confidence of the model. The practical results of the study include the development and training of three ANNs with different numbers of input neurons: the first ANN contains 8 input neurons and shows a test accuracy of 100% with a test sample size of 10 examples and an average confidence level of 0.628. The basic limitation of the study is a small amount of available expert data (30 samples). With such a volume, a statement of 100% accuracy on the test sample cannot be considered statistically reliable. Cross-validation results (average accuracy of 0.89, standard deviation of 0.07) provide a more realistic estimate. The cross-validation results (mean accuracy 0.89, standard deviation 0.07) provide a more realistic estimate. Therefore, the presented conclusions are preliminary. The increase in the average model confidence from 0.628 (8 inputs) to 0.658 (17 inputs), and then to 0.705 (29 inputs) is due to the following factors. First, defects in metal structures (residual deflections, rod deformations, local dents) and defects in bolted and riveted connections (tension weakening, corrosion, cracks) contain information partially independent of defects in the undercarriage and rope-and-pulley system. This allows the neural network to identify combinations in which, for example, minor wear of the travelling wheels (less than 30% of the rejection value) in combination with noticeable residual deflection of the metal structure (more than 50% of the limit value) may indicate the need to reduce the time between repairs (class 2), whereas each of these defects separately could be classified as operable (class 1). Secondly, increasing the dimensionality of the input space with a fixed training set size (30 samples) typically raises the risk of overfitting. However, in this case, the increase in confidence indicates that the added parameters indeed contain information relevant to classification and do not constitute noise [22]. Thirdly, the rejection indicators of metal structures and connections are normalized as a percentage of the limit values, which allows the network to take into account different types of defects with comparable significance, regardless of their physical nature.

Conclusion. In the course of research, three artificial neural network models were developed and tested for a comprehensive assessment of the technical condition of lifting structures based on rejection criteria established by federal industrial safety standards and regulations. The research results enabled the following tasks to be solved.

1. Twenty-nine rejection indicators for lifting structures have been systematized in accordance with the RTN[9]. The indicators are structured into three groups: defects in the undercarriage, brake, and rope-pulley systems (x_1–x_8); load-bearing metal structures (x_9–x_{17}); and bolted and riveted joints (x_{18}–x_{29}). These indicators serve as the basis for defining input data structures for neural network models.

2. Three multilayer perceptron models have been developed and trained with the same hidden layer architecture (three layers of eight neurons) and input layers of 8, 17, and 29 neurons, respectively. All models have an output layer of three neurons, corresponding to three technical condition classes.

3. Training (30 examples) and test (10 examples) samples were generated based on 40 expert sets of defects classified by three independent experts.

4. The developed models were trained and tested. All three models showed 100% classification accuracy on the test set.

5. It has been established that an increase in the number of input parameters raises the confidence level of classification, which indicates the importance of taking into account combinations of defects of various elements of the lifting structure.

The results are preliminary and demonstrate the fundamental feasibility of using a neural network approach for comprehensive LS assessment. Implementation into practical applications requires expanding the training sample to several hundred real expert opinions and conducting validation on an independent dataset.

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About the Authors:

Roman V. Khvan, Cand.Sci. (Eng.), Associate Professor of the Department of Transport Systems Operation and Logistics, Don State Technical University (1, Gagarin Sq., Rostov-on-Don, 344003, Russian Federation), SPIN-code, ORCID, ScopusID, ResearcherID, ResearchGate, khvanroman@yandex.ru

Anatoly A. Korotky, Dr.Sci. (Eng.), Professor, Head of the Department of Transport Systems Operation and Logistics, Don State Technical University (1, Gagarin Sq., Rostov-on-Don, 344003, Russian Federation), SPIN-code, ORCID, ScopusID, ResearcherID, korotaa@gmail.com

***Claimed Contributorship*:**

RV Khvan: methodology, project administration, investigation, visualization, formal analysis, validation, data curation, writing – original draft preparation, writing – review & editing.

AA Korotky: conceptualization, supervision.

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Об авторах:

Роман Владимирович Хван, кандидат технических наук, доцент кафедры «Эксплуатация транспортных систем и логистика» Донского государственного технического университета (344003, Российская Федерация, г. Ростов-на-Дону, пл. Гагарина, 1), SPIN-код, ORCID, ScopusID, ResearcherID, ResearchGate, khvanroman@yandex.ru

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Анатолий Аркадьевич Короткий, доктор технических наук, профессор, заведующий кафедрой «Эксплуатация транспортных систем и логистика» Донского государственного технического университета (344003, Российская Федерация, г. Ростов-на-Дону, пл. Гагарина, 1), SPIN-код, ORCID, ScopusID, ResearcherID, korotaa@gmail.com

Заявленный вклад авторов:

Р.В. Хван: разработка методологии, административное руководство исследовательским проектом, проведение исследования, написание рукописи, визуализация, формальный анализ, валидация результатов, курирование данных, написание черновика рукописи.

А.А. Короткий: разработка концепции, научное руководство.

Конфликт интересов: **авторы заявляют об отсутствии конфликта интересов.**

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