Application of Artificial Intelligence in Diagnosing the Stress-Strain State of Electric Locomotive Bogie Elements

Galina Khromova[1], Davran Radjibaev[1], Gulnora Kosimova[1], Jingyong Zhang[2], Assylbek Kassenov[3,4] and Diyorbek Bekmirzaev[5]

[1]*Tashkent State Transport University, Temiryolchilar Str. 1, 100167 Tashkent, Uzbekistan*
[2]*School of Material and Physics, China University of Mining and Technology, 221116 Xuzhou, China*
[3]*Toraighyrov University, Lomov Str. 64, 140000 Pavlodar, Kazakhstan*
[4]*Kazakh National University of Water Management and Irrigation, K. Satpayev Str. 28, 080000 Taraz, Kazakhstan*
[5]*Institute of Mechanics and Seismic Stability of Structures named after M.T. Urazbaev, Uzbekistan Academy of Sciences, Durmon Yuli Str. 33, 100125 Tashkent, Uzbekistan*
xromova_g@tstu.uz, radjibaev_railway@tstu.uz, kasimova_gulnora@tstu.uz, jyzhang@cumt.edu.cn, a.kassenov@kaznuvhi.edu.kz, diyorbek_84@mail.ru

Keywords: Electric Traction Rolling Stock, Electric Locomotive Bogie Frames, Stress-Strain State, Diagnostics, Reliability, Durability, Reliability Assessment Methodology, AI in the Form of Neural Network Modeling, Algorithm, Neural Networks with a Single-Layer Perceptron Architecture.

Abstract: Locomotive bogie frames take a long-term structural beating and catching deformation early matters for safety. Here we build a mathematical model and algorithm for the durability of VL80s electric locomotive bogie components, grounded in instrumented, non-destructive wheelset testing, and then ask a more specific question: can a neural network do useful diagnostic work on top of that deterministic model? The network we settle on draws in several classes of measurement data tied to the frame's load-bearing capacity. Each input gets weighted against the others, the weighted signals are summed, and an activation function carries out the final transformation - this is what sets the limits of what the network can actually learn. Tested against a modernized bogie frame reinforced with steel plates, the approach predicts load-bearing capacity reliably and holds up across a range of related engineering calculations. Of the architectures we tried, a single-layer perceptron worked best for the graphical diagnostics side.

1 INTRODUCTION

One of the most important areas for improving traffic safety and the economic efficiency of locomotive operations is the further development of non-destructive testing systems for critical components and parts of electric rolling stock, particularly undercarriages, the condition of which is directly related to traffic safety [1]-[5]. That puts methods and technologies for their non-destructive testing, analysis, and research squarely on rail transport's list of pressing concerns.

The issues of developing methods for calculating and analyzing indicators of reliability and durability, and determining the resource of equipment for electric rolling stock of railways, are given great attention in the research of scientists around the world [1]-[3]. Russian scientists such as I.P. Kiselev [4], E.S. Oganyan [5], I.S. Biryukov [6], A.N. Savoskin [7], and A.V. Gorsky [8], among others, have carried out similar research.

Leading scientists around the world have conducted and are conducting research on this topic, such as C.A. Brebbia (Wessex Institute of Technology, UK), G.M. Carlomagno (University of Naples di Napoli, Italy), A. Varvani-Farahani (Ryerson University, Canada), S.K. Chakrabarti (USA), S. Hernandez (University of La Coruña, Spain), and S.-H. Nishida (Saga University, Japan); in the CIS countries, authoritative scientific schools and leading scientists from MIIT, PGUPS, MAI, VNIIZhT, JSC VNIKTI, JSC Russian Railways, and others have worked on the issues raised [2]-[6].

A significant contribution to the solution of many complex problems, and to the verification of theoretical conclusions related to the calculation of durability indicators and the determination of the service life of parts and units of rolling stock, was made by the Russian Research Institute of Railway Transport (TsNII MPS) and the Russian Research Institute of Carriage Building (NIIV), which, along with theoretical research, conducted a large number of experimental studies, both bench and full-scale.

Despite years of research, experience, and improvements in running gear design, potential directions for further development continue to be identified [9]-[16].

In Uzbekistan, this line of work has been carried forward by academician of the Academy of Sciences of the Republic of Uzbekistan, professor Glushchenko A.D., and professors Fayzibaev Sh.S. and others, who have studied the optimization of wheel-rail contact stresses during dynamic wheel-pair interaction, methods for calculating the dynamic strength of complex-configuration locomotive frame structures, and resource calculation for transport engineering, and more recently by a cluster of studies on locomotive diagnostics, thermal and traction-system performance, and operational reliability [17]-[23].

2 METHODOLOGY

Two things anchor the theoretical side of this work. First, standard material-resistance, elasticity, vibration, and machine-dynamics methods go into building mathematical models of reliability and durability for traction rolling-stock equipment, using diagnostic results from the VL80s bogie as the empirical anchor; numerical work relies on approximation methods and spline interpolation throughout.

Second, that deterministic modeling doesn't stand alone - it is paired with supervised machine learning trained to predict stress-strain state and load-bearing capacity in reinforced VL80s bogie frame elements. Put together, the framework has three layers working in concert: deterministic mechanical modeling covering elasticity, vibration, and material strength; statistical analysis of operational data; and supervised regression through an artificial neural network. None of these run in isolation - the AI piece is built directly into the diagnostics workflow, not tacked on afterward as a separate prediction step.

Reproducibility and transparency were priorities from the start, which is why the AI component was set up formally as a learning-based regression problem aimed squarely at predicting load-bearing capacity and stress-strain parameters for the bogie's structural elements. The underlying dataset draws on diagnostic and experimental measurements collected from VL80s locomotives at the Uzbekistan locomotive repair depot (Table 1).

Table 1: Information about diagnostic and experimental measurements obtained from VL80s electric locomotives operated at the Uzbekistan locomotive repair depot.

№	Indicator	Value
1	Total samples	312 observations
2	Training set	69.9% (218 samples)
3	Validation set	15% (47 samples)
4	Test set	15% (47 samples)

The following input variables were defined when formulating the problem: relative strain (mm); sheet steel thickness (mm); steel grade (ST-3); elastic modulus (GPa); cross-sectional geometry coefficient; and strain gauge stress values (MPa).

When selecting the neural network architecture, the single-layer perceptron (SLP) architecture was chosen due to its stability for engineering regression problems with limited datasets. Training was performed using supervised learning with gradient-based weight updates (the single-layer, linear-activation special case of the backpropagation algorithm, which for this architecture reduces to the delta rule). The artificial intelligence component was formulated as a supervised regression problem.

When formulating the target variable, two engineering goals were defined: the primary goal was to determine the maximum equivalent stress (MPa) in the most heavily loaded section of the bogie frame, and the secondary goal was to determine the ultimate load-bearing capacity (kN) of the reinforced structural element. The predicted values were verified using strain gauge measurements during full-scale tests, and analytical calculations based on classical structural mechanics.

Given the chosen single-layer perceptron (SLP) architecture, the model equation will be as follows:

$$y = f(\Sigma_{i=1}^{n}\omega_i x_i + b).$$

Here ω_i denotes the synaptic weights, b the bias term, and f a linear activation function, consistent with a regression setting.

The training procedure used the following configuration: supervised learning, optimized by backpropagation, with a Mean Squared Error (MSE) loss function, a learning rate of 0.01, 500 epochs, and a batch size of 16. Training was stopped early once the validation loss ceased to improve.

3 THEORETICAL AND EXPERIMENTAL RESULTS

This section presents the methods used to apply artificial intelligence to diagnosing modernized electric locomotive bogie frames strengthened with reinforcing steel plates.

3.1 Neural Network and Deterministic Modeling

Three separate calculation tracks fed into this work. One ran through STATISTICA Neural Networks: preprocessing and normalizing the dataset, then training the network, optimizing weights, and driving down prediction error. A second track handled the deterministic engineering side in Mathcad 15 - interpolating experimental dependencies with splines, approximating wear parameters, working out empirical coefficients, and evaluating means and standard deviations statistically, which is where the analytical dependencies came from. The third track was manual: calculations by hand, following classical strength-of-materials theory, serving as an independent cross-check on the other two.

A fairly wide range of independent variables can populate the input layer: relative shear span, width, length, steel grade, the cross-section's geometry, material properties, the thickness, width, and length of the reinforcing plates and where they sit, the elasticity modulus of the materials involved, and other factors that feed into the bogie's load-bearing calculations. There is a practical constraint, though: for the independent variables to carry statistical weight, the experimental dataset needs to be at least three times larger than the variable count. STATISTICA Neural Networks (StatSoft) was the tool of choice here [10], partly because it sits inside the broader STATISTICA suite, so the same input data can feed other probabilistic-statistical methods without re-entry [10].

Networks with a single-layer perceptron architecture are most often used to predict the load-bearing capacity of electric locomotive bogie structural elements. A similar network is also used to model the reinforcement of bogie frames with reinforcing plates and to predict their stress-strain state.

The operation of a neural network is structured as follows:

1) a multitude of signals - the independent variables - are fed to the input of an artificial neuron, together with the dependent variable (the load-bearing capacity of the structural element of the electric locomotive bogie);
2) each signal's influence on the final computation comes from multiplying it by a weight relative to the other inputs, with the network automatically settling on the weights and thresholds that keep prediction error to a minimum;
3) these weighted products are summed to set the neuron's activation level;
4) the output signal then passes through the neuron's activation function for a final transformation, which is what defines the network's learning capacity.

Learning a function with error minimization cannot proceed, for a model without a fixed structure, past a certain saturation threshold in the number of training examples, since beyond that point the network risks underfitting or overfitting; in that case the network would be close to simply memorizing the parameters, which would not produce correct results in use. This risk is checked by testing the network on samples withheld from training, with the final model validated on a separate control batch before it is considered ready for use.

The characteristics of electric locomotive bogie frames upgraded with the installation of reinforcing steel plates, as well as the failure loads in the sample, have values that differ by an order of magnitude and have different units of measurement. In such cases, normalization of the values is advisable, since it allows forecasting results obtained using different methods to be compared.

The most suitable forecasting method for the implementation of the task is to normalize all values x_i for the input and output layers using their mean $\bar{x}_i$ and standard deviation σ_i according to the formula:

$$x_i' = (x_i - \bar{x}_i) / \sigma_i.$$

The STATISTICA Neural Networks module includes a procedure for searching for the desired network configuration. This procedure involves constructing and testing a large number of networks with different architectures and then selecting the network best suited to solving the given problem - a tool called the Intelligent Problem Solver.

For this problem, it helps to think of the neural network as a nonlinear function with “semiparametric” complexity control: adding or removing network elements changes how complex a solution the model can represent, even though the analyst never actually sees the regression function written out explicitly. The Intelligent Problem Solver was used to search this general space of network configurations, including multilayer architectures with nonlinear (e.g., logistic, hyperbolic-tangent) activation functions; however, for the present dataset and problem, these more complex candidates did not outperform the single-layer perceptron with linear activation on the validation set, and in several cases showed signs of overfitting given the limited number of available observations (Table 1). The single-layer linear-activation model was therefore retained as the final architecture on cross-validated accuracy and parsimony grounds; accordingly, as noted in Section 2, the term "nonlinear function" above describes the general STATISTICA search space explored, not a property of the specific linear SLP model ultimately selected and used for the results reported.

Building a neural-network model for the load-bearing capacity of modernized, welded-steel-plate-reinforced bogie frames in their most heavily loaded sections therefore calls for four steps:

1) determine which independent variables carry the most weight for the output parameter - the load-bearing capacity of the reinforced element - and how many of them are needed;
2) assemble a test batch of experimental studies for training the network under development (Table 2);
3) create an artificial neural network using, for example, the Neural Networks module of the STATISTICA system;
4) test the created artificial neural network on sample bogies that were not used for training, then confirm the convergence of the obtained results.

The measurements in Table 2 were obtained during instrumented full-scale field testing of the modernized bogie frame under normal in-service operating load (a loaded locomotive under typical traction conditions on the test track), with strain gauges and the N338 displacement sensor mounted at the body-frame check points indicated; ambient temperature and track conditions during testing were within the standard operating range for the VL80s locomotive and are not treated as separate experimental variables in this study.

Table 2: Information about the conducted experimental measurements.

Check Point	Max. amplitude, N338 (mm)	Max. amplitude, monitor (dB)	Vibration accel. (Hz)	Stress (MPa)
Body frame, vertical	31	66.8	2.07	bending, 68 MPa
Body frame, horizontal	87.5	160	6.0	longitudinal, 38 MPa

Note. N338 - model designation of the displacement sensor used to record this channel.

With this network in hand, it becomes possible to determine the stress-strain state of modernized bogie frames - specifically the ones reinforced with welded steel plates - in their most heavily loaded sections. Accuracy should keep improving as larger databases and ongoing training are fed into the network, bringing engineering calculations closer to what experimental studies and full-scale testing on operating locomotives actually show (Tables 1 and 3).

Furthermore, the implementation of artificial intelligence in transport engineering will generally enable:

1) transition to exclusively electronic information exchange between operating organizations in the railway industry;
2) raising the railway industry's “digital maturity” more broadly - updating the regulatory framework, converting technical documentation into machine-readable form, building basic classifiers and information registers, establishing machine-readable exchange formats, and generating digital data that information systems can process automatically and intelligently.

3.2 Reliability and Wear Distribution Analysis

Because the monitored parameter of a wearing part behaves as a continuous random variable, its distribution can be described by a probability density function [8]. Building the corresponding distribution histogram is described in [24], while methods for testing the conformity of the sample to the assumed distribution are presented in [24], [25]. Conformity itself can be assessed with any of several standard criteria - Pearson's goodness-of-fit test, for instance, which gives the probability that random factors alone would produce a discrepancy between the theoretical and statistical distributions at least as large as the one actually observed [8].

The samples of monitored parameters of wear parts correspond to the normal distribution law. The distribution density for this law is:

$$f(x) = 1 / (\sigma_x \cdot \sqrt{2\pi})\ e^{-(x-mx)^2/(2\sigma x^2)}, \quad (1)$$

where m_x is the mathematical expectation of the controlled parameter, σ_x is its standard deviation, and x is the current value of the controlled parameter.

The normal distribution law imposes two relationships on the random variable here: frequencies summed across all k intervals equal 1, and the sample parameters m_x and D_x converge toward their theoretical-distribution counterparts.

Because the normal distribution's numerical characteristics reduce to the mathematical expectation and variance of a random variable, both can be estimated directly - starting with the mean value:

$$m_x^* = (1/N)\ \Sigma x_i,\ i = 1 \ldots N, \quad (2)$$

and the dispersion estimate (standard deviation):

$$\sigma_x^* = \sqrt{[}\ (1/(N-1))\ \Sigma(x_i - m_x^*)^2, \quad (3)$$

where N is the sample size of the controlled parameter, and x_i is the value of the controlled parameter.

The distribution density functions of the tire thickness and the tooth thickness of the large gear wheel (LGR) of the wheel pairs, for fixed operating times of the VL-80s series electric locomotive at the locomotive repair depot in Uzbekistan, are presented in Figures 1 and 2.

The values of the numerical characteristics of the distribution law of the controlled parameter make it possible to predict their changes at the greatest operating time, which in turn determines the resource; for this, analytical dependencies of the average values m_x and standard deviations σ_x on the mileage are found.

The analytical dependence can be represented as a nonlinear function of one argument (mileage), the expression of which includes S parameters. Using this function, it is necessary to approximate the empirical regression given in the form of n points, where the dependent variable is understood as one of the parameters of the distribution law under consideration. The coefficients of the regression models obtained using approximation and spline interpolation procedures in Mathcad 15 are summarized in Table 3.

The obtained regression models describe the dependence of the wear parameters on locomotive mileage. For the average value of the large gear wheel (LGR) tooth wear, the regression relationship was obtained as:

$$m_x(l) = 0.0002398l + 0.2516718,\ r = 0.948.$$

The obtained correlation coefficient indicates a strong relationship between mileage and the mean wear value, confirming the applicability of the proposed regression approach for predicting wear progression.

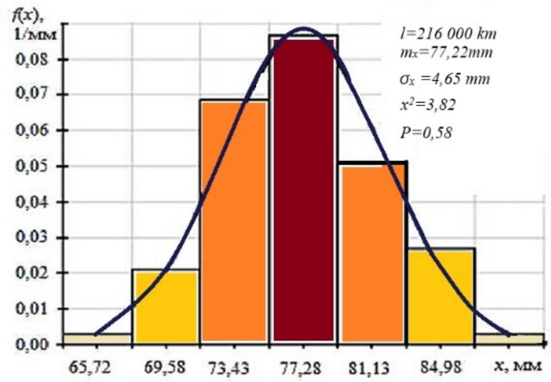

Figure 1: Distribution of the thickness of wheel pair treads for the VL-80s electric locomotive (according to data from the Uzbekistan locomotive repair depot).

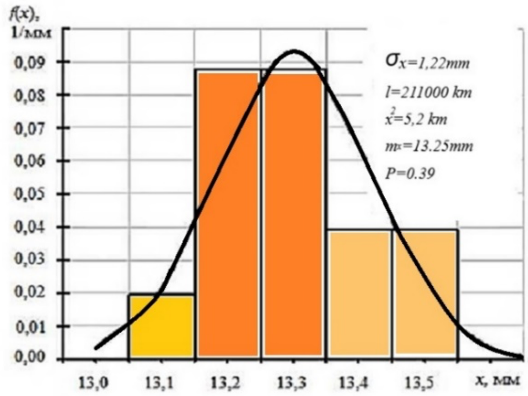

Figure 2: Distribution of the tooth thickness of the large gear wheel (LGR) of the wheel pairs for the VL-80s electric locomotive (according to the locomotive repair depot data).

Table 3: Coefficients of empirical regression models obtained by approximation and spline interpolation.

Coefficient	Bandage thickness	Gear tooth wear, LGR
m_x(l): a, mm/thd.km	-0.0859	0.0101
m_x(l): b, mm	96.83	0.01
σ_x(l): a, mm/thd.km	0.02321	1.37
σ_x(l): b, mm	1.5595	0.274
x_D, mm	45	3

The regression dependence of the standard deviation of LGR tooth wear on mileage was obtained as:

$$\sigma_x(l) = 0.0000171l + 0.2582241,\ r = 0.195.$$

Since the correlation coefficient is relatively small, its statistical significance was evaluated. For the sample of n = 42 wear measurements, the critical correlation coefficient at a two-tailed significance level of 0.05 with n−2 = 40 degrees of freedom is approximately $r_{crit} = 0.304$. The observed value $|r| = 0.195$is below this threshold (t = 1.25, p ≈ 0.22); therefore, the null hypothesis of zero correlation cannot be rejected. This indicates that the standard deviation of LGR tooth wear does not demonstrate a statistically significant dependence on mileage within the investigated operating range and can be considered approximately constant.

3.3 Full-Scale Experimental Studies

Accuracy here scales with data: larger operational databases and continued training push the network's output closer to how the structural elements actually perform, a point confirmed by experimental studies and full-scale tests on operating electric locomotives [25]. The underlying experimental work is itself a first - upgraded VL80s bogie frames fitted with reinforcing pads had not previously been studied this way [25] - and its main purpose is building a fundamental damage database that then feeds into modeling the locomotives' dynamic characteristics [1], [2], [5], [7], [11].

The modeling was carried out on the basis of the characteristics of the bogies of the VL80s electric locomotive, obtained during tests on the bench [17], [19] and during measuring trips [25]. During these trips, information is collected on the real loads that occur in the bogie frames and the main frame of the body of the VL80s electric locomotive, as well as data to test the developed on-board diagnostics algorithm under conditions of real rolling stock fluctuations.

The signals (possible diagnostic parameters) obtained during the measurements were evaluated using various algorithms as a function of time and frequency. In the first case, the statistical parameters were calculated and divided into classes; in the second case, the frequency spectra were analyzed and the transfer function was calculated. Only some of the evaluation algorithms turned out to be suitable for diagnostics.

Full-scale experimental studies on dynamic vibrations of the main body frame and bogie frames were carried out on VL80s electric locomotives, following standard practice for accelerometer-based structural vibration monitoring [26]. The objectives of the experimental studies were:

1) look at dynamic vibrations in the main body frame and bogie frames of in-service VL80s locomotives at "Uzbekistan Temir Yullari" JSC, now fitted with reinforcing pads;
2) pin down the dominant oscillation frequency spectrum and build amplitude-frequency characteristics (AFC) for sections of the body frame and bogie frames, checking these against theory and earlier experimental work [1], [2], [5], [7];
3) analyzing the stress-strained state of the main body frame and bogie frames of the VL80s electric locomotive under various loading conditions and comparing experimental data with theoretical data.

Testing stretched over several days in repeated series, with total elapsed time, the locomotive's speed mode, and vibrations and deformations of the main body frame all logged continuously.

Spectral analysis of the experimental records shows that, under the driving loads generated as the locomotive travels over track irregularities and through curves, the main body frame and bogie frames vibrate across a wide frequency band, from 0.1 to 5000 Hz. Higher-frequency vibrations also appear in the spectrum; these are not typical of the mechanical system itself and are attributable instead to harmonic components.

From the analysis it is obvious that the total oscillation frequency in the middle of the frame span of the bogie frame of the VL80s electric locomotive is equal to 6 Hz in terms of the first harmonic, and the longitudinal stresses are sign-alternating and do not exceed 40 MPa at a speed of V = 100 km/h and a total train weight of 2000 t. The experimental data are in good agreement with the theoretical values, with an error of 5-8% across various train loading modes; the error increases with locomotive speed but does not exceed 8%.

During the study, the model's performance was assessed using the following metrics: the coefficient of determination (R^2), the mean absolute error (MAE), and the root mean square error (RMSE). The performance indicators are presented in Table 4.

While the R^2 values in Table 4 (0.94/0.91/0.89) indicate strong overall fit, the practical accuracy of the model is better judged relative to the range of the predicted quantity: the test-set MAE of 5.2 MPa corresponds to approximately 8% of the higher bending-stress value (68 MPa) and about 14% of the lower longitudinal-stress value (38 MPa) reported in Table 2.

Table 4: Performance indicators of the study.

Dataset	R^2	MAE (MPa)	RMSE (MPa)
Training	0.94	3.8	5.1
Validation	0.91	4.6	6.3
Test	0.89	5.2	6.9

4 CONCLUSIONS

This study proposed an artificial intelligence–based methodology for diagnosing the technical condition of reinforced VL80s electric locomotive bogie frames. The developed approach combines artificial neural networks with regression analysis, spline interpolation, and engineering modeling to evaluate the load-bearing capacity and predict the condition of reinforced structural components.

Probability-distribution analysis and regression modeling demonstrated that the wear characteristics of wheel treads and large gear wheel (LGR) teeth can be effectively described as functions of locomotive mileage, providing a practical basis for predicting wear progression and estimating the remaining service life of critical components. Full-scale experimental investigations further confirmed the adequacy of the proposed methodology, with the difference between theoretical predictions and experimental measurements remaining within 5–8% under various operating conditions. In addition, the developed artificial intelligence model demonstrated high predictive performance, indicating its suitability for practical engineering applications.

Overall, the proposed computational framework provides a reproducible methodology for intelligent diagnostics and predictive maintenance of modernized electric locomotives. The integration of artificial intelligence with conventional engineering analysis enables more reliable condition assessment and supports data-driven maintenance planning, contributing to improved operational reliability and more efficient lifecycle management of railway rolling stock.

REFERENCES

[1] S. Timoshenko, Strength of Materials: Part II - Advanced Theory and Problems. St. Petersburg: Lan Publ., 2002.

[2] M. Spiryagin, C. Cole, Y. Sun, et al., Design and Simulation of Rail Vehicles, Ground Vehicle Engineering Series. Boca Raton, FL, USA: CRC Press, 2014.

[3] B. J. Wang, Q. Li, Z. S. Ren, and S. G. Sun, “Improving the fatigue reliability of metro vehicle bogie frame based on load spectrum,” International Journal of Fatigue, vol. 132, Art. no. 105389, 2020, [Online]. Available: https://doi.org/10.1016/j.ijfatigue.2019.105389.

[4] I. P. Kiselev, High-Speed Rail Transport. General Course, vol. 2. Moscow: Educational and Methodological Center for Railway Transport, 2014.

[5] E. Oganyan and G. Volokhov, Calculations and Strength Tests of Locomotive Structures. Moscow: Educational and Methodological Center for Railway Transport, 2013.

[6] I. S. Biryukov and A. N. Savoskin, Eds., Mechanical Part of Rolling Stock. Moscow: Transport, 1992.

[7] A. N. Savoskin, G. P. Burchak, and A. P. Matveevichev, Strength and Reliability of Railway Rolling Stock. Moscow: Mashinostroenie, 1990.

[8] A. V. Gorsky and A. A. Vorobiev, Reliability of Electric Rolling Stock. Moscow: Route, 2005.

[9] M. Sobáś, T. Antkowiak, R. Grzechowiak, and R. Miklasz, “Development trends in the construction of gear running systems of rail vehicles (Part 1),” Rail Vehicles/Pojazdy Szynowe, no. 3, pp. 33-51, 2017, [Online]. Available: https://doi.org/10.53502/RAIL-138448.

[10] V. Telichenko, V. Rimshin, V. Eremeev, and V. Kurbatov, “Mathematical modeling of groundwater pressure distribution in underground cylindrical structures,” MATEC Web of Conferences, vol. 196, Art. no. 02025, 2018, [Online]. Available: https://doi.org/10.1051/matecconf/201819602025.

[11] B. J. Wang, S. Q. Xie, Q. Li, and Z. S. Ren, “Fatigue damage prediction of metro bogie frame based on measured loads,” International Journal of Fatigue, vol. 154, Art. no. 106532, 2022, [Online]. Available: https://doi.org/10.1016/j.ijfatigue.2021.106532.

[12] H. Zhao, P. Li, and M. Fu, “Fatigue strength analysis of bogie frames under random loads,” Advances in Mechanical Engineering, vol. 11, no. 9, 2019, [Online]. Available: https://doi.org/10.1177/1687814019878018.

[13] J. Li, Z. Ren, Y. Wu, and R. An, “Fatigue damage assessment of high-speed train bogie frame load spectra based on phase reconstruction,” Engineering Failure Analysis, vol. 159, Art. no. 108008, 2024, [Online]. Available: https://doi.org/10.1016/j.engfailanal.2024.108008.

[14] Y. Lu, H. Zheng, J. Zeng, T. Chen, and P. Wu, “Fatigue life reliability evaluation in a high-speed train bogie frame using accelerated life and numerical test,” Reliability Engineering & System Safety, vol. 188, pp. 221-232, 2019, [Online]. Available: https://doi.org/10.1016/j.ress.2019.03.033.

[15] T. Gazdulski, J. Lewiński, and M. Far, “Possibility of optimizing the chassis of modern passenger wagons in relation to weight reduction,” Rail Vehicles/Pojazdy Szynowe, no. 4, pp. 27-34, 2018, [Online]. Available: https://doi.org/10.53502/RAIL-138522.

[16] P. Kessler, “Development of Automated Comparison Routines Between Calculation and Test Bench Results of Bogie Frames According to EN 13749,” Diploma thesis, Technische Universität Wien, Vienna, Austria, 2021, [Online]. Available: https://doi.org/10.34726/hss.2021.80505.

[17] S. Abdurasulov, N. Zayniddinov, O. Khamidov, A. Yusufov, and S. Jamilov, "Stress-strain state analysis of cross beam of main frame of industrial electric locomotives PE2M and PE2U," AIP Conference Proceedings, vol. 3256, no. 1, Art. no. 060011, 2025, [Online]. Available: https://doi.org/10.1063/5.0266927.

[18] S. Jamilov, A. Yusufov, O. Khamidov, O. Kasimov, and M. Vokhidov, "Mathematical modelling of heat exchange process of locomotive traction electric motors," AIP Conference Proceedings, vol. 3256, no. 1, Art. no. 060012, 2025.

[19] O. Khamidov, N. Zayniddinov, S. Kudratov, and B. Erkinov, "Analysis of malfunctions occurring in locomotive thermal power plant crankshafts during operation," E3S Web of Conferences, vol. 538, Art. no. 01027, 2024, [Online]. Available: https://doi.org/10.1051/e3sconf/202453801027.

[20] S. Kudratov, A. Yusufov, O. Khamidov, and S. Samatov, "Diesel locomotives: fault analysis and problem solving," AIP Conference Proceedings, vol. 3256, no. 1, Art. no. 060013, 2025, [Online]. Available: https://doi.org/10.1063/5.0266930.

[21] S. G. Tatarintseva, T. P. Satsuk, D. V. Udalova, and O. R. Khamidov, "Risk management and financial stability of transport companies," AIP Conference Proceedings, vol. 2624, no. 1, Art. no. 040056, 2023, [Online]. Available: https://doi.org/10.1063/5.0150187.

[22] O. Khamidov, A. Yusufov, S. Jamilov, and S. Kudratov, "Remaining life of main frame and extension of service life of shunting locomotives on railways of the Republic of Uzbekistan," E3S Web of Conferences, vol. 365, Art. no. 05008, Jan. 2023, [Online]. Available: https://doi.org/10.1051/e3sconf/202336505008.

[23] A. Yusufov, O. Khamidov, N. Zayniddinov, and S. Abdurasulov, "Prediction of the stress-strain state of the bogie frames of shunting locomotives using the finite element method," E3S Web of Conferences, vol. 401, Art. no. 03041, Jul. 2023, [Online]. Available: https://doi.org/10.1051/e3sconf/202340103041.

[24] G. Khromova, D. Radjibaev, A. Zabiyeva, A. Kenesbek, and A. Mavlanov, "Calculation of the main parameters of the two-line helical traction transmission of an electric locomotive based on diagnostic parameters," Applied Sciences, vol. 15, no. 4, Art. no. 1730, 2025, [Online]. Available: https://doi.org/10.3390/app15041730.

[25] G. Khromova, D. Radjibaev, and A. Zabiyeva, "Method of calculation for dynamic strength of complex configuration frame structures of locomotives for transport engineering," E3S Web of Conferences, vol. 474, Art. no. 01032, 2024, [Online]. Available: https://doi.org/10.1051/e3sconf/202447401032.

[26] A. Mamatov, X. Sotvoldiyev, M. Talipov, S. Shaumarov, K. Gafarbayli, and D. Bekmirzaev, "Metrological calibration and uncertainty evaluation of MEMS accelerometers for structural health monitoring in seismic regions," Vibroengineering Procedia, vol. 62, pp. 140-144, Jun. 2026, [Online]. Available: https://doi.org/10.21595/vp.2026.26360.