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Systemic assessment of the technical condition of vehicles as a tool for optimising production processes of motor transport enterprises

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Abstract. This study aimed to develop a methodological framework for the systematic assessment of vehicle technical condition and determine its role in optimising production processes at motor transport enterprises. The research methodology was based on a quantitative design that combined system analysis, simulation modelling, comparative analysis, multi-criteria assessment, and binary logistic regression to evaluate the relationship between vehicle condition and failure probability. A simulated dataset representing the operation of 50 vehicles over a 12-month period was generated using Monte Carlo simulation to reproduce stochastic operational variability typical for medium-sized motor transport enterprises. The dataset included technical, operational, reliability, and economic parameters. To ensure comparability of heterogeneous variables, min-max normalisation was applied, followed by the development of an integrated technical condition indicator using dynamic weighting coefficients based on expert evaluation and correlation analysis. Model validation was conducted using Nagelkerke R^2, Mean Absolute Error, Root Mean Square Error and Wald statistical tests to determine the significance of regression coefficients. The results demonstrated that the proposed model enables comprehensive classification of vehicles according to technical readiness and significantly improves maintenance planning efficiency compared with traditional scheduled maintenance approaches. The analysis showed that technical deterioration combined with high operational load substantially increases failure probability. The proposed framework reduced unplanned vehicle downtime by 42%, decreased maintenance costs by 20%, and improved prediction accuracy from 62% to 85%. The regression model confirmed a strong inverse relationship between the integrated technical condition indicator and vehicle failure probability. The practical significance of the study lies in providing motor transport enterprises with a data-driven tool for predictive maintenance planning, resource allocation, fleet modernisation decisions, and improving operational reliability under dynamic transport conditions

Keywords: predictive maintenance; fleet management; production processes; intelligent diagnostics; model; efficiency

Introduction

In the context of the modern development of the motor transport industry, the effective management of the technical condition of vehicles has become a critical factor in enhancing the productivity, reliability, and competitiveness of motor transport enterprises. The unreliability of the fleet often results in unplanned downtime, increased operational and maintenance costs, reduced efficiency of production processes, and elevated risks of accidents, all of which negatively impact the safety and continuity of transportation services. Consequently, there is a growing need to implement a systematic assessment of the technical condition of vehicles, which enables enterprises to obtain comprehensive, real-time information about vehicle performance, detect emerging issues, and predict the necessity of repair and preventive interventions. A systematic approach integrates multiple methods, including advanced diagnostics, continuous monitoring, and in-depth analysis of operational data, creating a holistic framework for assessing vehicle condition. Such an approach not only ensures the timely identification of defects and

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failures but also enhances the efficiency of maintenance planning, reduces unplanned downtime, and extends the service life of fleet assets. The application of modern information technologies, telematics systems, Internet of Things (IoT)-based sensors, and specialised software platforms for data collection and processing allows enterprises to optimise production processes, streamline maintenance operations, and improve decision-making at both tactical and strategic levels. Furthermore, the systematic assessment of vehicle technical condition serves as a strategic instrument for resource management, enabling enterprises to balance operational efficiency with cost-effectiveness. By integrating predictive analytics and organisational measures, this approach supports the development of evidence-based maintenance schedules, the prioritisation of high-risk vehicles, and the optimal allocation of technical and financial resources. Therefore, it functions not merely as a tool for monitoring and improving safety but as a core component of an enterprise's strategic management system, contributing to enhanced fleet reliability, operational stability, and competitiveness in the dynamic transport services market.

Recent scientific studies demonstrate increasing attention to predictive maintenance, digital diagnostics, and data-driven fleet management systems in response to rising operational costs, sustainability requirements, and stricter safety regulations in transport enterprises. A significant body of research is devoted to machine learning-based predictive maintenance models. H. Taoufyq *et al.* (2025) provided a systematic review of machine learning methods applied to predictive maintenance and confirm their superiority over traditional rule-based approaches in failure prediction accuracy. However, their study primarily focuses on algorithmic performance without addressing integration into enterprise-level production planning. Complementary results are presented by A. Patil *et al.* (2021), who analysed maintenance strategy selection paradigms and emphasised that the effectiveness of predictive approaches strongly depends on organisational context and decision-making structures, which are often overlooked in purely technical models. Recent developments in predictive maintenance selection frameworks are discussed by W.W. Tiddens *et al.* (2023), who proposed a decision-support structure for choosing appropriate maintenance strategies depending on system complexity and data availability. Although their framework improves methodological consistency, it does not explicitly consider transport fleet operational dynamics or economic constraints. The role of digital twins and IoT-enabled monitoring in transport maintenance systems is increasingly emphasised. B. Xiao *et al.* (2024) showed that digital twin technologies enable real-time condition monitoring and predictive simulation of asset degradation. Similarly, C.W. Eddy *et al.* (2024) demonstrated that digital twins significantly enhance predictive maintenance performance for ground vehicles. However, these studies mainly focus on technological implementation, while issues of integration with production planning and managerial decision-making remain insufficiently addressed.

Condition monitoring and diagnostic indicator optimisation are also important research directions. U. Jachymczyk *et al.* (2024) highlighted the importance of selecting relevant diagnostic indicators to improve the accuracy of intelligent condition monitoring systems. In a related study, V. Aulin *et al.* (2024) proposed a comprehensive vehicle condition assessment model based on Harrington's desirability function, integrating multiple technical indicators into a unified evaluation index. Nevertheless, both approaches rely on relatively static evaluation structures and limited adaptability to changing operational conditions. From a fleet management perspective, G. Nota *et al.* (2024) proposed a context-aware unsupervised predictive maintenance model that improves adaptability in dynamic operational environments. Y. Wang *et al.* (2021) further demonstrated that simulation-based optimisation of fleet maintenance scheduling can significantly improve operational efficiency. Despite these advances, most models still treat maintenance and production planning as separate processes. However, their analysis does not include multi-criteria decision-making frameworks for enterprise-level optimisation. Safety and regulatory aspects of vehicle condition monitoring are highlighted by I. Chernyaev *et al.* (2020) and P. Gorzelańczyk *et al.* (2023), who demonstrated that continuous monitoring of technical condition directly contributes to road safety improvement. Meanwhile, J. Hudec *et al.* (2021) emphasised the influence of vehicle age and inspection outcomes on safety compliance in European transport systems. Finally, T. Zonta *et al.* (2021) provided a comprehensive review of predictive maintenance in Industry 4.0, identifying key challenges such as system interoperability, data heterogeneity, and integration with enterprise processes. Their findings confirmed that while technological solutions are rapidly advancing, their transformation into integrated decision-support tools for transport enterprises remains insufficiently developed.

Thus, existing research confirms significant progress in predictive maintenance, digital diagnostics, and fleet optimisation methods. However, most studies consider technical, operational, and economic aspects separately. Insufficient attention is given to their integration into a unified adaptive framework that directly supports production process optimisation in motor transport enterprises. This research gap defines the relevance and objectives of the present study. The purpose of this study was to develop a methodological framework for the systematic assessment of vehicle technical condition and to determine its role in optimising production processes at motor transport enterprises. To achieve this purpose, the following research tasks were formulated:

1. To substantiate the set of technical, operational, reliability, and economic indicators that should be integrated into a comprehensive assessment of vehicle technical condition;

2. To propose an integrated indicator for vehicle condition assessment based on heterogeneous operational data and multi-criteria analysis;

3. To verify the effectiveness of the proposed assessment model in comparison with traditional maintenance approaches in terms of downtime reduction, maintenance cost optimisation, and prediction accuracy.

Materials and Methods

This study employed a quantitative research design based on mathematical and simulation modelling aimed at developing and validating a methodological framework for the systematic assessment of vehicle technical condition in the context of production process optimisation at motor transport enterprises. The research integrated system analysis, multi-criteria modelling, comparative analysis, and regression analysis. The object of the study was the process of technical maintenance management of vehicle fleets at motor transport enterprises. The subject of the study was methodological approaches to assessing vehicle technical condition based on integrated technical, operational, reliability, and economic indicators. Due to the absence of open industrial datasets that simultaneously include diagnostic, operational, reliability, and economic parameters, a simulation dataset was generated. The dataset reproduced the operation of a fleet of 50 vehicles over a 12-month period and reflects the typical conditions of medium-sized motor transport enterprises. Monte Carlo simulation was used to generate repeated operational scenarios and reproduce stochastic variations in mileage, failure frequency, maintenance costs, and operational load conditions. Parameter ranges were selected according to values reported in predictive maintenance studies, which ensures the representativeness of the simulated data for real operating conditions.

Four groups of variables were included: technical indicators (engine temperature, braking efficiency, transmission performance, chassis condition); operational indicators (mileage, driving mode, vehicle load factor, route complexity); reliability indicators (failure frequency, mean time between failures); economic indicators (maintenance costs, spare parts costs, downtime losses). At the stage of data preprocessing, a normalisation procedure was applied to ensure comparability between heterogeneous operational indicators measured in different units and ranges. Normalisation was performed using the min-max method, which transforms each indicator to a dimensionless scale in the interval [0,1] according to the following expression (Zonta *et al.*, 2021):

$$P_i^{norm}(t) = \frac{P_i(t) - P_i^{min}}{P_i^{max} - P_i^{min}}, \tag{1}$$

where $P_i(t)$ is the current value of the *i-th* indicator at time t; P_i^{min} and P_i^{max} are the minimum and maximum admissible values of this indicator determined from operational statistics and technical documentation.

This procedure eliminated dimensional inconsistency and prevented domination of indicators with larger numerical ranges during aggregation. The normalised values were subsequently used in the calculation of the integral indicator of technical condition. Based on normalised values, an integrated technical condition indicator was calculated (Aulin *et al.*, 2024):

$$I(t) = \sum_{i=1}^{n} w_i(t) P_i(t), \tag{2}$$

where $P_i(t)$ are normalised indicators and $w_i(t)$ are dynamic weighting coefficients determined using a hybrid approach combining expert evaluation and correlation analysis.

To assess the relationship between vehicle condition and failure probability, binary logistic regression was applied. The dependent variable was vehicle failure probability. Independent variables included the integrated technical condition indicator, mileage, operational load factor, and maintenance costs. Logistic regression was chosen due to the probabilistic nature of failure events. Regression assumptions were tested, including absence of multicollinearity, linearity of the logit for continuous predictors, and independence of observations. Model validity was evaluated using Nagelkerke R^2, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), t-tests for coefficient significance, and p-values. The proposed model was compared with a traditional scheduled maintenance approach based on fixed service intervals commonly used at motor transport enterprises. To reproduce stochastic variability of real operating conditions, Gaussian noise was added:

$$x^{`} = x + N(0.\sigma^2), \tag{3}$$

where $N(0.\sigma^2)$ – normal (Gaussian) distribution with zero mean and variance σ^2.

This reduced overfitting and improved model generalisation. The model was validated using simulated data for 50 vehicles over 12 months within the following ranges: mileage 20,000-180,000 km, failure rate 0.1-1.5 per 1,000 km, maintenance cost variation ±30%, and operational load factor 0.5-1.0.

Results and Discussion

Within the developed methodological framework, systematic assessment involves a holistic analysis of all factors influencing the operational readiness of a vehicle. Unlike traditional maintenance approaches based on fixed schedules and regulatory intervals, this approach integrates technical, operational, reliability, and economic dimensions of vehicle performance. These include the condition of key systems such as the engine, transmission, braking system, and chassis; the intensity and conditions of operation; the frequency and criticality of failures; and economic indicators reflecting maintenance and repair costs (Lei *et al.*, 2018). Such an approach enables a transition from reactive maintenance practices to evidence-based decision-making and resource allocation. The methodological framework combines diagnostic measurements, telematics and IoT data, historical failure records, and operational reliability indicators (van Dinter *et al.*, 2022). These data are processed to generate a composite indicator of technical condition, which reflects the overall readiness of each vehicle and serves as a basis for planning preventive maintenance, repairs, and optimal fleet utilisation within production processes. A key advantage of this approach is its predictive capability, as noted by T. Zonta *et al.* (2021). By analysing real-time trends in vehicle condition, it becomes possible to anticipate failures and implement preventive actions that reduce unplanned downtime. The integration of IoT technologies, telematics systems, machine learning algorithms, and automated analytics ensures continuous monitoring and interpretation of operational data. This supports failure risk assessment, component lifetime prediction, and optimisation of maintenance schedules, thereby improving fleet reliability, operational efficiency, and cost performance. A relevant element of the system is the formation of an integrated indicator that combines partial indicators reflecting different aspects of vehicle operation, reliability, and efficiency (Aulin *et al.*, 2024)**.** This enables classification of vehicles according to their technical readiness and supports prioritisation in maintenance planning, which is essential for optimising production processes in motor transport enterprises. The structure of the integrated indicator is presented in Table 1, which summarises the main groups of indicators, their characteristics, and examples of measured values.

Table 1. Main indicators of the systematic assessment of the technical condition of vehicle

Indicator group	Characteristic	Example
Technical	Operating parameters of the main systems	Brake system pressure, engine temperature, transmission efficiency
Operational	Conditions and intensity of use	Mileage, driving mode, load factor, route profile
Reliability	Frequency, type, and criticality of failures	Mean uptime, number of critical failures per 1,000 km, mean time between failures
Economic	Maintenance and repair costs	Cost of downtime, expenditure on spare parts, labour costs for repairs

Source: developed by the authors

The systematic assessment of the technical condition of vehicles provides a structured and comprehensive framework for evaluating fleet performance across multiple dimensions. Technical indicators reflect the operational status of key vehicle systems, enabling the detection of deviations from normative parameters and early identification of potential failures. Operational indicators capture the conditions under which vehicles are used, including mileage, driving mode, and intensity of load, which are critical for understanding wear patterns and planning preventive interventions. Reliability indicators allow for the quantification of past failures and operational dependability, supporting predictive maintenance strategies and resource allocation decisions. Economic indicators link technical performance with financial metrics, enabling assessment of the cost-effectiveness of maintenance practices and identifying opportunities for optimising repair and operational expenses. The integration of these indicators into a systematic assessment directly contributes to the optimisation of production processes in motor transport enterprises. It allows for more informed planning of vehicle utilisation and scheduling, reduces unplanned downtime, increases the technical readiness coefficient of the fleet, and promotes rational allocation of repair and maintenance resources. Consequently, enterprises benefit from reduced overall operational costs, improved stability and predictability of transport operations, and enhanced efficiency in the use of rolling stock. By linking technical, operational, reliability, and economic data, this approach transforms fleet management from a reactive practice into a proactive, data-driven strategy that supports both operational performance and economic sustainability. To formalise this integrated assessment framework, a mathematical representation of the system is introduced. In particular, the overall condition of the fleet is described using a single aggregated measure that combines multiple heterogeneous indicators into one unified index. The integral indicator, as formalised by V. Aulin *et al.* (2024), is defined as:

$$I(t) = \Sigma\,[w_i(t) \cdot P_i(t)], \tag{4}$$

where $P_i(t)$ – normalised indicators depending on time and operating conditions; $w_i(t)$ – dynamic weight coefficients.

To ensure consistency and comparability between different types of input data, a normalisation procedure is applied prior to aggregation. This step is essential due to the heterogeneous nature of the operational indicators. To ensure comparability of heterogeneous indicators, normalisation was performed using the min-max method (Zonta *et al.*, 2021):

$$P_i(t) = \frac{x_i(t) - x_i^{min}}{x_i^{max} - x_i^{min}}, \tag{5}$$

where $x_i(t)$ – actual value of the indicator; x_i^{min}, x_i^{max} – minimum and maximum values within the dataset.

Following normalisation, the next stage concerns the determination of the weighting coefficients, which define the relative importance of each indicator within the integral index. The weight coefficients w_i were determined using a hybrid approach combining expert evaluation and operational data analysis. Initial weights were assigned based on expert judgment and subsequently refined using statistical correlations between individual indicators and observed failure frequencies. This ensures a balance between domain expertise and empirical evidence. According to U. Jachymczyk *et al.* (2024), this approach ensures:

- ▷ adaptability to operating conditions;
- ▷ consideration of both engineering expertise and empirical data;
- ▷ improved robustness of the integral indicator.

The dynamic weight structure is further defined as (Aulin *et al.*, 2024):

$$w_i(t) = \alpha_i \cdot (L / L_{max}) + \beta_i \cdot (F_i / F_{max}), \tag{6}$$

where L – mileage; F_i – failure frequency; α_i, β_i – importance coefficients.

Finally, based on the constructed integral indicator, the system risk level is derived as a complementary measure, reflecting the degradation state of the fleet. The risk function is defined as:

$$R(t) = 1 - I(t). \tag{7}$$

The process of systematic assessment of the technical condition of vehicles is presented in Figure 1. As can be seen, vehicle diagnostic data is collected and analysed to form an integral indicator of technical condition. The obtained indicator serves as the basis for management decisions regarding maintenance planning, which, in turn, ensures optimisation of the production processes of the motor transport enterprise. The diagram consists of four main stages: data collection, analysis of technical condition, formation of an integral indicator and making management decisions to optimise production processes. Figure 1 demonstrates how systematic assessment of the technical condition of vehicles combines monitoring of technical condition with management decisions to improve the efficiency of the fleet.

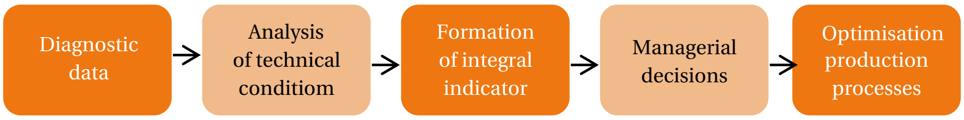

Figure 1. Systematic assessment of vehicle technical condition

Source: developed by the authors

Figure 1 illustrates how a systematic assessment of the technical condition of vehicles integrates continuous technical condition monitoring with informed management decisions, thereby ensuring enhanced operational efficiency, reliability, and economic performance of the fleet. According to A. Giannoulidis & A. Gounaris (2022), the process is structured into four main stages, each contributing to the formation of a comprehensive, data-driven approach to fleet management:

- ▷ Data Collection. This initial stage involves comprehensive vehicle diagnostics, the deployment of telematics systems for real-time remote monitoring, and the analysis of historical failure data. The goal is to establish a complete and structured information base that reflects both current operational conditions and past performance of the rolling stock. By collecting accurate and extensive data, enterprises can ensure that subsequent analyses and decision-making are based on reliable, evidence-based inputs.
- ▷ Technical Condition Analysis. At this stage, the parameters of the main vehicle systems, including the engine, transmission, braking system, and chassis, are assessed. Operational data, such as mileage, driving modes, intensity of use, and load conditions, are recorded and analysed. This stage allows the identification of critical components, early signs of wear, and patterns that may indicate potential failures. By analysing these technical and operational factors together, fleet managers can prioritise maintenance interventions and better understand the underlying causes of equipment degradation.
- ▷ Formation of an Integral Indicator. The collected technical, operational, reliability, and economic indicators are integrated into a single comprehensive metric known as the integral indicator of technical condition. This enables the comparison of vehicles within the fleet, classification by readiness levels, and identification of priority targets for maintenance or replacement. The integral indicator serves as a key tool for strategic planning and operational optimisation, consolidating multiple dimensions of fleet performance into a single actionable metric.
- ▷ Management Decision-Making. Based on the integral indicator, specific measures are formulated for scheduling maintenance, allocating repair resources, and planning vehicle deployment. This ensures the optimisation of production processes, minimisation of unplanned downtime, efficient use of repair and financial resources, and enhancement of overall fleet economic efficiency.

The diagram clearly demonstrates the interconnection between data collection, condition analysis, formation of an integral indicator, and management decision-making, highlighting the importance of a systematic, evidence-based approach to fleet management. Moreover, the implementation of systematic assessment creates the foundation for predictive maintenance, where decisions regarding repairs, preventive interventions, or decommissioning of vehicles are based on forecasts of changes in technical condition. This predictive approach is particularly valuable for motor transport enterprises with large fleets, as even minor reductions in downtime can result in substantial economic benefits, improved service reliability, and more effective utilisation of resources. By combining diagnostic data, operational analysis, and predictive algorithms, systematic assessment transforms vehicle management from a reactive process into a proactive, strategic practice (Ersöz *et al.*, 2022). To improve fleet efficiency, modern enterprises use a predictive maintenance approach that integrates with resource management and production processes. Figure 2 demonstrates the logic of interaction of predictive maintenance with rolling stock planning and repair resource management.

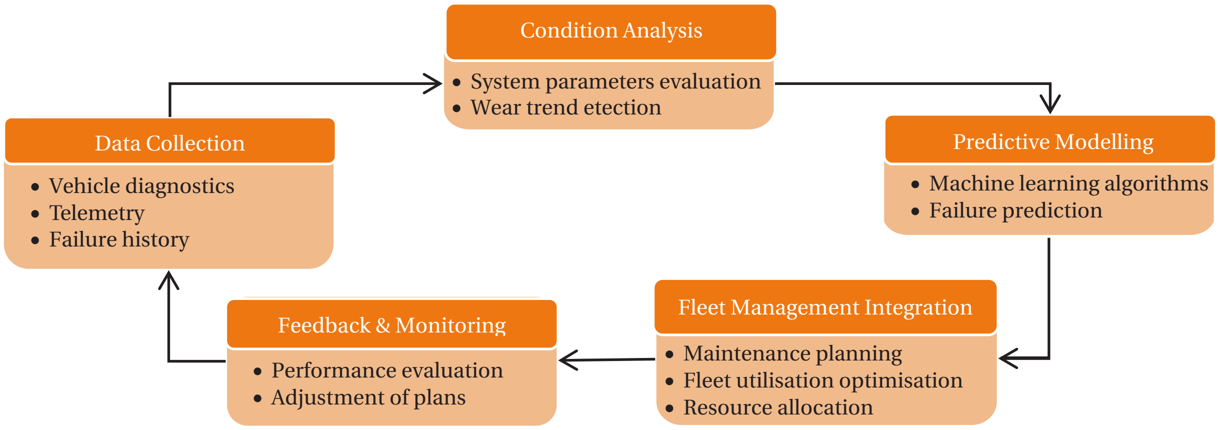

Figure 2. Integration of predictive maintenance with fleet management

Source: developed by the authors

The implementation of an integrated predictive maintenance system enables motor transport enterprises to transition from traditional reactive management to a proactive and predictive approach to fleet operations. Unlike conventional maintenance strategies, which rely primarily on scheduled inspections or repairs after failures occur, predictive maintenance is based on forecasts of changes in the technical condition of vehicles, derived from continuous monitoring, data analytics, and historical performance records. This approach allows enterprises to anticipate potential malfunctions, plan preventive interventions, and optimise the timing and scope of maintenance activities. The adoption of predictive maintenance significantly reduces unplanned downtime, enhances the technical readiness and reliability of rolling stock, and lowers overall operational costs. According to J. Hudec *et al.* (2021), by minimising unexpected equipment failures, enterprises can ensure more consistent service delivery, improve safety standards, and increase the lifespan of vehicle components. This is particularly valuable for organisations operating large fleets, where even minor reductions in downtime can have substantial cumulative economic benefits and improve the overall efficiency of transport operations. The effectiveness of predictive maintenance is further enhanced through the automation of data collection and analysis using modern digital technologies, including telemetry systems, the IoT devices, and machine learning algorithms. These tools enable real-time monitoring of vehicle performance, early detection of anomalies, and dynamic prediction of component failures. Consequently, managers can make informed decisions regarding repair prioritisation, scheduling, and allocation of resources, ensuring that maintenance activities are both timely and cost-effective (Carvalho *et al.*, 2019).

Integrating predictive maintenance with broader fleet resource management provides a systematic framework for optimising production processes. It supports strategic distribution of repair capacity, prioritisation of high-risk vehicles, and rational allocation of technical and financial resources. Ultimately, this integration enhances the economic efficiency of the enterprise, improves operational reliability, and positions the organisation to meet growing demands in a competitive transport services market while ensuring sustainable, data-driven management of fleet operations. Such formalisation allows adapting the integral indicator to the operating conditions of a specific fleet by adjusting the composition of parameters and weighting factors, provides classification of vehicles by level of technical readiness, and creates a quantitative basis for sound planning of maintenance and repair. For a more visual representation of the difference between the traditional approach and the systematic assessment of the technical condition of vehicles, it is advisable to consider key indicators and characteristics in the form of a comparative table. Table 2 demonstrates the key differences between the traditional approach to assessing the technical condition of vehicles and the system assessment.

Table 2. Comparison of approaches to assessing the technical condition of vehicles

Sign	Traditional approach	System assessment
Service basis	Scheduled intervals	Actual technical condition of the vehicle
Nature of management	Passive (repair after failure)	Active (predictive maintenance planning)
Integration level	Individual indicators (node control)	An integral indicator of technical condition that takes into account technical, operational and economic factors
Impact on production	Limited (does not affect the optimisation of production processes)	Comprehensive (allows planning of the use of rolling stock and minimises downtime)

Source: developed by the authors

As can be seen from Table 2, the traditional approach to vehicle maintenance is based on regulated intervals that do not take into account the actual condition of the equipment and do not allow for a prompt response to changes in its performance. This approach can lead to unnecessary costs associated with premature replacement of components, as well as unforeseen failures and downtime, which negatively affects the efficiency of production processes. Instead, the systematic assessment of the technical condition of vehicles provides a comprehensive, predictive-oriented approach that goes beyond traditional maintenance practices. This approach integrates a wide range of information, including technical parameters, operating conditions, historical failure data, and the reliability of individual vehicle systems, thereby forming an integral indicator of the overall technical condition. Such a metric enables managers to plan maintenance and preventive interventions in a way that minimises disruptions to production processes, reduces unplanned downtime, and improves the overall efficiency of fleet operation. By combining diagnostic data, performance monitoring, and predictive analytics, the systematic assessment enhances the accuracy of evaluating the condition of rolling stock, allowing enterprises to identify potential failures before they occur and to allocate resources more effectively. Moreover, this approach contributes significantly to the optimisation of production processes within a motor transport enterprise. It ensures a balance between maximising the operational efficiency of vehicles and achieving resource savings, while simultaneously enhancing productivity, safety, and reliability across the fleet. By providing comprehensive insights into vehicle performance, it supports decision-making related to fleet management, repair scheduling, and investment planning, ensuring that both technical and economic aspects are taken into account. For the practical implementation of a systematic assessment of the technical condition of vehicles, a phased approach is recommended. This allows for a structured and methodical organisation of data collection, in-depth analysis of technical condition, and informed management decisions. Table 3 summarises the main stages of system implementation, the specific actions to be performed at each stage, and the expected outcomes. Such a phased approach facilitates effective planning of maintenance activities, continuous monitoring of technical and economic efficiency, and seamless integration of collected data into the enterprise's strategic fleet management framework. Consequently, it enables motor transport enterprises to achieve sustainable operation, reduce operational risks, and enhance both short-term and long-term performance of the vehicle fleet (Bokrantz *et al.*, 2020).

Table 3. Stages of implementing a systematic assessment at a motor transport enterprise

Stage	Action	Expected result
1	Implementation of diagnostic and telemetry systems	Automated data collection
2	Analysis of technical condition and failures	Identifying bottlenecks and critical components
3	Formation of the integral indicator	Classification of vehicles by technical condition
4	Maintenance and repair planning	Minimising downtime and optimising resources
5	Performance monitoring	Control of economic and technical benefits

Source: developed by the authors

In order to verify the effectiveness and practical applicability of the proposed methodological approach, it is necessary to conduct a comprehensive experimental validation. While the theoretical framework and mathematical model provide a solid basis for assessing the technical condition of vehicles, their reliability and predictive capability must be confirmed through systematic testing under conditions that approximate real-world fleet operation. Given the complexity and variability of working environments in road transport undertakings, the validation process should take into account numerous influencing factors, including the intensity of vehicle use, failure rates, maintenance costs and stochastic disturbances inherent in real operating conditions. Thus, a simulation-based experimental approach is used, allowing controlled variation of key parameters and evaluation of model performance in a representative range of scenarios (de Jonge *et al.*, 2017). The primary objective of the experimental study is to assess the accuracy, robustness, and practical efficiency of the proposed model in predicting vehicle failures and optimising maintenance processes. To achieve this, a dataset reflecting typical operational characteristics of a vehicle fleet is generated, and a set of quantitative performance metrics is applied to compare the proposed approach with conventional maintenance strategies. Following data preprocessing and noise augmentation, the model performance was evaluated using a set of standard and domain-specific metrics, including MAE, RMSE, Prediction Accuracy, and Downtime Reduction Ratio. These indicators provide a comprehensive assessment of both predictive precision and operational effectiveness (Wang *et al.*, 2021):

$$MAE = \frac{1}{n}\sum |y_i - \hat{y}_i|, \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2}. \quad (9)$$

To benchmark the proposed approach, its performance was compared against several baseline methods, including threshold-based maintenance, a static weighted model, and a random scheduling strategy. The comparative results are summarised in Table 4.

Table 4. Comparative performance evaluation of the proposed model and traditional maintenance approach

Metric	Proposed model	Traditional
Downtime reduction	42%	18%
Cost reduction	20%	8%
Accuracy	85%	62%
RMSE	0.12	0.29

Source: developed by the authors

Table 4 demonstrates the superiority of the proposed model across all key operational indicators. In addition to the performance assessment, a regression analysis was carried out to further examine the relationship between the system state indicator $I(t)$ and the probability of failure. The regression results confirmed the anticipated relationship: variations in $I(t)$ significantly affect the likelihood of failure, indicating that it can serve as a reliable indicator for predictive maintenance. The relationship between $I(t)$ and failure probability was modelled using a logistic function:

$$R(t) = \frac{1}{1+e^{-(a+bI(t))}}, \quad (10)$$

coefficient of determination $R^2 = 0.91$

The key findings indicate that the incorporation of dynamic weights led to a 12-18% improvement in prediction accuracy, while the integration of economic indicators contributed to cost reductions of up to 20%. Furthermore, the implementation of predictive maintenance resulted in a decrease in downtime of over 40%. Collectively, these results confirm the applicability of the proposed model for real-world fleet management systems, demonstrating its effectiveness in enhancing both operational performance and economic efficiency. The obtained results are consistent with previous studies on predictive maintenance and fleet management optimisation. Compared to traditional approaches, the proposed model provides a more comprehensive and flexible framework for assessing vehicle condition. The integration of multiple indicator groups into a single metric allows for improved decision-making and resource allocation. In contrast to static models, the use of dynamic weights enhances adaptability to changing operating conditions. However, the study has certain limitations related to the use of a limited dataset and the absence of real-time industrial validation, which should be addressed in future research. Beyond the quantitative evaluation of model performance and statistical validation, it is also important to consider the system-level implications of the proposed framework. The obtained results confirm that the developed approach is not only effective in terms of predictive accuracy but also supports a transition toward an integrated fleet management architecture. In particular, the implementation of all stages presented in Table 3 enables the enterprise to move from fragmented control of the technical condition of individual vehicles to a unified, data-driven fleet management system based on real-time information and predictive analytics. Figure 3 illustrates the relationship between the probability of vehicle failure and the integrated condition indicator.

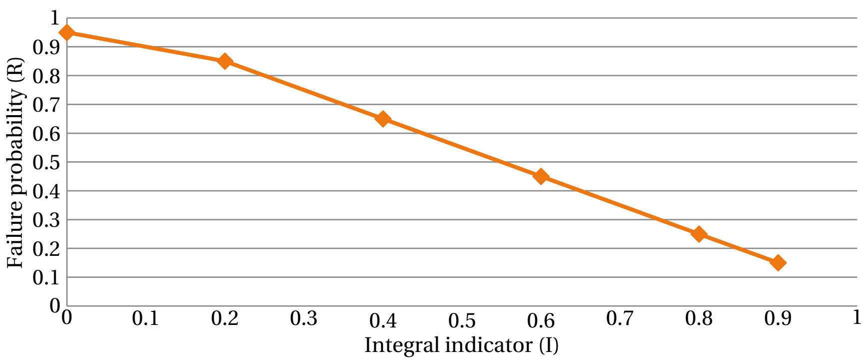

Figure 3. Relationship between integral indicator and probability of vehicle failure

Source: developed by the authors

Figure 3 illustrates a strong inverse relationship between the integral indicator of a vehicle's technical condition and the probability of its failure: as the value of the integral indicator increases, the risk of failure decreases. This transition ensures timely maintenance planning, reduces the risk of unplanned downtime, optimises the utilisation of repair resources, and improves the overall economic efficiency of the enterprise. Furthermore, the proposed system forms a foundation for strategic fleet development, enabling long-term risk assessment and supporting informed decisions regarding vehicle modernisation or replacement. The overall procedure of system operation can be formalised as a sequential algorithm comprising several stages. Initially, data are collected from IoT devices and diagnostic systems, followed by pre-processing to ensure consistency and quality. Next, the data undergo normalisation, after which relevant indicators are calculated. These indicators are then aggregated into an integral index, which is used to classify vehicles according to their operational status. Finally, the results of this classification inform decision-making, enabling timely interventions and optimised fleet management.

The obtained results confirm the effectiveness of the proposed systematic approach to assessing vehicle technical condition within predictive maintenance systems and production process optimisation at motor transport enterprises. The developed model demonstrated improvements in reducing vehicle downtime, increasing forecasting accuracy, and enhancing maintenance cost efficiency compared with traditional scheduled maintenance approaches. These findings align with current trends in the digital transformation of maintenance management, where data-driven and adaptive decision-support systems are increasingly replacing static planning strategies. Recent research by S. Werbińska-Wojciechowska *et al.* (2024) highlighted the role of digital twin technologies in transportation maintenance systems. Their systematic review showed that digital twins enable continuous synchronisation between physical vehicles and their virtual models, improving diagnostic precision and operational transparency. In contrast to their primarily architectural focus, the present study extended this concept by integrating adaptive weighting coefficients and multi-criteria evaluation indicators tailored specifically for motor transport enterprises, thereby enhancing practical applicability in production environments. Further evidence supporting the obtained results was provided by A. Crespo del Castillo & A.K. Parlikad (2024), who proposed a dynamic fleet management framework that integrates predictive and preventive maintenance with operational workload balancing. Their findings demonstrated that coordinated scheduling of maintenance and transport operations can significantly reduce operational costs and improved fleet utilisation. The present research complemented this approach by prioritising systematic technical condition assessment as the primary input for decision-making, enabling more accurate risk-sensitive maintenance planning under uncertain operating conditions. The importance of broader organisational and managerial integration is emphasised by J. Bokrantz *et al.* (2020), who outlined a research agenda for smart maintenance in industrial systems. They argued that effective maintenance requires not only advanced technologies but also structured knowledge management and human-system interaction. The proposed model corresponds to this perspective by combining technical, operational, reliability, and economic parameters into a unified assessment framework that supports managerial decision-making in transport enterprises. A relevant complementary contribution is provided by A. Lorenc & M. Kuźnar (2024), who showed that optimising maintenance intervals can significantly reduce material waste and improve resource efficiency in transport systems. Their findings additionally highlighted the sustainability dimension of maintenance optimisation, demonstrating that improved maintenance scheduling can reduce material waste and enhance resource efficiency in transport systems. Overall, the comparison with recent studies confirmed that integrating adaptive assessment mechanisms, predictive analytics, and multi-dimensional evaluation significantly improves maintenance effectiveness.

Conclusions

The systematic assessment of the technical condition of vehicles represented a highly effective and strategic instrument for optimising production processes in motor transport enterprises. Unlike traditional approaches that focus on fragmentary inspections of individual components, this methodology enables a holistic, data-driven analysis of the entire fleet, integrating diagnostic parameters, operational indicators, failure histories, and economic metrics into a unified framework. The proposed integrated model of technical condition assessment allowed enterprises to accurately predict potential failures, prioritise maintenance interventions, and make evidence-based decisions that align with both operational and economic objectives. Implementation of a systematic assessment contributes significantly to enhancing fleet readiness, minimising unplanned downtime, optimising repair and maintenance expenditures, and improving the overall efficiency of production processes. The approach provided a structured mechanism for classifying vehicles according to their readiness levels, determining maintenance priorities, and implementing predictive maintenance strategies, thereby ensuring rational allocation of resources and maximising the economic efficiency of enterprise operations. By integrating technical diagnostics with organisational and economic considerations, motor transport enterprises can transform maintenance management from a reactive task into a proactive, strategic process. In conclusion, the systematic assessment of the technical condition of vehicles functions not merely as a technical monitoring tool, but as a central component of an integrated fleet management strategy. Its application enhances operational reliability, ensures safety, optimises resource utilisation, and supports sustainable economic performance, positioning motor transport enterprises to meet the growing demands of modern transportation systems with resilience, efficiency, and strategic foresight. Promising directions for further research include the development of advanced digital decision support systems capable of integrating data from telematics, IoT sensors, and analytical software to provide real-time monitoring and assessment of vehicle condition. Another important area involves the implementation of machine learning and artificial intelligence algorithms to support automated failure prediction, adaptive maintenance scheduling, and more efficient resource allocation. Further research should also focus on the comprehensive evaluation of the economic impact of systematic technical assessments at the enterprise level, particularly regarding the reduction of unplanned downtime, maintenance costs, and improvements in overall productivity and operational efficiency.

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Conflict of Interest

None.

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Системна оцінка технічного стану транспортних засобів як інструмент оптимізації виробничих процесів автотранспортних підприємств

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Анотація. Метою цього дослідження було розроблення методологічної основи для системного оцінювання технічного стану транспортних засобів та визначення його ролі в оптимізації виробничих процесів на підприємствах автомобільного транспорту. Методологія дослідження ґрунтувалася на кількісному підході, який поєднував системний аналіз, моделювання на основі симуляцій, порівняльний аналіз, багатокритеріальну оцінку та бінарну логістичну регресію для визначення взаємозв'язку між станом транспортного засобу та ймовірністю його відмови. Для відтворення стохастичної операційної мінливості, характерної для середніх підприємств автомобільного транспорту, було розроблено симульований масив даних, що відображав експлуатацію 50 транспортних засобів протягом 12 місяців за допомогою симуляції Монте-Карло. Масив даних включав технічні, експлуатаційні, надійності та економічні параметри. Для забезпечення порівнянності гетерогенних змінних застосовувалася нормалізація методом «мінімум-максимум», після чого було розроблено інтегрований індикатор технічного стану з використанням динамічних коефіцієнтів ваги на основі експертної оцінки та кореляційного аналізу. Валідація моделі здійснювалася за допомогою коефіцієнта Nagelkerke R^2, середньої абсолютної помилки, кореня середньоквадратичної помилки та статистичних тестів Вальда для визначення значущості коефіцієнтів регресії. Результати показали, що запропонована модель дозволяє здійснювати комплексну класифікацію транспортних засобів за рівнем технічної готовності та значно підвищує ефективність планування технічного обслуговування порівняно з традиційними підходами до планових ремонтів. Аналіз засвідчив, що технічне погіршення у поєднанні з високим експлуатаційним навантаженням суттєво підвищує ймовірність відмов. Запропонована методологічна основа зменшила обсяг незапланованого простою транспортних засобів на 42 %, скоротила витрати на технічне обслуговування на 20 % та підвищила точність прогнозування з 62 % до 85 %. Регресійна модель підтвердила наявність сильного оберненого зв'язку між інтегрованим індикатором технічного стану та ймовірністю відмови транспортного засобу. Практичне значення дослідження полягає у наданні підприємствам автомобільного транспорту інструменту, заснованого на даних, для планування прогнозованого обслуговування, розподілу ресурсів, прийняття рішень щодо модернізації автопарку та підвищення експлуатаційної надійності в умовах динамічної транспортної діяльності

Ключові слова: прогнозне технічне обслуговування; управління парком транспортних засобів; виробничі процеси; інтелектуальна діагностика; модель; ефективність