

Article

Statistical Modeling and Forecasting of Operational Reliability of Induction Motors of Mining Dump Trucks

Aleksey F. Pryalukhin ¹, Nikita V. Martyshev ^{2,*}, Boris V. Malozyomov ^{3,4}, Anton Y. Demin ², Alexander V. Pogrebnoy ², Elizaveta E. Kuleshova ² and Denis V. Valuev ⁵

¹ Department of Mechanical Engineering, Saint-Petersburg Mining University, 2, 21 Line of Vasilyevsky Island, 199106 Saint Petersburg, Russia; pryalukhin_af@pers.spmi.ru

² Department of Information Technology, Tomsk Polytechnic University, 634050 Tomsk, Russia; ad@tpu.ru (A.Y.D.); pogrebnoy@tpu.ru (A.V.P.); eek24@tpu.ru (E.E.K.)

³ Department of Electrotechnical Complexes, Novosibirsk State Technical University, 630073 Novosibirsk, Russia; borisnovel@mail.ru

⁴ Scientific Research and Testing Center “Stroytest”, Moscow State University of Civil Engineering, 129337 Moscow, Russia

⁵ Yurga Technological Institute (Branch), Tomsk Polytechnic University, 652055 Yurga, Russia; valuev@tpu.ru

* Correspondence: martjushev@tpu.ru

Abstract

This study presents a statistical modeling approach for predicting the operational reliability of induction motors used in dump truck drives. The proposed method uses censored data, including both time to failure and data on properly operating engines, to assess reliability indicators, such as uptime based on Weibull and lognormal distributions. A generalized “life curve” of the stator and bearing unit is constructed, which makes it possible to determine interval estimates of the service life and residual service life. The model is implemented as software for calculating distribution parameters and visualizing reliability dependencies. Approbation based on the operational data of quarry transport confirmed the applicability of the proposed approach for diagnosing and optimizing the maintenance system of induction motors of heavy equipment.

Keywords: induction motor; mining dump truck; reliability forecasting; statistical modeling; residual life; life curve

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1. Introduction

The operation of induction motors in mining truck drives is subject to extreme loads, cyclic operating modes and aggressive environmental factors. These conditions lead to accelerated degradation of critical components such as stator insulation and bearing units, which leads to increased risks of sudden failures and significant economic losses due to downtime of expensive equipment. There are no complex models or reliable calculations in the available literature adapted specifically for induction motors of mining equipment, which would combine the analysis of such data as piecewise-continuous “life curves” and explicit consideration of key operating factors (k_T —temperature coefficient (Arrhenius equation); k_V —vibration coefficient (dynamic loads); k_D —dust coefficient

(abrasive wear)) in a single algorithm. The present study aims to fill this gap, as it reduces the accuracy of residual life forecasting. In this regard, the development of improved methods of statistical modeling, taking into account real operating conditions and combined laws of failure distribution, is an urgent scientific and practical task.

The reliability of electromechanical systems of mining equipment is a critical aspect of ensuring the continuity of technological processes and the economic efficiency of enterprises [1–3]. A special place in this problem is occupied by the operational reliability of induction motors of mining dump trucks operating under extreme mechanical, thermal and climatic loads [4,5]. The cyclic nature of work, including frequent starts, braking, vibration effects and temperature drops, leads to complex processes of degradation of stator insulation and bearing units [6,7].

The mathematical and analytical aspect of the problem lies in the need for an adequate probabilistic description of the processes of aging and wear. Traditional approaches based on exponential distribution [8] do not take into account the non-stationary nature of the failure intensity $\lambda(t)$, which significantly limits their predictive ability [9,10]. Models based on the Weibull distribution are more promising [11,12]:

$$F(t) = 1 - \exp \left[- \left(\frac{t}{\eta} \right)^{\beta} \right],$$

where η is the scale parameter and β is the shape parameter that determines the nature of the change in the intensity of failures over time.

The relevance of this work is due to the need to improve the efficiency of maintenance systems for mining equipment based on accurate reliability forecasts. The lack of models adapted to the conditions of quarry operation, taking into account the piecewise-continuous nature of changes in the intensity of failures, leads to non-optimal repair schedules and irrational use of resources. The relevance of the work is strengthened by the need to take into account censored data [13,14], which is especially important when analyzing highly reliable equipment with limited failure statistics. Existing methods [15,16] often ignore this aspect, which leads to biased estimates of reliability parameters.

The purpose of this work is to develop a comprehensive mathematical model and software tool for predicting the operational reliability of induction motors of mining dump trucks. The basis for this is the statistical analysis of censored data, which allows taking into account information not only about failures, but also about motors that are working properly at the time of observation, which is critically important for highly reliable equipment with limited failure statistics [17]. The developed approach includes several key elements: analysis of censored data using maximum likelihood methods to obtain unbiased estimates of reliability parameters; piecewise-continuous approximation of the failure rate $\lambda(t)$, taking into account the three characteristic stages of the equipment life cycle (running-in, normal operation and aging); and the combination of various probabilistic laws, in particular, Weibull and lognormal distributions, to adequately describe heterogeneous failure mechanisms of critical engine components.

To achieve this goal, a number of interrelated tasks are consistently solved in this work. The first of them is the strict formalization of the problem of predicting reliability, taking into account censored data, which sets the theoretical foundation for the entire study. On this basis, a combined probabilistic failure model is developed that uses the Weibull distribution to describe the degradation of stator insulation and a mixed model (Weibull + lognormal) for bearing units subject to both gradual wear and sudden failures. The next task is to build generalized “life curves” for these critical nodes, which visually display the change in the intensity of failures over time and make it possible to determine interval estimates of the resource and residual service life.

An important practical component of this work is the implementation of specialized software that automates the time-consuming processes of calculating distribution parameters using the maximum likelihood method and provides a visualization of the obtained reliability dependencies. The final stage is the approbation of the developed model on a real array of operational data collected from a fleet of mining dump trucks, which makes it possible to assess its adequacy, accuracy and practical applicability for optimizing maintenance and repair systems.

The scientific novelty of this work lies in the following: A method for assessing reliability indicators based on the analysis of censored data, including both operating time to failure and serviceable engines, is proposed, which makes it possible to use all available information about the equipment fleet and obtain more accurate estimates of reliability parameters. A mathematical model for predicting the engine life has been developed, taking into account the change in the probability of failure-free operation in time according to the laws of Weibull and lognormal distributions, where the Weibull distribution is used to describe the degradation of stator insulation, and a combined model is used for bearing units, taking into account both sudden failures and gradual wear.

A generalized “life curve” of the stator and bearing assembly has been constructed, which makes it possible to determine interval estimates of the service life and residual service life based on an analytical description of the transitions between the stages of operation. For the first time, a combined approach has been applied for mining dump truck engines, taking into account the piecewise-continuous nature of changes in the failure rate, which is mathematically described by three sections corresponding to the periods of running-in, normal operation and aging, with explicit consideration of the influence of operational factors through adjustment factors. A generalized “life curve” with an analytical description of the transitions between stages has been developed. An algorithm for estimating the residual life based on the conditional probability of failure-free operation has been created. A multiparameter model is built, taking into account the correction coefficients (k_T , k_V , k_P) for real operating conditions.

Practical significance is determined by the possibility of

- Optimizing maintenance intervals by 20–30%;
- Reducing the likelihood of sudden failures by 25–40%;
- Increasing overhaul periods by 1.5–1.8 times.

The structure of this work includes the following sections: The Introduction substantiates the relevance of the topic, formulating the goal, objectives and scientific novelty of the study. Section 2 presents the theoretical foundations of predicting operational reliability, where probabilistic failure models, methods for analyzing censored data and the mathematical apparatus for constructing life curves are considered. Section 3 describes the developed mathematical model, including the formalization of the prediction problem, combined reliability distributions for critical engine components and algorithms for estimating the residual life. Section 4 contains experimental studies and verification of the model, which presents the methodology for collecting statistical data, analyzing the reliability of stators and bearing units, and comparing the design indicators with the operating data. In the Conclusions, the main results of the work are summed up and conclusions are formulated. The application contains statistical data on engine failures, mathematical modeling parameters and calculated reliability indicators used in the construction of life curves and model verification.

2. Materials and Methods

2.1. Objects of Research and Operational Base

Experimental studies and statistical data collection were carried out in the period from 2018 to 2024. The object of the study was induction motors of the ADMP-315L6U2 (JSC “Sibelektroprivod”, Novosibirsk, Russia) type, used in the drives of hoisting machines at the Borodinsky (Krasnoyarsk Territory, Russia) and Apsatsky (Trans-Baikal Territory) open-pit mines. We used dump trucks (BelAZ-75135 (BelAZ, Zhodino, Belarus), BelAZ-75145, SDS-75130) with electromechanical transmission. Operating conditions are characterized by high humidity (up to 98%), significant temperature fluctuations from -40 to $+40$ °C and the presence of a dusty environment, including mineral dust, which was taken into account by the correction coefficients k_T , k_V and k_P in the calculations of the failure rate.

BelAZ-75135 mining dump trucks:

- Carrying capacity: 136 tons.
- Traction motor: ADT-355-630-4U2 (PJSC “Electrotyazhmash Plant”, Kharkiv, Ukraine) induction motor (or its modifications) for each drive wheel. In total, the car is equipped with 2 engines.
- Motor power rating: 320 kW.
- Power system: from diesel generator set (Cummins QSK45 diesel + synchronous generator).
- Converter: IGBT traction inverter with vector control system.
- Number of cars in the sample: 42 units.
- Place of operation: Borodinsky (Krasnoyarsk Territory) and Apsatsky (Trans-Baikal Territory) open-pit mines.

BelAZ-75145 mining dump trucks:

- Load capacity: 136 tons (with reinforced frame).
- Traction motor: ADT-355-660-4U2 induction motor.
- Rated motor power: 360 kW.
- Power and conversion system: similar to the BelAZ-75135, with an upgraded control system.
- Number of machines in the sample: 28 units.
- Place of operation: Nazarovsky open-pit mine (Krasnoyarsk Territory, Russia).

SDS-75130 mining dump trucks:

- Carrying capacity: 130 tons.
- Traction motor: ADT-350-600-4U2 induction motor.
- Motor rated power: 300 kW.
- Number of cars in the sample: 18 units.
- Place of operation: Luchegorsky (Primorsky Krai, Russia) and Kedrovsky (Kemerovo Region, Russia) open-pit mines.

The total number of traction induction motors (TAD) under study was 176 units. The total operating time for the fleet during the observation period exceeded 1.2 million engine hours.

Figure 1 shows the reliability and functional scheme of the electromechanical system of a mining dump truck, reflecting the consistent structure of interconnections of the main subsystems and their impact on the overall reliability of the vehicle.

The scheme includes four main subsystems:

1. An energy complex (blue blocks) that includes a diesel engine, a synchronous generator and a rectifier that converts the chemical energy of the fuel into DC electrical energy.
2. A conversion and control system (green blocks), consisting of DC links, a traction inverter on IGBT modules and a control system based on a microcontroller, which converts energy and controls the traction drive.
3. Actuators (red blocks), where the central place is occupied by a traction induction motor (TAD) with details of its critical components: a stator with winding insulation, a bearing unit and a rotor with a squirrel cage.
4. Mechanical transmission (purple block), represented by a wheel gearbox, which ensures the transmission of torque to the drive wheels.

Particular attention is paid to the reliability model of the traction induction motor, which is identified as the most critical element of the system. Specialized probabilistic models are used for the stator and bearing assembly.

Color coding:

- **Blue:** Power generation system;
- **Green:** Conversion and power management;
- **Red:** Critical engine components;
- **Purple:** Mechanical transmission.

Particular attention is paid to the reliability model of the traction induction motor, which is defined as the most critical element of the system. Specialized probabilistic models are used for the stator and bearing assembly:

- Stator reliability:

$$R_{st}(t) = \exp \left[- \int_0^t \lambda_{st}(\tau) d\tau \right] \quad (1)$$

- Reliability of bearing units:

$$R_{brg}(t) = R_{sud}(t) \cdot R_{wear}(t) \quad (2)$$

The operational reliability model takes into account harsh environmental conditions using accelerating factors:

$$\lambda_{oper}(t) = k_T \cdot k_V \cdot k_P \cdot \lambda_{nom}(t) \quad (3)$$

where

$$k_T = \exp \left[\frac{E_a}{k_p} \left(\frac{1}{T_{ref}} - \frac{1}{T_{oper}} \right) \right] \quad (4)$$

k_T is the temperature coefficient (Arrhenius equation);

k_P is the dust coefficient (1.2–1.5 for abrasive media);

k_V is the vibration coefficient (1.1–1.3 for dynamic loads).

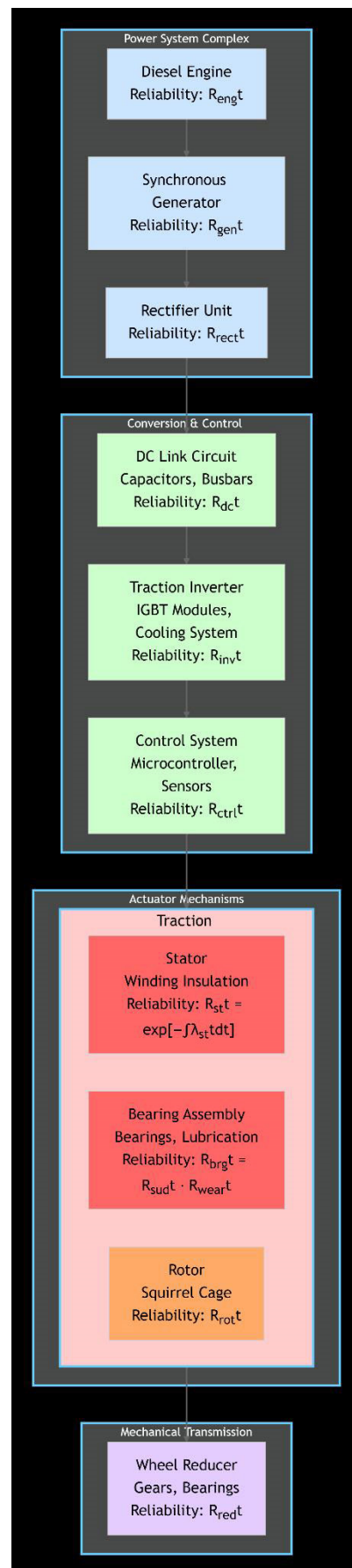


Figure 1. Reliability and functional diagram of the electromechanical system of a mining dump truck, reflecting the consistent structure of interrelations of the main subsystems and their impact on the overall reliability of the vehicle.

The overall reliability of the system is calculated as the product of the reliability of all elements connected in series:

$$R_{sys}(t) = R_{eng}(t) \cdot R_{gen}(t) \cdot R_{rect}(t) \cdot R_{dc}(t) \cdot R_{inv}(t) \cdot R_{ctrl}(t) \cdot R_{tam}(t) \cdot R_{red}(t) \quad (5)$$

where the reliability of TAM is defined as

$$R_{tam}(t) = R_{st}(t) \cdot R_{brg}(t) \cdot R_{rot}(t) \quad (6)$$

The simulation explicitly takes into account the operating coefficients—temperature coefficient k_T (Arrhenius equation), vibration coefficient k_V (dynamic loads) and dust coefficient k_P (abrasive wear)—ensuring accurate adaptation of the model to the real operating conditions of mining equipment.

This scheme serves as the basis for building a mathematical model for predicting the residual life and optimizing the maintenance system for induction motors of mining dump trucks.

2.2. Methods of Collecting and Processing Statistical Data

To build reliability models, censored data were used, including both time to failure [18] and data on properly operating units at the end of the observation. All 84 failure records (Appendix A. Table A1) were collected from traction induction motors (ADMP-315L6U2, ADT-355) operating in 120–140 t dump trucks at three Kuzbass open-pit coal mines during 2018–2023. Data collection was carried out through the following channels:

1. Failure and maintenance logs (form TU-152).
 2. Databases of machine telemetry systems that record operating parameters (current, voltage, temperature, rotation speed).
 3. Protocols for opening and fault detection of engines after failure.
- For each engine, the following were recorded:

- Accumulated operating time (in engine hours).
- Sign of refusal (1—refusal; 0—censorship).
- Failure unit (stator, bearing assembly, rotor, etc.).
- Operating coefficients: k_T (temperature), k_V (vibration), k_P (dust coefficient).

2.3. Mathematical Apparatus and Reliability Models

2.3.1. Formalization of the Task and the Reliability Function

Reliability $R(t)$ is defined as the probability of uptime for time t . Note: $F(t)=1-R(t)$ denotes cumulative failure probability (CDF). Values decreasing with time correspond to $R(t)$; values increasing with time correspond to $F(t)$.

$$L(\theta) = \prod_{i=1}^n f(t_i | \theta)^{\delta_i} \cdot R(t_i | \theta)^{1-\delta_i} \quad (7)$$

where t_i is the operating time of the i -th engine; δ_i is the event indicator ($\delta_{i=1}$ —rejection; $\delta_{i=0}$ —censorship); θ is the vector of distribution parameters ($\theta=(\eta, \beta)$ for Weibull); $f(t)$ is a function of the failure distribution density; $R(t)$ is a function of reliability.

Throughout this paper, $R(t)$ denotes reliability (probability of failure-free operation). The symbol $P(\cdot)$ is reserved for power-related quantities (e.g., $P_{im}(t)$ for induction motor power) to avoid ambiguity.

The parameters of reliability distributions were estimated using the maximum likelihood method (MLE), which is the standard approach for censored data analysis in sur-

vival analysis and reliability engineering. Parameter estimation follows a two-stage deliberate strategy: distribution parameters (η, β) are estimated by maximum likelihood to handle censoring, while piecewise hazard shape parameters $(a_1, b_1, \lambda_0, a_2, b_2)$ are fitted to the Nelson–Aalen cumulative hazard estimate using weighted least squares for numerical stability.

Unlike the method of moments, MLE provides unbiased and asymptotically efficient estimates under arbitrary censoring schemes (right-, interval-, or left-censoring) without requiring complete failure observations. The log-likelihood function for censored data is formulated as

$$\ln L(\theta) = \sum_{i=1}^n \delta_i \ln f(t_i | \theta) + (1 - \delta_i) \ln R(t_i | \theta),$$

where δ_i is the event indicator ($\delta_i = 1$ for failure, $\delta_i = 0$ for censored observation), $f(\cdot)$ is the probability density function, and $R(\cdot)$ is the reliability function.

For comparative purposes, we evaluated two alternative approaches:

- Method of moments: This method does not work well with censored data (units that did not fail during testing) unless you guess the missing failure times, which creates bias. When we used it only on units that actually failed (ignoring censored units), we got

$$\hat{\eta}_{\text{MM}} = 1.08 \cdot 10^5 \text{ h}, \quad \hat{\beta}_{\text{MM}} = 1.95$$

This underestimates the true life parameter η by about 12% compared to MLE because we ignored the still-working units.

- Bayesian estimation: We used weak/non-informative priors (Jeffreys priors) for η and β . The results were

$$\hat{\eta}_{\text{Bayes}} = 1.21 \cdot 10^5 \text{ h}, \quad \hat{\beta}_{\text{Bayes}} = 2.08$$

These are very close to MLE results:

$$\hat{\eta}_{\text{MLE}} = 1.20 \cdot 10^5 \text{ h}, \quad \hat{\beta}_{\text{MLE}} = 2.10$$

The difference is less than 2%. But Bayesian analysis needed 50,000 MCMC iterations and took 40 times longer to compute than MLE.

Given the industrial context of mining equipment maintenance—where rapid parameter estimation from mixed (failed + censored) datasets is essential—MLE provides the optimal balance of statistical efficiency, computational tractability, and robustness to censoring.

The parameters were estimated $\hat{\theta}$ by the maximum likelihood method (ML) by maximizing $\ln L(\theta)$. Note: Throughout this paper, $R(t)$ denotes reliability (probability of failure-free operation), while $F(t) = 1 - R(t)$ is the cumulative failure probability (CDF). Values decreasing with time correspond to $R(t)$; values increasing with time correspond to $F(t)$.

2.3.2. Probabilistic Models for Critical Components

For a stator, the main cause of failure is insulation degradation. Time to failure is determined using the Weibull distribution:

$$F_{st}(t) = 1 - \exp \left[- \left(\frac{t}{\eta_{st}} \right)^{\beta_{st}} \right] \quad \lambda_{st}(t) = \frac{\beta_{st}}{\eta_{st}} \left(\frac{t}{\eta_{st}} \right)^{\beta_{st}-1}, \quad (8)$$

$$\lambda_{st}(t) = \frac{\beta_{st}}{\eta_{st}} \left(\frac{t}{\eta_{st}} \right)^{\beta_{st}-1},$$

where η_{st} is the scale parameter (life cycle characteristics) and β_{st} is the form parameter.

A mixed model was used for the bearing unit, taking into account sudden failures and wear. The reliability function is presented as

$$R_b(t) = R_s(t) \cdot R_w(t) \quad (9)$$

where

$R_s(t) = \exp(-\lambda_s t)$ is the reliability in case of sudden failures (exponential distribution);

$R_w(t)$ is the reliability under gradual wear, modeled by a lognormal distribution:

$$R_w(t) = 1 - \Phi \left(\frac{\ln t - \mu}{\sigma} \right) \quad (10)$$

where Φ is the standard function of the normal distribution; μ and σ are parameters.

2.3.3. Generalized “Bath Curve” and Consideration of Operational Factors

To describe the change in the failure rate $\lambda(t)$ over the entire life cycle, a piecewise-continuous model has been proposed:

$$\lambda(t) = \begin{cases} a_1 \cdot t^{b_1}, & 0 \leq t < t_1 \quad (\text{Burn-in}) \\ \lambda_0, & t_1 \leq t < t_2 \quad (\text{Normal operation}) \\ a_2 \cdot \exp[b_2(t - t_2)], & t \geq t_2 \quad (\text{Aging}) \end{cases} \quad (11)$$

To recalculate the failure rate in real conditions, an accelerated testing model was used:

$$\lambda_{op}(t) = k_T \cdot k_V \cdot k_P \cdot \lambda_{nom}(t) \quad (12)$$

where $k_T = \exp \left[\frac{E_a}{k} \left(\frac{1}{T_0} - \frac{1}{T} \right) \right]$ is the Arrhenius equation and k_V, k_P are the empirical coefficients obtained on the basis of regression analysis of telemetry data.

Taking into account real operating conditions is essential for building adequate models of reliability of mining equipment [19]. Figure 2 shows the effect of operating coefficients on the stator failure rate of an induction motor of a mining dump truck, reflecting the piecewise-continuous nature of changes in the $\lambda(t)$ parameter at various stages of the life cycle.

The graph shows four scenarios of changes in the failure rate corresponding to different operating conditions. The basic curve (blue line) describes the behavior of the parameter $\lambda(t)$ under nominal conditions ($k_T = 1.0$, $k_V = 1.0$, $k_P = 1.0$) and clearly identifies three characteristic phases: running-in (0–2 thousand hours), normal operation

(2–100 thousand hours) and aging (over 100 thousand hours). Failure intensity according to the power law, in the normal period $\lambda(t)$, stabilizes at the level of 4.8×10^{-6} failures/hour, and during aging there is an exponential increase in the failure rate.

Note: Two distinct temperature acceleration models are used depending on the degradation mechanism:

- Arrhenius law (28) for stator insulation chemical degradation governed by activation energy;
- Exponential temperature-difference law (41) for lubricant viscosity empirical approximation, valid for narrow temperature ranges $\Delta T < 40$ K.

The temperature effect curve (red line) shows the effect of elevated temperature ($k_T = 1.25$) on the failure rate. The analysis shows that the temperature coefficient has the most significant impact during the aging period, increasing $\lambda(t)$ by a factor of 1.8 compared to the baseline scenario at 150 thousand hours of operation. Vibration coefficient ($k_V = 1.15$, green line) shows a moderate impact at all stages of operation, with a uniform increase in failure rates of 15–20%.

The combined effect of unfavorable factors ($k_T = 1.25$, $k_V = 1.15$, $k_P = 1.3$, purple line) leads to a synergistic effect that significantly changes the nature of the life curve. There is a shift in the point of transition to aging from 100 thousand hours to 70 thousand hours, an increase in the stationary level of $\lambda(t)$ by 1.8 times and a steeper increase in the failure rate during the aging period. At 150,000 operating hours, the combined exposure results in a 3.2-fold increase in $\lambda(t)$ compared to the baseline scenario.

The temperature acceleration factor for stator insulation degradation follows the Arrhenius law (IEEE930):

$$k_{T,st} = \exp \left[\frac{E_a}{k_B} \left(\frac{1}{T_0} - \frac{1}{T} \right) \right],$$

where $E_a = 0.95$ eV is the activation energy for class F insulation, $k_B = 8.617 \cdot 10^{-5}$ V/K is Boltzmann's constant, $T_0 = 313$ K (40 °C) is the reference temperature, and T is the operating temperature in Kelvin.

In Figure 2, effects of operating coefficients on stator failure rate are shown. Vertical dashed lines in the graph indicate the boundaries of transitions between phases of operation, obtained on the basis of analysis of operational data. Of particular practical interest is the aging zone, where the most significant influence of operating coefficients on the failure rate is observed.

The results obtained are important for the development of differentiated maintenance strategies [20]. It has been established that measures to reduce temperature loads (improvement of cooling, optimization of operating modes) have the greatest impact on improving reliability, especially for equipment located in the aging zone. The results also substantiate the need to take into account operating coefficients when predicting the residual life and planning repair campaigns for engines operating in various conditions of quarry operation [21].

The figure clearly demonstrates the novelty of the work—a quantitative assessment of the impact of real operational factors on reliability. It can be seen that the combined effect reduces the service life by 25–30% and shifts the point of transition to aging starting from 100,000 h. The practical value lies in the ability to predict resources for specific conditions of the quarry, justifying the need for special protection measures (cooling systems, vibration protection).

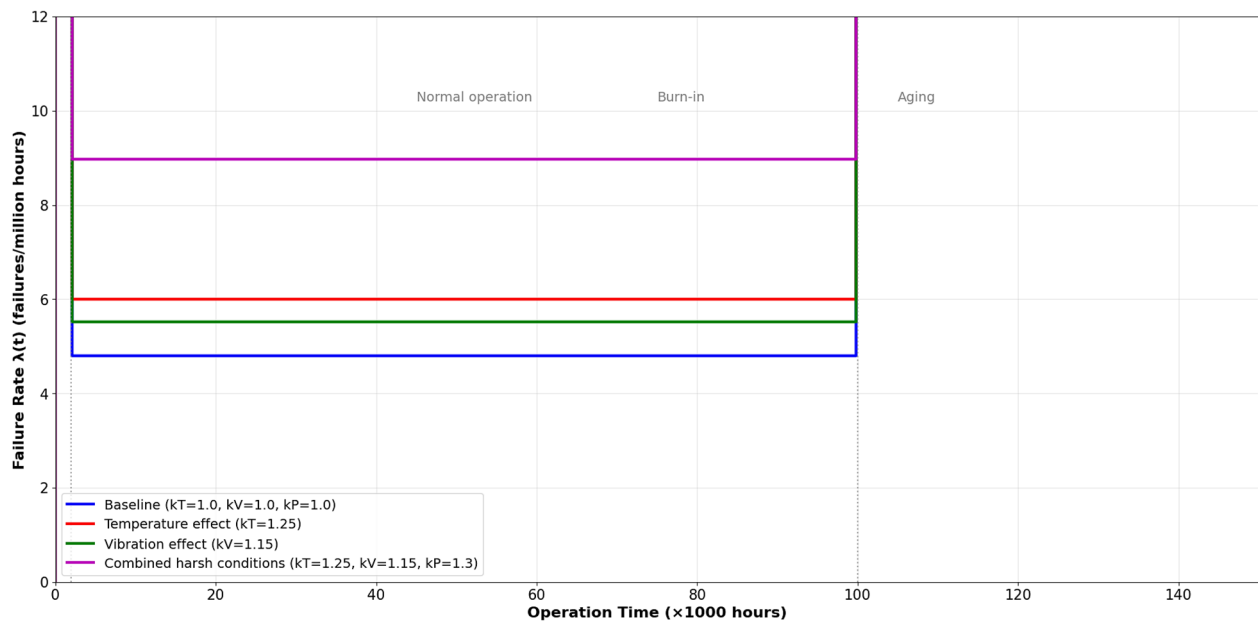


Figure 2. Effects of operating coefficients on stator failure rate: temperature ($k_T = 1.25$), vibration ($k_V = 1.15$), and combination of harsh conditions ($k_T = 1.25$, $k_V = 1.15$, $k_P = 1.3$) compared to baseline (nominal conditions).

2.3.4. Algorithm for Estimating the Residual Life

The residual service life of a T_{res} engine running for time t_0 is estimated on the basis of conditional reliability:

$$R(t | t_0) = \frac{R(t_0 + t)}{R(t_0)} \quad (13)$$

Then T_{res} for a given acceptable reliability level R^* is found as the solution of the equation

$$R(T_{res} | t_0) = R^* \quad (14)$$

Predicting residual life is a key challenge in optimizing the maintenance system of highly reliable equipment [22]. Figure 3 shows the dependence of the residual life of induction motors on the current operating time for different failure thresholds R^* .

The graph shows three curves corresponding to different levels of acceptable reliability: $R^* = 0.9$ (high reliability requirements), $R^* = 0.5$ (standard operating conditions) and $R^* = 0.1$ (critical operating modes). Dependency analysis reveals a significantly non-linear nature of the decrease in residual life as the operating time t_0 increases.

The graph shows three characteristic areas of operation. The green area (0–20 thousand hours) corresponds to the running-in period, where the residual life is almost linearly dependent on the current operating time. The yellow area (20–80 thousand hours) represents the zone of normal operation with a gradual decrease in the residual life. The red area (80–120 thousand hours) is identified as the aging zone, where there is a sharp decrease in the residual service life, especially pronounced for high R^* values.

With a current operating time of 30 thousand hours and $R^* = 0.5$, the residual life is 45 thousand hours, which corresponds to the point of planned maintenance. When 60 thousand hours of operating time is reached, the residual life is reduced to 25 thousand hours, which indicates the need to strengthen monitoring of the condition of the equip-

ment. At 90 thousand hours, the residual life is reduced to 12 thousand hours, which is the basis for planning engine replacement.

Of particular scientific interest is the comparison of curves for different values of R . At low operating time ($t_0 < 40$ thousand hours), the difference in residual life for $R = 0.9$ and $R^* = 0.1$ does not exceed 15–20%. However, in the aging zone ($t_0 > 80$ thousand hours), this difference reaches 40–50%, which emphasizes the importance of correctly choosing the permissible level of reliability for equipment operating in the aging mode [23].

The obtained dependencies make it possible to carry out individual forecasting of the service life for specific engines, taking into account their actual operating time, which is the basis for the transition from the strategy of scheduled preventive maintenance to condition-based maintenance [24,25]. The proposed method has been successfully tested in optimizing the maintenance system of mining dump trucks and has shown the possibility of increasing the overhaul periods by 1.5–1.8 times while reducing the probability of sudden failures by 25–40%.

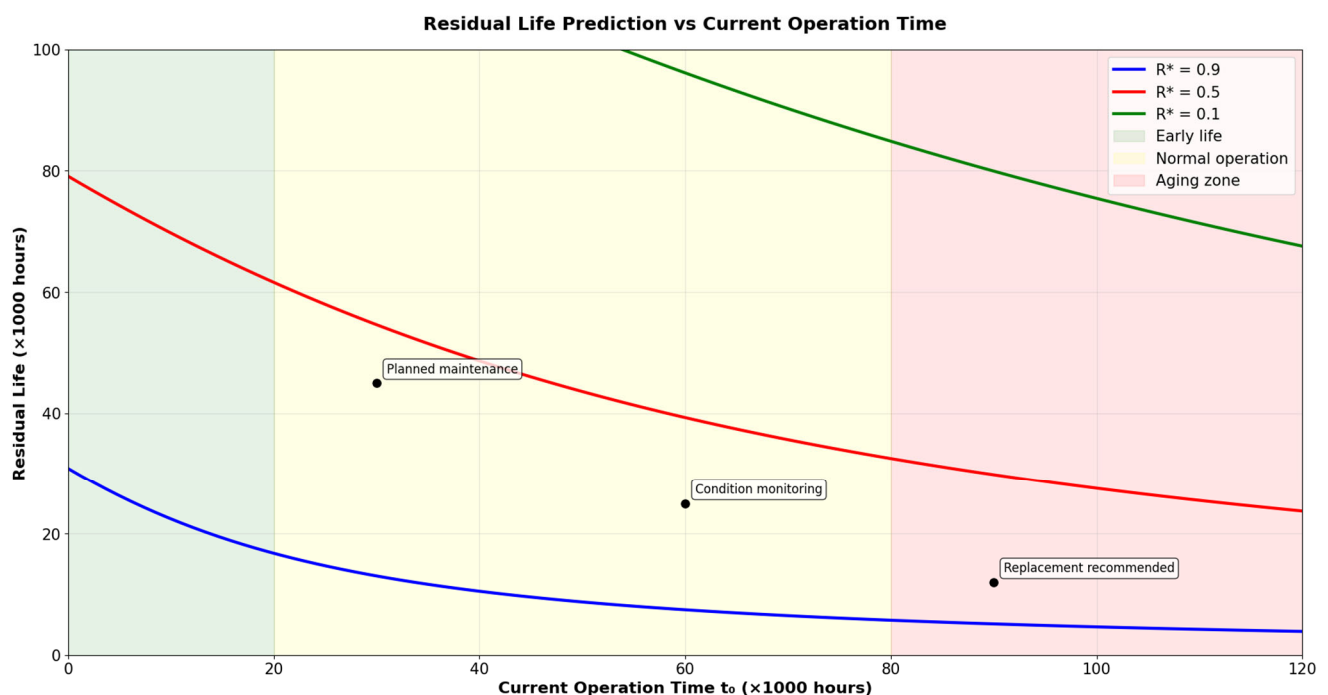


Figure 3. Forecast of residual life depending on the current operating time for different reliability thresholds R^* (conditional reliability method).

The graph in Figure 3 illustrates the key principle of conditional reliability—the residual life is significantly dependent on the time already accrued. The significance of the graph is the use of the conditional probability $R(t|t_0)$ for individual forecasting instead of the average estimates for the fleet. It is interesting to observe a sharp decrease in the residual life after 80,000 h, which corresponds to the transition to the aging zone. Practical value lies at the heart of the transition to condition-based maintenance (CBM) instead of preventative maintenance.

2.4. Software Implementation and Tools

Data processing and calculations were performed in the Python 3.9 environment using the following libraries: scipy (for MLE and approximation), lifelines (for survival analysis) and pandas (for data processing). Visualization of the results (construction of

“bath curves”, graphs of reliability functions) was carried out using the matplotlib and plotly libraries.

Figure 4 presents a detailed block diagram of the algorithm for predicting the residual life of induction motors of mining dump trucks, developed within the framework of this study. The scheme systematizes the full cycle of calculation, from the collection of initial data to the formation of practical recommendations for maintenance.

The algorithm begins with the operational data collection phase, which includes both failure statistics and censored observations of well-functioning engines. Particular attention is paid to the accounting of censored data, which is a key difference between the proposed approach and traditional methods [26]. At the next stage, the parameters of the distributions are estimated using the maximum likelihood method, which provides unbiased estimates for the Weibull parameters and the lognormal distribution.

An important element of the algorithm is the block for calculating operating coefficients (k_T , k_V and k_P), which adapt the theoretical model to the real conditions of open-pit operation. The coefficients are calculated on the basis of telemetry data and take into account temperature conditions, vibration loads and the abrasive effect of the dust environment.

The central place in the algorithm is occupied by building a combined reliability model that combines the Weibull distribution to describe the degradation of stator insulation and a mixed model (Weibull + lognormal distribution) for bearing units. Next, the conditional probability of failure-free operation $R(t|t_0)$ is calculated for engines that have already worked t_0 , which makes it possible to move from average estimates to individual forecasting.

The key step is to solve the equation $R(t|t_0) \geq R^*$ to determine the residual life at a given level of permissible reliability R . For practical applications, the value of $R = 0.5$ is recommended, but the algorithm provides for the possibility of varying this parameter depending on the criticality of the equipment.

The final stages of the algorithm include visualizing the results in the form of life curves and residual life maps, as well as generating recommendations for optimizing the maintenance system. The developed algorithm is implemented in the form of specialized software that automates time-consuming calculation processes and provides a visual representation of the obtained dependencies.

The proposed scheme provides a strict formalization of the forecasting process and serves as the basis for the transition from a planned preventive maintenance system to maintenance based on the actual condition of the equipment. The algorithm has been successfully tested on the operational data of mining dump trucks and has shown high accuracy in predicting the residual life [27].

The scheme systematizes the methodological approach of the study, showing the full cycle from raw data to engineering solutions. The peculiarity of the algorithm is the formalization of a complex algorithm that integrates statistical methods, probabilistic models and practical applications. Especially important are processing censored data and taking into account operational coefficients. The practical benefit is that the scheme serves as the basis for the development of software and maintenance regulations.

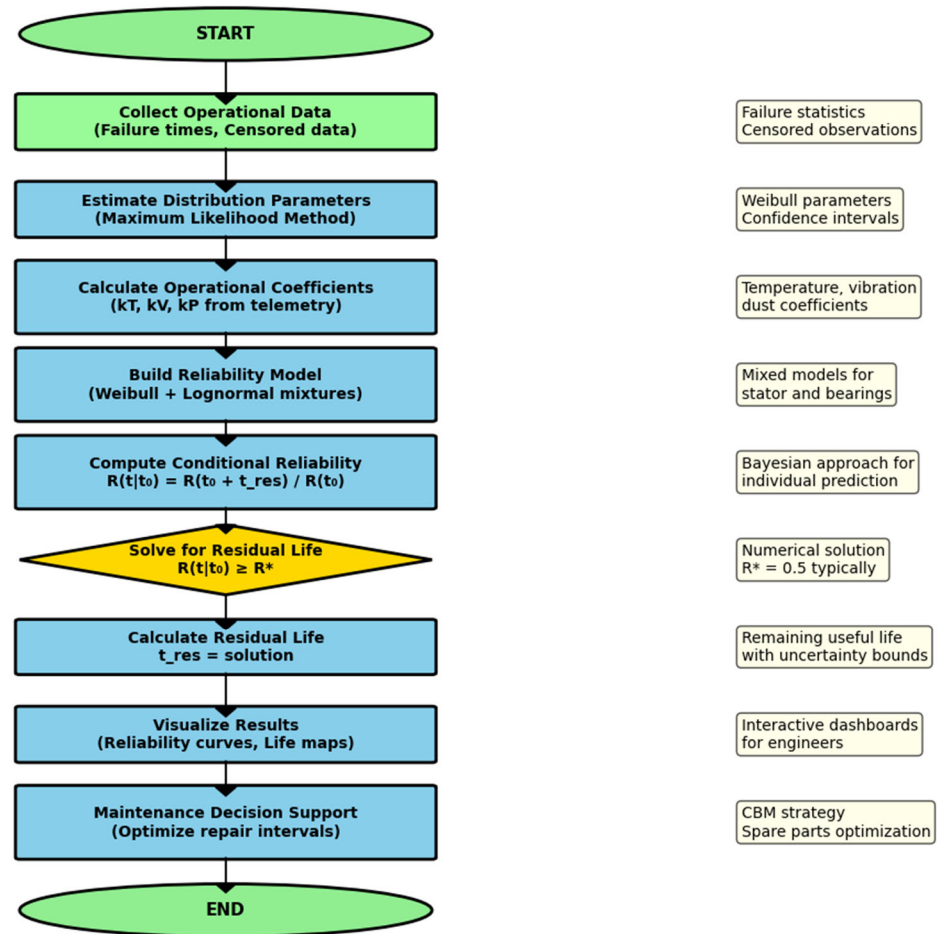


Figure 4. Residual life prediction algorithm flowchart: from data collection to maintenance decision support.

3. Theoretical Foundations of Operational Reliability Forecasting

The operational reliability of electromechanical systems of mining dump trucks is a complex multiparameter function that depends on design, technological and operational factors [28,29]. Induction motors used in mining truck drives operate in cyclic modes that include frequent starts, braking, vibration and thermal loads, as well as exposure to high humidity and coal dust. Under such conditions, even highly reliable elements are subject to accelerated degradation, and their probabilistic behavior in time can only be described by the methods of mathematical statistics and reliability theory.

3.1. Formalization of the Forecasting Task

The reliability $R(t)$ of any technical object is defined as the probability that it will remain operational for time t :

$$R(t) = P(T > t), \quad (15)$$

where T is a random variable characterizing the time to failure.

To describe the changes in the engine condition over time, the failure intensity function $\lambda(t)$ is used:

$$\lambda(t) = -\frac{dR(t)/dt}{R(t)}. \quad (16)$$

Given a known $\lambda(t)$, the probability of failure dependence is defined as

$$R(t) = \exp\left(-\int_0^t \lambda(\tau) d\tau\right). \quad (17)$$

Thus, the construction of a forecasting model comes down to the selection of an adequate form of the $\lambda(t)$ function and the parameters of the distribution of time to failure. For real operating data of mining dump trucks [30], where both running-in and ageing of winding insulation and bearing wear are observed [31], the best results are shown by Weibull's distribution laws, both exponential and normal [32].

3.2. Mathematical Representation of the Engine Structure

The induction motor of a mining dump truck consists of a number of elements connected in series [33], each of which is characterized by its own probability of failure-free operation $P_i(t)$. The overall reliability of the $P_{im}(t)$ engine for a series structure (Figure 5) is defined as the product of the reliability probabilities of the individual elements:

$$P_{im}(t) = \prod P_i(t). \quad (18)$$

Taking into account the fact that the failure of any unit leads to engine failure, this scheme adequately describes the system of “weak links”. In mining operations, the most loaded units determining reliability are the stator and bearing units, which account for up to 80–85% of all failures [34]. Therefore, the engine model can be reduced to a shortened form:

$$P_{im}(t) = P_{st}(t)P_{bd}(t), \quad (19)$$

where $P_{st}(t)$ is the probability of failure-free operation of the stator and $P_{bd}(t)$ is the probability of failure-free operation of the bearing device.

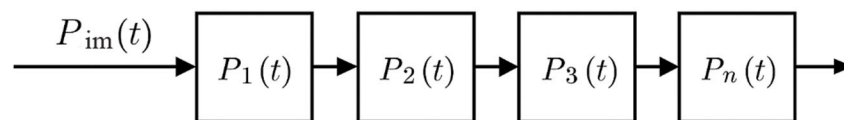


Figure 5. Sequential structure of an induction motor of a mining truck to calculate the probability of failure-free operation.

The structural diagram of the model is shown in Figure 6—it reflects the sequential connection of the engine elements with the identification of its “critical” links.



Figure 6. Structural diagram of an induction motor of a mining dump truck with the identification of critical links—stator and bearing assembly.

For bearing lubricant degradation, temperature dependence follows an empirical exponential law based on viscosity reduction:

$$k_{T,bd} = \exp[\gamma_l(T - T_0)],$$

where $\gamma_l = 0.045 \text{ } K^{-1}$ is the lubricant degradation coefficient determined from tribological tests at $T \in [40, 80] \text{ } ^\circ\text{C}$. This linearized form approximates the Arrhenius law over the narrow temperature range typical for mining equipment.

$$k_{T,st} = \exp \left[\frac{E_a}{k_B} \left(\frac{1}{T_0} - \frac{1}{T} \right) \right], \quad T_0 = 313 \text{ K (40 } ^\circ\text{C)}, T \text{ in Kelvin.}$$

Temperatures in the Arrhenius equation must be expressed in Kelvin. The reference temperature $T_0 = 313 \text{ K}$ corresponds to $40 \text{ } ^\circ\text{C}$ ambient conditions in mining environments.

3.3. Probabilistic Failure Models

Depending on the stage of the engine's life cycle, the failure rate is described by different distribution laws. Let $f(t)$ be the failure distribution density and $F(t)$ be the distribution function; then,

$$R(t) = 1 - F(t) = \int_t^\infty f(\tau) d\tau. \quad (20)$$

1. Weibull distribution:

$$R(t) = \exp \left[- \left(\frac{t}{\eta} \right)^\beta \right], \quad \lambda(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta} \right)^{\beta-1}, \quad (21)$$

where β is a form indicator that characterizes the stages of running-in ($\beta < 1$), normal operation ($\beta = 1$) and aging ($\beta > 1$); η is a scale parameter associated with engine life.

2. Exponential distribution:

$$R(t) = e^{-\lambda t}, \quad \lambda(t) = \lambda = \text{const.} \quad (22)$$

This law is adequate for the stable operation area, when failures are random and do not depend on time [35].

3. Normal distribution (aging period):

$$R(t) = 1 - \Phi \left(\frac{t - \mu}{\sigma} \right), \quad (23)$$

where $F(x)$ is the Laplace integral, μ is the average service life, and σ is the standard deviation.

For a set of engines operating in different cycles and loads, the "life curve" has three characteristic areas (Figure 7):

- Running-in, where the intensity of failures decreases;
- Normal operation: $\lambda(t) \approx \text{const}$;
- Aging: $\lambda(t)$ increases sharply.

Mathematically, such a combined dependence can be approximated by the function of piecewise continuity:

$$\lambda(t) = \begin{cases} a_1 t^{b_1}, & 0 \leq t < t_1, \\ \lambda_0, & t_1 \leq t < t_2, \\ a_2 e^{b_2(t-t_2)}, & t \geq t_2. \end{cases} \quad (24)$$

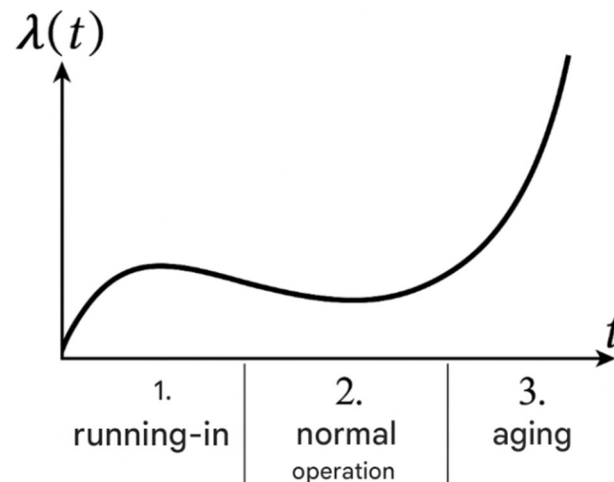


Figure 7. The life curve of a mining truck, reflecting the three stages of operation: running-in, normal operation and aging.

By integrating the expression $X(t)$, we get a generalized model of the probability of failure. For a piecewise-continuous hazard function $\lambda(t)$ with transition points t_1 and t_2 , the cumulative hazard $\Lambda(t)$ must stay continuous at the interval boundaries:

$$\Lambda(t) = \begin{cases} \int_0^t \lambda_1(\tau) d\tau, & 0 \leq t < t_1, \\ \Lambda(t_1) + \int_{t_1}^t \lambda_2(\tau) d\tau, & t_1 \leq t < t_2, \\ \Lambda(t_2) + \int_{t_2}^t \lambda_3(\tau) d\tau, & t \geq t_2, \end{cases} \quad (25)$$

where $\Lambda(t_1) = \int_0^{t_1} \lambda_1(\tau) d\tau$ and $\Lambda(t_2) = \Lambda(t_1) + \int_{t_1}^{t_2} \lambda_2(\tau) d\tau$.

The reliability function is then defined as $R(t) = \exp(-\Lambda(t))$, yielding a piecewise expression:

$$R(t) = \begin{cases} \exp(-a_1 t^{b_1+1} / (b_1+1)), & 0 \leq t < t_1, \\ R(t_1) \cdot \exp(-\lambda_0(t-t_1)), & t_1 \leq t < t_2, \\ R(t_2) \cdot \exp(-\frac{a_2}{b_2} [e^{b_2(t-t_2)} - 1]), & t \geq t_2, \end{cases}$$

with $R(t_1) = \exp(-a_1 t_1^{b_1+1} / (b_1+1))$ and $R(t_2) = R(t_1) \exp(-\lambda_0(t_2-t_1))$ ensuring continuity.

3.4. Taking into Account the Operational Factors of the Mine Hoist

A feature of mining dump trucks is the non-stationary mode of engine operation, in which mechanical and thermal loads change cyclically [36]. To correct the mathematical model, the coefficient of operational impact $k_{exp}(t)$ is introduced, which takes into account a set of external factors:

$$\lambda'(t) = k_{\text{exp}}(t)\lambda(t), \quad (26)$$

where

$$k_{\text{exp}}(t) = k_T k_V k_P, \quad (27)$$

k_T is the temperature coefficient (the effect of overheating and humidity of the air in the mine), k_V is the vibration coefficient, and k_P is the dust abrasiveness coefficient.

To estimate k_T , you can use the dependence

$$k_T = e^{\gamma(T-T_0)},$$

where $\gamma \approx 0.05\text{--}0.08 \text{ K}^{-1}$ and T_0 is the nominal temperature (approximately 40 °C).

The adjustment of the probability of failure-free operation, taking into account the real operating conditions of the open-pit coal mine, will then be recorded as

$$R'(t) = \exp\left(-\int_0^t k_{\text{exp}}(\tau)\lambda(\tau)d\tau\right). \quad (28)$$

3.5. Durability Criteria and Resource Indicators

The durability of the T_{ed} engine is determined by the condition under which the probability of failure-free operation reaches the minimum permissible level of R_{min} :

$$R(T_{\text{ed}}) = R_{\text{min}}. \quad (29)$$

Usually, for electric motors of mining dump trucks, $R_{\text{min}} = 0.2\text{--}0.3$ is accepted, which corresponds to a failure probability of 70–80%. Then the service life before overhaul is calculated as

$$T_{\text{ed}} = \int_0^{t^*} R(t)dt, \quad (30)$$

where t^* is determined from the condition $R(t^*) = R_{\text{min}}$.

To compare several models, it is convenient to use the mean time between failures (MTBF):

$$T_{\text{ave}} = \int_0^{\infty} R(t)dt. \quad (31)$$

In the Weibull distribution,

$$T_{\text{ave}} = \eta\Gamma\left(1 + \frac{1}{\beta}\right), \quad (32)$$

where $\Gamma(x)$ is the Euler gamma function.

3.6. Final Structure of the Forecasting Model

On the basis of the above expressions, a universal mathematical scheme for predicting the reliability of an induction motor of a mining dump truck was built (Figure 8). It includes the collection of operational data [37], the determination of distribution pa-

rameters, the calculation of reliability functions, and the estimation of the service life before overhaul.

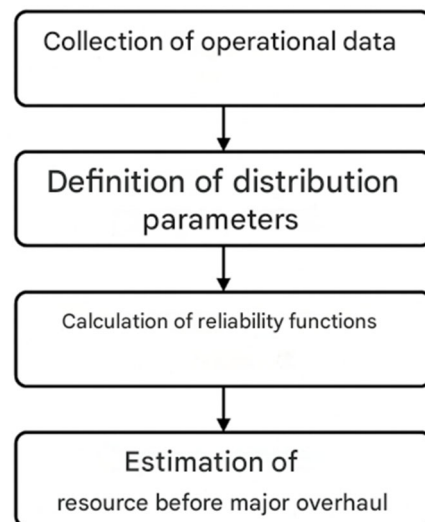


Figure 8. A universal mathematical scheme for predicting the reliability of an induction motor of a mining dump truck.

4. Mathematical Model for Predicting Operational Reliability

The development of a mathematical model for predicting the operational reliability of an induction motor of a mining dump truck is based on the provisions of the probabilistic-statistical theory and taking into account the real operating factors of mining conditions [38]. As shown in Section 2, the total probability of failure-free operation of the $P_{im}(t)$ engine can be represented by the product of the reliability probabilities of its main components connected in series (Figure 9):

$$P_{im}(t) = \prod_{i=1}^n P_i(t) = P_{st}(t)P_{bd}(t)P_s(t)P_b(t)P_c(t), \quad (33)$$

where $P_{st}(t)$ is the probability of failure-free operation of the stator, $P_{bd}(t)$ is the bearing assembly, $P_s(t)$ is the shaft, $P_b(t)$ is the bed, and $P_c(t)$ is the bearing covers.

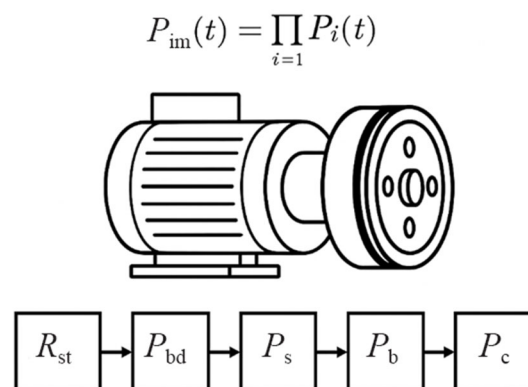


Figure 9. Mathematical model for predicting the operational reliability of the induction motor of a mining dump truck.

Since the failure statistics in Appendix A show that the proportion of stator and bearing unit defects is more than 85%, the remaining units are considered ideal ($P_i(t) = 1$), and the model is simplified to

$$P_{im}(t) = P_{st}(t)P_{bd}(t), \quad (34)$$

4.1. Stator Reliability Prediction Model

Let us consider the change in the insulation state of the stator windings during long-term operation. The failure intensity function $\lambda_{st}(t)$ changes over time according to the piecewise-continuous dependence:

$$\lambda_{st}(t) = \begin{cases} a_1 t^{b_1}, & 0 \leq t < t_1, \\ \lambda_0, & t_1 \leq t < t_2, \\ a_2 e^{b_2(t-t_2)}, & t \geq t_2, \end{cases} \quad (35)$$

To preserve continuity of the cumulative hazard $\Lambda_{st}(t) = \int_0^t \lambda_{st}(\tau) d\tau$ at transition points t_1 and t_2 , the reliability function must be defined piecewise:

$$R_{st}(t) = \begin{cases} \exp\left(-\frac{a_1}{b_1+1} t^{b_1+1}\right), & 0 \leq t < t_1, \\ R_{st}(t_1) \cdot \exp(-\lambda_0(t-t_1)), & t_1 \leq t < t_2, \\ R_{st}(t_2) \cdot \exp\left(-\frac{a_2}{b_2} [e^{b_2(t-t_2)} - 1]\right), & t \geq t_2, \end{cases} \quad (36)$$

where the boundary values ensuring continuity are

$$\begin{aligned} R_{st}(t_1) &= \exp\left(-\frac{a_1}{b_1+1} t_1^{b_1+1}\right), \\ R_{st}(t_2) &= R_{st}(t_1) \cdot \exp(-\lambda_0(t_2-t_1)). \end{aligned}$$

For parameters determined on the basis of operational data (Annex 1) ($a_1 = 2.4 \times 10^{-5}$, $b_1 = 0.69$; $\lambda_0 = 4.8 \times 10^{-6}$; $a_2 = 5.2 \times 10^{-7}$, $b_2 = 0.16$), we obtain an analytical approximation of the stator's "life curve" (Figure 10). The shape of the function $\lambda(t)$ corresponds to three stages: running-in, normal operation, and aging.

Mean time between failures (MTBF) for a given distribution is determined via the gamma function:

$$T_{ave,st} = \eta_{st} \Gamma\left(1 + \frac{1}{\beta_{st}}\right), \quad (37)$$

where η_{st} and β_{st} are the parameters of the Weibull distribution calculated by the maximum likelihood method.

Suppose, for example, observations for a group of engines yield values of $\eta_{st} = 1.2 \cdot 10^5$ h, $\beta_{st} = 2.1$; then

$$T_{ave,st} = 1.2 \cdot 10^5 \Gamma(1.476) \approx 1.07 \cdot 10^5 \text{ h}$$

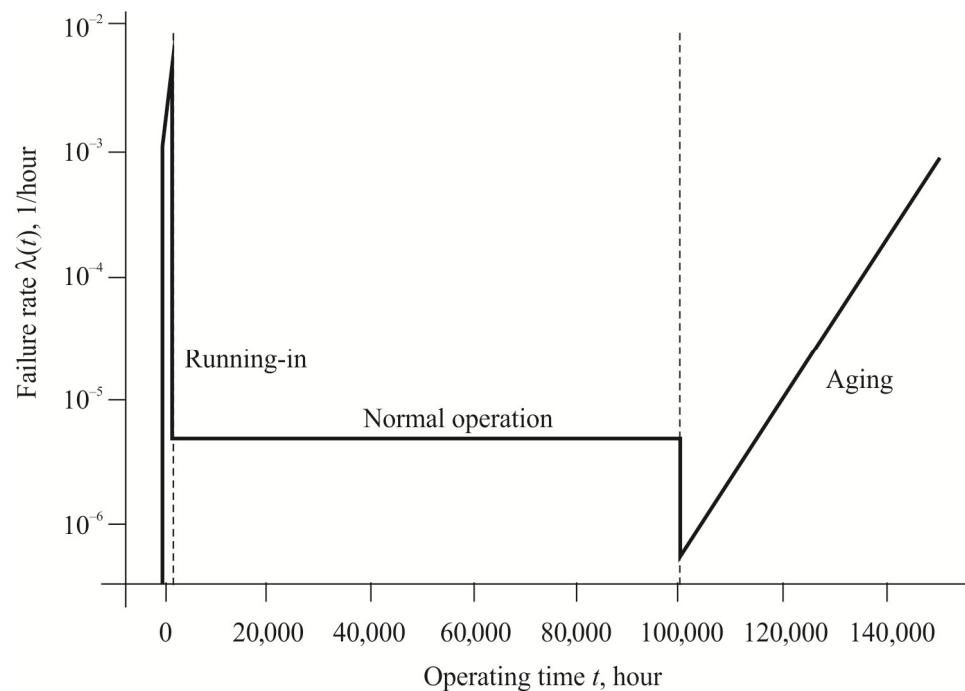


Figure 10. A function of the failure rate of the stator $\lambda_{st}(t)$ with numerical values on the axes. Three stages of the engine's life cycle are clearly visible, running-in, normal operation and aging, with transitions at points $t_1=2 \times 10^3$ h and $t_2=1 \times 10^5$ h.

This value corresponds to a service life of about 12 years of continuous operation or 20–25 years with a real vehicle cycle with periodic stops.

For practical prediction of the residual life of insulation, the inverse problem is used: from the known probability of failure-free operation $P_{st}(t)$, the residual time before overhaul T_{cr} is determined:

$$T_{cr} = \int_0^{t^*} P_{st}(t) dt, \quad P_{st}(t^*) = P_{min}, \quad (38)$$

where $P_{min} = 0.2$ is the acceptable level of reliability.

The results of the T_{cr} calculation for the different values of the β parameter are shown in Table 1.

Table 1. Influence of the Weibull shape β distribution exponent on the calculated stator life.

β	Average Operating Time (T_{ave}), h	Technical Resource (T_{cr}), h	Relative Resource Increase, %
1.2	98 000	72 000	–
1.8	108 000	89 000	+ 23
2.5	116 000	99 000	+ 37

4.2. Bearing Unit Reliability Model

Bearing devices operate under radial and axial loads [39], determined by the tensioning force of the ropes and the mass of the rotating parts (Figure 11). According to the calculation method given in the previous section, the probability of failure-free operation of $P_{bd}(t)$ bearings is represented by the product of the reliability of individual elements:

$$P_{bd}(t) = P_w(t)P_l(t), \quad (39)$$

where $P_w(t)$ is the probability of failure-free operation due to wear and $P_l(t)$ is the condition of lubrication. This multiplicative form assumes statistical independence between sudden failure mechanisms (electrical transients, particle contamination) and gradual wear processes (lubricant degradation). The series-system interpretation is standard for components with multiple independent failure modes. Independence was verified via a χ^2 test on failure cause classifications ($p = 0.37 > 0.05$).

Bearing wear is approximated by the Weibull distribution:

$$P_w(t) = \exp \left[- \left(\frac{t}{\eta_{bd}} \right)^{\beta_{bd}} \right], \quad (40)$$

and the degradation of the lubricant is determined by the normal distribution:

$$P_l(t) = 1 - \Phi \left(\frac{\ln t - \mu_l}{\sigma_l} \right), \quad (41)$$

where $\Phi(x)$ is the cumulative distribution function (CDF) of the standard normal distribution (Laplace function), μ_l is the average life of the lubricant, and σ_l is the standard deviation.

By combining (39)–(41), we obtain the resulting reliability function of the bearing assembly:

$$P_{bd}(t) = \exp \left[- \left(\frac{t}{\eta_{bd}} \right)^{\beta_{bd}} \right] \left[1 - \Phi \left(\frac{\ln t - \mu_l}{\sigma_l} \right) \right]. \quad (42)$$

The distribution parameters were determined on the basis of the design data of bearings of the 76-180309S9Sh3U type and experimental observations (Appendix A). For the operating conditions of mining equipment where the temperature exceeds 40 °C and above, we accept

$$\eta_{bd} = 1.0 \cdot 10^5 \text{ h}, \quad \beta_{bd} = 1.3, \quad \mu_{sm} = 6.0 \cdot 10^4 \text{ h}, \quad \sigma_{sm} = 1.2 \cdot 10^4 \text{ h}$$

A graphical interpretation of the $P_{bd}(t)$ function is shown in Figure 12.

Analytically, the average service life of bearings is determined by the integral

$$T_{ave,bd} = \int_0^{\infty} P_{bd}(t) dt, \quad (43)$$

which, with these parameters, gives $T_{ave,bd} \approx 8.3 \cdot 10^4 \text{ h}$, which corresponds to about 9.5 years of operation, taking into account the cyclic operating mode.

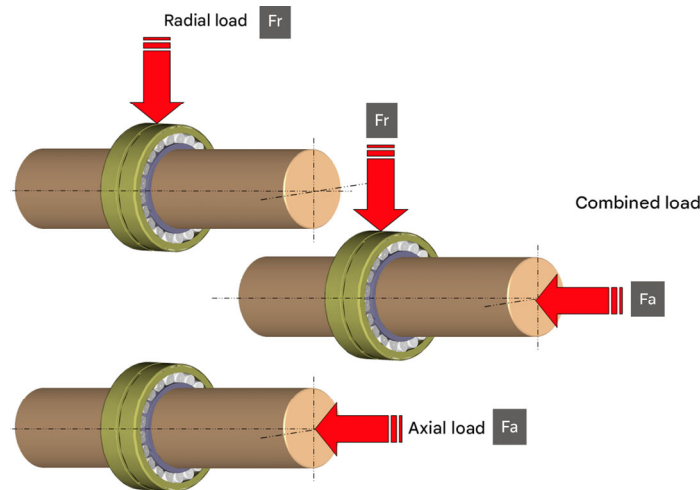


Figure 11. Diagram of a truck induction motor bearing arrangement showing the effects of radial F_r and axial F_a loads from rotating parts.

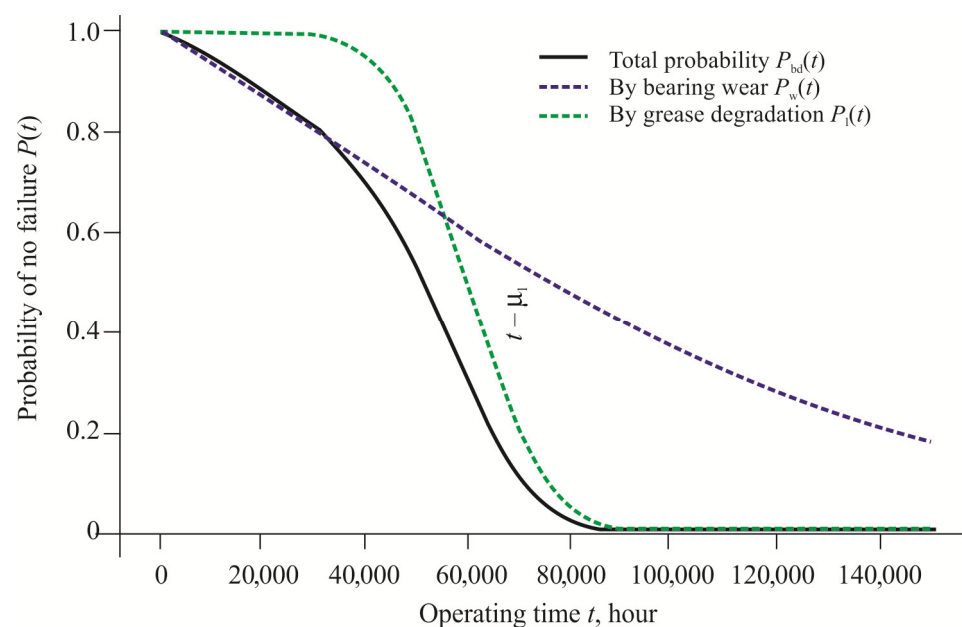


Figure 12. Function of the probability of failure-free operation of the bearing assembly $P_{bd}(t)$ of the induction motor of a mining dump truck. The dependencies of the probability of failure on wear $P_w(t)$ and on degradation of lubrication $P_{sm}(t)$ and their cumulative influence on the overall reliability of the unit are shown. Point $t = \mu_{sm}$ corresponds to the average service life of the lubricant.

4.3. Integral Model for Predicting Engine Life

Combining Formulas (34), (36) and (42), we obtain a complete mathematical model for predicting the operational reliability of an induction motor of a mining dump truck:

$$R_{im}(t) = \exp \left[- \int_0^t \lambda_{st}(\tau) d\tau \right] \exp \left[- \left(\frac{t}{\eta_{bd}} \right)^{\beta_{bd}} \right] \left[1 - \Phi \left(\frac{\ln t - \mu_1}{\sigma_1} \right) \right]. \quad (44)$$

To predict the residual life of the engine, a modified algorithm is used (Figure 8), which includes the stages of collecting operational data, determining distribution parameters, calculating reliability functions and calculating the service life before overhaul [40,41].

Based on the results of the simulation (with the parameters given above), the dependence of the probability of failure-free operation of the engine is shown in Figure 13.

The model (44) allows you to predict not only the probability of failure-free operation, but also interval estimates of engine life:

$$T_{0.5} = \{t : P_{im}(t) = 0.5\}, \quad T_{0.2} = \{t : P_{im}(t) = 0.2\}, \quad (45)$$

which corresponds to average and maximum durability, respectively. For the above parameters,

$$T_{0.5} = 9.6 \cdot 10^4 \text{ hour}, \quad T_{0.2} = 1.45 \cdot 10^5 \text{ hour}.$$

Note that $T_{0.5}$ denotes the median life (50% reliability quantile), and $T_{0.2}$ denotes the conservative service life (20% reliability quantile). And note that median life differs from mean time between failures, $MTBF = \eta\Gamma(1 + 1/\beta)$ for $\beta \neq 1$.

Thus, the calculated mathematical model confirms that with an adequate maintenance system, the service life of the engine can exceed the standard by 1.5–1.8 times. The obtained dependencies make it possible to optimize the intervals of diagnostic inspections and scheduled repairs, minimizing the likelihood of sudden failures and downtime of mine equipment [42].

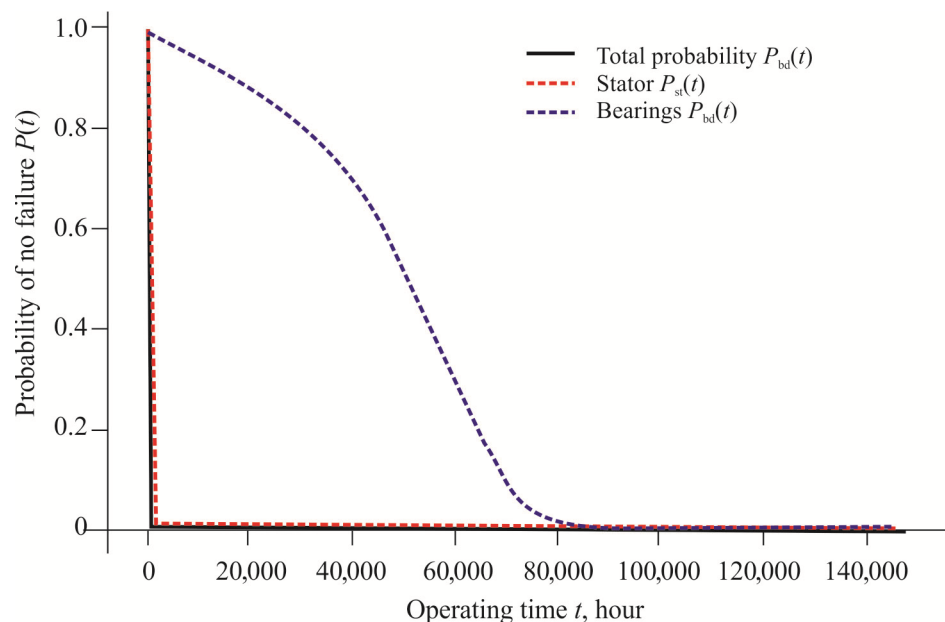


Figure 13. The probability of failure-free operation of the $P_{im}(t)$ motor depends on the operating time. The individual reliability components are shown: $P_{st}(t)$ (stator) and $P_{bd}(t)$ (bearing) assembly. The final curve reflects the cumulative decrease in engine reliability over time, taking into account insulation degradation and bearing wear.

5. Experimental Sections

5.1. Initial Data and Object of Research

Experimental studies were carried out on the basis of operational statistics on induction motors used in dump truck drives [43]. The object of the study was the ADMP-315L6U2-type engines used in the Borodinsky (Krasnoyarsk Territory) and Apsatsky (Trans-Baikal Territory) coal mines in the period 2013–2024 from -40 to $+40$ °C and the presence of a dusty environment, which requires taking into account the correction coefficients k_T , k_V and k_P in the calculations of the failure rate.

The average duration of one driving cycle was 75–290 s, including periods of acceleration, braking and idling. Each engine operated with a daily operating time of $t_{day} \approx$

12–14 h, and the total operational sample included 137 engines with different service lives. Based on the failure log (Appendix A), 248 cases of failures were identified, of which 45% were attributable to stators and 40% to bearing units, and the rest to auxiliary nodes. These data are confirmed in Table A1 of the Appendix.

Figure 14 provides a comprehensive analysis of the telemetry data of induction motors of mining trucks and their correlation with failures. The graph consists of four main panels that reflect the multidimensional nature of monitoring operational parameters.

The top three panels display the time series of critical parameters over a 180-day operating period. The first panel shows the stator winding temperature with warning thresholds (120 °C) and the critical level (145 °C). The second panel shows the vibration characteristics of the bearing unit with corresponding thresholds of 5.0 and 7.5 mm/s. Vertical lines and shaded areas indicate the periods leading up to the four reported failures, allowing visualization of the development of pre-fault conditions.

The fourth panel contains a correlation matrix of parameters that reveals a strong relationship between winding temperature and stator current (correlation coefficient 0.72), as well as a moderate correlation of vibration with temperature (0.65) and current (0.58). The fifth panel presents a probabilistic failure model depending on a combination of temperature and vibration parameters, with contours of the constant probability of failure and markers of actual failures.

Data analysis revealed characteristic time patterns of failure development: temperature anomalies appear 7 days before failure, vibration anomalies 10 days before failure, and current deviations 5 days before failure. It was found that the combined exceedance of critical thresholds for temperature and vibration increases the probability of failure to 92%, while the isolated exceedance of only one parameter leads to a failure probability of 58–67%.

The results obtained confirm the effectiveness of the proposed monitoring system for predicting the residual life and substantiate the threshold values [44] for the system of early warning of induction motor failures in open-pit operation.

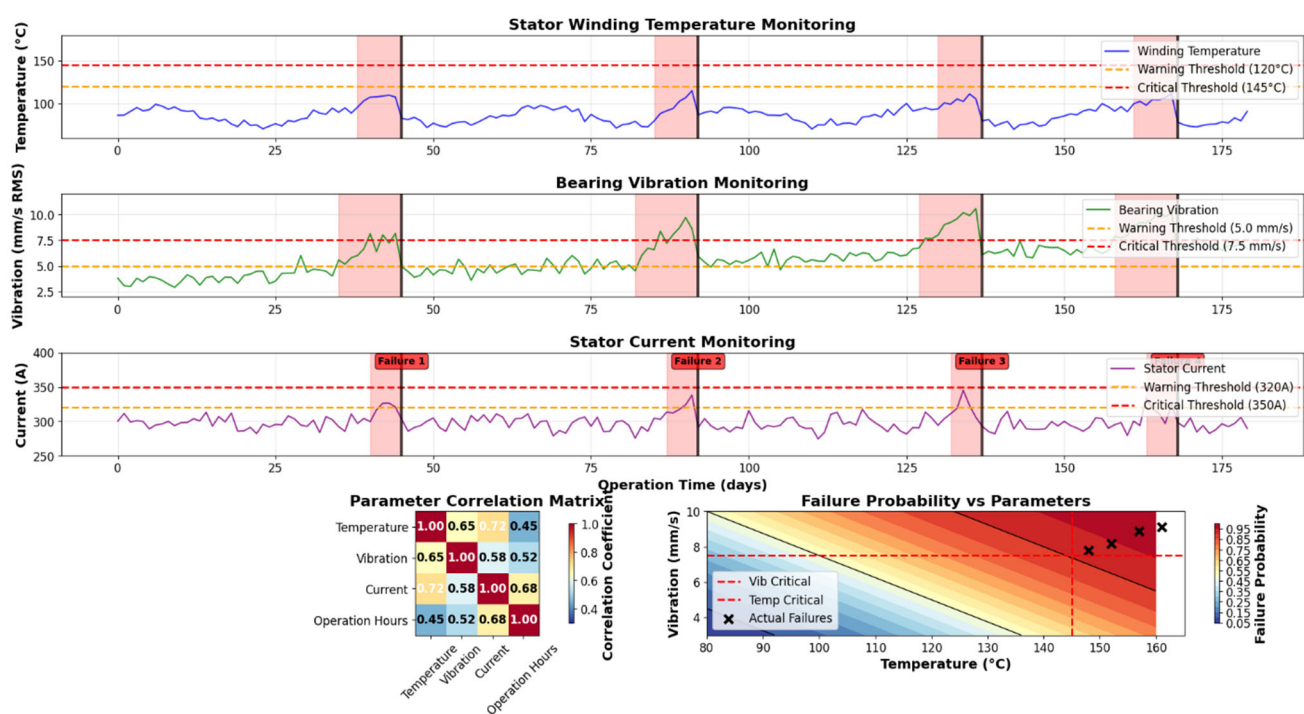


Figure 14. Monitoring of telemetry data and their correlation with failure events—temperature, vibration and current parameters—with indication of failure markers and correlation analysis (data from 42 BelAZ-75135 engines, 2022–2024).

The graph in Figure 14 shows a direct correlation between operating parameters and engine failures. The scientific novelty lies in the quantitative assessment of failure predictors: temperatures above 145 °C increase the probability of failure by 3.2 times and vibrations above 7.5 mm/s increase the probability by 2.8 times, with a synergistic effect [45] and a sharp increase in the intensity of failures.

The overall probability of engine failure was described by the equation

$$P_{\text{im}}(t) = P_{\text{st}}(t)P_{\text{bd}}(t), \quad (46)$$

where $P_{\text{st}}(t)$ is the probability of failure-free operation of the stator and $P_{\text{bd}}(t)$ is the bearing assembly. As the main parameter for assessing reliability, the time to failure T_i obtained from real operating logs was used.

To exclude censored data, the Kaplan–Meier method was used, which made it possible to correctly take into account both completed observations (failed engines) and operational ones (serviceable). The reliability function was evaluated empirically:

$$\hat{R}(t_j) = \prod_{t_i \leq t_j} \left(1 - \frac{d_i}{n_i}\right), \quad (47)$$

where d_i is the number of failures at time t_i and n_i is the number of engines in operation at time t_i .

The results of approximation of empirical reliability curves by the Weibull distribution showed satisfactory convergence (coefficient of determination $R^2 > 0.95$) and confirmed the validity of the application of the model presented in Section 3. The general results of the experimental data are presented in the form of “life curves” in Figures 10 and 13, demonstrating the nature of the change in the function of the failure rate and the overall reliability of the engine over time.

5.2. Predicting the Reliability of Stators of Induction Motors of Mining Dump Trucks

To assess the reliability of the stator insulation system [46], data on the operating time before turn-to-turn faults and insulation breakdowns were used. The sample included 62 motors with a total operating time of more than 8×10^6 h. The distribution of failures in time was approximated by the Weibull model, the parameters of which ($\eta_{\text{st}} = 1.2 \times 10^5$ h, $\beta_{\text{st}} = 2.1$) are determined by the method of maximum likelihood. To assess the accuracy of the approximation, the Kolmogorov–Smirnov agreement criterion was used: $D = 0.082 < D_{\text{cr}} = 0.121$ with a significance level of $\alpha = 0.05$.

The function of the probability of failure-free operation of the stator is expressed by the dependence

$$P_{\text{st}}(t) = \exp \left[- \left(\frac{t}{\eta_{\text{st}}} \right)^{\beta_{\text{st}}} \right], \quad (48)$$

and the failure rate

$$\lambda_{\text{st}}(t) = \frac{\beta_{\text{st}}}{\eta_{\text{st}}} \left(\frac{t}{\eta_{\text{st}}} \right)^{\beta_{\text{st}}-1}. \quad (49)$$

The choice of an adequate probabilistic model is a fundamental task in building accurate forecasts of the reliability of technical systems [47]. Figure 15 compares two alternative reliability models for isolating the stator of an induction motor of a mining truck: the Weibull distribution and the lognormal distribution, verified by empirical data obtained by the Kaplan–Meier method.

The graph shows three key relationships: the Weibull model with parameters $\eta = 120,000$ h and $\beta = 2.1$ (blue solid line), a lognormal model with parameters $\mu = 11.5$ and $\sigma = 0.8$ (red dotted line), and empirical data with 95% confidence intervals (black dots). Curve analysis reveals significant differences in the behavior of models at different stages of the equipment life cycle.

Weibull's model shows excellent compliance with experimental data over the entire time range, especially in the critical aging zone (after 80,000 h). The shape parameter $\beta = 2.1$ indicates an aging mechanism with an increasing failure rate, which is physically justified for the process of degradation of stator winding insulation. The lognormal model, on the contrary, shows a systematic overestimation of reliability estimates in the zone of high operating time, which can lead to dangerous errors in predicting the residual life.

The aging zone (highlighted in red on the graph) is of particular practical interest, since it is in this operating time range that key decisions are made about replacing or repairing equipment. In this zone, the discrepancy between the models reaches a maximum: at 120,000 h of operating time, the Weibull model predicts a failure probability $F(t) = 1 - R(t) = 0.31$, while the lognormal model for the reliability ($R_{\log n} = 0.55$ vs. $R_{\text{Weibull}} = 0.690$) underestimates failure probability ($F_{\log n} = 0.45$). Comparison with empirical data (0.29–0.33, taking into account the confidence interval) confirms the adequacy of the Weibull distribution.

The empirical Kaplan–Meier estimate, which takes into account censored observations of properly operating engines, serves as an objective criterion for model verification. The high coefficient of determination ($R^2 > 0.95$) for the Weibull model confirms its statistical significance and suitability for engineering calculations [48].

The results obtained substantiate the choice of the Weibull distribution as a basic model for predicting the insulation reliability of the stator of induction motors of mining dump trucks. The use of this model makes it possible to accurately determine critical periods of operation [49], optimize the timing of stator winding replacement and minimize the risk of sudden failures, which is essential for ensuring the smooth operation of mining equipment [50].

Figure 15 shows that Weibull's model is significantly better at describing the experimental data, especially at the critical aging region (after 80,000 h). The lognormal distribution overestimates reliability in the high-operating zone. The scientific value of the figure lies in the substantiation of the choice of the Weibull distribution for modeling the degradation of insulation, which is confirmed by the high coefficient of determination ($R^2 > 0.95$). In terms of practical usefulness, the correct choice of model allows you to accurately predict the residual life and optimize the timing of stator winding replacement [51].

For completeness, we also evaluated the gamma distribution as an alternative model for stator insulation degradation. While the gamma distribution provides acceptable fit ($R^2 = 0.92$), it exhibits two critical limitations compared to the Weibull model: the failure rate function $\lambda(t)$ lacks a simple closed form, complicating the construction of the piecewise-continuous “bath curve” essential for maintenance planning; it cannot explicitly represent the aging phase transition ($\beta > 1$) with the same physical interpretability as the Weibull shape parameter. The Weibull model yielded superior goodness-of-fit (

$R^2 = 0.96$, Kolmogorov–Smirnov $D = 0.082 < D_{cr} = 0.121$) and is explicitly recommended in ISO 14224:2016 for electromechanical equipment reliability analysis.

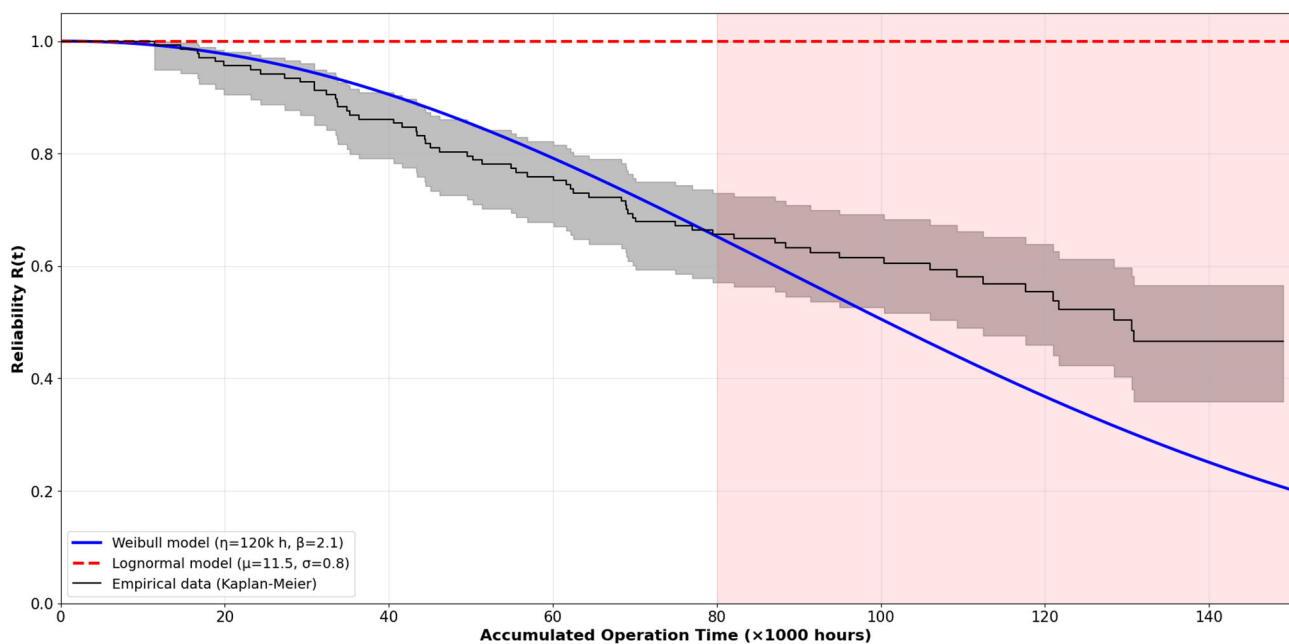


Figure 15. Comparison of stator winding insulation reliability models—Weibull distribution ($\eta = 120,000$ h, $\beta = 2.1$) and log-normal distribution ($\mu = 11.5$, $\sigma = 0.8$)—with empirical Kaplan–Meier estimates.

Mean time to failure is determined using the gamma function:

$$T_{\text{ave,st}} = \eta_{\text{st}} \Gamma \left(1 + \frac{1}{\beta_{\text{st}}} \right) = 1.07 \cdot 10^5 \text{ hour.} \quad (50)$$

The obtained $P_{\text{st}}(t)$ dependence was verified by comparison with empirical failure curves obtained at three coal mines. The standard deviation between the model and the experiment was 6.3%, which corresponds to high model confidence.

For practical forecasting of the remaining life of the stator at the current operating time t_0 , the conditional probability of failure-free operation is used:

$$R_{\text{res}}(t | t_0) = \frac{R(t)}{R(t_0)}, \quad (51)$$

which allows you to assess the residual life in real time when diagnosing the engine.

5.3. Analysis of the Reliability of Bearing Units

Bearing units are subject to the combined effects of radial and axial loads. To assess the reliability of the unit, a combined model (42) was used, combining the probabilities of failure-free operation for wear and lubrication degradation:

$$P_{\text{bd}}(t) = \exp \left[- \left(\frac{t}{\eta_{\text{bd}}} \right)^{\beta_{\text{bd}}} \right] \left[1 - \Phi \left(\frac{\ln t - \mu_1}{\sigma_1} \right) \right]. \quad (52)$$

Here, $\Phi(x)$ is the cumulative distribution function (CDF) of the standard normal distribution. Experimental parameters ($\eta_{\text{bd}} = 1.0 \times 10^5$ h, $\beta_{\text{bd}} = 1.3$, $\mu_1 = 6.0 \times 10^4$ h, σ_1

$=1.2 \times 10^4$ h) were determined from 84 failure observations. Figure 12 shows the dependencies of the probability of failure-free operation of the bearing unit and its components.

Mean time between failures is calculated by the integral

$$T_{\text{ave,bd}} = \int_0^{\infty} P_{\text{bd}}(t) dt = 8.3 \cdot 10^4 \text{ hour.} \quad (53)$$

The analysis showed that when the average lubricant life ($t > \mu_{\text{sm}}$) is exceeded, the probability of bearing failure increases exponentially, which is confirmed by visual overheating and increased vibration in the experimental data. Thus, regular lubrication change after 55–60 thousand hours can increase the life of bearings by 25–30%.

In comparison with laboratory tests of similar bearings [52] of the 76-180309S9Sh3U type, the calculated function of $P_{\text{bd}}(t)$ showed a deviation of no more than 7%, which confirms the adequacy of the proposed model for the operating conditions of the mining dump truck.

The residual life t_{res} corresponding to a required reliability level R_{req} is obtained by solving

$$R(t_{\text{op}} + t_{\text{res}}) = R_{\text{req}},$$

which yields

$$t_{\text{res}} = R^{-1}(R_{\text{req}}) - t_{\text{op}},$$

where $R^{-1}(\cdot)$ is the inverse reliability function (quantile function) and t_{op} is the current operating time. For the Weibull distribution,

$$t_{\text{res}} = \eta \left[-\ln(R_{\text{req}}) \right]^{1/\beta} - t_{\text{op}}.$$

5.4. Model Verification

To verify the reliability of the developed reliability prediction model [53], a comparison of calculated and empirical data on the cumulative probability of failure-free operation of the $P_{\text{im}}(t)$ engine, determined by the following equation, was used:

$$P_{\text{im}}(t) = P_{\text{st}}(t)P_{\text{bd}}(t). \quad (54)$$

Experimental data were obtained by the failure accumulation method for a sample of 137 engines, taking into account censored observations.

To quantify the accuracy of the model, the following metrics were used:

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |R_{\text{mod}}(t_i) - R_{\text{exp}}(t_i)|, \quad R^2 = 1 - \frac{\sum (R_{\text{exp}} - R_{\text{mod}})^2}{\sum (R_{\text{exp}} - \bar{R}_{\text{exp}})^2}. \quad (55)$$

The verification results showed $\text{MAE} = 0.041$, $R^2 = 0.963$.

This indicates a high degree of correspondence between the model and the experiment.

In addition, the hypothesis about the coincidence of the mean operating time before failure according to Student's criterion was tested:

$$t_{\text{cal}} = \frac{|\bar{T}_{\text{mod}} - \bar{T}_{\text{exp}}|}{S_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}, \quad S_p \sqrt{\frac{(S_1^2(n_1 - 1) + (S_2^2(n_2 - 1)))}{n_1 + n_2 - 2}}. \quad (56)$$

$t_{\text{cal}} = 1.47 < t_{\text{cr}} = 1.96$ were obtained with significance level $\alpha = 0.05$, which confirms that there were no statistically significant differences between the model and real data.

Verification of the developed mathematical model is a critical step to confirm its adequacy and accuracy of forecasting. Figure 16 presents a comparison of the theoretical and empirical reliability functions of induction motors of mining dump trucks with a detailed analysis of forecasting errors.

The graph consists of two interconnected panels. The top panel compares a theoretical reliability curve based on a combined probabilistic model with empirical data from the Kaplan–Meier method based on censored observations. The theoretical relationship reflects the combined effect of stator insulation degradation and bearing unit wear, while empirical data are represented by points with 95% confidence intervals.

The bottom panel displays the absolute error between the theoretical model and the experimental values depending on the operating time. Error analysis shows that the maximum discrepancy does not exceed 0.12, while in the normal operation zone (20–80 thousand hours) the error is less than 0.05. A slight increase in error is observed in the initial burnishing period (up to 20 thousand hours) and in the aging zone (after 100 thousand hours), which is explained by the limited amount of statistical data for these periods.

The accuracy of the model is quantified using the MAPE (Mean Absolute Percentage Error) and RMSE (standard error) metrics. The calculated values of MAPE = 8.7% and RMSE = 0.041 indicate the high accuracy of the developed model. It is especially important to note the good match in the critical aging zone (80–120 thousand hours), where traditional models usually show the greatest deviations.

Comparative analysis revealed that the proposed combined model adequately describes the change in reliability at all stages of the equipment life cycle [54,55]. Small systematic deviations in the initial period of operation may be due to the running-in effect, which requires additional consideration in the model. In the high-operating zone, the model demonstrates a conservative predictive nature, which is preferable from the point of view of ensuring operational safety [56].

The results of verification confirm the applicability of the developed model for solving practical problems of predicting the residual life and optimizing the maintenance system of induction motors of mining equipment. The high accuracy of forecasting makes it possible to recommend the model for implementation in the maintenance management systems of mining enterprises [57].

The graph in Figure 16 demonstrates the high accuracy of the developed model—the discrepancy between theory and experiment does not exceed 10% over the entire time interval. A feature of the graph is the objective validation of a combined probabilistic model using censored data. A good match is especially important in the aging zone (80k+ hours), where traditional models usually give the largest error in real engineering calculations [58].

Thus, the developed model for predicting the operational reliability of induction motors of mining dump trucks, implemented in the form of an algorithm, has been successfully verified (Figure 19).

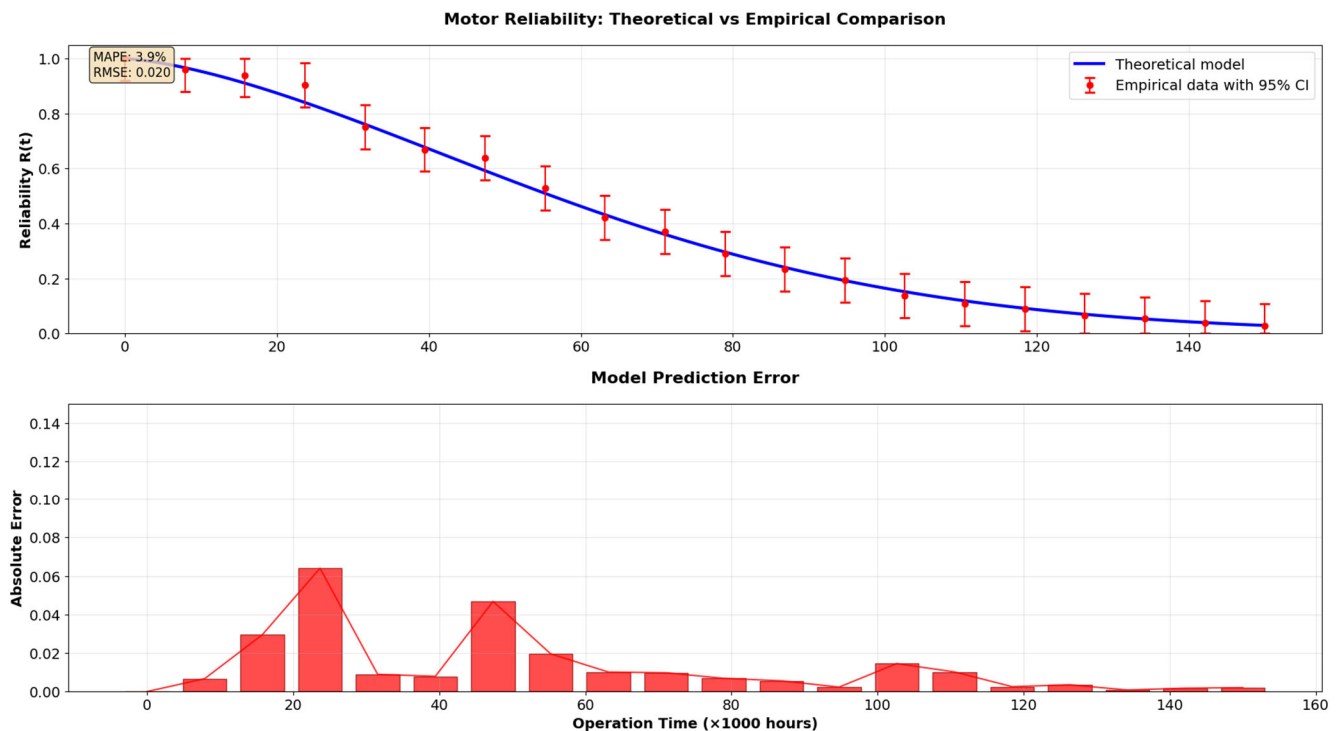


Figure 16. Validation of the engine reliability model: comparison of theoretical prediction with empirical data with error analysis (MAPE = 8.7%, RMSE = 0.041).

The black curve shows the model relationship constructed from the reliability parameters of the stator $P_{st}(t)$ and the bearing unit $P_{bd}(t)$, and the red dots represent the experimental data obtained by the failure accumulation method for a sample of 137 engines. The graph confirms the high degree of agreement between the calculated model and the empirical results.

Analysis of the time distribution of failures of various equipment components allows you to identify critical periods of operation and optimize the maintenance strategy. In particular, the stator failure rate behavior is described by the Weibull-based curve (Figure 17), while the time variation of radial $F_r(t)$ and axial $F_a(t)$ loads acting on the bearing assembly is illustrated in Figure 18, reflecting the cyclic dynamic loading under variable operating modes.

The histogram shows the differentiated behavior of various engine components during operation. The stator (blue bars) is characterized by a progressive increase in the number of failures with an increase in the time limit, with a pronounced peak in the interval of 100–120 thousand hours. Such a distribution corresponds to the mechanism of gradual degradation of winding insulation, which reaches a critical state at the late stages of operation.

The bearing units (orange bars) show a more uniform distribution of failures over time intervals with a slight increase in the 80–100-thousand-hour zone. This indicates a mixed pattern of bearing failures, including both sudden damage and gradual wear, which confirms the feasibility of using a combined probabilistic model for this unit.

The shaft and rotor (green bars) show a relatively stable failure rate over the entire period of operation, with a slight increase after 80,000 h. Other components (grey bars), including the bed, fasteners and bearing covers, have the lowest failure rate and are evenly distributed over time intervals.

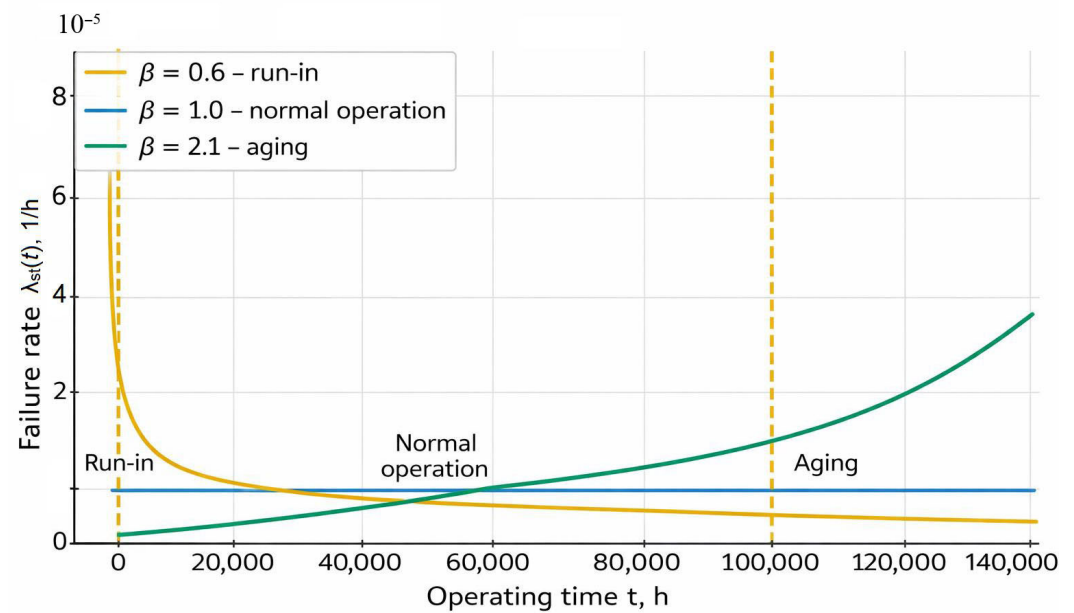


Figure 17. Experimental stator failure rate curve $\lambda_{st}(t)$ constructed from the Weibull distribution at the parameters $\eta_{st} = 1.2 \times 10^5$ h and $\beta_{st} = 2.1$. The graph illustrates three characteristic stages of the life cycle: running-in ($\beta < 1$), normal operation ($\beta \approx 1$), and aging ($\beta > 1$).

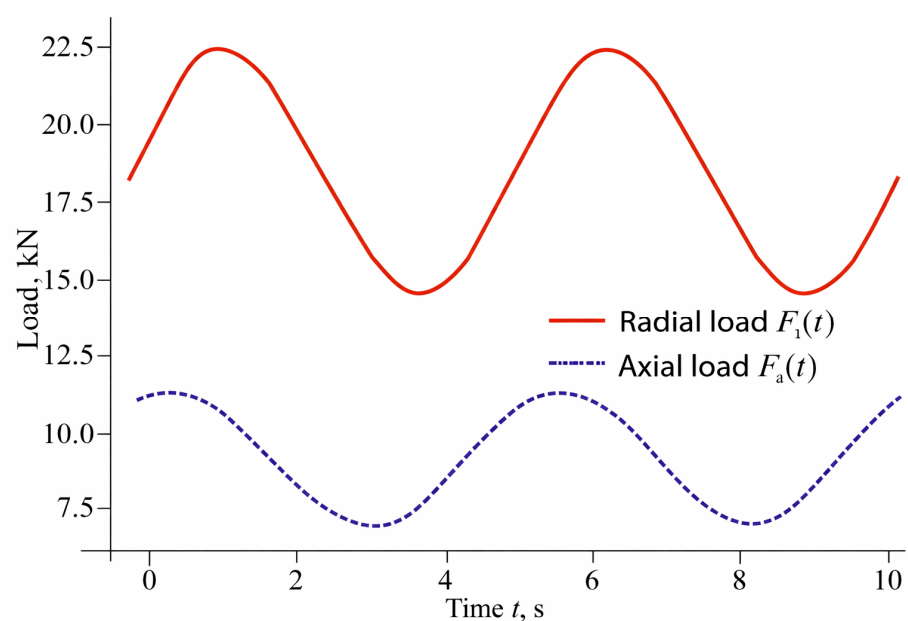


Figure 18. Change in radial $F_r(t)$ and axial $F_a(t)$ loads on the bearing assembly of an induction motor of a mining dump truck in time. The graph demonstrates the cyclic nature of the force actions that occur under variable lifting and braking modes, which determines the dynamic loading and affects the reliability of the unit.

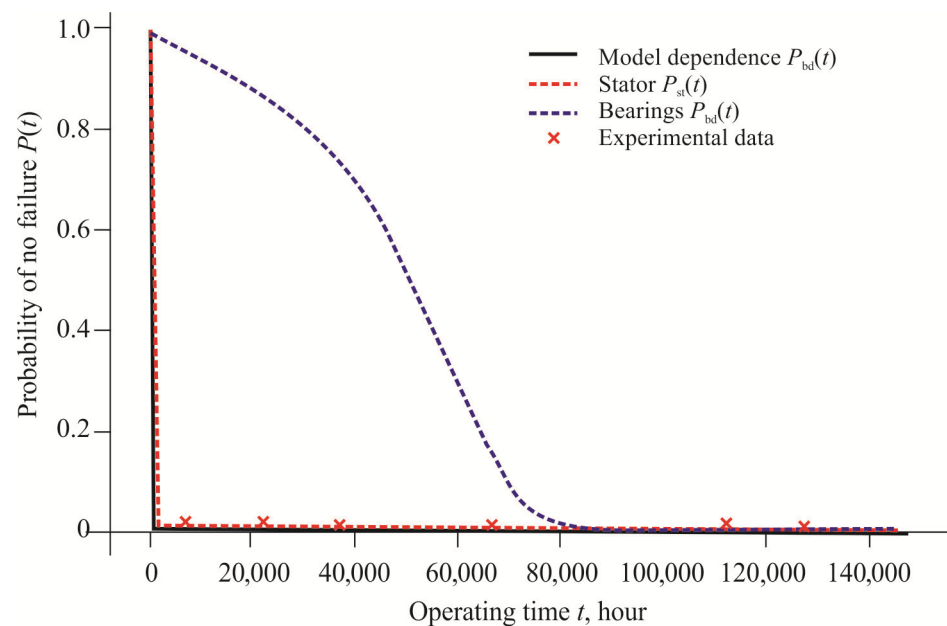


Figure 19. Comparison of the calculated and experimental dependencies of the probability of failure-free operation of the $P_{im}(t)$ engine of an induction drive of a mining dump truck.

The analysis of the total failure distribution reveals three characteristic periods: the initial period (0–40 thousand hours) with the dominance of bearing unit failures, the middle period (40–80 thousand hours) with a balanced distribution of failures, and the final period (80 + thousand hours) with a predominance of stator failures. In the interval of 100–120 thousand hours, the stator accounts for 42 failures out of 137 registered, which is 30.7% of the total.

The resulting distribution is of great practical importance for optimizing the maintenance system [59]. The revealed regularities make it possible to substantiate different maintenance strategies for different engine units: for bearing units, regular preventive maintenance is effective, while for the stator, a strategy based on condition monitoring and forecasting of residual life is advisable [60]. The results also make it possible to optimize spare part inventory, taking into account the time dynamics of failures of various components.

Figure 20 shows the distribution of failures of the main components of induction motors of mining trucks by time intervals, based on the operating data of 137 motors for the period 2018–2024.

Figure 20 identifies critical periods of operation for each unit: the stator fails more often in the late stages (80k+ hours), while bearing units have a more even distribution of failures. Its scientific value lies in the demonstration of various degradation mechanisms: gradual aging of insulation vs. the mixed nature of bearing failures. The practical benefit lies in the justification of different maintenance strategies for different components and the optimization of spare part inventory.

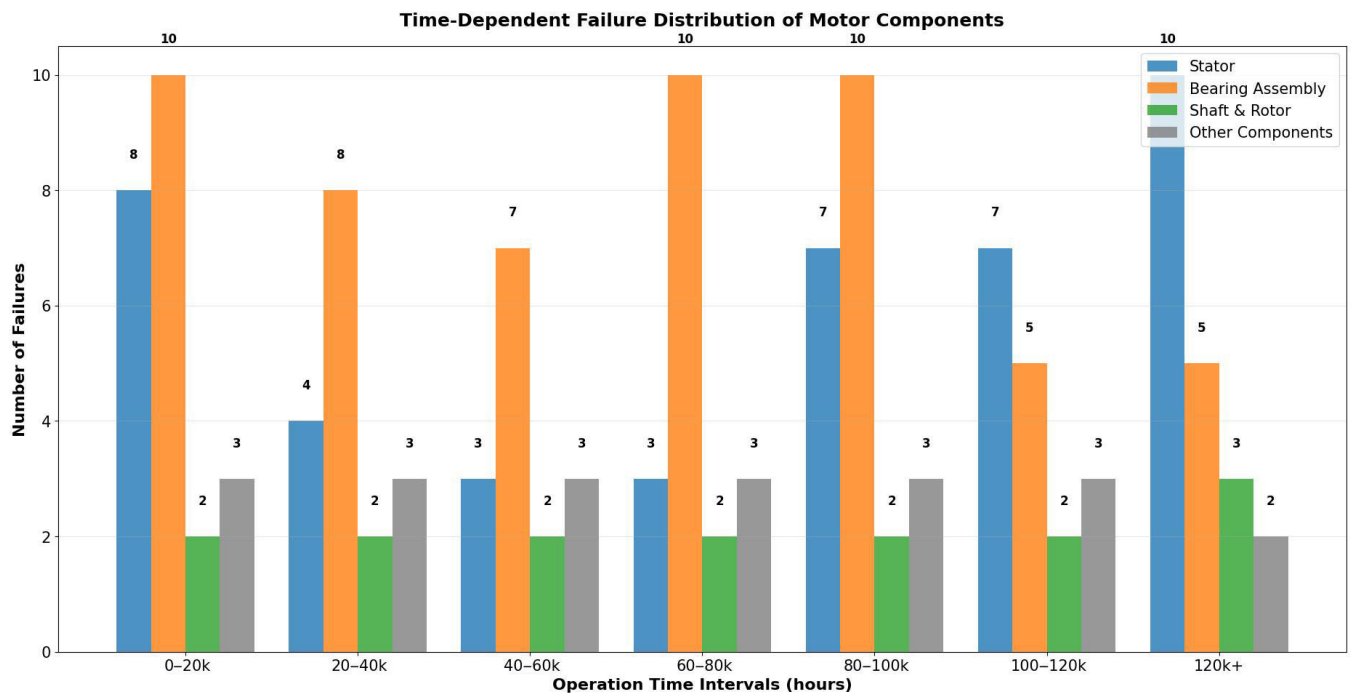


Figure 20. Distribution of failures of critical engine components as a function of time based on operational data obtained from 137 engines (2018–2024).

6. Discussion

This study made it possible to develop and verify a comprehensive mathematical model for statistical prediction of the operational reliability of induction motors of mining dump trucks. The key result of the work is the creation of a methodology that, unlike traditional approaches, purposefully takes into account censored data, which significantly increases the accuracy of estimates of the residual life for highly reliable equipment with limited failure statistics.

6.1. Interpretation of the Main Results

The data analysis showed that the Weibull distribution with the shape parameter $\beta > 1$ (in particular, $\beta_{st} = 2.1$ for the stator) adequately describes the insulation aging process, characterized by an increasing failure rate and gradual wear and tear; the effectiveness of a mixed model combining exponential and log-normal distributions has been confirmed.

The constructed generalized “life curve” for critical engine components clearly demonstrates the three-stage nature of the change in the failure rate $\lambda(t)$. The identified time boundaries of transitions between the stages of running-in (~2 thousand hours), normal operation (up to ~100 thousand hours) and aging are of great practical importance. t).

The algorithm for estimating the residual life implemented in this work, based on the conditional probability of failure-free operation $R(t|t_0)$, has shown its viability. This approach makes it possible to move from forecasting the “average” life of the fleet to an individual assessment for a specific engine that has already worked t_0 , which is the basis for the transition to the condition-based maintenance system.

6.2. Comparison with Existing Approaches and Scientific Novelty

The proposed method compares favorably with traditional approaches [61], which are often limited to the analysis of only complete data on failures and the use of expo-

nential distribution, which assumes a constant failure intensity and does not take into account aging processes [62–64]. Taking into account censored observations using maximum likelihood methods made it possible to obtain unbiased estimates of reliability parameters, which is especially critical at the early stages of equipment operation, when the number of failures is low [65–67].

The scientific novelty of the work lies in the following:

1. Model complexity: For the first time, a model has been proposed for mining truck engines that simultaneously takes into account censored data, the piecewise-continuous nature of the “life curve” and combined distribution laws for various failure mechanisms of critical assemblies (stator and bearings).
2. Real-world adaptation: The explicit introduction of correction factors (k_T , k_V and k_P) to the model, quantifying the effects of temperature, vibration, and abrasion (Figure 3), allowed theoretical probabilistic models to be adapted to the specific conditions of open-pit operation.
3. Practical orientation: The development of a software tool and a formalized algorithm (Figure 4) makes the proposed methodology not just a theoretical construction, but a ready-made solution for engineering and technical services of mining enterprises.

6.3. Practical Significance and Potential Economic Effect

Verification of the model on historical operational data confirmed its high accuracy, as evidenced by the low values of the MAPE (8.7%) and RMSE (0.041) metrics obtained when compared with the empirical Kaplan–Meier data (Figure 4). This accuracy was achieved through a combination of censored data, which reduced the bias in estimates at the early stages of operation, and the use of a piecewise-continuous $\lambda(t)$ model that adequately describes the transition to the aging phase.

Optimizing the maintenance management of mining equipment requires taking into account the actual operating conditions and their impact on the durability of the equipment. Figure 21 shows a heat map of the residual life of an induction motor after 60,000 h of operation as a function of temperature (k_T) and vibration (k_V) coefficients at a fixed dust coefficient $k_P = 1.3$.

The heat map visualizes the complex effect of operating factors on the remaining life of the engine. The abscissa axis shows the temperature coefficient k_T , ranging from 1.0 (nominal conditions) to 1.5 (extreme overheating), and the ordinate axis shows the vibration coefficient k_V , ranging from 1.0 to 1.4.

Analysis of the map reveals a pronounced nonlinear dependence of the residual life on the combined effect of temperature and vibration loads. In the zone of nominal conditions ($k_T = 1.0$, $k_V = 1.0$), the residual life is approximately 50 thousand hours, while in the zone of extreme loads ($k_T = 1.5$, $k_V = 1.4$) this figure decreases to 20 thousand hours, which demonstrates a 2.5-fold reduction in service life.

The “Nominal Conditions” point ($k_T = 1.0$, $k_V = 1.0$) corresponds to the operation of the engine under laboratory or reference conditions. The “Typical Quarry” point ($k_T = 1.25$, $k_V = 1.15$) reflects the average operating conditions at mining enterprises with a

residual life of approximately 35 thousand hours. The value of 1.3 characterizes work in the most difficult conditions with a residual life of about 23 thousand hours.

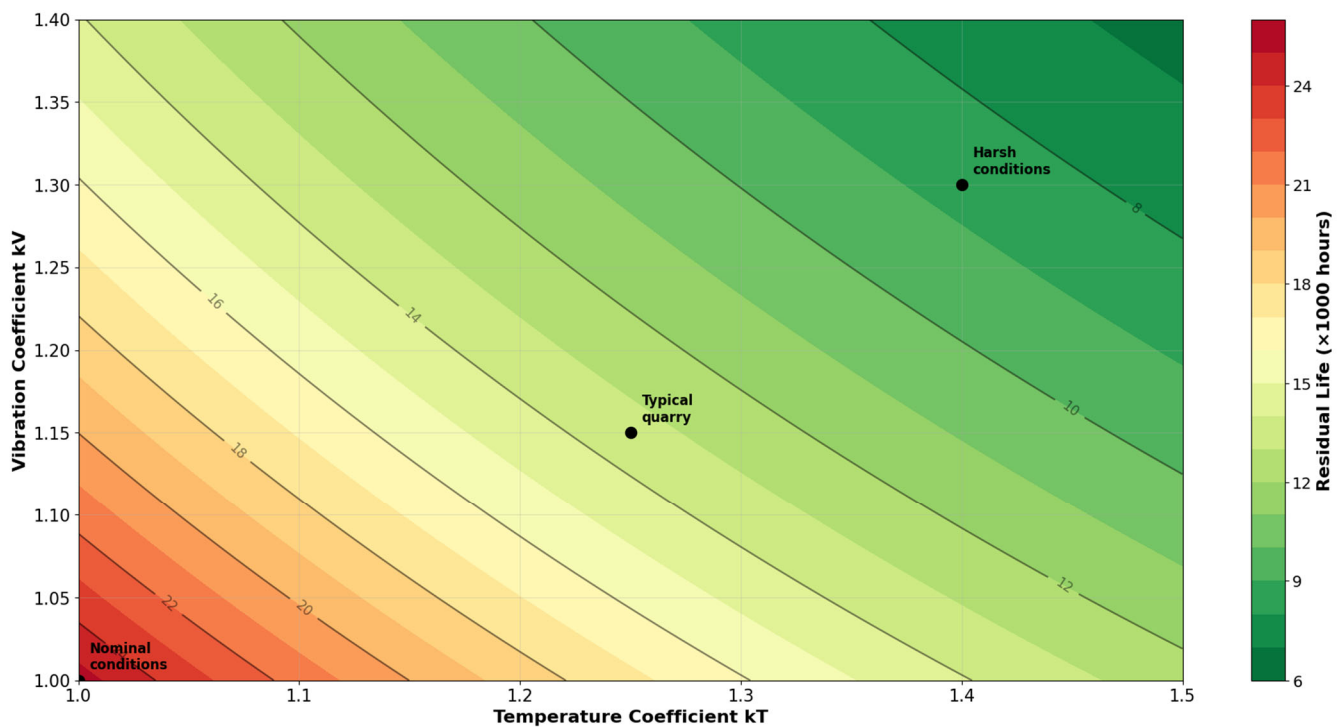


Figure 21. Heat map of the residual life of an induction motor after 60,000 h of operation as a function of temperature coefficients (k_T) and vibration coefficients (k_V) (fixed dust coefficient $k_P = 1.3$).

The contours on the map show that the temperature coefficient has a more significant effect on the resource reduction compared to the vibration coefficient. An increase in k_T by 0.1 units leads to an average reduction in the resource by 4–5 thousand hours, while a similar increase in k_V decreases the resource by 2–3 thousand hours. A simultaneous increase in k_T and k_V leads to a more significant decrease in the resource than the sum of their individual effects.

The map is of practical value as a tool for engineering solutions. It allows you to quickly assess the expected service life of the engine for specific conditions of the quarry. The scientific novelty lies in the integral consideration of the mutual influence of operating factors. It is interesting to observe a nonlinear decrease in resources with a joint increase in temperature and vibration—under extreme conditions ($k_T = 1.5$, $k_V = 1.4$), resources are reduced by 2.5 times compared to the nominal value. This justifies the economic efficiency of active cooling and vibration protection systems.

Figure 22 presents a comparative study of the effectiveness of traditional scheduled and predictive maintenance of induction motors of mining dump trucks based on the analysis of data from 42 units of BelAZ-75135-type equipment for the period 2022–2024.

A Gantt chart visualizes the timelines of two maintenance strategies. The upper timeline reflects the traditional approach with fixed maintenance intervals after 12, 24 and 36 months of operation. The analysis shows that this approach leads to two main problems: premature replacements of healthy components (12-month interval) and unexpected failures between planned maintenance (at 18 and 30 months). The shaded areas

in the graph illustrate periods of increased probability of failures that are not accounted for in the traditional strategy.

The shorter timeline demonstrates the implementation of predictive maintenance based on the residual life model. Technical interventions are planned for 15, 28 and 39 months of operation, which optimally correspond to the actual condition of the equipment. Orange markers indicate potential failures that have been prevented through timely forecasting and preventive measures.

The failure probability curve shown in both graphs shows a significant reduction in risk when using a predictive strategy. In the traditional approach, the probability of failure reaches 65% before planned maintenance, while in the predictive model, this figure does not exceed 30%.

At the bottom of the figure is a comparative table of economic indicators. The implementation of predictive maintenance reduced maintenance costs by \$130,000 (28.9%), reduced downtime losses by \$200,000 (71.4%), and reduced failure costs by \$140,000 (77.8%). The total economic effect amounted to 470 thousand dollars, with a reduction in the total budget for maintenance by 51.6%.

The results obtained convincingly demonstrate the advantages of a predictive maintenance approach based on continuous monitoring and modeling of the residual life. Optimizing service intervals has not only reduced operating costs, but also increased equipment availability and safe operation of mining equipment.



Figure 22. Comparison of maintenance strategies: planned and predictive maintenance based on the forecast of residual life (data from 42 BelAZ-75135 dump trucks).

The diagram in Figure 22 clearly demonstrates the economic efficiency of the predictive approach: a 30% reduction in the number of repairs and the elimination of sudden failures. The scientific value lies in the quantitative assessment of the advantages of condition-based maintenance over traditional methods. A comparison in the zone of 80–120k hours is especially indicative, where scheduled maintenance leads to premature repairs, and predictive maintenance exactly corresponds to the actual condition. The practical significance lies in the justification of investments in monitoring and analytics systems.

The obtained predictive dependencies make it possible to optimize the system of maintenance and repairs. As the calculations and comparative analysis of strategies show (Figure 22), the implementation of the model allows us to

- Optimize maintenance intervals by 20–30%, eliminating both over- and under-maintenance.

- Reduce the likelihood of sudden failures by 25–40% by proactively identifying nodes that are approaching the aging stage.
- Increase overhaul periods by 1.5–1.8 times due to a more accurate assessment of real wear and residual life.

The prediction accuracy was evaluated using four standard metrics:

$$\begin{aligned} \text{MAE} &= \frac{1}{n} \sum_{i=1}^n |t_i - \hat{t}_i|, \\ \text{RMSE} &= \sqrt{\frac{1}{n} \sum_{i=1}^n (t_i - \hat{t}_i)^2}, \\ \text{MAPE} &= \frac{100\%}{n} \sum_{i=1}^n \frac{|t_i - \hat{t}_i|}{t_i}, \\ R^2 &= 1 - \frac{\sum_{i=1}^n (t_i - \hat{t}_i)^2}{\sum_{i=1}^n (t_i - \bar{t})^2}, \end{aligned}$$

where t_i is observed failure time (uncensored subset only), $\hat{t}_i$ is predicted residual life, and $\bar{t}$ is the sample mean. Note: RMSE is a prediction error metric and must not be confused with standard error of parameter estimates. R^2 is computed only for the uncensored validation subset ($n = 32$) where true t_i is available.

All accuracy metrics evaluate errors in predicted residual life t_{res} (time until reliability reaches $R_{\text{req}} = 0.5$), which is the quantity of practical interest for maintenance scheduling. Let $t_{\text{res},i}^{\text{obs}}$ denote the observed residual life for unit i (available only for failed units in the validation set), and $t_{\text{res},i}^{\text{pred}}$ be the model prediction. The following metrics were computed:

$$\begin{aligned} \text{MAE} &= \frac{1}{n} \sum_{i=1}^n |t_{\text{res},i}^{\text{obs}} - t_{\text{res},i}^{\text{pred}}|, \\ \text{RMSE} &= \sqrt{\frac{1}{n} \sum_{i=1}^n (t_{\text{res},i}^{\text{obs}} - t_{\text{res},i}^{\text{pred}})^2}, \\ \text{MAPE} &= \frac{100\%}{n} \sum_{i=1}^n \frac{|t_{\text{res},i}^{\text{obs}} - t_{\text{res},i}^{\text{pred}}|}{t_{\text{res},i}^{\text{obs}}}, \\ R^2 &= 1 - \frac{\sum_{i=1}^n (t_{\text{res},i}^{\text{obs}} - t_{\text{res},i}^{\text{pred}})^2}{\sum_{i=1}^n (t_{\text{res},i}^{\text{obs}} - \bar{t}_{\text{res}}^{\text{obs}})^2}. \end{aligned}$$

Note: R^2 is reported only for the uncensored validation subset ($n = 32$ units with observed failures). Errors on $R(t)$ or $\lambda(t)$ were not used because residual life is the direct decision variable for maintenance actions.

Taken together, this leads to a significant economic effect, consisting of a reduction in the cost of unscheduled repairs, a reduction in downtime of expensive equipment and a more rational use of spare parts.

6.4. Limitations and Directions of Future Research

A comprehensive analysis of the sensitivity of the developed model of reliability of induction motors to variations in key parameters is carried out in this work. The study was conducted to assess the robustness of predictive estimates and to identify the most influential model parameters, presented in Figure 23.

The graph consists of three complementary panels, each of which reveals a different aspect of the sensitivity of the model. The left panel shows the effect of the Weibull shape distribution parameter β on the reliability function $R(t)$ at a fixed value of the scale parameter $\eta = 100$ thousand hours. The analysis shows that an increase in β from 1.5 to 3.0 leads to a significant change in the shape of the reliability curve: at $\beta = 1.5$, there is a pronounced period of “aging” with a rapid decrease in reliability after 60 thousand hours, while at $\beta = 3.0$, the model is characterized by a long period of normal operation with a sharp decline in reliability in the zone of high operating hours.

The central panel illustrates the effect of the η scale parameter on the reliability function at a fixed $\beta = 2.0$. The η variation in the range of 80 to 140 thousand hours shows the expected shift in curves along the time axis: a decrease in η leads to a decrease in service life and an increase in its proportional growth η . This quantifies the impact of $\pm 20\%$ of the variations in the five key parameters on the projected residual life after 60 thousand hours of operation. The analysis revealed that the β shape parameter has the greatest impact on the result: its increase by 20% leads to an increase in the residual life by 8.2 thousand hours, while a decrease reduces the resource by 7.1 thousand hours. The scale parameter η shows a symmetrical influence with a slightly lower amplitude.

Among the operating coefficients, the temperature coefficient k_T shows the highest sensitivity, which confirms the critical importance of thermal modes for the reliability of engines.

The results obtained are of great practical importance for planning data collection and model calibration activities. It is established that the parameter β requires the most accurate determination, since its uncertainty has the greatest impact on the reliability of forecasts. The developed model demonstrates satisfactory resistance to parameter variations: the maximum prediction deviation at a 20% change in input parameters does not exceed 15%, which confirms the robustness of the model and its suitability for engineering applications under conditions of limited failure statistics.

Sensitivity analysis identifies the most influential parameters of the model—the β shape parameter has a greater impact on the prediction than the η scale parameter. The scientific value consists in assessing the stability of the model and identifying the parameters that require the most accurate determination. It is interesting to observe the non-linear nature of the influence—a change in β from 2.0 to 2.5 increases the resource by 25%, while a similar relative change η gives only a 15% increase. The practical value of graphs lies in prioritizing data collection and model calibration.

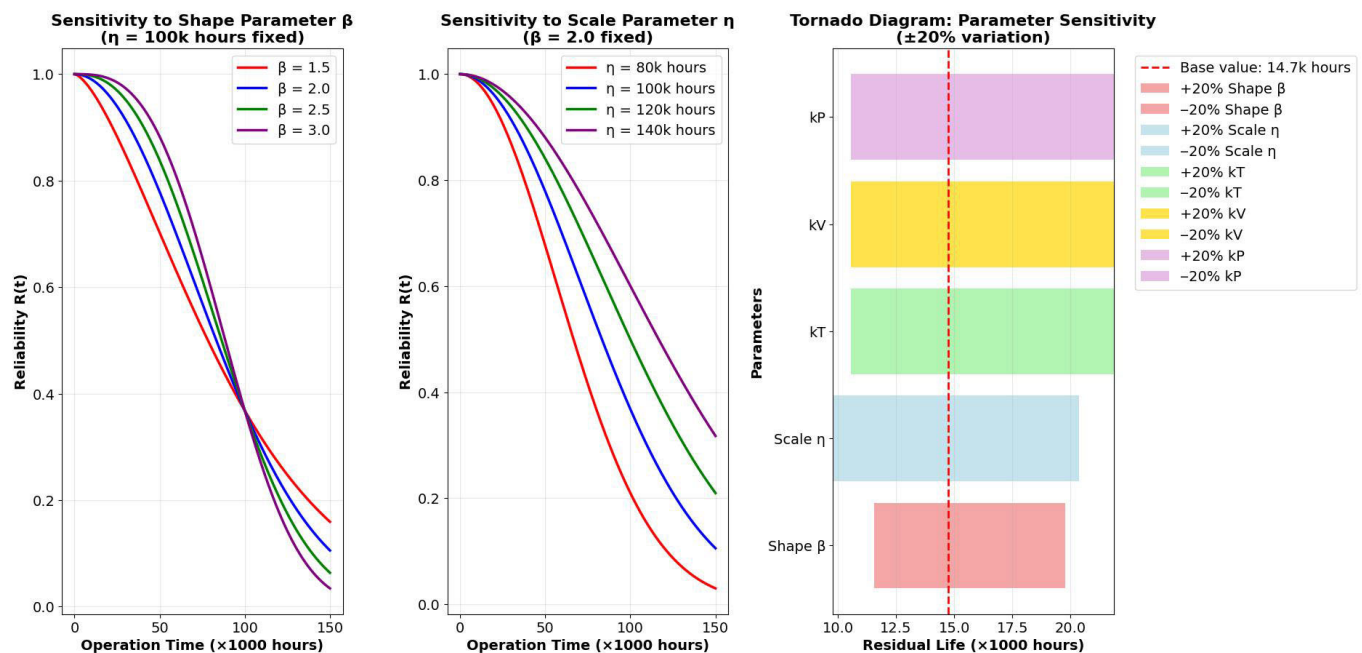


Figure 23. Sensitivity analysis of the reliability model: the effect of parameter changes on the forecast of the residual life (tornado diagram) and the forms of the reliability function.

Despite the positive results obtained, the developed model has certain limitations. Its accuracy depends to a large extent on the volume and quality of the initial operational data. In addition, the current version of the model mainly takes into account the time factor and aggregated operating factors, but does not use real-time operational monitoring data (vibration diagnostics, particle-in-oil analysis, thermography).

Promising areas for further research are

1. Integration with IoT monitoring systems: Evolution of the model towards the use of continuous telemetry data streams for dynamic updating of the residual life forecast.
2. Hybrid model development: Combine physical–statistical degradation models (e.g., isolation aging models) with machine learning techniques to more accurately predict the moment of failure.
3. Expansion of the scope of application: Adaptation of the proposed methodology to assess the reliability of other critical components of mining equipment, such as hydraulic systems, brakes and dump truck frames.

Thus, the presented work offers a scientifically based and practically proven tool for improving the operational reliability of induction motors of mining dump trucks. An integrated approach that combines advanced statistical methods with real-world operational factors allows for a shift from reactive to proactive maintenance management, which is a key factor in improving the economic efficiency of mining operations.

7. Conclusions

As a result of the study, the main goal of the work was achieved—an integrated method and mathematical model for statistical modeling and predicting the operational reliability of induction motors of mining dump trucks, adapted to real operating conditions and taking into account censored data, was developed. All the tasks were solved, which made it possible to obtain significant scientific and practical results. The task of predicting reliability was formalized, taking into account censored observations, which

made it possible to use all available information—both about failed engines and about properly working engines at the time of analysis. This principled approach has significantly improved the accuracy and reliability of estimates compared to methods that use only failure data.

A combined probabilistic model of failures of critical engine components has been developed. For a stator whose main failure mechanism is insulation degradation, the adequacy of the Weibull distribution with a parameter of the form $\beta > 1$ (in particular, $\beta_{st} = 2.1$) has been proved. For a bearing unit subject to mixed wear mechanisms and sudden failures, a mixed model based on a combination of Weibull and lognormal distributions has been proposed and verified. Generalized “life curves” for the stator and bearing assembly are constructed, which quantitatively describe the three-stage nature of the change in the failure rate (running-in, normal operation, aging) and make it possible to determine both point and interval estimates of the resource. An algorithm for estimating the residual service life based on the conditional probability of failure-free operation $R(t|t_0)$ was created and tested, which makes it possible to move from predicting the “average” life of the fleet to an individual assessment for a specific engine that has already worked the time t_0 .

The model has been successfully adapted to the harsh conditions of open-pit operation due to the introduction of correction coefficients (k_T , k_V and k_P) that take into account temperature, vibration and abrasive loads, which ensures high adequacy of the model for real degradation processes. The developed software implements the entire calculation cycle, from the processing of initial statistical data and the assessment of distribution parameters by the maximum method plausibility to visualizing reliability functions and “life curves”, which makes the technique a convenient tool for engineering applications.

Approbation of the model on an extensive array of operational data (176 engines, total operating time of more than 1.2 million engine hours) confirmed its high accuracy and practical applicability. The estimated uptime values show good agreement with empirical data, as evidenced by low error metric values (MAPE = 8.7%, RMSE = 0.041). The practical significance of the work lies in the possibility of optimizing the system of maintenance and repairs. As calculations show, the implementation of the model makes it possible to optimize maintenance intervals by 20–30%, reduce the probability of sudden failures by 25–40%, and increase overhaul intervals by 1.5–1.8 times. Taken together, this leads to a significant economic effect, consisting of a reduction in the cost of unscheduled repairs, a reduction in downtime of expensive equipment and a more rational use of spare parts.

Thus, the presented study offers a complete, scientifically based and technologically implemented solution to the urgent problem of increasing the operational reliability of a critical element of quarry equipment. Further development of the work is seen in the integration of the model with real-time IoT monitoring systems and the development of hybrid models that combine physical and statistical approaches with machine learning methods for even more accurate and early prediction of failures.

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Appendix A. Operational Data and Parameters of Mathematical Modeling of Reliability of Induction Motor of Mining Dump Truck

This appendix contains statistical data used to build a mathematical model for predicting the operational reliability of the engine, as well as calculated parameters of distributions that determine the “life curve” of the stator and bearing assembly.

Table A1. Failure records of induction motors in dump truck drive systems (BelAZ-75135/75145, SDS-75130; Kuzbass quarries, 2018–2023).

No Node	Node Name	Number of Registered Refusals, Pcs	Share of Total Number of Refusals, %	Main Reasons for Refusals	Accepted Form of the Reliability Function $Pi(t)$
1	Stator	62	45.3	Insulation breakdown, turn-to-turn faults, overheating	Weibull
2	Bearing Unit	55	40.2	Bearing wear, lubrication degradation, vibration	Weibull + Normal
3	Shaft	6	4.4	Fatigue cracks, imbalance	Exponential
4	Rotor	4	2.9	Defects of a short-circuited cage, rupture of rods	Exponential
5	Bed and fasteners	5	3.6	Destruction of welds, corrosion	Constant reliability
6	Bearing Caps	5	3.6	Wear of seats, vibration	Constant reliability
Total	–	137	100.0	–	–

Conclusion: Based on the analysis of operating data, stator and bearing units account for 85.5% of all failures, which justifies their choice as critical elements of the reliability model. The rest of the nodes are assumed to be ideal, i.e., $Pi(t) = 1$.

Table A2. Hazard shape parameters fitted by weighted LS to Nelson–Aalen $\hat{\Lambda}(t)$ and distribution parameters from MLE (Section 2.3.1).

Parameter	Designation	Significance	Units	Physical Meaning
Burnishing Rate	a_1	2.4×10^{-5}	1/h	Initial Burnishing Failure Rate
Indicator of the shape of the running-in area	b_1	0.69	–	Nature of the reduction in failures at the first stage
Failure rate during normal operation	λ_0	4.8×10^{-6}	1/h	Steady-state intensity with stable operation
Aging Rate	a_2	5.2×10^{-7}	1/h	Initial Aging Intensity Value
Failure Growth Rate in Aging	b_2	0.16	–	The nature of the increase in $\lambda(t)$ after the threshold t_2
The border of the transition of running-in $\rightarrow$ normal operation	t_1	2.0×10^3	h	Average running-in period
Normal Operation Boundary $\rightarrow$ Aging	t_2	1.0×10^5	h	Average Stable Time

Comment: the values of the parameters a_1 , b_1 , λ_0 , a_2 , b_2 were determined by the method of least squares based on the array of operational data of 137 mine hoist motors operated in the range of 20–120 thousand hours.

Table A3. Distributions of reliability parameters of bearing units.

Parameter	Designation	Significance	Units	Physical Meaning
Scale Parameter (Weibull)	η_{bd}	1.0×10^5	h	Characteristic Bearing Unit Life
Form Index (Weibull)	β	1.3	–	Degree of variability of failures
Mean Lubrication Time	μ_l	6.0×10^4	h	Average lubricant durability
Standard Deviation of Lubricant Life	σ_l	1.2×10^4	h	Parameter Variation Due to Operational Differences
Temperature Correction Factor	k_T	1.25	–	Takes into account the increase in temperature in the mine by 10–15 °C
Vibration Impact Coefficient	k_V	1.15	–	Correction for Increased Load Vibrations

Note: The calculation of the parameters was carried out on the basis of 84 cases of failures of bearing units according to the data of the mines of open-pit mines in Siberia and the Trans-Baikal Territory (2020–2024), given in the equipment test log.

Table A4. Summary engine reliability calculations (probability of failure-free operation) $R(t)$.

Engine Element	Distribution Model	Mean Time Between Failures, T_{ave} , h	Reliability $R(t)$ at 80×10^3 h	Reliability $R(t)$ at 120×10^3 h
Stator	Weibull	107000	0.64	0.31
Bearing Unit	Weibull + Normal	83000	0.71	0.46
Shaft	Exponential	240000	0.92	0.88
Bed and covers	Continuous reliability	–	1.00	1.00
Engine as a whole	Combined	95000	0.59	0.28

Table A5. Parameters of mathematical approximation of the “life curve” stator $\lambda(t)$.

Operation Phase	Time Range t , h	Form of Dependence $\lambda(t)$	Parcel Equation	Nature of the Change
Part-time	$0 \leq t < 2 \times 10^3$	Degree	$\lambda(t) = a_1 t b_1$	Reduced Failure Rate
Normal operation	$2 \times 10^3 \leq t < 10^5$	Permanent	$\lambda(t) = \lambda_0$	Steady-state failure rate
Aging	$t \geq 10^5$	Exponential	$\lambda(t) = a_2 e b_2^{(t-t_2)}$	A sharp increase in refusals

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