

Integrated Diagnostic System and Multi-level Reliability Modeling for Predictive Maintenance of Transport Induction Motors

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Abstract. The aim of this study is to develop the architecture of a diagnostic system and a multi-level reliability model aimed at improving the cost-efficiency and operational reliability of induction traction motors. To achieve this goal, a comprehensive development process was carried out: based on failure statistics, the main defects and types of damage to critical motor components were identified for monitoring and timely maintenance; the architecture of an integrated diagnostic system for assessing the technical condition of motor components (stator, rotor, bearings) was designed; and a reliability model was constructed, reflecting eight operational states of the motor from full functionality to catastrophic failure. The reliability assessment is based on the Kolmogorov-Chapman system of equations, which describes probabilistic transitions between operational states and allows accurate prediction of failure-free runtime and optimal maintenance intervals based on current parameters. The most important results include the formalization of the relationship between diagnostic signals and reliability states and the construction of the reliability function for dynamic maintenance scheduling. The significance of the results lies in the integration of diagnostics with probabilistic reliability modeling, which ensures higher failure prediction accuracy, reduced unplanned downtime, and improved operational readiness. A key contribution of the study is the practical implementation of the eight-state model, enabling dynamic maintenance planning and adaptation of service strategies to the real-time condition of equipment. The proposed strategy lays the foundation for intelligent control of traction drives and the implementation of predictive maintenance systems, which is especially relevant for rail transport and other industries using electric drives.

Keywords: induction motor, failure statistics, diagnostic system, reliability model, predictive maintenance, transport drives, Markov process.

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Sistem integrat de diagnosticare și modelare a fiabilității pe mai multe niveluri pentru mentenanța predictivă a motoarelor asincrone de transport

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Rezumat. Scopul studiului este de a dezvolta arhitectura unui sistem de diagnosticare și a unui model de fiabilitate pe mai multe niveluri, menit să îmbunătățească eficiența costurilor și fiabilitatea operațională a motoarelor de tracțiune cu inducție. Pentru a atinge acest obiectiv, a fost realizat un proces cuprinzător de dezvoltare: pe baza statisticilor de defecțiuni, au fost identificate principalele defecte și tipuri de deteriorare a componentelor critice ale motorului pentru monitorizare și întreținere la timp; a fost proiectată arhitectura unui sistem de diagnosticare integrat pentru evaluarea stării tehnice a componentelor motorului (stator, rotor, rulmenți); și a fost construit un model de fiabilitate, reflectând opt stări de funcționare ale motorului - de la funcționalitate completă până la defecțiune catastrofală. Evaluarea fiabilității se bazează pe sistemul de ecuații Kolmogorov-Chapman, care descrie

tranzițiile probabilistice între stările de funcționare și permite prezicerea precisă a timpului de funcționare fără defecțiuni și a intervalelor optime de întreținere pe baza parametrilor actuali. Cele mai importante rezultate includ: formalizarea relației dintre semnalele de diagnosticare și stările de fiabilitate și construirea funcției de fiabilitate pentru programarea dinamică a întreținerii. Semnificația rezultatelor constă în integrarea diagnosticării cu modelarea probabilistică a fiabilității, care asigură o precizie mai mare a predicției defecțiunilor, reducerea timpilor de nefuncționare neplanificată și o pregătire operațională îmbunătățită. O contribuție cheie a studiului este implementarea practică a modelului cu opt stări, care permite planificarea dinamică a mentenanței și adaptarea strategiilor de service la starea în timp real a echipamentelor. Strategia propusă pune bazele controlului inteligent al acțiunilor de tracțiune și implementării sistemelor de mentenanță predictivă, ceea ce este relevant în special pentru transportul feroviar și alte industrii care utilizează acționări electrice.

Cuvinte-cheie: motor cu inducție, statistici ale defecțiunilor, sistem de diagnosticare, model de fiabilitate, mentenanță predictivă, acționări de transport, proces Markov.

Интегрированная система диагностики и многоуровневое моделирование надежности для предиктивного обслуживания транспортных асинхронных двигателей

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Аннотация. Целью работы является разработка архитектуры диагностической системы и многоуровневой модели надёжности, направленных на повышение экономичности и надёжности при эксплуатации асинхронных тяговых электродвигателей. Для достижения поставленной цели была выполнена следующая комплексная разработка: на основе статистики отказов выявлены основные дефекты и виды повреждений ключевых элементов двигателя, подлежащие контролю и своевременному обслуживанию; разработана архитектура интегрированной диагностической системы контроля технического состояния элементов двигателя (статор, ротор, подшипники); построена модель надёжности на основе статистики отказов, отражающая восемь эксплуатационных состояний двигателя – от полного исправного до состояния катастрофического отказа. Диагностическая система обеспечивает выявление межвитковых замыканий в обмотке статора, структурных повреждений короткозамкнутого ротора и аномалий вибрации в подшипниковом узле. В основе оценки надёжности лежит система уравнений Колмогорова-Чепмена, позволяющая описывать вероятностные переходы между эксплуатационными состояниями, прогнозировать срок безотказной работы с учётом текущих параметров и оптимальные интервалы технического обслуживания. Наиболее важными результатами являются: формализация взаимосвязи между диагностическими сигналами и состояниями надёжности, разработка архитектуры диагностической системы с минимальным числом сенсоров (3 токовых, 2 вибрационных), а также получение функции надёжности для динамического планирования обслуживания. Значимость полученных результатов состоит в интеграции системы диагностики с вероятностным моделированием надёжности, что обеспечивает более высокую точность прогноза отказов, снижение незапланированных простоев и повышение уровня эксплуатационной готовности. Ключевым вкладом исследования является практическая реализация модели восьми состояний, что позволяет динамически планировать техническое обслуживание, принимать обоснованные решения на основе оценки риска и адаптировать стратегию обслуживания под реальное состояние оборудования. Предложенная в работе стратегия формирует основу для расширения возможностей интеллектуального управления ресурсом электропривода и создании возможности для внедрения систем предиктивного технического обслуживания, особенно актуальных для железнодорожного транспорта и других отраслей промышленности, использующих электрические приводы.

Ключевые слова: асинхронный двигатель, статистика отказов, система диагностики, модель надёжности, предиктивное обслуживание, транспортные приводы, Марковский процесс.

INTRODUCTION

Reducing the expenses of operating and maintaining transportation equipment while simultaneously increasing its efficiency and dependability is an ongoing concern. This is

because every country's transportation system needs to be more competitive, and logistical duties must be completed on time. One key component to resolving this issue is the creation of reliable diagnostic and monitoring systems for

the primary components of transportation equipment while they are in operation in real time. One may plan proactive actions to reduce unplanned downtime and unexpected failures if one may detect damage or degradation in the condition of components of the transportation equipment in a timely manner [1,2]. Furthermore, perceiving developing problems before they become major issues prevents the transportation system from going into emergency mode and stopping operations, which greatly impacts the amount and expense of eventual repairs. The induction motor is the most important part of contemporary transportation systems, and it needs to be controlled and monitored at all times. Due to their low cost, ease of maintenance and, most significantly, a high degree of reliability, induction motors with squirrel-cage rotors are most commonly utilized as drives in transportation equipment.

However, better maintenance and control go hand in hand with making sure induction motors work reliably. An improvement of engine status monitoring systems is a major focus of current research. In addition, a thorough diagnostic system is required to address the issues of induction motor condition monitoring [3,4]. This system should be able to track damage to the engine's main components, identify the type and extent of damage, and potentially track the progress of the defect over time [5].

If one wants to know how efficient and cost-effective transportation equipment will be, one needs to know how long it will be before any problems arise so one can schedule maintenance and repairs accordingly [6].

Future progress in this area of diagnostic equipment, when coupled with mathematical models for scheduling maintenance and anticipating electric motor failures using diagnostic indicators, is highly desirable and warranted. To minimize maintenance expenses and prevent unexpected emergency failures, it is essential to possess a well-organized and accepted strategy for the maintenance of engine components. This will ensure that the equipment operates reliably and efficiently.

These days, researchers in the transportation sector frequently turn to mathematical modeling techniques to minimize operational defects. Findings from this study help with a variety of organizational issues related to transportation facility administration and upkeep, as well as with the creation and refinement of new transportation system designs during design and production

phases. Modeling the operational processes of traction motors with an online diagnostic system allows the authors to boost the efficiency of railway transport, as presented in their studies [7-9].

For effective condition monitoring of induction motors, it is essential to implement a comprehensive diagnostic system capable of detecting damage to key motor components. Such a system should not only identify the type of fault but also assess its severity and enable continuous tracking of defect progression over time [10,11]. This is particularly important in transport applications, where the ability to predict failure-free operating periods is critical for scheduling maintenance and repair activities. Accurate forecasting directly influences both economic indicators and the overall operational efficiency of transport equipment.

To diagnose the current state during operation, the most suitable are non-invasive methods based on the analysis of vibration signals [12], stator current [13,14], vibration and current (temporal and spectral) using artificial intelligence [15,16], which meet modern requirements for diagnostic technology.

The integration of such diagnostic methods with mathematical modeling opens promising opportunities for the development of predictive maintenance strategies. By leveraging condition indicators obtained through diagnostics, it becomes possible to forecast motor failures and optimize maintenance scheduling [17,18].

A properly organized and adopted strategy for the maintenance of engine elements forms the basis for ensuring reliable and efficient operation of equipment while minimizing maintenance costs and preventing sudden emergency failures.

In modern research in the transport industry, mathematical modeling methods are actively used to solve various problems that arise during operation. The obtained research results are used both in the development and improvement of new designs of transport systems at the design and production stages, and for solving a number of organizational problems in the management and maintenance of transport facilities. The authors' works [19-21] present the results of modeling the operating processes of traction motors, with an online diagnostic system, which makes it possible to increase the efficiency of railway transport.

This study presents a novel approach to improving the operational reliability of transport induction motors by integrating a real-time diagnostic system with a multi-level reliability

model. Unlike traditional studies, where fault diagnostics and reliability modeling are considered separately, the proposed method combines both aspects within a unified framework.

During operation, specific technological railway transport systems possess deterioration processes that impact several internal states. The semi-Markov process explains how these systems work, which can be complex and show a slow decline in many parts because of different factors during operation. The primary emphasis of research aimed at enhancing railway transport dependability (the induction motor) and operational efficiency appears to be the management of production alongside the scheduling of maintenance and repairs during the planning phase. However, there is still shortage of studies on the coordination of maintenance and repairs for modern rolling stock. The importance of optimizing maintenance strategies and improving the accuracy of reliability assessments is growing as efforts to maintain the competitiveness of railway transportation continue. A key contribution of this study is the

development of a model for evaluating the reliability of railway systems equipped with induction motors, based on the condition of critical components and potential failure modes identified through an on-board diagnostic system.

I. BLOCK DIAGRAM OF THE DIAGNOSTIC SYSTEM FOR INDUCTION MOTORS

Diagnostic systems for induction motors must include modules for monitoring the condition of the main structural elements of the motor to accurately determine the type and extent of damage. When developing a structural diagram of the diagnostic system, it is necessary to analyze the frequency of failures of the stator, rotor and bearing unit – the three main structural elements of the induction motor. Statistical data vary depending on the motor type, its design, operating mode and operating conditions, but the general trend of the ratio of damage by elements is preserved. Figure 1 shows averaged data on the operational statistics of failures of induction motors with a squirrel-cage rotor with distribution by structural elements.



Fig. 1. Damageability of the main elements of an induction motor.

There are various types of damage that affect each motor component differently (Fig. 1). For each structural component, it is advisable to include in the diagnostic system those types of faults that are most common and do not lead to catastrophic failure over a certain period of time, although they degrade operational performance and may develop into an emergency condition. This approach allows for optimization of the structural diagnostic scheme and the selection of appropriate diagnostic methods. Winding faults account for the vast majority of stator failures (up to 80% of which are inter-turn short circuits in a winding phase) [22–24]. Depending on the number of shorted turns, an inter-turn fault may have a parametric nature and lead to a reduction in motor performance.

The vibration caused by the asymmetric spinning magnetic field during this damage also has a severe impact on the engine's structural elements, increasing the likelihood that they would break prematurely. A turn-to-turn short circuit causes the stator winding's insulation to deteriorate even further, leading to a secondary catastrophic failure and the engine switching off in emergency mode due to the elevated current and, by extension, heat in the closed section of the winding. Extra damage from secondary failures, on top of the emergency engine shutdown, increases the expense of restoration work and, in extreme circumstances, makes restoration and continued engine usage impossible.

A limited percentage of failures that can be observed during rebuilding or routine engine

maintenance are other stator damage problems. As a result, the diagnostic system must be able to detect turn-to-turn short circuits early on and track their progression. If transportation systems are to effectively monitor the state of induction motors, a diagnostic system must be able to detect the nature of the fault, the extent of damage, and the exceeding of specific operational parameters beyond their limitations.

Methods based on a spectral analysis of stator currents, vibration parameters of the electric motor, and an analysis of the machine's internal thermal balance are among the most promising approaches to monitoring turn-to-turn short circuits in on-board monitoring systems. The range of its usage is limited by the difficulty of evaluating and interpreting the temperature values obtained under running settings and forecasting the trouble-free operation life, which constitutes a drawback in utilizing the approach to monitor the thermal state of the induction motor's elements. Due to the features of changes in vibration parameters for various forms of turn-to-turn short circuits presented in [25], it is difficult to reliably evaluate the degree of damage when assessing the stator winding based on vibration parameters.

Results for establishing turn-to-turn short circuits utilizing the spectrum components of the stator current were the most practicable among the known methods. We can correctly identify the stator winding damage type from the vector pattern using the Park's vector approach method [26]. In order to accurately determine the number of short-circuited turns when the engine is operating under load with a possible poor-quality supply voltage system, researchers have adapted the Park's vector method to work in on-board diagnostic systems. The results of these studies are given in [19]. These research findings, such as the potential for exterior placement of current sensors for diagnostic system operation, ensure that this method completely complies with modern operational standards for diagnostic equipment.

The bearing assembly (Fig. 1) is the next most common structural component to fail in induction motors. Failure rates can range from 28 to 40 percent, depending on the operating modes and the application range. The majority of bearing failures in vehicles are caused by increased clearance and cracks that form on the bodies and raceways as a result of normal operation. Some of the most typical reasons for bearings to fail include:

- excessive loads: lack of proper sealing;
- incorrect installation;
- using a lubricant of poor quality, which leads to increased wear and overheating;
- heightened machine vibration while running.

When bearings wear out, technological clearances rise over the normative ones, leading to vibration and more heat. A parametric failure occurs when the vibration parameters of a bearing are exceeded: this failure can develop rapidly and result in an emergency failure of the bearing or its total destruction. The most catastrophic incidents occur when bearings are destroyed while engines are operating, particularly those with high power, and it is sometimes impossible to restore such an engine afterwards. Because of its enormous mass and inertia, the shattered bearing forces the spinning rotor to become eccentric, which in turn brings it into touch with the stator's structural components and damages them. The cost of such restoration is comparable to the price of a new motor. Therefore, the onboard diagnostic system for induction motors used in transport equipment requires continuous monitoring of the bearing condition as a critical element. Bearing diagnostic procedures based on vibration signal spectrum analysis are the most accurate and informative [27,28]. The presence of harmonics in the vibration spectrum indicating specific faults, along with their correlation, allows for accurate fault localization through spectral analysis.

To capture vibration signals during the vibration diagnostics of rotating machinery, piezoelectric vibration sensors are the most commonly used.

It is also important to monitor the rotor, which is another structural component of an induction motor, while it is running. The rotor's primary vulnerability is a contact failure in the short-circuited winding, specifically between the closing rings and the rods. In the early stages of a parametric engine failure, such damage occurs while the engine is operating. The engine's energy and mechanical properties degrade when this kind of damage is present. Additional sequential burnout of other rods occurs due to increased current on them as the engine continues running with a damaged rotor, which is accompanied by vibration and increased current on the remaining winding rods. This is particularly true during overload or difficult starting periods.

Centrifugal force can cause burned-out rods to migrate towards the air gap as the machine continues to operate. Consequently, it is essential

for the built-in diagnostic system of automobiles to identify the first symptoms of contact failure in the short-circuited rotor winding while induction motors are operating. Enhanced warmth, vibration and current consumption are diagnostic signs of squirrel-cage rotor winding deterioration. While there are a variety of approaches to condition determination utilizing these parameters, the Park's vector current method has yielded the most useful findings for diagnostics in industrial settings [14,29].

Utilizing the Park's vector technique to identify stator and rotor winding problems simultaneously optimizes the diagnostic system's architecture by allowing current sensors and multiple stator current converter units to work together. The induction motor's key structural elements were analyzed for their damageability (Fig. 1) and the types of damage that require control (Fig. 2). The related diagnostic blocks are shown in the block diagram below.

The induction method diagnostic system is composed of the following blocks:

- monitoring the condition of the stator with an assessment of the number of short-circuited turns in the phase windings;

- short-circuited rotor winding condition monitoring, which involves determining the integrity of the winding structure;

- bearing unit condition monitoring, which involves vibration parameters.

Three sensors that measure current and two that measure vibration ensure the correct operation of the diagnostic system. The controlled motor's bearing shields have vibration sensors attached to them. Several diagnostic processes involving current signals are executed by shared blocks, all because of the Park's vector approach to rotor and stator diagnostics. The display unit obtains information on the number of damaged rotor rods, the number of closed turns in the stator phase, and the value of a the bearing units whenever damage to engine elements is detected through monitoring [14].

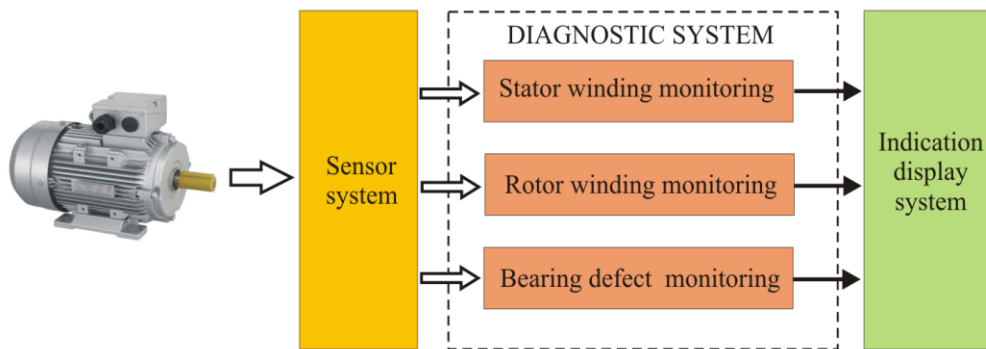


Fig. 2. Block diagram of diagnostics of an induction motor (authors' own elaboration).

The structural diagrams of the diagnostic method using the vector-based Park's method for detecting inter-turn short circuits in the stator phase and assessing the structural integrity of the rotor based on phase currents is shown in Figures 3a i b. It is advisable to use external transformer-type current sensors for each stator phase, designated as sensors D_{1sA} , D_{1sB} , and D_{1sC} .

The development of a methodology and algorithm for accurately determining the number of short-circuited turns in the stator winding using Park's method is based on the study of how the number of such turns affects the amplitude of the instantaneous stator current values in each phase, as well as the current increments in each phase. These parameters are utilized during the operation of both the stator diagnostics module and the rotor diagnostics module.

The studies were conducted using a mathematical model for both symmetrical and asymmetrical supply voltage systems of the induction motor.

Therefore, to obtain the required values for the subsequent application of Park's method, the use of a Fast Fourier Transform (FFT) algorithm is essential.

After determining the amplitude and phase values of the fundamental harmonics of the phase currents, as well as the phase shifts between the phase voltages and currents, a coordinate transformation is performed from the three-phase coordinate system to the two-phase rotating dq-coordinate system. Based on this, the parameters of the Park's vector figure are calculated [14].

The design of the structural diagram for the bearing condition monitoring block is based on

spectral analysis. This method ensures high diagnostic reliability due to its ability to clearly identify defects by correlating mechanical processes with the appearance of harmonics in the frequency spectrum that are characteristic of specific types of damage.

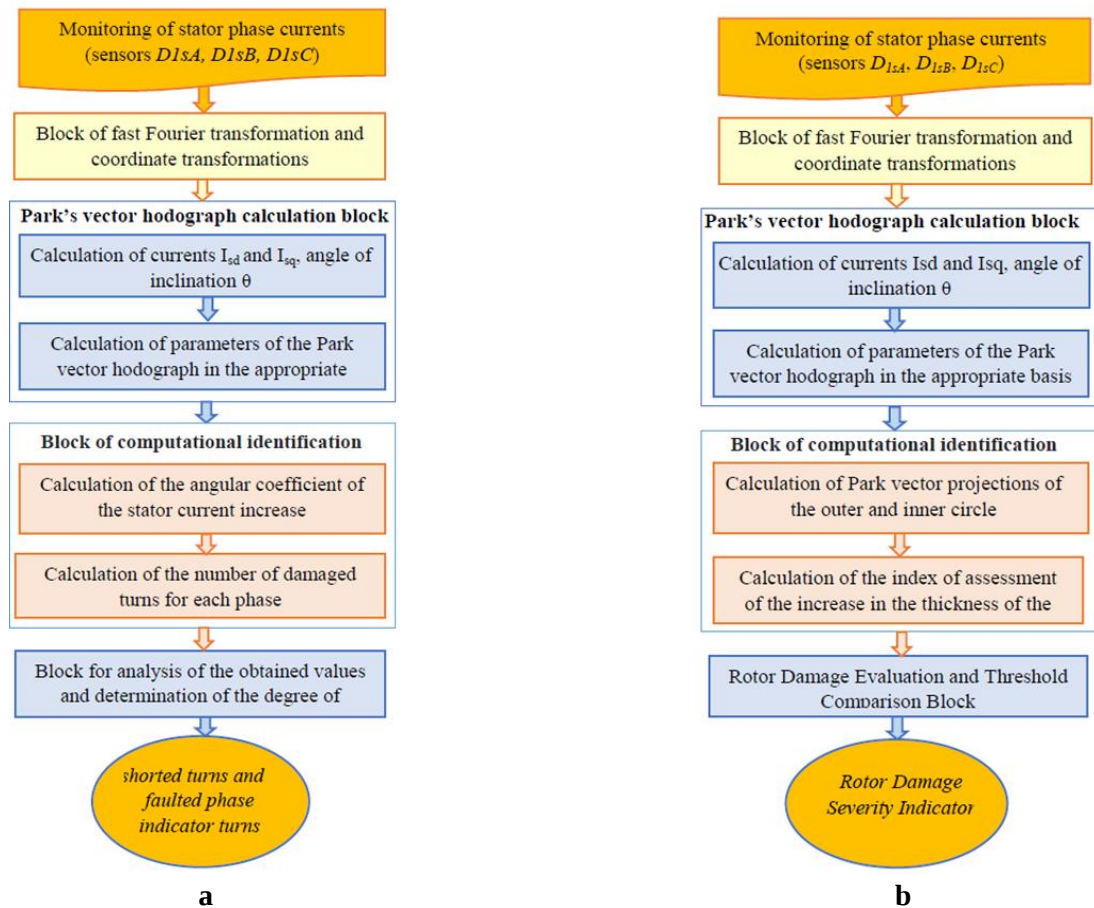


Fig. 3. Structural diagram of the diagnostic module for winding condition monitoring:
a – stator; b – rotor (authors' own elaboration).

The progression of a particular defect is tracked by observing amplitude spikes in the corresponding harmonics.

To detect and identify both the type and severity of a defect, the quantitatively assessed diagnostic parameters are compared against the threshold vibration levels of bearing components. This method fully meets the requirements for in-service diagnostic systems and supports automation of the diagnostic process.

The proposed diagnostic system allows monitoring the occurrence of the main types and kinds of defects during the operation of the engine and their development. The operation of the diagnostic system requires only five sensors: three current sensors and two vibration sensors. The system architecture was developed by a research

group led by PhD O. Gubarevych and confirmed through mathematical modeling.

However, the use of the diagnostic system primarily enables monitoring of defects that have already begun to manifest. To prevent the sudden occurrence of such defects, it is essential to implement a system of periodic maintenance for the motor, particularly for its critical components. Therefore, the next objective of this research is the development of a reliability model aimed at forecasting fault-free operation and scheduling maintenance activities.

The proposed reliability model will take into account potential stator failures, such as interturn short circuits, as well as structural integrity violations in the squirrel-cage rotor winding.

II. INDUCTION MOTOR TRANSPORT SYSTEM OPERATION 8-STATE MODEL

Possible engine states with a diagnostic system during operation

When determining the extent of damage to electric motor elements, the primary concern is forecasting the time of trouble-free operation and the best time to perform restoration or debugging, all while keeping in mind the details of the transport operation.

In the event that one of the engine's structural components fails, the engine's parameters and characteristics will degrade, or the engine will stop working altogether, depending on the kind of failure. Thus, the structural diagram of engine reliability has a sequential form of the relationship of individual blocks, symbolizing the reliability of its components.

Therefore, to build a reliability model of the operating process, it is important to consider all states of the engine structural elements preceding the complete loss of operability. Depending on the nature of the malfunction, the symptoms that appear before the engine's performance

completely disappear over varying durations. For maintenance or repair planning with a known restoration work volume and for averting emergency failures during operation, information on the occurrence of such states or the transition from one to another is crucial.

It was considered feasible to keep the engine running until a pre-emergency state was reached when describing all the conceivable engine states while it was operating, even if a parametric failure occurred in one of its elements. The engine must be taken out of operation and repair work must be completed before the emergency failure occurs, which is when the pre-emergency stage begins.

The reliability evaluation model is used to compile data for different scenarios in the presence of a diagnostic system. Remedial actions can be implemented at three points in the engine's operation, as shown in Fig. 4. Firstly, when the diagnostic system detects a defect in one of the elements early on. Secondly, during extended operation, when the defects are being detected gradually until they reach a critical stage of development. For the last time, this is after an emergency stop.

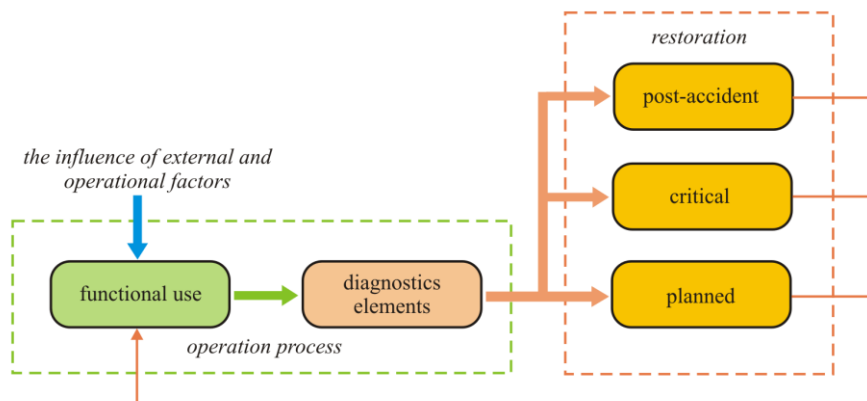


Fig. 4. Operating diagram of an induction motor with a diagnostic system (authors' own elaboration).

Maintaining restoration operations between scheduled and emergency maintenance (Fig. 4) is the most rational approach. Emergency repairs are significantly more complex and expensive than those performed preventively. A reliability model based on the failure behavior of each structural component allows determining optimal restoration timing, especially in transport applications.

The proposed model defines eight motor states:

S0 – fully operational: the engine operates within nominal parameters. However, deviations such as increased temperature, vibration,

overload, or frequent startups may initiate early-stage faults.

S1 – stator parametric failure: partial performance degradation caused by inter-turn short circuits in the stator winding. These faults are typically due to insulation breakdown from overloads or mechanical issues (e.g., bearing seizure), as well as environmental factors like moisture ingress. Resulting vibration can propagate damage to the rotor and bearings, increasing power losses and the risk of emergency shutdown.

S2 – bearing parametric failure: this state is characterized by increased vibration and heat,

indicating partial failure. Progressive bearing wear affects the entire motor system, accelerating stator winding insulation degradation and potentially leading to complete motor failure. Early detection of abnormal vibration levels is critical.

S3 –rotor parametric failure: this condition is caused by degraded contact in the squirrel-cage rotor windings. Poor soldering quality, material fatigue, or thermal stress may lead to broken or loosened rotor bars. The resulting current imbalance and increased vibration accelerate rotor wear and reduce operational stability. Under peak loads or during startup, this condition may lead to complete rotor failure. Restoration involves rewinding or replacing damaged rotor bars to restore structural and electrical integrity.

S4 – critical stator condition (pre-failure): the stator winding is subjected to significant thermal stress caused by prolonged inter-turn short circuits. Even minor overloads or frequent startup cycles further deteriorate the insulation, increasing the risk of sudden failure. The motor operates in a critical state with a high probability of emergency shutdown. Immediate intervention and corrective maintenance are required upon detection of this condition to prevent catastrophic damage.

S5 – critical bearing condition (pre-failure): excessive internal clearance and abnormal vibration suggest bearings are near failure. Small shocks or braking can lead to rotor eccentricity, rotor-to-stator contact, and structural damage. Prompt bearing replacement is necessary to avoid emergency stop.

S6 – critical rotor condition (pre-failure): high temperatures and rotor vibration signal pre-failure. Continued operation leads to rod deterioration and loss of output power. Urgent repair is required, potentially involving rewinding or full rotor replacement.

S7 – catastrophic failure: total inoperability due to failure of a major component (stator, rotor, or bearing). The motor ceases functioning and requires full restoration.

State-based model enables continuous monitoring and targeted maintenance planning. By linking diagnostic signals to these reliability states, the system allows for accurate prediction of failure progression, dynamic maintenance scheduling, and minimization of unscheduled downtimes.

Research on an 8-status model of the workflow of transport systems with induction motors

This study characterizes eight operational states of motor components using Kolmogorov-Chapman state equations to assess the reliability of a transport system that includes induction motors. This assessment must take into account the intermediate state, which corresponds to the state of the motor before the accident for each structural component.

In Figure 5, the operating states of transport systems using induction motors are interpreted as follows:

- S0 – state of full operability,
- S1 – state of parametric stator failure,
- S2 – state of parametric bearing failure,
- S3 – state of parametric rotor failure,
- S4 – state of pre-accident stator failure,
- S5 – state of pre-accident bearing failure,
- S6 – state of pre-accident rotor failure,
- S7 – state corresponding to an inoperative state.

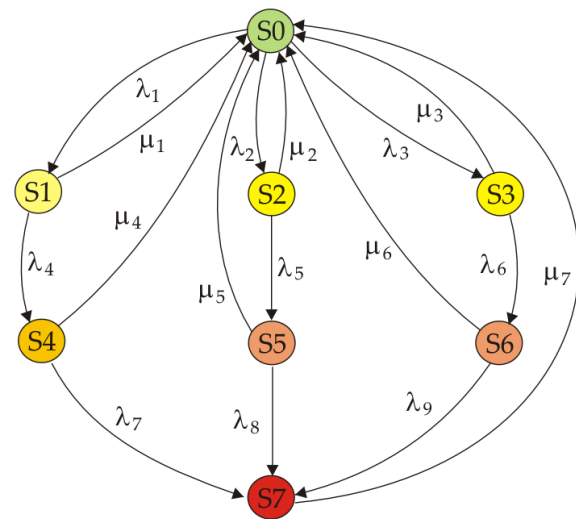


Fig. 5. An illustration of the eight-state model that describes how induction motors in transport vehicles operate: authors' own elaboration.

Descriptions of the transition relationships between states in the operation process model are as follows:

- λ_1 – transition from state S0 to state S1 in the event of a stator parameter fault;
- λ_2 – transition from state S0 to state S2 in the event of a bearing parameter fault;
- λ_3 – transition from state S0 to state S3 in the event of a rotor parameter fault;

λ_4 – transition from state S1 to state S4 in the event of a pre-accident stator failure;
 λ_5 – transition from state S2 to state S5 in the event of pre-accident bearing failure;
 λ_6 – transition from state S3 to state S6 in the event of pre-accident rotor failure;
 λ_7 – transition from state S4 to state S7 in the event of induction motor failure;
 λ_8 – transition from state S5 to state S7 in the event of induction motor failure;
 λ_9 – transition from state S6 to state S& during induction motor failure;
 μ_1 – transition from state S1 to state S0 during stator repair;
 μ_2 – transition from state S2 to state S0 during bearing repair;
 μ_3 – transition from state S3 to state S0 during rotor repair;
 μ_4 – transition from state S4 to state S0 during stator repair;
 μ_5 – transition from state S5 to state S0 during bearing repair;
 μ_6 – transition from state S6 to state S0 during rotor repair;
 μ_7 – transition from state S7 to state S0 during induction motor repair.

The system presented is characterized by the following Kolmogorov-Chapman equations:

$$\begin{aligned}
 R'_{S0}(t) &= -\lambda_1 \cdot R_{S0}(t) + \mu_1 \cdot Q_{S1}(t) - \lambda_2 \cdot R_{S0}(t) + \\
 &+ \mu_2 \cdot Q_{S2}(t) - \lambda_3 \cdot R_{S0}(t) + \mu_3 \cdot Q_{S3}(t) + \mu_4 \cdot \\
 &Q_{S4}(t) + \mu_5 \cdot Q_{S5}(t) + \mu_6 \cdot Q_{S6}(t) + \mu_7 \cdot Q_{S7}(t), \\
 Q'_{S1}(t) &= \lambda_1 \cdot R_{S0}(t) - \mu_1 \cdot Q_{S1}(t) - \lambda_4 \cdot Q_{S1}(t), \\
 Q'_{S2}(t) &= \lambda_2 \cdot R_{S0}(t) - \mu_2 \cdot Q_{S2}(t) - \lambda_5 \cdot Q_{S2}(t), \\
 Q'_{S3}(t) &= \lambda_3 \cdot R_{S0}(t) - \mu_3 \cdot Q_{S3}(t) - \lambda_6 \cdot Q_{S3}(t), \\
 Q'_{S4}(t) &= \lambda_4 \cdot Q_{S1}(t) - \mu_4 \cdot Q_{S4}(t) - \lambda_7 \cdot Q_{S4}(t), \\
 Q'_{S5}(t) &= \lambda_5 \cdot Q_{S2}(t) - \mu_5 \cdot Q_{S5}(t) - \lambda_8 \cdot Q_{S5}(t), \\
 Q'_{S6}(t) &= \lambda_6 \cdot Q_{S3}(t) - \mu_6 \cdot Q_{S6}(t) - \lambda_9 \cdot Q_{S6}(t), \\
 Q'_{S7}(t) &= \lambda_7 \cdot Q_{S4}(t) + \lambda_8 \cdot Q_{S5}(t) + \lambda_9 \cdot Q_{S6}(t) - \\
 &- \mu_7 \cdot Q_{S7}(t).
 \end{aligned} \quad (1)$$

Given the starting conditions:

$$\begin{aligned}
 R_{S0}(0) &= 1, \\
 Q_{S1}(0) &= Q_{S2}(0) = Q_{S3}(0) = Q_{S4}(0) = \\
 &= Q_{S5}(0) = Q_{S6}(0) = Q_{S7}(0) = 0,
 \end{aligned} \quad (2)$$

By utilizing the Laplace transformation, the subsequent system of linear equations is obtained:

$$\begin{aligned}
 s \cdot R_{S0}^*(s) - 1 &= -\lambda_1 \cdot R_{S0}^*(s) + \mu_1 \cdot Q_{S1}^*(s) - \\
 &- \lambda_2 \cdot R_{S0}^*(s) + \mu_2 \cdot Q_{S2}^*(s) - \lambda_3 \cdot R_{S0}^*(s) + \\
 &\mu_3 \cdot Q_{S3}^*(s) + \mu_4 \cdot Q_{S4}^*(s) + \mu_5 \cdot Q_{S5}^*(s) + \\
 &+ \mu_6 \cdot Q_{S6}^*(s) + \mu_7 \cdot Q_{S7}^*(s), \\
 s \cdot Q_{S1}^*(s) &= \lambda_1 \cdot R_{S0}^*(s) - \mu_1 \cdot Q_{S1}^*(s) - \lambda_4 \cdot Q_{S1}^*(s), \\
 s \cdot Q_{S2}^*(s) &= \lambda_2 \cdot R_{S0}^*(s) - \mu_2 \cdot Q_{S2}^*(s) - \lambda_5 \cdot Q_{S2}^*(s), \\
 s \cdot Q_{S3}^*(s) &= \lambda_3 \cdot R_{S0}^*(s) - \mu_3 \cdot Q_{S3}^*(s) - \lambda_6 \cdot Q_{S3}^*(s), \\
 s \cdot Q_{S4}^*(s) &= \lambda_4 \cdot Q_{S1}^*(s) - \mu_4 \cdot Q_{S4}^*(s) - \lambda_7 \cdot Q_{S4}^*(s), \\
 s \cdot Q_{S5}^*(s) &= \lambda_5 \cdot Q_{S2}^*(s) - \mu_5 \cdot Q_{S5}^*(s) - \lambda_8 \cdot Q_{S5}^*(s), \\
 s \cdot Q_{S6}^*(s) &= \lambda_6 \cdot Q_{S3}^*(s) - \mu_6 \cdot Q_{S6}^*(s) - \lambda_9 \cdot Q_{S6}^*(s), \\
 s \cdot Q_{S7}^*(s) &= \lambda_7 \cdot Q_{S4}^*(s) + \lambda_8 \cdot Q_{S5}^*(s) + \lambda_9 \cdot Q_{S6}^*(s) - \\
 &- \mu_7 \cdot Q_{S7}^*(s).
 \end{aligned} \quad (3)$$

III. RESEARCH RESULTS

The function $R_0(t)$ is the reliability function that indicates the likelihood that a specific technical item is fit for use in terms of its reliability. The value of the readiness indicator for a given duration is numerically comparable to this. Reliability tests of an operating induction motor allowed for a quick identification of the effects of operational and reliability indicator modifications on diagnostic system state-describing parameter values. Results were based on the severity ratings of system damage and repairs found in Table 1. The accepted values were calculated using average failure data and operational data obtained from railway energy companies [30–33].

Table 1.

Parameters for system reliability.

Parameter	Value [1/h]
λ	0.00001
λ_1	0.00002
λ_2	0.000025
λ_3	0.0000416
λ_4	0.00013
λ_5	0.000012
λ_6	0.000125
λ_7	0.0000167
λ_8	0.0000125
λ_9	0.0000137
μ	0.0208
μ_1	0.0416
μ_2	0.0208
μ_3	0.0416
μ_4	0.0516

μ_5	0.0208
μ_6	0.0316
μ_7	0.0116

Based on the inverse Laplace transform and the values from Table 1, the probabilities of the system tested being in distinct operating states are as follows, assuming equations (1)–(2) and exponential distribution.

The duration of testing for transport vehicle induction motor systems is one year:

$$T = 8760(h) \quad (4)$$

Although the calculations of the reliability function $R_0(t)$ and the transition probabilities between states were performed for a single motor over an interval of 8,760 hours, the basis for the model was formed using generalized operational data from a group of 12 motors with a total runtime of $T\Sigma = 105,120$ hours. This provided reliability and stability of the parameters used in the simulation analysis.

Thus, the duration of one year refers not to the operating time of a single motor, but to the total calendar period during which the group of motors was monitored under real operating conditions.

The likelihood that the induction motor utilized in transportation vehicles will maintain its optimal R_0 condition for the duration of one year:

$$R_0(1) = 0.999039097. \quad (5)$$

The likelihood of the induction motor in transport vehicles maintaining partial serviceability Q_1 for the duration of one year:

$$Q_1(t) = 0.000480307. \quad (6)$$

Considering the likelihood that the induction motor in transport vehicles will continue to be in the state of partial serviceability Q_2 for the period of one year:

$$Q_2(t) = 0.000480307. \quad (7)$$

One-year probability that the induction motor in transportation vehicles will continue to function at critical suitability level Q_3 :

$$Q_3(t) = 0.000479970. \quad (8)$$

One year prior to damage, the likelihood that the induction motor in a transportation vehicle will remain in the Q_4 condition:

$$Q_4(t) = 0.000000576. \quad (9)$$

One year prior to damage, the likelihood that the induction motor in a transportation vehicle will remain in the Q_5 condition:

$$Q_5(t) = 0.000000576. \quad (10)$$

One-year probability that the induction motor in a transportation vehicle will remain in the Q_6 pre-damage condition:

$$Q_6(t) = 0.000000576. \quad (11)$$

For a period of one year, the likelihood that the examined induction motor in transportation vehicles will persist in the Q_7 state of unsuitability (destructive condition):

$$Q_7(t) = 0.0000000481. \quad (12)$$

The reliability model presented in the article adopts the classical approach to building a Markov model of transitions between technical states of a system (in this case - an induction motor), where the sojourn times in states are modeled using the exponential distribution. This choice is justified both theoretically and practically, and finds broad support in the scientific literature on reliability theory and stochastic processes.

The exponential distribution is the only continuous distribution that satisfies the memoryless property, which forms the mathematical foundation of a continuous-time Markov process. This allows for the formulation of the Kolmogorov-Chapman system of equations, as demonstrated in the article.

In the specialized literature [34], the exponential distribution is commonly adopted as a baseline law for describing the time between failures in technical system reliability models. In Trivedi's work [35], the author emphasizes that models based on Markov processes with exponential distributions form the core of classical reliability analysis and enable efficient solutions for multi-state systems with state transitions.

Therefore, for the initial construction of the reliability model, the exponential distribution of time to failure and recovery time was used, which is a classical assumption in Markov processes. This distribution can be considered a special case of the Weibull distribution when the shape parameter is equal to 1. Then, using the exponential reliability function $R_0(t)$, the probability of occurrence of known conditions in the tested induction motor in vehicles should be calculated. To justify the applicability of the exponential distribution at the initial stage of modeling, a simulation analysis was conducted using the one-sample Kolmogorov–Smirnov test.

The chosen model is considered acceptable at the early development stage, with the potential for further refinement based on the Weibull distribution once a sufficient amount of statistical data is collected under real operating conditions of the studied equipment.

As shown in Figure 6, the probability values computed for the $R_0(t)$ characteristic dictate the appropriate time intervals for the distinct states.

Understanding the time distribution of a diagnostic condition's likelihood requires creating a complex $R_0(t)$ characteristic diagram. Figure 7 displays the typical analysis results ($R_0(t)$).

Relative to the $R_0(t)$ characteristic Fig. 13, the computed probabilities of the various sets of states ($Q_0, Q_1, Q_2, Q_3, Q_4, Q_5, Q_6, Q_7$) are located towards the bottom. Therefore, the characteristic ($R_0(t)$) was shown with a range of changes in its value below 0.001 for the purpose of future analyses (Figure 7). Next, the points that reflect the probabilities of the occurrence of individual states ($Q_i(t)$) were annotated on the $R_0(t)$ characteristic. Time intervals during which specified probabilities of individual states occur are shown in the ($R_0(t)$) chart (Fig. 7).

From Figure 7 the following intervals are obtained:

$$\begin{aligned} Q_0 &= 0.999039097 \rightarrow \langle 0 \div 1230 \rangle [h] \\ Q_1 &= 0.000480307 \rightarrow \langle 1230 \div 3840 \rangle [h] \\ Q_2 &= 0.000480307 \rightarrow \langle 1230 \div 3840 \rangle [h] \\ Q_3 &= 0.000479970 \rightarrow \langle 3840 \div 5620 \rangle [h] \\ Q_4 &= 0.000000576 \rightarrow \langle 5620 \div 6980 \rangle [h] \\ Q_5 &= 0.000000576 \rightarrow \langle 5620 \div 6980 \rangle [h] \\ Q_6 &= 0.000000576 \rightarrow \langle 5620 \div 6980 \rangle [h] \\ Q_7 &= 0.000000048 \rightarrow \langle t > 6980 \rangle [h] \end{aligned}$$

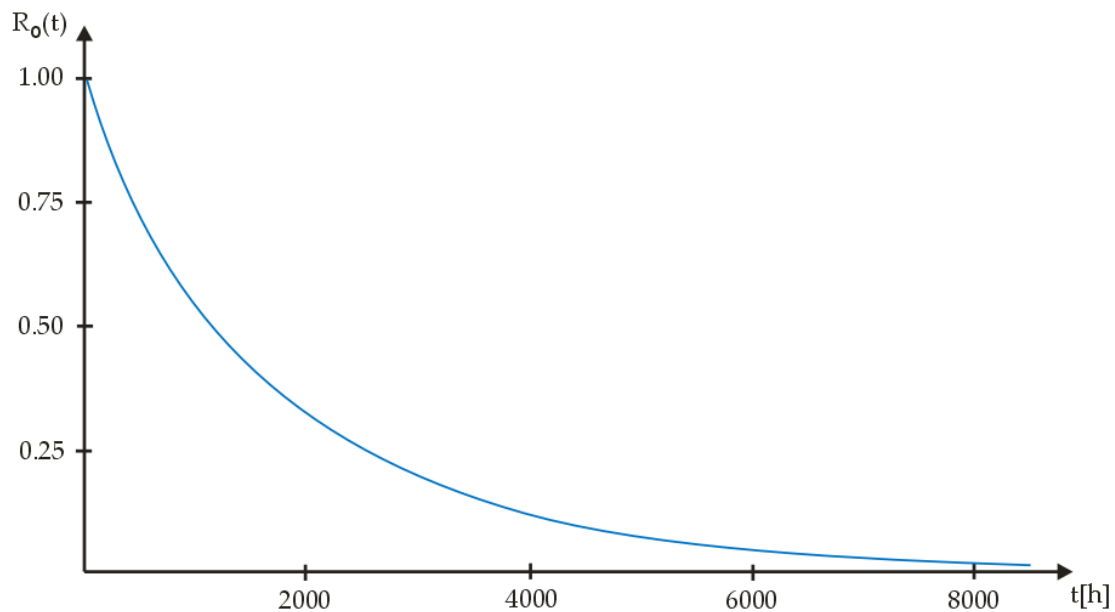


Fig. 6. Reliability function during a one-year period of operation of an induction motor in a transport vehicle: authors' own elaboration.

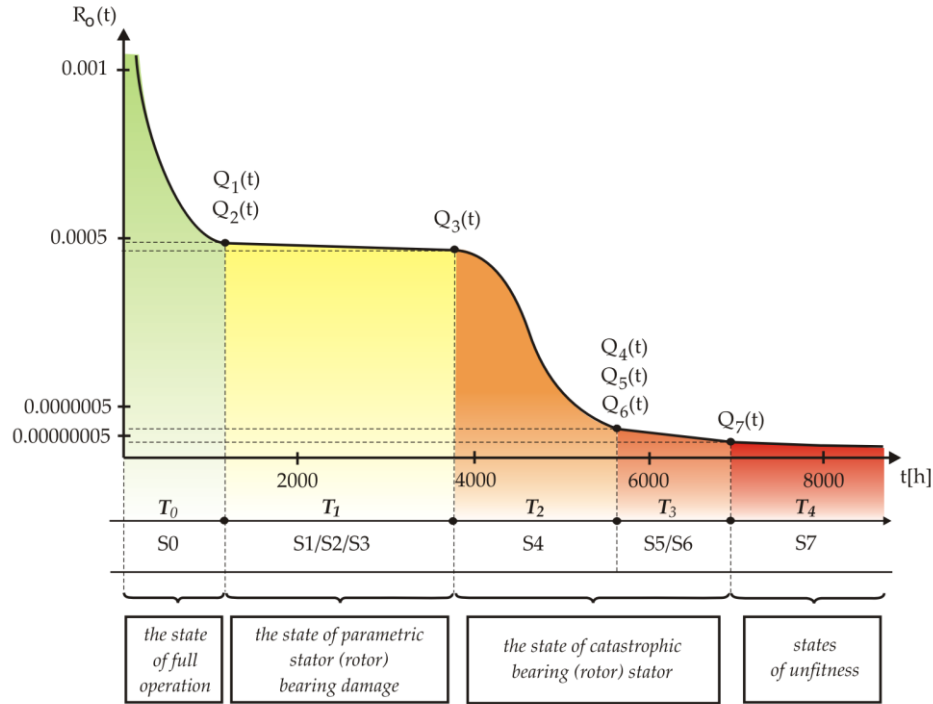


Fig. 7. Detailed graph that shows the reliability function of an induction motor in a transport vehicle throughout a 8640 – hour operation period: authors' own elaboration.

IV. DISCUSSION

The proposed model has a hierarchical (multi-level) structure, which enables step-by-step diagnostics of the technical condition of traction motors and assessment of their reliability. The model includes the following three functional levels:

1. Local Level

At this level, the diagnostic system monitors and evaluates individual components and assemblies of the traction motor.

2. Functional Level

At this stage, information from various components is integrated within functional subsystems (units) that ensure the motor's operation.

3. System Level

This level provides a comprehensive (aggregated) assessment and forecasting of the overall technical condition of the motor, based on data from the previous levels and using reliability models.

The model supports scalability, modular implementation, and allows integration with existing SCADA systems and dispatcher control platforms.

From the examination of the features and the probability values for the many conceivable

states that occurred during the testing period, we can deduce the following about the induction motor in transportation vehicles:

- The induction motor in transport vehicles reaches the serviceability state referred to as S_0 . Therefore, from 0 to 1230 [h], the object tested remains in state S_0 .
- Parametric damage states $\{S_1, S_2, S_3\}$ – states of partial usability – develop during time T_1 with the value of $T_1 = 3840[h]$. Consequently, in the time interval $\langle 1230; 3840[h] \rangle$, the object tested may be found in states $\{S_1, S_2, S_3\}$, which are degrees of parametric damage, also known as partial serviceability states. Under such conditions, induction motors used in transport vehicles do not operate at their maximum efficiency.
- The value $T_2 = 5620[h]$ indicates the occurrence of state S_4 , which is a pre-failure or a pre-critical state of the stator. Consequently, in the time interval $\langle 3840; 5620[h] \rangle$, the object tested may be found in one of three states: parameter damage states (S_1, S_2, S_3) or incomplete serviceability. Under these conditions,

induction motors used in transport vehicles can only perform specific tasks.

- The motor rotor and bearing were damaged prior to failure in states S5 and S6, as evidenced by the following test time, T_3 . ($T_3 = 6980[h]$) represents the condition of the motor before damage. The object tested may be in a pre-damage condition or in states S5 or S6 throughout the entire time interval $\langle 5620; 6980[h] \rangle$. States S5 and S6 are the most effective operating ranges of the induction motor tested in transport vehicles.
- State S7, i.e., the state of unfitness, occurred in the next test time, T_4 . In the state of unfitness, or state S7, the object tested is in a time interval greater than 6980 hours, and induction motors in transport vehicles are damaged and cease to operate in this situation.

Damage to a technical facility that occurs gradually over time while it is being used is referred to as non-critical damage. This kind of damage is mostly caused by the natural deterioration that comes with ageing and by the effects of environmental conditions (such as temperature and pressure).

The calculated operational characteristics and periods for the object under consideration may be of decisive importance for its effective use and restoration planning.

Although this study does not directly compute statistical confidence intervals or perform Bayesian inference, the proposed reliability framework using Kolmogorov-Chapman state modeling is well-suited for future extensions involving Maximum Likelihood Estimation and Bayesian updating once sufficient empirical failure data become available.

The multi-element Markov model structure supports Bayesian updating as new failure data is collected during system operation. This is particularly useful for fleets, where real-time feedback can refine reliability predictions over time.

The model was built on the assumption that all components follow an exponential distribution of time to failure over the normal operating life of the engine.

The study is considered as a methodological base capable of being scaled and refined with the increase in available statistical information.

CONCLUSIONS

The study proposes and develops a diagnostic system for induction motors focused on monitoring the most common types of faults. The primary components under control include the stator winding, the rotor winding, and the bearing units. The key defects targeted for detection are turn-to-turn short circuits in the stator winding, structural integrity failures in the squirrel-cage rotor winding, and abnormal vibration conditions of the bearings. The proposed diagnostic system enables monitoring of the onset and progression of these faults during motor operation. To prevent the occurrence of component defects, a reliability model has been proposed for forecasting failure-free operating periods and predicting the onset of critical conditions. Taking into account the specific nature of the selected failure types, the model incorporates eight operational states of the tested component, in accordance with diagnostic methodologies commonly applied to induction motors in transportation systems.

In developing the reliability model for the induction motor, state equations—also known as Kolmogorov-Chapman equations—are employed. Provided that failure rate data for individual components of the tested motor are available, reliability parameters have been calculated and validated through simulation. Based on the obtained reliability metrics, a system for scheduling maintenance and monitoring the condition of motor components is proposed. This system improves the overall reliability of the motor and reduces the risk of pre-failure or critical operating states. The proposed eight-level approach offers several advantages over classical reliability models, including more accurate localization of technical states, direct integration with diagnostic signals, and the ability to perform dynamic maintenance scheduling based on the current condition of the equipment.

A distinguishing feature of this study is the proposed and developed research strategy for complex technical systems, based on the sequence: failure statistics → diagnostic system → reliability model. This approach enables the most objective construction of a reliability model aimed at preventing any type of failure through timely maintenance of system components. Determining the time periods when the analyzed technical system becomes unsuitable for further operation—or when certain components enter a potential risk zone for critical failure—also opens

opportunities for developing new strategies to improve the tested elements.

The operational characteristics obtained in this study for the selected test object (the induction motor) make it possible to define the optimal timing for repairs and to determine the end-of-life period, i.e., the point at which the motor is deemed fully unserviceable. This sequential development approach enhances both the control over the condition of induction motor components and the accuracy of reliability modeling.

The multi-element Markov model structure supports Bayesian updating as new failure data is collected during system operation. This is particularly useful for fleets, where real-time feedback can refine reliability predictions over time. The presented model is flexible and can be adapted to work with complex probability distributions, such as the Weibull distribution. Its architecture supports expansion through the use of intelligent data analysis methods (data mining, machine learning), which opens up prospects for improving the accuracy of diagnostics and prognostics. The research component demonstrates scalability potential, making the model suitable for real-world application across various types of traction rolling stock.

The proposed new strategy for creating a predictive model of the technical system can be referred to as the "Strategy for planning updates of complex technical systems based on analysis of time to failure and condition monitoring status".

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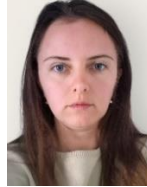
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