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MODELING AND DEVELOPMENT OF AN INTELLIGENT ELECTRICAL FAULT DIAGNOSIS SYSTEM FOR TRACTION MOTORS

Summary. This paper presents a fuzzy logic-based intelligent diagnostic system for the real-time detection of electrical faults in traction motors and the support of condition-based maintenance decisions. The proposed approach evaluates the electrical condition of the motor through a multi-criteria analysis of five key parameters: voltage, current, stator temperature, insulation resistance, and magnetic field. The system demonstrates stable diagnostic behavior under variable operating conditions and sensor noise due to the use of a Mamdani-type fuzzy inference algorithm and Gaussian membership functions. Based on the input parameters, a normalized health indicator, referred to as the Electrical Technical Condition Index (ETCI), is generated and used to estimate the remaining operating distance or time before maintenance is required. The modeling was performed in the MATLAB/Simulink environment and the decision output for different operating modes was evaluated based on a knowledge base consisting of 243 linguistic rules. The simulation results indicate that, under the considered modeling conditions, the proposed fuzzy model provides stable output behavior, with RMSE

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and MAE values of 0.065 and 0.051, respectively, and is suitable for real-time diagnostic implementation. The proposed system supports the application of Condition-Based Maintenance and Predictive Maintenance strategies by enabling reliable operational assessment of the technical condition of the electrical part of traction motors and has practical potential for use in real locomotive operations. It should be noted that the present study is based mainly on simulation modeling in the MATLAB/Simulink environment. Therefore, the obtained diagnostic results should be interpreted as simulation-based evidence of the applicability of the proposed fuzzy diagnostic framework. Further validation using long-term operational data from real traction motors and labeled fault cases is required before full-scale industrial implementation.

Keywords: traction motor, electrical faults, electrical technical condition, fuzzy logic, intelligent diagnostics, real-time control

1. INTRODUCTION

Traction motors are key components of railway traction systems, and their reliability directly affects transport safety, energy efficiency, and service continuity. Variable load regimes, high thermal effects, and long-term operating conditions cause electrical faults in traction motors, such as insulation aging, overheating of stator windings, phase current imbalance, and magnetic field distortion. Failure to detect these faults promptly leads to sudden motor failures, unplanned shutdowns, and reduced operational safety. Therefore, reliable diagnostics and early fault detection in traction motors remain important scientific and practical challenges [1- 2].

Traditional diagnostic methods are mainly based on monitoring fixed threshold values and periodic measurements and demonstrate limited effectiveness in real operating conditions due to measurement noise, transient processes, and variable loads. These approaches have limited ability to account for the nonlinearities and uncertainties inherent in traction motor electrical subsystems, which restricts their use in condition-based maintenance strategies.

In this context, fuzzy logic-based diagnostic approaches offer robust and flexible capabilities for processing imprecise and variable data. Rule-based fuzzy inference systems facilitate the integration of expert knowledge and ensure transparency of the decision-making process. The nonlinear and dynamic behavior of traction motor electrical parameters, including voltage, current, stator temperature, insulation resistance and magnetic field, makes fuzzy logic particularly suitable for this diagnostic task. These systems allow for reliable detection of such faults in conditions of variability of operating modes by describing smooth transitions between normal and emergency states and create an effective methodological basis for condition-based maintenance strategies.

The main scientific contribution of this study is the development of a quantitative and decision-oriented fuzzy logic framework for diagnosing electrical faults in traction motors. The innovation is determined by the following main points:

- The transformation of multi-parameter fuzzy diagnostic results into a normalized “Electrical Technical Condition Index (ETCI)” indicator in the interval [0-1] is ensured, which allows for an integral assessment of sensor data with different units of measurement in real time.
- The fuzzy outputs are directly linked to maintenance decisions (continuation of operation, planned repairs, protection) and the diagnostic results are integrated into the Condition-Based Maintenance (CBM) mechanism.

- The fuzzy knowledge base and membership functions are formed based on the real operating ranges of a specific 6FRA 4567 H traction motor, which makes the model suitable for industrial applications rather than laboratory ones.
- The use of Gaussian membership functions increases diagnostic stability in the presence of sensor noise and uncertain operating modes, preventing decision jumps.

At the same time, the study is positioned as a simulation-based methodological contribution. The proposed system is intended to demonstrate the feasibility of combining multi-parameter fuzzy diagnostics with a normalized electrical technical condition index. Its practical application requires further testing under real locomotive operating conditions, including long-term sensor measurements, maintenance history, and confirmed fault records.

The proposed approach created a structural framework that enables the use of diagnostic results as a key indicator for predictive maintenance (PdM) systems.

2. LITERATURE REVIEW AND PROBLEM STATEMENT

Electrical fault diagnosis in traction motors is an important research area for improving the reliability of railway transport systems. Traditional diagnostic methods are mainly based on deterministic threshold values and signal analysis methods such as multispectral current analysis, vibration diagnostics, and insulation resistance measurement. Although these approaches can detect certain types of faults, their effectiveness is limited under nonlinear dynamics, variable load conditions, and stochastic disturbances typical of traction motors [3-6].

In recent years, intelligent diagnostic methods have been widely studied to overcome these limitations. Artificial neural networks, support vector machines, and deep learning models have shown high fault classification accuracy in many diagnostic applications. However, their dependence on large labeled datasets and their limited interpretability can restrict their application in safety-critical systems [7-9].

Hybrid approaches combining signal processing and intelligent algorithms have also been developed. The integration of machine learning with time-frequency analysis has yielded effective results in rotor and stator fault detection. However, these methods require high computational resources and complex feature extraction steps [10-13].

In this context, fuzzy logic-based diagnostic systems are of particular interest due to their noise immunity, interpretability, and the ability to integrate expert knowledge. The effectiveness of fuzzy systems in power systems and electrical machine diagnostics has been confirmed in a number of studies. In particular, Mamdani-type fuzzy inference systems are dominant in industrial applications due to the transparency of the decision-making mechanism [14-16].

An analysis of existing studies (Table 1) shows that fuzzy logic allows for a more accurate assessment of the situation in dynamic operating conditions dominated by nonlinearities and uncertainties. However, there is limited work on the integration of fuzzy diagnostics with residual operating resource prediction. Another limitation of many existing studies is that diagnostic models are often validated using laboratory data, simulated signals or limited experimental datasets. As a result, their direct transfer to real traction motor operation remains challenging. This is especially important for railway traction applications, where the diagnostic decision is influenced by load variability, sensor uncertainty, thermal inertia, insulation ageing and maintenance history. This indicates the need to develop multi-parameter diagnostic and prognostic systems based on fuzzy logic for real-time monitoring of traction motors and optimization of maintenance.

Tab. 1

Comparative table of the proposed system with existing fuzzy logic-based diagnostics systems for traction motors

Comparison criteria	Existing fuzzy logic-based traction motor diagnostics	Proposed system
Diagnostic purpose	Discrete fault detection	Integrated assessment of the electrical technical condition
Number of input parameters	1-3 parameters (mainly current, vibration, or temperature)	5 electrical parameters
Parameter integration	Discrete fuzzy decisions	Normalized ETCI in the range [0-1]
Output format	Qualitative (normal/fault)	Quantitative health index + decision class
Real traction motor application	Often laboratory motors	6FRA 4567 H real traction motor
Operating conditions	Fixed or ideal models	Variable, real operating ranges
Membership functions	Mainly triangular/trapezoidal	Gaussian, S and Z type (noise-robust)
Sensor noise immunity	Limited	Improved through smooth transitions (smooth transitions)
Decision mechanism	Limited to diagnostics	Direct decision output for CBM and PdM
Repair planning	Not considered	Diagnostics-based planning
RUL / residual resource connection	Typically absent	Structurally available (ETCI-based)
Real-time mode	Partial	Suitable for real-time implementation
Practical applicability	Average	High (for locomotive systems)

3. THEORETICAL FOUNDATIONS OF DIAGNOSTICS OF ELECTRICAL FAULTS

Diagnostics of electrical faults in traction motors is based on the analysis of the main parameters characterizing electromagnetic, thermal, and insulation processes. Deviations from normal operating conditions are reflected in these parameters and may indicate the development of electrical faults. Stator voltage is one of the main parameters characterizing the electromagnetic operating mode of the motor. Deviation of the supply voltage from the nominal leads to a decrease in the electromagnetic moment, an increase in current, local heating of the windings, and accelerated aging of the insulation. Therefore, the analysis of the amplitude and dynamic changes of the voltage is important for the early detection of power supply and internal motor faults.

Stator current is one of the most informative diagnostic signs of electrical faults. Exceeding the nominal current is associated with inter-winding short circuits, phase symmetry violations, overloads, and deterioration of cooling conditions. The transient and stationary components of the current are closely correlated with the technical condition of the motor and allow faults to be identified at an early stage.

The temperature regime is one of the main factors determining the reliability of insulation. An increase in stator temperature may be caused by excessive current, magnetic losses, cooling system degradation or local insulation defects. Since the increase in temperature significantly reduces the service life of the insulation, temperature monitoring plays an important role in assessing the condition of the motor.

Insulation resistance is an important early-warning indicator of insulation degradation and moisture penetration. A decrease in resistance provides an early warning of insulation aging and the formation of short circuits in the windings. A change in the magnetic field in the interpole gap reflects the symmetry of the magnetic field, the eccentricity of the rotor, and defects in the magnetic system. Magnetic field analysis allows for earlier detection of some faults than traditional electrical measurements.

Table 2 shows the normal, permissible, and emergency ranges of the selected input parameters for assessing the technical condition of the electrical parts of the traction motor. It should be noted that the given values were obtained as a result of measurements in real conditions for 6 FRA 4567 H-type traction motors of Alstom's AZ4A and AZ8A electric locomotives.

Tab. 2

Allowable, Warning and Dangerous value ranges of input parameters

Parameters	Allowable	Warning	Dangerous
Voltage	U <1400 V	1400 -1540 V	U > 1540
Current	I < 550A	550 - 605 A	I > 605
Stator temperature	t < 100°C	100-120°C	t > 120°C
Insulation resistance	R >1 MOhm	1-0.5 MOhm	< 500k Ohm
Magnetic field	B < 0.5 T	0.5-1.2 T	B > 1.2 T

The selected parameters directly affect the service life and operational safety of the traction motor. Their joint analysis allows for a comprehensive description of the motor condition and the identification of interconnected faults that cannot be detected by a single parameter. The selected indicators reflect the main characteristics of the machine's operation, and even small deviations are considered informative for the detection of early defects. The parameters can be measured non-invasively with standard sensors and, since they have a continuous, fuzzy boundary between normal and emergency modes, are suitable for processing with fuzzy systems. Thus, these parameters serve as reliable input variables for intelligent diagnostic systems [16-20].

3.1. Architecture and methodology of the intelligent diagnostic system

The diagnostic system includes the following functional subsystems:

- Data acquisition module: collects voltage, current, stator temperature, insulation resistance, and magnetic field data.
- Signal preprocessing block - performs normalization of input data, noise filtering, and scaling.
- Fuzzy Inference System (FIS) - converts input parameters into an assessment of the technical condition of the motor.
- Technical condition assessment module: generates the Electrical Technical Condition Index (ETCI) in the range [0-1].
- Remaining distance predictor: converts the ETCI value into an estimate of the remaining operating distance before maintenance.
- Monitoring interface - provides visualization of results for maintenance personnel.

The structural scheme provides a continuous flow of information and the application of diagnostic rules in real time. Figure 1 shows the general structure of the proposed intelligent diagnostic system. The measured values of voltage, current, stator temperature, insulation resistance, and magnetic field are transferred from the sensor block to the fuzzy diagnostic module. After fuzzification, the inference engine processes the input data using the rule base. The defuzzified output is then used for real-time technical condition assessment, predictive maintenance support, and motor protection.

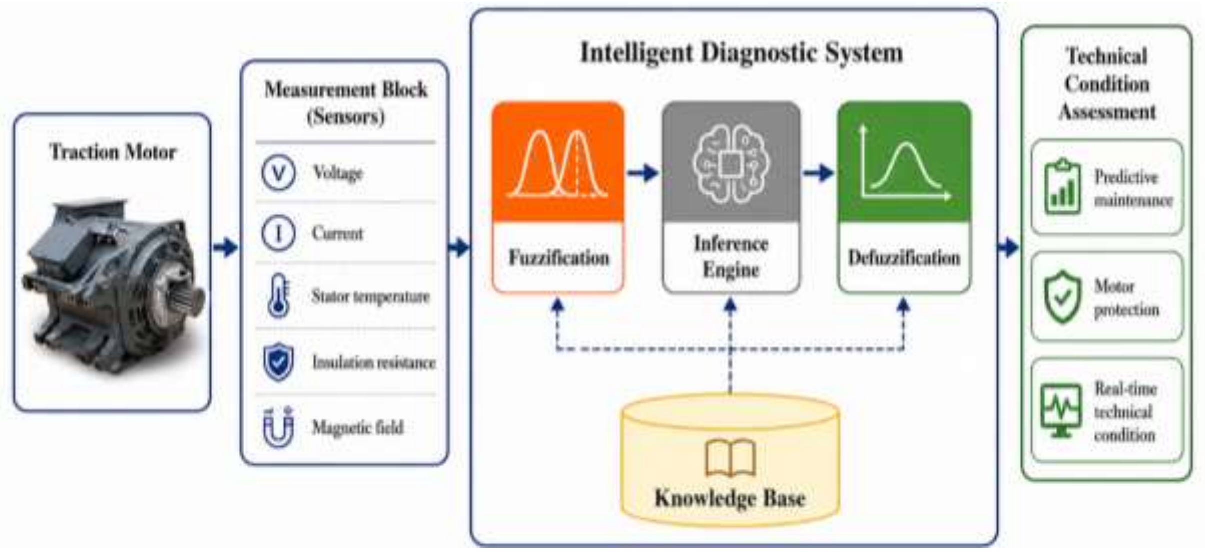

Fig. 1. Structure of the traction motor intelligent diagnostic system

3.2. Selection of fuzzy inference algorithm and membership function

Early detection and accurate diagnosis of faults in modern electric traction systems are essential for reliable operation. Traditional methods based on hard threshold values give limited results in uncertain and variable operating modes. Therefore, in recent years, intelligent diagnostic systems based on fuzzy logic have found wide application [14-16, 19].

In this study, a diagnostic system based on a fuzzy knowledge base is developed to assess the current technical condition of traction motors. The system models nonlinear dependencies between input and output parameters. A two-stage approach is applied: in the first stage, structural identification is performed using “if…then…” linguistic rules, and a fuzzy knowledge base is formed; in the second stage, possible faults in electrical components are assessed based on a Mamdani-type fuzzy inference system (FIS). The model is developed in the MATLAB Fuzzy Logic Toolbox environment.

The Mamdani inference algorithm was selected because of its interpretability, ability to process uncertain input data, and suitability for rule-based diagnostic decision-making with multiple input parameters. Compared with the Sugeno model, which is often used for control and optimization tasks with functional outputs, the Mamdani model provides more interpretable linguistic outputs after defuzzification.

There is no universal procedure for selecting membership functions for linguistic variables; therefore, their selection is usually based on expert knowledge and simulation-based tuning. The choice of Gaussian MF is justified by the following considerations:

• *Continuous and smooth transition.* Gaussian functions allow for continuous transition between parameter values without creating sharp boundaries, which more realistically models natural changes in physical systems.

• *Robustness to noise.* Gaussian functions provide more stable results against random noise and small fluctuations that may be present in sensor data.

• *Differentiability.* If the system is further expanded by optimization and learning, mathematical derivatives of the Gaussian function exist and can be used in algorithms of adaptive control systems.

Thus, Gaussian-type membership function curves allow for more flexible and objective conclusions in terms of adaptation to fluctuations in a fuzzy logic system.

The output of the model is determined in the "Decision" block, and this block determines the technical condition of the electrical part of the motor. The output values can be assessed as “Working”, “Maintenance” or “Protect” depending on the condition of the motor. This output can then be combined with the mechanical condition in a complex system to assess the overall technical condition and predict maintenance time.

4. MODELING OF A FUZZY DIAGNOSTIC SYSTEM FOR ELECTRICAL FAULTS IN A TRACTION MOTOR

After defining the system architecture, inference algorithm, and membership function types, the fuzzy diagnostic model can be formulated. The membership function matrix for the five input variables is formulated as follows:

$$\mu_G(X) = \begin{bmatrix} \mu_I(x_1), \mu_I(x_2), ..., \mu_I(x_n) \\ \mu_U(x_1), \mu_U(x_2), ..., \mu_U(x_m) \\ \mu_B(x_1), \mu_B(x_2), ..., \mu_B(x_k) \\ \mu_{R_{iz}}(x_1), \mu_{R_{iz}}(x_2), ..., \mu_{R_{iz}}(x_l) \\ \mu_T(x_1), \mu_T(x_2), ..., \mu_T(x_q) \end{bmatrix} \tag{1}$$

Here, $\mu_I, \mu_U, \mu_B, \mu_{R_{iz}}, \mu_T -$ current, voltage, magnetic field, insulation resistance, and temperature are membership functions of the terms of the input linguistic variables, respectively. Similarly, the membership function of the output variable is expressed as follows:

$$\mu_Ç(Y) = [\mu_D(y_1), \mu_D(y_2), ..., \mu_D(y_h)] \tag{2}$$

Let us mathematically express the $E_{ji}, \forall i, j = \overline{1,3}$ term subsets of the input linguistic variables. The linguistic variables "Current", "Voltage", "Magnetic field", "Insulation resistance" and "Temperature" can be written in general terms using the following algorithm:

$$\left.\begin{array}{ll} E_{ij} = A_1 & \underline{\underline{\Delta}}\left(I, \mu_{ij}(I)\right) \\ \dots\dots\dots\dots\dots\dots & \\ E_{ij} = A_2 & \underline{\underline{\Delta}}\left(U, \mu_{ij}(U)\right) \\ \dots\dots\dots\dots\dots\dots & \\ E_{ij} = A_3 & \underline{\underline{\Delta}}\left(B, \mu_{ij}(B)\right) \\ \dots\dots\dots\dots\dots\dots & \\ E_{ij} = A_4 & \underline{\underline{\Delta}}\left(R_{iz}, \mu_{ij}(R_{iz})\right) \\ \dots\dots\dots\dots\dots\dots & \\ E_{ij} = A_5 & \underline{\underline{\Delta}}\left(T, \mu_{ij}(T)\right) \end{array}\right\}, \quad i = \overline{1,5};\ j = \overline{1,3} \tag{3}$$

Here, $i-$is the number of input linguistic variables; j — is the number of terms of each input linguistic variable; $A_1, A_2, ..., A_5$ – is the term-subset of the input linguistic variables and can be written as follows:

$$A = \left[E_{ij}\right] = \left[A_1\ A_2\ A_3\ A_4\ A_5\right] = \left(\begin{bmatrix} N\ (low) \\ M\ (medium) \\ H\ (high) \end{bmatrix}\right)_i, \quad i = \overline{1,5} \tag{4}$$

Let us mathematically express the $E_\gamma, \forall \gamma = \overline{1,3}$ term subsets of the linguistic variables "Decision":

$$\left.\begin{array}{ll} E_{61} = L\ (low) & \underline{\underline{\Delta}}\left(D, \mu_{61}(D)\right) \\ E_{62} = M\ (medium) & \underline{\underline{\Delta}}\left(D, \mu_{62}(D)\right) \\ E_{63} = H\ (high) & \underline{\underline{\Delta}}\left(D, \mu_{63}(D)\right) \end{array}\right\} \tag{5}$$

Since the membership functions of the terms of the input linguistic variables $\mu_{1i}\ (I)$, $\mu_{2j}\ (U)$, $\mu_{3p}\left(B\right), \mu_{4g}\left(R_{iz}\right)$, $\mu_{5\upsilon}\ (T)$ are assumed to be Z-shaped, S-shaped, and Gaussian, they can be written in the following general form:

$$\left.\begin{array}{l} \mu_{ijk}(I)=\begin{cases}0, & I_k < a_{km} \\ \dfrac{I_k - a_{km}}{b_{km} - a_{km}}, & a_{km} < I_k < b_{km} \\ 1 & b_{km} < I_k \end{cases} \\ \mu_{ijk}(I)=\exp\left\{\dfrac{-[I_k - c_{ik}(I)]}{2\sigma_{ik}^2(I)}\right\} \\ \mu_{ijk}(I))=\begin{cases}1, & I_k < b_{km} \\ \dfrac{c_{ik} - \dot{I}_k}{c_{ik} - b_{km}}, & b_{km} < I_k < c_{ik} \\ 0, & c_{ik} < I_k \end{cases} \end{array}\right), \quad \forall i=\overline{1,5}; \ \ \forall j,k,m=\overline{1,3} \qquad (6)$$

Output for the membership function of the linguistic variable “Decision” $\mu_{6\gamma}(D)$

$$\left.\begin{array}{l} \mu_{61\gamma}(D)=\exp\left\{\dfrac{-[D_{j\gamma} - c_{ji}(D)]}{2\sigma_{6i}^2(D)}\right\} \\ \mu_{62\gamma}(D)=\exp\left\{\dfrac{-[D_{j\gamma} - c_{j\gamma}(D)]}{2\sigma_{j\gamma}^2(D)}\right\} \\ \mu_{53v}(D)=\exp\left\{\dfrac{-[D_{3\gamma} - c_{6i}(D)]}{2\sigma_{j\gamma}^2(D)}\right\} \end{array}\right), \ \forall j,\gamma=\overline{1,3} \qquad (7)$$

The parameters of the membership functions were selected based on the operating ranges of the considered 6FRA 4567 H traction motor and were then adjusted during simulation modeling. For the Z-shaped and S-shaped functions, the two parameters represent the lower and upper transition limits. For the Gaussian function, the first parameter represents the standard deviation, while the second parameter represents the center of the function.

Tab. 3

Characteristics of membership functions of input linguistic variables

Terms of linguistic variables	Membership function	Parameters of the membership function
Voltage		
Allowable	Z	[0 1607.80]
Warning	Gaussian	[98.6 377.33]
Dangerous	S	[1401.52 1626.0]
Current		
Allowable	Z	[0 651.05]
Warning	Gaussian	[47.3 549.56]

Dangerous	S	[569.36 650]
Stator temperature		
Allowable	Z	[0 230.6]
Warning	Gaussian	[7.86 110.37]
Dangerous	S	[107 149.91]
Insulation resistance		
Allowable	Z	[0.0119 2]
Warning	Gaussian	[0.158 0.802]
Dangerous	S	[0 1.236]
Magnetic field		
Allowable	Z	[0 2.2]
Warning	Gaussian	[0.106 1.3102]
Dangerous	S	[0.8873 2]

Tab. 4

Characteristics of the membership function of the output linguistic variable

Terms of linguistic variables	Membership function	Parameters of the membership function
Technical condition		
Allowable	Gaussian	[0.1896 0.0248]
Warning		[0.1899 0.4993]
Dangerous		[0.1814 0.9965]

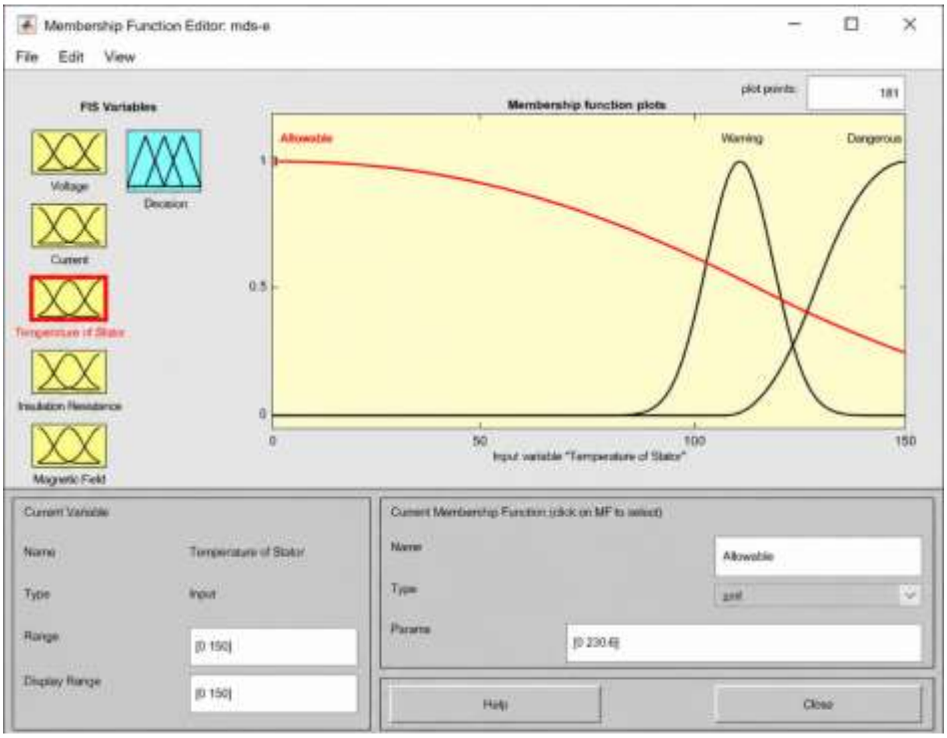

Fig. 2. Modeling results of MF in terms of input linguistic variables

The output linguistic variable represents the electrical technical condition of the traction motor. The output range is normalized in the interval [0; 1], where values close to 0 correspond to a dangerous condition, values around the middle of the interval correspond to a warning condition, and values close to 1 correspond to an allowable condition. This normalization makes it possible to use the fuzzy output not only for diagnostic classification but also for maintenance decision support.

Based on Equations (6) and (7) and the membership function parameters presented in Tables 3 and 4, the input and output membership functions were tuned through simulation modeling. The results obtained are presented in Figures 2 and 3.

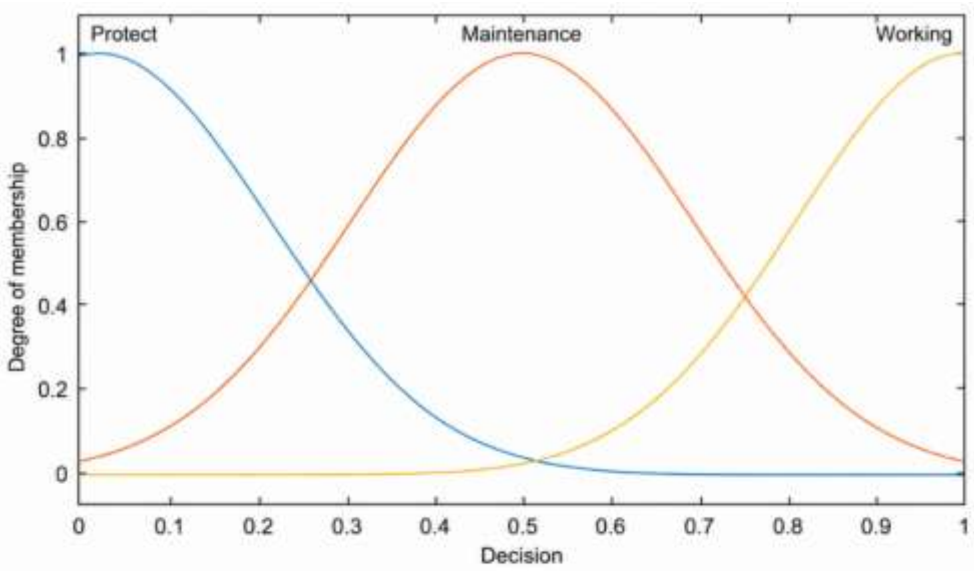

Fig. 3. Modeling results of MF in terms of the output linguistic variable

For the considered case, the membership function of the fuzzy relationship between input-output linguistic variables is determined by max-min composition:

$$\mu_R\left(I,U,B,R_{iz},T,D\right)=\max\left\{\begin{array}{l}\min\begin{bmatrix}\mu_{E_{11}}(I),\ \mu_{E_{21}}(U),\ \mu_{E_{31}}(B),\\ \mu_{E_{41}}(T),\mu_{E_{51}}(R_{iz}),\mu_{E_{61}}(D)\end{bmatrix},\\ \min\begin{bmatrix}\mu_{E_{12}}(I),\ \mu_{E_{22}}(U),\ \mu_{E_{32}}(B),\\ \mu_{E_{42}}(T),\mu_{E_{52}}(R_{iz}),\mu_{E_{62}}(D)\end{bmatrix},\ldots..,\\ \min\begin{bmatrix}\mu_{E_{16}}(I),\ \mu_{E_{26}}(U),\mu_{E_{36}}(B),\\ \mu_{E_{46}}(T),\mu_{E_{56}}(R_{iz}),\mu_{E_{66}}(D)\end{bmatrix}\end{array}\right\} \tag{8}$$

An intelligent diagnostic system for traction motor electrical faults was developed using fuzzy logic theory. The fuzzy diagnostic system includes five input linguistic variables corresponding to the selected diagnostic parameters and one output linguistic variable, “Technical condition”.

After the input parameters are processed by the fuzzy rule base, the system generates a diagnostic decision that characterizes the technical condition of the motor. The results of the fuzzy logic inference mechanism can evaluate the electrical condition of the traction motor as “Working”, “Maintenance” or “Protect”. The output value can be transferred to the execution block and combined with mechanical condition indicators to support an overall condition assessment and maintenance time prediction.

The block diagram of the operation algorithm of the fuzzy diagnostic system for assessing the technical condition of the traction motor is given in Figure 4.

As shown in Figure 4, real-time diagnostic parameters from sensor-measuring devices are transmitted to a fuzzy decision-making system.

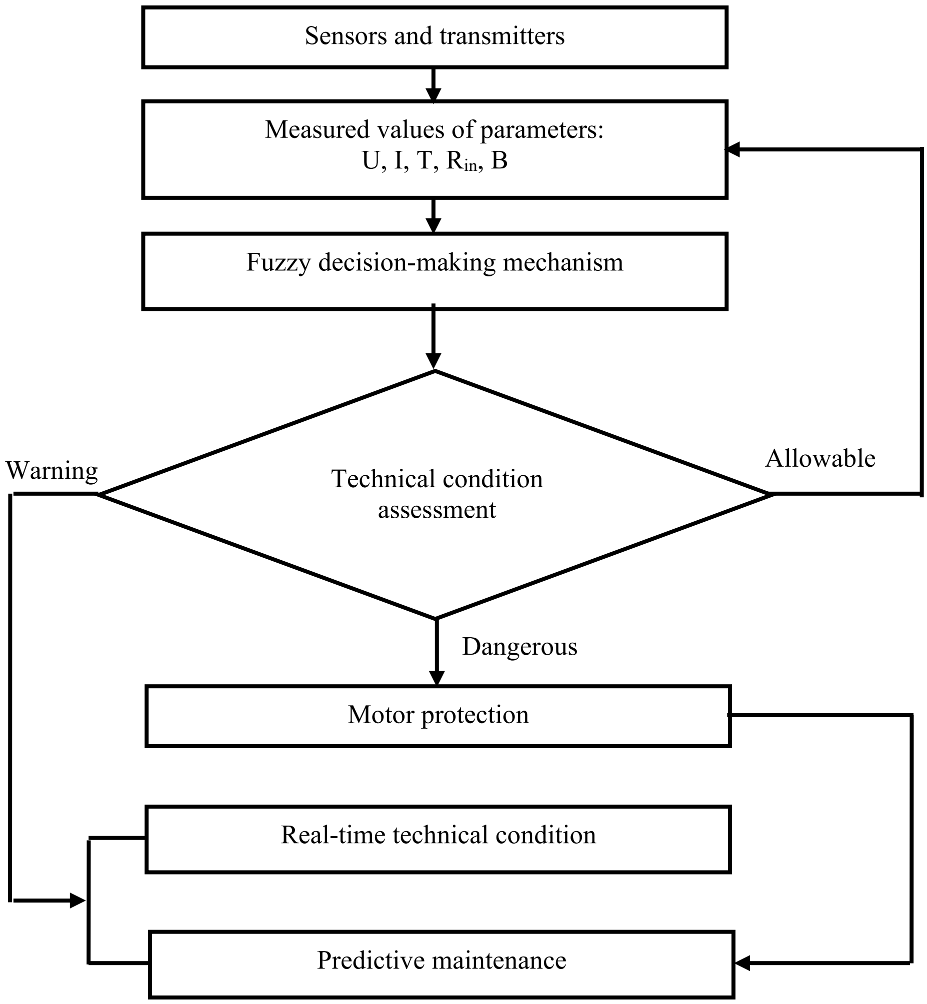

Fig. 4. Block diagram of the fuzzy diagnostic system for the technical condition of the traction motor

In this system, the technical condition of the traction motor is assessed based on linguistic rules, and measures are taken according to the result: in the case of a “dangerous” result, the protection system is activated, and the motor is disconnected from the power source; in the case of a “warning” result, the further operating time and distance are determined; in the case of an “allowable” result, the motor operation is continued.

The advantages of the proposed diagnostic system are:

- Allows decision-making under conditions of uncertain and stochastic changes in input parameters;
- Real-time operational analysis is performed based on sensor data;
- Automatic and intelligent assessment of motor removal for repair is provided;
- Mamdani's algorithm is transparent in terms of interpretation and understandable to technical specialists.

The system can be extended for predictive maintenance and allows for the assessment of the remaining service life of the traction motor. For this, a normalized electrical technical condition indicator (ETCI) is used. The remaining service life is calculated based on the current ETCI value, the critical limit, and the ETCI deterioration rate. In addition, the remaining service distance is determined based on the actual operating speed of the traction equipment.

4.3. Prognostic assessment of maintenance scheduling and remaining operational distance based on the technical condition index

The proposed system represents the electrical technical condition of the traction motor as a normalized index obtained from the fuzzy inference output. In this study, ETCI is used as an auxiliary prognostic indicator rather than as a directly measured physical quantity. It is obtained from the fuzzy inference output and reflects the integrated electrical condition of the traction motor based on the selected diagnostic parameters.

$$ETCI(t) \in [0,1],\ \overline{E}_k = \alpha E_k + (1-\alpha)\overline{E}_{k-1},\ 0 < \alpha \le 1 \tag{9}$$

where ETCI = 1 corresponds to a normal condition, while ETCI approaching 0 indicates a condition close to the critical failure level. The main idea of predictive maintenance is to estimate the remaining time or distance before maintenance based on the current ETCI value and its degradation rate [21, 22-25]. To reduce the sensitivity of the measurements to noise, ETCI(t) is exponentially smoothed (9). $E_k = ETCI(k\Delta t)$, Δt is the sampling step. Then the average degradation rate of the index is determined by the window method:

$$r_k = \max\left(\varepsilon, \frac{\overline{E}_{k-m} - \overline{E}_k}{m\Delta \mathrm{t}}\right) \tag{10}$$

where m - is the window length, ε - is a small positive number that prevents division by zero.

The critical limit E_{crit} - is chosen according to technical standards (or the "warning-dangerous" boundary). In this case, the remaining time to repair is estimated as follows:

$$RUL_k = \frac{\overline{E}_k - E_{crit}}{r_k},\ \overline{E}_k > E_{crit} \tag{11}$$

If the current or average speed of the locomotive is known, the remaining mileage until repair:

$$RUD_k = \overline{v}_k \cdot RUL_k \tag{12}$$

If $\overline{E}_k > E_{crit}$ is present, the system evaluates it as a "critical" condition and a repair/protection decision is activated. To account for noise, the standard deviation of the $\overline{E}_k$ values over the window, σE, can be taken to give a simple interval for prediction:

$$RUL_k^{\min} = \frac{(\overline{E}_k - \beta\sigma_E) - E_{crit}}{r_k},\ RUL_k^{\max} = \frac{(\overline{E}_k + \beta\sigma_E) - E_{crit}}{r_k} \tag{13}$$

where β can be chosen in practice to be 1-2 (e.g., $\beta = 2$ for a conservative forecast). Analogously, the (RUD) interval is calculated with $RUD = \overline{v}_k \cdot RUL$.

5. RESULTS OF MODELING OF A FUZZY DIAGNOSTIC SYSTEM FOR ELECTRICAL FAULTS IN A TRACTION MOTOR

The calculations were performed using the Simulink model. The model included the linguistic variables defined in Equations (3)-(5), the membership functions described in Equations (6) and (7), the adjusted parameters presented in Tables 3 and 4, and the fuzzy relations given in Equation (8). The measured values of the parameters characterizing the electrical state of the motor in real operating conditions were used to perform the modeling. Table 5 presents the simulated stator temperature values corresponding to the allowable, warning and dangerous states. Similar datasets were generated for the other input parameters. Other parameters are also set analogously to Table 5.

The simulation dataset was generated to cover the three diagnostic states. The values were selected according to the operating ranges presented in Table 2. Therefore, the dataset should be considered as a structured simulation dataset rather than a real operational dataset collected from long-term locomotive operation.

Tab. 5

Temperature values of the stator windings of the motor corresponding to the technical condition

Stator temperature, ^{0}C			
№	Allowable	Warning	Dangerous
	t < 100°C	100-120°C	t > 120°C
1	3.5°C	100.5°C	121.4°C
2	7.8°C	101.8°C	124.7°C
3	12.1°C	102.9°C	128.2°C
4	18.6°C	104.3°C	130.6°C
5	21.9°C	105.7°C	134.1°C
6	27.3°C	106.5°C	137.8°C
7	32.8°C	107.9°C	140.3°C
8	36.5°C	109.2°C	144.9°C
9	41.2°C	110.4°C	147.2°C
10	45.6°C	111.8°C	150.6°C
11	51.3°C	112.3°C	154.3°C
12	55.7°C	113.5°C	157.1°C
13	60.4°C	114.7°C	160.8°C

14	64.8°C	115.9°C	163.4°C
15	70.2°C	116.3°C	167.2°C
16	74.9°C	117.5°C	170.6°C
17	80.5°C	118.1°C	173.1°C
18	85.1°C	118.9°C	176.4°C
19	90.3°C	119.3°C	178.9°C
20	96.7°C	119.8°C	179.5°C

The input parameter values used in the model were generated as artificial simulation data covering all three technical states: *allowable, warning and dangerous*. In future work, these simulated values can be replaced or supplemented with measurements obtained from real operating conditions. Figure 5 shows the 10-step value changes of the stator temperature for a conditional 10-second time period. These values are formed according to the values of each parameter during the simulation (Figure 5).

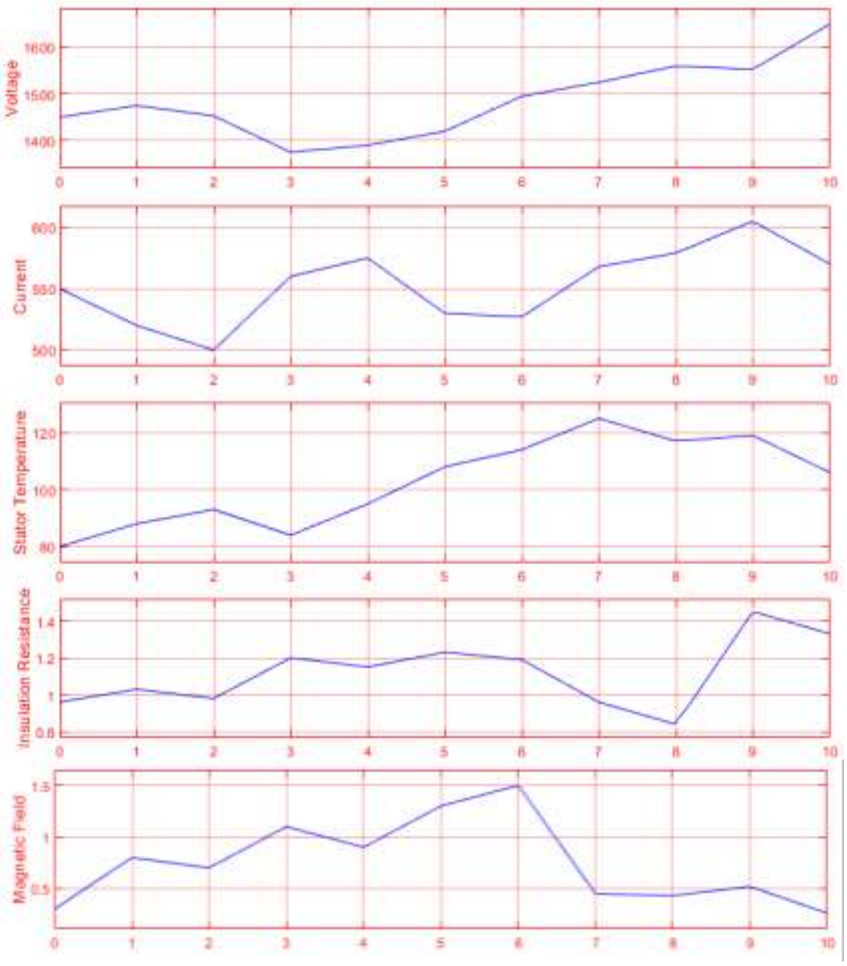

Fig. 5. Simulation curves of selected informative parameters in various technical states of the traction motor

The results of the simulation modeling of the linguistic approximation of the input and output variables based on the decision-making matrix of the fuzzy diagnostic system and the decision-making fragments for the considered case are given in Figures 6 and 7, respectively. In the proposed fuzzy diagnostic system, 243 linguistic rules are formed based on the combinatorial structure of the input variables. The system consists of 5 input linguistic variables, and each input variable is described by 3 linguistic terms (Allowable/Warning/Dangerous). In this case, the total number of fuzzy rules is determined as follows: $N=3^5=243$. The rules are based on the "if-then" structure and are compiled taking into account the existing technical standards, standard limits, and expert knowledge on the operation of traction motors.

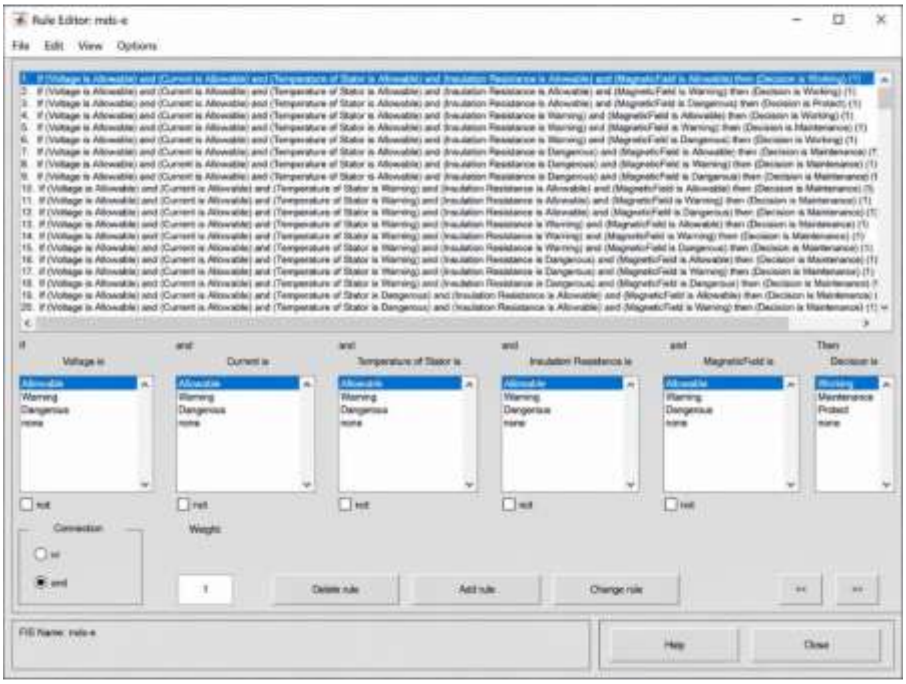

Fig. 6. Simulink fuzzy rules matrix of an electrical fault diagnosis system

Fig. 7. Fragment of fuzzy decision-making for power failure

The rule base covers all possible main operating modes of the electrical parameters of the motor and allows for adequate differentiation of allowable, warning, and dangerous states. This approach provides the integrity and consistency properties of the fuzzy system and has sufficient computational efficiency for real-time diagnostics. In the current situation considered, as can be seen from Figure 7, a decision was made based on the 28th linguistic fuzzy rule of the knowledge base.

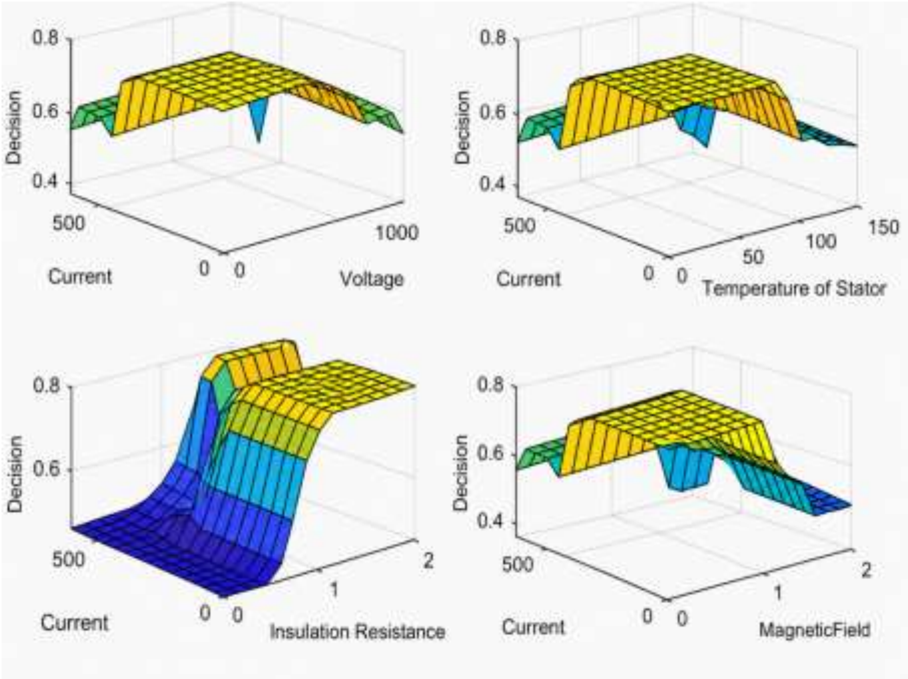

Fig. 8. Pairwise dependence surface representations of the diagnostic system $D = F(I, U, B, T, R_{iz})$

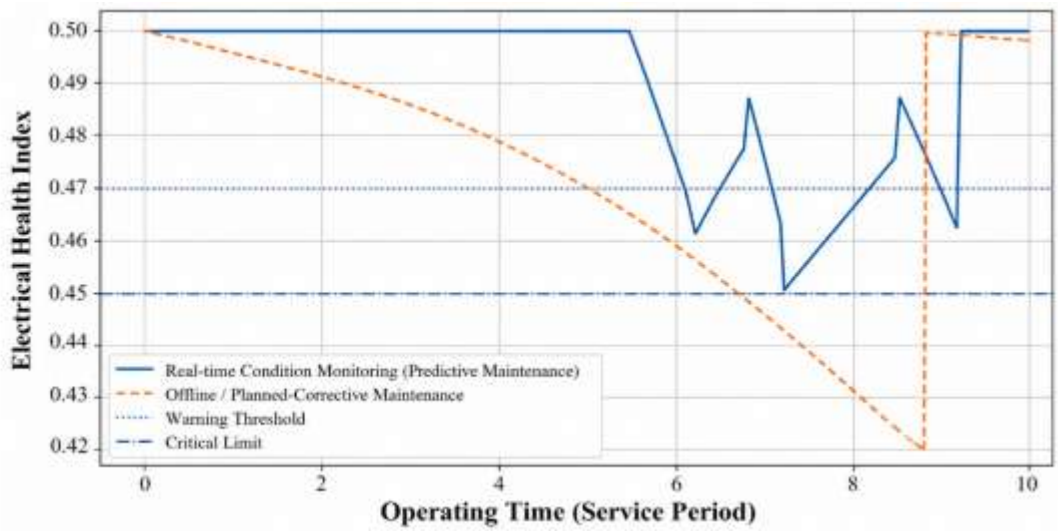

Fig. 9. Comparison chart of real-time and offline assessment of the "Electrical Technical Condition" of a traction motor

Figure 8 presents pairwise surface plots showing the relationship between the selected input parameters and the diagnostic output. These plots illustrate how changes in the input variables affect the technical condition indicator. The smooth transitions between the surface regions confirm that the proposed fuzzy model avoids abrupt decision changes near the boundaries between allowable, warning and dangerous states. This behavior is important for real-time diagnostics because short-term fluctuations and sensor noise should not lead to unstable maintenance decisions.

Other surface dependencies of the assessment of the technical electrical condition of the traction motor can be analyzed similarly.

Based on the methodology given above, a Simulink implementation of a fuzzy diagnostic system for the electrical condition of the traction motor, based on five electrical parameters, was developed. Figure 9 compares the behavior of the proposed real-time condition monitoring approach with a conventional offline planned-corrective maintenance strategy. In the real-time monitoring scenario, the degradation trend can be detected before the critical limit is reached. In contrast, the offline approach may identify the deterioration later because the technical condition is assessed only during scheduled inspections or after fault occurrence.

Up to states 5-6, the electrical condition of the motor remains within the normal operating range. Between states 6 and 9, the electrical parameters indicate a deterioration trend, and the diagnostic system generates the corresponding maintenance recommendations. After state 9, the modelled condition returns to the normal operating range.

If real-time diagnostics are not applied, the technical conditions of traction motors are assessed only based on scheduled inspections and failure events. This leads to late detection of the degradation process and sudden failures.

To take into account the uncertainty of sensor measurements, white Gaussian noise with a mean value of zero was added to the input signals. The standard deviation of the noise was taken as 2% of the measured quantity, which corresponds to the typical accuracy level of industrial sensors:

$$x_n(t) = x(t) + N(0, \sigma^2) \tag{14}$$

where *x(t)* – ideal measurement; $x_n(t)$ – noisy measurement; σ – is chosen according to the technical accuracy of the sensor and is taken as 2%.

After simulating the same scenario with noise $N=30$ times, the mean and standard deviation were calculated using the following expression:

$$CI = \overline{E} \pm 1.96 \frac{\sigma_E}{\sqrt{N}} \tag{15}$$

A 95% confidence interval was obtained for the ETCI output.

Table 6 presents a comparative evaluation of the proposed fuzzy logic-based diagnostic model with traditional and machine learning-based approaches using the same input parameters. The compared models were implemented using standard configurations without extensive hyperparameter optimization. The comparative analysis under the considered simulation conditions shows that the proposed fuzzy logic-based approach provides lower error values and more stable output behavior than the selected baseline diagnostic methods. However, these results should not be interpreted as final proof of superiority over data-driven models, because the comparison was performed using simulated input scenarios and standard model configurations without extensive hyperparameter optimization. Although data-driven models demonstrate competitive accuracy, their real-time application and interpretation are limited. The proposed method provides a balanced trade-off between accuracy, stability, and real-time feasibility.

Tab. 6

Comparison of diagnostic methods

Method	RMSE	MAE	Output stability	Real-time compatibility
Threshold-based	0.142	0.118	Allowable	Dangerous
ANN	0.091	0.074	Warning	Warning
SVM	0.084	0.069	Warning	Allowable
Random Forest	0.079	0.063	Warning	Allowable
ANFIS	0.072	0.058	Dangerous	Warning
Proposed Fuzzy model	0.065	0.051	Dangerous	Dangerous

Therefore, Table 6 should be interpreted as a simulation-based comparative assessment. The purpose of this comparison is to demonstrate the feasibility and stability of the proposed fuzzy diagnostic framework rather than to provide a complete experimental benchmark against machine learning methods. Note: values are calculated based on the normalized technical condition index.

The results show that the proposed method provides a favorable balance between diagnostic accuracy, output data stability, and real-time application.

The obtained modeling results confirm the feasibility of using a fuzzy logic-based approach for the electrical fault diagnosis of traction motors. However, several limitations should be noted. First, the validation of the proposed system was performed mainly in the MATLAB/Simulink simulation environment. Therefore, the obtained RMSE, MAE and output stability indicators should be interpreted as simulation-based performance measures rather than final evidence of diagnostic reliability under real locomotive operating conditions.

Second, the simulation scenarios were generated according to predefined allowable, warning, and dangerous ranges of the selected electrical parameters. Although these ranges reflect the operating characteristics of the considered traction motor, they do not fully reproduce all degradation mechanisms that may occur during long-term railway operation. In practice, the diagnostic output may be affected by sensor drift, environmental disturbances, changing load profiles, cooling conditions, insulation ageing, and maintenance history.

Third, the present study does not use a large labeled dataset of confirmed electrical faults. For this reason, classification metrics such as accuracy, precision, recall, and F1-score were not used as the main validation criteria. The proposed system should therefore be considered as a simulation-validated diagnostic framework. Future research will focus on testing the model using long-term operational data from real traction motors and comparing the diagnostic results with maintenance records and confirmed failure cases.

6. CONCLUSION

This study developed a fuzzy logic-based diagnostic model for the real-time assessment of electrical faults in traction motors. The proposed system uses five input parameters - voltage, current, stator temperature, insulation resistance, and magnetic field, and generates one output variable representing the electrical technical condition of the motor.

The proposed fuzzy logic-based diagnostic model can detect and assess electrical faults under uncertain operating conditions. The combination of the Mamdani inference mechanism and Gaussian membership functions improves the smoothness and stability of diagnostic decisions under the considered simulation conditions.

The main advantages of the model are its real-time applicability, direct processing of sensor data, and ability to support maintenance decision-making. Unlike traditional hard-limit diagnostic methods, this approach lays the groundwork for the development of predictive maintenance systems and is fully consistent with the concept of Condition-Based Maintenance (CBM).

In future work, the proposed approach may be adapted for other electric machines and industrial equipment after validation using real operational data. The present study has several limitations. The proposed fuzzy diagnostic model was tested mainly in a simulation environment, and long-term time-series data from real locomotive traction motors were not used at this stage. In addition, the absence of labeled fault cases limits the possibility of calculating classification-based validation metrics such as accuracy, precision, recall, and F1-score. Therefore, the results should be interpreted as simulation-based confirmation of the feasibility of the proposed approach. Future research will focus on experimental validation using real operational data, refinement of membership function parameters, analysis of incorrect diagnostic decisions, and integration of the electrical diagnostic module with mechanical and thermal condition monitoring systems.

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