ARCHIVES OF TRANSPORT *ISSN (print):* *0866-9546*
Volume 77, Issue 1, 2026 ***e-ISSN (online):*** *2300-8830*
DOI: *10.61089/aot2026.ydgd6v85*

DEVELOPMENT OF A SCADA-BASED REAL-TIME ADVANCED MONITORING SYSTEM FOR THE TECHNICAL CONDITION OF THE TRACTION MOTOR

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Abstract:

Reliable and continuous operation of electric locomotives requires continuous and accurate assessment of the technical condition of traction motors. Traditional SCADA monitoring systems used in rail transport are typically limited to independent threshold monitoring of a small number of electrical and thermal parameters, which reduces their sensitivity to complex and early-stage faults. This paper proposes a multiparameter approach to real-time traction motor technical condition diagnostics based on a formalized condition assessment model. The proposed methodology combines seven diagnostic parameters of electrical, thermal, mechanical, acoustic, and magnetic nature into a single diagnostic framework. Each parameter is converted into a normalized local condition index based on engineering threshold values, and its diagnostic significance is determined using correlation weighting. This is the basis for the formation of an integrated technical condition index, which is used to automatically classify motor condition into three classes: normal, warning, and critical. This article presents the Pearson correlation coefficients between diagnostic parameters and the degradation indicator, as well as the corresponding normalized weighting factors used to calculate the integral index. To quantitatively assess the diagnostic effectiveness, formal statistical validation was performed using a confusion matrix, as well as precision, recall, F1-score, and overall accuracy metrics. The approach was validated on a mixed dataset, including limited real-world operational measurements and simulated degradation scenarios in the Siemens TIA Portal environment, which allowed for verification of the diagnostic logic under controlled conditions. The obtained results demonstrate that multiparameter correlation-weighted diagnostics provide a more sensitive and interpretable assessment of the technical condition of a traction motor compared to traditional single-parameter SCADA monitoring and create a basis for the development of predictive maintenance for traction rolling stock.

Keywords: *SCADA systems, traction motors, condition monitoring, health index, multi-parameter diagnostics, railway transport*

To cite this article:

Manafov, E., Husynov, F. (2026). Development of a SCADA-based real-tıme advanced monıtorıng system for the technıcal condıtıon of the tractıon motor. Archives of Transport, 77(1), 45-61. https://doi.org/10.61089/aot2026.ydgd6v85

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1. Introduction

Reliable and uninterrupted operation of railway traction systems is a critical requirement for modern rail transport, directly affecting safety, energy efficiency, and maintenance costs. Traction electric motors are among the most heavily loaded and failure-prone components of electric locomotives, operating under variable mechanical loads, thermal stresses, and environmental conditions. Consequently, continuous monitoring of their technical condition is an essential task for railway operators seeking to improve system reliability and reduce unplanned downtime.

Contemporary electric locomotives are commonly equipped with SCADA-based monitoring systems that provide real-time access to operational data. However, in most practical implementations, these systems are primarily focused on supervisory control and basic alarm functions. Monitoring is typically limited to a small set of electrical and thermal parameters - such as current, voltage, and winding temperature - evaluated independently using fixed threshold values. While such indicators are sufficient for detecting severe or already developed faults, they offer limited diagnostic sensitivity to early-stage degradation processes, particularly those of mechanical and electromechanical origin [Nandi et al., 2005; Tavner, 2008].

Numerous studies have demonstrated that early faults in traction motors - such as bearing wear, rotor imbalance, insulation degradation, or electromagnetic asymmetry - often manifest through subtle changes in mechanical, acoustic, or magnetic characteristics before significant deviations appear in conventional electrical measurements [Henao et al., 2014; Capolino, 2012; Isermann, 2006; Randall et al., 2011].

In practical traction motor diagnostics, specific fault mechanisms are typically associated with characteristic variations in parameters. Bearing wear and lubrication degradation primarily affect vibration levels and bearing temperature, while rotor asymmetry and eccentricity manifest through changes in magnetic field distribution and electromagnetic harmonics. Insulation ageing and thermal overloading are reflected by increased stator temperature, whereas abnormal loading conditions influence current and voltage behaviour. Parameters related to vibration behaviour, acoustic emissions, and magnetic field distribution have therefore been recognised as valuable sources of diagnostic information. Nevertheless, these indicators are rarely integrated into standard SCADA-based monitoring architectures, mainly due to methodological complexity and the lack of unified diagnostic models suitable for real-time implementation.

Recent research in the field of condition monitoring and predictive maintenance has increasingly emphasised multi-parameter diagnostic approaches. Data-driven and hybrid methods combining information from multiple physical domains have been shown to improve fault detection accuracy and robustness compared to single-parameter monitoring. However, many of these approaches rely on high-frequency signal acquisition, complex signal processing, or machine learning techniques that are difficult to integrate into conventional SCADA environments used in railway applications. As a result, there remains a gap between advanced diagnostic concepts proposed in the literature and practical, real-time diagnostic solutions deployable within existing railway monitoring infrastructures.

In typical railway applications, SCADA systems operate with update cycles on the order of seconds and are subject to strict constraints on communication bandwidth and computational load. Diagnostic algorithms implemented within deterministic PLC control cycles must therefore remain computationally simple, interpretable, and compatible with real-time execution requirements.

Another important limitation of existing SCADA-based diagnostic solutions lies in the absence of formalised health assessment models. In many systems, diagnostic decisions are implicitly embedded in implementation-specific logic (e.g., controller programs or alarm configurations), making the underlying diagnostic principles difficult to interpret, reproduce, or adapt. The lack of explicit mathematical definitions of health indices and decision rules further complicates the objective evaluation and comparison of different diagnostic approaches.

These challenges highlight the need for a diagnostic methodology that combines the advantages of multi-parameter analysis with the practical constraints of SCADA-based monitoring systems. Such a methodology should provide a formally defined, interpretable, and computationally efficient diagnostic model that can integrate heteroge-

neous diagnostic parameters into a unified assessment of traction motor condition.
In this context, the present study proposes a multi-parameter diagnostic framework for assessing the real-time condition of traction motors. The approach transforms electrical, thermal, mechanical, acoustic, and magnetic parameters into normalized local health indices, then aggregates them with weights to produce an integral health index. The diagnostic significance of individual parameters is quantified using a correlation-based weighting strategy, and the resulting health index is then used to classify motor conditions into predefined states automatically. The proposed model is explicitly formulated in mathematical and algorithmic terms, ensuring transparency, reproducibility, and independence from specific hardware or software implementations.
The main contributions of this study can be summarised as follows:

- a formalised diagnostic model for traction motor condition assessment based on normalised local health indices and an integral health index;
- a correlation-based weighting strategy that quantifies the diagnostic significance of heterogeneous electrical, thermal, mechanical, acoustic, and magnetic parameters;
- an explicit and SCADA-compatible diagnostic decision logic, validated through modelling and simulation under representative operating and degradation scenarios.

International experience shows that establishing multi-parameter, real-time diagnostic systems is necessary to ensure the longevity and efficiency of locomotives. Implementing such systems in the traction motors of Alstom locomotives operating on Azerbaijani railways will enable complete and accurate monitoring of the motor's condition, timely detection of malfunctions, and timely implementation of preventive maintenance measures. This approach addresses the diagnostic limitations of existing systems and enables earlier fault detection, leading to more reliable traction-motor operation and reduced maintenance disruptions (Table 1).

2. Research method and methodology

To monitor the technical condition of traction motors in large-power electric locomotives in real time and detect faults at an early stage, this study develops a multi-parameter diagnostic system on the SCADA platform. The proposed approach aims to eliminate the limitations of existing SCADA systems and provide a comprehensive technical condition assessment of motors. Seven main diagnostic parameters were selected in the study. The technical condition of a traction electric motor at a discrete time, a vector of monitored parameters describes instant t:

$$x(t)=[U(t), I(t), T_s(t), T_b(t), v(t), n(t), B(t)]^T \tag{1}$$

where
$U(t)$ is the voltage,
$I(t)$ is the current,
$T_s(t)$ is the stator temperature,
$T_b(t)$ is the bearing temperature,
$v(t)$ is the vibration level,
$n(t)$ is the noise level,
$B(t)$ is the magnetic field between the rotor and stator.

Table 1. Technical characteristics of the traction motor

Designation	6 FRA 4567 H
Type	Asynchronous, 6 poles, squirrel cage
Continuous rating	1122 kW
Voltage (phase and phase-to-phase)	810 / 1403 V
Current	551,5 A
Speed	1153 rpm
Frequency	58,5 Hz
Speed range	0 - 2768 rpm

The parameter vector is updated at a constant sampling interval Δt, as defined by the monitoring system.
The proposed approach envisioned the use of primarily standard sensors or interoperable measuring instruments suitable for integration into the locomotive's onboard diagnostic system architecture and standard SCADA/PLC interfaces.
To monitor the vibration condition of bearing assemblies, the installation of sensors near the bearing housings was considered. This allows for recording changes in the vibration response without significant design modifications. However, the specific implementation of such an installation is determined by the locomotive's design features and should be refined through pilot integration. The

assessment showed that incorporating the proposed diagnostic parameters and ranges into the locomotive's standard system is technically feasible, although it requires adapting threshold levels, standardizing signal formats, and configuring data exchange with the existing monitoring system

The allowable, warning, and dangerous value ranges of these operating parameters were determined and included in the system (Table 2).

To ensure comparability between heterogeneous physical quantities, each diagnostic parameter $x_i(t)$ is transformed into a dimensionless **local health index** $h_i(t) \in [0,1]$, which reflects the degree of deviation from normal operating conditions.

For each parameter, three threshold levels are defined based on regulatory limits and expert knowledge: a_i - allowable limit, w_i - warning limit, d_i - dangerous limit. The threshold values presented in Table 2 were adopted based on manufacturer technical specifications, railway maintenance regulations, and expert calibration using operational experience.

The local health index is defined using a continuous piecewise-linear mapping:

where α∈ (0,1) denotes the health index value at the warning threshold. In this study, α=0.5.

$$h_i(t) = \begin{cases} 1, & x_i(t) \le a_i, \\ 1 - \dfrac{x_i(t) - a_i}{\omega_i - a_i}(1 - a), & a_i < x_i(t) \le \omega_i \\ a - \dfrac{x_i(t) - \omega_i}{d_i - \omega_i} a, & \omega_i < x_i(t) \le d_i, \\ 0, & x_i(t) > d_i, \end{cases} \quad (2)$$

This formulation guarantees continuity of the health function, preserves physical interpretability, and ensures direct consistency with engineering threshold values.

The selected diagnostic parameters represent complementary physical domains and jointly enable a comprehensive assessment of traction motor technical condition. Electrical parameters (voltage and current) reflect operating stability and loading conditions, while thermal parameters (stator and bearing temperatures) provide information on insulation ageing, friction effects, and prolonged overloads. Mechanical and acoustic indicators, represented by vibration and noise levels, are particularly sensitive to early-stage bearing defects, rotor imbalance, and mechanical wear. In addition, variations in the magnetic field distribution between the rotor and stator capture electromagnetic asymmetries associated with rotor faults, short circuits, and harmonic distortions. The simultaneous analysis of these heterogeneous parameters significantly enhances diagnostic reliability, as certain fault types may not be detectable using individual indicators. Their combined evaluation reduces diagnostic uncertainty and enables earlier identification of degradation processes than single-parameter monitoring.

Experimental data for traction motor condition assessment are obtained from onboard sensors and the SCADA-based monitoring system operating in real time. The data acquisition process uses a fixed sampling interval Δt, selected to ensure a timely diagnostic response while remaining compatible with typical SCADA system constraints.

The monitored signals include electrical, thermal, mechanical, acoustic, and magnetic parameters, namely voltage, current, stator temperature, bearing temperature, vibration level, noise level, and magnetic field intensity. All measurements are time-synchronized and combined into a unified diagnostic feature vector $x(t)$.

Table 2. Normal and limit values of selected parameters of the traction motor

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
Bearing temperature	t < 90°C	90-110°C	t > 110°C
Vibration level	υ < 2.0 mm/s	2.0-3.0 mm/s	υ >3.0 mm/s
Noise level	ν < 95 dB	95-105 dB	ν > 105 dB
Magnetic field	B < 0.5 Tl	0.5-1.2 Tl	B > 1.2 Tl

To ensure the robustness and reliability of the proposed diagnostic model, the raw measurement data undergo preliminary preprocessing before health index computation. This preprocessing includes noise filtering, consistency checking, and normalization to eliminate spurious fluctuations and measurement artefacts. In cases of missing or corrupted samples, interpolation or exclusion is applied depending on the duration and impact of the data loss.

These preprocessing procedures reduce the influence of measurement noise and transient disturbances, providing stable, consistent inputs for subsequent calculations of local health indices and the integral health index.

The correlation weights and relative significance of diagnostic parameters were determined using a comprehensive approach that included analysis of scientific sources, expert assessment of electrical machine failure mechanisms, and statistical processing of data obtained from modeling in the TIA Portal environment.

To account for the unequal diagnostic significance of individual parameters, a weighted aggregation scheme is employed.

Let *y(t)* denote a degradation indicator representing the technical condition of the motor (e.g., discrete condition classes or a continuous severity score). For each parameter $x_i(t)$, the absolute value of the Pearson correlation coefficient is calculated:

$$r_i = |corr(x_i(t), y(t))| \quad (3)$$

The weighting coefficients are obtained by normalisation:

$$\omega_i = \frac{r_i}{\sum_{j=1}^{7} r_j}, \quad \sum_{j=1}^{7} \omega_i = 1 \quad (4)$$

This approach assigns stronger influence to parameters that exhibit stronger statistical dependence on the degradation process and ensures a reasonable distribution of the diagnostic contribution of each parameter to the final traction motor technical condition indicator.

After selecting the diagnostic parameters, an analysis was performed of the relationship between the main traction motor failures and changes in the diagnosed parameters. For each parameter, the frequency with which it reflected various types of defects was determined, as well as the early stage of damage development. The obtained results formed the basis for a preliminary expert assessment of the parameter significance.

To quantify the influence of each parameter on the traction motor's technical condition, the Pearson correlation coefficient was used. The modeling generated data sets reflecting the behavior of parameters in three diagnostic states: “Acceptable”, “Warning”, and “Dangerous”. For each parameter, the correlation coefficient between its change and the level of traction motor degradation was calculated.

The resulting correlation matrix allowed us to determine how linearly and consistently each parameter reflected the deterioration in technical condition. Parameters characterizing long-term thermal processes and mechanical failures typically demonstrated the highest absolute correlation values.

Field tests on real locomotives were limited pilot tests and were used primarily to verify the correctness of diagnostic data collection, transmission, and display, while the primary evaluation of the diagnostic logic was performed in a simulated environment.

Figure 1 illustrates the Pearson correlation matrix among the monitored diagnostic parameters. The matrix is provided for interpretability purposes, highlighting interdependencies between electrical, thermal, mechanical, acoustic, and magnetic indicators under different operating conditions.

It should be noted that the correlations shown in Figure 1 describe relationships between the diagnostic parameters themselves and are not directly used for diagnostic decision-making. The weighting coefficients employed in the computation of the integral health index are derived from correlations between individual parameters and the degradation indicator. Consequently, the correlation matrix serves as a complementary analytical tool rather than a basis for parameter weighting. (Alaswed et al., 2025; Bhoi et al., 2024; Gozali et al., 2025; Kostrzewski et al., 2021; Kunthong et al., 2017; Manafov et al., 2026).

Table 3 presents the Pearson correlation coefficients between each diagnostic parameter and the degradation indicator, as well as the normalized weights used in calculating the integral technical condition index. This table complements Figure 1, which reflects the cross-correlations between the parameters and is interpretative in nature, but is not directly used in calculating the weights.

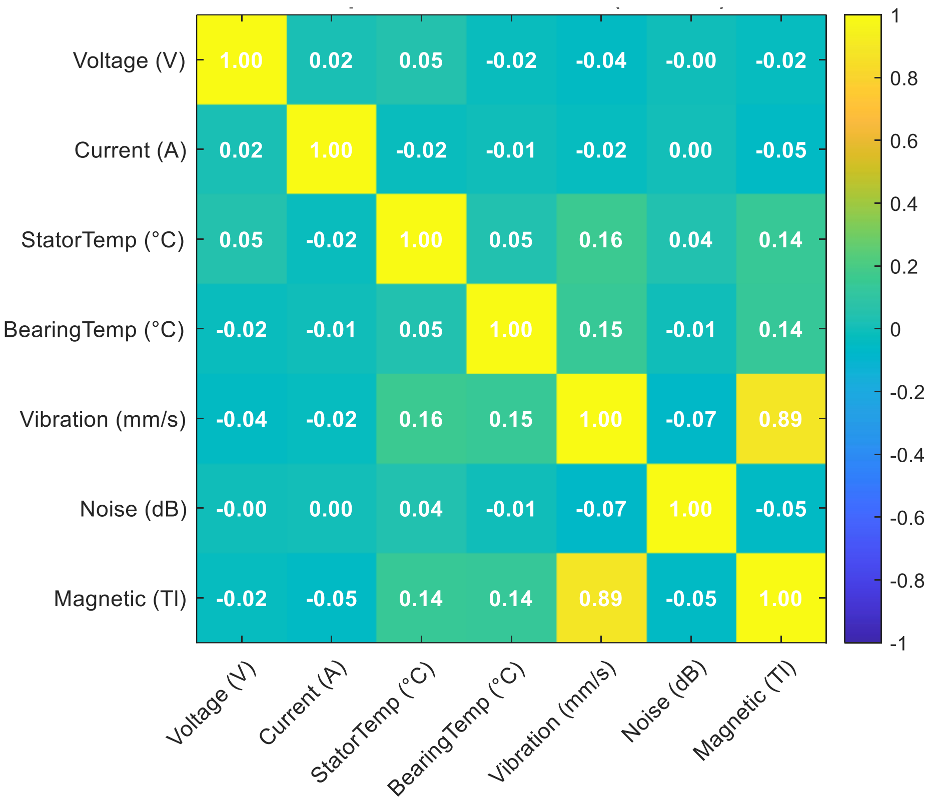

Fig. 1. Pearson correlation matrix of diagnostic parameters

Table 3. Pearson correlation coefficients and normalized weights of diagnostic parameters

Parameters	**Pearson correlation coefficient with a degradation indicator |*r*|**	**Standardized weight *(w_i)***
Voltage	0.44	0.093
Current	0.52	0.110
Stator temperature	0.71	0.150
Bearing temperature	0.93	0.196
Vibration level	0.96	0.203
Noise level	0.64	0.135
Magnetic field	0.53	0.112
Total		**1.000**

The correlation coefficient values were converted into normalized weighting factors used in calculating the integral technical condition indicator in the SCADA system. Parameters with a high correlation level were assigned a high diagnostic weight, parameters with a medium correlation were assigned a medium weight, and less informative signals were assigned a low weight. This principle enables the formation of a final traction motor technical condition indicator that takes into account the actual diagnostic significance of each parameter, and also reduces the influence of parameters sensitive to operating technical conditions but less closely associated with failures.

The overall technical condition of the traction motor is characterised by an **integral health index**:

$$HI(t) = \sum_{i=1}^{7} \omega_i h_i(t) \tag{5}$$

To reduce sensitivity to measurement noise and short-term fluctuations, exponential smoothing is applied:

$$\tilde{HI}(t) = \beta \tilde{HI}(t - \Delta t) + (1 - \beta) HI(t) \tag{6}$$

where $\beta \in [0,1]$ is the smoothing coefficient.

Based on the smoothed health index $\tilde{HI}(t)$, the technical condition of the traction motor is classified into three discrete states:

$$Condition(t) = \begin{cases} Normal, & \tilde{HI}(t) \geq \tau_A, \\ Warning, & \tau_D < \tilde{HI}(t) < \tau_A, \\ Critical, & \tilde{HI}(t) \leq \tau_D, \end{cases} \tag{7}$$

where τ_A and τ_D are predefined decision thresholds.

To ensure operational safety, a conservative override rule is introduced. If at least one diagnostic parameter exceeds its dangerous limit d_i, the condition is immediately classified as **Critical**, regardless of the integral index value.

To prevent unstable switching between states, condition transitions are confirmed only after persistence over N consecutive sampling intervals; hysteresis is applied when returning to less severe states.

The dataset used for model development and validation consists of time-series measurements collected from traction motors operating under both normal and degraded conditions. The data include measurements from $N_m=4$ traction motors with a total recording duration of approximately $T_{total}=72$ hours. After preprocessing and synchronization, the dataset contains $N=129\ 600$ valid time samples with a uniform sampling interval $\Delta t=2$ *sec*. Of these, approximately 30% were real operational measurements obtained during normal locomotive operation, while the remaining 70% were generated as controlled degradation scenarios in the Siemens TIA Portal simulation environment. The simulated scenarios were used to represent warning and critical conditions that are difficult or unsafe to reproduce during real locomotive operation.

Diagnostic Algorithm for Traction Motor Condition Assessment.

Input:

Diagnostic parameter vector $x(t)$;
thresholds a_i, w_i, d_i;
weights w_i;
decision thresholds τ_A, τ_D;
smoothing coefficient β;
persistence length N.

Output:

Technical condition class C(t)∈{Normal, Warning, Critical}.

The diagnostic procedure can be summarised as follows:

– **Acquire data.** Measure diagnostic parameters and form vector $x(t)$.
– *Check safety limits.*

If $\exists i : x_i(t) > d_i$, *then set C(t)=Critical and go to Step 7.*

– **Compute local health indices.** For each parameter $x_i(t)$, compute $h_i(t)$ using *Eq. (X)*.
– *Compute integral health index*

$$\boldsymbol{HI(t) = \sum_{i=1}^{7} \omega_i h_i(t)}$$

– *Apply temporal smoothing*

$$\boldsymbol{\tilde{HI}(t) = \beta \tilde{HI}(t - \Delta t) + (1 - \beta) HI(t)}$$

– *Classify technical condition*

If $\boldsymbol{\tilde{HI}(t) \geq \tau_A}$, then $C(t) = Normal$;
else if $\boldsymbol{\tau_D < \tilde{HI}(t) < \tau_A}$, then$C(t) = Warning$;
else$C(t) = Critical$.

– **Apply persistence rule.** Confirm state C(t) only if it persists for N consecutive samples.
– **Output diagnostic decision.** Output condition class and diagnostic signal.

Figure 2 shows the correlation weights of each monitored parameter with a specific fault index of the traction motor. The analysis shows that for the fault under consideration, vibration and bearing temperature have the highest correlation coefficients, indicating their dominance in early detection of mechanical faults. The noise level and magnetic field parameters exhibit significant weights, especially in determining rotor unbalance and harmonic distortion. Voltage and current exhibit moderate correlations, mainly serving as auxiliary indicators to confirm electrical faults. Operating parameter weights based on fault correlation have been determined for many faults (Ahmadov et al., 2025; Heisei et al., 2021; Siddiqui et al., 2014; Yin et al., 2023).

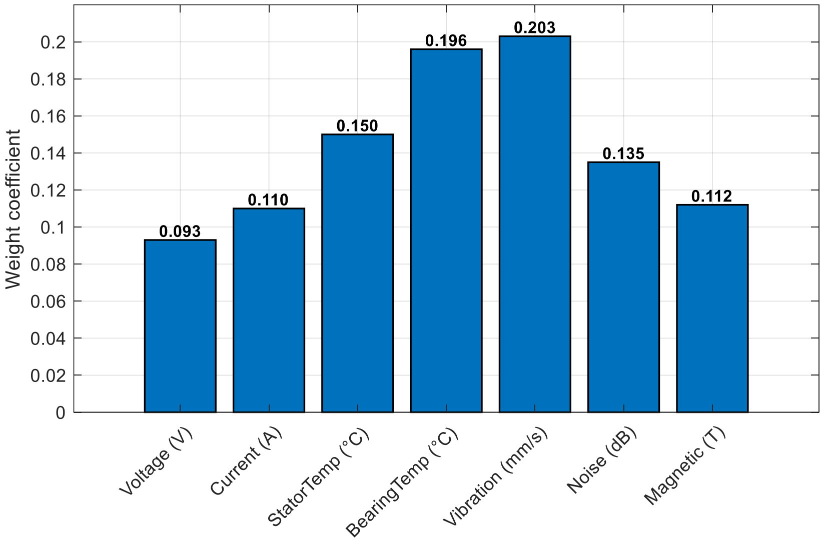

Fig. 2. Operating parameter weights based on fault correlation

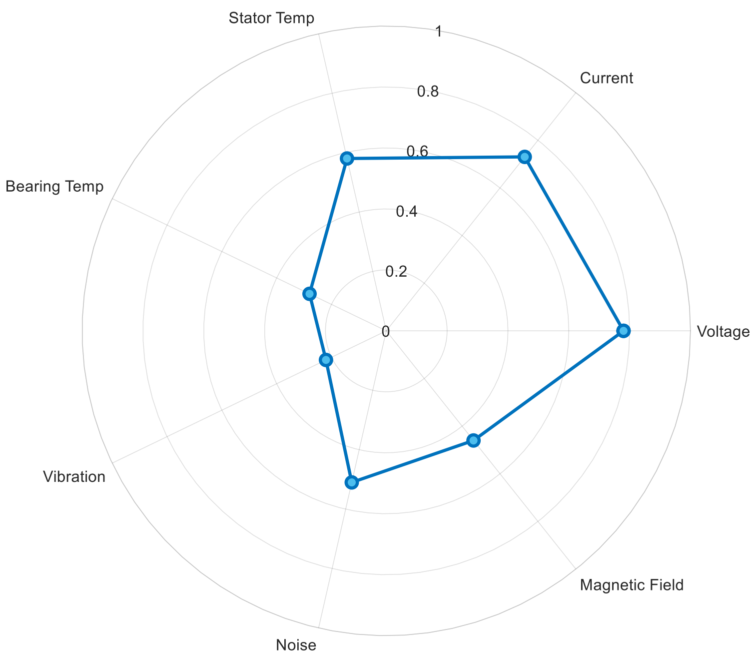

Fig. 3. Health index radar diagram

These results demonstrate that evaluating multiple electrical, thermal, mechanical, and magnetic parameters simultaneously provides a more accurate assessment of the traction motor's technical condition than single-parameter monitoring. Mechanical and thermal indicators provide the earliest signs of degradation, while electrical and magnetic indicators help to confirm diagnostic results. Consequently, the integration of these correlated weighting factors into SCADA-based diagnostic logic provides higher reliability and predictability in fault detection. The proposed methodology provides a scientifically substantiated distribution of diagnostic parameter contributions, combining expert knowledge of failure mechanisms and quantitative statistical assessment, and serves as the basis for building a reliable and robust real-time traction motor technical condition monitoring system.
Figure 3 shows a radar diagram of the standardized condition indices for the main diagnostic parameters of a traction motor. The resulting profile shows that the greatest deterioration is observed for bearing vibration and temperature, which is consistent with the results of the correlation analysis and the weighting factors presented in Table 3. At the same time, voltage and current parameters maintain relatively high condition index values, indicating their lower sensitivity to the degradation scenario under consideration. Thus, the radar diagram clearly confirms that bearing vibration and temperature are the most informative indicators for detecting deterioration in the technical condition of a traction motor. This radar-based representation improves interpretability by providing a compact visualization of multi-parameter interactions and complements the quantitative diagnostic model described earlier.
To quantitatively confirm the diagnostic effectiveness of the proposed approach, a formal assessment of the classification quality was conducted using a confusion matrix and standard statistical metrics. The model's output diagnostic solutions were compared with reference classes corresponding to three traction motor technical conditions: "Normal," "Warning," and "Critical."
The confusion matrix, presented in Figure 4, demonstrates that the majority of samples were correctly assigned to the corresponding classes, while the number of classification errors remains insignificant and is primarily associated with transient conditions near the decision boundaries. The overall classification accuracy was 91.67%, confirming the high reliability of the proposed model. Additionally, the calculated precision, recall, and F1-score metrics demonstrate reliable and balanced recognition of all conditions under consideration. The results of the quantitative assessment of the classification quality are presented in Figure 4.
Table 4 presents the quantitative classification performance metrics calculated for the three-state diagnostic model. Analysis of precision, recall, and F1-score values shows that the proposed approach provides the most reliable recognition of normal and critical traction motor states. The somewhat lower metric values for the warning state are due to its intermediate position between the normal and critical modes, which objectively complicates the classification procedure. Nevertheless, even for this class, the achieved performance remains quite high, and the overall accuracy of 91.7% confirms the practical applicability and statistical validity of the proposed diagnostic model.

Table 4. Classification performance indicators of the diagnostic model

Diagnostic state	**Precision**	**Recall**	**F1-score**
Normal	0.940	0.940	0.940
Warning	0.898	0.880	0.889
Critical	0.912	0.930	0.921
Overall accuracy			**0.917**

The research methodology consists of several stages. First, sensor signals programmed in Ladder Diagram (LD) language in the TIA Portal environment are obtained through Siemens PLC controllers for the collection of selected parameters. Appropriate sensors are installed for each parameter: temperature sensors for stator and bearing, an accelerometer for vibration, a microphone for noise analysis, Hall effect or magnetic sensors for magnetic field measurement, and electrical measurement modules for current and voltage. The collected data is visualized in real time on the HMI panel via WinCC interface and reflected on the dashboards of the locomotive driver and dispatch center (Figure 5).
In the second stage, real-time monitoring of parameters and detection of abnormalities are carried out. Bases are created for normal and abnormal operating modes, and the type and severity of faults are determined by applying correlation and statistical analysis

methods between parameters. More accurate diagnostics are provided by combining vibration, temperature, and magnetic field signals with voltage and current changes (Blessed et al., 2025; Garramiola et al., 2018; Guliyev et al., 2026; Karmakar et al., 2016; Sun et al., 2024).

In the final stage, the results of real-time analysis are integrated into an automatic warning module. This module ensures early detection of faults and implementation of preventive maintenance. The proposed methodology, overcoming the limitations of existing SCADA systems, provides multi-parameter real-time diagnostics of locomotive traction motors, allowing for timely detection of faults and optimization of maintenance. Unlike traditional SCADA systems that analyze voltage, current, and temperature independently, the proposed system uses a multiparameter, correlation-based diagnostic model that combines electrical, mechanical, thermal, and magnetic parameters in real-time. Several research studies were reviewed, and comparative analyses were conducted to assess the advantages of the proposed diagnostic approach. The comparison criteria included the number of monitored parameters, data update rate (response time), diagnostic accuracy, and the presence of predictive analysis features (Dattatraya et al., 2024; Doorsamy, W., 2025; Mosleh et al., 2024). The results are presented in Table 5.

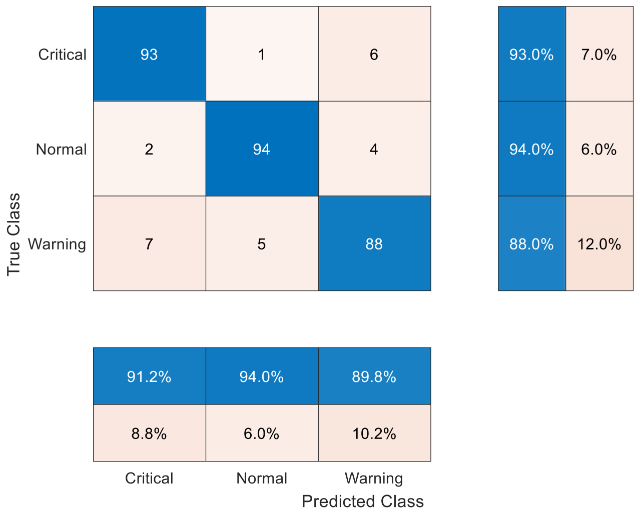

Fig. 4. Confusion matrix of the proposed three-state diagnostic model for traction motor condition classification

Table 5. Comparative analysis of SCADA-based diagnostic systems

Study	Number of monitored parameters	Data update	Diagnostic accuracy	Predictive analysis	Main characteristics
Siddiqui et al. (2014)	3 (current, voltage, temperature)	5–10 s	70%	No	Conventional SCADA; limited signal set
Karmakar et al. (2016)	4 (electrical and thermal parameters)	3–5 s	75%	Partial	Basic alarm logic; low signal correlation
Garramiola et al. (2018)	5 (vibration, current, temperature, noise, rotor current)	2–3 s	82%	Limited	Threshold-based fault recognition
Tomar et al. (2022)	6 (electrical, vibrational, thermal)	2 s	88%	Partial	Statistical correlation analysis implemented
Proposed system (2025)	7 (voltage, current, stator temp., bearing temp., vibration, noise, magnetic field)	< 2 s	90–95%	Yes (correlation-predictive model)	Integrated Siemens TIA Portal + WinCC SCADA; automatic classification "Allowable–Warning–Dangerous."

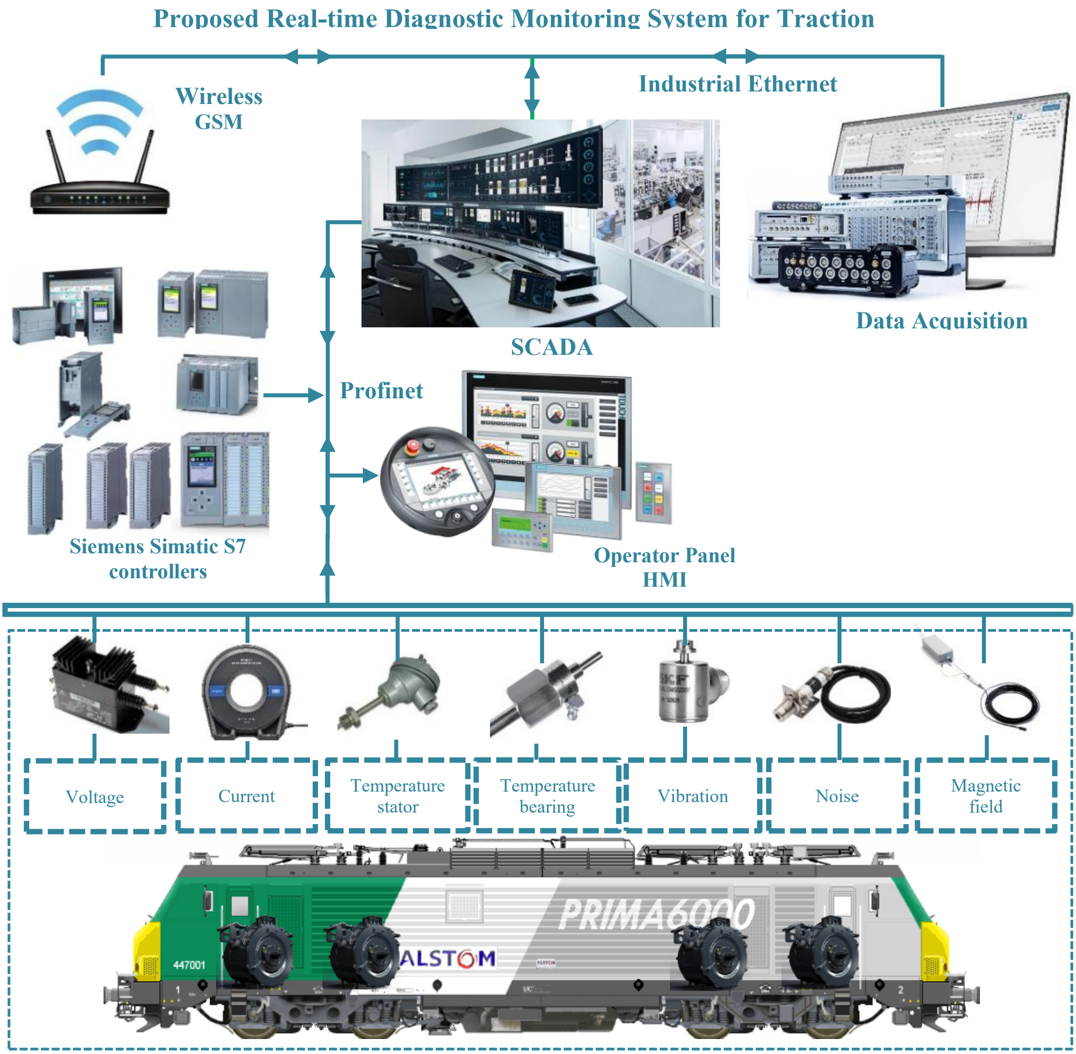

Fig. 5. Model of the proposed real-time diagnostic system of a traction motor

The results show that the proposed system outperforms existing approaches in terms of the number of diagnostic parameters, real-time response speed, and diagnostic accuracy. Unlike traditional SCADA systems based on limit value control, the presented multi-parameter model combines electrical, thermal, mechanical, and magnetic parameters and supports predictive detection of faults. This is an important step towards intelligent and autonomous control of locomotives (Gorobchenko et al., 2024; Manafov et al., 2025; Szkoda et al., 2020).

3. Modeling and simulation

Modeling and simulation were employed to validate the proposed multi-parameter diagnostic model under controlled and reproducible conditions. The primary objective of this stage was not the verification of specific hardware or control logic, but the assessment of the diagnostic model's ability to correctly identify and distinguish different traction motor condition states based on multi-parameter inputs.

The simulation environment was implemented using an industrial SCADA development platform that supports real-time signal generation, parameter manipulation, and logical condition emulation. This environment was selected because it allows a realistic representation of traction motor operating conditions while ensuring repeatability of diagnostic scenarios. The simulation platform served as a virtual test bench for the proposed diagnostic methodology.

The key objectives of the simulation stage were:

- to reproduce representative operating conditions corresponding to normal, degraded, and critical traction motor states;
- to evaluate the behavior of local health indices and the integral health index under parameter deviations;
- to verify the stability of the diagnostic decision logic under transient conditions;
- to assess the consistency of the classification results with predefined degradation scenarios.

Simulation scenarios were designed to represent three predefined technical condition classes: Normal, Warning, and Critical. For each scenario, a time series of diagnostic parameters was generated in accordance with the threshold ranges defined in the above section.

Normal operating scenarios were characterized by parameter values remaining within allowable limits with moderate stochastic fluctuations, representing typical variations caused by load changes and measurement noise. Warning scenarios were generated by gradually shifting selected parameters into the warning range, simulating early-stage degradation processes such as bearing wear, increased friction, or thermal overload. Critical scenarios were modeled by forcing one or more parameters to exceed dangerous thresholds, representing severe fault conditions that require immediate intervention.

Both single-parameter and multi-parameter degradation patterns were considered. This allowed evaluation of the diagnostic model's response not only to isolated parameter violations, but also to combined fault manifestations, which are common in real traction motor operation.

For each simulation scenario, local health indices were computed for all diagnostic parameters, followed by the calculation of the integral health index using the correlation-based weighting scheme. The evolution of the integral health index was analyzed with respect to parameter changes and compared with the expected condition class.

The simulation results demonstrated that the integral health index decreases monotonically as operating conditions deteriorate, providing a consistent and interpretable representation of traction motor health. In warning scenarios, the index exhibited a gradual decline, enabling early detection of degradation before critical thresholds were reached. In critical scenarios, the index dropped sharply, triggering the appropriate diagnostic classification.

Temporal smoothing and persistence rules were observed to effectively suppress false alarms caused by short-term parameter fluctuations, while maintaining sufficient responsiveness to sustained degradation.

The simulation environment enabled systematic verification of the diagnostic decision logic. State transitions between Normal, Warning, and Critical conditions were analyzed under controlled parameter changes. The results confirmed that the proposed logic correctly classifies motor condition based on the integral health index and enforces conservative safety rules when dangerous thresholds are exceeded.

Special attention was given to transient conditions occurring near decision boundaries. The applied persistence and hysteresis mechanisms prevented unstable switching between states and ensured robust diagnostic behavior, which is essential for practical railway applications.

The modeling and simulation stage provided a controlled framework for validating the internal consistency, stability, and interpretability of the proposed diagnostic model. By separating diagnostic logic verification from long-term field operation, this approach enabled systematic testing of a wide range of degradation scenarios that are difficult or unsafe to reproduce during real locomotive operation.

While the simulation results confirm the feasibility and robustness of the proposed diagnostic approach, long-term validation using operational data from traction motors under real service conditions remains a necessary step for future research.

At this stage, the Siemens TIA Portal software package was selected, since this platform offers both programming and simulation capabilities and allows for effective testing of real PLC solutions (Ghazali et al., 2026; Mitra et al., 2016; Phanthanachai et al., 2023; Tomar et al., 2023. Previous studies have shown that establishing a PLC-HMI connection over Profinet improves the system response time and supports real-time diagnostics (Guillén et al., 2025; Nguyen et al., 2025; Sainz-Aja et al., 2025; Tomar et al., 2022; Mishra et al., 2021;. Tai et al., 2026).

Thanks to this modeling stage, the functional parameters of the system were simulated, and optimizations were made to prevent potential failures and minimize operator intervention. As a result, the system implemented with PLC-HMI integration provided an effective solution in the fields of control, monitoring, and data recording.

The program written in LD language in Figure 6 is designed for processing analog signals and controlling the motor operating mode. It reads the analog current signal after starting the motor, passes it through the normalization and scaling stages, and then controls the output variables by comparing it with certain ranges in real time.

The following figure (Figure 7) shows a visual control panel built using the Siemens SIMATIC HMI interface.

The novelty of the proposed system lies in the transition from traditional threshold-based SCADA monitoring to a fully integrated, correlation-driven multi-parameter diagnostic model that simultaneously analyzes electrical, thermal, mechanical, acoustic, and magnetic indicators of traction motors. Existing SCADA solutions used in locomotive monitoring typically observe only a limited set of low-frequency parameters—mainly current, voltage, and basic temperature readings and treat them independently, which restricts their ability to identify complex or early-stage faults.

In contrast, the developed system introduces three fundamentally new elements that are absent in current industrial implementations:

1. a unified acquisition and analysis framework for seven diagnostic parameters, enabling synchronous multi-domain assessment of motor condition;
2. a data-driven correlation weighting method (based on Pearson coefficients) that quantifies the diagnostic significance of each parameter and captures cross-parameter relationships overlooked by conventional SCADA logic;
3. a real-time health index integrated into the PLC–HMI environment, which automatically classifies motor condition (“Allowable–Warning–Dangerous”) and provides an interpretable visualization for operators and dispatch centers.

This combination of multi-domain sensing, correlation-based analytics, and real-time interpretive diagnostics clearly differentiates the proposed solution from existing SCADA systems, which lack both multi-parameter integration and predictive diagnostic capabilities. As a result, the system enables earlier detection of mechanical and electromechanical faults, improved reliability, and stronger support for preventive maintenance strategies.

4. Limitations and future work

Despite the obtained results, the study has several limitations. First of all, the validation of the proposed diagnostic model was mixed: along with limited real-world operational measurements, a significant portion of the degradation scenarios were reproduced in the Siemens TIA Portal environment. This allowed the algorithm's performance to be verified under controlled conditions, but does not replace lengthy, full-scale testing on a real fleet of locomotives.

A second limitation relates to the size and structure of the available dataset. Although the article presents formal classification quality metrics, including confusion matrix, precision, recall, F1-score, and overall accuracy, the obtained results should be viewed as confirmation of the approach's performance at the pilot/proof-of-concept stage, rather than as final operational validation.

A third limitation concerns the composition of the diagnostic parameters and the correlation-weighted approach used. The proposed model covers key electrical, thermal, mechanical, acoustic, and magnetic parameters, but with more real-world data, the composition of the features and weighting coefficients can be refined.

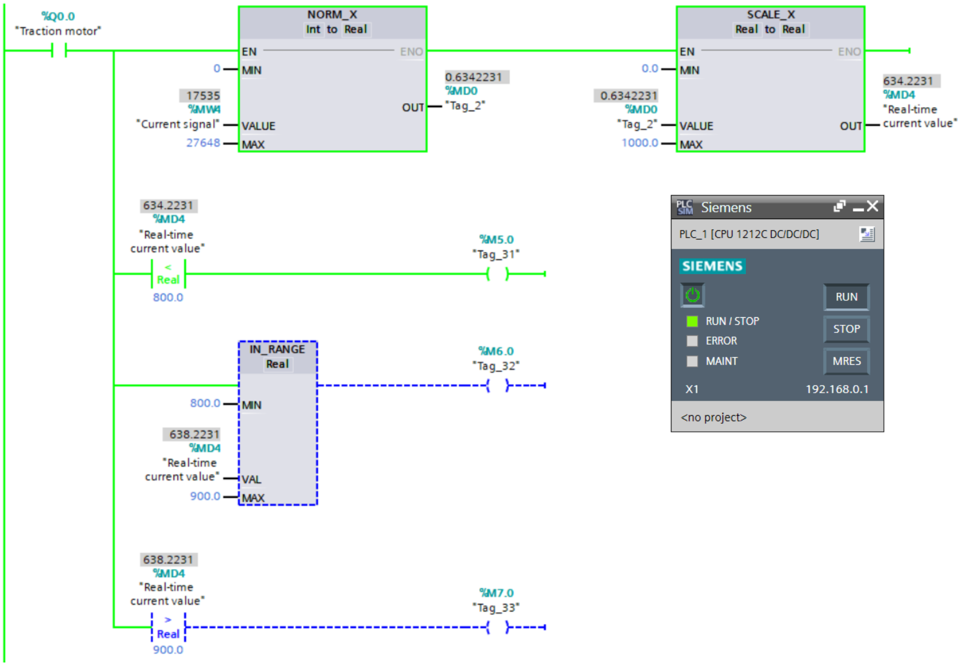

Fig. 6. Real-time control of the current value and processing of decisions under various conditions

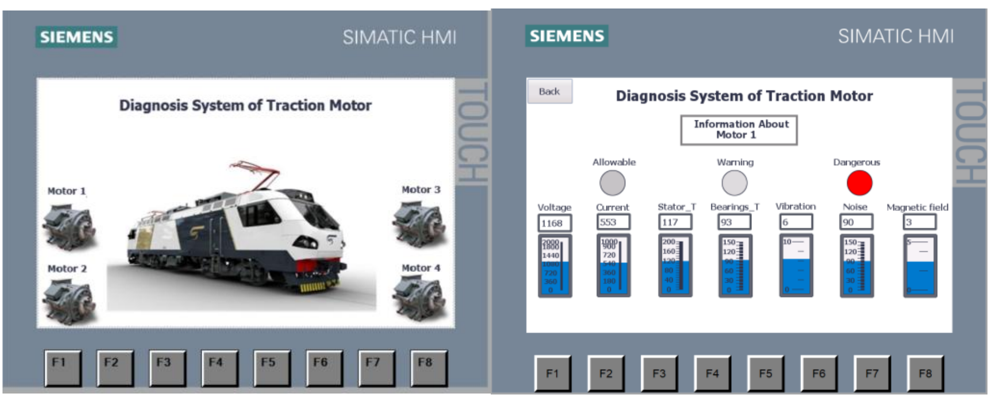

Fig. 7. Main screen view of the HMI panel and visual view of the real-time control panel of motor 1

Therefore, further work should focus on long-term field validation on real locomotives, expanding the set of diagnostic features, and adapting the model based on more representative operational data.

5. Conclusion

Unlike traditional monitoring systems based on independent monitoring of a limited number of electrical and thermal parameters, the proposed approach integrates electrical, thermal, mechanical, acoustic, and magnetic indicators into a single condition assessment framework. The scientific novelty of this work lies in the use of normalized local condition indices, correlation weighting of diagnostic parameters, and an integral technical condition index with explicitly defined decision-making logic suitable for interpretable and reproducible implementation in a SCADA/PLC environment. A correlation analysis revealed that parameters related to mechanical and thermal processes, primarily vibration and bearing assembly temperature, possess the greatest diagnostic significance, while electrical and magnetic parameters serve a complementary and confirmatory function. Another important result of the study was the introduction of a formal quantitative assessment of the classification quality performed using the confusion matrix, precision, recall, F1-score, and overall accuracy, which increased the scientific rigor of the presented diagnostic model. However, the article demonstrates that the experimental validation was mixed: limited field tests on real locomotives were used primarily to confirm the operability of the data collection, transmission, and visualization architecture, while the main verification of the diagnostic logic and degradation scenarios was performed in the simulated Siemens TIA Portal environment. Therefore, the obtained results should be interpreted as confirmation of the operability and internal consistency of the proposed approach within the framework of a pilot/proof-of-concept study, rather than as a complete full-scale operational validation. The practical significance of the work lies in the fact that the proposed methodology can be integrated into the existing SCADA infrastructure of railway transport without significantly complicating the computational logic and can be used for earlier detection of degradation processes and support for preventive maintenance decisions.

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