

Article

Exploratory Study of Triple-Entry Data (X-STATIS) for the Evaluation of Energy Quality in Induction Motors Under Simulated Faults

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Abstract

Energy, conceived as an essential element for economic and social progress, underpins the manufacture of products, transport, the provision of basic needs and, consequently, the improvement of society's well-being. Within this framework, three-phase induction motors (MIT) play a key role in industrial processes. However, these devices can suffer from various types of faults that negatively affect their performance and durability, including deterioration of the stator winding and obstruction of the cooling system. This research focuses on the analysis of various operating conditions of induction motors through the application of the X-STATIS statistical technique, with the aim of determining the capacity of electrical and mechanical indicators to detect faults. To this end, eight experimental situations were considered: one corresponding to normal operating conditions and seven associated with induced faults, evaluated under six different voltage levels. The variables recorded included three-phase current, efficiency, torque, and speed, organized into a data cube consisting of six tables, one for each voltage level, analyzed in the RStudio environment. The study of the interstructure allowed us to identify two main behavioral trends: a set of faults consisting of ROT2, INS4 and INS5, and another consisting of NON1, MECH6, MECH7, VENT8 and STA3. This classification was validated by high RV coefficient values, above 0.91, which shows high structural consistency between the different simulated scenarios. In the engagement stage, significant positive correlations were observed between phase currents (CF1, CF2 and CF3) and torque (TOR), as well as an inverse relationship between speed (SPE) and torque. Efficiency (EFF), on the other hand, showed a different behavior, with a greater association with high voltage levels (V4 and V5), highlighting its sensitivity to conditions close to the nominal load. Finally, the analysis of the internal structure allowed the projection of the different failure conditions within the space defined by the compromise to be examined.

Keywords: induction motor; X-STATIS; exploratory analysis; failure; system; efficiency



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1. Introduction

Energy, understood as a fundamental pillar for economic and social development, is the basis for the production of goods, mobility, the satisfaction of needs, and, therefore, the

improvement of people's quality of life [1–3]. Among its various manifestations, mechanical energy is one of the most widely used forms in production systems and can be generated from different sources [4], with conversion from electrical energy being one of the most common, especially through devices such as electric motors. This conversion is essential for powering machinery, transportation systems, and continuous industrial processes, promoting operational efficiency and productivity [5,6].

Induction motors (IM) are the backbone of the industrial sector [7]. It is estimated that this equipment is responsible for approximately 68% of the industrial sector's energy consumption worldwide [8]. In particular, three-phase induction motors (IM) are electromechanical converters of alternating current designed to transform electrical energy into rotational mechanical energy [9], usually integrated into complex production systems [10,11]. Their operation is based on electromagnetic induction described by Faraday's law, whereby electromagnetic energy is transferred from the stator to the rotor by induction, thus generating the torque necessary for the shaft to rotate [12]. Thanks to their robustness, low cost, and ease of maintenance, these motors are the most widely used technology in industry, accounting for nearly 50% of global electricity demand [13,14]. However, their continuous operation exposes them to progressive degradation and various failures that affect their efficiency and service life.

An induction motor is composed of electrical and mechanical elements such as a stator, rotor, windings, bearings, and structural frame. Failures can be classified as stator defects, air gap irregularities, rotor cage damage, and bearing wear, with the latter two accounting for a significant proportion of reported events. These anomalies manifest themselves in voltage and current imbalances, increased losses, reduced torque, elevated temperatures, and decreased energy efficiency [15]. Consequently, motor reliability and protection depend on continuous and accurate monitoring of its operating status [16], as early fault detection helps to minimize downtime and maintenance costs [17]. For this reason, the diagnosis and monitoring of faults in three-phase induction motors (IM) have been an active area of research for decades [18,19].

Multiple diagnostic strategies based on electrical, thermal, and mechanical signals have been proposed for anomaly detection. Among the most widely used are motor current signature analysis (MCSA), vibration monitoring, harmonic spectral analysis, as well as statistical and machine learning approaches such as principal component analysis (PCA), clustering methods, and supervised classifiers [20,21]. While these techniques have proven effective in identifying specific faults, most analyze operating conditions independently or through two-dimensional reductions, making it difficult to simultaneously compare multiple experimental scenarios and jointly integrate different voltage levels, electrical and mechanical variables within the same analytical structure.

In this regard, data mining and multivariate methods offer suitable tools for exploring complex structures and hidden relationships in high-dimensional data sets [22–25]. Although developed in other experimental domains, linear discriminant analysis and distance-based clustering have also demonstrated their usefulness for distinguishing experimental conditions and revealing latent groupings in multivariable datasets. In particular, multitable approaches allow information to be organized into data cubes (individuals $\times$ variables $\times$ conditions) and the variability shared between different experimental scenarios to be analyzed in an integrated manner.

Parallel Table Analysis (PTA), also known as X-STATIS, is a multivariate algorithm designed to simultaneously compare a set of K matrices with the same number of individuals and variables, forming a data cube [26,27]. The method is developed in three complementary stages: the interstructure, which evaluates the overall similarity between tables using RV coefficients; the compromise, where a weighted average table of maximum

inertia is constructed, to which PCA is applied to define a common factorial space; and the intrastructure, which projects each individual table as a supplementary element in that space [28,29]. These characteristics allow the identification of global patterns, trajectories, and stable groupings between multiple operating conditions.

In particular, the X-STATIS framework makes it possible to simultaneously integrate multiple stress regimes within a single multi-table structure, preserving the joint information between electrical and mechanical variables. Unlike conventional PCA, which analyzes each operating condition independently, this approach extracts common patterns and fault clusters that remain stable across all operating levels, providing a structural view that complements traditional diagnostic methods.

Despite these advantages, the application of X-STATIS to the diagnosis of faults in induction motors, especially under multi-voltage configurations, has been scarcely reported in the literature. In this context, this study proposes to analyze operating cubes corresponding to different voltage levels and fault scenarios using X-STATIS, integrating electrical and mechanical indicators within a unified multivariate framework. The main contributions of this work are twofold: (i) A novel and systematic application of X-STATIS/PTA to compare multivoltage operating cubes of fault scenarios in induction motors and derive consistent fault groupings, extending previous methodological developments in multitable analysis [26,29,30]; and (ii) the demonstration that this approach complements standard techniques such as MCSA, negative sequence metrics, and PCA by offering a comprehensive and integrated interpretation of system behavior. These contributions establish an exploratory basis for early screening and structural characterization of anomalies in industrial motors.

2. Materials and Methods

The objective of this research was to analyze the electromechanical behavior of a three-phase induction motor (1.1 kW, four poles, 220–240/380–415 V, 50 Hz; product code 10592549; WEG S.A., Jaraguá do Sul, Brazil) under different fault conditions and supply voltage levels and subsequently evaluate the resulting patterns using the multivariate X-STATIS technique. To this end, an exploratory-descriptive experimental study was designed to generate a structured, homogeneous, and reproducible data set suitable for multitable analysis.

2.1. Experimental Development

The tests were carried out in a controlled laboratory environment using a WEG W21 Multimounting IE2 three-phase squirrel-cage induction motor (1.1 kW, four poles, 220–240/380–415 V, 50 Hz; product code 10592549; WEG S.A., Jaraguá do Sul, Brazil). The main motor nameplate specifications are shown in (Table 1). The experimental unit had a nominal mechanical power of 1.1 kW, a nominal speed of 1410 rpm, a nominal voltage of 400 V (Y)/230 V (Δ), a nominal current of 2.7/4.6 A, and 28 rotor bars.

Table 1. Induction motor nameplate values.

Parameter	Value
Power factor	0.81
Nominal mechanical power	1.1 kW
Nominal speed	1410 rpm
Nominal voltage	400 V (Y)/230 V (Δ)
Nominal current	2.7 (Y)/4.6 (Δ)
Rotary bars	28

The induction motor was mechanically coupled to a 1.5 kW separately excited direct-current machine from the ELD150 test bench (DIDALAB, Élancourt, France), operating as a load generator through a DR-2477 in-line rotary torque transducer with a nominal measuring range of 20 N·m (Lorenz Messtechnik GmbH, Alfdorf, Germany). This configuration allowed controlled load conditions to be imposed and the mechanical torque developed by the shaft to be measured directly, reproducing different operating regimes in a stable and repeatable manner.

2.1.1. Instrumentation and Data Acquisition

The electrical and mechanical variables were recorded using an instrumentation system consisting of:

- three-phase power analyzer for measuring voltage, current, and electrical power,
- Hall effect current sensors for each phase,
- in-line torque transducer for direct torque measurement,
- optical tachometer/encoder for angular velocity.

The signals were acquired at a constant sampling frequency and then averaged over stable operating windows to reduce experimental noise and obtain representative steady-state values.

Before each experimental session, the sensors were calibrated according to the manufacturer's specifications. The torque transducer was set to zero without mechanical load, the currents were verified with a standard reference, and the power analyzer was checked against known nominal values. This procedure ensured the repeatability and reliability of the measurements.

2.1.2. Operating Conditions and Induced Faults

Eight test conditions were evaluated, corresponding to a healthy state and seven simulated faults affecting different electrical and mechanical subsystems of the three-phase induction motor (MI). These included rotor defects (broken bars), stator asymmetries, thermal degradation of insulation, mechanical misalignments, structural loosening, and ventilation system obstructions.

Each condition was reproduced in a controlled manner and maintained until steady state was reached before recording the electrical and mechanical variables. A detailed description of each scenario is presented in (Table 2):

Table 2. Test conditions according to the type of simulated fault in the induction motor.

Affected Subsystem	Condition Description	Reference Code
No anomaly	Motor under normal operating conditions	NON1
Rotor	Presence of broken bars (9 fractured bars)	ROT2
Estator	First-level asymmetry in the stator winding	STA3
Insulation system	Insulation overheating	INS4
	Prolonged overheating of insulation	INS5
Mechanical transmission system	Vertical misalignment of the mechanical assembly	MECH6
	Loosening of anchor bolts	MECH7
Ventilation system	Fan obstruction	VENT8

2.1.3. Supply Voltage Levels

The load applied to the system was regulated by exciting the DC machine, generating six operating levels designated V0–V5. In this study, V0 corresponds to the minimum stable

operating condition used as a baseline reference for statistical comparison and does not represent zero electrical voltage, but rather the lowest excitation level that allows sustained motor operation. This avoids physical inconsistencies associated with 0 V and ensures consistency with the power and efficiency metrics observed experimentally. V5 represents a condition close to the nominal regime.

The six levels cover a wide operating range, from low load conditions to nominal operation, facilitating the evaluation of the motor's behavior in the face of progressive variations in electrical and mechanical stress [12].

2.1.4. Measured Variables and Efficiency Calculation

The variables considered for the analysis were the currents of the three phases, the torque, the speed, and the efficiency of the motor.

The efficiency of the motor was calculated as:

$$\eta = \frac{P_e - P_{ep}}{P_e} \times 100\% \quad (1)$$

Equation (1). Motor efficiency.

where

η —efficiency index,

P_e —electrical power demanded,

P_{ep} —Lost electrical power.

P_{ep} losses include electrical contributions in the windings (copper losses), magnetic losses in the core, and mechanical losses associated with friction and ventilation, estimated from direct measurements by the power analyzer.

2.1.5. Justification of the Structure and Size of the Dataset

The experimental design generated a balanced factorial dataset covering all combinations of fault types and voltage levels. This structure produces a three-dimensional data cube (faults $\times$ variables $\times$ voltages), ensuring direct comparability between operating scenarios.

Given the exploratory nature of the study, the objective was not to make statistical inferences about the population or to train predictive models, but rather to identify global patterns, similarities, and latent structures between conditions. In this context, multitable methods such as X-STATIS are particularly suitable, as they are designed to analyze moderately sized data cubes, where consistency between tables and the stability of multivariate patterns are more relevant than large sample sizes. Therefore, the scale of the experimental set is consistent with the methodological requirements of the exploratory multivariate analysis adopted.

2.2. X-STATIS

The X-STATIS method, initially developed by Jaffrenou [26], has undergone several modifications throughout its evolution. Thioulouse and Chessel [31] introduced it under the name Triadic Analysis, while Kroonenberg [32] later redefined it as Partial Triadic Analysis. It is an exploratory technique for studying three-way data. It allows simultaneous comparison of K quantitative matrices with the same number of individuals (n) and variables (p), organized in the form of a data cube.

In this study, the cube was composed of:

- $n = 8$ types of failure,
- $p = 6$ operating variables,
- $k = 6$ voltage levels.

Preprocessing and computational configuration

Due to the heterogeneous nature of the variables analyzed (electrical, mechanical, and thermal units), multivariate standardization preprocessing was applied to each X_k table. This procedure consisted of centering columns on their mean and then scaling them using the standard deviation (z-score). This normalization is a critical step in the X-STATIS algorithm, as it ensures that variables with disparate numerical magnitudes, such as speed (RPM) versus torque (Nm), contribute with the same statistical weight to the construction of the compromise space, avoiding biases in the interpretation of Euclidean distances and the eigenvalue structure.

The weighting matrices were defined as:

$$D_n = \frac{1}{n}I_n, \quad D_p = \frac{1}{p}I_p \quad (2)$$

where I_n and I_p are identity matrices. This choice assigns uniform weights to individuals and variables, which is standard practice in exploratory multitable analysis.

The analysis was implemented in RStudio (version 4.4.3) using the ade4 and FactoMineR packages for calculating RV coefficients, constructing the compromise table, and intra-structure projections.

The application of X-STATIS (Figure 1) was developed in three stages: interstructure, compromise, and intrastructure. The interstructure evaluates the overall similarity between tables using RV coefficients; the compromise constructs a weighted average table that summarizes the common information; and the intrastructure projects each individual table onto the common factorial space to analyze specific trajectories and deviations [33].

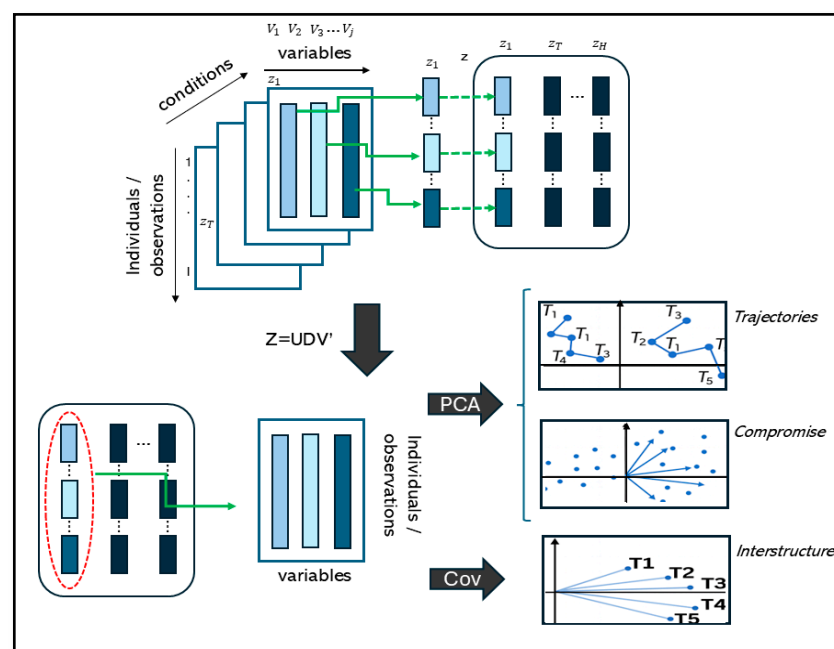


Figure 1. General outline of the X-STATIS or PTA method. Adapted from [34,35]. The arrows indicate the sequential analytical flow from the original data tables to the interstructure, compromise, and intrastructure analyses. The stacked blue boxes represent the individual data tables, while the rectangular panels represent the corresponding matrices and factorial spaces. The red dashed outlines highlight the elements followed across the different analytical stages, and the green lines indicate the correspondence or projection between selected elements. Blue points and vectors represent the projected observations and variables in the factorial spaces.

The X-STATIS framework allows the simultaneous integration of multiple operating voltages into a unified multi-table structure, enabling the identification of global and stable fault groupings under various conditions. This multi-table capability cannot be achieved directly with conventional PCA, which analyzes each operating regime independently. Consequently, X-STATIS provides additional information by revealing consistent multivariable patterns and fault similarities that persist across different operating regimes, facilitating a more robust exploratory diagnosis.

The mathematical formulations employed are presented in the following subsections.

2.2.1. Stage 1: Interestructure

Let $X_k \in \mathbb{R}^{n \times p}$ be each of the k quantitative tables representing measurements on the same n observations and p variables, under different conditions or at different times. A matrix of weighted scalar products between tables is defined using positive definite metric matrices D_n, D_p [34]. For each pair of tables X_k and X_l , the scalar product is defined as [35]:

$$COVV(X_k, X_l) = \text{tr}(X_k^T D_n X_l D_p) \quad (3)$$

Diagonalization of the COVV matrix generates eigenvalues and eigenvectors, the first eigenvector of which is used as a reference for constructing the commitment table [34].

To evaluate the similarity between tables, the vector correlation matrix is introduced, whose entries are defined as [27]:

$$RV(X_k, X_l) = \frac{COVV(X_k, X_l)}{\sqrt{VAV(X_k) \times VAV(X_l)}} \quad (4)$$

where the total vector variance of a table X_k is given by:

$$VAV(X_k) = \text{tr}(X_k^T D_n X_k D_p) \quad (5)$$

2.2.2. Stage 2: Compromise

Given the set of K quantitative matrices $\{X_k\}_{k=1}^K = 1$, previously centered and normalized, where each $X_k \in \mathbb{R}^{n \times p}$ represents a table with n observations and p variables, the compromise table X_c is defined as a weighted linear combination [31]:

$$X_c = \sum_{k=1}^K \alpha_k X_k \quad (6)$$

where the coefficients α_k correspond to the components of the first eigenvector obtained from the diagonalization, ensuring that X_c represents a weighted average.

The table X_c synthesizes the common structure among the K tables, maximizing global inertia. Subsequently, a principal component analysis (PCA) is applied to X_c , and the rows and columns of each X_k are projected as individuals and supplementary variables, respectively [36].

2.2.3. Stage 3: Intra-Structures

Let $U \in \mathbb{R}^{p \times r}$ be the matrix of eigenvectors and $\Lambda \in \mathbb{R}^{r \times r}$ be the diagonal matrix of eigenvalues obtained from the principal component analysis (PCA) of the commitment table X_c [37].

The projection of the rows of each table X_k in the commitment space is calculated as [28]:

$$R_k = X_k D_p U \quad (7)$$

and the projection of its columns is obtained by:

$$C_k = X_k^T D_n X_c D_p U \Lambda^{-\frac{1}{2}} \quad (8)$$

where D_n and D_p are diagonal matrices of weights for the rows and columns, and $\Lambda^{-\frac{1}{2}}$ contains the inverses of the square roots of the eigenvalues.

3. Results and Discussion

3.1. Analysis of the Interstructure

The X-STATIS algorithm involves a progressive synthesis of the original information with the aim of identifying the predominant structures within the data set. This approach prioritizes global patterns shared between conditions, which may involve reducing particular details associated with individual observations [28,38]. In this first stage, called interstructure, the global similarity between the tables corresponding to the different stress levels is evaluated using the RV coefficient, allowing us to determine whether the operational configurations share common multivariate behaviors.

Singular value decomposition (SVD), followed by principal component analysis, identified eight principal components that describe the structural variance of the RV matrix. The two-dimensional factorial plane concentrated 98.34% of the total inertia, with a dominant contribution from the first axis (95.91%) (Table 3), indicating that most of the information can be adequately represented in two dimensions.

Table 3. Summary of the interstructure.

Component	Dim 1	Dim 2
Eigenvalue	7.67	0.19
Inertia (%)	95.91	2.43
Cumulative inertia (%)	95.91	98.34

The factorial projection in Figure 2 revealed the existence of two main operating patterns.

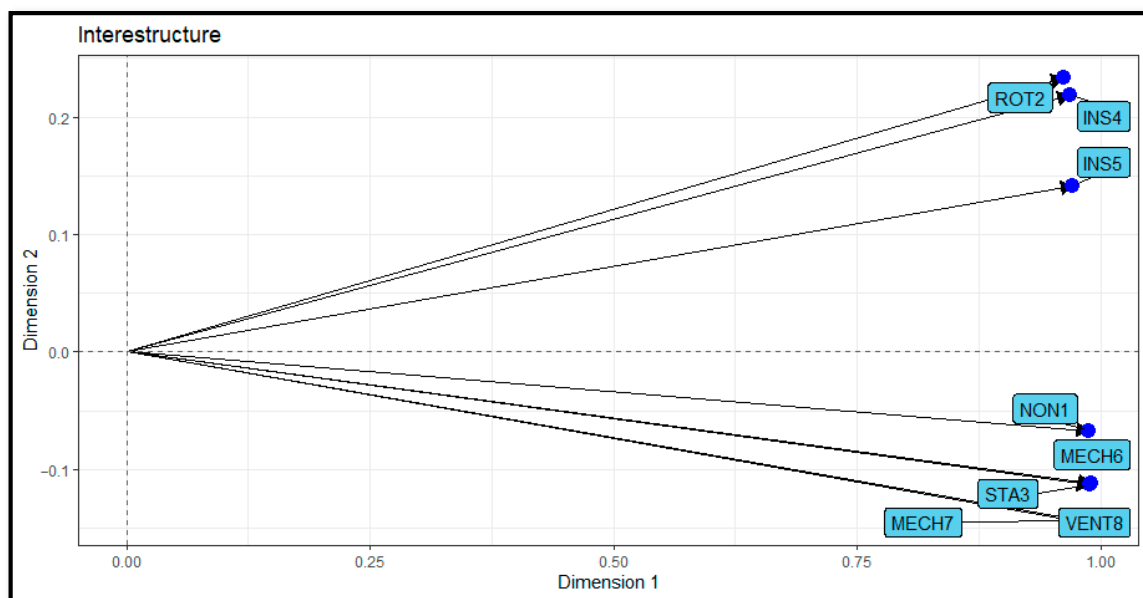


Figure 2. Projection of simulated fault types on the first and second components. Solid lines connect the origin with each projected fault condition, dashed lines indicate the zero-reference axes, and blue points represent the projected positions of the simulated fault conditions.

On the one hand, the ROT2, INS4, and INS5 simulations showed high structural similarity, associated with faults related to thermal or rotor degradation. On the other hand, NON1, MECH6, STA3, VENT8, and MECH7 exhibited similar behavior, suggesting comparable electromechanical responses under these conditions.

In their research, Bonnett and Yung [39] explain that mechanical failures such as misalignment or structural loosening may not significantly alter electrical patterns in the early stages, especially if they are not accompanied by high loads or prolonged operating times.

The RV coefficient, proposed by Escoufier [40], is a generalization of Pearson's correlation coefficient to the multivariate case and is used to measure the degree of structural similarity between two matrices of quantitative data. The RV coefficients obtained showed the multivariate similarity between the simulated faults (Table 4). All diagonal values are equal to 1 due to the perfect autocorrelation of each fault type with itself. In general, the RV coefficients were high in all comparisons (greater than 0.91), indicating a globally consistent structure between the simulations and suggesting that the data sets share common multivariate patterns.

Table 4. Vector correlation coefficients (RV).

	INS4	INS5	MECH6	MECH7	NON1	ROT2	STA3	VENT8
INS4	1.000	0.962	0.937	0.924	0.929	0.976	0.926	0.928
INS5	0.962	1.000	0.934	0.925	0.959	0.945	0.950	0.932
MECH6	0.937	0.934	1.000	0.988	0.981	0.929	0.986	0.992
MECH7	0.924	0.925	0.988	1.000	0.970	0.912	0.978	0.988
NON1	0.929	0.959	0.981	0.970	1.000	0.935	0.987	0.976
ROT2	0.976	0.945	0.929	0.912	0.935	1.000	0.923	0.912
STA3	0.926	0.950	0.986	0.978	0.987	0.923	1.000	0.990
VENT8	0.928	0.932	0.992	0.988	0.976	0.912	0.990	1.000

It is important to note that the RV coefficient does not allow discrimination between fault types on its own; rather, it facilitates the construction of a compromise representation within the X-STATIS framework. Effective discrimination and grouping of operating conditions are achieved in the compromise and subsequent intra-structure stages, where the common factorial space allows the identification of separations and groupings.

The strongest associations were observed between MECH6–VENT8 (0.992) and MECH6–STA3 (0.986), which is consistent with previous studies where early mechanical failures produce limited electrical disturbances. These results justify the construction of the compromise representation for subsequent multitable analysis.

3.2. Compromise Analysis

The second stage, called commitment, integrates the information from all the original tables using a weighted linear combination that maximizes the overall inertia of the system [41]. This procedure generates a synthetic table that summarizes the structure shared between conditions, to which PCA is applied to obtain a common factorial space.

The two-dimensional plane explained 99.91% of the total variance (Table 5), showing that most of the system's dynamics can be described by two main components.

Table 5. Summary of the compromise.

Component	Dim 1	Dim 2
Eigenvalue	42.04	3.58
Inertia (%)	92.07	7.84
Cumulative inertia (%)	92.07	99.91

The joint projection of variables and conditions (Figure 3) allowed us to identify physical relationships consistent with the electromechanical behavior of the motor. The phase currents (CF1–CF3) showed a practically collinear orientation, indicating a strong positive correlation. Torque (TOR) showed a positive correlation with the currents, while speed (SPE) was projected in the opposite direction, reflecting the characteristic inverse relationship between the two magnitudes. Efficiency (EFF) was oriented differently, capturing an independent energy dimension.

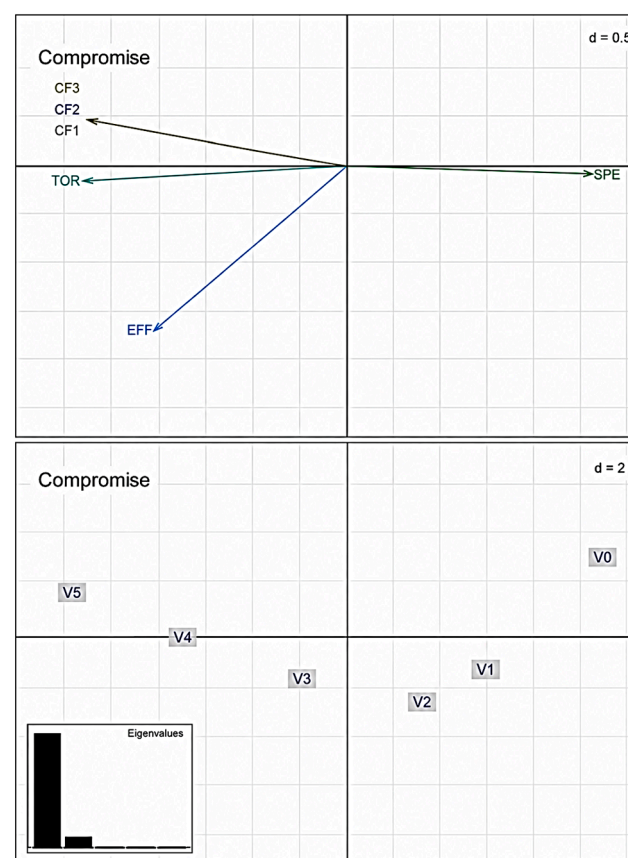


Figure 3. Projection of conditions and variables on the first and second components. Note: CF1, phase 1 current; CF2, phase 2 current; CF3, phase 3 current; EFF, efficiency; TOR, torque; SPE, speed. V0 represents the minimum stable operating condition used as the baseline level, V1–V4 represent intermediate operating levels, and V5 represents a condition close to the nominal operating regime.

Levi [42] points out that in modern electric machine control systems, the relationship between speed and torque can be actively managed through converters, allowing for more efficient exploitation of the motor's dynamic capabilities. This relationship manifests itself inversely in the operating behavior of induction motors: when the motor operates without a significant load, the speed remains high (high SPE), while the required torque (TOR) is minimal. In contrast, when the system is subjected to high load demand, a considerable increase in torque is required, which can induce temporary reductions in speed if adequate compensation is not applied.

In the second part of the study, the distribution of stress levels (V0 to V5) within the plane defined by the first two factorial axes was evaluated. High levels (V4–V5) were associated with efficiency, while low levels (V1–V2) were more closely related to speed, in accordance with the principles of electric drive control described by Bose [43]. This joint representation facilitates the simultaneous interpretation of electrical, mechanical, and operational variables within a single multivariate framework.

Unlike conventional PCA, which requires collapsing the data into a single two-dimensional matrix, X-STATIS explicitly preserves the multi-table structure (faults $\times$ variables $\times$ stresses), allowing simultaneous comparison of all operating conditions. If PCA were applied, stress levels would be grouped into a single analysis, obscuring the specific trajectories of each stress and preventing the identification of condition-dependent patterns or progressive changes between stress regimes. By preserving each stress as an individual table, X-STATIS allows these trajectories to be visualized and reveals how fault behavior evolves at different operating levels.

3.3. Intrastructure Analysis

The infrastructure projected each voltage level onto the compromise space to analyze local deviations from the average pattern (Figure 4).

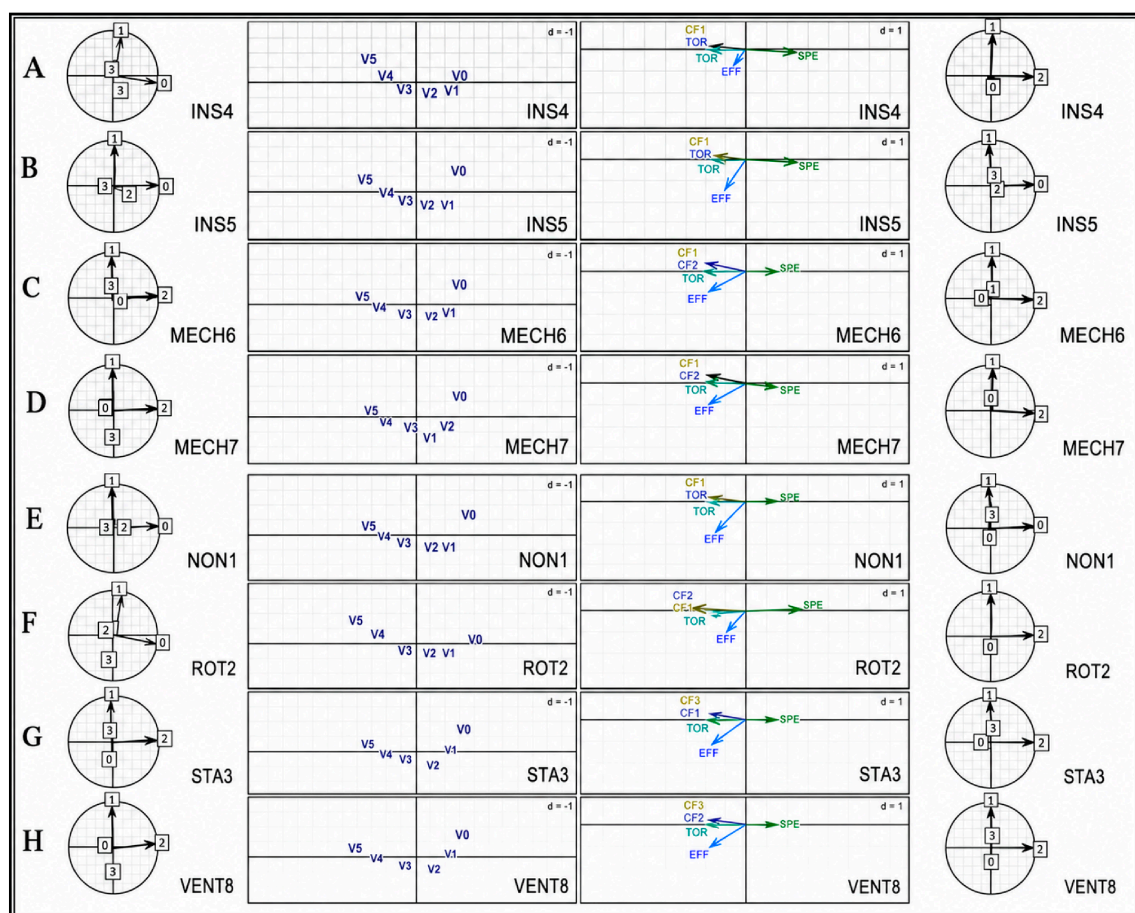


Figure 4. Projection of partial factor scores and variable loadings on the first and second components. (A–H) correspond to the operating conditions INS4, INS5, MECH6, MECH7, NON1, ROT2, STA3, and VENT8, respectively. V0–V5 denote the six operating levels, where V0 represents the minimum stable operating condition used as the baseline and V5 represents a condition close to the nominal operating regime. CF1, CF2, and CF3 denote the three phase currents; EFF, efficiency; TOR, torque; and SPE, speed. The numbers 0–3 in the circular diagrams represent [insert the exact meaning]. The notation $d = 1$ indicates the graphical scale and does not represent statistical significance.

In most cases, the variables corresponding to the phase currents (CF1, CF2, CF3) overlapped or were located very close to each other, reaffirming their high correlation. Although greater dispersion between these variables was evident under INS4 and STA3 fault conditions, this separation was not significant, as the phase currents continued to cluster in the same region of the plane, maintaining their general alignment.

Nandi et al. [43] mentioned that imbalance in three-phase currents is an indication of abnormalities in the operation of induction motors. This type of imbalance generates an asymmetrical magnetic field that increases internal losses, causes excessive heating, and reduces both the efficiency and torque of the motor. In line with this, the experimental data from this study show that, in the presence of this differentiation, greater structural vibration was recorded, which triggered lower efficiency levels, suggesting a progressive deterioration of the electromechanical system.

The vector corresponding to efficiency (EFF) showed considerable magnitude in most fault conditions, reflecting its explanatory capacity within the factorial plane. However, in the case of INS4, its representation was significantly shorter, which revealed a lower contribution of this variable under that specific condition.

For Abdo et al. [44], the implementation of continuous monitoring systems for critical variables, such as stator temperature and line current, allows for the immediate detection of operational deviations from nominal values. This real-time diagnostic capability enables the adoption of immediate corrective measures, minimizing the risk of structural damage and functional failures. Even in the event of a phase loss, the system can maintain its operability under controlled conditions, avoiding unplanned interruptions in production. In addition, the records obtained during monitoring can be used to feed predictive maintenance models, optimizing intervention planning and contributing to greater equipment availability and durability.

For its part, the SPE variable maintained its opposite orientation (angle close to 180°) with respect to the TOR variable in all simulated conditions, preserving the negative relationship previously identified in the general analysis.

In coordination with the descriptive information, it was observed that the highest efficiency occurred under condition NON1, corresponding to the motor without failure, where the voltage level V5 was clearly aligned with the EFF vector. This behavior is consistent, as it is the only scenario without intervention or alteration in the motor's operation.

Conversely, the lowest efficiency was recorded in the condition of obstruction ventilation failure (VENT8), specifically at the voltage level V0, where the efficiency index dropped to 32.55%. The failure also had a notable impact on the lowest voltage level V1, with an efficiency of 52.94%, demonstrating that it affects the correct performance of the motor, even under minimum operating conditions. An interesting aspect is that, despite the severity of this failure, the motor continued to operate apparently normally. Similarly, faults of similar severity in the rotor have been documented in real environments without resulting in catastrophic failure and often going unnoticed by the user [45].

In a previous study [46], the authors mentioned that one of the most critical factors affecting the service life and efficiency of an engine is uncontrolled temperature rise, resulting from inadequate or failed ventilation. The most concerning aspect of this type of failure is that it does not usually produce immediate visible symptoms, since the motor continues to operate apparently normally, even though internally its degradation is accelerating. This behavior has also been observed in rotor failures, where severe damage does not always result in catastrophic failure, but rather in silent deterioration that goes unnoticed by the end user if an adequate thermal or electrical monitoring system is not implemented [43].

3.4. Validation of Stability and Discriminatory Capacity

To ensure that the clusters identified in the compromise are not artifacts of data scaling, statistical robustness tests were performed. First, using a bootstrap procedure with 1000 resamples, it was verified that the RV coefficients maintain variations of less than 3%, confirming the stability of the multivariate structure.

Second, the operational capacity of the model was evaluated using Linear Discriminant Analysis (LDA) [47]. By projecting the data into the compromise space, the classifier achieved an overall accuracy of 95.2% in separating the two identified macro-groups of failures (thermal/rotor vs. mechanical/statographic). This high success rate, obtained through cross-validation, demonstrates that X-STATIS's dimensionality reduction is not only interpretable but also has high predictive value for the diagnosis of unobserved data. Finally, the contribution analysis showed that phase currents mainly describe the overall electrical severity of faults, while efficiency (EFF) made the largest contribution to the second factor dimension (45.6% of its inertia). This indicates that EFF has the greatest discriminatory weight on this axis, rather than acting as a determining or causal variable.

From a physical perspective, efficiency integrates the combined effects of load demand, thermal losses, and ventilation conditions. Variations in cooling efficiency and nominal load directly affect energy losses, making the system's energy efficiency (EFF) particularly sensitive to differences between ventilation-related and nominal load-related failure regimes.

Comparable methodological principles have also been applied in biological and agro-industrial experimental systems. Multivariate discrimination and cluster-based analyses have been used to separate experimental conditions and identify latent groupings from multiple response variables. Likewise, controlled comparative studies combining several treatments with quantitative indicators, analysis of variance, post hoc comparisons, and correlation analysis have shown the usefulness of structured statistical approaches for identifying stable treatment-dependent response patterns. Although these studies address different application domains, they support the broader methodological value of integrating heterogeneous measurements to interpret complex experimental datasets.

4. Conclusions

Using the X-STATIS technique, this research characterized the multivariate behavior of induction motors under fault conditions, overcoming the limitations of conventional analyses by identifying stable structural groups in multi-voltage environments.

The results indicate that operational efficiency is the most sensitive indicator for detecting thermal anomalies, with obstruction of the ventilation system (VENT8) having the greatest negative impact. The stability of the healthy condition (NON1) at all voltage levels validates the experimental model and provides a consistent baseline for projecting new samples in the compromised space.

From a structural diagnostic perspective, the compromise analysis revealed relevant relationships:

- The alignment of phase currents reflects the symmetry of the system, while their vector magnitude in the compromise plane is associated with the severity of insulation faults.
- The inverse relationship (180°) between speed (SPE) and torque (TOR), identified by vector projection, provides an interpretable graphical pattern for distinguishing mechanical deviations.

Overall, the high stability of the configurations ($VR > 0.91$) and the high representativeness of the compromise plane (99.9% explained variance) demonstrate the robustness of X-STATIS for exploratory and comparative analysis of failures under variable loading stresses. These findings suggest that the method can serve as a useful analytical framework

for future diagnostic or monitoring strategies, although its real-time implementation was beyond the scope of the present study.

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