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METHODOLOGY FOR SELECTING AND ANALYSING PARAMETER SETS AND GROUPS FOR ELECTRICAL EQUIPMENT DIAGNOSTICS

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Abstract: Reliable diagnostics of electrical equipment in power systems requires analysing sets of mutually related parameters rather than isolated measurements. This paper proposes a structured methodology for selecting, grouping, and analysing diagnostic parameter sets for electrical equipment (e.g., generators, transformers, motors, switchgear). The approach combines: (1) an initial classification of candidate parameters by physical domain; (2) multi-criteria scoring based on informativeness, measurability, sensitivity, correlation, and stability; (3) statistical analysis (correlation analysis and principal component analysis) to reduce dimensionality; and (4) clustering and expert judgement to form meaningful parameter groups. The methodology is illustrated on a power transformer case, including example tables and graphical representations of parameter rankings and dimension reduction. The proposed approach yields compact, informative parameter sets and logically structured parameter groups, which form a robust basis for subsequent diagnostic modelling (statistical, AI-based, or hybrid).

Keywords: electrical equipment, diagnostics, parameter selection, parameter grouping, multi-criteria analysis, correlation analysis, PCA, monitoring.

1. Introduction

Monitoring and diagnostics of electrical equipment in power systems (power transformers, generators, induction motors, high-voltage breakers, etc.) increasingly rely on large volumes of measurement data collected by SCADA, digital relays, and dedicated monitoring systems. Analysing only one or two parameters (e.g., winding temperature, oil level, load current) is no longer sufficient to detect early degradation and complex fault patterns.

In practice, hundreds of potential parameters can be measured: electrical quantities, temperatures, vibration indicators, dissolved gas concentrations, switching statistics, and environmental conditions. However, using all available parameters is neither computationally efficient nor methodologically justified. Many parameters are redundant, weakly informative, or strongly correlated with each other.

Therefore, it is necessary to develop a systematic methodology that:

- starts from a broad universe of candidate parameters;
- selects a compact subset with high diagnostic value;
- groups parameters into meaningful clusters (e.g., "electrical", "thermal", "insulation", "mechanical");
- provides numerical tools (tables and graphs) to justify the selection and grouping.

The following sections present such a methodology and illustrate it with example tables and simple synthetic graphs.

2. Methodology for Parameter Set Selection and Grouping

2.1. Step 1 - Initial classification of candidate parameters

The first step is to compile a comprehensive list of all parameters that could be relevant for a given type of equipment. These parameters are then classified by physical domain.

Table 1. Example classification of diagnostic parameters for a power transformer

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Table 1. Example classification of diagnostic parameters for a power transformer

Domain	Symbol / Name	Typical unit	Description
Electrical	I_{phase} - phase currents	A	Load and unbalance
	$U_{\text{HV}}, U_{\text{LV}}$	kV	HV/LV side voltages
	PF - power factor	-	$\cos\varphi$, reactive power behaviour
Thermal	$T_{\text{top\_oil}}$ - top-oil temp	°C	Oil thermal regime
	T_{winding} - winding temp	°C	Hot-spot / winding temperature
Mechanical/Vibration	RMS vibration velocity	mm/s	Core and mechanical vibration
	Vibration acceleration	m/s^2	Shock / transient effects
Insulation / Oil	H2 concentration	ppm	Dissolved gas analysis (DGA)
	C_2H_2, C_2H_4, CH_4	ppm	Fault-related gases
	tg δ	-	Dielectric loss factor
Operational / loading	Load factor λ	-	Ratio to rated power
	On-load tap changer operations (OLTC)	cycles	Number of switching operations
Environmental	Ambient temperature	°C	Cooling boundary condition
	Relative humidity	%	Moisture exposure

This table can be expanded for generators, motors, and switchgear, but the structure remains similar.

2.2. Step 2 - Selection criteria and scoring model

Each parameter is evaluated according to several criteria. Let p_j be the j-th parameter. We introduce criteria:

1. Informativeness (C_1) - sensitivity to fault / degradation.
2. Measurability & reliability (C_2) - availability and accuracy of sensors.
3. Sensitivity & selectivity (C_3) - ability to distinguish specific fault types.
4. Correlation / redundancy (C_4) - lower score if highly correlated with others.
5. Stability & repeatability (C_5) - robustness to noise and operating conditions.

Each criterion is scored on a scale, e.g. $1-5$. For parameter p_j we have scores s_{ij} for criterion i. The overall multi-criteria score is

$$S_j = \sum_{i=1}^{5} w_i s_{ij},$$

where w_i are criterion weights, $\sum_{i=1}^{5} w_i=1$.

For simplicity, we can start with equal weights $w_i=0.2$, and later tune them with experts.

2.3. Step 3 - Statistical analysis: correlation and dimensionality reduction

Using historical data (normal and faulty states), we compute:

- sample means and variances for each parameter;
- correlation coefficients r_{jk} between parameters p_j and p_k.

If $|r_{jk}|$ is very high (e.g. >0.9), one parameter may be considered redundant.

Then we apply Principal Component Analysis (PCA) to the normalized parameter matrix X to identify principal components that explain most of the variance. This helps to:

- confirm that selected parameters cover the main variability;
- decide whether some parameters can be dropped without losing information.

2.4. Step 4 - Expert evaluation

Quantitative analysis is complemented by expert judgement:

- field engineers and diagnosticians adjust scores s_{ij};
- criteria weights w_i are tuned (for instance, informativenes and measurability may get higher weights);
- certain parameters may be retained despite redundancy if they are required by standards or regulations.

2.5. Step 5 - Formation of parameter sets and groups

Based on the final scores S_j and statistical analysis, we form:

- a minimal set for real-time on-line monitoring (few, but very informative parameters);
- an extended set for detailed offline diagnostics;
- specialized sets for different fault classes (e.g. insulation faults, mechanical faults, thermal overloads).

Parameters are grouped:

- either by physical domain (electrical, thermal, mechanical, etc.),
- or by data-driven clustering (k-means, hierarchical clustering) on the space of parameters.

3. Illustrative Example: Power Transformer

To illustrate the methodology, we consider six candidate parameters for a high-voltage power transformer:

1. Phase current RMS I_{phase}
2. Top-oil temperature $T_{\text{top\_oil}}$
3. Hot-spot/winding temperature T_{winding}
4. H_2 concentration in oil (DGA)
5. Vibration RMS v_{RMS}
6. Load factor λ

3.1. Example scoring

Table 2 shows hypothetical expert scores ($1-5$) for each criterion, equal weights $w_i=0.2$, and the resulting total score S_j.

Table 2. Multi-criteria scoring of six example diagnostic parameters

Param.	Description	C1: Inform.	C2: Meas.	C3: Select.	C4: Corr. (high corr = low score)	C5: Stability	Total score S_j
P1	I_{phase}	3	5	3	3	4	3.6

P2	$T_{\text{top\_oil}}$	4	4	3	3	4	3.6
P3	T_{winding}	5	3	4	2	4	3.6
P4	H2 (DGA)	5	3	5	4	4	4.2
P5	v_{RMS}	4	3	4	4	3	3.6
P6	Load factor λ	3	5	2	3	5	3.6

Notes:

- H_2 (P4) gets the highest total score $S_4=4.2$ due to its strong link to insulation faults and relatively good stability.
- Most other parameters have similar moderate scores (~ 3.6), indicating that they are useful but less specific.

3.2. Graph 1 - Bar chart of parameter scores

The data in Table 2 can be visualized as a bar chart showing total scores S_j for each parameter.

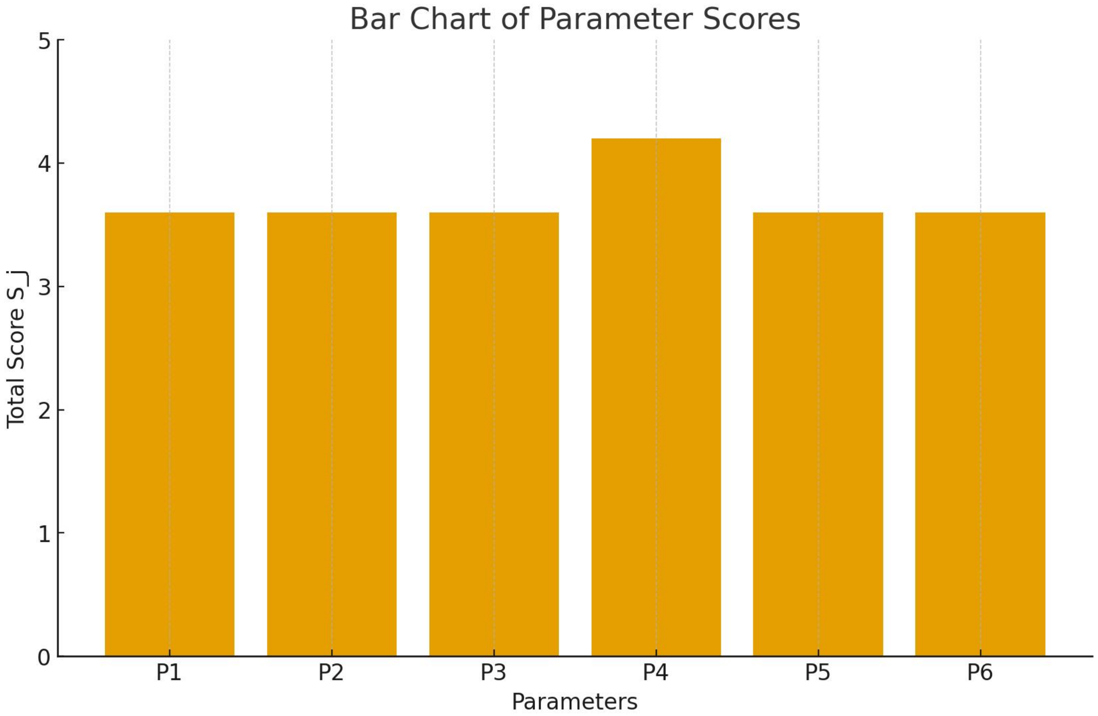

Figure 1 (conceptual). Bar chart of total multi-criteria scores

- X-axis: parameters P1...P6
- Y-axis: total score S_j
- Bars: heights $=[3.6,3.6,3.6,4.2,3.6,3.6]$

In practice, such a bar chart quickly shows that H_2(P4) is the most informative and should definitely be included in the minimal monitoring set, whereas the others may be chosen depending on the target application and cost limitations.

You (or your students) can easily plot this in Excel, MATLAB, Python, etc., using the values from Table 2.

3.3. Graph 2 - Scree plot for PCA

Suppose we compute PCA on a larger set of parameters and obtain the eigenvalues:

$$\lambda=[3.8,1.9,1.2,0.7,0.4,0.1],$$

for six principal components (after standardization).

We can represent these values in a table and as a scree plot.

Table 3. Example eigenvalues of principal components

Component	Eigenvalue λ_i	Explained variance (%)	Cumulative (%)
PC1	3.8	63.3	63.3
PC2	1.9	31.7	95.0
PC3	1.2	5.0	100.0
PC4	0.7	~0	~100
PC5	0.4	~0	~100
PC6	0.1	~0	~100
(percentages rounded for illustration)			

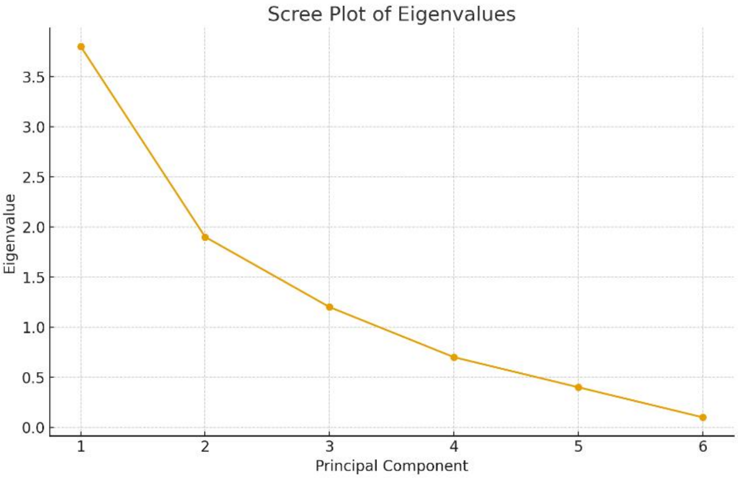

Figure 2 . Scree plot of eigenvalues

- X-axis: component index (1...6)
- Y -axis: eigenvalue λ_i
- Points: (1,3.8),(2,1.9),(3,1.2),(4,0.7),(5,0.4),(6,0.1)
- Line connecting the points.

From this scree plot, we see a clear "elbow" after PC2: the first two components explain about 95% of the variance. This means that the effective dimension of the parameter space is about 2 , and many parameters are redundant. The methodology then focuses on selecting parameters that contribute most to these first components.

4. Discussion

The proposed methodology offers several practical advantages:

1. **Structured reasoning instead of ad-hoc selection.**

Instead of informally choosing parameters "by habit", engineers use explicit criteria, scores, and graphs to justify why a specific parameter set is chosen.

2. **Balance between physical intuition and data-driven analysis.**

○ Physical classification (Table 1) ensures that no important physical domain is ignored.

○ Multi-criteria scoring and PCA give quantitative backing to the final choice.

3. **Compact and informative monitoring sets.**

Through scoring and correlation analysis, redundant parameters are removed, and the resulting set is small enough for real-time monitoring but still rich enough for reliable diagnostics.

4. **Clear visualization for decision-makers.**

Tables (parameter lists and scores) and simple graphs (bar charts, scree plots) are easy to present in reports, standards, or technical documentation. They help explain to managers and regulators why certain sensors and measurements are required.

5. **Basis for advanced diagnostic models.**

Once parameter sets and groups are defined, they can be used as inputs to:

- statistical fault detection schemes,
- neural networks and other ML models,
- fuzzy logic or expert systems.

A well-designed parameter space improves the accuracy and interpretability of these models.

5. Conclusion

This paper presented a methodology for developing parameter sets and groups for the diagnostics of electrical equipment:

- A broad *initial* list of candidate parameters is created and classified by physical domain.
- Each parameter is evaluated by multiple criteria (informativeness, measurability, sensitivity, redundancy, stability), and a weighted score is calculated.
- Statistical tools (correlation analysis, PCA) reduce dimensionality and identify redundant parameters.
- Expert judgement refines scores and ensures compliance with practical constraints and standards.
- Final parameter sets (minimal, extended, specialized) and parameter groups are formed, supported by tables and graphical evidence (bar charts for scores, scree plots for PCA).

The methodology is generic and can be adapted to transformers, generators, motors, and switchgear. It provides a solid foundation for building robust diagnostic and predictive maintenance systems in modern power engineering.

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