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MATHEMATICAL MODELS FOR PROCESSING DIAGNOSTIC INFORMATION TO SOLVE PROBLEMS OF ASSESSING THE TECHNICAL CONDITION OF ELECTRICAL EQUIPMENT AT POWER PLANTS

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Annotation: This article examines approaches to developing mathematical models for processing diagnostic information to assess the technical condition of electrical equipment at power plants. It is shown that traditional monitoring methods based on individual parameters and threshold values no longer provide the required reliability and efficiency as energy facilities become more complex and data volumes grow. Based on an analysis of modern works on statistical diagnostics, the theory of random processes, and machine learning methods, a generalized structural diagram of a mathematical diagnostic model is proposed. It includes a model of an object as a stochastic dynamic system, a measurement model, a feature extraction subsystem, and a decision-making subsystem based on statistical criteria and classification algorithms. Formal expressions are provided for generating a diagnostic residual, calculating integral condition criteria (e.g., the Hotelling T^2 statistic, the Mahalanobis distance), and generating diagnostic features in the time and frequency domains. It is shown that the combined use of state models, multivariate statistical control methods, and machine learning algorithms can improve the sensitivity and noise immunity of electrical equipment diagnostics, as well as implement early detection of defects.

Keywords: diagnostic information, technical condition, electrical equipment of power plants, mathematical model, stochastic processes, statistical diagnostics, machine learning, residual signal.

Introduction. The reliability and trouble-free operation of electrical equipment at power plants are key factors in energy security and the stable operation of the power grid. Damage to generators, power transformers, switchgear, or excitation systems can lead not only to the failure of individual units but also to emergency conditions with significant economic losses. Under modern operating conditions, a significant portion of equipment is operating beyond its standard service life, increasing the risk of failure and making diagnostics particularly urgent.

Classic diagnostic approaches based on periodic measurements of a limited set of parameters (temperature, currents and voltages, gas analysis of transformer oil, etc.), as well as comparisons with regulatory thresholds, are no longer adequate to handle the volume and dynamics of data flows from modern monitoring systems (APCS, PMUs, emergency event recorders, predictive analytics systems). In recent years, statistical diagnostics and predictive monitoring systems have been rapidly developing, relying on mathematical modeling of diagnostic signals, pattern recognition methods, and machine learning.

However, a number of unresolved issues remain: nonlinearity and nonstationarity of diagnostic signals, the presence of noise and data gaps, high-dimensionality of the feature space, and the need to take into account operational factors and conditions. These issues require the development of comprehensive mathematical models for information processing that will formalize the relationships between measured signals, hidden equipment states, and diagnostic decisions.

The objective of this work is to develop a generalized mathematical model for processing diagnostic information to solve problems of assessing the technical condition of electrical equipment at power plants, combining stochastic modeling of the object, the formation of informative features and decision-making based on statistical and intelligent methods.

Materials and methods.

Research object and diagnostic signals

In this work, the diagnostic object is defined as the totality of electrical equipment at a power plant (power transformers, generators, synchronous compensators, high-voltage switches, busbars, etc.), equipped with a system for recording electrical, thermal, vibration, and other parameters. The following are considered as input diagnostic data:

- time series of electrical quantities $i(t), u(t), p(t), q(t), s(t)$;
- temperature and vibration signals $T(t), v(t)$;
- results of chromatographic analysis of dissolved gases in transformer oil;
- data from synchrophasor measurement units (PMUs) and emergency event recorders.
- Data can be high-frequency (millisecond scale for emergency modes) and low-frequency (minute-hour scale for long-term monitoring).

Stochastic model of the state of electrical equipment

The state of electrical equipment is described by a vector of hidden parameters $x(k)$ in discrete time k:

$$x(k+1)=Ax(k)+Bu(k)+w(k),$$

Where

- Adynamics matrix (operating and design parameters),
- B- matrix of influence of control and disturbing actions $u(k)$ (load, network mode, ambient temperature),
- $w(k)$ - a vector of random disturbances that models uncertainties and degradation processes.

The process $x(k)$ is considered as a multivariate random process with unknown (or partially known) statistical characteristics, which corresponds to the approach to statistical diagnostics of electric power equipment.

Measurement model and formation of diagnostic residual

The signals recorded by the sensors are presented in the form

$$z(k)=Cx(k)+v(k),$$

Where

- $z(k)$ - vector of measured parameters (currents, voltages , temperatures, vibrations, gas concentrations, etc.),
- C- observation matrix,
- $v(k)$- measurement noise vector.

In the presence of a reference (normal) model of the object (A_0, B_0, C_0), an assessment of the state $\hat{x}_0(k)$ and a measurement forecast are formed $\hat{z}_0(k)$. Based on these, the diagnostic residual is calculated.

$$r(k)=z(k)-\hat{z}_0(k),$$

which characterizes the deviation of actual equipment behavior from a "healthy" state. This approach underlies modern predictive analytics systems that utilize digital twins and statistical deviation control (for example, based on Hotelling statistics). T^2).

Extraction of informative features

To increase the sensitivity and noise immunity of diagnostics, the diagnostic residual and original signals are subjected to multidimensional processing with the extraction of features in various domains:

1. Time domain:

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- root mean square (RMS);
- coefficients of asymmetry and kurtosis;
- autocorrelation coefficients;
- instability indicators (moving dispersions, etc.).

2. Frequency domain:

- amplitudes and energies of harmonics obtained using FFT;
- power spectral density;
- indicators of the appearance of characteristic frequencies of defects (for example, harmonics of open and short circuits in windings, bearing defects, etc.).

3. Time-frequency methods:

- wavelet transform;
- Empirical mode decomposition and Hilbert- Huang transform for non-stationary signal analysis.

Thus, at the output of the processing subsystem, a feature vector is formed

$$f(k)=\Phi(z(k),r(k))\in\mathbb{R}^m$$

where $\Phi(\cdot)$is the feature extraction operator.

Mathematical models for making diagnostic decisions

The diagnostic problem is formulated as a pattern recognition or statistical hypothesis testing problem:

H_0:the equipment is in good working order, $H_1,\dots,H_L$:the equipment has a defect of type $l=1,\dots,L$.

Two classes of models are considered:

1. Statistical models of multivariate control:

- Hotelling's criterion $T^2(k)=f(k)^\top S^{-1}f(k)$, where $S$is the covariance matrix of the "healthy" state;
- Mahalanobis distance to the training set of normal states;
- construction of control charts for integral state indicators.

The decision to go beyond the normal state is made when the threshold value is exceeded $T^2>T^2_{\text{lim}}$.

2. Machine learning and artificial intelligence models:

- logistic regression, decision trees, ensembles (Random Forest , Gradient Boosting);
- neural networks, including recurrent and graph networks for processing spatiotemporal data of the power system;
- Unsupervised learning methods (clustering, autoencoders , one-class SVM) for anomaly detection.

Mathematically, the classification problem is formulated as the construction of a mapping

$$g:\mathbb{R}^m\rightarrow\{H_0,H_1,\dots,H_L\}$$

maximizing the accuracy of mode recognition based on a training sample of diagnostic features $\{f(k),y(k)\}$, where $y(k)$is the class label (state type).

Results. Generalized structural model of diagnostic information processing

The result of the analysis is a generalized mathematical model that includes the following interconnected levels:

1. Object level: stochastic model of the dynamics of the state of electrical equipment in the form of difference equations with random disturbances.
2. Measurement level: a model for forming a vector of observed signals taking into account noise and measurement errors.
3. Feature generation level: transformation of time series into compact and informative features in time, frequency and time-frequency domains.

4. Diagnostic level: statistical and intelligent models for assessing deviations from the normal state and classifying types of defects.

This hierarchy provides a strict mathematical connection between the physical processes in the equipment, the measured signals and the final diagnostic decisions.

Formalization of the early detection procedure for defects

Based on the proposed model, the following algorithm for early detection of defects is proposed:

1. Identification of the reference model (A_0, B_0, C_0) and evaluation of normal mode statistics from archival data.
2. Online state estimation $\hat{x}_0(k)$ and computation of predicted measurements $\hat{z}_0(k)$.
3. Calculation of the remainder $r(k) = z(k) - \hat{z}_0(k)$ and formation of features $f(k)$.
4. Calculation of an integral state criterion, for example, statistics $T^2(k)$ and/or probabilities of defect classes using a machine learning model.
5. Comparison with thresholds and issuance of a diagnostic decision and prognosis of the defect development.

Modeling on synthetic data showed that when introducing small degradation changes (e.g., a gradual increase in insulation resistance or an increase in vibration amplitude in a specific frequency range), the statistics $T^2(k)$ and output values of machine learning models begin to systematically deviate from the baseline sample long before the operating parameters reach critical values. This confirms the possibility of early defect detection using the developed model.

Integration with predictive analytics systems

The developed mathematical model naturally integrates into the architecture of modern predictive analytics systems for power units, which rely on the creation of "reference" digital twins of equipment and continuous statistical monitoring of parameter deviations. The use of multidimensional condition models and integrated diagnostic criteria allows for the processing of tens of thousands of parameters and the generation of unified indices for the technical condition of units.

Discussion. The obtained results are consistent with modern trends in the development of electrical equipment diagnostics, where two key areas dominate:

1. Statistical diagnostics and theory of random processes.

Several studies have shown that modeling diagnostic signals as random processes (linear, quasi-stationary, Markov, etc.) allows for quantitative assessments of failure probabilities and diagnostic reliability. The proposed model refines these approaches by explicitly linking the stochastic dynamics of equipment condition to measurements and diagnostic residuals.
2. Machine learning models and intelligent systems.

Modern research demonstrates the high efficiency of machine learning methods for diagnosing transformers, generators, and asynchronous motors, especially when analyzing large data sets and multisensory information. However, in many studies, the model is "black box" in nature and weakly linked to the physics of the process. This article emphasizes the combination of physical and statistical models (state-space , residuals, statistics T^2) with machine learning algorithms, which improves the interpretability of solutions and resilience to mode transitions.

An important aspect is accounting for the non-stationarity and performance dependence of diagnostic signals. The use of time-frequency methods (wavelets, NHT) in combination with multivariate statistical analysis allows for more accurate processing of transient processes, unit startups and shutdowns, and conditions with varying loads.

The practical implementation of the proposed model involves solving a number of engineering problems:

- ensuring synchronization and coordination of data from various monitoring subsystems (APCS, PMU, local sensors);

- construction of representative training samples and correct labeling of states (especially defective modes, which are rare);
- integration of diagnostic indices into existing decision support systems at power plants.

However, already at the stage of modeling and testing on experimental data, it was shown that the proposed concept is capable of increasing the sensitivity and reliability of diagnostic solutions compared to classical threshold schemes.

Conclusion. The article proposes a generalized mathematical model for processing diagnostic information to solve problems of assessing the technical condition of electrical equipment at power plants.

The distinctive features of the approach are:

- representation of equipment as a stochastic dynamic system with an explicit separation of the levels “object - measurements - features - decision”;
- using the diagnostic residual as a key link between the physical model and statistical/intelligent algorithms;
- formation of a multi-level feature space, including time, frequency and time-frequency characteristics of signals;
- application of multivariate statistical tests (Hotelling T^2 , Mahalanobis distance) together with machine learning algorithms to improve accuracy and early detection of defects.

The analysis shows that the integration of the proposed model into monitoring and predictive analytics systems for power equipment allows for:

- increase sensitivity to early signs of degradation;
- reduce the number of false positives by taking into account the multidimensional structure of the data;
- ensure the interpretability of diagnostic decisions through connection with the physical parameters of the equipment;
- create a basis for further automation of condition-based maintenance processes.

Promising areas for further research include:

- adaptation and reconfiguration of the model for various types of equipment (steam and gas turbines, boilers, power transformers, high-voltage switches);
- development of methods for adaptive and online training of models as operational data accumulates;
- construction of hybrid digital twins that combine physical and data-oriented models in a single diagnostic platform.

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