

DEVELOPMENT OF AN INTELLIGENT REPAIR MANAGEMENT SYSTEM FOR COMBINED-CYCLE AND BOILER EQUIPMENT

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The development of an intelligent repair management system involves creating a software and hardware complex that ensures the automation of planning, monitoring, and analysis of repair activities. The main goal of the system is to improve resource management efficiency, reduce repair time, and minimize costs. The system architecture is built on a modular principle and includes the following main components: a data collection and storage module, an intelligent analysis module, a planning and forecasting module, a user management module, and a user interaction interface. The architecture is based on a client-server model. The server side is responsible for data processing, information storage, and execution of intelligent algorithms.

The client side provides a convenient interface for users (managers, engineers, and technicians). A relational database is used for data storage, containing information about repair objects, technical condition of equipment, maintenance schedules, resources (personnel, materials, tools), and the history of completed work. The intelligent analysis module implements algorithms for processing accumulated data in order to identify patterns, predict failures, and optimize repair schedules. Decision support is an integral part of the system. The intelligent component is based on the application of data analysis methods and elements of machine learning. The implementation of an intelligent repair management system significantly improves the efficiency of equipment operation and reduces operational costs of the enterprise.

The architecture of the intelligent repair management system has been developed, algorithms for analysis and forecasting have been defined, the database has been designed, and the software implementation has been described. The proposed solution ensures automation of key repair management processes, enables informed managerial decision-making based on data analysis, and increases the overall reliability of technical facilities.

Architecture of the Intelligent System

The architecture of the intelligent repair management system for combined-cycle and boiler equipment represents a set of interconnected modules that ensure data collection, processing, analysis, and the formation of management decisions. In the RepairIntelligence system, decision support is a mechanism that helps engineers, operators, and administrators make correct decisions regarding equipment repair and maintenance. The system not only displays data, but also analyzes it, draws conclusions, and suggests actions. In the repair management system, decision support performs the following tasks.

Table 1. Decision Support

№	System Function	Description	Key Parameters / Actions
1	Equipment Condition Monitoring	Continuous monitoring of parameters in real time	Temperature, pressure, vibration, load
2	Early Fault Diagnosis	Detection of deviations and prevention of accidents	Anomaly detection, alerts (e.g., temperature rise and overheating)
3	Failure Prediction (Predictive Maintenance)	Identification of future failures	When a failure will occur, how soon maintenance is required
4	Repair Recommendations	Decision support for maintenance activities	What to repair, when to repair, and how to repair
5	Planning Optimization	Improving maintenance efficiency	Repair schedules, resource allocation, reduction of downtime

The system implements a full cycle of information processing - from the acquisition of primary data to the generation of management decisions and reporting.

Sensors (Data Collection). Operational parameters of equipment are collected using sensors and measuring devices.

Database. The collected data are stored in a database, which ensures: storage of historical information, structuring of indicators, creation of technical condition archives, and maintenance of data integrity and reliability. Intelligent analysis is based on the data stored in the database.

Data Processing. At this stage, the following operations are performed: noise filtering, parameter normalization, removal of anomalous values, and data aggregation over time intervals. Data processing creates the conditions for high-quality analytical analysis. For efficient data processing and analysis, mathematical models are applied to identify hidden patterns, predict the technical condition of equipment, and detect deviations from normal operating conditions in a timely manner.

Regression Analysis for Condition Prediction. One of the main methods is multiple linear regression, which makes it possible to establish the relationship between equipment parameters and its condition:

$$\gamma = \beta_0 + \sum_{i=1}^n \beta_i x_i + \varepsilon \quad (1)$$

where γ is the predicted indicator of the equipment condition (for example, the probability of failure or the degree of wear); x_i are the input parameters (temperature, pressure, vibration, load, etc.); β_i are the coefficients reflecting the influence of each parameter; β_0 is the intercept of the model; ε is the random error. This model makes it possible to predict potential failures based on historical data and to make informed decisions regarding maintenance.

Time Series Analysis. To analyze changes in parameters over time, a time series model is used:

$$\gamma_t = \alpha + \beta_t + \varepsilon_t \quad (2)$$

where γ_t is the value of the parameter at time t ; α, β are the model parameters; ε_t is the random error. The application of this model makes it possible to identify trends in parameter changes, such as an increase in temperature or equipment wear, which is important for maintenance planning.

Anomaly Detection. To identify deviations from normal operating conditions, the standardization method is used:

$$z = \frac{x - \mu}{\sigma} \quad (\text{Formula 3})$$

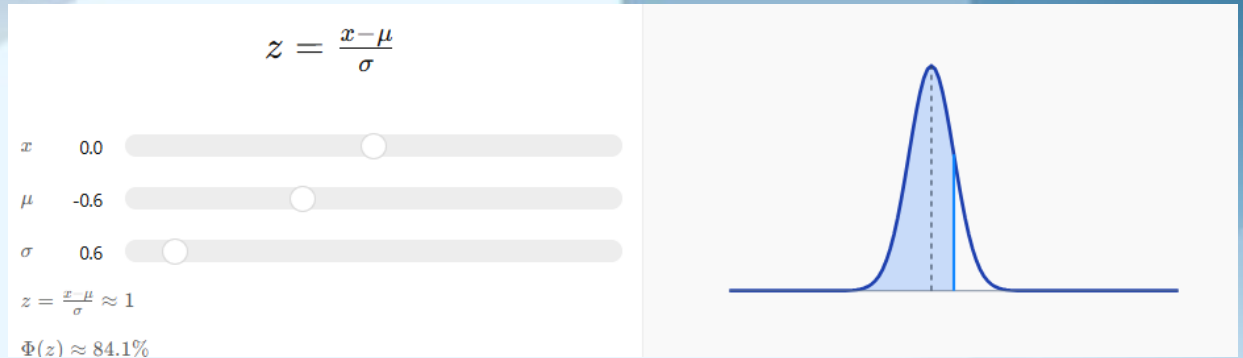


Figure 1. Anomaly Detection

where x is the current value of the parameter; μ is the mean value; σ is the standard deviation; z is the standardized deviation. If the value of z exceeds acceptable limits, this indicates the presence of an anomaly and a possible equipment malfunction.

Failure Probability Estimation. Logistic regression is used to estimate the probability of equipment failure:

$$P(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \sum_{i=1}^n \beta_i x_i)}} \quad (4)$$

where $P(y = 1)$ is the probability of equipment failure; x_i - are the input parameters; β_i - are the model coefficients. This method makes it possible to classify the condition of equipment and assess the risk of emergency situation. Analysis of relationships between parameters.

To determine the relationship between parameters, the correlation coefficient is used:

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \quad (5)$$

where r - is the correlation coefficient; x, y - are the studied parameters; $\bar{x}, \bar{y}$ - are the mean values. This indicator makes it possible to determine the degree of influence of one parameter on another, which is important for identifying the causes of equipment failures. The application of intelligent data analysis methods in the repair management system improves the reliability and efficiency of operation of combined-cycle and boiler equipment. The use of regression models, time series

analysis, anomaly detection methods, and failure probability estimation ensures timely fault detection and optimization of maintenance processes.

Analysis. The analysis module evaluates the current technical condition of the equipment. The following methods are used: statistical analysis, correlation analysis, detection of deviations from standard values, and diagnosis of hidden defects. In the development of the repair management system for combined-cycle and boiler equipment, statistical analysis, correlation analysis, deviation detection, and hidden defect diagnostics methods are applied. The use of these methods makes it possible to process large volumes of technological information and make well-informed decisions regarding equipment maintenance.

Statistical Data Analysis. For primary data processing, basic statistical characteristics such as the mean value are used:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^n x_i \quad (6)$$

Where $\bar{x}$ - is the mean value of the parameter; x_i - is an observation; n - is the number of observations. The mean value makes it possible to determine the normal operating level of equipment and serves as a basis for further analysis.

Correlation analysis. To identify relationships between equipment parameters, the correlation coefficient is used (Formula 5). Detection of deviations from standard values. To detect deviations, the standardization method (Z-transformation) is applied (Formula 3). Diagnosis of hidden defects. To identify hidden defects and assess the probability of failure, a logistic model is used (Formula 4). The application of statistical and correlation analysis methods, as well as algorithms for detecting deviations and diagnosing hidden defects, improves the efficiency of the repair management system. The use of intelligent data analysis ensures timely fault detection, reduces failure rates, and optimizes maintenance costs. The system determines the degree of component wear and identifies pre-failure conditions. In the developed repair management system for combined-cycle and boiler equipment, special attention is paid to assessing the degree of component wear and identifying pre-failure conditions. For this purpose, intelligent data analysis methods based on processing operational equipment parameters are applied. Assessment of component

wear. The degree of wear of a component is determined based on a set of monitored parameters using a weighted model:

$$W = \sum_{i=1}^n \omega_i x_i \quad (7)$$

where W is the integral wear indicator of a component; x_i are the normalized values of parameters (temperature, vibration, pressure, etc.); ω_i are the weight coefficients reflecting the significance of each parameter; n - is the number of considered parameters. This formula makes it possible to account for the contribution of each parameter to the overall equipment wear. The values of the coefficients ω_i are determined based on the analysis of historical data and expert assessments. Detection of pre-failure conditions. To diagnose pre-failure conditions, the method of deviation of parameters from standard values is used:

$$z = \frac{x - x_{norm}}{\sigma} \quad (8)$$

Where x is the current value of the parameter; x_{norm} is the standard (allowable) value; σ is the standard deviation; z is the deviation value. If the value of z exceeds the defined threshold, this indicates that the equipment has entered a pre-failure condition. Comprehensive Failure Risk Assessment. For a more accurate determination of the pre-failure state, a probabilistic model is used:

$$P = \frac{1}{1 + e^{-w}} \quad (9)$$

where P is the probability of equipment failure; W is the integral wear indicator.

when the probability P reaches a critical value, the system generates a warning indicating the need for maintenance. The use of an integral wear assessment and deviation detection methods makes it possible to timely diagnose pre-failure conditions of equipment. This ensures the transition from preventive maintenance to intelligent maintenance based on the actual technical condition of components.

Forecasting. Based on the collected data, the system performs forecasting of equipment failure probability, remaining useful life, and the optimal time for repair. Using the collected and processed data, the repair management system for combined-cycle and boiler equipment implements forecasting methods aimed at assessing failure probability, determining the remaining useful life, and selecting the optimal time for maintenance. The use of intelligent data analysis enables the transition from

scheduled maintenance to condition-based maintenance. Failure Probability Prediction. Logistic regression is used to estimate the probability of equipment failure (Formula 4). Remaining Useful Life Estimation. The remaining useful life of equipment is defined as the difference between the maximum allowable and the current condition:

$$R = T_{max} - T_{current} \quad (10)$$

where R is the remaining useful life; T_{max} is the maximum allowable life (service life); $T_{current}$ is the current operating time of the equipment. In a more general form, the remaining useful life can be adjusted taking into account operating conditions and the technical condition of the equipment.

Determination of Optimal Repair Time. The optimal time for repair is determined based on minimizing total costs:

$$C(t) = C_{repair} + C_{failure} * P(t) \quad (11)$$

where $C(t)$ is the total cost; C_{repair} is the cost of planned maintenance; $C_{failure}$ is the loss in case of equipment failure; $P(t)$ is the probability of failure at time t . The optimal repair time corresponds to the minimum of the cost function $C(t)$, which ensures the economic efficiency of equipment operation. The use of models for failure probability prediction, remaining useful life estimation, and optimization of repair timing improves the reliability and efficiency of equipment operation. Intelligent data analysis ensures timely decision-making, reduces failure rates, and enables rational planning of maintenance. Calculation of the Integral Condition Indicator. A central element of the repair management system for combined-cycle and boiler equipment is the calculation of the integral technical condition indicator. This indicator makes it possible to combine multiple diagnostic parameters into a single numerical criterion characterizing the current state of the equipment.

Integral Condition Indicator. The integral indicator is defined as a weighted sum of normalized parameters:

$$I = \sum_{i=1}^n w_i x_i \quad (12)$$

where I is the integral technical condition indicator; x_i are the normalized values of the monitored parameters (temperature, pressure, vibration, load, etc.); w_i are the weight coefficients reflecting the significance of each parameter; n is the number of

parameters. Parameter normalization is performed to bring them to a unified measurement scale.

Normalization of parameters. For correct aggregation of parameters, the following normalization formula is used:

$$x_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \quad (13)$$

where x_i is the normalized value of the parameter; $x_{\min}$, $x_{\max}$ are the minimum and maximum allowable values of the parameter. This allows all indicators to be scaled to a range from 0 to 1. Interpretation of the Integral Indicator. The resulting value of the integral indicator is used to assess the condition of the equipment:

$I \approx 0$ - Normal condition;

$I \rightarrow 1$ - Critical condition;

Intermediate values -Transitional modes.

When a threshold value is reached, the system detects a pre-failure condition and generates a signal indicating the need for repair. This is related to the probability of failure. The integral indicator can be used to estimate the probability of failure:

$$P = \frac{1}{1 + e^{-I}} \quad (14)$$

Where P is the probability of failure, and I is the integral condition indicator. The higher the value of I , the higher the probability of the equipment failing. Calculating the integral indicator of the technical condition is a key element of an intelligent repair management system. This indicator makes it possible to aggregate heterogeneous parameters, objectively assess the current state of the equipment, and make well-founded decisions regarding the need for maintenance or repair. The integral indicator provides a quantitative assessment of the level of technical condition, helps determine the priority of repair work, and allows the equipment to be ranked according to the risk level of failure.

For intuitive interpretation of results, an evaluation scale is used, presented in the form of color indicators:

- **green zone** — normal technical condition of the equipment;
- **yellow zone** — a condition in which scheduled maintenance is required;

- **red zone** — critical condition, characterized by a high failure risk and the need for immediate intervention.

Report Generation and Management Decisions. In an intelligent repair management system for combined-cycle power and boiler equipment, report generation and management decision-making are carried out based on aggregating diagnostic data and calculating key performance indicators. This enables the automation of equipment condition analysis and the generation of evidence-based management recommendations.

Integral Indicator for Reporting. For an overall assessment of the equipment fleet, a weighted average indicator is used:

$$I_{sys} = \frac{1}{N} \sum_{j=1}^N I_j \quad (15)$$

where I_{sys} is the integral condition of the system; I_j is the condition of the j -th equipment unit; N is the total number of equipment units. It is used to generate an overall report on the condition of all units. The share of equipment in different conditions is:

$$K = \frac{N_{kp}}{N_{общ}} * 100\% \quad (16)$$

where K is the share of critical equipment %; N_{kp} is the number of equipment units in a critical condition; $N_{общ}$ is the total number of equipment units. It is used for: assessing the level of risk at the facility. The system risk indicator is:

$$I_{sys} = \frac{1}{N} \sum_{j=1}^N P_j \quad (17)$$

where I_{sys} is the average risk of the system; P_j is the probability of failure of the j -th equipment unit. It is used for making repair decisions and setting maintenance priorities. Report generation and management decision-making in an intelligent equipment repair system are carried out based on aggregated technical condition indicators and the calculation of probabilistic failure models. Based on the individual values of the integral indicators, an overall assessment of the system's condition is formed. The share of equipment units in a critical condition is then calculated, which allows the level of operational risk to be evaluated. The system computes an average risk metric based on the failure probability of individual equipment units. Using the obtained values, a management decision is generated, which may include carrying out

a repair, switching the equipment to a monitoring mode, or continuing normal operation. The intelligent system provides automated decision support based on quantitative indicators of equipment condition.