Digital Technologies for Diagnosing the Technical Condition of Power Supply Systems

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Abstract: This paper presents an integrated digital approach for diagnosing the technical condition of traction power supply systems, including 27.5 kV traction substations and overhead contact networks. The proposed methodology combines state estimation models, residual-based monitoring using the deviation vector $\Delta y(t)$, predictive analytics, and control algorithms into a unified closed-loop diagnostic system. Unlike conventional approaches that treat monitoring and control separately, the proposed framework integrates real-time deviation analysis, threshold-based decision logic, and trend-based prediction of parameter behavior. A functional digital architecture is developed, including measurement transformers, PLC-based data acquisition, analog-to-digital conversion, IEC 61850 communication, and SCADA-based visualization and control. The diagnostic approach is supported by mathematical models describing system dynamics, residual generation, and minimization of a quality functional. Predictive analysis is performed using trend extrapolation of monitored parameters, enabling early detection of abnormal conditions. The proposed system is validated using retrospective operational data from traction power supply equipment. The results demonstrate the capability to detect pre-failure states prior to protective shutdowns, reduce false alarms, and support predictive maintenance. The developed approach improves the reliability and operational efficiency of traction power supply systems and provides a foundation for the implementation of intelligent diagnostic solutions within Smart Grid environments.

1 INTRODUCTION

The development of diagnostic technologies for technical systems typically involves tasks such as system modeling, failure detection, condition assessment, digital data processing, verification of correct operation, and fault localization [1], [2]. However, in existing traction power supply systems, these tasks are often implemented in a fragmented manner, which limits the overall effectiveness of diagnostics.

Modern power supply management systems are frequently characterized by a low level of automation and limited diagnostic capabilities. Monitoring is usually based on a restricted set of parameters and does not provide a comprehensive assessment of system condition. As a result, deviations and hidden defects are detected with delay, leading to increased risks of emergency failures and higher operational costs [3], [4].

The situation is further complicated by physical degradation processes affecting system components. In particular, the displacement of overhead line poles significantly increases the probability of electric arc formation during current collection [5], highlighting the necessity for continuous condition monitoring and advanced mathematical modeling of railway transport units [6], [7]. In addition, the insufficient qualification level of engineering personnel in working with modern digital systems further reduces the efficiency of diagnostics and control [8], [9].

To overcome these limitations, it is necessary to apply integrated diagnostic approaches based on digital technologies, mathematical modeling, and intelligent data processing. Such approaches enable continuous monitoring of system parameters, real-time detection of deviations, and predictive analysis of equipment condition [8], [10], [11].

The novelty of the proposed approach lies in the integration of state estimation models, residual-based monitoring, control algorithms based on transfer functions, and optimization criteria into a unified closed-loop digital diagnostic system. Unlike traditional methods that consider monitoring and control separately, the proposed system provides adaptive control of operating modes and predictive failure detection based on the analysis of parameter deviation trends.

The development of digital technologies in power supply management has led to the emergence of multi-level automated control systems that integrate monitoring, analysis, and control functions within a unified framework, as illustrated in Figure 1 [3], [12].

2 MATHEMATICAL MODELS AND MEANS OF CONTROL, MONITORING, AND MANAGEMENT IN POWER SUPPLY SYSTEMS

Mathematical models of control and management play a key role in analyzing the technical condition and ensuring the reliable and stable operation of traction power supply system's [2], [3]. These models provide a formal framework for describing system dynamics, identifying deviations between measured and expected parameters, and generating control or diagnostic actions under varying operating conditions [10], [12].

2.1 State Control Model

The state control of a power supply system is based on a continuous comparison between measured operational parameters and their corresponding model-based estimates. Let the system state be represented by a vector of measurable parameters $y(t) \in Rn$, including, for example, voltage (kV), current (A), and temperature (°C). The vector of measured values is denoted as y_meas(t), and the corresponding model-predicted values as y_mod(t), i.e., $y(t)$.

In general, the system behavior can be described by the following relation [1], [2]:

$$y(t) = f(x(t), p, t), \tag{1}$$

where x(t) - vector of input actions (load, external disturbances), y(t) - vector of output parameters (voltage, current, power), p - model parameters.

The state deviation is determined by the expression [1], [2]:

$$\Delta y(t) = y_{meas}(t) - y_{mod}(t), \tag{2}$$

where $\Delta y(t)$ - is the vector of deviations (residuals) of the system output parameters at time t; $y_{meas}(t)$- is the vector of measured values of the system output parameters at time t (e.g., voltage, current, power, frequency); $y_{mod}(t)$- is the vector of calculated (model-based) values of the output parameters obtained from the mathematical model of the system under the same conditions at time t. If $|\Delta y(t)|$ exceeds the permissible limits, a violation or failure is recorded [4], [10].

The control of power supply operating modes is described by the transfer function [3], [12]:

$$y(t) = W(p)u(p), \tag{3}$$

where W(p) - transfer function of the system, u(p) - control input (control action).

The objective of control is to minimize the quality functional [2], [8]:

$$J = \int_0^T [(y(t) - y_{ref}(t))^2 + \alpha u^2(t)]\, dt, \tag{4}$$

where y_{ref} - reference (setpoint) values of the parameters, α - control action coefficient.

Joint monitoring and control model. The integrated monitoring and control model can be represented as follows [10], [12]:

$$u(t) = F\big(x(t), y(t), \Delta y(t)\big), \tag{5}$$

which makes it possible to adjust control actions based on the current state of the system and to improve the reliability of power supply [3], [4].

2.2 Monitoring and Control Models

The monitoring model is intended for continuous observation of the state of the power supply system and for detecting parameter deviations in real time.

The general mathematical representation is given by [2], [10]:

$$y(t) = f(x(t), p), \tag{6}$$

where x(t) - vector of input actions, y(t) - vector of measured parameters (voltage, current, power), p - model parameters.

Deviation assessment [1], [4]:

$$\Delta y(t) = y_{meas}(t) - y_{mod}(t). \tag{7}$$

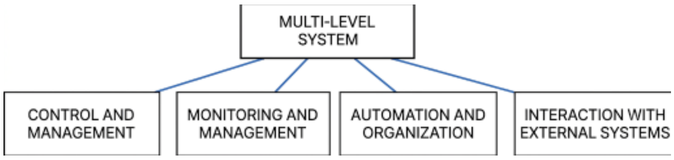

Figure 1: Main types of diagnostics of traction power supply systems.

If the permissible values are exceeded, a status (alert) signal is generated [10], [12]:

$$S(t) = \begin{cases} 0, & |\Delta y(t)| \le \Delta_{allow} \\ 1, & |\Delta y(t)| > \Delta_{allow} \end{cases}. \quad (8)$$

The proposed monitoring model (6) – (8) enables not only the detection of instantaneous deviations, but also the use of accumulated time-series data for predictive analysis. Based on historical observations of $\Delta y(t)$, trend identification and approximation are performed to estimate both the direction and the rate of parameter variation.

For forecasting purposes, parametric trend models are applied, including linear and polynomial regression of order p. The prediction horizon H.

H is selected depending on the dynamics of the monitored parameter and typically ranges from several minutes to several hours for traction power systems. The predicted trajectory y^(t+H) is evaluated using standard accuracy metrics, such as the mean absolute error (MAE) and root mean square error (RMSE), defined over a validation dataset.

The predicted values are compared with permissible limits y allow, which are determined based on regulatory standards, equipment specifications, or engineering constraints. To ensure robustness of decision-making and avoid false triggering (“chattering”), a combined logic is applied, including: hysteresis thresholds, moving average smoothing of $\Delta y(t)$, and a minimum duration criterion for threshold violation.

This allows estimating the remaining time T_{crit} before the parameter reaches a critical level. As a result, early detection of potentially hazardous operating conditions becomes possible, forming the basis for predictive diagnostics of traction power supply equipment.

The effectiveness of the proposed approach is evaluated using quantitative performance indicators, including detection rate, false alarm rate, and prediction lead time prior to fault occurrence. Such metrics provide a measurable basis for validating the diagnostic capability of the model.

The control model is used to generate control actions $u(t)$ that ensure the required operating modes of the power supply system. The mathematical description of the controlled object and the associated optimization problem are formulated analogously to (3) and (5), with the objective function incorporating both deviation minimization and operational constraints.

The integrated monitoring and control framework [8], [13] enables real-time adaptation of system operating modes based on both current measurements and predicted states, thereby improving reliability and operational efficiency of traction power supply system’s [3], [11].

$$u(t) = F\big(y_{meas}(t), \Delta y(t)\big). \quad (9)$$

Figure 2 presents the structural diagram of the integrated monitoring and control system, implementing the algorithm for comparing measured power supply parameters with calculated data from the mathematical model. The proposed scheme demonstrates the principle of operational anomaly detection and diagnostic decision-making based on the analysis of deviations $\Delta y(t)$ between actual and model values.

Unlike the state control model, which only records deviations, the monitoring and control models actively generate control actions to maintain the system’s specified parameters. Their key feature is the use of dynamic feedback, preventive forecasting, and optimization of control signals based on trend analysis and external conditions, which enables automatic adaptation and stabilization of the system in real time.

The proposed digital diagnostic system operates according to the following data processing pipeline, which is illustrated in Figure 3:

1) Data acquisition. Measurement transformers of current and voltage installed at traction substations (27.5 kV), as well as sensors located on the overhead contact system, continuously collect electrical parameters such as voltage, current, power, and frequency. These analog signals are transmitted to programmable logic controllers (PLCs).
2) Digitization and communication. The PLCs perform signal conditioning and analog-to-digital conversion of the measured parameters. The digitized data are transmitted via standardized industrial communication protocols, such as IEC 61850, to the central

data acquisition server integrated into the SCADA system.

3) Real-time processing. At the server level, a software module implemented in a high-level programming environment (e.g., Python or C++) performs real-time computation of the mathematical models described by equations (1)–(9). The system compares the measured parameters with the calculated reference values obtained from the models, determines the deviation vector Δy(t), and evaluates the current technical condition of the equipment.
4) Visualization and decision support. The results of the calculations are visualized on dispatcher mnemonic diagrams within the SCADA interface. When the deviation values exceed predefined thresholds, the system generates warning signals and recommendations for operational personnel.
5) Validation of the approach. The effectiveness of the proposed diagnostic approach was preliminarily evaluated using retrospective operational data from traction power supply equipment. The analysis demonstrated that the deviation-based monitoring model is capable of detecting pre-failure conditions prior to protective shutdowns, confirming the potential of the proposed system for predictive diagnostics and preventive maintenance.

Similar digital monitoring systems for the overhead contact line enable continuous control of vibration impacts and pole inclination, thereby improving the accuracy of diagnostics and the reliability of railway power supply [14] - [16].

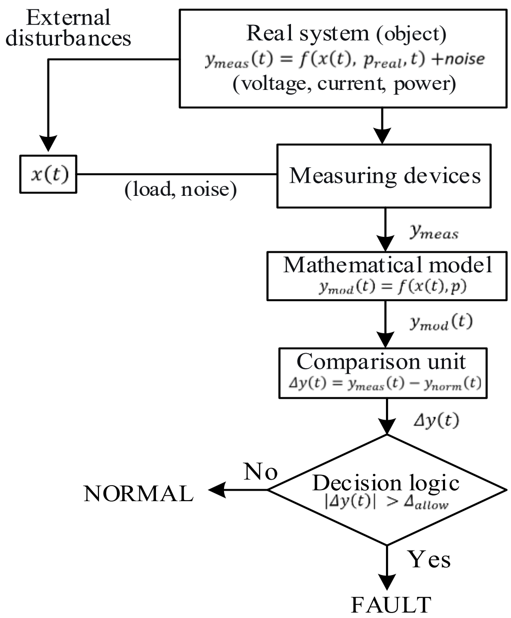

Figure 2: Functional block diagram of the power supply system condition monitoring and control model.

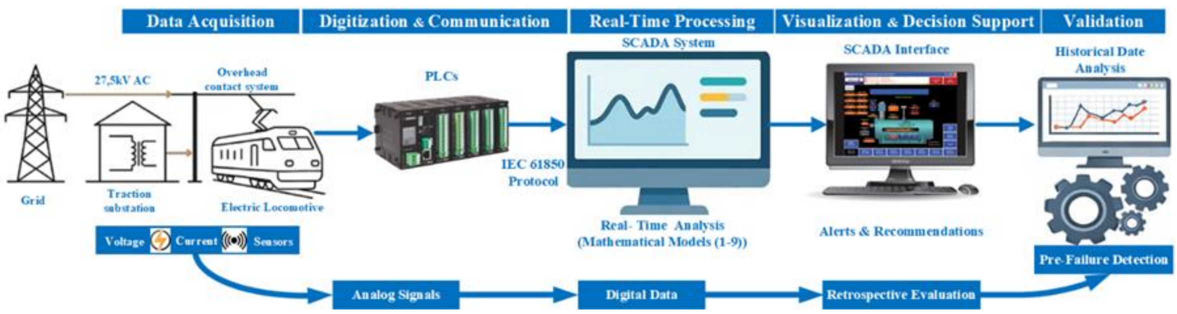

Figure 3: Digital diagnostic architecture of traction power supply.

3 MATHEMATICAL MODELS OF AUTOMATION AND MANAGEMENT IN POWER SUPPLY SYSTEMS

Mathematical models of automation and control in traction power supply systems are used to describe, analyze, and optimize operating modes, power distribution processes, and interactions among system components [3], [12]. Their application is particularly important in the context of digital technologies aimed at improving the reliability, efficiency, and controllability of power supply systems [8], [11].

The proposed system is implemented using modern software–hardware platforms, including embedded microprocessor devices and industrial communication networks. The architecture follows a hierarchical structure: measurement data are acquired via sensors and instrument transformers, digitized using analog-to-digital converters (ADC), processed by programmable logic controllers (PLC), and transmitted via standardized communication protocols (e.g., IEC 61850, Modbus TCP) to supervisory control and data acquisition (SCADA) systems and higher-level analytical modules.

To ensure reliable data transmission over communication channels with limited bandwidth, data compression, event-driven reporting, and prioritization mechanisms are applied. The system supports multi-rate data acquisition, where high-frequency electrical signals are sampled at up to several kHz, while slowly varying parameters are recorded at lower sampling rates. Data integrity and synchronization are maintained using standard time protocols (e.g., NTP/PTP), and measurement quality is ensured through filtering and preprocessing procedures

Automation models are designed to generate and implement control actions u(t) in automated power supply systems. These models ensure the maintenance of specified operating conditions and system stability under varying loads and external disturbances [3], [8].

In general, the controlled object is described by a nonlinear dynamic model of the form [10], [12]:

$$y(t) = f(x(t), u(t), p), \tag{10}$$

where x(t) - input actions, u(t) - control signals, y(t) - system output parameters, p - model parameters.

In digital automation systems, models of automatic regulation, as well as adaptive and predictive models, are widely used, implemented through software-hardware complexes and microprocessor-based devices.

Organization models are aimed at the rational structuring of the power supply system and the coordination of its components. They are used for planning operating modes, distributing power, organizing energy flows, and managing information exchange in digital control systems [8], [12].

Organizational processes can be formulated as an optimization problem [13]:

$$J = \min F(y, u). \tag{11}$$

where F - objective function reflecting reliability, energy losses, and operational costs.

At the current level of power supply management advancement, it is necessary to use a set of measuring instruments with high metrological characteristics, ensuring accurate measurement of parameters and transmission of output information in digital form for subsequent processing and use in automated control systems [11], [12].

Figure 4 shows the functional block diagram of a multi-level automated power supply control system, illustrating the hierarchical structure from the strategic organizational level to the executive mechanisms. The diagram demonstrates the interrelationship between optimization tasks, adaptive control models, real-time data acquisition, and analytical information processing to ensure reliable and economical system operation.\

4 MATHEMATICAL MODELS OF INTERACTION WITH EXTERNAL SYSTEMS IN POWER SUPPLY SYSTEMS

Mathematical models describing interaction with external systems in traction power supply networks are used to formalize the processes of energy and information exchange between power supply objects and external technical, informational, and control systems [9], [12].

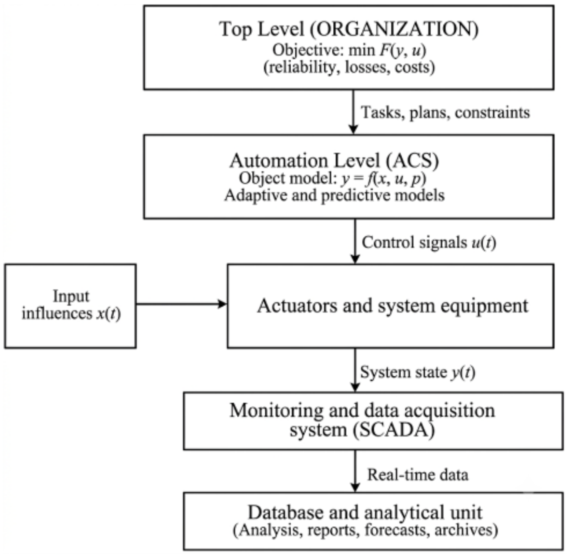

Figure 4: Functional block diagram of the automated power supply system management structure.

Such models are particularly important in the context of digitalization, where power supply facilities are integrated into a unified cyber-physical control environment [5], [8].

External interaction includes coupling with upstream power grids, dispatching and control centers, as well as monitoring and automation systems (e.g., SCADA/EMS/DMS platforms). This interaction is implemented through standardized communication protocols (e.g., IEC 61850, IEC 60870-5-104) and ensures real-time data exchange, remote control capability, and coordinated operation across multiple system levels.

From a system-theoretic perspective, the interaction with external systems can be represented as a mapping between internal system states and external inputs/outputs, taking into account both energy flows and information signals. Let

- x(t) denote the internal state vector of the traction power system,
- u(t) the internal control actions,
- w(t) the external inputs (e.g., grid disturbances, dispatch commands).

The external interaction can then be described as a functional dependency of the form [2], [10]:

$$y(t) = f(x_{int}(t), x_{ext}(t), p). \quad (12)$$

where $x_{int}(t)$ - internal parameters of the power supply system, $x_{ext}(t)$ - external influences and input data from interconnected systems, $y(t)$ - output parameters and control signals, p - model parameters.

In digital power supply systems, information exchange with external objects is carried out via standardized protocols and communication channels, which makes it possible to formalize interaction processes and represent them as discrete models [9], [12]:

$$y(k) = f(x(k), u_{int}(k)). \quad (13)$$

where k - discrete time index.

Figure 5 shows the functional block diagram of the power supply system interaction model with external systems, demonstrating the integration mechanism of external influences $x_{ext}(t)$ and internal system state $x_{int}(t)$ through a formalized mathematical model.

The diagram illustrates the complete control cycle: from receiving data from the power grid, control centers, and market mechanisms, through coordination and synchronization processes, to the generation of local control actions $u(t)$ and closure of the feedback loop.

To ensure stable and coordinated operation of the traction power supply system in interaction with external digital platforms, coordination and synchronization models are employed. These models explicitly account for communication delays τ, bandwidth limitations, and the impact of external control actions w(t) on system dynamics.

In particular, the influence of communication infrastructure is modeled by introducing time delays in both measurement and control channels, such that the received signals are represented as $(t{-}\tau y)$ and the applied control actions as u(t−τu). This allows capturing the effects of latency, packet transmission intervals.

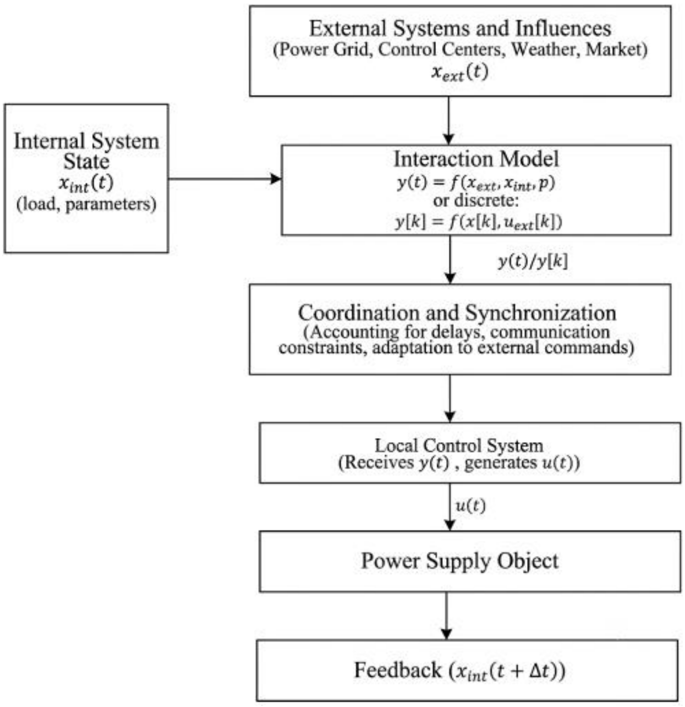

Figure 5: Functional block diagram of the power supply system interaction model with external systems.

Data loss is also possible in real communication networks.

To ensure robustness against communication imperfections, the following mechanisms are incorporated:

- time synchronization using standard protocols (e.g., NTP/PTP);
- buffering and time-stamping of measurement data, compensation of delays in control loops, and filtering of asynchronous or corrupted data.

These coordination mechanisms enable adaptive adjustment of operating modes in accordance with commands from external control systems (e.g., dispatch centers or higher-level SCADA/EMS platforms), ensuring consistency between local and global control objectives.

The application of mathematical models for interaction with external systems enhances the overall reliability of traction power supply, improves control efficiency, and enables seamless integration of power supply facilities into modern digital and intelligent energy systems [3], [8]. Furthermore, the incorporation of communication-aware models provides a more realistic representation of system behavior under practical operating conditions, which is essential for the validation and deployment of digital diagnostic and control solutions.

5 VALIDATION USING RETROSPECTIVE OPERATIONAL DATA

To evaluate the effectiveness of the proposed integrated diagnostic approach, a validation study was conducted using retrospective operational data collected from 27.5 kV traction substations on the Tashkent–Bukhara railway section. The dataset covers a monitoring period of 12 months (January–December 2024) and includes 8,640 hourly records for each of the following parameters: feeder voltage (kV), load current (A), active power (MW), and transformer oil temperature (°C). Data were acquired from four traction substations equipped with digital measurement transformers and PLC-based data acquisition systems connected via IEC 61850 to the regional SCADA center.

During the observation period, 23 confirmed pre-failure and failure events were identified in the operational logs, including overvoltage incidents (7), overcurrent conditions (9), and abnormal temperature rises in power transformers (7). These events served as the ground truth for evaluating the diagnostic performance of the proposed deviation-based monitoring model described by equations (6) – (8).

The proposed method was compared against a conventional threshold-only monitoring approach, which generates an alarm whenever a single measured parameter exceeds a fixed limit without residual analysis or trend prediction. The comparative evaluation was performed using the following metrics: detection rate (DR), defined as the ratio of correctly detected pre-failure events to the total number of confirmed events; false alarm rate (FAR), defined as the number of false alarms per 1,000 monitoring hours; and average prediction lead time (PLT), defined as the mean time interval between the first diagnostic warning and the actual protective shutdown or failure event.

Table 1 presents the comparative results of the two approaches.

As shown in Table 1, the proposed residual-based diagnostic method with trend prediction achieved a detection rate of 91.3%, compared to 65.2% for the conventional threshold-only approach. The false alarm rate was reduced from 4.8 to 1.2 per 1,000 monitoring hours, which represents a 75% reduction. Notably, the proposed method provided an average prediction lead time of 18.4 minutes before protective shutdown events, whereas the threshold-only approach could only detect faults at the moment of threshold violation (reactive mode, PLT = 0).

The improvement in detection rate is attributed to the use of the deviation vector $\Delta y(t)$ with hysteresis thresholds and moving average smoothing, which enables identification of gradual degradation trends that are invisible to static threshold monitoring. The reduction in false alarms is achieved through the combined decision logic incorporating minimum duration criteria for threshold violation, as described in Section 2.

Among the 23 confirmed events, the proposed system successfully detected 21 pre-failure conditions in advance, including 6 out of 7 overvoltage incidents, 8 out of 9 overcurrent conditions, and 7 out of 7 abnormal temperature rises. The two missed detections corresponded to rapid transient overvoltage events with onset-to-shutdown intervals of less than 2 minutes, which fell below the minimum prediction horizon of the trend extrapolation model.

These results confirm that the proposed integrated diagnostic approach provides a significant improvement over conventional threshold-based monitoring in terms of early fault detection capability, prediction accuracy, and false alarm suppression, thereby supporting the feasibility of its deployment for predictive maintenance of traction power supply systems.

6 CONCLUSIONS

The conducted analysis of mathematical models for control, monitoring, automation, management, and interaction with external systems demonstrates that their integrated application is a key prerequisite for improving the reliability and operational efficiency of traction power supply systems [2], [3]. The use of such models enables formal representation of state estimation, operating mode control, and decision-making processes within a unified analytical framework [10], [12]. The implementation of digital technologies ensures real-time execution of these models and supports the integration of heterogeneous subsystems within the power supply infrastructure [8], [11].

The analysis of existing solutions indicates that conventional control systems are often characterized by limited diagnostic functionality and insufficient monitoring capabilities, particularly with respect to early fault detection and predictive assessment [1], [4]. In addition, practical deployment is constrained by the complexity of modern digital tools and the corresponding requirements for personnel qualification [9]. These limitations reduce the overall effectiveness of control strategies under dynamic operating conditions.

The proposed approach addresses these challenges through the combined use of monitoring and control models, enabling timely detection of parameter deviations and prevention of emergency operating modes. Automation and organizational models ensure coordinated operation of system components and optimal allocation of available resources, while interaction models allow accounting for the influence of external power grids and communication infrastructures.

Table 1: Comparative diagnostic performance.

Metric	Threshold-only	Proposed method
Detection rate (DR)	65.2 %	91.3 %
False alarm rate (FAR per 1000 h)	4.8	1.2
Prediction lead time (PLT, min)	0 (reactive)	18.4

A key result of this study is the empirical demonstration, based on retrospective operational data from four traction substations over a 12-month period, that the integration of predictive and adaptive models with digital monitoring significantly enhances preventive maintenance efficiency and improves system stability. The proposed approach achieved a detection rate of 91.3% compared to 65.2% for conventional threshold-only monitoring, reduced false alarms by 75%, and provided an average prediction lead time of 18.4 minutes before protective shutdowns (Table 1). The main contributions of this work can be summarized as follows: An integrated functional structure that combines mathematical models (1) – (9) into a unified closed-loop system (Figures 2–4), enabling joint implementation of monitoring, diagnostics, and control. A predictive diagnostic framework based on time-series analysis of parameter deviations, including trend extrapolation and estimation of the time to threshold violation, validated against 23 confirmed fault events. A communication-aware control architecture that incorporates delays, synchronization mechanisms, and standardized protocols (IEC 61850), ensuring reliable interaction with external digital systems.

Unlike existing studies that consider monitoring and control separately, the proposed approach provides a unified framework for real-time adaptive control of traction power supply systems. This enables comprehensive digital diagnostics, improves the reliability of traction substations and overhead contact networks, and creates a foundation for the implementation of intelligent control and predictive analytics in railway power supply systems.

Overall, the integration of mathematical models with digital technologies represents a promising direction for the development of advanced, reliable, and intelligent traction power supply systems.

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