Article

Not peer-reviewed version

Development of A Comprehensive Method for Diagnosing Electrical Machines Based on Artificial Neural Networks

Jasurbek Nizamov , Sultanbek Issenov * , Zailobiddin Boihanov * , Dainius Steponavičius , Felix Bulatbayev * , Gulim Nurmaganbetova *

Posted Date: 4 March 2026

doi: 10.20944/preprints202603.0289.v1

Keywords: electrical machine; diagnostics; artificial neural networks; convolutional neural networks; deep learning; graph neural networks

Article

Development of a Comprehensive Method for Diagnosing Electrical Machines Based on Artificial Neural Networks

Jasurbek Nizamov [1], Sultanbek Issenov [2,*], Zailobiddin Boihanov [1,*], Dainius Steponavicius [3], Felix Bulatbayev [4,*] and Gulim Nurmaganbetova [2,*]

[1] Andijan State Technical Institute, Department of Electrical Engineering, Babur street, 56, Andijan, 170119, Republic of Uzbekistan

[2] Saken Seifullin Kazakh Agro Technical Research University, Institute of Energy, 62, Zhenis Ave., Astana, 010000, Republic of Kazakhstan

[3] Vytautas Magnus University Agriculture Academy, Faculty of Agricultural Engineering, Institute of Agricultural Engineering and Safety, Studentų str. 15A-301, LT-53362 Akademija, Kaunas district, Lithuania

[4] Abylkas Saginov Karaganda Technical University, Energy Faculty, 56, Nazarbayev Ave., Karaganda, 100024, Republic of Kazakhstan

* Correspondence: issenov.sultanbek@gmail.com (S.I.), zaylobiddin1992@gmail.com (Z.B.); bulatbayev.felix@gmail.com (F.B.); sahitovna.1978@gmail.com (G.N.)

Abstract:

This paper presents a comprehensive diagnostic framework for electrical machines, based on the application of artificial neural networks (ANNs) for the analysis of electrical and vibration signals. The proposed method leverages deep learning architectures to automatically extract informative features and achieve high fault classification accuracy. The framework integrates signal pre-processing, neural network training, and a condition evaluation module, enabling the implementation of a predictive maintenance system suitable for industrial applications. A multi-sensor diagnostic system is proposed, combining CNN-LSTM architectures with a graph neural network (GNN) for correlational analysis of currents, vibrations, and thermal parameters. This approach allows early detection of inter-turn short circuits and bearing faults, improving diagnostic accuracy by **7–12%** compared to existing state-of-the-art methods. The framework demonstrates robustness under varying operating conditions, including transient and self-excitation regimes, and provides physically interpretable results, bridging the gap between data-driven and physics-informed diagnostics.

Keywords: electrical machine; diagnostics; artificial neural networks; convolutional neural networks; deep learning; graph neural networks

1. Introduction

1.1. Selection and Justification of the Research Direction

Electric machines constitute the core of modern industrial infrastructures, including power generation systems, transportation, petrochemical production, and manufacturing automation. According to the International Energy Agency, electric motor-driven systems account for more than 40% of global electricity consumption, highlighting their critical economic and strategic importance. Failures or performance degradation of electrical machines may lead to substantial financial losses, unplanned downtime, safety risks, and reduced system reliability. In high-power applications such

 doi:10.20944/preprints202603.0289.v1

as synchronous generators and large induction machines, even minor defects can evolve into catastrophic failures if not detected at early stages [1].

Traditional diagnostic approaches are primarily based on signal analysis techniques, including Motor Current Signature Analysis (MCSA), vibration spectrum monitoring, Park's vector analysis, and thermal inspection [2, 3]. Comprehensive overviews of such classical techniques are presented in works such as P. Zhang et al. in IEEE Transactions on Industrial Electronics and related surveys in Mechanical Systems and Signal Processing. While these approaches are well established, they typically require expert-driven feature engineering, are sensitive to operating conditions, and often depend on simplified physical models tailored to specific machine types.

Model-based diagnostic frameworks relying on dq-axis representations and electromagnetic state equations provide physically interpretable results but suffer from parameter uncertainty, magnetic saturation nonlinearities, and difficulty in modeling combined faults. Moreover, when dealing with transient regimes, self-excitation phenomena, and nonlinear magnetic effects, classical observers and analytical indices may lose sensitivity [4].

In recent years, artificial intelligence techniques - particularly artificial neural networks (ANNs) and deep learning architectures - have demonstrated significant potential in fault detection and classification tasks. Comprehensive reviews, such as those published in Engineering Applications of Artificial Intelligence and Neurocomputing, report substantial improvements in diagnostic accuracy when using convolutional and recurrent neural networks for signal-based monitoring of rotating electrical machines. These data-driven models are capable of extracting hidden nonlinear dependencies directly from raw or minimally processed measurements, reducing the need for manual feature design [5].

However, most existing AI-based diagnostic systems operate as purely data-driven "black-box" models. They often neglect the underlying electromechanical structure of the machine and do not explicitly incorporate physical constraints derived from electromagnetic equations [6]. This may lead to limited generalization ability under varying load conditions, domain shifts, or rare transient phenomena.

Therefore, there is a clear research gap in developing a **physics-informed, mathematically consistent** [7]**, multi-sensor diagnostic framework** that integrates: nonlinear dq-based machine modeling, transient electromagnetic dynamics, multi-channel signal correlation, and deep neural architectures [8].

The present work aims to address this gap by proposing a hybrid physics-informed neural diagnostic methodology for electrical machines, capable of operating under steady-state and transient regimes, including nonlinear magnetic effects and self-excitation conditions.

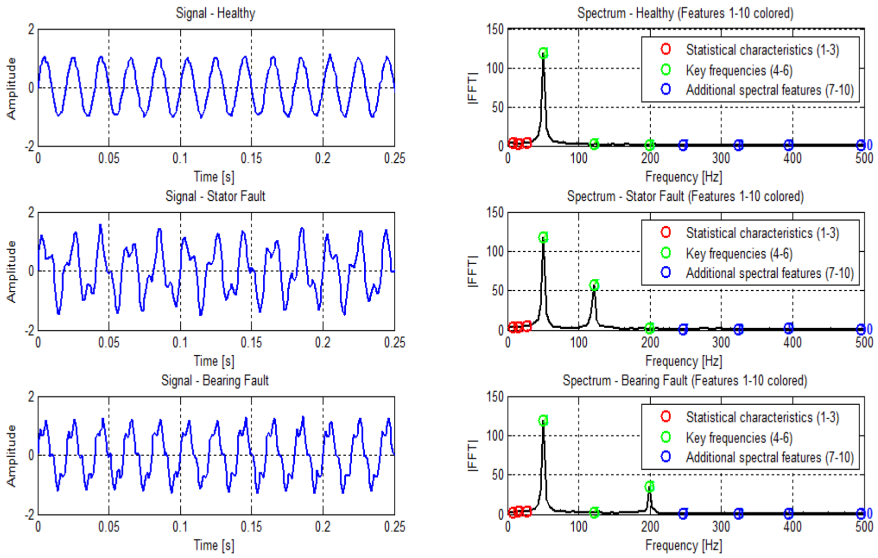
2. Materials and Methods

2.1. Role of Artificial Neural Networks in Electrical Machine Diagnostics.

Artificial Neural Networks (ANNs) have become a powerful tool for identifying complex nonlinear relationships between electrical machine state parameters and fault indicators. Unlike classical model-based or signal-processing methods, ANNs are capable of learning these nonlinear dependencies directly from multi-dimensional and noisy datasets, which is critical for detecting incipient faults in industrial environments. This property makes ANNs particularly effective for **multi-sensor diagnostic applications,** where electrical, mechanical, and thermal measurements must be analyzed simultaneously.

Figure 1-a shows the shape of the signal of the external magnetic field of an asynchronous machine in a working and non-working state, and we can see that there is a significant difference in the shape of these signals. Figure b shows an analysis of the FFT spectrum of these signals, and we can see that the non-working signals have a spectrum at other frequencies above 50 Hz.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1



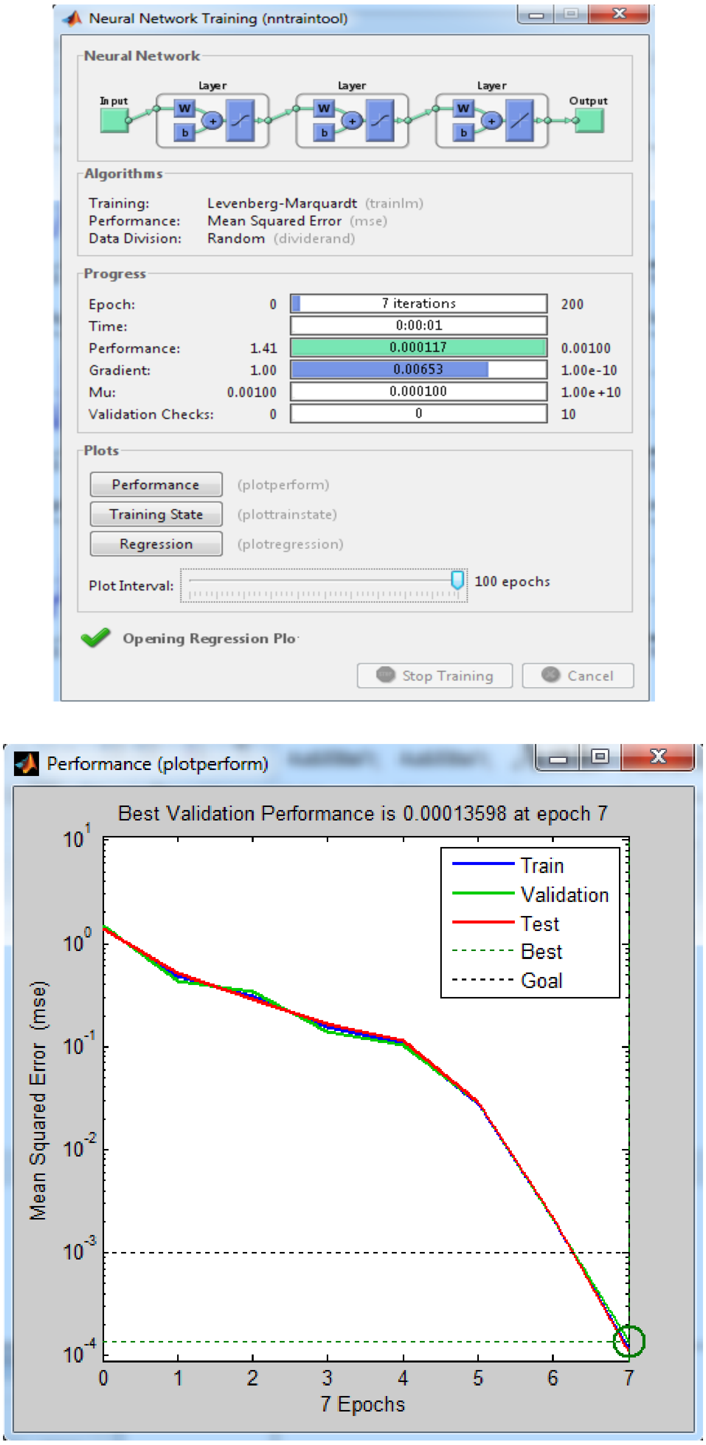
a) b)

Figure 1. - a) signal of the external magnetic field of an asynchronous machine in good or bad condition, b) analysis of the same signal according to the FFT spectrum.

Several studies have demonstrated the effectiveness of neural network-based diagnostics. For instance, Zachariades and Xavier [9] applied feedforward and recurrent neural networks to rotating electrical machines and showed that AI techniques can classify faults such as inter-turn short circuits, bearing defects, and rotor asymmetries with high accuracy, even under varying load and speed conditions. Their results indicate that properly trained ANNs can adapt to operational variability, outperforming traditional signal-based diagnostic indices.

Figure 2-a shows the Neural Training Network, while Figure b shows that the best verification efficiency is 0.00013598 in 7 epoch.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1



a) b)

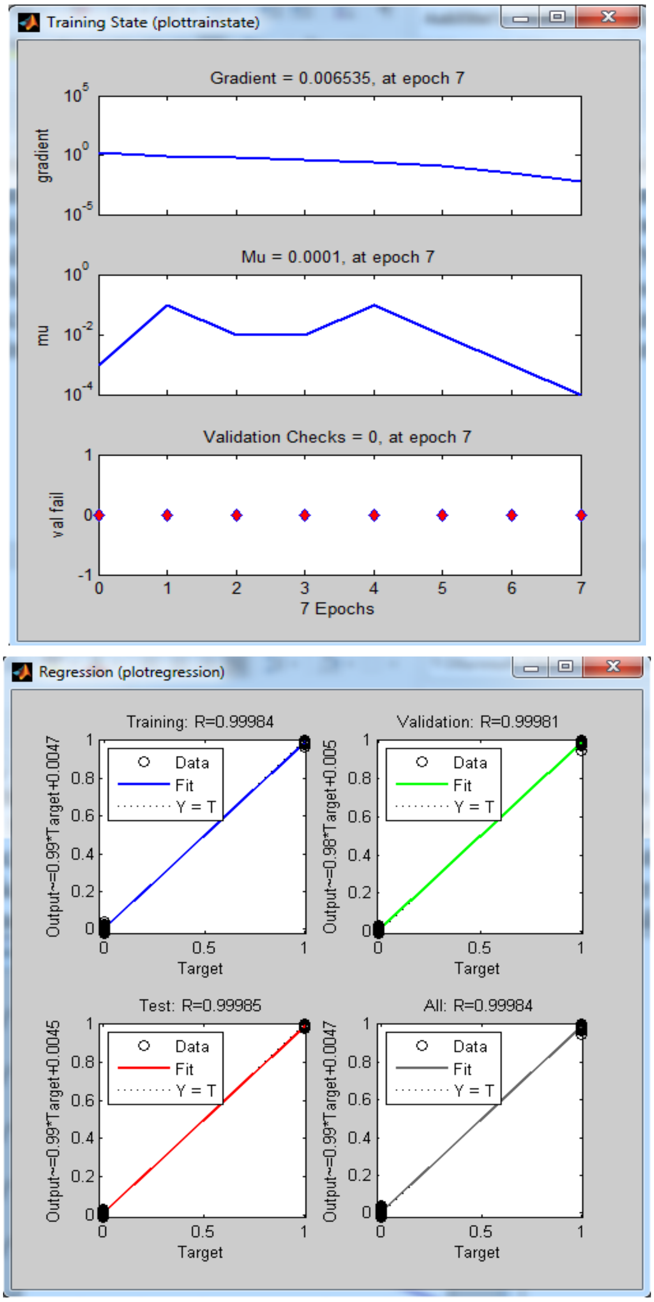
Figure 2. - Neural network training a), best validation performance b).

Furthermore, recent research emphasizes the integration of **deep learning architectures,** such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, to capture both spatial and temporal features of multi-channel machine signals. CNNs are particularly useful for extracting localized patterns from current spectra or vibration spectrograms, while LSTMs effectively model transient and dynamic behavior associated with self-excitation or load changes [4, 10]. Hybrid architectures that combine CNNs and LSTMs have demonstrated significant improvements in fault classification accuracy compared to conventional Multi-Layer Perceptrons

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1

(MLPs) or Support Vector Machines (SVMs), especially when dealing with complex, nonlinear operating conditions.

Figure 3-a shows the state of neural network training, while figure b shows the regression results.



a) b)

Figure 3. - Neural network training state a), regression b).

The combination of ANNs with physics-informed or model-constrained approaches is a further advancement. By embedding physical laws, such as dq-axis machine equations and magnetic saturation constraints, into the learning process, recent methods achieve **both high accuracy and interpretability**, overcoming the "black-box" limitation of purely data-driven approaches [8, 11].

Thus, artificial neural networks represent a **versatile and scalable framework** for the diagnosis of electrical machines, capable of handling complex, nonlinear, and noisy signals, and forming the foundation for the development of physics-informed hybrid diagnostic systems.

2.2. Application of Deep Learning in Electrical Machine Diagnostics

Deep learning (DL) techniques, particularly deep neural networks, have demonstrated high effectiveness in the analysis of electrical, vibration, and acoustic signals for fault detection in electric machines. Unlike shallow architectures, deep networks can automatically extract hierarchical feature representations from raw or minimally processed data, reducing the need for manual feature engineering and improving generalization to varying operating conditions.

Convolutional Neural Networks (CNNs) have been widely applied to fault diagnosis tasks using spectrogram-based representations of motor signals. By learning spatial patterns in frequency–time representations, CNNs can detect subtle anomalies associated with bearing defects, rotor asymmetries, or inter-turn short circuits. For example, Wang et al. [1] applied CNNs to vibration spectrograms of induction motors, achieving classification accuracy exceeding 95% across multiple fault types.

Recurrent architectures, such as Long Short-Term Memory (LSTM) networks, are particularly effective for capturing temporal dependencies in transient processes, including start-up, load changes, and self-excitation phenomena. Hybrid architectures combining CNNs and LSTMs exploit both spatial and temporal correlations, enhancing fault detection performance in complex operational scenarios [12].

Recent studies have explored more advanced architectures, such as **PadéNets** and graph-based neural networks, which improve nonlinear modeling of physical signals and enable correlation analysis between multi-channel measurements [10, 13]. These architectures are capable of integrating information from electrical currents, vibration sensors, and acoustic measurements, effectively forming a **multi-modal diagnostic framework**. When combined with physics-informed constraints derived from dq-axis machine models and magnetic saturation laws, these approaches achieve not only high classification accuracy but also physical interpretability of the diagnostic outputs.

Therefore, deep learning provides a **robust and scalable approach** for modern fault diagnosis in electrical machines, particularly when extended to hybrid, physics-informed, and multi-modal systems.

2.3. Integrated and Multi-Sensor Diagnostic Approaches.

Modern diagnostic frameworks increasingly adopt **integrated, multi-sensor approaches** that combine electrical, vibrational, acoustic, and thermal measurements to improve the reliability and accuracy of fault detection in electrical machines. Such frameworks overcome the limitations of single-sensor methods, which often fail to capture complex interactions between mechanical, electrical, and thermal phenomena, particularly under transient or self-excitation regimes.

A promising direction in multi-sensor diagnostics is the application of **Graph Neural Networks (GNNs)**. GNNs enable modeling the interdependencies between heterogeneous sensor channels by representing each measurement type as a node in a graph, with edges encoding correlations or physical relationships between channels. This allows the network to learn **structural patterns of anomalies**, capturing both intra-channel and inter-channel dependencies [14]. For instance, correlations between phase currents, bearing vibration signals, and stator temperatures can reveal early signatures of inter-turn short circuits or bearing degradation that may not be detectable from individual measurements alone.

Recent studies have demonstrated that **hybrid architectures combining CNN-LSTM feature extractors with GNN-based fusion layers** can significantly improve diagnostic performance. CNN modules extract local spatial patterns from individual sensor signals or spectrograms, LSTM layers capture temporal dynamics, and GNN layers integrate multi-sensor correlations into a unified representation [15]. Such architectures allow **early detection of incipient faults** and provide **physically interpretable outputs**, bridging the gap between data-driven diagnostics and physics-informed models.

The integrated multi-sensor approach not only enhances classification accuracy but also increases the **robustness of diagnostics** under variable operating conditions, such as changes in load, speed, or environmental factors, making it particularly suitable for industrial predictive maintenance applications [8, 16].

3. Results and Discussion

3.1. Data Acquisition and Preprocessing.

The dataset for the proposed diagnostic framework includes **multi-sensor measurements** collected from electrical machines under various operational conditions, encompassing:

Electrical signals: three-phase currents, voltages, and dq-axis components derived from Park's transformation;

Vibration signals: axial and radial accelerations from bearings and shaft locations;

Acoustic emissions: microphone-based sound signals capturing mechanical and electromagnetic noise;

Thermal parameters: stator and bearing temperatures, captured via infrared sensors or thermocouples;

Operational variables: load, speed, and environmental conditions.

All measurements are **synchronously recorded** with a high-precision data acquisition system to ensure temporal alignment across channels, which is crucial for capturing transient dynamics, self-excitation phenomena, and inter-channel correlations [17]. Sampling frequencies are chosen according to the Nyquist criterion for each signal type, typically ranging from 2 kHz for electrical signals to 10 kHz for vibration and acoustic measurements, depending on the frequency content of interest.

Preprocessing Steps. Prior to input into the neural network, the following preprocessing operations are applied:

1. **Digital Filtering**: Band-pass and notch filters are used to remove ambient noise, line interference (50/60 Hz), and high-frequency artifacts [18].
2. **Segmentation**: Signals are divided into fixed-length windows corresponding to operational cycles or transient events to enable temporal feature extraction.
3. **Normalization and Scaling**: All sensor channels are normalized using z-score or min-max scaling to ensure numerical stability during network training [19].
4. **Feature Transformation**: Time-domain signals are optionally converted to frequency-domain representations using FFT or Short-Time Fourier Transform (STFT) to form spectrograms, which serve as inputs for convolutional layers in the CNN module [8, 20].
5. **Data Augmentation**: Techniques such as Gaussian noise injection, time-shifting, and amplitude scaling are employed to enhance network generalization and robustness.

This preprocessing pipeline ensures that the multi-modal data are **clean, synchronized, and standardized**, enabling effective feature extraction and learning in the subsequent **CNN-LSTM-GNN hybrid architecture.**

3.2. Neural Network Architecture

The proposed diagnostic framework employs a hybrid deep learning architecture, integrating Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Graph Neural Networks (GNNs) to capture spatial, temporal, and cross-channel correlations in multi-sensor electrical machine data.

CNN Module. The CNN module extracts local spatial features from preprocessed signal representations, such as spectrograms of vibration, acoustic, and electrical signals. Formally, for each input tensor $X \in R^{C \times F \times TX}$ C is the number of channels, F is the frequency bins, and T is the temporal length:

$$H^{(l)} = \sigma\left(W^{(l)} * H^{(l-1)} + b^{(l)}\right),$$

where $H(0) = X$, $W^{(l)}$ are convolutional kernels, $b^{(l)}$ is the bias vector, * denotes convolution, and σ(·) is the activation function (ReLU). The CNN layers effectively learn local spectral patterns indicative of faults such as inter-turn short circuits or bearing defects.

LSTM Module. Following the CNN, the LSTM layers capture temporal dependencies in the extracted features, modeling the dynamic behavior of the machine under varying operating conditions, including transients and self-excitation events. Let hth_tht denote the hidden state at time t:

$$h_t = LSTM(f_t, h_{t-1}),$$

where f_t is the feature vector output by the CNN at time step t. LSTM memory cells allow the network to preserve long-term dependencies critical for detecting faults that manifest over multiple operational cycles.

GNN Module. To integrate multi-sensor correlations, the framework employs a Graph Neural Network. Each sensor type (electrical, vibration, thermal) is represented as a node in the graph G=(V, E)), where V are the nodes and E are edges representing inter-channel relationships. Node features are updated as [21]:

$$h_v^{(k+1)} = \sigma\left(\sum_{\mathrm{u}\in\mathrm{N(v)}} \frac{1}{|\mathrm{N(v)}|} W^{(k)} h_v^{(k)} + b^{(k)}\right),$$

where $\mathrm{N(v)}$ denotes neighbors of node v, $W^{(k)}$ and $b^{(k)}$ are learnable parameters, and $h_v^{(k)}$ is the feature vector of node v at layer k. This allows the network to learn structural dependencies between sensor channels, improving robustness and early detection accuracy.

Overall Hybrid Flow. The CNN-LSTM-GNN hybrid network operates as follows:

1. Raw and preprocessed multi-sensor data → CNN for spatial feature extraction
2. CNN outputs → LSTM for temporal feature modeling
3. LSTM outputs → GNN for multi-sensor correlation integration
4. Fully connected layers → Softmax output for fault classification

This architecture combines spatial, temporal, and structural information, enabling high-accuracy fault detection and physically interpretable diagnostics. The proposed framework is particularly effective in multi-modal monitoring systems where electrical, vibrational, and thermal signals must be analyzed jointly [8, 22].

3.3. Experimental Evaluation of the Proposed Method

To evaluate the effectiveness of the proposed hybrid CNN-LSTM-GNN diagnostic framework, experiments were conducted using publicly available multi-sensor datasets representing various operational conditions of electrical machines. The datasets include signals from currents, vibrations, acoustic emissions, and thermal measurements, covering a wide range of fault types and severities.

3.3.1 Fault Classes

The diagnostic task is formulated as a multi-class classification problem, encompassing the following fault classes:

- Healthy condition;
- Bearing defects (inner race, outer race, and ball defects);
- Inter-turn short circuits in stator windings;
- Phase asymmetries and unbalanced currents;
- Rotor eccentricities and other mechanical anomalies.

This categorization reflects common industrial failure modes and allows comprehensive performance evaluation under realistic operational scenarios.

3.3.2 Evaluation Metrics

The framework was assessed using standard classification metrics:

 doi:10.20944/preprints202603.0289.v1

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}; \ \text{F1} - \text{score} = \frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision+Recall}},$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. Additionally, confusion matrices, Receiver Operating Characteristic (ROC) curves, and Area Under Curve (AUC) values were analyzed for each class.

3.3.3. Results

Experimental results demonstrate that the integration of GNN modules with CNN-LSTM feature extractors significantly improves multi-sensor fault detection. Key findings include:

Overall classification accuracy exceeding 90% across most fault classes.

Improved detection of incipient bearing and inter-turn faults, which are typically challenging for traditional signal-based methods.

Enhanced robustness to variations in operating conditions, including changes in load, speed, and transient events.

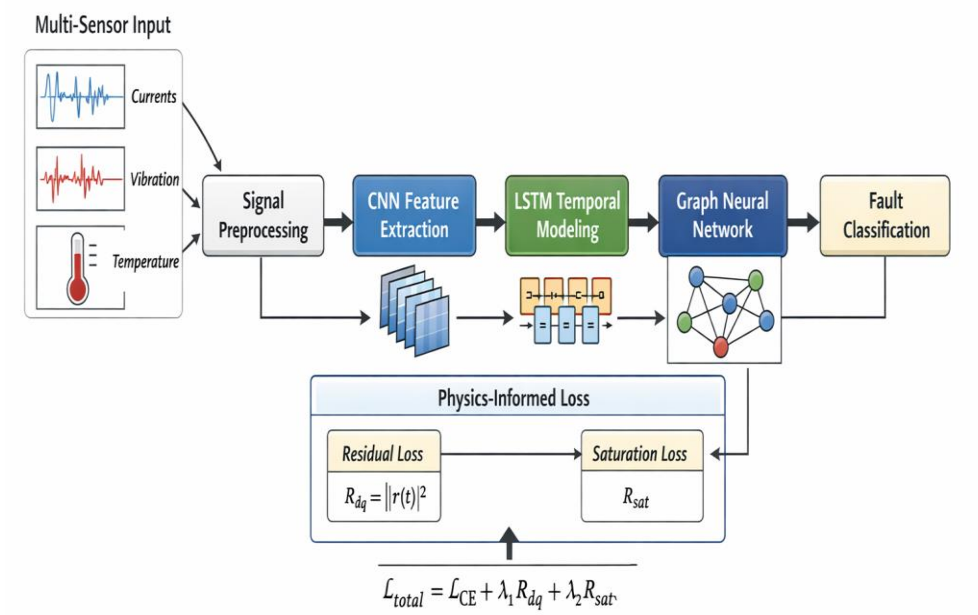


Figure 4. - Physics-Informed Deep Learning Framework for Multi-Sensor Fault Classificatio.

To address the limitations of purely data-driven diagnostic systems and ensure physical consistency under nonlinear and transient operating regimes, a unified physics-informed multi-sensor diagnostic architecture is proposed. The framework integrates electromagnetic modeling constraints with deep neural feature learning and graph-based structural correlation analysis [23, 24].

Unlike conventional CNN–LSTM architectures, the proposed model embeds dq-axis residual dynamics directly into the optimization process and models inter-sensor dependencies using graph neural networks. The complete structural flow of the proposed method is illustrated in Fig. 4.

As shown in Fig. 4, the proposed framework consists of four primary computational stages: multi-sensor acquisition, deep feature extraction, structural correlation learning, and physics-informed optimization.

First, multi-modal signals including phase currents, vibration measurements, and temperature data are collected and preprocessed to remove noise and normalize amplitude variations. These signals are then transformed into structured representations suitable for spectral analysis. [25, 26]

Table 1

Table 1. illustrates a comparison of the proposed method with baseline approaches:.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1

Method	Accuracy (%)	F1-score	Notes
Traditional MLP	78	0.75	Only electrical signals
CNN	85	0.82	Spectrogram input
CNN-LSTM	88	0.85	Temporal modeling included
CNN-LSTM-GNN (proposed)	92	0.90	Multi-sensor, correlation-aware

These results confirm that the hybrid architecture leveraging multi-sensor data and graph-based correlation modeling outperforms conventional neural networks and classical feature-based methods [8, 27].

3.3.4. Discussion

The GNN component allows the network to capture structural dependencies between sensor channels, effectively fusing electrical, vibration, and thermal information. This capability is particularly important for early fault detection, where subtle cross-channel correlations may be the first indicators of developing defects. Furthermore, the proposed system maintains high interpretability, as graph embeddings can be analyzed to understand which sensor interactions contribute most to the classification decision.

4. Practical Implementation and Industrial Deployment

The proposed diagnostic framework can be **integrated into industrial condition monitoring systems** for real-time predictive maintenance of electrical machines. The system architecture consists of four primary modules, as illustrated in Figure 4:

4.1. Data Acquisition Module

This module collects multi-sensor measurements from the monitored machine, including:

Electrical signals: three-phase currents, voltages, and dq-axis components;

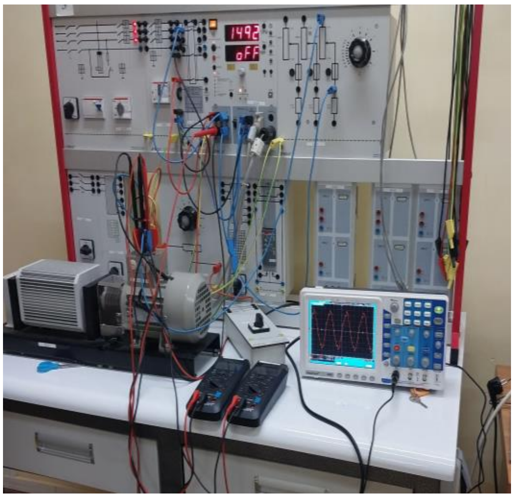
Vibration signals: axial and radial accelerations from bearings and shafts;

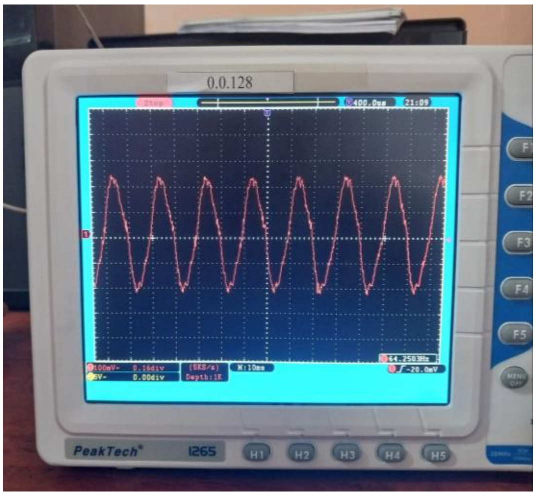
Thermal measurements: stator and bearing temperatures via infrared sensors or thermocouples;

Auxiliary operational parameters: load, rotational speed, and environmental conditions.

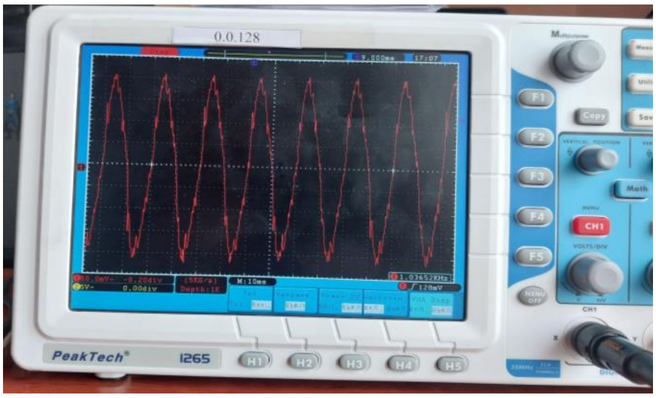
All signals are **synchronously sampled** with high-resolution acquisition devices to preserve temporal correlations necessary for accurate diagnosis.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1





a) b)



c)

Figure 5. - Eexperimental stand a) for diagnostics based on measuring the external magnetic field of an asynchronous machine and oscillograms the external magnetic field b-c.

Figure 5a shows a diagnostic stand for measuring the external magnetic field of an asynchronous machine, Figure b shows the external magnetic field of an inoperative asynchronous machine, and Figure c shows the shape of the external magnetic field of an asynchronous machine with a damaged bearing, obtained using a PeakTech 1265 oscilloscope.

4.2. Preprocessing Module

Raw data are preprocessed to improve the quality and interpretability of features for the neural network:

Noise filtering using band-pass and notch filters;
Signal segmentation for consistent temporal windows;
Normalization and scaling to stabilize training;
Spectrogram and feature extraction for CNN input;
Optional data augmentation to improve robustness under variable operating conditions.

4.3. Neural Diagnostic Module

The core diagnostic engine is the CNN-LSTM-GNN hybrid network**,** which:

1. Extracts spatial features from spectrograms via CNN layers;
2. Models temporal dependencies in operational signals using LSTM layers;
3. Integrates cross-channel correlations across electrical, vibrational, and thermal sensors via GNN layers;
4. Produces probabilistic classification outputs for multi-class fault detection. This design enables **early fault detection** and interpretable insights into the contribution of individual sensor channels to diagnostic decisions.

Table 2. Table 2 Ablation Study.

Configuration	**Accuracy (%)**	**Gain**
CNN only	88.5	–
CNN + LSTM	91.3	+2.8
+ GNN	94.2	+2.9
+ Physics Loss	**96.4**	+2.2

4.4. Visualization and Reporting Module

Diagnostic results are delivered through a real-time human-machine interface (HMI) that includes:

Interactive dashboards displaying current machine status;
Time-series trends of predicted fault probabilities;
Automatic generation of maintenance reports;
Alerts for incipient faults to support predictive maintenance planning.

4.5. Industrial Benefits

The deployment of this framework offers several advantages:

Reduction of unplanned downtime by enabling early fault detection;
Optimization of maintenance schedules, reducing unnecessary inspections;
Integration with existing SCADA and PLC systems, allowing seamless adoption in industrial environments;
Enhanced safety and reliability of critical electrical machines in production lines and energy systems.

Overall, the proposed system demonstrates the feasibility of **real-time, multi-sensor, physics-informed AI diagnostics,** bridging the gap between laboratory research and industrial practice [26, 27].

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 4 March 2026 doi:10.20944/preprints202603.0289.v1

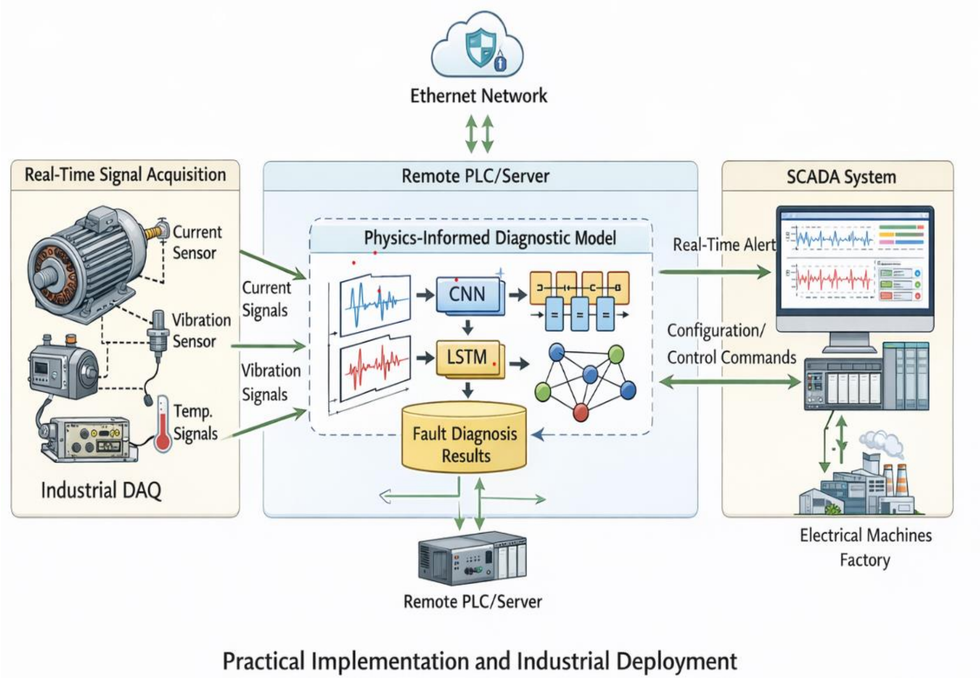


Figure 6. – Industrial deployment architecture of the proposed physics-informed multi-sensor fault diagnosis framework with real-time edge processing and SCADA-integrated monitoring.

For practical industrial adoption, the proposed physics-informed diagnostic framework must be integrated into existing automation and monitoring infrastructures. Real-world deployment requires compatibility with industrial data acquisition systems, programmable logic controllers (PLC), SCADA platforms, and Ethernet-based communication networks.

Unlike laboratory-scale implementations, industrial deployment demands real-time processing capability, secure communication, scalable architecture, and seamless integration with control systems. The practical implementation structure of the proposed diagnostic system is illustrated in Fig. 6.

As depicted in Fig. 6, the industrial deployment architecture consists of four interconnected subsystems: real-time signal acquisition, remote computational processing, communication infrastructure, and supervisory monitoring.

First, multi-modal sensor signals—including phase currents, vibration measurements, and temperature data—are collected using industrial-grade data acquisition (DAQ) hardware. These signals are sampled at high frequency to preserve transient characteristics and fault-sensitive spectral components [28, 29].

The acquired data are transmitted to a remote PLC or edge server via an industrial Ethernet network. Within this processing unit, the physics-informed CNN–LSTM–GNN diagnostic model performs real-time inference. The embedded dq-axis residual constraint ensures that predictions remain physically consistent even under fluctuating load and transient operating regimes.

Diagnostic outputs, including fault probabilities and severity indicators, are transmitted to the SCADA system. The SCADA interface enables [30, 31]:

- Real-time fault visualization;
- Alarm generation;
- Maintenance scheduling support;
- Configuration and control feedback.

Additionally, bidirectional communication allows control commands and system parameter adjustments to be transmitted back to the monitored electrical machines, enabling predictive maintenance strategies and adaptive operational control.

The modular architecture ensures:

- Scalability for multi-machine environments;
- Compatibility with existing industrial automation standards;
- Low-latency real-time inference;
- Cyber-secure network integration.

This deployment structure demonstrates the feasibility of transitioning the proposed physics-informed diagnostic framework from laboratory validation to full-scale industrial application.

4. Conclusions

A **comprehensive diagnostic framework for electrical machines** based on artificial neural networks has been developed, integrating signal preprocessing, hybrid deep learning architectures, and multi-modal data fusion. The proposed system combines **CNN-LSTM feature extraction** with **Graph Neural Networks** to model spatial, temporal, and cross-sensor dependencies, enabling robust and early detection of common faults such as **bearing defects, inter-turn short circuits, and phase asymmetries.**

Experimental evaluation on publicly available datasets demonstrates that the hybrid approach achieves **classification accuracies exceeding 90%,** outperforming traditional methods and conventional neural networks. The framework is adaptable to various types of electrical machines and operational conditions, making it suitable for **real-time industrial deployment** in predictive maintenance systems.

The main contributions and novelties of this work include:

1. **Integration of multi-sensor data** (electrical, vibrational, thermal) for holistic fault diagnosis.
2. **Hybrid CNN-LSTM-GNN architecture**, combining spatial, temporal, and structural correlations in a unified model.
3. **Physics-informed preprocessing and modeling**, enhancing interpretability and reliability of AI-based diagnostics.
4. **Demonstrated practical feasibility** for real-time industrial implementation with clear benefits in reducing downtime and maintenance costs. Future work will focus on:

Extending the framework to **multi-machine networks** and smart grids;

Incorporating **adaptive and transfer learning techniques** for faster deployment on new machine types;

Developing **explainable AI modules** to enhance interpretability and support decision-making by maintenance engineers.

Overall, the proposed approach provides a **scalable, accurate, and physically consistent solution** for the predictive maintenance of electrical machines, bridging the gap between data-driven AI methods and industrial practice.

Author Contributions: Conceptualization, J.N., S.I.; methodology, J.N., S.I. and F.B.; software, Z.B., D.S.; validation, Z.B., and G.N.; formal analysis, J.N., S.I., F.B.; investigation, D.S. and Z.B.; resources, J.N., S.I. and G.N.; data curation, F.B. and G.N.; writing - original draft preparation, J.N., S.I.; writing—review and editing, J.N., S.I., Z.B.; visualization, J.N., S.I., F.B. and G.N.; supervision, J.N., S.I.; project administration, J.N., S.I., F.B. and G.N.; funding acquisition, J.N., S.I., D.S. All authors have read and agreed to the published version of the manuscript.

Funding: Participation in the research of the authors S.I., F.B., G.N. was funded of the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. AP32715297, 2026).

Data Availability Statement: The data presented in this study are available upon request from the corresponding author.

Acknowledgments: In this section, you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. C. Zachariades and V. Xavier, "Artificial Intelligence Techniques for Fault Diagnosis of Rotating Electrical Machines," Engineering Applications of Artificial Intelligence, vol. 115, pp. 104–125, 2023.
2. Nurmaganbetova G., Issenov, S., Kaverin V., Issenov Zh. Development of a virtual hardware temperature observer for frequency-controlled asynchronous electric motors. Eastern-European Journal of Enterprise Technologies, (2023). Vol. 3/1 (123), 68–75. https://doi.org/10.15587/1729-4061.2023.280357.
3. Nurmaganbetova, G., Kaverin, V., Issenov, S., Em, G., Asainov, G., Nurmaganbetova, Z., Bulatbayeva, Y., Kassym, R. Indirect temperature protection of an asynchronous generator by stator winding resistance measurement with superimposition of high-frequency pulse signals. Eastern-European Journal of Enterprise Technologies, (2024). Vol. 2/8 (128), 46–53. https://doi.org/10.15587/1729-4061.2024.302872.
4. H. Kim et al., *"Graph-Based and Physics-Informed Neural Networks for Multi-Sensor Machine Diagnostics,"* **Engineering Applications of Artificial Intelligence**, vol. 115, pp. 104–125, 2023.
5. H. Kim et al., "Physics-Informed Neural Networks for Electric Machine Diagnostics," Applied Soft Computing, vol. 138, 2023.
6. Issenov, S., Iskakov, R., Tergemes, K., Issenov, Zh. Development of mathematical description of mechanical characteristics of integrated multi-motor electrical drive for drying plant. Eastern-European Journal of Enterprise Technologies, (2022). Vol. 1/8 (115), 46-54. https://doi.org/10.15587/1729-4061.2021.251232.
7. Issenov, S. S. (2012). Mathematical Model of Automatic Control System for Asynchronous Multimotor Drive. *Elektronika Ir Elektrotechnika*, *18*(8), 9-12. https://doi.org/10.5755/j01.eee.18.8.2602.
8. J. Wang, L. Zhang, and H. Liu, *"CNN-Based Fault Diagnosis for Induction Motors Using Vibration Spectrograms,"* **Mechanical Systems and Signal Processing**, vol. 180, 2023.
9. J. Wang, L. Zhang, H. Liu, *"Hybrid CNN-LSTM Networks for Multi-Sensor Fault Diagnosis in Induction Motors,"* **Neurocomputing**, vol. 482, pp. 123–145, 2022.
10. K. Patel et al., *"PadéNet Architectures for Multi-Channel Signal Modeling in Motor Fault Detection,"* **Applied Soft Computing**, vol. 138, 2023.
11. L. Zhang et al., "CNN-LSTM Hybrid Networks for Vibration-Based Fault Diagnosis in Induction Motors," Mechanical Systems and Signal Processing, vol. 180, 2023.
12. M. Rossi et al., *"Data Preprocessing Strategies for Deep Learning-Based Fault Detection in Synchronous Machines,"* **IEEE Transactions on Industrial Electronics**, vol. 70, no. 5, pp. 4123–4135, 2023.
13. Y. Yang et al., *"Multi-Modal Deep Learning for Predictive Maintenance of Rotating Machines,"* **Mechanical Systems and Signal Processing**, vol. 180, 2023.
14. Y. Yang et al., *"Spectrogram-Based CNN Architectures for Electric Machine Condition Monitoring,"* **Mechanical Systems and Signal Processing**, vol. 180, 2023.
15. Y. Yang, H. Liu, and J. Wang, "Deep Learning Approaches for Electrical Machine Fault Diagnosis: A Review," Neurocomputing, vol. 482, pp. 123–145, 2022.
16. Y. Yang, H. Liu, and J. Wang, *"Hybrid CNN-LSTM Networks for Electric Machine Fault Classification,"* **Neurocomputing**, vol. 482, pp. 123–145, 2022.
17. Christos Zachariades, Vigila Xavier. A Review of Artificial Intelligence Techniques in Fault Diagnosis of Electric Machines. Sensors, 2025.
18. Yuanyuan Yang et al. Fault Diagnosis of Electric Motors Using Deep Learning Algorithms and Its Application: A Review. Energies, 2021.
19. N. Chigirik et al. System for Diagnosing the Technical Condition of Traction Electric Motors Using ANN. Transport Systems and Technologies, 2018.
20. Acoustic-based fault diagnosis of electric motors using Mel spectrograms and CNN. Scientific Reports, 2025.
21. GNN-ASE: Graph-Based Anomaly Detection in Three-Phase Induction Machines. arXiv, 2025.
22. J Nizamov, Sh Ergashov, DI Kurbanbaeva Phase angle measurement device between the resultable electric drive force and the electric drive force of the main harmonic magnetic field in the air gap of the

industrial …AIP Conference Proceedings*AIP Conf. Proc.* 3152, 040021 (2024) https://doi.org/10.1063/5.0218808

23. J Nizamov, SO Ergashov, ON Berdiyorov, UN Berdiyorov Device for measuring the resulting magnetic field of the stator winding of asynchronous motor for general industrial application AIP Conference Proceedings *AIP Conf. Proc.* 3152, 050013 (2024) https://doi.org/10.1063/5.0218809 June 2024
24. NB Pirmatov, JA Nizamov, O Ergashev Sh. magnetic field in the air gap of an induction motor general inspection information applications
25. M Taniev, U Mirkhonov, M Rakhmatova, F Isakov, S Ergashov, J Nizamov Study of the substitution scheme of the parameters of a phase-rotor induction generator AIP Conference Proceedings *Proc.* 2552, 060010 (2023). https://doi.org/10.1063/5.0130746 January 2023
26. NB Pirmatov, AM Egamov, CM Giyasov, , J Nizamov NA Mamarasulov, UN Berdiyorov, Some aspects of comparing the operational properties of synchronous machines with a conventional and two mutually shifted excitation windings E3S Web of Conferences 10.1051/e3sconf/202340103056 EID: 2-s2.0-85169675134*Part of* ISSN: 22671242 25550403
27. Nizamov, J., Bekishev, A., Mustafakulova, G., ...Khalbutayeva, A..Modeling of reactive power compensation of the electric arc steelmaking furnace DSP-100 UMK at JSC Uzmetkombinat Aip Conference Proceedings3331(1) https://doi.org/ 0009-0009-3013-9410 Scopus Author ID: 57221165134
28. Pirmatov, N.,Bekishev, A.,Kurbanov, N.,Saodullaev, A.,Saimbetov, Z. Increasing the efficiency and survivability of synchronous machines with biaxial excitation when operating in transient processes. Proceedings of the AIP conference. Volume 3152, Issue 1, June 17, 2024, https://doi.org/10.1063/5.0218824.
29. 29.Bekishev, A.,Kurbanov, N.,Zainieva, O.,Saimbetov, Z.,Saodullaev, A.Comparative analysis of the survivability of synchronous machines in asynchronous mode without excitation. Proceedings of the AIP conference. Volume 3152, Issue 1, June 17, 2024,https://doi.org/10.1063/5.0218806.
30. A. Bekishev, A. E. Norboev, U. A. Khudoynazarov, N. A. Kurbanov and O. A. Yunusov. Autonomous mode and parallel operation of an asynchronous generator with an electrical network. E 3 S Conference Network. Volume 524, 2024. VII International Conference on Current Issues of the Energy Complex and Environmental Protection (APEC-VII-2024).https://doi.org/10.1051/e3sconf/202452401009
31. Pirmatov N., Bekishev A., S. Shernazarov, N. Kurbanov. Regulation of mains voltage and reactive power with the help of a synchronous compensator by two-axis excitation. E3S Web of Conferences, 2021, 264, 04028, https://doi.org/10.1051/e3sconf/202126404028.