

A hybrid classification model for high-precision fault mode detection in three-phase electrical networks

Arai Tolegenova¹, Lyailya Kurmangazyieva², Kenzhessulu Kuptleuova³, Yerbol Yerbayev³, Saniya Kubentayeva⁴, Nurgaisha Almagazyieva⁵, Ainura Aripbayeva⁶, Marhabat Slamkulova⁷

¹Department of Information Security, Faculty of Information Technology, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan

²Department of Software Engineering, Kh. Dosmukhamedov Atyrau University, Atyrau, Kazakhstan

³Polytechnic Institute, Non-profit Joint Stock Company West Kazakhstan Agrarian and Technical University named after Zhangir Khan, Uralsk, Kazakhstan

⁴Department of Computer Modeling and Information Technology, Non-Profit Joint-Stock Company "East Kazakhstan University named after S. Amanzholov", Ust-Kamenogorsk, Kazakhstan

⁵Department of Normal Physiology with a Course of Biophysics, Non-profit Joint Stock Company S.Asfendiyarov Kazakh National Medical University, Almaty, Kazakhstan

⁶Center for Epidemiology and Management, Astana Medical University, Astana, Kazakhstan

⁷Department of Digital Technologies and Artificial Intelligence, M.Kh. Dulaty Taraz University, Taraz, Kazakhstan

Article Info

Article history:

Received Jan 17, 2026

Revised Aug 27, 2026

Accepted Sep 4, 2026

Keywords:

Ensemble methods

Extreme gradient boosting

Fault classification

Machine learning

Short-circuit detection

Three-phase electrical networks

ABSTRACT

In modern electric power systems, accurately identifying short-circuit conditions is essential for reliable network monitoring and protection. This study proposes a hybrid machine learning framework for multi-class fault mode classification in three-phase electric networks. The experimental dataset included 15 operating modes, including normal mode, single-phase mode, phase-to-phase mode, three-phase mode, and ground fault mode. Input variables included phase current measurements and positive, negative, and zero-sequence current components. The preprocessing pipeline included logarithmic transformation, standardization, and correlation-based feature selection. The processed data was split into training and independent test subsets in an 80/20 ratio. Next, k-means clustering with 15 clusters was used to generate additional structural features, while random forest and extreme gradient boosting (XGBoost) algorithms created probabilistic class predictions, which were integrated by a logistic regression metaclassifier. According to the adopted testing protocol, the proposed hybrid model achieved an accuracy of 96.98%, a macro precision of 0.973, a macro recall of 0.969, and a macro F1-score of 0.968, outperforming the baseline random forest model, which achieved an accuracy of 93.91% and a macro F1-score of 0.937. These results demonstrate the potential of the proposed multi-level framework for accurate multi-class fault diagnosis in three-phase electrical networks.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



Corresponding Author:

Lyailya Kurmangazyieva

Department of Software Engineering, Kh. Dosmukhamedov Atyrau University

Atyrau, Kazakhstan

Email: Kurmangazyieva475@gmail.com

1. INTRODUCTION

Modern electric power systems are characterized by a high degree of complexity, increasing loads, and a growing number of nonlinear equipment operating modes [1], [2]. With the expansion of power grids, the integration of distributed generation, and the digitalization of monitoring processes, the need for timely and accurate fault detection is particularly acute. The most critical of these are short-circuit faults in three-phase

electrical networks, as such faults lead to serious disruptions in the power supply, equipment destruction, and significant economic losses [3]–[6]. Despite the high technical development of the energy industry, the problem of short-circuit diagnostics remains challenging. Traditional engineering methods based on direct analysis of currents, voltages, and symmetrical components are sensitive to noise, rapid mode changes, and the specific features of real operating data [7], [8]. Furthermore, classical algorithms are often unable to capture complex nonlinear relationships between phase parameters and network conditions, which leads to a decrease in the accuracy and reliability of fault recognition [9]. All of this creates a research challenge: the need for models capable of classifying various types of short circuits in the context of multivariate, non-stationary, and hidden-structured data. The relevance of developing new approaches is determined by the fact that modern power systems are transitioning to the concept of smart energy, in which automated network state analysis and predictive diagnostics play a key role [10]–[12]. The volume of data coming from measuring devices is growing, and the requirements for the speed and accuracy of decision-making are becoming increasingly stringent. In such conditions, machine learning and intelligent signal processing methods are becoming not just an auxiliary tool, but a necessary component of monitoring systems. Hybrid approaches, which combine the advantages of several algorithms and improve the stability and accuracy of diagnostic systems [13]–[16], are particularly significant. When combined with ensemble models and clustering algorithms, such methods enable a deeper analysis of the data structure and improve the quality of fault mode recognition.

Recent studies [17]–[20] have demonstrated the effectiveness of machine learning and deep learning approaches for electrical fault diagnosis. Tree-based ensemble models provide highly nonlinear classification, while clustering methods can reveal hidden operating modes in electrical measurements. Other studies have explored boosting, support vector machine approaches, neural networks, and ensemble classifiers. However, three limitations remain in the existing literature. First, many approaches rely on a single supervised classifier and therefore do not explicitly exploit the hidden structure in the feature space. Second, clustering and supervised fault classification are typically evaluated separately rather than integrated into a single diagnostic pipeline. Third, comparatively little attention has been paid to merging the probabilistic layers of additional ensemble classifiers for multi-class identification of a wide range of three-phase short-circuit modes. These limitations motivate the development of a hybrid framework in this study. Therefore, the research gap addressed in this study is the absence of a unified fault classification framework that simultaneously exploits latent cluster structure, complementary tree-based ensemble predictions, and probability-level meta classification for multi-class diagnosis of three-phase electrical faults.

The aim of this study is to develop a hybrid classification model for highly accurate detection of short circuit modes in three-phase networks. Achieving this goal requires the creation of an integrated architecture capable of accounting for hidden dependencies in the data, combining information obtained at different stages of analysis, and ensuring higher classification accuracy than traditional single models [21]–[23]. The source data includes phase currents and positive, negative, and zero-sequence components, enabling the modeling of a wide range of operational conditions. The target variable covers fifteen fault types, including single-phase, two-phase, three-phase, and grounded, making the problem nontrivial and multidimensional. The scientific novelty of the proposed solution lies in the creation of a hybrid architecture integrating k-means clustering, random forest and extreme gradient boosting (XGBoost) ensemble algorithms, and a final meta-classification based on logistic regression [24], [25]. This combination significantly expands the information content of the feature space and improves the model's ability to recognize subtle and hidden patterns. Adding cluster labels as new features enhances class separability, while using two independent ensemble models enables more robust data interpretation. The metaclassifier, in turn, combines the results of the base models and generates a final solution, minimizing the likelihood of errors. This results in classification accuracy of up to 96.98%, demonstrating the advantage of the proposed approach over traditional methods. A logical continuation of this work is expanding the model's capabilities for processing streaming data in real time, which is especially important as energy systems transition to digital substations and smart grids of the future. Another promising area is the integration of physical and mathematical network models and machine learning algorithms to create digital twins of energy infrastructure. Of additional interest is the use of deep neural networks, recurrent structures, and graph models capable of accounting for network topology and spatial relationships. All this opens up broad opportunities for further improving the accuracy, adaptability, and reliability of diagnostic systems, a strategically important area for the development of the modern electric power industry. The main findings of this study are as follows:

- A hybrid diagnostic architecture combining k-means-based latent structure extraction with random forest and XGBoost classifiers is developed for multi-class three-phase fault identification;
- Cluster membership is included as an additional feature to enrich the electrical characteristic representation;
- The probabilistic outputs of additional ensemble classifiers are integrated using logistic regression metaclassification;

- The entire framework is experimentally compared with the baseline random forest classifier using precision, macro accuracy, macro recall, macro F1-score, and weighted classification metrics.

2. METHOD

The data for the study is a table with n rows and m columns, where the rows correspond to individual observations and the columns correspond to various characteristics of the electrical network. Formally, the sample can be described as (1):

$$D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\} \quad (1)$$

where $x_i = \{x_{i1}, x_{i2}, \dots, x_{im}\}$ is the feature vector for the i -th observation (m is the number of features), $y_i = target$ is the vector of target variables, $target \in \{0, 15\}$. Features x_{ij} include I_a, I_b, I_c - the values of currents in phases A, B, C; I_1, I_2, I_0 - the values of the components of positive, negative and zero sequence currents. These parameters are measured during the operation of the electrical network and represent the initial data for the analysis. Table 1 shows examples of data for training the fault classification model. The table includes the values of currents in phases (I_a, I_b, I_c) and their components (I_1, I_2, I_0), as well as the *target* variable, which denotes the fault class.

Table 1 contains examples of input data used to train a fault mode classification model for a three-phase electrical network. The table includes current values in phases A, B, and C, as well as components of positive, negative, and zero-sequence currents, which allow for a more accurate accounting of network balance and imbalance under various fault conditions. The last column, "target," represents the target label corresponding to one of fifteen fault types. Each target variable class reflects a specific fault configuration in the network. Thus, classes 1–3 correspond to single-phase faults: when a fault occurs on phase A (class 1), a sharp increase in current is observed in this phase, while currents in phases B and C decrease to minimum values. Similar behavior is typical for classes 2 and 3, where the fault occurs on phases B and C, respectively.

Table 1. Characteristic features of phase currents and sequences for each emergency condition

I_a	I_b	I_c	I_1	I_2	I_0	Target
50.0	10.0	10.0	70.0	60.0	20.0	1
10.0	140.0	10.0	60.0	70.0	10.0	2
10.0	10.0	160.0	80.0	70.0	20.0	3
120.0	120.0	5.0	90.0	20.0	10.0	4
5.0	130.0	130.0	100.0	25.0	15.0	5
140.0	5.0	140.0	110.0	20.0	20.0	6
120.0	120.0	120.0	100.0	15.0	25.0	7
130.0	10.0	10.0	75.0	50.0	35.0	8
10.0	140.0	10.0	65.0	60.0	30.0	9
10.0	10.0	140.0	70.0	65.0	40.0	10
130.0	130.0	5.0	95.0	20.0	30.0	11
5.0	140.0	140.0	105.0	15.0	35.0	12
140.0	5.0	145.0	110.0	20.0	45.0	13
130.0	130.0	130.0	115.0	10.0	50.0	14
110.0	112.0	108.0	90.0	10.0	10.0	0

Classes 4–6 represent phase-to-phase faults. During a fault between phases A and B (class 4), the currents in both phases increase, while the current in phase C decreases significantly. During a fault between phases B and C (class 5), increased values are observed in the currents of phases B and C, while the current in phase A decreases. A fault between phases C and A (class 6) results in similar changes, but in phases C and A. Class 7 characterizes a three-phase ABC fault, in which the currents in all phases become approximately equal and the total load on the system increases significantly, making this mode the most critical. Classes 8–10 describe single-phase-to-ground faults. In these modes, the current in the corresponding phase increases sharply, while the currents in the other two phases remain minimal. An important feature is the increase in the zero-sequence fault I_{0I_0I0} , which is caused by the appearance of a current leakage path through the ground.

Classes 11–13 reflect phase-to-ground faults. For example, when phases A and B are faulted to ground (class 11), the currents in both phases increase, the current in phase C decreases, and the I_0 component becomes noticeable. B–C–ground (class 12) and C–A–ground (class 13) faults exhibit a similar pattern of phase current and zero-sequence behavior. Class 14 corresponds to a three-phase ground fault, in which the currents in all phases increase simultaneously with a maximum increase in the zero-sequence. This mode leads to the

most pronounced network destabilization. Finally, class 0 denotes normal network operation without faults: the currents in all phases are balanced, and the zero-sequence is practically zero, indicating the absence of faults. Thus, the data in Table 1 not only demonstrate examples of input features but also reflect the characteristic features of the phase currents and sequences for each fault condition, which is an important part of forming the training set for the classification model.

The description is based on the laws of electrical engineering and electrostatics. Phase currents (I_a, I_b, I_c) depend on the short circuit configuration, the nature of the circuit, and the resistance through which the short circuit occurs. Zero (I_2) and negative (I_2) sequences reflect the presence of imbalances and short circuits.

- Elimination of missing values. Real data may contain missing values due to technical errors or measurement errors.

$$x_{ij} = \begin{cases} \mu_j, & \text{if } x_{ij} \text{ is missing} \\ x_{ij} & \text{else} \end{cases} \quad (2)$$

- Feature normalization. To equalize the feature scales, z-normalization is used, which transforms the data so that the mean value of a feature is zero and the standard deviation is one (3):

$$z_{ij} = \frac{x_{ij} - \mu_j}{\sigma_j} \quad (3)$$

where μ_j is the mean value of feature j , σ_j is the standard deviation of feature j . An alternative approach is Min-Max normalization, which brings the feature values to the range [0,1] (4):

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (4)$$

These methods improve the stability and accuracy of algorithms that are sensitive to data scale.

- Correlation analysis. To eliminate redundant features, a correlation analysis is performed using a correlation matrix (5):

$$R = \{r_{ij}\}, r_{ij} = \frac{\text{cov}(x_i, x_j)}{\sigma_{x_i} \sigma_{x_j}} \quad (5)$$

where $\text{cov}(x_i, x_j)$ is the covariance between features x_i and x_j , σ_{x_i} , σ_{x_j} are their standard deviations. If the correlation between two features exceeds a given threshold ($|r_{ij}| > 0.8$), one of them is removed to prevent redundancy. The mathematical model for data loading and processing includes a formalized approach to eliminating gaps, normalizing features, encoding target variables, and analyzing correlations. These steps form the foundation for successfully training machine learning models, ensuring the accuracy and reliability of fault classification in electrical networks. The mathematical methods used and the described transformations make the data preparation process understandable, reproducible, and adaptable to solve other types of problems.

Machine learning model training is the process of optimizing model parameters to identify relationships between input features X and a target variable y based on data. Let's consider the mathematical model of training, including the definition of training, validation, and test sets, as well as a mathematical description of the machine learning algorithms used in this work. Training is performed on training data $D_{\text{train}} = \{(X_{\text{train}}, y_{\text{train}})\}$, validation is performed on $D_{\text{val}} = \{(X_{\text{val}}, y_{\text{val}})\}$, and the final accuracy check of the model is performed on test data $D_{\text{test}} = \{(X_{\text{test}}, y_{\text{test}})\}$. Here, $X \in \mathbb{R}^{n \times m}$ is the feature matrix, where n is the number of observations, m is the number of features, and $y \in \mathbb{R}^n$ is the target variable vector representing classes (closure type). random forest is an ensemble method that constructs multiple decision trees on random subsamples of data. The basic idea is to use tree "voting" to predict the final class. Each tree node divides the data by a specific feature to maximize the difference in the target variable. Let $T = \{t_1, t_2, \dots, t_k\}$ be the set of trained trees. The prediction of class $\hat{y}$ for object x is defined as (6):

$$\hat{y} = \text{mode}(t_1(x), t_2(x), \dots, t_k(x)) \quad (6)$$

where $t_i(x)$ is the prediction of the i -th tree, and mode is the most frequently occurring value among the tree predictions. Each tree is trained based on an uncertainty reduction criterion, such as the Gini criterion (G) (7):

$$G = 1 - \sum_{i=1}^C p_i^2 \quad (7)$$

where p_i is the probability of observing class i at node, C is the number of classes. XGBoost is a boosting method that trains trees sequentially, minimizing the errors of previous models. The new algorithm corrects the errors made by previous trees, resulting in more accurate predictions. The model's prediction is determined by the sum of the predictions of individual trees (8):

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (8)$$

where $f_k(x_i)$ is the prediction function of the k -th tree and K is the total number of trees. The optimization function (9):

$$L(\hat{y}, y) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (9)$$

where $l(y_i, \hat{y}_i)$ is the loss function, e.g., the mean squared error, and $\Omega(f_k)$ is the regularization that controls the complexity of the model. The regularization is defined as (10):

$$\Omega(f_k) = YT + \frac{1}{2} \lambda \sum_{j=1}^T w_j^2 \quad (10)$$

where T is the number of leaves, w_j is the weight of the leaf. The support vector machine constructs a hyperplane that maximally separates classes in the feature space. If the data is not linearly separable, kernel functions are used to map the data to a higher dimension. For a linear kernel, the classification problem is formulated as (11):

$$\min_{w, b} \frac{1}{2} \|w\|^2 \text{ under conditions } y_i(w * x_i + b) \geq 1, \forall i \quad (11)$$

where $\phi(x)$ is the kernel function, ξi is the penalty for misclassifications, and C is the regularization coefficient.

The k -nearest neighbors method classifies a new object based on the labels of its k -nearest neighbors in the feature space. Class prediction is performed by simple majority. For an object x , the distances to all other objects are calculated, for example, using the Euclidean metric (12).

$$d(x, x_i) = \sqrt{\sum_{j=1}^m (x_j - x_{ij})^2} \quad (12)$$

The class $\hat{y}$ is defined as (13):

$$\hat{y} = \text{mode}(\{y_i | x_i \in N_k(x)\}) \quad (13)$$

where $N_k(x)$ is the set of k -nearest neighbors for object x . Logistic regression predicts the probability of an object belonging to a class using the logistic function. The probability of an object x belonging to class $y = 1$ (14):

$$P(y = 1|x) = \frac{1}{1 + e^{-(w \cdot x + b)}} \quad (14)$$

Training is carried out with minimization of the loss function (Log Loss) (15):

$$L(y, \hat{y}) = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (15)$$

A deep neural network consists of an input layer, one or more hidden layers, and an output layer. Each neuron in the layer transforms the input value through a weighted sum with activation. For layer l , the output is calculated as (16):

$$a^{(l)} = \sigma(W^{(l)} a^{(l-1)} + b^{(l)}) \quad (16)$$

where W_l is the weight matrix, b_l is the bias vector, and σ is the activation function (e.g., ReLU or sigmoid). The loss function for binary classification is (17):

$$L(y, \hat{y}) = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (17)$$

Each machine learning model is based on its own mathematical formulation and principles, making them unique and well-suited to specific problems. In this paper, each of the presented models was adapted for classifying faults in three-phase electrical networks, ensuring high accuracy and reliability of predictions. Thus, the proposed methodology combines complementary stages: data preprocessing, feature extraction, cluster structure formation, training of multiple ensemble models, and the application of meta-classification to provide a holistic and multi-layered approach to short-circuit diagnostics. This architectural design not only reveals the hidden structure of the data and eliminates the influence of noise but also significantly improves the model's generalization ability by combining the strengths of various algorithms. The developed methodological framework provides the foundation for obtaining robust and reproducible results and enables further system expansion, including processing streaming data in real time and integrating more complex features.

3. RESULTS

An experimental evaluation of the developed hybrid model allowed us to verify its effectiveness and compare the results with a baseline single classification model. Based on the methodology outlined in the previous section, we sequentially trained, validated, and tested the models using the same dataset and unified quality assessment metrics. This approach ensures an objective comparison and allows for a comprehensive assessment of the impact of clustering, ensemble algorithms, and a meta-classifier on the overall short-circuit diagnostic accuracy. This section presents the obtained metric values, performs a comparative analysis of the models, and discusses key patterns that demonstrate the advantages of the hybrid architecture over the traditional approach. Figure 1 illustrates the sequential workflow of the proposed hybrid classification model, combining the stages of data preparation, feature space formation, clustering, and multi-level classification. The first step uses the initial dataset, including phase currents and voltages, which are considered as input features, and the corresponding target labels representing classes of different fault modes. Before feeding the data into the model, a logarithmic transformation is performed to smooth out the impact of outliers and reduce scale differences between values. Next, normalization is performed, converting each feature to a uniform scale, ensuring the correct operation of machine learning algorithms. The next important step is selecting the most significant features based on correlation analysis. From the original dataset, only those variables that have the strongest correlation with the target variable are selected, improving the quality of training and reducing the risk of overfitting. After feature selection, the prepared dataset is split into training and test sets at an 80/20 ratio, allowing for an objective assessment of the model's generalization ability.

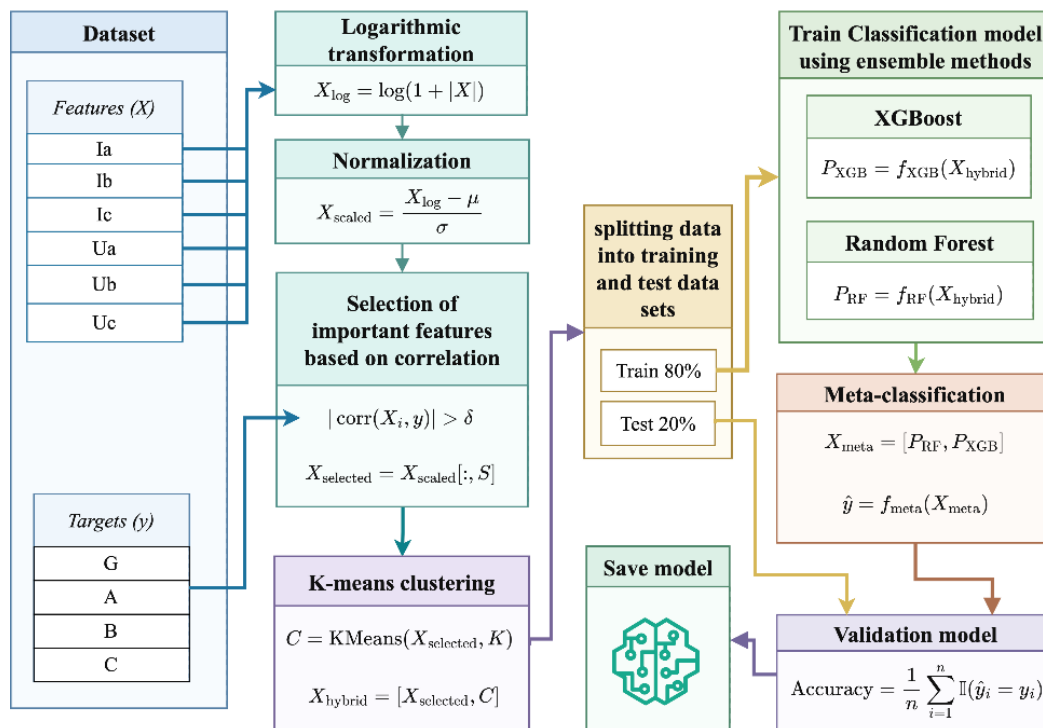


Figure 1. Structural diagram of the proposed hybrid classification model

The next step involves k-means clustering. The algorithm forms hidden clusters in the data, identifying groups of objects with similar characteristics. Cluster labels are added as new features, forming an expanded hybrid feature space. This allows classifiers to account for structures that are not obvious in the original data and improves the distinguishability of fault classes. After generating an expanded set of features, the classification models are trained. Two ensemble methods—XGBoost and random forest—are used as the base algorithms. Each is trained independently using hybrid features, generating its own predictions. These predictions are then combined and fed to a meta-classifier, which generates the final decision. Using meta-classification allows for the correction of potential errors in the base algorithms and improves the overall accuracy of the model. The final stage of the scheme includes a validation procedure, which evaluates the quality of the predictions using a test set. The final accuracy of the hybrid model is calculated by comparing the predicted labels with the true ones. After successful validation, the trained model is saved and can be used for subsequent diagnostics of short-circuit conditions in three-phase electrical networks.

The proposed hybrid model incorporates sequential data processing, clustering, ensemble model training, and meta-classification. This approach accounts for internal dependencies in the data, combining the advantages of various machine learning methods to ensure high classification accuracy and model robustness. To evaluate the effectiveness of the proposed hybrid model, a comparative analysis was conducted using the baseline single-model random forest classifier. The evaluation was conducted using key classification metrics: accuracy, macro precision, macro recall, macro F1-score, as well as weighted precision, weighted recall, and weighted F1-score. These metrics provide a comprehensive assessment of both the generalization ability of the model and its resilience to class imbalance. The results are presented in Table 2. They demonstrate the differences in the performance of the single-model and hybrid models, reflecting the latter's ability to more accurately recognize complex patterns of emergency conditions. It should be noted that the hybrid architecture utilizes additional features generated by clustering and combines the predictions of multiple classifiers, which should theoretically improve the accuracy of the final solution.

Table 2. Results of single and hybrid models

Metrics	Single model (random forest classifier)	Hybrid model (k-means+RF+XGBoost+LR)
Accuracy	93.91%	96.98%
Macro precision	0.942	0.973
Macro recall	0.939	0.969
Macro F1-score	0.937	0.968
Weighted precision	0.945	0.974
Weighted recall	0.938	0.971
Weighted F1-score	0.940	0.972

As can be seen from the table, the hybrid model demonstrates superiority across all key metrics. The increase in accuracy from 93.91% to 96.98% confirms that the multi-level approach combining clustering, ensemble methods, and meta-classification provides a deeper analysis of the data structure and improves the generalization ability of the model. The increase in macro precision, macro recall, and macro F1-score values indicates that the hybrid model more evenly classifies all classes, including those represented by a smaller number of examples. The increase in weighted metrics demonstrates that the model reliably processes the sample taking into account the class distribution and does not lose accuracy even in the presence of potential data imbalance. Overall, the obtained results confirm that the proposed hybrid architecture can improve the efficiency of detecting various short-circuit modes in three-phase electrical networks and can be recommended for implementation in intelligent power system monitoring and diagnostics systems.

To physically interpret the electrical quantities used in the proposed fault classification system, Figure 2 illustrates the phasor representation of three-phase current and voltage signals in the complex plane. The figure provides a reference representation of the relationships among phases A, B, and C and demonstrates their relative angular displacement under balanced operating conditions. These relationships are important for fault diagnosis because short-circuit faults can alter both the magnitude and phase characteristics of electrical signals. Figure 2(a) shows the current phasors of the three phases, which are separated by approximately 120 degrees. This representation demonstrates the normal relationship among the phase currents and provides a reference for identifying deviations caused by fault conditions. Figure 2(b) presents the corresponding voltage phasors, which also exhibit a 120-degree phase displacement. Changes in these voltage relationships may indicate phase imbalance or abnormal operating conditions. Thus, Figure 2 provides a physical interpretation of the current and voltage characteristics subsequently considered during feature processing and fault classification.

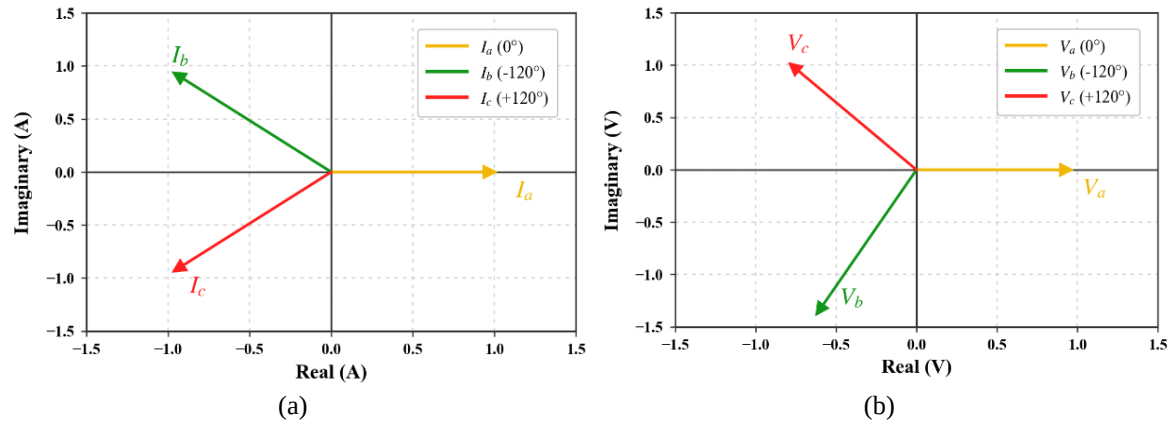


Figure 2. Phasor representation of three-phase currents and voltages: (a) current phasors and (b) voltage phasors

To further illustrate the temporal behavior of electrical signals during a fault, Figure 3 presents representative three-phase current and voltage waveforms over the analyzed time interval. Figure 3(a) shows the three-phase current waveforms. During the highlighted fault interval, the phase currents exhibit a pronounced increase in amplitude compared with the normal operating intervals before and after the fault. In contrast, Figure 3(b) presents the corresponding three-phase voltage waveforms, where the fault interval is characterized by a substantial reduction and distortion of the voltage amplitudes. After the fault is cleared, both current and voltage signals return to their normal periodic behavior. Thus, the two subfigures illustrate complementary electrical responses to the same fault event: Figure 3(a) demonstrates the current response, whereas Figure 3(b) demonstrates the associated voltage response.

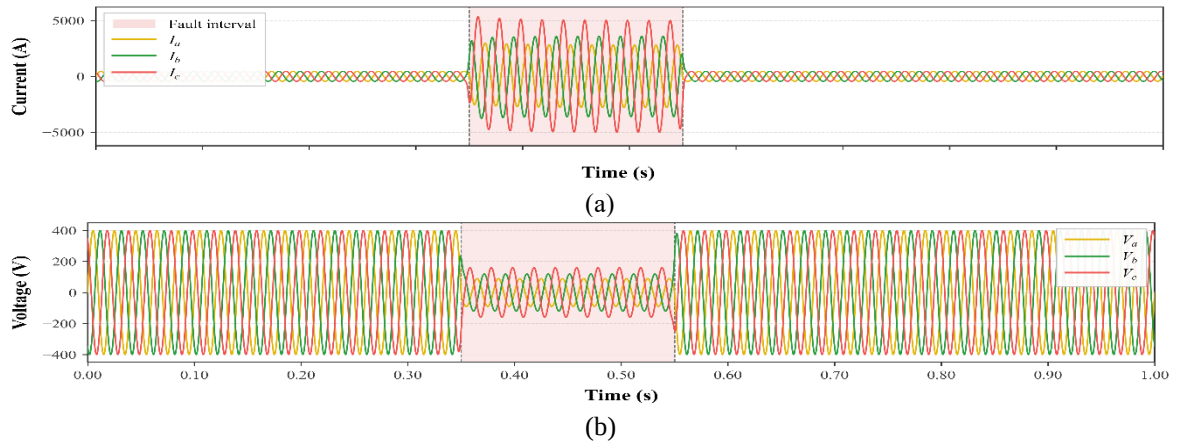


Figure 3. Representative three-phase electrical waveforms during a short-circuit fault event: (a) three-phase current waveforms and (b) three-phase voltage waveforms

The distribution of observations across 15 operation and fault classes is presented in Figure 4. The dataset exhibits a pronounced class imbalance: normal operation accounts for 82.2% of observations, while individual fault categories account for a significantly smaller share. Among fault scenarios, the most represented class is three-phase-to-ground fault (9.6%), followed by three-phase-to-ground fault (3.5%) and phase B–C fault (3.4%). Several other fault types account for less than 1% of observations. This imbalance justifies the use of class-sensitive evaluation metrics in addition to overall accuracy. In particular, macro accuracy, macro recall, and macro F1-score are presented, as they assign equal importance to each class and, therefore, provide a more informative assessment of classification performance for both the majority and minority fault types.

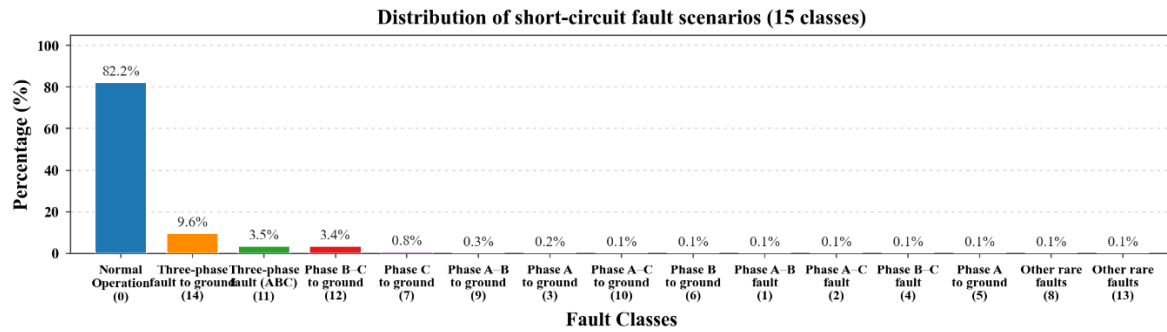


Figure 4. Distribution of observations across the 15 operating and short-circuit fault classes

Figure 5 presents the results of data clustering using the k-means algorithm. For visualization, principal component analysis (PCA) was applied to reduce the feature space to two principal components. The resulting projection illustrates the distribution and separation of the identified clusters in the two-dimensional PCA space.

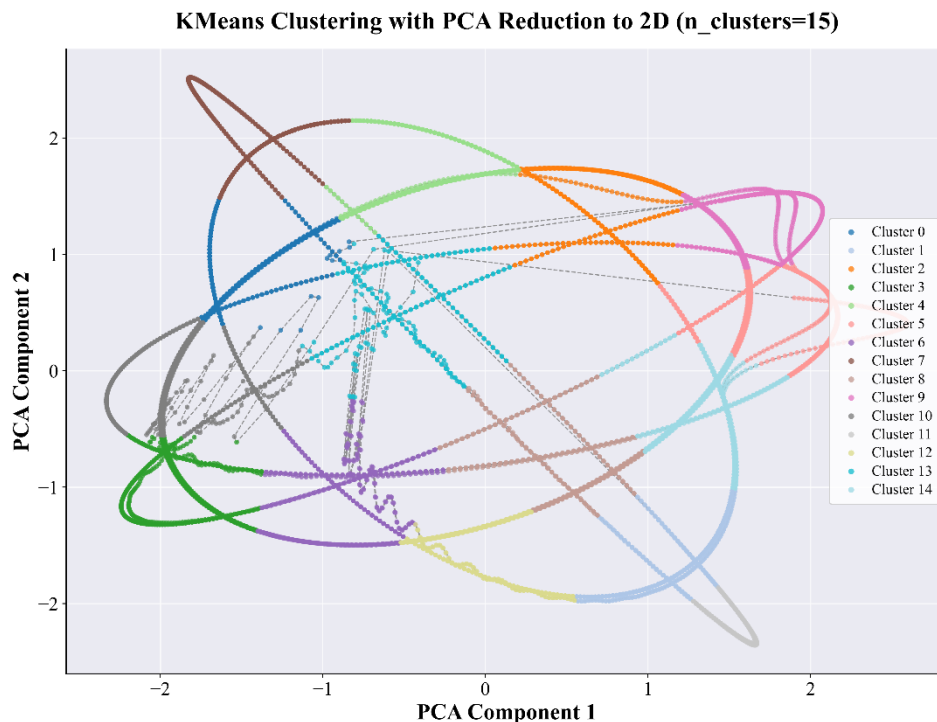


Figure 5. Data visualization

Figure 5 illustrates the 15 clusters identified in the original data, with color coding for each cluster. Each point in the graph represents one observation, plotted against two principal components (PCA Component 1 and PCA Component 2), which capture the majority of the variability in the original features after standardization. The contours of each cluster (depicted as dashed lines) were generated using the Convex Hull algorithm, allowing visualization of the boundaries of the data distribution within each cluster. These contours clearly show the boundaries that separate one cluster from another and help identify the area where the data is most densely clustered. Each cluster is clearly distinct from the others, forming unique groups where observations share similar characteristics. Some clusters are also noticeably elongated or asymmetrical, suggesting possible hidden dependencies between features. This visualization confirms that the k-means clustering method was able to effectively segment the data into groups, an important step for improving the

performance of the subsequent hybrid model. PCA visualization provides qualitative evidence that observations contain a hidden clustering structure that is not explicitly encoded in the original electrical measurements. By assigning a cluster membership attribute to each observation, subsequent classifiers gain additional information about the operating mode to which the sample most closely resembles. This representation can facilitate the distinction between fault classes exhibiting partially overlapping patterns of current components. However, Figure 5 alone does not establish a causal improvement in classification performance; therefore, the quantitative contribution of enhanced clustering should be interpreted in conjunction with comparative classification results.

The advantage of the hybrid model lies in its ability to account for hidden patterns in the data by incorporating cluster labels as additional informative features, which enhances class separability and improves prediction accuracy. Thanks to the integrated use of ensemble methods random forest and XGBoost, the model effectively handles nonlinear dependencies, remains robust to noise and outliers, and demonstrates more consistent results compared to single algorithms. A key element of the architecture is the meta-classifier, which combines the probabilistic predictions of the base models, thereby reducing the likelihood of errors that arise when using a single method. Overall, the integration of clustering, ensemble algorithms, and meta-classification enables the hybrid model to achieve significantly higher accuracy and reliability, as confirmed by the experimental results obtained.

4. CONCLUSION

In this study, a hybrid machine learning model was developed and evaluated for highly accurate multi-class classification of fault modes in three-phase electrical networks. The proposed approach combines k-means clustering, random forest, XGBoost, and logistic regression-based metaclassification to exploit both the latent structure of electrical measurements and the additional predictive capabilities of ensemble classifiers. Phase current measurements and positive, negative, and zero-sequence current components were used to distinguish 15 operating modes, covering normal operation and various single-phase, phase-to-phase, three-phase, and ground fault modes. The preprocessing procedure included log transformation, standardization, correlation-based feature selection, and k-means cluster expansion prior to supervised classification. Under the adopted experimental protocol, the proposed hybrid model achieved an accuracy of 96.98%, a macro precision of 0.973, a macro recall of 0.969, and a macro F1-score of 0.968. In comparison, the baseline random forest classifier achieved an accuracy of 93.91%, a macro precision of 0.940, a macro recall of 0.937, and a macro F1-score of 0.937. Thus, the hybrid approach improved the accuracy by 3.07 percentage points and the macro F1-score by 0.031. These results indicate that integrating the information obtained from clustering with additional ensemble predictions and meta-classification can provide more consistent discrimination between the considered fault modes than the evaluated baseline method based on a single model. Thus, the obtained results validate the main objective of the study, namely, developing a unified machine learning framework capable of improving multi-class identification of short-circuit conditions in three-phase electrical networks.

However, several limitations should be considered when interpreting these results. The current evaluation is based on a single dataset and does not establish generalizability to different power networks, metering systems, load conditions, or sensor configurations. Furthermore, the experiments were conducted using a train-and-test evaluation protocol in offline mode; therefore, real time computation latency, resilience to communication interference, and the operational performance of the deployed protection systems were not assessed. The presented feature representation is also primarily based on phase current and sequence component information and, therefore, does not cover the wider range of measurements that may be available in practical power system monitoring. Furthermore, visualization of k-means clusters using PCA provides qualitative evidence of the underlying structure of the data, but should not be interpreted as quantitative evidence of the contribution of clustering to the final classification performance.

Therefore, future research should validate the proposed framework on additional independent datasets and power grid configurations, investigate its robustness to measurement noise and changing operating conditions, and evaluate its computational performance in real time. Further work should also include systematic ablation experiments to quantify the individual contributions of k-means clustering, random forest, XGBoost, and meta classification, as well as explore additional electrical measurements and adaptive feature representations. These additions will help determine the generalizability and practical applicability of the proposed framework for intelligent fault monitoring and decision support in modern power systems.

FUNDING INFORMATION

This research received no external funding.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Arai Tolegenova	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Lyailya		✓				✓		✓	✓	✓	✓	✓		
Kurmangaziyeva														
Kenzhessulu	✓		✓	✓			✓			✓	✓		✓	✓
Kuptleuova														
Yerbol Yerbayev		✓				✓		✓	✓	✓	✓	✓		
Saniya Kubentayeva					✓		✓			✓		✓		✓
Nurgaisha Almbayeva		✓				✓		✓	✓	✓	✓	✓		
Ainura Aripbayeva					✓		✓			✓		✓		✓
Marhabat Slamkulova					✓		✓			✓		✓		✓

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] T. Anwar *et al.*, “Robust fault detection and classification in power transmission lines via ensemble machine learning models,” *Scientific Reports*, vol. 15, no. 1, p. 2549, Jan. 2025, doi: 10.1038/s41598-025-86554-2.

[2] R. Nawaz, H. A. Albalawi, S. B. A. Bukhari, K. K. Mehmood, and M. Sajid, “Timeseries fault classification in power transmission lines by non-intrusive feature extraction and selection using supervised machine learning,” *IEEE Access*, vol. 12, pp. 93426–93449, 2024, doi: 10.1109/ACCESS.2024.3423828.

[3] O. Turanlı and Y. B. Yakut, “Classification of faults in power system transmission lines using deep learning methods with real, synthetic, and public datasets,” *Applied Sciences*, vol. 14, no. 20, p. 9590, Oct. 2024, doi: 10.3390/app14209590.

[4] M. A. Khan, B. Asad, T. Vaimann, A. Kallaste, R. Pomarnacki, and V. K. Hyunh, “Improved fault classification and localization in power transmission networks using vae-generated synthetic data and machine learning algorithms,” *Machines*, vol. 11, no. 10, p. 963, Oct. 2023, doi: 10.3390/machines11100963.

[5] K. Al Kharusi, A. El Haffar, and M. Mesbah, “Adaptive machine-learning-based transmission line fault detection and classification connected to inverter-based generators,” *Energies*, vol. 16, no. 15, p. 5775, Aug. 2023, doi: 10.3390/en16155775.

[6] A. S. Alhanaf, H. H. Balik, and M. Farsadi, “Intelligent fault detection and classification schemes for smart grids based on deep neural networks,” *Energies*, vol. 16, no. 22, p. 7680, Nov. 2023, doi: 10.3390/en16227680.

[7] C. Li and B. Wang, “A knowledge graph method towards power system fault diagnosis and classification,” *Electronics*, vol. 12, no. 23, p. 4808, Nov. 2023, doi: 10.3390/electronics12234808.

[8] A. El Ghaly, “Hybrid ml algorithm for fault classification in transmission lines using multi-target ensemble classifier with limited data,” *Eng*, vol. 6, no. 1, p. 4, Jan. 2025, doi: 10.3390/eng6010004.

[9] M. Hassan, S. P. Biswas, S. A. H. Chowdhury, S. Mondal, M. R. Islam, and R. Shah, “Fault classification and localization of multi-machine-based ieee benchmark test case power transmission lines using optimizable weighted extreme learning machine,” *Electric Power Systems Research*, vol. 235, p. 110857, Oct. 2024, doi: 10.1016/j.epsr.2024.110857.

[10] N. Q. Minh, N. T. Khiem, and V. H. Giang, “Fault classification and localization in power transmission line based on machine learning and combined cnn-lstm models,” *Energy Reports*, vol. 12, pp. 5610–5622, Dec. 2024, doi: 10.1016/j.egyr.2024.11.061.

[11] V. R. Kumar and P. A. Jeyanthi, “Fault classification and detection in transmission lines by hybrid algorithm associated support vector machine,” *Transactions on Emerging Telecommunications Technologies*, vol. 36, no. 3, Mar. 2025, doi: 10.1002/ett.70034.

[12] W. Sheng, K. Liu, D. Jia, and Y. Wang, “An improved high-impedance fault identification scheme for distribution networks based on kernel extreme learning machine,” *International Journal of Electrical Power & Energy Systems*, vol. 155, p. 109543, Jan. 2024, doi: 10.1016/j.ijepes.2023.109543.

[13] D. Bhattacharya and M. K. Nigam, “Energy efficient fault detection and classification using hyperparameter-tuned machine learning classifiers with sensors,” *Measurement: Sensors*, vol. 30, p. 100908, Dec. 2023, doi: 10.1016/j.measen.2023.100908.

[14] R. M. A. Velásquez, “Ensembled methodology for the comtrade analysis regarding medium voltage side in wind park,” *Results in Engineering*, vol. 23, p. 102751, Sep. 2024, doi: 10.1016/j.rineng.2024.102751.

[15] Z. Mian *et al.*, “A literature review of fault diagnosis based on ensemble learning,” *Engineering Applications of Artificial*

- Intelligence*, vol. 127, p. 107357, Jan. 2024, doi: 10.1016/j.engappai.2023.107357.
- [16] M. Fayazi, A. Saffarian, M. Joorabian, and M. Monadi, "An ai-based fault detection and classification method for hybrid parallel hvac/hvdc overhead transmission lines," *Electric Power Systems Research*, vol. 238, p. 111083, Jan. 2025, doi: 10.1016/j.epsr.2024.111083.
 - [17] C. D. Ukwuoma, D. Cai, C. C. Ukwuoma, C. I. Otuka, and Q. Huang, "Comparative analysis of data-driven models on detection and classification of electrical faults in transmission systems: explainability, applicability and industrial implications," *Alexandria Engineering Journal*, vol. 127, pp. 75–91, Aug. 2025, doi: 10.1016/j.aej.2025.04.097.
 - [18] T. Giri, B. B. Thapa, B. Paneru, and B. Paneru, "An xai-driven cnn-transformer model for transmission line fault detection and classification," *Energy Reports*, vol. 15, p. 108929, Jun. 2026, doi: 10.1016/j.egy.2025.108929.
 - [19] L. Yutong, C. C. Ukwuoma, and L. N. M. Kemayou, "Enhancing machine-learning-based anomaly detection in transmission lines models using robust features from neural networks," *Progress in Engineering Science*, vol. 2, no. 4, p. 100151, Dec. 2025, doi: 10.1016/j.pes.2025.100151.
 - [20] H. Okumus, F. M. Nuroglu, and S. McLoone, "Ensemble learning for short circuit fault location estimation in distribution networks," *Engineering Applications of Artificial Intelligence*, vol. 159, p. 111640, Nov. 2025, doi: 10.1016/j.engappai.2025.111640.
 - [21] M. Senyuk, S. Beryozkina, I. Zicmane, M. Safaraliev, V. Klassen, and F. Kamalov, "Bulk low-inertia power systems adaptive fault type classification method based on machine learning and phasor measurement units data," *Mathematics*, vol. 13, no. 2, p. 316, Jan. 2025, doi: 10.3390/math13020316.
 - [22] Ö. Özdemir, R. Köker, and N. Pamuk, "Fault classification and precise fault location detection in 400 kv high-voltage power transmission lines using machine learning algorithms," *Processes*, vol. 13, no. 2, p. 527, Feb. 2025, doi: 10.3390/pr13020527.
 - [23] A. S. Altaie, M. Abderrahim, and A. A. Alkhazraji, "Transmission line fault classification based on the combination of scaled wavelet scalograms and cnns using a one-side sensor for data collection," *Sensors*, vol. 24, no. 7, p. 2124, Mar. 2024, doi: 10.3390/s24072124.
 - [24] P. Pohakar, R. Gandhi, S. Hans, G. Sharma, and P. N. Bokoro, "Analysis of multiple faults in induction motor using machine learning techniques," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 12, p. 101007, Jun. 2025, doi: 10.1016/j.prime.2025.101007.
 - [25] A. Nanfak, S. Eke, F. Meghnefi, I. Fofana, G. M. Ngaleu, and C. H. Kom, "Hybrid dga method for power transformer faults diagnosis based on evolutionary k -means clustering and dissolved gas subsets analysis," *IEEE Transactions on Dielectrics and Electrical Insulation*, vol. 30, no. 5, pp. 2421–2428, Oct. 2023, doi: 10.1109/TDEI.2023.3275119.

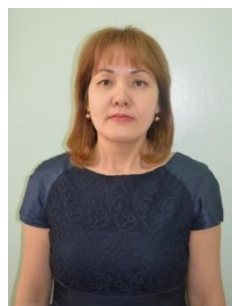
BIOGRAPHIES OF AUTHORS



Arai Tolegenova    is a citizen of Kazakhstan. She was born in the East Kazakhstan region on May 18, 1982. She has two higher education degrees from the Almaty Institute of Energy and Communications: i) Engineer in Telecommunications and ii) Economics and Management in the Communications Industry. She holds a Ph.D. in Occupational Safety and Health, specializing in 052601. Her Ph.D. thesis is titled "Protection against Structural and Airborne Noise Generated by Ventilation and Air Conditioning Systems." The defense took place in Kazakhstan, in Almaty, at the K.I. Satpayev Kazakh National Technical University, in 2010. Currently, she works as an Associate Professor at the Department of Information Security, Faculty of Information Technology, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan. She can be contacted at email: aibike_7474@mail.ru.



Lyailya Kurmangazyeva    candidate of Technical Sciences, associate Professor Department of Scientific Research: Mathematical Modeling and Control of Object Structures; formation and development of methods for solving problems, decision making in a fuzzy environment and engineering education. Currently she is a professor at the Department of Software Engineering at Atyrau University named after Kh. Dosmukhamedov. She takes an active part in fundamental and applied research. She is the author of more than 80 scientific and educational works. Under her leadership, 12 master's theses were successfully defended. She can be contacted at email: Kurmangazieva475@gmail.com.



Kenzhessulu Kuptleuova    is a senior lecturer specializing in Power Supply by Industry, currently working at the Zhangir Khan West Kazakhstan Agrarian and Technical University at the Polytechnic Institute. She has more than 20 years of scientific and pedagogical experience and more than 70 scientific papers, including 1 article in the Scopus database, 2 patents, 1 utility model patent and more than 30 teaching aids. The Hirsch index is 1. Her research interests lie in the fields of electric power engineering, automation, and information technology. She can be contacted at email: kuptleuova-k@mail.ru.



Yerbol Yerbayev    Ph.D. in the specialty "Electric power Industry", currently, he works at the NJSC West Kazakhstan Agrarian and Technical University named after Zhangir Khan at the Polytechnic Institute, as an associate professor. He has over 20 years of scientific and pedagogical experience, with more than 70 scientific papers, including 15 articles in the Scopus database, and 10 teaching aids. The Hirsch index is 4. His research interests lie in the fields of electric power engineering, automation, and information technology. He can be contacted at email: erbol.erbaev@mail.ru.



Saniya Kubentayeva    is a Candidate of Pedagogical Sciences (Ph.D. equivalent) specializing in 13.00.01 – General Pedagogy, History of Pedagogy and Education, and Ethnopedagogy. She is a senior lecturer in the Department of Computer Modeling and Information Technology. Her research interests focus on methods of teaching computer science. She also serves as an expert reviewer of textbooks and curricula in the subject of Computer Science. She can be contacted at email: saniya_kub@mail.ru.



Nurgaiша Almabayeva    completed her Ph.D. in Information Systems at L. Gumilyov Eurasian National University in 2021. In her master of pedagogical sciences, at the department of Normal physiology with a course in biophysics, Asfendiyarov Kazakh National Medical University, Almaty, Republic of Kazakhstan. Her research interests: the constant development of biophysics and pedagogica, modern effective methods of teaching. She is an author of more than 63 scientific articles and 3 textbooks. She can be contacted at email: ANMNuri@mail.ru.



Ainura Aripbayeva    graduated from Turan-Astana University in 2010, specialising in 'information systems. In 2022, she defended her thesis on the speciality 'information systems' and received the academic degree of Master of Technical Sciences. Currently she is a senior lecturer at the Department of Biostatistics, Bioinformatics, and Information Technology. She is the author of more than 10 scientific papers, 2 articles in Scopus database. She can be contacted at email: aripbaeva81@mail.ru.



Marhabat Slamkulova    Master of Technical Sciences: Mathematical Modeling and Control of Object Structures; formation and development of methods for solving problems, decision making in a fuzzy environment and Information Systems. Currently she is a Senior Lecturer at Taraz Regional University named after M.Kh. Dulaty. She takes an active part in fundamental and applied research. She is the author of more than 15 scientific and educational works. She can be contacted at email: slamkulova.markhabat@gmail.com.