

Intelligent control and optimization of power system facilities using artificial neural networks

Oksana Porubay¹, Dilnoza Umurzakova²

¹Department of Software Engineering and Cybersecurity, Faculty of Telecommunications and Cybersecurity, Fergana State Technical University, Fergana, Uzbekistan

²Department of Computer Engineering and Artificial Intelligence, Faculty of Information Technology and Artificial Intelligence, Fergana State Technical University, Fergana, Uzbekistan

Article Info

Article history:

Received Oct 29, 2025

Revised Aug 30, 2026

Accepted Sep 4, 2026

Keywords:

Artificial neural networks
Automated decision support systems
Multi-criteria analysis
Power grids
Reconstruction
Technical re-equipment

ABSTRACT

As electric power systems modernize, the need to develop intelligent decision support methods for the technical refurbishment and reconstruction of electrical grid facilities is increasing. This study aims to develop an intelligent approach to selecting priority alternatives for modernizing power grid facilities based on artificial neural networks (ANN). This paper proposes a two-level decision-making structure: a tactical level for selecting preferred alternatives for individual power grid facilities, and a strategic level for setting modernization priorities at the regional power grid level. To evaluate alternatives, a system of specific criteria was developed, encompassing economic, technical, reliability, and socio-environmental indicators. A new criterion for unifying equipment nomenclature is proposed, enabling the classification of technical solutions and the clustering of alternatives using Kohonen self-organizing maps (SOM). A multilayer neural network trained with backpropagation was employed to evaluate alternative preferences. Experimental studies have shown that the best results are achieved with the Levenberg-Marquardt (LM) algorithm and a three-layer network architecture, yielding an F-score of up to 0.979 and a classification accuracy of 99.04%. The results confirm the effectiveness of neural network methods for intelligent decision support in modernizing the electric power infrastructure.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Oksana Porubay
Department of Software Engineering and Cybersecurity
Faculty of Telecommunications and Cybersecurity, Fergana State Technical University
Mustakillik street 185, Fergana, 150100, Uzbekistan
Email: oksanaporubay@gmail.com

1. INTRODUCTION

The electric power industry is the basis of socio-economic development and a key factor in ensuring the sustainable functioning of industry, transportation, housing, utilities, and other sectors. One of the most important indicators of the state of the country's electric power industry is the reliability and efficiency of electric grids, which ensure the transmission and distribution of electric power from generation sources to end consumers. In the context of growing energy consumption, technical wear and tear of equipment, and new requirements for the stability of power systems, it becomes extremely important to maintain a high level of infrastructure readiness. This requires large-scale measures for technical re-equipment and reconstruction (TRR) of substations and power transmission lines [1].

In the scientific literature, the modernization and development of electric power systems are addressed using various decision-support methods, including multicriteria analysis, optimization models, and artificial

intelligence. In particular, methods such as the analytic hierarchy process, fuzzy logic, and evolutionary algorithms are widely used, enabling consideration of numerous technical, economic, and operational factors when selecting energy infrastructure development alternatives. In recent years, particular attention has been paid to the use of machine learning methods and artificial neural networks (ANN), which can process large volumes of data, identify hidden dependencies, and adapt to changing operating conditions in energy systems.

Solving the tasks of power grid modernization is a complex and multilevel process associated with large amounts of calculations and the need to process data, which are often characterized by uncertainty and the presence of interference [2]. Therefore, an urgent task is the use of advanced information technologies that can not only facilitate the process of information processing, but also support informed decision-making at different levels of management [3]. In this context, automated decision support systems (ADSS) represent an important tool to improve the efficiency and accuracy of planning and management of the process of TRR of power system facilities [4]. Despite significant research on the application of intelligent methods in the energy sector, several important issues remain understudied. In particular, existing decision support methods often focus either on local optimization of individual facilities or on strategic planning for the development of the energy system as a whole. Furthermore, approaches to integrating tactical and strategic decision-making within a unified intelligent system remain underdeveloped. In addition, most studies insufficiently account for the standardization of technical solutions and equipment classification, which can significantly affect the efficiency of energy infrastructure operations and modernization.

In this regard, a pressing scientific challenge is the development of intelligent decision-support methods that enable a comprehensive assessment of energy facility modernization alternatives, accounting for multiple criteria and the uncertainty inherent in the initial information. Of particular interest is the use of ANN to classify and analyze alternative solutions based on multi-criteria data. The paper proposes a two-level structure of the decision-making process for TRR of a regional power system (RPS). This structure includes tactical and strategic levels of decision-making [5]. At the tactical level, the evaluation and selection of preferred alternatives among the power grid facilities to be modernized is carried out. The strategic level defines priority alternatives for the TRR of RPS, which are formed from pre-selected alternatives of grid facilities. This approach allows taking into account both short-term and long-term perspectives, increasing flexibility and adaptability of the power system to changing conditions [6].

Unlike ANN-based approaches focused primarily on prediction, operating-mode optimization, or classification as isolated tasks, the proposed approach integrates the generation, multi-criteria evaluation, clustering, and selection of modernization alternatives within a unified two-level tactical-strategic decision-making structure. Its distinctive feature is the introduction of an equipment nomenclature unification criterion, which incorporates the recurrence of standardized technical solutions into the evaluation of modernization alternatives. Thus, the novelty lies not in the ANN or self-organizing map (SOM) algorithms themselves, but in their integration into a structured decision-making procedure for TRR of power grid facilities.

2. A REVIEW OF THE LITERATURE

Analysis of modern research in the field of decision-making in the reconstruction and modernization of energy systems shows that this process can be divided into several key stages: the formation of alternatives, their evaluation, and the selection of priority solutions for implementation. Numerous studies emphasize the importance of a multi-criteria approach that allows taking into account a wide range of factors influencing the development and operation of energy facilities [7], [8]. This approach is particularly relevant under conditions of uncertainty and dynamically changing external factors typical for modern power systems.

At the tactical level of decision-making, a number of studies highlight several important requirements for algorithms used in power system management [9]-[11]. These requirements include multi-criteria evaluation that considers reliability, cost, service life, and environmental impact. In addition, decision support systems should demonstrate high adaptability to changing operating conditions. Other important characteristics include minimizing human involvement to reduce subjectivity, ensuring rapid response, and maintaining robustness against data uncertainty and disturbances.

To address these challenges, artificial intelligence technologies, particularly ANN, have been increasingly applied in recent years [12]-[14]. Neural networks have demonstrated strong capabilities in solving classification and pattern recognition problems without direct expert intervention. Their ability to identify hidden relationships in complex datasets makes them especially suitable for decision support tasks in energy systems. Further research has contributed to the development of training algorithms and neural network architectures, which enabled their broader application in various engineering domains, including power system management [15].

Recent studies have also demonstrated that neural network models can effectively process large volumes of heterogeneous data, including incomplete and noisy information [16], [17]. This capability allows such models to operate efficiently under uncertainty and complex operating conditions typical of energy

infrastructure systems. Moreover, artificial intelligence methods have shown significant potential in enhancing ADSS and improving the efficiency of managing complex energy facilities [18], [19].

The integration of ANN into decision support systems for power system modernization has also been actively investigated in recent studies [20], [21]. These approaches improve the reliability and efficiency of planning reconstruction and modernization measures by enabling more accurate evaluation and prioritization of alternatives. Adaptive and data-driven models allow systems to respond to changing operational conditions and increase the overall resilience of power systems [22].

Based on the analysis of existing scientific research, the main stages of the decision-making process can be summarized as follows: formation of a set of alternatives, their comprehensive evaluation using quantitative and qualitative criteria, and the selection of the optimal solution. At the tactical level, decision-making methods should satisfy several key requirements, including multi-criteria evaluation, adaptability, reduced human influence, high processing speed, and robustness. ANN meet these requirements due to their ability to learn from data, process large volumes of information, operate in real time, and maintain high adaptability in dynamic environments.

3. MATERIALS AND METHODS

The dataset was generated from combinations of technical and operational parameters of power grid facilities, including equipment condition, transmission-line configuration, substation equipment characteristics, load indicators, and operating conditions. The source parameter ranges were derived from operational characteristics and standard technical specifications of power-grid equipment; therefore, the generated alternatives represent technically feasible modernization configurations rather than arbitrary synthetic samples. The data were normalized to a dimensionless scale and separated into training and independent test sets, with the latter used exclusively for performance evaluation.

The decision-making process using an ANN is considered a classification problem. To solve it, a multilayer perceptron architecture trained by backpropagation is used [23]. The architecture of the neural network used for classification of modernization alternatives is shown in Figure 1. This approach is characterized by high efficiency, relative ease of implementation, and the ability to vary the network structure, including the number of hidden layers, the number of neurons, and the training algorithms used. To solve the problem of clustering alternatives, Kohonen SOM are used, which offer several advantages, such as high learning speed, robustness to noisy and incomplete data, the ability to identify hidden patterns, and the ability to visually analyze multidimensional data [24].

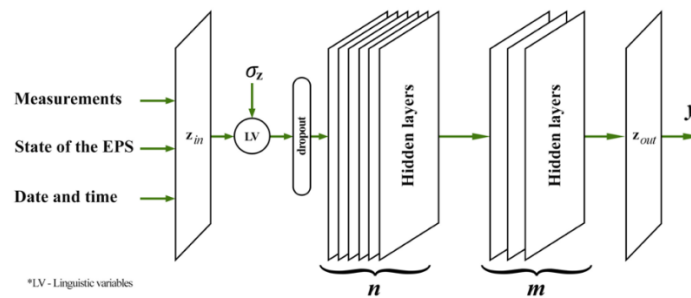


Figure 1. Architecture of the ANN used for classification of modernization alternatives

The proposed DSS implements a sequential decision-support workflow for power grid modernization. Technical and operational data of grid facilities are first processed to assess equipment condition and prospective load. Feasible TRR alternatives are then generated and evaluated using the proposed multi-criteria system. At the tactical level, the ANN classifies these alternatives as preferred or unacceptable, while at the strategic level, the preferred alternatives are prioritized for regional modernization planning. Thus, the DSS transforms facility data into ranked modernization recommendations for the decision maker. The following mathematical models implement the main stages of this workflow:

- Model of power reserve assessment. Depending on the level of current and prospective load, installed capacity of the ES object equipment, the maximum prospective load S_{max} , and load growth factor k_{li} were determined;
- Model for assessing the technical condition of the main technological equipment, developed based on the methods set out in regulatory documents, by determining the technical condition index (TCI):

$$TCI_{ob} = \begin{cases} 50 | \sum WSn_i \cdot TCIn_i > 50, TCIn_i < 25 \\ \sum WSn_i \cdot TCIn_i \end{cases} \quad (1)$$

where, WSn_i is the normalized weighted score of node i and $TCIn_i$ is an integral index of technical serviceability of node i ;

- Model of selection of measures for TRR of ES objects and type of nomenclature works, based on the above models:
if $S_{max} < 100\%$, $k_{li} \leq 1$ and $0 \leq TCI \leq 50$, then technical re-equipment;
if $S_{max} < 100\%$, $k_{li} \leq 1$ and $50 \leq TCI \leq 70$, then reconstruction;
if $S_{max} \sim 100\%$, $k_{li} > 1$ $TCI = \forall$, then technical re-equipment.
- Model for determining the parameters of the ES object alternatives, which takes into account the characteristics of the object, the type of equipment to be replaced and the type of nomenclature works. Each alternative of the ES object is proposed to be represented as a set of agreed parameters, selected from a possible set of values entered into the database: «Number of lines» $NL\{nl_1, nl_2, \dots, nl_m\}$ – number of transmission lines; «distance to power source» $DP\{dp_1, dp_2, \dots, dp_z\}$ – distance to the power source (e.g., substation); «Conductor Type» $CT\{ct_1, ct_2, \dots, ct_n\}$ – conductor type (cable brand: AC, ASC, and CIP); «Number of Circuits» $NC\{nc_1, nc_2, \dots, nc_k\}$ – number of electric circuits (single-circuit/double-circuit line); «Support Type» $ST\{st_1, st_2, \dots, st_j\}$ – type of support (reinforced concrete, steel, and wooden); «Area of Wire» $AW\{aw_1, aw_2, \dots, aw_g\}$ – wire cross-section (in mm²); «Scheme Number» $SN\{sn_1, sn_2, \dots, sn_i\}$ – substation circuit number (e.g., 110 kV-1 and 110 kV-2); «Circuit Breaker Type (High Voltage)» $CB_{HV}\{cb_{HV1}, cb_{HV2}, \dots, cb_{HVh}\}$ – type of circuit breaker on the higher voltage side; «Circuit Breaker Type (Low Voltage)» $CB_{LV}\{cb_{LV1}, cb_{LV2}, \dots, cb_{LVh}\}$ – type of breaker on the low voltage side; «Transformer Power» $TP\{tp_1, tp_2, \dots, tp_v\}$ – transformer power (in MVA).
- Model of compiling a tuple of alternatives of the ES object. For the formation of alternatives, it is proposed to use cyclic search, in the course of which the elements of sets are matched and the conformity of the current equipment to the level of prospective load is checked. By determining the Cartesian product of the nomenclature data, a set of alternatives is formed:

$$ALT\{ALT_1, ALT_2, \dots, ALT_q\} = NL \times DP \times CT \times NC \times ST \times AW \times SN \times CB_{HV} \times TP \times CB_{LV} \quad (2)$$

Each of the alternatives is a tuple of length equal to 10:

$$ALT_q\{dp_z, ct_n, nl_m, nc_k, aw_g, st_j, sn_i, cb_{HVh}, tp_v, cb_{LVh}\} | nl_m \in NL \wedge dp_z \in DP \wedge ct_n \in CT \wedge nc_k \in NC \wedge st_j \in ST \wedge aw_g \in AW \wedge sn_i \in SN \wedge cb_{HVh} \in CB_{HV} \wedge tp_v \in TP \wedge cb_{LVh} \in CB_{LV} \quad (3)$$

To evaluate the formed alternatives of the ES object, mathematical models of the following private evaluation criteria are justified and adapted:

- Total discounted cost criterion TDC (economic criterion):

$$TDC = \sum_{t=0}^{t_{TRR}} (C_{Lt} + C_{Pct} + C_{dist} - C_{rest}) \cdot (1 + E_{norm})^{-t} + \sum_{t=t_{TRR}}^{t_{exp}} a_{ser} (C_{Lt} + C_{Pct}) (1 + E_{norm})^{-t} \quad (4)$$

where, C_{Lt} is capital investments for construction of lines in the t -th year; C_{Pct} is capital investments for construction of substations in the t -th year; C_{dist} is cost of equipment dismantling in the t -th year; C_{rest} is residual value of equipment in the t -th year; E_{norm} is normative coefficient of capital investments efficiency; a_{ser} is rate of deductions for current repair and maintenance; t_{TRR} and t_{exp} are current years of TP&R and operation of the facility;

- Criterion of annual electricity loss ΔW (technical criterion):

$$\Delta W = \Delta W_{XX} + \Delta W_{loadT} + \Delta W_{constPC} + \Delta W_{constL} + \Delta W_{loadL}, \quad (5)$$

where, $\Delta W_{XX}, \Delta W_{loadT}$ – constant and load losses in transformers; $\Delta W_{constPC}$ – aggregated constant power losses in substation; and $\Delta W_{constL}, \Delta W_{loadL}$ – aggregated constant and load power losses in lines;

- Criterion of economic losses from power supply disruption EPI (technical and economic criterion):

$$EPI = P_{max} \cdot (EPI_0 + EPI_{un}) \cdot (C_{B1} + 0,5 \cdot C_{B2}) + \sum_{i=1}^k z_{rep.i}^{ab} \cdot p_i \cdot \omega_i, \quad (6)$$

where, P_{max} is maximum power demand of consumers; EPI_0 is specific damage caused by power supply interruptions; EPI_{un} is unearned income from the transmission of electricity to consumers; C_{B1} is forced downtime coefficients in the event of a complete power outage; C_{B2} is forced downtime coefficients for

consumers connected to one of the substation sections; $z_{rep.i}^{ab}$ is cost of restoring damaged equipment; p is number of units of the same type of equipment; ω is equipment failure rate; and k is number of equipment types.

– Criterion of the area of land to be withdrawn (socio-ecological criterion):

$$S = S_{sqL} \cdot L + S_{sqPC}, \quad (7)$$

where, S_{sqL} is land area allocation for standard transmission line supports per 1 km of overhead line (OHL); L is length of the overhead line; and S_{sqPC} is land area allocation for the substation.

It was proposed and justified the introduction of a new technical and operational criterion into the system of private criteria – the criterion of unification of the electric grid facilities nomenclature, the value of which makes it possible to assess how often a set of parameters of equipment of the same standard size is encountered in the existing practice of operation:

$$N = n_i / T_{obj} \quad (8)$$

where, n_i is the number of ES objects with relatively similar equipment (number of objects in the i -th cluster) and T_{obj} is the total number of existing ES objects.

To calculate the unification criterion, existing technical and operational solutions were preliminarily typified using a Kohonen SOM. The clustering procedure identified four recurrent groups of equipment configurations; therefore, four output neurons were used, each corresponding to one identified cluster. The cluster size was subsequently used to calculate the recurrence of standardized technical solutions according to (8).

A method for evaluating alternatives to an ES object has been developed and implemented using neural networks. The ANN was trained using the backpropagation algorithm, which allows for adjusting the values of the weights that connect neurons during training until the error value reaches a specified minimum. A set of input value vectors consisting of the criteria for evaluating the alternative X and the corresponding output values of the preference coefficient T was used to train the ANN:

$$(Alt_i, Pref_i), \quad (9)$$

where, i is the number of the alternative in the training sample and $Pref_i$ is a binary output vector taking the values 0 or 1.

The binary target value T was assigned according to the multi-criteria evaluation of each alternative: alternatives satisfying the admissible technical and operational requirements and demonstrating preferable values of the normalized evaluation criteria were assigned to the preferred class ($T=1$), whereas alternatives failing these requirements were assigned to the unacceptable class ($T=0$); X is the vector of input criteria reduced to unit scale.

$$Alt_i = \{CE_i/N, \Delta E_i/N, Y_i/N, S_i/N, Q_i\}, \quad (10)$$

where, CE_i is cost efficiency; ΔE_i is energy losses. Y_i is productivity; S_i is safety level; Q_i is quantity of resources; and N is normalization parameter.

A multilayer perceptron architecture with multiple hidden layers was used to train the neural network. The input layer was formed based on a vector of alternative evaluation criteria, including economic, technical, operational, and resource indicators. The network was trained using various optimization algorithms, including Levenberg-Marquardt (LM), resilient backpropagation, adaptive gradient descent, quasi-Newton, and scaled conjugate gradient. To assess generalization performance, the data were separated into training and independent test sets; the test data were not used during training and were employed exclusively for the final performance evaluation. To evaluate the efficiency of the ANN functioning within the framework of the problem being solved, two indicators were used: the share of correctly classified solutions and F-measure, which characterizes the balance between the accuracy and completeness indicators as a harmonic average of the values of these metrics:

$$F = 2 \cdot CR / (2 \cdot CR + MS + FA) \quad (11)$$

where, correct resolutions (CR) is the number of correct solutions; missed solutions (MS) is number of missed solutions; and false alarms (FA) is number of false alarms.

The neural network training process was carried out iteratively with classification error function minimization. At each training step, the network weights were adjusted based on the calculated error between actual and predicted values. To assess potential overfitting, the model was evaluated on an independent test set. Model performance was assessed based on classification accuracy and the F-score, which enabled the identification of the most effective network architecture and training algorithm.

To ensure reproducibility of the experimental results, the neural network architecture parameters, training algorithms, and performance evaluation criteria were fixed and used uniformly for all network configurations studied. This allowed for a fair comparison of the various training algorithms and the determination of the optimal neural network architecture for classifying energy system modernization alternatives.

4. RESULTS AND DISCUSSION

4.1. Selection of training architecture and algorithm

This experimental study aims to evaluate the effectiveness of ANN for classifying alternatives for modernizing electric power grid facilities. Similar classification and optimization problems are widely considered in modern research on the application of machine learning methods in the energy sector, where neural networks demonstrate high efficiency in analyzing complex multi-criteria data and making management decisions under uncertainty.

The experiments evaluated the performance of various neural network architectures and training algorithms using test data not included in the training set. The primary evaluation criterion was the F-score, a metric characterizing the balance between classification accuracy and recall, where a value close to 1 indicates high model performance. The use of the F-measure as an integral indicator of classification quality is widely used in data mining and neural network training tasks, since this indicator allows one to simultaneously take into account the accuracy and completeness of the classification of machine learning models [25]. Additionally, the percentage of correct answers (%) was calculated, reflecting the proportion of correctly classified objects. The network architecture and training algorithm were selected experimentally and evaluated based on the performance of the ANN on data not used in the training process. The experiment utilized neural networks with two and three hidden layers, with the number of neurons ranging from 2 to 30, as shown in Figure 2. The obtained F-measure values and the corresponding ANN architectures for different training algorithms are summarized in Table 1.

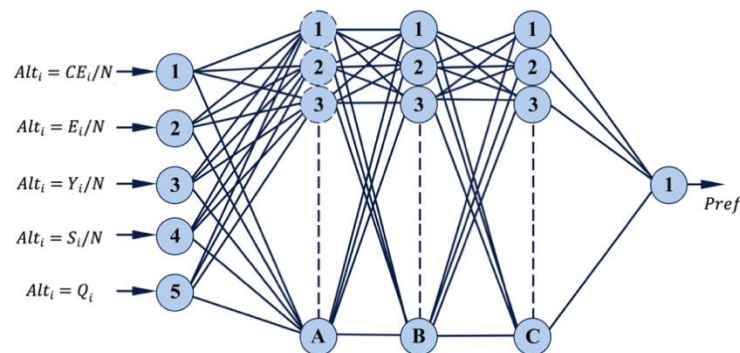


Figure 2. Neural network architectures used in the experimental study

Table 1. Main characteristic parameters of ANN

ANN training algorithm	Number of layers	Number of neurons in hidden layers	Maximum F-measure	% correct answers
LM algorithm	2	19; 9	0.957	97.83
	3	5; 17; 26	0.979	99.04
Resilient backpropagation algorithm	2	17; 25	0.949	97.38
	3	9; 13; 25	0.949	97.47
Gradient descent with adaptive learning	2	19; 23	0.938	97.02
	3	11; 29; 13	0.937	97.22
Quasi-Newton method	2	12; 27	0.930	96.78
	3	4; 10; 16	0.941	97.21
Scaled conjugate gradient method	2	3; 15	0.911	95.69
	3	5; 10; 9	0.919	96.13

The reported performance was evaluated on independent test data not used during ANN training. In addition, sensitivity analysis was performed by varying the number of hidden layers, neurons, and training algorithms; the comparative results in Table 1 show that the classification performance remained high across the evaluated configurations (F-score 0.911–0.979 and accuracy 95.69–99.04%). Thus, the 99.04% accuracy represents the best-performing configuration rather than a single isolated training result. Nevertheless, further validation using larger real-world datasets and cross-validation is required to confirm the model's generalization under broader operating conditions.

The ANN architecture was selected experimentally rather than predefined. Among the evaluated two- and three-hidden-layer configurations with 2–30 neurons per layer, the 5→17→26 architecture trained by the LM algorithm achieved the best performance, with an F-score of 0.979 and 99.04% correctly classified alternatives (Table 1). Therefore, this configuration was selected as the final model.

Compared with recent intelligent power-system approaches, including graph neural networks, transformer-based models, reinforcement learning, and federated learning, the proposed method addresses a different task: multi-criteria classification and prioritization of modernization alternatives rather than network-state prediction or operational control. Its advantage is the relatively simple integration of heterogeneous technical and economic criteria into a two-level decision-making workflow, while more advanced architectures may provide greater scalability and adaptability for large dynamic power systems. Therefore, their integration and comparative evaluation represent an important direction for further research.

4.2. Discussion of results

The superior performance of the LM algorithm in the present problem can be associated with the nonlinear and interdependent nature of the economic, technical, reliability, resource, and operational criteria used to evaluate modernization alternatives. For this multi-criteria classification task, LM provided the best balance between model complexity and classification performance, reaching an F-score of 0.979 and an accuracy of 99.04% with the 5→17→26 architecture. In contrast, the other evaluated algorithms achieved F-scores of 0.911–0.949 and accuracies of 95.69–97.47%, indicating that the choice of training algorithm has a measurable influence on alternative classification. However, the higher computational requirements of LM should be considered for real-time deployment; less computationally demanding methods may remain preferable when processing resources are limited. These results are specific to the investigated modernization-alternative classification problem and should not be interpreted as demonstrating universal superiority of LM over other learning methods.

From a practical perspective, the proposed workflow is intended to support, rather than replace, the power-system decision maker. The ANN performs automated screening of modernization alternatives, while the final prioritization remains available for engineering and managerial assessment. Such a workflow reduces the number of alternatives requiring manual analysis and can support regional TRR planning; however, practical deployment requires integration with operational databases and validation under real operating conditions.

The present study has several limitations. The framework was evaluated under the considered technical and operational conditions; robustness to noisy or missing measurements, cyber-physical disturbances, parameter uncertainty, and scalability to larger networks with high renewable penetration require further investigation. Although sensitivity analysis demonstrated the influence of ANN architecture and training parameters, additional explainability techniques, including feature-importance analysis, could improve the transparency of decisions for power-system operators. Future work will therefore focus on robustness, explainability, scalability, and validation of the framework under broader real-world operating conditions.

5. CONCLUSION

The paper proposes an intelligent approach to decision support for the TRR of electrical grid facilities based on ANN. A two-level decision-making structure has been developed, including a tactical level for selecting preferred alternatives for individual power grid facilities and a strategic level for setting modernization priorities at the regional power grid level. A system for multi-criteria evaluation of alternatives has been developed within the study, taking into account economic, technical, reliability, and socio-environmental indicators. The scientific novelty of the work lies in the introduction of a criterion for the unification of equipment nomenclature, which makes it possible to take into account the degree of standardization of technical solutions and use clustering methods to analyze modernization alternatives. Experimental studies have demonstrated the high efficiency of using neural networks for classifying alternatives for power grid facility modernization. The best results were obtained using the LM algorithm, which provided a maximum F-measure value of 0.979 and a classification accuracy of 99.04%. The obtained results confirm the potential of applying artificial intelligence methods in intelligent decision support systems

for the modernization of electric power infrastructure. In the future, it is planned to expand the model by integrating digital twins of energy facilities and developing adaptive self-learning models.

FUNDING INFORMATION

Authors state there is no funding involved

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
Oksana Porubay	✓	✓	✓		✓	✓		✓	✓	✓	✓	✓	✓	
Dilnoza Umurzakova	✓	✓		✓		✓	✓	✓		✓				✓

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

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [OP], upon reasonable request. The data, which contains information that could compromise the privacy of research participants, is not publicly available due to certain restrictions.

REFERENCES

[1] N. G. Semenova, A. D. Chernova, and L. A. Vlatskaya, "Decision-making algorithm for the development of the district of electrical grids," in *IOP Conference Series: Materials Science and Engineering*, vol. 1089, no. 1, pp. 1–10, 2021, doi: 10.1088/1757-899X/1089/1/012012.

[2] S. Yucheng, M. Haiyan, and X. Chunhua, "Cloud computing based data processing and automated management of power dispatch," *Applied Mathematics and Nonlinear Sciences*, vol. 9, no. 1, pp. 1–12, 2024, doi: 10.2478/amns-2024-1483.

[3] Z. Zhang, "Energy system optimization based on fuzzy decision support system and unstructured data," *Energy Informatics*, vol. 7, 2024, doi: 10.1186/s42162-024-00396-2.

[4] A. Rajagopalan, R. Sundararajan, and R. Sundararajan, "Modernized planning of smart grid based on distributed power generations and energy storage systems using soft computing methods," *Energies*, vol. 15, no. 23, pp. 1–18, 2022, doi: 10.3390/en15238889.

[5] H. Lv, Q. Wu, H. Ren, Q. Li, and W. Zhou, "A two-stage decision-making approach for optimal design and operation of integrated energy systems considering multiple uncertainties and diverse resilience needs," *Energy*, vol. 305, p. 132375, 2024, doi: 10.1016/j.energy.2024.132375.

[6] U. Pandey, S. K. Panda, and R. K. Behera, "Applications of artificial intelligence in power system operation, control and planning: A review," *Clean Energy*, vol. 7, no. 6, pp. 1199–1218, 2023, doi: 10.1093/ce/zkad061.

[7] S. Das, R. Dutta, S. De, and S. De, "Review of multi-criteria decision-making for sustainable decentralized hybrid energy systems," *Renewable and Sustainable Energy Reviews*, vol. 202, p. 114676, 2024, doi: 10.1016/j.rser.2024.114676.

[8] M. M. Samy, R. E. Almamlook, H. I. Elkhoully, and S. Barakat, "Decision-making and optimal design of green energy system based on statistical methods and artificial neural network approaches," *Sustainable Cities and Society*, vol. 87, p. 104015, 2022, doi: 10.1016/j.scs.2022.104015.

[9] M. R. Shadi, H. Mirshekali, and H. R. Shaker, "Explainable artificial intelligence for energy systems maintenance: A review on concepts, current techniques, challenges, and prospects," *Renewable and Sustainable Energy Reviews*, vol. 216, pp. 1–24, 2025, doi: 10.1016/j.rser.2025.115668.

[10] A. A. A. Lateef, S. I. A. Al-Janabi, and O. A. Abdulteef, "Artificial Intelligence Techniques Applied on Renewable Energy Systems: A Review," in *Proceedings of the International Conference on Computing and Communication Networks*, vol. 394, pp. 297–308, 2022 doi: 10.1007/978-981-19-0604-6_25.

[11] Y. M. Banad, S. S. Sharif, and Z. Rezaei, "Artificial intelligence and machine learning for smart grids: From foundational paradigms to emerging technologies with digital twin and large language model-driven intelligence," *Energy Conversion and Management: X*, vol. 28, pp. 1–35, Oct. 2025, doi: 10.1016/j.ecmx.2025.101329.

[12] T. Zhang *et al.*, "Novel artificial intelligence applications in energy systems: A systematic review," *Energies*, vol. 18, no. 14, pp. 1–51, 2025, doi: 10.3390/en18143747.

[13] J. Jing, H. Di, T. Wang, N. Jiang, and Z. Xiang, "Optimization of power system load forecasting and scheduling based on artificial neural networks," *Energy Informatics*, vol. 8, pp. 1–20, 2025, doi: 10.1186/s42162-024-00467-4.

- [14] E. B. Beşikçi, O. Arslan, O. Turan, and A. I. Ölçer, "An artificial neural network based decision support system for energy efficient ship operations," *Computers & Operations Research*, vol. 66, pp. 393–401, Feb. 2016, doi: 10.1016/j.cor.2015.04.004.
- [15] Y. Lim *et al.*, "Power System Decision Making in the Age of Deep Learning: A Comprehensive Review," *Energies*, vol. 18, no. 18, pp. 1–50, 2025, doi: 10.3390/en18184867.
- [16] T. K. Roy, S. S. Yu, M. A. Mahmud, and H. Trinh, "Robust LFC design using adaptive neuro-fuzzy inference-aided optimal fractional-order PIDA control for perturbed power systems with solar and wind power sources," *IET Generation, Transmission & Distribution*, vol. 18, no. 12, pp. 2193–2212, 2024, doi: 10.1049/gtd2.13185.
- [17] R. Bahmani and M. Afrasiabi, "Noisy PMU Data Recovery in Transient Conditions through Self-Attention Neural Networks," in *2024 IEEE PES Innovative Smart Grid Technologies Europe (ISGT EUROPE)*, Dubrovnik, Croatia, 2024, pp. 1-5, doi: 10.1109/ISGTEUROPE62998.2024.10863227.
- [18] Z. Nishtar, F. Wang, F. H. Jaskani, and H. Afzaal, "Real-Time Fault Detection and Isolation in Power Systems for Improved Digital Grid Stability Using an Intelligent Neuro-Fuzzy Logic," *Computer Modeling in Engineering & Sciences*, vol. 143, no. 3, pp. 2919–2956, 2025, doi: 10.32604/cmescs.2025.065098.
- [19] F. Henao, R. Edgell, A. Sharma, and J. Olney, "AI in power systems: a systematic review of key matters of concern," *Energy Informatics*, vol. 8, pp. 1–30, 2025, doi: 10.1186/s42162-025-00529-1.
- [20] N. Shahverdi, A. Saffari, and B. Amiri, "A systematic review of artificial intelligence and machine learning in energy sustainability: Research topics and trends," *Energy Reports*, vol. 13, pp. 5551–5578, Jun. 2025, doi: 10.1016/j.egy.2025.05.021.
- [21] A. Alabbasi, J. Sadhukhan, M. Leach, and M. Sanduk, "Accelerating the Transition to sustainable energy: An intelligent decision support system for generation expansion planning with renewables," *Energy*, vol. 304, p. 131999, 2024, doi: 10.1016/j.energy.2024.131999.
- [22] A. Safari, M. S. Hossain, and M. A. Mahmud, "A systematic review of artificial intelligence for energy systems and virtual power plants," *Applied Sciences*, vol. 14, pp. 1–41, 2024, doi: 10.3390/app142311112.
- [23] O. Porubay and D. Umurzakova, "Integration of Neutrosophic Methods into Adaptive Control of Nonlinear Systems Using Neuro-Fuzzy Networks With B-Spline Functions," *IIUM Engineering Journal*, vol. 27, no. 2, pp. 506–528, May 2026, doi: 10.31436/iiumej.v27i2.4021.
- [24] C. Goutte and E. Gaussier, "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation," in *Proceedings of the European Conference on Information Retrieval (ECIR)*, 2005, pp. 345–359, doi: 10.1007/978-3-540-31865-1_25.
- [25] P. Christen, D. J. Hand, and N. Kirielle, "A review of the F-measure: Its history, properties, criticism, and alternatives," *ACM Computing Surveys*, vol. 56, no. 3, pp. 1–24, 2023, doi: 10.1145/3606367.

BIOGRAPHIES OF AUTHORS



Oksana Porubay    received her Ph.D. degree in Technical Sciences from Tashkent State Technical University, Uzbekistan, in 2024. She is currently an Associate Professor at the Department of Software Engineering and Cybersecurity, Fergana State Technical University. Her research interests include intelligent control, optimization, and adaptive models for electric power system operations. She can be contacted at email: oksanaporubay@gmail.com.



Dilnoza Umurzakova    holds a Ph.D. in technical sciences from the National Research University "Tashkent Institute of Irrigation and Agricultural Mechanization Engineers". She is currently an Associate Professor in the Department of Computer Engineering and Artificial Intelligence, Fergana State Technical University. She can be contacted at email: umurzakovadilnoz@gmail.com.