

Formation of structural model of objects of power systems on the basis of artificial neural networks

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ABSTRACT

The article presents an approach to optimizing the processes of the technical re-equipment and reconstruction (TRR) of power grid facilities using artificial neural networks (ANN). A two-level decision-making structure is proposed, including the tactical level (selection of preferred alternatives for individual facilities) and the strategic level (prioritization for the regional power system or RPS). Mathematical models of private criteria have been developed to evaluate alternatives: economic costs, technical efficiency, reliability, socio-ecological consequences, and equipment unification. The concept of “nomenclature unification criterion” was introduced, which allows clustering of solutions based on the typing of equipment parameters. Training of neural networks was carried out using the algorithm of error back propagation, which provided high accuracy of classification of alternatives (F-measure up to 0.979). Experiments showed the effectiveness of the Levenberg-Marquardt method for training networks with three hidden layers. The integration of ANN into automated decision support systems (ADSS) allows minimizing subjective factors, increasing the adaptability of power systems to changing conditions, and optimizing resource allocation. Results demonstrate the ability to reduce risks and improve infrastructure reliability by processing noisy and incomplete data, as well as real-time analysis. The approach applies to large-scale power systems, balancing short-term and long-term modernization goals.

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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].

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].

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].

The use of the proposed system allows for the optimization of resource allocation and reduces risks in the implementation of TRR projects, which ultimately contributes to improving the reliability and efficiency of the regional energy system (ES). In particular, the integration of artificial neural networks (ANNs) enables the processing of heterogeneous and uncertain data within a unified decision-making framework. This approach enhances the objectivity and adaptability of planning decisions at both tactical and strategic levels.

2. LITERATURE REVIEW

Analysis of modern research in the field of decision-making in the reconstruction and modernization of ESs shows that this process can be divided into key stages: formation of alternatives, their evaluation, and selection of the priority alternative for implementation. Studies [7]–[9] emphasize the importance of a multi-criteria approach that allows taking into account the variety of factors affecting the state and prospects of development of energy facilities. This approach is especially relevant in conditions of uncertainty and dynamically changing external factors inherent in the industry.

At the tactical level of decision making, a number of international researchers emphasize several key requirements for methods and algorithms used in decision support systems. In particular, Saaty [10] highlights the importance of multi-criteria evaluation frameworks that allow the simultaneous consideration of heterogeneous indicators such as reliability, cost, service life, and environmental impact. Similarly, Keeney *et al.* [11] emphasize that effective decision-making under complex conditions requires the integration of conflicting criteria within a unified analytical structure. In addition, the authors [12], [13], underline the role of adaptive and fuzzy-based approaches that enable decision-making systems to operate under uncertainty and changing operating conditions. Modern studies also stress the importance of minimizing human involvement to reduce subjective bias, ensuring high computational efficiency for rapid response, and providing robustness to data uncertainty and disturbances, as demonstrated in multi-objective optimization research [14].

To fulfill these requirements, the application of artificial intelligence technologies, in particular ANNs, has been actively considered in recent years [15]. Studies [16], [17] were among the first to propose the architecture of multilayer neural networks and demonstrate the effectiveness of the backpropagation learning algorithm, proving its capability in classification and pattern recognition tasks without expert involvement [16]. Their studies showed that such networks significantly improve the accuracy and autonomy of decision-making processes. Subsequently, other researchers made fundamental contributions to the development and training of neural networks, establishing the theoretical and practical foundations for their widespread application in ESs and other industries [17].

The authors [18]–[20] confirm that neural networks can process large amounts of data, including noisy and incomplete data, which allows them to effectively deal with uncertainty in information flows. An important characteristic of neural networks is their real-time learning ability and high adaptability, which is particularly useful for long-term planning and strategic-level decision-making [21], [22]. Recent studies demonstrate that the application of artificial intelligence and neural networks in ADSS significantly improves the operational efficiency of complex energy facilities and reduces decision-making risks [23], [24]. Furthermore, the integration of ANNs into decision support systems enhances the reliability and efficiency of power system reconstruction and modernization by enabling more accurate prioritization of alternatives and adaptive responses to changing operating conditions [25], [26].

The analysis of scientific sources and practical research in the field of decision-making theory allowed identifying the key stages of the decision-making process, which are systematized in this article as

follows: i) formation of alternatives; ii) evaluation of possible alternatives; and iii) selection of a priority alternative. At the same time, the main requirements for decision-making methods at the tactical level include multi-criteria evaluation, adaptability, minimization of human participation, computational efficiency, and robustness. ANNs are proposed as a core technology to meet these requirements due to their ability to perform classification and learning tasks without expert involvement. In addition, ANN-based models enable real-time data processing and demonstrate high adaptability when operating under uncertainty.

3. MATERIALS AND METHODS

Decision-making with the help of an ANN in this work is proposed to be considered as a classification problem, for the solution of which the architecture in the form of a multilayer perceptron trained by the algorithm of error backpropagation is used [27]. The advantage of this method is high efficiency, ease of implementation, and the possibility of using different configurations of the number and dimensionality of layers and training algorithms. To solve the problem of clustering of alternatives, it is proposed to use self-organizing Kohonen maps, the advantages of which are fast learning, robustness to noisy or incomplete data, detection of hidden regularities, ability to generalize, and the possibility of visual analysis of multidimensional data. The structural model of the formation of alternatives of objects of the ES is developed. The following modules and their mathematical models are proposed:

- i) 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.
- ii) 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) according to (1).

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

Where WSn_i is the normalized weighted score of nodes i ; $TCIn_i$ is an integral index of technical serviceability of node i . These indicators provide a quantitative assessment of the technical condition of equipment nodes and serve as input parameters for further decision-making and classification procedures.

- iii) Model of selection of measures 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.
- iv) 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, CIP, etc.); «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, wooden, etc.); «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, 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).
- v) 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 nomenclature data, a set of alternatives is formed (2).

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

Each of the alternatives is a tuple of length equal to 10. This representation ensures a unified description of technical and operational parameters for different ES objects. Such formalization allows the effective application of neural network models for classification and clustering tasks.

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

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) in (4).

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

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} is current years of TP&R and operation of the facility.

- Criterion of annual electricity loss ΔW (technical criterion) as defined in (5).

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

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

- Criterion of economic losses from power supply disruption *EPI* (technical and economic criterion) as presented in (6).

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

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) as defined in (7).

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

Where S_{sqL} is land area allocation for standard transmission line supports per 1 km of overhead line (OHL); L is length of the OHL; 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 as given in (8).

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

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 object.

To calculate the unification criterion, a preliminary typification of existing technical and operational solutions was performed, and the number and size of clusters were determined using Kohonen self-organizing maps. To distribute alternatives of ES objects into clusters, a single-layer ANN was used in the work, consisting of an input layer with several neurons equal to the size of the tuple of the alternative of the ES object, one hidden layer, and an output layer with four neurons that take the values 0 or 1, depending on the number of the cluster to which the alternative belongs. A method for evaluating alternatives to an ES object has been developed and implemented using neural networks. The proposed method enables automated classification of alternatives based on multiple normalized evaluation criteria. This reduces subjective bias and improves the consistency of decision-making results.

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 as defined in (9). The input criteria vector as defined in (9). The input criteria vector Alt_i was normalized to unit scale, as given in (10). was normalized to unit scale, as given in (10).

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

Where i is the number of the alternative in the training sample; $Pref_i$ is a binary output vector taking the values 0 or 1. The value “0” indicates that the alternative belongs to the class of unacceptable solutions, and the value “1” is to the class of preferred solutions; Alt_i is 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.

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 as given in (11).

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

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.

4. RESULTS AND DISCUSSION

4.1. Selection of training architecture and algorithm

The experiments evaluated the performance of various neural network architectures and training algorithms using test data not included in the training set [16], [17]. The primary evaluation criterion was the F1-score, a metric characterizing the balance between classification accuracy and recall, where a value close to 1 indicates high model performance. 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 [16]. The experiment utilized neural networks with two and three hidden layers, with the number of neurons ranging from 2 to 30. Figure 1 illustrates the general architecture of the ANN used in the study, including the input layer, hidden layers, and output layer. This architecture serves as the basis for evaluating the influence of different training algorithms and network configurations on classification performance [8], [9].

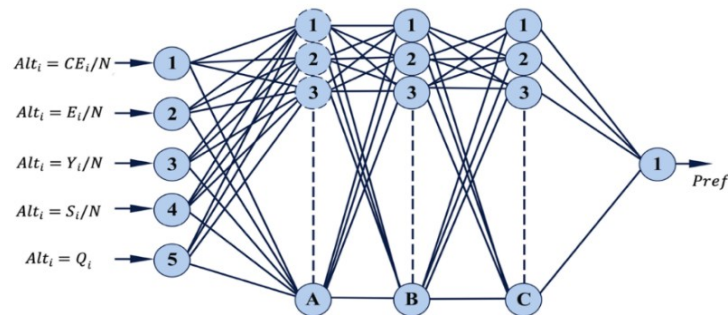


Figure 1. Neural network architecture

The obtained F-measure values and the corresponding ANN architectures for different training algorithms are summarized in Table 1. This table provides a comparative analysis of different training methods and network configurations in terms of classification accuracy and robustness. The presented results allow identifying the most effective ANN architecture for solving the decision-making problem under consideration.

Table 1. Main characteristic parameters of ANN

ANN training algorithm	Number of layers	Number of neurons in hidden layers	Maximum F-measure	% Correct answers
Levenberg–Marquardt 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 closer the F-measure value is to 1, the more effective the ANN is in classifying decisions into preferred and inappropriate ones [8], [9]. The best results were achieved using the Levenberg-Marquardt algorithm. Using a three-layer architecture with the number of neurons $5 \rightarrow 17 \rightarrow 26$, the F-measure was 0.979, and the proportion of correct answers was 99.04%. This significantly outperforms the performance of other algorithms:

- For the two-layer architecture, Levenberg-Marquardt provided an F-measure of 0.957 (97.83% correct answers) with the number of neurons $19 \rightarrow 9$.
- The elastic backpropagation algorithm provided maximum F-measure of 0.949 (97.47%) in three-layer configuration of $9 \rightarrow 13 \rightarrow 25$.
- The adaptive gradient descent method (adaptive gradient descent) achieved an F-measure of 0.937-0.938 (97.02-97.22%), while the quasi-Newton method (quasi-Newton) achieved an F-measure of 0.930-0.941 (96.78-97.21%).
- The scaled conjugate gradients method was the least efficient, with an F-measure of 0.911-0.919 (95.69-96.13%).

Overall, the comparative analysis of training algorithms demonstrates that both network architecture and optimization strategy significantly influence classification performance. Second-order optimization methods consistently outperform first-order approaches, especially when applied to deeper neural network architectures. These observations form the basis for the subsequent discussion of the obtained results and their implications for decision support systems in power system modernization.

4.2. Discussion of results

The advantage of the Levenberg-Marquardt algorithm can be attributed to its ability to efficiently minimize the error function through a combination of gradient descent and second-order Gaussian methods. This avoids getting stuck in local minima and accelerates convergence, which is especially important for complex multidimensional spaces typical of deep architectures. The three-layer architecture with the number of neurons $5 \rightarrow 17 \rightarrow 26$ showed superiority over the two-layer models. This is probably due to the possibility of hierarchical feature extraction: the first hidden layer performs coarse filtering of the data, the second layer performs granularity, and the third layer performs complex nonlinear boundary formation. The decrease in the number of neurons in the first layer (from 19 to 5) during the transition from a two-layer to a three-layer model may indicate a reduced risk of overtraining due to the simplification of internal representations at early stages of processing.

The limitations of the other algorithms require further analysis. For example, the elastic backpropagation algorithm, despite its relative efficiency, lost to Levenberg-Marquardt due to its greater sensitivity to initial conditions and potentially insufficient adaptation speed. First-order methods (gradient descent, quasi-Newton) demonstrate lower performance under conditions of high dimensionality of the parameter space, which is consistent with theoretical expectations.

The number of neurons in the hidden layers turns out to be critical. For example, in the three-layer Levenberg-Marquardt architecture, the number of neurons in the first layer decreased by a factor of 3.8 (from 19 to 5), whereas it increased in the second and third layers (from 9 to 17 and 26, respectively). This may indicate the need for a balance between the compactness of data representation and its detail at different levels of the hierarchy. The results confirm that the choice of training algorithm is a key factor in ANN optimization, especially when dealing with deep architectures. The Levenberg-Marquardt algorithm is recommended for tasks requiring high classification accuracy, whereas first-order methods may be preferred in cases of limited computational resources.

5. CONCLUSION

Modern power systems operate under conditions of high variability of technical solutions and increasing requirements for the processes of TRR, which necessitate the use of intelligent decision support methods. In this study, a two-level decision-making structure for power grid modernization was proposed, integrating tactical selection of preferred alternatives for individual facilities and strategic prioritization at the regional level. A system of multi-criteria evaluation models was developed, incorporating economic, technical, reliability, socio-ecological, and unification criteria, enabling quantitative assessment of modernization alternatives under uncertainty. The scientific novelty of the work lies in the introduction of a nomenclature unification criterion based on clustering of equipment parameters using self-organizing Kohonen maps and ANNs trained by the backpropagation algorithm. Experimental results confirm that the proposed ANN-based approach ensures high classification accuracy and improves the objectivity, adaptability, and efficiency of decision-making processes. The practical implementation of the proposed methodology can significantly reduce risks, optimize resource allocation, and enhance the sustainability and reliability of power systems, while future research will focus on extending the criteria set and integrating adaptive self-learning models operating in real time.

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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

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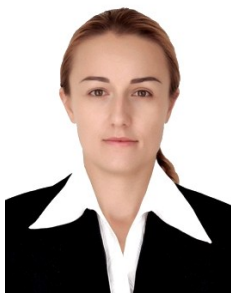
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