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Confirmation of Electrical Network Configuration from Telemetry Data Based on Convolutional Neural Networks

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Abstract—The reliability function of electrical-network configuration is an important part of decision-support systems and increases the reliability and efficiency of managing the operating mode of an electrical network. Classically, the function is implemented on the basis of the condition assessment method and does not have the proper response rate to changes in the electrical network, and also requires large computing resources. Meanwhile, there are modern tools that ensure a high reaction rate due to the exclusion of calculations of the electrical network mode in real-time control of it. Such tools include neural networks. The article proposes a system for confirming electrical network configurations based on convolutional neural networks. The initial data for the neural network are telemetry data of the operating parameters presented in 2D format, and the result is localized errors in the representation of the current configuration of the electrical network with an assessment of the level of reliability of the result. The operation of the system is demonstrated by the example of evaluating the configurations of a nine-node electrical circuit of the IEEE standard. The neural network demonstrates high efficiency and accuracy of recognition of the current configuration, including in conditions of distortion and insufficiency of telemetry.

Keywords: electrical networks, telemetry, convolutional neural networks, reliability of representation of electrical-network configuration

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Effective management of a power system's operating mode constructing building a calculation model of the current mode and updating it in real time. The modern view on the implementation of this task involves the use of various intelligent systems for assessing the state, decision-support systems, and digital twins of the controlled electrical network. In such systems, the graphical representation of the electrical network is traditionally constructed in the form of a single-line diagram, and the updating of its configuration is carried out mainly on the basis of telemetry data on the state of switching devices. Meanwhile, the formation of the current configuration of the electrical network based on telemetry is complicated by the distortion of information on the actual position of switching devices due to noise or data losses. It goes without saying that errors in the configuration representation affect the reliability of the results of the operation of various applications of modern energy supply management systems and must be promptly eliminated.

In this regard, the development of means for verifying the configuration of an electric network in real time is of particular relevance, and this article is devoted to solving this problem. The system for confirming the configuration of a controlled electric network developed in it using the advanced tools of a convolutional neural network is positioned as an integral part of a digital decision support system or an electric-network state assessment system and is designed to improve the reliability of power-system management.

MAIN TRENDS IN THE DEVELOPMENT OF METHODS FOR ASSESSING THE TOPOLOGY OF AN ELECTRICAL NETWORK

To confirm the configuration of the electrical network, software packages for assessing the state of electrical systems[1] are still used, using telemetry and data from SCADA systems in their algorithms and, more recently, from synchronous vector measurement devices [1]. Correction of gross errors and replenishment of missing measurements are often performed using the control equation method, which is essen-

[1] Assessment of the state of an electrical system is traditionally understood as solving the problem of calculating the current mode. This purely mathematical aspect of the problem statement sometimes leads to confusion, since electrical-network operators often perceive it as the task of assessing the state of electrical equipment and the network itself.

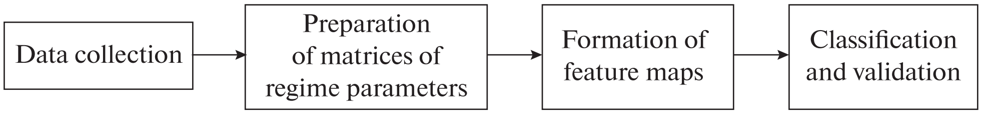


Fig. 1. Functional diagram of the electrical-network configuration verification system.

tially a generalization of the areas of application of Kirchhoff's laws.

Among the many methods for detecting inconsistencies in the representation of the electrical network configuration, one example is the so-called "correlation index calculation method" [2]. These indices determine the degree of correlation between the data that is marked as possibly incorrect due to a configuration anomaly and the data that is expected to respond to the incorrect configuration of network elements. These indices are used to answer the question "can the detected anomaly be caused by any of the suspected configuration elements?".

At the same time, a clear trend towards the introduction of intelligent systems into the practice of managing an electrical system also influences the choice of methods for verifying the topology of electrical networks. For example, in [3, 4], methods based on the use of a multiagent system are considered, the interaction of agents of which is carried out on the basis of control equation methods or methods for assessing target indicators for nodes and branches of an electrical network, called imbalance indices. The second method develops the provisions of the first method, also calculating the indicators under consideration according to the relationships that follow directly from Ohm's and Kirchhoff's laws, and forming a characteristic set from them during the configuration assessment. It is assumed that the imbalance indices take a zero value when the configuration of the electrical system has no errors, and the telemetry is not distorted. Configuration verification includes many interdependent self-organizing subprocesses performed by intelligent agents.

Another type of intelligent analysis method used to confirm the configuration of the electrical network is the deep learning method based on various types of neural networks [5]. It is implied that the use of synchronized vector measurements will increase the efficiency of electrical network configuration analysis systems due to the growth of the information value of data obtained from the electrical network [6].

The approach to verifying the configuration of the electrical network proposed in the article is also based on the use of neural networks and, as shown by the computational experiment, exhibits high efficiency in identifying network-configuration errors in conditions of noisy and distorted telemetry data [7, 8].

PROBLEM FORMULATION

The problem of verifying the configuration of an electrical network involves recognizing the current network diagram and identifying erroneous representations of its elements at the dispatcher's workplace in real time. Information about the network configuration is usually presented as a set of links between nodes and data on the status (on/off) of switching devices. Changing the status of devices and, consequently, links in one way or another affects the current operating parameters, such as voltages of electrical-system nodes and power in nodes and branches of the electrical-network diagram. This property of the network is used in solving the problem of verifying the configuration of an electrical network.

Thus, by "recognizing the current electrical-network diagram" in the article we mean choosing a configuration that is closest to the current measurements of the operating parameters from a set of configurations created at the stage of setting up and training the neural network.

Centralized collection of measurements of operating parameters can be carried out using a SCADA system. The received information variables from each node of the electrical network are presented in the form of so-called "measurement vectors," brought to a single measurement format by normalization and then combined into a matrix of operating parameters corresponding to the current configuration of the electrical network.

Operational processing of matrices of mode parameters and identification of features characterizing the current configuration of the electrical network is performed by a neural network. The idea of the electrical-network configuration obtained as a result of neural-network operation is compared with the electrical-network configuration constructed on the control stand according to the position of the switching devices, as a result of which a conclusion is formed about its reliability.

It is proposed to implement a system for verifying the configuration of an electrical network based on a software package, the functional diagram of which is presented in Fig. 1.

To illustrate the provisions of the article, a nine-node diagram of the IEEE standard electrical network is used, the single-line diagram of which is shown in Fig. 2. The nodes of the electrical network are represented by buses 1–9, and the connections between nodes 4–9 are established by power-transmission lines, whose statuses are monitored by the verification system. The connections represented by transformers are not considered in the article, and their state is not monitored.

DATA COLLECTION AND PREPARATION

It is assumed that the configuration verification system has access to measurements of the active $P_{n,\,m}$ and reactive $Q_{n,\,m}$ powers of lines and loads in nodes (the number of measurements in each node is $2M_n$, $m = \overline{1, M_n}$), as well as the effective values of voltages U_n of all nodes ($n = \overline{1, N}$). The SCADA system, which combines telemetry of the listed parameters into a vector of measurements for each node of the electrical network (Fig. 3), is selected as the data source:

$$s_n^T = \left[U_n, P_{n,1}, \dots P_{n,M_n}, Q_{n,1}, \dots Q_{n,M_n}\right].$$

Number of connections M_n in the nodes may differ, which is reflected in length $L_n = 2M_\text{n} + 1$ of measurement vectors $\mathbf{s}_n \in R^{L_n}$.

Measurement vectors $\mathbf{s}_n$ are transformed into normalized measurement vectors $\mathbf{x}_n$ of the greatest length $L = \max\{L_n\}$:

$$\mathbf{x}_n \xleftarrow{L=\max\{L_n\}} \mathbf{s}_n,$$

replacing the missing measurements with zeros and bringing the measurement—in order to increase their information content—to a single format. During normalization, the corresponding nominal parameters of the transformer with maximum power are taken as the basic values of voltage and power. The normalized measurement vectors obtained in this way form a matrix of mode parameters[2] controlled by the electrical network at the current moment in time (Fig. 4):

$$\mathbf{X} = \left[\mathbf{x}_1, \dots, \mathbf{x}_n, \dots, \mathbf{x}_N\right]^T \in R^{N \times L}. \quad (1)$$

First, at the training stage, the neural network classifies the network configuration under the control of the teacher (developer) and forms a set of configuration classes. Then, when used as part of a decision-support software package, the trained neural network verifies the current configuration of the electrical network presented on the dispatcher's stand. The difference in the operation of the neural network in these modes is that if, during training, the neural network forms an idea of the configuration's belonging to a particular class based on the teacher's reaction, then, when operating in the electrical network monitoring mode, the matrix of operating parameters (1) received by it is processed by it in real time, and it itself acts as an arbitrator, verifying and correcting the current network configuration.

[2] This matrix is often formed as a two-dimensional image, each cell of which represents a color shade corresponding to the numerical value of the cell in the adopted color gradation scale. Therefore, in the English-language literature, it is usually called Heatmap.

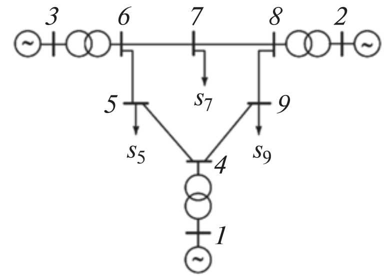


Fig. 2. Single-line diagram of a nine-node electrical network.

FORMATION OF FEATURE MAPS

The configuration verification system receives data on operating parameters from the SCADA system with a specified frequency, and so the matrix of operating parameters (1) formed on their basis can be interpreted as a kind of snapshot of the current configuration of the electrical network [9]. As is known, the analysis of data presented in image format is successfully performed by convolutional neural networks, which easily identify important areas in the analyzed image (matrix of operating parameters) and form characteristic feature maps. With further analysis of a certain set of them in subsequent layers of the convolutional network, it is possible to establish (in the system operating mode) or confirm (during system training) that the current configuration belongs to one of the designated classes.

The feature map generation block consists of three layers: input, convolutional and activation layers (Fig. 5). It may seem that the operation of the layers does not depend on the operating mode of the system being developed, but this is not true at all. Indeed, in the training mode, the configuration classes are already defined by the developer, so the convolutional layer and its filters $\mathbf{W}_k$ will be consistent with the configuration class of the training sample. But already in the operating mode, the convolutional layer is formed as a result of performing multiple convolution operations of the matrix of mode parameters $\mathbf{X}$ with filters $\mathbf{W}_k$ configured during training.

The convolution problem is reduced to extracting features from the matrix of regime parameters $\mathbf{X}$ using two-dimensional filters $\mathbf{W}_k \in R^{3\times3}$. Number of provided features K determines number of necessary filters $\mathbf{W}_k$; in this work, the number of features is limited and equals 32; i.e., $K = 32$.

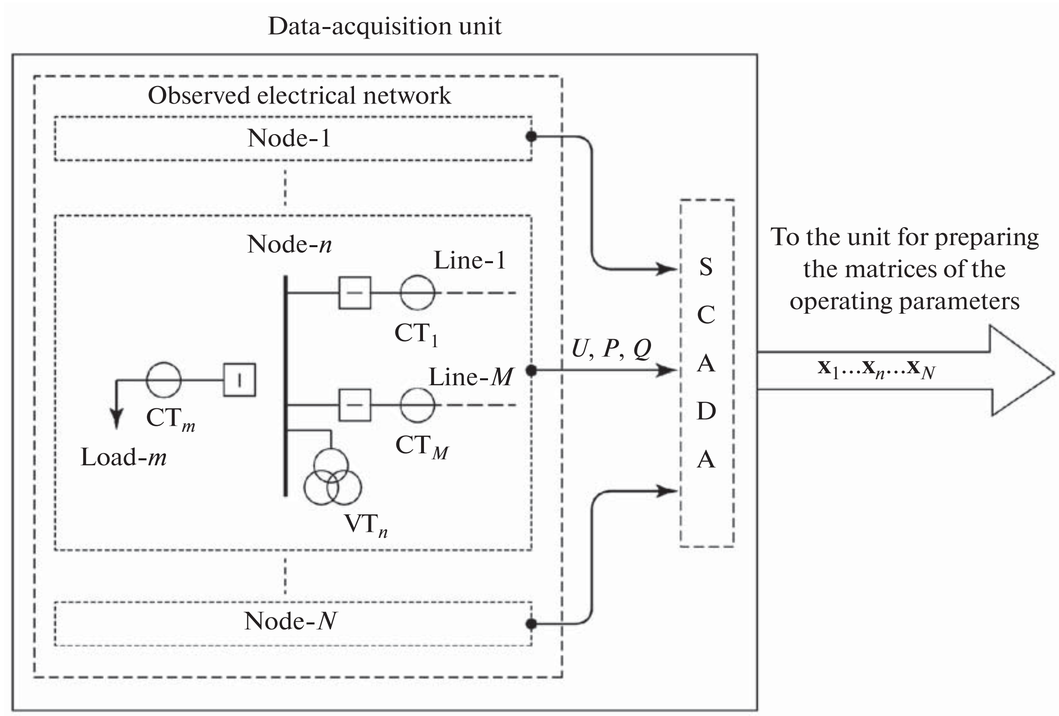
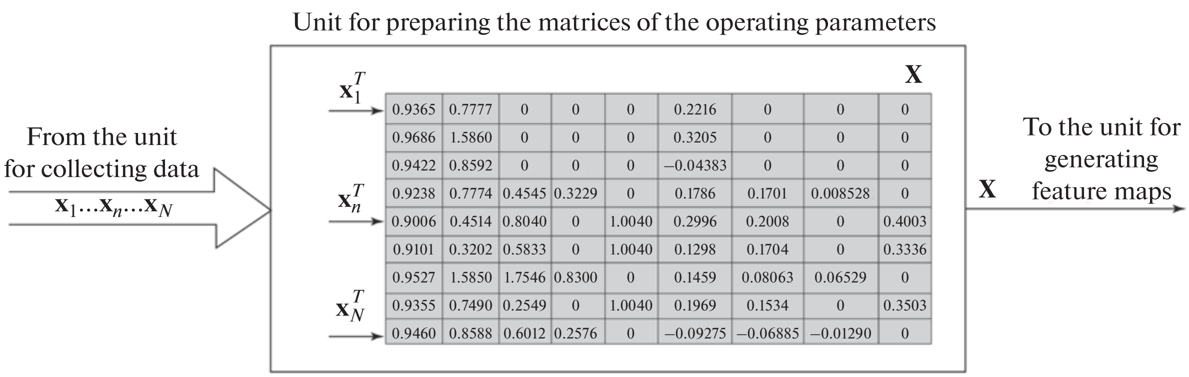


Fig. 3. Data-collection diagram.



$\mathbf{x}_1^T$	0.9365	0.7777	0	0	0	0.2216	0	0	0
	0.9686	1.5860	0	0	0	0.3205	0	0	0
	0.9422	0.8592	0	0	0	–0.04383	0	0	0
	0.9238	0.7774	0.4545	0.3229	0	0.1786	0.1701	0.008528	0
$\mathbf{x}_n^T$	0.9006	0.4514	0.8040	0	1.0040	0.2996	0.2008	0	0.4003
	0.9101	0.3202	0.5833	0	1.0040	0.1298	0.1704	0	0.3336
	0.9527	1.5850	1.7546	0.8300	0	0.1459	0.08063	0.06529	0
	0.9355	0.7490	0.2549	0	1.0040	0.1969	0.1534	0	0.3503
$\mathbf{x}_N^T$	0.9460	0.8588	0.6012	0.2576	0	–0.09275	–0.06885	–0.01290	0

Fig. 4. Scheme of formation of the current matrix of operating parameters.

Each filter $\mathbf{W}_k$ creates its own feature map, the values of the elements of which are determined by the convolution

$$y_k^{'}(p,q) = \mathrm{tr}\left[\boldsymbol{\chi}(i,j)\mathbf{W}_k^T\right] + b_k, \quad (p = \overline{1,P};\ q = \overline{1,Q}), \quad (2)$$

where $p = i - 1$ and $q = j - 1$ are the cell number of the feature map $\mathbf{Y}_k$, in which the result of the convolution of the kth filter $\mathbf{W}_k$ with its perception field $\boldsymbol{\chi}(i, j)$ on the matrix of mode parameters with the center with coordinates (i, j) is stored; tr is the function for calculating the trace of the matrix; and b_k is the bias coefficient of the kth channel.

The values of the elements of the feature map depend on the degree of correlation between filter weights $\mathbf{W}_k$ and the data that are in its field of perception $\boldsymbol{\chi}(i, j)$, and can be positive or negative. Due to the properties of filters, it is believed that elements with positive signs have an advantage in representing features, and therefore all elements of the feature maps are subjected to the so-called “activation operation” in order to exclude uninformative elements.

In the developed convolutional network, the activation layer consists of *ReLu* activation functions, which have many application variations, mainly related to solving the problems of taking into account the contribution of the activated element with a nega-

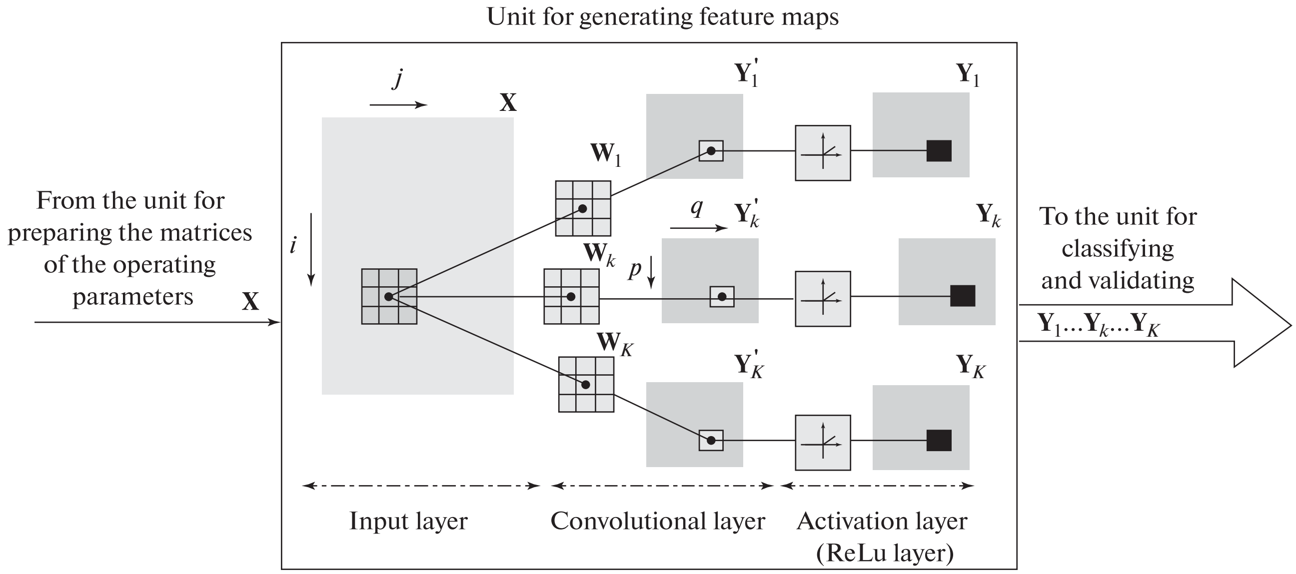


Fig. 5. Scheme of formation of feature maps.

tive sign [10]. A computational experiment showed that the *ReLu* function in its classical representation,

$$f_{\mathrm{ReLu}}(y') = \begin{cases} y', & y' > 0; \\ 0, & y' \le 0, \end{cases}$$

in which negative features are considered uninformative and are replaced by zero values, ensures satisfactory accuracy of classification of the topology of the electrical network under consideration.

In the usual practice of using convolutional networks, a pooling layer is used after the activation layer to increase the contrast between different areas of the feature map and reduce the size of the fully connected layer. A computational experiment showed that when analyzing the topology of the electrical network of the example under consideration (Fig. 2), the pooling layer does not have a significant positive effect on the operation of the neural network, and, therefore, the reasonableness of its use was questioned.

NORMALIZATION OF FEATURE MAPS

Many measurements of electrical quantities in an electrical network of the same configuration differ in level, which leads to a variation in the proportions between the elements of the feature map and the so-called "covariant shift" [11]. This property of a neural network leads to a deterioration in the convergence of models and the learning rate. To eliminate the influence of the level of measured electrical quantities on the quality of learning, normalization of the elements of feature maps is used.

The most practical way to regularize a convolutional neural network is considered to be batch normalization of the feature map [11]. In the system under consideration, at each step, a batch is normalized, which includes column vector $\mathbf{y}_{k,q}$ of the feature map $\mathbf{Y}_k$ $(k = \overline{1, K})$:

$$\hat{\mathbf{y}}_{k,q} = \frac{\mathbf{y}_{k,q} - \mu_{k,q}}{\sqrt{\sigma_{k,q}^2 + \varepsilon}},$$

where $\mu_{k,q}$ and $\sigma_{k,q}$ are the mathematical expectation and variance of features for the processed packet, regularization constant ε is taken to be equal to 10^{-5}.

The normalization undertaken may change the representation of features. To avoid this influence, a linear transformation of the packet with compression parameters $\gamma_{k,q}$ and shift $\beta_{k,q}$ is performed in the next step:

$$\mathbf{z}_{k,q} = \gamma_{k,q}\hat{\mathbf{y}}_{k,q} + \beta_{k,q}.$$

Parameters $\gamma_{k,q}$ and $\beta_{k,q}$ are adjusted during training along with all the parameters of the configuration representation.

The resulting normalized map does not lose the accuracy of the feature representation and contributes to high dynamics of training convergence.

When the trained neural network operates as part of the validation system, normalization of feature maps is carried out based on fixed values of the mathematical expectation and variance obtained as the average of all mathematical expectations and variances for all training packages.

CLASSIFICATION OF FEATURES

In the neural network under consideration, the role of the classifier is assigned to the fully connected layer. The source of its input data is the normalization layer; in this case, all vectors—columns $\mathbf{z}_{k,q}$ of the matrices of

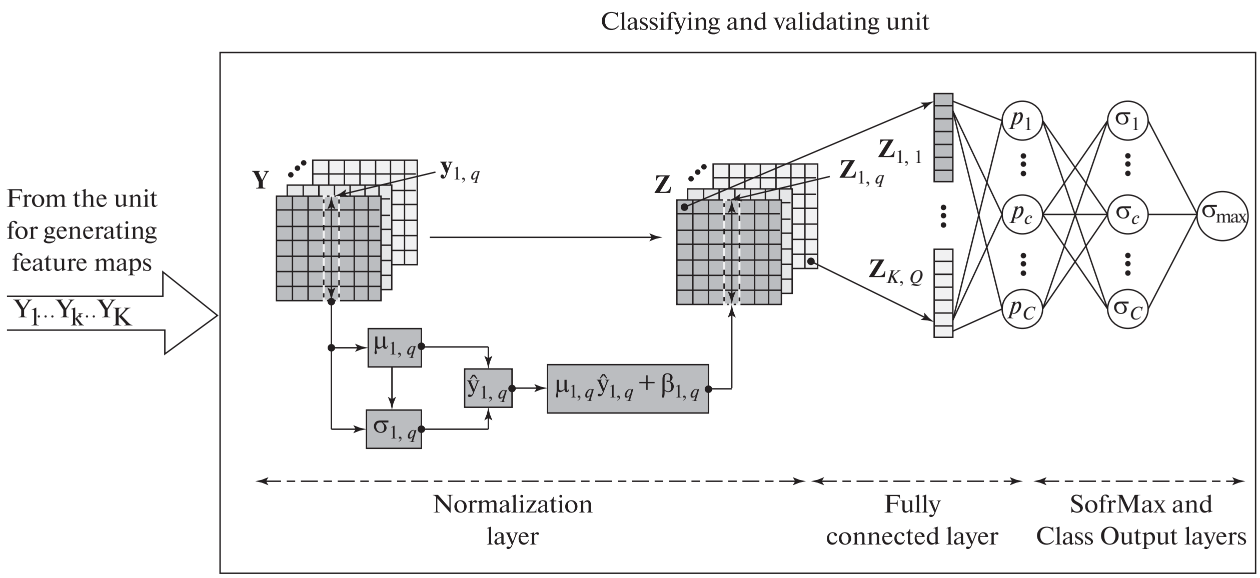


Fig. 6. Scheme of operation of normalization and classification layers.

normalized features $\mathbf{Z}_k$, $(k = \overline{1, K})$—are unfolded into a single vector of input data according to the following rule (Fig. 6):

$$\boldsymbol{\zeta} = [\zeta_1 \ldots \zeta_k \ldots \zeta_K], \tag{3}$$

where $\boldsymbol{\zeta}_k = \left[\mathbf{z}_{k,1}^T \ldots \mathbf{z}_{k,q}^T \ldots \mathbf{z}_{k,Q}^T\right]$ is a row vector created by sequential concatenation of columns of the matrix of normalized features $\mathbf{Z}_k$. In this case, the size of input vector ζ will be equal to $S = P \times Q \times C = 7 \times 7 \times 64 = 3136$.

The number of neurons in a fully connected layer is taken to be equal to the size of the set of classes of recognizable configurations C; in this example, $C = 64$. The vector of output data of neurons of a fully connected layer,

$$\mathbf{p} = \left[p_1, \ldots, p_c, \ldots, p_C\right]^T,$$

is formed as a result of weighing a single vector (3) by a matrix of neuron input weights, $\mathbf{\Phi} \in R^{C \times S}$

$$\mathbf{p} = \mathbf{\Phi}\boldsymbol{\zeta} + \boldsymbol{\beta},$$

where $\boldsymbol{\beta}$ is the vector of bias coefficients.

In the output layer, the degree of belonging of the current electrical network configuration to each of the provided configuration classes is first estimated. For this purpose, an estimate of the probability of classifying the current configuration into each of the provided configuration classes is formed, assuming that the total probability of belonging to all classes is equal to one. The activation function SoftMax is used, forming the probability of belonging of the current configuration to the class with number $c \in C$:

$$\sigma_c = \frac{e^{p_c}}{\sum_{n=1}^{C} e^{p_n}}.$$

Then the result of the SoftMax activation layer is interpreted as an assessment of the accuracy of determining the configurations of the electrical network and the desired result of the network operation is declared to be the configuration belonging to the class with the maximum probability:

$$\sigma_{\max} = \max\{\sigma_1, \sigma_2, \ldots, \sigma_C\}.$$

CONVOLUTIONAL NETWORK TRAINING

The designed neural network is implemented based on the tools of the Deep Learning library of the MATLAB software environment, and the stochastic gradient descent with momentum (SGDm) method is used for network training. The structural diagram of the designed convolutional network consists of a cascade of blocks (Figs. 2–6).

When training a convolutional network, the teacher (developer) designates the class of the current configuration and the corresponding matrix of mode parameters $\mathbf{X}$. At the end of each stage of convolutional network training, the training environment measures the proximity of the configuration estimate to the designated class and, depending on its result, adjusts the parameters of the convolutional network using the backpropagation method. The training process is repeated until the desired quality of neural net-

Table 1. Example of a neural network in operation

Class Name	Accuracy	Line State					
		4–5	4–9	5–6	6–7	7–8	8–9
Class 39	99.88%	1	0	0	1	1	1

work training is achieved within a specified number of training stages.

The training sample in the form of a set of matrices of mode parameters X, supplied with discriminants of belonging to a certain class of the electric network configuration, is formed by simulating a nine-node scheme (Fig. 4) in the PSCAD software package for simulating power systems. Achieving the required quality of training is supported by including a wide range of steady-state modes of the electric network for each of its configuration options in the simulating modeling plan. A suitable variety of operating modes is achieved by randomly changing nodal loads and generator voltage levels in regulated ranges.

For the electrical circuit under consideration, a list of classes is formed, covering all possible configurations. The topology of each configuration is defined as the topology of a certain class and depends on the position of the switching devices of the connections. The number of connections determines the maximum number of possible configurations of the electrical network, which in the case of a nine-node circuit is $C = 2^6 = 64$.

As noted, for each topology of the electrical network, a training sample is formed during the simulation from a set of matrices of mode parameters. The computational experiment shows that, for a nine-node scheme, a training sample consisting of a set of 120 matrices of mode parameters **X** for each configuration class is sufficient.

CLASSIFIER TESTING

The quality of training and the correctness of the convolutional network are assessed on a test set of matrices of mode parameters for each configuration of the electrical network; the test set should not repeat the data of the training sample. To check the system's resistance to distortions in measurements, part of the test set data is randomly intentionally damaged by zeroing some data or adding noise to them with a level of up to 10th of the measurement itself.

The configured neural network generates a solution in the format of a table, an example of which is given in Table 1, which shows the neural-network message when it evaluates the configuration with disconnected communication lines between nodes 4–9 and 5–6 (the signals "1" or "0" correspond to the on or off states of the switching devices).

The level of reliability of the configuration assessment is controlled using the trust threshold; the results of the neural network with an accuracy below it are discarded and signals are issued about the unreliability of the assessments. The average values of the accuracy of the electrical-network topology assessment for each type of configuration when testing the designed neural network are given in Table 2. As testing the system on a nine-node scheme showed, the accuracy indicator of the configuration assessment developed by the neural network does not fall below 99%.

CONCLUSIONS

(1) The convolutional neural network evaluates the topology of the current configuration of the electric network reliably and with a sufficiently high confidence threshold. This opens up the possibility of monitoring the reliability of the current configuration on the dispatcher's stand and correcting errors in the topology representation in real time. Such efficiency of the configuration verification system is achieved by training the neural network on a set of data obtained, for example, as a result of simulation modeling of the operating modes of the electric network.

(2) The source of data on the current mode of the electric network is the SCADA system, which provides information in real time. The developed convolutional neural network does not impose specific requirements on the input data interface and, as shown by the computational experiment, exhibits robustness to distortion of the input data.

Table 2. Test results

Configuration type	Average accuracy of configuration detection, %	
	test data without noise	test data with noise and damage
All lines on	100.00	100.00
1 line off	99.32	99.21
2 lines off	99.65	99.45
3 lines off	99.59	99.40
4 lines off	99.77	99.63
5 lines off	99.96	99.85

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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