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Identification of the actual state and entity availability forecasting in power engineering using neural-network technologies

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Abstract. A growing number of severe accidents in RF call for the need to develop a system that could prevent emergency situations. In a number of cases accident rate is stipulated by careless inspections and neglects in developing repair programs. Across the country rates of accidents are growing because of a so-called “human factor”. In this regard, there has become urgent the problem of identification of the actual state of technological facilities in power engineering using data on engineering processes running and applying artificial intelligence methods. The present work comprises four model states of manufacturing equipment of engineering companies: defect, failure, preliminary situation, accident. Defect evaluation is carried out using both data from SCADA and ASEPCR and qualitative information (verbal assessments of experts in subject matter, photo- and video materials of surveys processed using pattern recognition methods in order to satisfy the requirements). Early identification of defects makes possible to predict the failure of manufacturing equipment using mathematical techniques of artificial neural network. In its turn, this helps to calculate predicted characteristics of reliability of engineering facilities using methods of reliability theory. Calculation of the given parameters provides the real-time estimation of remaining service life of manufacturing equipment for the whole operation period. The neural networks model allows evaluating possibility of failure of a piece of equipment consistent with types of actual defects and their previous reasons. The article presents the grounds for a choice of training and testing samples for the developed neural network, evaluates the adequacy of the neural networks model, and shows how the model can be used to forecast equipment failure. There have been carried out simulating experiments using a computer and retrospective samples of actual values for power engineering companies. The efficiency of the developed model for different types of manufacturing equipment has been proved. There have been offered other research areas in terms of the presented subject matter.

1. Introduction
In the energy sector, there occur an increasing number of accidents with severe systemic consequences and an increasing accident rate, which leads to eliminate the causes of this. The main risk areas (for electric power facilities) are: not eliminated defects detected during planned inspections, insufficient number of inspections. There is a trend to reduce the residual life of equipment, its aging, which leads to failures and accidents due to inadequate investment in the renewal of fixed assets. At the same time,
accumulated statistical data, including identified defects, which in case of its false elimination, led to failures and accidents.

Official document considers as an indicator of reliability the accident rate of power facilities. For example, it is possible to note the increase of accidents, taking into account the following: incorrect actions of technological protections (7% - 7.5%); incorrect actions of protective automatic devices (4.5% - 5.5%); wrong or incorrect actions of operational personnel (4% - 5%). One of the main tasks for the medium term is "Reducing the accident rate of the electric power complex".

Thus, the actual task is to identify the condition of technological equipment, as well as forecasting the occurrence of failures and the development of emergency (pre-emergency) situations (reliability of energy facilities), which allows to reduce the accident rate at the enterprises of the electric power complex.

2. Statement of the research task

2.1. Defects and failures

Similar units of equipment are combined into the corresponding groups. Equipment groups operating as part of power distribution grid companies have a certain set of defects. Defects occur at different times and differ for equipment groups. For example, for the group of "110 kV vacuum circuit breakers" there are 46 defects, and for the group of "Porcelain suspended suspension plates insulators" they are only 6.

If the considered unit of equipment has a defect, this means that at least one of its parameters is out of the limit (normative) value or one of the requirements of regulatory documentation for operating conditions is not done (not met). Defects of the equipment arising in the period of functioning lead to failures. A failure characterizes a malfunction of a group of equipment.

Identification of defects can be made not only on the basis of data obtained from SCADA and ASCME, but also using qualitative information (verbal assessments of domain experts, photo and video inspection materials, converted to the required form using the methods of theory of pattern recognition).

Failure may arise as a result of having one or more defects in a piece of equipment, but the appearance of defects does not always mean a failure. Therefore, the actual task is to establish the functional dependence of the appearance of failure in the event of various defects in equipment. Let’s construct a model of this process. The failure of the equipment is due to availability of defects and their combination, as well as the reasons that lead to this.

2.2. Formalization of the mission statement

Denote by \( D_{ij}, i = 1, n; j = 1, m \) defects, through \( R_i, i = 1, n \) failures, where \( n \) - the total number of groups of equipment, \( m \) - the total number of types of defects inherent in this group of equipment, and through \( C_{int}^{int}, k = 1, l \) internal and \( C_{ext}^{ext}, k = 1, l' \) external causes of failure. The causes are external and internal to a particular group of equipment.

The mathematical model is built not for a specific unit, but for the entire group of equipment. Therefore, the structure of the model units and equipment groups will be the same, the differences are in the parameters of the model. Then, in general, the problem of establishing the functional dependence ( \( f( ) \) ) of outputs ( \( R_i \) ) on inputs ( \( D_{ij}, C_{int}^{int}, C_{ext}^{ext} \) ) is reduced to finding:

\[
R_i = f(D_{ij}, C_{int}^{int}, C_{ext}^{ext})
\]  \hspace{1cm} (1)

From the point of view of mathematical modeling, we will identify \( D_{ij} \) and \( C_{int}, C_{ext} \), because they arrive at the input of the model that is external and internal reasons belong to the input set \( \{D\} \).
As external causes, weather conditions and the human factor (unqualified actions of maintenance personnel, improper organization of events, managing mistakes, etc.) are identified. And for internal reasons are related explicit (can be determined using existing rules, methods and resources) and hidden (for them, rules, methods and means of identification are missing) defects.

Reasons by their nature are random factors for which there is no possibility of obtaining (calculating) and realizing the control effect. Elimination of defects and/or causes leads to the probability of reducing the failure, and the appearance of a new defect causes its increase. Based on the obtained model probability failure values, a residual resource can be calculated. The implementation of measures aimed at increasing the residual resource and reducing the probability of failure will ensure high performance indicators.

3. Selection and justification of the type of mathematical model

3.1. Neural network for failure prediction

The task of obtaining predictive values of reliability indicators of technological equipment is extremely topical. For example, there is a system of "PRANA" [1], using empirical models based on statistics, which requires recalculation of the coefficients of dependencies and involves significant calculation difficulties. Similarly, based on probabilistic statistical models, the problem is solved in work [2] and has the same drawbacks. To establish the dependence of failures on the occurrence of defects, it is required to use a mathematical device that allows you to do this without constructing a model based on the study of internal processes and at the same time has the properties of adaptation to changing environmental conditions. This method is artificial neural networks (ANN), which are universal approximating systems, so they provide the realization of the function of the dependence of the output data on the input. The process, as a result of which this becomes possible, is called learning, and the theoretical basis for asserting their universality is a consequence of the Kolmogorov-Arnold-Hech-Nielsen theorem, the essence of which can be stated as follows: "Any multidimensional continuous function can be approximated by functions, which are calculated by neural networks of fixed dimension (size) "[3]. ANN have a wide application in the energy sector: forecasting electricity consumption [4]; forecasting of electric load [5]; Forecasting the demand for electricity [6]; Forecasting the maximum price in the energy market [7]; Diagnostics of condition and localization of faults in energy equipment [8]; Reliability assessment [9]; Optimization of load distribution [10]; Creation of dispatching systems [11].

Thus, the literature review allows us to state that ANN can be used to predict energy equipment failures, and that at the moment there is no single methodological basis for solving this task, despite some successes achieved by a number of researchers. As an ANN, a multi-layer perceptron of direct signal distribution was selected [12].

3.2. Selection of the neural network structure

Under choosing the structure of ANN we mean the choice of the number of hidden layers, the number of neurons in them, and also the activation functions of the neurons themselves. At the same time, the ANN structure used to predict the failure of energy equipment should allow to adequately reproducing the required dependence of failures from defects on the one hand, and, on the other, to be simpler as possible, because complexity increases the learning time, the network begins to reproduce noise, etc.

When choosing the number of layers, the following heuristic rules are taken into account: the availability of nonlinearity leads to the necessity of using a multilayer perceptron; the higher the complexity and nonlinearity of the problem, the more hidden layers are used, but usually no more than two.

To solve the problem of predicting failures of power equipment depending on the arising defects, will be used a perceptron of direct distribution of the signal with one hidden layer.
On the base of the corollaries of the Kolmogorov-Arnold-Hech-Nielsen theorem, it can be asserted that a universal transducer is a perceptron with one hidden layer and sigmoid activation functions [3]. From this we can obtain the following correlations:

\[
\frac{N_R \cdot o}{1 + \log_2(o)} \leq N_w \leq N_R \left(1 + \frac{o}{N_D}\right)(N_D + N_R + 1) + N_R
\]  

(2)

Where \(N_D\) is the dimension of the input signal; \(N_R\) - the dimension of the output signal; \(N_w\) - the required number of synaptic connections for the hidden layer; \(o\) - number of elements in the training sample.

Knowing the number of weights \(N_w\), we calculate the number of neurons in a single hidden layer \(H\):

\[
H = \frac{N_w}{N_D + N_R}
\]  

(3)

However, in practice it may turn out that not all combinations of defects will be fixed during the entire time of observation (the collection of statistical data for the formation of training and test samples), which reduces in significant way the size of both the training and, as a consequence, the test (control) samples in a. The number of neurons in the hidden layer is chosen for each neural network model of a specific group of equipment, taking into account the desired accuracy, adequacy and training time (retraining, adaptation).

4. Experimentation and discussion of the results

4.1. Description of experiments

To confirm the principle possibility of realization the proposed approach to the problem solution of forecasting failures of some abstract group of technological equipment, a number of experiments were carried out.

The statistics on the defects and the probability values of the corresponding faults are resulted into generate the total number of combinations of defects (the probability of failures are calculated by the Bayes formula), the number of ANN inputs corresponds to the number of possible defects (the number of combinations of defects is 256), the only output is the probability of failure. The learning method is the Levenberg-Marquardt algorithm, as a criterion, the mean square error of the neural network model on the training sample was used. Parameters of the computer on which the neural network model was trained and tested - a Pentium Dual-Core T4300, 2.1 GHz processor; 2 GB of RAM.

4.2. The research of the influence of the number of elements for the training sample.

Experiment number 1. The number of elements of the training sample is equal to 131. The number of hidden layers is equal to one, the number of neurons in the hidden layer (calculated by the formulas 2 and 3) lies in the interval [2, 19]. Accuracy of reproducing results is close to 100%, errors are close to zero.

Experiment number 2. The number of elements of the training sample is equal 105 (decreased by reducing the uniformity of the training sample, the test sample is accordingly increased to 151 elements). The number of neurons in the hidden layer lies in the interval [2, 15]. The results of the experiments indicate that for this training sample up to 10 neurons in the hidden layer, training takes 1000 epochs, and the gradient does not reach a minimum value of $10^{-10}$. Starting with 10 neurons in the hidden layer, the gradient reaches a minimum value for several dozen epochs, while reducing the accuracy of reproducing the probability of failure. The values probability obtained for this series of experiments indicate about deterioration of the accuracy and quality of training with an increase in the number of neurons in the hidden layer of more than 9.
Experiment number 3. The number of elements of the training sample is 79, the test is 177 elements. The results of the experiments also confirm the conclusion that reducing the number of elements in the training sample (including, by reducing of its quality and uniformity) leads to a decrease in accuracy, an increase in the number of errors, and significantly affects the adequacy of the constructed neural network mathematical model.

In this case, the learning time for a small number of neurons (less than 5) is preserved for the experiments of series 2 and 3 is the same as for the experiments of the series 1. Above the value of 5, the time is significantly reduced due to the gradient reaching its minimum value within 20-50 epochs, which significantly affects the quality of education.

4.3. Learning a Neural Network
For example, we will provide training and testing the neural network model. The network was trained on 131 elements of the general aggregation, and was tested on 125 elements. The training time was 26 sec. The results obtained indicate a high accuracy with which ANN approximates the required functional dependence of the failure of technological equipment of the power industry on the defects that arise during its operation (Fig. 1-2).

Figure 1. Decrease in mean-square error (MSE) for the learning epochs.

Figure 2. Modelling parameters for the learning epochs.

The obtained simulation results allow us to state that the ANN accurately reproduces the required values of the test sample (there are no deviations from the regression line). All this allows us to go directly to the simulation based on the real historical data.
5. Conclusion
As a result of this research, the expediency of using a multilayer perceptron for the direct distribution of a signal with a single hidden layer and sigmoid neuron activation functions for the problem being solved is confirmed. The number of neurons of a single hidden layer is determined by the number of elements of the training sample; the greater the number of elements in the training sample, the more accurately the ANN reproduces the functional dependence of the equipment group failures on the existing defects. The uniformity and representativeness of the training sample influences the accuracy of the results and the adequacy of the resulting neural network model, so it is necessary to ensure the uniformity and representativeness of the training sample, that is to remove duplicate data and add rare data, it may be necessary to increase the period of time for monitoring a group of equipment for the purpose of forming a training sample.

As further directions of the research it is necessary to explore the accuracy and adequacy of the neural network model, to ensure the adaptation of the neural network model (due to the nonstationarity of the object), to determine the minimum and maximum number of elements in the training sample sufficient to provide the required accuracy of the neural network model for forecasting the failure of power equipment.

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