Predicting the Technical Status of equipment Through Neural Networks

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***Abstract*— The presence of a stable trend to reduce the residual life of equipment in various industries in the Russian Federation is a very important complex problem that requires immediate solution. In this regard, there are problems of assessing the current technical condition of the equipment and its forecasting for a certain time interval. The paper shows the solution of these problems using artificial neural networks, which realize the functional dependence of defects arising in the operation of the equipment on the parameters characterizing the modes of its operation. Experimental data confirming the applicability of the developed approach are presented.**

***Keywords*— forecast; technical condition; equipment; neural network; parameter; defect;, failure; industry; energy**

I. Introduction

Predicting robustness of equipment by electric companies is no small task [1]. It is based on the calculation of failure probability per piece of equipment at energy enterprises depending on total detected defects [2].

Equipment is operated for tens of years, and its failure is extremely rare, thus, building mathematical models of such assets lacks enough statistical data.

Registration of apparent defects (or when they actually take place, regardless of registration) can lead to the failure of a piece of power equipment with certain probability (0.1). Here, the impact of this defect – the conditional failure probability when it appears – becomes additive, that is, independent of other defects.

In some cases, two or more defects may have a synergistic effect on failure rates, but this phenomenon is extremely rare and is very complicated to capture, analyze and measure [3].

Apparent defects of process equipment at electric companies can be considered as technical reasons that lead to the failure of the component. These input points are similar to controls – in the process of drawing up and running a repair program, a control action takes place – a defect can be repaired [4].

Besides defects of power equipment, there are also causes that can be divided into two groups: internal and external.

Reasons, unlike defects, lead to failure with probability = 1. Controlling causes is not feasible. The control effect is applied only after the cause takes place, which means that the failure has already occurred.

Internal reasons (technical) can include: latent defects (to make determination it is necessary to stop the equipment and perform diagnostic activities), apparent defects that were not registered during the operation of process equipment of energy facilities (insufficient control by the staff with the use of appropriate techniques and technical means).

External reasons (organizational) can include: misguided staff action, poor organization (management mistakes), weather conditions (external operating conditions) in places, where relevant equipment is operated, for example, power lines, etc. [5].

A review of the literature references in the subject domain concerned allows us to state that the mathematical apparatus of artificial neural networks is the most suitable for predicting failures of power-generating equipment [6].

In addition, now there is no uniform methodological basis to solve prediction of the equipment technical condition, despite some successes achieved by a number of researchers [7–8]; reliability assessment [9–10].

II. Problem statement

Let us identify through $D_{ij}, i=\overline{1,n}; j=\overline{1,m}$ defects, through $R_i, i=\overline{1,n}$ failures of process equipment pieces at electric enterprises, where n are total equipment groups, m are total defect types that can be detected for a given group of equipment, and through $C_k^{\text{int}}, k=\overline{1,l}$ internal and $C_{k'}^{ext}, k=\overline{1,l'}$ external causes of failure.

For the purpose of simplification, it should be pointed out that the mathematical model of the predicting the technical status of equipment is built without detailed consideration of processes occurring within the group of equipment and impacting failure probability during operation.

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The construction of the model includes only statistical details of apparent defects, causes and failures of equipment pieces within one group.

Then, it becomes feasible to trace the dependence of $f(\ )$ failure probability $Q_{R_i}, i=\overline{1,n}; j=\overline{1,m}$ on the combination of defects for process equipment of electric companies according to the following expression:

$$Q_{R_i} = f(D_{ij})$$

Failure probability for a piece of equipment is affected by internal C_k^{int} and external $C_{k'}^{ext}$ causes. This means that failure probability depends, among others, on the condition of its occurrence, i. e., the probability of some reason.

Let us identify through P_{int} the probability of the internal reason of C_k^{int} failure per a piece of process equipment at electric enterprises, and through P_{ext} the probability of the external reason C_k^{ext}.

Then, the conditional failure probability R_i provided that the event has occurred, and the internal cause of failure C_k^{int} will be denoted $P\left(R_i \middle| C_k^{\text{int}}\right)$, and the conditional failure probability R_i provided that the event has occurred, and the external cause of failure C_k^{ext} will be denoted $P\left(R_i \middle| C_k^{ext}\right)$.

Then the probability of joint occurrence of R_i and C_k^{int} is equal to:

$$P\left(R_i C_k^{\text{int}}\right) = Q_{R_i} \cdot P\left(R_i \middle| C_k^{\text{int}}\right)$$

Then the probability of joint occurrence of R_i и C_k^{ext} is equal to:

$$P\left(R_i C_k^{ext}\right) = Q_{R_i} \cdot P\left(R_i \middle| C_k^{ext}\right)$$

As noted earlier, forecasting the reliability of energy companies ' equipment presents a number of challenges. It is based on the calculation of the probability of a technological equipment unit failure of energy enterprises, depending on the totality of the registered defects for it.

III. NEURAL NETWORK STRUCTURE

The efficiency of forecasting the failure of an equipment unit is determined by the quality of training of an artificial neural network. To solve this problem, it is extremely important to ensure the selection of the structure of the artificial neural network (Figure 1), by which we will understand the definition of the number of hidden layers, the number of neurons in them, and the activation functions of the neurons themselves.

At the same time, the structure of an artificial neural network should be as simple as possible, since the complexity of the network increases the time spent on training and the network starts reproducing noise, etc.

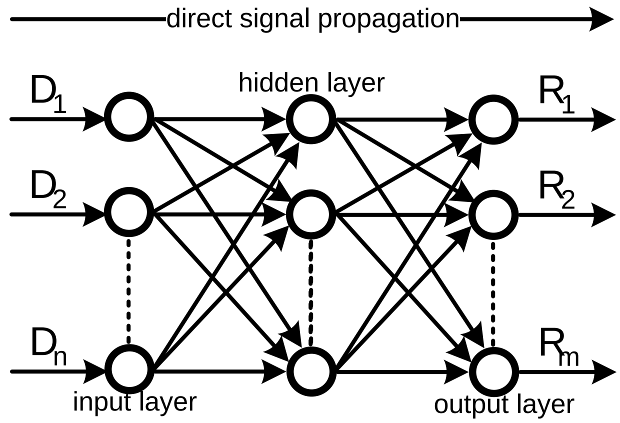

Fig. 1. Perceptron structure with one hidden layer

When selecting the number of layers, it is necessary to take into account the following set of heuristic rules: the availability of non-linearity (as a rule, all real functional dependencies are non-linear) leads to the need of using a multilayer perceptron; the higher the complexity and non-linearity of the task, the more hidden layers can be used, but usually not more than two.

Subject to the corollaries of Kolmogorov-Arnold-Hecht-Nielsen theorem, we can state that a perceptron featuring one hidden layer and sigmoid activation functions is a multiple converter [1]. This ratio results in the following ratio:

$$\frac{N_R \cdot o}{1+\log_2(o)} \le N_w \le N_R\left(1+\frac{o}{N_D}\right)(N_D+N_R+1)+N_R$$

where N_D is the size of the input signal (number of equipment group defects); N_R is the size of the output signal (the probability of a piece of equipment failure); N_w is the required number of synoptic connections for the hidden layer; o is the number of components in the training sample.

Knowing the number of weights N_w, we can calculate the number of neurons in the hidden layer H, which is the only one:

$$H = \frac{N_w}{N_D + N_R}$$

The sigmoid function can be represented as follows (as a consequence of the Kolmogorov-Arnold-Hecht-Nielsen theorem):

$$Fa(S) = \frac{1}{1+e^{-S}}$$

where $Fa(S)$ is a sigmoid activation function; S is a neuron input signal.

The size of the training sample has a strong effect on the number of neurons entering the hidden layer of the perceptron.

Therefore, it is necessary to carry out an experimental study of this effect on the quality of reproduction of the functional dependence and the generalizing ability of the artificial neural network.

In general, the procedure of constructing a mathematical model as an artificial neural network for the purpose of predicting failures of process equipment at power enterprises can be represented by the sequence of phases.

At the first stage, the adequacy, diversity and uniformity of data in the general population are assessed. It is the characteristics of the general population, which determine the quality and speed of training, the accuracy of reproduction of the functional dependence, as well as the summarizing ability of the artificial neural network.

The second stage consists in the separation of the general population into two samples – training and testing samples. The first of them serves to obtain a neural network, and the second one is necessary to verify the reproducibility of the desired result, accuracy and summarizing ability.

The third stage is the selection of the structure of an artificial neural network, including the selection of the number of layers, the number of neurons in the intermediate layers, and the type of the neuron activation functions (in our case there will always be a sigmoid activation function due to the application of the corollary of the Kolmogorov-Arnold-Hecht-Nielsen theorem).

During the implementation of the fourth stage, the artificial neural network is trained using the training sample, which was obtained during the implementation of the stage two. Training ends when the stop conditions become reached.

The first condition for stopping training is the up-front achievement of a predetermined number of training epochs. The second stop condition is the achievement of the required accuracy of reproduction of the functional dependence of the failure probability of an equipment unit from a set of defects fixed for it.

The fifth stage is the testing of an artificial neural network model, which is required to confirm the achieved accuracy of reproduction of the functional dependence and quality of the network summarizing ability.

Following that, traditional methods can be used to assess the adequacy of the neural network mathematical model obtained, as well as the reproducibility of the results achieved with its use.

Forecasting is carried out in the following manner. Due to the fact that the input of an artificial neural network receives a set of zeros (the absence of an obvious defect) and units (the availability of an obvious defect), and the yield is the probability of a process equipment unit failure, then supplying the input with the required set of zeros and units (a set of defects that can occur over a certain time interval), it is possible to predict the technical condition (possible failure of a process equipment unit) for a certain time interval.

IV. Experimental investigation of forecasting of the technical condition

As an example, a group of equipment "PKT-101 fuses" was chosen to conduct an experimental study of technical condition forecasting.

For PKT-101 fuses as a group of equipment, 13 defects are highlighted: contamination of contact connections; faulty contact connections; oxidation of contact connections; miscalibration of the contact system; overheating of contact connections; heating of contact connections; overheating of contact connections; heating of contact connections; uncalibrated fuse-link; poor contact of the holder fuses; no fuse-link; blow-out fuse-link; destruction of the fuse-link body.

Thus, the artificial neural network to calculate the probability of failure of the fuse PKT-101 has 13 inputs.

The size of the training sample is deemed sufficient, if the network reaches the asymptote of accuracy, i.e., ensures proximity of learning and generalization errors.

Variety and uniformity are measured by the necessity of including initial statistical data (sets of zeros and ones) of as many images of defects as possible in the population. The more different combinations of defects are included in the training examples, the more accurate the result of the generalization by the neural network will be.

For example, for a selected group of process equipment, 14,059 values (more than three hundred pieces of equipment) collected for more than five years of registering defects and failures of process equipment were selected out of the database of the accounting information system of the interregional energy company.

The total defect combinations with their overall number equal to 13 will reach 8,192. After uploading the population in the software module, the failure rate was calculated for the same set of defects. After this procedure, the number of components in the population was reduced to 1,318.

Due to the fact that the set of defects (any input training image) is a set of zeros (no specific defect) and units (their presence), there is no need to additionally ensure diversity, uniformity, etc. The sample is representative.

2/3 of components included in the general population should refer to the training sample, 1/3 is to be included in the test sample. This ratio was obtained in the course of the study, the results of which are presented in [12]. Thus, the total number of components in the training sample must be equal to 879, and in the test – 439.

For training and testing, sets of defects are ranked in a special way so that the same defects (which are critical and have the greatest impact on the failure of a piece of equipment) fall into both the training and the test sample. This will ensure the required summarizing ability of the artificial neural network and the reproducibility of the simulation results with its use.

The result of training and testing of the artificial neural network that uses the functional dependence of failures of the process equipment group – PKT-101 fuses – from the set of detected defects in Matlab engineering environment is shown in Fig. 2–3.

The figures show the decrease in the mean square error (MSE) through the epochs of training the artificial neural network and the deviation of the simulation results from the direct regression line.

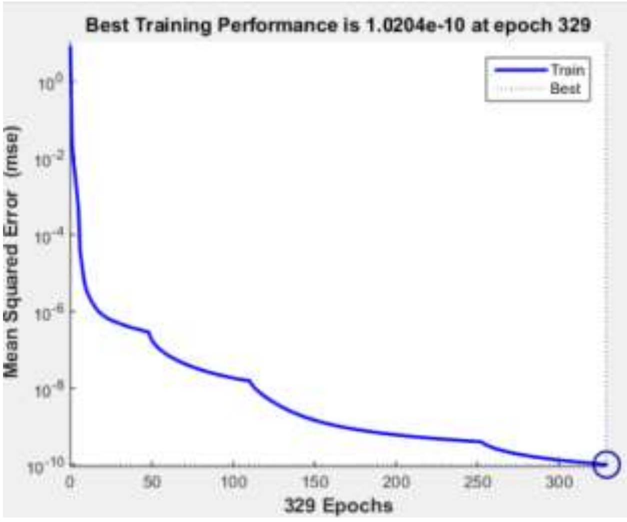

Fig. 2. Decrease of the root mean square error (MSE) on the training epochs

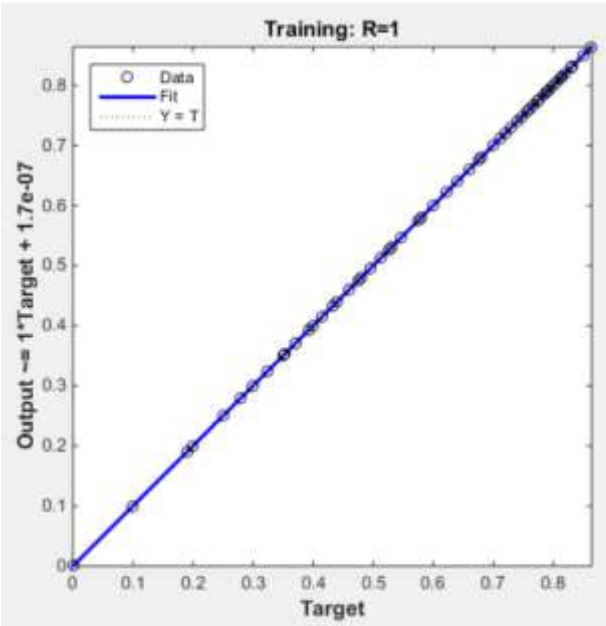

Fig. 3. Deviation of the result (Data) from the direct regression (Fit)

V. Conclusion

The result of the built linear regression and the coefficient R > 0.8 indicates that the obtained neural network model adequately describes the functional dependence of failures on the detected defects and has the required accuracy (the error of the generalizing ability is fairly close to the learning error of the neural network).

Calculation of the probability of failure of a unit of equipment ensures more efficient planning of allocation of financial resources to bring the equipment in a proper technical condition as compared to the traditional methods that are currently used in the industry [13].

This aspect is due to the fact that it becomes possible to forecast the probability of a failure based on a specific set of defects that may arise during the operation of the equipment. The solution to the problem of reliability forecasting based on multilayer perceptrons of direct signal propagation makes it possible to establish a functional relationship between defects and failures avoiding studying the internal processes taking place in complex process equipment, while ensuring the required accuracy of the results obtained [14].

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