Modeling the processes of predicting the characterictics of faults in information systems

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Abstract. In connection with the widespread use of information systems in various activities, an urgent problem is to estimate their characteristics. One of the possible types of characteristics can be various failures and malfunctions. In this paper, to estimate the characteristics of malfunctions in information systems, it is proposed to use the apparatus of neural networks. In this paper, the process of dividing the initial set of objects into homogeneous groups is carried out. This is due to the fact that the forecasting accuracy will be improved before the models are formed. For an algorithm that makes it possible to form predictive models, the main steps that are included in it are indicated. The algorithm for learning a neural network is given. The illustration of a block diagram of a neural network is shown. The results of verification of models that allow predicting failure of communication devices are demonstrated. The investigation can be useful for characterizing a wide class of information systems.

Keywords: Information system, predicting, model, neural network, fault.

1 Introduction

At present, information systems in their structure and characteristics of functioning belong to the class of complex systems. In this regard, when solving various problems of predicting their parameters, it is necessary to rely on the methods of system analysis. Among the various processes taking place in information systems [1-2], the occurrence of various malfunctions can be noted. They need to be predicted.

The aim of this paper is to develop an approach within which it is possible to predict the characteristics associated with malfunctions in information systems.

2 The use of neural network modeling in the course of forecasting the processes of observation of faults in information systems

Faults in information systems are of a heterogeneous nature [3]. This determines that in order to eliminate them, it is important to focus on an individual approach. The appropriate steps are selected during the fault analysis. We must define the specifics of the control system [4]. It is based on two basic processes. In the first, we determine the state of the information system. In the second, optimal influences are developed for this state. When a troubleshooting tactic is selected, then predicting how the monitored parameters will change can be considered an important step. In this case, predictive models are used [5-6].

Methods of active and passive experiment provide opportunities in order to obtain mathematical descriptions. For many cases, approaches that are associated with regression analysis are used. We can take into account the specifics of the problem under consideration. In the course of the modeling processes, we use a passive experiment. It requires consideration of experimental and archival information. There are still opportunities to observe the ongoing process. An active experiment can also be considered. Then it is necessary to rely on the method of directed survey of specialists.

How will the controlled indicator depend on each of the analyzed attribute-factors? Regression predictive models are often effective.

This is due to the fact that on their basis it is possible to visually demonstrate the necessary dependencies. But on their basis, there is no opportunity to carry out the identification of hidden, "confusing" dependencies. When considering this class of problems, it is of interest to use neural network models.

When using them, it is possible to create more efficient predictive models in comparison with the approaches in traditional statistical modeling. Spaces can be characterized by large dimensions [7]. This is due to the large number of telecommunication facilities in modern networks. Then approaches based on regression analysis in mathematical modeling will lead to the emergence of artificial constructions.

It is necessary to ensure the operability of information and telecommunication systems. At the same time, the accuracy of the approximation, which is obtained by the methods of neural networks, will increase noticeably.

Information and telecommunication systems are formed in different ways. In the course of solving problems in the field of information technology, in almost all cases, there will be several ways of solving. From the point of view of practical implementation, their answer is characterized by "fuzziness" [8-9].

That is, during the solution, it is necessary to analyze certain intervals, within which the parameters of interest will be located. A similar mechanism can be noted in this when compared with the way in which the result is demonstrated based on neural networks. How can the values of the parameters of systems influence their behavior?

We can only indicate an approximate set of such conditions, which will be the most important. The number of parameters under study can be quite large. In practice, some of the conditions are ignored. Why the answer will be rough? This is due to the fact that it will be characterized by inaccuracy. Another difficulty is related to the fact that we cannot record the algorithm for determining the answer in a precise way.

On the other hand, training a neural network can be carried out based on those examples that are quickly collected. If a neurosimulation process is underway, then there is no need to explicitly highlight clear rules. This is due to the fact that. instead of forming an appropriate algorithm of work, we can carry out the process of "training" the neural network using known statistics.

Let's show some conditions under which neural networks are formed. Suppose there is some set of input-output vector pairs.

There is a certain condition for them. It consists of arbitrary dimension $\{(X_k, Y_k), k=1...K\}$. In such cases, there will be a two-layer homogeneous neural network. It has the general properties of neural networks. It highlights sigmoidal transfer functions. There is one more characteristic. It has serial connections [10, 11]. There are a finite number of neurons. Such a network is useful for solving a wide range of practical problems. Due to the use of such a neural network for each input vector X_k, the corresponding output vector Y_k will be formed.

A similar model is used in data processing. We need to carry out the process of forming models for forecasting. In a network [12, 13], in general, there can be a different number of layers. To solve our problem, we will consider a network that will be characterized by several layers. It will also be homogeneous

Sigmoidal transfer functions can be written in different ways:

$$f(s) = \frac{1}{1+e^{-2\alpha s}}, \tag{1}$$

Formula (1) is written in general form.

In the above formula, s - is considered as the output of a neuron adder, α - is considered as a parameter,

2. Rational sigmoid:

$$f(s) = \frac{s}{s+|\alpha|}, \tag{2}$$

Functions (1) and (2) will be monotonically increasing. Their peculiarity lies in the fact that they are characterized by nonzero derivatives over the entire domain of definition. This is important from the point of view of improving the accuracy in calculations.

These characteristics ensure the proper functioning and training of the network. It is important to make the choice of sigmoidal transfer functions. The most efficient transfer function is the rational sigmoid.

The structure of the network is selected during research. It will influence the accuracy characteristics of neural network models. Another characteristic is the number of neurons. For the hidden layers of a three-layer network, to assess the number of neurons, we will consider the specified expression:

$$\frac{N_y N_p}{1+log_2(N_p)} \le N_w \le N_y\left(\frac{N_p}{N_x}+1\right)(N_x+N_y+1)+N_y, \tag{3}$$

It is used for a large number of practical cases.

In the specified expression, N_y is considered as the dimension of the output signal,

N_p - is considered as the number of elements that are included in the training sample,

N_x - shows the dimension that will correspond to the input signal.

The “back propagation” algorithm can be considered effective from the point of view of its practical application when training neural networks. The features of a multilayer network are described by the following expressions:

$$s_{i_m} = \sum_{i_{m-i}=1}^{N_{m-i}} w_{i_m i_{m-i}} y_{i_{m-i}} - b_{i_m}, \quad i_m = 1,2,\ldots,N_m, \quad m = 1,2,\ldots,L, \tag{4}$$

$$y_{i_m} = f\left(s_{i_m}\right), \quad i_m = 1,2,\ldots,N_m, \quad m = 1,2,\ldots,L, \tag{5}$$

In the specified expression, f - is the activation function, y - denotes the output of the neuron, s - denotes the output of the adder, b - shows the bias value, w - shows the weight of the connection, i - shows the number of the neuron, N - shows the number of neurons that are in the layer, L - shows the number of layers, m - shows the layer number. During the process of training the network, we can indicate the following basic stages:

1) The process of initializing the network is in progress. That is, the initial values of the parameters are set. Then there will be assignment of weights and biases of the network of small random values over certain ranges. A similar assignment of parameters can be implemented for a wide range of practical tasks [14-15].

2) The element in the training sample is determined: *(<current input>, <desired output>)*. For the current inputs $(x_0, x_1 \ldots x_{N-1})$, the difference should be ensured for all elements that are in the training set. There may be different options for implementation. If a multilayer perceptron is used as a classifier, then the output signal $(d_0, d_1 \ldots d_{N-1})$, which we should receive, is formed on the basis of zeros.

There is a peculiarity. In this case, there is one single element. It is considered as a classifier. It belongs to the class to which the considered input signal will belong.

3) The output in question is calculated. It is required for analysis. In this case, we are based on how the traditional scheme will be taken into account, on the basis of which the multilayer neural network works.

4) It is required to prepare the neural network for work. Synaptic weights are adjusted. This can be done in different ways.

This process uses a recursive algorithm. It consists of several steps. At the first step, we apply it to the output neurons of the network. This takes a little time. After that, in the opposite direction, we will go through the network to the first layer. The synaptic balance adjustment process takes place based on what is indicated in the formula:

$$w_{ij}(t+1) = w_{ij}(t) + r\, g_j\, x_j', \tag{6}$$

In the specified expression, g_j - is considered as the value of the error for neuron j, r - shows the value of the learning step, x_i' - is considered as the output of the neuron for the i or i-th element of the input signal, w_{ij} - is the weight of the neuron i or the element that is associated with input signal i which refers to neuron j for time t.

When the neuron that has the number j will be on the last layer, then

$$g_j = y_j(1 - y_j)(d_j - y_j), \tag{7}$$

In the above expression, y_j is considered as the current output of neuron j, d_j is considered as the desired output of neuron j.

If the neuron that has the number j belongs to one of the layers that is not the last, then

$$g_j = x'_j(1 - x'_j)\sum g_k w_{jk}, \tag{8}$$

In the above expression, k will change in accordance with all neurons in the layer, whose numbers will be one more than for the one to which neuron j will correspond.

We use a similar approach in order to adjust the external displacements of neurons b. In order to train neural networks when building models for forecasting, we propose to use a modified backpropagation algorithm (Fig. 1). In the course of its formation, such an inertial ratio was used, which makes it possible to find the step size for each of the iterations

$$w_{ij}(t+1) = w_{ij}(t) + r g_j x'_j + \alpha\left(w_{ij}(t) - w_{ij}(t-1)\right), \tag{9}$$

In the above expression, α - is considered as a coefficient of inertia, $0 \le \alpha \le 1$.

The learning rate is significantly reduced due to this modification.

Making an optimal choice in terms of control actions is an important step in predicting a change parameters in information systems [16].

The process of dividing the initial set of objects into homogeneous groups is in progress. Then the accuracy in forecasting is increased before the models are formed [17]. The main approach is based on the fact that we apply the partition by biohomogeneous components [18]. There can also be a partition using the methods of cluster analysis. The construction of models for forecasting occurs within each of the groups in a separate way. If there are difficulties in the course of creating homogeneous groups, then indicators that take into account the fact that malfunctions in information systems are heterogeneous will be included in the generalized predictive model. They will be considered as additional dependent variables. In order to select the most effective troubleshooting tactics, for predictive models, the dependent variables are considered as control values for the time that corresponds to the end of the observation [19]. If independent variables are considered, then they will correspond to the values of the same indicators before the start of observation. The algorithm for generating predictive models contains the following steps.

1. The set of indicators X_i $\left(i = \overline{1, N}\right)$ is determined using a survey of experts. On their basis, it is possible to fully identify the state of information systems. In addition, one can take into account their individual inhomogeneities.

2. We indicate one or more monitored indicators Y_j $\left(j = \overline{1, M}\right)$. The way they change over time has an impact on the assessment of the state of the information system. On their basis, we can consider the features of the effectiveness of management influences.

3. We filter information so that reliable measurements are selected.

4. Parametric redundancy is eliminated. This is due to the choice of the optimal feature space.

5. The structure is selected for the model [20-21].

6. Model building in progress.

7. The model is tested in terms of how adequate it will be. If it is confirmed that the model will be adequate, then the algorithm will be terminated. Otherwise, we can complicate the model. Then we will go to step 5.

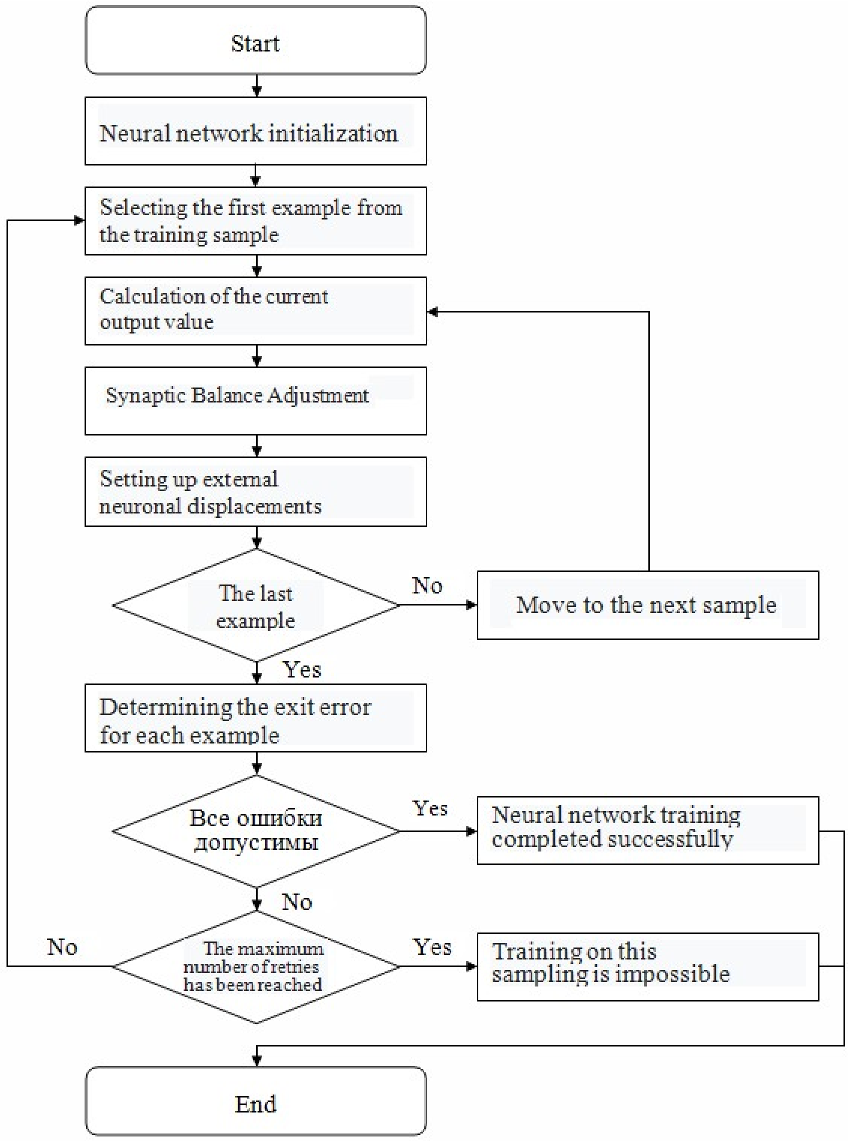

Fig. 1. Algorithm for learning a neural network.

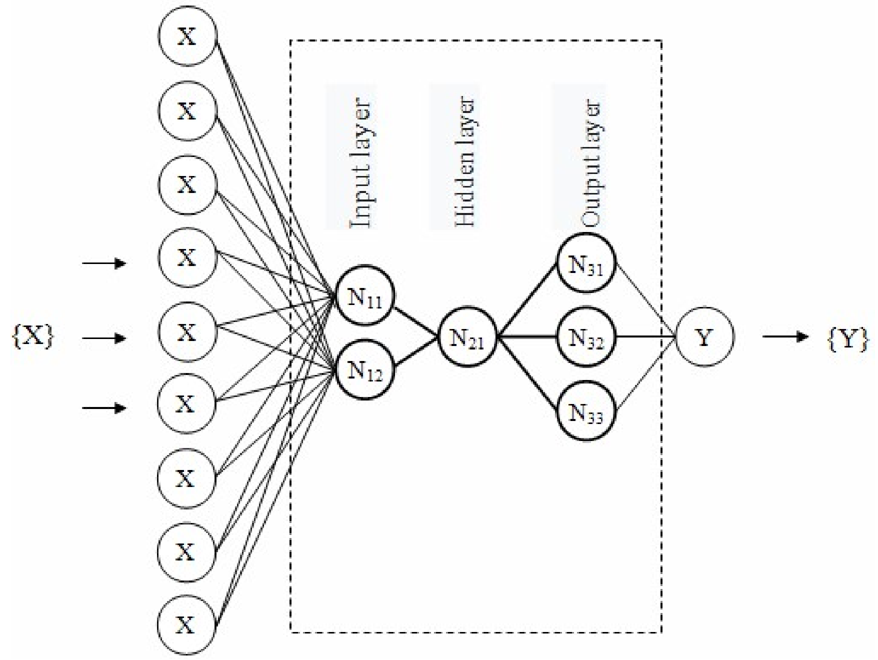

Fig. 2. Illustration of a block diagram of a neural network.

Otherwise, adjustments should be made to the original sample. In such cases, it can provide growth in its volume. There will be a reduction in the number of unreliable measurements. In the course of modeling the development of malfunctions caused by the failure of communication devices, 5 neural network models were formed.

For some of x from, the information processing time is used as a parameter t, for others, the duration of the fault is considered.

From an architectural point of view, the created neural networks will be multilayered. The formed neural networks will contain up to 30 neurons. They are on 3 layers. They will be as follows: input, internal and output.

The specified number of neurons will be sufficient to fully train neural networks to simulate the failure of communication devices. Moreover, there is no redundancy in the number of neurons. In such cases, the relationship between input and output parameters can be shown very accurately. Neural networks will not carry out a simple process of memorizing by examples in a training set. Figure 2 illustrates a block diagram of one of the resulting models. It corresponds to the failure of the switches.

3 Results of modeling

The process of learning neural networks is underway. Then the backpropagation algorithm will be implemented. We consider the multicriteria optimization problem for the backpropagation method as a set of single-criterion ones. For each of the iterations, the values of the network parameters are changed.

They will improve on only one example in the training set. Due to the application of this approach, we significantly reduce the speed when learning. In order to increase the convergence rate during the training of the neural network, we used a modified backpropagation algorithm. In the course of its practical implementation, the step size for each iteration will be determined using the inertial ratio.

We carried out the neural network training process on the basis of training samples. They were in the database. As a result of training, all neural networks created during the study turned out with a sufficient level of accuracy.

To verify the obtained models, we used control samples. For each of them, at least 10 objects were included that were not included in the main group.

To assess the effectiveness of the models, we calculated such indicators as the average and maximum error of the output value. The results of testing the generated models for forecasting are shown in table. 1.

Table 1. Results of verification of models that allow predicting failure of communication devices.

Head 1	Volume of Samples	Samples Average Error	Maximum Error
Voltage instability in the electrical network of level 1	12	7.34	10.00
Voltage instability in the electrical network of level 2	10	7.55	10.00
Failure of the first level communicators	19	10.43	45.98
Failure of the second level communicators	13	7.06	34.99
Failure of the third communicators level	10	6.48	9.95

After the forecast is obtained, it is necessary to choose an adequate troubleshooting scheme

4 Conclusion

The paper shows the possibility of solving a problem aimed at predicting faults in information systems. An algorithm for learning a neural network is developed, an illustration of a structural diagram of a neural network is given. To verify the obtained models, we used control samples. For each of them, at least 10 objects were included that were not included in the main group. To assess the effectiveness of the models, we calculated such indicators as the average and maximum error of the output value. Results of verification of models that make it possible to predict the failure of communication devices

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