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# Use of Fuzzy Neural Networks in Identification of the State of Data Transmission System Elements

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***Abstract*—The possibilities of using direct distribution neural networks with a different number of hidden layers and fuzzy neural networks in the process of identifying operational states of data transmission system elements are compared. As input, it is proposed to use the data collected by monitoring systems of the telecommunications network operator. It takes into account factors that are presented not only in quantitative, but also in qualitative forms, used to fill the knowledge base of a fuzzy neural network, which allows a more complete analysis of the elements of complex socio-technical systems. Automation of the analysis of the operational states of the elements of data transmission systems will allow not only to relieve highly qualified specialists from routine work and improve the quality of decisions on repair or modernization, but also to predict critical, pre-emergency conditions of elements that can reduce the performance of the data transmission network in time.**

***Keywords*—direct distribution neural network, fuzzy neural network, forecasting, data transmission system, expert methods, uncertainty.***

## I. Introduction

When making decisions, one of the most important steps is forecasting. The experience and knowledge gained during operation can be used in the process of improving forecast models. Basically, there are three types of methods. The first, formalized, uses the data obtained in the monitoring process. The second, expert, uses the intuitive abilities of specialists. The third type has incorporated the advantages of the first two, becoming their combination. When choosing a forecasting method, it is necessary to consider in what form the data from the elements of data transmission systems (EDTS) is received. The data transmission system (DTS), a telecom operator, is in most cases in a continuous process of scaling [1,2,3,4,5,6]. It varies depending on demand from consumers of services, whose quality reviews can often only be obtained in verbal form. Thus, in order to obtain the correct forecast, it is necessary to choose the forecasting methods that most fully take into account the data presented in quantitative and qualitative forms. Modern DTSs have a complex structure generating uncertainty when taking into account the number and level of influence of factors that arise during operation. This makes it difficult to use common formalized methods. Expert methods, due to the significant extent of DTS, in the analysis of similar elements increase the level of errors. On this basis, the use of the apparatus of fuzzy sets in the third, combined type of forecasting, is more reasonable. The most promising direction of forecasting is considered to be neural and fuzzy neural methods. In relation to solving the problem of predicting the state of DTS based on switching packets with a high level of uncertainty, it is proposed to use the above methods, due to the difficulty of creating models with a clear specification [7,8].

## II. Data Preparation

Preparation for data collection begins with the formation of an expert group that includes production specialists with at least ten years of experience and occupying key positions in the organization. The group includes both technical specialists and specialists in the field of management and risk assessment of existing and promising projects. Further selection, by the expert group, of the most significant parameters takes place on the basis of filling out questionnaires and rating on a ten-point scale. After the agreement of expert opinions, the parameter that most fully characterizes the performance of the EDTSis selected “connection speed”. Monitoring data can be obtained from monitoring programs and software systems that are part of the OSS / BSS (Eng. Operation Support System / Business Support System, operation support system business support system) systems used in the field of telecommunications [9,10,11,12,13].

## III. Direct Distribution Network

To train artificial neural networks with any number of layers, it is possible to use the back propagation rule, which is a generalization of the rule used in the perceptron. The type of gradient descent used in the algorithm allows you to adjust the weight coefficients in the direction of the minimum. As an activation function, the algorithm uses a sigmoid function. The sigmoid function allows you to save computational resources and limits the value of the unit to strong signals and enhances the weak due to the simplicity of the derivative:

$$\left(\frac{1}{1+e^{-x}}\right)' = \frac{1}{1+e^{-x}}\left(1 - \frac{1}{1+e^{-x}}\right) \quad (1)$$

The operation of the error back propagation algorithm can be divided into the following steps:

1. Preparation of the collected data for training $(Y, X^{*})$ where the value of $Y$ is fed to the input of the neural network;

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2. The definition of the output of the neural network $X = F(Y)$;
3. Calculation of the output error of the neural network *Error*;
4. Correction of weights to minimize the level of error;
5. Returning to step number 1 to reduce the error level to the minimum level by going through a new cycle;

Steps 1 and 2 are direct propagation, steps 3 - 5 are reverse propagation through the neural network..

The data used in training is divided into training and test samples. Test sample is used to test the quality of network training. A neural network is well trained if, when using test data, it produces values close to test ones. In the modeling process, direct distribution neural networks with 2 and 3 hidden layers were created for one data set. The results of a comparative analysis of modeling 2-and 3-layer networks and test samples are given in table. I.

TABLE I. COMPARISON OF SIMULATION DATA OF A 2-AND 3-LAYER NETWORK WITH MEASUREMENT DATA

| Measure ments | Neural network (forecast) | Test sample (real data) | The discrepancy between the predicted and real values% |
|---|---|---|---|
| **2-layer** | | | |
| 1. | 8269200 | 8282203 | 0.16% |
| 2. | 8262900 | 8279528 | 0.20% |
| 3. | 8298000 | 8282608 | 0.19% |
| 4. | 8273200 | 8283080 | 0.12% |
| **3-layer** | | | |
| 1. | 8273900 | 8282203 | 0.10% |
| 2. | 8288900 | 8279528 | 0.11% |
| 3. | 8271100 | 8282608 | 0.14% |
| 4. | 8273800 | 8283080 | 0.11% |

The accuracy shown by direct distribution neural networks is sufficient for the current task. However, in the process of their preparation for work, significant time and computational resources are required to select the number of hidden layers and the number of neurons in them to compare the simulation results and identify the best.

## IV. FUZZY NEURAL NETWORK

A fuzzy neural network is a structure, with a certain number of layers that do not have feedbacks, they use not fuzzy signals, but weight coefficients, activation functions Fig. 1. [14].

Fixed T-norms and S-conorms or other continuous operations are used for summation. Fuzzy neural networks use retrospective information to determine the parameters of membership functions. Training is used to find the values of these parameters. In the present work, the Sugeno algorithm was taken as a basis, which allows one to automatically determine the form of nonlinearity. This allows you to reduce the level of influence of the human factor, due to the refusal to select data by the researcher at the beginning of the process. The Sugeno model, with the number of rules $L$ and $T$ by the number of variables $d_j$, is represented as:

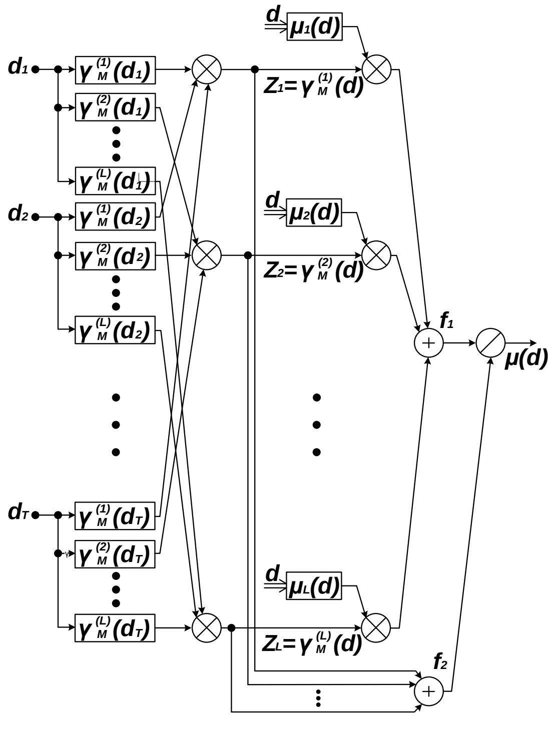


Fig. 1. The scheme of the fuzzy neural network

$$IF\left(d_1 IS\ M_1^{(1)}\right) AND \left(d_2 IS\ M_2^{(1)}\right) AND \ldots AND \left(d_n IS\ M_n^{(1)}\right), \\ THEN b_1 = p_{10} + \sum_{j=1}^{T} p_{1j} d_j$$

$$\ldots\ldots\ldots\ldots$$

$$IF\left(d_1 IS\ M_1^{(L)}\right) AND \left(d_2 IS\ M_2^{(L)}\right) AND \ldots AND \left(d_n IS\ M_n^{(L)}\right), \\ THEN b_L = p_{L0} + \sum_{j=1}^{T} p_{Lj} d_j \tag{2}$$

Here $IF(d_j ISM_1^{(L)})$ is based on a generalization of the Gauss function individually for each input variable $d_j$ and which is a fuzzification function:

$$\gamma_M(d_i) = \frac{1}{1+(\frac{d_i - c_i}{\tau_i})^{2b}} \tag{3}$$

where $\gamma_M(d_i)$ is the algebraic product of the $v$ th rule:

$$\gamma_M^{(v)}(d_i) = \prod_{j=1}^{T}\left[\frac{1}{1+\left(\frac{d_i - c_j^{(v)}}{\tau_j^{(v)}}\right)}\right]$$

Aggregation of the result taking into account the $L$ rules:

$$\mu = \sum_{i=1}^{L} \frac{z_i}{\sum_{j=1}^{T} z_j}\left(p_{i0} + \sum_{j=1}^{T} p_{ij} d_j\right) \tag{4}$$

Formula (2) will get the form:

$$\mu(d) = \frac{1}{\sum_{v=1}^{T} z_v}\left(\sum_{v=1}^{L} z_v \mu_v(d)\right) \tag{5}$$

where $\mu_v(d) = p_{v0} + \sum_{j=1}^{T} p_{vj} d_j$ . The weight coefficients z_v in formula (4) are interpreted with respect to

$\gamma_M^{(v)}(d)$ as the significance of the components calculated on the basis of formula (3). Using classical implication, the model in question, out of 81 rules, will take the form:

$$IF(d_1 IS\ CLUSTER_1), THEN\ \mu = p_{10} + p_{11}d_1 + p_{12}d_2 + p_{13}d_3 + p_{14}d_4$$
.........
$$IF(d_4 IS\ CLUSTER_3), THEN\ \mu = p_{810} + p_{811}d_1 + p_{812}d_2 + p_{813}d_3 + p_{814}d_4 \quad (6)$$

where $p_{10}, p_{11}, p_{12}, p_{13}, p_{14}, \dots, p_{810}, p_{811}, p_{812}, p_{813}, p_{814}$ are parameters.

In this example, the number of fuzzy production rules is established during the training of a fuzzy neural network. Figure 2 shows an example of a graph of the dependence of the output variable on the input variables $d_3$ and $d_2$ formed on the basis of fuzzy production rules.

However, as a training sample, it is possible to use a matrix of cluster centers. We obtain the matrix during fuzzy clustering based on previously collected data, having previously determined the number of groups with special properties that allow us to assess the state of ESPD [1,6,7,11].

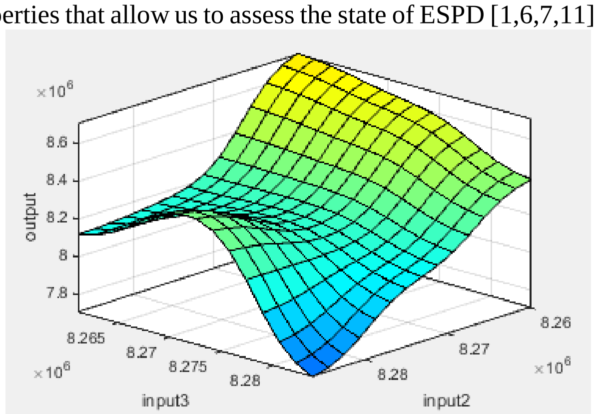


Fig. 2. The graph of the dependence of the output variable on the input variables $d_3$ and $d_2$

That is, clustering is carried out on the basis of retrospective data, based on them, groups of states of the analyzed equipment are determined, in the future these data are used as a target function when a fuzzy neural network works with real-time data. This allows you to pre-define the group of operational states for a particular equipment and further carry out the classification based on them, revealing, including boundary conditions. The appropriate, within the framework of the problem to be solved, the number of fuzzy rules can be formed taking into account the ratio of membership functions, in this example, to Gaussian functions. The data used to construct the forecasting model are represented as n-dimensional arrays $d_r = (d_{1,r}. d_{2,r}, \dots, d_{n,r})$ r=1,3…,mexplanatory variables and explained variables as one-dimensional observations $\mu_1, \mu_2, \dots, \mu_n$. The construction of the model is iterative, the beginning of a new cycle occurs with the choice of the format of the fuzzy rules system.

The values of $H_i$ and the coefficients of the linear equation for fuzzy rules of the form are calculated

$$IF(d_1 = M_i^1) AND \dots AND (d_n = M_i^n) THEN \dots \quad (7)$$

Where $M_i^1, M_i^2, \dots, M_i^n$ - fuzzy sets, $i = 1,2, \dots, I$.

Each cycle includes two steps: 1 step. The degree of membership is calculated. n-dimensional observations are divided into a given number of clusters using the c-means fuzzy clustering algorithm. This allows you to attribute the state of the data transmission network element to several clusters describing different levels of loading with different degrees of affiliation. The number of clusters is equal to the number of fuzzy rules *I*.

2 step. Calculation of the coefficients of linear equations of each fuzzy rule. Here, the parameters are determined based on the least squares method. Given that the predicted value is $\hat{\mu}$ defined as:

$$\hat{\mu} = \frac{\sum_{i=1}^{I} H_i \mu_i}{\sum_{i=1}^{I} H_i} \quad (8)$$

Where $H_i$ is the number denoting the truth level $i$ of the rule; $H$ is the number of fuzzy rules, $\mu$ will be calculated using independent variables

$$\frac{H_i}{\sum_{w=1}^{I} H_w} \text{ and } \frac{H_i d_{j,r}}{\sum_{w=1}^{I} H_w} \quad (9)$$

where r = 1,2, ..., m; i = 1,2, ..., I; j = 1,2, ..., n., *w*- is the number of the stage of comparing the rules of fuzzy production. Here, the least squares method is estimated by a linear model with $I * (n+1)$ coefficients. The evaluation criteria are the mean square error of the forecast RMSE, as well as the average absolute error MAPE:

$$RMSE = \sqrt{\frac{\sum_{r=1}^{n} (\mu_r - \hat{\mu}_r)^2}{m}} \quad (10)$$

$$MAPE = \frac{1}{m} \sum_{r=1}^{m} \frac{|\mu_r - \hat{\mu}_r|}{\mu_r} \quad (11)$$

The cycle works using different fuzzy production rules in terms of quantity and different sets of variables in each rule, until the minimum absolute percentage error is generated. Each iteration uses the same number of fuzzy rules, but the look of these rules changes from iteration to iteration. With each new iteration, the system of fuzzy rules changes relative to the previous one. At each new iteration, the RMSE and MAPE values are calculated, the MAPE value is used to determine whether the process should continue.

As a result, the values generated by model 8289900 and the data from the control sample 8283075 showed significant proximity, since the discrepancy between the predicted and real values was 0.08% (Table II).

TABLE II. COMPARISON OF SIMULATION DATA OF A FUZZY NEURAL NETWORK AND CONTROL MEASUREMENT DATA

| Data source | Value | The discrepancy between the predicted and real values% |
|---|---|---|
| Fuzzy neural network (forecast) | 8289900 | 0.08% |
| Test sample (real data) | 8283075 | |

## V. CONCLUSIONS

It is possible to use direct distribution neural networks to analyze accumulated data on the state of EDTS. However, the accuracy of the prediction increases with an increase in the number of layers in the neural network. This, in turn, can have a negative impact on the choice of platform for the implementation of multilayer models due to proportionally increasing requirements for hardware performance. Fuzzy neural networks in this case, due to the introduction of an expert component, will make it possible, without using significant hardware resources, to obtain predictions similar in accuracy. As a result, highly qualified personnel will be freed from solving routine tasks, and the efficiency of movement, spare parts stored in the operator's warehouses will increase.

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