Route Selection Method in Military Information and Telecommunication Networks Based on ANFIS

Yuriy Zdorenko[1], Oleksandr Lavrut[2], Tetiana Lavrut[2], Vasyl Lytvyn[3], Yevhen Burov[3] and Victoria Vysotska[3]

[1]*Military Institute of Telecommunications and Informatization, Moskovskaya Street, 45/1, Kyiv, 01011, Ukraine*
[2]*Hetman Petro Sahaidachnyi National Army Academy, Heroes of Maidan Street, 32, Lviv, 79012, Ukraine*
[3]*Lviv Polytechnic National University, S. Bandera street, 12, Lviv, 79013, Ukraine*

Abstract

Military information and telecommunication networks (MITNs) are characterized by increased requirements for the reliability of data transmission. Existing routing methods allow the transmission of information flows on different routes, balancing the load on network routers. Therefore, routing methods should consider reliability indexes when calculating route metrics. Route reliability indexes are used in modern dynamic routing protocols. However, their values are obtained based on heuristic algorithms for polling the state of the interfaces of neighbouring routers. It is proposed to use a priori information about the reliability of the route, which allows to make the right decision beforehand when transmitting information flows and avoid deterioration of QoS in case of equipment failures. It is proposed to use ANFIS (Adaptive Neuro-Fuzzy Inference System) to obtain such information.

Keywords 1

Telecommunication network, metric, router, neuro-fuzzy system, dynamic routing protocol, reliability index, route metric, routing protocol, mobile ad hoc network, time interval, military telecommunication network, membership function, fuzzy logic, priory information

1. Introduction

In modern military information and telecommunication networks, ensuring the quality of service for various information flows is one of the high priority tasks. An integral part of this process is the use of a properly configured dynamic routing protocol. Based on any dynamic routing protocol are route metrics used to decide on the transmission route of the data stream. The military information and telecommunication networks are characterized by dynamic topology associated with the specifics of the operation of such networks. The change in the configuration of such networks can be caused by many random factors: the change of location of routers due to hostilities, equipment failure due to destruction by the enemy, loss due to a diagnostic fault. Therefore, the dynamic routing protocol for such networks should be based on metrics that consider the reliability of intermediate nodes (routers). Such provisions are currently implemented, for example, in the Enhanced Interior Gateway Routing Protocol (EIGRP) [12]. However, this protocol does not use a reliability criterion with the default settings when calculating the route metric. And additional locations to consider the reliability criterion in the general metric of the route are based on measurements of time parameters of links on the corresponding interfaces and can lead to the calculation of erroneous values of the reliability criterion of the node. For instance, it is difficult to determine whether a particular node is active at the current time, leading to incorrect calculation of metrics and sending information on a non-existent route. As a

MoMLeT+DS 2021: 3rd International Workshop on Modern Machine Learning Technologies and Data Science, June 5, 2021, Lviv-Shatsk, Ukraine
EMAIL: zdorenkoviti@gmail.com (Y. Zdorenko); alexandrlavrut@i.ua (O. Lavrut); Lavrut_t_v@i.ua (T. Lavrut); vasyl.v.lytvyn@lpnu.ua (V. Lytvyn); Yevhen.V.Burov@lpnu.ua (Y. Burov); Victoria.A.Vysotska@lpnu.ua (V. Vysotska)
ORCID: 0000-000L-5649-771X (Y. Zdorenko); 0000-0002-4909-6723 (O. Lavrut); 0000-0002-1552-9930 (T. Lavrut); 0000-0002-9676-0180 (V. Lytvyn); 0000-0001-6124-3995 (Y. Burov); 0000-0001-6417-3689 (V. Vysotska)

result, this will lead to packet losses, an increase in their average delay, and a deterioration in overall service quality. Therefore, to provide up-to-date information on the reliability of routes, it is necessary to have the appropriate tools.

One of the promising solutions to the problem of obtaining a priori information is the use of systems for predicting the values of the required parameters [8], [10], [13]. For example, network administrators have statistics of issues and failures of a particular type of equipment for a certain period of its operation. Failures are usually random and have various causes. Therefore, such a data set can be used to determine the failure rate in the future. The capabilities of modern forecasting systems are used to do this. One way to implement this is to use adaptive fuzzy neural networks [8, 9] - ANFIS.

Each segment of the military network has its specifics of the operation, which is determined by the set of equipment used and the conditions of use (network topology, the temperature of equipment, the nature of hostilities, etc.). The determining specific factors influence the number of possible failures of the network equipment. Therefore, it is essential to properly train the forecasting system based on the specifics of the functioning of the military telecommunication network. The obtained value of the failure rate of the router can be used to calculate the reliability of the node shortly time interval. In addition, using this indicator to calculate the overall metrics of the route will allow making the right decision about the routing of data flows in advance.

2. Problem formulation

Existing dynamic routing protocols use a set of indexes to calculate route metrics [12, 14-16], including delay, line throughput, probability of loss, reliability, congestion and others. Modern military networks require the mandatory use of a priori information about the value of the reliability index for calculating route metrics by the dynamic routing protocol. Therefore, it is proposed to improve the existing active routing methods by developing and applying forecasting systems to obtain early information about changes in the network topology and update the route metrics based on it.

It is assumed that such an approach will significantly improve the quality of service of packages in the military telecommunication networks.

3. Related works

The metrics in modern routing protocols are formed based on the obtained values of the corresponding partial parameters of the metric, which are contained in the header of IP packets. For example, in the EIGRP protocol, the metric M_j for the current *j*-th time interval can be determined by the formula [12]:

$$M_j = \left(K_1 * BW + \left(\frac{K_2 * BW}{256 - L} \right) + K_3 * D) \right) * \left(\frac{K_5}{R + K_4} \right) * 256\text{,} \quad (1)$$

where K_i for i = {1; 5} - indices, indicating the partial inclusion indicator in the overall metric; they take the value 0 or 1; BW is the minimum value of bandwidth among all interfaces to the destination network; D - the total value of all delays to the destination network; R is the reliability of the route, the values of which are in the range {1; 255}; L is network load rate.

The routing procedure includes several steps:

- Obtaining information about the components of the metrics that are transmitted in the packet header;
- Calculation of the general metric for available routes according to the routing protocol;
- Deciding on the transmission of packets using a determined way.

However, an approach allows not calculating metrics for predetermined components. Therefore, it works in uncertain and incomplete information and uses the specifics of a particular network segment. Furthermore, this approach is based on ANFIS to determine the final metric route. Thus, in [3], the value obtained by the procedure of fuzzy inference [4-6] is used as a metric. For this purpose, the values of the components of the metric measured during the operation are fed to the ANFIS input. Nevertheless, this article does not disclose the learning mechanism of such ANFIS, namely, what data was used for this and how the correct output values (route metrics) were obtained. Therefore, it is not always advisable to use such an approach.

On the other hand, such systems can be used to obtain predictive values of a specific parameter according to preliminary statistics. The use of ANFIS in such a context is considered in this paper. The general form of ANFIS is shown in Fig.1 [1, 2, 3, 7]:

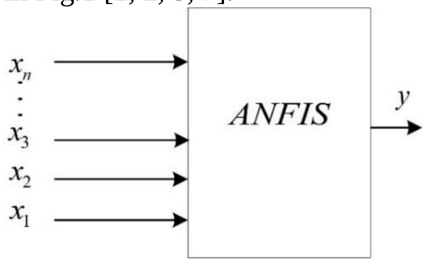

Figure 1: Generalized representation of ANFIS

The mechanisms that underlie ANFIS allow finding the functional dependencies in the form:

$$\tilde{y}_i = f(x_1, x_2, ..., x_i). \quad (2)$$

However, obtaining the correct value using formula (2) depends on the correctness of the data for training such systems. Thus, one of the most common ways of training is the backpropagation method [11]. The basis of the training sample is the data obtained during the observation of the input values and the desired values of the output. The internal structure of ANFIS is determined based on the number of input values, the number and form of their membership functions and the fuzzy inference algorithm [8] (Fig. 2).

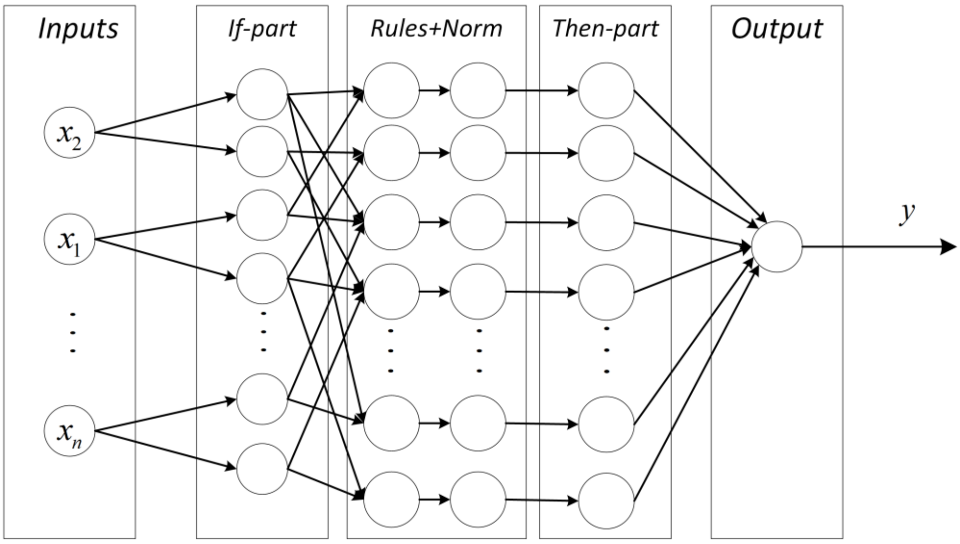

Figure 2: ANFIS layers

In [8, 10], ANFIS was used to predict various parameters and demonstrated high efficiency in solving the problem. Therefore, this article proposes to use this type of system to predict the failure rate of routers in the military telecommunication networks.

4. Updating the route metrics based on predicted reliability values

The statistics on the reliability of military network units can be grouped into classes of possible failures, for example, due to equipment failure (software or hardware failures), or failures related to the intensity and nature of hostilities (destruction of units) and other classes of periodic or random factors. The number of such classes $k = \{1, m\}$ is determined by the conditions of operation of the military network. For each such failure class, it is proposed to implement its ANFIS. The result of its work should be the predicted value of the number of failures of the corresponding k-th class in the nearest time interval. Data on the number of failures during previous periods will be used as input. Based on the forecast of the number of failures, the data obtained are used to calculate the reliability index R_j for the j-th time interval of the military network node. To do this, it is proposed to use the following formula (3):

$$R_j = \frac{\sum_{k=1}^{m} \tilde{y}_k}{y_{all}}, \qquad (3)$$

where $\tilde{y}_k$ is the predicted value of the failure rate of the k-th class; y_{all} is the total number of single observation intervals, into which the entire observation time is divided.

The duration of each single time interval is selected based on the recording of one event.

The diagram of the metric update system based on the approach described above involves implementing several stages and is shown in Fig. 3.

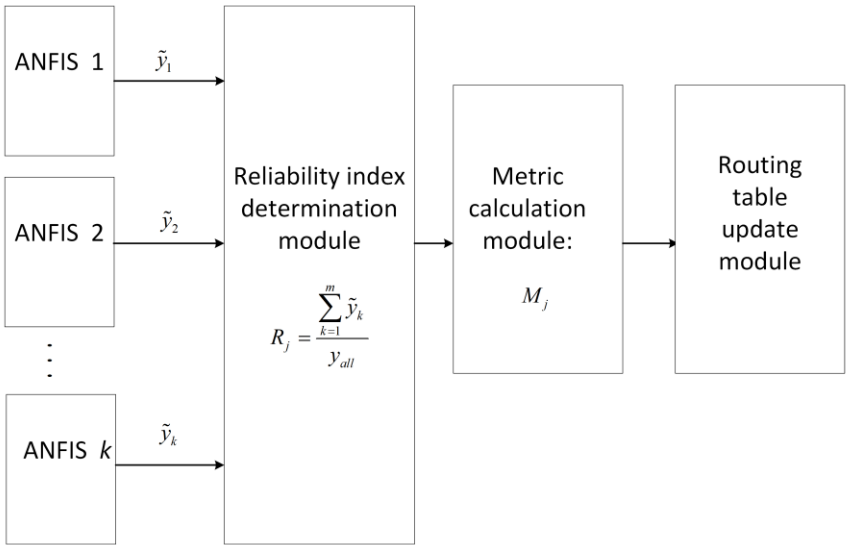

Figure 3: Block diagram of the metric update system

The part of the network considered using the proposed approach is shown in Fig. 4.

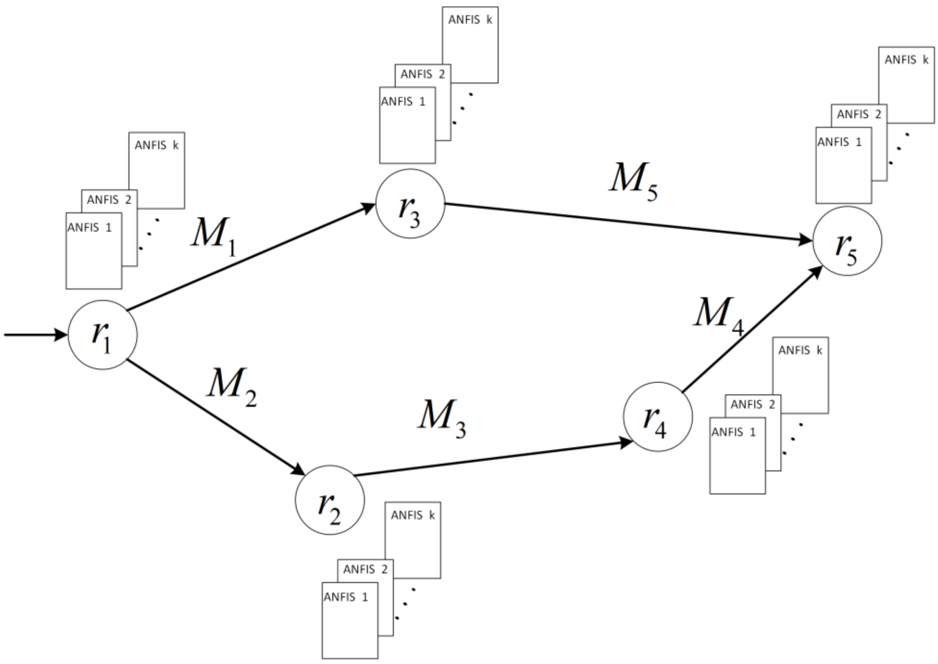

Figure 4: A segment of network for which the route is build-using ANFIS

Each intermediate node (router) of the considered network segment contains trained ANFIS of *k*-th class, corresponding to the number of defined failure classes *m*. Each such system predicts the number of failures of the corresponding *k*-th class in the next time interval of duration T. Based on these data, the reliability index of the node is calculated using formula (3), and the route metric is calculated, according to the algorithm for use in the dynamic routing protocol. Next, the routing tables are updated, and the route information with the best metrics is transmitted.

5. Route selection method based on the use of ANFIS

Based on the described process of route metrics updating, a method of route selection using ANFIS is proposed, which involves the following steps:

1. Determining the failure classes of routers in the military telecommunication network;
2. Implementation of the appropriate number of ANFIS on each network node to predict failures for a specific class;
3. Determining the ANFIS architecture according to the method [11], the main stages of which include: determining the number and type of input values, the number and form of membership functions of each input value, the number of layers of fuzzy neural network;
4. Training ANFIS based on statistics collected for previous periods for specific failure classes;
5. Predicting the values of the number of failures of the *k*-th class in the nearest time interval using ANFIS of the corresponding classes;
6. Calculation of the overall reliability index of the node according to formula (3), and its conversion into the reliability index of the corresponding dynamic routing protocol;
7. Calculate the route metric according to the rules defined by the dynamic routing protocol, taking into account the reliability index.
8. Update routing tables by transmitting partial metric data to neighbouring routers, according to the dynamic routing protocol

Router failure classes are determined based on the analysis of network operating conditions and are the initial data for further ANFIS synthesis on each network router. Each ANFIS of k-class is designed to predict a particular *k*-th failure class and provide the necessary prediction accuracy. To do this, we need to choose the exemplary architecture of such a system and data for its training. On the one hand, the choice of architecture is limited by the requirements for forecasting accuracy, and on the other hand, the ability of routers to perform additional tasks. The most straightforward ANFIS architecture synthesis with its further training will be carried out in the following part.

We assume that the failure rates of different classes that are predicted are random and uniform. Therefore, the total number of failures during the forecast *j*-th time interval is calculated as the sum of losses of different classes indicated by other ANFIS classes.

The basis of any dynamic routing protocol is the calculation of the route metric. We propose to use such a routing protocol that considers the reliability index when calculating the route metric. In addition, the proposed method can be used for new dynamic routing protocols. One of the existing protocols that consider the reliability in the calculation of the overall metric is EIGRP. However, the reliability index in this protocol is taken into account only if the network topology changed. Let's calculate the route metric using this protocol in the router r_1 for the network architecture shown in Fig. 4.

Determine that the router r_1 is the entry router and the router r_5 is the exit router of the network segment. So, we have the following values of partial metrics for different parts of the route: $BW_{1-3} = 100Mb/s$, $BW_{3-5} = 100Mb/s$, $BW_{1-2} = 100Mb/s$, $BW_{2-4} = 100Mb/s$, $BW_{4-5} = 100Mb/s$, $D_{1-3} = 10mks$, $D_{3-5} = 10mks$, $D_{1-2} = 10mks$, $D_{2-4} = 10mks$, $D_{4-5} = 10mks$, $R_{EIGRP_i} = 255$, $L = 255$.

The values of coefficients are $K_i = 1$ for *i={1;5}*. Then, according to formula (1), for route *1:* r_1 - r_3 - r_5, the metric will have a value *M=202,* and for route *2*: r_1 - r_2 - r_4 - r_5 *M*= 203. If a priori information about the reliability index of the router r_3 is available, for example, $R^3{}_j = 0,5$ the metric will be recalculated.

The appropriate steps of the proposed method were executed to obtain the value $R^n{}_j$. For the EIGRP protocol, the value of the reliability index is in the range {1; 255}. Therefore, it is necessary to establish the correspondence of the obtained values of the reliability index R_j, which is in the range {0,1}, with the range of the EIGRP protocol. The paper proposes a gradation of the correspondence values, shown in Table 1 to do this.

Table 1
The correspondence of the values of the predicted reliability index with the EIGRP protocol index

#	EIGRP reliability index, R_{EIGRP}	Predicted reliability index, R_j
1.	1	0,0039
2.	2	0,0078
3.	3	0,011
…	…	…
128.	128	0,5019
129.	129	0,5058
…	…	…
255.	255	1

Thus, for the values of the reliability index defined for the router r_3 - $R^3{}_j$, we have the corresponding value of the reliability index according to the EIGRP protocol - $R_{EIGRP_1} = 127$.

The metrics of both routes from router r_1 to router r_5 were calculated using the obtained reliability index. Thus, the metric of route 1: r_1 - r_3 - r_5, obtained taking into account the reliability index will be M = 404, and for route 2: r_1 - r_2 - r_4 - r_5, M = 203. Therefore, the data streams will be directed along the route with a smaller value of the metric. The obtained a priori information about the reliability of the nodes based on the proposed method allowed updating the metrics and taking into account possible failures on the packet transmission route. As a result, the route will be selected, which in the *j*-th time interval will be more reliable, namely route 2: r_1 - r_2 - r_4 - r_5.

Possible failures of network nodes during the operation of the telecommunication network can lead to a deterioration in QoS: increased network delays, increased packet loss, packets sent on a non-existent route. Therefore, it is mandatory to consider the reliability index in the general metric of the network route. Subsequently, ANFIS was synthesized and trained to predict *k*-th class failures.

For the synthesis of ANFIS, the method defined in [8] was used. Thus, as input values, we use the value of the number of failures of the *k*-th class during the last four periods of time, namely: $y_{(i-1)}$, $y_{(i-2)}$, $y_{(i-3)}$, $y_{(i-4)}$. Thus, the initial value is $\tilde{y}_k$ - the number of failures of the *k*-th class during the following time interval. It is proposed to use the Sugeno algorithm of the 1st type to obtain an accurate prediction. For each input value, two triangular membership functions were defined. Then the synthesized ANFIS will have the following structure on Fig. 5.

The complete knowledge base will contain sixteen rules, which have the following form (4) - (19):

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_1), \quad (4)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_2), \quad (5)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_3), \quad (6)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_4), \quad (7)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_5), \quad (8)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_6), \quad (9)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_7), \quad (10)$$

$$\text{If } (y_{(i-1)} = O_1) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_8), \quad (11)$$

$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_9), \quad (12)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_{10}), \quad (13)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_1) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_{11}), \quad (14)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_{12}), \quad (15)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_{13}), \quad (16)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_1) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_{14}), \quad (17)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_1), \text{ then } (\tilde{y}_k = Z_{15}), \quad (18)$$
$$\text{If } (y_{(i-1)} = O_2) \text{ and } (y_{(i-2)} = P_2) \text{ and } (y_{(i-3)} = R_2) \text{ and } (y_{(i-4)} = S_2), \text{ then } (\tilde{y}_k = Z_{16}). \quad (19)$$

where O_1 is the first term of the input value $y_{(i-1)}$; O_2 is the second term of the input value $y_{(i-1)}$; P_1 is the first term of the input value $y_{(i-2)}$; P_2 is the second term of the input value $y_{(i-2)}$; R_1 is the first term of the input value $y_{(i-3)}$; R_2 is the second term of the input value $y_{(i-3)}$; S_1 is the first term of the input value $y_{(i-4)}$; S_2 is the second term of the input value $y_{(i-4)}$; Z_1 , Z_2, Z_3 …, Y_k are the values of the individual conclusions of the fuzzy rules number k ($1 \le k \le 16$).

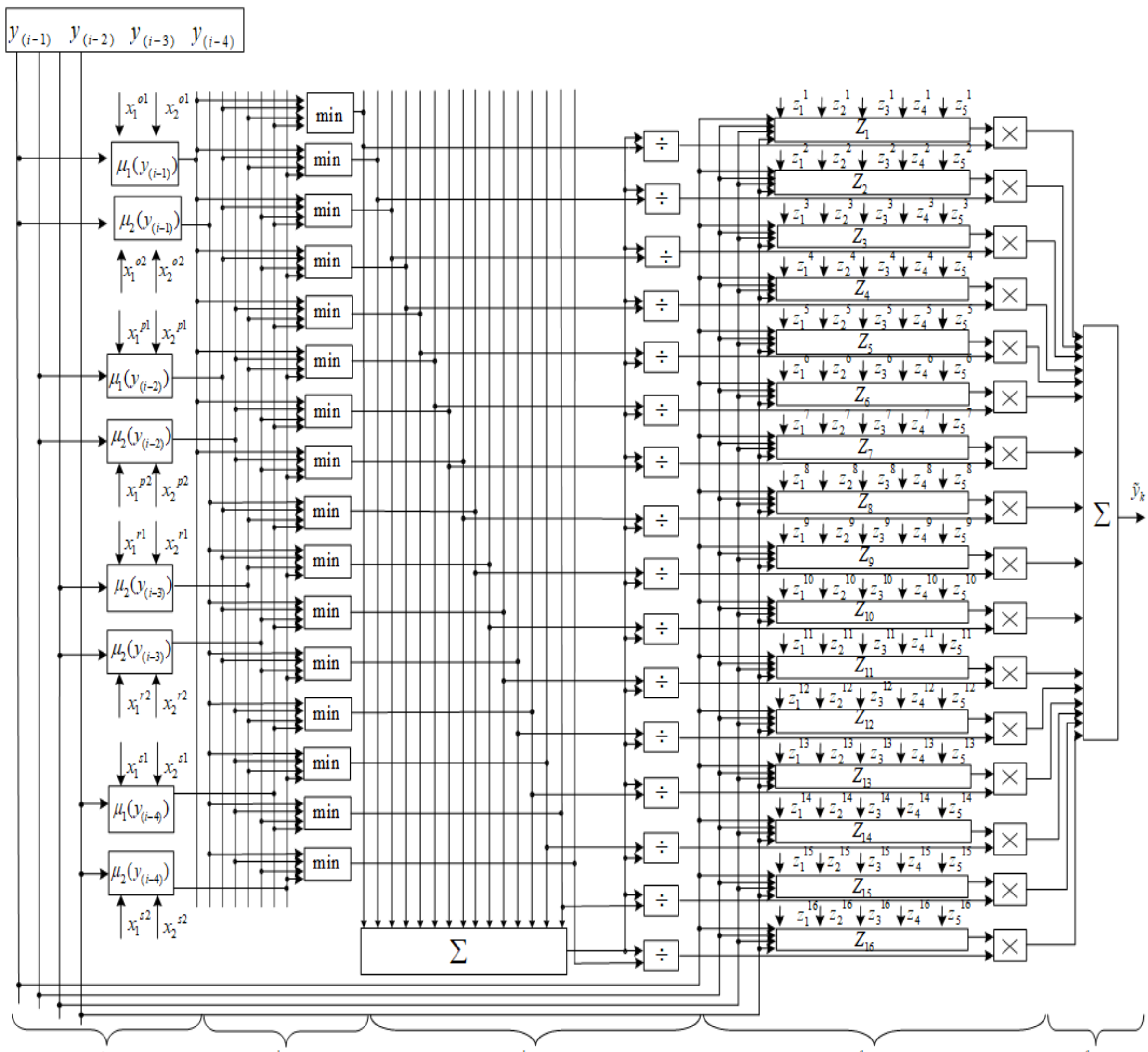

Figure 5: The synthesized ANFIS structure

The training of such ANFIS, expressions for membership functions of input values was obtained as a result of:

$$\mu_1(y_{(i-1)}) = \begin{cases} 1, & y_{(i-1)} < 15; \\ \dfrac{27 - y_{(i-1)}}{27-15}, & 15 \le y_{(i-1)} < 27; \\ 0, & y_{(i-1)} \ge 27; \end{cases} \tag{20}$$

$$\mu_2(y_{(i-1)}) = \begin{cases} 0, & y_{(i-1)} < 18; \\ \dfrac{y_{(i-1)} - 18}{42-18}, & 18 \le y_{(i-1)} < 42; \\ 1, & y_{(i-1)} \ge 42; \end{cases} \tag{21}$$

$$\mu_1(y_{(i-2)}) = \begin{cases} 1, & y_{(i-2)} < 10; \\ \dfrac{37 - y_{(i-2)}}{37-10}, & 10 \le y_{(i-2)} < 37; \\ 0, & y_{(i-2)} \ge 37; \end{cases} \tag{22}$$

$$\mu_2(y_{(i-2)}) = \begin{cases} 0, & y_{(i-2)} < 16; \\ \dfrac{y_{(i-2)} - 16}{45-16}, & 16 \le y_{(i-2)} < 45; \\ 1, & y_{(i-2)} \ge 45; \end{cases} \tag{23}$$

$$\mu_1(y_{(i-3)}) = \begin{cases} 1, & y_{(i-3)} < 12; \\ \dfrac{22 - y_{(i-3)}}{22-12}, & 12 \le y_{(i-3)} < 22; \\ 0, & y_{(i-3)} \ge 22; \end{cases} \tag{24}$$

$$\mu_2(y_{(i-3)}) = \begin{cases} 0, & y_{(i-3)} < 16; \\ \dfrac{y_{(i-3)} - 16}{37-16}, & 16 \le y_{(i-3)} < 37; \\ 1, & y_{(i-3)} \ge 37; \end{cases} \tag{25}$$

$$\mu_1(y_{(i-4)}) = \begin{cases} 1, & y_{(i-4)} < 9; \\ \dfrac{20 - y_{(i-4)}}{20-9}, & 9 \le y_{(i-4)} < 20; \\ 0, & y_{(i-4)} \ge 20; \end{cases} \tag{26}$$

$$\mu_2(y_{(i-4)}) = \begin{cases} 0, & y_{(i-4)} < 15; \\ \dfrac{y_{(i-4)} - 15}{35-15}, & 15 \le y_{(i-4)} < 35; \\ 1, & y_{(i-4)} \ge 35; \end{cases} \tag{27}$$

and the obtained values of the coefficients of individual conclusions of fuzzy rules, which are the result of training neurons of the fourth layer (Table 2):

Table 2
The results of forth neuron layer training

Rule number, k	The value of the coefficient				
	z_1^k	z_2^k	z_3^k	z_4^k	z_5^k
1	0,09625	0,005382	0,7238	0,2093	-0,5021
2	0,0004083	-0,1041	0,04222	0,03792	0,07806
3	0,12625	0,025382	0,8238	0,6083	-0,4061
4	0,000605	-0,4107	0,082	0,05592	0,088
5	0,01625	0,00732	0,658	0,4093	-0,6024
6	0,04086	-0,5643	0,05642	0,03891	0,04386

7	0,00725	0,00765	0,00234	0,0054	-0,341
8	0,00055	-0,00125	0,0675	0,0743	0,0125
9	0,0356	0,00567	0,0004	0,02437	-0,0556
10	0,00044	-0,1055	0,0542	0,06492	0,00406
11	0,15525	0,03532	0,4438	0,0554	-0,0065
12	0,00705	-0,06607	0,002	0,02392	0,0508
13	0,0955	0,07582	0,0039	0,20043	-0,00561
14	0,0081	-0,1001	0,00242	0,03002	0,07006
15	0,10025	0,0202	0,808	0,6003	-0,40061
16	0,00545	-0,40007	0,0052	0,0502	0,0803

The values of the individual conclusions of the rules by the Sugeno algorithm of type 1 are determined according to expression (28):

$$Z_k = z_1^k y_{(i-1)} + z_2^k y_{(i-2)} + z_3^k y_{(i-3)} + z_4^k y_{(i-4)} + z_5^k . \tag{28}$$

Synthesized ANFIS consists of five layers. The first layer is designed to fuzzily the input values according to formulas (21) - (27) to find membership functions.

The second layer of ANFIS performs aggregation based on expressions (29) - (44):

$$G_1 = \mu_1(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{29}$$

$$G_2 = \mu_1(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{30}$$

$$G_3 = \mu_1(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{31}$$

$$G_4 = \mu_1(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{32}$$

$$G_5 = \mu_1(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{33}$$

$$G_6 = \mu_1(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{34}$$

$$G_7 = \mu_1(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{35}$$

$$G_8 = \mu_1(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{36}$$

$$G_9 = \mu_2(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{37}$$

$$G_{10} = \mu_2(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{38}$$

$$G_{11} = \mu_2(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{39}$$

$$G_{12} = \mu_2(y_{(i-1)}) \wedge \mu_1(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{40}$$

$$G_{13} = \mu_2(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) , \tag{41}$$

$$G_{14} = \mu_2(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_1(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) , \tag{42}$$

$$G_{15} = \mu_2(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_1(y_{(i-4)}) \tag{43}$$

$$G_{16} = \mu_2(y_{(i-1)}) \wedge \mu_2(y_{(i-2)}) \wedge \mu_2(y_{(i-3)}) \wedge \mu_2(y_{(i-4)}) . \tag{44}$$

In the third layer of neurons, normalization of the result of aggregation is carried out:

$$\bar{G}_k = \frac{G_k}{\sum_{k=1}^{16} G_k}; \; 1 \le k \le 16 . \tag{45}$$

In the fourth layer of ANFIS activation is carried out, and the product of the results of activation and normalization is calculated using the formula:

$$J_k = \bar{G}_k Z_k , \; 1 \le k \le 16 . \tag{46}$$

The fifth layer performs the procedure of defuzzification:

$$\tilde{y}_k = \sum_{k=1}^{16} J_k . \tag{47}$$

The result of defuzzification is a crisp value of the predicted number of failures of the *k*-th class.

To teach ANFIS to predict the number of failures of the k-th class, test data were obtained by generating random numbers with a uniform distribution. The test sample was divided into two parts. The first part was used for ANFIS training. The method of inverse error propagation was used in the learning algorithm.

The second part of the test data was used to verify the learning outcomes of ANFIS. The data used for training were organized in matrix form:

$$\begin{bmatrix} y_1 & y_2 & y_3 & y_4 & \tilde{y}_5 \\ y_5 & y_6 & y_7 & y_8 & \tilde{y}_9 \\ . & . & . & . & . \\ y_{i-4} & y_{i-3} & y_{i-2} & y_{i-1} & y_k \\ . & . & . & . & . \\ y_{I-4} & y_{I-3} & y_{I-2} & y_{I-1} & \tilde{y}_I \end{bmatrix}, \tag{48}$$

where $\tilde{y}_k$ is the predicted number of failures of the *k*-th class in the time interval *i*, $1 \le i \le I$. The training was based on data for $I = 5000$ cycles and was conducted in the Matlab environment [11]. The result of the training was finding the correct values of the corresponding parameters of the membership functions of formula (20) - (27) and coefficients (Table 2).

After training, data from the second test part were submitted to the ANFIS input, and the initial value was compared with the expected result. As a result of numerical simulation simulations, it was found that the accuracy of predicting the value $\tilde{y}_k$ is 94-96%.

6. Conclusion

The paper proposes an approach for updating route metrics using a priori data on the reliability of military network routers based on ANFIS. ANFIS allows getting the reliability index value, which provides an early decision on using backup routes in the next time interval and helps to ensure better QoS parameters. The ANFIS synthesis was performed to predict the number of *k*-th class failures. This system was trained on test data, and its effectiveness was investigated. Further research aims to determine the dependences of QoS indicators using the proposed approach in implementing the military telecommunication network.

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