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Improving the recognition of operating modes in intelligent electrical networks based on machine learning methods

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Abstract. Digitalization in the power industry makes it possible to form in real time and accumulate large amounts of data about the state of connections, equipment at substations and the power system as a whole (currents, voltages, power, phase between current and voltage, discrete signals, etc.). The processing and use of data arrays makes it possible to develop fundamentally new algorithms for the operation of automation systems, relay protection and control of electrical networks. The article analyzes the prospects of using methods based on multiple simulation, statistical processing of the results of model experiments and machine learning in relay protection and automation of electrical networks. New methods are proposed for combining logical signals from various triggering elements of a multidimensional relay protection device to increase the reliability and recognizability of normal and emergency operating modes of the power system using an artificial neural network and the decision tree method. The parameters of actuation of individual one-dimensional triggering elements are determined according to the Bayesian criterion for minimizing the average risk.

1 Introduction

In recent years the development of sources of distributed generation (gas turbine, gas piston, diesel generating plants, solar and wind power plants) causes a variety of possible circuit-mode situations that didn't exist earlier. This leads to the impossibility of visual recognition of modes and manual control of them, complicates the task of control of modes due to the increase in its dimension. The existing algorithms of relay protection and automation (RPA) devices of power systems not always meet the requirements of power supply systems with distributed generation facilities [1-3]. The basic algorithms of RPA devices have not fundamentally changed over the past decades and, in fact, they are digital analogs of their electromechanical predecessors [4]. Because of this, there are more frequent accidents at small power plants, unnecessary shutdowns of power plants, which brings damage to consumers.

At the same time, modern RPA devices supporting the IEC 61850 allow access to the large amount of information about the protected or controlled power facility in real time. All this creates the prerequisites for the construction of modern power systems with new generation RPA devices operating according to new algorithms.

One of the most promising options for organizing RPA are multidimensional protection (automation) and an "information approach" based on multiple simulation and statistical processing of simulation results [6-9]. In particular, it is advisable to use elements of artificial intelligence and machine learning to improve the recognition of the states of electrical networks (normal, emergency and pre-emergency modes). It is known to use methods of processing redundant relay protection information and, in particular, voting schemes to improve reliability [10-11]. Technical solutions for RPA using artificial intelligence and machine learning, including algorithms for recognizing the modes of an electric network based on artificial neural networks (ANN) and a decision tree (DT), were discussed in [12-17]. However, for the organization of a logical part that unites several triggering elements of multi-dimensional relay protection, artificial intelligence methods were not used.

2 Purpose of the research

The purpose of the research is to build multidimensional relay protection with the combination of individual triggering elements through the logical part of the RPA system to increase the reliability and recognizability of normal and emergency operating modes using methods based on ANN and machine learning.

3 Information approach in multidimensional protection

The information approach provides for the mandatory use of multiple simulation of normal and emergency modes of electric power networks. The simulation results

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are used to create and test the developed algorithms for relay protection and automation. Conditions are created for the development of multidimensional relay protection, which internally combine several observed parameters of the power system [6-9]. Thus, in one relay protection device there are several one-dimensional relays, and each triggering element (TE) can be considered as a separate relay protection. An increase in the dimension of protection (two or *p*-dimensional) entails complication of the determination of settings and the implementation of algorithms for combining information from individual TE of relay protection.

In the course of the research, a simulation model of a 220 kV electrical network was used (Figure 1). It is implemented in the Matlab/Simulink software package (Figure 2). The model represents three sections of the overhead line 220 kV, two power supplies and a short-circuit breaker through the transition resistance in the reserve protection zone RP1. The data accumulation of the measured currents and voltages was carried out in the place of installation of the protection RP1 at the beginning of the overhead line (Figure 1). They are necessary for the implementation and research of the developed relay protection and automation system.

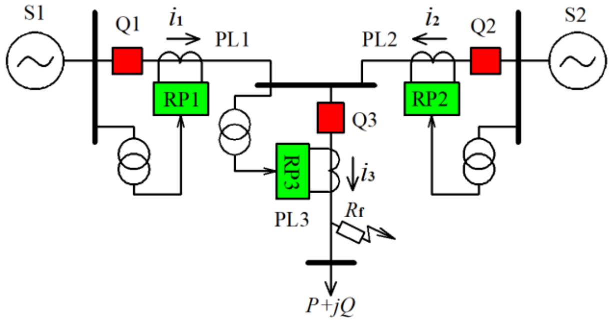

Fig. 1. Circuit of the observed section of the 220 kV electrical network.

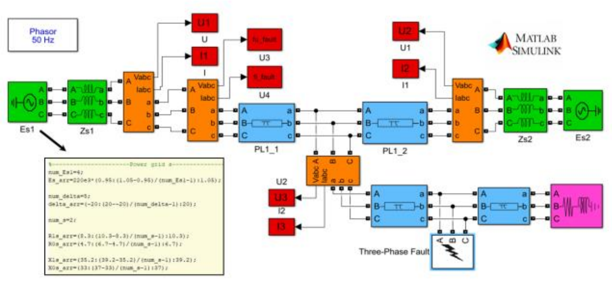

Fig. 2. Model of the observed section of the 220 kV electrical network.

The parameters of the elements of the simulation model are shown in Table 1, 2. It should be emphasized that during the operation of the network section (Figure 1), the parameters of the elements may deviate from the specified values during design. According to this, in order to obtain the required statistics on the network operation modes, the model parameters are divided into deterministic and stochastic ones, varying in the specified ranges. The indices "1" and "0" (Table 1, 2) mark the parameters of the direct and zero sequences.

Table 2 includes the following coefficients that specify the range of voltage variation of power systems and the phase shift angle between them:

$$k_1 = Es1 / U_{nom}, k_2 = Es2 / U_{nom}, \delta = arg(Es1 / Es2). \quad (1)$$

To obtain statistical distributions of the parameters of normal and emergency modes of electrical simulation, it was assumed to carry out 10 000 iterations, including in the conditions of single-phase short circuits along the line PL3, which represents the reserve zone of the observed protection PR1.

Table 1. Deterministic parameters of the elements of the simulation model

Parameter	Value
U_{nom}, kV	220
$L1$, km	100
$L2$, km	100
$L3$, km	100
$b1^{1,2,3}$, Cm/km	$j0{,}65 \cdot 10^{-6}$
$b0^{1,2,3}$, Cm/km	$j0{,}65 \cdot 10^{-6}$
$R1^{s1,s2}$, Ohm/km	0
$R0^{s1,s2}$, Ohm/km	0

Table 2. Stochastic parameters of the elements of the simulation model

Parameter	Value	Parameter	Value
$X1^{s1}$, Ohm/km	25,09 (±1)	l_{line}	0,0001…0,9999
X0s1, Ohm/km	1,31 (±1)	R_f, Ohm	0,1…40
$X1^{s2}$, Ohm/km	9,75 (±1)	δ, °	-30°… 30°
$X0^{s2}$, Ohm/km	0,87 (±0,1)	k_1	0,95…1,05
$R1^{1,2,3}$, Ohm/km	0,13 (±0.01)	k_2	0,95…1,05
$R0^{1,2,3}$, Ohm/km	0,27 (±0.1)	P, MW	300 (±10)
$X1^{1,2,3}$, Ohm/km	0,332 (±0.01)	Q, MVar	150 (±10)
$X0^{1,2,3}$, Ohm/km	0,332 (±0.01)		

When constructing a multiparameter RPA system, five separate one-dimensional triggering elements were used: TE1 - by the current modulus; TE2 - by the voltage modulus; TE3 - by the voltage phase; TE4 - by active power; TE5 - by reactive power. The obtained data statistics in the form of histograms, permissible and emergency modes of each triggering elements, are approximated by a normal (Gaussian) distribution. An example for current is shown in Figure 3. On the graphs of densities of normal distribution, the horizontal axes represent measurements of the observed parameters of triggering elements in permissible (normal) and emergency modes along the overhead PL3 (Figure 1). The ability to recognize normal and emergency modes of the electrical network by the relay protection device is determined by the size of the intersection area of the curves of statistical distributions. Ideal, 100% recognizability is carried out in the absence of intersection of these curves.

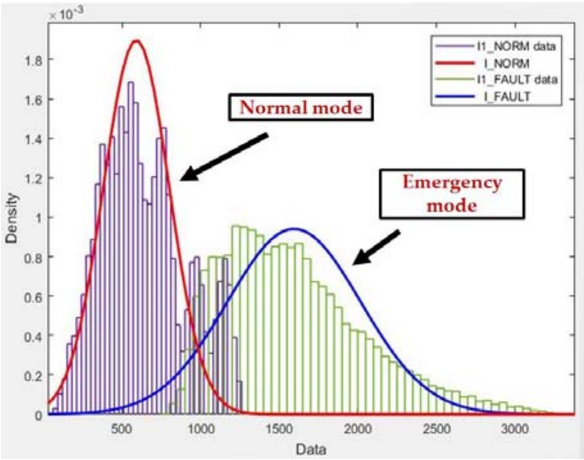

Fig. 3. Probability density graph of normal distribution of normal and emergency modes of the current module.

4 Determination of settings of triggering elements of multidimensional relay protection

As a method for determining the settings of individual one-dimensional protections (triggering elements), a statistical approach is proposed with the solution of a two-hypothetical binary tasks. If the measurement belongs to the area of normal modes, the hypothesis H_0 is accepted (output signal "0" - not operation of the RPA). If the measurement belongs to the area of emergency modes, hypothesis H_1 is accepted (output signal "1" - relay operation). Determination of the settings η of individual TE is possible based on the Bayesian decision criterion [18, 19]. The Bayesian criterion provides complete detuning from all normal modes. In this case, the relay must not work.

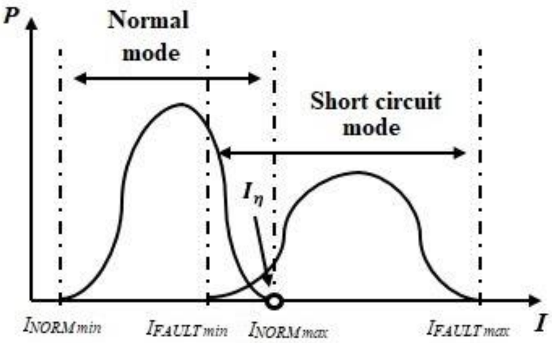

Fig. 4. Determination of settings (presence of a non-recognition zone).

Determination and calculation of the setpoint η according to the Bayesian approach makes sense only when the areas of normal and emergency modes intersect, i.e. the probability density functions $P_{H0}(p_i(t)|H_0)$ and $P_{H1}(p_i(t)|H_1)$. For example, for a triggering element by current (Figure 4), the intersection area refers to the segment ($I_{FAULT\ min}$, $I_{NORM\ max}$). In this case, the setpoint corresponds to the $I_{NORM\ max}$ value. If the zone of normal and emergency modes does not intersect, there is no recognition. As a result, the determination of the settings is considered simple and can be located at any point of the segment ($I_{NORM\ max}$, $I_{FAULT\ min}$) (Figure 5).

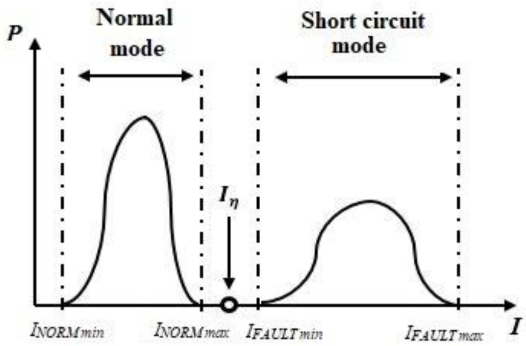

Fig. 5. Determination of settings (absence of a non-recognition zone).

The settings for each individual TE were determined according to the two-hypothesis principle (Figure 6). To determine the probability of the zones of operation and non-operation belonging to the hypotheses H_0 (permissible mode) and H_1 (emergency mode), the features of the normal distribution of a continuous value were used. Table 3 shows the probability of operation (p_1) and non-operation ($q_1 = 1\text{-}p_1$) of each TE for the curve belonging to the emergency mode. The probability of operation p_1 corresponds to the area under the emergency mode curve belonging to the hypothesis H_1, and the probability of non-operation q_1 of the area under the same curve belonging to the hypothesis H_0. Based on the above, the curve of normal modes completely belongs to the hypothesis H_0 ($p_0 = 0$, $q_0 = 1$).

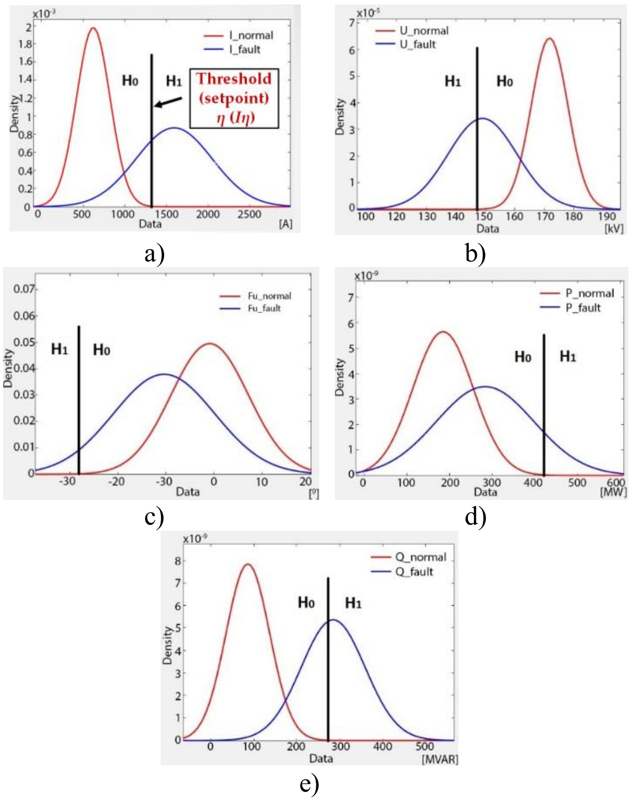

Fig. 6. Determination of the set values: a) TE1 - by the current module; b) TE2 - by the voltage modulus; c) TE3 - by the voltage phase; d) TE4 - by active power; e) TE5 - by reactive power.

Table 3. Probabilities of recognition of emergency modes of individual triggering elements

Triggering elements	Parameter	p_1 (%)	q_1 (%)
TE1 - by the current module	I_m	69,27	30,73
TE2 - by the voltage modulus	U_m	38,09	61,91
TE3 - by the voltage phase	φ_u	20,52	79,48
TE4 - by active power	P	13,03	86,97
TE5 - by reactive power	Q	47,98	52,02

The set of binary (0 or 1) random variables from the outputs of N protections (triggering elements) makes up the N-dimensional vector of the received signal $X = \{\varphi 1, \varphi 2, \ldots \varphi i, \ldots, \varphi N\}$. Each realization of the vector X at the moment t arrives at the input of the solver. Its task is to determine in the best way whether the received sample characterizes normal operation or it refers to an emergency. To increase the sensitivity of the relay protection and recognition of emergency modes, it is necessary to correctly combine binary signals in the logical part of the multidimensional relay protection and automation system.

5 Combining binary signals from individual triggering elements using an artificial neural network

Let us consider the essence of this method on a short description of simple ANN configurations. The structure of network connections can be represented by a directed graph, which, in fact, is a multi-layer network with separate neural layers connected by synapses (synoptic connections). Each synapse represents a weighted coefficient *w*. For such a multilayer structure, one layer is input, the other is output, and the rest of the inner layers are intermediate. It should be emphasized that the nature of the connections of neurons within layers and between layers can be different. Communications between elements of one layer, communications of elements with themselves are allowed, and there is also the possibility of feedback between layers.

From the point of view of one neuron (Figure 7), the rule for calculating the activity signal is called the activation function *f(s),* and the corresponding output value is the activity of the element. The activation function limits the activity to 0 or 1 depending on the value of the combined input and can be linear or non-linear. Most neural networks use non-linear activation functions. A frequently used nonlinear activity function is the so-called “sigmoidal function”, which continuously fills the range from 0 to 1 (2) [20]:

$$f(s) = \frac{1}{1 + e^{(-\beta \times s)}}, \qquad (2)$$

where β - a coefficient that determines the slope of the transfer function

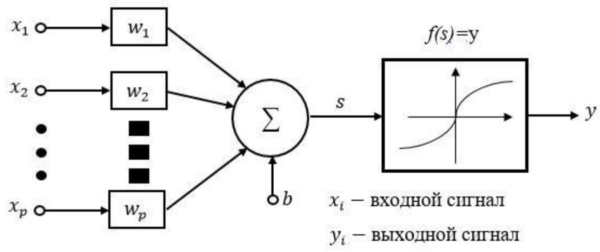

Fig. 7. Block diagram of a single neuron.

The purpose of the ANN is to combine the binary signals of the input sample *X*, which fell on the logical part (LP) of a multidimensional relay protection device and correctly classify the set of input data into one of two classes: normal mode (signal "0" at the output) and emergency mode (signal "1" at the output).

To combine signals and increase the recognition of emergency modes, the "*Neural Network Pattern Recognition (nprtool)*" application of the Matlab software package was used. When training ANN for the requirements of relay protection, a simple structure with one intermediate layer with ten neurons was used. The input layer contains five neurons corresponding to each element of the sample of the vector *X*. The output layer contains two neurons (0 or 1) that determine recognizability and decide whether the protection is triggered or not (Figure 8). The block diagram of the combination of logical signals of individual TE using ANN is shown in Figure 9.

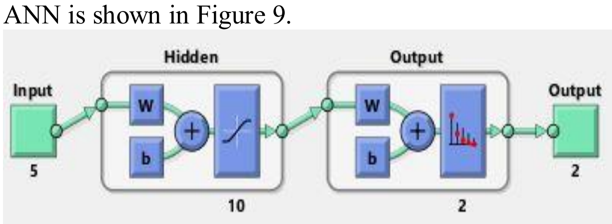

Fig. 8. Artificial neural network model.

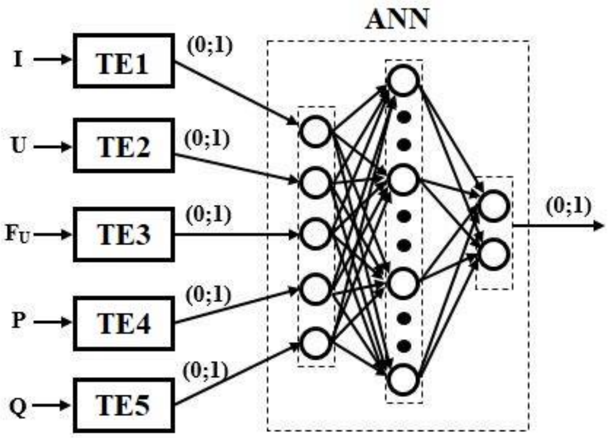

Fig. 9. ANN signal combining circuit.

To train the ANN, 14 000 combinations of normal and emergency modes (70% of the total sample loaded for experiments with ANN) were used. These combinations were chosen at random. Also 3000 combinations (15%) were used for validation and 3000 (15%) - for testing. The training of the neural network model was achieved in 25 iterations with a duration of about 1ms. The final confusion matrix (Figure 10) displays the ratio of recognizable and unrecognizable relay protection and automation modes, as well as the number of used experimental measurements of normal modes (10000 = 50%) and emergency modes (10000 = 50%).

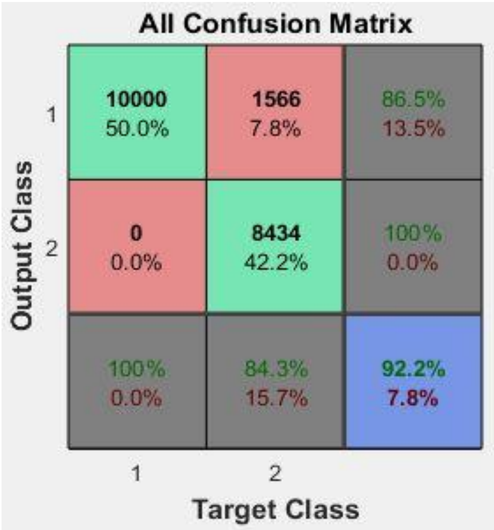

Fig. 10. ANN confusion matrix.

The matrix element (1,1) represents the normal modes recognized by the ANN, and (2,2) - emergency modes. The element of the matrix (1,2) characterizes the modes that are considered emergency, but turned out to be normal during training (incorrect recognition of emergency modes). Field (2,1) corresponds to modes that are considered normal, but turned out to be emergency during training (incorrect recognition of normal modes). Analysis of Figure 10 it can be seen that the complete detuning from normal modes is performed correctly (field (2,1) is equal to 0), and when signals are combined in the logical part of a multidimensional relay protection and automation system, the recognition of emergency modes increased and is 84.34%.

6 Combining binary signals from individual triggering elements using the decision tree method

To combine the output binary signals of the TE within the logical part of a multidimensional relay protection and automation system, a decision tree method is proposed. The implementation of signal combining by the DT method was carried out in the "*Classification Learner (fitctree)*" application of the Matlab software package. The classification of signals was carried out with 20 000 observations (10 000 observations of emergency and 10 000 observations of normal modes), constituting a database of parameters of the electrical network mode at the installation site of RP1. The structure of the resulting tree and the scheme for combining signals in the logical part using the DT method are shown in Figure 11 and Figure 12.

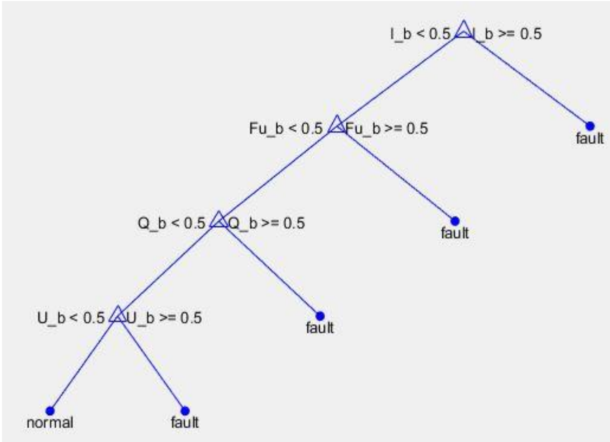

Fig. 11. The structure of the observable decision tree.

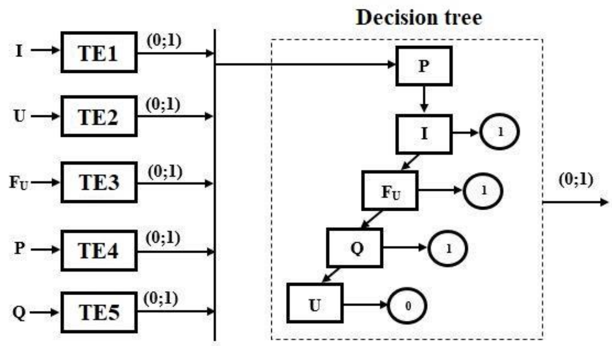

Fig. 12. Signal combining scheme using the decision tree method.

From the analysis of the structure of the decision tree (Figure 11) it was determined that when combining logical signals, only four TE are sufficient. TE4 in terms of active power does not affect the increase in the recognition of modes, i.e. it is superfluous when forming a multi-parameter relay protection and automation system. Active power monitoring is optional. Thus, protection is simplified and its reliability is additionally increased, while maintaining high recognizability of emergency modes.

Calculations of the confusion matrix DT (Figure 13) show that it corresponds to the confusion matrix of the ANN.

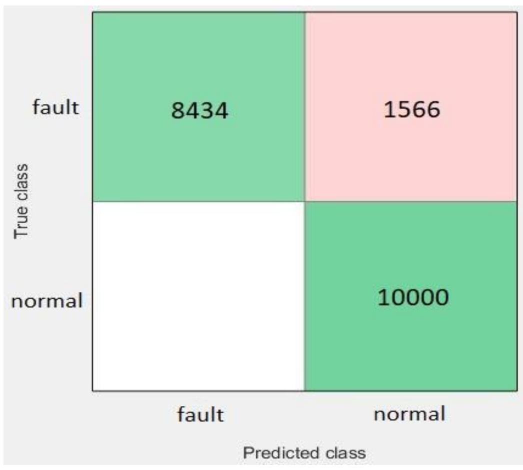

Fig. 13. Decision tree confusion matrix.

The diagonal fields (fault, fault) and (normal, normal) represent the correct recognition of fault and normal modes. The (normal, fault) field, representing the number of modes in which the relay protection device does not work correctly, turned out to be zero. The number of unrecognizable emergency modes was 15.66% (fault, normal). Thus, when the logical signals from the TE are combined by the decision tree method, the protection will work correctly, and the recognition of emergency modes increases to 84.34%.

7 Combined method

To increase the reliability of the multidimensional relay protection system, it is proposed to organize the logical part of the protection device with a combination of ANN and DT methods based on voting according to the "1 out of 2" principle. To assess the reliability of such a logical part, a failure model of non-recoverable systems was used. The combination of methods is carried out by means of parallel connection of the blocks implementing them (Figure 14).

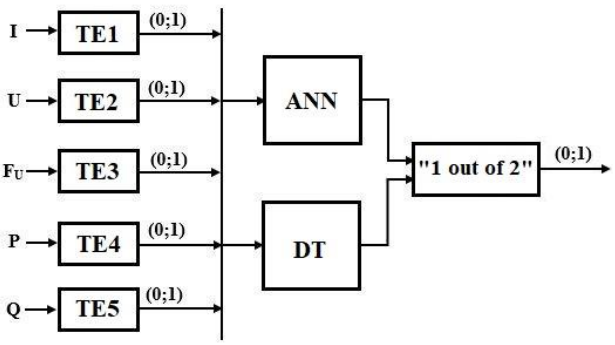

Fig. 14. Diagram of the logical part for the combined method.

Based on the fact that ANN and DT are considered reliable methods, we assume that the probabilities of failure-free operation of the ANN and DT units (Figure 14) are the same. They correspond to the probabilities of microprocessor logic solvers used at high security facilities and is 99.4% during the operation period [21].

The failure model of non-recoverable systems implies that: $p_i(t)$ is the probability of failure-free operation of the *i*-th system; $q_i(t)$ is the probability of failure of the *i*-th system. From the assumption that the methods (systems) have the same probability of failure-free operation during the operation of relay protection and automation ($p_1(t) = p_2(t) = 0.994$) the probability of failure is defined as:

$$q_i(t) = 1 - p_i(t) . \qquad (3)$$

As a result, it turns out that $q_1(t) = q_2(t) = 1\text{-}0.994 = 0.006$. With parallel connection of logical blocks of ANN and DT, the probability of failure of the combined voting principle "1 out of 2" of the system is [15]:

$$q(t) = \prod_{i=1}^{n} q_i(t) . \qquad (4)$$

Setting numerical values in equation (4) leads to the probability of failure of the integrated relay protection system equal to $q(t)=3.6\cdot10^{-5}$. Based on this, the probability of no-failure operation is

$p(t) = 1\text{-}q(t) = 1\text{-}3.6\cdot10^{-5} = 0.99996\approx100\%$.

Thus, the combination of methods for organizing the relay protection and automation equipment based on the "1 out of 2" principle leads to a significant increase in the reliability of RPA.

Conclusion

For the implementation of multidimensional relay protection and automation, the results of simulation of the electrical network and statistical methods for processing the results of model experiments were used. The settings of five separate triggering element were determined according to the Bayesian criterion.

The applicability of methods for combining signals in the logical part of a multidimensional relay protection and automation system with the use of artificial intelligence is analyzed: artificial neural network, decision tree and voting schemes according to the "1 out of 2" principle.

A multidimensional relay protection and automation system with five single one-dimensional triggering elements is investigated. TE1 according to the current module has the highest recognizability of emergency modes. The recognition probability is 69.27%. Combining logical signals using the three proposed methods provided an increase in the probability of recognizing an emergency mode up to 84.34%.

The choice of the method for combining the output signals from the triggering elements in the logical part of the multidimensional relay protection and automation system depends on the features of the modes of the electrical network and the requirements for organizing the protection of an electrical power facility.

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