Досліджено можливість розробленої підсистеми самодіагностики інформаційно-вимірювальної системи випробувань гідравлічних передач тепловозів. Запропоновано використання нейро-фаззі контролерів для прогнозування окремих параметрів гидропередачі з подальшим порівнянням прогнозованих даних з даними, отриманими від датчиків вимірювання цих параметрів. Істотна відмінність даних прогнозу і вимірювання говорить про можливу несправність датчиків. Результати дослідження підсистеми на реальних даних випробування показали ефективність

Ключові слова: гідравлічна передача тепловоза, інформаційно-вимірювальна система, датчики вимірювання параметрів, нейро-фаззі контролер

Исследована возможность разработанной подсистемы самодиагностики информационно-измерительной системы испытаний гидравлических передач тепловозов. Предложено использование нейро-фаззи контроллеров для прогнозирования отдельных параметров гидропередачи с последующим сравнением спрогнозированных данных с данными, полученными от датчиков измерения этих параметров. Существенное различие данных прогноза и измерения говорит о возможной неисправности датчиков. Результаты исследования подсистемы на реальных данных испытания показали ее эффективность

Ключевые слова: гидравлическая передача тепловоза, информационно-измерительная система, датчики измерения параметров, нейро-фаззи контроллер

UDC 629.424.1-82:004.318
DOI: 10.15587/1729-4061.2018.123591

DEVELOPMENT OF A SELF-DIAGNOSTICS SUBSYSTEM OF THE INFORMATION-MEASURING SYSTEM USING ANFIS CONTROLLERS

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1. Introduction

Information-measuring systems (IMS) are used in many industries. Numerous object parameters are measured by these systems using specialized sensors. Any information-measuring system requires diagnostic tools. Usually, these are additional hardware and software means. In order to cut costs, it is necessary to avoid additional costs of hardware diagnostics.

To reduce the cost of specialized equipment, a mechanism of indirect diagnosis with analysis of measurement results can be used. Self-diagnostic algorithms will detect malfunction using only the data sets obtained from existing sensors. Such a method of self-diagnostics can be used in the process of the working cycle of the information-measuring system. This ensures high speed of obtaining diagnostic data.

The problem of such indirect mechanisms of self-diagnostics involves development of some mechanisms for analyzing measurement results, especially in the event of a possible large scatter of measurement results. The measurement results can be compared with theoretical calculations based on the results of measuring other system parameters. However, the functional relationship between system parameters is weak or not known at all in some cases. Therefore, it is relevant to study the possibilities of predicting values of one system parameters using values of other parameters in conditions of an indefinite functional connection between them.

2. Literature review and problem statement

In the course of this study, a number of questions arose regarding determination of the status of correct and adequate operation of the information-measuring system, that is, the organization of a self-diagnostics task. Certainly, work can be confined to creation of a simulator based on an industrial computer (e. g., Advantech, Siemens, Segnetics, Mitsubishi, OBEH, etc.) [4, 5]. Such a simulator would simply perform simulation of sensors based on previously recorded readings of the system instruments. However, this method has a significant drawback: it does not allow one to check serviceability of the sensors themselves installed on the test bench.

Papers [6, 7] describe the mechanism of checking technical state of the system sensors and the lines of communication with them based on several data samples obtained during this system testing. Next, calculations that relate the sample data with other system parameters are made. The results of these calculations are compared with the data samples taken from other sensors. Sufficient coincidence of the calculated data with the sample data confirms serviceability of the sensors and communication lines.

Calculation of the rotational speed at idle motor rotation does not present much difficulty and is nothing but a solution of a simple problem of mechanics and electrical engineering. However, in a large number of other cases (at not the idle motor run when determining dependence of the drive motor rotational speed from the pump wheel), significant difficulties arise. Since the hydraulic transmission is a rather complicated technical device, solution of such a problem requires solution of a rather voluminous system of nonlinear differential equations [8].

As study [8] show, solving a system of differential equations for checking the parameters obtained from one hydrotransformer requires both significant computational resources and a large volume of initial data on the hydrotransformer design. In practice, it is difficult to obtain such data. The hydraulic transmissions for which the system has been developed contains also a hydrotransformer, a hydraulic coupling, a lubrication system, a working fluid circulation loop, etc. Also, all these components contain sensors necessary for checking and therefore these components must be considered as separate subsystems solution of which requires setting up not less cumbersome systems of differential equations.

In addition, to obtain the calculation data, it is necessary to compare them in some way with the real data and establish reliability of the system operation. Since it is impossible in this case to clearly define correctness or inaccuracy of the results obtained, it is advisable to introduce elements of fuzzy logic [9, 10].

Thus, it is expedient to divide all system parameters being measured into two groups. The first group of parameters is related to mathematical dependencies which can be easily solved in operation of the diagnostic subsystem. This enables the use of the mechanism of comparison of measured and calculated values of the same parameters in the self-diagnostic subsystem. For other group of parameters, relation is described by a rather voluminous system of nonlinear differential equations and contains a large number of nondetermined initial data. To predict values of this group of parameters, it is advisable to use a neural-fuzzy controller. To verify operation of sensors of individual subsystems of the hydraulic transmission test bench, it is necessary to create separate neural networks. This approach greatly simplifies development and allows one to completely abandon rather complex mathematical calculations by introducing elements of artificial intelligence. There is a lot of studies devoted to elaboration of neural-fuzzy controllers [10, 11].

Fuzzy neural or hybrid networks are designed to combine benefits of the neural networks and the fuzzy inference systems. They ensure development and presentation of the system models in a form of rules of fuzzy inferences and the possibilities of the neural network are used for creation of rules of fuzzy inferences. Studies [12, 13] indicate that it is advisable to use an adaptive network-based fuzzy inference system (ANFIS) in this case. Means for designing such a network are implemented in the Fuzzy Logic Toolbox of the MATLAB system. ANFIS is one of the first variants of hybrid neuraln-fuzzy networks whose architecture is isomorphic to the fuzzy knowledge base. Typically, differential realizations of triangular norms and smooth membership functions are used in neural-fuzzy networks of the ANFIS type [14, 15].

As studies have shown, there are practically no systems of self-diagnostics of the information-measuring systems of testing hydraulic transmissions of diesel locomotives. Based on the review of works devoted to creation of such systems in other industries, one can conclude that creation of a hybrid self-diagnostic system using the ANFIS neural-fuzzy network is the most promising.

3. The aim and objectives of the study

The study objective was to elucidate the way of constructing the mechanism of self-diagnostics using the ANFIS controllers to predict chosen parameters of the system based on the results of measurement of other parameters. Thereafter, the prediction results are compared with the results obtained by the sensor. This makes it possible to quickly determine technical state of the sensor and the communication line within the system operating cycle and without additional hardware costs.

To achieve this objective, the following tasks were solved:

– analyze the dependencies describing relations of the parameters measured by the information-measuring system of testing hydraulic transmissions of diesel locomotives;

– conduct analysis of the neural networks and the systems of fuzzy logic for the purpose of their application in development of the self-diagnostic subsystem of the information-measuring system for testing hydraulic transmissions of diesel locomotives;

– study applicability of the neural-fuzzy controllers (ANFIS) in development of the self-diagnostics subsystem of the information-measuring system of testing hydraulic transmissions of diesel locomotives;

– construct and test the self-diagnostics subsystem (checking the technical state of sensors) of the information-measuring system of hydraulic transmissions of diesel locomotives using the hybrid ANFIS system.

4. Materials and methods for studying the application of neural-fuzzy networks in the design of the self-diagnostic subsystem

As an example, the information-measuring system of the locomotive hydraulic transmission [1, 2] test bench is considered. The block diagram of the system is shown in Fig. 1. According to the factory test program, 13 most needed and critical process parameters were selected for measurement. Oil temperature and pressure at different points of the hydrotransformers, rotational speed of various shafts of the test bench and hydrotransformer should be monitored. Besides, current and voltage in coils of the drive motor and the loading generator have to be monitored.

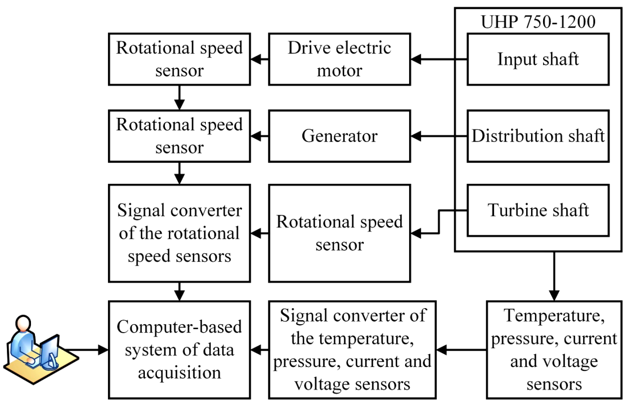


Fig. 1. Block diagram of the information-measuring system for testing hydraulic transmissions of diesel locomotives [2]

Thus, this information-measuring system requires an additional study related to solving the problem of self-diagnostics. In the future, it is possible to create a complex of diagnostics of hydraulic transmission based on the self-diagnostics subsystem.

To develop a subsystem of self-diagnostics of the information-measuring system of testing hydraulic transmissions of diesel locomotives, it is necessary to determine the mode of operation of the system in which the process of self-diagnostics will be performed. Proceeding from [8], conducting self-diagnostics in transient operation conditions of hydraulic transmission is inappropriate. Therefore, self-diagnostics of the system in the steady-state conditions will be considered. Since the system performs measurement of parameters of the hydraulic transmission of UHP 750 type where there are two separate hydrotransformers, the self-diagnostics system must be divided into two separate systems: for the first and the second hydrotransformers, respectively.

As is well known from the theory of designing hydraulic transmissions [1], some of the measured parameters can be calculated and interconnected in steady-state conditions. These parameters include: current I_m, voltage U_m and rotational speed n of the drive motor. The statistical parameters of these quantities can also be interrelated.

These parameters can be related through the loading characteristic. Theoretically, the loading characteristic of the hydrotransformer can be calculated by the following formula [1]:

$$M_{P(theor)}^{\mathrm{HTR}} = A_P^{\mathrm{HTR}} \cdot \gamma \cdot D_a^5 \cdot n_P^2 \cdot 9{,}81 \cdot 10^{-4}, \tag{1}$$

where $M_{P(theor)}^{\mathrm{HTR}}$ is the theoretical loading characteristic of the hydrotransformer, N·m; $A_P^{\mathrm{HTR}} \cdot \gamma$ is the torque factor of the pump wheels, $(n_{\mathrm{t}}/n_{\mathrm{p}})$; D_a^5 is the active diameter of the hydrotransformer, m; n_H^2 is rotational speed of the pump wheel, min^{-1}.

Proceeding from the fact that a DC motor is used as a drive motor, it will be practical to express the obtained loading characteristics through the moment of force of the drive motor which is represented by formula [1]:

$$M_m = \frac{I_m \cdot U_m \cdot \eta_m \cdot 9549}{n}, \tag{2}$$

where M_m is the moment at the drive motor, N·m; I_m is the motor current, A; U_m is the motor voltage, V; η_m is the motor efficiency; n is the motor rotational speed, min^{-1}.

Thus, the obtained loading characteristic of the hydrotransformer can be practically calculated by the following formula [1]:

$$M_{\mathrm{P(pract)}}^{\mathrm{HTR}} = \frac{M_m \cdot \eta_{\mathrm{kzp}} \cdot \eta_{\mathrm{kb}} \cdot \eta_{podsh} \cdot \eta_{dop}}{i_{kzp}}, \tag{3}$$

where $M_{\mathrm{P(pract)}}^{\mathrm{HTR}}$ is the practical loading characteristic of the hydrotransformer, N·m; η_{kzp} is efficiency of the toothed pair, correct.; η_{kb} is efficiency of bearings; η_{podsh} is the engine efficiency; i_{kzp} is reduction ratio of the toothed pair, correct.; η_{dop} is the efficiency taking into account losses on the drive motor caused by additional units.

By linking (1)–(3), it is possible to express some parameters through others. For example, the motor current can be represented by the following formula [1]:

$$I_m = \frac{M_{P(theor)}^{\mathrm{HTR}} \cdot i_{kzp} \cdot n}{\eta_{kzp} \cdot \eta_{kb} \cdot \eta_{podsh} \cdot \eta_{dop} \cdot U_m \cdot \eta_m \cdot 9549}. \tag{4}$$

In the same way, it is possible to present calculation of the drive motor voltage, rotational speed of the drive motor, rotational speed of the speed sensor with application of known regularities:

$$n_t = n^* K_t, \tag{5}$$

$$n_p = n_s^* K_p, \tag{6}$$

where n_t is rotational speed of the turbine wheel of the hydrotransformer, min^{-1}; n_p is frequency of rotation on the pump wheel of the hydrotransformer, min^{-1}; n_s is rotational speed on the speed sensor, min^{-1}; K_t, K_p are reduction ratios of the corresponding gear wheels.

The information-measuring system assumes obtaining of a number of other parameters shown in Fig. 2. The mathematical dependencies describing connections of these parameters [1] are quite complex and cannot be implemented without significant simplifications. Therefore, to calculate (predict) these dependencies, it is expedient to use the mechanism of neural networks. According to data of [2], the ANFIS model performance is better than that of the conventional neural network models. As can be seen in Table 1, the root-mean-square error (RMSE) is the smallest in an ANFIS-based model.

It can be concluded from the above that although the difference between the conventional neural network and the

ANFIS system is negligible, the ANFIS system is much more clear and convenient to use. Therefore, in this case, it would be advisable to use the adaptive network-based fuzzy inference system (ANFIS), the artificial neural network based on the Takagi-Sugeno fuzzy inference system.

Table 1

Root-mean-square error of various prediction models

Prediction model	Rules	Iterations	RMSE
Multiple regression	–	10	7.9221
Neural network	–	10	2.8082
Sugeno-Yakusawa	6	10	4.8290
ANFIS	7	10	2.6301

The ANFIS network makes it possible to work with both fuzzy and clear data. Rows of clear data can be described by statistical dependencies. In this case, the fuzzy mechanism of the ANFIS compensates for uncertainty of the mathematical model of the system. It is precisely the mechanism of working with clear time series of data having its statistical dependencies which is used in the proposed subsystem of self-diagnostics.

Since there are two hydrotransformers, it is necessary to create two pairs of sets of systems of neural-fuzzy logic for each hydrotransformer. Each set contains 7 systems of neural-fuzzy logic (ANFIS) to predict each of the required parameters based on all others. Fig. 2 shows the diagram of data flows of the self-diagnostic system taking into account the above problem statement.

To design the ANFIS system, the MATLAB Fuzzy Logic Toolbox extension package was used.

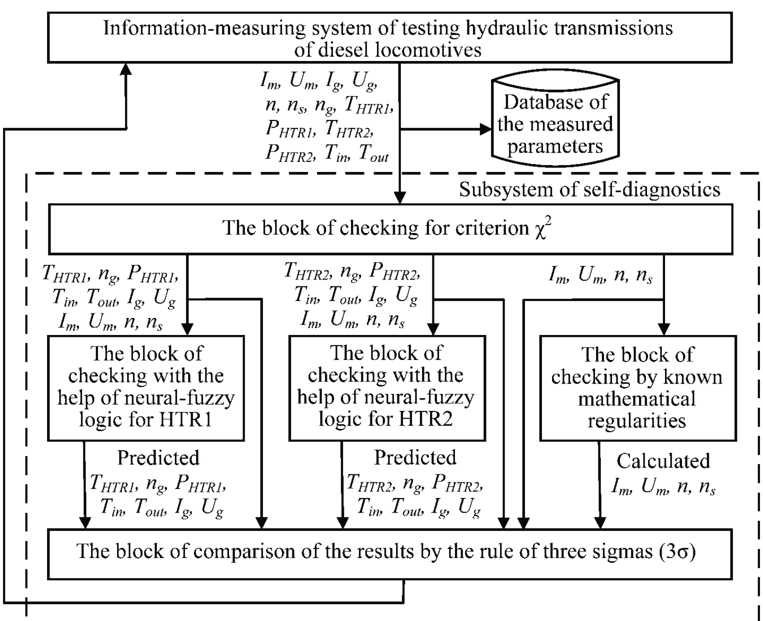


Fig. 2. Diagram of data flows of the system self-diagnostics: I_g is generator current; U_g is generator voltage; T_{HTR1} is oil temperature of the first hydrotransformer; T_{HTR2} is oil temperature of the second hydrotransformer; n_g is rotational speed of the loading generator; P_{HTR1} is oil pressure of the first hydrotransformer; P_{HTR2} is oil pressure of the second hydrotransformer, T_{in} is oil temperature at the inlet of the hydraulic transmission; T_{out} is oil temperature at the output of the hydraulic transmission

Fig. 3 shows the structural diagram of implementing one of 14 constructed classical neural-fuzzy ANFIS networks with reference to the MATLAB development environment.

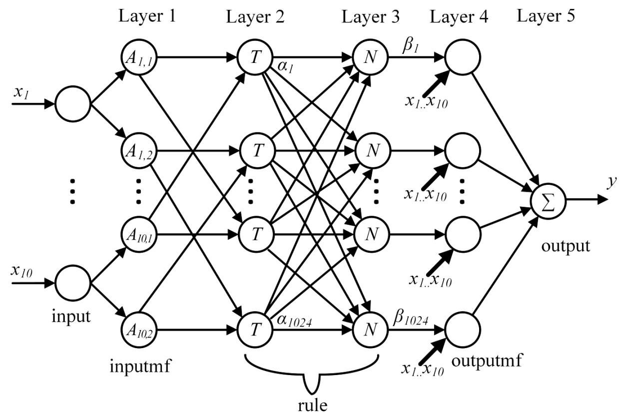


Fig. 3. The structure of the neural-fuzzy ANFIS network

In MATLAB, the input layer performs the function of parameter input, e.g. to predict T_{HTR1}, the inputs $x_1 ... x_{10}$ obtain the following parameters: I_m, U_m, n, n_s, , P_{HTR1},, T_{in}, T_{out}, I_g, U_g, n_g.

Layer 1 (inputmf in MATLAB) determines values of the membership functions at the corresponding assigned input values $x_1 ... x_{10}$. As in this case, the Gaussian membership functions are often applied:

$$A_{i,j}(x_i) = \exp\left(-\frac{1}{2}\cdot\left(\frac{x_i - a_{i,j}}{b_{i,j}}\right)^2\right),$$

$$i=1..10, j=1,2, \tag{7}$$

where $a_{i,j}$, $b_{i,j}$ are parameters requiring adaptation (adjustment) in the training process.

The membership functions of the two terms of the first input (oil temperature at the inlet of the hydrotransformer (T_{in})) during the test of the first hydrotransformer are shown in Fig. 4. It is seen that the initial value $a_{1,1}$=223.5 is the lower boundary of the input parameter. It is also evident that the membership functions are "trimmed" at the upper and lower boundary value of the parameter.

Layer 2. The number of nodes (neurons) in this layer is equal to the number of fuzzy rules in the rule base. For the network being designed, 1,024 rules are defined. Each node of the second layer is connected to 10 (out of a total of 20) nodes of the first layer which form antecedents of the corresponding rule. Outputs of the neurons of this layer are clear values of the degree of the pulsing truth of each k-th rule of the knowledge base of the system calculated by the formula:

$$\alpha_k = \prod_{i=1}^{10} A_{i,j(i,k)}(x_i), \quad k \in (1;1024). \tag{8}$$

That is, an output from the first or second term of each input signal of the network is sent to the input of each neuron of this layer.

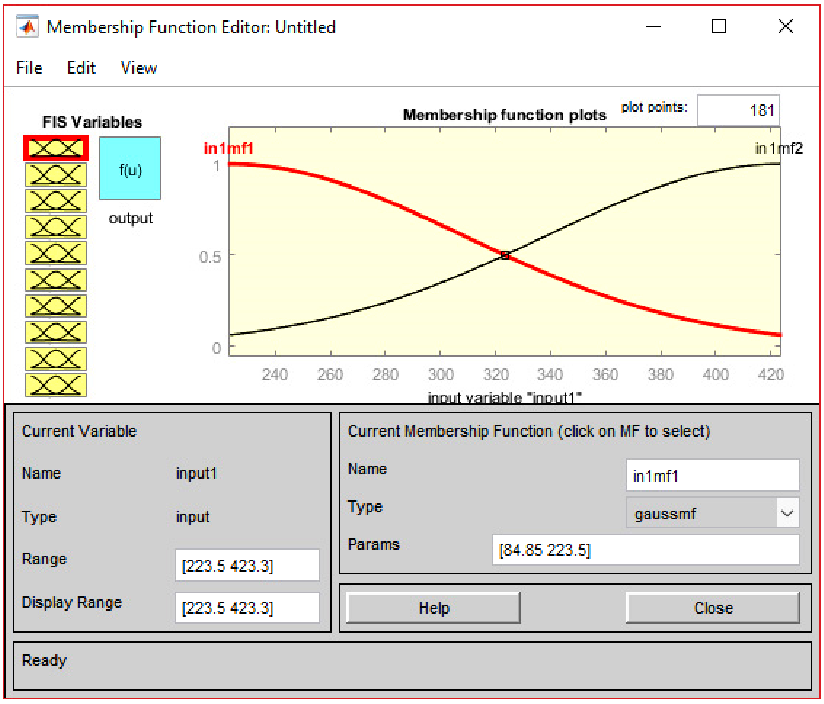


Fig. 4. Membership functions for the first input (oil temperature at the input of the hydraulic transformer (T_{in})) during the test of the first hydrotransformer

The rules of the fuzzy value of the output base (e. g., the first two of them) have the form:

1) If (inputl is in1 mf1) and (input2 is in2mf1) and (input3 is in3mfi) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf1) and (inputl0 is in10mf1) then (output is out1mf1);

2) If (inputl is in1 mf1) and (input2 is in2mf1) and (input3 is in3mfi) and (input4 is in4mf1) and (input5 is in5mf1) and (input6 is in6mf1) and (input7 is in7mf1) and (input8 is in8mf1) and (input9 is in9mf1) and (inputl0 is in10mf2) then (output is out1mf2).

This layer is non-adaptive.

Layer 3 normalizes the levels of truth of each rule, i.e., calculation of the relative degree of fulfillment of the fuzzy rule using the formula:

$$\beta_k = \frac{\alpha_k}{\sum_{i=1}^{1024} \alpha_i}. \qquad (9)$$

In MATLAB, layers 3 and 4 are merged into one layer, a rule.

Layer 4 (outputmf in MATLAB). The number of nodes in the layer 4 is also 1024. Each node is connected to one node of the layer 3 and to all inputs of the network. This node calculates contribution of each fuzzy rule to the network output, i. e. it applies operation of product of the normalized values of the levels of truth of the rules by the corresponding rule outputs:

$$\gamma_k = \beta_k \left(\sum_{i=1}^{10} (c_{i,k} x_i) \right), \quad k \in (1;1024). \qquad (10)$$

Layer 5 (output in MATLAB) performs an adaptive sum of outputs of the neurons of the previous layer in order to obtain the final result of prediction using the formula:

$$y = \sum_{k=1}^{1024} \gamma_k, \; k \in (1;1024). \qquad (11)$$

Fig. 5 shows a block diagram of the algorithm of self-diagnostics of common sensors and sensors of the first hydraulic transmission. The measured parameters are checked by the Pearson consistency criterion. This action is performed in order to test the hypothesis that the obtained data are distributed according to the normal law, i. e. the conditions in which they were obtained are fixed. If the Pearson criterion is not met, the sensor on which the criterion is not fulfilled is considered to be defective.

Verification of truth of the measured results, I_m, U_m, n, n_s, is realized by comparison with theoretical calculations. In order to determine how much the measured value corresponds to the calculated one, the rule of “three sigmas” is applied. The mathematical expectation of the measured value must not differ from the calculated mathematical expectation more than the triple value of the calculated mean root square deviation [16].

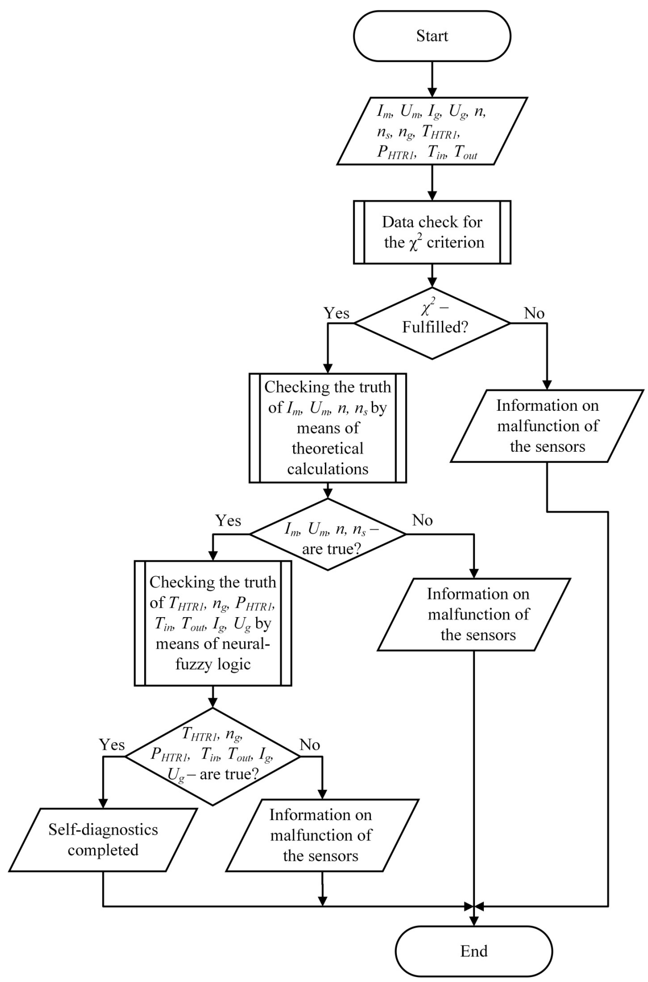


Fig. 5. Block diagram of the algorithm of self-diagnostics of common sensors and sensors of the first hydraulic transmission

In case of non-fulfillment of this condition, the corresponding sensor is considered to be malfunctioning.

Next, parameters T_{HTR1}, T_{HTR2}, P_{HTR1}, P_{HTR2}, T_{in}, T_{out}, I_g, are predicted by corresponding ANFIS networks. The "three sigmas" rule is also used to determine how much the measured value corresponds to the predicted value.

5. Results of studying the designed self-diagnostic subsystem

To train 14 above-mentioned ANFIS networks, a part of data (approximately half of them) obtained during tests of hydraulic transmissions of the UHP 750 type were used. The tests were carried out at Promteplovoz diesel locomotive repair plant (Dnipro, Ukraine). There were 4 series of tests for HTR1 hydrotransformer and 6 series of tests for HTR2 hydrotransformer. In each series, 150 to 200 measurement points were obtained for each parameter in about one minute of testing.

In the training process, it is necessary to set rational values of the parameters $a_{i,j}$, $b_{i,j}$, at $i\in(1;10)$, $j\in(1;2)$ that would minimize the least squares error (LSE):

$$LSE = \frac{1}{2}\sum_{r=1}^{n}\left(y_r - y_r^{'}\right)^2, \qquad (12)$$

where y_r are data at the network output obtained when applying the training sample of size n with the reference data of prediction results y_r'.

To train the network in MATLAB, an algorithm of inverse error propagation or a hybrid method can be used. As shown by the study (Fig. 6), application of the algorithm of inverse error propagation gives a slightly worse result. Therefore, a hybrid method was used to train the network.

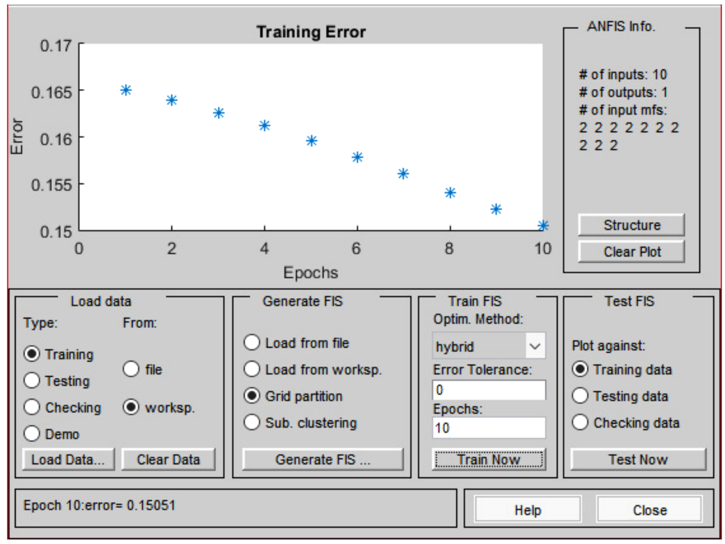
The values of the parameters $a_{i,j}$, $b_{i,j}$ are determined by the use of LSE in each training iteration (epoch) using the method of gradient optimization [15].

Fig. 6 shows an example of network training. As can be seen from Fig. 6, the maximum error in determining oil temperature at the inlet of the hydraulic transmission was 0.150 °C. For the other six predicted parameters shown in Fig. 2, similar results were obtained with minor deviations of no more than 2 %.

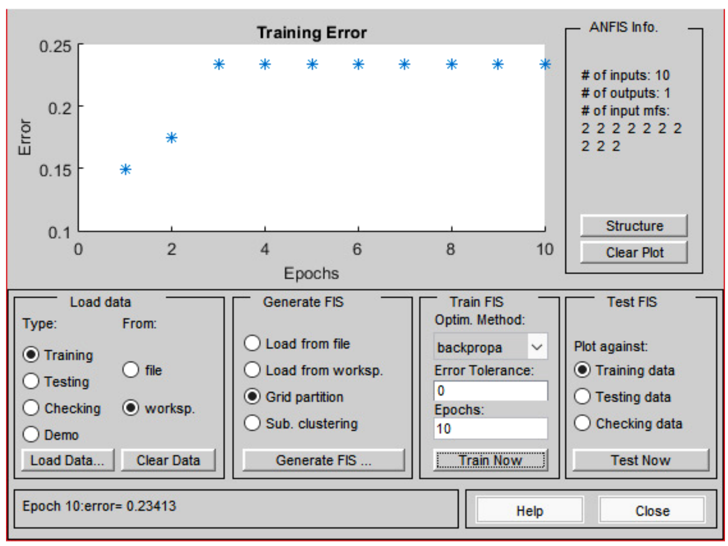
In order to test neural networks, another portion of the test samples of each hydrotransformer was used. Fig. 7 shows the ANFIS system test results for predicting oil temperature at the hydraulic transmission input (T_{in}). Similar results were obtained for the other thirteen ANFIS systems.

Although the number of samples used for training was small, the error was rather small already at this stage and such a neural-fuzzy system can be used for the self-diagnostics tasks. Usually, new data will be accumulated in the process of operation of the system which will enable better training of the neural networks and even obtaining smaller errors in the future.

Comparison of the results obtained from HTR1 is shown in Table 2, and the comparison of the results obtained from HTR2 is shown in Table 3.



a



b

Fig. 6. ANFIS training to predict oil temperature T_{in} at the hydraulic transmission input: the hybrid algorithm (*a*); the algorithm of the inverse error propagation (*b*)

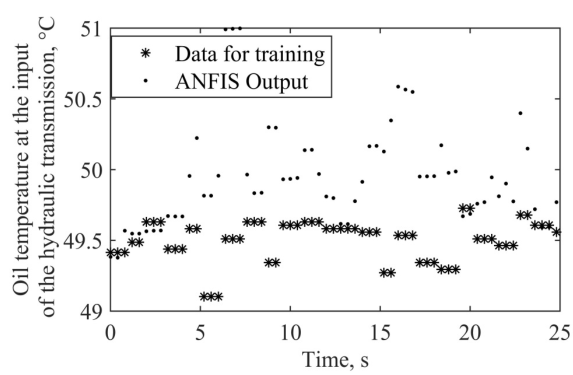


Fig. 7. Results of ANFIS system testing for predicting oil temperature T_{in} at the input of HTR1 hydraulic transmission

Table 2

Comparison of results obtained from HTR1

Parameter	Mathematical expectation of the measured parameter sample (m_{meas})	Root-mean-square deviation of the measured parameter sample (σ_{meas})	Mathematical expectation of the predicted parameter sample (m_{pred})	Root-mean-square deviation of the predicted parameter sample (σ_{pred})	Relative deviation of the mathematical expectation of the measured parameter from the predicted parameter $\left(\frac{\lvert m_{pred}-m_{meas}\rvert}{\sigma_{pred}}\right)$
Oil temperature at the hydrotransmission input, °C	49.50	0.186	49.95	0.362	1.23
Oil temperature at the hydrotransmission output, °C	69.48	0.507	69.06	0.254	1.67
Hydrotransformer oil pressure, kg/cm^2	0.759	0.011	0.737	0.022	1.00
Hydrotransformer oil temperature, °C	77.23	0.435	76.91	0.500	0.65
Generator shaft rotational speed, min^{-1}	458.6	15.19	416.4	13.28	3.18
Generator voltage, V	3.192	0.015	3.210	0.026	0.692
Generator current, A	0.757	0.058	0.655	0.045	2.26

Table 3

Comparison of the results obtained from HTR2

Parameter	Mathematical expectation of the measured parameter sample (m_{meas})	Root-mean-square deviation of the measured parameter sample (σ_{meas})	Mathematical expectation of the predicted parameter sample (m_{pred})	Root-mean-square deviation of the predicted parameter sample (σ_{pred})	Relative deviation of the mathematical expectation of the measured parameter from the predicted parameter $\left(\frac{\lvert m_{pred}-m_{meas}\rvert}{\sigma_{pred}}\right)$
Oil temperature at the hydrotransmission input, °C	35.61	0.229	34.959	0.668	0.98
Oil temperature at the hydrotransmission output, °C	56.77	0.291	56.796	0.509	0.04
Hydrotransformer oil pressure, kg/cm^2	Not measured				
Hydrotransformer oil temperature, °C	60.03	1.598	58.694	1.670	0.80
Generator shaft rotational speed, min^{-1}	773.1	14.48	732.712	16.581	2.44
Generator voltage, V	5.585	0.129	5.608	0.094	0.24
Generator current, A	0.763	0.054	0.717	0.048	0.96

6. Discussion of research results of applying neural-fuzzy networks in the design of self-diagnostic subsystems

Analysis of the dependencies describing relations between the parameters measured by the information-measuring system of testing hydraulic transmissions of diesel locomotives was made. Based on study [8], it was decided that only the steady-state conditions of operation of hydraulic transmissions of diesel locomotives should be used when creating a self-diagnostic subsystem of the information-measuring system. Analysis of the published information sources showed that interrelations in a form of mathematical dependencies were investigated only for a small part of parameters of the information-measuring system of hydraulic transmissions of diesel locomotives, even for the steady-state operation conditions. Therefore, it was decided to apply an additional procedure based on the principles of artificial intelligence, in particular, use of neural networks. However, to train neural networks, it is quite difficult to get a large number of data sets for the steady-state conditions. An adaptive neural-fuzzy inference system (ANFIS) was chosen to create a more flexible system that could adapt to new data. The ANFIS system, in contrast to the conventional multilayer perceptron, uses the rules of fuzzy inference. This enables adaptation to various sets of data taken from various types of hydraulic transmissions.

To check operation of the sensors installed in separate subsystems of the hydraulic transmission test stand, it is necessary to create separate neural networks with an integrated fuzzy logic controller to check truth of the data. This approach greatly simplifies development and makes it possible to completely abandon the rather complex mathematical calculations. There are many studies dedicated to designing neural-fuzzy controllers [10, 11] in which validity of the foregoing is confirmed.

A hybrid self-diagnostics system was designed. It allows us to assess correctness of operation of the sensors of the information-measuring system for testing hydraulic transmissions of diesel locomotives of UHP 750 type. The system features the possibility of checking four parameters determined for the steady-state conditions with the help of known mathematical dependencies. For the other 14 parameters, 14 neural-fuzzy ANFIS networks were designed. The networks have allowed us to predict 14 parameters of the test bench with corresponding sensors installed for testing hydraulic transmissions of UHP 750 type.

Experimentally it was established that for checking sensors, it is necessary and sufficient to have measurement results taken within one minute (100–150 measurement points).

Statistical parameters of the test and predicted data obtained in operation of the designed ANFIS networks were calculated. They show minor prediction errors. Similar results were obtained by other researchers in development of similar systems [10–14].

At the final stage of the system development, comparison of the results obtained from HTR1 and HTR2 according to the "three sigma rule" was performed to determine sensor malfunction and correctness of the system operation (Tables 2, 3). Table 2 shows that deviation of the mathematical expectations of the measured and predicted values of the HTR1 generator shaft rotation speed exceeds the value of "three sigma" (equal to 3.18). This can be explained by low quality of the speed sensor of old design. A new design of the sensor was proposed in [17, 18]. An experimental sensor was installed on HTR2 where the diagnostics subsystem showed normal operation of this sensor (Table 3).

The experiment was conducted under conditions of use of properly functioning sensors and hydraulic transmission. Under these conditions, all average values of the parameters measured in the process of self-diagnostics were within three sigma from the calculated or predicted values. That is, self-diagnostics showed the actual state of the system.

Also, it should be noted that when the hydraulic transmission is in an unsatisfactory technical condition, discrepancy between the measured and calculated or predicted results of self-diagnostics may also be possible. That is, the proposed method of self-diagnostics can indicate the technical state of not only the sensors but also the hydraulic transmission itself. Such cases require further studies.

As indicated in the paper, self-diagnostic subsystems of the information-measuring system for testing hydraulic transmissions of diesel locomotives were designed and tested at Promteplovoz diesel locomotive repair plant. Disadvantages of the system study include the fact that training of the neural-fuzzy networks was not conducted on a sufficiently large data volume. However, data will be accumulated in the process of the system operation and the neural networks will improve their efficiency through self-training.

This system can be easily adapted with minor modifications for self-diagnostics of information-measuring systems of testing other complex assemblies and units of diesel locomotives, heavy wheeled equipment of airports, mines, and military equipment. After all, there is no rigid tie to a particular object in such a system, and after a series of several tests, the system can carry out self-training and adaptation to the corresponding test object using the collected reference data.

7. Conclusions

1. A separate group of parameters measured by the information-measuring system of testing hydraulic transmissions of diesel locomotives was determined. Parameters of this group are related by mathematical dependencies which allow the self-diagnostics system to simply calculate values of some parameters by the measured values of other parameters. This enables use of the mechanism of comparison of the measured and calculated values of the same parameters by the self-diagnostic subsystem. Another group of parameters with a relationship between them described by a rather cumbersome system of nonlinear differential equations was found. Numerical solution of such a system requires significant computational resources and a large amount of input data. In practice, obtaining of such data is rather complicated at production enterprises.

2. To enable use of the mechanism of comparison of measured and predicted values of the same parameters in the self-diagnostic subsystem, application of elements of artificial intelligence was proposed. It was shown that for predicting parameters of the second group, it is expedient to use adaptive network-based fuzzy inference system (ANFIS).

3. Algorithms of self-diagnostics were developed with the use of ANFIS controllers. The algorithms provide prediction of individual parameters of the system with the help of ANFIS controllers and further comparison of the predicted parameters with those that were measured was made. The structure of the ANFIS controller with the proposed Sugeno rule set was worked out and its efficiency was demonstrated.

4. The diagnostics subsystem of the information-measuring system of testing hydraulic transmissions of diesel locomotives was constructed. To determine truth of 14 parameters of the hydraulic transmission, 14 neural-fuzzy ANFIS networks were constructed. For training and testing of the networks, experimental data obtained in testing hydraulic transmissions of UHP 750 type at Promteplovoz diesel locomotive repair plant were used. Testing of the networks showed the correct result of the self-diagnostic subsystem operation. That is, the subsystem has indicated a malfunctioning sensor and when new sensor was installed instead of the malfunctioning one its correct functioning was indicated.

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