Asesorías y Tutorías para la Investigación Científica en la Educación Puig-Salabarría S.C.
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RFC: ATI120618V12

Revista Dilemas Contemporáneos: Educación, Política y Valores.
http://www.dilemascontemporaneoseducacionpoliticayvalores.com/

Año: VI Número: Edición Especial Artículo no.:95 Período: Diciembre 2018.

TÍTULO: Vector de Control para pruebas automatizadas de hielo y sistema de diagnóstico.

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RESUMEN. En la sociedad moderna, los problemas de ahorro de combustible y recursos energéticos se agudizan. El transporte por carretera cada vez es más caro y uno de las mayores fuentes de contaminación. La moderna construcción de automóviles está en camino de mejorar el rendimiento económico, ambiental y operativo de los motores. Esto se debe principalmente al uso de sistemas de modernos sistemas de control electrónico. En el proceso de operación y uso se producen un deterioro de sus indicadores de eficiencia. En este sentido, para mantener el motor en buen estado e identificar oportunamente las desviaciones en los parámetros que conducen a un deterioro de su desempeño el sistema de pruebas ICE, es líder su por validez científica y excelencia.

PALABRAS CLAVES: Motor, Diagnóstico, Prueba, Red Neuronal, Lógica Difusa.

TITLE: Control vector for ice automated test and diagnostic system.

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ABSTRACT. In modern society, the problems of saving fuel and energy resources are exacerbated. Road transport is becoming more expensive and one of the biggest sources of pollution. Modern automobile construction is on track to improve the economic, environmental and operational performance of engines. This is mainly due to the use of modern electronic control systems. In the process of operation and use there is a deterioration of its efficiency indicators. In this sense, in order to keep the engine in good condition and to identify opportunely the deviations in the parameters that lead to a deterioration of its performance, the ICE test system is the leader due to scientific validity and excellence.

KEY WORDS: engine, diagnostic, test, neural network, fuzzy logic.

INTRODUCTION.

At present, there are a number of methods and means of testing an internal combustion engine, based on various aspects and patterns of its operation (Z. Fan, M. Huang, 2009). The most common are motor testers and integrated diagnostic systems.

Devices that realize the possibility of self-diagnostics are aimed at detecting malfunctions of the electronic unit and sensors of the engine management system (Y. Shatnawi, M. Al-Khassaweneh, 2014). Motor-testers have a set of their own sensors, that are able to measure various parameters of the engine systems and implement test modes of diagnostics. At the same time, these devices have weak capabilities for assessing the general state of ICE and are intended primarily to locate and locate faults or fault locations already after they occur.

The estimation of the general condition of the engine is made on the effective parameters of its operation, which include the effective torque and power on the motor shaft, fuel and air consumption, ignition timing, and harmful emissions in the exhaust gases (X. Li, F. Yu, H. Jin, J. Liu, Z. Li, X. Zhang, 2011). The work of systems implementing this approach is based on braking and non-brazing methods.

Brake methods involve the use of special loading stands with running drums. This method was not widely used due to the high cost of equipment (Y. Yu, J. Yang, 2011). Non-brake methods are simpler and do not require the use of special braking devices. In this case, the angular acceleration is measured when the engine is accelerated without an external load from a minimum stable speed to a maximum due to the sudden opening of the throttle (fuel pump rail - in diesel engines) (M. Tian, 2012). This method allows carrying out diagnostics in real operating conditions, and equipping modern ICE with electronic control systems to increase the number of monitored parameters.

Disadvantages of systems implementing the best-mode method are low accuracy due to the need for numerical differentiation of the angular velocity variation, incompleteness and narrow range of the rotational frequencies of the obtained characteristics (L.A. Galiullin, R.A. Valiev, 2016).

Thus, the task is to develop a test system for a modern internal combustion engine, taking into account its features and in real operating conditions, according to its high-speed characteristics, for the timely detection of deviations in parameters leading to deterioration in the economic, environmental and efficient performance of the engine (Z.T. Yao, H.X. Pan, 2014).

This is achieved by solving the following tasks:

1. Determination of the structure of the ICE test system for real operating conditions. Selection of the test mode.

2. Determination of the minimum required composition of sensors and actuators of the engine management system, whose signals contain the necessary information for determining the characteristics of ICE.

3. Development of algorithms and information processing software that guarantee high accuracy in calculating the effective performance of the engine.

DEVELOPMENT.

Methods.

The properties of the internal combustion engine, as a dynamic system, are described by a set of external speed characteristics (ESC) - the dependencies of the change in the main operating parameters on the rotational speed (angular velocity). The composition of the ESC includes the following characteristics (as a function of the rotational speed) (N. Deng, C.-S. Jiang, 2012): fuel consumption; air consumption; effective power and torque developed on the motor shaft.

Distinguish complete and partial ESC.

A full characteristic is obtained by ensuring the maximum filling of the engine cylinders with air (maximum fuel delivery) at a constant load on the shaft. Partial characteristics - respectively, with incomplete fuel supply. Important here is the fact that the values of the partial characteristics lie within the region bounded by the values of the total characteristic (L.A. Galiullin, 2016).

It should also be noted that in order to obtain adequate model, a necessary condition is the constancy of the position of the fuel supply control body. The magnitude of the fuel supply and the driver's control action is the degree of opening of the fuel pump rail in percent. This value is more convenient for perception and interpretation than the angle of rotation of the crankshaft in degrees (D. Wei, 2011).

Results and Discussion.

The selection of the test mode is reduced to providing such an operating mode of the engine, in which its properties are presented more fully. This mode corresponds to the mode of full fuel supply (L.A. Galiullin, R.A. Valiev, 2017). This is due primarily to the maximum wide frequency range of the engine and the maximum work of inertial forces and frictional forces.

Thus, as a test mode, the engine operating mode is selected with full fuel delivery. At the same time, it is necessary to develop a decision-making mechanism on the sufficient provision of such a regime.

High degree of equipping of modern electronic control systems of the ICE work process by primary converters determines the saturation of information flows between the electronic control unit (ECU), sensors and actuators. ECU based on signals coming from the primary transducers (sensors), determines the mode of operation of the engine (idling, power mode) and forms control actions on the actuators.

Based on the composition of the ESC, it is possible to determine the list of sensor signals and actuators of the engine management system that contain the necessary information for the indirect evaluation of each parameter.

When studying ICE and constructing its mathematical model, as a rule, the problem arises of obtaining the law of the functioning of an object as a whole or some of its parts (A. N. Iliukhin, Sh. Sh. Khuzyatov, 2017). Most often, the model cannot be built on the basis of known regularities and the form of the object's functioning law is unknown. In such cases, the solution to this problem can be reduced to isolating in the object significant input and output characteristics and conducting a series of experiments to obtain data on the functioning of the object in special cases.

The implemented structure of ATS ICE can be divided into static and dynamic parts.

The static part of the ATS developed ICE takes a direct part in the process of testing ICE and does not change.

The dynamic part of the ATS ICE is used for setting the ICE test modes and for obtaining fuzzy knowledge base rules using the ANFIS hybrid neural networks.

The construction of the base of the rules of fuzzy inference in this scheme is connected with certain difficulties of conceptual nature. The task of controlling ICE in the process of its testing is the task of forecasting, as well as non-linear and control.

To solve this problem, it is proposed to use hybrid neural networks to configure fuzzy systems. The merits of models built on the basis of neural networks include the possibility of obtaining new information in the form of a prediction (L.A. Galiullin, R.A. Valiev, 2017); for example, the forecast of the control vector of the test of an unknown ICE model.

Fuzzy logic can be used to control the engine during testing. The determination of the control effect is carried out with the help of fuzzy rules. To obtain fuzzy rules, experts can be attracted, or it is possible to automatically create fuzzy rules using an unclear neural network such as ANFIS (adaptive network for fuzzy inference system). The basic idea behind the model of fuzzy neural networks is to use the existing data sample to determine the parameters of the membership functions of input and output variables to fuzzy sets.

The implementation of ANFIS is a hybrid neural network for learning the parameters of the Sudzen system of fuzzy inference (L.A. Galiullin, R.A. Valiev, “2017). Such systems realize the base of fuzzy rules of the form:

$$R^{(k)}: IF\ (x_1 \in A\ AND\ \dots\ AND\ x_n \in Z)\ THEN\ y=f^{(k)}(x_1, \dots, x_n), \qquad (1)$$

where k – number of fuzzy rules;

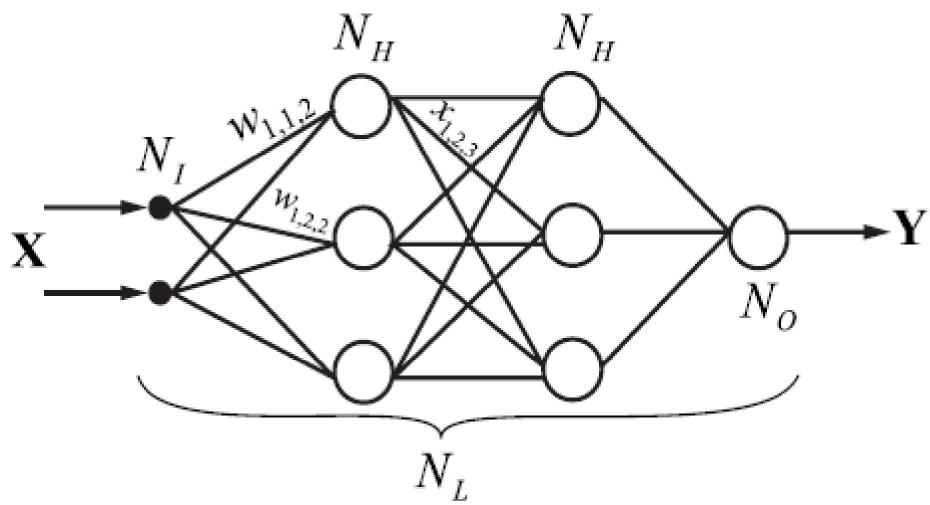
$x_1, \dots, x_n$ – input parameters of internal combustion engines;

$y=f^{(k)}(x_1, \dots, x_n)$ – output control;

A,…, Z – fuzzy sets.

The fuzzy neural network for controlling the internal combustion engine during the tests should be a multi-layer perceptron (Fig. 1), where X, Y – input and output vector, N_1, N_H, N_O – input, hidden and output layer respectively, w_{ijk}, x_{ijk} – weight bonds.

Fig. 1. Fuzzy neural network for controlling ICE



A multilayer perceptron is a unidirectional multilayer neural network of direct propagation. The transmission of signals in such a network occurs only in one direction - from the input to the output. When a given network functions, its topology and activation functions of all neurons are predetermined, and the bond weights are parameters and can change. In a multilayer perceptron, individual neurons are grouped into layers, according to the nature of the problems they solve (the definition of a parameter belonging to a fuzzy set, the choice of a fuzzy rule, the calculation of a clear value).

A multilayer perceptron can calculate the output vector Y for any input vector X, those give the value of some vector function $y = f(x)$. Consequently, the condition of a problem that can be posed to a perceptron must be a set of vectors $\{x^1,\dots,x^S\}$ with N^1 components:

$$x^s = \begin{pmatrix} x_1^s \\ \dots \\ x_{N_1}^s \end{pmatrix}. \qquad (2)$$

The solution of the problem is a set of vectors $\{y^1,\dots, y^S\}$, each vector y^s with N^2 components: $y^s=f(x^s)$, where s=1,…, S – number of the presented image.

Thus, the perceptron forms a mapping $X \rightarrow Y$ for $\forall x \in X$. This display cannot be "extracted" from the perceptron in the form of mathematical models. The perceptron only calculates the mapping of an arbitrary number of points:

$$\begin{pmatrix} x^1 \rightarrow y^1 \\ \dots \\ x^s \rightarrow y^s \end{pmatrix}, \qquad (3)$$

where the set of vectors $x^1,\dots, x^S$ – the condition of the problem, and the set $y^1,\dots, y^S$ – decision.

The neurons of the input layer of the fuzzy neural network receive information from the internal combustion engine sensors (crankshaft speed, N; torque, M_H; fuel consumption, G_T, etc.). Before entering the neural network input, each ICE input parameter is scaled, since the neural networks are sensitive to the parameter change ranges. Then the received data is processed by transformations in the neurons of the hidden layers. The output layer consists of one neuron. The fuzzy neural network thus calculates the control effect on the ICE. For example, for diesel ICE, the output control action can be the movement of the fuel rail of a high-pressure fuel pump, h.

Thus, the fuzzy neural network generates an arbitrary multidimensional function at the output with an appropriate choice of the number of layers, the range of signal changes and the parameters of the neurons. Multilayer networks are a universal tool for approximating functions:

$$f(x) = F\left(\underbrace{\sum_{i_N} w_{i_N j_N N} \cdots \underbrace{\sum_{i_2} w_{i_2 j_2 2} F\left(\underbrace{\sum_{i_1} w_{i_1 j_1 1} \cdot x_{i_1 j_1 1} - \theta_{j_1 1}}_{1}\right) - \theta_{j_2 2}}_{2} \cdots - \theta_{j_N N}}_{N}\right) \qquad (4)$$

where x_{ijl} – i-th input signal of j-th neuron in the layer l;

w_{ijl} – weight coefficient i-th input neuron number j in the layer l;

θ_{ijl} – threshold level of a neuron j in the layer l.

The function approximated by the fuzzy rules of the fuzzy neural network as applied to diesel ICE has the form:

$h=F(N, M_H, G_T, \ldots)$ (5)

Thus, the received structure of the fuzzy system based on the hybrid network type ANFIS allows approximating the parameters of the operation mode of the internal combustion engine over the entire range of their values.

A hybrid network for each vector of input parameters generates a control effect on the motor. For a diesel engine, the control action can be the movement of the fuel injection pump rail – h, mm.

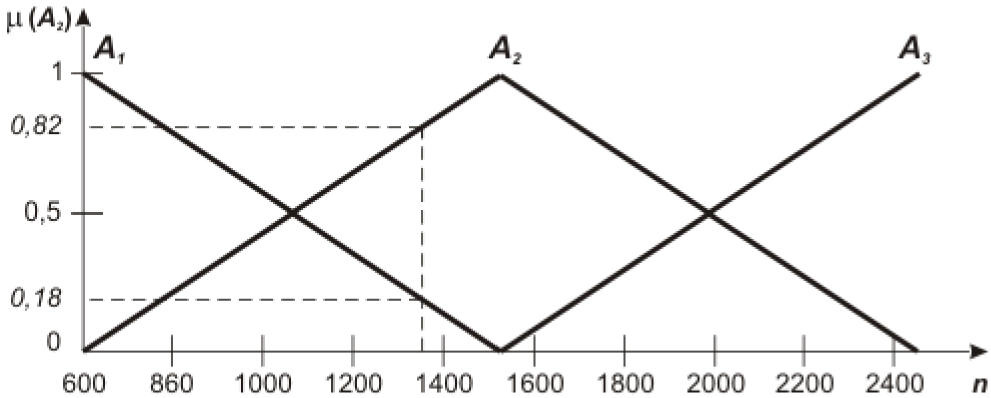
Calculate the output of the trained network for the input vector:

x = (1355; 126; 35,9).

As input parameters, the speed of the crankshaft is selected, n (min^{-1}); load torque on the motor shaft, M_H (Nm); hourly fuel consumption, G_T (kg/hour).

In the first layer, the degrees of belonging of the input parameters to the fuzzy labels are calculated. The membership functions of the first layer assumed the form shown in Fig. 2.

Fig. 2. The membership functions for the first input parameter *n*, min^{-1}



Speed value 1355 min^{-1} belongs to the first and second fuzzy label:

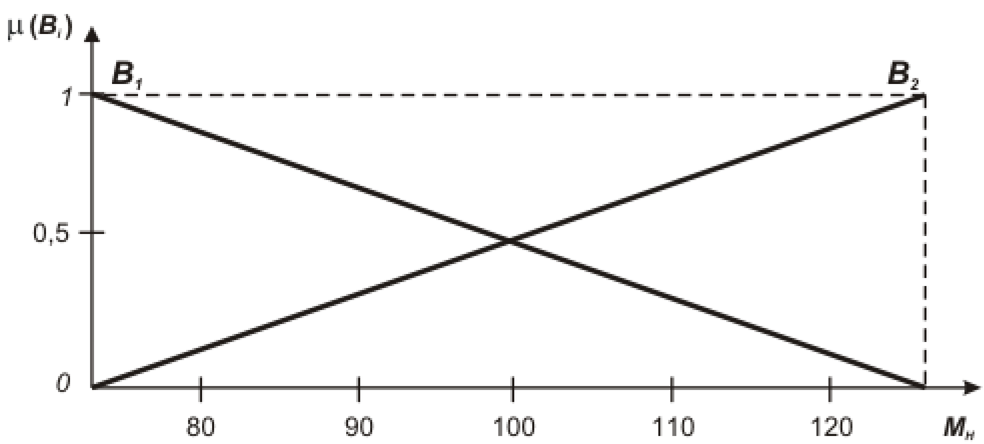
$\mu(A_1)$ = 0,1838;

$\mu(A_2)$ = 0,8162;

$\mu(A_3)$ = 0.

The membership functions for the second input parameter are shown in Fig. 3.

Fig. 3. The membership function for the second input parameter, M_H, Nm



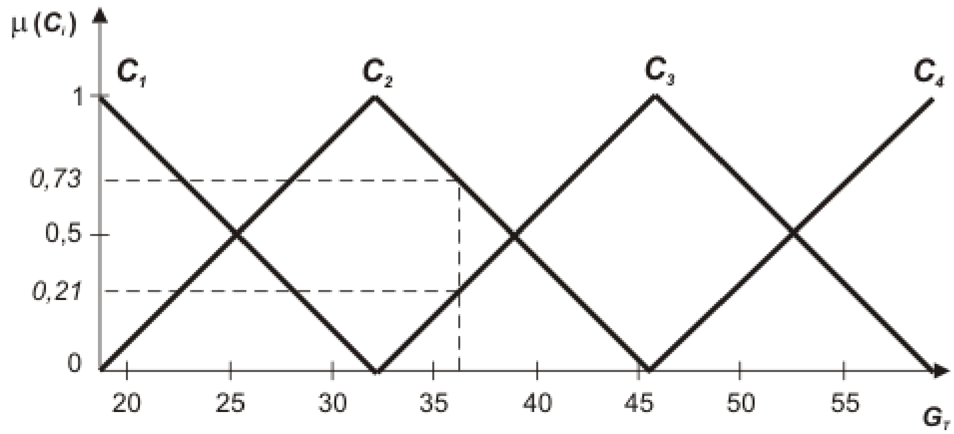
The value of the load moment on the motor shaft is 126 Nm belongs to the second fuzzy set:

$\mu(B_1)$ = 0;

$\mu(B_2)$ = 1.

The membership functions for the third input parameter are shown in Fig. 4.

Fig. 4. The membership function for the third input parameter G_T, kg/hr



The value of the hourly fuel consumption of 35.9 kg/hour belongs to the second and third fuzzy sets:

$\mu(C_1) = 0;$

$\mu(C_2) = 0{,}7281;$

$\mu(C_3) = 0{,}2719.$

$\mu(C_4) = 0$

As a result of training the fuzzy neural network, the width and shape of each membership function has changed.

In the second layer, the degree of activation of 24 fuzzy rules of the form: *IF*… *THEN*…:

$\bar{\tau}_1 = \mu(A_1) \bullet \mu(B_2) \bullet \mu(C_2) = 0{,}594;$

$\bar{\tau}_2 = 0{,}222;$

$\bar{\tau}_3 = 0{,}05;$

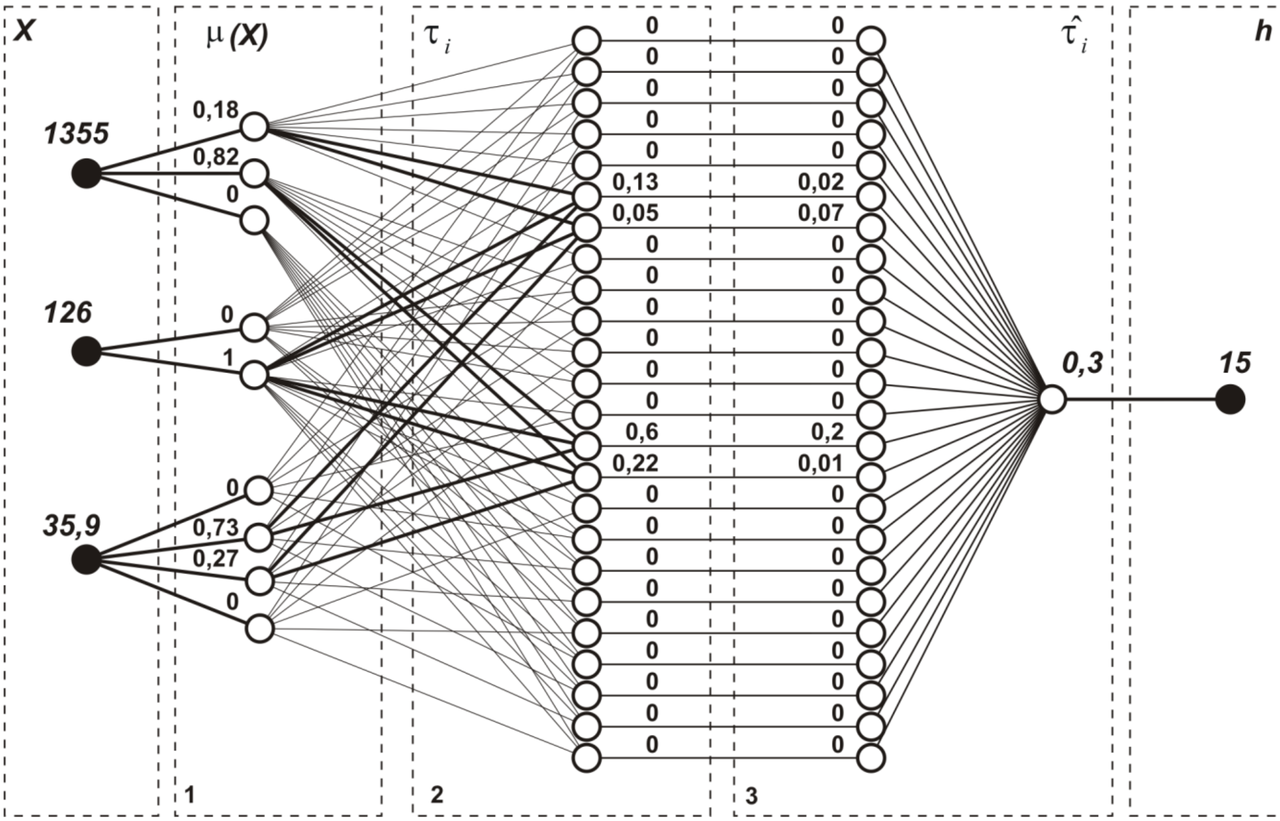
$\bar{\tau}_4 = 0{,}133.$

The degrees of activation of the remaining rules are zero; at least one of the members of the product is zero.

In the third layer, the products of the degrees of activity of the rules and weights of neurons are calculated:

$y = \tau_1 c^{(1)} + \tau_2 c^{(2)} + \tau_3 c^{(3)} + \tau_4 c^{(4)} = 15.$

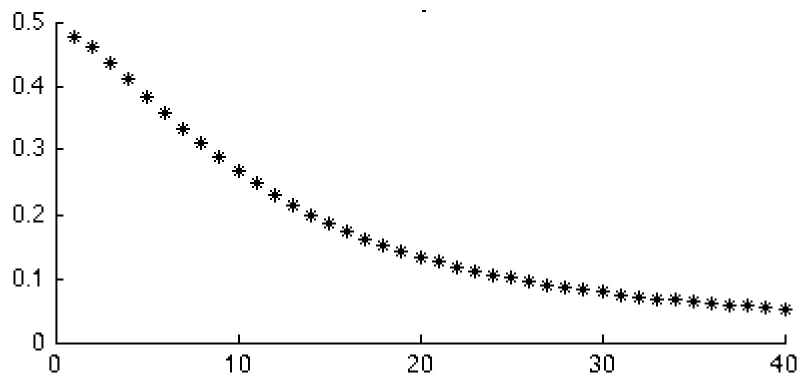
Fig. 5. Calculation of the vector x = (1355; 126; 35,9)



CONCLUSIONS.

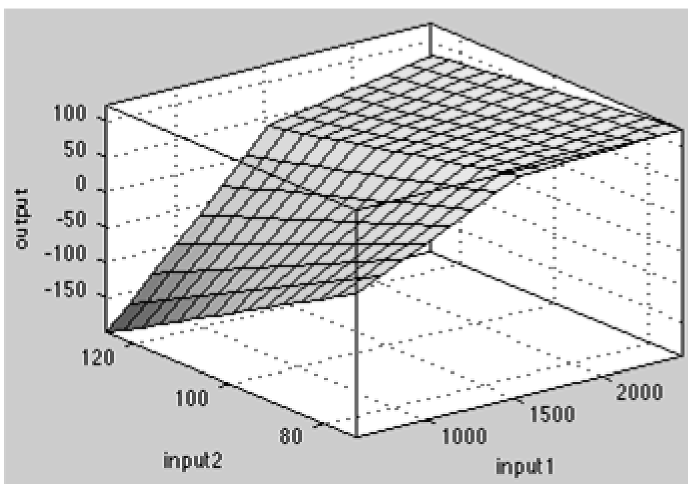
Reduction of the network error in the learning process is shown in Fig. 6. The training of a fuzzy neural network consists of epochs - a sequence of obtaining the results of a network with the given parameters of the first and third layer and comparison with the reference values. As can be seen from the figure, during the training, the parameters of the hybrid network were selected, giving an error of 0.1 units for each parameter.

Fig. 6. Hybrid network error of learning.



The cutoff of the output surface over the 2-mm input parameters of a projected fuzzy neural network is shown in Fig. 7. The surface has a smooth appearance, which shows the possibility of obtaining a control action for any values of input variables from a given range.

Fig. 7. The cut of the surface of the output by the 2-mth input parameters



Acknowledgements.

The work is performed according to the Russian Government Program of Competitive Growth of Kazan Federal University.

BIBLIOGRAPHIC REFERENCES.

[1] D. Wei, (2011). Design of Web based expert system of electronic control engine fault diagnosis; BMEI 2011 - Proceedings 2011 International Conference on Business Management and Electronic Information, 1, art. no. 5916978, pp. 482 - 485, 2011.

[2] Deng, N; Jiang, C.-S, (2012). Fault diagnosis technology based on the fusion of neural network and fuzzy Logic; 2012 International Conference on Systems and Informatics, pp. 419-422.

[3] Fan, Z; Huang, M. (2009). Fuzzy rule set based engine fault diagnosis; in Proc. Asia-Pacific Power and Energy Engineering Conference, no. 4918394, pp. 17-21.

[4] Galiullin, L.A, (2016). Development of Automated Test System for Diesel Engines Based on Fuzzy Logic; 2016 2ND International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM).

[5] Galiullin, L.A; Valiev, R. A. (2017). Mathematical Modelling of Diesel Engine Testing and Diagnostic Regimes; Turkish Online Journal of Design Art and Communication, vol. 7, pp. 1864-1871.

[6] Galiullin, L.A; Valiev, R.A, (2016). Automation of Diesel Engine Test Procedure; 2016, 2ND International Conference on Industrial Engineering, Applications and Manufacturing (ICIEAM),

[7] Galiullin, L.A; Valiev, R.A, (2017). Diagnosis System of Internal Combustion Engine Development; Revista Publicando, 4 No 13(2), pp. 128-137.

[8] Galiullin, L.A; Valiev, R.A, (2017). Diagnostics Technological Process Modeling for Internal Combustion Engines; 2017 International Conference on Industrial Engineering, Applications And Manufacturing (ICIEAM).

[9] Iliukhin, A. N; Khuzyatov, Sh. Sh, (2017). Modelling of diesel engine's operating conditions on the basis of fuzzy logic; QUID-Investigacion Ciencia y Tecnologia, Vol. 1(SI). pp. 2557-2563.

[10] Li, X; Yu, F; Jin, H; Liu, J; Li, Z; Zhang, X. (2011). Simulation platform design for diesel engine fault; 2011 International Conference on Electrical and Control Engineering, ICECE 2011 - Proceedings, art. no. 6057562, pp. 4963 – 4967.

[11] Shatnawi, Y; Al-Khassaweneh, M. (2014). Fault diagnosis in internal combustion engines using extension neural network; IEEE Transactions on Industrial Electronics, 61 (3), art. no. 6511979, pp. 1434-1443.

[12] Tian, M. (2012). Fuzzy neural network diagnose expert system of engine; in Proc. Intelligent Control and Information Processing, no. 6391477, pp. 154-156.

[13] Yu, Y; Yang, J. (2011). The development of fault diagnosis system for diesel engine based on fuzzy logic; Proceedings - 2011 8th International Conference on Fuzzy Systems and Knowledge Discovery, FSKD 2011, 1, art. no. 6019556, pp. 472 - 475.

[14] Z.T. Yao, H.X. Pan. (2014). Engine fault diagnosis based on improved BP neural network with conjugate gradient; Applied Mechanics and Materials, №536-537, pp. 296-299.

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RECIBIDO: 1 de noviembre del 2018. **APROBADO**: 13 de noviembre del 2018.