Neuro-fuzzy modeling of diesel fuel consumption under dynamic loads

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***Abstract* — The article discusses the construction of a neuro-fuzzy model of diesel fuel consumption in various modes of its operation. The structure of a neuro-fuzzy network trained according to the results of field tests is presented. To train the neural network, a hybrid method was used in the form of an error back propagation algorithm and a least squares method. In the process of training, the parameters of the neural-fuzzy network were selected that provide the maximum error of an individual measurement of 3.5375% with an average error of the model of 0.4429%. The neuro-fuzzy diesel model makes it possible to simulate various modes of its operation in accordance with the test cycle ETC EK UN No. 49. Using well-known optimization methods from the obtained model of fuel consumption under unsteady loads, it is possible to determine diesel parameters close to optimal when calibrating the electronic control unit.**

Keywords — fuel consumption, diesel, speed, load, neural-fuzzy network, simulation.

I. Introduction

The operation of diesel engines, especially those installed on vehicles, is characterized by stochastic operating modes. Fluctuations in the operating modes of diesel engines are associated with the operating conditions of the machines themselves. In particular, the road conditions affect the cars: road surface, condition of the surface, longitudinal profile, traffic intensity, frequency of stops and other factors [1-4]. Unstable working conditions cause fluctuations in the torque on the crankshaft and its rotation frequency, increased fuel consumption, increased wear of rubbing surfaces and a decrease in the life of a diesel engine.

One of the main solutions to these problems is to compensate for the expected deterioration that will result from the introduction of toxicity restrictions. This means that it is necessary to look for solutions that counteract the increase in fuel consumption, the deterioration of reliability and durability and the increase in the cost of the product. In this segment, the consumer will never make any compromises, especially regarding fuel consumption and diesel durability [5-8].

Thus, future toxicity requirements can be satisfied only by intensive development and improvement of diesel operation in transient conditions, and the former predominantly stationary approach to diesel optimization is outdated. Optimization of various solutions and technologies allows not only to satisfy all the requirements of the world legislation on toxicity, but also to maintain or even improve fuel consumption, without compromising driving performance that is important for the consumer [6-9].

From the foregoing, we conclude: to improve the environmental friendliness and energy efficiency of the diesel engine, it is important to correctly configure its control unit.

A close to optimal tuning of the diesel engine control unit is impossible without mathematical modeling, which allows analyzing the course of individual work processes and the entire working cycle and predicting the main indicators and characteristics of the diesel engine [9].

II. Metodology

Improving the key indicators of diesel engines is possible only with a thorough study of the processes occurring in them, since the easily accessible reserves for improving their design are practically exhausted.

In this regard, the study of engines in various non-standard modes of its operation with the use of test benches created for these purposes has become particularly significant. Since the assessment of the design, the determination of its compliance with the technological and general requirements of the time, is ultimately carried out by these studies, which significantly reduces the time and duration of finishing work.

Using mathematical modeling, the analysis of the implementation of individual work processes and the entire working cycle is carried out, the main indicators and engine characteristics are predicted. The model cannot be fully adequate to the object and reflects only certain of its properties that are of interest for the purpose of a specific study [10-20].

Emissions of harmful substances from the engine, the level of which is to be measured, include gaseous substances (carbon monoxide; total amount of hydrocarbons - for diesel and gas engines only in the ESC test; hydrocarbons not containing methane - for diesel and gas engines only in the ETC test; methane - for gas engines only in the ETC test and nitrogen oxides), harmful particles and smoke (only for diesel engines in the ELR test). In addition, carbon dioxide is often used as an indicator gas for determining the dilution coefficient in full and partial flow dilution systems. As engineering practice has shown, measuring the total carbon dioxide content can be an effective tool for identifying problems encountered during measurements during testing [1-2].

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To build a neuron-fuzzy model, the effectiveness of which for constructing non-linear models was proved in [21–28], a diesel engine was tested as part of a KAMAZ automobile on a public road, namely on the Ufa – Moscow highway. The experiment was made by truck with the following characteristics:

Version - D3
Category - N3
Wheel formula - 4x2
The maximum rotary speed of bent shaft – 2500 rpm.
The maximum torque is 950 N*m
Fully loaded mass – 15000 kg
Engine power - 210 kW
Quantity of cylinders of the engine - 6
Engine capacity - 6.7 liters
The system of fuel feeding of the engine - Bosch of the electronic engineer.

After preliminary adjustment of the equipment and the engine break-in were recorded for t = 7102 s. the following parameters: torque on driving wheels; angular speed ω of the driving wheels; diesel speed n; fuel consumption. Having processed this data, we obtained the dependence presented in Fig. 1. This time section was chosen due to the fact that the form of the dependence presented on it coincides with the ETC EK UN No. 49 test cycle.

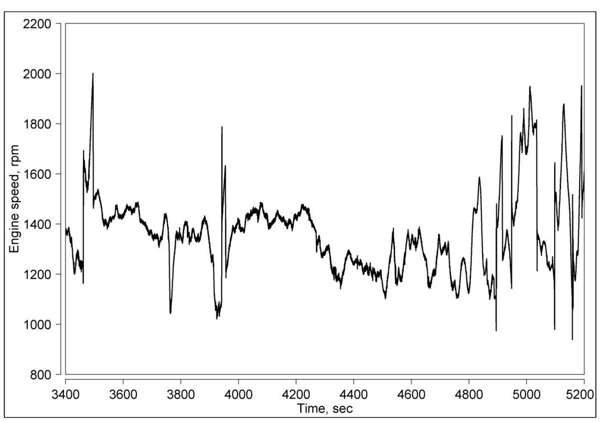

Fig. 1. The measured engine speed

This EK UN No. 49 is used for certification of a vehicle in relation to its diesel engine and certification of a diesel engine as a separate technical unit. For this purpose, EK UN No. 49 provides certification testing. One of such test cycles is ETC, which consists of 1800 consecutive second-second transient regimes [1-2].

To obtain the neural-fuzzy network structure, 29 fuzzy labels were selected for the first input parameter - the frequency *n* of the diesel shaft rotation, and the second input parameter *M* - the load on the diesel shaft, which further determines the number of neurons on each layer.

When a vector of training data is fed to the input of a neural network, the first layer will determine whether each value belongs to the corresponding fuzzy label.

These neurons will combine fuzzy sets of input parameters into a structure of the form:

$$n_i \quad A^i \text{ AND } M_j \quad B_j$$

This layer determines the degree to which the values of the input signals correspond to the conditions of the rules. The relationship between the inputs and outputs of neurons has the form.

$$Y=T[S(w_1,x_1),S(w_2,x_2)],$$

$$f(x)=exp[-b*(x2-a)].$$

The outputs of the neurons of the first layer are the degrees of belonging of the input values to fuzzy sets associated with neurons. For the first input parameter A_i, fuzzy marks were determined in the range $n = 600 \div 2450$ min^{-1}.

Thus, the membership functions of the first input parameter took the form shown in Fig. 2.

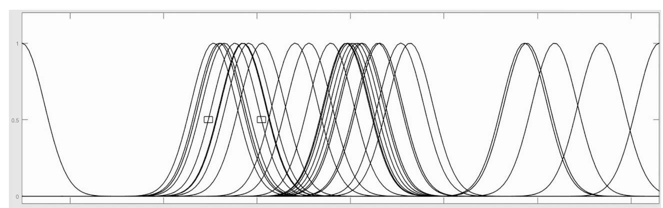

Fig. 2. The measured engine speed

For the second input parameter B_j, fuzzy marks are defined in the range from *0* to *-100 N*m*.

Thus, the membership functions of the second input parameter took the form shown in Fig. 3.

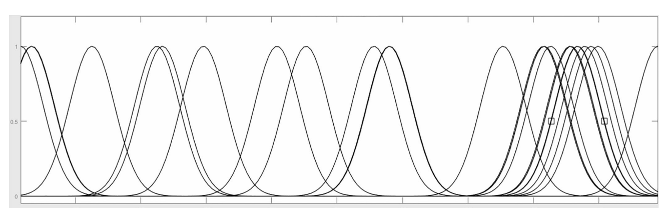

Fig. 3. The measured engine speed

Layer 2 determines the degree to which the values of the input signals correspond to the conditions of the rules. The signal at the output of layer 3 is the sum of the products of the weights and the normalized degrees of activity of the rules.

Based on the specified parameters, layer descriptions and experimental data the structure of the neural network was designed as shown in Fig. 4.

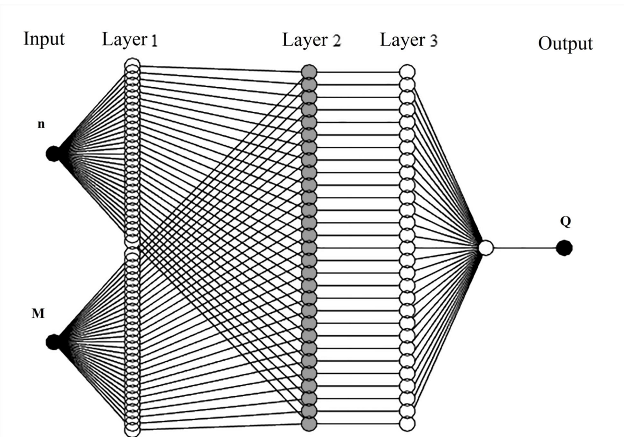

Fig. 4. Neural network structure

We will train the neural network using a hybrid algorithm - one of the most effective ways to train fuzzy networks. Its main feature is the division of the learning process into two time-separated stages. At each stage, only part of the network parameters is specified.

If we take into account that the computational complexity of each optimization algorithm is proportional (non-linear) to the number of parameters, then reducing the dimension of the optimization problem significantly reduces the number of mathematical operations and increases the speed of the algorithm. Therefore this the hybrid algorithm is much more efficient than the usual error back propagation algorithm, according to which all network parameters are refined in parallel and simultaneously.

In the hybrid algorithm, the parameters to be adapted are divided into two groups. The first of them consists of linear parameters p_{kj} of the third layer, and the second group consists of the parameters of the nonlinear membership function of the first layer. Refinement of parameters is carried out in two stages.

At the first stage, when fixing certain values of the parameters of the membership function (in the first cycle, these are the values obtained as a result of initialization), linear parameters p_{kj} of the output polynomial are calculated by solving a system of linear equations.

This expression can be written in abbreviated matrix form:

$$A \cdot p = d.$$

The dimension of matrix A is $p \cdot (N + l) \cdot M$, and usually the number of rows is much larger than the number of columns $(N+1) \cdot M$. The solution to this system of equations can be obtained in one step using the pseudo-inversion of matrix A:

$$p = A^{+} \cdot d.$$

The pseudo-inversion of the matrix consists in decomposition according to the SVD algorithm, followed by a reduction in its dimension.

At the second stage, after fixing the values of the linear parameters p_{kj}, the actual output signals $y(i)$ of the network are calculated for $i = 1,2, \ldots, p$, for which a linear dependence is used and after them - the error vector $\varepsilon = y - d$. Error signals are routed through the connected network towards the network input (back propagation) up to the first layer, where the components of the gradient of the objective function relative to specific parameters can be calculated $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$.

After the formation of the gradient vector, the parameters are refined using one of the gradient teaching methods. After clarifying the non-linear parameters, the process of adapting the linear parameters of the fuzzy network function (the first stage) and non-linear parameters (the second stage) starts again. This cycle is repeated until all process parameters are stabilized. Formulas require calculating the gradient of the objective function relative to the parameters of the membership function. The final form of these formulas depends both on the definition of the error function used at the output of the network and on the form of the membership function.

Despite the complex structure of the formulas used, which express the components of the gradient vector, they allow one to analytically determine the quantities needed to refine the parameters of a fuzzy network.

In the practical implementation of the hybrid method of training fuzzy networks, the first stage is considered the dominant factor in their adaptation, in which the weights p_{kj} are selected using pseudoinversion in one step. To balance its effect, the second stage (the choice of nonlinear parameters by the gradient method) is repeated many times in each cycle.

III. Results

As mentioned above, the training of a neural network was carried out on the basis of a hybrid method in the form of an algorithm for back propagation of error and a least-squares method. The learning outcomes are summarized in table I.

The simulation results in comparison with the real values of the fuel consumption Q at unsteady loads are presented in the form of a histogram in Fig. 5.

A histogram was built to more clearly demonstrate the actual fuel consumption and fuel consumption according to the model due to the almost complete coincidence of these graphs.

The error of individual measurements was calculated by the formula:

$$\Delta X = X\_mod - X\_fact$$

Where ΔX is the absolute error of the model;

X_mod - The value of fuel consumption according to the model;

X_fact - Actual fuel consumption.

TABLE I. THE LEARNING OUTCOMES

Engine speed, rpm	Engine Torque, N * m	Actual fuel consumption, L / h	Fuel consumption according to the model, L / h
695,86243	-18,4954	2,1314	2,13
1106,5106	-76,6884	22,7603	22,8
1118,6279	-98,3416	20,2642	20,3
1122,8898	-14,2851	19,1595	19,2
1130,1602	-54,7345	18,7223	18,7
1137,5975	-10,2251	18,3976	18,4
1149,21,34	-12,1799	11,8509	11,9
1152,2218	-13,2325	10,7407	10,8
1168,4338	-76,6884	9,3584	9,36
1170,1051	-44,3590	8,3426	8,34
1181,7209	-17,3677	3,4430	3,44
1210,3844	-96,6123	1,1265	1,13
1281,0822	-70,4105	11,2305	11,2
1310,7484	-11,2025	2,6539	2,56
1357,6295	-10,1499	29,0567	29,1
1390,1371	-18,3451	7,9272	7,93
1392,1427	-87,4398	1,7541	1,75
1396,4045	-12,1799	1,5764	1,63
1404,6777	-98,3416	1,0594	1,06
1413,2015	-59,1703	3,7622	3,76
1421,224	-18,4954	17,3310	17,4
1425,2352	-14,4355	11,5098	11,5
1458,3278	-13,3077	6,6937	6,71
1462,339	-24,6606	13,0753	12,8
1507,2740	-42,0475	20,2080	20,2
1526,9644	-41,9675	16,1881	16,2
1771,8711	-77,5154	14,6861	14,7
1776,8851	-13,3077	11,1416	11,1
1836,7191	-96,6875	11,7801	11,8
1935,3281	-13,3077	1,6435	1,64
2061,1802	-0,9774	4,5296	4,53

TABLE II. THE CALCULATION RESULTS

Actual fuel consumption, L / h	Fuel consumption according to the model, L / h	Absolute error	Relative error, %
2,1314	2,13	0,0014	0,0680
22,7603	22,8	0,0397	0,1746
20,2642	20,3	0,0358	0,1767
19,1595	19,2	0,0405	0,2116
18,7223	18,7	0,0223	0,1191
18,3976	18,4	0,0024	0,0131
11,8509	11,9	0,0491	0,4146
10,7407	10,8	0,0593	0,5522
9,3584	9,36	0,0016	0,0168
8,3426	8,34	0,0026	0,0310
3,4430	3,44	0,0030	0,0863
1,1265	1,13	0,0035	0,3112
11,2305	11,2	0,0305	0,2716
2,6539	2,56	0,0939	3,5375
29,0567	29,1	0,0433	0,1492
7,9272	7,93	0,0028	0,0356
1,7541	1,75	0,0041	0,2359
1,5764	1,63	0,0536	3,4024
1,0594	1,06	0,0006	0,0589
3,7622	3,76	0,0022	0,0585
17,3310	17,4	0,0690	0,3984
11,5098	11,5	0,0098	0,0854
6,6937	6,71	0,0163	0,2441
13,0753	12,8	0,2753	2,1056
20,2080	20,2	0,0080	0,0394
16,1881	16,2	0,0119	0,0733
14,6861	14,7	0,0139	0,0943
11,1416	11,1	0,0416	0,3733
11,7801	11,8	0,0199	0,1688
1,6435	1,64	0,0035	0,2120
4,5296	4,53	0,0004	0,0098

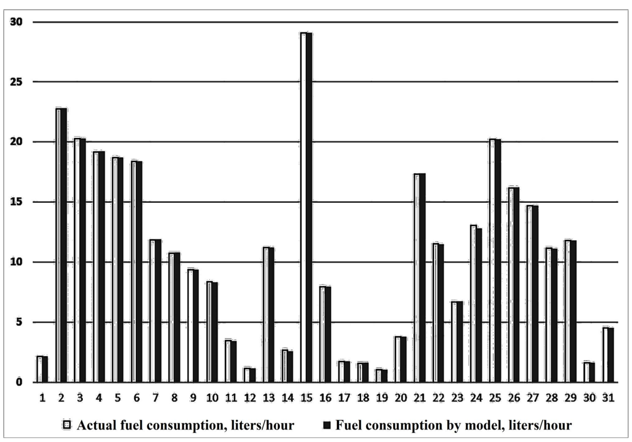

Fig. 5. Histogram of actual (□) fuel consumption and fuel consumption according to model (■)

The relative error of the model was calculated by the formula:

$$\delta = \Delta X / X\_fact * 100\%.$$

The calculation results are shown in table II. During the training, the parameters of the neural-fuzzy network were selected that provide the maximum error of an individual measurement of 3.5375% with an average error of the model of 0.4429%.

The graph of fuel consumption versus two input parameters obtained by simulation using a neural-fuzzy network is shown in Fig. 6. 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.

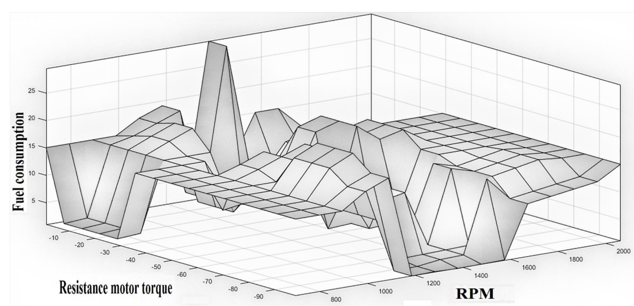

Fig. 6. The graph of the dependence of the diesel fuel consumption Q on the input parameters n and M obtained by simulation

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Under operating conditions of cars, the unsteady load mode is the most common. Engine tests in factories are often carried out at stands for which it is important to reproduce real loads. At their incorrect reproduction indicator and effective indicators of engines during operation are reduced. The effective power is reduced by 20 - 25%, the specific fuel consumption is always greater than that obtained at the test benches, by 15 - 20%.

The study of engines in dynamic modes involves the study of the unit, that is, a two-mass system is being investigated: the engine plus the reduced moment of inertia. In these studies, we obtain the dynamic characteristics of the engine operating processes in the unit. In the process of testing, preparing for serial production, manufacturing companies are fighting to reduce funds and time spent on work. In a market economy, this becomes one of the determining factors. Bench and simulation tests of engines significantly reduce the time and cost of testing compared to laboratory road tests and operational tests. Therefore, a stand for dynamic research of engines should provide the ability to reproduce the transient nature of the load, as well as typical loading signals of the engine under study.

Thus, the developed neuro-fuzzy diesel model makes it possible to simulate various modes of its operation in accordance with the ETC test cycle according to EK UN No. 49, which allows using this model to determine fuel consumption when exposed to dynamic loads and to obtain an output surface using two main input parameters. Using well-known optimization methods, it is possible to determine the best parameters from the developed model when compiling a table of the electronic engine control unit, avoiding excessive fuel consumption values, which will improve the environmental friendliness and energy efficiency of diesel operation under the influence of unsteady loads.

There is a definite shortage of works devoted to the virtual physical tests of automotive diesel engines at aggregate stands. In this regard, it seems necessary to conduct a scientific analysis of the management of load conditions in systems of virtual physical tests and justify the method of their calculation.

To improve the technology of virtual physical tests of diesel engines at aggregate stands, it seems advisable to develop a load control method that will ensure stability of its regulation, insensitivity to measurement and control inaccuracies, and also provide a control system structure that allows using car models of any necessary complexity to reproduce the required driving modes, including when testing diesels with several power units.

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