

# ARTICLE

## NEURAL NETWORK FOR INTERNAL COMBUSTION ENGINES TESTING

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### ABSTRACT

In the present world the problems of the fuel and energy resources' optimization consumption belong to challenging issues. Transport consumes more than 30% of the produced hydrocarbons, and the fuel costs account for about 20% of the product cost. More highly charged is the environmental contamination, and more than half of the emissions can be attributed to the share of internal combustion engines (ICE). Production of the internal combustion engines is enhanced towards improving the engine's environmental, economic and operational parameters. This involves the use of electronic control units - ignition control and fuel injection systems. It allows to greatly reducing the ICE energy consumption and emission toxicity. During the vehicle operation corresponding units and knots always wear and age. This leads to deterioration of economic, environmental and effective parameters of a vehicle. Therefore, in order to maintain an ICE in the optimum condition and to early detect any changes in the parameters that lead to deterioration of the environmental, economic and effective parameters of its operation, the main aspect includes the maintenance and repair system, its scientific validity and perfection. In such case the technical diagnostics is of paramount importance.

### INTRODUCTION

Enhanced production of cars, tractors and their increasing role in meeting the modern society's needs lead to a continuous improvement of the machinery power units - internal combustion engines (ICE) [1]. Declared ICE power, cost effectiveness, toxicity and other estimates, as well as its reliability and durability are set by the tests in the bench and in operation conditions [2]. Currently, all newly created, modernized and serial car and tractor engines are subject to various kinds of tests, which nature, scope and content are determined by their purpose and specified in the GOST [3]. The tests constitute the final stage of the complex process of creating and improving the internal combustion engines [4]. In this regard, all newly created, modernized and serial internal combustion engines are tested in a different way [5]. The tests allow to estimate the engine's quality and to compare its performance with that of other engines [6]. The test process specifies engine's traction and dynamic, economic, environmental, and other indicators and establishes compliance of these indicators to the standards and specifications [7]. The tests reveal the engine's characteristics and the comparison of test results of different types of engines allows to estimate the effectiveness of their design features, workmanship and technical condition.

At present, the ICE tests represent a complicated and time-consuming process, which little different from the experimental study [8]. Therefore, ICE automated inspection systems (ICE AIS) are created.

When studying an ICE and designing its mathematical model, a problem of obtaining the object operation law as a whole or some parts thereof usually arises [9]. Such model cannot most often be designed based on the known regularities, and a type of the object operation law is unknown. In such cases, solution to this problem can be reduced to allocating any significant input and output characteristics of the object and conducting a series of experiments in order to obtain any object operation data in particular cases.

In order to solve this problem, the hybrid neural networks are proposed to be used to adjust the fuzzy systems.

### MATERIALS AND METHODS

A fuzzy hybrid neural network represents a clear neural network, which is based on a multi-layer perceptron [Fig. 1].

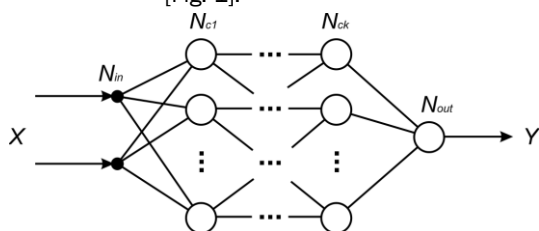


Fig. 1: Multilayer structure of hybrid network.

#### KEY WORDS

Tests, neural network, automatization, system, engine.

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where

X means a vector of input parameters;  
Y means a vector of output parameters;  
Nin, Nout means an input and output layer;  
Nc1, Nck means hidden layers.

The hybrid network for the adjustment of fuzzy system, as opposed to a multi-layer perceptron, includes an adaptive layer of membership functions; logical AND-, OR-neurons (logical neurons modelling logical connectives) [10].

The network visualizes an input vector to an output one  $X \rightarrow Y$ :

$$y = \frac{\sum_{i=1}^M w_i}{\sum_{j=1}^N w_j} \left( p_{i0} + \sum_{j=1}^N p_{ij} x_j \right)$$

which can be expressed as

$$y(x) = \frac{1}{\sum_{k=1}^M w_k} \sum_{k=1}^M w_k y_k(x)$$

where ;

$$y_k(x) = p_{k0} + \sum_{j=1}^N p_{kj} x_j$$

N means a number of input variables;  
wk means weights of various neuronal links;  
p0, p1, ..., pN means digital weights selected in the adaptation (learning) of a network.

The weights wk present in this expression are interpreted as a significance of the components  $\mu_A^{(k)}(x)$  (degree of membership of a specific numerical value to a fuzzy mark A) [11]. Under this condition, the formula can be compared to the multilayer network structure.

If  $y_i(x)=c_i$ , then:

$$y(x) = \frac{\sum_{i=1}^M c_i w_i}{\sum_{i=1}^M w_i} = \frac{\sum_{i=1}^M c_i \cdot \prod_{j=1}^N \mu_{ij}(x_j)}{\sum_{i=1}^M \prod_{j=1}^N \mu_{ij}(x_j)}$$

where ci means a weight ratio (in terms of fuzzy systems, this is the membership function centre of the right part of fuzzy rules);

$\mu_{ij}()$  means the Gaussian function in exponential form with parameters of the centre  $c_{ij}$ , width  $\sigma_{ij}$  and shape  $b_{ij}$ . From the point of the fuzzy systems,  $\mu_{ij}()$  means a membership function to a fuzzy set. The engine operation during the tests is represented as vector X of a desired variation in time of the ICE input parameters [12]. The engine operation time with the specified parameters depends on a type of tests and it is specified in the test program.

x1 = {603; 73,4; 18,6} – for a moment of 15 minutes;  
x2 = {825; 99; 23,1} – for a moment of 30 minutes;  
xn = {2458; 110; 59.3} – for a moment of 180 minutes.

The crankshaft speed n, rpm; load torque to motor shaft Mh, Nm; hourly fuel consumption Gt, kg/h, respectively [13], are selected as input parameters.

In order to generate a control action as a vector of the rack motion values of the high-pressure fuel pump (HPFP) for a diesel engine, the hybrid network should consist of three layers.

## RESULTS AND DISCUSSION

Layer 1 is represented by the radial basis neurons, and it simulates membership functions of the fuzzy output system.

In [14] demonstrated a possibility to control an ICE during the tests using the fuzzy logic methods.

The parameterized shape function (Gaussian curve with parameters  $c, \sigma, b$ ) is chosen as a membership function; its parameters are configured using a hybrid network. When designing a hybrid network, the condition of fuzzy rules IF ( $x_i \in A_i$ ) is implemented via the russification function, which is represented by the generalized Gaussian function separately for each variable  $x_i$ :

$$\mu_A(x_i) = \frac{1}{1 + \left(\frac{x_i - c_i}{\sigma_i}\right)^{2b}}$$

where

$\mu_A(x_i)$  means the degree of membership of an explicit value  $x_i$  to a fuzzy mark  $A_i$ .

The generalized Gaussian function at an appropriate choice of the exponent  $b$  may be degenerated both in the standard Gaussian function ( $b = 1$ ), triangular ( $b = 0.6$ ) or trapezoidal function.

Fuzzy sets [15] should be determined for given input parameters of the engine operation. The greater number of fuzzy sets of a parameter increases the accuracy of the resulting control action; however, it is computer-intensive [16]. Three fuzzy sets should be defined for the engine speed, two fuzzy sets - for the load torque and four fuzzy sets - for the hourly fuel consumption.

The first layer's task is to calculate the input data degree of membership to the respective fuzzy sets. For this purpose the numerical values of the parameters are subject to normalization:

$x_1 = \{0.24; 0.58; 0.31\}$  - for a moment of 15 minutes;  
 $x_2 = \{0.38; 0.80; 0.39\}$  - for a moment of 30 minutes;  
 $x_n = \{1; 0.81; 1\}$  - for a moment of 180 minutes.

Degree of membership of the normalized values of the input parameters to the fuzzy marks:

$\mu(x_1) = \{(0,84; 0,1; 0,06); (0,42; 0,48); (0,78; 0,1; 0,1; 0,02)\};$   
 $\mu(x_2) = \{(0,62; 0,2; 0,18); (0,23; 0,77); (0,25; 0,40; 0,2; 0,05)\};$   
 $\mu(x_n) = \{(0,1; 0,12; 0,78); (0,25; 0,75); (0,1; 0,2; 0,15; 0,65)\}.$

This parametric layer with parameters  $c_j^{(k)}, \sigma_j^{(k)}, b_j^{(k)}$  subject to adaptation during learning.

Layer 2 - the layer consists of AND-neurons [17], which model a logical connective AND using the following formula [18]:

$$w_i = \mu_{A_i}(x_1) \cdot \mu_{B_i}(x_2)$$

Links with the previous layer are set so as to obtain all possible combinations of the membership functions of two input signals [19].

Assume that the input space is evenly divided with  $N_1$  membership functions for signal  $x_1$  and, respectively, with  $N_2$  membership functions for signal  $x_2$  [20].

In other words,  $N_1$  of fuzzy sets for the first input signal should be defined [21]:  $A_1^1, \dots, A_1^{N_1}$  and  $N_2$   $A_2^1, \dots, A_2^{N_2}$ , - for the second signal. It will result in  $N_1 \times N_2$  rules of the following form [22]:

$R(k): \text{IF } (x_1 \in A_1^k \text{ AND } \dots \text{ AND } x_n \in A_n^k) \text{ THEN } y = c(k)$

For

$k=1, \dots, N$ , where  $R(k)$  means the fuzzy  $k$ -th rule [23],  
 $x_1, \dots, x_n$  means input parameters of the engine operation [24];  
 $A_1^k, \dots, A_n^k$ , means fuzzy sets from components of conditions [25];  
 $c(k)$  means constant [26];  
 $N$  means a number of rules [27].

This layer determines the extent, to which the input signal values correspond to the conditions of the rules [28]. The input and output relationship is as follows [29]:

$$\tau_k = \prod_{i=1, \dots, n} \mu_{A_i^k}(\bar{x}_i)$$

$$\hat{\tau}_k = \prod_{i=1, \dots, n} \mu_{A_i^k}(\bar{x}_i)^{def} = \frac{\tau_k}{\sum_{i=1}^N \tau_i}$$

where

$\mu_{A_i^{(k)}}(\bar{x}_i)$  means a degree of compliance of the input data with the conditions of the rules,

$\tau_k$  means a degree of the activity of the k-th rule,

$\hat{\tau}_k$  means normalized value  $\tau_k$

The outputs of this layer represent normalized degrees of activity of the rules.

$$\begin{aligned} \tau_k(x1) &= 0,84 \cdot 0,42 \cdot 0,78 = 0,28; & (x1) &= 0,28/(0,84+0,42+0,78)=0,14; \\ \tau_k(x2) &= 0,62 \cdot 0,77 \cdot 0,40 = 0,19; & (x1) &= 0,19/(0,62+0,77+0,40)=0,11; \\ \tau_k(xn) &= 0,78 \cdot 0,75 \cdot 0,65 = 0,38; & (x1) &= 0,38/(0,78+0,75+0,65)=0,17. \end{aligned}$$

Layer 3 represents a function generator that calculates the values  $y_k(x) = p_{k0} + \sum_{j=1}^N p_{kj} x_j$ . In this layer

the signals  $y_k(x)$  are multiplied by the values  $w_k$  generated in the previous layer. This is a parametric layer, in which linear weights  $p_{kj}$  are to be adapted for  $k = 1, 2, \dots, M$  and  $j = 1, 2, \dots, N$ .

This layer implements the defuzzification method. At its output the signal represents a sum of products of weights and normalized activity degrees of the rules  $\hat{\tau}_k$ .

$$\begin{aligned} y(x1) &= (x1) \cdot (x1) = 0 \cdot 0,14 = 0; \\ y(x2) &= (x2) \cdot (x2) = 0 \cdot 0,11 = 0; \\ y(xn) &= (xn) \cdot (xn) = 0 \cdot 0,17 = 0 \end{aligned}$$

The weights of links marked with the symbol correspond to the constant  $c(k)$  in the rules. They should have zero initial values, which reflects the lack of conclusions before the start of the network's learning. Therefore, it can be argued that the modification of these weights during learning leads to the rules building. After the process of learning of the hybrid network the parameters  $(x_n)$  will be changed, so that the output will result in a normalized rack motion value of HPFP  $h$ .

The first layer comprises three M·N nonlinear parameters of the Gaussian function (M - number of received rules, N - total number of fuzzy sets for the input vector), and the third - M linear parameters  $c_i$ .

## CONCLUSIONS

The hybrid network for each vector of the input of parameters generates an engine's control action. For diesel the motion of HPFP rack -  $h$ , mm can represent the control action.

For a given input vector the hybrid network received the control vector:

$$h = \{0; 1,35; 3,21; 4,62; 15; 17,3; 24,1; 27,6; 38,8; 42,4; 49,3\}$$

The resulting deviations of the calculation indices from the experimental ones was due to the appropriate selection of the learning sample, which was used during the hybrid network's learning.

The advantages of the model based on the fuzzy neural network include a possibility to obtain new information in the form of a certain forecast. For example, forecast for the test control vector of unknown ICE model.

In order to create the knowledge base in the form of fuzzy control rules, the hybrid network based on the multilayer perceptron is selected; it allows to approximate the ICE operation mode parameters in the whole range of their values.

The hybrid network contains only two parametric layers (first and third), which parameters are specified in the learning process. The errors of 4% correspond to GOST 15995-80, and they are caused by the non-linearity of the crankshaft speed in the range of 800-1500 rpm.

**CONFLICT OF INTEREST**

There is no conflict of interest.

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None.

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