Automated test system of internal combustion engines

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Abstract. The method of engine test bed control based on fuzzy neural network is considered. The structure of fuzzy neural network to control the engine during the test is suggested.

1. Introduction

Leading engine company conducts intensive research and development work to improve the reliability and durability of the internal combustion engine (ICE), and in particular diesel engines [1].

Research and testing of diesel engines are one of the main means of checking the quality of the manufacture of parts and assemblies, sub-assemblies and engine as a whole, its proper mounting, compliance of the essential characteristics of a diesel engine with the requirements of technical documentation [2].

Types of diesel tests are regulated by GOST and international standards ISO, which govern the the rules of an acceptance and requirements to the technical level of engines. After acceptance and putting diesel engines into production an improvement of their designs and technical and economic indicators continues.

Currently, testing of diesel engines is a complex and time-consuming technological process, very similar to the pilot study. Therefore, an engine automated test system (ASI) has been created.

Modern requirements to continual improvement of the technical level of manufactured diesel engines lead to the fact that the share of the costs of the tests in the process of creation of new engine models grows more and more. Particularly large, these costs are in the case of non-compliance of the level of production automation and scientific research one. In this regard, test technological process automation is one of the main objectives of improving the technological level of production and quality of the diesel engines.

Normalization of the input parameters of a diesel engine

AST should perform optimal control diesel engine during the tests at established modes, ensuring at any time the required values of engine output parameters.

To do this, AST on the basis of forming fuzzy neural network knowledge base generates control action [3]. Control action for diesel is moving the high pressure fuel pump (HPFP), h regulator.

The knowledge base has the form of fuzzy control rules. Control rules are constructed using the theory of fuzzy sets and fuzzy logic:

$$R^{(k)}\text{: IF } \omega \text{ AND } M_H \text{ AND } G_T \text{ AND } \dots \text{ THEN } h, \tag{1}$$

wherein k – the total number of fuzzy rules;
$R^{(k)}$ – the entire set of rules;
ω – linguistic variable characterizing the engine speed;
M_H – linguistic variable characterizing the torque load;

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G_T – linguistic variable characterizing the fuel consumption;
h – linguistic variable characterizing the position of the injection pump regulator.

Fuzzy rules are clear and simple, in contrast to the differential equations describing the engine and its system [4].

Mathematical algorithm of AST diesel work provides preliminary input of parameters of the engine. Let the input parameters for AST in the test set: crankshaft speed – ω (min^{-1}), torque – M_H (Нм), hourly fuel consumption – G_T (kg/hour). However, it is possible to set a greater number of input parameters.

Next is the normalization of each input parameter.

1-st step – calculation of the arithmetic mean of the parameter:

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \tag{2}$$

wherein x_i – parameter value;
n – the number of observations.
2-nd step – calculation of standard deviation:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x})}{n-1}} \tag{3}$$

3-d step – translation values of the points in the 10-point scale :

$$St_i = \frac{(x_i - \bar{x})}{\sigma} \times 2 + 5{,}5 \tag{4}$$

2. Fuzzification of normalized engine parameters

Determination of membership level of normalized parameter of the engine to the given functions (fuzzification) is carried out using standard Gaussian function represented in a rational form:

$$\mu_A(x_i) = \frac{1}{1 + \left(\frac{x_i - c_i}{\sigma_i}\right)^{2b_i}} \tag{5}$$

wherein x_i – the normalized value of an indicator;

c_i – parameter of center of formal neuron set on the interval [0, 10] points of 10-point scale. Depending on the given number of formal neuron the 10-point scale is divided into corresponding number of sections, where the parameter c_i – midpoint of the segment;

σ_i – parameter (ratio) of function latitude. Originally is generated by the automated system is equal to 2/3 of the segment setting by the parameter c_i.

b_i – shape parameter of function. Originally is generated by an automated system to 1, which corresponds to the standard Gaussian function.

AST conducts fuzzification for each vector of the input parameters of the engine.

3. Formation of fuzzy inference rules for the knowledge base of AST

For each of the formal neurons is determined the integral degree of membership of all parameters of the engine introduced into AST. Для каждого из формальных нейронов определяется интегральная степень принадлежности всех введенных в АСИ параметров двигателя.

It is used in the AST the degree membership aggregation of individual parameters using the procedure of the algebraic product, from which it follows that for the k-th rule of inference::

$$\mu_A^{(k)}(x) = \prod_{j=1}^{N}\left[\frac{1}{1+\left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}}\right] \tag{6}$$

4.Calculation of control actin to the diesel

Approximation of fuzzy sets into the exact solution h is conducted by the system using a model of Mamdani-Zade.

When M inference rules and the use of the generalized Gaussian function as membership function, moving the high pressure pump regulator is determined by the formula:

$$h(X) = \frac{\sum_{i=1}^{M} c_i \left[\prod_{j=1}^{N}\left[\frac{1}{1+\left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}}\right]\right]}{\sum_{i=1}^{M}\left[\prod_{j=1}^{N}\left[\frac{1}{1+\left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}}\right]\right]} \tag{7}$$

wherein $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$ determine center parameters, width and shape of the j-th component x to the k-th fuzzy inference rule.

The structure of fuzzy neural network to diesel engines [5] AST, which implements the approximation (7) function is shown in Figure 1.

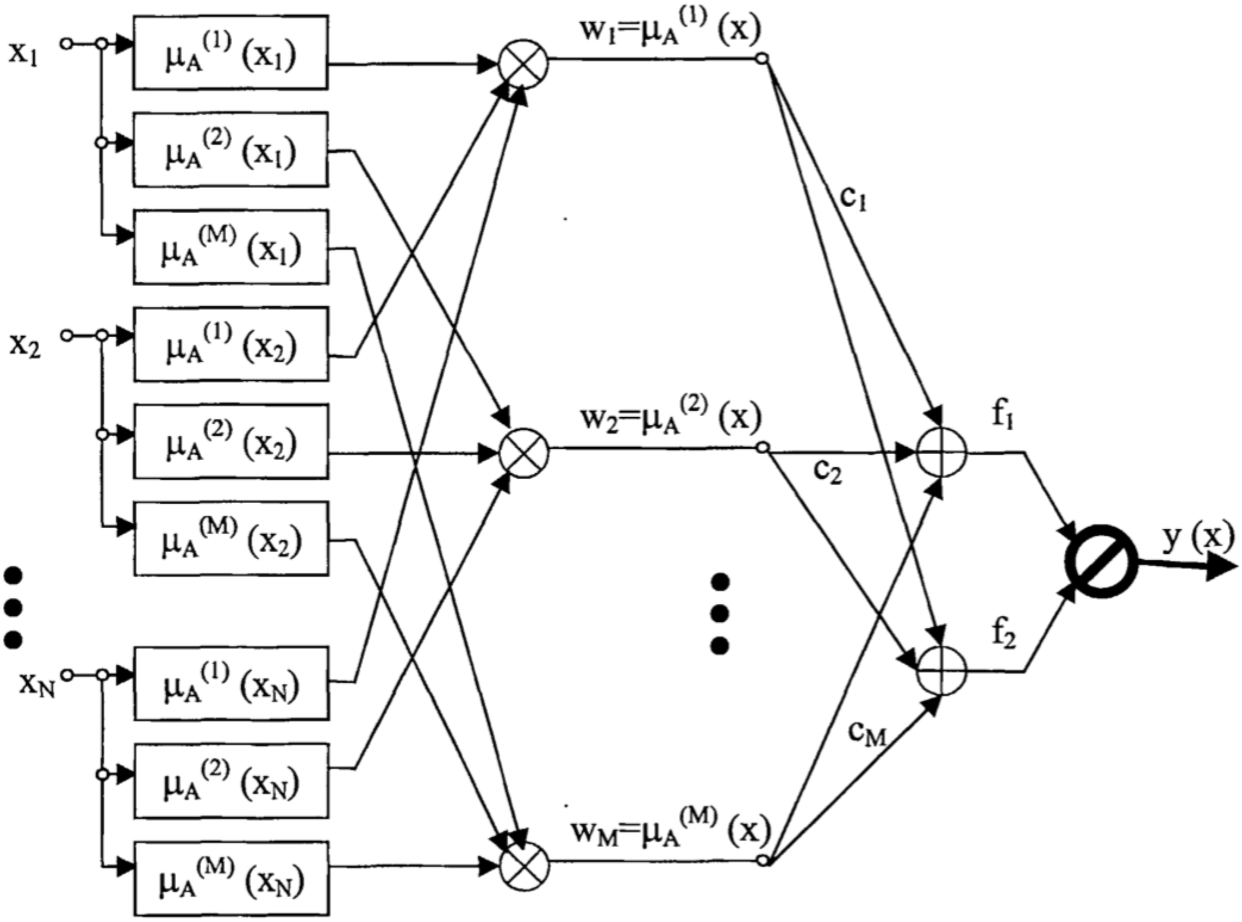

Figure 1. The structure of the fuzzy neural network diesel AST

This four-layer structure in which the first layer performs separate fuzzification of each of the input variables x_i (i=l, 2, ..., N), determining for every k-th inference rule coefficient of belonging value $\mu_A^{(k)}(x_i)$ [6].

The second layer performs the aggregation of individual variables x_i, determining resultant coefficient of belonging value $w_k = \mu_A^{(k)}(x)$.

The third layer – aggregation of M inference rule (the first neuron – f_1) and generation of normalizing signal (the second neuron – f_2):

$$f_1 = \sum_{i=1}^{M} c_i \left[\prod_{j=1}^{N} \left[\frac{1}{1 + \left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}} \right)^{2b_j^{(k)}}} \right] \right],$$

$$f_2 = \sum_{i=1}^{M}\left[\prod_{j=1}^{N}\left[\frac{1}{1+\left(\frac{x_i - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}}\right]\right] \tag{8}$$

A fourth layer consisting of one neuron generates an output signal $y(x)$.

5.Conclusion

The proposed methods and algorithms are implemented in the form of a computer program "Automated Information System “Testing diesel internal combustion engine based on fuzzy neural network”".

1. When AST works with a first pair of data ($y_1(x)$, d_1) is created the first cluster with the center c_1=$y_1(x)$. It is taken, that w_1=d_1 and that the cardinality of the set L_1=l. Let r denotes the marginal Euclidean distance between $y(x)$ and the center, in which data will be interpreted as belonging to the generated cluster. To preserve the generality of the solution is assumed that at the moment of the training start there are M clusters with the centers $c_1, c_2, ..., c_M$ and the corresponding values w_i и L_i (i=1, 2, ..., M).

2. After reading the k-th training couples ($y_к(x)$, d_k) are calculated the distances between $y_к(x)$ and all existing centers $\|y_к(x)-c_l\|$ for l=1, 2, ..., M. Assume that the nearest center is c_{lk}. In this case, depending on the value $\|y_k(x)-c_l\|$, may appear one of two situations :

- if $\|y_k(x)-c_l\|>r$, it will be created a new cluster c_{M+1}=$y_к(x)$, and $w_{M+1}(k)$=d_k, $L_{M+1}(k)$=1. Parameters of the prior established clusters do not change, i.e. $w_l(k)$=$w_l(k\text{-}l)$, $L_l(k)$=$L_l(k\text{-}1)$ for 1=1, 2, ..., M. Number of clusters M is incremented by 1 ($M = M$+1);

- if $\|y_k(x)-c_l\|<r$, data will be included into l_k-th cluster, the parameters of which are specified in accordance with the formulas:

$$w_{lk}(k) = w_{lk}(k-1) + d_k \tag{9}$$

$$L_{lk}(k) = L_{lk}(k-1) + 1 \tag{10}$$

$$c_{lk}(k) = \frac{c_{lk}(k-1) \times L_{lk}(k-1) + y_k(x)}{L_{lk}(k)} \tag{11}$$

3. After verifying the parameters of the fuzzy system, function that approximates the AST diesel input data, is defined as:

$$f(y(x)) = \frac{\sum_{l=1}^{M} w_1(k)\exp\left(-\frac{\|y(x)-c_1(k)\|^2}{\sigma^2}\right)}{\sum_{l=1}^{M} L_1(k)\exp\left(-\frac{\|y(x)-c_1(k)\|^2}{\sigma^2}\right)} \tag{12}$$

whereas other clusters do not change, i.e. at $l \neq l_k$, $w_l(k)$=$w_l(k\text{-}l)$, $L_l(k)$=$L_l(k\text{-}l)$ для l=1, 2, ..., M.

By repeating these steps of the algorithm until k=p clarifying each time values of M data space is divided into M clusters, wherein the power of each of them is defined as L_l=$L_l(к)$, center – as c_l= $c_l(k)$, and the value of the accumulated function attributed to him d – as w_l=$w_l(k)$.

Separation of data space into clusters occurs independently and without the participation of a technologist, in accordance with a predetermined threshold value r. In developed diesel engine AST value of r is set at the established amount of formal neurons:

$$r = \frac{10}{v} \tag{13}$$

wherein 10 –points of 10-point scale;

v – number of formal neurons set by the user of the system.

The effectiveness of the proposed neuro-fuzzy system to control diesel is examined. Since the setup time of the stand is reduced, time savings is 25% , as the result the fuel savings is 17% .

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