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Automated Test System of Diesel Engines Based on Fuzzy Neural Network

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Abstract: This study deals with the method for controlling a test stand of diesel engines based on fuzzy neural network. Structure and training algorithm have been proposed for a fuzzy neural network to control a diesel engine during testing. A knowledge base structure has been proposed. Fuzzy rules have been described to control a diesel engine. Techniques and algorithms have been realized in the form of a computer program. The effectiveness of the proposed automated diesel engine test system has been analyzed.

Key words: Diesel engine, automated test system, information technology, fuzzy rules, neuro-fuzzy network

INTRODUCTION

Leading engine companies are engaged in intensive research and development work to improve the reliability and durability of the Internal Combustion Engine (ICE) and in particular, diesel engines (Zhou *et al*., 2014).

Research and testing of diesel engines are one of the main means of checking the manufacturing quality of parts and assembly units, sub-assemblies and engine as a whole, its assembling adequacy, compliance of the essential characteristics of a diesel engine with requirements of technical documentation (Zhou *et al*., 2008).

Types of diesel engine tests are regulated by GOST and international standards ISO which prescribe the acceptance procedure and requirements to the technical level of engines (Stefanovsky *et al*., 1972). After accepting and launching diesel engines into manufacture, an improvement of their design and technical and economic indicators continues further.

Currently, testing of diesel engines is a complex and time-consuming process, little different from the pilot study. Therefore, the Automated Test Systems (ATS) for engines are created.

Modern requirements to a continuous improvement of the technical level of manufactured diesel engines has resulted in increasing the share of the costs for tests carried out when creating new models of engines. These costs become heavier in case of inconsistency between the levels of manufacturing automation and research research. In connection there with an automation of technological processes of testing is one of the main objectives of improving the technological level of production and quality of the diesel engines.

Normalization of input parameters of a diesel engine ATS shall optimally control a diesel engine during tests in a steady state, ensuring at any time the required values of output parameters of the engine. For this purpose, the ATS generates control action on the basis of knowledge base formed by fuzzy neural network (Zubkov and Galiullin, 2011). A control action for diesel engine is the movement of the regulator of a High-Pressure Fuel Pump (HPFP) h.

A knowledge base has the form of fuzzy control rules. Control rules have been developed using the theory of fuzzy sets and fuzzy logic:

$$R^{(k)}\text{: If } \omega \text{ AND } M_H \text{ AND } G_T \text{ AND ... THEN } h \qquad (1)$$

Where:

- k = The total number of fuzzy rules
- $R^{(k)}$ = The entire set of rules
- **ω** = Linguistic variable characterizing the engine speed
- $M_н$ = Linguistic variable characterizing the load moment
- G_T = Linguistic variable characterizing the fuel consumption
- h = Linguistic variable characterizing the position of the HPFP regulator

Fuzzy rules are clear and simple, unlike the differential equations describing the engine and its systems (Yao and Pan, 2014).

Mathematical algorithm for diesel ATS performance provides a preliminary input of the engine parameters. Suppose the ATS input parameters in the test program are as follows: crankshaft speed-**ω** (per min) the torque-$M_н$ (Н**м**) fuel consumption per hour-G_T (kg/h). However, it is possible to set more input parameters.

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Each input parameter will be further normalized. 1st step is the calculation of the parameter arithmetic mean:

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

Where:
x_i = A parameter value
n = Number of observations

2nd step is the calculation of the standard deviation:

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

3rd step is transfer of indicator values to the points on a 10-point scale:

$$St_i = \frac{(x_i - \bar{x})}{\sigma} \times 2 + 5.5 \tag{4}$$

FUZZIFICATION OF NORMALIZED ENGINE PARAMETERS

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

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

Where:
x_i = A normalized value of the indicator
c_i = Parameter of the formal neuron center set up in the interval of [0, 10] on a 10-point scale. Depending on the set number of formal neurons, a 10-point scale is divided into the corresponding number of segments where c_i is a midpoint of the segment
σ_i = A parameter (coefficient) of the function latitude. It is originally generated by an automated system as equal to 2/3 of the segment set by c_i
b_i = A parameter of the function form. It is originally generated by an automated system as = 1 which corresponds to the standard Gaussian function. ATS performs fuzzification for each vector of the engine input parameters (Makushin *et al*., 2009)

FORMATION OF FUZZY INFERENCE RULES FOR THE ATS KNOWLEDGE BASE

An integral degree of membership of all engine parameters entered in the ATS shall be determined for each of formal neurons. ATS applies an aggregation of membership degrees of individual parameters using the procedure of the algebraic product, suggesting that for the k-rule of inference:

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

CALCULATION OF CONTROL ACTION ON THE DIESEL ENGINE

The system approximates fuzzy set to an accurate solution h using the Mamdani-Zadeh model (Kruglov *et al*., 2000). In case of M inference rules and using the generalized Gaussian function as the membership function, the movement of the HPFP regulator is determined by the equation:

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

where, $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$ shall indicate the parameters of the center, width and shape of j component x for k fuzzy inference rule.

Figure 1 shows the structure of fuzzy neural network for diesel ATS implementing the approximation function Eq. 7.

This is a four-layer structure where the first layer performs separate fuzzification of each of input variables x_i (i = l, 2,...,N), determining the value of the membership coefficient $\mu_A^{(k)}(x_i)$ for each k rule of inference.

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

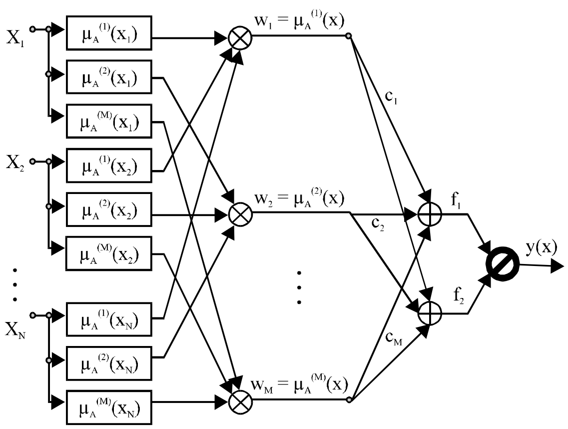

Fig. 1: Structure of the diesel ATS fuzzy neural network

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

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

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

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

TRAINING ALGORITHM FOR THE ATS FUZZY NEURAL NETWORK

First stage (gradient method of steepest descent). After formation of the output signal y(x), training error is calculated which is defined with the Euclidean norm as:

$$E = \frac{1}{2}\sum_{l=1}^{p}\left(y\left(x^l\right)-d^l\right)^2 \tag{8}$$

Where:
d = Expert evaluation
p = Number of training pairs (y, d)

Fuzzy network training is based on error minimization. Initially, the parameters $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$ are set according to the set number of neurons in the network and the distance between the thresholds of their sensitivity. Training error is a model of feedback. Error signals are sent through the connected network to the network input (back propagation) up to the first layer where the components of the objective function gradient can be calculated with respect to specific parameters $c_j^{(k)}$, $\sigma_j^{(k)}$, $b_j^{(k)}$.

After formation of the gradient vector, the parameters are specified by the gradient method of steepest descent (Shatnawi and Al-Khassaweneh, 2014):

$$c_j^{(k)}(n+1) = c_j^{(k)}(n) - \eta_c \frac{\partial E(n)}{\partial c_j^{(k)}} \tag{9}$$

$$\sigma_j^{(i)}(n+1) = \sigma_j^{(i)}(n) - \eta_\sigma \frac{\partial E(n)}{\partial \sigma_j^{(i)}} \tag{10}$$

$$b_j^{(i)}(n+1) = b_j^{(i)}(n) - \eta_b \frac{\partial E(n)}{\partial b_j^{(i)}} \tag{11}$$

Derivatives:

$$\frac{\partial w_r'}{\partial c_j^{(k)}}, \frac{\partial w_r'}{\partial \sigma_j^{(k)}}, \frac{\partial w_r'}{\partial b_j^{(k)}}$$

are calculated as:

$$\frac{\partial w_r'}{\partial c_j^{(k)}} = \frac{\delta_{rk} m(x_j) - l(x_j)}{\left[m(x_j)\right]^2} \prod_{i=1,\, j\neq i}^{N} \left[\mu_A^{(k)}(x_i)\right] \frac{\left[\frac{2b_j^{(k)}}{\sigma_j^{(k)}}\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}-1}\right]}{\left[1+\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}\right]^2} \tag{12}$$

$$\frac{\partial w_r'}{\partial \sigma_j^{(k)}} = \frac{\delta_{rk} m(x_j) - l(x_j)}{\left[m(x_j)\right]^2} \prod_{i=1,\, j\neq i}^{N} \left[\mu_A^{(k)}(x_i)\right] \frac{\left[\frac{2b_j^{(k)}}{\sigma_j^{(k)}}\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}\right]}{\left[1+\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}\right]^2} \tag{13}$$

$$\frac{\partial w_r'}{\partial b_j^{(k)}} = \frac{\delta_{rk} m(x_j) - l(x_j)}{\left[m(x_j)\right]^2} \prod_{i=1,\, i\neq j}^{N} \left[\mu_A^{(k)}(x_i)\right] \frac{\left[-2\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}} \ln\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)\right]}{\left[1+\left(\frac{x_j - c_j^{(k)}}{\sigma_j^{(k)}}\right)^{2b_j^{(k)}}\right]^2} \tag{14}$$

For r = 1, 2,....M where δ_{rk} is the Kronecker delta ($\delta_{rk} = 1$ if $y(x)>d$ and $\delta_{rk} = 0$ if $y(x)\leq d$):

$$m(x_j) = \sum_{k=1}^{M}\left[\prod_{j=1}^{N}\left[\mu_A^{(k)}(x_i)\right]\right]$$

$$l(x_j) = \prod_{j=1}^{N}\left[\mu_A^{(k)}(x_i)\right]$$

Network training is carried out cyclically as long as the training error stops decreasing (Hao, 2014). Second stage (an adaptive self-organization algorithm of fuzzy network).

After training the network by gradient method of steepest descent, the obtained result of ATS $y(x_i)$ research is subjected to training again by an adaptive self-organization algorithm. As a result of its implementation by the number of membership functions and their location in the part corresponding to the conditions (set of $y(x_i)$) and conclusions (set of expected scalar values d_i) of fuzzy rules are determined.

DISCUSSION

The first cluster with a center $c_1 = y_1(x)$ is created when the ATS works with the first pair of data $(y_1(x), d_1)$. It is accepted that $w_1 = d_1$ and the cardinality of the set $L_1 = 1$. Let r be the critical Euclidean distance between the y(x) and the center where the data will be interpreted as being members of the cluster created. In order to retain the generality of the solution it is assumed that there are M clusters with centers c_1, c_2, ..., c_M and their corresponding values w_i **и** L_i (I = 1, 2,...,M) at the beginning of training process.

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

If $||y_k(x)-c_l||>r$, than a new cluster $c_{M+1} = y_к(x)$ is created while $w_{M+1}(k) = d_k$, $L_{M+1}(k) = 1$. Parameters of previously created clusters remain the same, i.e., $w_l(k) = w_l(k-1)$, $L_l(k) = L_l(k-1)$ for l = 1, 2, ..., M. The number of clusters M increases by 1 (M = M+1).

If $||y_k(x)-c_l||<r$ than data are incorporated into l_k cluster, the parameters of which are specified in accordance with Eq. 15-17:

$$w_{lk}(k) = w_{lk}(k-1)+d_k \tag{15}$$

$$L_{lk}(k) = L_{lk}(k-1)+1 \tag{16}$$

$$c_{lk}(k) = \frac{c_{lk}(k-1)\times L_{lk}(k-1)+y_k(x)}{L_{lk}(k)} \tag{17}$$

After specifying the parameters of fuzzy network, the function approximating the input data of diesel ATS is defined as:

$$f(y(x)) = \frac{\sum_{l=1}^{M} w_l(k)\exp\left(-\frac{\|y(x)-c_l(k)\|^2}{\sigma^2}\right)}{\sum_{l=1}^{M} L_l(k)\exp\left(-\frac{\|y(x)-c_l(k)\|^2}{\sigma^2}\right)} \tag{18}$$

whereas other clusters remain the same, i.e., if $l \neq l_k$, $w_l(k) = w_l(k-1)$, $L_l(k) = L_l(k-1)$ for l = 1, 2, ..., M.

When repeating the above stages of the algorithm up to k = p, each time specifying the M value, the data space is divided into M clusters and the capacity of each of them is defined as $L_l = L_l(\kappa)$, the center as $c_l = c_l(k)$ and the value of accumulated function d attributed there to as $w_l = w_l(k)$.

Separation of data space into clusters occurs independently and without the participation of a test engineer in accordance with a predetermined threshold value r. Value r in the developed diesel ATS is assigned at a set number of formal neurons:

$$r = \frac{10}{v} \tag{19}$$

where, 10 points of a 10 point scale; v: number of formal neurons, set by the system user.

CONCLUSION

The proposed techniques and algorithms have been realized in the form of a computer program "Automated information system for testing diesel internal combustion engines based on neuro-fuzzy network" (Galliulin and Zubkov, 2011).

The effectiveness of the proposed neuro-fuzzy system for diesel engine control has been analyzed. Due to the reduction of time for stand setting, the economy of setting time will be 25% which results in 17% economy of fuel.

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