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Original Research Article

Estimating Engine Performance and Emission Values Using ANFIS

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Abstract

In this study, the effect of methanol mixtures in different proportions to emission and performance of the motor has been estimated using Adaptive Neuro Fuzzy Inference System (ANFIS) model. Training data and test data have been obtained from the results of experiments on a single cylinder, four-stroke engine with direct-injection under different spraying pressures. An ANFIS model has been developed using these experimental data. The estimated performance of the model has been obtained by comparison of the estimated results of the ANFIS model and the experimental results. It is seen that the obtained ANFIS model can make solid estimations about output emission and performance values of an internal combustion engine with different methanol mixtures.

Keywords: ANFIS Modeling, Engine Performance, Engine performance estimating

1. Introduction

It is known that despite its positive effect of facilitating human life, the internal combustion engine working with gasoline and diesel fuels have negative effects on environment such as increasingly significant amount of air pollution in the world. In the last decade a significant impact of exhaust emissions on health and the environment have been discussed [1]. The fact that the exhaust gases pollutes the environment, causes global warming and due to the increase in price of fossil fuels leads to the development of alternative fuel sources [2].
For this purpose, studies have been carried out for the development of alternative fuel types which decrease the use of oil based fuel consumption for the internal combustion engine and reduce the harmful substances in exhaust gases [3]. In recent years, in the studies of diesel-methanol blends, additives have been used to solve the problems such as; phase separation, phase number and the dual fuel work opportunities have been investigated by modifying the injection pressure of single-cylinder compression-ignition engines [4-6].

In this study, modeling the effect of diesel and methanol mixtures in different proportions on engine emissions and engine performance are aimed. Adaptive Neuro Fuzzy Inference System (ANFIS) for modeling of Engine Performance and Emission Values using experimental data has been proposed. ANFIS is a kind of neural network that is based on Takagi–Sugeno fuzzy inference system [7-9] which integrates both neural networks and fuzzy logic principles. Contrast to fuzzy systems which require an expert system, the ANFIS approach learns the rules and membership

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functions from data. In fact, ANFIS is an adaptive network.

2. Experimental works

The samples were prepared in volumes. There are four different types of fuels which are produced from diesel, methanol, Isobutanol and Di-Tert Butil Peroksit mixtures. The mixture rates of the fuels produced and their names are given in Table 1. In this study the results were obtained from the experiments carried out based on a single cylinder direct-injection four-cycle engine under different injection pressures. Test engine properties are given Table 2.

Table 1.The names and mixture percentages (in terms of volume) of the fuels.

	Diesel fuel	**methanol**	**Isobutanol**	**Di-Tert Butil Peroksit**
M0	*% 100*	*% 0*	*% 0*	*% 0*
M5	*% 94*	*% 5*	*% 1*	*% 0*
M10	*% 89*	*% 10*	*% 1*	*% 0*
M15	*% 84*	*% 15*	*% 1*	*% 0*
M5D1	*% 93*	*% 5*	*% 1*	*% 1*
M10D1	*% 88*	*% 10*	*% 1*	*% 1*
M15D1	*% 83*	*% 15*	*% 1*	*% 1*

Table 2. Specifications of the test engine.

Type	*Specifications*
Engine type	*Diesel engine*
Combustion	*Direct injection*
Cylinder number	*1*
Cylinder volume	*0.77 lt*
Stroke	*100 mm*
Compression ratio	*17:1*
Power	*6,62 kW 1800 rpm*
Rated speed	*2300 rpm*
Cooling system	*Water cooling*

Engine torque, specific fuel consumption, air consumption, efficiency and lambda values were obtained from seven different mixtures used with different speeds (1000, 1200, 1400, 1600, 1800, 2000 rpm) and injection pressures (165,170,175,185,195 bar). The change in engine torque for 165 bars injection pressure is given in Figure 1.

3. Adaptive neural-based fuzzy inference system (ANFIS)

Today, as an alternative to traditional methods in solving problems, neural network-based intelligent systems are used. ANFIS structure is a representation of Sugeno-type fuzzy systems as a network structure capable of neural learning. The network is a combination of the nodes placed in each of layers which performs a specific function. For the ANFIS structure, both the form of fuzzy logic and neural networks are used. ANFIS, in terms of structure, consists of if-then rules in fuzzy inference system and input and output information pairs. ANFIS, can assign all the possible rules or regulations for the addressed problem created by the structure or allows the experts to assign the rules by the help of the data. ANFIS consists of six layers. This system is shown in Figure 2. Node functions each of layers in ANFIS structure and functioning of the layers, are as follows respectively [7-9].

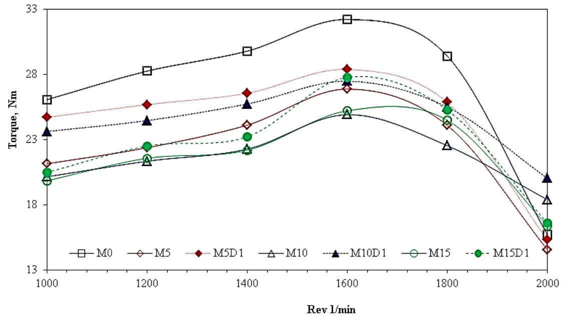

Figure 1. Relationship between engine speed and torque.

1st Layer: The first layer is called as the input layer. The input signal received from each node in this layer is transferred to other layers.

2nd Layer: The second layer is called as the fuzzification layer. Jang's ANFIS model used for the separation of input values in fuzzy sets, uses Bell activation function generalized as a membership function. Here, each node output consists of the input values and the membership degrees depending on the used membership functions and the membership degrees derived from the 2nd layer are shown as $\mu_{A_j}(x)$ and $\mu_{B_j}(y)$.

3rd Layer: It is known as the rule layer. Each node in this layer represents the rules and the numbers created by the Sugeno fuzzy inference system. The output of each rule node μ_i is the product of the membership degrees obtained from the 2nd layer. It is shown how to obtain the μ_i values is below,

$$y_i^3 = \prod_i = \mu_{A_j}(x) \times \mu_{B_j}(y) = \mu_i \qquad (1)$$

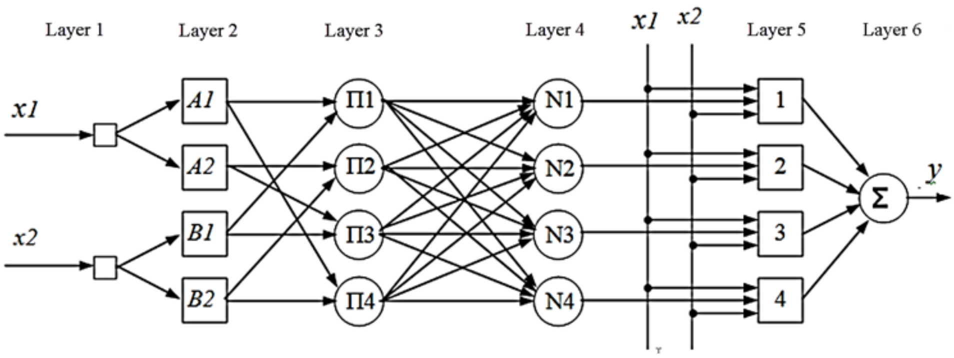

Figure 1. Architecture of ANFIS.

where (j = 1,2) and (i = 1, ...,., n). Here, y_i^3 represents the output value of the 3rd layer; n represents the number of nodes in this layer.

4th Layer: It is known as the normalization layer. Each node in this layer accepts all the nodes from the rule layer as input values and calculates the normalized firing level of each rule.

Calculation of normalized the firing rate $\bar{\mu}_i$ is performed according to the formula below,

$$y_i^4 = \bar{\mu}_i = \frac{\mu_i}{\sum_{i=1}^{n} \mu_i}, i = (1, n) \quad (2)$$

5th Layer: It is known as the purification layer. Weighted resulting values of a given rule on each node in the purification layer are calculated. The output value of a i th node in the 5th layer is as follows.,

$$y_i^5 = \bar{\mu}_i [p_i x_1 + q_i x_2 + r_i], i = (1, n) \quad (3)$$

(p_i, q_i, r_i) variables are the outcome parameter set of the i th rule.

6th Layer: It is known as the addition layer. There is only one node in this layer and the output value of each node in the 5th layer is summed and so the actual value of ANFIS system is obtained

$$y = \sum_{i=1}^{n} \bar{\mu}_i [p_i x_1 + q_i x_2 + r_i] \quad (4)$$

4. Modeling with ANFIS

In this study, the purpose is to estimate torque, specific fuel consumption, air consumption, efficiency and lambda values for the types of engine fuels with different injection pressures and speed by creating a fuzzy inference model based on adaptive neural network structure.

From a data set consists of 210 records, 85% of the data is used for training and 15% of the data is used for testing of the model. In order to prevent the problems created by large attribute values, the data set have been normalized to [0,1] in the estimation process.

$$x_i' = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (5)$$

here, x_i' is the scaled value, x_i is the input value, x_{max} and x_{min} are maximum and minimum values of the input values respectively. In this study, for a three input & one output system subtractive clustering are used in ANFIS structure and a hybrid algorithm are used for training steps. In the training phase, it is defined that the range of influence of subset parameter values is 0.5, squash factor is 1.25, acceptance ratio is 0.5, rejection ratio is 0.5 and epoch number is 15. For the estimation of 5 different output values, 5 separate ANFIS structures were created according to the specifications above. The ANFIS structure model for the estimation process is given in Figure 3 and this structure is applied using MATLAB fuzzy logic toolbox.

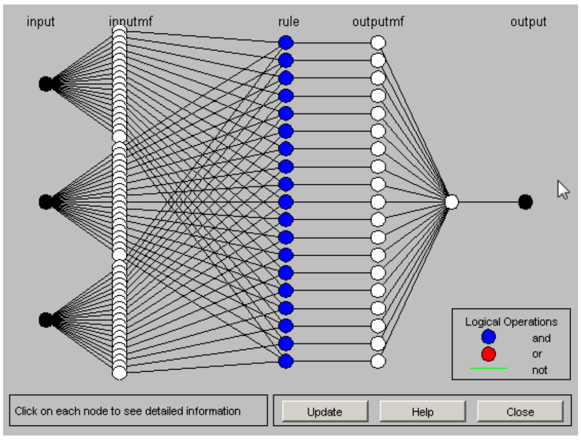

Figure 2. The general structure of ANFIS for the estimation of engine performance

The comparison between the testing values of torque output and ANFIS estimation values are shown in Figure 4 as an example. According to test results obtained, the estimation values is observed to be very similar to the actual output value.

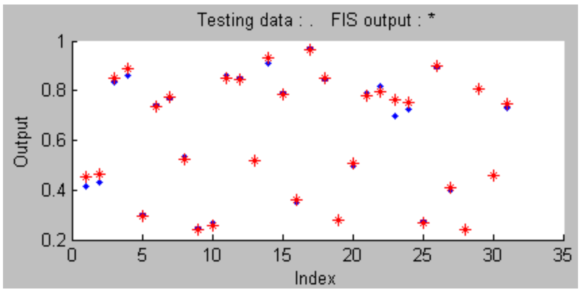

Figure 3. The comparison of Torque testing values and ANFIS estimation values

The evaluation of the prediction model was done by using statistical measurements. These measurements are root mean square error (RMSE) and Correlation coefficient (R).

Root mean squared error (RMSE):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(A_t - F_t)^2} \quad (6)$$

where At and Ft are actual (desired) and fitted (or predicted) values, respectively, and N is the number of training or testing samples.

Correlation coefficient (R):

$$R = \frac{\sum_{t=1}^{N}(A_t - \bar{A})(F_t - \bar{F})}{\sqrt{\sum_{t=1}^{N}(A_t - \bar{A})^2 \sum_{t=1}^{N}(F_t - \bar{F})^2}}$$

where $\bar{A} = \frac{1}{N}\sum_{t=1}^{N} A_t$ and $\bar{F} = \frac{1}{N}\sum_{t=1}^{N} F_t$ are the average values of $A_t$and F_t over the training or testing dataset. The smaller RMSE and larger R mean better performance.

5. Results

In this study, ANFIS has been used for the modeling of the parameters affecting the engine emission and engine performance for different proportions of diesel methanol mixtures. Each ANFIS model was developed for an output parameter.

Five separate ANFIS model performances are given in Table 3 for the estimation of torque, specific fuel consumption(SFC), air consumption(AC), efficiency and lambda output values These five ANFIS models were trained with the same training data set entries and it is verified that they are confirmed by the same test data set entries.

Estimation accuracy increases when the correlation coefficient get closer to 1. In this study, it is seen that the correlation coefficients obtained are closer to 1, so the estimated values of ANFIS structure is a good match to experimentally measured values.

Table 3. Performances of ANFIS in Modeling Motor Performances

ANFIS Model	Training Data Set		Testing data Set	
	RMSE	*R*	*RMSE*	*R*
Torque	0.028	0.9902	*0.102*	*0.8964*
SFC	0.027	.0.9924	*0.069*	*0.9333*
AC	0.028	0.9998	*0.018*	*0.9973*
Efficiency	0.007	0.9993	*0.028*	*0.9903*
Lambda	0.033	0.9794	*0.086*	*0.8908*

Also in Table 3 it is seen that RMSE values, given separately for training and testing values, are very small.

It is observed from the results of ANFIS estimation model, the structure can estimate the engine performance successfully and the emission parameter values for different diesel methanol mixtures, injection pressures and speed values. Experiments on the engines are difficult, time consuming and costly processes. Considering the fact that it cannot be possible to process these values except from boundary values, it is seen that the specified difficulties can be eliminated by the designed model in this study.

The obtained model can be improved by using different artificial intelligence techniques and modeling methods.

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