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Full Length Research Paper

Prediction of a diesel engine characteristics by using different modelling techniques

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In this study, the characteristics of a four-stroke internal combustion diesel engine have been investigated by means of artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) modelling techniques, using injection pressure, engine speed and torque. Injection pressure of diesel engine has been designed with a pressure of 150 bars for the turbo charger and pre-combustion chamber. The experiments have been implemented for four different pressure values, namely 100, 150, 200 and 250 bars with throttle positions of 50, 75 and 95%. Brake means effective pressure (BMEP), fuel flow (FF), specific fuel consumption (SFC) were obtained from experimental results for four different injection pressure. The proposed ANNs and ANFIS models are composed of the results of implemented measurements. ANNs model of the diesel engine has two subsystem. The first subsystem has two outputs (BMEP, FF) and the second subsystem has single output as specific fuel consumption (SFC). In first subsystem ANNs model, both mean effective pressure and fuel flow parameters are computed concurrently. ANFIS model of system has three inputs and outputs as injection pressure, engine speed, torque, BMEP, FF and SFC, respectively. The performance of ANNs and ANFIS models are compared with each other in same figures for same experimental data. The results of modeling techniques of a four-stroke internal combustion diesel engine are observed to be very close with the experimental results.

Key words: Diesel engine, brake mean effective pressure, fuel flow, specific fuel consumption, artificial neural network and adaptive neuro-fuzzy inference system.

INTRODUCTION

Nowadays, fuel injection systems and injection pressure can be succesfully adjusted in high pressure. This process increases the efficiency of diesel engine. Injection characteristics of diesel engine with direct injection have been studied by several researchers (Yang et al., 1996). In this study parameters have been calculated according to rotation and injection pressure. Employing some mathematical models to estimate emissions and characteristics of engine is another important approach. But high accuracy of these approaches may not be ensured (Massie, 2001).

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Experiment-based approaches which are like artificial neural netwok and fuzzy logic methods can be an alternative to mathematical models. The digital computer provided a rapid means of performing many calculations involving the artificial neural network (ANN) and fuzzy logic (FL) methods. Along with the development of high speed digital computers, applications of ANN and FL approaches could be at a very impressive rate (Kastrevc et al., 2005; Chi et al., 2008; Jain et al., 2008; Kouremenos et al., 1993; Erentürk, 2005). Although reliable results can be obtained, experimental studies conducted to measure characteristic values and performance of diesel engines are complex, time consuming and expensive (Arcaklioğlu and Çelikten, 2005). For example in some performance experiments of an internal combustion diesel engine, interval of engine speed is

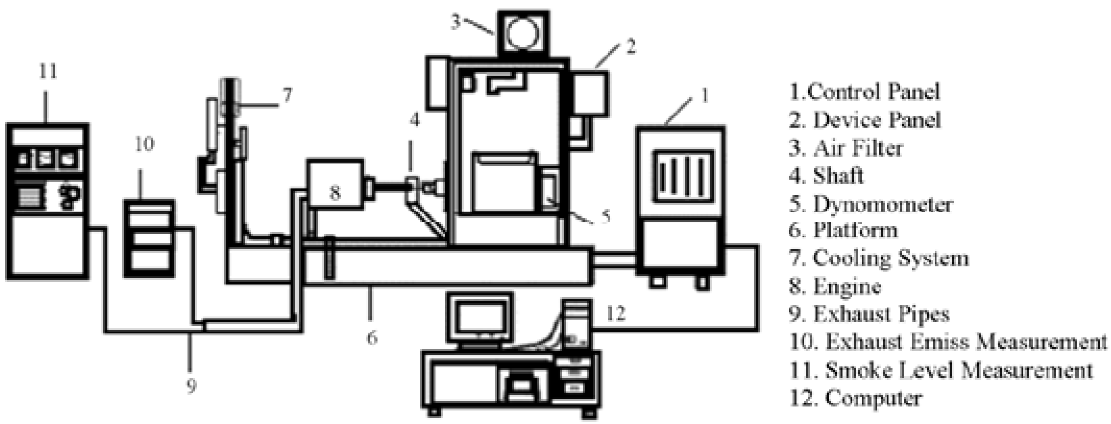

Figure 1. Schematic picture of engine test bed.

chosen as great to do less experiment (500 to 1000 to 1500...etc). Interval values which are not obtained from experiments can be calculated by using some simulation methods (750 to 1250 to 1750…etc).

For this issue some simulation models can be developed such as ANN and fuzzy logic approaches to estimate experimental results. These models are capable to determine some specific interval values which are not obtained by using experimental works. In this manner if dependable results are obtanined from these model approaches, cost and number of experiments can be decreased using ANN or fuzzy logic model and another experiment may not be needed any more.

In recent years, these methods have been applied on various disciplines including automotive engineering and forecasting of engine thermal characteristics for different working conditions. Artificial neural network approach has been used for modeling systems which are related to internal combustion engine (Arcaklioğlu et al., 2005; Canakci et al., 2006; Parlak et al., 2006; Çelik et al., 2005; Çelikten, 2005; Beck et al., 1988), nuclear energy (Şahin et al., 1999; Şahin and Sözen, 1999; Knudsen et al., 2005), medical science (Yildiz et al., 2002) and electronics (Güney et al., 2004; Sağıroğlu et al., 2003; Şahin et al., 2002).

Although ANN and fuzzy logic methods are similar from the wiew point of theorical work, the formation structures of them are different. ANN structure depends on experimental data but fuzzy logic is constituted by experienced specialist's knowledge. In this paper two simulation models are adopted to predict experimental results for a diesel engine and they are compared with each other according to their results.

In the existing literatures, it has been shown that the use of ANN is a powerfull modeling tool that has the ability to identify complex relationship between input and output data (Canakcı et al., 2006). However, no investigation to predict brake mean effective pressure (BMEP), fuel flow (FF) and specific fuel consumption (SFC) for diesel engine, and using fuzzy logic approach appears to have been published in the literature to date. Therefore, this study investigates the applicability of ANN and fuzzy logic methods for predicting the aforementioned parameters and defining which method is more realistic.

EXPERIMENTAL SET UP AND MEASUREMENTS

Energy supplied to an internal combustion engine is the heat revealed from burning of fuel in air. Some of this energy can be exploited, that is some of the energy fuel included can be converted to mechanical energy in engine shaft and the rest of the energy is wasted through thermal losses. Two fundamental fractions of lost energy consist of the heat carried by exhaust gases and the heat transferred to cooler fluid. Obtaining sufficient data related with the thermal distribution of an engine requires the determination of friction power, fuel and air consumptions, exhaust gas temperature, exhaust gas components and engine input and output temperature values in a given engine speed and power. In designing of internal combustion engine, thermal parameters and mechanical properties are interrelated and they are the vital elements employed in studies such as exhaust gas emission, engine specific fuel consumption and motor efficiency.

In this paper, an electrical dynamometer assembled on 4-cylinder and 4-stroke indirect injection diesel engine was used. As shown in Figure 1, there are different thermocouples and electrical units on the dynamometer and the engine. Circuits in all units have been connected to each other, and they have been also controlled using a computer. In addition, there are two exhausts emission measurement equipment working separately. One of the equipment was used for O_2, SO_2, CO, CO_2, and NO_x measurements (Knudsen et al., 2005); the other for smoke level (Yildiz et al., 2002). After nozzles which change adjusting pressure are assembled and, they have been investigated according to engine performance and emission for different throttle position. Experiments have been conducted on a diesel engine connected with an electrical dynamometer. Before starting the engine, the nozzles were taken off and adjusted 150 bar which is factory demand.

For the adjustment, washer(s) has been used to change the nozzles pressures. After that, the nozzles adjusted have been fitted to the engine. Then, the air in the nozzles has been transferred to the atmosphere and the engine was run. The computer controlled

Table 1. Specifications of the test engine.

Make and model	Ford-XLD 418T.1998
Motor type	Turbo charged, diesel, pre-combustion chamber, four-stroke
Number of cylinders and volume	Four-cylinders and 1.81
Engine power and torque	44kW AT 4800 RPM, 110 Nm at 2500 rpm
Fuel system and injectors	Lucas DPC type fuel-injection pump, single-point fuel injectors

Table 2. Measurement ranges and accuracies of the LOY-Gaco-SN equipment.

Combustion efficiency (%)	B = 100 - (T_G-T_A)/CO_2 x K (calculated)
λ	$\lambda = 1 + O_2\%(20.9 - O_2\%)xV_{a,\min}/L_{\min}$ (calculated)
Gas temperature ℃ (T_G)	Range = 0-1000 ℃, Accuracy = 1℃
Ambient temperature℃ (T_A)	Range = 0-199.9 ℃, Accuracy = 0.1℃

Table 3. Measurement ranges and accuracies of VLT 2600-S equipment.

Exhaust fume darkness (K, %)	Accuracy = 0.01	0.99%
K factor	Accuracy = 0.01	0.1%
Engine speed	0.9 - 999d/dk	

diesel engine connected to the electrical dynamometer was loaded in throttle position of 50%. Engine was tested in range of 1500 to 4500 rpm with the interval of 500 rpm. In the throttle position, no maximum torque level of 4500 rpm was reached. In the experiments, torque, power, brake mean effective pressure (BMEP), specific fuel consumption (SFC) and fuel flow (FF) rate were recorded by computer. In addition, emission and smoke level (or PM) have been measured using an exhaust probe connected to tail pipe. Similarly, these measurements were repeated in throttle positions of 75 and 100%. Fuel–air equivalence ratios are measured in the experiments, as well. But, no fuel–air ratio was given in graphics since SFC partly informs about the ratio presented in Figure 1.

Here, the specification of our test environment (the diesel engine) and the accuracy of the equipment used to collect the necessary data is given in details. Make and model; Ford-XLD 418T, 1998, Motor type; Turbocharged, diesel, pre-combustion chamber, four-stroke, Number of cylinders and volume; Four-cylinders and 1.8 l Engine power and torque; 44 kW at 4800 rpm, 110 Nm at 2500 rpm, Fuel system and injectors; Lucas DPC type fuel-injection pump, single-point fuel injectors are given in Table 1. Measurement range and accuracie of the LOY-Gaco-SN equipment, measurement range and accuracie of VLT 2600-S equipment are also given in Tables 2 and 3, respectively.

In this study, engine characteristics of a four-stroke internal combustion diesel engine have been investigated by means of artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) modelling techniques. For this aim, experiments have been performed for both full and partial loads on a turbocharger diesel-engine with four-cylinder, four-stroke, indirect injection by changing the injection pressures from 100 to 250 bar with intervals of 50 bar and for throttle positions of 50, 75 and 100%.

ARTIFICIAL NEURAL NETWORKS (ANNS) MODELING

ANNs are artificial systems, designed to mimic human brain by extracting the relationships that underlie the data with which it is presented. They produce results very fast because of their property of working in parallel to solve a specific problem. Thereby, they are quite effective in real-time problem solving. In the most general sense, ANN can be assumed as a complex interconnected system formed from connection of a great deal of neurons in human brain or connection of simple processing elements artificially with different impact levels (Canakcı et al., 2006; Minai et al., 1990).

ANN is created by a means of interconnection of network neurons and usually organized into layers. Various ANN architectures are present (Canakci et al., 2006). Of these, multilayer perceptron (MLP) structure has been used to estimate motor performance by using injection pressure, engine speed, throttle positions and torque values of an internal combustion four-stroke diesel engine.

Multilayer perceptrons (MLPs)

Multilayered perceptrons (MLPs) are the simplest and therefore most commonly used neural network architectures (Parlak et al., 2006). As shown in Figure 2, an MLP consists of three layers which are an input layer, output layer and an intermediate or hidden layer. Neurons (indicated in Figure 2 with the circle) in the input layer only act as buffers for distributing the input signals x_i to neurons in the hidden layer. Each neuron j in the hidden layer sums up its input signals x_i after weighting them with the strengths of the respective connections w_{ji} from the input layer and computes its output y_j as a function f of the sum.

$$y_j = f(\sum w_{ji} x_i) \quad (1)$$

f can be a simple threshold function, a sigmoidal or hyperbolic tangent function. The output of neurons in the output layer is computed similarly.

Training a network consists of adjusting weights of the network

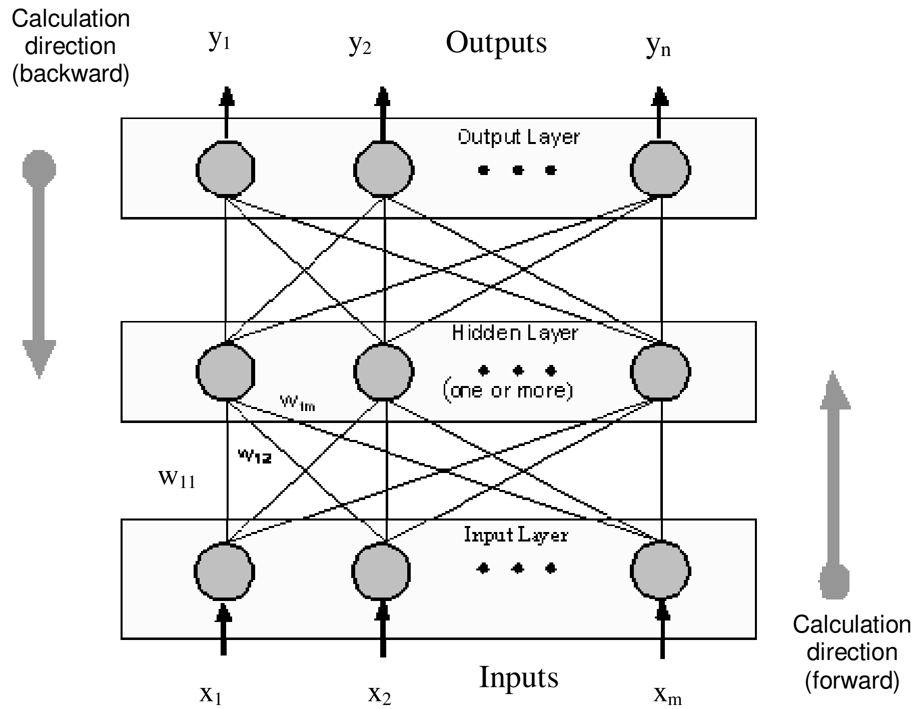

Figure 2. General form of multilayered perceptrons.

Table 4. Training set data samples with BMEP and FF outputs (Model-1).

Inputs				Outputs	
Throttle position	**Injection pressure**	**Engine speed**	**Torque**	**BMEP**	**FF**
50	100	4266	5.2	0.4	5.7
75	100	4502	99.7	7.1	15.9
95	100	4501	94.8	6.8	15.4
:	:	:	:	:	:
:	:	:	:	:	:

using the different learning algorithms. A learning algorithm gives the change Δw_{ji} (k) in the weight of a connection between neurons i and j at time k. The weights are then updated according to the following formula.

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji}(k+1) \tag{2}$$

In this study, extended delta bar delta (EDBD) algorithm has been used to train MLPs.

Extended delta bar delta (EDBD)

The EDBD algorithm (Çelik et al., 2005) is an extension of the DBD algorithm and based on decreasing the training time for multilayered perceptrons. The use of the momentum heuristics and avoiding the cause of the wild jumps in the weights are the features of the algorithm. The EDBD algorithm includes a little-used error recovery feature which calculates the global error of the current epoch during the training. If the error measured during the current epoch is greater than the error of the previous epoch, then the network's weights revert back to the last set of the weights that produced the lower error. However, a patience factor has been included into the error recovery feature, which may produce the better performance of the networks through the use of this feature.

Performance estimation of a four-stroke internal combustion diesel engine by using ANN

The two models use MLP type neural networks, which are trained and tested by EDBD training algorithm. 84 different measured values were used for training and testing. This set of data set has been obtained for estimation of pressure, speed and torque values, BMEP, FF and SFC for the corresponding values of throttle positions of 50, 75 and 95%. 60 of these values have been used in training and 24 of these have been used in testing. Training and testing sets of data samples have been summarized for BMEP and FF (model-1) in Tables 4 and 5 respectively.

As shown in Figures 3 to 4, in the first model multi output as BMEP and FF, in the second model a single output structure as

Table 5. Testing set data samples with BMEP and FF outputs (Model-1)

Inputs				Outputs	
Throttle position	**Injection pressure**	**Engine speed**	**Torque**	**BMEP**	**FF**
50	100	1992	120.5	8.6	6.7
75	100	2003	123.3	8.8	7.2
95	100	1998	117.7	8.4	7
:	:	:	:	:	:
:	:	:	:	:	:

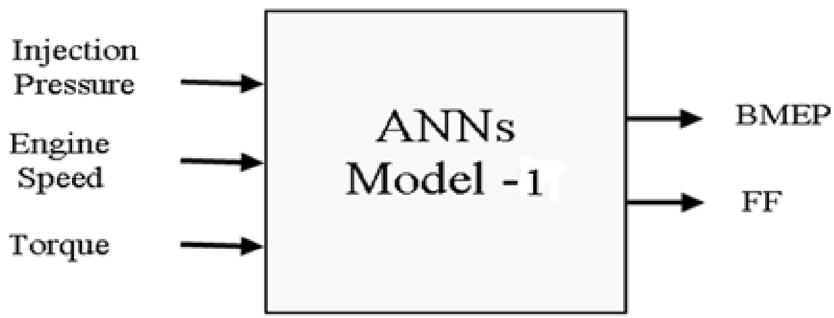

Figure 3. Two output Model-1 structure for BMEP and FF.

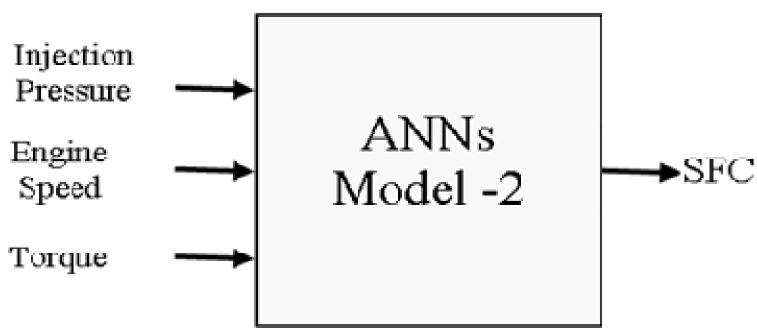

Figure 4. Singleoutput model-2 structure for SFC.

as SFC has been used. In multi output network structure with two output, injection pressure, engine speed and torque parameters are inputs to the network and BMEP and FF parameters are the outputs, which are computed concurrently. In the network with single output (model 2), using same input parameters only SFC has also been computed.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM MODELING

The field of fuzzy system has been making a big progress motivated by the practical success in modelling and control of industrial process (Kastrevc et al., 2005; Chi et al., 2008). Fuzzy systems can be used as system modelling. In this case fuzzy modelling provides appropriate system outputs from real experimental data sets. The fuzzy logic model uses a form of quantification of imprecise information (input fuzzy sets) to generate an inference scheme, which is based on a knowledge base of modelling. The advantage of this quantification is that the fuzzy sets can be represented by a unique linguistic expression, such as small, medium and large, etc. The linguistic representation of a fuzzy set is known as a term, and a collection of such terms defines a term-set, or library of fuzzy sets. Fuzzy logic converts a linguistic modelling strategy usually based on expert knowledge into a system of fuzzy logic modelling strategy.

Fuzzy logic is made of four main components: (1) Fuzzifier; (2) Knowledge base containing fuzzy IF-THEN rules and membership functions; (3) Fuzzy reasoning; and (4) Defuzzifier interface. The basic configuration of the fuzzy system with fuzzifier and defuzzifier used in this study is shown in Figure 5.

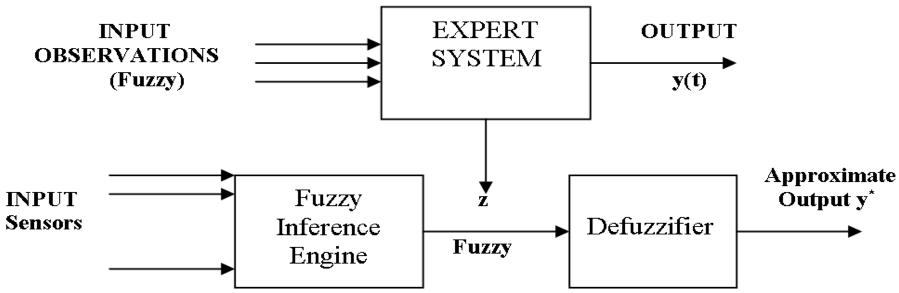

Figure 5. The basic configuration of the fuzzy system.

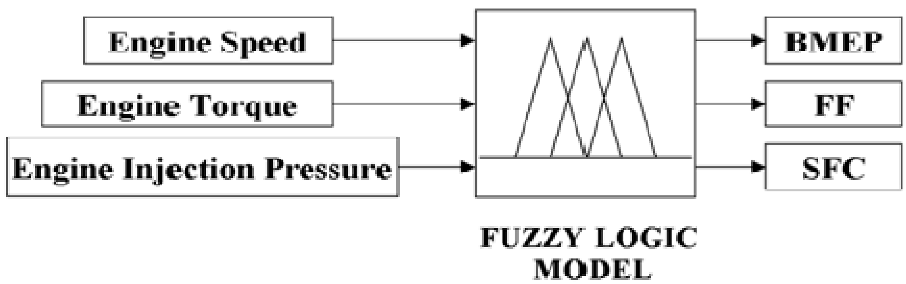

Figure 6. Fuzzy logic modelling of engine test system.

In this study, adaptive neuro-fuzzy inference system (ANFIS) modelling of engine test system is realized and compared with actual experimental output data sets and artificial neural network modelling of diesel engine system.

Primarily we obtain real data sets to create fuzzy logic model inputs and outputs and to know how many inputs and outputs are determined from experiments of engine test system. Fuzzy logic model membership functions and rule bases are obtained by actual data sets results. In Figure 6, fuzzy logic modelling of engine test system is seen. In this configuration, we can say that fuzzy logic model has three inputs such as engine speed, engine torque and engine injection pressure, and three outputs, BMEP, FF and SFC.

In this study, mean % error was used to compare experimental and modeling results and it showed testing performances of ANN and ANFIS models for 25 test values.

Formulation of mean % error is described as:

$$Mean\ \%\ error = \left[\sum_{i=1}^{m} \frac{\sum_{i=1}^{n} \left| X_{i_{Experimental}} - X_{i_{Modeling}} \right|}{\sum_{i=1}^{n} X_{i\,Modeling}} \times 100 \right] \Big/ m \quad (3)$$

where $X_{i_{Experimental}}$ is experimental outputs, $X_{i_{Modeling}}$ is outputs of ANN and fuzzy Logic modeling, n is the number of test data, m is the number of outputs of ANN and ANFIS models.

Membership functions and fuzzy rules

Two of the difficulties with the design of any fuzzy logic modelling are the shape of the membership functions and choice of the fuzzy rules. In fact, the decision-making logic is the way in which the model output is generated. It uses the input fuzzy sets and the decision is taking according to the values of the inputs. Moreover, the knowledge base comprises knowledge of application domain and the attendant modelling goals. It consists of a database and a fuzzy logic model rule base. The fuzzification uses membership functions to determine the degree of inputs. The aim of modelling is to obtain suitable outputs according to real engine experiment.

In this study, sugeno-type inference system is used for modelling as fuzzy inference system. It applies a combination of the least-squares method. Fuzzy logic model of engine test system has three membership functions for each input. Triangular type membership functions are used in fuzzification process.

Membership functions of fuzzy logic model are given in Figures 7, 8 and 9. Fuzzy logic rule base is made of 27 rules and these rules are determined by adaptive neural network based fuzzy inference system (ANFIS) of engine test system. ANFIS obtains optimum range of membership functions and rules which are based on experimental data easily. But it permits only one output. In anfis output values are constant, not fuzzy. After ANFIS model, we combine all rules and outputs in one sugeno type fuzzy inference system (FIS). This modelling is called interval Type-2 fuzzy logic modelling in literature. Rule base is given in Table 6.

Adaptive neural network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined largely by the connections between elements. We can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly neural

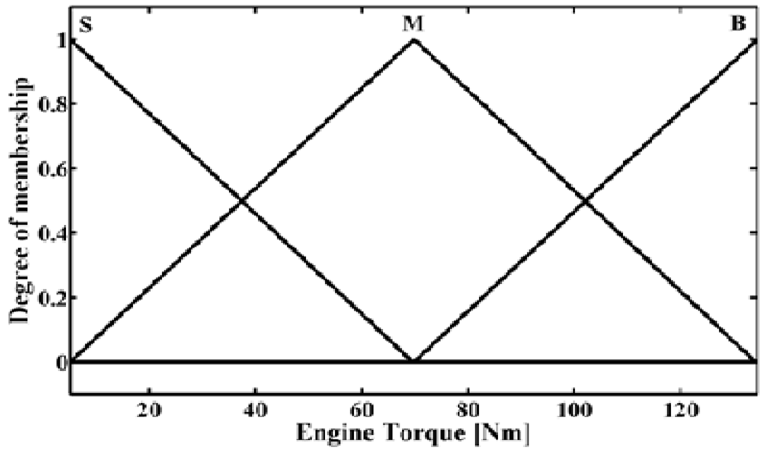

Figure 7. Membership functions of engine torque [Nm].

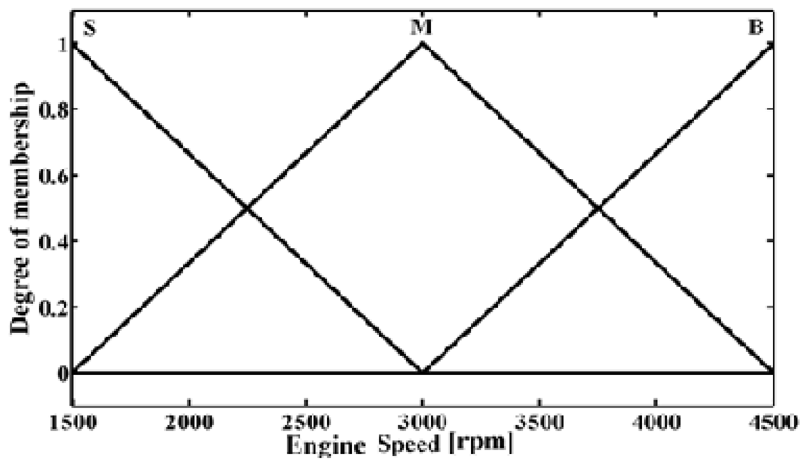

Figure 8. Membership functions of engine speed [rpm].

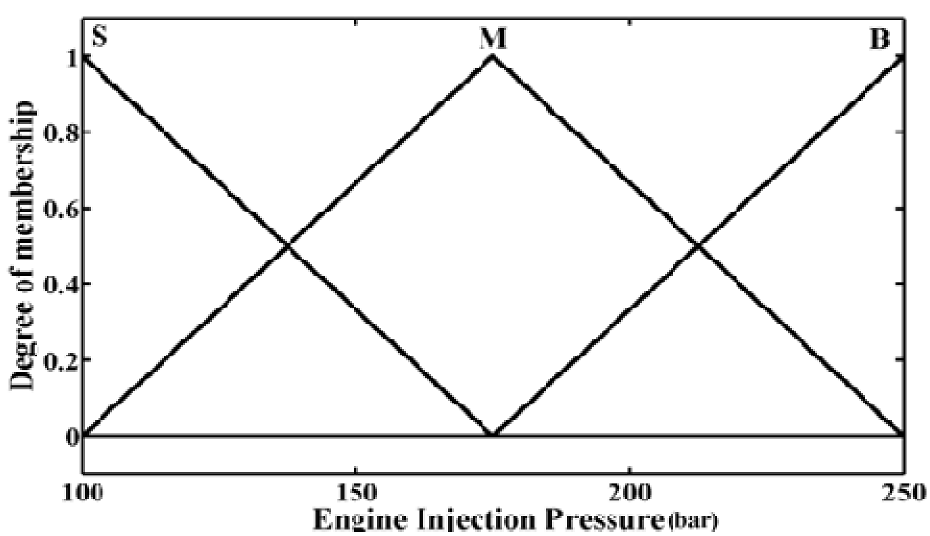

Figure 9. Membership functions of engine injection pressure [bar].

Table 6. Rule base of fuzzy logic modelling of diesel engine test system.

Input/	Rules																										
Output	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R18	R19	R20	R21	R22	R23	R24	R25	R26	R27
Engine speed	S	S	S	S	S	S	S	S	S	M	M	M	M	M	M	M	M	M	B	B	B	B	B	B	B	B	B
Engine torque	S	S	S	M	M	M	B	B	B	S	S	S	M	M	M	B	B	B	S	S	S	M	M	M	B	B	B
Injection pressure	S	M	B	S	M	B	S	M	B	S	M	B	S	M	B	S	M	B	S	M	B	S	M	B	S	M	B
BMEP	BC1	BC2	BC3	BC4	BC5	BC6	BC7	BC8	BC9	BC10	BC11	BC12	BC13	BC14	BC15	BC16	BC17	BC18	BC19	BC20	BC21	BC22	BC23	BC24	BC25	BC26	BC27
FF	FC1	FC2	FC3	FC4	FC5	FC6	FC7	FC8	FC9	FC10	FC11	FC12	FC13	FC14	FC15	FC16	FC17	FC18	FC19	FC20	FC21	FC22	FC23	FC24	FC25	FC26	FC27
SFC	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10	SC11	SC12	SC13	SC14	SC15	SC16	SC17	SC18	SC19	SC20	SC21	SC22	SC23	SC24	SC25	SC26	SC27

Exp: In this table, BC_i, FC_i and SC_i, are output constants of BMEP, FF and SFC respectively. R_i: Rule (i = 1...27).

networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 10. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are needed to train a network. Neural networks have been trained to perform complex functions in various fields, including pattern recognition, identification, classification, modelling, speech, vision, and control systems.

ANFIS architecture consists of five layers with the output of the nodes in each respective layer represented by $O_{i,l}$, where i is the i^{th} node of layer l.

Layer 1: Generates the membership grades

$$O_{i,l} = \mu_{A_i}(x) \text{ , } i = 1,2 \tag{4}$$

or

$$O_{i,l} = \mu_{B_i\,2}(y) \text{ , } i = 3,4 \tag{5}$$

Where x (or y) is the input to the node and A_i (or B_{i-2}) is the fuzzy set associated with this node.

Layer 2: Generates the firing strengths by multiplying the incoming signals and outputs the t-norm operator result, for example,

$$O_{2,i} = w_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \text{ , } i = 1,2 \tag{6}$$

Layer 3: Normalizes the firing strengths

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \text{ , } i = 1,2 \tag{7}$$

Layer 4: Calculates rule outputs based on the consequent parameters $\{p_i, q_i, r_i\}$

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{8}$$

Layer 5: Computes the overall outputs as the summation of incoming signals

$$O_{5,l} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f}{\sum_i w_i} \tag{9}$$

We follow these steps for creating of ANFIS modelling as shown subsequently,

(1) 760 training and 190 checking data have been used for neural network based on ANFIS modelling.
(2) The number and type of membership functions have been determined.
(3) Hybrid learning algorithm and 40 epochs have been chosen to train network.

Hybrid learning algorithm

In this study, forward hybrid learning algorithm is used for neural network part of ANFIS modelling (Figure 11). Nearly 40 epochs later, error rate is close to 10^{-5}. In the forward pass of the hybrid learning algorithm, node outputs go until layer 4 and the consequent are identified by the least-squares method. When the values of the promise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \overline{w}_1 f_1 + \overline{w}_2 f_2 \\ &= \overline{w}_1.x.p_1 + \overline{w}_1.y.q_1 + \overline{w}_1.r_1 + \overline{w}_2.x.p_2 + \overline{w}_1.y.q_2 + \overline{w}_1.r_2 \end{aligned} \tag{10}$$

which is linear in the consequent parameter

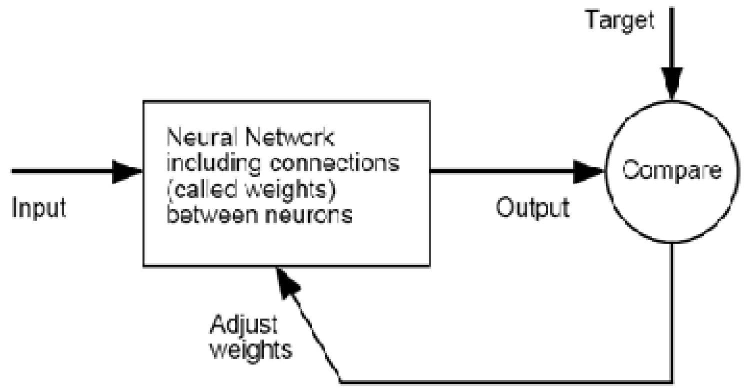

Figure 10. Neural network structure.

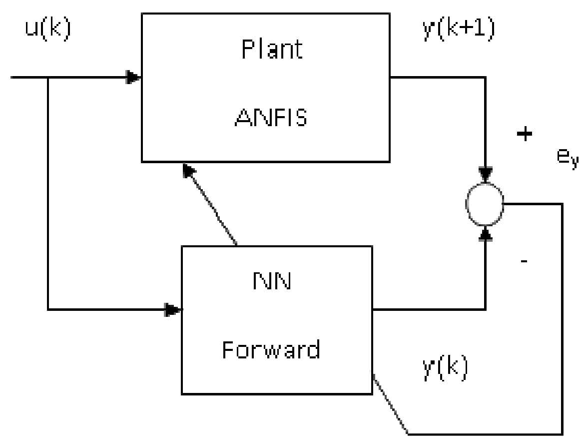

Figure 11. Training of NN forward model.

p_1, q_1, r_1, p_2, q_2 and r_2,

$$f = XW \tag{11}$$

If X matrix is invertible then

$$W = X^{-1} f \tag{12}$$

Otherwise a pseudo- inverse is used to solve for W.

$$W = (X^T X)^{-1} X^T f \tag{13}$$

Due to the adaptive capability of ANFIS, their applications to adaptive and learning control are immediate. The most common design techniques for ANFIS modelling are derived directly from neural networks counterpart methodologies. However certain design techniques apply exclusively to ANFIS.

Defuzzification process

Once the fuzzy controller is activated, rule evaluation is performed and all the rules are true and fired. Utilizing the true output membership functions, defuzzification is then applied to determine a crisp control action. The defuzzification is to transform the fuzzy output into an exact model output. For Sugeno-style inference, we have to make choose weighted average (wtaver) or weighted sum (wtsum) defuzzification method. In defuzzification process of fuzzy logic modelling, the method of weighted average (wtaver) has been used:

$$u = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i} \tag{14}$$

Modelling surfaces of fuzzy logic model for BMEP, FF and SFC are shown in Figures 12 to 14.

RESULTS AND DISCUSSION

The aim of using the artificial neural network (ANN) and fuzzy logic (FL) models considered as a practical

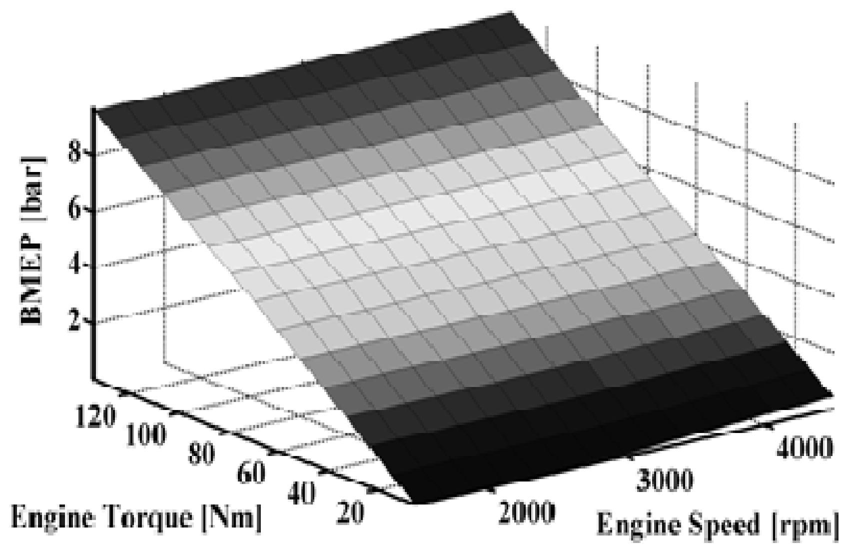

Figure 12. Modelling surface of fuzzy logic model for BMEP.

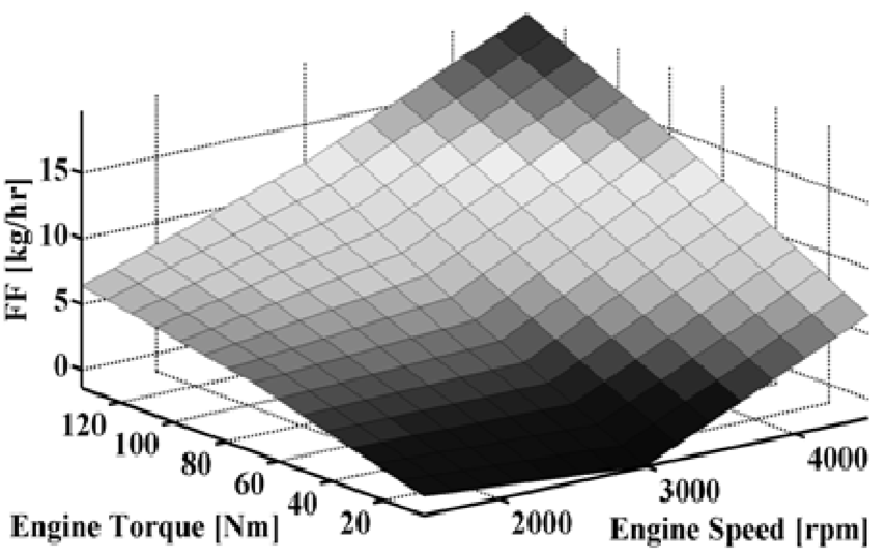

Figure 13. Modelling surface of fuzzy logic model for FF.

approach is to test the ability to predict brake mean effective pressure (BMEP), fuel flow (FF) and specific fuel consumption (SFC) for a diesel engine. The proposed ANN and fuzzy logic models are composed of using the results of implemented measurements. ANN model of the diesel engine has two subsystems. The first subsystem has two outputs (BMEP, FF) and second subsystem has single output as specific fuel consumption (SFC). In first subsystem ANN model, both mean effective pressure and fuel flow parameters were computed concurrently. In the first model of artificial neural network modeling (ANN) in which outputs were both BMEP and FF, two hidden layers were used with a number of 5 hidden neurons in each of the hidden layer and at the end of 240.000 iterations. In the second model of artificial neural network modeling, in which output was the SFC, three hidden layers have been used with a number of 6 hidden neurons in each of the hidden layer and at the end of 2.500.000 iterations. For both models, sigmoid activation functions have been used. Fuzzy logic model of system has three inputs and outputs as injection pressure, engine speed, torque, BMEP, FF and SFC respectively.

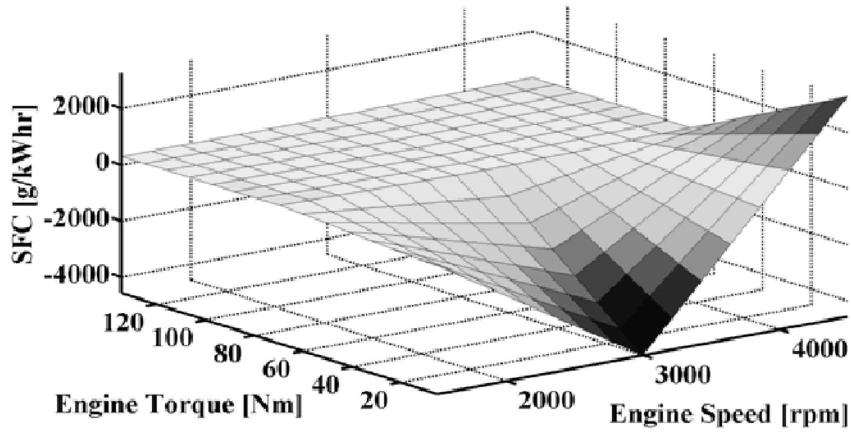

Figure 14. Modelling surface of fuzzy logic model for SFC.

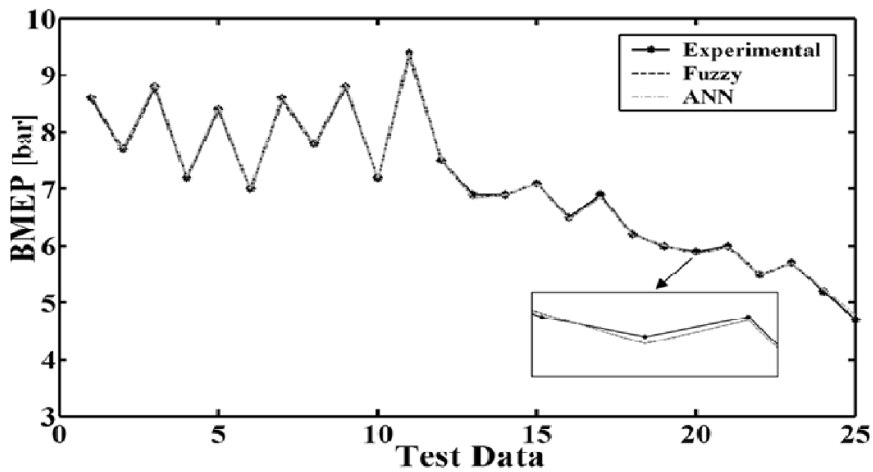

Figure 15. BMEP results of ANN, fuzzy and experimental for 25 test data.

Triangular type three membership functions and 27 rules have been used in fuzzy logic model.

Experimental, ANN and fuzzy logic results are given in Figures 15, 16 and 17. The mean % errors of ANN and fuzzy logic models for BMEP, FF and SFC results are given in Table 7. During the testing validation period, the mean % errors of ANN and fuzzy logic models for BMEP have been found to be smaller than 1% error. This can clearly be seen from Figures 15 and 18. In the testing period, for FF, the mean % error was found to be less than 1.6% and it can be seen in Figures 16 and 19. According to these results we can say that fuzzy logic model is more effective than ANN model, but predictive ability of both models for BMEP and FF has been found to be quite satisfactory.

A comparatively presentation of the error for SFC during testing by using both models and experimental results has been shown in Figures 17 and 20. The mean % error of ANN and fuzzy logic models for SFC during testing period has been found to be 3.41 and 1.6143% respectively. Figure 20 shows the numerical differences between experimental and predictive values for 25 different test points one by one. Once again SFC result of fuzzy logic model has been found better than ANN's.

In literatures, the mean % errors of BMEP and FF are approximately same with our given results, but the mean % errors for SFC have been found to be 1.93 (Canakcı et al., 2006), 2.09 (Parlak et al., 2006), 2.43 (Al-Hinti et al., 2009), 2.054% (Yücesu et al., 2007). Therefore, in this paper predictive ability of SFC obtained using fuzzy logic model has been found to be better than that in the literatures.

Conclusion

The aim of this paper has been to show the possibility of using artificial neural network and fuzzy logic for

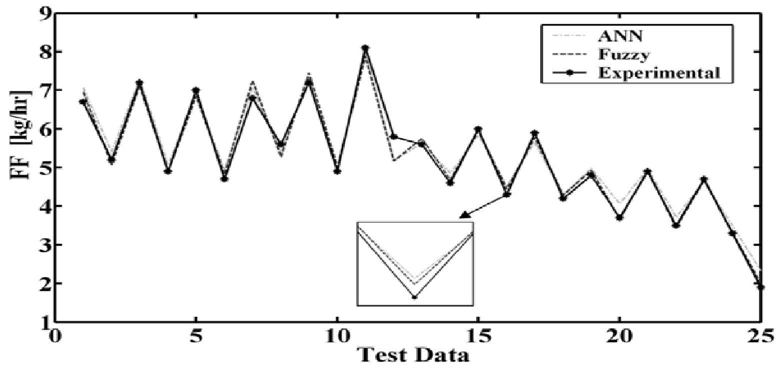

Figure 16. FF results of ANN, fuzzy and experimental for 25 test data.

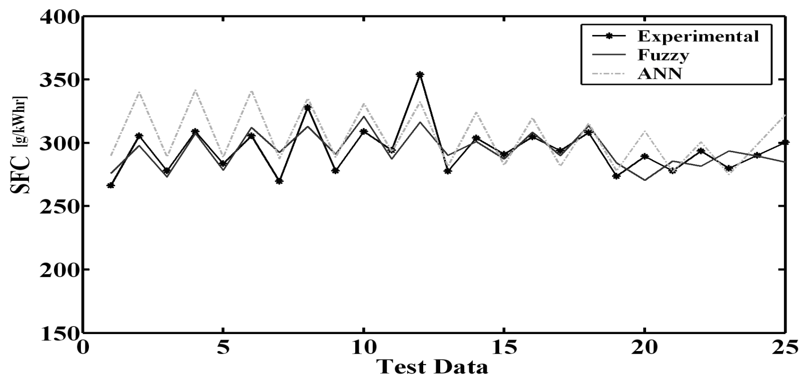

Figure 17. SFC results of ANN, fuzzy and experimental for 25 test data.

Table 7. Mean % errors of modeling results.

Modeling method	Output parameters		
	BMEP (%)	FF (%)	SFC (%)
ANN	0.87	1.56	3.41
Fuzzy logic	0.303	0.123	1.6143

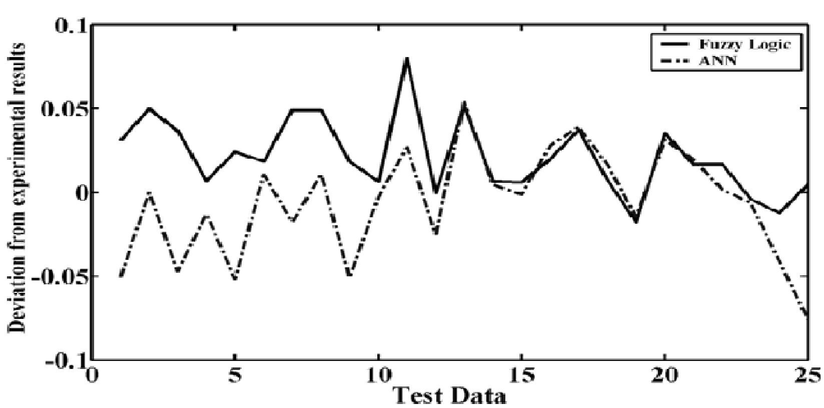

Figure 18. BMEP results' deviation of ANN and fuzzy logic modelling from experimental results.

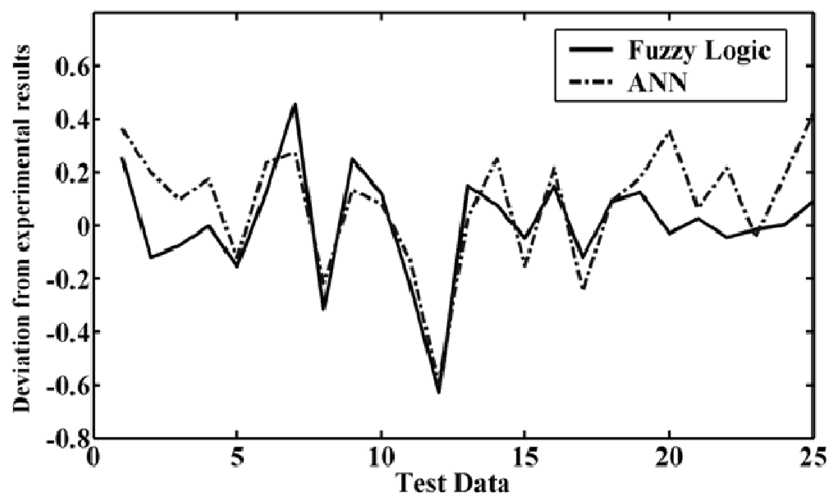

Figure 19. FF results deviation of ANN and fuzzy logic modelling from experimental results.

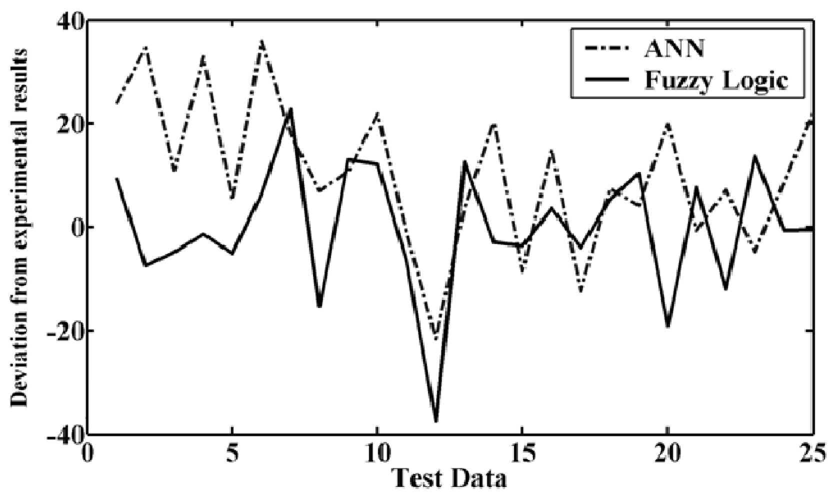

Figure 20. SFC results deviation of ANN and fuzzy logic modelling from experimental results.

predictions of a diesel engine performance of brake mean effective pressure (BMEP), fuel flow (FF), specific fuel consumption (SFC). Results show that, in most of the cases, the models produce results parallel to the experimental ones; therefore they can be used as an alternative way in these systems. According to obtained results fuzzy logic approach has more predictive ability than ANN. This makes fuzzy logic a powerful tool for solving complicated engineering problems.

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