Artificial Neural Network Based Modeling of Injection Pressure in Diesel Engines

M.ALI AKCAYOL[1], CAN CINAR[2], H.IBRAHIM BULBUL[3], ALI KILICARSALAN[4]
[1] Department of Computer Engineering, Gazi University, Maltepe, 06570, Ankara, TURKEY

[2] Department of Mechanical Education, Gazi University, Besevler, 06500, Ankara, TURKEY

[3] Department of Computer Education, Gazi University, Besevler, 06500, Ankara, TURKEY

[4] Department of Mechanical Engineering, Gazi University, 19030, Corum, TURKEY

Abstract: **-** Injection pressure in diesel engines has an important effect on the engine performance and soot formation. During performing the experimental work, the measurement of the torque, power, specific fuel consumption (SFC) and soot formation values in the diesel engines is a time consuming work and it also requires specific tools, an expert. In addition to the difficulties mentioned earlier, some of the operating points can be only investigated and evaluated because of difficulties of measuring the parameters at the operating conditions.

In this study, to overcome these difficulties, an artificial neural network (ANN) is used for prediction of performance and soot formation in diesel engines. The training data for ANN is obtained from experimental measurements. In comparison of performance analysis of ANN, the deviation coefficients of torque, power, SFC, and soot formation for the test pressure conditions are less than 1.66, 3.2, 2.89, and 3.47, respectively. The statistical coefficient of multiple determinations for the investigated cases is about 0.9934 to 0.9983. The degree of accuracy is acceptable in predicting the parameters of the system. So, it can be concluded that ANN provides a feasible method in predicting the system parameters.

Key-Words: **-** Artificial neural network, injection pressure, diesel engine

1 Introduction

Diesel engines have been penetrating a number of markets all around the world because of their good fuel economy and high reliability. The diesel engines are widely used in heavy-duty engine applications such as bus, truck, power generation. They are preferred over spark ignition engines because they can achieve greater efficiencies and higher indicated mean effective pressures due to the higher compression ratios where they operate [1,2].

Diesel engines produce lower amounts of HC (Hydrocarbon), and CO (Carbonmonoxide) emissions than the spark ignition engines because of more complete combustion of the air-fuel mixture. Soot or particulate emissions occur when there is insufficient air to completely burn the fuel [3]. And it is well established that these emissions from diesel engines may have a harmful effect on human health [4].

There are several factors that the engine designer considers to provide both low emission levels and high performance with good fuel economy. Some of these factors are the shape of the combustion chamber, the injection rate and nozzle spray pattern, injection timing, and injection pressure [3].

In recent years, a number of studies have been conducted on injection pressure to increase engine performance and to decrease exhaust emissions in diesel engines [5].

In these experimental studies, some of the operating points of the system have been investigated. For this type of experimental works, experts and special equipments are needed. It also requires too much time and high cost [6]. In the last decade, ANNs have been widely used for many different industrial areas such as control, prediction, pattern recognition, classification, speech and vision. ANNs have been trained to solve nonlinear and complex problems that are not exactly modeled mathematically [7]. ANNs eliminate the limitations of the classical approaches by extracting the desired information using the input data. Applying ANN to a system needs sufficient input and output data instead of a mathematical equation. Furthermore, it can continuously re-train for new data during in operation, thus it can adapt to changing of the system. Also, ANNs can be used to deal with the problems with incomplete and imprecise input data [8,9].

In this study, an ANN has been used for predicting the performance and soot formation in diesel engines. The ANN predicted and experimental results are extensively compared under different operating conditions.

2 Experimental apparatus and procedure

The experiments in the present study were conducted by operating a direct injection diesel engine. The general specifications of the engine are shown in Table 1. A Leclasrege Electriou brand electrical dynamometer was used for the tests. Soot formation was measured by means of VLT 2600 S brand diesel emission device having 0.01% accuracy. The schematic view of the test equipments is shown in Fig. 1.

Table 1. General specifications of the test engine

Item	Specification
Engine type	Direct injection, Diesel
Stroke (mm)	100
Bore (mm)	98
Displacement (cc)	754
Cycle	Four stroke
Max. Power	7 kW at 1800 rpm
Compression ratio	17:1

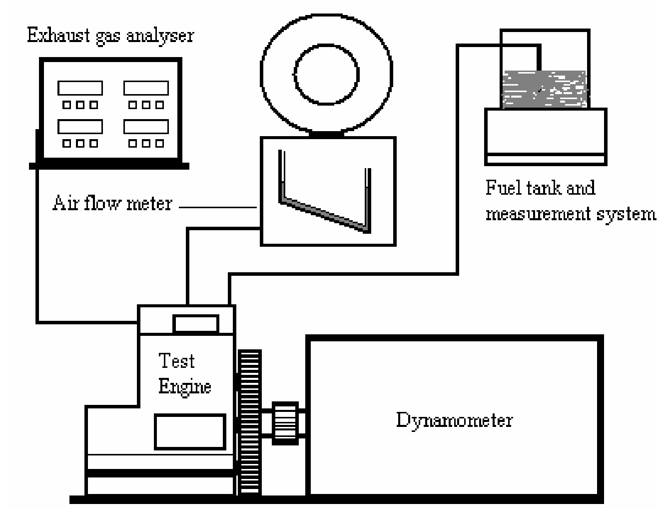

Fig.1. Schematic of the test facility

The experiments were performed at full load operating conditions. The engine was loaded by the electrical dynamometer. During the experiments, engine speed was changed from 900 rpm to 1900 rpm with 200-rpm intervals. Injection pressure was changed from 125 bar to 250 bar with 25 bar intervals. Injection pressure is changed by means of adjusting the injector spring tension. During the experiments, the average ambient temperature and atmospheric pressure were 22^{o}C and 752 mm-Hg, respectively. The tests were conducted after the engine reached the working temperature of 80^{o}C

Fig.2 shows the variation of engine torque with respect to the engine speed at different injection pressures. As the injection pressure increases, the engine torque also increases. Depending on the increase in injection pressure, droplet size becomes smaller and air-fuel mixture formation becomes better. An increase in the engine torque can be seen as the injection pressure at a certain level (225 bar) is taken into consideration. After this point the engine torque decreases with the increasing value of the injection pressure. Furthermore, depending upon the air-fuel mixture formation, the engine torque decreases drastically at low injection pressures

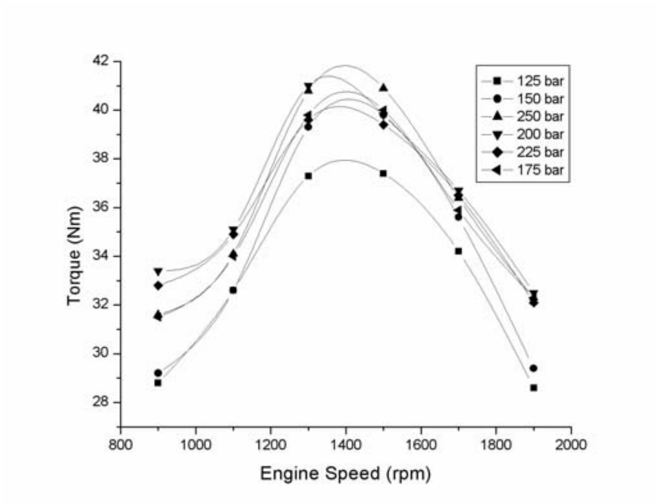

Fig.2. Variation of engine torque as a function of engine speed

Fig.3 shows the variation of power output with respect to the engine speed at different injection pressures. The increase of injection pressure causes the engine power to increase at a certain level. This trend is similar to of the engine torque. Power output decreases at low injection pressures.

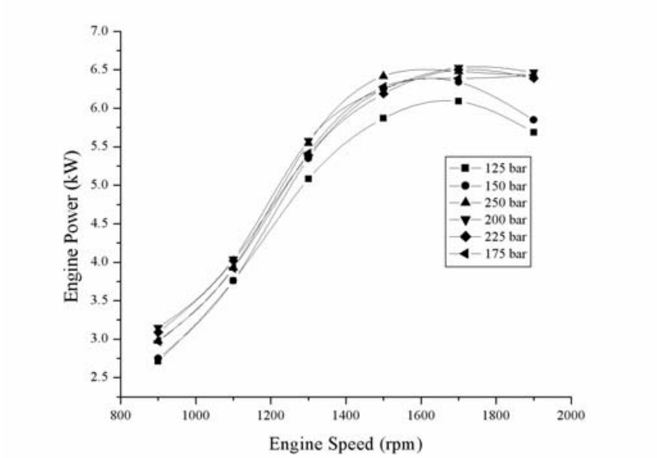

Fig.3. Variation of power output as a function engine speed

Fig.4 shows the variation of SFC with respect to the engine speed at different injection pressures. As the injection pressure increases, the SFC decreases. SFC increases drastically at low injection pressures.

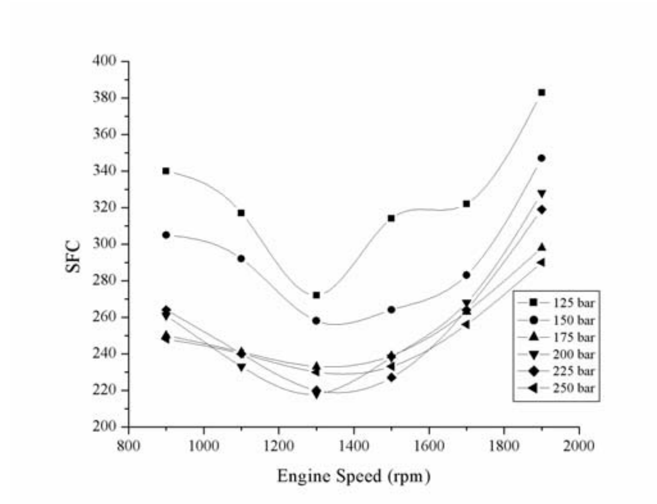

Fig.4. Variation of SFC as a function of engine speed

Fig.5 shows the variation of soot formation with respect to the engine speed at different injection pressures. Depending on the increase in injection pressure, droplet size becomes smaller and air-fuel mixture formation becomes better. A considerable reduction in soot formation is obtained when the injection pressure is increased. Soot formation increases drastically at low injection pressures.

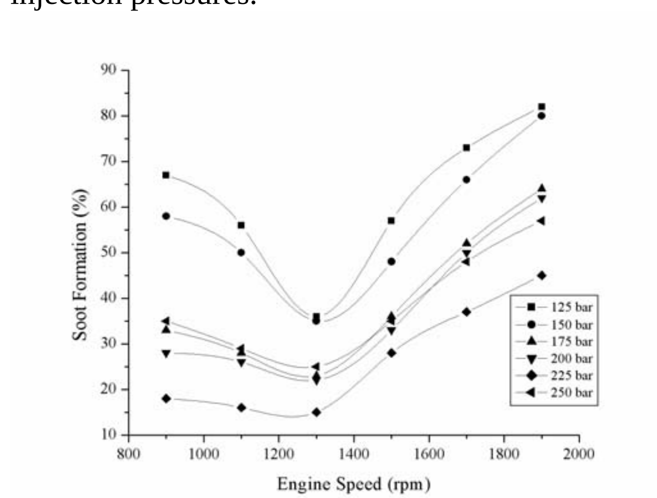

Fig.5. Change of soot formation as a function of engine speed

3 Application of ANN

There are many types of ANN architectures in the literature; however, multi-layer feed-forward neural-network is the most widely used for prediction. A multi-layer feed-forward neural-network typically has an input layer, an output layer, and one or more hidden layers [10]. In multi-layer feed-forward networks, neurons are arranged in layers and there is a connection among the neurons of other layers. The input signals are applied to the input layer, the output layer contributes to the output signal directly. Other layers between input and output layers are called hidden layers. Input signals are propagated in gradually modified form in the forward direction, finally reaching the output layer. One neuron can receive signals from other neuron and transfer output signal into other nodes using transfer function as an input. A sigmoid function is widely used for transfer function [11] whose output lies between zero and unity and is defined as

$$f(x) = \frac{1}{1+e^{-x}} . \qquad (1)$$

The function is differentiable throughout its domain. During learning, the weights of the neurons are adjusted according to the generalized delta rule which is the learning algorithm for a back-propagation multi-layer feed-forward network. The error is the sum of the squares of the overall errors of the network and is minimized by the generalized delta rule, defined as

$$E_p = \sum_p (y_p - o_p)^2 \qquad (2)$$

where E_p is the square errors, p is the index of pattern in the training set, o is the desired output and y is the calculated output of network. The weight modification for a neuron is done in proportion to the gradient of E_p with respect to the neuron weights [12]. In this way, each updated weight in a layer depends on all the error terms of the output layer. Thus, the error of the output layer is propagated back to each layer. Faster learning can be done by changing the learning-rate constant, but improper learning rate constant may cause the weights to bounce around the local minima, thus failing to learn properly.

A four layers ANN is applied to the system to predict of torque, power, SFC, and soot formation under different injection pressures. The ANN structure used in this application is shown in Fig.6.

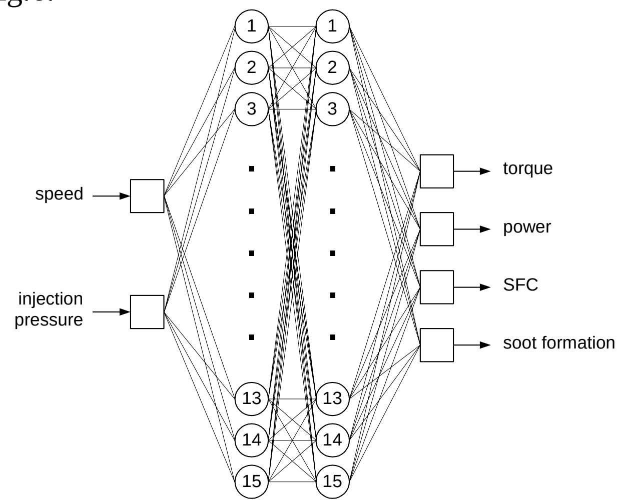

Fig.6. ANN architecture used for estimation of torque, power, SFC, and soot formation

The ANN has four layers namely, an input, an output, and two hidden layers. The input layer consists of two neurons, the output layer consists of four neurons, and each of hidden layers consists of 15 neurons. The input variables in the network are the speed (n) and the pressure. The output variables are the torque, the power, the SFC, and the soot formation.

The back-propagation algorithm has been implemented to calculate errors and adjust weights of the hidden layer neurons. In order to avoid long training time or network being trapped in local error minima, various learning rate constants are tried. The ANN structure and number of neurons in each of hidden layers have been selected by using an evolutionary algorithm. All of the data have been normalized in the range of [0, +1]. Sigmoid function is chosen for transfer function, with 0.5-threshold value as defined,

$$f(x) = \frac{1}{1+e^{-4(x-0.5)}} . \qquad (3)$$

Figs.2-5 show a parity plot between experimental and computed data by ANN for torque, power, SFC, and soot formation. The predictions have R^2-values equal to 0.9964 for torque, 0.9983 for power, 0.9934 for SFC, and 0.9976 for soot formation. It can be clearly seen from Figs.7-10, the developed ANN gives a very accurate representation of R^2-values over the all range or working conditions.

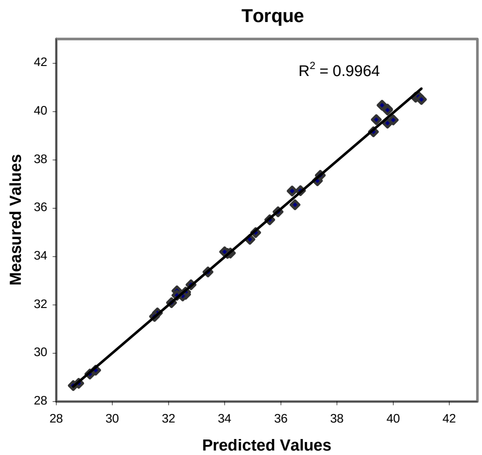

Fig.7. Comparison of measured and predicted values for the engine torque

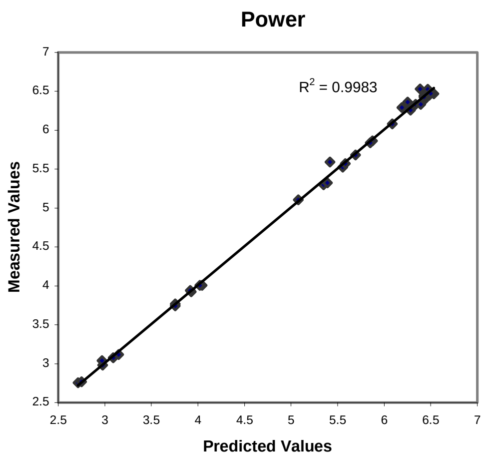

Fig.8. Comparison of measured and predicted values for the power

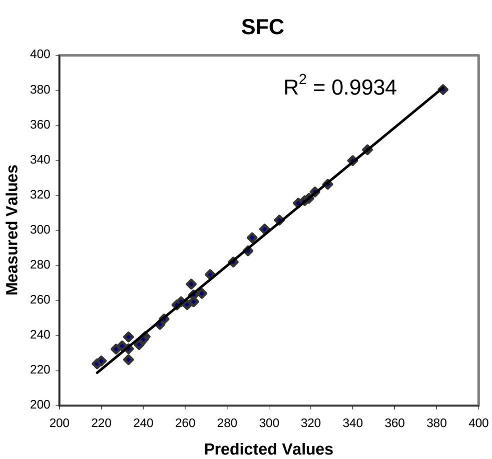

Fig.9. Comparison of measured and predicted values for the SFC

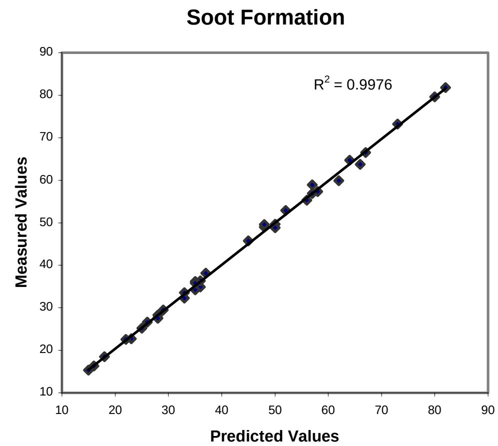

Fig.10. Comparison of measured and predicted values for the soot formation

Since experimental results are very close to the calculated values that can be obtained by using ANN, those cannot be graphically shown together. For this reason, the following equations (Eqs.4-7) are used to calculate the deviation values, and these values have been shown graphically.

$$\mathrm{dtorque} = \frac{\mathrm{torque}_{\mathrm{ANN}} - \mathrm{torque}_{\mathrm{experimental}}}{\mathrm{torque}_{\mathrm{experimental}}} \tag{4}$$

$$\mathrm{dpower} = \frac{\mathrm{power}_{\mathrm{ANN}} - \mathrm{power}_{\mathrm{experimental}}}{\mathrm{power}_{\mathrm{experimental}}} \tag{5}$$

$$\mathrm{dSFC} = \frac{\mathrm{SFC}_{\mathrm{ANN}} - \mathrm{SFC}_{\mathrm{experimental}}}{\mathrm{SFC}_{\mathrm{experimental}}} \tag{6}$$

$$\mathrm{dsoot\_formation} = \frac{\mathrm{soot\_formation}_{\mathrm{ANN}} - \mathrm{soot\_formation}_{\mathrm{experimental}}}{\mathrm{soot\_formation}_{\mathrm{experimental}}} \tag{7}$$

The standard deviations for torque, power, SFC, and soot formation are illustrated in Figs.11-14.

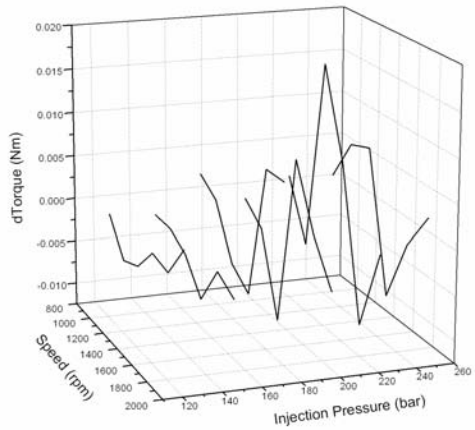

Fig.11. Variation of the dTorque as a function of speed at different injection pressures

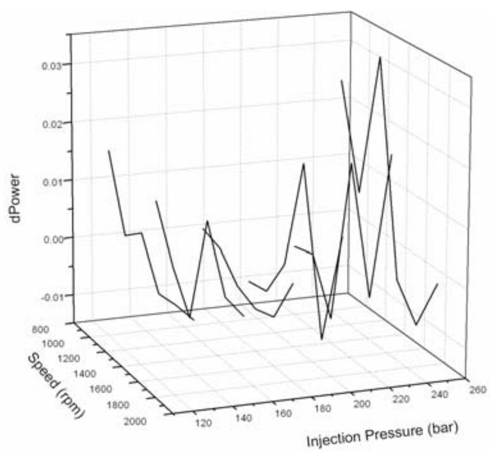

Fig.12. Variation of the dPower as a function of engine speed at different injection pressures

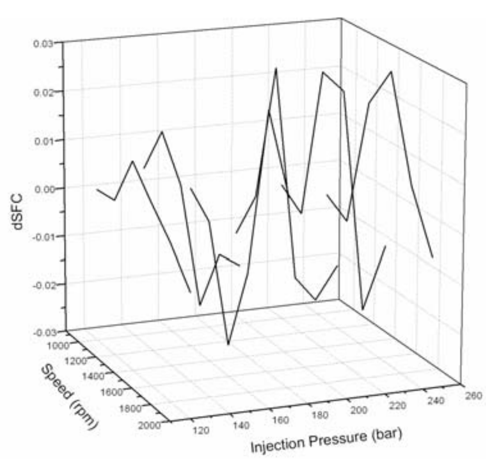

Fig.13. Variation of the dSFC as a function of speed at different injection pressures

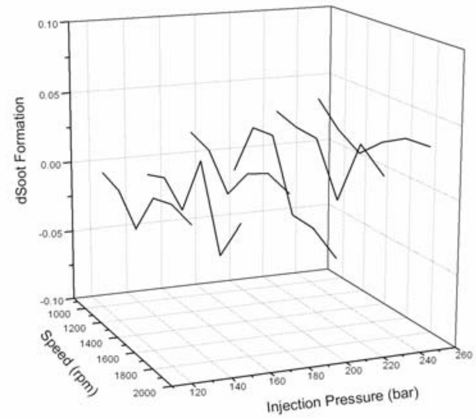

Fig.14. Variation of the dSoot Formation as a function of speed at different injection pressures

According to the results, maximum deviations in torque (dTorque) is 1.66%, in power (dPower) is 3.2%, in SFC (dSFC) is 2.89%, and in soot formation (dSoot formation) is 3.39%.

Table 2 shows the minimum and maximum deviations for each of the output. These results prove that the proposed ANN can be used successfully for the prediction of performance and soot formation in diesel engines.

Table 2. Maximum and minimum deviations of torque, power, SFC, and soot formation

Output	Min/ Max	n (rpm)	Pressure (bar)	Deviations (%)	Experimental Value
Torque	Min	1900	225	0.042196	32.1
Torque	Max	1300	225	1.665270	39.6
Power	Min	1900	250	0.014502	6.42685
Power	Max	1300	250	3.204691	5.41837
SFC	Min	1700	125	0.000865	322
SFC	Max	1300	175	2.898515	233
Soot formation	Min	1500	125	0.151989	57
Soot formation	Max	1900	250	3.390556	57

4 Conclusions

In this study, an artificial neural network is used for prediction of performance and soot formation in diesel engines. Engine performance and soot formation are measured for stroke single cylinder, 754cc direct injection diesel engine.

Measurements are conducted for each of the injection pressures 125, 150, 175, 200, 225, and 250 bar.

The deviations for torque, power, SFC, and soot formation for different injection pressures are obtained by using ANN. The maximum deviations for all pressures are 1.66% for torque, 3.2% for power, 2.89% for SFC, and 3.47% for soot formation. The statistical coefficients are above 0.99. This degree of accuracy shows that the proposed ANN can be used for obtained the experimental engine performance and soot formation. To sum up, this study is considered to be helpful in predicting the performance of the diesel engine.

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