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ARTIFICIAL INTELLIGENT MODELING OF THE BI-FUEL ENGINE

B. Behnam [1] K. Rezapour [2] A. Nikranjbar [2] A.D. Tafti [1]

1. Department of Electrical Engineering, Faculty of Engineering, Karaj Branch, Islamic Azad University, Karaj, Iran
2. Department of Mechanical Engineering, Faculty of Engineering, Karaj Branch, Islamic Azad University, Karaj, Iran
rezapour@kiau.ac.ir

Abstract- In this paper, a new method for modeling of bi-fuel (Gasoline and liquid natural gas (LNG)) SI (spark ignition) engine is studied and introduced; using feed forward (FF) artificial neural network (ANN). The engine (for each fuel) has 3 inputs including the engine speed, ignition spark timing (IGT), and air fuel ratio (AFR), and 4 outputs including, brake power (BP), brake torque (BT), brake mean effective pressure (BMEP) and brake specific fuel consumption (BSFC). For improving in this model, eight parallel ANN's have been used, each has three of the mentioned inputs and one output. Experimental data obtained from testing on a real engine is used for training and evaluation of ANN. Moreover, the data for training and evaluation are divided into two methods; Group and Points and one for training of ANN's both standard back propagation and its modified method are used. ANN's training is done with 70% of experimental data and evaluated with the remaining 30%. Model validation results with comparison of experimental data show that modified back propagation with classification of Points method, significantly improves the engine ordinary ANN models performance for prediction.

Keywords: Artificial Neural Network, Back Propagation, Bi-fuel SI Engine, Modeling.

I. INTRODUCTION

Since the today's, internal combustion engines (ICE) including spark ignition (SI) engines and compression ignition (CI) engines were for the first time introduced by Otto and Diesel in 1879 and 1892 respectively. These engines have had an increasing growth in different applications in particular transportation systems.

The expanding trend of the application of various types of internal combustion engines and their innate nature in producing environmental pollutants have crated serious concerns on air pollution. In addition, increasing of fuel cost value and competition in sale, have led to macro investments for energy efficiency, and finally definition of new environmental and energy efficiency standards and research in this area. In other words, among the main goals of engine producers, one may refer to the presentation of more high efficient systems, reduction of fuel consumption and production of less polluting gasses in their outputs. Therefore, for the improvement of the performance of engines, vast researches have been done in using alternative fuels such as hydrogen, liquid natural gas (LNG) and Ethanol.

Since, the combustion in internal combustion engine is very complex [1, 2] and is dependent on chemical, combustion, electrical and mechanical parts. With respect, the mathematical relations governing the engine is fully nonlinear changeable with the time and dependent on environmental conditions and its load , therefore, it is not possible to simply obtain the governing equations of an engine to obtain the engine response analytically and solve it. However, by innovation and application of computers, and proper measuring equipments, the analysis of theoretical analysis of an engine in particular the complex process of combustion has become possible with the help of numerical methods. One of the effective methods of computer modeling is the method of using the artificial intelligence (AI) in internal combustion engines [3-7].

Using ANN for modeling of the systems for which it is not to the model them by ordinary methods or their modeling is very complex; this method is tested and acceptable. For this purpose, ANN is trained by a sufficient number of experimental data, which is obtained in laboratories or in the condition of the actual performance of the system. Using the experimental data, which did not have any role in the training of ANN, they are evaluated. If the structure of ANN is selected and trained properly, that can be used to model of the system and predict the behavior of the system [8-10].

In recent years, vast studies have been done in using ANN to the model engines for predict their behaviors [3-7]. The type of ANN, the number of its hidden layers, method of training, selection of proper input and output and evaluation of the behavior of trained ANN with the experimental data which did not have a role in the teaching of ANN has a great role in reaching a good model [10]. Therefore, having a proper the model of engine, it is possible to observe the performance of engine based on changes on the model inputs before applying experimental data and costly changes on the engine and by evaluating the response of the model into the real engine efficiency could be performed.

Using ANN and the method of back propagation, Sayin et al modeled an engine with gasoline fuel and applying ANN model of the engine, they could predict the brake thermal efficiency, BSFC, BMEP, temperature and the rate of pollution exhaust gases in the engine. They showed that the ANN model of engine can obtain the mentioned outputs with the correlative coefficient between 0.98-0.983 of the relative error between 1.41-6.66% and very low mean square error (MSE) [3].

Kiyani et al also modeled an internal combustion engine with the blending of ethanol and gasoline by using ANN. The ANN model of their engine could obtain the output of torque, brake torque and rate of pollution exhaust gases with the correlative coefficient between 0.71-0.99 [4]. In addition, by working on a single cylinder bi-fuel, Yusaf showed that the ANN model of engine can predict the outputs of torque, brake torque (BT), BSFC and rate of pollution exhaust gases with a correlative coefficient higher than 0.957 [5].

In this paper, first, with tests performed on a bi-fuel engine, which worked with gasoline and LNG fuels, the experimental data related to input and output of the engine are recorded and saved. Then the data are divided in two methods of Groups and Points. For training of the ANN model that it has studied the first time, 70% of data is used for training and the remaining 30% is used to evaluate the ANN engine model. For the improvement of ANN's performance engine model, eight ANN sub model with a structure with three inputs and one output is used.

The outputs of model were including BP, BT, BSFC, BMEP, and the model inputs, were consist of the engine speed, IGT and AFR. By introducing new method for training and classification, the obtained results show that the training of ANN engine model in modified method of back propagation and using the Points division of data will improve the performance of ANN engine model for prediction the behavior of engine output as compared with ordinary method of back propagation remarkable.

II. SPECIFICATIONS OF THE ENGINE AND

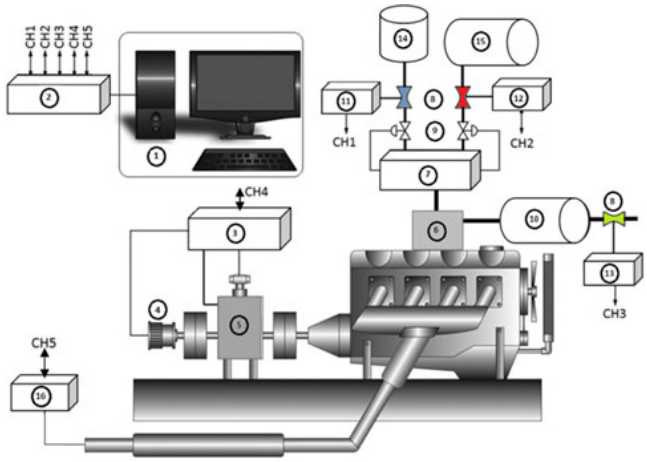
The engine under testing is a bi-fuel SI engine with the specifications included in Table 1. The engine is operated over its speed range, 1000-10000 r/min, at wide open throttle (WOT). The test engine is converted from a gasoline engine into a bi-fuel (LNG and gasoline) engine and equipped with an appropriate bi-fuelling system.

III. PREPARING THE ENGINE TESTING ROOM

Among the cases of preparing testing room, is the installation of data acquisition circuit (DAC) and preparing the place of location of the engine on the test platform. Then, the engine is installed in the respective place and all sensors of water, oil temperature, input multi-way temperature, temperature fuels, input air pressure, gas pressure in the regulator of gas pressure, Lambda sensor and etc, along with the fuel and ignition terminals are installed on the engine (Figure1). The dynamometer being used is of the type of eddy current and with a power of 230 kw manufactured by Schenck Company.

Table 1. Specifications of the engine under testing

Type	In line
Intake	Naturally aspirated
Number of cylinders	4 cylinders
Cylinder diameter	86.99 mm
Piston course	90.77 mm
Total volume of cylinders	2156.9 cm^3
Condensation ratio	11.10
The engine fuel	Gasoline + LNG
Spark start	25° bTDC
Initial temperature	335 K
Initial pressure	100000 Pas



1. Computer, 2. Switch board and data acquisition system, 3. Velocity measuring system and dynamometer control, 4. Sensor of velocity, 5. Dynamometer, 6. Carburetor, 7. Fuel control system, 8. Sensor, 9. Valves control, 10. Air tank, 11. measuring system of gasoline consumption, 12. measuring system of gas consumption, 13. Measuring system of air consumption, 14. Gasoline tank, 15. *LNG* tank, 16. Measuring system of the engine's exhaust gases

Figure 1. Schematic of different parts of testing room

IV. A STUDY OF TESTING ROOM RESULTS

The operational data obtained in the testing room is classified in the following form:

- The recorded data of the engine under testing

A) The speed of the engine in terms of 1000<*RPM*<10000 with a *step*=500 RPM.

B) The time of application of spark for fuel combustion in piston in terms of 20<*IGT*<40 is with the *step*=5. This time is adjusted by giving proper commands to the electronic control unit (ECU).

C) The weight ration of air to fuel 11<*AFR*<15 with a *step*=1. This ratio is adjusted by giving proper commands to the ECU.

- The recorded output from the engine under testing

A) Brake torque (*BT*), N.m
B) Brake power (*BP*), kw
C) Brake mean effective pressure (*BMEP*), bar
D) Brake Special Fuel Consumption (*BSFC*), gr/kw.hr

This model is shown in Figure 2. Then we divide the recorded data related to gasoline or natural gas fuels in 25 separate groups in which the existing data of each related group to one *IGT* and *AFR* is fixed. In Figure 3, one of data groups for torque output and gasoline fuel is shown.

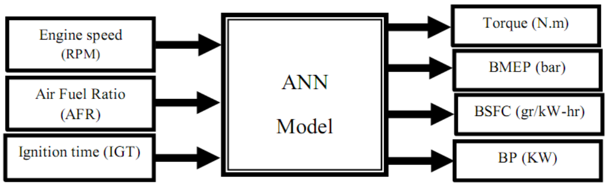


Figure 2. The engine model along with its input and output

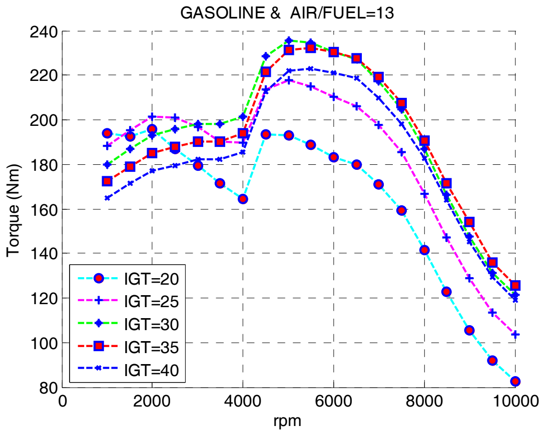


Figure 3. The engine output torque in *AFR*=13 and different IGT's and RPM's

V. THE ENGINE MODEL BASED ON ANN

Each neural network is constructed of a number of Neurons and their method of their connection. The mathematical model of a Neuron is as follow (Figure 4):

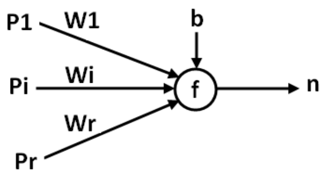


Figure 4. The mathematical model of a Neuron

$$n = f\left\{\sum_{i=1}^{r} p_i w_i + b\right\} \qquad (1)$$

In which that p is the input vector, w is the matrix of weights, b is Bias, f is an operational function and n is the output of this neuron. The matrix w and bias b are obtained in the stage of training the ANN and the proper selection of f operational function has effectiveness in the method of ANN performance.

In multilayer feedback ANN, three general layers are defined:

- The input layer that specifies the connection of ANN with the concerned inputs of the model.
- The output layer, which shows the connection of ANN with the outside i.e. the model outputs.
- The middle or hidden layers that can be exist or not exist. The numbers of these layers and Neurons inside them are of the important factors in ANN performance.

Usually, for modeling the systems, the ANN's in the form of multi inputs and multi outputs (MIMO) are used (Figure 5).

This method has some disadvantage as follows:

- The ANN outputs cannot be taught independently in order to reach a better response for that output.
- Due to increase of the number of outputs, it is necessary to increase the number of hidden layers and number of Neurons considerably. This makes ANN training more difficult, so that more time will be spent on training and it will be accompanied with a higher relative error.

Therefore, in this paper, the ANN's models in the form of multi inputs and single output (MISO) have been used and in that state, for each engine output, one independent neural network is considered (Figure 6).

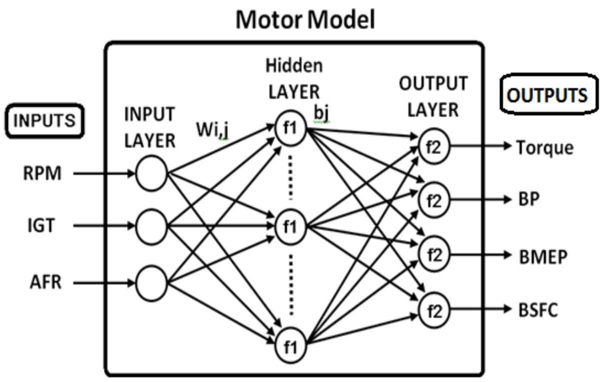


Figure 5. The engine modeling in the form of multi inputs and multi outputs (MIMO) by ANN

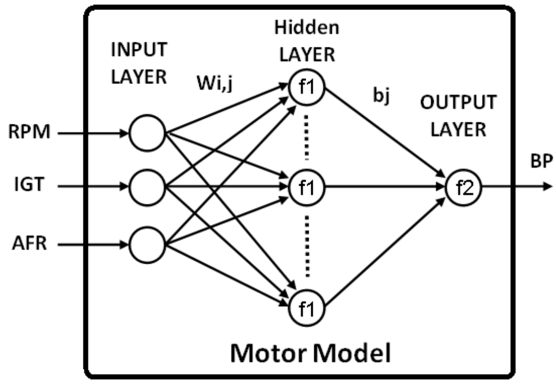


Figure 6. Modeling of one of the engine outputs in the form of MISO by ANN

In addition, this method has some advantages:

- Having the ability to do independent training of ANN's for each output to reach an ideal result for that output.
- The dimensions of each ANN, i.e. the number of hidden layers and number of necessary Neurons for it, are easily changeable and adjustable.
- The method of training each ANN, can be changed based on necessity and response of its evaluation

We intend to model the bi-fuel engine, so the general block diagram of ANN model of the engine is introduced as the form of Figure 7. As it is clear, in this method of modeling, we will need eight parallel ANN (from ANN to ANN), each of which can be taught and evaluated independently.

VI. METHOD OF TRAINING DATA SELECTION AND EVALUATION OF ANNs

The experimental recorded data in the laboratory are divided based on 2 methods of Groups and Points for training and performance evaluation of ANN. The Figures 8 and 9 show the method of data selection for the engine torque output in Groups method and Figure 10 represent the method of data selection in Points method with 70% of data for training and 30% of data and evaluation of ANN1 model of the engine. The signs O and * are for training and evaluation data, respectively. In each group, 19 output data exist which are related to one *AFR*, *IGT* and $1000<RPM<10000$ with $step=500$. The selection of training data and evaluation data of performance of the model is done randomly.

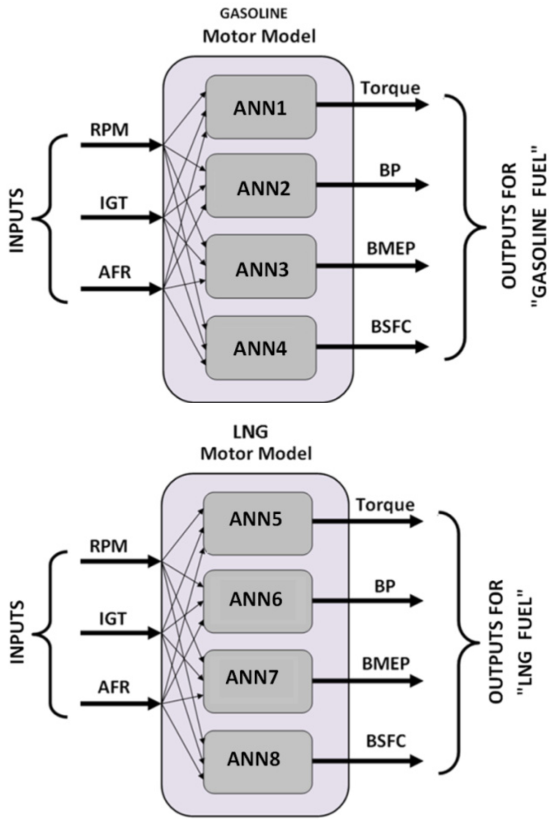


Figure 7. Modeling of the engine by using 8 ANNs, parallel MISO for gasoline and LNG fuels

Figure 8. Method of data group selection for training and evaluation of ANN of the existing 25 groups

VII. THE SELECTION OF ANN STRUCTURE

In all ANNs, a hidden layer with 11 Neurons and 11 operational functions of the type of f_1=tansig (hyperbolic tangent sigmoid transfer function) have been used.

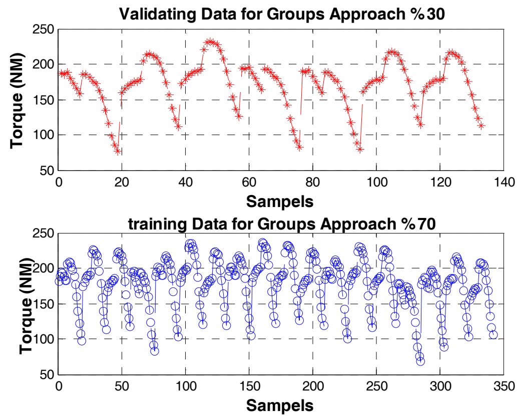


Figure 9. Separation of data in Groups method, 18 groups for training and 7 Groups for evaluation of ANN model

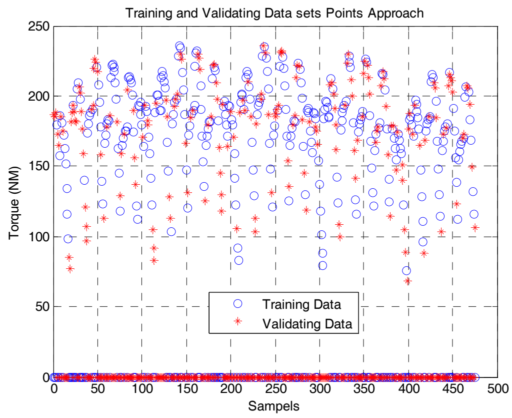


Figure 10. Separating the data in Points method (There are 292 Points for training and 183 Points for the evaluation of the ANN model)

Since each neural network has one output, so in its output layer, we have only one Neurons whose operational function is selected of the type of f_2=purelin (linear transfer function) [13]. So, all of eight ANNs have hardwares structure with 12 Neurons and in totally, the engine ANN model for gasoline and LNG fuels will need to 96 Neurons.

VIII. METHOD OF TRAINING ANNs

In previous section, each ANN is trained independently and for each of the engine outputs. At the end of training, the performance of ANN is studied with the evaluation data.

In the beginning, the primary value of weights and biases of all ANN Neurons are selected randomly and with the uniform distribution between zero and one. For training all ANNs, the simple method of back propagation (trainlm) (Training Levenberg Marquardt Back Propagation) and its modified form in this paper is presented. In addition, the method of data grouping in the form of Groups and Points is used.

The main purpose of ANN training is to gain their weights and biases, such that the standard function mean square error (*MSE*) to become minimized [13].

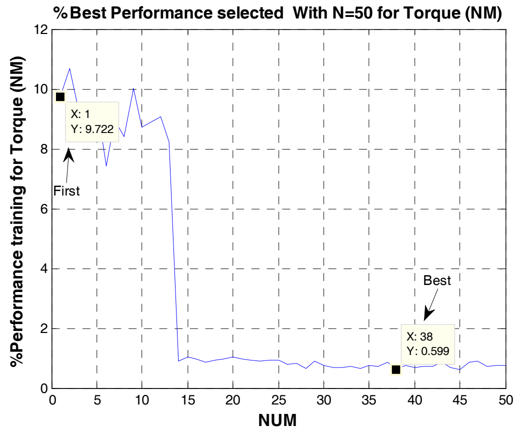
$$MSE = \frac{1}{m}\sum_{i=1}^{m}\left[Y_{motor}(i) - Y_{model}(i)\right]^2 \quad (2)$$

In the *MSE*'s relation, i=1, 2, …, m that m is the number of training data. By specifying the percentage of training data and evaluation and method of classification of data, the ANN training for minimizing the standard function is located in one circle with k=1, 2, …, 50. The ANN model is trained per k=1 with the standard method of back propagation, therefore weights, biases and standard function related to its *MSE*(1) is saved to be used and compared with the modified method of back propagation. By locating in the iteration loop of k, the ANN model with the considered data for training and the method of standard back propagation of trainlm will undergo retraining and the ANN performance is obtained based on the standard function of *MSE*(k) in each stage. In order to prevent from the phenomenon of over training of ANN and out of local minimums, the quantities of weights and biases are changed at the end of each stage of training with a specific possible distribution at the rate of ±10%. Then the standard function of *MSE*(k) is compared with the minimum of obtained standard function from the previous stage of training (*MSE*(min)). If the rate of standard function of *MSE*(k) is less than minimum of obtained standard function of previous stages, *MSE*(k) is saved as the minimum standard function up to this stage along with weights and trained biases for ANN.

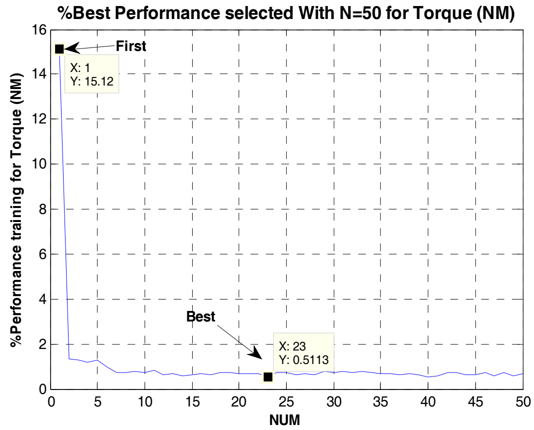
After the end of iteration loop of 50 folds, the ANN training is ended and the selected quantity for weights and biases of network based on the minimum of observed quantity for the standard function in the repetition circle is obtained. In order to describe the discussed algorithm that it brought in appendex1, we will consider the ANN1 model related to the torque output with the gasoline fuel. Then by using the two methods of modified and simple training of back propagation and the two methods of classification of training, we will have training in the form of Groups and Points. The results observed in Figure 11 specify that for ANN1 as follows:

* In the classification method of data in the form of Groups and back propagation training (Groups, n=1), the quantity of *MSE*(1)=9.722 is obtained.
* In the method of classification of data in the form of *Groups* and modified back propagation of (Groups, n=50), at the stage of k=38, the quantity of *MSE*(min)=*MSE*(38)=0.599 is obtained.
* In method of classification of data in the form *Points* and simple back propagation of (Points, n=1), the quantity of *MSE*(1)=15.12 is obtained.
* In method of classification of data in the form of Points and modified back propagation of (Points, n=50) at the stage of k=23, the quantity of *MSE*(min)=*MSE*(23)=0.5113 is obtained.

The quantities of trained weights and biases in each of the four mentioned methods are stored for the purpose of reuse and evaluation of ANN1 with evaluation data.



Classification of training data in the form of Groups



Classification of training data in the form of *Points*

Figure 11. The quantity of the mean square error *(MSE)*, in each state of ANN1 training for the modified and simple training methods

It must be noticed that up to this stage, for each of the eight *ANN* model of the engines (from ANN1 to ANN8) , we have obtained four set of trained weights and biases which are related to the two methods of training and two methods of data classification. In the next stage, all trained ANN's will be studied by the evaluation data.

IX. EVALUATION OF TRAINED ANN PERFORMANCE

After the end of training of each of the ANN's, it is necessary to study their general performance by using the evaluation data, which did not have any role in ANN training. The used evaluated functions in the study of the behavior of *ANN* model of the engine have been absolute error, absolute relative error (*ARE*), mean square error (*MSE*), and relative quantity of *MSE* or *RMSE* and correlative coefficient (*R*). For example, the correlative coefficient is obtained between the real output quantities of the engine and output of the engine model and is displayed with *R*. The relationship between correlative coefficient and real quantity and the model output is as follows:

$$R(Y_{motor}, Y_{model}) = \frac{\mathrm{cov}(Y_{motor}, Y_{model})}{\sqrt{\mathrm{cov}(Y_{motor}, Y_{motor}).\mathrm{cov}(Y_{model}, Y_{model})}} \quad (3)$$

The phrase cov(Y_{motor}, Y_{model}), is the covariance between real output Y_{motor} of the engine and output Y_{model} of the engine model. The correlation coefficient is a value between $-1<R<+1$ and to the extent the quantity of R is closer to one, to the same extent it shows the existence of a stronger and more linear relationship between the model and real system.

In addition, the regression coefficient shows the model evaluation that it is the rate of linear relation between the engine outputs and the engine model. The one to one link between the real output (target T) and the model output (Y) is shown with a linear relation and based on two quantities of line slope (m) and width from the origin (b) as follows:

$$Y = mT + b \tag{4}$$

It is clear that if the quantity of m=1 and b=0, then we will have Y=T, i.e., the real and the model outputs are identical with each other and the response of the model is more suitable. The Figures 12 and 13, show the rate of relative error and coefficient of the regression of ANN1 model for the torque output with gasoline fuel and Groups , n=50 training.

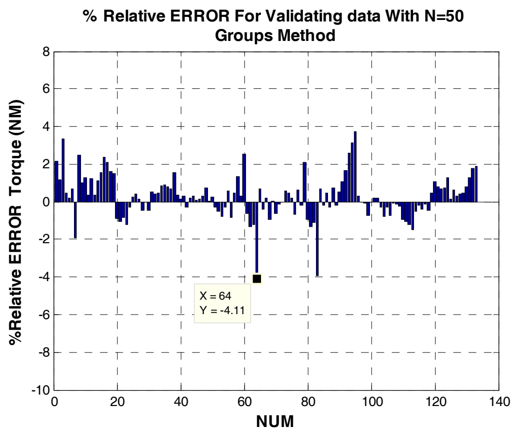


Figure 12. The relative error for ANN1

X. RESULTS AND DISCUSSIONS

The accuracy of the *ANN* model of the engine depends of the type and topology of selected *ANN*, number of training data, method of their classification and method of ANNs training. The inputs of all ANN's are *RPM, IGT* and *AFR* and each *ANN* has the duty of forecasting of each of the outputs of *BMEP, BP, T* and *BSFC* for each of gasoline and LNG fuels. Each of ANNs, separately and with the training data obtained from the laboratory results went under training in the four mentioned methods (training methods with Groups classification, modified Groups classification, Points classification and modified Points classification).

After the training of ANNs, 4 groups of weights and biases related to each of ANNs were obtained. The evaluation of each of ANNs was done with the evaluation data which did not have any role in the training of ANN. These evaluations were done based on the function of standards (R), m, b, *ARE, MSE, RMSE*. For example for *ARE* and *RMSE*, the Figures 14 and 15, show the performance of the model of ANN of the engine for two types of gasoline and LNG fuels and methods of the mentioned training for comparison. As it is learned from the results, specially, the Figures 14 and 15, the modified method of back propagation with Points classification has better response as compared with the other methods.

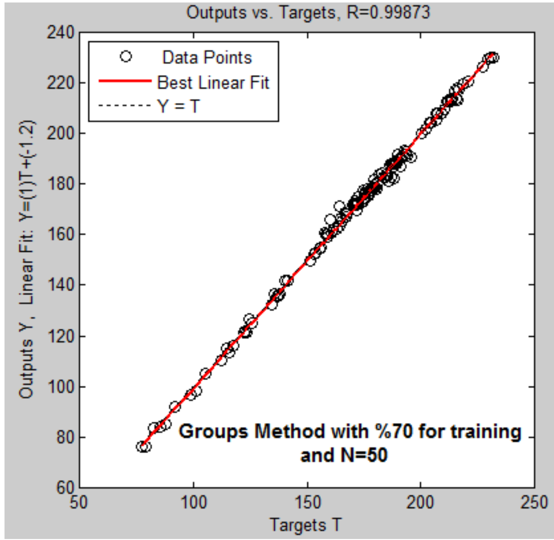


Figure 13. Evaluation of the response of the neural network of regression coefficient

XI. CONCLUSIONS

In this paper, a model of ANN was presented for the internal combustion engines. In this model, eight ANN single outputs and multi input was used to create the ability for the selection of the number of neurons and hidden layers and method of their training for the improvement of performance of each of ANN models of the engine. The data obtained from the laboratory was used for training and for evaluation of the model ANN of the engine. Two methods of training and two methods of data classifications were put forth. The results of validation of ANN model with the evaluation data showed that the modified back propagation method improves the performance of the model ANN of the engine meaningfully as compared with the simple back propagation method. In addition, the type of classification of Points classification of data in 87.5 % of cases has a better performance in comparison with the method of data classification in Groups form.

NOMENCLATURES

b: Bias
b: Width from the origin
cov: Covariance
f:: Operation function
m: line slope
p: The inputs
R: Correlation coefficient
T : Target

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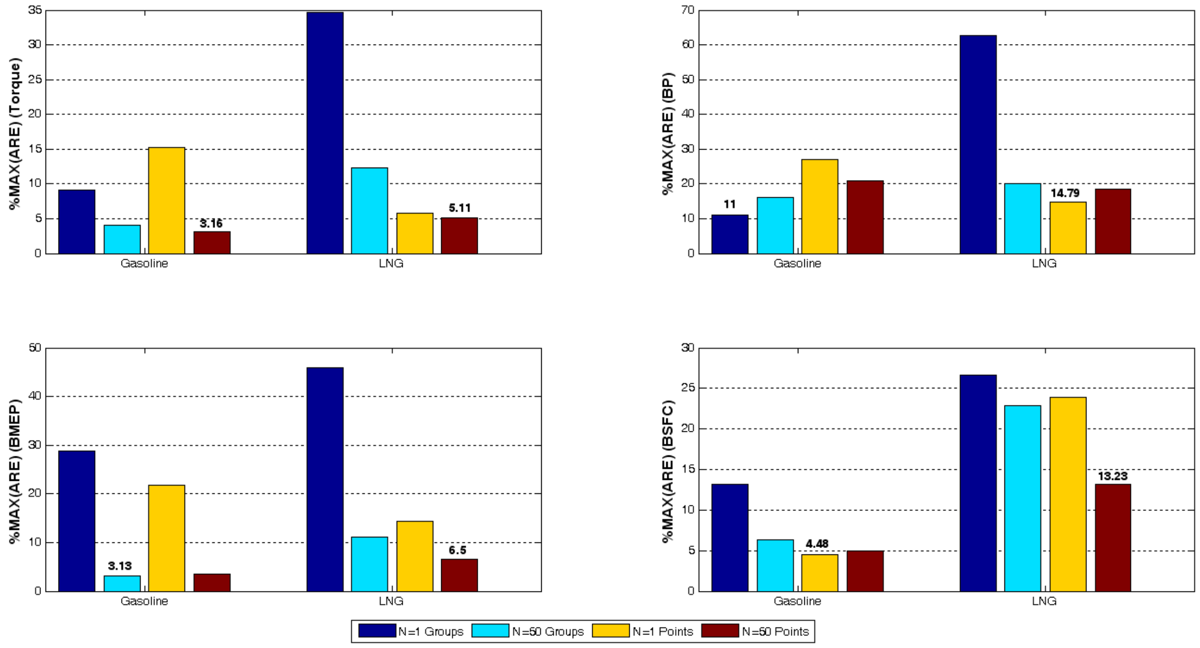

Figure 14. Evaluation of the model with evaluation data and Index of *ARE*

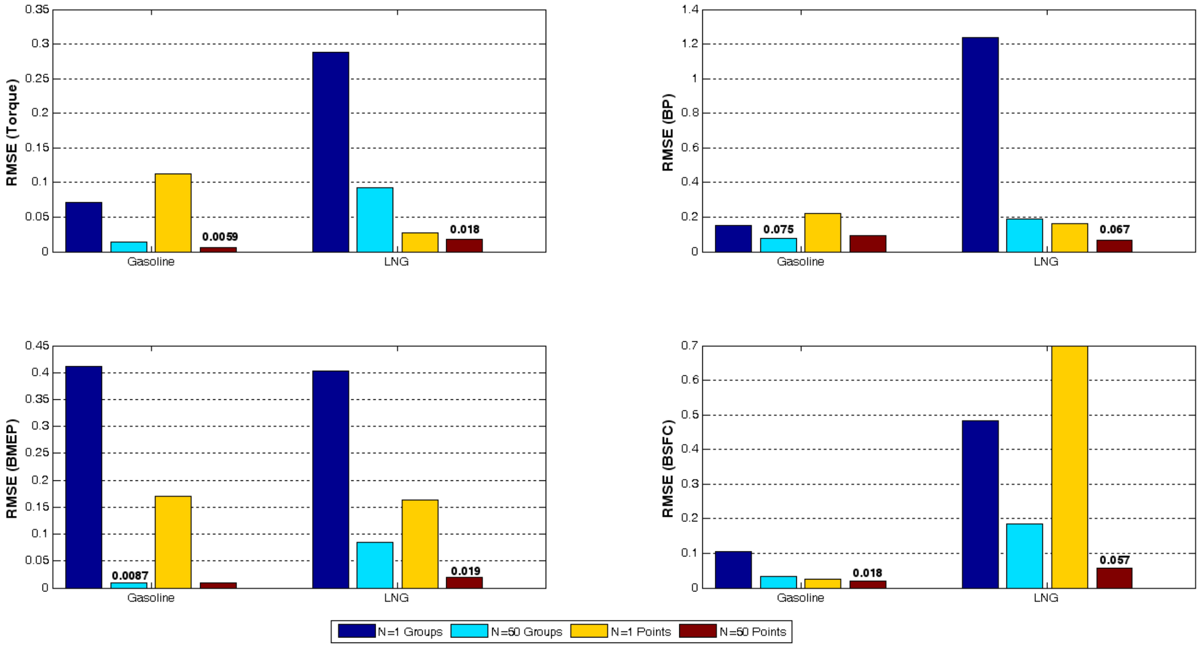

Figure 15. Evaluation of the model with evaluation data and Index of *RMSE*

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BIOGRAPHIES

Behzad Behnam was born in Karaj, Iran, 1965. He received M.Sc. degree from K.N. Toosi University of Technology, Tehran, Iran. He has carried out a number of research projects and has published over 5 international scientific papers and five books in the fields of control. He is senior lecturer of Electrical Engineering Department Karaj Branch, Islamic Azad University, Karaj, Iran.

Kambiz Rezapour was born in Karaj, Iran. He received his B.Sc., M.Sc. and Ph.D. degrees all in Mechanical Engineering. He has graduated in Ph.D. degree at the University of Bradford, UK. He is currently an Assistant Professor of Mechanical Engineering Department, Karaj Branch, Islamic Azad University, Karaj, Iran. He has 18 years experience in energy efficiency, energy management, energy conservation in residential, commercial and industrial sectors, combined heat and power, renewable energy, energy resources, internal combustion engine, Exergy analysis, artificial neural networks and optimization. He fulfilled a number of research projects in these fields and published 25 technical papers in journals, international and national conferences, and four technical books.

Abolfath Nikranjbar was born in Karaj, Iran. He received his B.Sc. degree in Mechanical Engineering from Sharif University of Technology, Tehran, Iran and the M.Sc. in Mechanical Engineering degree from Amirkabir University of Technology, Tehran, Iran, and Ph.D. degree in Mechanical Engineering from University of Bradford, UK, respectively. He is currently a lecturer in Mechanical Engineering in Karaj Branch, Islamic Azad University, Karaj, Iran. His main research interests include the fault detection and diagnosis of dynamical systems, application of artificial intelligence systems in identification and control, the dynamics and control of mechanical systems, numerical analysis, and software development for scientific applications.

Abdolreza Dehghani Tafti was born in Karaj, Iran, on December 6, 1976. He received his B.Sc. degree in Electronic Engineering from Karaj Branch, Islamic Azad University, Karaj, Iran in 1999, and the M.Sc. degree in Control Engineering from South Tehran Branch, Islamic Azad University, Tehran, Iran in 2001. He got his Ph.D. degree in Control Engineering from Science and Research Branch, Islamic Azad University, Tehran, Iran in 2010. His fields of research areas include pattern recognition, estimation and neuro-fuzzy networks.