

APPLICATION OF ARTIFICIAL NEURAL NETWORK TO PREDICT BRAKE SPECIFIC FUEL CONSUMPTION OF RETROFITTED CNG ENGINE

M. I. Jahirul, R. Saidur and H. H. Masjuki

Department of Mechanical Engineering
University of Malaya,
50603 Kuala Lumpur, Malaysia
Email: md_jahirul@yahoo.com

ABSTRACT

In this paper the applicability of artificial neural networks (ANN) is investigated for a retrofitted compressed natural gas (CNG) fueled spark ignition (SI) internal combustion engine (ICE). A four cylinder carbureted petrol engine is converted to run with NG and used throughout the work. The neural networks toolbox of Matlab 6.5 is used to develop and test the ANN model on a personal computer. An optimal design is completed for the 3 to 12 hidden neurons on single hidden layer with six different algorithms: batch gradient descent (GD), resilient back-propagation (RP), levenberg-marquardt (LM), batch gradient descent with momentum (GDM), variable learning rate (GDX), scaled conjugate gradient (SCG) in the back-propagation neural network model. The training data for ANN is obtained from experimental measurements. Engine speed (rpm), throttle position, fuel-air equivalence ratio (ϕ) and torque (N-m) were used in input layer while brake specific fuel consumption (gm/kWh) was used as output layer. Statistical analysis in terms of Root-Mean-Squared (RMS), absolute fraction of variance (R^2), as well as mean percentage error is used to investigate the prediction performance of ANN. LM algorithm with 10 neurons on single hidden layer in back-propagation of ANN model has shown best result in the present study. The degree of accuracy of the ANN model in prediction is proven acceptable in all statistical analysis and shown in results. So, it can be concluded that ANN provides a feasible method in predicting specific fuel consumption of CNG driven SI engine.

Keywords: Internal combustion engine (ICE), Compressed natural gas (CNG), Artificial neural network (ANN) and Specific fuel consumption (SFC)

1. INTRODUCTION

It is well known that fossil fuel reserves all over the world are diminishing at an alarming rate and a shortage of crude oil is expected within the next few decades. The world total natural gas (NG) reserve as of January 1, 2007 was 6,183 Tscf and based on the current

consumption rates, the estimated total recoverable gas, including proven reserves is adequate for about 66.7 years (IEO,2008). This has resulted in an increased interest to use CNG as fuel for internal combustion engines. The merits of CNG as an automotive fuel over conventional fuels are many and presented comprehensively by Nylund *et al.* (2002) and Aslam *et al.* (2003). Due to some of its favorable physio-chemical properties, CNG appears to be an excellent fuel for the spark ignition (SI) engine. Moreover, SI engines can be converted to CNG operation quite easily with the addition of a second fueling system. CNG has been used in vehicles since 1930's and the current worldwide NGV population is more than 4.5 million according to the International Association for Natural Gas Vehicle (IANGV) statistics and this figure is fast increasing everyday (Aslam *et al.*, 2006).

To investigate experimentally the performance of an engine is complex, time consuming and costly, especially for studies, which use many, different blends. Therefore, a mathematical model is used to predict the performance and emissions of the engines. But, the resulting accuracies may not always be satisfactory. One alternative to the mathematical model is the experiment-based approach, such as artificial neural-networks (ANNs). Neural networks are nonlinear computer algorithms, which can model the behavior of complicated nonlinear processes. For the development of high speed digital computers, the application of ANN approach could be progressed at a very impressive rate. In recent years, this method has been applied to various disciplines including automotive engineering, in forecasting of engine thermal characteristics for different working conditions. Some researchers studied this method to predict internal combustion engine characteristics. Artificial neural network approach has been used by Yuanwang *et al.* (Aslam *et al.*, 2006), to analyze the effect of cetane number on exhaust emissions from engine, Lucas *et al.* (Yuanwang *et al.*, 2003), to model Diesel particulate emission, Hafner *et al.* (Lucas *et al.*, 2001), for diesel engine control design, Shayler *et al.* (2000), in automotive engine management systems, Tan and Saif, (2000), to model the intake manifold and

throttle body processes in an automotive engine. Those studies do not need an explicit formulation of the physical relationships of concerned problems. Several studies have also used ANNs in different engineering areas (Sozen *et. al.*, 2005).

In the existing literatures, it was shown that the use of ANN is a powerful modeling tool that has the ability to identify complex relationships from input–output data. However, no investigation to predict engine specific fuel consumption (SFC, gm/kWh), retrofitted CNG fueled IC engine using ANN approach appears to have been published in the literature to date. Therefore, the present work investigates the applicability of ANN method for predicting the specific fuel consumption parameter.

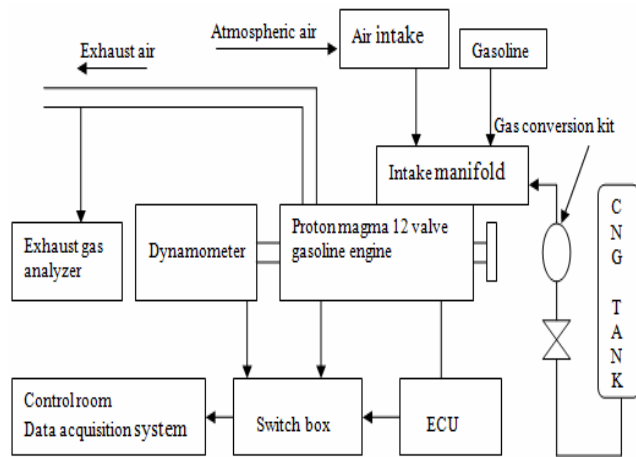


Figure 1: Layout of the experimental setup

2. EXPERIMENTAL SETUP AND TEST PROCEDURE

The layout of the experimental setup has shown in Figure 1. The test engine has been converted from a gasoline (Proton Magma) engine and has been equipped with a bi-fuelling system. The main specifications of the test engine are listed in Table 1.

Table 1: Specifications of the research engine

| | |
|---------------------|-----------------------|
| Characteristic | :Proton Magma12-Valve |
| Displacement | :1,468 cc |
| Compression ratio | :9.2: 1 |
| Bore | :75.5 mm |
| Stroke | :82 mm |
| Max output (kW/rpm) | :64/6000 |
| Max torque (Nm/rpm) | :122/3500 |
| Carburetor | :Down-draft 2-barrel |

An AG 150 (Froude Consine) eddy-current dynamometer has been used for testing the engine. All the electronic equipment, together with its manipulative controls and

indicators, etc was mounted on ‘CP Cadet10’ control unit. The engine has been operated at constant throttle 30%, 40%, and 50% and 100% with a variable speed range of 1500-3500 RPM at a constant increment of 100 RPM. CNG consumption has been measured with Kobold gas flow meter (Model WFM 2705). The CNG flow meter was incorporated with engine control system through interface cards. A PC-based data acquisition and control system has been used for controlling all the operation regarding the test where every stage was allowed to run around 6–8 min with updating data in every 30 s. Torque, power and fuel consumption have been measured to calculate SFC.

3. ARTIFICIAL NEURAL NETWORKS

A widely used NN model called the multi-layer perception (MLP) NN is shown in Figure 2. The MLP type NN consists of one input layer, one or more hidden layer (s) (middle) in between input and output layers and one output layer. Each layer employs several neurons (nodes), and each neuron in a layer is connected to the neurons in the adjacent layer with different weights. The weights, after training, contain meaningful information, whereas before training they are random and have no meaning (Erol *et al.*, 2004).

Signals flow into the input layer, pass through the hidden layer(s), and arrive at the output layer. With the exception of the input layer, each neuron receives signals from the neurons of the previous layer. The incoming signals or input (x_{ij}) are multiplied by the weights (v_{ij}) and summed up with the bias (b_j) contribution. Mathematically it can be expressed as:

$$\text{net}_j = \sum_{i=1}^n X_i V_{ij} + b_j \quad (1)$$

The output of a neuron is determined by applying an activation function to the total input and calculated using Equation 1 (Kreider *et al.*, 1992). If the computed outputs do not match the known (*i.e.* target) values, NN model is in error. Then, a portion of this error is propagated backward through the network. This error is used to adjust the weight and bias of each neuron throughout the network so the next iteration error will be less for the same units. The procedure is applied continuously and repetitively for each set of inputs until there are no measurable errors, or the total error is smaller than a specified value.

The following procedures have been executed in all the models developed; (i) database collection; (ii) analysis and preprocessing of the data; (iii) training of the neural network; (iv) testing the train network; and (v) using the trained ANN for simulation and prediction using trained network. An important stage of a neural network is the training step, in which an input is introduced to the

network together with the desired output: the weights and bias values are initially chosen randomly and the weights adjusted so that the network produces the desired output. After training, the weights contain meaningful information, contrary to the initial stage where they are random and meaningless. When a satisfactory level of performance is reached, the training stops, and the network uses the weights to make decisions.

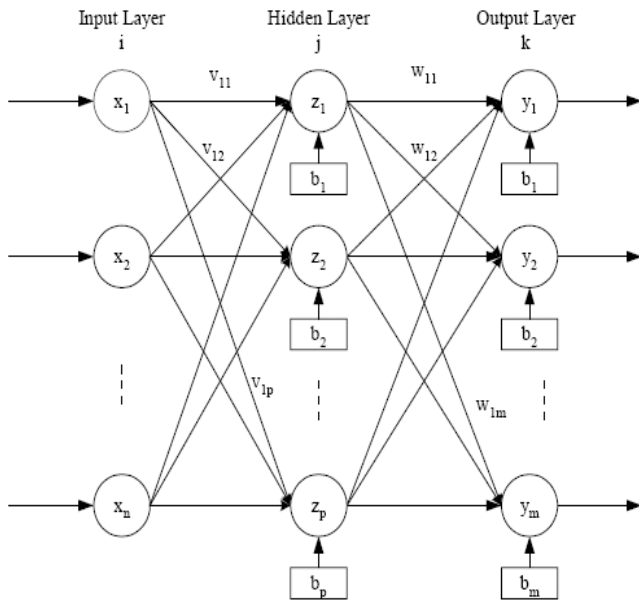


Figure 2: Architectural graph of a Multilayer Perception (MLP) with one hidden layer

4. APPLICATION OF NEURAL NETWORKS IN THE PRESENT STUDY

Three data sets are needed for ANNs: for training, validation and testing the network. The usual approach is to prepare a single data-set, and differentiate it by a random selection. In this study, the experimental results mentioned above were used to train, validate and test an artificial neural-network. Engine speed (rpm), throttle position, fuel-air equivalence ratio and torque (N-m) are used in input layer while break specific fuel consumption (gm/kWh) used as output layer. The learning algorithm called the back-propagation was applied for the single hidden layer. Batch gradient descent (GD), resilient backpropagation (RP), levenberg-marquardt (LM), batch gradient descent with momentum (GDM), variable learning rate (GDX), scaled conjugate gradient (SCG) algorithms have been used for the variants. The Neural Network has been optimized using the MATLAB Version 6.5 Neural Network Toolbox. In the training stage, to define the output accurately, we tried to increase the number of neurons step-by-step (i.e 3–12) in the hidden layer. Inputs and outputs have been normalized in the range of (0.1–0.9) as NN works efficiently within this

range. Neurons in the input layer have no transfer function. Logistic sigmoid (logsig) transfer function has been used in hidden layer while purelinear (purelin) transfer function has been used in output layer. After the successful training of the network, the network was tested with the test data. Using the results produced by the network, statistical methods have been used to make comparisons.

Table 2: Data sets used for training the network

| 30%T ht | RPM | Equivalence ratio, ϕ | Torque (N- m) | SFC (gm/kWh) |
|------------|------|------------------------------|------------------|-----------------|
| 30 | 1500 | 1.030 | 68.14 | 301.49 |
| 30 | 1700 | 1.039 | 67.06 | 295.81 |
| 30 | 1900 | 1.048 | 64.31 | 295.42 |
| 30 | 2100 | 1.056 | 60.27 | 299.82 |
| 30 | 2300 | 1.065 | 55.32 | 308.48 |
| 30 | 2500 | 1.074 | 49.86 | 320.91 |
| 30 | 2700 | 1.083 | 44.25 | 336.57 |
| 30 | 2900 | 1.092 | 38.89 | 354.98 |
| 30 | 3100 | 1.100 | 34.17 | 375.60 |
| 30 | 3300 | 1.109 | 30.45 | 397.93 |
| 30 | 3500 | 1.118 | 28.14 | 421.46 |
| 40 | 1500 | 1.060 | 70.00 | 313.00 |
| 40 | 1600 | 1.063 | 69.95 | 300.95 |
| 40 | 1800 | 1.070 | 69.71 | 292.82 |
| 40 | 2000 | 1.080 | 69.00 | 287.93 |
| 40 | 2200 | 1.091 | 67.59 | 285.78 |
| 40 | 2400 | 1.104 | 65.39 | 286.00 |
| 40 | 2600 | 1.116 | 62.43 | 288.40 |
| 40 | 2800 | 1.129 | 58.87 | 292.92 |
| 40 | 3000 | 1.140 | 55.00 | 299.66 |
| 40 | 3200 | 1.150 | 51.23 | 308.89 |
| 40 | 3400 | 1.157 | 48.11 | 321.00 |
| 50 | 1500 | 1.200 | 76.81 | 331.51 |
| 50 | 1700 | 1.193 | 75.46 | 323.64 |
| 50 | 1900 | 1.191 | 74.29 | 317.00 |
| 50 | 2100 | 1.193 | 73.20 | 311.59 |
| 50 | 2300 | 1.199 | 72.10 | 307.42 |
| 50 | 2500 | 1.207 | 70.88 | 304.48 |
| 50 | 2700 | 1.217 | 69.47 | 302.78 |
| 50 | 2900 | 1.227 | 67.75 | 302.31 |
| 50 | 3100 | 1.236 | 65.63 | 303.08 |
| 50 | 3300 | 1.244 | 63.02 | 305.08 |
| 50 | 3500 | 1.250 | 59.81 | 308.31 |
| 100 | 1600 | 0.975 | 72.74 | 320.97 |
| 100 | 1800 | 0.981 | 76.28 | 298.77 |
| 100 | 2000 | 0.984 | 78.02 | 285.96 |
| 100 | 2200 | 0.986 | 78.71 | 279.08 |
| 100 | 2400 | 0.988 | 78.94 | 275.41 |
| 100 | 2600 | 0.989 | 79.12 | 272.98 |
| 100 | 2800 | 0.991 | 79.47 | 270.54 |
| 100 | 3000 | 0.994 | 80.03 | 267.60 |
| 100 | 3200 | 0.999 | 80.67 | 264.41 |
| 100 | 3400 | 1.007 | 81.07 | 261.98 |
| 100 | 3500 | 1.011 | 81.03 | 262.02 |

Table 3: Data sets used for validation

| 30%Tht | 30%Tht RPM | Equivalence ratio, ϕ | Torque (N-m) | SFC (gm/kWh) |
|--------|------------|---------------------------|--------------|--------------|
| 30 | 1600 | 1.034 | 67.84 | 297.95 |
| 30 | 2000 | 1.052 | 62.43 | 297.05 |
| 30 | 2400 | 1.070 | 52.63 | 314.26 |
| 30 | 2800 | 1.087 | 41.52 | 345.46 |
| 30 | 3200 | 1.105 | 32.16 | 386.58 |
| 40 | 1900 | 1.075 | 69.43 | 306.44 |
| 40 | 2300 | 1.097 | 66.59 | 290.00 |
| 40 | 2700 | 1.123 | 60.71 | 285.61 |
| 40 | 3100 | 1.145 | 53.07 | 290.39 |
| 40 | 3500 | 1.160 | 47.00 | 303.94 |
| 50 | 1800 | 1.191 | 74.86 | 327.42 |
| 50 | 2200 | 1.196 | 72.66 | 314.14 |
| 50 | 2600 | 1.212 | 70.21 | 305.80 |
| 50 | 3000 | 1.232 | 66.74 | 302.39 |
| 50 | 3400 | 1.247 | 61.50 | 303.93 |
| 100 | 1700 | 0.978 | 74.79 | 308.45 |
| 100 | 2100 | 0.986 | 78.45 | 281.97 |
| 100 | 2500 | 0.989 | 79.02 | 274.14 |
| 100 | 2900 | 0.993 | 79.73 | 269.13 |
| 100 | 3300 | 1.003 | 80.92 | 263.01 |

Table 4: Data sets use for test network

| 30%Tht | Engine Speed RPM | Equivalence ratio, ϕ | Torque (N-m) | SFC (gm/kWh) |
|--------|------------------|---------------------------|--------------|--------------|
| 30 | 1800 | 1.043 | 65.87 | 294.98 |
| 30 | 2200 | 1.061 | 57.89 | 303.65 |
| 30 | 2600 | 1.078 | 47.05 | 328.37 |
| 40 | 1800 | 1.070 | 36.43 | 296.44 |
| 40 | 2200 | 1.091 | 29.10 | 286.54 |
| 40 | 2600 | 1.116 | 69.87 | 286.94 |
| 40 | 3000 | 1.140 | 68.39 | 296.00 |
| 40 | 3400 | 1.157 | 64.00 | 314.55 |
| 50 | 1800 | 1.191 | 56.95 | 320.16 |
| 30 | 3000 | 1.096 | 49.55 | 365.04 |
| 30 | 3400 | 1.114 | 76.11 | 409.58 |
| 50 | 2200 | 1.196 | 73.74 | 309.35 |
| 50 | 2600 | 1.212 | 71.51 | 303.48 |
| 50 | 3000 | 1.232 | 68.65 | 302.54 |
| 50 | 3400 | 1.247 | 64.39 | 306.54 |
| 100 | 1800 | 0.981 | 70.01 | 291.42 |
| 100 | 2200 | 0.986 | 77.32 | 276.99 |
| 100 | 2600 | 0.989 | 78.86 | 271.80 |
| 100 | 3000 | 0.994 | 79.27 | 265.99 |
| 100 | 3400 | 1.007 | 80.35 | 261.55 |

5. MEASURES OF PREDICTION PERFORMANCE

Using the results produced by the network, statistical methods have been used to investigate the prediction

performance of NN results. To judge the prediction performance of a network, several performance measures are used. Those include statistical analysis in terms of Root-Mean-Squared (RMS), absolute fraction of variance (R^2), as well as mean error percentage values [11]. Those are defined bellow:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{\sum_{i=1}^{i=N} (E_a - E_M)^2} \right) \quad (3)$$

$$RMS = \sqrt{\frac{\sum_{i=1}^{i=N} (E_a - E_p)^2}{N}} \quad (4)$$

$$\text{Mean \% Error} = \frac{1}{N} \sum_{i=1}^{i=N} \left(\frac{|E_a - E_p|}{E_a} \times 100 \right) \quad (5)$$

where

E_a -Actual result

E_p -Predicted result

E_m -Mean value

N -Number of pattern

The coefficient of multiple determinations R^2 compares the accuracy of the model to the accuracy of a trivial benchmark model. A perfect fit would result in an R^2 value of 1 and a very good fit near 1.

6. RESULTS AND DISCUSSIONS

The aim of using the Artificial Neural Network (ANN) is to test the ability to predict specific fuel consumption of retrofitted CNG engine. The network has four input parameters: Engine speed (rpm), throttle position, fuel-air equivalence ratio and torque (N-m) and one output parameter: specific fuel consumption. The experimental data set includes 84 values, of which 44 values were used for training network, 20 values were used for validation and 20 values were selected randomly to test the performance of the trained network. The experimental results are shown in Tables 1-3. All of the input and output values were normalized into the range 0.1–0.9. Validation values were used for early stop of training and to avoid over tainting. After 30 training cycles the level of error was satisfactory and further cycles had no significant effect on error reduction of testing. This can clearly be seen in Fig. 3. In the training, an increased number of neurons (from 3 to 12) are used in the hidden layer to define the output accurately for the batch gradient descent (GD), resilient backpropagation (RP), levenberg-marquardt (LM), batch gradient descent with momentum (GDM), variable learning rate (GDX), scaled

conjugate gradient (SCG) algorithms. The testing accuracy of trained networks is shown in Figs. 4-6.

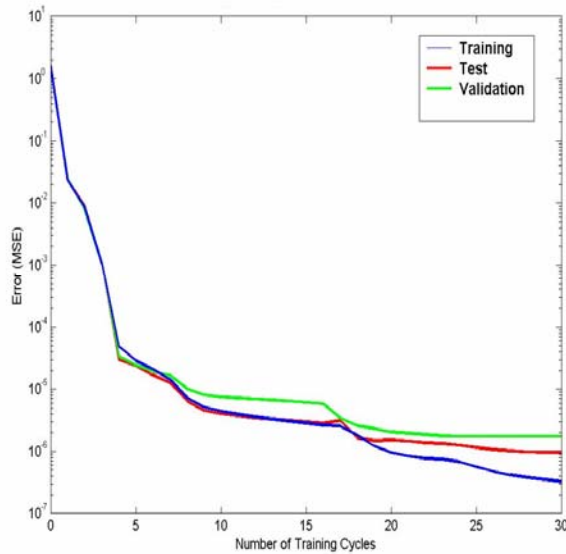


Figure 3: Network training cycles

Table 4: Performance of optimized network

| | R^2 | RMS (gm/kWh) | Mean Error (%) |
|------------|----------|-----------------|-------------------|
| Training | 0.999998 | 0.040 | 0.090 |
| Validation | 0.999996 | 0.223 | 0.207 |
| Test | 0.999931 | 0.242 | 0.224 |

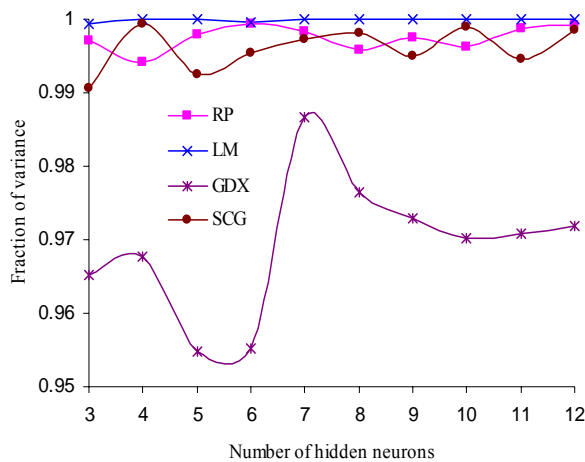


Figure 4: R^2 value of test for different algorithms with increasing number of hidden layer.

The performances of GD and GDM were not in satisfactory level and the statistical values were out of the range for Figs. 5-6. The accuracies of algorithms RP, GDX and SCG have shown good result but not consistent with hidden neurons. LM algorithm has shown good

performance accuracy and consistency with changing number of hidden neurons. The best network was found to be the LM algorithm with 10 hidden neurons. In Table 4, the statistical values of the outputs for this algorithm have been shown for the training, validation and testing data. The actual and predicted outputs of training and testing have been shown graphically in Figs. 7-8. The ANN predictions for the BSFC yield a mean relative error of 0.224%, a root mean square error of 0.242 gm/kWh and a correlation coefficient of 0.999931. These values show that the ANN predicts the BSFC quite well despite wide ranges of operating conditions. It is clear that the performance of the ANN would have been even better, if a higher number of test runs had been performed to provide a larger amount of experimental data for the network training.

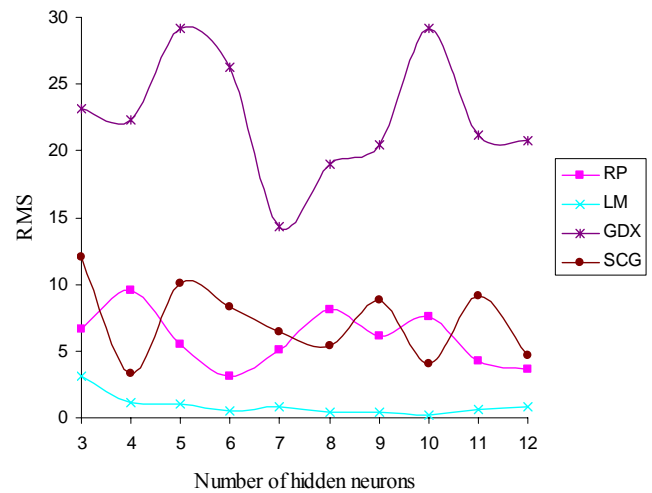


Figure 5: RMS value of test for different algorithms with increasing number of hidden layer.

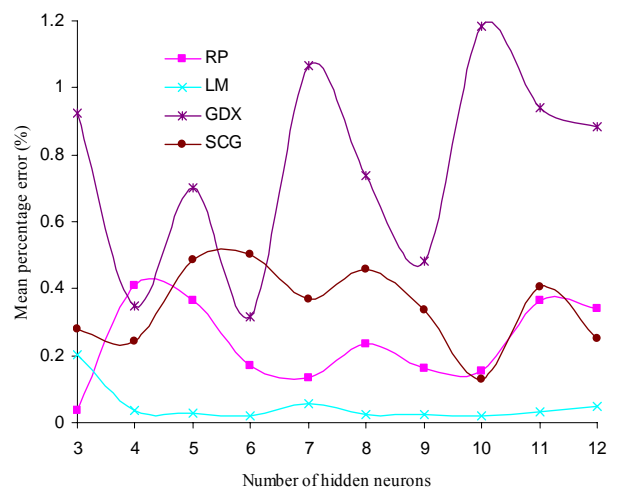


Figure 6: Mean percentage error of test for different algorithms with increasing number of hidden layer

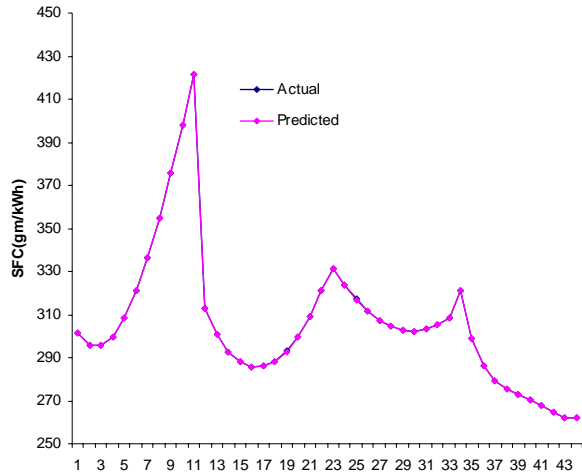


Figure 7: Comparison of actual and predicted values for BSFC of training data

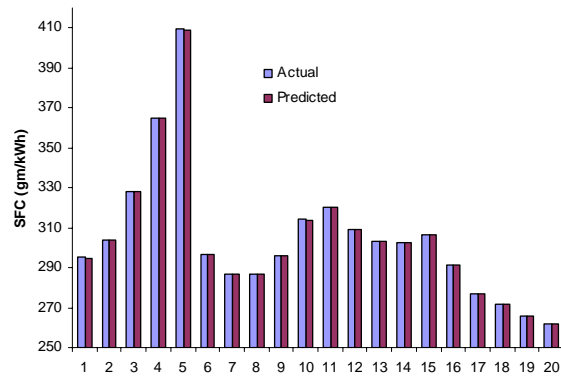


Figure 8: Comparison of actual and predicted values for BSFC test data.

The formulations of the outputs obtained from the weights are given using Eqs. 5–6.

BSFC

$$= \frac{1}{1 + e^{-(-2.3928F_1 - 0.1048F_2 + 2.3337F_3 - 1.4424F_4 - 0.2199F_5 + 0.1241F_6 - 0.5182F_7 - 0.8952F_8 + 0.3647F_9 + 1.8742F_{10} - 0.7597)}}$$

(6)

Where $F_i = (i = 1, 2, 3, \dots, 10)$ can be calculated according to equation (7).

$$F_i = \frac{1}{1 + e^{-E_i}} \quad (7)$$

Where E_i is the weighted sum of the of the input and is given by equation as seen in the Tables 5.

Table 5. The weights (C) between input layer and hidden layer for BSFC

| i | $E_i = C_1 T_{ht} + C_2 N_s + C_3 \phi + C_4 T + C_5$ | | | | |
|----|---|---------|----------|---------|---------|
| | C_1 | C_2 | C_3 | C_4 | C_5 |
| 1 | -2.8529 | 7.5086 | -21.2481 | -4.057 | 8.8613 |
| 2 | 2.7587 | -4.0614 | 0.9233 | 10.9504 | -5.2455 |
| 3 | -10.0031 | -1.9646 | -26.0019 | 6.8492 | 5.1912 |
| 4 | 2.6867 | 8.1041 | -32.6024 | -2.9196 | 8.9578 |
| 5 | -4.6516 | 5.9319 | -14.4598 | 8.387 | -0.2843 |
| 6 | 3.8218 | -7.2814 | 7.8886 | -13.59 | 6.5203 |
| 7 | -5.2524 | -7.9815 | 28.3589 | 4.1564 | 0.4495 |
| 8 | 6.7635 | -4.7433 | 28.1554 | 1.8058 | -8.1378 |
| 9 | -4.5086 | 8.1115 | 19.0278 | 2.344 | -8.1517 |
| 10 | 4.3511 | -7.246 | -26.3438 | -5.1709 | 11.8424 |

7. CONCLUSION

The aim of this paper has been to show the possibility of using the neural networks for predictions of dual fuel engine performance. The network produces the predicted results of brake specific fuel consumption parallel to the experimental ones. The *RMS* error values are smaller than 0.05 gm/kWh, R^2 values are about 0.9999 and mean error smaller than 0.25%, which may easily be considered within the acceptable range. A back propagation (BP) neural network model with GD, RP, LM, GDM, GDX and SCG algorithms have been studied in single hidden layer. Number of neurons on hidden layer also varied to optimize network. In most cases, the best results were obtained from the LM algorithm. On the other hand GD and GDM algorithms showed very poor prediction performance. The overall results show that the networks can be used as an alternative for predicting the performances of CNG fueled internal combustion engine.

The result of this study shows that ANN has ability to learn and generalize a wide range of experimental conditions. Therefore, the usage of ANNs may be highly recommended to predict the engine performance instead of having to undertake complex and time-consuming experimental studies.

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