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International Journal of Ambient Energy

ISSN: 0143-0750 (Print) 2162-8246 (Online) Journal homepage: www.tandfonline.com/journals/taen20

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To cite this article: Puli Danaiah, P. Ravi Kumar & Y.V.H. Rao (2015) Performance and emission prediction of a *tert* butyl alcohol gasoline blended spark-ignition engine using artificial neural networks, International Journal of Ambient Energy, 36:1, 31-39, DOI: 10.1080/01430750.2013.820147

To link to this article: https://doi.org/10.1080/01430750.2013.820147

Published online: 01 Sep 2013.

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International Journal of Ambient Energy, 2015
Vol. 36, No. 1, 31–39, http://dx.doi.org/10.1080/01430750.2013.820147

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Performance and emission prediction of a *tert* butyl alcohol gasoline blended spark-ignition engine using artificial neural networks

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(*Received 9 April 2013; accepted 5 June 2013*)

This paper proposes the mathematical modelling using artificial neural network (ANN) for predicting the performance and emission characteristics of spark-ignition (SI) engine using *tert* butyl alcohol (TBA) gasoline blends. The experiments are performed with a four-stroke three cylinder carburetor type SI engine at three different revolution per minutes such as 1500, 2000, and 2500 with different blends ranging from 0% to 5% and at 10%. Experimental data are used for training an ANN model based on the feed-forward back-propagation approach for predicting the data at 6–9% with the same speeds. Results show that the blending of TBA with gasoline improves the emission characteristics compared with the gasoline. From the experimental testing data, root mean squared-error was found to be 0.9997% with the network 3-1-10. During this study, The ANN model accurately anticipates the performance and emissions of the engine.

Keywords: artificial neural network; TBA; gasoline blends; spark-ignition engine

1. Introduction

The increased use of automobiles and the rapid rate of industrial development in the world made petroleum supplies unable to keep up with the demands. Moreover, petroleum fuels pollute the environment with their combustion products. Control devices were used to reduce pollution, but resulted in about 15% reduction in the vehicle mileage. It is, therefore, worthwhile to look into the suitability of using 'clean' burning fuels for use in spark-ignition (SI) engines (Najjar 2009). Hence, the usage of the alcohol fuels for SI engines come into existences.

The alcohols are oxygenates fuels in which the alcohol molecules decrease due to the combustion heat. Practically, any of the organic molecules of the alcohol family can be used as a fuel. The alcohols can be used for motor fuels are methanol (CH_3OH), ethanol (C_2H_5OH), propanol (C_3H_7OH), and butanol (C_4H_9OH) (Demirbas 2007).

Oxygenates are used by refiners not so much as a crude oil supplement but as an important and much needed source of octane. Octane demand has increased dramatically due to the removal of lead anti-knock compounds from gasoline. Allowed lead levels in leaded gasoline are being reduced as recent medical evidence shows that current automotive lead emissions are a serious and costly health hazard (Mays 1989).

Farkade and Pathre (2012) investigated on the study of methanol, ethanol, and butanol on the basis of blending percentage and also the role of oxygen percentage in the blend. The result shows highest replacement of gasoline by butanol at 5% of oxygen content, the performance of same oxygen percentage for other two alcohols are also better. Presence of oxygen gives you more desirable combustion resulting into low emission of carbon monoxide (CO), hydrocarbons (HC), and higher emission of carbon dioxide (CO_2) as a result of complete combustion, higher temperature is also favourable for NO emission resulting higher emissions for it.

The influence of butanol addition to gasoline in a port fuel injection and SI engine. The experiments were realised in a single-cylinder ported fuel injection SI engine with an external boosting device. The optically accessible engine was equipped with the head of a commercial SI turbocharged engine with the same geometrical specifications (bore, stroke, and compression ratio) as the research engine (Merola et al. 2012). The effect on the SI combustion process of 20% and 40% of *n*-butanol blended in volume with pure gasoline was investigated through cycle-resolved visualisation. The engine worked at low speed, medium boosting and wide-open throttle. Fuel injections both in closed-valve and open-valve conditions were considered. Comparisons between the parameters related to the flame luminosity and the pressure signals were performed. Butanol blends allowed to work in more advanced spark timing without knocking occurrence. The duration of injection for butanol blends was increased to obtain a stoichiometric mixture. In open-valve injection condition, the fuel deposits on the intake manifold and piston surfaces decreased, allowing a reduction in fuel consumption. BU40 granted the

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performance levels of gasoline and, in open-valve injection, allowed to minimise the abnormal combustion effects including the emission of ultrafine carbonaceous particles in the exhaust. In-cylinder investigations were correlated to engine out emissions.

Butanol or butyl alcohol can be demonstrated to work in the Internal Combustion (IC) engine designed for use with gasoline without modification. It can be produced from biomass (biobutanol) as well as fossil fuels (petrobutanol). Both biobutanol and petrobutanol have the same chemical properties. Butanol is less corrosive than ethanol and has higher energy content than ethanol, similar energy content in gasoline. In comparison to ethanol, butanol is less prone to water contamination. As a result, it could be distributed using the same infrastructure used to transport gasoline. It can be used alone in an internal-combustion engine, or it can be mixed with gasoline. Four butyl alcohols can be distinguished (Szwaja and Naber 2010). They all have the same chemical composition consisting of 4 carbon atoms, 10 hydrogens, and singlet oxygen, and examined by the identical chemical pattern $C_4H_{10}O$, but they differ from each others with respect to their structure. They are as follows:

- 1-butanol: (*n*-butanol) $CH_3–CH_2–CH_2–CH_2OH$,
- sec-butanol: $CH_3CH(OH)CH_2CH_3$,
- *tert*-butanol: $(CH_3)3COH$, and
- iso-butanol: $CH_3(CH_2)3OH$.

Danaiah (2013) investigated the effect of gasoline and tertiary butyl alcohol TBA blends on the performance and emission features of a SI engine. In this study, a four-stroke three cylinder carburetor type SI engine was used for leading the experiments. Exhaust emissions were analysed for CO_2, oxides of nitrogen (NO_x), CO, unburned HC, with gasoline TBA blends of 0%, 3%, 5%, and 10% blends at 2000 rpm. The results depict that the gasoline TBA blends lead to decrease in break specific fuel consumption as the blend percentage increases with respect to the revolution per minute (rpm) and also the break thermal efficiency increases as the blend percentage increases. The engine exhaust emissions concentrations such as CO, NO_x, and HC decrease.

Soheil, Seyed Morteza, and Fathollah (2012) investigated to study the effect of oxygenate additives into gasoline for the improvement of physicochemical properties of blends. Methyl tertiary butyl ether, methanol, tertiary butyl alcohol (TBA), and tertiary amyl alcohol blend into unleaded gasoline with various blended rates of 2.5%, 5%, 7.5%, 10%, 15%, and 20%. All oxygenates improve both motor and research octane numbers. Among these four additives, TBA shows the best fuel properties.

The artificial neural network (ANN) technique can be used as an alternative method in modelling highly complex and ill-defined problems, engineering analysis and prediction. ANNs do not require a precise formulation of the physical relationship of the concerned problem. In other words, they only need solution examples concerning the problem. ANNs have been used for energy systems, such as internal-combustion engine performance (Arcaklioğlu and Çelıkten 2004).

Sayin et al. (2006) investigated the ANN modelling for the gasoline engine to predict the brake specific fuel

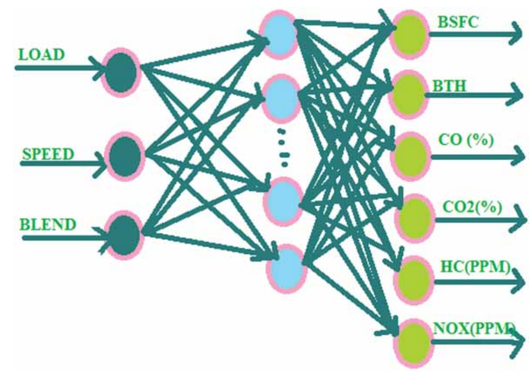

Figure 1. Schematic architecture of the ANN model.

Table 1. Specifications of the engine.

Engine make and model	Maruti 800
Stroke	72 mm
Cylinders	3
Cooling media	Water
Piston displacement	796cc
Bore	68.5 mm
Compression	8.8:1
Maximum output	37 bhp at 5000 rpm
Maximum torque	59 Nm at 2500 rpm
Fuel	Petrol

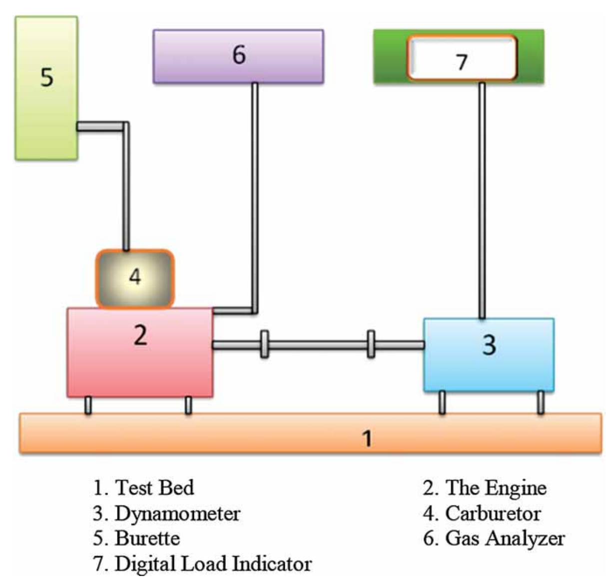

Figure 2. The schematic diagram of the engine setup with the instrumentation: (1) test bed, (2) the engine, (3) dynamometer, (4) carburetor (5) burette (6) gas analyzer, and (7) digital load indicator.

consumption (BSFC), brake thermal efficiency, exhaust gas temperature, and exhaust emissions of the engine. For acquiring the data for training experiments were carried out using gasoline having various octane numbers (91, 93, 95, and 95.3), and operated at different engine speeds and torques.

An ANN model is developed based on standard back-propagation algorithm for the engine with the experimental data. Then, the performance of the ANN predictions was measured by comparing the predictions with the experimental results which were not used in the training process. It was observed that the ANN model can predict the engine performance, exhaust emissions, and exhaust gas temperature quite well with correlation coefficients in the range of 0.983–0.996, mean relative errors in the range of 1.41–6.66% and very low RMSEs.

Çay et al. (2012) studied to predict the BSFC, effective power and average effective pressure, and exhaust gas temperature of the methanol engine using ANN. Experiments were performed with a four-cylinder, four-stroke

Table 2. Technical specifications of five gas analyzer.

NPM-MGA-2 give gas analyzer				
Gases measured	Method	Measurement range	Resolution	Accuracy
HC	NDIR	0–20,000 ppm	1 ppm	±10 ppm abs
CO	NDIR	0–9.99%	0.01%	±0.03% abs
CO_2	NDIR	0–20.00%	0.10%	±0.04% abs
O_2	Electrochemical	0–25%	0.01%	±0.1% abs
NO_x	Electrochemical	0–10,000	1 ppm	±25 ppm abs

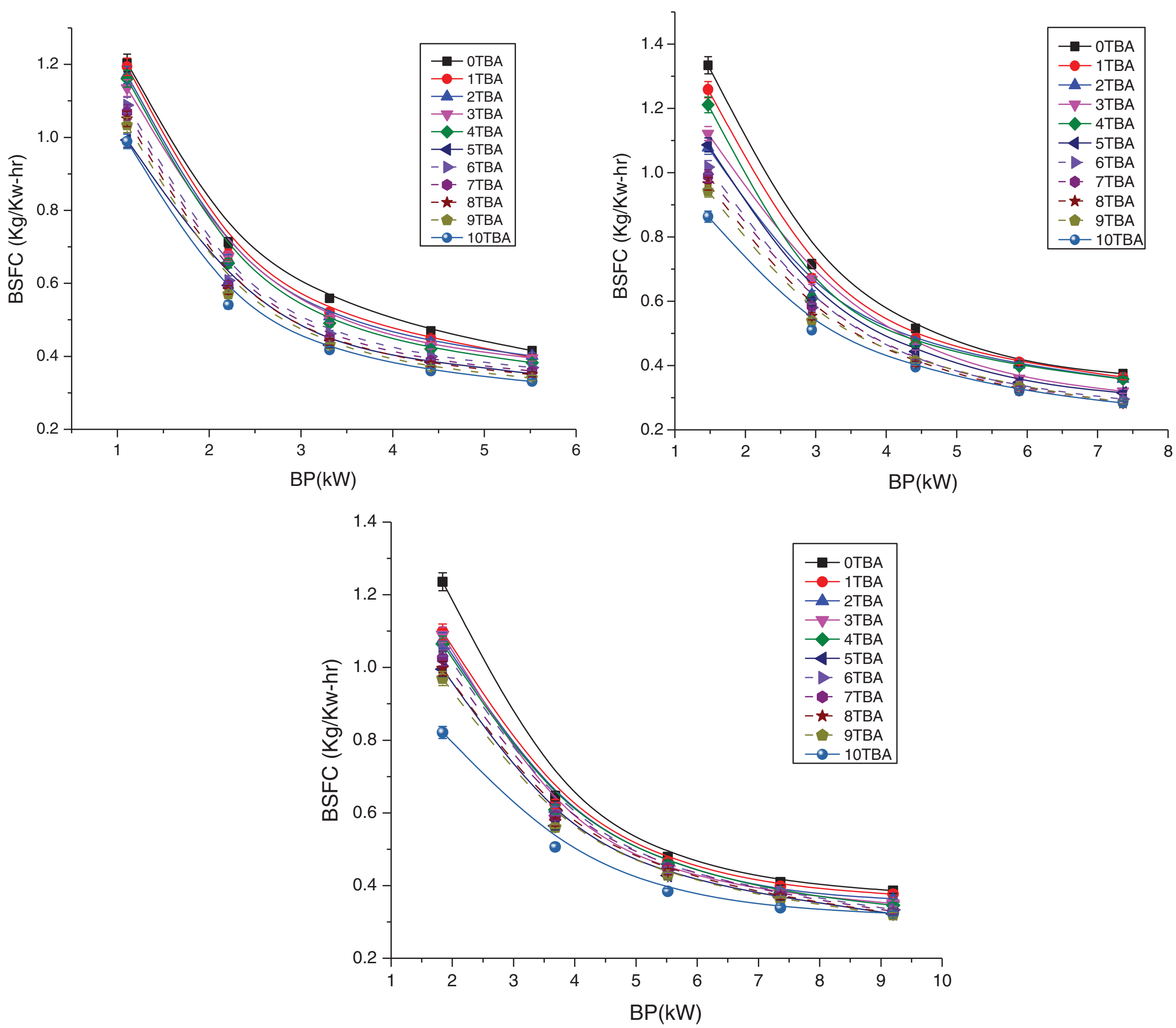

Figure 3. Variation of the BSFC with BP at 1500, 2000, and 2500 rpm.

test engine operated at different engine speeds and torques. Using some of the experimental data for training, an ANN model based on standard back-propagation algorithm was developed. Then, the performance of the ANN predictions was measured by comparing the predictions with the experimental results. And found that the R^2 values are close to 1 for both training and testing data. RMS values are smaller than 0.015 and mean errors are smaller than 3.8% for the testing data. This shows that the developed ANN model is a powerful one for predicting the BSFC, effective power and average effective pressure, and exhaust gas temperature of internal-combustion engines.

Yusaf, Saleh, and Said (2012) estimated the performance and emission concentration of liquefied petroleum gas SI using engine ANN. For the estimation, a feed-forward back-propagation algorithm is used for the training of the ANN model. The result of the simulation reveals that ANN model is appropriate to estimate the engine performance and gas exhaust emissions with correlation coefficient ranging from 0.9 to 0.99 with low RMSE and low mean relative error.

2. Artificial neural-networks

One efficient way of solving complex problems is following the lemma 'divide and conquer'. A complex system may be decomposed into simpler elements, in order to be able to understand it. Also simple elements may be gathered to produce a complex system. Networks are one approach to achieving this. There are a large number of different types of networks, but they all are characterised by the following components: a set of nodes and connections between nodes. The nodes can be seen as computational units. They receive inputs, and process them to obtain an output. This processing might be very simple (such as summing the inputs), or quite complex (a node might contain another network, etc.). The connections determine the information flow between nodes. They can be unidirectional, when the

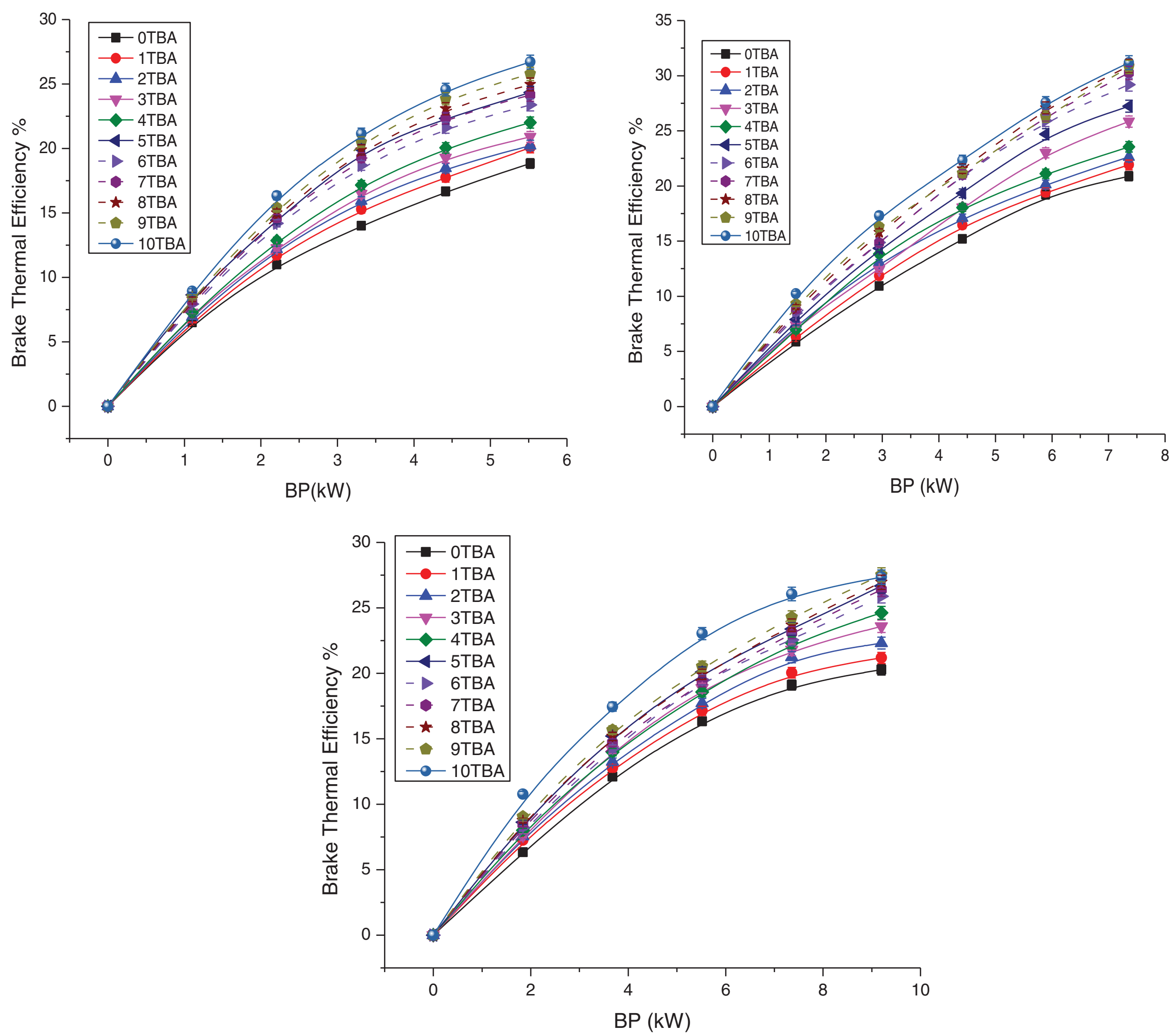

Figure 4. Variation of the BTH with BP at 1500, 2000, and 2500 rpm.

information flows only in one sense, and bidirectional, when the information flows in either sense. The interactions of nodes though the connections lead to a global behaviour of the network, which cannot be observed in the elements of the network. This global behaviour is said to be emergent. This means that the abilities of the network supersede the ones of its elements, making networks a very powerful tool (Gershenson 2003).

ANNs can be trained to reach from a particular input to a specific target output using a suitable learning method until the network output matches the target. The error between the output of the network and the desired output is minimised by modifying the weights and biases. When the error falls below a determined value or the maximum number of epochs is exceeded, the training process is ceased. Then, this trained network can be used for simulating the system outputs for the inputs which have not been introduced before.

Then, the six output parameters were predicted using a three-layer feed-forward ANN. Utilising standard back-propagation algorithm, the input vectors and the corresponding target vectors from the training set were used for training the network. The training procedure adjusted the weighting coefficients using Levenberg–Marquardt algorithm. The output of the network was compared with the desired output at each presentation, and an error was computed. This error was then back propagated to the ANN and used for adjusting the weights such that the error decreases with each iteration. Consequently, the training procedure approximates a function between the input and output variables. Then, the input vectors from the test data set were presented to the trained network and the output parameters predicted by the network were compared with the experimental ones for the performance measurement. The computer code solving the back-propagation algorithm and measuring the network performance was implemented under the MATLAB environment.

Hence, in this paper, ANNs are used to predict the BSFC, brake thermal efficiency, and exhaust emissions such as carbon monoxide (CO), CO_2, unburnt HC, and NO_x, using TBA gasoline blends on SI engine. Experimental studies were complete to obtain training and test data. The results of the system indicate a relatively good agreement between the predicted values and the experimental ones. Figure 1 shows the architecture of the ANN Model.

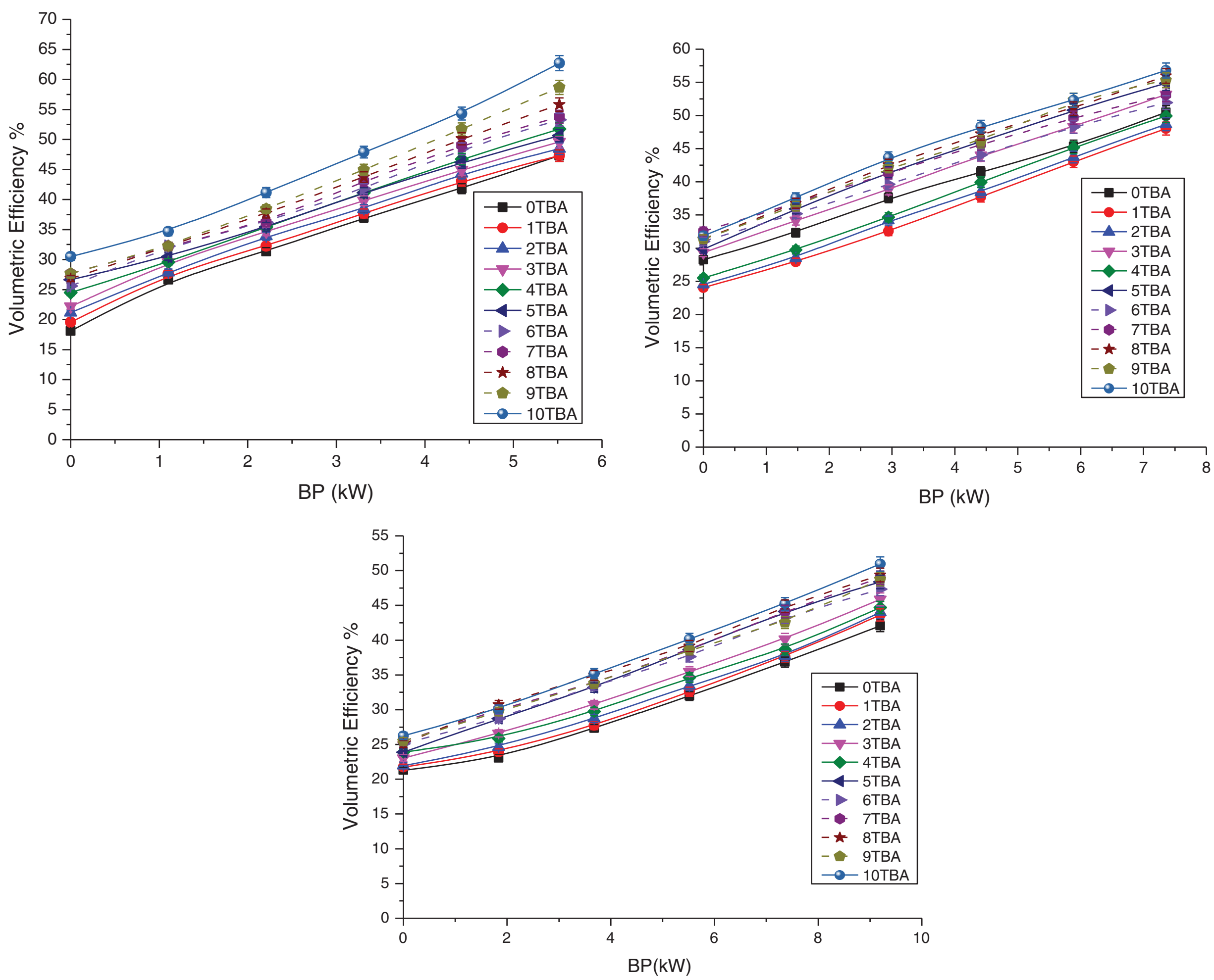

Figure 5. Variation of the volumetric efficiency with BP at 1500, 2000, and 2500 rpm.

3. Experimental work and description

The engine employed is three cylinder, four-stroke, SI, water cooled, and Carburetor type SI MARUTI 800 engine loaded by a water brake dynamometer. For several decades, Carburetors were used on most SI engines as the means of adding fuel to the intake air. The basic principle on which the carburetor work is extremely simple. The basic carburetor is a venturi tube mounted with a throttle plate (butterfly valve) and a capillary tube to input fuel. It is usually mounted on the upstream end of the intake manifold, with all air entering the engine passing first through this venturi tube. Most of the time, there will be an air filter mounted directly on the upstream side of the carburetor. Some detailed specifications of the engine are shown in Table 1. The schematic figure of the erect is shown in Figure 2

The engine was coupled to a water brake dynamometer made by the TECHNOMECH which is equipped with digital load indicator. Fuel consumption was measured by using a calibrated burette and a stopwatch. The engine speed is measured with a fine-tuned tachometer. The concentration of the exhaust emissions CO, CO_2, HC, NOx, and O_2 from the engine is measured with a NETEL made five-gas analyzer model NPM-MGA-2. Table 2 gives the technical specifications of the five-gas analyzer. The engine was started and allowed to warm up for a period of 15–20 min. For the experimental safety, the engine has not been run at rated brake power and speed (i.e. 37BHP at 5000 rpm), and run at 10BHP at 2500 rpm instead and is referenced as full load. The fuel consumption was constant at 10cc for each performance. Engine tests were performed at speeds of 1500, 2000, 2500 rpm, and by varying the loading conditions for each individual fuel. Before running the engine to a new fuel blend, it was allowed to run for sufficient time to consume the remaining fuel of the previous experiment. For each experiment, average of four readings

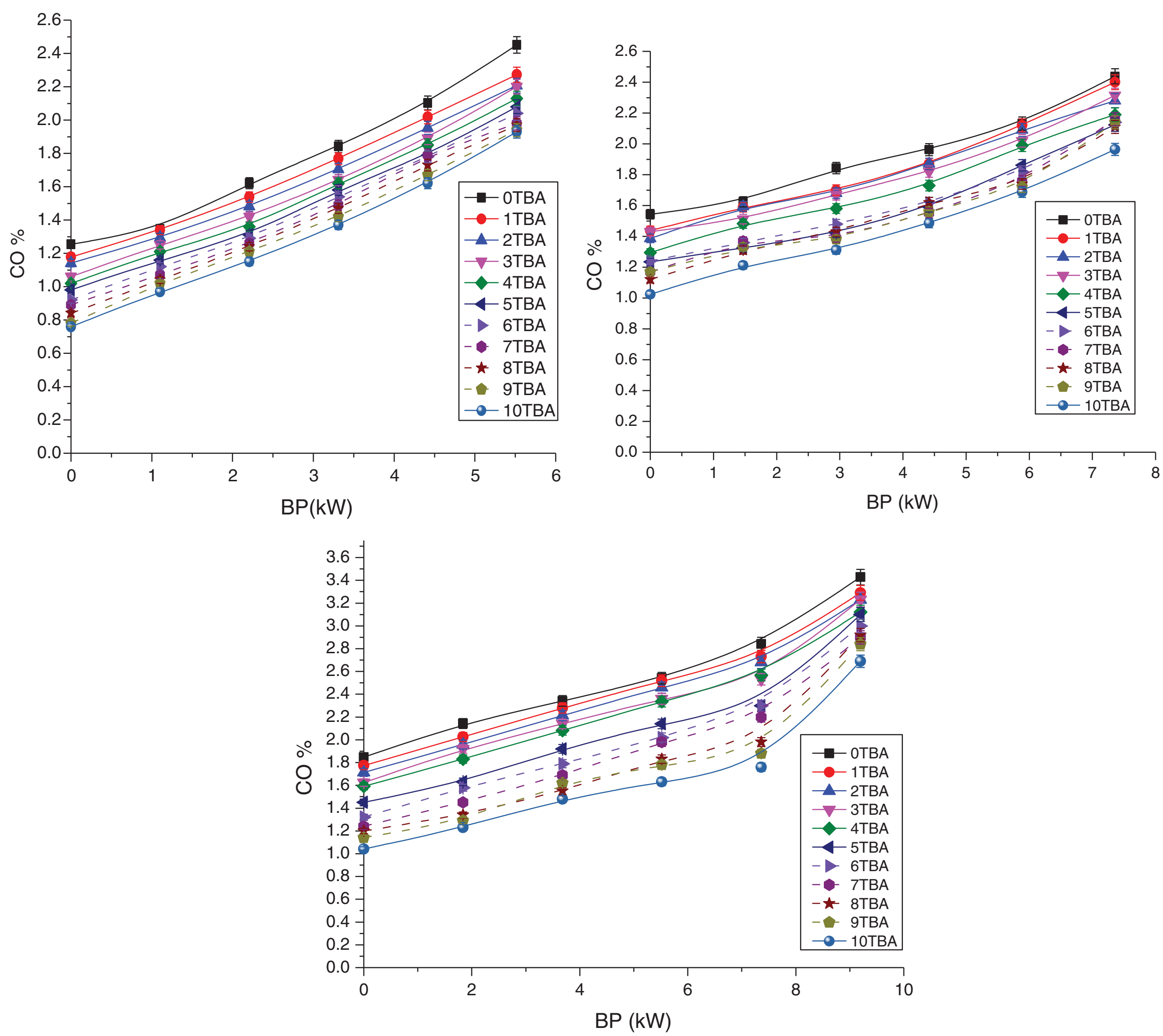

Figure 6. Variation of the CO emissions with BP at 1500, 2000, and 2500 engine rpm.

has been taken for the evaluation of the performance of the engine. The variables that were continuously measured while performing the experiments are time taken to consume 10cc of the fuel, the difference between the heights of two columns of the manometer, exhaust temperature with tail pipe emissions, i.e. CO, CO_2, HC, NO_x, and O_2 from the engine. The parameters such as brake power, brake thermal efficiency, BSFC, and volumetric efficiency are calculated based on the observations.

4. Results and discussion

The experimental results for different load conditions with various percentages of TBA gasoline blends such as 0–5% and 10% are investigated at 1500, 2000, and 2500 rpm's experimentally and blends of 6–9% are predicated with the ANN.

4.1. *BSFC*

The comparability of the calculated experimental data and the predicted data using ANN at three different engine speeds, i.e. at 1500, 2000, and 2500 rpm are shown in Figure 3. The blends 0TBA to 5TBA and 10TBA are the calculated experimental data and represented by the solid lines and from 6TBA to 9TBA are the predicted data using ANN and represented by the dashed lines as shown in Figure 3. From the figure, it is observed that 10TBA has lower BSFC values compared with the other blends. It is pointed out that as the blend percentages increase, the BSFC decreases. By observing the figure at three different speed operations of the engine, the BSFC at no load condition is decreasing as the blend and speed increases. An ANN was developed based on this experimental work. The results showed that the training algorithm of back propagation was sufficient for predicting engine BSFC.

4.2. *Brake thermal efficiency*

The comparison of the calculated experimental data and the predicated data with ANN at three different engine speeds, i.e. at 1500, 2000, and 2500 rpm are shown in Figure 4. Figure 4 presents the effect of TBA blends on

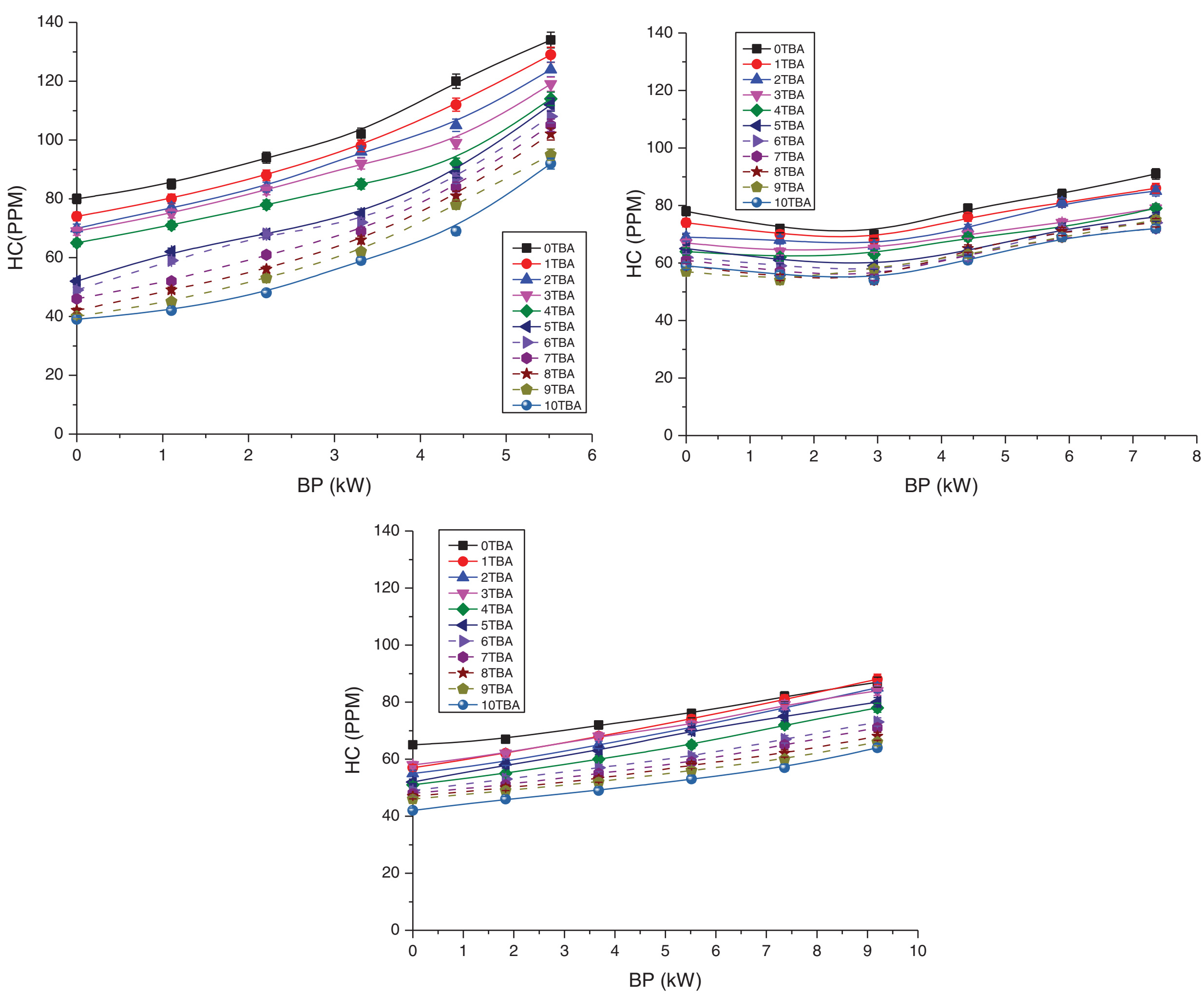

Figure 7. Variation of the HC emissions with BP at 1500, 2000, and 2500 engine rpm.

the brake thermal efficiency. As shown from the figure that the brake thermal efficiency increases as the TBA percentage increases. From the figure, it is observed that by running the engine at 2000 rpm the brake thermal efficiency is high comparing with the operating of the engine at 1500 rpm. For TBA10 by operating the engine at 2500 rpm, it has higher brake thermal efficiency compared with the other blends.

The ANN predicated blended values, i.e. 6–9% are shown in the dashed lines from the figures by operating the engine at three different speeds ranging from 1500, 2000, and 2500 rpm. The ANN predication gives good results for the brake thermal efficiency as shown in the figure.

4.3. *Volumetric efficiency*

The variation of volumetric efficiency with the brake power at three different engine speeds, i.e. at 1500, 2000, and 2500 rpm are shown in Figure 5. From the figure, it is observed that as the brake power increases the volumetric efficiency increases. Therefore, by looking at the blend percentage, it is evident that the volumetric efficiency increases as the blend percentage increases from 0TBA to 5TBA and 10TBA this is referable to the decrease in the temperature. From the figures, it is observed that as the TBA% increases the property like fuel volatility and the latent heat of the fuel blend increases. By running the engine at 2000 rpm, the volumetric efficiency of the blends of 1TBA, 2TBA, and 3TBA decreases and remaining blends increases as compared with base fuel. For the predication of volumetric efficiency for the blends 6TBA to 9TBA is predicated using the ANN environment using MATLAB. For the predication, experimental data are used for training the network and the results are best fitted with the experimental data as shown in the figure.

4.4. *CO*

The effect of CO emissions with the brake power by running the engine at 1500, 2000, and 2500 rpm is depicted in Figure 6. The consequence of the figures represented that as the brake power increases the CO emissions increases at all three different engine rpms. Basically, the formation of CO shows to loss in the engine power so that there is lack of oxygen for complete combustion. Hence

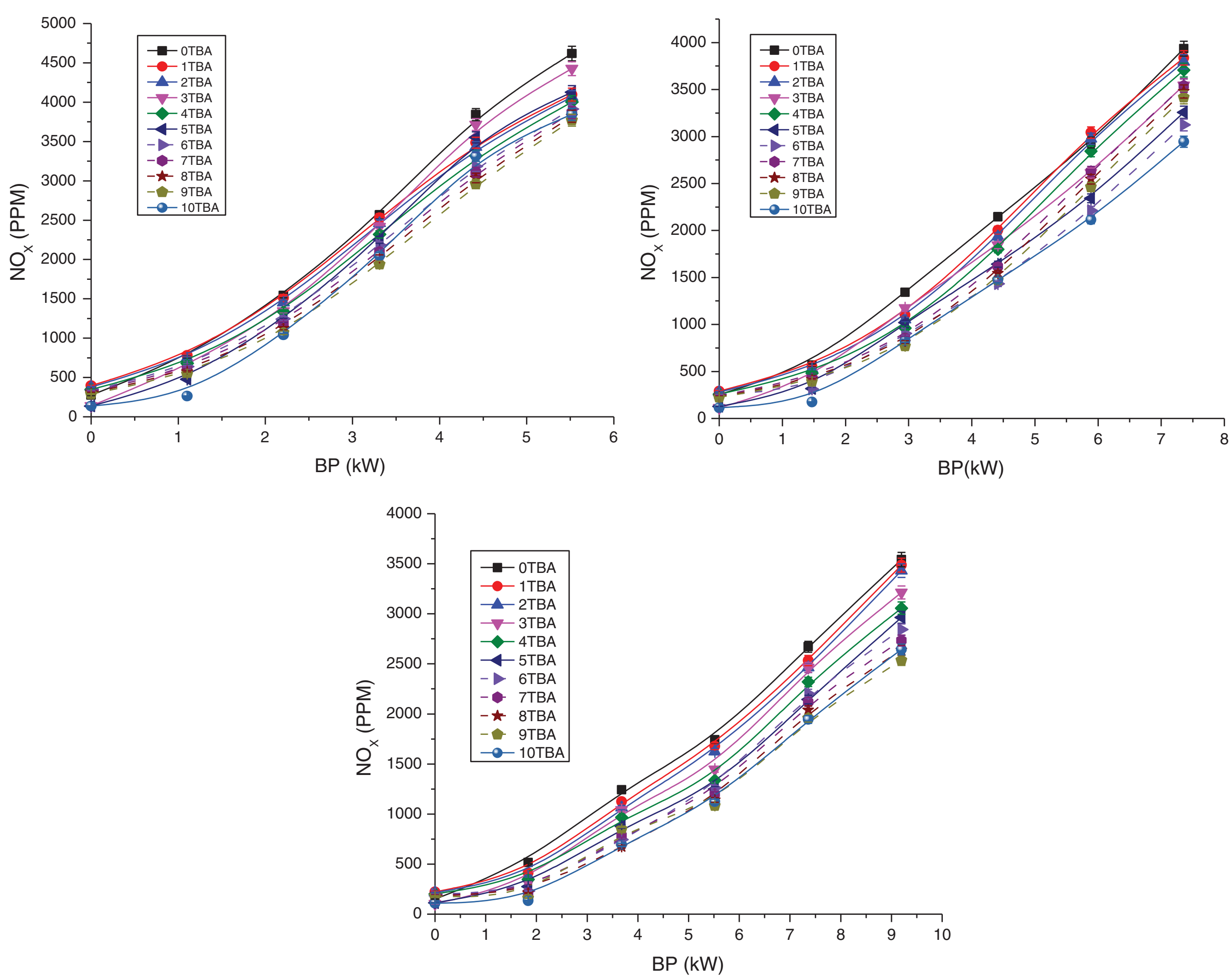

Figure 8. Variation of the NO_x emissions with BP at 1500, 2000, and 2500 engine rpm.

from the figures, it is observed that the formation of the CO emissions is high by operating the engine at higher loads due to improper mixing and originates for the CO emissions from the engine. By operating the engine at different blends of TBA ranging from 0TBA to 5TBA and 10TBA experimentally the CO emissions reduces as shown in the figure compared with the pure petrol because of the oxygen percentage. The experimental data are used for predicating the CO emissions for the blends of 6TBA to 9TBA in ANN environment as shown in the figure at three different speeds of the engine. The ANN environment predication gives best predicated values with the experimental values.

4.5. *HC*

The variation of HC emissions with brake power operating the engine at three different speeds, i.e. at 1500, 2000, and 2500 rpm is shown in Figure 7. The main thing for the formation of the HC emissions from the engine is due to the deficiency of air for the complete combustion of the engine. Operating the engine at 1500 rpm causes the increase in the HC emissions with respect to the brake power as shown in the figure, and by operating the engine at 2000 and 2500 rpm causes a decrease in the HC emissions up to part load operation of the engine and suddenly it increases. From the figure, it is observed that HC is reduced from 31.34% with 0TBA to 10TBA at 1500 engine rpm, similarly 20.879%, 26.437% reduces at 2000, 2500 engine rpms.

4.6. *NO_x*

The variation of NO_x with brake power is shown in Figure 8 at engine speeds of 1500, 2000, and 2500 rpm. It can be noticed from the figure the trend of the NO_x is increasing drastically with respect to the brake power. It can be seen that as the TBA% increases the NO_x decreases compared with pure petrol (0TBA) at all three operating conditions of the engine, i.e. at 1500, 2000, and 2500 rpm. From the experimental data at full load operation of the engine at 1500 rpm the NO_x having 4618 ppm with 0TBA and 4002 ppm with 6TBA there by 13.339% reduction takes place as the blend percent increases from 0TBA to 6TBA then from 0TBA to 10TBA the 16.739% reduction takes place with experimental and predicted data. Similarly from 0TBA to 10TBA 25.159% reduction takes place at 2000 rpm, 25.325% reduction takes place at 2500 engine rpm. Hence, the ANN environment in MATLAB and obtained a best results from the training of the results.

5. Conclusions

The present work proves that the use of gasoline TBA blends will decrease in the BSFC and conversely increase in the brake thermal efficiency. It can be examined that as the gasoline TBA percentage increases the brake thermal efficiency and volumetric efficiency increases. The exhaust emission such as CO, HC, and NO_x decreases as the blend percentage increases compared with the pure petrol (0TBA). The predication of the blends from 6TBA to 9TBA in ANN is very good and from the test data, RMSE was found to be 0.9997%. Therefore, the analysis of the experimental data by using ANN brought out that there is a good correlation between the ANN-predicted results and the experimental data. Therefore, ANN environment from MATLAB showed to be a useful tool for correlation and simulation of engine parameters. Hence, ANN provided the accurate analysis of the complex problems and the analysis of the performance and emission analysis of SI engines.

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