Mechanics and Mechanical Engineering
Vol. 19, No. 1 (2015) 31–49

Hydrous Methanol Fuelled HCCI Engine Using Ignition Improver CAI Method - ANN Approach

M. Venkatesan
Department of Mechanical Engineering
University College of Engineering Nagercoil
Konam, Nagercoil - 629004, Tamil Nadu, India
mechvenkatesan2013@gmail.com

N. Shenbaga Vinayaga Moorthi
Department of Mechanical Engineering
University V.O.C College of Engineering
Thoothukudi, Tamil Nadu, India

P. Arul Franco
Department of Mechanical Engineering
University College of Engineering Nagercoil
Konam, Nagercoil – 629004, Tamilnadu, India

A. Manivannan
Department of Mechanical Engineering
Regional Centre, Anna University
Tirunelveli, Tamil Nadu, India

R. Karthikeyan
Department of Mechanical Engineering
Shri Andal alagar College of Engineering and Technology
Mamandur, Tamil Nadu, India

Received (21 January 2015)
Revised (16 February 2015)
Accepted (21 February 2015)

The present study is to examine the performance and emission characteristics of a Homogeneous Charge Compression Ignition (HCCI) engine where hydrous methanol (85% methanol and 15% water) is used as primary fuel and Diethyl ether (DEE) as an ignition improver. A modified diesel engine has been used as a HCCI engine. By measuring the excess air ratio (λ_{DEE}), the quantity of DEE flow rate is measured and excess air ratio (λ_{DEE}) is varied from λ_{DEE}5.6 to λ_{DEE} 9.5. Experimental results reveal that HCCI engine gives better brake thermal efficiency (BTE) at high loads (λ_{DEE} 9.5). It shows decrease in oxides of nitrogen (NO_{x}) emission, slightly high emission of carbon monoxide (CO) and unburned hydrocarbon (HC) compared to conventional compression ignition

(CI) engine. Radial basis function neural network (RBFN) model has been developed with brake power, excess air ratio and energy share as input and BTE, CO, HC, NO_x, rate of pressure rise as output. About 80% of total experimental data is used for training purposes, and 20% is used for testing. The performance of the developed RBFN model were compared with experimental data, and were statistically evaluated which was found to be in good agreement.

Keywords: Radial basis function neural network, HCCI Engine, hydrous methanol, diethyl ether and DEE Excess air ratio.

1. Introduction

Spark ignition (SI) and Compression ignition (CI) engines are used for generating power in transportation vehicles. Compared to CI engines, SI engines have low smoke emissions with HC and CO as their major components. Even though the CI engines show comparatively higher brake thermal efficiency, these engines give out NO_x and smoke emissions. The homogeneous charge compression ignition (HCCI) engine is an alternative engine technology for future development of automobile engines and power plants. HCCI engine is very suitable for using all kind of fuels, irrespective of its octane and cetane number. Hence, the application of methanol in HCCI engine is not an issue. However, it has fewer advantages than that of other fuel of this category [1]. The HCCI combustion has the potential to achieve negligible smoke emissions with very low NO_x than SI and CI engines. In addition, fuel efficiency as high as for the DI diesel engines. Methanol or methyl alcohol has many desirable qualities such as high octane number, high volatility and lean burn properties [2–5]. Methanol is very good alternate fuel and it has been successfully used in SI engines due to high latent heat of vaporization and clean burning behaviour [6, 7]. Diethyl ether (DEE) can be made from renewable feedstock and waste because ethanol can be converted by dehydration to DEE [8]. Low auto ignition, high cetane value and low boiling temperature are reason for selecting DEE as an ignition improver. The properties of hydrous methanol and DEE as shown in Tab. 1.

Table 1 General Properties of hydrous methanol and Diethyl Ether

Properties	Hydrous methanol	Diethyl Ether
Chemical Structure	CH_3OH	$CH_3CH_2OCH_2CH_3$
Autoignition Temperature	480^0C	160^0C
Density	793 Kg/m^3	713 Kg/m^3
Calorific Value	19.9 MJ/Kg	33.9 MJ/Kg
Boiling Point	65^0C	34.4^oC
Stoichiometric air fuel ratio	6.45:1	11.1

Onishi et al. (1979) have investigated that two stroke SI engines which achieves better fuel consumption and exhaust emissions at part load conditions [9]. Najt et al (1983) have investigated compression ignition homogeneous charge combustion in four stroke gasoline engine [10]. Zheng et al. (2004) investigated that methanol can be used as a fuel for HCCI engine and Dimethyl ether (DME) as an ignition improver [11]. Venkatesan et al (2014) introduced dual fuel HCCI engine of hydrous methanol with Dimethyl ether (DME) as an ignition improver. They found that duel fuel operation gave better brake thermal efficiency than that of CI engine [12]. Vinayagam et al (2014) have investigated wet ethanol fuelled HCCI engine with DEE as an ignition improver. They point out that DEE excess air ratio (λ_{DEE}=10.5) gave maximum brake thermal efficiency and low NO_x[13]. Venkatesan et al. (2014) experimentally proved the suitability of hydrous methanol in HCCI combustion. They used air preheater assisted controlled auto ignition for combustion control and combustion phasing [14]. Sudheesh et al. (2010) investigated DEE as an ignition improver for a biogas fuelled HCCI operation [15]. They found that biogas –DEE HCCI mode of operation is possible in a load range of zero to 4.52 bar BMEP. It has been reported that many experimental studies with DEE as an additive along with different fuels are studied at length [16-20]. Though predictions and experimental investigations on the performance and emission characteristics of HCCI engine which is fuelled with methanol as fuel and DEE as additive is not studied at length.

Artificial neural networks can be used to solve a wide range of problems in science and engineering, when the conventional modelling methods fail. ANN is one among the sophisticated modelling and prediction making technique that is capable of modelling extremely complex functions and data relationships. The ability to learn by examples have many features of neural networks that enable the user to model data and establish accurate rules that govern the underlying relationship that exist between various data attributes [21, 22]. Neural networks have the ability to accurately predict data that were not the part of the training dataset, given by these characteristics and their broad applicability; neural networks are capable for applications of real world problems that are in research & science, business and industry [23]. The main aim of this study is developing ANN model for higher engine performance and emissions of an HCCI engine fuelled with hydrous methanol with respect to its input variables. The objective of the present study is to investigate the effects of hydrous methanol on performance and exhaust emissions with the assistance of ignition improver controlled auto ignition. A compression ignition engine when operated in the HCCI mode with hydrous methanol and DEE inducted along with air shows the effect of DEE flow rate on the performance, emissions and operating load range of a hydrous methanol-fuelled HCCI mode, when running at a constant speed of 1500 rev/min. Radial basis function neural network model was developed to predict the performance and emission characteristics of the experimental data that is obtained during the operation of HCCI engine.

2. Experimental work

2.1. *Explanation of the experimental test rig*

A single–cylinder, water–cooled, direct injection CI engine was modified to operate in HCCI mode. A suitable eddy current dynamometer was coupled to the engine for loading and measurement purpose. The engine specifications are shown in Tab. 2.

Table 2 Technical specifications of the test engine

Characteristics	Specifications
Make and Model	Kirloskar, AVI
General	Four stroke, compression ignition, constant speed, vertical, direct injection
Number of cylinders	1
Bore x Stroke	87.5 mm x 110 mm
Length of Connecting rod	231 mm
Cubic capacity	661 cc
Compression ratio	17.5:1
Speed	1500 rpm
Rated output	4.4 kW

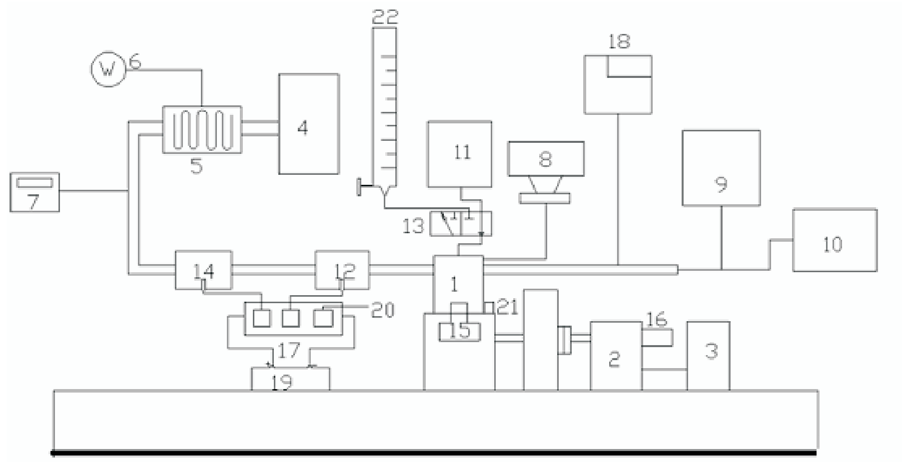

Figure 1 Experimental installation. 1. CI Engine, 2. Eddy current Dynamometer, 3. Dynamometer Control accessories, 4. Anti pulsating drum, 5. Air preheater, 6. Watt meter, 7. suction temperature indicator, 8. Data acquisition system, 9. Exhaust Gas Analyser, 10. Smoke sampling pump, 11. Diesel tank, 12 hydrous methanol injector, 13. Three way cock 14.DEE Injector, 15. Fuel Injection Pump, 16. Crank angle encoder 17. Engine Control Module, 18.Exhaust gas temperature indicator, 19. Battery, 20. Input signal for ECM operation, 21. Inductive pickup for ECM operation, 22. Burette

The inlet side of the engine has two electronic fuel injectors to supply hydrous methanol into the engine separately. The inlet side of the engine also consists of an anti–pulsating drum and air temperature indicator. The outlet side of the engine consists of an exhaust gas temperature indicator, gas analyser and smoke meter. The hydrous methanol was stored in separate fuel tanks and injected into the suction manifold using two independent electronic fuel injectors. The fuel flow rate of hydrous methanol has been measured using injector calibration curve. The injector used for hydrous methanol injection has been recalibrated before the application. The calibration curve has been prepared using amount of fuel discharge and pulse width of the pulse delivered by the ECM. The inductive pickup located near the flywheel provides an input signal for the ECM operation. Three way cock used in the setup helps to determine the diesel flow rate. During the fuel flow measurement it is used to changes the fuel path from normal position to measuring position.

The excess air ration is used to calculate the flow rate of DEE. In-between the two electronic fuel injectors on the intake side of the engine, a measuring probe has been connected to measure the excess air ratio of DEE provided by the DEE injector. The facility for measuring the diesel consumption is also provided in the engine. A 16-bit data learning system was used to obtain the Cylinder pressure data. The schematic of the experimental setup is shown in Fig. 1.

2.2. *Methodology*

It is difficult to auto ignite the hydrous methanol fuel because of its high self–ignition temperature and low cetane value and hence it is necessary for an external ignition aid for the ignition of HCCI engines. Hence, the use of Auto ignition is compulsory when the engine is supplied with hydrous methanol fuel. Diethyl Ether (DEE) has proved to be a good ignition improver as it has a high cetane value and it is supplied along with the fuel through fuel admission devices. The inlet side of the engine which has two fuel injectors supplies the hydrous methanol and DEE separately. The amount of DEE and hydrous methanol were deliberated and the amount is controlled by an Engine Control Module (ECM). The DEE mixed along with hydrous methanol will increase the Cetane number and the mixture will get Ignited well. The fuel used in the HCCI engine in hydrous methanol and it has a very poor self–ignition property to improve this property a fractional quantity of Diethyl ether(DEE) mixed with methanol fuel while induction. This addition of DEE improves auto ignition property and reduces CO, HC and smoke emission. Hence, the emission parameters CO, HC and smoke are used to assess the quality of combustion.

3. Results and discussion

The experimental results at different engine operating conditions at a constant engine speed of 1500 rev/min are presented with hydrous methanol as primary fuel and DEE as an ignition improver are discussed in this section.

3.1. *Operating Range*

Fig. 2 shows the operating range of Hydrous methanol fuelled HCCI engine for various DEE excess air ratios and methanol flow rates. The operating range of methanol varies with respect to load and DEE flow rates. Fuel was admitted along with methanol fuel and the mixture was inducted during suction stroke. Higher quantity of DEE admission caused knocking and lesser quantity of DEE caused misfiring. The operating range is limited by misfire and knock limit. The misfire is identified by COV and the knock limit is identified by rate of pressure rise. The combustion analysis software used in the set up helped to acquire 100 cycles and used for calculating the above said limits. The COV is usually expressed in terms of percentage. Since the drive train problems in automobiles normally arise when COV exceeds 10% [12, 13], this value was used for fixing misfire limit in the present investigation.

In this work, the misfire limit and knock limit at each and every DEE flow rate has been identified by increasing and decreasing the methanol flow rates. Experiment result reveals that the methanol flow rate was increased up to the misfire limit and decreased up to the knock limit. The stable operating range obtained between the knock and misfire limit is called as the operating range of the HCCI engine at that particular DEE excess air ratio.

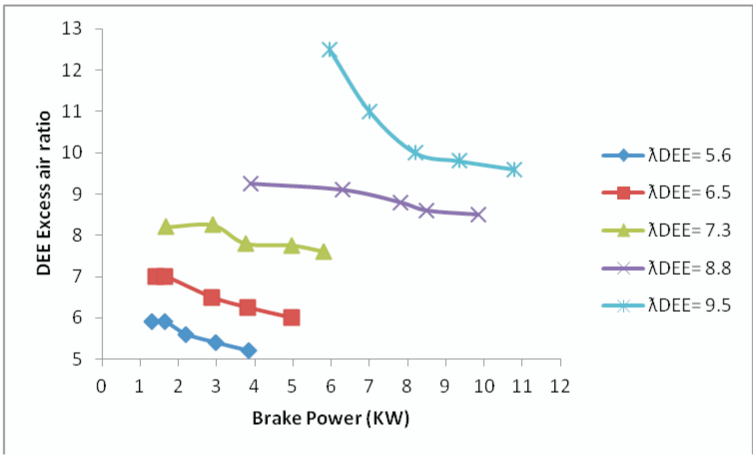

Figure 2 Operating range of HCCI engine

3.2. *Artificial neural network modelling*

To experimentally investigate the performance and emissions of an HCCI engine is complex, time consuming and costly, particularly for studies which use different DEE Excess air ratio different operating conditions. Therefore, a mathematical model is used to predict the performance and emissions of the HCCI engines. But the accuracies of the results of the mathematical model may not always be satisfactory. One substitute to the mathematical model is the experiment–based methodology, such as Artificial Neural Networks (ANNs). In contrast to mathematical correlations which are based on algebraic equation. ANNs involve parallel processing algorithms and they are used in obtaining accurate correlations which involves non–linear data. Neural networks are non–linear computer algorithms, which can model the behavior of complicated non–linear processes. They do not need any clear interpretation of the physical relationships of concerned problems. Thus ANN is a powerful modeling tool especially for complex systems. It is composed of simple computational units, called neurons that are connected in a parallel structure. These units are inspired by biological neurons in the human brain. ANNs have been applied successfully in different areas such as function approximation and pattern recognition. Fig 3 shows the architecture of the ANN model with a single hidden layer concept.

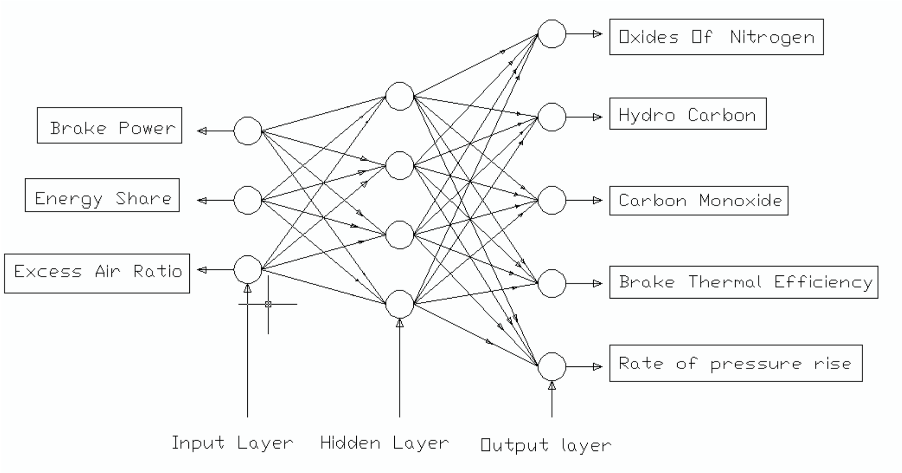

Figure 3 Architecture of ANN model with a single Hidden layer

An ANN model was developed to predict a correlation between the input and output layer of the present study. Approximately 80% of the total experimental data was selected at random and was used for training purpose, while the remaining 20% was reserved for testing. Radial Basis Function Network (RBFN) with two feed–forward back–propagation was created for the prediction of brake thermal efficiency, carbon monoxide, unburned hydro carbon, Oxides of Nitrogen and rate of pressure rise. The network consists of an output layer, hidden layer and an input layer. The input for the network includes the excess air ratio, Brake power and energy share and the output parameters are brake thermal efficiency, carbon monoxide, unburned hydro carbon, Oxides of Nitrogen and rate of pressure rise. The hidden and output activation function for RBFN is of Gaussian and Identity form. However, to determine the optimum number of series of hidden nodes, a series of topologies were used, in which the number of nodes were diverse from 1 to 25.

The back propagation algorithm is applied as follows:

1. Initialize all weights and bias (normally a small random value) and normalize the training data.

2. Compute the output of neurons in the hidden layer and in the output layer (net) using

$$n_i = \sum w_{ij} x_i + \theta_i \tag{1}$$

Where w_{ij} the weight for node j to i is calculated as follows

$$w_{ij}(n+1) = w_{ij}(n) + \alpha \delta_i(n) x_j(n) \tag{2}$$

Where x_j is the transformation function, $\delta_i(n)$ is the weighted sum of error, θ_i is the bias, α is the step size.

3. Compute the error and weight update. Back propagation algorithm uses modified delta rule to tune the weights in the network.

4. Update all weights, bias and repeat steps 2 and 3 for all training data.

5. Repeat steps 2 to 4 until the error converges to an acceptable level.

The performance of the models was validated by deploying the models with an independent verification dataset and calculating Mean absolute error (MAE), Root mean square error (RMSE) correlation coefficient (R^2), and experimental results vs. predicted results. The formulas used for the statistical performance of the model are listed in Tab. 3.

Table 3 Error function and its equations

Error Function	Formulae
Mean Absolute error	$\frac{1}{n}\sum_{i=1}^{n}\lvert f_i - y_i\rvert$
Root mean square error	$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\lvert f_i - y_i\rvert^2}$
Correlation coefficient	$R^2 = \frac{\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - yf_i\rvert}{\frac{1}{n}\sum_{i=1}^{n}\lvert y_i - f_i\rvert^2}$
Mean Absolute Percentage error	$\frac{100}{n}\sum_{i=1}^{n}\lvert f_i - y_i\rvert$

Where f_i is the experimental value and y_i is the predicted value.

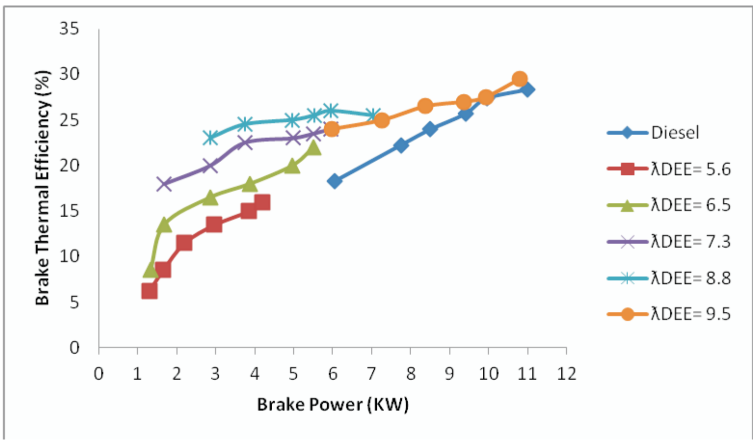

Figure 4 Brake Thermal Efficiency at various DEE excess air ratios

3.3. *Brake Thermal Efficiency*

Fig 4 shows the variation of Brake power with brake thermal efficiency (BTE) for different air ratio and methanol flow rates. Mass flow rate of DEE depends on each load condition of the optimum BTE point. BTE increases with increasing methanol flow rates and decrease due to sluggish burning and misfiring of methanol fuel. Better combustion phasing and higher cetane value of combusting mixture increases the trend of BTE [24]. The optimum brake thermal efficiency has obtained at excess ratio $\lambda_{DEE=}9.5$ and maximum DEE flow rate. When compared with diesel fuel, $\lambda_{DEE=}9.5$ shows comparatively higher brake thermal efficiency at all high load conditions. Due to presence of volatile low cetane fuel (hydrous methanol) in the excess air ratio, the efficiency of BTE is slightly lower than diesel fuel mode at higher load conditions [13].

4. Engine Emission Studies

4.1. *Oxides of Nitrogen Emission*

Fig. 5 depicts the emission of NO_x emissions at various DEE excess air ratios. The measurement of the combustion efficiency is an indirect measure to NO_x [25]. The higher NO_x emission shows higher and lower NO_x emission indicates lower combustion efficiency. Quantity of DEE flow in the combustion is directly proportional to the combustion temperature . The higher quantity DEE flow rates are used at lower BP and the lower quantity of DEE flow rates are used in higher BP. Fig 5 shows that the NO_x emission increases due to increase hydrous methanol flow rate and increased in Brake power (BP). This mechanism reversed when the engine used in higher BP. In the high BP, the temperature of combustion was higher. The higher BP increased the reaction kinetics of nitrogen with oxygen. It also causes higher NO_x emission [12, 14]. At any particular DEE flow rate, even though, the emissions of NO_x in HCCI engine have 10-18 times lower than DI CI mode [26]. The emission variation in HCCI mode due to the lean mixture combustion. The risk of the formation of thermal NO_xhas very low because in this combustion, high temperature regions are eliminated [27, 28]. Fig 5 conclude that at in all load conditions the nitric oxide concentrations are less than the conventional direct injection Compression ignition(CI) engine. NO_xvalues in HCCI engine have 3% lower than CI engine.

4.2. *Carbon Monoxide Emission*

Fig. 6 shows the variation of CO emissions for various DEE excess air ratios with respect to BP. Carbon monoxide (CO) emission is generally an indication of incomplete oxidation of fuel. From the Fig. 6, It is seen that the CO emission decreases with increase in hydrous methanol flow rate. It is also observed that the CO emission decreases with increase in BP. The reason for lowering of CO emission is an increase in combustion temperature that is caused due to the higher quantity of methanol utilization [14, 29]. The higher quantity of hydrous methanol usage increases the combustion temperature and lowers the CO emission.

At lower loads due to lower combustion temperature more CO emission can be observed and at higher loads due to higher combustion temperature less CO emission can be observed. The flame quenching near the cylinder wall due to lower the combustion temperature also causes the liberation more CO [14, 30]. From the Fig. 6, it was concluded that the CO emission of HCCI engine is slightly higher than conventional CI engine.

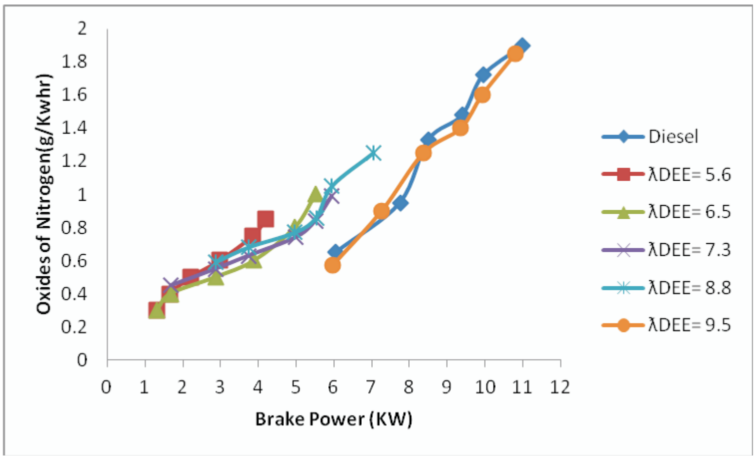

Figure 5 Oxides of Nitrogen emission at various DEE excess air ratios

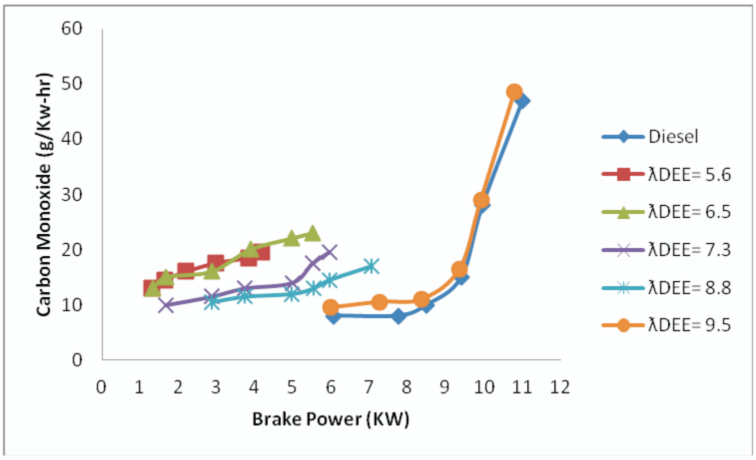

Figure 6 Carbon Monoxide emission at various DEE excess air ratios

4.3. *Unburned Hydrocarbon Emission*

Fig. 7 shows the variation of unburned hydrocarbon (HC) emissions for various DEE excess air ratio and hydrous methanol flow rates. From the figure it can be noticed that the HC emission increases with increase in methanol energy share. Usually, the fuel having a low cetane number is volatile in nature and produces a wider range of air fuel mixture after evaporation. This phenomenon increases with respect to decrease in cetane number [12, 15]. In addition lower DEE flow rate results in weakened ignition during auto-ignition. At higher loads, due to flame quenching the methanol vapour that are close to the cylinder wall and present in the crevices does not get combusted and emitted as HC emission [12, 14]. The high latent heat of vaporization of hydrous methanol is also one of the reasons for higher HC emission. From the experiment, it is understood that at low load conditions HC emissions are low but increase in load HC emissions are higher than the standard diesel engine. However, HC emission of HCCI engine is significantly higher than conventional Diesel engine.

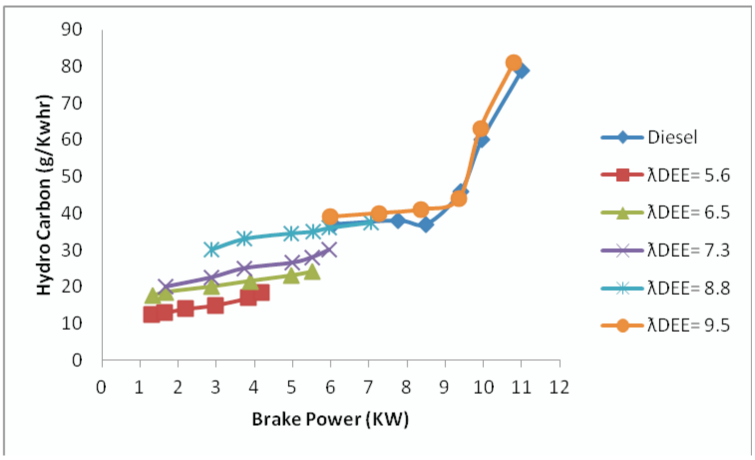

Figure 7 Unburned Hydrocarbon emission at various DEE excess air ratios

4.4. *Prediction of HCCI engine performance and exhaust emissions using artificial neural network*

An artificial neural network (ANN) was developed based on the data obtained from the experimental work. A Radial basis function network (RBFN) with feed-forward back propagation neural-network architecture and topologies were tested for the estimation and prediction of performance and emission characteristics. Different topologies by varying the hidden neurons were examined, and the optimum topology was determined based on the minimum error of testing. To avoid random correlation due to the random initialization of the weights each topology was repeated five times. After repeated trials it was found that RBFN neural network with 20 hidden neurons produced the best performance. The performance and accuracy of the models is validated by deploying the models with independent verification dataset by calculating MAE, RMSE, MAPE, correlation coefficient (R^2) and predicted values vs. experimental values. The summary of the trained network with different topologies is tabulated in table 4. The stastical performance of the network with architecture 3-21-5 for training and testing data are summarized and presented in table 5 and are found to be in good agreement.

It is clear from Tab. 5, the prediction performances for both training and testing sets of performance parameter and emission characteristics showed that RBFN with topology 3-21-5 provides a quite satisfactory accuracy. Regarding correlation coefficient (R^2) values were close to 1 for both the training and testing set when the hidden neurons were increased. The ANN predictions for, BTE, NOx, CO, HC, rate of pressure rise yield a correlation coefficient (R^2) of 0.9991, 0.9989, 0.9998, 0.9995 and 0.9994 for training data set similarly for testing data set ANN predictions yield a Correlation coefficient of 0.9904, 0.9520, 0.9994, 0.9959, 0.9930, 0.9981 and 0.9999. The ANN predictions for BTE, CO, HC, NO_x and Rate of pressure rise of MAE value of 0.1155, 0.0861, 0.0881, 0.0131 and 0.0389 for training set for the network topology RBF 2-29-7. Similarly for testing set the ANN predictions for BTE, CO, HC, NO_x and Rate of pressure rise yield a MAE of 0.9361, 0.4949, 0.4363, 0.0416 and 0.2195 respectively. Regarding Mean Absolute percentage Error of BTE, CO, HC, NO_x and Rate of pressure rise yield a MAE of 0.007, 0.0051, 0.0041, 0.0220 and 0.0075 for training set. Similarly for testing set the ANN predictions for BTE, CO, HC, NO_x and Rate of pressure rise yield a MAE of 0.0801, 0.0371, 0.0171, 0.774 and 0.0548 respectively. The RMSE values of ANN predictions for engine parameters BTE, CO, HC, NO_x and Rate of pressure rise yield a RMSE value of 0.0458, 0.3306, 0.0227, 0.0005 and 0.0047 for training set. Similarly for testing set the ANN predictions for BTE, CO, HC, NO_x and Rate of pressure rise yield a RMSE of 1.76, 0.7178, 0.3050, 0.0023, and 0.0723 respectively. The statistical performance results indicate that the difference between MAE, RMSE and MAPE is insignificant indicating the variance in the individual errors of the testing set is almost of the same magnitude. Comparisons of the ANN predicted values and experimental results for both training and testing sets of engine performance parameters are demonstrated in Fig. 8 to 12.

Table 4 Summary of the evaluated Network

Net. Name	Training perf.	Test perf.	Training error	Test error	Training algorithm	Error function	Hidden activation	Output activation
RBF 3-5-5	0.8834	0.9300	0.0347	0.0470	RBFT	SOS	Gaussian	Identity
RBF 3-10-5	0.9576	0.9648	0.0143	0.0235	RBFT	SOS	Gaussian	Identity
RBF 3-15-5	0.9661	0.9828	0.0114	0.0246	RBFT	SOS	Gaussian	Identity
RBF 3-16-5	0.9714	0.9815	0.0095	0.0089	RBFT	SOS	Gaussian	Identity
RBF 3-17-5	0.9771	0.9840	0.0087	0.0109	RBFT	SOS	Gaussian	Identity
RBF 3-18-5	0.9704	0.9746	0.0102	0.0114	RBFT	SOS	Gaussian	Identity
RBF 3-19-5	0.9777	0.9783	0.0075	0.0103	RBFT	SOS	Gaussian	Identity
RBF 3-20-5	0.9937	0.9777	0.0021	0.0132	RBFT	SOS	Gaussian	Identity
RBF 3-21-5	0.9994	0.9741	0.0002	0.0063	RBFT	SOS	Gaussian	Identity
RBF 3-22-5	0.9991	0.9758	0.0003	0.0069	RBFT	SOS	Gaussian	Identity
RBF 3-23-5	0.9987	0.9724	0.0004	0.0075	RBFT	SOS	Gaussian	Identity
RBF 3-24-5	0.9975	0.9847	0.0009	0.0075	RBFT	SOS	Gaussian	Identity
RBF 3-25-5	0.9963	0.9823	0.0009	0.0081	RBFT	SOS	Gaussian	Identity

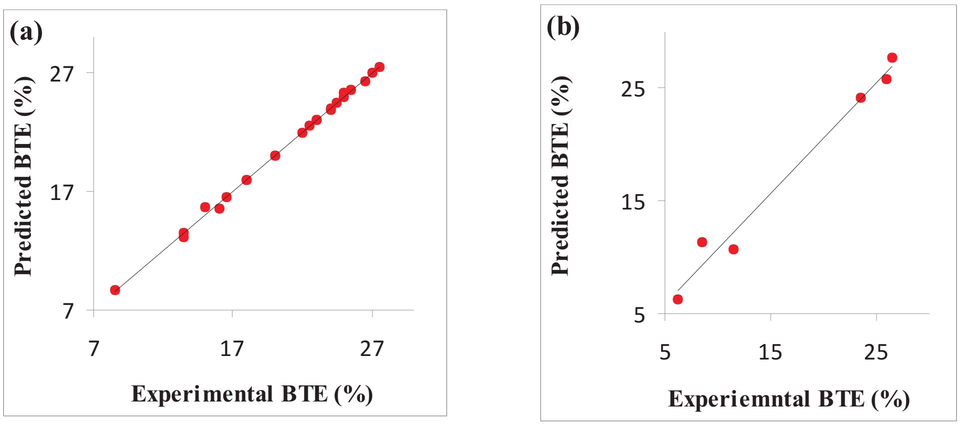

Figure 8 Experimental BTE vs predicted BTE (a) Training (b) Testing

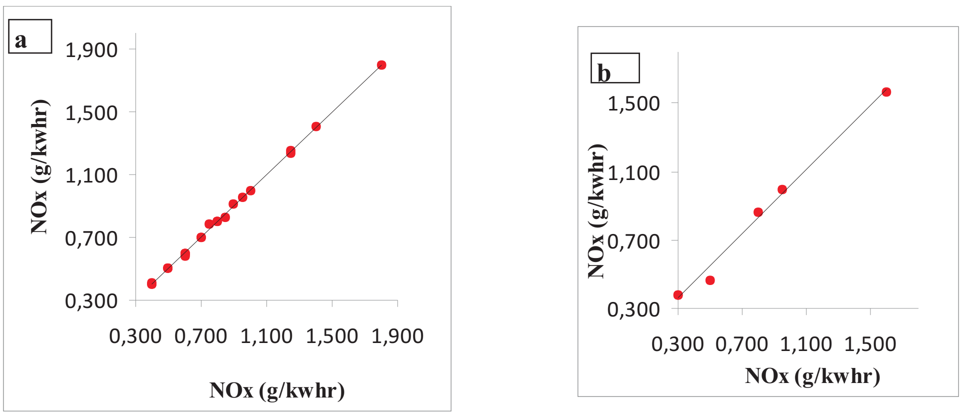

Figure 9 Experimental NO_x vs predicted NO_x (a) Training (b) Testing

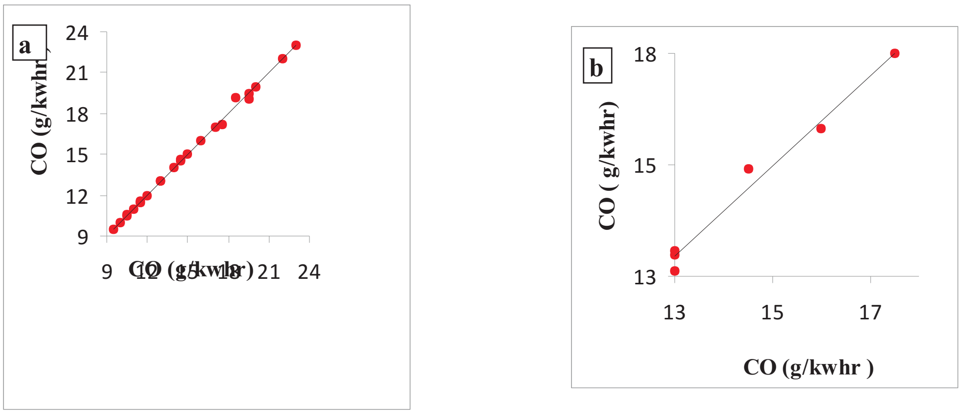

Figure 10 Experimental CO vs predicted CO (a) Training (b) Testing

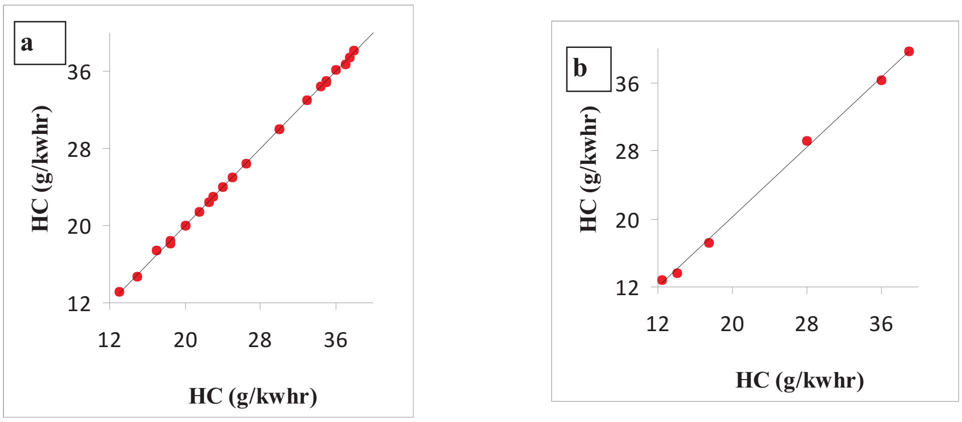

Figure 11 Experimental HC vs predicted HC (a) Training (b) Testing

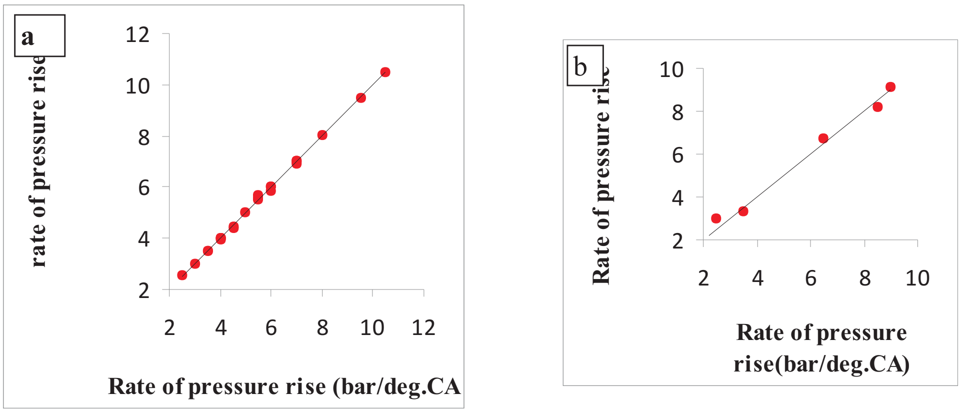

Figure 12 Experimental Rate of pressure rise vs predicted Rate of pressure rise (a) Training (b) Testing

Table 5 Statistical Performance of the artificial neural network model

Statistical parameters	Mean absolute error		Root mean square error		Mean absolute percentage error (%)		Coefficient of determination (R^2)	
	Training set	Testing set	Training set	Testing set	Training set	Testing set	Training set	Testing set
BTE (%)	0.1155	0.9361	0.0458	1.76	0.007	0.0801	0.9991	0.9904
CO (g/KWhr)	0.0861	0.4949	0.3306	0.7178	0.0051	0.0371	0.9989	0.9020
HC (g/KWhr)	0.0881	0.4363	0.0227	0.3050	0.0041	0.0171	0.9998	0.9994
NO_x (g/KWhr)	0.0131	0.0416	0.0005	0.0023	0.0220	0.774	0.9995	0.9959
Rate of pressure rise	0.0389	0.2195	0.0047	0.0723	0.0075	0.0548	0.9994	0.9930

5. Conclusion

The present work reveals that the hydrous methanol assisted with DEE will literally increase brake power decrease the NOx emission. It was also concluded that brake thermal efficiency increases while hydrous methanol assisted with DEE. The NOx concentrations are decreased while the concentrations of HC and CO were increased. An ANN model was developed to predict a correlation between the input and output layer of the present study. Radial Basis Function Network (RBFN) with two feed-forward back-propagation was created for the prediction of BTE, CO, HC, NOx and rate of pressure rise as output data. ANN model predicted very good result, correlation coefficient (R^2)values are very closer to 1, mean absolute error, mean absolute percentage error and root mean square error also found to be very low. Therefore ANN proved to be a useful tool for correlation and simulation of HCCI engine parameters. ANN provided precise and easy approach in the analysis of the complex problem, analysis of the HCCI engine performance and engine emission. Hence, the use of ANN is strongly recommended for the prediction of BTE, HC, CO, NO_x and rate of pressure rise without more expensive. It was obvious that the developed ANN model is fairly powerful for predicting the brake thermal efficiency and exhaust emissions of internal combustion engines.

References

[1] **Ganesh, D. and Nagarajan, G.**: Homogeneous charge compression ignition (HCCI) combustion of diesel fuel with external mixture formation, *Energy*, 35, 148–157, **2010**.

[2] **Miyamoto, N., Ogawa, H., Arima, T. and Kanji, M.**: Improvement of diesel combustion and emissions with addition of varies oxygenated agents to diesel fuels, *SAE*, pp. 962115, **1996**.

[3] **Miyamoto, N., Ogawa, H., Nurun, N., Kouichi, O. and Tetuyoshi, A.**: Smokeless, Low NO_x, High thermal efficiency and low noise diesel combustion with oxygenated agents as main fuel, *SAE Trans J Fuels Lubricants*, 107, 171–177, **1998**.

[4] **Tsurutani, K., Takei, Y., Fujimoto, Y., Junichi, M. and Mitsuhiro, K.**: The effects of fuel properties and oxygenates on diesel exhaust emissions, *SAE*, pp. 952349, **1995**.

[5] **Richards, B. G.**: Methanol fuelled caterpillar 3406 engine experience in on high way trucks, *SAE Trans J Fuels lubricants*, 99, 1033–1045, **1990**.

[6] **Black, F.**: An overview of the technical implications of methanol and ethanol as high way motor vehicle fuels, *SAE*, pp. 912413, **1991**.

[7] **Mc Callum, P. W., Timbario, T. J., Bechtold, R. L. and Eckland, E. E.**: Methanol/ethanol: alcohol fuels for high way, *Vehicles*, CEP, pp. 52–59, **1982**.

[8] **Bailly, B., Eberhardt, J., Gougen, S. and Ervin, J.**: Diethyl ether (DEE) as a Renewable Diesel Fuel, *SAE*, paper No. 972978, **1997**.

[9] **Onishi, S., JO, S. H., Shoda, K., Jo, P. D. and Kato, S.**: Active thermo–atmospheric combustion (ATAC) – a new combustion process for internal combustion engines, *SAE*, Paper No. 790501, **1979**.

[10] **Najit, P. M. and Foster, D. E.**: Compression ignited homogeneous charge combustion, *SAE*, Paper No. 830264, **1983**.

[11] **Zheng, Z., Yao, M., Chen, Z. and Zhang, B.**: Experimental study on HCCI combustion of dimethyl ether (DME) / Methanol dual fuel. *SAE*, Paper No. 2004-01-2993, **2004**.

[12] **Venkatesan, M., Moorthi, N., Karthikeyan, R. and Manivannan, A.**: Dimethyl Ether as an Ignition Improver for Hydrous Methanol Fuelled Homogeneous Charge Compression Ignition (HCCI) Engine, World Academy of Science, Engineering and Technology, International Science Index 85, *International Journal of Mechanical*, Industrial Science and Engineering, 8, 1, 244–249, **2014**.

[13] **Vinayagam, N. and Nagarajan, G.**: Experimental study of performance and emission characteristics of DEE assisted minimally processed ethanol fuelled HCCI engine, *International Journal of Automotive Technology*, 15, 4, 517–523, **2014**.

[14] **Venkatesan, M., Moorthi, N., Karthikeyan, R. and Manivannan, A.**: Experimental study on hydrous methanol fuelled HCCI engine using Air preheater assisted controlled auto ignition, *Transactions of FAMENA*, 38, 2, 53–66, **2014**.

[15] **Sudheesh, K., Mallikarjuna, J. M.**: Diethyl ether as an ignition improver for biogas homogeneous charge compression ignition operation, *Energy*, 04, 052, **2010**.

[16] **Can Cinar, Özer Can, Sahin, F. and Serdear Yucesu, H.**: Effects of premixed diethyl ether (DEE) on combustion and exhaust emissions in a HCCI–DI diesel engine, *Applied Thermal Engineering*, 30, 360–365, **2010**.

[17] **Singh, G., Pratap Singh, A. and Kumar Agarwal, A.**: Experimental investigations of combustion, performance and emission characterization of biodiesel fuelled HCCI engine using external mixtureformation technique, *Sustainable Energy Technologies and Assessments* 6, 116–128, **2014**.

[18] **Mack, J. K., Flowers, D. L., Buchholz, B. A. and Dibblea, R. W.**: Investigation of HCCI combustion of diethyl ether and ethanol mixtures using carbon 14 tracing and numerical simulations, *Proceedings of the Combustion Institute*, 30, 2693–2700, **2005**.

[19] **Kim, D. S. and Lee, C. S.**: Improved emission characteristics of HCCI engine by various premixed fuels and cooled EGR, *Fuel*, 85, 695–704, **2006**.

[20] **Ma, J., Lü, X., Ji, L. and Huang, Z.**: An experimental study of HCCI–DI combustion and emissions in a diesel engine with dual fuel, *International Journal of Thermal Sciences*, 47, 9, 1235–1242, **2008**.

[21] **Patterson, D.**: Artificial Neural Networks, Singapore: *Prentice Hall*, **1996**.

[22] **Haykin, S.**: Neural Networks: A Comprehensive Foundation, New York: *Macmillan Publishing*, **1994**.

[23] **Cay, Y., Korkmaz, I., Cicek, A. and Kara, F.**: Prediction of engine performance and exhaust emissions for gasoline and methanol using artificial neural network, *Energy*, 1–10, **2013**.

[24] **Sayin, C.**: Engine performance and exhaust gas emissions of methanol and ethanol diesel blends, *Fuel*, 89, 3410–3415, **2010**.

[25] **Heywood, J. B.**: Internal Combustion engine fundamentals, NewYork: *McGraw–Hill Book Company*, **1988**.

[26] **Christensen, M., Johansson, B., Amnjus, P. and Mauss, F.**: Supercharged Homogeneous Charge Compression Ignition, Society of Automotive Engineers, *Technical Paper*, 980787, **1998**.

[27] **Zhao, H.**: HCCI and CAI engines for the automotive industry, *Cambridge: wood head publishing limited*, **2007**.

[28] **Merker, G. P., Schwarz, C. and OTTO, F.**: Simulating combustion, Heidelberg, Berlin: *Springer*, **2006**.

[29] **Garcia, M. T., Aguilar F. J. E. and Lencero, T. S.**: Experimental study of the performances of a modified diesel engine operating in HCCI combustion mode versus the original diesel combustion mode, *Energy*, 34, 159–171, **2009**.

[30] **Christensen, M. and Johansson, B.**: Homogenous charge compression ignition with water injection, *SAE Paper*, No. 1999-01-0182, **1999**.