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PERFORMANCE AND EMISSION CHARACTERISTICS OF A 4 STROKE C.I. ENGINE OPERATED ON HONGE METHYL ESTER USING ARTIFICIAL NEURAL NETWORK

Shivakumar[1], Srinivas Pai P.[2], Shrinivasa Rao B. R.[2] and Samaga B. S.[2]
[1]Department of Mechanical Engineering, MIT, Manipal, India
[2]Department of Mechanical Engineering, NMAMIT, Nitte, India
E-Mail: shiva_katipalla@yahoo.co.in

ABSTRACT

In wake of the present energy environment crises it has become essential to identify renewable and alternative clean burning fuels. One of the significant routes to tackle the problem of increasing prices and the pollution problems of petroleum fuels is by the use of vegetable oil fuels known as biodiesels. In the present work biodiesel was prepared from Honge oil (Pongamia) and used as a fuel in C.I engine. Performance studies were conducted on a single cylinder four-stroke water-cooled compression ignition engine connected to an eddy current dynamometer. Experiments were conducted for different percentage of blends of Honge oil with diesel at various compression ratios. Experimental investigation on the Performance parameters and Exhaust emissions from the engine were done. Artificial Neural Networks (ANNs) were used to predict the Engine performance and emission characteristics of the engine. To train the network compression ratio, blend percentage, percentage load were used as the input variables where as engine performance parameters together with engine exhaust emissions were used as the output variables. Experimental results were used to train the ANN. Back-propagation algorithm was used to train the network. ANN results showed good correlation between the ANN predicted values and the desired values for various engine performance values and the exhaust emissions. The R^2 values were very close to 1 and the mean relative error values were less than 9 percent.

Keywords: honge oil, blend, transesterification, emissions, artificial neural network.

1. INTRODUCTION

Using straight vegetable oils in diesel engines is not a new idea. Rudolf diesel used peanut oil as a fuel for his demonstration of the new engine in the year 1910. Later with the availability of cheap petroleum, crude oil fractions were refined to serve as diesel a new fuel for I.C engines. Agricultural sector of India is completely dependent on diesel for its motive power and to some extent for stationary applications. Increased farm mechanization in agriculture thus further increased the requirement of diesel. Nowadays due to the limited resources of fossil fuels, rising crude oil prices and the increasing concerns for the environment, there has been renewed focus on the vegetable oils and animal fats as an alternative fuel sources. Among the attractive feature of the biodiesel are (i) if it a plant, non petroleum derived and as such its combustion does not increase the current net atmospheric levels of CO_2, a green house gas. (ii) it can be domestically produced offering the possibility of reducing petroleum imports, (iii) It is biodegradable (iv) relative to the conventional diesel its combustion products have reduced the levels of particulate matter, UBHC, and CO [1,2,3]. Various vegetable oils both edible and non edible can be considered as alternative sources for diesel engines. In most of the developed countries sunflower, peanut, palm and several other feed stocks are used as alternative sources which are edible in the Indian context. Therefore in the developing countries like India, it is desirable to produce biodiesel from non edible oils which can be extensively grown in the waste lands of the country. It has been reported that non edible oils available in India are Pongamia, Jathropa rubber seed etc. however the major disadvantage of vegetable oils is their viscosity, which is very much higher than the diesel. The fuel injection systems in diesel engines are very much sensitive to the viscosity changes. High viscosity of the vegetable oils leads to poor atomization, which in turn may lead to poor combustion, ring sticking, injector coking, injector deposits, injector pump failure and lubricating oil dilution by crank case polymerization [4, 5, 6]. Viscosity of the vegetable oils must be reduced to improve its engine performance. Heating, blending with diesel, Transesterification are some of the methods used by the researchers to reduce the viscosity of vegetable oils. [7]. Heating and blending of vegetable oils may reduce the viscosity and improve the volatility of oils, but its molecular structure remains unchanged. Deepak Agarwal *et al.*, [8] conducted experiments with esters of linseed, mahua, rice bran and Lome. They observed that the performance and the emission parameters were very close to diesel. They even observed that a diesel engine can perform satisfactorily by esterified biodiesel blends without any hardware modifications. B. Baiju *et al.*, [9] used methyl and ethyl ester from Karanja oil to run CI engine. They observed good engine performance with reduced emissions of HC and Smoke. Suresh Kumar *et al.*, [10] carried out experiments with Pongamia Pinnata methyl ester and revealed that blends upto 40% by volume with diesel provide better engine performance and reduced emissions. From the literature it is found that converting vegetable oils into simple esters is an effective way to overcome all the problems associated with the vegetable oils [11, 12]. In the present study Honge (Pongamia) oil was used as an alternative fuel. Methyl ester of biodiesel was prepared by transesterification process. Prepared biodiesel was blended with diesel and used as a fuel to run the engine. Engine was run using different blend percentages ranging from 0 to 25% by volume mixed diesel in a variable compression ratio engine from no load to full load condition. Experimental investigation was carried out from the above experiments to analyze the performance and emission characteristics. Manufacturers and the researchers are interested in knowing the performance of the C.I engine for various proportions of blends and for various compression ratios. This requirement can be met either by conducting comprehensive testing study or by modeling the engine operation. Testing the engine under all possible operating conditions and fuel cases are both time consuming and expensive, on the other hand developing an accurate model for the operation of a C.I engine fuelled with blends of biodiesel is too difficult due to the complex processes involved. As an alternative, performance and exhaust emissions of the engine can be modeled using ANNs. This new modeling technique can be applied to estimate the desired output parameters when enough experimental data is provided. This study deals with the experimental investigation of the Honge oil methyl ester blends on the performance and emission characteristics of C.I engine for various compression ratios and ANN modeling using those experimental results.

1.1 Pongamia oil and its properties

Pongamia pinnata(Honge) is one of the forest based tree borne non- edible oil with a production potential of 135,000 metric tons per year in India. It is capable of growing in all types of lands (sandy and Rocky). It grows even in salt water and can withstand extreme weather conditions with a temperature range of 0-50°C. and annual rainfall of 5-25 dm. The oil content is around 30-40%. It is a fast growing medium sized tree which grows to height of around 40ft. flowers are pink, light purple, or white. Pods are elliptical, 3-6cm long and 2-3 cm wide thick walled and usually contains a single seed. Seeds are 10-15 mm long, oblong and light brown in color. A thick yellow-orange to brown non edible oil is extracted from the seeds. Usually this is used for tanning leather, soap and as illuminating oil. It is also used as a lubricant, water paint binder, and a pesticide. In the recent days this oil has been tried as a fuel in diesel engines showing good thermal efficiency which is comparable with diesel [11, 12]. The comparison of properties of Pongamia oil with diesel is presented in Table-1. Since the high viscosity of Pongamia oil poses problems in pumping, atomization etc it is very essential to reduce the viscosity by transesterification.

1.2 Transestreification

The formation of methyl esters by transestrification of vegetable oils requires 3 moles of alcohol stiochiometrically. However it is an equilibrium reaction in which excess alcohol is required to drive the reaction close to completion. The vegetable oil was chemically reacted with an alcohol in the presence of a catalyst to produce vegetable oil esters. Glycerol was produced as a byproduct of transestrification reaction.

The mixture was stirred continuously and then allowed to settle under gravity in a separating funnel. Two distinct layers will form after gravity settling. The upper layer of ester and the lower layer of glycerol. The lower layer was separated out. The separated ester was mixed with warm water to remove the catalyst present in the ester and allowed to settle under gravity. The catalyst gets separated. After transesterification process, the viscosity of the Pongamia oil was found to be reduced to 5.6 mm^2/sec from 41.06 mm^2/sec which is nearer to the diesel value as given in the Table-1. Prepared Pongamia ester was then blended with mineral diesel in various concentrations for preparing biodiesel blends to be used in CI engines for conducting various engine tests.

Table-1. Properties of pongamia oil and neat diesel.

S. No.	Properties	Pongamia oil	Diesel
1.	Flash point (°C)	263	49
2.	Specific gravity	0.912	0.83
3.	Acid value (mg/KOH)	1.52	-
4.	Kinematic viscosity (mm^2/s)	41.06	2.4
5.	Kinematic viscosity after TES	5.6	-
6.	Calorific value (MJ/kg)	34	41.86

2. EXPERIMENTAL SETUP

The performance test was conducted in a single cylinder four stroke diesel engine. Figure-1 Shows the schematic diagram of the complete experimental setup for determining the effects of Pongamia ester as biodiesel on the performance and emission characteristics of compression ignition engine. It consists of a single cylinder four stroke water cooled compression ignition engine connected to an eddy current dynamometer. The compression ratio can be varied from 12:1 to 18:1. It is provided with temperature sensors for the measurement of jacket water, calorimeter water, and calorimeter exhaust gas inlet and outlet temperature. It is also provided with pressure sensors for the measurement of combustion gas pressure and fuel injection pressure. An encoder is fixed for crank angle record. The signals from these sensors are

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interfaced with a computer to an engine indicator to display P-θ, P-V and fuel injection pressure versus crank angle plots. The provision is also made for the measurement of volumetric fuel flow. The built in program in the system calculates indicated power, brake power, thermal efficiency, volumetric efficiency and heat balance. The software package is fully configurable and averaged P- θ diagram, P-V plot and liquid fuel injection pressure diagram can be obtained for various operating conditions. An AVL flue gas analyzer is used to measure the NOx in the engine exhaust. A smoke meter also used to measure the smoke intensity in the engine exhaust. The specifications of the engine are shown in Table-2. The procedure followed during the experiments is given below.

- Initially engine was run with the neat diesel for the compression ratio of 16 with the injection pressure of 190 bar and at an injection advance of 24˚btdc. Engine was run from no load to full load condition with an increment of 25% of load in each run.
- Once the steady state is reached the parameters such as the fuel consumption, brake power and the exhaust emissions NOx, smoke, UBHC and CO were noted.
- Engine was then run on blends of Pongamia methyl ester and diesel mixed in various concentrations 10%, 15%, 20%, and 25% by volume represented by B10, B15, B20, and B25, respectively. Performance parameters and the emissions were noted.
- Whole set of experiments were repeated for compression ratios 17.5 and 18.

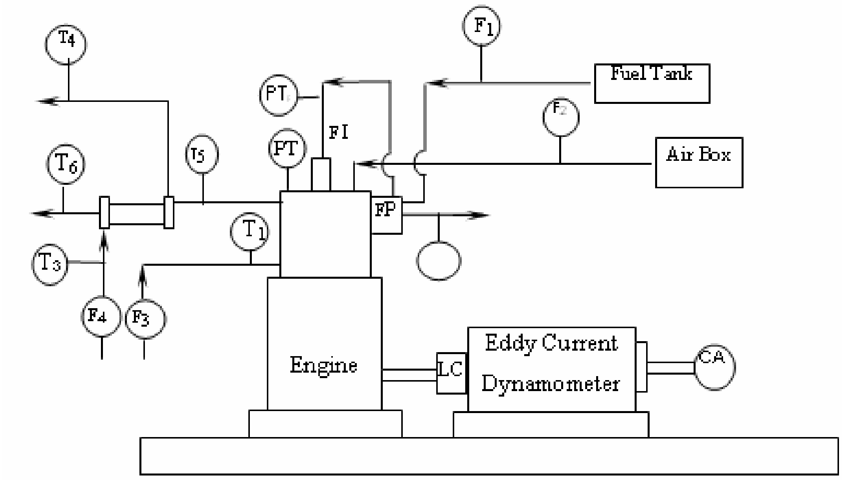

Figure-1. Schematic diagram of the experimental set up.

PT Combustion Chamber Pressure Sensor
PT_F Fuel Injection Pressure Sensor
FI Fuel Injector
FP Fuel Pump
T_1 Jacket Water Inlet Temperature
T_2 Jacket Water Outlet Temperature
T_3 Inlet Water Temperature at Calorimeter
T_4 Outlet Water Temperature at Calorimeter
T_5 Exhaust Gas Temperature before Calorimeter
T_6 Exhaust Gas Temperature after Calorimeter

F_1 Liquid fuel flow rate
F_2 Air Flow Rate
F_3 Jacket water flow rate
F_4 Calorimeter water flow rate
LC Load Cell
CA Crank Angle Encoder

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Table-2. Specifications of the engine.

Engine	**Four stroke, single cylinder, water cooled, constant speed diesel engine**
Rated power	3.2 kW
Speed	1500 rpm
Bore	87.5 mm
Stroke	110 mm
Compression ratio	12 to 18: 1
Crank angle sensor	Resolution 1^o
Engine indicator	For data scanning and interfacing with pentium III processor
swept volume	661cc
Software	For average P-θ and P-V plots
Temperature indicator	Digital PT -100

3. EXPERIMENTAL RESULTS AND DISCUSSIONS

3.1 Engine performance

3.1.1 Brake thermal efficiency

From the experiments it was observed that BTE increases with the load for both diesel as well as pongamia oil methyl ester blends. Figure-2 shows the variation of BTE for 20B pongamia methyl ester for three compression ratios. For the compression ratio of 16 the BTE values at full load were 34.2, 32.3, 32.72, 33.4, 33 for diesel and B10, B15, B20, B25 blends. Which shows that B20 blend is having a higher value for the biodiesel operation and is 0.8% less than that of neat diesel. Similar results were observed for the other compression ratios. For B25 the thermal efficiency was lesser than B20 for all compression ratios as viewed from Figure-3. Hence B20 is the optimized blend. Decrease in BTE values for higher blend percentages may be due to the lower heating value of the pongamia methyl ester. Figure-3 shows the variation of BTE for the full load operation for diesel as well as different blend percentages. A gain of 0.3 % and 0.72% in BTE was noticed when the compression ratio was increased to 17.5 and 18 respectually. Increasing the compression ratio will increase the operating temperature and hence a small gain in the BTE at higher compression ratios.

3.1. 2. Brake specific energy consumption

Figure-4 shows the variation of BSEC for the optimum blend for the three different compression ratios. It can be observed BSEC for the compression ratio 18 will be lesser than the other two. At higher compression ratios energy required per kW is lesser than that at lower compression ratios. Figure-5 shows the variation of BSEC for different blends at full load operation. For the biodiesel blends BSEC values are slightly higher than diesel. This may be due to the lower calorific value of Honge methyl ester compared to the diesel value. For the biodiesel operation BSEC of B20 is lower than the other blends which show that 20% blending is optimum the combination as far as the thermal efficiency and BSEC are concerned.

3.1.3. Exhaust gas temperature

Figure-6 shows the variation of exhaust gas temperature for B20 with the load for three compression ratios of 16, 17.5 and 18. Exhaust gas temperature increases with increase in load for diesel as well as for all combination of blends. As the load increases fuel air ratio increases and hence the operating temperature increases which results in higher exhaust temperature. For Honge biodiesel operations the exhaust gas temperature is more than the diesel. In biodiesel operation the combustion is delayed due to higher physical delay period. As the combustion is delayed, injected Honge-biodiesel fuel particles may not get enough time to burn completely before TDC, hence some fuel mixtures tends to burn during the early part of expansion, consequently afterburning occurs and hence increase in the exhaust temperature. Figure-7 shows the variation of exhaust gas temperature for diesel as well as biodiesel blends at full load operation for various compression ratios. For higher compression ratios exhaust gas temperature also increased which may due to the higher operating temperature at higher compression ratios.

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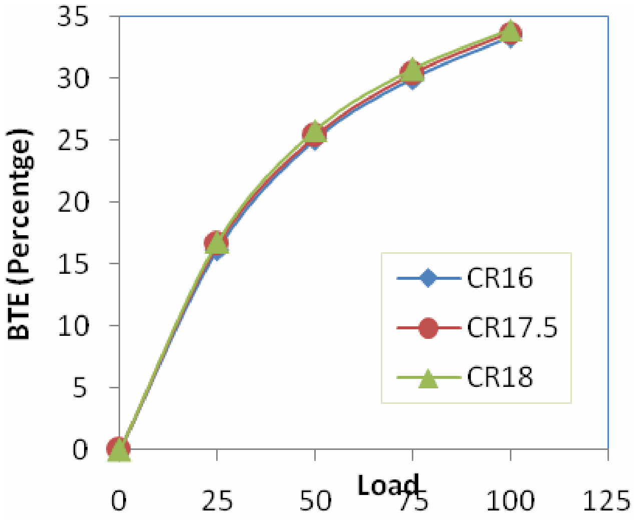

Fig 2. Variation of BTE with Load for B20

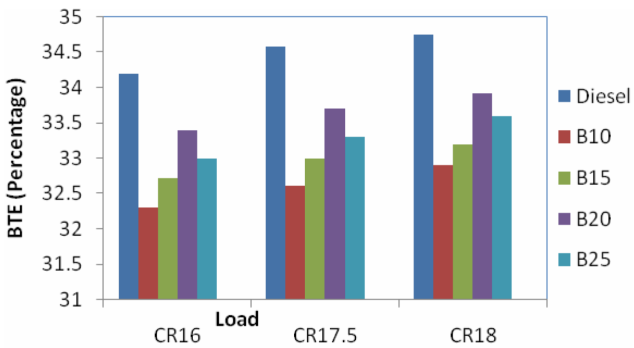

Fig 3. Variation of BTE at full Load for diesel, B10, B15, B20, B25 for different compresion Ratios

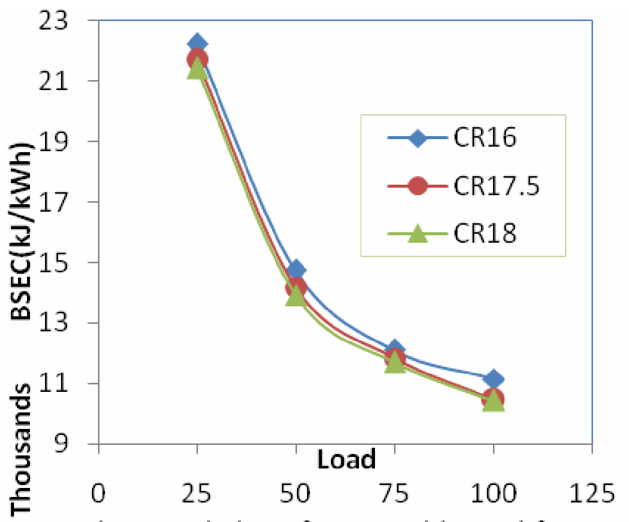

Fig 4. Variation of BSEC with Load for B20

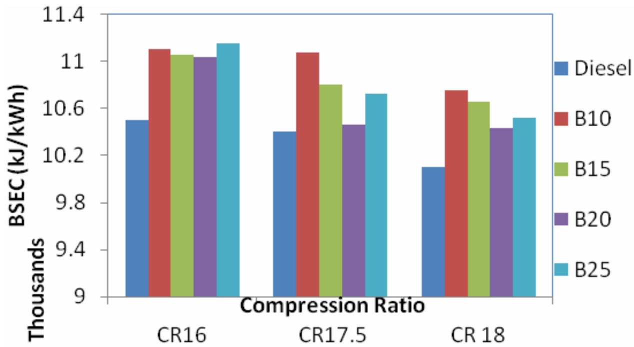

Fig 5. Variation of BSEC at full Load for Diesel, B10, B15, B20, B25 for different Compression Ratios

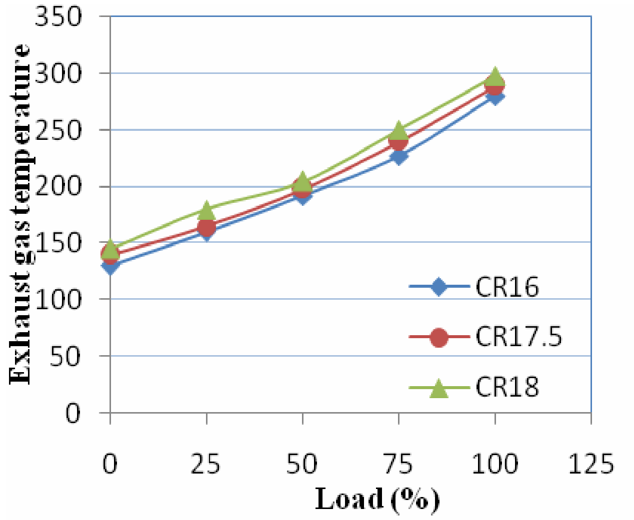

Fig 6. variation of Exhaust gas Temperature with load for B20

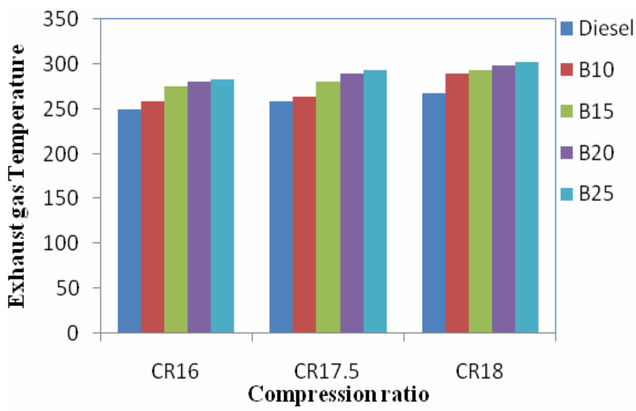

Fig 7. Variation of Exhaust Gas Temperature for Diesel,B10,B15,B20andB25 for different Compression ratios

3.2. Emission characteristics

3.2.1. NOx emission

Figure-8 shows the variation of NOx emission for 20B with the load for various compression ratios. From the graph it can be observed that NOx emission increases with the load and the minimum value of NOx emissions are corresponding to a compression ratio of 16 and it increases as the compression ratio is increased since the formation of NOx is dependent on the operating temperature of the cylinder and the oxygen availability. Figure-9 shows the variation of NOx for diesel as well as the WCO blends at full load operation. NOx emission for biodiesel blends is higher than the neat diesel for all compression ratios since they contain in built oxygen in their molecular structure. Also the NOx emission increases with the increase in the blend percentage because of increased oxygen content in higher percentage blends.

3.2.2. Smoke emission

Smoke formation occurs at the extreme air deficiency. Air or oxygen deficiency is locally present inside the diesel engines. It increases as the air to fuel ratio decreases. Experimental results indicate that smoke emissions are increased with increase in the load for all compression ratios as the formation of smoke is strongly dependent on the load. Figure-10 shows variation of smoke emissions for B20 blend with the load for three different compression ratios. Smoke values for the compression 18 were the least amongst them. Since at higher compression ratios better combustion may take place inside the engine cylinder trying to reduce the smoke emissions. Figure-11 shows the smoke values of diesel and biodiesel blends at full load operation. For biodiesel operation the smoke values reduced because of the atomic bounded oxygen which helps in better combustion, thus reducing the smoke.

3.2.3 Unburnt hydrocarbon

Anther emission product that is produced by the diesel engines is UBHC. It consists of fuel that is completely unburned or only partially burned. The amount of UBHC depends on the engines operating conditions and fuel properties. Figure-12 shows the variation of UBHC for B20 Honge methyl ester for different compression ratios. At higher compression ratios UBHC emissions were low, may be because of increased temperature and pressure at higher compression ratios and better combustion can be ensured. Figure-13 shows the UBHC emissions for Diesel and biodiesel blends at full load condition. HC emissions were lower for biodiesel blends. HC emissions in the exhaust had decreased with the increasing amount of biodiesel in the fuel blend which can be clearly seen from the Figure-13. The inbuilt oxygen content in its molecular structure may be responsible for complete combustion and thus reducing the HC levels.

3.2.4 CO emission

CO in the diesel engines is formed during the intermediate combustion stages. However the diesel engines which operate on the lean side of stiochiometric ratios the CO emissions are low. Figure-14 shows the variation of CO with load for B20. Emissions at part loads will be lower and it increases for full load as can be viewed from the graph. Figure-15 gives the CO emissions at full load for diesel as well as biodiesel blends at three different compression ratios. For biodiesel operation CO emissions were lower compared to the diesel values. The emissions have decreased with increased amounts of biodiesel in the blend. The additional amount of oxygen in the biodiesel accounts for better combustion inside the cylinder and hence for reduced CO emissions. On comparing the emissions for different compression ratios emissions were less for compression ratio of 18.

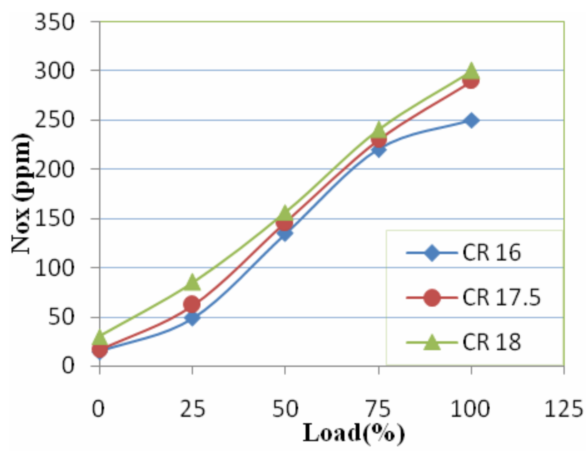

Fig 8. Variation of NOx with Load for B20

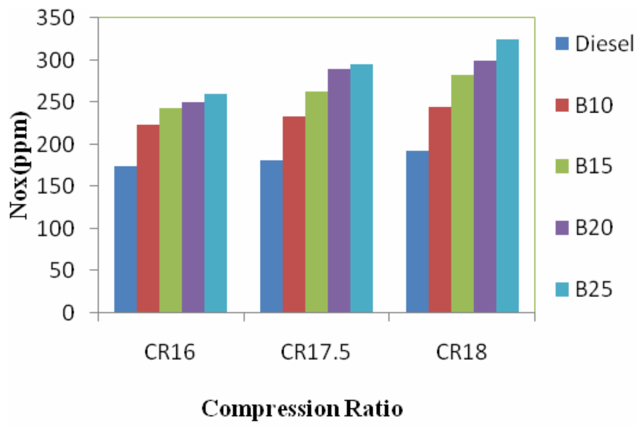

Fig 9. variation of NOx at full load for Diesel, B10, B15, B20, B25 for different Compression Ratios

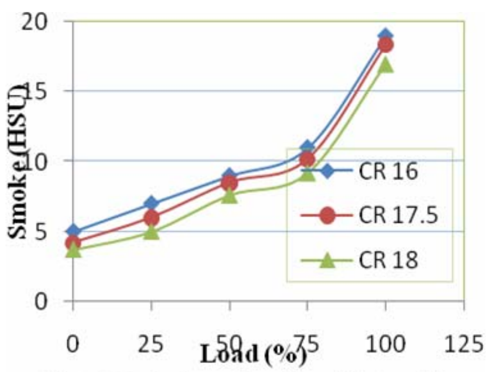

Fig 10. Variation of smoke with Load for B20

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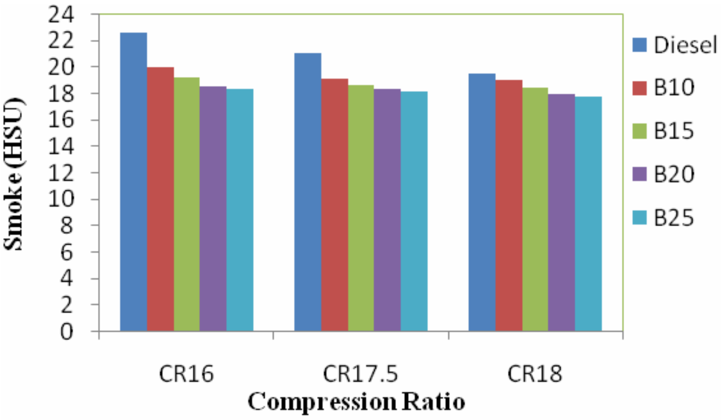

Fig 11. Variation of smoke at full Load for Diesel,B10,B15,B20,B25 for various compression ratios

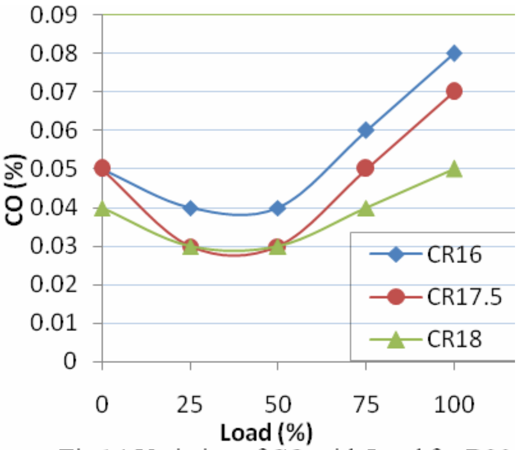

Fig 14. Variation of CO with Load for B20

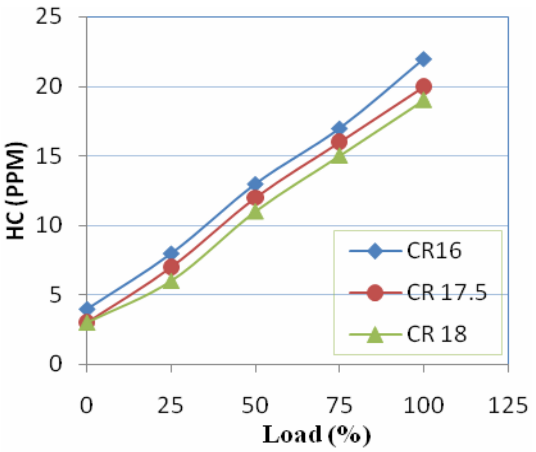

Fig 12. Variation of HC with Load for B20

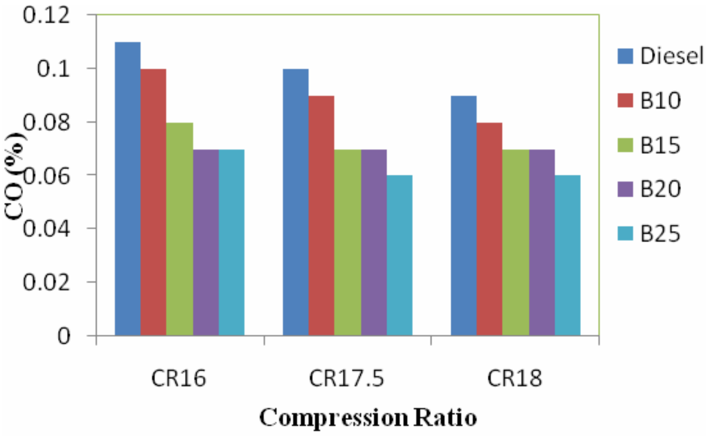

Fig 15. Variation of CO at full Load for Diesel, B10, B15, B20, B25 for different compression ratios

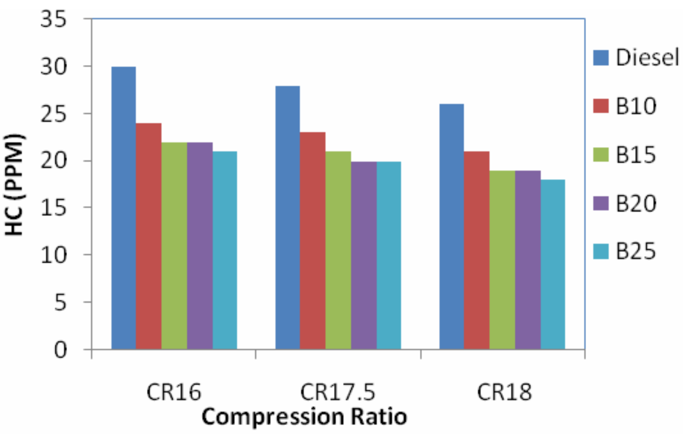

Fig 13. Variation of HC at full Load for Diesel, B10, B15, B20, B25 at different Compression Ratios

4. ARTIFICIAL NEURAL NETWORKS

Artificial intelligence systems are widely used as a technology offering an alternative way to tackle complex and ill defined problems. Neural networks are a type of artificial intelligence systems that attempts to imitate the way the human brain works. They are nonlinear information processing devices, which are built from interconnected elementary processing devices called neurons. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non linear problems and once trained can perform prediction and generalization at high speeds [13]. An ANN has the capability to relearn to improve its performance if new available data. They can accommodate multiple input variables to predict multiple output variables. They differ from conventional modeling approaches in their ability to learn about the system that can be modeled without the prior knowledge of the process relationships. The prediction by a well trained ANN is much faster than the conventional simulation programs or mathematical models as no lengthy iterative calculations are needed to solve differential equations using numerical methods. They have been used in diverse applications in control systems, robotics, pattern

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recognition, forecasting, medicine, power systems, manufacturing, optimization, signal processing social and psychological sciences [14]. The use of ANN for modeling the operation of internal combustion engines is a more recent progress. This has been used for the prediction of emissions from a Diesel engine, a gasoline engine [15-20. They have been used for the prediction of diesel emissions using in cylinder combustion pressure [21]. Neural networks were used for studying the effect of cetane number on the diesel emissions [22]. This technology was also used for the modeling of valve timing in a S.I engine [23]. An ANN consists of massively interconnected processing nodes known as neurons. It receives the input from the other sources combines them in some way, performs generally a nonlinear operation on the result and then outputs the final result. Network usually contains an input layer, some hidden layers and an output layer. Each neuron in the network accepts a weighted set of inputs and responds with an output. Such a neuron first forms the sum of weighted inputs give by N=$\sum_{i=1}^{p} wi + b$ Where p and wi are the number of elements and the interconnection weight of the input vector Xi respectually and b is the bias for the neuron. The method of modifying the weights in the connections between network layers with the objective of achieving the expected output is called training a network. The internal process that takes place when a network is trained is called as Learning. The two types of training are supervised and unsupervised training. Supervised training is the process of providing the network with a series of sample of inputs and comparing the outputs with the expected responses. The training continues until the network is able to provide the expected responses. The weights will be adjusted according to learning algorithm till it reaches the actual outputs. In the neural network if for the training input vectors, the target output is not known the training method adopted is called as unsupervised training. The net may modify the weight so that the most similar input vector is assigned to the same output unit. The net is found to form a exemplar or code book vector for each cluster formed. Various training functions can be used to train the networks reach from a particular input to a specific target output. The error between the network output and the actual output is minimized by modifying the network weights and biases. When the error falls below a determined value or the maximum number of epochs have been reached the training process stops. Then this trained network can be used for simulating the system outputs for the inputs which have not been introduced before. Different algorithms are used for training the network. Of them most popular one is back propagation algorithm which has different variants. Back propagation algorithm with gradient descent and gradient descent with momentum are very slow for practical problems since they require a slow learning rate for stable learning. On the other hand conjugate gradient, Levenberg -Marquardt, Quasi -newton is some of the fast learning algorithms. The performance of the network outputs is evaluated by a regression analysis between the network outputs and the actual outputs. The criteria used for measuring the network performance are the correlation coefficient, mean relative error. The correlation coefficient assesses the strength of the relation between the predicted and the experimental results and it ranges between -1 and +1. R values close to +1 indicate a strong positive relationship.

5. ANN MODELING

An ANN model for the biodiesel engine was developed by using the steady state experimental data. In the model 70% of the experimental data were used for the training set, 15% for the validation set, remaining 15% were employed for the test purpose. The inputs to the ANN are WCO blend percentage (B), load percentage (W), and the compression ratio (CR). The output parameters from the ANN are Brake thermal efficiency (BTE), Brake specific energy consumption, (BSEC), Exhaust gas Temperature (T_{exh}) and the emissions which include Oxides of nitrogen (NOx), Smoke (SN), Unburnt Hydrocarbon (UBHC),and Carbon Monoxide (CO). Schematic representation of the network inputs and the outputs are shown in the Figure-16. The number of hidden layers and the neurons within each layer was designed by the complexity of the problem and the data set. To ensure that each input provides an equal contribution in the ANN, the inputs of the model were preprocessed and scaled into a common numeric range (-1, 1). By trial and error with different ANN configurations the network was decided to consist of 1 hidden layer with 20 neurons in the hidden Layer. Furthermore the activation function in the hidden layer was chosen to tangent sigmoid and the linear in the case of output layer. Using the standard back

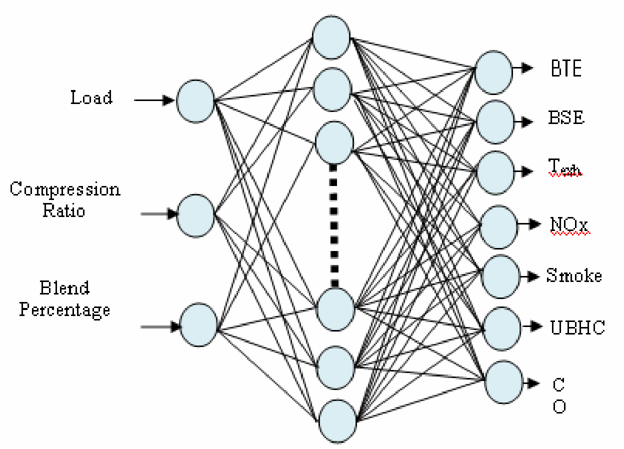

Figure-16. ANN architecture with single hidden layer.

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Table-3. Network performance using various training algorithms.

S. No.	Activation function	Training rule	Number of neurons in the hidden layer	Number of iterations	R^2
1.	Tansig/purelin	Trainscg	05	63	0.9485
		Traindx	05	159	0.9459
		Trainrp	05	333	0.9462
		Trainlm	05	20	0.9418
2.	Tansig/purelin	Trainscg	10	47	09604
		Traindx	10	160	0.9671
		Trainrp	10	96	0.9558
		Trainlm	10	20	0.9816
3.	Tansig/purelin	Trainscg	15	46	0.98813
		Traindx	15	167	0.9689
		Trainrp	15	101	0.9777
		Trainlm	15	18	0.9910
4.	Tansig/purelin	Trainscg	20	35	0.9819
		Traindx	20	160	0.9742
		Trainrp	20	88	0.9748
		Trainlm	20	12	0.9955
5.	Tansig/purelin	Trainscg	25	22	0.9817
		Traindx	25	153	0.9793
		Trainrp	25	120	0.9769
		Trainlm	25	11	0.9949

propagation algorithm input vectors and the corresponding target vectors from the training set were used to train the network. The output of the network was compared with the desired output at each presentation and the error was computed. This error was then back-propagated to the network and used for adjusting the weights such that the error decreases with each iteration. Training will be ceased if the performance goal is met or if the validation error exceeds the training error. The maximum number of epochs selected was 600 in the present study. Once the training has been ceased the training procedure has approximated a function between the input and the output variables and this network may be used for the prediction of unseen data. Various training algorithms were used to train the input and output data. Statistical values for those training methods are given in Table-3. Even the network performance was tested with different number of neurons in the hidden layer and their performance is shown in Table-3. From the Table it can be observed that trainlm algorithm converges faster than the others since the number of epochs taken for the convergence is lesser than the other types of algorithms. Tranirp, Traingdx, Trainscg are slow and took more number of epochs for convergence. Trainlm algorithm with 20 number of neurons in the hidden layer gave the best performance. The R^2 Value is 0.99559 which is higher than the R^2 values obtained by other training algorithms. Hence it was decided to have 20 number of neurons in the hidden layer and Trainlm alogirithm is used for training the network. The computer code for training the network using the back-propagation algorithm and measuring the network performance was implemented under the MATLAB environment.

The trained network was subjected for testing. Mean Relative error and the regression analysis was carried out for the trained as well as the test data. Statistical values for the training data and the test data are shown in Table-4. The R^2 values for the training data for BTE, BSEC, T_{exh} are 0.996, 0.979 and 0.996 respectively which is very close to unity showing good correlation between the experimental values and the network outputs. MRE values for the above training set are within 1-3.4 %. For the test data the R^2 values for the above performance parameters are 0.998, 0.972, 0.996 respectively and the MRE are 1.01, 3.83, 1.24% respectively which are within the acceptable limits. Hence there is a strong correlation between the experimental and ANN predicted values. As far as the engine emissions are concerned, R^2 values of

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training data for NOx, Smoke, UBHC and CO are very close to 1. And the MRE are 4.407, 5.403, 5.503, 4.256 respectively. For the test data R^2 values for the above outputs are 0.984, 0.985, 0.890, and 0.973 respectively and the Mean Relative errors are 5.49, 7.77, 8.7722, 5.27% respectively which are considered to be within the acceptable limits. The emission of smoke and CO show slightly higher values. The complexity of the burning process and the measurement errors in the experimental study may be responsible for slight higher mean errors. However for the entire test data the MRE is within 1- 9% considered to be acceptable The relation between the Experimental and ANN predicted data for various engine performance and emissions are shown in Figures 17- 23. It shows a good statistical performance with the regression values closer to unity and the MRE within 1- 9%. Therefore ANN proved to be desirable prediction method in the evaluation of diesel engine parameters. Hence Artificial Neural Networks can be effectively used for modeling the engine performance parameters and exhaust emissions since other mathematical and numerical algorithms might fail due to complexity and multivariate nature of the problem.

Table-4. Statistical values of ANN predictions.

Outputs	**R^2 Training**	**MRE** (Percentage) **training**	**R^2 Test**	**MRE** (Percentage) **test**
BTE	0.996	1.7736	0.998	1.0172
BSEC	0.979	3.404	0.972	3.833
Texh	0.996	1.282	0.996	1.2483
NOx	0.991	4.407	0.984	5.49
Smoke	0.992	5.403	0.985	7.77
CO	0.961	5.503	0.890	8.7722
HC	0.991	4.2564	0.973	5.27

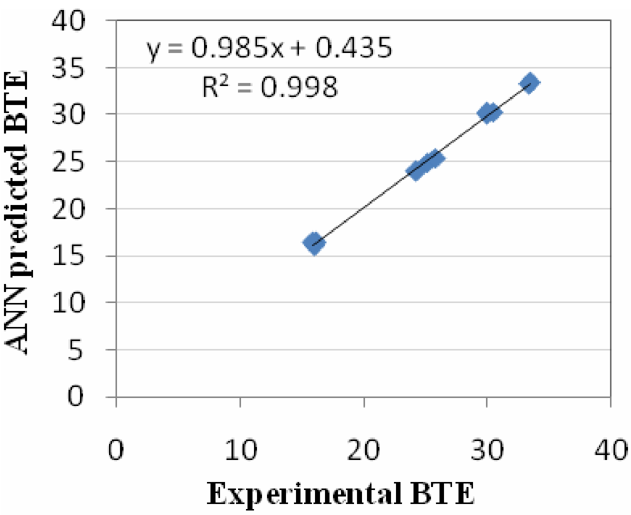

Fig 17.Experimental Vs ANN predicted BTE

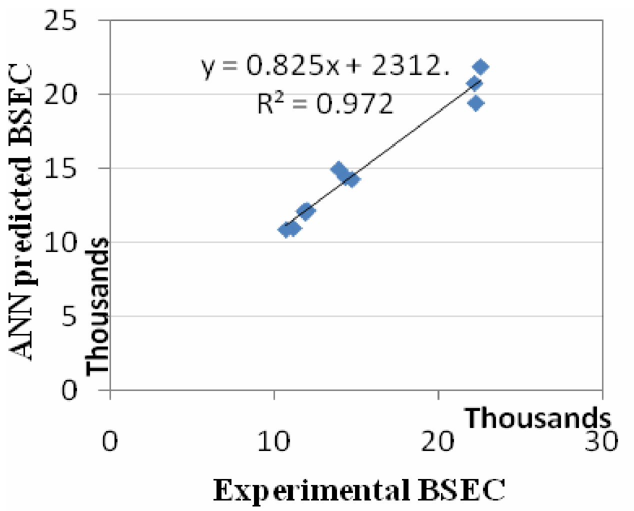

Fig 18 Experimetal Vs ANN predicted BSEC

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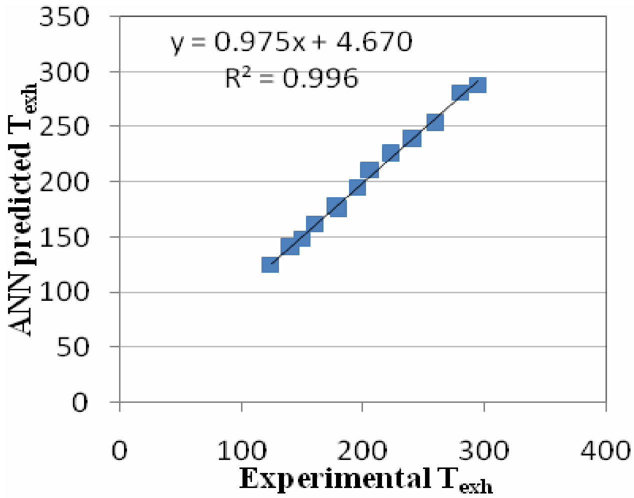

Fig 19.Experimental Vs ANN predicted T_{exh}

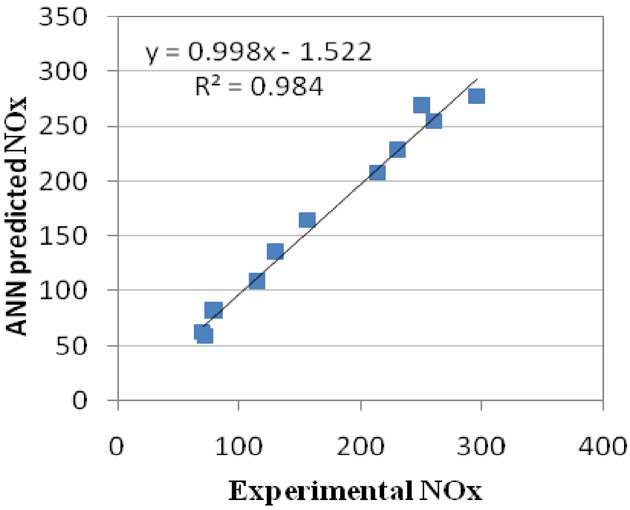

Fig 20. Experimental Vs ANN Predicted NOx

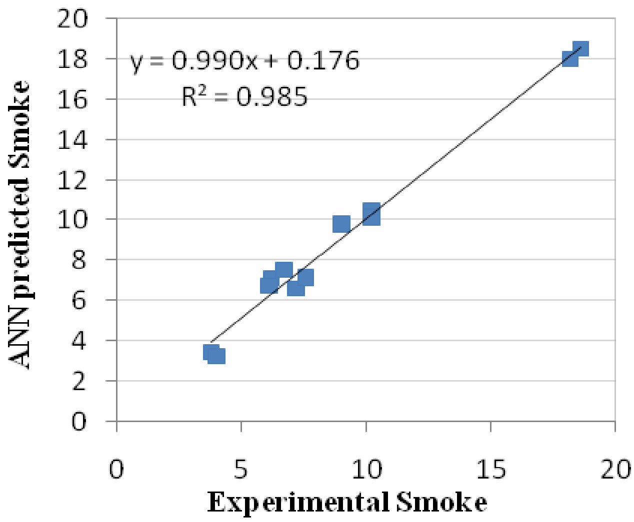

Fig 21.Experimental Vs ANN predicted Smoke

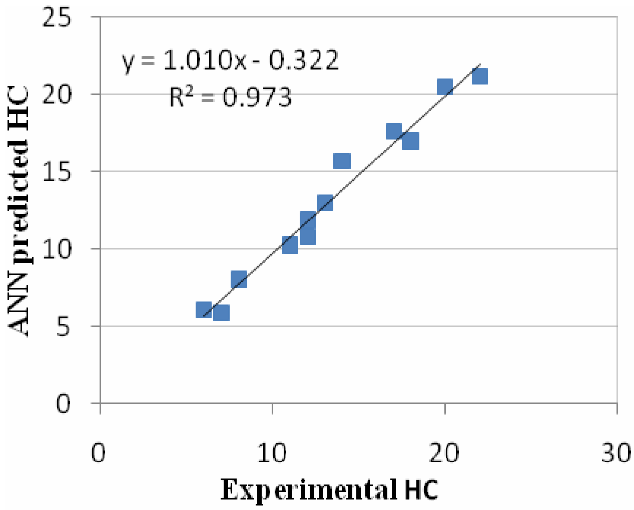

Fig 22.Experimental Vs ANN predicted HC

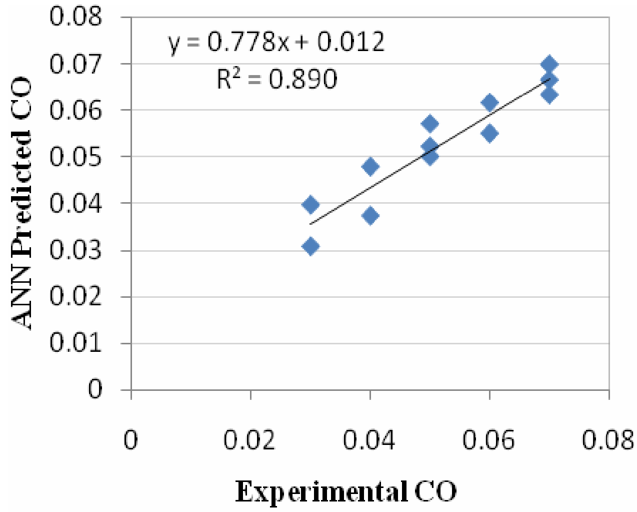

Fig 23. Experimental Vs ANN predicted CO

6. CONCLUSIONS

a) Brake thermal efficiencies of Pongamia oil methyl ester blends are very close to diesel and 20% blend with diesel, B20 provided the maximum efficiency for biodiesel operation for all compression ratios.
b) An improvement in BTE was observed for higher compression ratios.
c) Brake specific energy consumption for biodiesel blends is more than that of diesel and decreases for higher compression ratios.
d) Exhaust emissions Smoke, CO, HC were reduced for WCO biodiesel blends when compared with diesel values for all compression ratios and higher compression ratios have the advantage further reduction in those emissions.
e) Increase in NOx emission was observed for biodiesel blends compared to that of diesel for all compression ratios.

f) ANN approach applied to predict the performance and emission characteristics. Satisfactory results were observed with the regression coefficients lying closer to 1 and the Mean relative error is within 1-9% for the entire test data which is considered to be within the acceptable limits.
g) Hence ANN approach can be used for the prediction of engine performance and emission characteristics of I.C engines by performing a limited number of tests instead of detailed experimental study thus saving both engineering effort and funds.

REFERENCES

[1] A.K Hossain, P.A Davies. 2010. Plant oils as fuels for compression ignition engines. A technical review and life cycle analysis, Renewable Energy. 35: 1-13.

[2] Babu A.K Devaradjane G. 2003. Vegetable oils and their derivatives as fuel for CI engines - an overview. SAE 01-0767.

[3] Ramdas A.S Jayaraj. 2004. Muraleedharan, Use of vegetable oils as IC engine fuels- A Review. Renewable energy. 29: 727-742.

[4] Surendra R. 2010. Kalbande, Plant oils as fuels for C.I engines, a technical review and life cycle analysis. Renewable energy. 35: 1-13.

[5] Ziejewski M, Goettler HJ. Design modifications for durability improvements of diesel engines operating on plant oil fuels. SAE 921630 USA.

[6] Hyun Kyu Suh, Hyun Gu Roh. 2008. Spray and combustion characteristics of biodiesel /diesel blended fuel in a direct injection common rail diesel engine. Journal of Gas turbines and Power. 130: 1-12.

[7] A. Serddari K Fragioudakis. 2000. Impact of using biodiesels of different origin on the performance of a stationary diesel engine. Transactions of ASME. 122: 624-630.

[8] Deepak Agarwal, Lokesh kumar, Avinash Kumar agarwal. 2008. Performance Evaluation of a vegetable oil fuelled compression ignition engine. Renewable Energy. 33: 1147-1156.

[9] B. Baiju, M.K naik, L.M Das. 2009. A Comparative Evaluation of Compression ignition characteristics using methyl and ethyl esters of karanja oil. Renewable Energy. 34: 1616-1621.

[10] Suresh Kumar, R Velraj, R Ganesan. 2008. Performance and emissions of a C.I engine fuelled with PPME and its blends with diesel. Renewable Energy. 82: 1311-1325.

[11] Avinash Kumar agarwal, K. Rajamanoharan. 2009. Experimental investigations of performance and emissions of Karanja oil and its blends in a single cylinder agricultural diesel engine. Applied Energy. 86: 106-112.

[12] T. Venkateshwara Rao, G. prabhakar rao, K. Hema Chandra reddy. 2008. Experimental investigation of pongamia, Jatropa, Neem metyl esters as biodiesel in CI engine. JJMIE. 2: 117-122.

[13] Haykin S. 1984. Neural networks- a comprehensive foundation. Newyork; Mac-millan.

[14] Magali R.G Meireles, Paulo E.M Almeida. 2003. A comprehensive Review for industrial applicability of ANNs. IEEE transactions on Industrial Electronics. 50: 585-602.

[15] Arcaklioglu E. celikten. 2005. A Diesel engine's performance and exhaust emissions using ANN. Applied Energy. 80: 11-22.

[16] Jose M Alonso, Fernando Alavariuz. 2007. Combining ANN with Genetic algorithm to reduce diesel engine emissions. IEEE Transaction on Evolutionary computation. 11: 46-55.

[17] Lucas A. Duran A, Caramona M. 2002. Modeling diesel particulate emission with neural networks. Fuel. 81: 1963-1970.

[18] Cenk Sayin, H. Metin Ertunc. 2007. Performance and exhaust emissions from a gasoline engine using ANN. Applied Thermal Engineering. 27: 46-54.

[19] Jose M. D Esantes, Jose J. Lopez, Jose M. Garcia. 2002. Application of Neural Networks for prediction and optimization of exhaust emissions in a H.D diesel engine. SAE. 1144: 1993-2001.

[20] Mustafa Canakci, Ahmet Erdil, Erol Arcakliglu. 2006. Performance and exhaust emissions of a biodiesel engine. Applied Energy. 83: 594-604.

[21] Michel L. Traver Richard J. Atkinson. 1999. Neural network based diesel engine emission prediction using in cylinder combustion pressure. SAE International. 1532: 1-15.

[22] Yuanwang D, Meilin Z, Dong X. 2002. An analysis for the effect of cetane number on the Exhaust emissions from the diesel engine with neural networks. Fuel. 81: 1963-1970.

[23] Golci M Sekmen Y, ErduranliP Salman MS. 2005. Artificial Neural Network based modeling of a variable valve timing in a spark ignition engine. Applied Energy. 81: 187-197.