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Development of ANN model for prediction of performance and emission characteristics of hydrogen dual fueled diesel engine with Jatropha Methyl Ester biodiesel blends

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ABSTRACT

The present study investigates the use of Artificial Neural Network modeling for prediction of performance and emission characteristics of a four stroke single cylinder diesel engine with Jatropha Methyl Ester biodiesel blends along with hydrogen in dual fuel mode. ANN model was developed to predict BTE, BSFC, CO, O_2, CO_2, NO_X, HC and EGT based on initial experimental studies by varying load, blends of biodiesel and hydrogen flow rates. Seven training algorithms each with five combinations of trainings functions were investigated. Levenberg-Marquardt backpropagation training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer function results in best model for prediction of performance and emissions characteristics. The overall regression coefficient, MSE and MAPE for the model developed are 0.99360, 0.0011 and 4.863001% respectively. It is found that the neural networks are good tools for simulation and prediction of dual fueled hydrogen jatropha biodiesel engine.

1. Introduction

The need of energy is ever increasing, so as to cater the growing population and industrialization. Currently petroleum products are the main source of energy for diesel motor vehicles and near future the scarcity of it is knocking the door. Also the emission from these conventional diesel engines is on the higher side. The search for alternate fuels is all time high to compensate energy necessity (Agarwal and Agarwal, 2007). Researchers are trying to find an alternate fuel to these ever increasing demand, which is cheap and environment friendly. One of the alternatives which look feasible and attractive is the use of biodiesel (Ramachandran et al., 2013).

To evaluate performance and emission characteristic of a CI engine, strenuous and dull experimentation has to be carried out. In order to overcome this, researchers have utilized the Artificial Neural Network (ANN) prediction tool, which when properly trained with sufficient data will predict with tremendous accuracy depicting the actual value. So for an efficient and effective ANN model, meager experimentation has to be carried out and this data will be used for training the network. The reason for considering ANN compared to other prediction tools is its ability to learn, model non-linear process and adaptability to changes in real time. The effectiveness of prediction using ANN for diesel engine performance characteristics was studied by Parlak et al., 2006 and Uzan, 2012. Bietresato et al., 2015 demonstrated feasibility of ANN prediction of specific fuel consumption, exhaust gas temperature and torque on different engines with high accuracy. Taghavifar et al., 2014, 2015 have substantiated the use of ANN prediction models for wall heat flux modeling of diesel engine and spray characteristic of diesel engine.

The verification of feasibility in using biodiesel is costly and time consuming experimental affair. Researchers have pondered upon the performance characteristic of conventional diesel fuel with blends of alternate fuels. Oğuz et al., 2010 conducted experiments with biofuels blends and used the experimental data to train neural network to predict engine torque and specific fuel consumption, the reliability of prediction was 99.94%. Yücesu et al., 2007 and Çay et al., 2012 also demonstrated ANN prediction with different fuels.

The use of waste cooking oil as a blend with diesel was studied by Ghobadian et al., 2009 and Shivakumar et al., 2011. The performance and emission characteristics were studied and neural network prediction model was developed, the ANN prediction was excellent with acceptable error. The efficacy of ANN prediction

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Table 1
Fuels and their representation.

Sl. No.	Diesel %	Jatropha Methyl Ester %	Representation
1	100	0	B0 (Neat Diesel)
2	95	5	B5
3	90	10	B10
4	85	15	B15
5	80	20	B20
6	70	30	B30
7	0	100	B100 (Pure Biodiesel)

model of CNG-diesel fuel for engine performance and exhaust emission was demonstrated by Yusaf et al., 2010, Roy et al., 2014a, 2014b, 2014c and Roy et al., 2014d.

To meet stringent emission requirement of diesel engines, the paradigm of the day is to use bio friendly fuel for diesel engine which emits low harmful emissions. ANN prediction of NO_x and CO emission for crude palm oil with diesel blend was shown by Yusaf et al., 2011. Effectiveness of ANN in tuning engine parameters to regulate emission was manifested by Yap and Karri, 2012. Emission prediction of a scooter by various neural network models was studied by Yap et al., 2012. Ismail et al., 2012 studied the biodiesel emission characteristics using ANN. Optimization of piston bowl using ANN for reduction of soot and NO_x was illustrated by Costa et al., 2014.

The current study is initial experimentation with diesel and Jatropha Methyl Ester (JME) biodiesel blends along with hydrogen in dual fuel mode. The experimental data is used to train the neural network. The trained neural network is used to predict performance and emission characteristics when load, biodiesel blend and hydrogen flow rates were given as input.

1.1. Motivation of present study

Diminution of fossil fuels and stringent global emission norm demands researches to look for renewable fuels with better

Table 2
Technical specifications of test rig.

Parameter	Specifications
Make	Kirloskar
Model	AV1
Type	Single Cylinder, 4 Stroke, Direct Injection and Water cooled
Rated Power	3.7 KW, 1500RPM
Bore & Stroke	80 × 110 mm
Swept Volume	553cc
Compression Ratio	16.5:1, Range: 13.51 to 20
Injection Pressure	240 bar
Cylinder Pressure	Piezo Sensor, Range: 200PSI
Dynamometer	Electrical AC Alternator, PF:0.8
Orifice Diameter	20 mm

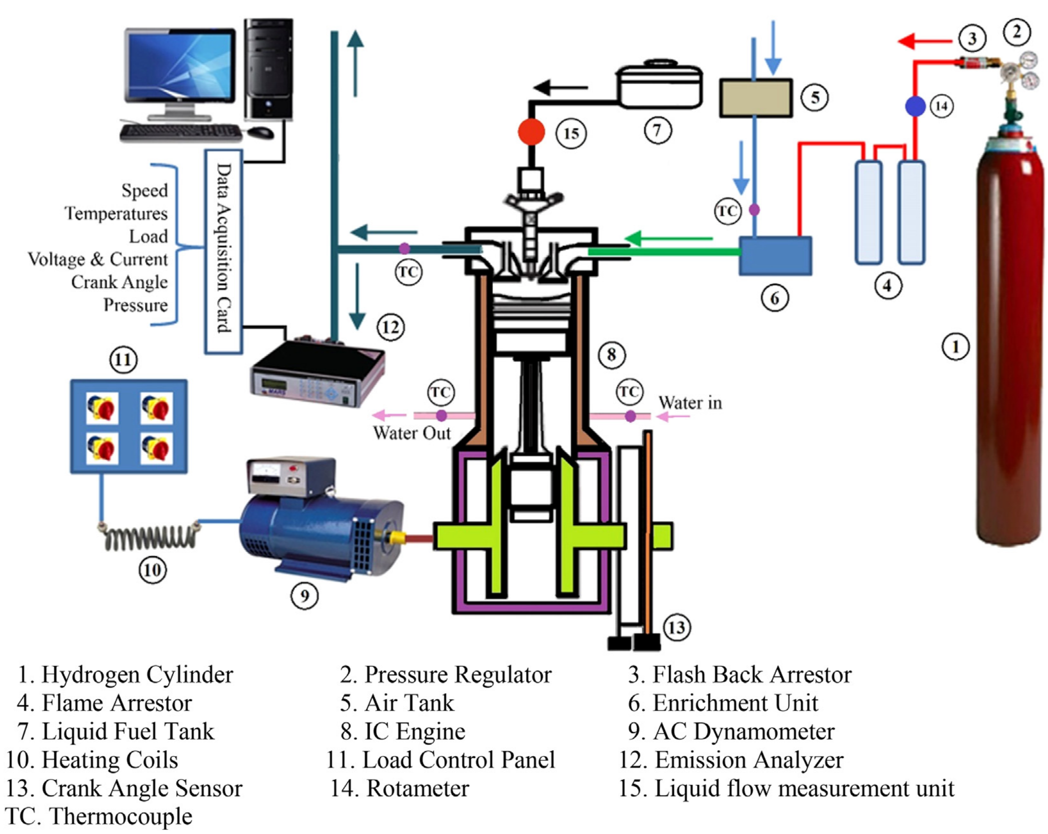

Fig. 1. Schematic block diagram of the experimental setup.

Table 3
Experimental methodology with different fuels and loads.

Phase	Primary fuel	Secondary fuel: Hydrogen (l/min)	Load (kW)	No. of trail cases
Phase-1	B0	0, 0.5, 1, 1.5	0.5, 1,2,3	16
Phase-2	B5,B10,B15, B20,B30	0.5, 1, 1.5	0.5, 1,2,3	60
Phase-3	B100	0.5, 1, 1.5	0.5, 1,2,3	12

Table 4
Multi gas analyzer MN-05 measurement specifications.

Sl. No.	Measurement	Range	Resolution
1	Carbon monoxide: CO	0–9.99% Vol	0.001% Vol
2	Oxygen: O_2	0–25% Vol	0.01% Vol
3	Carbon dioxide: CO_2	0–20% Vol	0.01% Vol
4	Hydrocarbon: HC	0–15,000 ppm	1 ppm
5	Nitric Oxide: NO_x	0–5000 ppm	1 ppm

performance and emission characteristics (Agarwal and Agarwal, 2007). In the prospect of looking for an alternate fuel to conventional petro diesel with clean energy, biodiesel is a strong contender. During the last decade extensive research has been carried out with biodiesel, LPG, CNG and hydrogen as an alternate fuel (Berchmans and Harita, 2008; Lata, 2010). Feasibility of ANN model to predict performance and emission characteristics of a JME biodiesel along with hydrogen dual fueled CI engine is unexplored. Hence, an attempt is made to fill this void.

2. Experimental investigation

2.1. Preparation of Jatropha Methyl Ester

Jatropha seeds contains 30–40% jatropha oil. Degumming of crude jatropha oil is done using orthophosphoric acid (0.6 Vol %) and then two-stage transesterification was adapted as mention by Berchmans and Harita, 2008. During first stage, esterification with sulfuric acid (1% w/w) was done to reduce free fatty acids to less than 1% and in second stage transesterification with sodium hydroxide base (1% w/w) was adapted to prepare JME from crude jatropha oil. Five different blends were prepared for the experimentation and are as shown in Table 1.

2.2. Experimentation

Kirloskar AV1, compression ignition four stroke direct injection diesel engine test rig was used in the present study. Compression ratio of 16.5 was selected for experimentation. Injection pressure of 240 bar was adopted using standard mechanical injector (Bosch Inc.). Technical specifications of test rig are tabulated in Table 2. Hydrogen being highly inflammable and its flames are nearly invisible, possesses potential risk in using hydrogen as a fuel in IC Engine. To avoid back fire propagation of hydrogen flames, flame arrestor and flash arrestor were implied to the test rig. Hydrogen is premixed with air which is known as enrichment process and inducted through the inlet valve of the engine. Hydrogen volume flow rate were varied from 0.5 to 1.5 l/min using rotameter and allowed to flow at pressure of 1 bar using pressure regulator. An electric digital tachometer having photo reflective type sensor was used to record engine speed. Thermocouples were implied to record temperatures (°C) at various positions of the test rig. All the

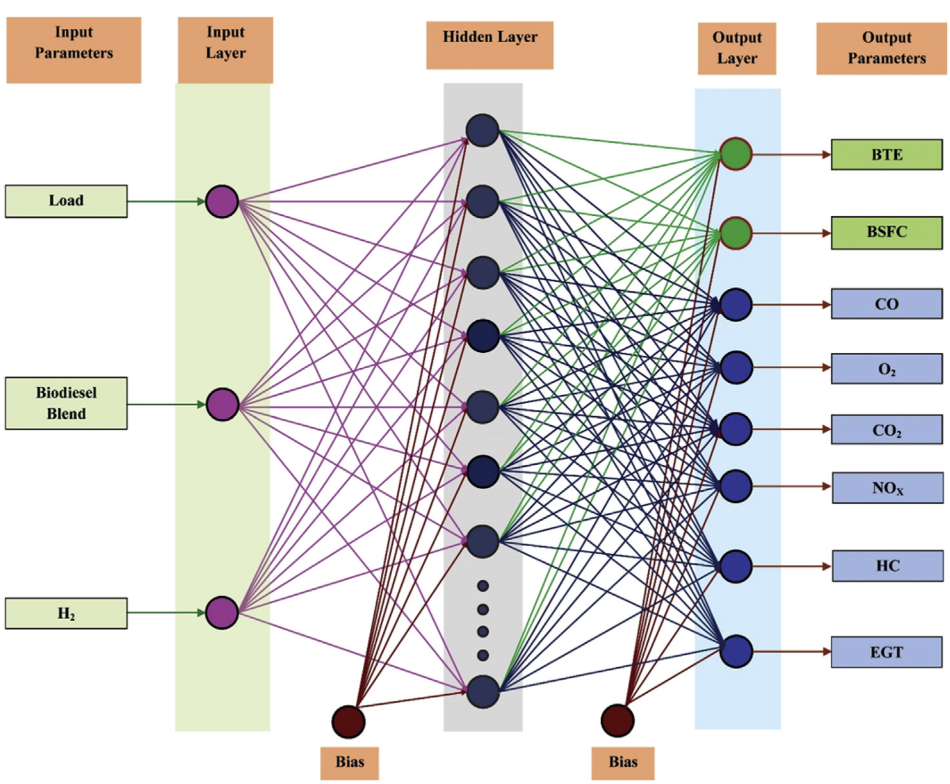

Fig. 2. Network configuration of ANN model.

signals from the sensors were connected to data acquisition card and were recorded on CPU during the experimentation. Schematic block diagram of the experimental setup is shown in Fig. 1.

During the course of experimental investigation:

- Volumetric flow rate of liquid fuel was measured using burette (ml/min), evaluated mass flow rate of liquid fuel (kg/sec)and U tube manometer was used to measure volumetric air flow rate, mass flow rate of air is maintained at 0.005081 kg/s.
- Engine speed of 1500 rpm and cooling water flow rate of 4.5 l/min were maintained.
- Steady state operating condition of engine is ensured before recording the parameters.
- Before each experiment, engine was allowed to cool to room temperature.
- At every load, performance and emission parameters were recorded.
- Every set of experimentation was repeated for three times and mean readings were recorded.

Experimental methodology implemented is shown in Table 3. Dynamometer was loaded with electric loads in steps of 0.5 kW. Performance parameter i.e. BTE and BSFC were evaluated for every set of experimentation and formulations are shown below.

$$\text{BTE} = \left\{ \frac{\textit{Brake Power} \times 100}{\left(M_{lf} \times CV_{lf}\right) + \left(M_{H_2} \times CV_{H_2}\right)} \right\}\% \tag{1}$$

$$\text{Brake Power} = \left\{ \frac{V \times I}{0.8 \times 1000} \right\} \text{kW} \tag{2}$$

$$\text{BSFC} = \left\{ \frac{\left(M_{lf} + M_{H_2}\right) \times 3600}{BP} \right\} \text{kg/kW} - \text{hr} \tag{3}$$

Mars 5 gas analyzer, certified by the Automotive Research Association of India was used to test the exhaust emissions of the engine. CO, O_2 and CO_2 were recorded in volume percentages whereas HC and NO_x in ppm. Specifications of the analyzer used in the experimentation are as shown in Table 4. Analyzer was calibrated with span gas before the experimentation.

3. Artificial Neural Network model

An Artificial Neural Network is a computational configuration modeled on biological processes, particularly on the functioning of human brain, comprising number of interconnected processing elements called as neurons, which process information based on their dynamic state in reply to inputs. Neural networks process data presented to them using interconnected neurons, the processing of the data depends on the strength between two adjusted neurons called as weight which contain the knowledge gained during training, testing and validation. Learning is gained by adaptation of weights with reference to input patterns. Adaptability to new situations is achieved through alterations in the weights. The great ability of ANN is to predict the output for an unknown input presented to it. As forecasting is performed via prediction of future from the experience achieved in the past, neural network is being used for decision support system. The neural networks are good tools for simulation and prediction in engineering applications.

In the current research feed-forward with back propagation neural network model is utilized. Feed forward multi-layer perceptron network is used, the various algorithms and training

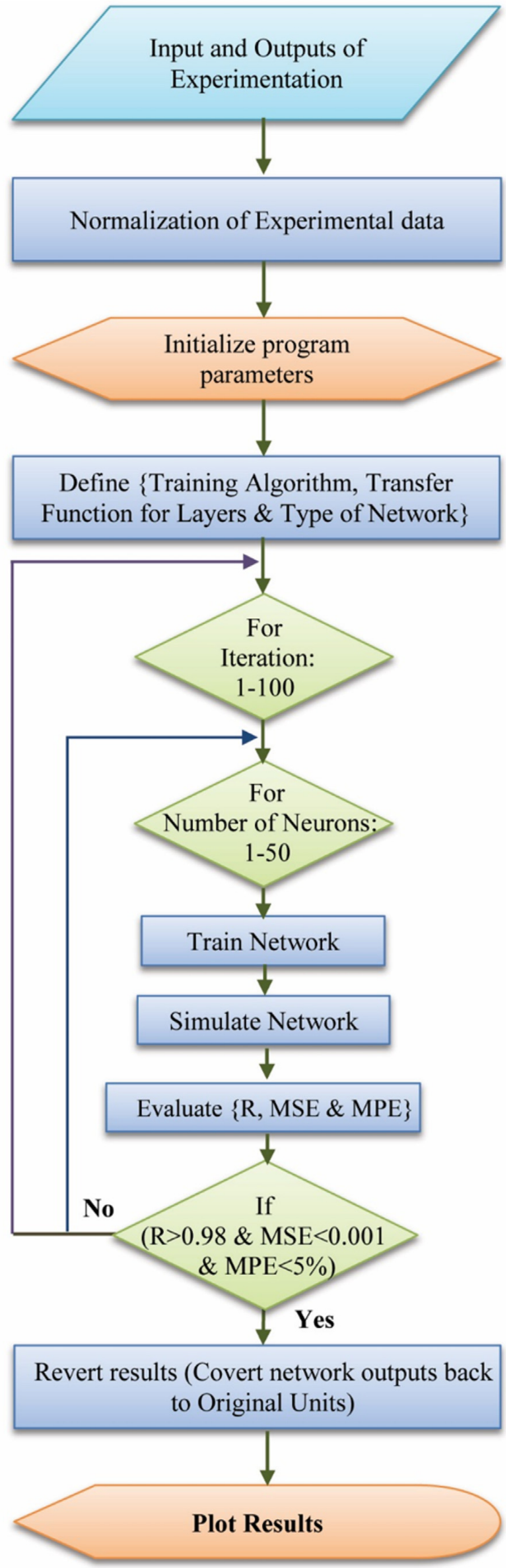

Fig. 3. Flow chart of ANN algorithm.

function that updates weight and bias values are investigated. The operating parameters of the experimentation and their outcomes were used to train the neural network model.

3.1. Preprocessing of data

Performance of ANN depends upon the data presented to it, hence scaling of input and output data is vital. Experimental input and output data were normalized using simple normalization method (Taghavifar et al., 2015). The data was normalized between the range 0.1–0.9 (Çay et al., 2012). After normalization, the data was randomized before training the network. From randomized data, 70% (63 cases) of the data was randomly selected for training the model and the model was validated with 15% (13 cases) of the data. The remaining 15% (13 cases) of the data were used for testing the efficacy of the developed model.

3.2. Modeling and simulation

MATLAB was used for developing ANN model. Load, biodiesel blend and hydrogen flow rates of all the experimental trail cases were used as inputs to the ANN model. Performance and emissions characteristics obtained during the course of experimentation were taken as targets of the ANN model. Network configurations of input, hidden and output layers are as shown in Fig. 2.

The ANN model developed in MATLAB is evaluated for different algorithms and training functions while varying the number of neurons in the network. The different training algorithms assessed are Levenberg–Marquardt (trainlm), Gradient descent with adaptive learning rate (traingda), Gradient descent with momentum and adaptive learning rate backpropagation (traingdx), Resilient backpropagation (trainrp), Conjugate gradient backpropagation with Fletcher-Reeves updates (traincgf), Scaled conjugate gradient backpropagation (trainscg) and BFGS quasi-Newton backpropagation (trainbfg). The transfer functions used in the algorithms for layer-1 & layer-2 are Hyperbolic tangent sigmoid (tansig), Logarithmic sigmoid (logsig) and Linear (purelin). As the MATLAB ANN model initially chooses weights and bias of neurons in the network randomly, network was iterated for 100 iterations to overcome this short coming (Taghavifar et al., 2015). During each ANN model training, minimum gradient of 10^{-7} and 10,000 epochs were used as stopping criteria.

Trained model was simulated for all inputs to realize corresponding respective outputs of the model. Using targets and outputs of the model, regression coefficients, MAPE and MSE were evaluated using the following expressions:

$$\text{Regression Coefficient}(R) = \sqrt{1 - \left\{\frac{\sum_{i=1}^{n}(T_i - O_i)^2}{\sum_{i=1}^{n}O_i^2}\right\}} \tag{4}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \left\{\frac{100}{n}\sum_{i=1}^{n}\left|\left(\frac{T_i - O_i}{T_i}\right)\right|\right\}\% \tag{5}$$

$$\text{Mean Squared Error (MSE)} = \frac{1}{n}\left\{\sum_{i=1}^{n}(T_i - O_i)^2\right\} \tag{6}$$

Table 5
Results of various training algorithms and transfer functions.

Training algorithm	Transfer function (Layer1-Layer2)	No. of neurons	Regression				MSE	MAPE (%)	Time (sec)
			Training	Validation	Testing	Over all			
trainlm	tansig-tansig	13	0.99523	0.989193	0.9827	0.99219	0.0013	7.033627	50.713
	logsig-tansig	16	0.99651	0.9878	0.9871	0.99360	0.0011	4.863001	78.135
	purelin-tansig	16	0.91233	0.944356	0.9710	0.92570	0.0129	21.28914	0.376
	tansig-logsig	10	0.84416	0.911755	0.8638	0.85662	0.0607	99.92174	37.954
	logsig-logsig	19	0.86244	0.855499	0.8217	0.85629	0.0605	99.87598	14.238
traingda	tansig-tansig	7	0.98901	0.980262	0.9783	0.98604	0.0024	9.652677	8.031
	logsig-tansig	9	0.98737	0.963749	0.9724	0.98195	0.0033	9.67066	7.807
	purelin-tansig	7	0.92779	0.918274	0.9509	0.93017	0.0119	24.74029	8.327
	tansig-logsig	3	0.85993	0.851859	0.8459	0.85667	0.0613	100.683	8.101
	logsig-logsig	16	0.84052	0.890257	0.8191	0.84425	0.0624	101.5352	1.084
traingdx	tansig-tansig	10	0.98931	0.981543	0.9902	0.98817	0.0020	8.916077	8.082
	logsig-tansig	16	0.99040	0.971503	0.9786	0.98478	0.0026	9.280357	8.108
	purelin-tansig	5	0.92764	0.927487	0.9481	0.93007	0.0119	23.82977	7.701
	tansig-logsig	16	0.85031	0.850182	0.8892	0.85614	0.0609	100.3334	0.81
	logsig-logsig	13	0.84016	0.891603	0.8883	0.85427	0.0612	100.6638	0.924
trainrp	tansig-tansig	15	0.99363	0.980911	0.9777	0.98974	0.0018	8.760247	8.016
	logsig-tansig	16	0.99124	0.977924	0.9748	0.98651	0.0024	7.75283	7.979
	purelin-tansig	8	0.93201	0.909592	0.9390	0.92990	0.0119	24.25677	0.142
	tansig-logsig	20	0.86892	0.811561	0.8724	0.86059	0.0607	99.90162	8.001
	logsig-logsig	16	0.85063	0.893396	0.8497	0.85704	0.0606	100.0105	8.114
traincgf	tansig-tansig	23	0.99255	0.99355	0.9646	0.98918	0.0018	7.902894	19.321
	logsig-tansig	16	0.99719	0.984374	0.9649	0.99047	0.0016	7.170078	18.742
	purelin-tansig	2	0.92120	0.929822	0.9553	0.92764	0.0123	26.00293	0.817
	tansig-logsig	7	0.85743	0.903327	0.8372	0.86051	0.0609	100.2095	16.76
	logsig-logsig	10	0.83161	0.879011	0.8798	0.84501	0.0612	100.3596	18.303
trainscg	tansig-tansig	14	0.99546	0.988566	0.9861	0.99285	0.0012	7.209672	11.576
	logsig-tansig	20	0.99766	0.98719	0.9921	0.99538	0.0008	5.662024	11.193
	purelin-tansig	16	0.93321	0.910409	0.9365	0.93036	0.0118	24.69444	0.819
	tansig-logsig	22	0.85680	0.854789	0.8665	0.85721	0.0606	99.96272	11.195
	logsig-logsig	11	0.86109	0.860086	0.8636	0.86122	0.0608	100.024	10.722
trainbfg	tansig-tansig	12	0.99538	0.972151	0.9906	0.99130	0.0015	7.468701	51.46
	logsig-tansig	23	0.99745	0.981907	0.9649	0.99016	0.0017	6.005519	163.60
	purelin-tansig	16	0.93159	0.918803	0.9350	0.93012	0.0119	23.91998	1.881
	tansig-logsig	7	0.84690	0.838689	0.8823	0.85024	0.0607	100.0571	8.669
	logsig-logsig	6	0.82891	0.87872	0.8652	0.84099	0.0613	100.5228	33.008

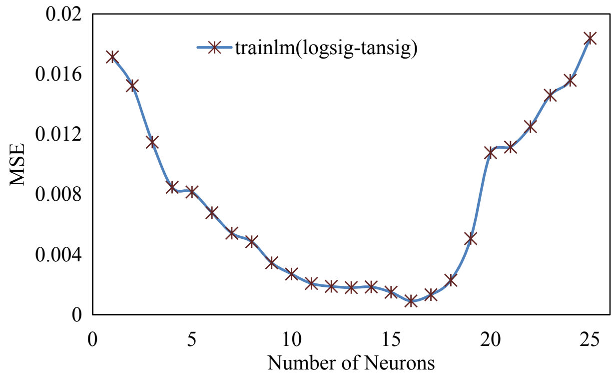

Fig. 4. Variation of MSE with respect to number of neurons.

The above statistical benchmark indicators were combinedly used to assess the ANN model, the values of indicators (R > 0.98, MSE<0.001 & MPE<5%) which when satisfied by the ANN model will terminate the iterative process. If the values are not attained during the course of iterations, the loop ends after 100 iterations. Model was retrained and evaluated by varying number of neurons till regressions, MAPE and MSE attains the values defined. Flow chart representing ANN algorithm developed is as shown in Fig. 3.

3.3. Post processing of data

In order to assess the results obtained it is prerequisite to revert the outcomes of ANN model. The results obtained from the ANN model were converted back to original units using the de-normalization process. The 15% (13 cases) of the data were used to simulate the model and results obtained are used for assessing the efficacy of the model.

4. Results and discussions

ANN model training was carried out for different training algorithms & training functions for 100 iterations and respective best results were tabulated as shown in Table 5. Levenberg–Marquardt training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer function for layer-1 and layer-2 respectively, yields best regression, MAPE and MSE compared to all other algorithms. Variation of MSE with respect to number of neurons in hidden layers are depicted in Fig. 4, MSE decreases initially, reaches a minimal point and increases thereafter. MSE is high if the number of neurons is less, reiterating the fact that the less number of neurons drive the decision making strenuous. Whereas, MSE is high for higher number of neurons as adjustment of weights to minimize error is cumbersome. The optimal number of neurons for which MSE is minimal is found to be 16 (Ismail et al., 2012).

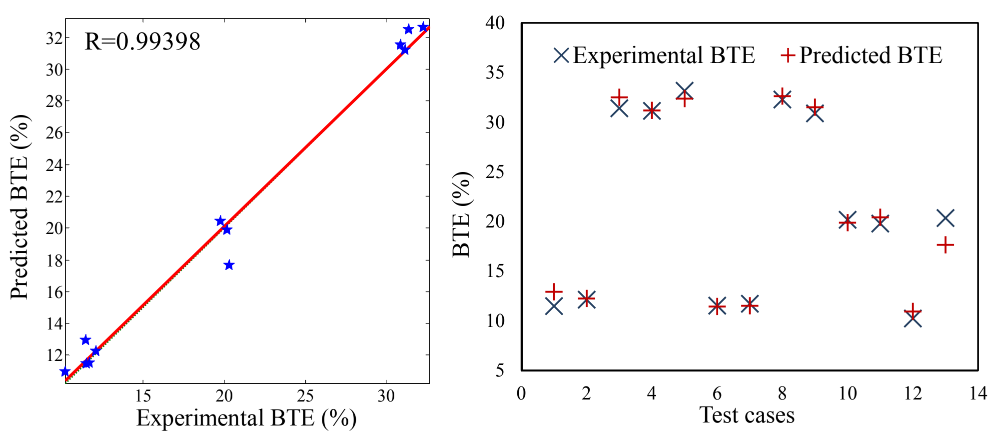

Fig. 5. Regression coefficient, experimental and predicted BTE (%).

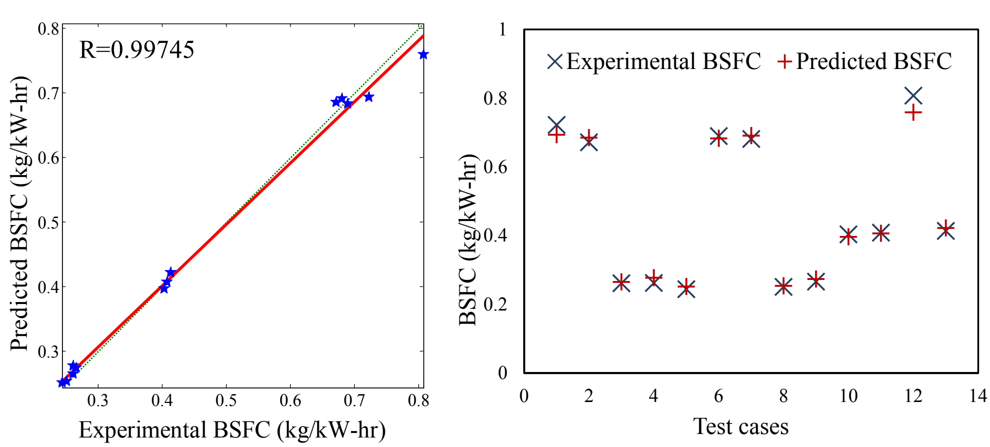

Fig. 6. Regression coefficient, experimental and predicted BSFC (kg/kW-hr).

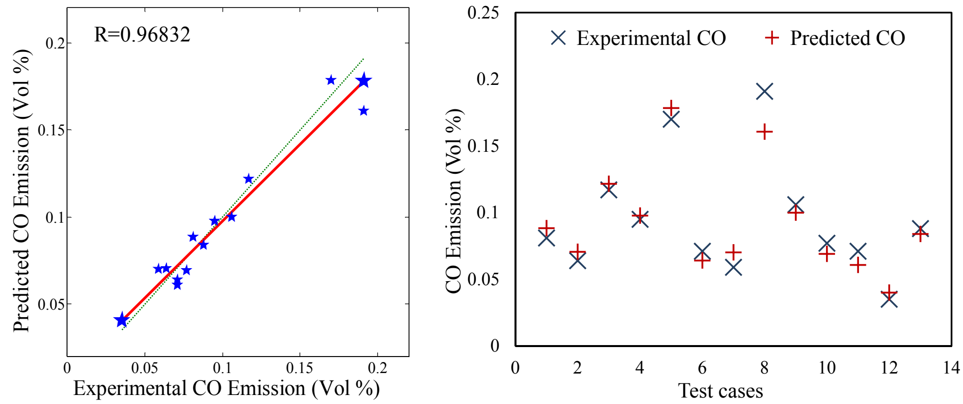

Fig. 7. Regression coefficient, experimental and predicted CO (Vol%) emission.

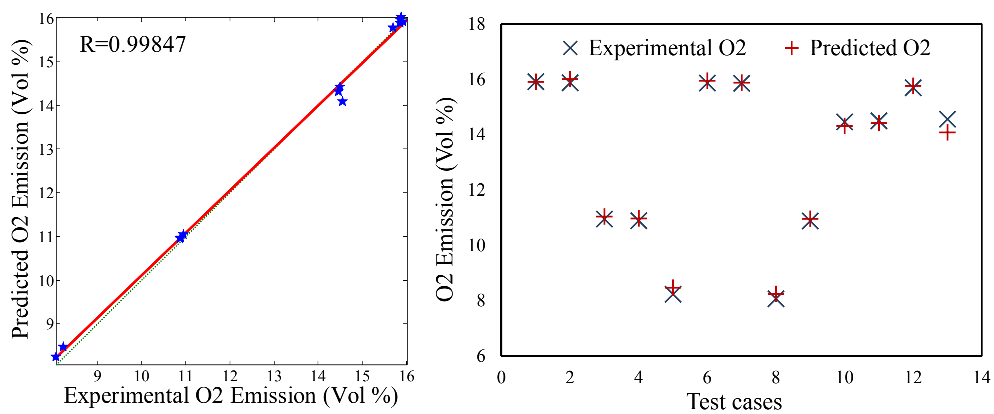

Fig. 8. Regression coefficient, experimental and predicted O_2 (Vol%) emission.

In pursuance of parameters to access the closeness of actual and predicted values, MSE alone was not ample (Table 5). As for the case of any training algorithm, even though MSE was in the acceptable range, MAPE and regressions were not. Hence the competent ANN model was developed by taking regression, MSE and MAPE as an evaluation criteria.

Levenberg–Marquardt training algorithm with logarithmic sigmoid and hyperbolic tangent sigmoid transfer functioned ANN predictions for test cases with corresponding actual experimental values along with regression coefficient are recorded and are depicted from Fig. 5–12. ANN prediction was meticulously matching with the actual value, as demonstrated by the values of regression coefficient. The ANN regression coefficient of performance parameters are 0.99398 and 0.99745 for BTE and BSFC respectively. Emission regression coefficient's using ANN is 0.96832, 0.99847, 0.9988, 0.99929, 0.94012 and 0.99754 for CO, O_2, CO_2, NO_x, HC and EGT respectively.

5. Conclusion

Experimental investigation was done on a standard diesel engine test rig with diesel/biodiesel as primary fuel and hydrogen in a

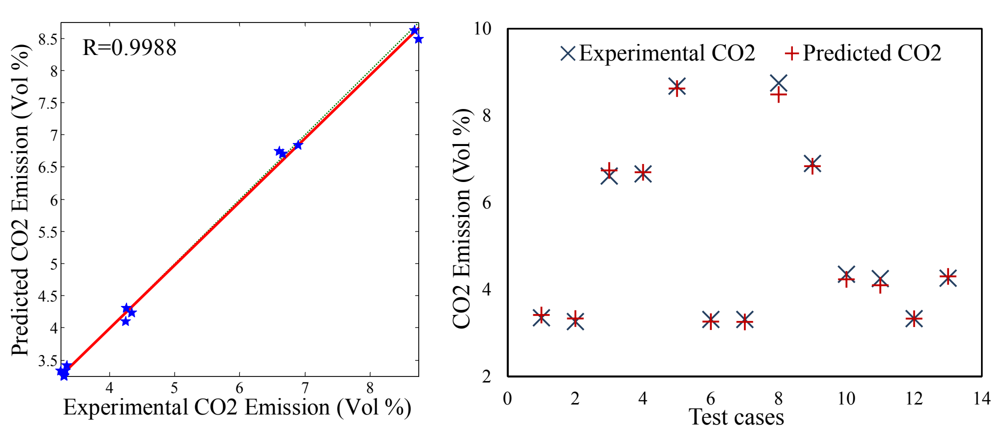

Fig. 9. Regression coefficient, experimental and predicted CO_2 (Vol%) emission.

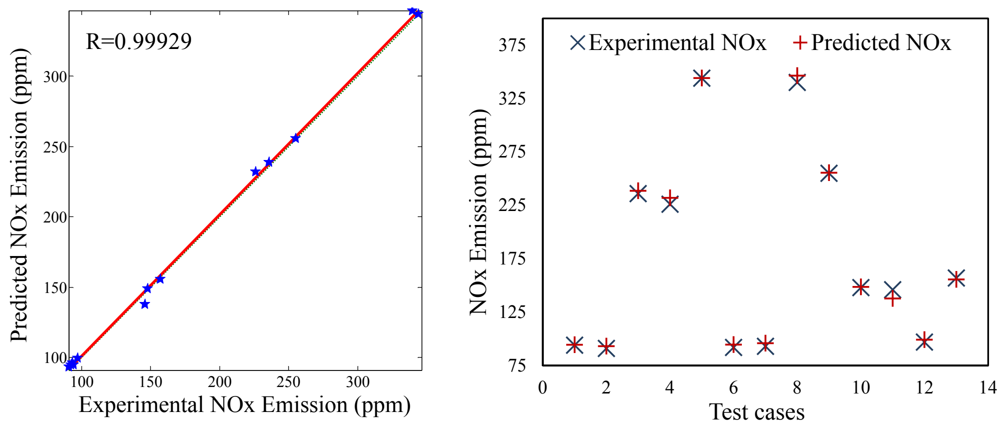

Fig. 10. Regression coefficient, experimental and predicted NO_x (ppm) emission.

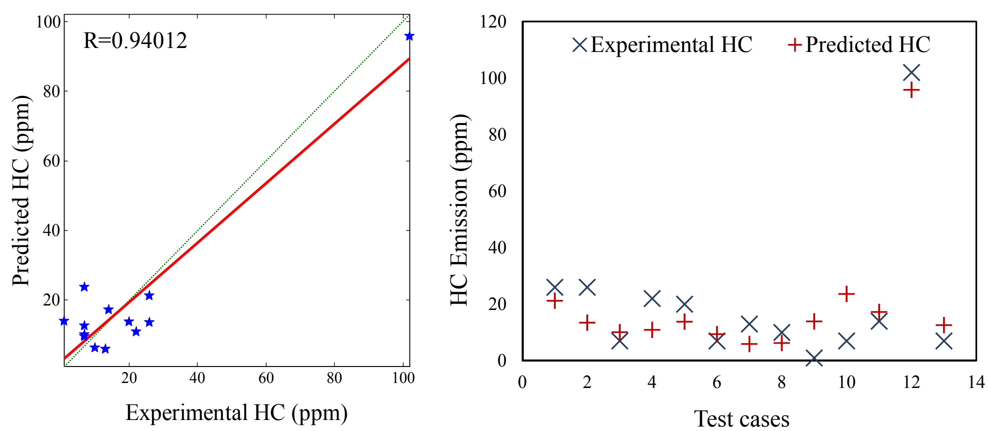

Fig. 11. Regression coefficient, experimental and predicted HC (ppm) emission.

dual fuel mode. Biofuel for the investigation was prepared in home from jatropha seeds. Diesel was blended with varying percentages of biodiesel. The experimental data obtained were used to train the different ANN models. Three input parameters load, percentage of biodiesel blend and hydrogen flow rate were used as input layer. Performance characteristics represented by BTE, BSFC and emissions CO, O_2, CO_2, NO_x, HC and EGT where used as targets in output layer. The trained ANN models were evaluated for various training algorithms and transfer functions by varying the number of neurons in the hidden layers. Seven different training algorithms were assessed along with five combinations of transfer functions as tabulated in Table 5. Logarithmic sigmoid and hyperbolic tangent sigmoid transfer function for Levenberg–Marquardt with 16 neurons was found to be having best regression value of 0.99360, MSE of 0.0011, MPE of 4.863001% with a training time of 78.135 s. ANN prediction abutted closely with experimental outcome. The proficient ANN model developed will benefit the researchers and designers to predict the performance and emission characteristics of a

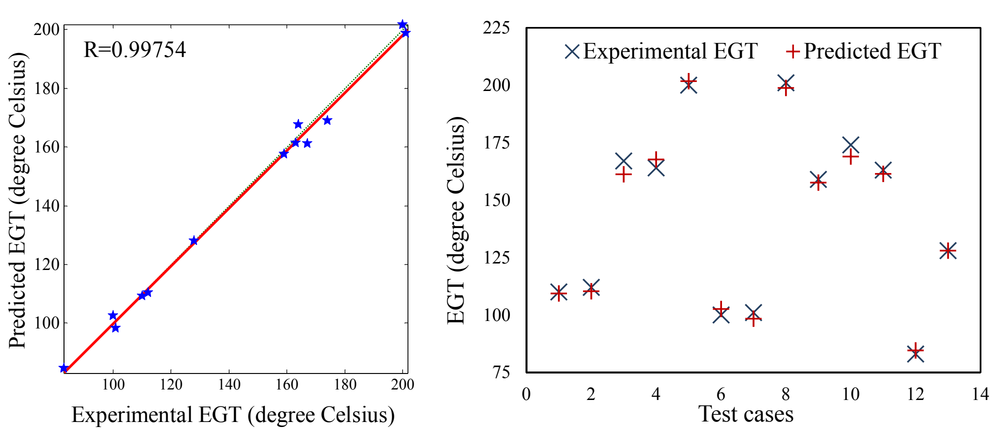

Fig. 12. Regression coefficient, experimental and predicted EGT (degree Celsius).

JME biodiesel hydrogen dual fueled CI engine. The ANN modeling has taken out costly, time consuming and strenuous experimentation.

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Glossary

CV_{lf}: Calorific value of liquid fuel (kJ/kg)
CV_{H_2}: Calorific value of H_2 (kJ/kg)
I: Current generated by AC dynamometer (amp)
M_{lf}: Mass flow rate of liquid fuel (kg/sec)
M_{H_2}: Mass flow rate of H_2 (kg/sec)
n: Number of trail cases
O_i: Output for ith trail case
T_i: Target for ith trail case
V: Voltage generated by AC dynamometer (V)