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ANALYSIS OF PERFORMANCE AND EMISSION CHARACTERISTICS BY ARTIFICIAL NEURAL NETWORK FOR SINGLE CYLINDER VARIABLE COMPRESSION RATIO DIESEL ENGINE USING JATROPHA AND COTTONSEED BIODIESELS

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ABSTRACT

This paper presents an artificial neural network (ANN) model to predict various performance parameters and emission characteristics of a single cylinder variable compression ratio diesel engine using Jatropha, Cottonseed and Jatropha-cottonseed mix biodiesel. Calorific value, viscosity, density, compression ratio, engine speed and load are input parameters while brake thermal efficiency, brake specific fuel consumption, exhaust gas temperature, NOx, CO, CO_2, HC and smoke opacity are output parameters. Levenberg Marquardt training algorithm is used for multilayer perception to minimize the error for the particular training pattern. The network is trained and observed that the ANN model can predict the engine performance parameters and emission characteristics quite well with correlation coefficient as R 0.99524.

Keywords: Artificial neural network, biodiesel, performance, emission

Nomenclature

ANN Artificial Neural Network
BSFC Brake Specific Fuel Consumption
BTE Brake Thermal Efficiency
CB Cottonseed Biodiesel
CR Compression Ratio
JB Jatropha Biodiesel
JCB Jatropha-Cottonseed Biodiesel
LMA Levenberg Marquardt Algorithm
W Load

I.INTRODUCTION

Pollution is the major issue associated with the increase in the utilization of the fossil fuels. Though the biodiesel derived from vegetable oil is not the new fact and the exhaustive study have been done on the biodiesel, but still the biodiesel is not commercialized yet [1]. The encouragement to use the renewable energy sources, not only can deplete the pollution effect but also raise the energy efficiency [2].

Due to depletion of the petroleum fuels, it is the necessity to obtain the alternative fuel that could be used with or without mixing up with the petroleum fuel. For the contrary, biodiesel seems to be a better alternative fuel which can be used as a pure biodiesel and could be mixed up with petroleum diesel to acquire the better results. Engine performance and emission analysis is necessary to investigate the optimum result for commercialization of the biodiesel. However, experimental investigation is tedious, intricate and time consuming and expensive, especially for the investigation including usage of various mixtures.

Literatures show that fuel properties [3] and engine parameters affects the performance and emission characteristics of engine. Different models are developed to understand effect of these parameters on engine with different approaches like dimensional analysis, simulated thermodynamic model analysis, artificial neural network, Taguchi approach, etc.

The advancement of technology in the field of neurobiology has allowed researchers to build mathematical models of neurons to simulate neural behavior. There are some areas where the conventional method of modeling fails in wide variety of problems in Engineering and sciences; hence use of Artificial Neural Network can overcome it. A well trained ANN can be used as a predictive model for a specific application which is a data processing system inspired by biological neural system. ANN predicts and validates independent data using training data based on experimentations [4].

An ANN has the ability to relearn and adapt for improving its performance with the availability of updated data [5].

Literatures show that artificial neural network is a powerful modeling and optimization tool that has the ability to identify complex relationships from input and output data. Gholamhassan Najafi et.al [6] used artificial neural network with back propagation algorithm for predicting Engine torque, SFC, HC and CO parameters with speed and blend ratio as variable using waste cooking biodiesel. Brake thermal efficiency and NOx are most important parameters which were not studied. T. Hari Prasad et.al [7] applied artificial neural network with Conjugate gradient method for predicting NOx, HC, CO, and CO_2 with load as variable, during this study, performance parameters were neglected. R. Manjunatha et.[8] Al studied prediction of NOx, HC, and CO using ANN with back propagation algorithm with input parameters as blend ratio, density, calorific value, Cetane number and load. This model is limited to study of emission characteristics that to excluding CO2 and smoke. Mustafa Canakci et. Al [9] applied ANN for predicting engine performance and exhaust emissions with different blends at different engine speeds with full load. Fuel properties, engine speed and environmental conditions were taken as input parameters while load, injection pressure, flow rates, emissions, maximum cylinder gas pressure and thermal efficiency. BTE, BSFC and EGT were ignored. B. Ghobadian et. al [10] studied effect of speed and blend on torque, BSFC, HC and CO using ANN and waste cooking biodiesel.

There is no uniformity with respect to number of performance parameters and emission characteristics used while developing models. Moreover, researchers have not yet attempted for developing similar models for remaining emission characteristics and performance parameter of engine. ANN, though most preferred technique for simulation, has not been so far tried for comprehensive modeling for engine variables and emission together. Major important fuel properties, engine design and controlling parameters are required to be studied to get a generalized algorithm. Therefore the objective of this study is to develop a neural network model for predicting most important performance parameters such as brake thermal efficiency, brake specific fuel consumption, exhaust gas temperature and emission characteristics as NOx, CO, CO_2, HC, smoke opacity. This model is of a great significance due to its ability to predict engine performance and emission characteristics under varying conditions.

II.EXPERIMENTATION

An experimental setup as shown in Fig. 2 consists of single cylinder, four stroke, water cooled Variable Compression Ratio diesel engine of Kirloskar make connected to eddy current type dynamometer for loading.

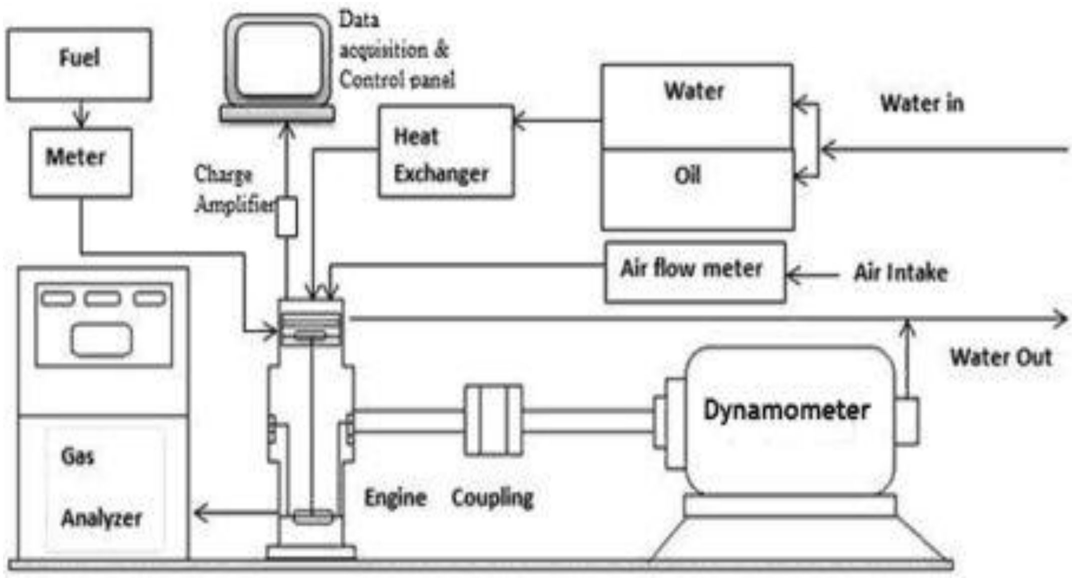

Fig.1 Schematic diagram of single cylinder VCR test rig

Each reading is taken for three times and average value is considered for further calculation.

In this study biodiesel is produced from Jatropha and Cottonseed oils through transesterification. Jatropha, Cottonseed and Jatropha-cottonseed mix biodiesels with 20%, 40% and 60% blends with neat diesel were used for experimentation. The respective fuel properties of blends such as viscosity, calorific value and density along with engine operating parameters such as load, compression ratio, speed were considered as input parameters while brake thermal efficiency, brake specific fuel consumption, exhaust gas temperature and emission characteristics as NOx, CO, CO_2, HC, smoke opacity were considered as output parameters of ANN network. The experiments were conducted on single cylinder variable compression ratio diesel engine with varying

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compression ratio, engine speed and load for different biodiesel blends. The engine was connected to eddy current dynamometer with all sensor and facility to measure, calculate and store data. The emission analysis was carried by five gas analysis with smoke opacity measurement. The engine was operated at different loads as 3kg, 6kg, 9kg, with varying compression as 17.5 and 18 at 1500rpm, 1600rpm and 1700rpm for different blends. The engine performance and emission characteristics were obtained. Total 54 trials were conducted as shown in Table 1. All the tests were conducted in the same environment and under the same conditions.

Table 1 Experimental Result of the Engine Performance and Emissions

Trial No.	ϑ	ρ	**CV**	**CR**	**SPEED**	**LOAD**	**NOX**	**CO**	**CO2**	**HC**	**SM**	**BTE**	**SFC**	**EGT**
	cSt	Kg/m^3	**MJ/kg**		**rpm**	**Kg**	**ppm**	**%**	**%**	**ppm**	**%**	**%**	**g/kW.h**	^{0}**C**
1	3.93	844.32	47.082	17.5	1500	3	65	0.08	2.24	24	17.25	14.61	0.46	99
2	4.36	855.74	45.848	17.5	1500	3	78	0.08	2.28	20	15.70	14.38	0.49	118
3	4.79	867.16	44.614	17.5	1500	3	94	0.08	2.39	20	14.50	13.54	0.51	125
4	3.93	844.32	47.082	17.5	1600	3	71	0.08	2.48	19	14.20	13.25	0.54	137
5	4.36	855.74	45.848	17.5	1600	3	84	0.08	2.74	18	13.15	13.10	0.56	140
6	4.79	867.16	44.614	17.5	1600	3	101	0.07	2.84	18	11.64	12.69	0.56	140
7	3.93	844.32	47.082	17.5	1700	3	77	0.07	2.11	17	9.95	10.63	0.60	143
8	4.36	855.74	45.848	17.5	1700	3	89	0.07	2.16	17	9.20	9.17	0.65	143
9	4.79	867.16	44.614	17.5	1700	3	117	0.06	2.18	17	8.76	9.04	0.71	149
10	3.9	844.3	47.08	18	1500	3	62	0.0	1.9	17	8.05	25.4	0.20	157

	3	2	2					6	3			7		
11	4.36	855.74	45.848	18	1500	3	73	0.06	2.05	16	7.65	22.00	0.30	160
12	4.79	867.16	44.614	18	1500	3	88	0.06	2.07	14	7.40	17.83	0.30	163
13	3.93	844.32	47.082	18	1600	3	65	0.05	1.76	14	7.03	16.10	0.35	179
14	4.36	855.74	45.848	18	1600	3	77	0.05	1.79	14	6.49	15.88	0.36	184
15	4.79	867.16	44.614	18	1600	3	96	0.05	1.85	12	6.30	15.77	0.38	187
16	3.93	844.32	47.082	18	1700	3	72	0.05	1.53	12	5.00	15.50	0.41	203
17	4.36	855.74	45.848	18	1700	3	90	0.04	1.67	10	3.50	15.18	0.41	206
18	4.79	867.16	44.614	18	1700	3	114	0.03	1.75	9	2.10	15.11	0.44	211
19	3.93	844.32	47.082	17.5	1500	6	148	0.09	2.86	27	30.40	21.74	0.34	138
20	4.36	855.74	45.848	17.5	1500	6	159	0.08	2.97	24	23.93	20.91	0.34	148
21	4.79	867.16	44.614	17.5	1500	6	204	0.07	4.06	23	22.50	20.76	0.36	162
22	3.93	844.32	47.082	17.5	1600	6	155	0.07	3.49	22	17.50	19.69	0.38	164
23	4.36	855.74	45.848	17.5	1600	6	165	0.07	3.73	21	15.50	18.88	0.39	164
24	4.7	867.1	44.61	17.5	1700	6	179	0.07	2.60	20	15.70	18.50	0.40	165

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	9	6	4												
25	3.93	844.32	47.082	17.5	1700	6	161	0.06	3.91	20	15.41	14.63	0.43	167
26	4.36	855.74	45.848	17.5	1700	6	172	0.06	2.69	19	14.66	13.57	0.48	175
27	4.79	867.16	44.614	17.5	1700	6	196	0.06	2.72	19	13.90	12.51	0.66	179
28	3.93	844.32	47.082	18	1500	6	143	0.06	2.40	20	18.81	29.02	0.19	188
29	4.36	855.74	45.848	18	1500	6	154	0.05	2.50	18	11.60	27.13	0.22	192
30	4.79	867.16	44.614	18	1600	6	199	0.05	2.55	17	11.15	24.70	0.23	204
31	3.93	844.32	47.082	18	1600	6	150	0.05	2.18	17	10.60	24.06	0.25	219
32	4.36	855.74	45.848	18	1600	6	154	0.05	2.21	15	10.04	23.75	0.26	222
33	4.79	867.16	44.614	18	1700	6	174	0.04	2.23	15	9.30	23.27	0.28	228
34	3.93	844.32	47.082	18	1700	6	157	0.04	1.94	15	7.20	22.87	0.28	240
35	4.36	855.74	45.848	18	1700	6	168	0.04	2.04	11	5.70	22.88	0.31	246
36	4.79	867.16	44.614	18	1700	6	191	0.03	2.07	9	4.96	22.19	0.31	274
37	3.93	844.32	47.082	17.5	1500	9	233	0.08	3.57	37	41.00	26.31	0.28	152
38	4.3	855.7	45.84	17.5	1500	9	257	0.07	3.67	35	34.00	25.61	0.29	16

	6	4	8											
39	4.79	867.16	44.614	17.5	1600	9	286	0.06	3.77	35	31.90	25.30	0.30	184
40	3.93	844.32	47.082	17.5	1600	9	242	0.06	4.01	29	30.85	23.98	0.32	189
41	4.36	855.74	45.848	17.5	1600	9	265	0.06	4.12	27	27.80	22.84	0.34	191
42	4.79	867.16	44.614	17.5	1600	9	286	0.06	4.46	26	27.13	21.34	0.35	190
43	3.93	844.32	47.082	17.5	1700	9	252	0.06	3.20	25	20.10	16.50	0.46	193
44	4.36	855.74	45.848	17.5	1700	9	261	0.05	3.28	24	19.80	14.85	0.72	196
45	4.79	867.16	44.614	18	1500	9	295	0.05	3.34	24	18.65	13.80	0.78	206
46	3.93	844.32	47.082	18	1500	9	226	0.05	2.97	22	17.30	32.59	0.17	217
47	4.36	855.74	45.848	18	1500	9	249	0.04	3.08	21	16.80	30.66	0.19	220
48	4.79	867.16	44.614	18	1600	9	279	0.04	3.06	21	14.88	29.86	0.19	226
49	3.93	844.32	47.082	18	1600	9	235	0.04	2.74	20	13.88	29.54	0.22	245
50	4.36	855.74	45.848	18	1600	9	265	0.04	2.78	18	12.65	28.94	0.22	257
51	4.79	867.16	44.614	18	1700	9	279	0.04	2.88	16	9.00	28.73	0.23	266
52	3.9	844.3	47.08	18	1700	9	245	0.03	2.20	16	8.20	28.02	0.23	279

	3	2	2											
53	4.36	855.74	45.848	18	1700	9	252	0.02	2.34	12	6.60	27.69	0.25	288
54	4.79	867.16	44.614	18	1700	9	289	0.01	2.50	9	5.10	27.14	0.27	318

III. PROPOSED METHODOLOGY

The semi empirical models developed using dimensional analysis is based on the assumptions that the each of the variables considered are independent and the linear relationship exists among them. However, such a situation is considered to be very ideal in any real application. As has been pointed our earlier, artificial neural network (ANN) is expected to address such situations. This section shall be dealing with application of ANN for the modeling of the process with the same experimental data collected so far.

3.1 Artificial Neural Network's Structure

Artificial neural networks (ANNs) are a structure consisting of a large number of very simple units which combine to represent any given relationship of inputs and outputs. ANNs, a data processing tool analogous to biological neural system, are used to solve a wide variety of problems in science and engineering, particularly for areas where the conventional modeling methods fail. It is a powerful modeling tool that can identify complex relationships from input and output data [11]. A well trained ANNs can be used as a predictive model for solving specific problems. The predictive ability of ANNs results from the training on experimental data and then validation by independent data. An ANN has the ability to relearn to improve its performance with new available data [12].

The advancement of technology in the field of neurobiology has allowed researchers to build mathematical models of neurons to simulate neural behavior [13]. A neural network is composed of large numbers of highly interconnected processing elements known as neurons. The basic elements of an artificial neuron are shown in Figure 4.5. The ANNs usually consist of an input layer, some hidden layers and an output layer. Multilayer perceptions are the best known and most widely used kind of ANNs. In its simple form each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. The ANNs use a learning model in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. Artificial neuron mainly consists of weight bias and activation function. Each neuron receives inputs x_1 , x_2 ,. . ., x_n attached with a weight x_i which shows the connection strength for a particular input for each connection . Data is usually stored as a set of connection weights. The weights after training contain meaningful information whereas before training they are random and have no meaning.

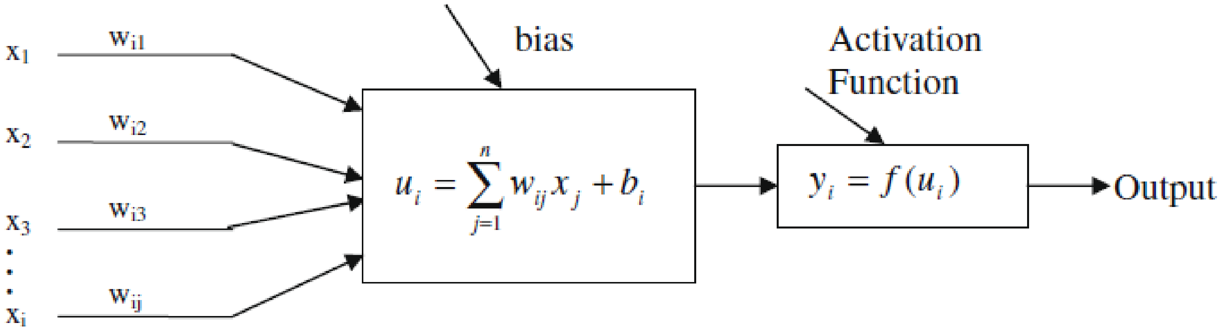

Figure 2 Basic Elements of an Artificial Neuron

Every input is then multiplied by the corresponding weight of the neuron connection. A bias b_i can be defined as a type of connection weight with a constant non zero value added to the summation of inputs and corresponding weights w_{ij} *as* given below;

$$u_i = \sum_{j=1}^{n} w_{ij} x_j + b_i$$

The summation u_{ii}s, transferred using a scalar to scalar function to yield a value called the unit'*s* activation or transfer function *f(ui)* is given as

$$y_i = f(u_i)$$

Activation functions serve to introduce nonlinearity into neural networks which makes it more powerful than linear transformation. Levenberg Marquardt algorithm (LMA), a gradient descent technique, which is the most widely used training algorithm for the multilayer perception is used to minimize the error for a particular training pattern [14-15]. Accordingly, for a given input pattern a flow of activation is forwarded from the input layer to the output layer via hidden layer(s). Then the errors in the output are initiated. LMA is used to adjust the weights, a small amount at a time, in a way that reduces the error. The training of the network is accomplished by adjusting the weights and is carried out through a large number of training sets and training cycles (epochs). The goal of learning procedure is to find the optimal set of weights which in the ideal case would produce the right output for any input. The output of the network is compared with a desired response to produce an error. Once the ANN is adequately trained, it can generalize to similar cases which it has never seen [16-17].

3.2 Artificial Neural Network Model and Parameters

Fig. 3 shows the architecture of a general three layered feed forward neural network model. It has six input parameters as calorific value, density, kinematic viscosity, load, speed and compression ratio while eight output parameters, three performance parameters and five emission characteristics. The neural network considered is fully connected in the sense that every unit belonging to each layer is connected to every unit belonging to the adjacent layer.

. Fig. 3 shows the architecture of a general three layered feed forward neural network model

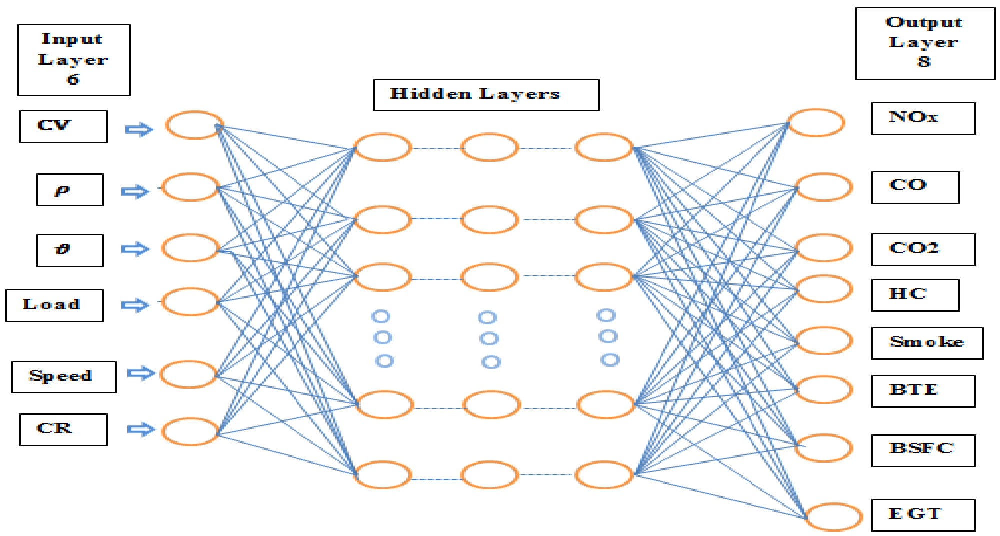

Figure 3 An Architecture of a General Three Layered Feed Forward Neural Network Model

IV.ANALYSIS OF RESULTS AND DISCUSSION

The entire experimental data collected so far was straight way used by considering all biodiesels together to avoid spending excessive time running experimental tests. Out of total data available**,** 75% of samples were used for training the network (modeling), 10% dataset were used for validating the network and 15% dataset were chosen randomly for testing the performance of the trained network by using Levenberg Marquardt algorithm in feed forward mode.

The input and output experimental data is shown in Table 1. An ANN computer program was developed using MATLAB 2010. Out of 54 trials, the experimental results corresponding to 40 samples, randomly selected, were used for training the model and remaining 14 are used for testing and validation as per the proportion mentioned above.

One of the most important tasks in ANN studies is to determine the optimal network architecture which is related to the number of hidden layers and neurons in it. Usually the trial and error approach is used. In this study the best architecture of the network was obtained by trying different number of hidden layers and neurons. The trial started on hidden layer with ten neurons and the performance of each network was checked based on the values of correlation coefficient (R). The goal here is to maximize correlation coefficient to obtain a network with the best generalization. Many different network models are tried and their R values are calculated.

Fig. 4 shows the sum square error (R^2) of the network corresponding to training data, test data and validation data individually, with different learning parameters. (Learning coefficient (η) and momentum factor (α)). The marked circle shows optimum number of iteration where R^2 values of three categories of data approximately matches with each other and gives the best R^2 value for these individual categories and their combined effect.

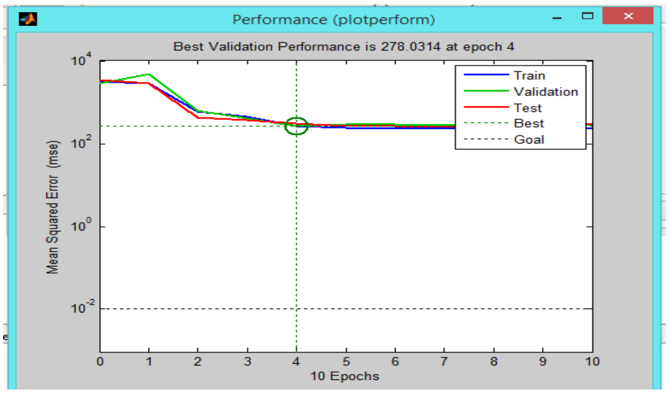

Figure 4 Influence of Iteration Limit on the Sum Squared Error

In order to assess the accuracy of ANN estimations, the regression curves are plotted for estimated and experimental data (3 categories, individually and together) of all performance parameters and emission characteristics together and are shown in Fig. 5. As mentioned before, the criterion R was selected to evaluate the networks to find the best activation function and number of neuron. The regression values (R^2) is found to be 0.99534 for complete data set. The correlation coefficient close to unity indicates that ANN is capable of generalizing relationship between input variables and output parameters reasonably well.

The results show that the training algorithm is at the optimum point (Circled) found at epoch 4 and got satisfactory R^2 values nearest to 1 for predicting performance parameters and emission characteristics. A high prediction capability was achieved for both training and testing data sets of output parameters. Therefore, the ANN appears to have a high generalization capability.

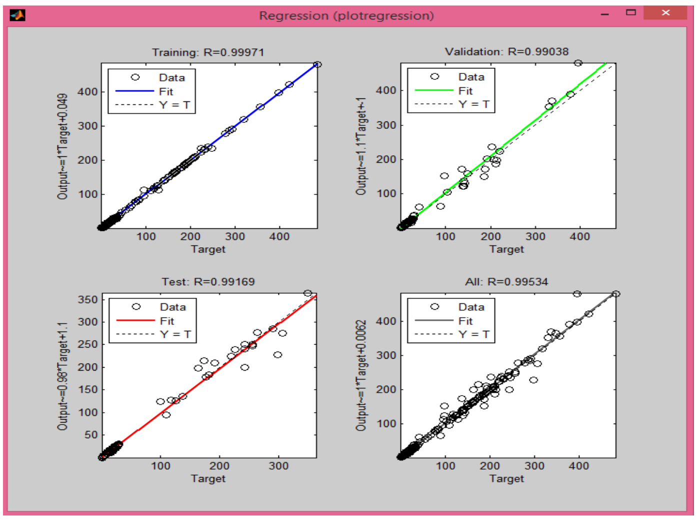

Figure 5 Regression Curve

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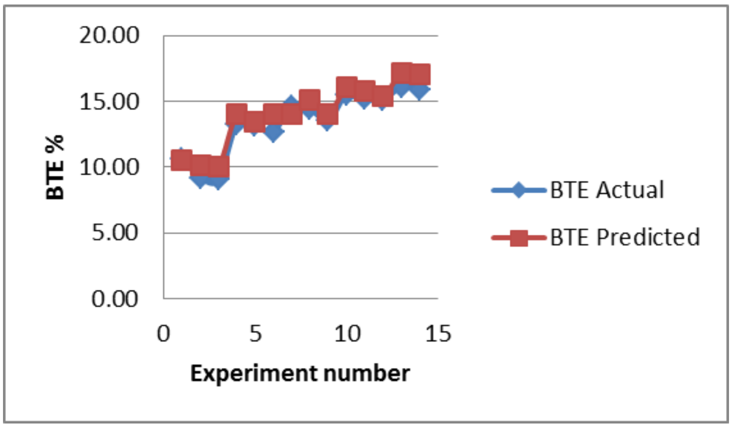
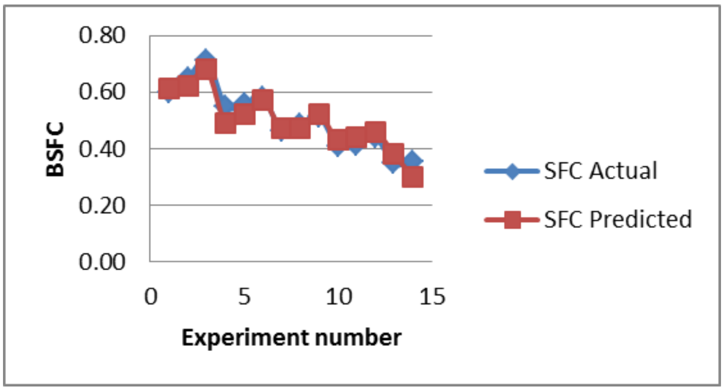
Using weights and biases of trained ANN model, output parameters (performance parameters and emission characteristics) can be predicted. The experimental and predicted values (using ANN) for each performance parameters and emission characteristics are plotted and are shown in Fig. 6. The correlation coefficients for brake thermal efficiency, brake specific fuel consumption, exhaust gas temperature, NOx, CO, HC, CO2 and smoke opacity at the training stage are found to be 0.9726, 0.9918, 0.9932, 0.976, 0.9916, 0.9923, 0.9951, 0.9921 and 0.9908 respectively. The correlation coefficients close to unity for all output parameters indicate good accuracy of the models developed. Thus, ANN models can be used to predict emission and performance parameter for diesel engine with adequate accuracy.

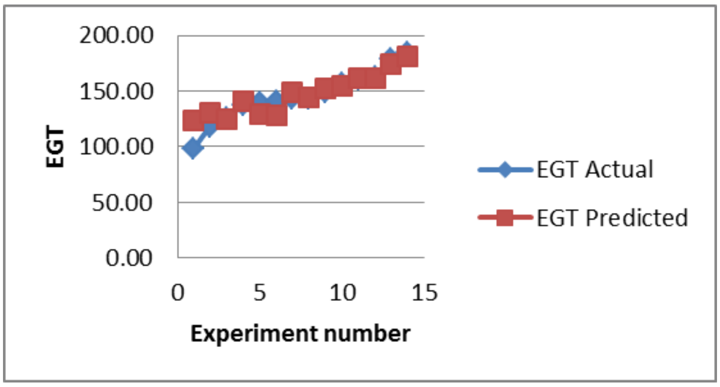
The Comparisons of the ANN-predicted results and experimental (actual) results are indicated in Fig. 6 from a to h.



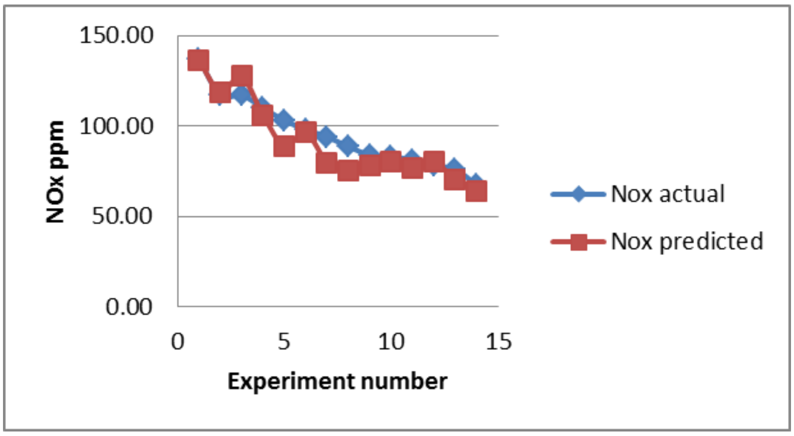
a. Actual and Predicted Relationship for BTE using ANN



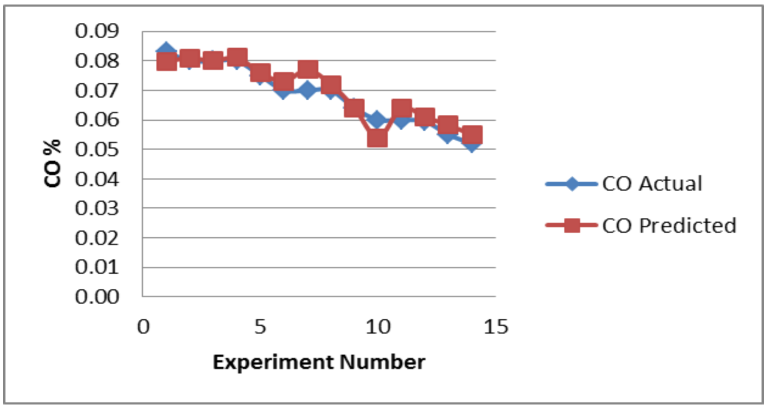
b. Actual and Predicted Relationship for BSFC using ANN



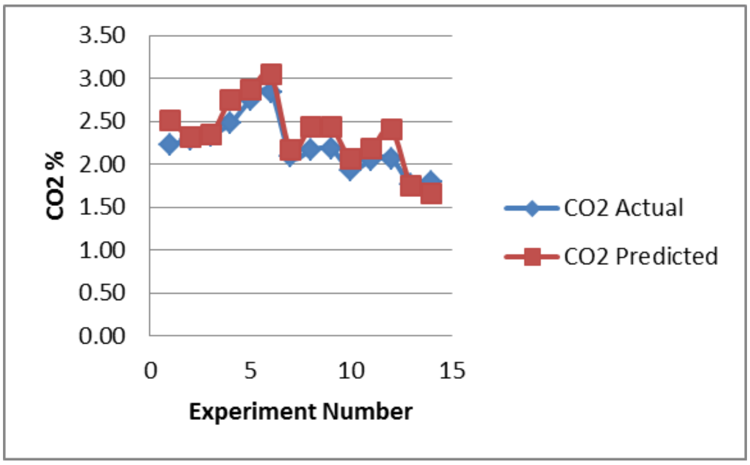
c. Actual and Predicted Relationship for EGT using ANN



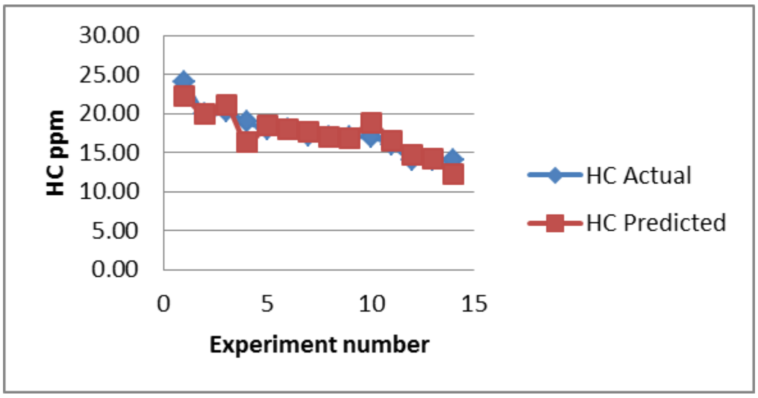
d. Actual and Predicted Relationship for NOx using ANN



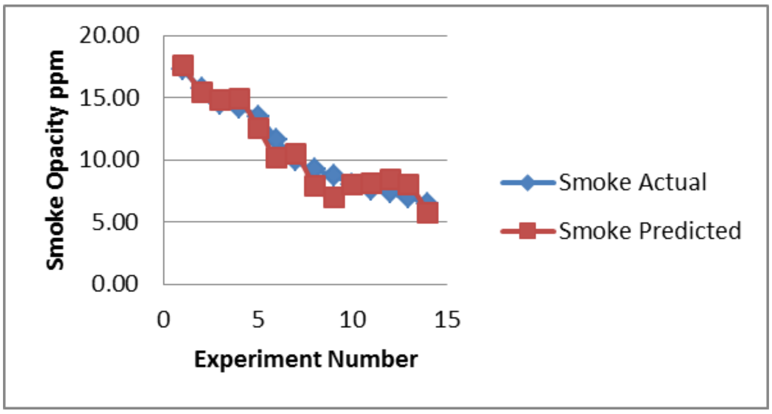
e. Actual and Predicted Relationship for CO using ANN



f. Actual and Predicted Relationship for CO2 using ANN



g. Actual and Predicted Relationship for HC using ANN



h. Actual and Predicted Relationship for Smoke Opacity using ANN

Figure 6 ANN-Predicted Results and Experimental Results

Correlation factors, which define accuracy of model, are found better using ANN as compared with other analysis. The correlation coefficients for all output parameters are close to unity indicating good accuracy of the model developed by ANN. In actual practice during experimentation, many parameters show different dominating effects over each other which create non-linearity. ANN can be applied to linear and non-linear relationship. Another advantage of ANN is that it can be used to predict all parameters for other biodiesels without conducting experimentation. The setting up of the input parameters for a certain range of output parameters as per emission standards of respective country is also possible using ANN.

As all performance parameters and emission characteristics considered are equally important, a multi-parametric optimization approach is expected to provide breakthrough in bringing biodiesel into reality.

V. CONCLUSIONS

- The model developed using an Artificial Neural Technique predicts input-output relationship for all performance parameters and emission characteristics with highest accuracy as it takes care of non-linear behaviour.
- The non-linearity occurs mainly due to following reasons;

i) Uncertainty in interaction effect of input variables in different situations leading to formation of unexpected swirl and turbulence patterns,

ii) Atomization of heterogeneous air fuel mixture converting into better vaporization readiness for combustion at proper timing affecting ignition delay,

iii) Uncertain behaviour of mixture during uncontrolled combustion phase may change percentage of emission components due to chemical reactions such as change in percentage of NOx changing percentage of CO, CO_2 and HC.

iv) Formation of soot in cylinder during new cycle affecting performance.

- ANN provides a single model with virtual hidden algorithm considering training, testing and validating data together and helps to predict all performance parameters and emission characteristics in a single iteration.
- The correlation coefficients for brake thermal efficiency, brake specific fuel consumption, exhaust gas temperature, NOx, CO, HC, CO_2 and smoke opacity are found to be 0.9726, 0.9918, 0.9932, 0.976, 0.9916, 0.9923, 0.9951, 0.9921 and 0.9908 respectively. The coefficients close to unity indicate good accuracy of the models.
- The model can be used to predict output data for any type of biodiesel without further experimentation.

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