PERFORMANCE AND EMISSIONS MODELLING BIOETHANOL OPERATED SPARK-IGNITION ENGINE USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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Abstract : Bioethanol is a most promising substitute fuel for gasoline. National biofuel policy 2018, redefined the usage of bioethanol blended up to 10% with petrol to be made available for the transportation sector. There is a requirement for analysing SI engine's performance and emission characteristics for various blends of bioethanol with gasoline. Artificial neural networks is a diagnostic software paradigm suitable for simulating the function approximation problems such as petrol engine performance and emission analysis. Analysing thermodynamic relationship between the input and output variables of a spark ignition engine operated with various bioethanol blends is complex and experimentation is time consuming. Hence, in this work, operating data of bioethanol blends is utilized and a prediction model is developed. Input variables of combustion modeling are percentage of gasoline, percentage of ethanol, calorific value, octane number, specific gravity of the blends, compression ratio, brake pressure, brake specific fuel consumption and exhaust gas temperature (EGT). Output variables are Brake Thermal Efficiency (BTE), and emissions (CO and HC). Simulation & modeling of the input-output relationship is performed using advanced neuro-fuzzy modelling technique known as Adaptive Neuro-fuzzy Inference System (ANFIS). The experimental data on bioethanol-gasoline blends of single cylinder variable compression ratio engine is taken as basis to train ANFIS. After successful training, neuro-fuzzy algorithm predicts the output values for new testing data. The RMSE values are found to be 0.00024 for BTE, 0.000133 for CO and 0.000256 for HC emissions and Coefficient of Determination R^2 is 0.96, 0.95 and 0.94 respectively for BTE, CO and HC. This work successfully demonstrates the application of ANFIS for performance and emissions modeling of petrol engine operated with bioethanol blends.

IndexTerms - Adaptive Neuro-Fuzzy Inference System (ANFIS), Clustering, Alternate fuel-Ethyl alcohol, VCR Engine Performance, Exhaust Emissions-(Co and HC), CoD, MAPE.

I. INTRODUCTION

With the advent of renewable energy technologies, worldwide there is flat trend observed during 2019 in global energy related CO_2 emissions. Bioethanol is a promising second generation biofuel that can reduce the CO_2 and other emissions when operated in internal combustion engines. CO_2 contributes to 76% of the global greenhouse gas emissions. Today, China is the world's largest CO_2 emitting country with more than 25% of the global CO_2, where in USA, Europe and India are contributing to 15%, 10% and 7% respectively. Globally, 36 billion Tonnes of CO_2 is emitted per annum. Nearly 25% of these emissions are resulting due to tailpipe emissions from transportation sector till date [1]. Bioethanol being rich in oxygen content (35%) supports combustion in fuel rich zone of Gasoline Direct Injection engines. Blending Bioethanol with gasoline reduces Soot and polycyclic aromatic hydrocarbon (PAH) significantly. CO and CO_2 emissions are reduced by 81% and 17% respectively [2]. Bioethanol produced from switchgrass and miscanthus will reduce the life cycle emissions by more than 75% [3].

The production and usage of bioethanol is maximum in Brazil and USA and India is in 5th position with a production capacity of 530 Millions of Gallons per annum [4]. In India, Ministry of New and Renewable Energy has set an ambitious target of blending petrol with 20% bioethanol by 2030 [5]. Bioethanol blending with petrol up to 5% and 10% is already certified under BIS published under IS: 2796: 2008 [6] in India.

Analysing the exhaust gas emissions of petrol engine operated with bioethanol blends is a complex task. It involves the parametric analysis of thermodynamic, thermochemical and chemical kinetics apart from the engine operating conditions. Many researchers have carried out experiments on bioethanol blended with gasoline and tested the engine performance and emissions. Bioethanol blended with petrol has shown higher brake power and reduced CO and UHC (Unburnt Hydrocarbons) [7]. Various tests were done on the engine using different blends of ethanol and gasoline [8,9,10]. Because of the bioethanol is having high octane number, it is preferred that the engine should be operated at high compression ratios that is 10:1 and 11:1 for the better performance [11]. The torque of the engine increases with the increasing compression ratio and the highest torques are attained at the compression ratio 13:1 with highest blends E40 and E60 because of having high octane number [12]. With the increase in the volume percentage of bioethanol in the blend, the BSFC (Brake Specific Fuel Consumption) decreases and the BMEP (Brake Mean Effective Pressure) increase with increasing compression ratio [13]. It is observed from the experimental results that when running with the E50 fuel blend, the engine power rises up to 29% compared to running with pure gasoline fuel. In addition, there is a reduction in BSFC, CO, CO_2, HC and NOX emissions about 3%, 53%, 10%, 12% and 19%, correspondingly [11]. Ceviz et al. [14], performed various experiments in order to found out the ways to decline cyclic variability. They found that CO and HC emission concentrations decreases for the E10 fuel blend. After E10 fuel blend, a reverse effect was witnessed on the parameters. Ansari et al. [15] conducted tests with blends of 0%, 20%, 40%, 60%, 80% and 100% of Ethanol with Gasoline. Compression Ratio varying from 8:1 to 10:1, and at different loading conditions (330, 600, 900, 1200, 1500, 1800Watt). They too observed similar trends in emissions and performance.

Present work makes an attempt to relate the influencing parameters of petrol engine combustion with its performance and emissions. To achieve this objective, petrol engine is operated for various bioethanol blends under varying operating conditions. After that, the performance and emissions data is utilized to model the combustion problem of a petrol engine using artificial neural networks. Artificial neural networks is a competent technology tool to simulate and model the petrol engine performance and emission modeling as tried out by various researchers [16,17]. Sekmen et al used ANNs to relate Engine speed, injection pressure as inputs and torque, injection pressure, specific fuel consumption as outputs. MAPE and R^2 are found to be within acceptable limits [18]. A Adarsh Rai et al. [19] worked on the artificial intelligence tools of ANFIS, Fuzzy Logic, and Genetic Algorithms for predicting the various performance and emission parameters on dual fuel diesel engine. The models developed were validated for test data to obtain converging results.

The subsequent sections of this paper explain bioethanol formation, blend preparation, experimentation and modeling.

1.1. Bioethanol:

The primary step in the making of Bio-Ethanol is the preparation of feed stock. The preparation of feedstock is different for different generation biofuels [20]. But the initial work among all the biofuels generation is the selection of plants or seeds or algae or synthetic seeds that can produce either simple sugar directly or starch and cellulose. Cereals and plant tubers are taken as the feedstock for the preparation of the bioethanol [21]. After crushing them, the Oil is obtained and hydrolysis and fermentation are performed.

$$\underset{(glucose)}{C_6H_{12}O_6} \rightarrow \underset{(ethanol)}{2C_2H_5OH} + \underset{(Carbondioxide)}{2CO_2} + heat \quad \text{--- (1)}$$

Equation (1) depicts the bioethanol production in presence of yeast at 260^0C-320^0C. From the fermentation process, hydrous bioethanol is obtained which is sent to the distillation chamber [21]. This concentrated ethanol-water solution is again sent to the condenser and process goes on upto the final ethanol solution with 96% concentration is obtained.

1.2. Engine experiments with bioethanol:

In this work, bioethanol is procured from local sugarcane manufacturing plant in Andhra Pradesh. Characteristic fuel properties for various bioethanol blends are measured by using standard labouratory procedures. The observations are recorded in table 1. The percentage of bioethanol is increasing from 10% to 100% and is termed as E0 to E100. The respective values of The calorific value for the pure gasoline fuel is more when compared to the pure ethanol fuel but the octane number for the pure ethanol is higher than that of the pure gasoline.

Fuel Blend	Calorific Value (kJ/kg)	Octane Number	Specific Gravity
E0	43932	91	0.7474
E20	41286	94	0.7605
E40	37448	97	0.7792
E60	34541	100	0.7812
E80	30703	104	0.7834
E100	26981	129	07890

Table 1. Fuel Properties of bioethanol blends obtained from fermented Sugar

The detailed specifications of the engine are shown in the table 2. The schematic of experimental setup is represented in fig 1.

Make	Enfield, Spark Ignition, Air and Water Cooled
Number of Cylinders	1
Rated Speed	2700RPM
Rated Power	2kW
Bore	70mm
Stroke	66.7mm
Compression Ratio	2.5:1 to 10:1
Loading	Water Rheostat
Starting	Crankshaft

Table 2: Engine Specifications of experimental setup

For every load, brake power, mass of the fuel consumed, Brake Thermal Efficiency, Exhaust gas temperature, BSFC, Air-Fuel ratio and CO, HC emissions are recorded. CO and HC exhaust emissions are measured by Planet 5G-10 model of a 5-Gas analyzer.

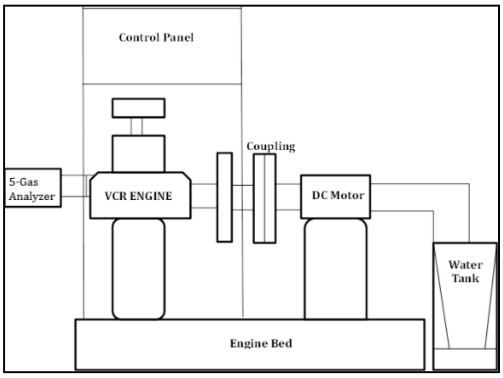

Fig.1 Single line diagram of of a Variable Compression Ratio (VCR) SI Engine Test rig

II. PERFORMANCE AND EMISSION PARAMETERS OF SI ENGINE

The basic data required to estimate the performance and emission parameters of SI engine with measured constant engine speed are as briefed below:

2.1 Brake Thermal Efficiency (BTE): - The brake thermal efficiency, η_{bte}, is the ratio of brake power to power supplied by the fuel, Q_{in}, [28] and is given by

$$\eta_{bte} = \frac{BP}{Q_{in}} \qquad \text{--(2)}$$

Where BP = Brake Power which is the actual power available at the crank shaft, given by

$$BP = \frac{2\pi NT}{60000} \qquad \text{--(3)}$$

Q_{in}= the heat power supplied by the fuel

$$Q_{in} = m_f Q_{LV} \qquad \text{--(4)}$$

Where m_f is mass flow rate of fuel and Q_{LV} is the lower calorific value of the fuel.

2.2 Formation of CO Emission: - During the combustion fuel rich mixtures CO emissions are formed due to the deficiency of oxygen. Aldehydes are formed when a hydrocarbon radical is oxidized, and this aldehyde is further oxidized then it leads to ketones and when this ketone is oxidized then it leads to CO formation [28].

$$RH \rightarrow R \rightarrow \rightarrow R + O_2 \rightarrow RCHO \rightarrow \rightarrow RCO \rightarrow CO \qquad \text{-- (5)}$$

Generally, the air-fuel ratio is the most significant engine parameter affecting CO emissions. Other causes influence CO emissions mostly indirectly through changes in mixture composition and/or promotion of slow oxidation reactions resulting in incomplete combustion.

2.3 Formation of HC Emission: - If the fuels are rich in aromatics and olefins then the HC emissions are formed due to the photochemical reaction of aromatics and olefins. There are more mechanisms for the formation HC emissions [28]. They are

a) Flame Quenching
b) Quench Layer Thickness
c) Wall Quenching
d) Crevice HC

a) Flame Quenching occurs due to lowering the temperature of reaction zone because of heat transfer from flame to walls leads to the flame extinguishing. Due this, improper combustion happens and unburnt HC emissions come out of the tailpipe.
b) The quench distance or quench layer thickness is defined as the normal distance from the wall where the flame gets quenched, or the gap between two parallel plates, or diameter of the tube in which flame is just unable to propagate under the given charge conditions.
For a laminar flame and also the flame is very close to the walls

$$k.\frac{\Delta T_c}{\delta_q} \textbf{(Heat Transfer)} = \rho_u.S_L.h \textbf{(Heat Released)}$$

$$= \rho_u.S_L.\overline{c_{pb}}.\Delta T_f \qquad \textbf{-- (6)}$$

Where
k = Thermal Conductivity of Unburned Mixture,
ΔT_c = Characteristic Temperature Difference for heat transfer
δ_q = Quench Distance,

ρ_u = Unburned Mixture Density,

S_L = Laminar Flame Speed,

h = Heat released per unit mass of mixture burned,

ΔT_f = Temperature rise on combustion in Flame.

c) As the engine load increases, the quench walls thickness decreases due to the reduction of high wall temperature from reaction zone to walls. Basically thickness of quench layer varies from 0.05 to 0.1mm

d) Crevices are the irregular shapes in an engine. During compression and combustion, unburned charge is pushed into these crevices and at peak pressure, maximum gas would be stored in the crevices. The maximum fraction of the unburned charge stored in crevices, E_s occurs at peak pressure and is given by;

$$E_s = \frac{m_{cr}}{m_0} = \frac{V_{cr} P_{\max} T_0}{V_0 P_0 T_{cr}} \quad \text{-- (7)}$$

Where m, V, T and P are mass, volume, pressure and temperature. The subscripts cr and o refer to the conditions in the crevices and at the end of intake stroke in the cylinder, respectively. P_{max} is the peak pressure in the cylinder.

III. EXPERIMENTAL RESULTS

Fig.2 shows the comparison of various blends of bioethanol with BTE at three different compression ratios. It is clearly seen that for higher compression ratio, the brake thermal efficiency is high because of the direct relationship between them. With the increase in ethanol percentage in the fuel, the BTE is goes on increasing up to a certain extent then decreases and again increases for all the values of compression ratio (CR)s. For lower CR's, E40 blend gives higher BTE and for higher CR, E60 blend gives higher BTE comparably.

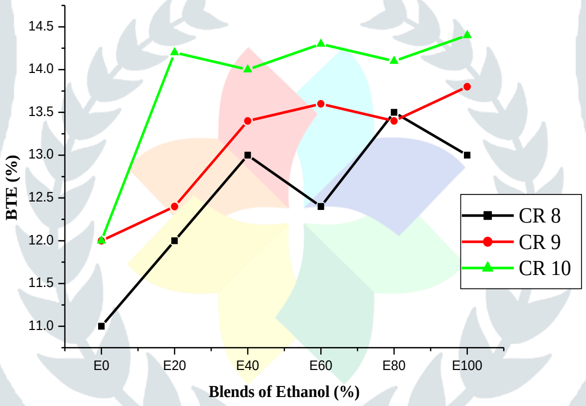

FIG. 2: Various blends of Bio-Ethanol Vs BTE for different compression ratios.

It is clearly seen from the fig.3 that with the increase in the volume percentage of the bioethanol in the fuel, the brake specific fuel consumption (BSFC) increases because the bioethanol is an oxygenated fuel in which the combustion of it takes place very easily. If the compression ratio increases, BSFC decreases because with the increase in compression ratio there is decrease in the clearance volume. It is observed that, BSFC value is low for blends E20 and E40 that too for the CR10.

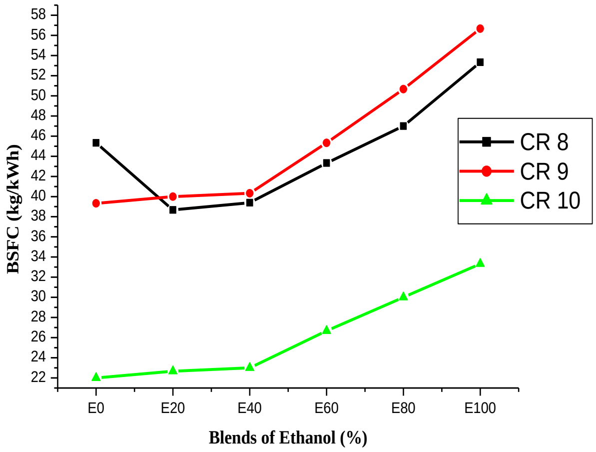

Fig.3: Various blends of Bio-Ethanol Vs BSFC for different compression ratios.

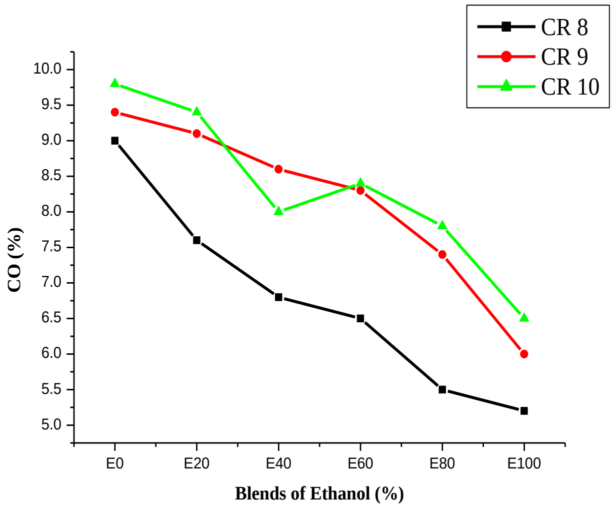

Fig.4: Various blends of ethanol Vs % of CO for 3 different compression ratios

With the increase in the volume percentage of the bioethanol in the fuel, there is a decrease in the percentage of CO because bioethanol contains high amount of oxygen which leads to complete combustion of the fuel. As shown in fig. 4, As the compression ratio increases, the percentage of CO also increases due to the time taken for the combustion of the fuel is low which leads to the formation CO. CO Emissions are less for the low compression ratio that too for the 100% pure ethanol fuel.

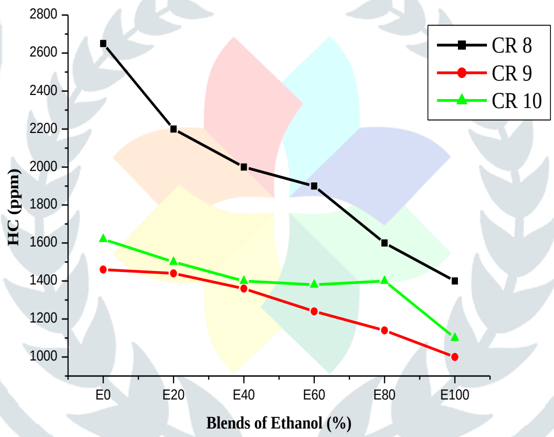

Fig.5: Various blends of ethanol Vs ppm of HC for different compression ratios

Due to the presence of fewer hydrocarbons in the bioethanol fuel, the HC emissions coming out of the engine are also very low compared to gasoline fuel. Thus as observed in the fig.5, the HC emissions are very low with the increase in the percentage of bioethanol in the fuel. If the compression ratio increases, the fuel entering into the engine decreases which leads to the decrease in the HC Emissions. Thus for CR8, the HC emissions are high and for CR9, CR10 the HC emissions are comparably low.

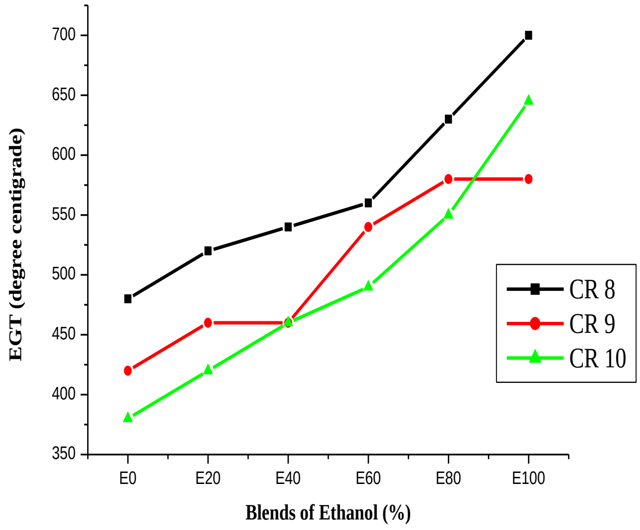

Fig.6 various blends of ethanol Vs EGT for 3 different compression ratios

An EGT value depends on the combustion of the volume of the fuel. Fig.6 clearly explains that with the increase in the compression ratio, there is decrease in the value of EGT because of the combustion of less fuel. With the increase in the percentage volume of the bioethanol in the fuel, there is an increase in the value of EGT because the bioethanol fuel is an oxygenated fuel. Thus there is a complete combustion of that fuel which leads to the increase in the value of EGT.

IV. ESTABLISHMENT OF ANFIS PREDICTION MODEL

A modified Network Based Fuzzy Inference (ANFIS) is a combination of two soft Computing methods of ANN and Fuzzy Logic in such a way that neural network is used to determine the parameters of Fuzzy System. ANN has the ability to construct architectural structures, to develop non-linear models and is used to solve a wide variety of tasks. Fuzzy logic has the ability to change the qualitative aspects of human knowledge and insights into the process of precise quantitative analysis. However, it does not have a defined method that can be used as a guide in the process of transformation and human thought into Rule-base Fuzzy Inference system (FIS), and it also takes quite a long time to adjust the membership functions (MF's). ANFIS largely removes the requirement for manual optimization of the fuzzy system parameters [29]. The Neuro-Fuzzy system with the learning capability of neural network and with the advantages of fuzzy rule base systems can improve the performance significantly and can provide a mechanism to incorporate the past observations into the classification process. With the help of ANFIS, the system is built by Fuzzy Logic Definitions and is then refined using Neural Network Training Algorithms. The architecture of ANFIS is shown in fig.3.

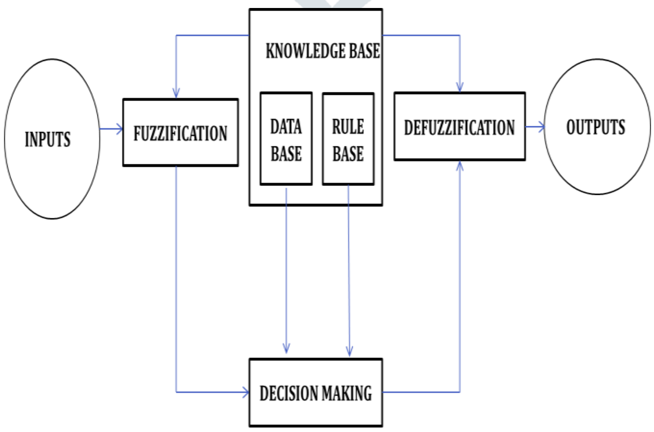

Fig.7 ANFIS Architecture

Since there are many different neural networks and types of fuzzy logic, there are also many types of Neuro-fuzzy implementations. ANFIS is one implementation that has gained some popularity partly because it is included in MATLAB family of products. The basic architecture of ANFIS consists of 5 layers in which the layer 1, layer 4 are adaptive nodes such that in layer 1 inputs adapt one of the membership functions of {trimf, trapmf, gaussmf, gauss2mf, pimf, dsigmf, psigmf} and in layer 4 outputs adapt linear membership function and the remaining nodes are fixed nodes. ANFIS architecture implemented by MATLAB ANFIS toolbox is presented in fig. 7. There are 4 steps to develop an ANFIS model. They are:

1. Load the input and output data patterns.
2. Generate the FIS structure with the help of membership functions.
3. Train the FIS structure with ANN based Algorithms.
4. Test the FIS structure against Training data.

Table 3 shows the selected input-output mapping of the function approximation problem of SI engine combustion performance and emissions.

Since ANFIS works on Takagi Sugeno fuzzy Output (Multiple Input Single Output model, the external data for each output is separately trained and tested. Once the trained data is loaded, Fuzzy Inference (FIS) Structure will be generated so that the system creates mapping between input and output data points with the help of membership functions. For Input Parameters the membership functions are {trimf, trapf, gaussmf, gauss2mf, pimf, dsigmf, gbellmf, psigmf} and for output parameters {linear} should be selected in GENFIS1(GRID PARTITION). Generally, GENFIS 1 is chosen for $< =$ 5 inputs and 1 output and for $>$ 5 inputs and 1 output GENFIS 2 (Sub clustering) is selected. In this paper, there are 9 inputs and 3 outputs so GENFIS2 is best for generating FIS structure. By performing more number of trials, the best values are taken for getting better results. Range of Influence is 0.9, Scale Factor is 0.1, Acceptance Ratio is 0.9 and Rejection Ratio is 0.1. The generated FIS structure is trained with the help of hybrid algorithm and the training error is plotted between epochs and RMSE for BTE, CO, HC separately. The trained FIS structure is tested against the train data and the results can be obtained in rules box. The untrained inputs are given in rules box for which the predictions are obtained.

s.no.	Input Parameters	Output Parameters
1	Percentage of Gasoline (%)	Brake Thermal Efficiency (%)
2	Percentage of Ethanol (%)	
3	Calorific Value (kJ/kg)	
4	Octane Number	CO (%)
5	Specific Gravity	
6	Compression Ratio	
7	Brake Power (kW)	HC (ppm)
8	Mass of Fuel (kg/h)	
9	Exhaust Gas Temperature (^{0}C)	

Table 3: Input-Output mapping for ANFIS

4.1 EXPERIMENTAL VS PREDICTED RESULTS

The following figures 8, 9 and 10 gives a comparison between BTE, percentage of CO and ppm of HC predicted by ANFIS developed in this work against the experimental values taken. The engine operating parameters considered in the analysis are compression ratio, Brake Power, Mass of Fuel and Exhaust Gas Temperature. The output parameters analysed here required different combination of membership functions for input parameters to achieve a desired level of performance. The statistical analysis parameters such as Coefficient of Determination (CoD) and Mean Absolute Percentage Error (MAPE) are found for the testing datasets of 26 rows out of 108 datasets. CoD is given by equation (2) always indicates the proportion of predictor variable from the independent variable. This value should be nearer to unity for a perfect curve fitting relation between the experimental and predicted values (from ANFIS simulation model) in order to specify the goodness of fit function. MAPE value less than 10% demonstrates that any model is successful in predicting the value, same is presented in table 5. It expresses the prediction accuracy as a ratio. In this simulation, 26 values predicted under ANFIS model, have an average MAPE as given in the table 5.

$$CoD\left(R^2\right) = 1 - \frac{\sum\left(y_i - \hat{y}_i\right)^2}{\sum\left(y - \bar{y}_i\right)^2}$$

---- (8)

Where - xj is the experimental value of dependent variable (BTE, CO and HC) and yj is the predicted value of dependent variable (BTE, CO and HC) or predictor.

Where – $\hat{y}_i$ is the output of linear regression of y, $\bar{y}_i$ is the mean of y from the values of i=1 to 26.

y is predictand or dependent variable of all the datasets ranging from i=1 to 26.

MAPE = | xj - yj | / [xj] * 100 **---- (9)**

Performance and Emission parameters	R2 (CoD)	Average of MAPE
CO	0.9636	5.7050
HC	0.9508	6.9442
BTE	0.9497	6.0187

Table 5: Statistical analysis of Experimental and Predicted Data

In the fig 8, it is clearly seen that the experimental and predicted values of BTE with variable compression ratios are nearly equal. Later, multiple regression is performed to relate the dependent variable Brake thermal efficiency with the independent input variables of the model. Brake Power, mass of the fuel, Exhaust Gas Temperature, percentage of bioethanol blend and Calorific Value happened to be most influencing parameters in predicting the Brake Thermal Efficiency for variable compression ratio petrol engines. In the fig 9, it is clearly seen that the experimental and predicted values of CO emissions for variable compression ratios are matching. Multiple regression is carried out to relate the CO value and its influencing parameters. Mass of the fuel (bioethanol blend) and exhaust gas temperature have negative impact on CO emissions. Load is influencing the CO emissions in a direct proportion. The increase in ppm of Hydrocarbons is due to the low temperature region in the combustion chamber. Since the calorific value and octane number of ethanol is higher than the gasoline the formation of hydrocarbons is low. Fig 10 shows the successful curve fitting of predicted Vs. experimental values of HC. It can be seen that 100% pure ethanol the quantity of hydrocarbons is less comparable to other blends. Ethanol has fewer hydrocarbons in its chemical structure than gasoline. Thus by these values it is clearly stated that with the use of ethanol as a blend in the SI engine gives the decrease in the quantity of hydrocarbons. This was visible in multiple regression performed between HC and other input parameters of Brake Power, Mass of the fuel, Exhaust gas temperature and calorific value.

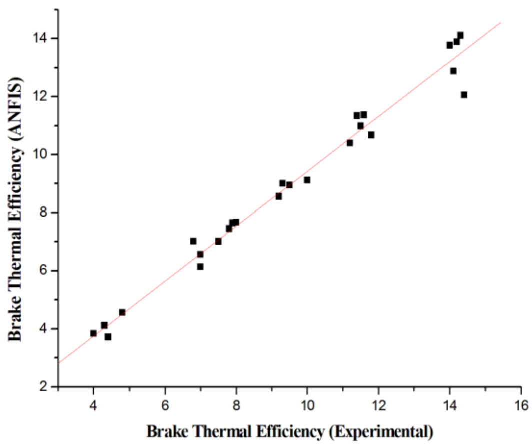

Fig 8. Curve Fitting Diagram of BTE predicted data

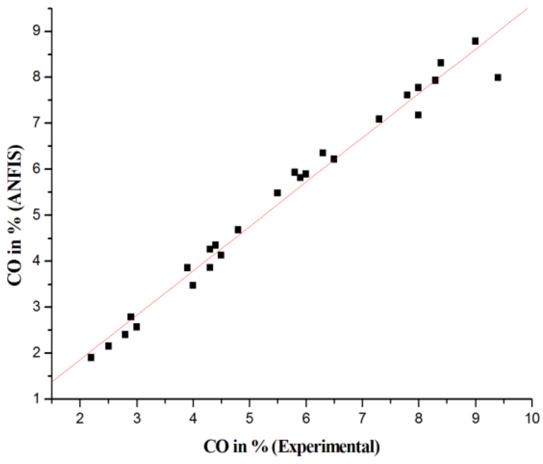

Fig 9. Curve Fitting Diagram of Carbon Monoxide

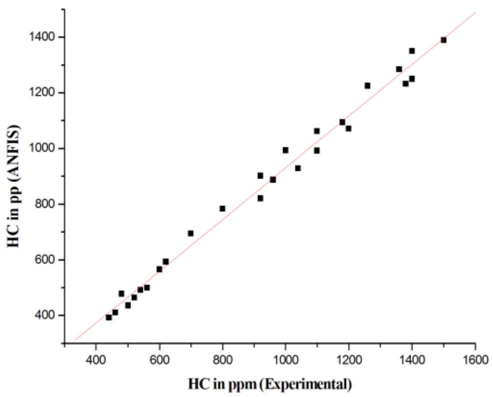

Fig 10. Curve Fitting Diagram of HC predicted data

Overall, ANFIS simulation results are very close to the experimental results indicating that the neuro fuzzy algorithm is able to capture the nonlinear relationship between petrol engine performance and emissions for bioethanol blended fuel.

V. CONCLUSIONS

Biofuel feedstock and usage of biofuels in internal combustion engines will lead to the carbon credit advantage. Bioethanol as a blended fuel choice with petrol engine is a most promising sustainable solution for Indian transportation sector. Bioethanol and its blends of petrol when used in a SI engine will increase the thermal efficiency of the engine and reduces CO and HC emissions. This paper work demonstrated the performance and emission modeling of SI engine operated with bioethanol blends, using a neuro fuzzy approach. ANFIS is more suitable for the problems where there is limited data and performs efficiently saving more time for modeling. The ANFIS predictions of performance and emission parameters for the tested bio-ethanol fueled engine yielded a good statistical performance and convergent results. The R^2 (coefficient of determination) value and prediction accuracy of test data patterns are highly encouraging. This work proves that ANFIS technique can be adopted to SI engine performance and emission modeling when running the engine with bioethanol and its blends. Eventually, increase of bioethanol proportion in blending is a sustainable alternative for gasoline engines. Future work will include development of similar neuro-fuzzy model for diesel engine performance and emissions predictions for both bioethanol and biodiesel blends.

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