Research Inventy: International Journal of Engineering And Science
Vol.14, Issue 3 (March 2024), PP 34-40
Issn (e): 2278-4721, Issn (p):2319-6483, www.researchinventy.com

Prediction of performance and emission attributes of biodiesel blends in a Single Cylinder Engine Using Adaptive Neuro Fuzzy Inference System

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In this study, the grid partitioning practice was employed to generate the Sugeno-based FIS structure in order to launch a relationship among the input factors, and output responses contingent on specific framed rules and an optimum training of the neuro-fuzzy algorithm were contingent on the hybrid learning technique. The performance of the Sugeno was estimated by feeding the input dataset to the fuzzy interface system, and the output response was characterized with reference to a co-relation matrix among the actual and predicted values. The ANFIS model revealed its adeptness with a higher degree of accuracy between the predicted and experimental datasets and demonstrated a good agreement. The strength of the model is assessed using conventional metrics as well as some sophisticated metrics like MAPE, MSRE and NSE, the AI model showed satisfactory results with MAPE of 0.577–2.01% and acceptable RMSE threshold of 0.0093–0.0324. The special error metrics MSRE was 0.0000951–0.00013, NSE was 0.9967-0.9996, and Theil U2 0.019–0.055.

Keywords: *ANFIS, machine learning, NOx, CO, NSE, KGE, Theil U2*

Date of Submission: 05-03-2024 Date of acceptance: 18-03-2024

ANFIS is a fuzzy inference system implemented in an adaptive framework. It is a machine learning algorithm which uses fuzzy inference system integrated in the neural network environment. It has found application in various domains e.g. function approximation, classification, prediction etc. to name a few [1]. In ANFIS, Fuzzy logic membership functions are tuned with the help of hybrid learning algorithm i.e. a combination of least-square method and back-propagation gradient descent method for adapting to the environments. Fuzzy logic brings human-like reasoning feature into the ANFIS [2]. Such hybrid combination provides a dual advantage of human-like reasoning along with an adaptive network which is responsible for refining the fuzzy rules. Such hybrid learning scheme makes it an efficient method for leaning non-linear functions and consequently an efficient and robust predictor [3]. In a traditional fuzzy system, an expert is responsible for crafting the if-else based relationship in between the input and output. On the other hand, ANFIS is adaptive in nature and can automatically tune the fuzzy membership rules according to the environment [4].

The model was trained with part of the database sourced from the experimental results. The database was divided into 2 parts: a checking set and a training set. An endorsed technique in ANFIS was the use of checking set alongside the training set to guarantee model simplification and to avoid over-fitting of the model in the training dataset.[5]

Fuzzy inference system (FIS) as the basis of ANFIS is a technique concerning fuzzy rules that are engaged to derive a new approximated fuzzy-set inference while captivating fuzzy-set as the foundation [6]. FIS is predominantly applied to circumstances in which either the system is extremely complex to be quite sculpted or when the depiction about the reviewing issues are equivocal and confusing [6][7]. An ANFIS model has the following components:

- A grid of rules, some entailing the IF-THEN rules.
- A decision-making component that executes the inference system of the rules.
- A fuzzification system interface, which transfers the input of the system to a fuzzy ruled set processed by a FIS unit.
- A defuzzification system interface, which swaps the fuzzy ruled conclusion to the original output.

FIS is used to map input factors to membership functions (MFs), input MF into a bunch of if-then rule matrices, rules into a set of output responses, output responses into MFs, and the output MFs to output or a decision linked with the output response [8][9]. Typical ANFIS model is comprised of 5 layers with 2 input factors x, y. The very first one is a fuzzy layer in which the membership functions are constructed. The following equation gives a membership function for a node i with a node function *Φ*:

$$K_i^1 = \Phi_{F_i}(y), \qquad \text{Eq (1)}$$

Where, y is an input to the node i, Fi is a membership function for the output K. The second layer is the product layer in which it acts as a simple multiplier [10]. The output of the node can be depicted as follows:

$$K_i^2 = \alpha_i = \Phi_{F_i}(y) \times \Phi_{F_i}(x) \qquad \text{Eq (2)}$$

For i =1, 2, 3,…etc.

α_i is called the firing strengths of all rules framed. The normalized layer is the third layer and is given by the ratio of firing strength to the total strength.

$$K_i^3 = \bar{\alpha}_i = \frac{\alpha_i}{\alpha_1+\alpha_2} \qquad \text{Eq (3)}$$

For i=1, 2, 3 …etc.

The fourth layer is the defuzzyfying layer, in which the consequential parameters further process the output of the third layer [11].

$$K_i^4 = \bar{\alpha}_i g_i = \bar{\alpha}_i(a_i x + b_i y + r_i) \qquad \text{Eq (4)}$$

For i=1, 2,..etc.

The last and final layer is a summing junction where all input signals are added up.

$$K_i^5 = \sum_{i=1}^{2} \bar{\alpha}_i g_i = \frac{\sum_{i=1}^{2} \alpha_i g_i}{\sum_{i=1}^{2} \alpha_i} \qquad \text{Eq (5)}$$

For i = 1, 2,..etc.

In general, the two adaptable parameter sets {a_i, b_i, c_i} termed as premise parameters and {p_i, q_i, r_i} termed as the following parameters are in practice. The goal of the training algorithm intended for this architecture was to tune the overhead parameter sets to sort the ANFIS output maps and the training data [12]. ANFIS supports the Sugeno-type architectures and should have equal and unit weightage value. All membership functions should be either linear or constant type or the rules should not be shared among the membership functions. In this study, 2 input factors and 5 output responses were used. Five necessary modifications can be performed to increase the precision of the network and minimize the errors. These settings include the various membership functions, nature of MFs (i.e., triangular, Gaussian trapezoidal, sigmoid, and bell-shaped), type of output MFs (linear or constant), optimization approach (hybrid or BP), and the number of epochs.

The entire experimental dataset is separated into 2 major classes explicitly training and validation sets and, therefore, 70% of the entire experimental dataset is arbitrarily designated for training, and the residual data set is used for performance analysis of the generated ANFIS predictions[13]. The MATLAB-16 tool box is used for building the designated ANFIS model. At this juncture, the grid partitioning practice was employed to generate the Sugeno-based FIS structure in order to launch a relationship among the input factors, and output responses contingent on specific framed rules and an optimum training of the neuro-fuzzy algorithm were contingent on the hybrid learning technique. Once the training program was completed, the performance of the Sugeno was estimated by feeding the input dataset to the fuzzy interface system, and the output response was characterized with reference to a co-relation matrix among the actual and predicted values.

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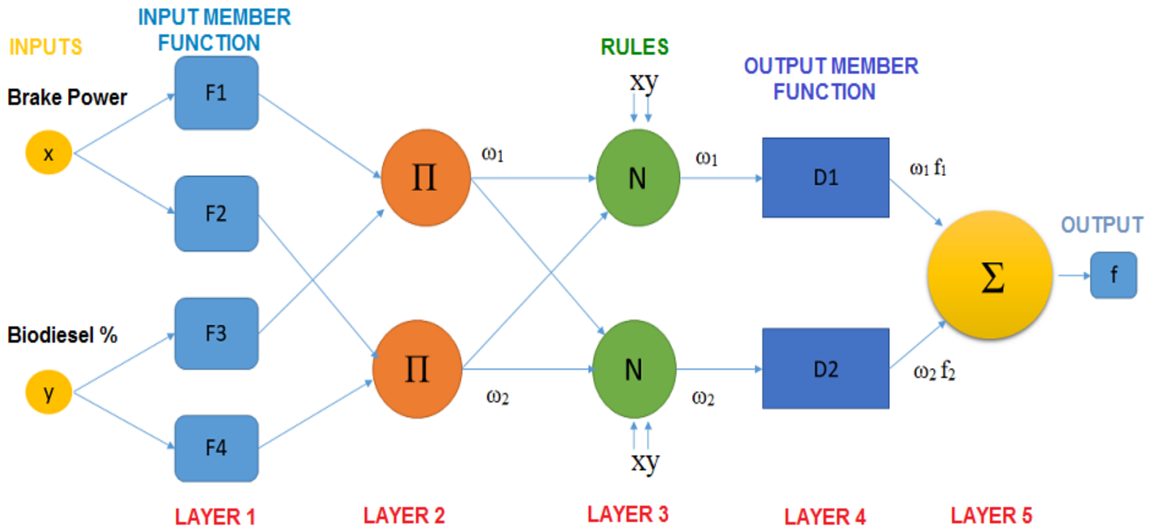

Fig 1: Structure of ANFIS model

3 Modelling with ANFIS: Similar developing strategies such as inputs and responses have been made and divided in a similar fashion as in the case of ANN model development. In this study, Gaussian membership function (gaussmf) with 3 subclasses (High, Medium and Low) was utilized in the development, and an epoch range of 1000 was adopted. This particular hybrid learning algorithm is accountable for initiating the fuzzy-rules and helped make the model learn non-linear problems extremely quickly.

4 The developed AI model was tested on the statistical platform under Correlation coefficient R, mean square error (MSE), and mean absolute percentage error (MAPE). The R depicts the degree of association among the data. RMSE gives the sample SD of the predicted and the observed data. MAPE is the measure of prediction reliability in forecasting method. Mean Squared Relative Error (MSRE) and Nash–Sutcliffe Coefficient of Efficiency (NSE) are special error matrices that are used to measure the strength of the model. The following mathematical formulae were used to quantify the above parameters:

$$R = \sqrt{\mathbf{1} - \left\{\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{\sum_{i=1}^{n}(p_i)^2}\right\}} \qquad \text{Eq 6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{n}} \qquad \text{Eq 7}$$

$$MAPE = \sum_{i=1}^{n}\left|\frac{e_i - p_i}{e_i}\right| \boldsymbol{X}\,\frac{\mathbf{100}}{n} \qquad \text{Eq 8}$$

2 Special performance metrics:

The stability of the model was further analyzed by adopting some special error matrices NSE and MSRE.

$$MSRE_{\,k} = \left|\frac{\mathbf{1}}{n}\,\boldsymbol{x}\,\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{\sum_{i=1}^{n} e_i^{\,2}}\right|_{\mathbf{k}} \qquad \text{Eq 9}$$

$$NSE_{\,k} = \left[\mathbf{1} - \left\{\frac{\sum_{i=1}^{n}(p_i - e_i)^2}{\sum_{i=1}^{n}(e_i - e_m)^2}\right\}\right]_{\mathbf{k}} \qquad \text{Eq 10}$$

Where, $\mathbf{e_i}$, $\mathbf{e_m}$, $\mathbf{p_i}$, and **n** are experimentally obtained value, mean of the experimental data, the model predicted value, and total data set, respectively. K is the model type [14]. The essence of ANN and ANFIS models in this experiment was to test the predictive ability in order to determine the BTE, BSFC, UHC, CO, and NOx for the 4-stroke diesel engine. the Kling-Gupta Efficiency (KGE) was integrated to increase the model evaluation and assessment by associate error recompense to seize and variability modules and thus deliver a more reliable mean of agreement among the model predicted and the actual experimental output values. [15]. KGE is given in Equation 11.

$$KGE = \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad \text{where } \alpha = \sigma_p / \sigma_a \text{ and } \beta = , \overline{e_i} / \overline{p}_i \qquad \text{Eq 11}$$

Where, n is the number of experimental data set, $\boldsymbol{i}$ is the iteration number, $\boldsymbol{e_i}$ is the actual experimental output, $\boldsymbol{p_i}$ is the model predicted value, K is the Pearson's coefficient, , $\overline{\boldsymbol{e}}_i$ is the mean of the actual experimental output. $\overline{\boldsymbol{p}}_i$ is the mean of the model predicted data σ_a is standard deviation of actual experimental output and σ_p is the standard deviation of the model predicted data [16].

3 Model Uncertainity: In the present study, Theil uncertainty recognized as "Theil U2" [1], [7] method was adopted in the interest of approval and the assessment of prediction quality of proposed AI-based models. The following equation gives the mathematical equation of uncertainty:

$$[\mathbf{U2_{Theil}}]_{\mathbf{k}} = \frac{\sqrt{\sum_{i=1}^{n}(o_i - t_i)^2}}{\sqrt{\sum_{i=1}^{n}(t_i)^2}} \qquad \text{Eq 12}$$

The essence of ANFIS models in this experiment was to test the predictive ability in order to determine the BTE, BSFC, UHC, CO, and NOx for the 4-stroke diesel engine.

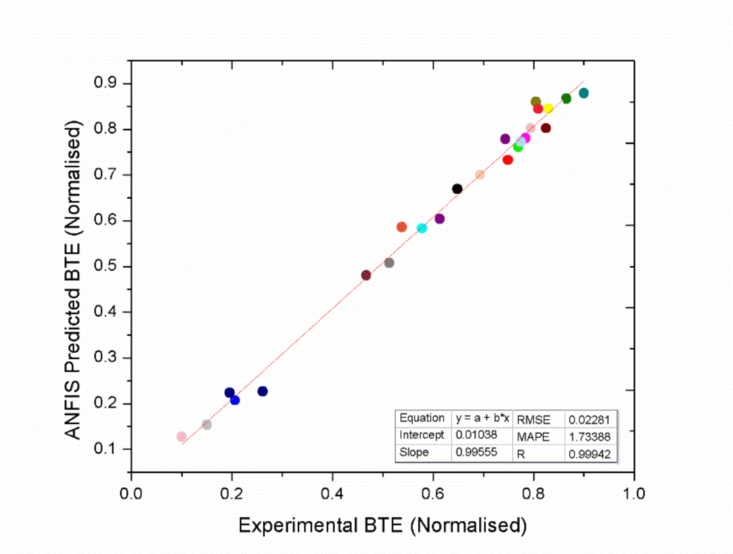

Figure 2: Comparison of Experimental BTE and ANFIS Predicted BTE

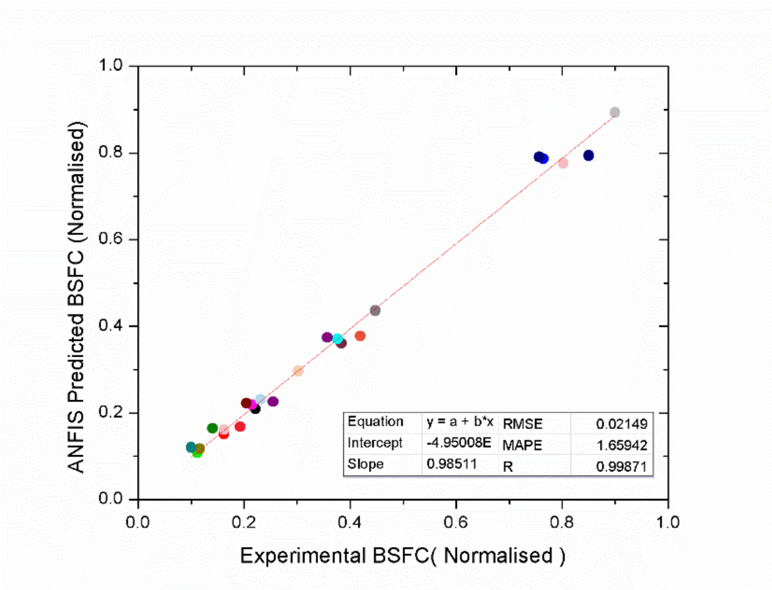

Figure 3 : Comparison of Experimental BSFC and ANFIS Predicted BSFC

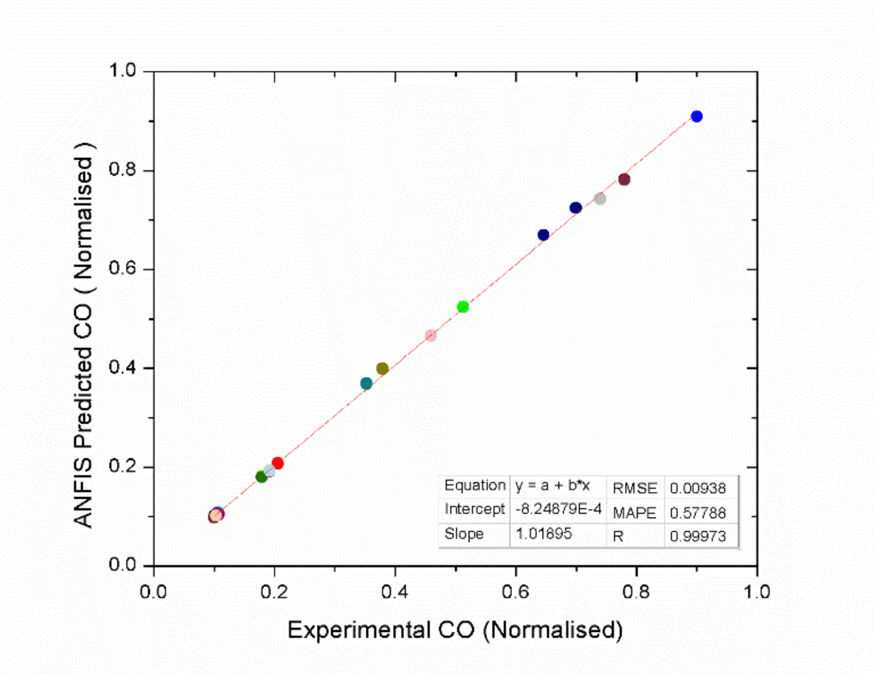

Figure 4 : Comparison of Experimental CO and ANFIS Predicted CO emission

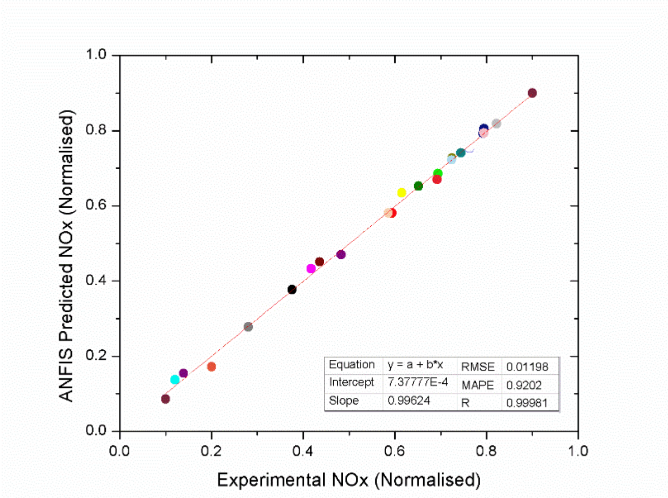

Figure 5 : Comparison of Experimental NOx and ANFIS Predicted NOx

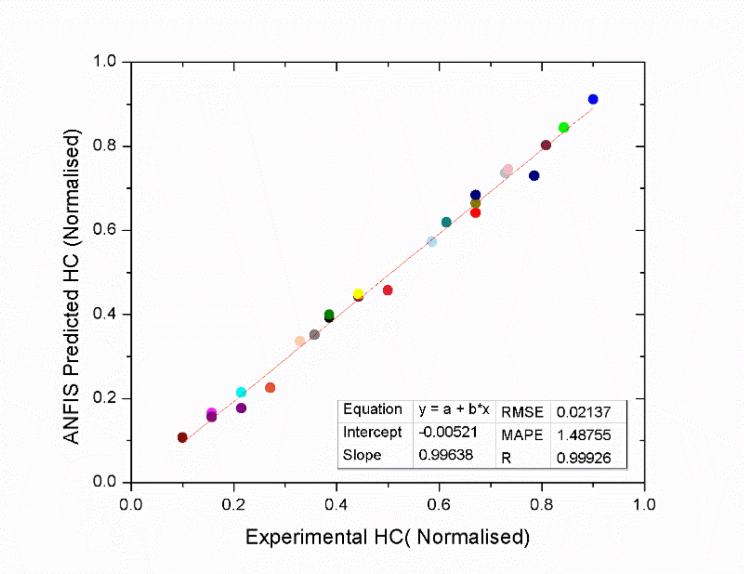

Figure 6 : Comparison of Experimental HC and ANFIS Predicted HC emission

	BTE	BSFC	HC	CO	NOx
RMSE	0.022806	0.021486	0.02137	0.009379	0.011985
MAPE	1.733882	1.659421	1.487546	0.577881	0.920202
MSRE	4.7E-05	9.9E-05	5.84E-05	2.16E-05	1.51E-05
R	0.999423	0.99871	0.999259	0.999732	0.999812
Theil U2	0.03428	0.049747	0.038196	0.02322	0.019437
NSE	0.998825	0.997525	0.998541	0.999461	0.999622
KGE	0.99914	0.9991	0.99847	0.99231	0.99484

The numerical divergence and the statistical errors of the experimental and both model predicted values of the test points are demonstrated and compared in table 1 which depicts the robustness of the models in mapping the performance-emission responses of the test engine with the pilot fuels. On the continuous assessment of the engine performance metrics, BTE with that of the predicted values generated by the ANFIS models produced correlation coefficient (R) of the order 0.9994. A noteworthy covenant of ANFIS predicted, and experimental values of BTE recorded MAPE of 1.733, respectively. Afterward, they are escorted by marginal RMSE values of 0.022806, respectively. The ANFIS model produced shallow MSRE scores, 0.000047. Subsequently, the special performance metrics NSE of ANFIS is 99.88%, and KGE 0.99914 respectively. Similarly, another engine performance metric BSFC produced Regression value of 0.9987, ANFIS generated MAPE of 1.76 and 1.65 and very low MSRE of 0.000132 and 0.0000989, respectively. And again, they are followed by 99.67% and 99.75% NSE as well as 0.99061 and 0.99847 respectively. Furthermore, the experimental data sets of engine emission responses HC, CO and NOx, and that of ANFIS predicted datasets produced 0.9992, 0.9997 and 0.99981. The MAPE values of ANFIS model are 1.48, 0.577 & 0.92 respectively. A moderate presentation on MAPE for HC, CO, and NOx ANFIS models were found to be 1.487%, 0.577 and 0.92, respectively. It can be seen that the MSRE and RMSE are also very low. The special error metrics NSE of ANFIS model are 99.85%, 99.94%, and 99.96%. Similarly, another special performance metrics, KGE of ANFIS model are 99.847%, 99.231 and 99.484 the respectively.

During the test validation process, the results indicated that the MAPE for all output parameters in ANFIS models was <2%, and RMSE was in the acceptable threshold. The average values of MAPE and RMSE obtained in this experiment for ANFIS models were 1.063% and 0.0174, respectively.

Conclusion:

The ANFIS model also showed its adeptness with a higher degree of accuracy between the predicted and experimental datasets and demonstrated better agreement. The proposed model has MAPE range of 0.577-1.73, and RMSE range of 0.009-0.022. The special error metrics, MSRE of 1.51E-5-9.9E-5 and Theil U2 of 0.019 – 0.049 and special performance metrics like NSE of 99.8%- 99.9% and KGE of 99.23%-99.91% demonstrates the robustness of the model.

The AI model showed satisfactory results and proved their ability in predicting the emission-performance paradigm precisely with shallow and acceptable threshold of error metrics and scored high in performance metrics also.

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