Prediction of Performance and Emission Attributes of Biodiesel Blends in a Single Cylinder Engine Using Artificial Neural Networks

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Abstract: ***The present investigation delivers a comprehensive viewpoint on the current artificial intelligence (AI) meta-modelling in diesel engine system, particularly in the domains of multi-objective optimization. A Lavenberg–Marquardt feed-forward backpropagation learning algorithm was perceived to be good for ANN. The ANN 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: Artificial intelligence, diesel engine optimization, Accuracy metrics, error analysis

1. Introduction

Motivated by the biological neural system, a neural network approach for a specific problem includes 2 stages: the training stage and the implementation stage. During the training stage, the network is trained using training data. In general, the input and output test data are first normalized between 0 and 1. The normalized test data is fed to the neural network for training the model. The entire experimental test dataset can be split into 3 sets. Initially, 70% of the dataset is employed to train the model, the second set of 15% is utilised to test the model, and the remaining 15% is accustomed to validate the perception capability of the model. Training is performed via sequentially feeding inputs and fine-tuning network weights in accordance with a predetermined procedure. Subsequent to training, the networks are verified through another input and output data set. Once the training and testing of the network are completed, the network is prepared for validation. Haykin [1], [2] provided the analytical background of the testing, training, and validating strategies of ANN.

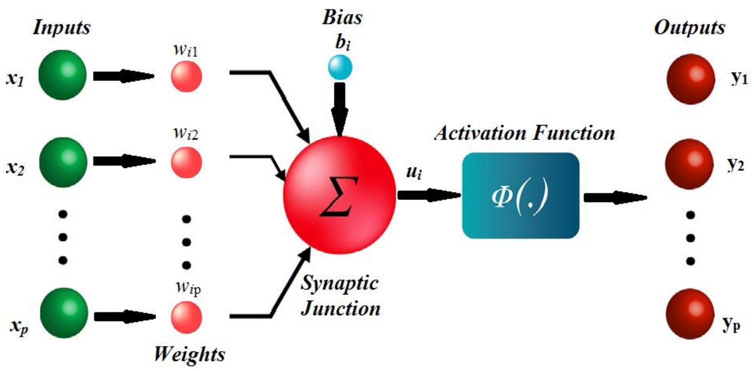

Figure 1: Schematic of a neuron model

Eq. 1 and 2 depict the detailed descriptive illustration of a typical neuron model, which is established on the ANN technique, as follows:

$$u_i = \sum_{j=1}^{p} w_{ij} x_j \quad (1)$$

$$y_j = \varphi(u_i + b_i) \quad (2)$$

In Eq. (2), b_i signifies the bias value, which has the facility to increase or decrease the net input score for activation function. The Inputs are designated by $x_1, x_2, x_3, \ldots, x_p$ as well as weights by $w_{i1}, w_{i2}, w_{i3}, \ldots, w_{ip}$ for neuron j. u_i turns to the linear combiner of the output through the input signals. While φ (.) as the activation function and y_j is the output signal to the neuron, respectively.

The proposed Multiple-input Multiple-Output (MIMO) model has 3 layers. Each layer can dwell with any number of neurons. Usually, it is a 3-layer model of input, output, and hidden layers. The input layer consists of 2 neurons, and the output layer consists of 5 neurons. The parameters for the input layer are load on the engine and biodiesel percent, and the corresponding parameters for the output layer are BSFC, BTE, CO, UHC, and NOx to develop an ANN model. An essential step when designing a neural network is the training procedure, whereby an input is brought into a network alongside the desired output. On the other hand, weights and biases in value are controlled through, first, by selecting them randomly and then adjusting to ensure that the network attempts to give the desired output [3] [4]. A feed-forward neural network (FFNN) [5] with a back proragation learning algorithm (BP) has been utilised for training the model, which is widespread in the recent times, and it is built on the MATLAB-16 toolbox. Features such as simplicity and feeding the gradient back to the network support in building a robust network ANN knowledge of predicting the weight of the particular neuron has been enhanced through the use of BP algorithms. BP has 2 phases: the processing of knowledge from the input layer to the output layer and comparing the feedforward value and the output value to give tolerance and the error value [6]. Among the distinct training algorithms, TrainLM (Lavenberg–Marquardt) was selected owing to its ability of quick learning by updating the bias values and weights. The algorithm always trims up the performance function, which makes it a quick learning algorithm. With the adoption of TrainLM Training function, LearnGDM [7] adaptive learning function and Tangent-sigmoid transfer function, the proposed model gave satisfactory results [8], [9]. An adaptive learning function, LearnGDM, was selected to keep the objective function to a minimum. The Selection of Transfer function was based on the type of input and output indices. In the present study, the Tangent–Sigmoid transfer function was used to develop the architecture of the model in order to avoid nonaligned learning. After the training procedure is achieved, weights give crucial information, although they are initially deemed unhelpful before training. After attaining a satisfactory level of performance, the training is halted, and the network utilizes these weights to reach a decision. The neurons of the hidden layer varied from 10 to 25 in order to have a better fit to the data with the Correlation coefficient R, MSE, RMSE, and MAPE as the model testing performance indices. In addition to the above mentioned conventional metrics, some special error metrics like MSRE, Theil U2 and performance metrics like NSE, and KGE were also utilized in this study.

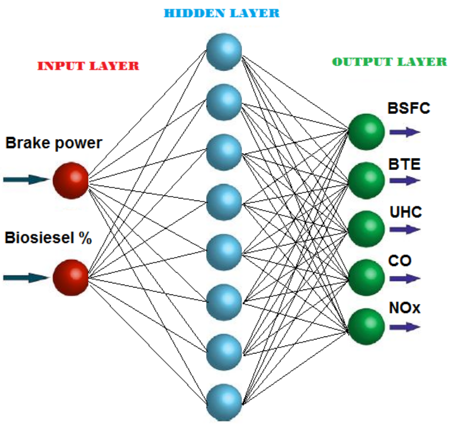

Figure 2: ANN Structure

2. Modelling with ANN

A set of 250 data sets were used in modelling. The entire test data was normalized according to the formula in Eq. 3 in order to bring the uniformity among the engine responses. Moreover, the diversity in the range of the inputs and outputs may affect the overall performance of the model. The parameters were kept between 0.1 and 0.9 instead of 0 and 1 to eliminate premature saturation in the activation function (sigmoid) [10].

$$\text{Normalised value} = \frac{AcV - MiD}{MxD - MiD} \times (\text{Hi} - \text{Lo}) + \text{Lo} \qquad \text{Eq[3]}$$

Where, **AcV, MiD,** and **MxD** are Actual, Minimum, and Maximum values of the parameter. **Hi,** and **Lo** are limiting, which takes 0.9 and 0.1, respectively.

The proposed MIMO network comprised of an input layer consists of 2 neurons, and the output layer consists of 5 neurons [11]. The figure 4.3 gives the topology of the best fit. (2-10-5) with an overall R value of 0.9961.

3. Model Graphs

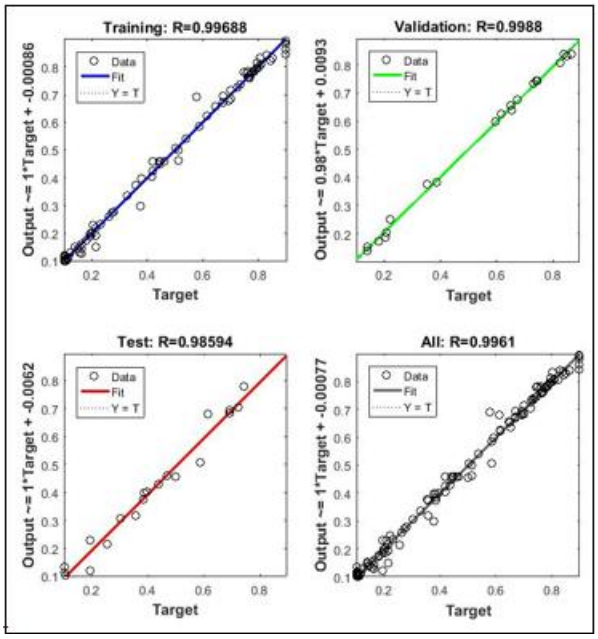

Figure 3: Topology of the best fit

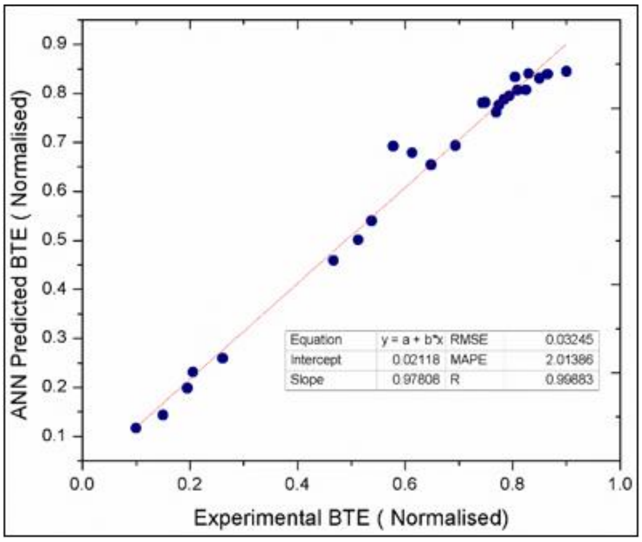

Figure 4: Comparison of Experimental BTE and ANN Predicted BTE

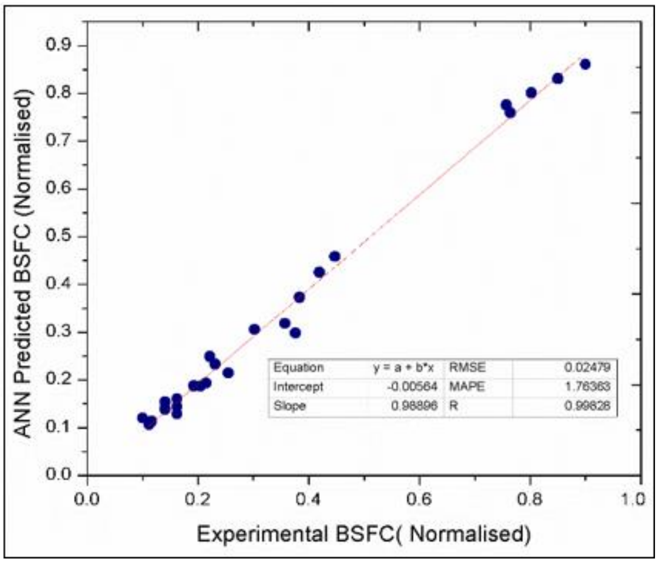

Figure 5: Comparison of Experimental BSFC and ANN Predicted BSFC

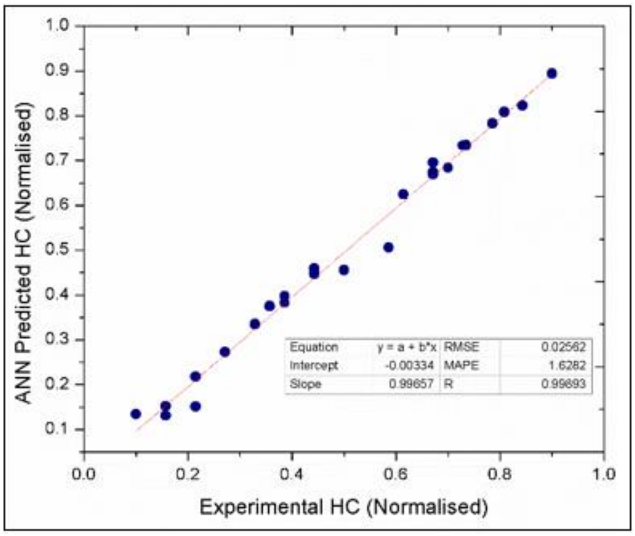

Figure 8: Comparison of Experimental HC and ANN Predicted HC emissions

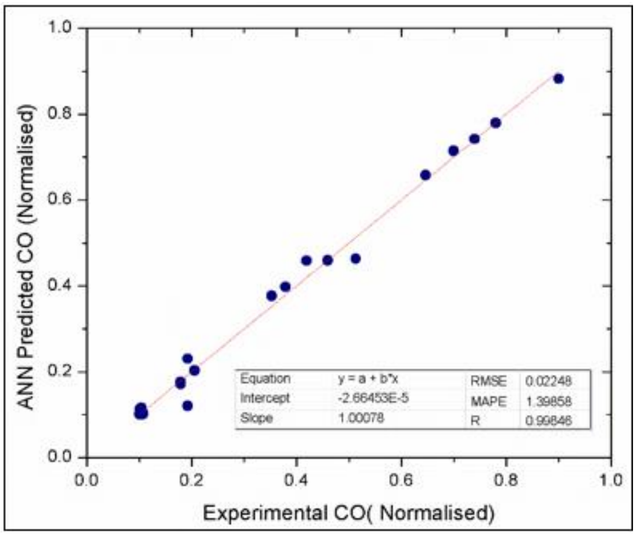

Figure 6: Comparison of Experimental CO and ANN Predicted CO

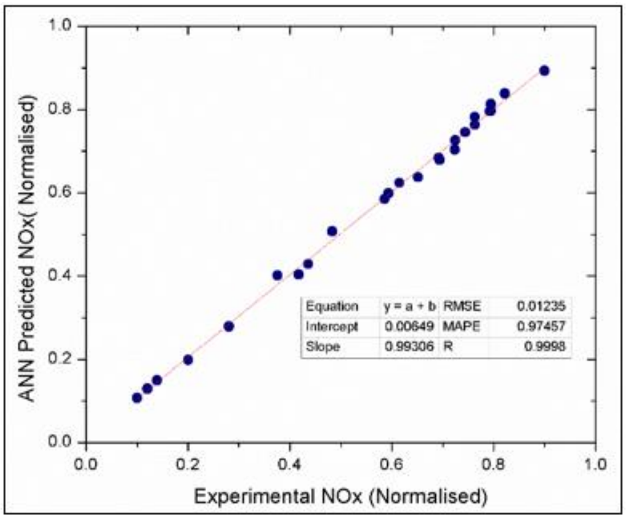

Figure 7: Comparison of Experimental NOx and ANN Predicted NOx

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)[1] 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:

$$R = \sqrt{\mathbf{1} - \left\{\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{\sum_{i=1}^{n}(p_i)^2}\right\}} \quad \text{Eq 4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(e_i - p_i)^2}{n}} \quad \text{Eq 5}$$

$$MAPE = \sum_{i=1}^{n}\left|\frac{e_i - p_i}{e_i}\right| X \frac{100}{n} \quad \text{Eq 6}$$

1) Special performance metrics:

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

$$MSRE_{\,k} = \left|\frac{1}{n} x \frac{\sum_{i=1}^{n}(e_i - p_i)^2}{\sum_{i=1}^{n} e_i^2}\right|_{k} \quad \text{Eq 7}$$

$$NSE_{\,k} = \left[\mathbf{1} - \left\{\frac{\sum_{i=1}^{n}(p_i - e_i)^2}{\sum_{i=1}^{n}(e_i - e_m)^2}\right\}\right]_{k} \quad \text{Eq 8}$$

Where, $\mathbf{e_i}$, $\mathbf{e_m}$, $\mathbf{p_i}$, and $\mathbf{n}$ are experimentally obtained value, mean of the experimental data, the model predicted value, and total data set, respectively. K is the model type [12]. The essence of ANN model 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. [13]. KGE is given in Equation 9.

$$KGE = \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2}$$ where $\alpha = \sigma_p / \sigma_a$ and $\beta = , \overline{e_i} / \overline{p_i}$ Eq 9

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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, , $\bar{\boldsymbol{e}}_i$ is the mean of the actual experimental output. $\bar{\boldsymbol{p}}_i$ 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 [3].

2) Model Uncertainity

In the present study, Theil uncertainty recognized as "Theil U2" [1], [10] 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:

$$[U2_{Theil}]_k = \frac{\sqrt{\sum_{i=1}^{n}(o_i - t_i)^2}}{\sqrt{\sum_{i=1}^{n}(t_i)^2}} \quad \text{Eq 10}$$

The essence of ANN model 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 overall R value of the network proposed was found to be 0.996. Table 1 shows the aggregate performance data of the model, which shows that both the proposed models were found to be satisfactory.

Table 1: Performance and error metrics

	BTE	BSFC	HC	CO	NOx
RMSE	0.03244 5	0.02478 8	0.02562	0.02247 9	0.01234 7
MAPE	2.01386	1.76362 7	1.62820 4	1.39857 7	0.97456 7
MSRE	9.51E-05	0.00013 2	8.39E-05	0.00012 4	1.6E-05
R	0.99883 1	0.99828 3	0.99893 4	0.99845 7	0.99980 1
Theil U2	0.04876 9	0.05739 1	0.04579 3	0.05565 2	0.02002 5
NSE	0.99762 2	0.99670 6	0.99790 3	0.99690 3	0.99959 9
KGE	0.99045	0.99061	0.99064	0.99023	0.99039

4. Results and Discussion

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 ANN is produced correlation coefficient (R) of the order 0.998. A noteworthy covenant of ANN predicted, and experimental values of BTE recorded MAPE of 2.013 and 1.733, respectively. Afterward, they are escorted by marginal RMSE values of 0.032445 and 0.022806, respectively. The RMSE of ANN values of 0.0000951. Subsequently, the special performance metrics NSE of ANN is 99.76 % and KGE of 0.99045 respectively. Similarly, another engine performance metric BSFC produced Regression value of 0.9982. Subsequently, the experimental and predicted data sets of ANN MAPE of 1.76 and very low MSRE of 0.000132, respectively. And again, they are followed by 99.67% NSE as well as 0.99061 respectively. Furthermore, the experimental data sets of engine emission responses HC, CO and NOx, and the ANN predicted data sets generated regression of 0.9989, 0.9984 and 0.9998 produced 0.9992, 0.9997 and 0.99981 followed by the ratio The MAPE values ANN model are1.62, 1.39 & 0.974. A moderate presentation on MAPE for HC, CO, and NOx of both ANN is found to be 1.628% and 1.487%, 1.398 and 0.577 and 0.974 and 0.92, respectively. It can be seen that the MSRE and RMSE are also very low. The special error metrics NSE of ANN model for emission profiles are 99.79%, 99.69% and 99.95%. Similarly, another special performance metrics, KGE of ANN model are 99.064%, 99.023 % and 99.039% respectively.

During the test validation process, the results indicated that the MAPE for all output parameters in both the ANN models was <2%, and RMSE was in the acceptable threshold. The average values of MAPE and RMSE obtained in this experiment for the ANN models were 1.524%, 1.063%, respectively. Accordingly, the predictive ability of the output parameters through the ANN models from this article was confirmed to be better than that reported in the literature

5. Conclusion

Artificial Intelligence is one of the significant ways to forecast the performance and emission paradigm of an internal combustion engine and can be adopted to solve significant problems in engineering science. Motivated by the biological neural system, a well-trained ANN is a feasible prognostic model and a data-processing complex structure like IC engines. And again. which unites the advantages of both neural networks with a humanlike cognitive thinking like fuzzy logic, is a robust system identification tool. In the present study, an endeavor was made to investigate the performance-emission paradigm of a single cylinder 4-stroke DICI engine fueled with different blends of diesel, methyl esters of cottonseed biodiesel and DEE blends and the entire experimental data set is fed to the two AI model (ANN), which were incorporated to test the inherent capability of predicting the engine responses BSFC, BTE, HC, CO, and NOx with brake power and percent of biodiesel as input parameters. The following conclusions were drawn from the analysis:

A Lavenberg–Marquardt FFBP (TrainLM) learning algorithm is thus the ideal model for ANN. The proposed ANN model proved its expertise with a good accuracy among the experimental and predicted datasets and showed a decent fit. The model produced MAPE range of 0.974-2.013, and RMSE range of 0.012-0.032. The special error metrics like MSRE of 1.6E-05-0.00013 and Theil U2 of 0.02 – 0.057 and special performance metrics like NSE of 99.6%- 99.9% and KGE of 99.02%-99.06% demonstrates the robustness of the model.

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