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ANN-BASED PREDICTION OF DIESEL ENGINE PERFORMANCE AND EMISSIONS USING TAMARIND BIODIESEL BLENDED WITH IRON OXIDE (II, III) NANOPARTICLES

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ABSTRACT

This paper presents an artificial neural network model that was developed to accurately predict the performance and emission characteristics of a diesel engine fueled with tamarind biodiesel blends enhanced with iron (II, III) oxide nanoparticles. The model uses input parameters, such as the biodiesel blend ratio, nanoparticle concentration, engine load, and calorific value. Kolmogorov's theorem is applied to vary neurons number from 5 to 9 in the hidden layer, while the Levenberg-Marquardt (Trainlm) algorithm is used for training with the backpropagation method for prediction. Optimal ANN architectures for performance parameters, including specific fuel consumption (SFC) and brake thermal efficiency (BTE) were 4-5-1 and 4-6-1, with respective RMSE/MAPE values of 0.0101/1.865 and 0.6153/1.982. For emission parameters (HC, CO, NOx, and smoke), the best models were 4-9-1, 4-5-1, 4-6-1, and 4-6-1, with RMSE of 0.0087, 0.1850, 19.7955, and 1.0502 and MAPE values of 5.1731, 2.9295, 1.6329, and 1.3463, respectively. These results highlight the effectiveness of ANN in modeling complex engine behaviors and the potential of nanoparticle-enriched tamarind biodiesel as a sustainable, low-emission alternative fuel.

Keywords: Tamarind Biodiesel, Iron Oxide (II, III) Nanoparticles, Artificial Neural Network, Diesel Engine, Performance Prediction, Emission Characteristics.

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INTRODUCTION

Growing concerns about environmental pollution and the depletion of petroleum resources have shifted the focus toward renewable and sustainable energy alternatives. Biodiesel, a renewable fuel produced from animal or vegetable fats, is a promising alternative to conventional diesel. A major advantage of biodiesel is its potential to significantly reduce harmful exhaust emissions, such as carbon monoxide, hydrocarbons, and particulate matter, while maintaining fuel efficiency comparable to traditional diesel. However, challenges remain, particularly in the control of nitrogen oxides (NOx), which are difficult to control during the combustion of biodiesel blends. To address these issues, researchers have explored various methods for improving the performance and emission parameters of biodiesel-powered diesel engines. One approach involves the addition of nanoparticles, like iron (II, III) oxide nanoparticles, to biodiesel blends, which has demonstrated improvements in fuel properties and engine performance. For instance, Y. *et al.*[1] observed significant performance gains and emission reductions in diesel engines using orange peel-based biodiesel with cerium oxide nanoparticles, with improvements of 12% in performance and reductions in smoke, CO, and NOx emissions of 7%, 6.5%, and 27%, respectively. Similarly, Bitire *et al.*[2] examined the use of green-synthesized copper oxide nanoparticles in parsley biodiesel, which resulted in a 33.8% increase in BTE, a 3.28% decrease in BSFC, and reductions in CO, HC, and NOx emissions by 5.7%, 1.6%, and 4.7%, respectively. Further studies have explored varying

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nanoparticle dosages and their effects on performance and emissions. Gad *et al.*[3] tested titanium, alumina, and carbon nanotube (CNT) nanoadditives in waste-cooking biodiesel blends and observed in thermal efficiency improvement of 6, 4, and 11.5%, along with reductions in HC, CO, and smoke emissions. However, these studies also noted an increase in the NOx emissions. Jit Sarma *et al.*[4] demonstrated that titanium oxide nanoblended mahua biodiesel significantly reduced HC, CO, and NOx emissions by 2.8%, 46.54%, and 2.3%, respectively. Similarly, Muthusamy *et al.*[5] found that adding Fe_3O_4 nanoparticles to pongamia-based biodiesel improves its performance and decreases harmful emissions. Hosseini *et al.*[6] observed that nanoscale graphene oxide in *Ailanthus altissima* biodiesel reduced CO and HC emissions but increased CO_2 and NOx emissions. Over the past few years, artificial neural networks have emerged as powerful tools for modeling and forecasting the performance of diesel engines running on biodiesel blends. ANN, inspired by neural networks of the human brain, can learn from data and make predictions based on identified patterns. Researchers have successfully applied ANNs to forecast the engine performance and emissions with high accuracy. Rao *et al.*[7] used ANNs to study the impact of rice bran biodiesel with isopropanol fuel additive on diesel engine characteristics, demonstrating the effectiveness of the back-propagation algorithm for training. Leo *et al.* [8] reported a high predictive accuracy for engine performance and emissions using ANN models with correlation coefficients (R^2) close to 1.0. Similarly, Ramalingam *et al.*[9] and Muralidharan *et al.*[10] used ANNs to predict the performance of biodiesel blends, achieving a high accuracy in emissions and performance forecasting. Roy *et al.*[11] applied ANNs to model a 1-cylinder 4-stroke engine under various EGR strategies, also achieving high correlation coefficients. Odufuwa *et al.*[12] employed an Artificial Neural Network (ANN) model to forecast the efficiency and emissions of mini-diesel engines, achieving regression (R) values exceeding 0.9 and a mean squared error (MSE) of 0.0046 across various configurations. Srinivasarao *et al.*[13] examined the impact of compression ratio variations on diesel engine performance and emissions, achieving high accuracy with R values between 0.99951 and 0.99998 and a mean absolute percentage error (MAPE) ranging from 0.346 to 3.339%. The primary purpose of this study is to develop an accurate artificial neural network (ANN) model capable of predicting the performance and emission characteristics of a diesel engine fueled with tamarind biodiesel blends enhanced with iron (II, III) oxide (Fe_3O_4) nanoparticles. While several studies have explored biodiesel as an alternative fuel and others have applied ANN for engine performance prediction, limited research exists on the integration of ANN modeling with experimental analysis involving nanoparticle-enriched biodiesel blends, especially using tamarind oil as a feedstock. Furthermore, the combined influence of critical parameters such as biodiesel blend ratio, nanoparticle dosage, engine load, and calorific value has not been thoroughly modeled using advanced machine learning approaches. This study addresses this gap by offering a predictive tool that minimizes the reliance on extensive engine testing, thereby enhancing the evaluation of biofuels in a cost-effective and time-efficient manner.

EXPERIMENTAL

Experimental Engine Setup

The experimental setup comprised a Kirloskar TV-1 instrumentation unit integrated with a single-cylinder, four-stroke diesel engine and an eddy current dynamometer. The engine, rated at 5.2 kW and operating at a constant speed of 1500 rpm, was coupled with the dynamometer to apply controlled loads for a precise performance evaluation. The Kirloskar TV-1 unit housed essential instruments for monitoring key parameters, including the torque, speed, exhaust gas temperature, and fuel consumption, via a dedicated control panel. The torque (in N·m) and engine speed (in rpm) were electronically measured, while the inlet air suction was monitored to assess the intake efficiency. The exhaust gas temperature served as an indicator for analyzing the brake thermal efficiency, and the specific fuel consumption was calculated to evaluate the emissions. Real-time data acquisition enabled the continuous monitoring and analysis of engine performance using diesel fuel. A schematic of the experimental setup is shown in Fig.-1.

Parameter Selection for the Input and Output

The input and output variable selection for ANN modeling in the context of internal combustion engines using nanoblends is crucial for identifying variables that significantly impact performance and emission

characteristics. The input variables included the biodiesel blend ratio, nanoparticle concentration, engine load, and calorific value (CV). The output parameters should focus on key performance metrics such as the BTE, SFC, and emission levels, including NOx, CO, HC, and smoke density.

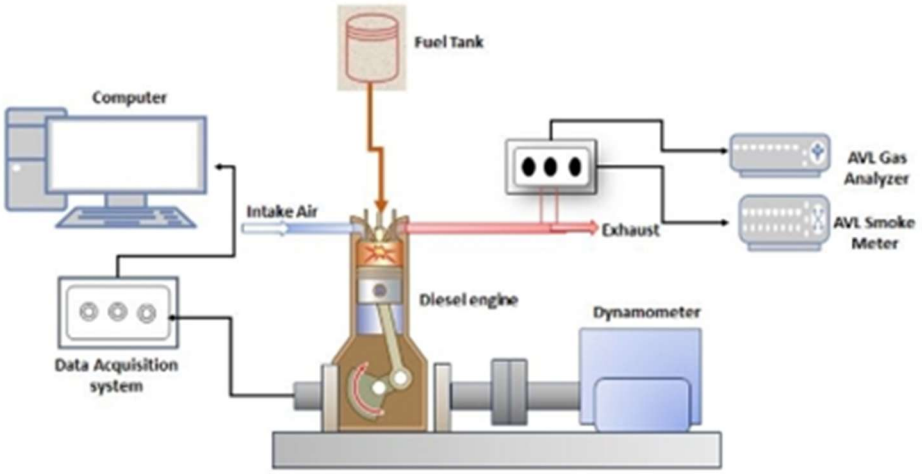

Fig.-1: Diagrammatic Layout of the Experimental Engine Setup

The dataset was divided into 3 parts: 70% (training), 15% (validation), and 15% (testing). The ANN model's structure must be carefully designed with an appropriate number of neurons, and its accuracy is validated against experimental data using statistical metrics, such as RMSE, MAPE, and R^2. This meticulous selection and validation process ensures that the ANN model accurately predicts engine behavior under various conditions.

Development of ANN Models for Diesel Engines

The engine modeling process facilitates the simulation and analysis of engine operations, enhancing our understanding of their behavior. MATLAB 2023a was used to predict the performance and emission parameters. The performance of the model was evaluated during the training and validation phases, with careful adjustment of the network variables, including neuron counts in the hidden layer. ANNs perform an initial linear transformation through individual neurons, followed by a nonlinear transformation via activation functions, allowing them to capture both nonlinear and linear data features. Their adaptability and efficiency in modeling intricate relationships make ANNs particularly effective for simulating internal combustion engine behavior, where fuel and engine parameters influence the performance in diverse nonlinear ways. This study utilizes a feed-forward backpropagation (FFBP) model, which is well regarded for its ability to effectively solve nonlinear problems.

Choice of the Network Patterns

Figure-2 illustrates the layout of the feedforward backpropagation (FFBP) network architecture. The network comprises 3 layers, i.e, input, hidden, and output layers. For each parameter to be predicted, the network included 4 inputs and 1 output neuron. Different network topologies were developed for each parameter, specifically 4-5-1, 4-6-1, 4-7-1, 4-8-1, and 4-9-1, and the 4-6-1 topology is shown in Fig.-2. The Kolmogorov theorem was used to establish the range of neuron numbers in the hidden layer, because it is critical for the functioning of the artificial neural network.

$$No.of\ hidden\ layers\ neurons\ \leq\ No.of\ input\ layer\ neurons\ +1 \qquad (1)$$

$$\sqrt{\frac{No.of\ hidden\ layers\ neurons}{(No.of\ input\ layer\ neurons * No.of\ output\ layer\ neurons)}} \qquad (2)$$

The hidden layer neuron count was adjusted from 5 to 9, based on the equations provided in Eqs. (1) and eq. (2). The Levenberg-Marquardt backpropagation algorithm (trainlm) was employed to train the models because it offers faster convergence and requires fewer epochs. Selecting an appropriate transfer function is crucial in ANN development because it converts inputs into outputs for the network. In general,

continuous and differentiable functions, particularly nonlinear functions, yield better results. As a result, this study utilized a tan-sigmoid transfer function with the Mean Squared Error as the performance metric.

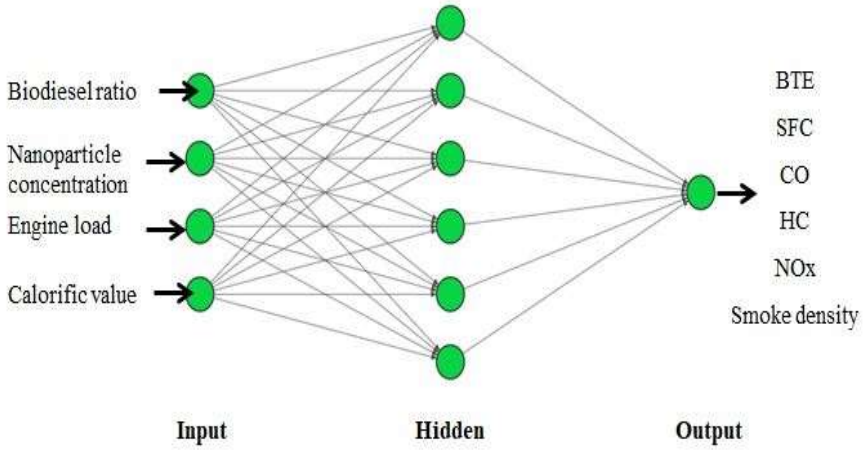

Fig.-2: Schematic Representation of the Developed Network Structure

ANN Model Evaluation Indices

To assess the predictive performance of the ANN model, we employed the correlation coefficient (R), aligned with approaches used in similar studies.[14-15] Most studies on ANN application in the performance and emission parameters of diesel engines[16-17] have assessed model accuracy using statistical error metrics, particularly the Mean-Absolute Percentage Error (MAPE) and Root Mean-Square Error (RMSE). The formulas for calculating the errors defined by MAPE and RMSE are as follows:

$$R^2 = 1 - \left\{\frac{\sum_{i=1}^{n}(E_i - P_i)^2}{\sum_{i=1}^{n}(P)^2}\right\} \quad (3)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|100\ \frac{E_i - P_i}{P_i}\right| \quad (4)$$

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

Where n = Number of data values, P = Predicted values, and E = Test value.

RESULTS AND DISCUSSION

Performance Parameters

Brake-Thermal Efficiency

During the training of the BTE prediction model, various neuron configurations ranging from 5 to 9 were evaluated. The optimal performance was achieved using 6 neurons as shown in Fig.-3(a), resulting in a 4:6:1 network architecture. As illustrated in Fig.-3(b), the model exhibited an excellent fit, achieving a high coefficient of determination (R^2) of 0.9995, which exceeded the 0.999 value reported by Leo *et al.*[8] for BTE modeling using biodiesel from waste cooking oil in an HCCI-DI engine. Figure-3(c) shows the prediction error for each measured sample, with the model's performance characterized by an RMSE of 0.6153 and MAPE of 1.9820 (Table-1). These low error values confirm the accuracy of the BTE predictions, with the RMSE slightly lower than the 0.62 reported by Yusaf *et al.*[18]

Specific-Fuel Consumption

The training of the specific-fuel consumption model involved testing neuron counts ranging from 5 to 9, with the best results obtained using 5 neurons, as shown in Fig.-4(a), leading to the selection of a 4:5:1 architecture. As shown in Fig.-4 (b), the model displayed a high R^2 value of 0.9992, reflecting a superior fit compared with the R^2 value of 0.9313 reported by Mustafa *et al.*[19] for modeling the BSFC of a 1-cylinder engine with biodiesel/diesel blends. Figure-4(c) shows the individual error for each sample's SFC prediction, with the model yielding an RMSE of 0.0101 and an MAPE of 1.8656 (Table-1). These low

error values highlight the high accuracy of the SFC predictions, with the RMSE being even lower than that reported by Ramalingam *et al.*[9]

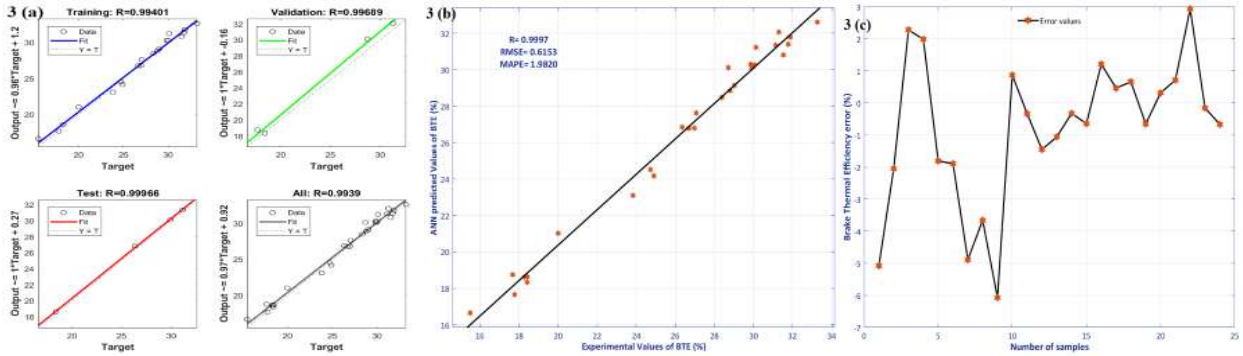

Fig.-3: (a) BTE Network performance (b) Experimental vs. ANN BTE (c) Errors related to BTE

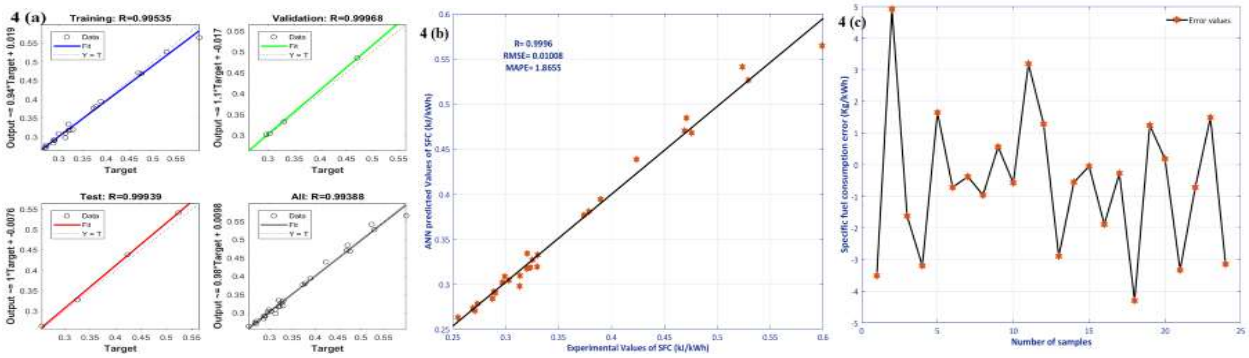

Fig.-4: (a) SFC Network performance (b) Experimental vs. ANN SFC (c) Errors related to SFC

Table-1: Performance Evaluation Indices for the Performance Prediction Models

Parameter	Model	No. of neurons	R-Train	R-Validation	R-Test	R-All	RMSE	MAPE	R^2
BTE	4-5-1	5	0.99154	0.99996	0.99113	0.99394	0.6594	1.8297	0.9993
	4-6-1	6	0.99401	0.99689	0.99966	0.9939	0.6153	1.982	0.9995
	4-7-1	7	0.99348	0.99491	0.98681	0.99045	0.7455	2.0255	0.9992
	4-8-1	8	0.99591	0.98771	0.9912	0.99319	0.6339	1.9349	0.9994
	4-9-1	9	0.97586	0.99086	0.99572	0.98297	0.9882	2.8763	0.9986
SFC	4-5-1	5	0.99535	0.99968	0.99939	0.99388	0.0101	1.8656	0.9992
	4-6-1	6	0.9934	0.99995	0.98733	0.99333	0.011728	2.2249	0.999
	4-7-1	7	0.99098	0.99089	0.99974	0.9921	0.01155	2.3002	0.999
	4-8-1	8	0.99484	0.99926	0.99873	0.99333	0.010653	2.139	0.9991
	4-9-1	9	0.97097	0.99669	0.97946	0.97744	0.019415	3.2976	0.9971

Emissions Parameters

Carbon Monoxide

The modeling of Carbon Monoxide (CO) involved training the network with neuron counts ranging from 5 to 9, with optimal results achieved using 9 neurons as shown in Fig.-5(a). Therefore, the 4:9:1 architecture was selected for the CO model. Figure-5(b) shows an R^2 value of 0.9992, indicating an excellent fit for the CO model. This value is notably higher than the 0.993 reported by Leo *et al.*[8] for CO modeling of an HCCI-DI engine using biodiesel from waste cooking oil. The individual errors for each sample's CO predictions, shown in Fig.-5 (c), confirm the model's high accuracy, with an RMSE of 0.0087 and a MAPE of 5.173 (Table-2).

These low-error metrics underscore the model's strong prediction accuracy, with the RMSE being slightly lower than the value reported by Babu *et al.*[16]

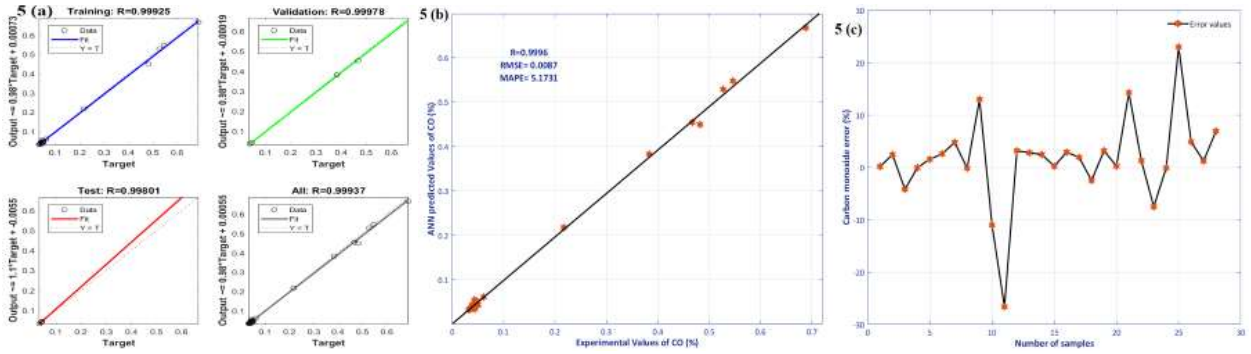

Fig.-5: (a) CO Network performance (b) Experimental vs. ANN CO (c) Errors related to CO

Hydrocarbons

The HC network was trained with neuron counts ranging from 5 to 9, achieving the highest performance with 9 neurons as shown in Fig.-6(a). Consequently, a 4:9:1 architecture was selected for HC modeling. Figure-6 (b) shows a strong correlation between the predicted and experimental data with an R^2 value of 0.9993, indicating an excellent fit of the HC model. This R^2 value is slightly higher than the 0.9986 reported by Bhowmik *et al.*[20] in their study on HC modeling of oxygenated fuels. The individual errors associated with HC prediction for each measured sample using the HC model are shown in Fig.-6(c). The HC model demonstrated high accuracy, as evidenced by its low error rates, with a Root Mean Square Error (RMSE) of 1.1443 and Mean Absolute Percentage Error (MAPE) of 1.9873 (Table-2). Notably, the RMSE is slightly lower than that reported by Syed *et al.*[21]

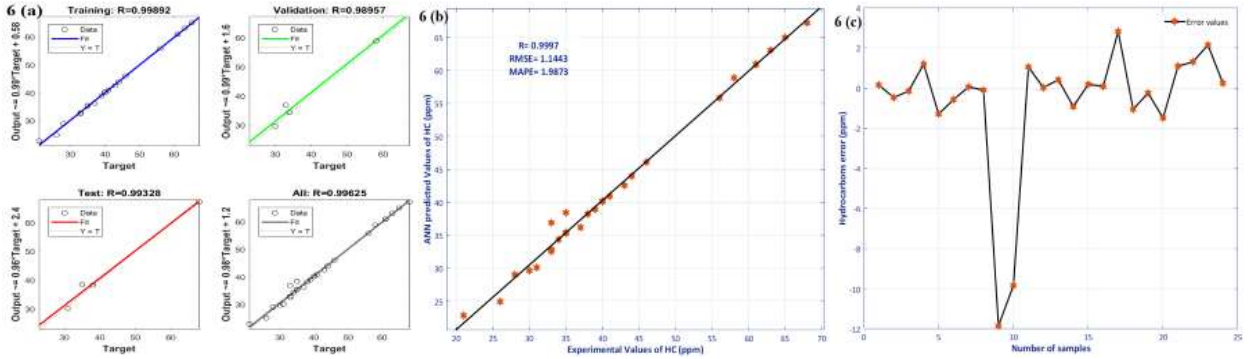

Fig.-6: (a) HC Network performance (b) Experimental vs. ANN HC (c) Errors related to HC

Oxides of Nitrogen

The NOx network training involved testing various neuron counts from 5 to 9, with the best performance achieved using 6 neurons as shown in Fig.-7(a). This led to the selection of a 4:6:1 architecture for the NOx model. Figure-7 (b) shows an R^2 value of 0.9996, indicating an excellent fit for the NOx model. This R^2 value exceeds 0.9982, as reported by Liu *et al.*[22]. For NOx modeling in spark-ignition engines using butanol–gasoline blends. The accuracy of the model, which displays the individual errors for NOx prediction, is further demonstrated in Fig.-7 (c). The model attained a low RMSE of 19.7955 and MAPE of 1.6329 (Table-2), reflecting a high prediction accuracy and outperforming the values reported by Samet *et al.*[23]

Smoke Density

The Smoke density network was trained with neuron counts ranging from 5 to 9, achieving the best performance with 6 neurons as shown in Fig.-8(a). Therefore, a 4:6:1 architecture was selected for the smoke-density model. Figure-8(b) further confirms the accuracy of the model with an R^2 value of 0.9996, indicating an excellent fit for the smoke density model. This R^2 value is slightly higher than the 0.99918 value reported by Amitav *et al.* [24] for LPG soot modeling in the dual-fuel mode. The accuracy of the model is also reflected in Fig.-8(c), which shows the individual errors in the smoke density predictions. The model attained a very low RMSE of 1.0502 and a MAPE of 1.3463 (Table-2), demonstrating high

prediction accuracy. These minimal values indicate superior performance, with the RMSE being lower than that reported by Samet *et al.*[25]

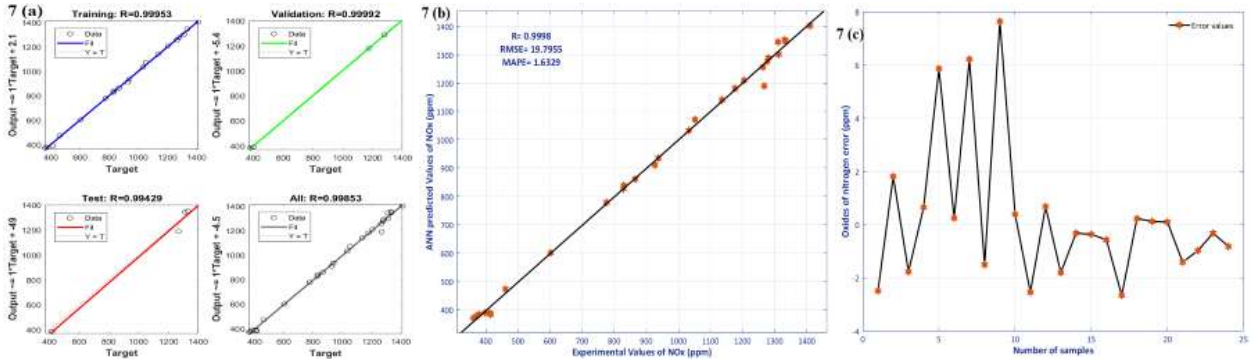

Fig.-7: (a) NOx Network performance (b) Experimental vs. ANN NOx (c) Errors related to NOx

Table-2: Performance Evaluation Indices for the Emission Prediction Models

Parameter	Model	No. of neurons	R-Train	R-Validation	R-Test	R-All	RMSE	MAPE	R^2
CO	4-5-1	5	0.9996	0.99986	0.99997	0.99506	0.0219	6.2153	0.9937
	4-6-1	6	0.99924	0.99984	0.99997	0.99757	0.014	9.9923	0.9968
	4-7-1	7	0.98115	0.99998	0.99822	0.98523	0.0435	9.3608	0.9804
	4-8-1	8	0.99968	0.99486	0.99997	0.99911	0.0085	9.7556	0.9988
	4-9-1	9	0.99925	0.99978	0.99801	0.99937	0.0087	5.173	0.9992
HC	4-5-1	5	0.99605	0.99926	0.99255	0.9954	1.271	2.1414	0.9991
	4-6-1	6	0.99492	0.9999	0.99926	0.99593	1.2065	1.9479	0.9993
	4-7-1	7	0.99086	0.99751	0.99738	0.99158	1.6503	3.5265	0.9985
	4-8-1	8	0.98262	0.99944	0.9982	0.98603	2.2105	3.2281	0.9974
	4-9-1	9	0.99892	0.98957	0.99328	0.99625	1.1443	1.9873	0.9993
NOx	4-5-1	5	0.99485	0.99975	0.99387	0.99513	37.0631	3.4473	0.9989
	4-6-1	6	0.99953	0.99992	0.99429	0.99853	19.7955	1.6329	0.9996
	4-7-1	7	0.98296	0.99997	0.99995	0.98894	53.9799	4.2222	0.9971
	4-8-1	8	0.9993	0.99999	0.99471	0.99846	20.2696	1.3822	0.9996
	4-9-1	9	0.9906	0.99958	0.99992	0.99309	43.4971	3.35	0.9981
Smoke density	4-5-1	5	0.99955	0.99942	0.98878	0.99688	1.5542	2.2035	0.999
	4-6-1	6	0.99993	0.99842	0.99677	0.99861	1.0502	1.3463	0.9996
	4-7-1	7	0.99509	0.98665	0.98791	0.99357	2.1967	4.2932	0.9981
	4-8-1	8	0.99692	0.99365	0.99591	0.99522	1.9251	3.8568	0.9985
	4-9-1	9	0.99174	0.99488	0.98902	0.98179	3.7076	8.975	0.9944

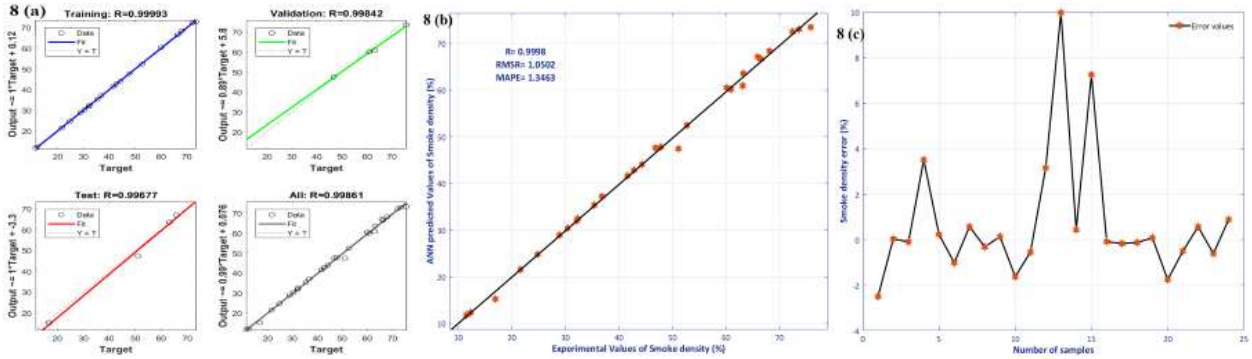

Fig.-8: (a) Smoke Network performance (b) Experimental vs. ANN smoke (c) Errors related to smoke density

CONCLUSION

An Artificial Neural Network (ANN) model was successfully developed to predict the performance and emissions of a diesel engine fueled with iron (II, III) oxide nanoparticle-enhanced tamarind biodiesel blends. Using 70% of the experimental data for training and 30% for testing, the model employed inputs such as calorific value, biodiesel ratio, nanoparticle concentration, and engine load to estimate outputs, including SFC, BTE, and emissions (CO, HC, NO_x, and smoke). The model achieved excellent accuracy, with R^2 values of 0.9995 for BTE and 0.9992 for SFC and low RMSE values of 0.6153 and 0.0101, respectively. Emission predictions also showed high precision, with R^2 values above 0.9992 and MAPE values ranging from 1.3463 to 9.9923. Overall, the ANN model proved to be a reliable and effective tool for predicting the engine behavior with nanoparticle-enhanced biodiesel blends, offering valuable potential for optimizing engine performance and reducing emissions.

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CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS

The present work is related to *SDG-7: Affordable and Clean Energy*. All the authors contributed significantly to this manuscript, participated in reviewing/editing and approved the final draft for publication. The research profile of the authors can be verified from their ORCID ids, given below:

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