



Application of Artificial Neural Network in Determining Performance Profile of Compression Ignition Engine Operated with Orange Peel Oil-Based Biodiesel

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Authors' contributions

This work was carried out in collaboration with both authors. Authors SKF and CUO designed the study. Author CUO performed the simulation and wrote the first draft of the manuscript. Author SKF and Author CUO managed the analyses of the study and literature searches. All authors read and approved the final manuscript.

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ABSTRACT

Literature including one of our previous studies have confirmed the environmental friendliness of orange peeled oil biodiesel (OPOB) when applied to run compression ignition (CI) heat engines. There is also high degree of compatibility of physicochemical properties of OPOB with fossil diesel. However, there is limited knowledge on its performance indices in the same heat engines. This perhaps may have been due to few interests shown by researchers in the area or obviously due to difficult time and other quantum resources required in conducting the rigorous engine tests. To this end, this work conducted experimental study of performance profile of OPOB in direct injection CI engine; and afterwards applied artificial neural networks (ANNs) to ascertain the engine brake thermal efficiencies (BTE) and brake specific energy consumptions (BSEC). The ANN utilized the Levenberg Marquardt (LM), Scaled Conjugate Gradient (SCG) and Gradient Descent with Momentum and Adaptive Learning (GDX) training algorithms for the performance prediction. The

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choice of the three algorithms was to effect better comparative assessment. The input variables of the neural network were brake load, orange oil-diesel mixture percentages and engine speed. Statistical parameters such as correlation coefficient (R), mean absolute percentage error (MAPE) and root mean squared error (RMSE) were employed to investigate the performance of the neural networks. Among the three training algorithms, the Levenberg Marquardt trained algorithm estimated the BTE and BSEC with highest precision and accuracy; and lowest error rates. From the study, it is concluded that the performance profile of compression ignition heat engines operated with orange peel biodiesel compares favourably with fossil diesel. It also affirmed that Artificial Neural Network is a reliable tool in the prediction of performance indices of compression ignition engines when run with orange-peel oil based biodiesel.

Keywords: Artificial neural network; levenberg marquardt training algorithm; parametric performance indicators; orange peel oil biodiesel; engine performance; direct injection compression ignition engine.

1. INTRODUCTION

Regardless of energy transition [1], biodiesel will be crucial in mitigating harmful emissions. Fossil fuels have been largely used in operating internal combustion engine [2, 3]. However, due to depleting global oil reserve, intensification of air pollution [4,5] and concerns for environmental protection and sustainability, exploration of more efficient alternative fuels for industrial activities has intensified since many decades ago [6,7]. Again, emissions from diesel engines are major constituent of environmental pollution [8, 9] and its associated health issues. Laws and strict regulations are already being imposed in some countries [10] and the UN has begun deliberations in order to reduce toxic emissions [11]. However, to reduce these emissions requires major improvement in performance variables of the engine [12]. Though, since the invention of diesel engine, biodiesel has been in use; however, difficulties in its production and some unsuitable qualities for proper engine operation placed limitation to its usage. Continuous research into numerous agricultural products and biomass, engine materials, configuration and shape of engine parts may have helped to offer better engine performance [13]. Chemical analysis shows that biodiesel is not a long alkyl esters and is obtained from non-fossil based sources, especially agricultural biomass, through a chemical reaction process called transesterification. The transesterification process converts the triglyceride (TAG) and alcohol into alkyl esters, fatty acid and glycerol [14]. The process ensures that the viscosity of the oil is reduced by the reverse process of removal and addition of glycerine in the oil with radicals of the alcohol [15]. Biodiesel can be applied to compression ignition engine with little or no modification [2]; and it has been found as a very good alternative diesel fuel [16,17].

Biodiesel contains between 10-11% oxygen by weight, almost sulphur free; in contrast with pure diesel- it has higher cetane number [18]. Orange peel oil methyl ester (OPOME) blends produced higher BTE and lower BSEC than diesel, and such possibilities are attributed to complete combustion due to its high oxygen content [19]. The increase in BTE depends on oxygen content, higher cetane number, rapid premixed combustion due to viscosity, and ignition delay [20]. Table 1 shows closeness of the properties of orange oil and those of petroleum diesel.

A necessary factor for the use of ANN focuses on the application of biodiesel for commercial application. The objective for this centres on the optimisation of suitable and acceptable mixture (biodiesel + diesel) needs tedious series of iterative experiments which are time draining, financially costly and generally complex [22,23]. In recent times, ANN has been identified as a useful estimating tool for identifying the linearity or nonlinearity between input and output parameters [24]. In this study, we used blended orange peel oil to determine the performance of a CI engine. Thereafter, we used the experimental results to train the developed neural network models. The artificial neural network is an information system that imitates the human biological nervous system [25]. Among existing estimation models that perform advanced data analysis, ANN has the best capacities and the most applied structure is the multilayer perceptron (MLP) structure [26]. The MLP is formed by at least three or more layers: an input layer, one or more hidden layer, and an output layer. All the layers are interconnected to each other by linking weights [27-29]. Each layer contains specified neurons which are connected to the neurons of other layer by means of interconnected weights. The interconnected weights support in signal transfer, while the

neurons interpret and process the signals. The input layer neurons only send information to the hidden layer neurons without making calculations. Each of the hidden layer neurons adds up all the inputs values, in a way that an output is obtained once the summation of the input values exceeds activation value. After the hidden layer makes computation of the input signals, the adjusted values are moved to the output layer; and the procedure could undergo repetition after the number of iterations and error values are considered. The error is back-propagated into the system until the interconnect weights are fully and sufficiently reduced. A well trained neural network model has a fully developed predictive ability [30]. The mathematical expression which shows the relation between output, activation function, interconnected weights, and input values is shown:

$$U, \kappa = \sigma \left(\sum_{j=1}^M W_{kj} \sigma \left(\sum_{i=0}^d W_{ji} X_i \right) + B_i \right) \quad 1$$

Where U, κ is the output, σ is the activation function, W_{kj} weights of the output layer, W_{ji} weights of the hidden layer, X_i are the values of the inputs, B_i is the value of the Bias.

The summation is transferred by activation or transfer function $f(h_i)$. For any given input, activation flow is transferred from input layer to output layer through the hidden layer [31], which carries out the computation. Fig. 1 shows how ANN performs computations.

From the foregoing discussion, ANN has been applied in many fields and it is an efficient tool for prediction of systems whose output depends on other quantities. The novelty of this study centers on the development of ANN model for comprehensive estimation of the performance of CI engine operated by orange peel oil based biodiesel. The novelty lies in our detailed description of the CI engine ANN model which considered three input parameters: engine load, engine speed and blend percentages; and two output variables: BTE and BSEC. Three major separate cases were considered with respect to number of hidden layer neurons and the types of algorithms. While the use of these algorithms is not new, their combined application is novel because it enhances the choice of reliably efficient ANN model for the ANN assessment. Another novelty of the work is the meticulous exposition of the performance of unblended orange peel oil biodiesel in the CI engine. Therefore, this paper focused on bridging the existing gap in utilisation of biodiesel and also proposes a new approach in CI engine data processing.

In this paper, the experimental and ANN models were presented in detail. Section 1 made general introduction of renewable energy, biodiesel and ANN. The section 2 detailed the production of OPOB and evaluation of engine performance. Section 3 discussed the obtained experimental and ANN results; while section 4 is the conclusion of the study.

Table 1. Properties of orange peel oil and diesel [19, 21]

Properties	ASTM Method	Orange Peel Oil	Diesel
Calorific value KJ /kg	D-4809	34,650	43,000
Density@30°lit/C Kg	D-4052	0.8169	0.8284
Viscosity @ 40°C, cSt	D-445	3.52	2.70
Flash point, °C by PMCC method	D-93	74	52
Fire point, °C by PMCC method	D-2500	82	65
Cetane Number	D-613	47	49
Oxygen content	-	10.23	-

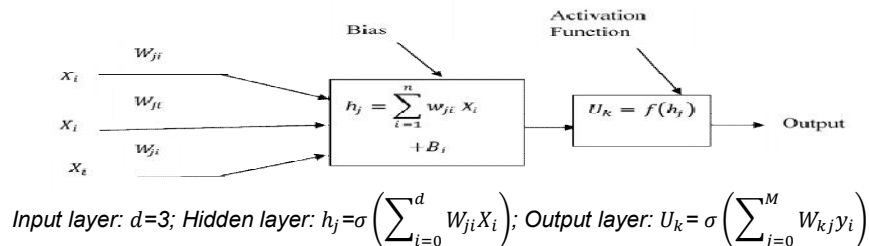


Fig. 1. Structural depiction of ANN mode of computing input signals in the hidden layer through to the output layer

2.MATERIALS AND METHODS

2.1 Materials for the Biodiesel Production and Engine Test

Three separate procedures were followed. The first two required experimental materials and reagents, while the third process was simulation and computations. The materials used for the production of the biodiesel include orange peel, sucrose, urea, distilled water, stirrer, foil paper, watmann No1 filter paper, piece of folded cheese cloth and baker's yeast, include glass beakers, graduated cylinders, conical flask, test tubes, micro pipettes, wash bottles, electronic weighing machine, autoclave, incubator. Also, for the engine test, the materials used, centrifuge, alchometer hydrometer, thermometer, distillation unit, heating mantle, magnetic stirrer with hot plate and water bath.

2.2 Processess for the Production of Orange Peel Oil Biodiesel

The orange peel biodeisel preparation involves pre-treatment which supports the separation of the collected orange peels, washing the separated peels with clean water, and air-drying of the washed peels. The air-dried peels were grinded and sieved and enclosed in air tight polythene. The actaul purpose for this was to induce the quality of the fermentable starch. The next step was the Inoculums process. In this process chemical additives and reagents were measured and prepared. Afterwards,in order to optimise biodiesel production, fermentation process occurred under 20 – 30°C. The fementation process was followed with filtration of thefermented mixtures; and subsequently the usage of the distilling pot and heating mantle for the distillation of the filtrate. Fig. 2 is a

diagramatic representation of the procedures taken in the production of orange peel oil biodiesel.

2.3 Experimental Engine Test

To conduct the engine test and experimentally determine the suitability of OPOB, a test rig was set up. The engine test rig consists a compression ignition engine that is connected to an electrical brake dynamometer for brake load adjustment, a container of blended biodiesel and natural diesel, and funnel. The engine is a single cylinder, constant speed, air cooled, direct injection, four stroke, stationary diesel engine. The Blended percentages (natural diesel + orange peel biodiesel) which contains orange peel oil in the proportion of 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90% and 100% were prepared.

To obtain the baseline data, the first experiment was conducted using natural diesel for the different brake loads. Following the same procedure, the engine was appropriately switched over to the various orange peel biodiesel-diesel blends. The engine was finally operated using diesel fuel after completing operations on the prepared blend percentages and natural OPOB, to erase difficulties that may be encountered during later application of the engine. Th fuel consumption rate for each brake load was recorded using the burette and stopwatch. The engine performance based on brake thermal efficiency and brake specific energy consumption was evaluated using the recorded fuel consumption rate for each brake load and for all the tested blends. Fig. 3. is the experimental set up of the engine test rig, while Table 2 shows the specifications of the engine.

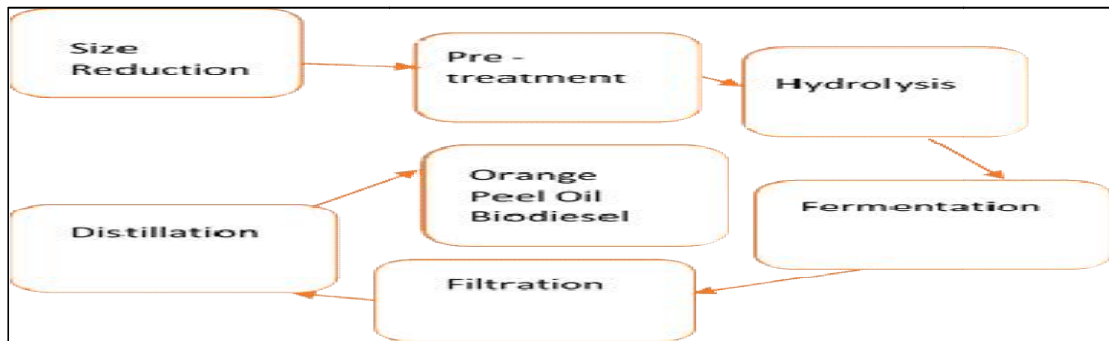


Fig. 2. Procedure for the production of orange oil



Fig. 3. Experimental setup of the engine test rig

Table 2. Engine specification

	Engine parameter	Value
1	Rated power	4.4kW
2	Stroke	110mm
3	Cylinder bore	87.5mm
4	Compression ratio	17.5:1
5	Swept volume	661cc

2.4 Procedure for Running the ANN Model

After experimental determination of the engine performance operated on the blended fuels, ANN models for the engine using the engine and biodiesel properties were developed. The ANN model was executed on the MATLAB environment. Since ANN consists three layers, the inputs of the networks were percentage of the blends, operating speed, and brake load; while the outputs variables were the engine performance parameters which are brake thermal efficiency and brake specific energy consumption. For all training algorithms, there was consistent increase in the number of neurons in the hidden layer until better output values were predicted. The simulation utilised 70% of the obtained experimental data for training the neural network models and 30% for testing and validation of the neural network models. The Levenberg-Marquardt (LM), Scaled conjugate gradient (SCG) and gradient descent with momentum and adaptive learning (GDX) training algorithms were adopted in executing the task. The reason for this was to necessitate qualitative estimation of network models. 3-10-2, 3-12-2, and 3-15-2 network structures were used. Which indicates three input parameters, varying hidden layer neurones and two output

parameters. This use of three different structures and three different training algorithms is to effect solid scientific grounds for performance comparison.

2.5 The Neural Network Performance Indicators

For effective determination of the performance of the neural network, some statistical formulae were used, since the model involves numerical mapping of the data set. To investigate the strength of the relationship between the predicted and the experimental data the correlation coefficient R, the mean absolute percentage error (MAPE), and the root-mean-squared error (RMSE) were chosen. The equations are shown below:

$$R = \frac{\sum_{i=1}^n (a_{in} - \tilde{a}_{in})(a_{ij} - \tilde{a}_{ij})}{\sqrt{\sum_{i=1}^n (a_{in} - \tilde{a}_{in})^2 \cdot \sum_{i=1}^n (a_{ij} - \tilde{a}_{ij})^2}} \quad 2$$

$$MAPE = \frac{1}{n} \sum_{i=1}^n \left| \frac{a_{in} - a_{ij}}{a_{in}} \right| \times 100 \quad 3$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_{in} - a_{ij})^2} \quad 4$$

3. RESULTS AND DISCUSSION

3.1 Engine Performance Evaluation

3.1.1 Brake thermal efficiency

Both experimental and ANN predicted results show improved thermal efficiency when diesel is blended with orange peel oil. From the experimental approach, an increasing brake thermal efficiency was observed under increasing brake load conditions for all the blends and B100. Basically, oxygenation is an important distinguishable unique property of fuels because it aids combustion. Therefore, a necessary factor that possibly enabled the increase in thermal efficiency may be the sufficient oxygen content of orange peel oil biodiesel which is shown to be 10.23% of all the components of orange peel oil in Table 1. Since oxygen supports thermal strength, there is always a rise the in-cylinder temperature of the engine. The increased in-cylinder temperature results in improved combustion process. In addition to the energy content per volume, blends stoichiometry, higher flame velocity and ignition limits - which are factors dependent on fuel type – may contribute to the higher thermal efficiency. Fig. 4 shows that pure orange oil (B100) yielded maximum brake thermal efficiency. It also shows that brake thermal

efficiency is directly proportional to the percentage of orange peel biodiesel in the blends, since higher blend percentages show increased brake thermal efficiency.

3.1.2. Brake specific energy consumption (BSEC)

The graphical connection between brake specific energy consumption and brake power is shown in Fig.. 5. From the plot we observed a decrease in BSEC with increase in orange peel biodiesel in the blends. Comparative assessment of the fuels indicates that pure orange oil and all the blends produced lower BSEC than diesel. B100 has the least BSEC. It is clear that the viscosity of orange peel oil biodiesel is higher than the viscosity of natural diesel. The decreasing BSEC in the blends and B100 may have been impacted by the large viscosity value and low calorific value of the orange peel biodiesel. The resultant higher viscosity enforces ignition delay. Experimental results have shown that heating values of fuels are influenced by carbon, hydrogen and oxygen content. The carbon, hydrogen and sulphur constituents of any fuel affects the low heating value (LHV) of the fuel. Similarly, the improved the oxygen content of a fuel, the reduced its low heating value. Putting this into perspective, orange peel biodiesel possesses higher oxygen content than diesel, thus a reduced LHV.

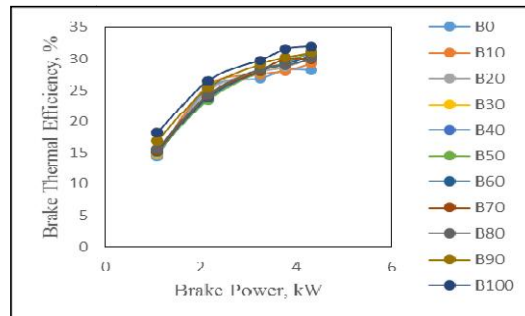


Fig. 4. Brake thermal efficiency against brake power

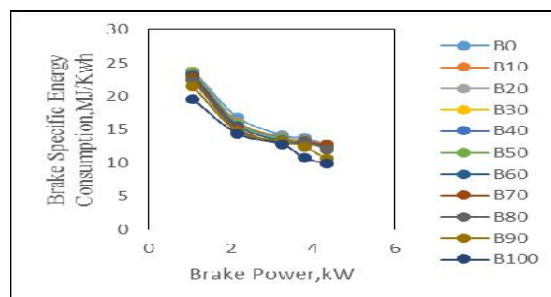


Fig. 5. Brake specific energy consumption against brake power

3.2 Evaluation of Correlation Among Parameters – Sensitivity Analysis

The first step for proper analysis of the experimental data is establishing the connections that exist among all the input and output variables. This process is called sensitivity analysis. The correlations were established using Pearson correlation. The Pearson correlation operates in the bound of -1 to +1 [32, 33]. Table 3 shows the evaluated correlation coefficients which exist between input and output parameters.

Important information can be obtained here. The maximum correlation coefficients among the output parameters are related to the engine load (EL), followed by engine speed (ES), and percentage fuel blends (PFB). These correlations show the contribution effect of the various input parameters in the prediction of the neural network models. The correlations are of great percentages; hence would tilt towards linearization with the output parameters.

3.3 ANN Model Results with Different Training Algorithms

In the study, BTE and BSEC of a diesel engine running in blends of orange peel oil based biodiesel were investigated using ANN model with experimental method. The neural network predicted data were compared with the engine

test obtained data using the already stated performance indicator equations. The ANN utilised three input parameters, which are engine speed, diesel-orange oil blend percentage and brake load. To determine the number of neurons in the hidden layer equation 5 is used.

$$NN = \frac{I+O}{2} + \sqrt{S} \tag{5}$$

Where *NN* represents the number of neurons in the hidden layer, *S* represents the number of training data set used in the neural network. *I*, is the number of input parameters and *O* is number of output parameters respectively. The actual number of neurons for the hidden layer during ANN training is usually varied by ±5 from the value obtained using eq. (5) [24]. Using eq. (5), we obtained a hidden layer neuron value of 10±5. After training with the various values within the range, 10, 12, and 15 were used. For better evaluation, the neural network models were trained using three different algorithms. Table 4 shows the performance of the network models based on the values of the performance indicators.

From Table 4, it can be seen that the Levenberg Marquardt algorithm trained with 15 neurons in the hidden layer offered the best results with maximum value of correlation, least value of the MAPE, and lowest value of the RMSE.

Table 3. The correlation coefficients among inputs to outputs

	PFB	EL	ES	BTE	BSEC
PFB	1	-	-	0.1541	-0.1391
EL	-	1	-0.8944	0.8891	-0.8349
ES	-	-0.8944	1	-0.6405	0.5586
BTE	0.5312	0.8891	-0.6405	1	-0.9760
BSEC	-0.1391	-0.8349	0.5586	-0.9760	1

Table 4. Performance of the neural network models based on the performance indicators

Training algorithm	NN	R	MAPE	RMSE
LM	10	0.99922	0.16268	0.4033361
LM	12	0.99927	0.16437	0.4054257
LM	15	0.999605	0.21930	0.1042192
SCG	10	0.99738	0.47849	0.6917297
SCG	12	0.99803	0.49563	0.7040099
SCG	15	0.99353	1.06130	1.0301942
GDX	10	0.98842	2.02279	1.4222482
GDX	12	0.95951	12.3431	3.5132748
GDX	15	0.96464	6.31210	2.5123890

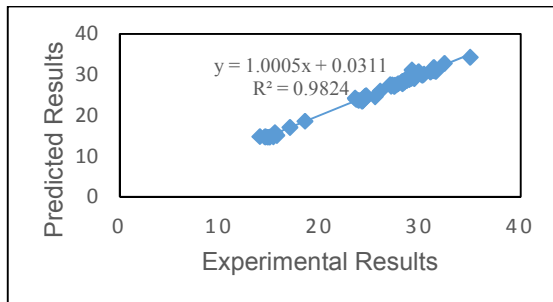
3.3.1 ANN result for brake thermal efficiency

We have initially noted that performance of ANN is determined by the correlation coefficients, the MAPE and the RMSE. For effective determination of the network strength, different algorithms and different values of neurons were employed to train the experimental data values. Equation 5 and its accompanying explanation were used to determine the number of neurons in the hidden layer. A selection of 10 to 15 neurons was made. Table 5 shows the performance of the neural network with respect to brake thermal efficiency. From the table it can be found that the Levenberg-Marquardt algorithm

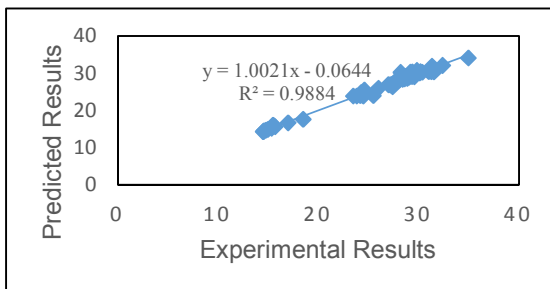
produced the highest correlation coefficient value, least value of MAPE, and least value of the RMSE, particularly for 15 hidden layer neurons. The SCG results were better than the GDX results. With the obtained results, the ANN model was able to linearize the second order Taylor's series equation; and the predicted results were largely consistent with experimental. Fig. 6, 7 and 8 show the connection between predicted and experimental values of BTE. Fig 6 shows that LM offered very good linearization as most data points are found within the linear line. By contrast, this was better than similar observation made for Figure 7 and Fig. 8.

Table 5. correlation coefficients and error values of the neural network models for BTE

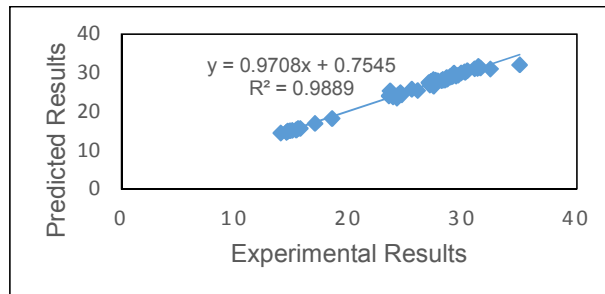
Training algorithm	NN	R	MAPE	RMSE
LM	10	0.99618	1.51247	0.50579
LM	12	0.99446	1.62784	0.59145
LM	15	0.99844	1.39940	0.35869
SCG	10	0.98917	2.55059	0.84380
SCG	12	0.98761	2.59588	0.88160
SCG	15	0.95950	6.28184	1.70781
GDX	10	0.94490	5.63948	1.95414
GDX	12	0.80329	18.6080	5.91118
GDX	15	0.79335	16.8637	5.18158



1. LM of NN=10



2. LM of NN=12



3. LM of NN=15

Fig. 6. Predicted values against experimental results for Levenberg Marquardt (LM) algorithm when the network model has 10, 12 and 15 hidden layer neurons

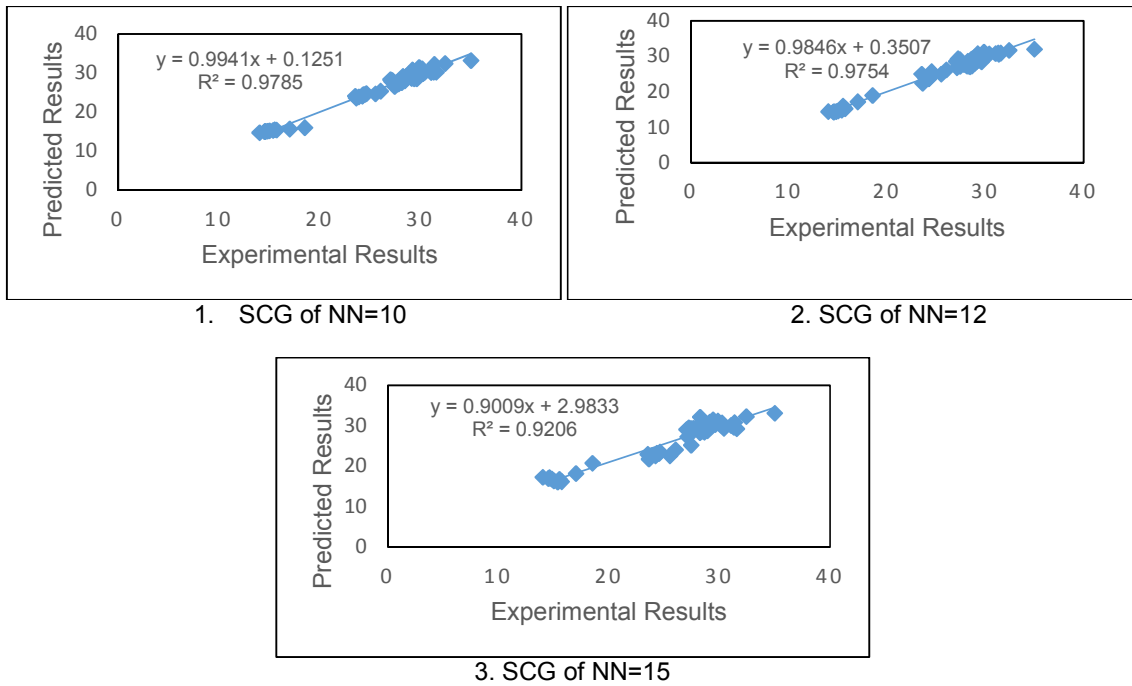


Fig. 7. Predicted results against experimental results for Scaled Conjugate Gradient (SCG) algorithm when the network model has 10, 12, and 15 hidden layer neurons

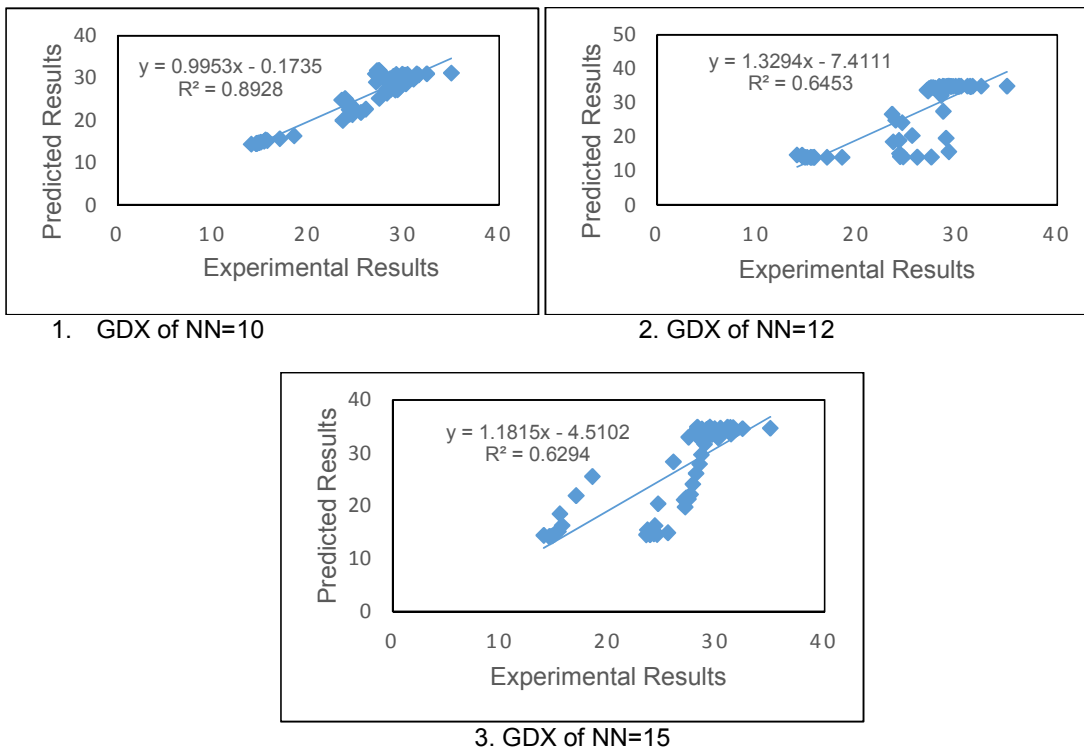


Fig. 8. Predicted results against experimental results for Gradient Descent (GD) algorithm when the network model has 10, 12, and 15 hidden layer neurons

3.3.2 ANN Result for BSEC

Table 6 shows the extent to which the BSEC predicted results and the experimental results are related and the errors between the two results. The table shows the correlation coefficients, mean absolute percentage error and root mean squared error for the chosen algorithms and number of neurons in the hidden layer. There is minimal error values for the Levenberg Marquardt algorithm, in which the lowest error value was gotten from the 12 hidden layer neurons. It is important to note that the error and correlation coefficient values marginally increased with the number of neurons in the hidden layer. Figures and 9, 10 and 11 show the

direct proportionality between predicted and experimental results for the various algorithms and numbers of neurons at the hidden layer. After comparative assessment of the performance of the three algorithms for the number of neurons, the Levenberg-Marquardt (LM) simulated with 15 hidden layer neurons showed a more consistent linear result than any other training algorithm. The true reflection of the linearization is shown in Fig. 9. Most of the data points are closer to the straight line. This indicates that the network’s predicted values are almost the same as the experimental results. The error values are sufficiently low when compared to those of other algorithms with the same number of neurons.

Table 6. correlation coefficients and error values of the neural network models for BSEC

Training algorithm	NN	R	MAPE	RMSE
LM	10	0.996975	1.6741	0.3205618
LM	12	0.995239	1.6703	0.4104904
LM	15	0.997802	1.7334	0.3029373
SCG	10	0.986660	2.9706	0.7257455
SCG	12	0.987876	3.8290	0.6637192
SCG	15	0.941334	8.4832	1.4682692
GDX	10	0.970820	14.7523	2.3107767
GDX	12	0.941470	18.3716	2.9747500
GDX	15	0.790795	14.8679	2.7531787

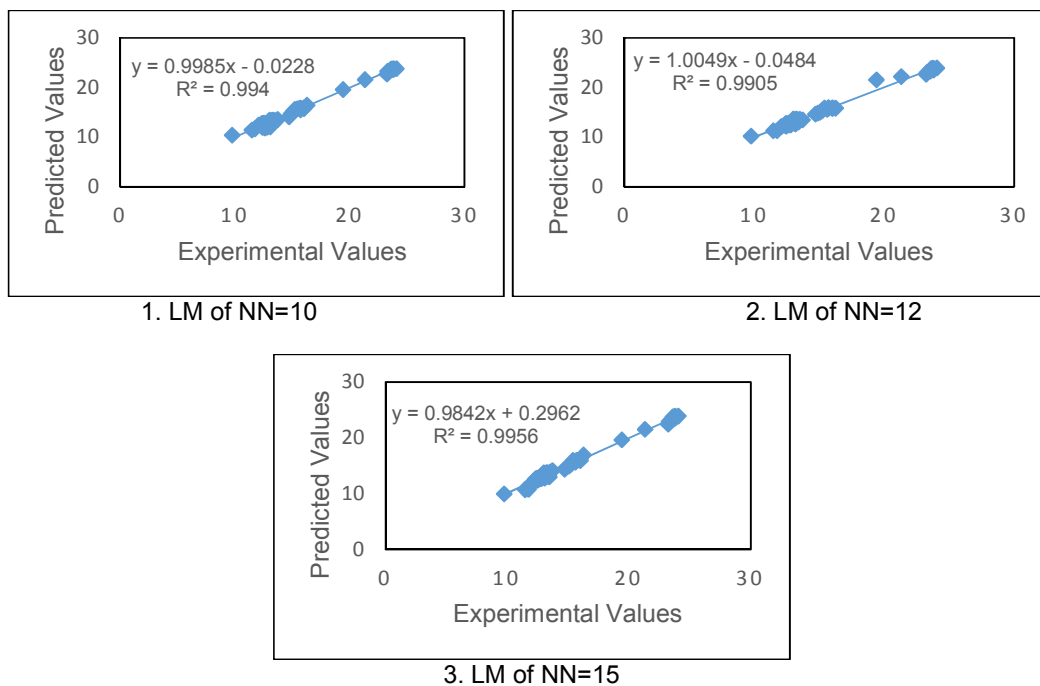


Fig. 9. Predicted values against experimental results for Levenberg Marquardt (LM) algorithm when the network model has 10, 12 and 15 hidden layer neurons

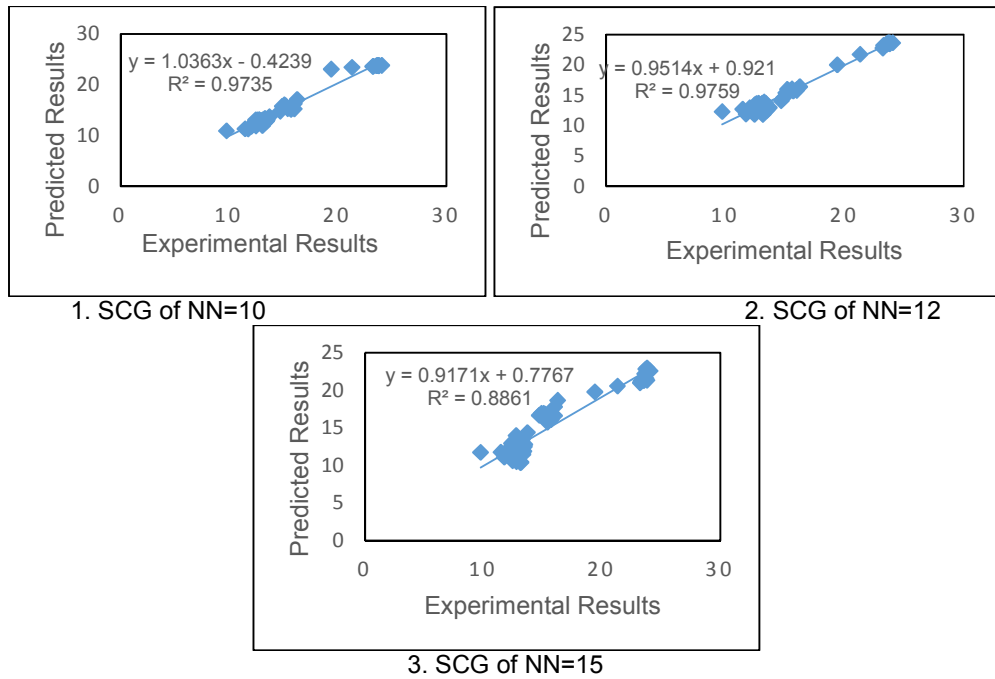


Fig. 10. Predicted results against experimental results for Scaled Conjugate Gradient (SCG) algorithm when the network model has 10, 12, and 15 hidden layer neurons

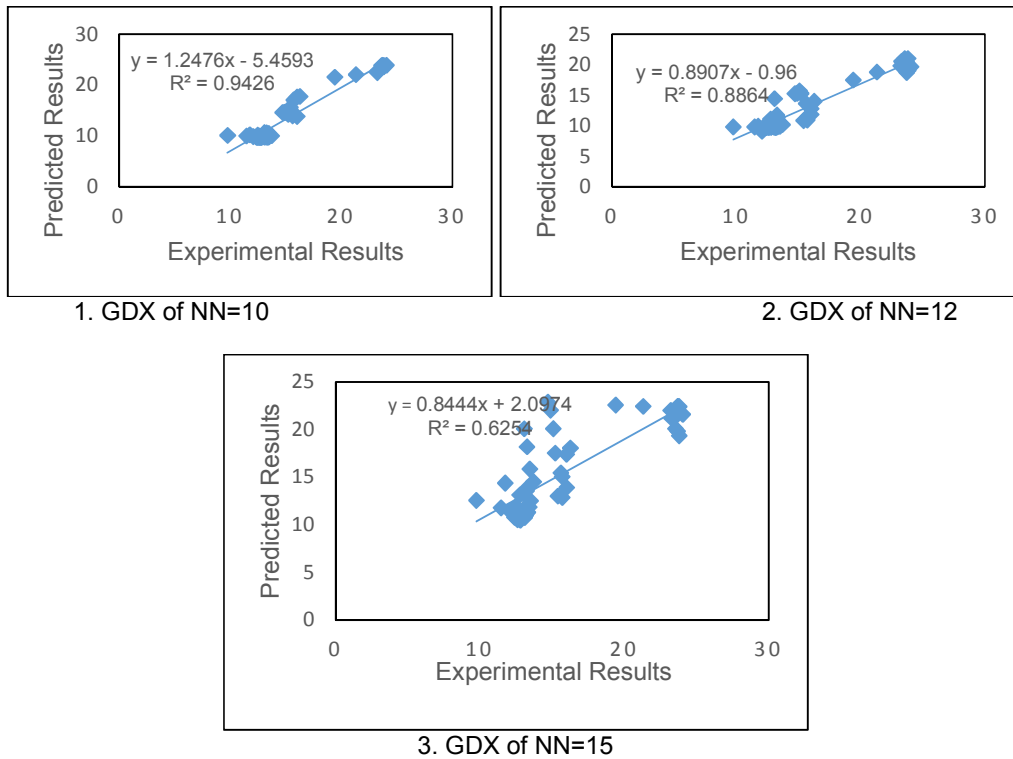


Fig. 11. Predicted results against experimental results for Gradient Descent (GD) algorithm when the network model has 10, 12, and 15 hidden layer neurons

4. CONCLUSION

The current study focuses on the investigation of the BTE and the BSEC values of CI engine operated with blends of orange peel biodiesel and natural diesel using both experimental and ANN methods. The experimental results established a baseline which shows that application of neat OPOB and the blended fuels produced improved values of BTE and BSEC. After that, BTE and BSEC were predicted as outputs of neural network models which used the engine speed, blend percentages, and brake load as input parameters. To understand the strength of the relationships and errors between the predicted ANN results and the experimental values, comparative statistical parameters were used as expressed in equations 2 – 5. The results of the neural networks show high reliability and accuracy of ANN in solving complex engineering problems. Summarily, certain critical deductions are made from the study and are as follows:

- (i) Artificial neural network prediction is a reliably efficient and powerful toolbox for determining performance of CI engine with less complexities and less time consumed.
- (ii) The correlation coefficient values for BTE and BSEC approached +1. This indicates a strong positive linear connection between input parameters and output parameters. It is important to note that among the three algorithms, using the performance indicators, the Levenberg Marquardt algorithm produced the best results. Indications of high performance of the neural network model are the values of the determined MAPE and RMSE which were low. MAPE values for BTE and BSEC were 1.3994 and 1.7334, while RMSE values of BTE and BSEC were 0.358699 and 0.302937 respectively. Thus, Levenberg Marquardt algorithm is recommended highly for application in other prediction conditions.
- (iii) Experimentally, 100% OPOB produced the maximum BTE and the least BSEC values. This necessitates its recommendation for industrial scale application.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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