Computational modeling and multi-objective optimization of engine performance of biodiesel made with castor oil

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ABSTRACT

In this research the engine performance of biodiesel made with castor oil through homogeneous alkali catalyzed transesterification was analyzed. The input variables for the performance analysis were biodiesel blend and engine speed while the response variables were brake power (BP), basic specific fuel consumption (BSFC), break thermal efficiency (BTE), torque and unit cost. The engine performance was modeled using artificial neural network (ANN) and the ANN was subsequently used as the objective function for a non dominated sorting genetic algorithm (NSGA-II) for multi objective optimization of the engine performance. The ANN was equally coupled with a desirability function whose outputs were optimized using simulated annealing for multi objective optimization of the engine performance. Subsequent comparison of the two optimization models was done. The results show that biodiesel from castor oil could be a good replacement for biodiesels from fossil fuels. The ANN model predicted engine performance very well with the lowest value of the correlation coefficient between the experimental responses and ANN predictions being 0.9733. The multi objective optimization using desirability function performed excellently well with the optimum blend and speed being 78.7% and 1754.48 rpm respectively. The Pareto front from the NSGA-II algorithm generally has high desirability values. The Pareto front solution which is more flexible than the desirability function solution would serve as an excellent guide for engine designers. Finally, castor oil based biodiesel cost was for the first time integrated into engine performance optimization studies.

1. Introduction

In recent times climate change and environmental pollution have been burning issues among scientists, engineers and policy makers. One of the main culprits of climate change and environmental pollution is emissions from fossil fuels. According to Radhakrishnan et al. (2018), emissions from conventional diesel engines are a serious source for concern all over the world. This has generated a flurry of activities in researches to develop renewable and sustainable energy sources (Vel-laiyan and Partheeban, 2018). One of these researches is on the use of biodiesel as substitute for diesels from fossil fuels for energy generation. According to Avhad and Marchetti (2015), biodiesels derived from plant oils and animal fats are considered as promising substitutes to diesels from fossil fuels because it has several advantages such as renewability, biodegradability, less environmental toxicity, and superior combustion efficiency. Biodiesel being a good substitute for diesel from petroleum has had wide acceptance globally (Baskar and Aiswarya, 2016). One of the main challenges of researchers involved in the development of biodiesels is on minimization of cost of biodiesel production (Baskar and Aiswarya, 2016). This quest to minimize cost has necessitated researchers to concentrate on production of biodiesel from non edible oils and waste oils (Hajjari et al., 2017; Chaurasiya et al., 2019). Castor oil was used in this research because it is non edible and cheap (Santana et al., 2010). A cost reduction in the region of 60–90% has been reported when non edible oils from algae, microalgae, jatropha and grease are used for biodiesel production (Baskar and Aiswarya, 2016). Dharma et al. (2016) used non edible oils derived from Jatropha curcas and Cieba pentandra for biodiesel production. They optimized the
biodiesel production using response surface methodology (RSM) based on Box–Behnken experimental design. The results they obtained showed that physicochemical properties of the optimized biodiesel conform to the requirements of ASTM D6751 and EN14214 standards.

A very important aspect of research on biodiesel has to do with its effects on engine performance and emissions (Ghazali et al., 2015). Such researches evaluate engine performance characteristics and emission levels using such indicators as brake torque, brake power, brake thermal efficiency (BTE), brake specific fuel consumption (BSFC), Nitrogen Oxide (NOx), PM,CO,CO2, HC, smoke density etc and compare them with pure diesel and biodiesel blends (Ude et al., 2017; Rathore et al., 2019). Investigation by Ganesan et al. (2019) on engine performance of mustard oil based biodiesel showed that biodiesel can be used effectively as substitute for mineral diesel without redesigning the engine. Balan et al. (2019) studied the emission pattern of Decanol combined Jatropha biodiesel (JBD100) fueled diesel engine and compared it with mineral diesel. The results of their research showed that JBD100 produced a lower level of carbon monoxide (CO) hydrocarbon (HC), and smoke emissions with an increase in NOx and carbon dioxide (CO2) emissions. They equally found out that addition of 20% Decanol in JBD100 under full brake power reduced emissions.

Optimizing biodiesel production and engine performance analysis using biodiesel requires conduction of experiments and development of mathematical or computational models that relate the responses to the process input variables (Dharma et al., 2016). In order to reduce the cost of experiments, scientists and engineers usually develop mathematical models for predicting responses from experimental data (Nwobi-Okye and Umeonyiagu, 2013). Quite often developing such models is cumbersome and complex (Nwobi-Okye et al., 2013). Hence, in modern times as a result of advancement in complex software and hardware technology, scientists and engineers have increasingly resorted to development of computational models for prediction of responses from experimental data (Nwobi-Okye and Umeonyiagu, 2015, 2016). Umeonyiagu and Nwobi-Okye (2015a, 2015b) demonstrated extensively the use of computational models for prediction of properties of engineering materials. Such computational tools include ANN, ANFIS, Fuzzy Logic etc. The computational models have proved to perform better than mathematical models in several studies (Umeonyiagu and Nwobi-Okye, 2013).

Optimization could be single or multi objective optimization. Often the engineer is faced with multi and conflicting objectives. For example a designer might desire to minimize hardness while at the same time maximizing the toughness of a material. But variations of the process input variables may not necessarily simultaneously achieve these objectives. Hence, a balance must be struck between the two objectives to achieve a win-win situation. In this study, the engine designer is faced with five conflicting objectives which are minimization of cost and basic specific fuel consumption (BSFC) and maximization of brake thermal efficiency (BTE), brake power (BP) and torque. Hence, this study is centered on multi objective optimization.

There are several mathematical and computational methods for multi objective optimization. The computational methods include Non-dominated Sorting Genetic Algorithm I (NSGA-I), Non-dominated Sorting Genetic Algorithm II (NSGA-II), SPEA I, SPEA II etc (Nwobi-Okye et al., 2019b). The mathematical methods include desirability function, utility concept, TOPSIS, AHP etc (Garg et al., 2017). The difference between mathematical methods and computational methods is that conventional mathematical methods generate several Pareto efficient solutions on the Pareto front while mathematical methods often generate single or several optimal solutions that are not Pareto efficient (Nwobi-Okye et al., 2020). Optimization models use fitness functions or response functions to predict responses to experimental input variables. Fitness functions based on computational models like ANN often perform better than those based on mathematical models, especially in non linear relationships (Nwobi-Okye and Uzochukwu, 2020).

Nwobi-Okye et al. (2019a) used NSGA-II coupled with ANN for multi objective optimization of age hardening process of Al365/Cow horn particulate composite. Objectives were maximization of hardness and minimization of cost. They obtained Pareto efficient solutions that would serve as excellent design guides for engineers using the composite material for engineering applications. Umeonyiagu and Nwobi-Okye (2019) used NSGA-II for multi objective optimization of Bamboo reinforced concrete beams. Flexural and tensile strength maximization as well as minimization of cost were their objectives. The Pareto efficient solutions they obtained showed how the strength could be optimized at minimum cost. Nwobi-Okye and Uzochukwu (2020) used NSGA-II for multi objective optimization of Al6531/Egg shell composite produced through stir casting technique. The process input parameters were stirring speed, time and temperature while the responses were hardness and toughness. The objectives were minimization of hardness and maximization of toughness to achieve improved ductility in order to use the composite for applications that requires ductility. The NSGA-II performed very well and obtained Pareto efficient solutions that would enhance the applicability of the composite in ductile applications.

Bukzem et al. (2016) carried out multi objective optimization of engine performance of biodiesel made with castor oil and fossil diesel blends using NSGA-II and TOPSIS. BP and PM maximization and minimization of emissions and BSFC were their objectives. They showed from their results the utility of NSGA-II and TOPSIS in optimal design of diesel engines using FAME from castor oil and its blends with mineral diesel. Sakhivel et al. (2019) performed multi objective optimization of biodiesel (FAME) from fish oil and its blends with mineral diesel using genetic algorithm (GA) and TOPSIS. They optimized each output parameter namely: NOx, BP, BSFC with GA at various loads (0%, 25%, 50%, 75% and 100%) and selected the best output parameter combination at each load through TOPSIS.

Quite significant is the use of desirability function for multi objective optimization. Bukzem et al. (2016) used desirability function and RSM to optimize the synthesis of carboxymethyl chitosan synthesis using the multi objective optimization methodology. Pandey and Panda (2015) used fuzzy based desirability approach and Taguchi methodology to performed multi objective optimization of bone drilling. Garg et al. (2017) used desirability function for multi objective optimization of process parameters for wire electrical discharge machining (WEDM). The process input parameter namely: pulse on time, pulse off time, spark gap voltage and wire feed were varied experimentally to monitor the responses of three output variables, such as cutting speed, gap current, and surface roughness. Based on the results two optimum process parameters with the same desirability values were obtained. Further works on multi objective optimization using desirability function could be found in the works of Nwobi-Okye et al., 2020, Nwobi-Okye and Uzochukwu, 2020, Sadhukhan et al. (2016) etc.

The literature above has shown the widespread use of NSGA-II and desirability function for multi objective optimization. The major shortcomings of previous studies in this area is that previous researchers did not consider biodiesel cost in their multi objective optimization studies of engine performance of biodiesel fired diesel engines. Also, previous studies used TOPSIS to complement genetic algorithm but other multi criteria decision analysis (MCDA) tools like desirability function, utility function etc were not explored.

In general, the objectives of this research are:

1. To develop an ANN model to predict the relationship between engine speed and blend and BP, BSFC, BTE, torque and cost.
2. Use the ANN as fitness function for NSGA-II algorithm for multi objective optimization of engine performance.
3. Couple the ANN to a desirability function optimized with simulated annealing for multi objective optimization of engine performance.
4. Use the desirability function modelling results to check the NSGA-II algorithm multi objective optimization results for efficiency of its Pareto front.

5. Use the results of both models complementarily for optimal design of diesel engines using biodiesel from castor oil and it’s blend with mineral oil.

2. Materials and methods

2.1. Materials

Castor seed was sourced locally. The methanol, n-hexane, sodium hydroxide, ethanol, chloroform, iodine, acetic acid, potassium iodine, starch indicator, sodium thiosulphate, HCl, chloroform and sulphuric acid etc were all purchased from De-Cliff Integrated Services Ltd, Enugu. The following equipment were used in the course of this research work: viscometer, magnetic hot plate, refractometer, separatory funnels, conical flask, distillation column, gas chromatography mass spectrometry (M910 Buck scientific gas chromatography, GCMS-QP2010 plus Shimadzu, Japan.) and Fourier transform infrared spectroscopy (MS530 Buck scientific FTIR).

2.2. Methods

2.2.1. Extraction and characterization of oil from castor seed

10Kg of the castor seed was measured with an analytical weighing balance into containers, pulverized with a blender and soaked for two days with 3 L each of n-hexane. In order to avoid the evaporation of the n-hexane, the containers were made to be airtight. Decantation was carried out, followed by sieving and then filtration. Distillation of the filtrate to recover the n-hexane was done at a temperature of 65 °C. Eq. (1) was used to calculate the percentage yield of the oil as follows:

\[
\text{% yield} = \frac{\text{weight of the oil extracted}}{\text{weight of the sample used}} \times 100
\]

After the extraction of the oil from castor seed, the oil was characterized to obtain the physiochemical properties. The physiochemical properties of the castor oil as obtained are shown in Table 1.

2.2.1.1. Gas chromatography-mass spectrometry (GC-MS) methods. GC-MS was the apparatus used to measure the fatty acid composition of the oil. The model of the apparatus which was used for the gas chromatographic analysis was GC-MS-QP2010 plus, which was made in Japan by Shimadzu Instrument Company. In order to calibrate the Gas Chromatography (GC) Column oil was used, while dilution of the sample with a small amount of ethyl acetate was used to achieve good separation. Hydrogen was used as the carrier gas. By comparing the retention time and mass spectra with spectra library (NIST05s LIB), the peaks were identified.

2.2.2. Pretreatment of the castor seed oil extracted

A pre-treatment procedure was followed to reduce the excess free fatty acid (FFA) of the castor oil below 1% before converting it to biodiesel. In order to do this, the oil was heated to remove the moisture content. After this, methanol of 60%w/w of oil mixed with concentrated sulphuric acid of 7% w/w of oil was added. A reflux condenser was fitted into the middle arm of the flask and water circulated at the outer jacket of the condenser. A thermometer was inserted into the sample in the flask from one of the side arms. The whole setup was placed on a magnetic heating mantle and heated at 60 °C for 120 min at an agitation speed of 450rpm. The mixture was then put into an apparatus where the oil, water and methanol separated from each other. The upper layer contains methanol, the middle layer contains the pretreated oil while the bottom layer contains the pretreated oil. The components were subsequently separated from each other, water first, followed by the oil and finally methanol. Hot distilled water was poured into the oil in a separating flask, shaken and allowed to stand when it separated into water and oil layers below and above the flask respectively. The water was tapped off from the separating funnel and the pre-treated oil was poured into beakers and dried carefully in an oven regulated at a temperature of 105 °C until the residual water evaporated completely. After this process, the pre-treated oil was made ready for transesterification.

% biodiesel yield = (Volume of biodiesel produced ÷ volume of oil used) x 100

% biodiesel yield = (182 ÷ 200) x 100 = 91%

2.3. Biodiesel production

2.3.1. Transesterification process

The pretreated castor seed oil was transesterified using methanol and sodium hydroxide catalyst in three necked round bottomed flask. Specified quantity of the oil (200ml) sample was introduced into the flask and the flask content heated to the temperature established for the reaction (65 °C). Then methanol and the catalyst mixture (NaOH) were added in the amount established for the reaction (methanol (76ml) and NaOH (2g)), and the stirrer switched on at a specified speed of 250rpm, taking this moment as zero time of the reaction.

In order to complete the reaction at the required time, the mixed reactants were stirred vigorously and refluxed. The transesterified product after methanolsysis was left for a day inside a separating funnel to separate into an upper layer containing the biodiesel and the lower layer containing the glycerol. The lower layer which contains glycerol was first removed from the separating funnel and subsequently the biodiesel was finally removed.

2.3.2. Biodiesel purification

After transesterification, the upper ester layer may contain traces of methanol and glycerol. The remaining unreacted wood spirit, NaOH and glycerin have safety risks that could lead to engine damage and must be removed from the biodiesel. The biodiesel was purified by adding 1M sulphuric acid and hot distilled water to the biodiesel which was held in a separating funnel. The mixture was vigorously shaken and allowed to settle into two layers, the upper layer which is the biodiesel and the lower layer which consists of water and water soluble impurities. The water was removed and subsequently tested for purity with three drops of phenolphthalein indicator. Purification of the biodiesel continued until the water does not turn pink when tested with phenolphthalein. The washed biodiesel was subsequently heated to a temperature of 105 °C to make sure all the water molecules evaporated.
The percentage biodiesel yield was obtained by the following expression:

\[ \text{Percentage yield} = \left( \frac{W}{W_0} \right) \times 100 \]

where

- \( W \) is the weight of the biodiesel
- \( W_0 \) is the weight of the oil used

2.4. Determination of fuel properties of the biodiesel

2.4.1. Flash point

Flash point was determined by pouring the esters sample in a glass petri-dish so that the surface of the dish is covered. A mercury-in-glass thermometer is immersed into the sample in the petri dish so that the tip of the thermometer just touches the esters sample. The thermometer was held to position using a retort stand and clamp. The petridish which contains the sample was put on a laboratory heating mantle. The sample was gradually heated and light source was applied at intervals. The lowest temperature at which the sample just ignites and goes off is called the flash point.

2.4.2. Cloud point and pour point

Cloud point is the temperature at which the esters begin to form mass of cloud at the surface of the diesel. Pour point is the temperature at which the sample solidifies or forms wax-like mass. In order to determine the cloud and pour points, the biodiesel was put in a medium sized test tube and the test tube with its content placed in a test tube rack. This was placed in a refrigerator and monitored. The cloud point occurs at the temperature that heavier components form mass of colloids while the sample solidifies at the temperature called the pour point. Temperature was determined using mercury-in-glass thermometer.

2.4.3. Kinematic viscosity

A u-tube viscometer manufactured by Poulten Selfe and Lee Ltd. (PSI ASTM-IP 350) was used to determine the kinematic viscosity. A micro-pipette was used to introduce 5 ml of biodiesel sample into the viscometer and to bring up the sample to the upper meniscus of the bulb. The flow time of the fuel sample from the upper to the lower meniscus of the bulb was determined in seconds at 40 °C.

\[ \text{Kinematic viscosity} = \frac{c t}{(mm^2/s)} \]  

where

- \( c \) = viscosity constant = 0.4891
- \( t \) = flow time of the oil from the upper to the lower bulb meniscus.

2.4.4. Aniline point

To determine the aniline point, 20ml each of aniline and biodiesel were mixed and stirred in a test tube. The mixture was heated until it formed a homogeneous solution and then cooled. The temperature at which the two phases of aniline and biodiesel separated out was recorded as the aniline point.

2.4.5. Calorific value

Calorific value was determined using bomb-calorimeter. The crucible of the calorimeter was filled with 5g of the samples and then ignited. This ignited biodiesel sample heats up the surrounding water, and the initial and final temperature (\( T_1 \) and \( T_2 \)) of the water were recorded using a thermometer.

\[ \text{Calorific value} = \left( M_w \times C_p \times (T_2 - T_1) \right) / M_f \]  

where

- \( M_w \) = mass of water (kg)
- \( C_p \) = specific heat capacity of water
- \( T \) = Temperatures
- \( M_f \) = Mass of the fuel

2.4.6. Acid value

0.5g of the biodiesel (W) was separately weighed into three dry 250ml conical flasks. 20ml of ethanol and 3 drops of phenolphthaleine indicator were added into each of the flask and their contents well shaken. The solution was titrated with 0.1N sodium hydroxide until a pink colour which persists for 20–30 s was observed (V).

\[ \text{Acid Value} = \frac{\text{Titre Value} \times \text{Normality of the base} \times 56.1}{\text{Weight of the sample used}} \]  

\[ \text{Acid Value} = \frac{V \times N \times 56.1}{W} \]  

where,

- \( 56.1 = \text{Molecular mass of potassium hydroxide} \)
- \( N = \text{Normality of potassium hydroxide} \)
- \( V = \text{Titre value} \)
- \( W = \text{Weight of the oil used} \)

Percentage free fatty acid (% FFA) was determined by multiplying the acid value with the factor 0.503. Thus;

\[ \% \text{FFA} = 0.503 \times \text{acid value} \]

2.4.7. Refractive index

Refractive index was determined using a digital table top refractometer (HI96800) manufactured by Hanna Instruments, Romania. The device was initially calibrated to zero using distilled water. Samples were placed at the glass prism and refractive index value read off using the refractive index key. Air bubbles were eliminated from distilled water and sample respectively before calibration.

2.4.8. Ash content

ASTM D874 measures sulphated ash that may come from abrasive solids, solid metallic soaps, and unremoved catalysts in the biodiesel. In ASTM D874 procedure used, the biodiesel was ignited and burned in a muffle furnace after being treated with sulphuric acid to determine the percentage of sulphated ash present in the biodiesel. The residue ash is calculated as a percentage of quantity of the biodiesel.

| Property                        | Value       |
|--------------------------------|-------------|
| 1. Oil yield (%)               | 45          |
| 2. Colour                      | pale straw  |
| 3. Specific gravity            | 0.966       |
| 4. Moisture content (%)        | 0.02        |
| 5. Refractive index (g/100g)   | 1.467       |
| 6. Saponification value (mg KOH/g) | 174.36     |
| 7. Iodine value (g/100g)       | 38.61       |
| 8. Peroxide value (meq/Kg)     | 0.17        |
| 9. Acid value (mgKOH/g)        | 6.08        |
| 10. Free fatty acid (%)        | 3.04        |
| 11. Ash content (%)            | 0.02        |
| 12. Kinematic viscosity (mm²/s @ 40 °C) | 35.94     |
| 13. Smoke point (°C)           | 40          |
| 14. Fire point (°C)            | 271         |
| 15. Flash point (°C)           | 263         |
| 16. Cloud point (°C)           | 5           |
| 17. Pour point (°C)            | 0.5         |
| 18. Titre point (°C)           | 45          |
| 19. Calorific value (MJ/Kg)    | 31.25       |
2.4.9. Smoke point

Smoke point is the maximum height in millimeters of smokeless flame of fuel burned in a wick-fed lamp of specified design. To determine the smoke point, the biodiesel sample was burned in an enclosed wick-fed lamp. The maximum height of flame that can be achieved with the test biodiesel without smoking was determined to the nearest 0.5mm.

2.4.10. Cetane number

D4737 Test Method for Calculated Cetane number was employed. 20ml each of aniline and biodiesel were mixed and stirred in a test tube. The mixture was heated until it formed a homogeneous solution and cooled. Then the temperature at which the two phases separated out was recorded as the aniline point. Cetane number is calculated using equations below:

\[ \text{API gravity} = \frac{141.5}{SOG} - 131.5 \]  
(7)

Cetane Index = Aniline point (F) x \( \frac{\text{API}}{100} \)  
(8)

Cetane number = 0.72 Diesel Index + 10  
(9)

2.4.11. Conductivity

Conductivity of a biodiesel is a measure of its ability to conduct electricity. The conductivity of biodiesel vary with the mineral composition of the feedstock.

2.5. Engine test analysis and performance evaluation

A Perkins 4:108 diesel engine was used for the performance evaluation of the bio-diesel. The engine is a four cylinder, water-cooled, naturally aspirated and 4-stroke CI engine. The specifications of the is shown in Table 2. The experiments were conducted with standard diesel fuel, biodiesel and blends. The blends are 20% biodiesel (B20), 40% biodiesel (B40), 60% biodiesel (B60) and 80% biodiesel (B80).

2.5.1. Engine test at varying speed (constant load)

In carrying out this test, the engine was started. The engine speed in RPM was measured with a dynamometer. The measured engine speed was kept at 1000rpm while the torque value was observed and recorded. The rate of fuel consumption at this speed was recorded, as well as the exhaust temperature and manometer readings. The process was carried out again at speed values of 1200 rpm, 1400 rpm, 1600 rpm and 1800rpm.

2.5.2. Engine emission test at constant speed (varying load)

In order to carry out this test, the engine was kept running at a speed of 1900 rpm and subsequently loaded with a body weighing 20kg. The values of exhaust gases including: NOx, CO, HC, and SO2 were determined using a digital gas analyzer. After taking the necessary readings at this specified speed, the load on the engine was varied using the dynamometer loading wheel. The process was carried out again at loads of 40kg, 60kg, 80kg and 100kg. Table 3 shows the physiochemical properties of FAME from castor oil and blends at 40 °C.

2.5.3. Variation of engine speed with torque for FAME from castor oil

Figure 1 shows the plot of engine torque against speed for FAME from castor oil, its blends and diesel at full load. The torque increases as the engine speed increases. When the maximum torque was attained with B0, B20 and B40 at an engine speed of 1600rpm and maximum torque reached with B60, B80 and B100 at 1900rpm, the torque started decreasing. This could be as a result of increase in the fuel temperature and reduction in the viscosity and the lubricity. However, the torque of the engine with standard diesel (B0), B20 and B40 was higher and better than that for B60, B80 and B100. This may be as a result of low calorific value attributed to FAME. However, the torque for B20 and B40 shows a very good energy content. The difference in maximum speed between the standard diesels (B0), B20, B40, and FAME could be due to high density and viscosity of FAME over standard diesel.

2.5.4. Variation of Engine Speed with break specific fuel consumption (BSFC)

Figure 2 shows that fuel consumption increases when the engine is running with 100% FAME, but this trend will be weakened as the proportion of FAME reduces. B100 has the highest BSFC. This could be attributed to its low heating value, high density and viscosity. B20 has the lowest and best BSFC. The trend illustrated in Figure 2 also implies that the BSFC decreases as the engine speed increases until minimum BSFC is found at 1600 rpm for fossil fuel, B20, B40 and 1900 rpm for FAME, B60 and B80 then increases as the engine speed increases until 2200 rpm. The difference in value may be as result of difference in feedstock used for FAME production. BSFC of B20 from castor oil is lowest and best, also very close to that of standard diesel.

2.5.5. Variation of Engine Speed with break thermal efficiency (BTE)

Figure 3 shows the variation between engine speed and thermal efficiency using standard diesel, FAME and blends. It was observed that the BTE gradually increases with increase in engine speed at full fuel. After reaching the maximum value, it then decreased. The reason for this is because in the beginning as the speed of the engine increases, the engine torque increases, hence efficiency increases. But at higher rpm (>1600 rpm) for fossil fuel, B20 and B40 and (>1900 rpm) for B60, B80 and B100 the engine gets larger quantity of fuel per cycle and because of higher engine speed this fuel does not get sufficient time to burn completely which reduce the efficiency of the engine. In addition, it was seen that biodiesel and blends have lower thermal efficiency than standard diesel, except B20. This could be due to their lower heating value. Figure 3 equally shows that the efficiency of the engine operating with B20 is the highest. The BTE of B20, even though higher, is almost similar to that of standard diesel (B0) up to the maximum BTE.

### Table 2. Engine specifications.

| Components                  | Values                          |
|-----------------------------|---------------------------------|
| **Type**                    | Perkins 4:108                   |
| **Bore**                    | 79.735mm                        |
| **Stroke**                  | 88.9mm                          |
| **Swept volume**            | 1.76 litres/cycle               |
| **Compression ratio**       | 22:1                            |
| **Maximum BHP**             | 38                              |
| **Maximum speed**           | 3000rpm                         |
| **Number of cylinder head** | 4                               |
| **Diameter of exhaust**     | 1.5”                            |
| **Length of exhaust pipe**  | 36’31’                          |
| **Dynamometer**             |                                 |
| **Capacity**                | 112kw/150hp                     |
| **Maximum speed**           | 7500rpm                         |
| **KW**                      | \( (N_{x} x \text{rev/min})/9549.305 \) |
| **Fuel gauge**              |                                 |
| **Capacity**                | 50—100 cc                       |
| **Air box**                 |                                 |
| **Orifice size**            | 58.86mm                         |
| **Coefficient of discharge**| 0.6                             |

Source: Department of Mechanical Engineering, University of Nigeria Nsukka.
2.5.6 Variation of Engine Speed with break power (BP)

Brake power is regarded as the engine net output. From Figure 4 it could be seen that brake power increases as the speed increases at full load and decreased after reaching a maximum value at 1900rpm for diesel, biodiesel and the blends. This is attributed to reduction in lubricity at higher speed. Moreover, brake power of the engine with diesel was higher than for biodiesel and blends at any speed due its high torque and caloric value (Abdullah et al., 2012). In addition, the brake power of B20 is comparable with that of standard diesel and this is due to its relative close properties with fossil diesel.

2.5.7 Variation of CO and HC emissions with biodiesel fraction of castor oil

Digital gas analyzer was employed to carry out the emission test, and it was discovered that biodiesel brought about reduction in hydrocarbon (HC) and carbon monoxide (CO) emissions. Figures 5 and 6 show the variation of CO and HC emissions with biodiesel fraction of castor oil at different loads. It could be seen that CO and HC emissions reduced as FAME content increases. This could be due to high oxygen content and lower carbon to hydrogen ratio in biodiesel and due to the fact that oxygen molecules in biodiesel enhanced vaporization and atomization of biodiesel and blends compared to diesel fuel (Ong et al., 2014). Also as the engine load increases, the CO and HC emissions increase due to decrease in air-fuel ratio in the engine.

2.5.8 Variation of NOx emission with biodiesel fraction from castor oil

Figure 7 shows the variation of NOx with biodiesel fraction from castor oil at different loads. It indicates that NOx emissions increase with increase in biodiesel fraction. This is mainly due to high oxygen content and cetane number of biodiesel. According to Mueller et al. (2009), biodiesels have higher bulk modulus than mineral diesel and this is responsible for the increased cetane number of biodiesel and advanced injection in diesel engines. According to them this results to combustion starting earlier leading to longer resident time and higher in-cylinder temperature which possibly increases NOx emission. Also, biodiesel contains oxygen, consequently due to increased heat release which occurs at certain phase during combustion NOx emission is likely to be lower.

### Table 3. Physiochemical properties of FAME from castor oil at 40 °C and the ASTM and EN standards.

| Properties                   | Castor Oil FAME (B100) | B80 | B60 | B40 | B20 | Mineral Diesel (B0) | ASTM D6751 Biodiesel | EN 14214 Biodiesel |
|------------------------------|------------------------|-----|-----|-----|-----|---------------------|----------------------|---------------------|
| Biodiesel yield (%)          | 91.0                   | -   | -   | -   | -   | -                   | -                    | -                   |
| Density (kg/m³)              | 866                    | 863 | 858 | 852 | 848 | 835                 | 880                  | 860-900             |
| Moisture content (%)         | 0.03                   | -   | -   | -   | -   | -                   | 0.05 max.            | 0.05 max.           |
| Refractive index             | 1.4600                 | -   | -   | -   | -   | -                   | 1.4580               | 1.4540              |
| Acid value (mgKOH/g)         | 0.460                  | -   | -   | -   | -   | -                   | 0.5                  | 0.5                 |
| Free fatty acid (%)          | 0.230                  | -   | -   | -   | -   | -                   | 0.25                 | 0.25                |
| Iodine value (g I₂/100g oil) | 35.2                   | -   | -   | -   | -   | -                   | 42-46               | 120 max.            |
| Saponification value (mgKOH/g) | 174.36               | -   | -   | -   | -   | -                   | 170-240              | 170-240             |
| Ash content (%)              | 0.02                   | -   | -   | -   | -   | -                   | 0.02                 | 0.02                |
| Kinematic viscosity (cst)    | 4.78                   | 4.5 | 4.4 | 4.32| 4.28| 4.2                | 1.9-6.0              | 3.5-5.0             |
| Smoke point (°C)             | 25                     | 24.8| 24.7| 24.5| 24.4| 24.3               | 30                   | 30                  |
| Flash point (°C)             | 156                    | 150 | 144 | 140 | 120 | 80                 | 130                  | 120                 |
| Cloud point (°C)             | 7                      | 6.8 | 6.4 | 4.3 | -1.1| -5                 | -3 to 12             | -1 to 10            |
| Pour point (°C)              | 3                      | 1   | -3  | -5  | -12 | -17                | -15 to 16            | -10 to 8            |
| Calorific value (kJ/kg)      | 40.02                  | 40.06| 41.1| 41.6| 42  | 42.5               | 42-46               | 35                  |
| Conductivity (μs/cm)         | 0.61                   | -   | -   | -   | -   | -                   | 2.5                  | 2.5                 |
| Anilin point (°C)            | 87                     | -   | -   | -   | -   | -                   | 80                   | 80                  |
| Cetane number                | 60.90                  | 60.28| 60.10| 59.58| 58.90| 55                 | 47                   | 51                  |
| Peroxide value (meq/kg)      | 0.17                   | -   | -   | -   | -   | -                   | 0.1                  | 0.1                 |

Figure 1. Variation of engine speed with torque for diesel, biodiesel and blends.
produced. It also shows that NOx emission increases with increase in load due to higher combustion chamber temperature and higher fuel consumption.

2.6. Biodiesel cost calculations

The biodiesel cost was estimated based on the methodology developed by Santana et al. (2010). We assumed that the producers of the biodiesel must have their own farm in order to make the production of the biodiesel economically viable. Based on the local farming conditions, we estimated the castor seed production cost to be $0.15/kg or N73/kg. Applying the method of Santana et al. (2010), an estimate of $0.5634/Litre or 205.71/Litre for biodiesel commercially produced from castor oil was obtained.

Cost of a litre of Diesel in Nigerian Naira is N227.92.
Let \( C_D \) be cost of Diesel, \( C_B \) cost of Biodiesel and \( b \) is the percentage of diesel in the biodiesel blend.
Cost of biodiesel blend \( C_{blend} \) is given by:

\[
C_{blend} = \frac{(100 - b)C_D}{100} + \frac{bC_B}{100}
\]  

3. ANN modelling

Artificial Neural Network (ANN) is one of the nature inspired computing algorithms that mimics the mode of operation of the nervous system in animals which consists of a network of computational units called neurons (Atuanya et al., 2014). The computational units of ANN
are called artificial neurons. Figure 8 shows a typical two-input single hidden layer feed forward neural network model.

The ANN model developed for the modeling done in this research is made up of three layers as shown in Figure 9. The layers are input, hidden and output layers. In order to train the ANN, seventy percent (70%) of the input data obtained from experiment were used, while for validation and testing 15% each were used respectively. Levenberg-Marquardt algorithm was the algorithm used for training the experimental data (Atuanya et al., 2014; Nwobi-Okoye et al., 2019a, 2019b; Umeonyiagu and Nwobi-Okoye, 2019).

Figures 10, 11, 12, 13, and 14 show the R values for the experimentally obtained torque, BP, BTE, BSFC and unit cost and the ANN predictions of their values. The correlation coefficients for torque, BP, BTE, BSFC and unit cost, shown in Figures 10, 11, 12, 13, and 14, were 0.9735, 0.9792, 0.9733, 0.9758 and 1 respectively.

The high values of R values shown in Figures 11, 12, 13, 14, and 15 indicates that the ANN model predicted the relationship between the independent variables (blend and speed) and the dependent variables (torque, BP, BTE, BSFC and unit cost) very well. Hence, coupling the ANN model to NSGA-II algorithm and desirability function would give very accurate optimal values. Table 4 shows the experimentally determined values of Torque, BP, BTE, BSFC and Cost and ANN Predicted values.

4. Multi objective optimization

In the Multi objective optimization carried out in this research, two methods namely Non-dominated Sorting Genetic Algorithm (NSGA-II) and Desirability function were used. The objectives were minimization of cost and basic specific fuel consumption (BSFC) and maximization of brake thermal efficiency, brake power and torque. These objectives constitute the responses while the input variables were blend and speed.

4.1. Multi objective optimization with NSGA-II algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a version of the classical genetic algorithm heuristics that is used for solving multi objective optimization problems.

![Figure 4. Variation of engine speed with break power.](image-url)

![Figure 5. Variation of CO emission with biodiesel fraction from castor oil at different loads.](image-url)
Figure 15 shows the flow chart for an NSGA-II algorithm. The algorithm shows that an initial population is generated. A fitness function calculates the fitness of the population members. The fitness of the population members is obtained by ranking them from the fittest to the least fit. The fittest population members, which are usually half the initial population, are selected for breeding (crossover) and mutation to produce the next generation (Igboanugo and Nwobi-Okeye, 2011; Oky et al., 2017).

For example, assuming the responses are two namely $y_1$ and $y_2$ and the objectives are maximize $y_1$ and minimize $y_2$. Assuming the following responses in Table 5 were obtained after fitness evaluation:

The solution in serial number 1 dominates the other solutions. If this solution was obtained in the final population, the solution is said to be Pareto efficient and becomes part of the Pareto front which contains other combinations of $y_1$ and $y_2$. However, if the solution occurs in a generation that is not the final generation, the non-dominated solutions are selected for breeding and mutation to produce the next generation for evaluation.

In the NSGA-II algorithm used in this research, the well-trained ANN developed in section 3 was used as the fitness function. The population size used by the NSGA-II algorithm was 50 while the crossover and mutation rates were 0.8 and 0.1 respectively. The final Pareto front obtained after 211 iterations are shown in Table 6.

4.2. Multi objective optimization with desirability function

4.2.1. Desirability function development

Desirability function is a popular multi-objective optimization tool. The function is such that if the objective is to maximize, the following relationship obtains:

Figure 6. Variation of HC emission with biodiesel fraction from castor oil at different loads.

Figure 7. Variation of NOx emission with biodiesel fraction from castor oil at different loads.
Figure 8. Two-input feed forward neural network model.

Figure 9. The 2-input, 10 hidden neurons and five output feed forward neural network model (2-10-5).

Figure 10. ANN predictions of Torque vs experimental data.
Similarly, if the objective is to minimize, the following relationship obtains:

\[
d_i = \begin{cases} 
0 & \hat{y} \leq L_i \\
\left(\frac{\hat{y} - L_i}{U_i - L_i}\right)^s & L_i < \hat{y} < T_i \\
1 & \hat{y} \geq T_i 
\end{cases}
\]  

(11)

The variable \( s \) is a constant that defines the shape of the desirability function. For \( s = 1 \), the desirability function is linear, similarly if \( s < 1 \), the desirability function is convex while for \( s > 1 \) the desirability function is concave.

The composite desirability (DC) is given by:

\[
DC = (d_1 \times d_2 \times \ldots \times d_n)^{1/n} = \left( \prod_{i=1}^{n} d_i \right)^{1/n}
\]  

(13)

where \( n \) is the number of variables.

---

Figure 11. ANN predictions of BP vs experimental data.

Figure 12. ANN predictions of BTE vs experimental data.

Figure 13. ANN predictions of BSFC vs experimental data.
If weights are assigned to $d_i$, and the weights $w_i$ is such that:

$$w_1 + w_2 + w_3 + \ldots + w_n = 1$$

(14)

where $0 < w_i < 1$.

$w_i$ could be determined from principal component analysis, rank order centroid method, analytic hierarchical process (AHP), entropy etc.

$$DC = (d_1^1 \times d_2^2 \times d_3^3 \times \ldots \times d_n^n)^{1/2}$$

(15)

Using rank order centroid method, the following weights 0.4567, 0.2567, 0.1567, 0.09 and 0.04 were assigned to cost, basic specific fuel consumption, brake thermal efficiency, brake power and torque respectively. The parameter settings for the optimization program were done according to Table 7.

This research is unique because the desirability function program written was coupled with the ANN developed in section 3 to generate the responses according to the conceptual model shown in Figure 16. The

| Blend (%) | Speed (RPM) | Torque (Nm) | ANN Predicted BP (kw) | ANN Predicted BTE (%) | ANN Predicted BSFC (kg/KWh) | ANN Predicted Unit Cost |
|-----------|-------------|-------------|------------------------|------------------------|-----------------------------|------------------------|
| 0         | 1000        | 70          | 67.66                  | 7.33                   | 6.94                        | 0.35                   |
| 0         | 1300        | 75          | 73.97                  | 10.21                  | 11.46                       | 0.44                   |
| 0         | 1600        | 80          | 77.10                  | 13.10                  | 13.89                       | 0.49                   |
| 0         | 1900        | 75          | 75.24                  | 14.53                  | 14.31                       | 0.47                   |
| 0         | 2200        | 70          | 69.58                  | 14.13                  | 14.50                       | 0.46                   |
| 20        | 1000        | 67          | 65.64                  | 7.02                   | 7.03                        | 0.37                   |
| 20        | 1300        | 70          | 70.98                  | 9.53                   | 9.54                        | 0.48                   |
| 20        | 1600        | 72          | 72.01                  | 12.06                  | 12.50                       | 0.52                   |
| 20        | 1900        | 60          | 62.25                  | 11.94                  | 11.96                       | 0.50                   |
| 20        | 2200        | 59          | 58.02                  | 13.59                  | 13.60                       | 0.55                   |
| 40        | 1000        | 64          | 64.02                  | 6.70                   | 6.72                        | 0.31                   |
| 40        | 1300        | 66          | 67.65                  | 8.98                   | 9.04                        | 0.38                   |
| 40        | 1600        | 70          | 66.66                  | 11.73                  | 11.79                       | 0.41                   |
| 40        | 1900        | 68          | 65.54                  | 13.53                  | 13.28                       | 0.40                   |
| 40        | 2200        | 60          | 58.68                  | 13.82                  | 12.60                       | 0.38                   |
| 60        | 1000        | 58          | 52.10                  | 6.07                   | 5.35                        | 0.37                   |
| 60        | 1300        | 62          | 62.53                  | 8.44                   | 8.48                        | 0.35                   |
| 60        | 1600        | 65          | 65.27                  | 10.89                  | 10.83                       | 0.39                   |
| 60        | 1900        | 67          | 68.11                  | 13.33                  | 13.29                       | 0.40                   |
| 60        | 2200        | 59          | 58.02                  | 13.59                  | 13.60                       | 0.55                   |
| 80        | 1000        | 52          | 53.37                  | 11.98                  | 12.29                       | 0.33                   |
| 80        | 1300        | 58          | 62.56                  | 7.90                   | 7.32                        | 0.32                   |
| 80        | 1600        | 63          | 63.53                  | 10.56                  | 10.66                       | 0.38                   |
| 80        | 1900        | 65          | 63.76                  | 12.93                  | 12.69                       | 0.38                   |
| 80        | 2200        | 50          | 48.87                  | 11.52                  | 12.19                       | 0.32                   |
| 100       | 1000        | 46          | 50.19                  | 5.24                   | 5.33                        | 0.32                   |
| 100       | 1300        | 59          | 59.89                  | 7.49                   | 7.43                        | 0.27                   |
| 100       | 1600        | 59          | 58.02                  | 10.39                  | 10.44                       | 0.35                   |
| 100       | 1900        | 45          | 45.75                  | 12.73                  | 12.74                       | 0.36                   |
| 100       | 2200        | 35          | 36.04                  | 11.29                  | 12.20                       | 0.28                   |

Table 4. Experimental values of Torque, BP, BTE, BSFC and Cost and ANN Predicted values.

Table 5. Illustration of dominated solution.

| S/N | $y_1$ | $y_2$ |
|-----|-------|-------|
| 1   | 20    | 300   |
| 2   | 20    | 200   |
| 3   | 20    | 100   |
The desirability function was later used as the objective function in a simulated annealing optimization program to obtain the optimum value of desirability, cost, basic specific fuel consumption, brake thermal efficiency, brake power and torque values and the corresponding values of blend and speed.

### 4.3. Desirability optimization procedure using simulated annealing

Simulated annealing (SA) is an optimization method that simulates the annealing process used by metallurgists to improve the quality of metals. A significant advantage of SA is that it is a proven fact that given sufficiently large number of iterations at each temperature, SA will almost surely converge to the global optimum (Nwobi-Okoye and Ochieze, 2018).

In order to use simulated annealing for desirability optimization, the ANN described in section 3 was used as the fitness function to develop a function whose output is the desirability while the inputs were blend and speed. The developed function was used as the objective for a SA program which optimized the desirability in order to obtain the optimum values of cost, basic specific fuel consumption, brake thermal efficiency, brake power and torque values and the corresponding values of blend and speed. The upper and lower limits of the input variables (blend and speed) were determined based on the experimental results.

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**Table 6. Process decision variables corresponding to each of the Pareto optimal solutions.**

| S/N | Blend (%) | Speed (RPM) | Torque (Nm) | BP (kw) | BTE (%) | BSFC (kg/KWh) | Unit Cost |
|-----|-----------|-------------|-------------|--------|---------|---------------|-----------|
| 1   | 0.01      | 1536.33     | 77.25       | 13.57  | 0.49    | 0.16          | 227.92    |
| 2   | 95.87     | 1935.95     | 49.56       | 12.60  | 0.31    | 0.26          | 206.76    |
| 3   | 0.01      | 1991.57     | 74.37       | 15.11  | 0.47    | 0.16          | 227.92    |
| 4   | 0.17      | 2132.95     | 71.54       | 15.84  | 0.48    | 0.17          | 227.91    |
| 5   | 0.00      | 1794.09     | 75.87       | 13.61  | 0.47    | 0.16          | 227.92    |
| 6   | 99.99     | 1239.57     | 58.44       | 5.91   | 0.24    | 0.36          | 205.71    |
| 7   | 100.00    | 2026.52     | 40.04       | 12.46  | 0.28    | 0.28          | 205.70    |
| 8   | 14.96     | 2135.42     | 60.07       | 13.61  | 0.54    | 0.17          | 225.34    |
| 9   | 99.99     | 1226.09     | 57.99       | 5.65   | 0.23    | 0.37          | 205.71    |
| 10  | 100.00    | 1282.28     | 59.56       | 6.93   | 0.26    | 0.32          | 205.71    |
| 11  | 100.00    | 1167.60     | 55.63       | 4.88   | 0.21    | 0.41          | 205.71    |
| 12  | 94.33     | 1869.97     | 55.34       | 12.65  | 0.32    | 0.24          | 207.22    |
| 13  | 100.00    | 1938.75     | 43.63       | 12.69  | 0.28    | 0.26          | 205.70    |
| 14  | 83.97     | 1466.55     | 63.61       | 10.95  | 0.35    | 0.22          | 209.69    |
| 15  | 86.33     | 1343.05     | 63.12       | 8.70   | 0.32    | 0.25          | 209.34    |
| 16  | 100.00    | 2061.04     | 39.04       | 12.38  | 0.28    | 0.29          | 205.70    |
| 17  | 25.55     | 1290.36     | 71.10       | 9.52   | 0.40    | 0.19          | 221.45    |
| 18  | 98.43     | 1845.93     | 51.44       | 12.55  | 0.30    | 0.25          | 206.10    |
| 19  | 16.97     | 1900.45     | 64.01       | 12.04  | 0.53    | 0.17          | 224.71    |
| 20  | 59.93     | 1458.42     | 63.95       | 7.60   | 0.38    | 0.21          | 214.62    |

---

**Figure 15.** NSGA-II algorithm (Source: Nwobi-Okooye et al., 2020).
were used as the upper and lower bounds of the optimization algorithm. The values of the experimental variables (blend and speed) which gave the highest desirability value were used as the starting point values for the optimization. The negative values of the desirability were the outputs of the objective function because the objective of the simulated annealing algorithm is to minimize the objective function.

After 30 runs of the optimization program, the 22 best results in descending order of decreasing desirability is shown in Table 8.
5. Discussion

The optimized Pareto front solution shown in Table 6 shows that according to serial number 18, if an engine designer wants the cost of the fuel to be 206.10, the minimum BSFC is 0.25 and the maximum torque, BP and BTE are 51.44, 12.55 and 0.30 respectively. Similarly, according to serial number 16, if an engine designer wants the efficiency to be 53%, the minimum cost and BSFC are 224.71 and 0.17 respectively while the maximum torque and BP are 64.01 and 12.04 respectively. The implication of this is that increase in efficiency is at the expense of fuel cost. Similarly, reduction in fuel cost is at the expense of reduced efficiency.

In the optimization results using desirability function as shown in Table 8, the best desirability value of 0.93 was obtained. As shown in Table 8, two combinations of blend and speed gave a desirability value of 0.93. Table 9 shows the desirability values of the process parameters on the Pareto front. Non-dominated Sorting Genetic Algorithm (NSGA-II) is more objective than the desirability function because it attaches equal importance to all response variables. This obviously accounts for high variability of desirability values on Table 9 compared to Table 8.

Since cost carries the highest weight in the desirability function calculations, a plot of the cost values on the Pareto front and their corresponding desirability values is shown in Figure 17. As Figure 17 shows, generally high cost values on the Pareto front corresponds to low desirability values while low cost values generally have high desirability values.
values. It is noteworthy that desirability values on the Pareto front are generally high.

The implication of this is that if the designer does not pay attention to any particular engine response parameter like power or torque, it is most suitable to use desirability function as the basis for selection of the optimum engine characteristics. If for example the designer wants an application that requires high power. The highest brake power (BP) value on the Pareto front is 15.84 and the minimum cost to obtain such torque value is 227.91 and the desirability is 0.46 as shown in Table 9. In order words, when such requirements are desired the Pareto front solutions becomes the basis for the selection of the appropriate blend and speed even though the desirability value of such selection is less than optimum.

In comparing this research with others, pertinent to note that existing literature studies on biodiesel produced from castor oil concentrated on its effects on engine performance and emission studies. For instance, Attia et al. (2018) focused on engine performance and emission studies of FAME from castor oil produced in Egypt without optimizing the engine performance. Similarly, Aboelazayem et al. (2018) carried out similar studies on FAME from castor oil without optimizing the engine performance. The same goes for Attia et al. (2018), Bueno et al. (2017), Hurtado et al. (2019), Das et al. (2018) who carried out similar studies without considering engine performance optimization. As a matter of fact virtually all the studies in the available literature dealt solely on engine performance and emission studies of biodiesel produced from castor oil.

In terms of novelty, comparing this work with that of Eghani et al. (2013), it is clear that they never considered biodiesel cost in their multi objective optimization of engine performance of biodiesel produced from castor oil and its blends with mineral diesel. Also they considered only BP, BSFC and emissions whereas this study considered BP and BSFC as well as Torque, BTE and Cost which are critical to the choice of biodiesel and engine performance. Also, this study used NSGA-II and desirability function coupled with ANN to determine the optimum biodiesel blend but Eghani et al. used TOPSIS and NSGA-II.

Furthermore Sakhivel et al. (2019) never considered cost of biodiesel in their multi objective optimization of biodiesel made from fish oil and its blend with diesel from fossil fuel. They used ordinary GA for single objective optimization and later refined their results to obtain multi objective optimal solutions using TOPSIS. Whereas this study used computationally superior GA algorithm (NSGA-II) for multi objective optimization and complemented it with a robust desirability function model coupled with ANN and optimized with simulated annealing to obtain excellent multi objective optimal results.

6. Conclusion

Based on the research results, the following conclusions can be drawn from this study:

(i) The engine performance analysis shows that FAME from castor oil can be an effective replacement for diesel from fossil fuels. The experimental observations show that fuel consumption increases when the engine is running with 100% FAME, but B20 had the least BSFC. Maximum BSFC for B0, B20, B40, B60, B80 and B100 were 0.23, 0.22, 0.27, 0.33, 0.38 and 0.42 respectively while the minimum BSFC B0, B20, B40, B60, B80 and B100 were 0.17, 0.15, 0.20, 0.21, 0.22 and 0.24 respectively. In addition, with the exception of B20, it was seen that biodiesel and blends have lower thermal efficiency than standard diesel. Maximum BTE for B0, B20, B40, B60, B80 and B100 were 0.49, 0.55, 0.41, 0.40, 0.38 and 0.36 respectively while the minimum BTE B0, B20, B40, B60, B80 and B100 were 0.35, 0.37, 0.31, 0.26, 0.22 and 0.20 respectively. B100 had the least torque while B0 had the highest torque. Maximum torque for B0, B20, B40, B60, B80 and B100 were 80, 72, 70, 67, 65 and 59 respectively while the minimum torque B0, B20, B40, B60, B80 and B100 were 70, 59, 60, 52, 50 and 35 respectively. Also, brake power increases as the speed increases at full load and decreased after reaching a maximum value at 1900rpm for diesel, biodiesel and the blends. Furthermore, the emission studies showed that CO and HC emissions reduced as FAME content increases. Also, NOx emissions were found to increase with increase in biodiesel fraction.

(ii) ANN can predict the engine performance of FAME from castor oil very well with the correlation coefficient between experimental values and ANN predictions having a least value of 0.9733 and maximum value of 1.

(iii) Non-dominated Sorting Genetic Algorithm (NSGA-II) which used ANN as its fitness function can perform multi objective optimization of engine performance of FAME from castor oil.

(iv) Desirability function coupled with ANN is a good tool for multi objective optimization of engine performance of FAME from castor oil. Although desirability function is less flexible than NSGA-II algorithm. The highest desirability of 0.93 was obtained with the speed and blends being 78.72 and 1754.48 respectively as well as 78.30 and 1755.67 respectively.

(v) Finally, castor oil based biodiesel cost was for the first time integrated into engine performance optimization studies.

For future research, Fuzzy Logic Systems and Adaptive Neuro-Fuzzy Inference System (ANFIS) have shown great promise as a modeling tool for predicting process outputs. We therefore suggest the use of NSGA-II which uses Fuzzy System or ANFIS as fitness function and a multi criteria decision analysis (MCDA) tool like DF, TOPSIS, Utility Function etc coupled with FS or ANFIS and optimized with SA, PSO, ACO etc for modeling the performance of biodiesel and its blends with mineral diesel on engine performance. The blends can be increased in increments of 5 or 10% to obtain more accurate results. Furthermore, the experiments could be performed using other kinds of diesel engines like multi-cylinder and variable compression-ratio engines.

Declarations

Author contribution statement

Jonah Chukwudi Umeuzuegbu: Conceived and designed the experiments; Performed the experiments.

Stanley Okiy: Contributed reagents, materials, analysis tools or data.

Chiudzie Chukwuwemeka Nwobi-Okaye: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Okechukwu Dominic Onukwuli: Analyzed and interpreted the data.

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Data will be made available on request.

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The authors declare no conflict of interest.

Additional information

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