Kufa Journal of Engineering
Vol. 16, No. 1, January 2025, P.P. 298-323
Article history: Received 11 July 2024, last revised 22 August 2024, accepted 13 September 2024

A GREY WOLF OPTIMIZATION APPROACH FOR EVALUATING THE ENGINE RESPONSES OF VARIOUS BIODIESEL BLENDS IN AN INTERNAL COMBUSTION ENGINE

Chukwuka Prosper Ozule[1], Bayo Yemisi Ogunmola[2], Adeyinka Oluwo[3], Nehemiah Sabinus Alozie[4], John Rajan[5], Swaminathan Jose[6], Sunday Ayoola Oke[7], Ugochukwu Sixtus Nwankiti[8]

[1,2,3,4,7,8] Department of Mechanical Engineering, University of Lagos, Lagos, Nigeria

[5] Department of Manufacturing Engineering, Vellore Institute of Technology, Vellore, India.

[6] School of Mechanical Engineering, Vellore Institute of Technology, Vellore, India

[*] Corresponding author: sa_oke@yahoo.com

https://doi.org/10.30572/2018/KJE/160118

ABSTRACT

The knowledge of the exact thresholds of parameters in the diesel engines, during combustion, is essential to simulate the combustion process, establish parametric values, reduce cost and predict exhaust emissions. Accordingly, the present paper applies the grey wolf optimization method to determine the optimal threshold of parameters and engine responses in a direct ignition engine. Twelve formulated linear equations of engine responses are introduced to the objective function of the grey wolf optimizer. A computer program in C++ was applied successfully using literature data to validate the grey wolf optimization procedure based on the encircling, hunting and attacking of prey by the wolf. The results show that load demand and turbocharge boast air pressure have the least and highest values of engine outputs, respectively. The blend ratio had its highest values when optimized alongside the main injection duration. The responses and parameters greatly improved from initial values to stopping criterion of 200 iterations. Instances reported include brake specific fuel consumption, which improved from 2.6468 to 1.0816 g/kWhr, blend ratio changes from 0.5031 to 0.4760%, speed drop from 0.0031 to 0.0010rpm, and load drop from 0.0017 to 0.0010%. The main contribution of this paper is to establish the optimal thresholds of engine responses using the grey wolf optimizer in a diesel engine combustion chamber. The development of a new method to optimize response and parameters of an internal combustion process using grey wolf optimizer is the novel aspect of this work. The results have essential practical significance to establish new emission profile for biodiesel. The practising engineers and researchers have a holistic insight into the problem's solution and can utilize the results to enhance their engine responses.

KEYWORDS

Ignition, biodiesel, engine operation, optimization, fuel blends, engine response.

1. INTRODUCTION

Today, engine manufacturers are increasingly pressured to comply with the stringent emission regulations concerning combustion engines and the rapidly changing replacement attitudes of engine users from fossil fuels to biofuels (Jasim, 2019; Hassan et al., 2018; van Niekerk *et al.*, 2020). Moreover, direct ignition engine responses, which measure how quickly the engine can increase its power, is a recent research interest in the field of combustion. For example, (Mohamed *et al.*, 2024) analyzed the possible enhancement to engine responses while changing fuel between hydrogen and gasoline in direct injection and spark ignition engines respectively, using an experimental approach. At variance to this approach, (Windarto and Lim, 2024) deployed a machine learning approach termed neural network to evaluate the engine response for a compression ignition engine that worked on propane. However, the prevailing engine response improvement approach in the industry is to maintain a good air fitter in the engine, regularly clean the engine body and replace the fuel filter when due for changes. The major drawbacks of this conventional approach are that it involves numerous tasks, intensive planning, huge cost involvement in monitoring the engine and many more. When attempting to enhance the performance of the engine responses, it is challenging to understand what ratios of these tasks mentioned earlier should be established. The results are also sometimes ineffective due to the sub-optimal thresholds that the parameters of the engine responses would yield. More importantly, attaching equal significance to the tasks of choosing a good air filter, fuel filter replacement and engine's body cleaning may lead to under-emphasis of some of the tasks and over-emphasis in others, resulting in inaccurate or sub-optimal decision-making on direct ignition engine operation and maintenance. Therefore, establishing optimal thresholds of parameters, especially using contemporary evolutionary methods is of huge importance in enhancing the engineering manager's assessment and plan to achieve optimized results.

Generally, the Taguchi method is commonly used to optimize process parameters as proposed in several studies discussed as follows: (Wei et al., 2024) deployed the Taguchi method to enhance engine responses of an engine while focusing on process parameters such as ignition timing, injection timing and injection pressure. Specifically, the L16 orthogonal array was used to achieve improved engine performance. (Zhang et al., 2023) introduced the Taguchi method to assess the influence of control parameters to lower the calibration work. The L18 orthogonal array was used as the starting point for achieving the signal-to-noise ratios while focusing on the following process parameters: the premixed strategies, speed, energy ratio, excess air ratio and engine load. (Xie et al, 2024) utilized the Taguchi method in an experiment to select the optimal mix of process parameters, which include ignition timing, the energy distribution of the engine, injection timing, excess air coefficient and torque. The analysis of variance was added to the Taguchi method to produce better results than the Taguchi method alone. (Teoh *et al.* , 2022) reported on an L16 orthogonal array optimization scheme to define the optimal biodiesel blend proportion and the best engine response in a diesel engine. The analyzed process parameters representing the engine process are the engine load, engine speed and blend ratio. The Taguchi method was integrated with the grey theory as Taguchi grey technique and 13 performance indices were analyzed.

Furthermore, (van Niekerk et al., 2020) evaluated the emissions produced from a compression ignition engine feed with the blend of ethanol, diesel and biodiesel utilizing various fuel delivery methods and the exhaust gas circulation process. The similarity of the article with the present work is the common benchmark of optimization applied in both studies. While the central composite design methodology scheme was the optimization tool used in their work, the present article uses the grey wolf optimization method whose strength is a fast convergence behaviour. Their work concludes that using the centre composite design revealed that NO_x emissions were reduced by 25% when a 45% threshold of the exhaust gas circulation was the upper boundary. Notwithstanding, the issue of fast convergence of algorithms was not considered in the work. (Pedrozo et al., 2021) studied the influence of natural gas fuel properties on the performance and emission of engine activities in the reactive-controlled compression ignition and conventional dual-fuel states. It was concluded that the gas mixture exhibiting the least methane number lessened the methane slip at the expense of heightened emissions from nitrogen oxides and total unburned hydrocarbon emissions. (Ebrahimi et al. , 2019) executed an optimization scheme comprising multiple inputs and multiple outputs in a compression-ignition combustion system that uses a heavy-duty diesel engine fed with natural gas as well as diesel fuel. The optimization scheme is common to the reviewed article and the present study. However, this type of optimization varies and the grey wolf method proposed in the present study seems less reported in the literature than the fractional factorial approach based on the design of the experiment approach implemented in the work. (Wang et al. , 2023) analyzed the combustion features and engine accomplishment of kerosene subjected to compression ignition status information which is required for performance optimization. It was reported that kerosene exhibited reduced carbon monoxide than diesel. Also, kerosene gives out less thermal efficiency and particle emissions than diesel. Nonetheless, the emissions from NO_X and hydrocarbon are higher in kerosene than diesel. Furthermore, the issue of optimization has been downplayed in the article and the emergence and implementation of the grey wolf algorithm is novel in the area of combustion engine performance optimization.

It is clear from the literature review that optimization can enhance the combustion process performance by reducing combustion emission and improve engine responses. Moreover, the multi – objective optimization is one of the key dominant techniques in the performance and emission optimization of engine parameters during combustion (Yotchou et al., 2023). Through multi – objective optimization has been proven effective in enhancing engine tongue and reducing fuel consumption (Yotchou et al., 2023), it produces a Pareto front against a single optimal solution of the problem. The weakness is that it exhibits inefficient tradeoffs when solving practical problems. Furthermore; the Taguchi method is used by several papers. (Sakthivel and Illangkumaran, 2017) deployed combined Taguchi-fuzzy method to enhance fishoil biodiesel performance and reduce emission from a compression ignition engine. (Saluja et al., 2024) optimized the integrated influence of engine operating and injection parameters on the reduction of fuel, emissions and elevation of the combustion ignition engines performance using Taguchi method and Jatropha-karanja biodiesel blends.

Notwithstanding one of the key issues with the Taguchi method is its inability to showcase parameters with the highest influence on the process. Furthermore, response surface methodology has been applied to the optimization of performance of combustion ignition engine (Raj et al., 2024). However the response surface methodology has limitation, including the requirement to carefully design experiment; and this method may not be useful in solving highly non-linear system problems. The above limitation of the major methods such as the Taguchi method, response surface methodology and multi-objective optimization make it compelling to search for more efficient optimization techniques particularly that overcome these limitations and in addition could process results in a quick convergence rate, which the mentioned methods are not capable to do. This mentioned attribute will enable quick decision making by engineers thus promoting acceptability of optimization methods. Thus; a new approach is needed to bridge this knowledge gap. The new approach introduced to solve this problem is the use of experimental data from the literature to solve the problem.

From the previous discussion, a few studies have utilized the Taguchi method or combined it with other methods such as the engine responses to obtain the best performance for the engine using diverse parameters including the following engine load, engine speed, blend ratio, ignition timing, energy distribution of the engine, injection timing, torque, injection pressure and many more. However, the Taguchi method, which is the prevalent method in this research area often gives results, which are relative but offer no clear indication of what parameter exhibits the greatest influence on the performance feature value of interest in the investigations reviewed. To address this limitation, the use of the evolution algorithm as an effective way of optimizing process parameters has attracted much attention from researchers.

The evolutionary algorithm could solve engine response problems by using schemes that mimic the characteristics, feeding behaviour, order in animal habitation and conducts of living things within their territories (i.e. grey wolves). The common mechanisms associated with evolutionary algorithms are their biological evolution, which is often specified as reproduction, mutation and recombination. Moreover, among the evolutionary algorithms, the grey wolf algorithm seems to be a pragmatic and promising tool for the optimization of engineer response indirect ignition engines. The uniqueness of the grey wolf algorithm lies in the fact that it can balance mining and exploration. Besides it is capable of accelerating the convergence speed when operating a global search using the linear convergence scheme. It could also enhance optimization accuracy in local search (Long et al., 2018; Rezaei et al., 2022). Therefore, the grey wolf optimizer exhibits numerous advantages in establishing optimal thresholds of parameters and in enhancing the effectiveness and scientific success of the engine response optimization endeavour. Therefore, this research aims to fill the research gap identified here, which is the absence of an efficient optimization scheme in the contemporary optimization perspectives.

To date, few optimization studies have been found on the combustion research related to the present study. Still, no report was found to have implemented the grey wolf optimization method in the optimization of process parameters during the testing period of fields in internal combustion engines. Therefore, the present method has been developed to bridge this important gap. In this article, the grey wolf optimization method has been proposed to optimize the parameters of the combustion process using biodiesel blends with data obtained from the literature. The primary value of the work is about the technical and non-technical issues around the combination process, which can be planned for and tackled before operating the engines. These issues will aid in producing quality engines that conform to the standard emission thresholds. Thus, to deliver its primary value and uniqueness, this article is the first to offer the grey wolf algorithm as a robust and new method for optimizing the combustion process parameters. The attraction to implementing the grey wolf algorithm is the characteristics of the grey wolf algorithm that includes elegance as predators and being lightly social animals with tight nuclear packs, being elegant predators, the algorithm displays the clever attribute of the grey wolves in sustaining their lives by killing and eating other animals. Applied to the parametric optimization problem, it means that the algorithm of the grey wolves works on the formulated problem and solves it in such a way the final solution is obtained, similar to the capture and killing of the prey by the grey wolf. The second attribute of being highly social animals with close nuclear packs is advantageous to the system. Once an animal gets to the pack, it encircles it and each of the group members functions in the designated responsibilities, taking instructions from the alpha wolves. These attributes are used to solve the combustion process parametric optimization problem. This means that once a problem is to be solved, the procedures organize themselves such that the responsibility to produce optimal results is distributed among the grey wolves by categories. Moreover, the grey wolf algorithm presents a big picture of the cooperative attitudes of the members of the pack in solving the combustion process optimization problem.

The purpose of this paper is to apply the grey wolf optimizer as an optimization structure to enhance the engine responses in a direct ignition engine. The main contribution of this study is along the following paths: firstly, the present study allows engineering managers to employ quantitative judgements through the application of a grey wolf optimizer to determine the optimal thresholds of parameters for the direct ignition engine with optimized responses in a biodiesel blend for the engine operation. Secondly, an experimental study, whose data was retrieved from the literature, using the grey wolf optimizer, demonstrated the effectiveness as well as the benefits of the proposed method. Accordingly, this paper contributes to the literature by developing an approach that can predict a parametric threshold capable of informing engineers of the level of emissions expected from operating the direct ignition engine with the operating fuel of Karanya biodiesel.

This paper introduces the grey wolf optimizer, a simplified model to evaluate the engine responses of various biodiesel blends in an internal combustion engine. It extends beyond the traditional use of the Taguchi method of optimization or its merging with the grey, relational analysis (Teoh et al. 2019). The translation of analysis of variables results into objective functions based on responses into the grey wolf optimization framework presents a novel optimization approach. The developed empirical models serve as a valuable tool to establish and compare the optimal scenarios and related outcomes. Moreover, the grey wolf optimization adopted in the present study is capable of balancing mining exploration and acceleration of convergence speed in a global search. It achieves this through a linear convergence while enhancing optimization accuracy in a local search. It avoids the development of local extreme points within a small region.

Furthermore, to illustrate the limitations of the work, the simplification of the mathematical model of the grey wolf optimizer and the assumptions about hunting behaviour may not be valid in all cases. Future studies may be refined. The simplified grey wolf optimization model introduces additional parameters such as the effect of unexpected changes in the weather conditions such as sudden heavy rainfall while chasing prey. The emergency of an additional animal in the environment, such as a lion to distract the attention of the grey wolves may introduce a more comprehensive analysis into the modelling of the optimization of the process parameters. The findings of this study could support manufacturing policy associated with resource utilization during the operation of the internal combustion engine.

Moreover, the necessary applications of the model are diverse. However, the optimization of alternative fuels for internal combustion engines is a key concern in the several applications of the present model. Specifically, the tyre pyrolysis oil as an alternative source of fuel that may be approached through the optimization perspective. Tyre pyrolysis oil may be produced through pre-processing, pyrolysis, oil and gas separation and sludge discharge. Within the gas holders, liquefaction of substances into crude oil occurs. This oil is the alternative fuel that may be used in the internal combustion engine and should be optimized.

2. METHODOLOGY

The summary of the methodology employed in the implementation of the grey wolf algorithm in this work is shown in Fig. 1. However, in the attainment of the optimal parameters in the biodiesel-diesel mixture ratio as well as the engine input parameters, objective functions in linear programming were formulated and solved using the grey wolf optimization procedure. Then a program in C++ was developed to ease the computational procedure. First, random numbers are generated between 0 and 1 to have sufficient data for analysis and to predict the behaviour of the grey wolf algorithm which is difficult to obtain in the paucity of data. Usually, a stochastic behaviour is assumed in the variables on the use of the random members. Furthermore, the p-value (probability value) was deployed to understand the likelihood of the data generated complying with the will hypothesis. This is achieved as the likelihood of the test statistic is computed; this is the obtained member through statistical testing of the data. The results are then collected to obtain the objective function that is used as the framework for implementing the grey wolf algorithm. The objective function was used to associate the variables of the engine combustion process in a linear programming form. In this article, the operations on the responses to obtain the objective functions are both in the minimization and maximization aspects. In this situation, for the problem solved, there are twelve responses out of which seven responses are associated with the minimization of responses while five responses are associated with the maximization of responses. To understand the responses in detail, the following information is provided; the minimized responses are the BSFC, exhaust gas temperature, exhaust O_2 CO(%), smoke (%), NO_x(ppm) and load demand (%). Furthermore, the responses for the maximization procedure are brake-specific energy consumption, start of fuel injection, main injection duration, rail pressure, and turbocharge boast air pressure.

2.1. Some information on responses

Here, a selected number of responses are explained to understand them in detail.

BSFC: This response is to be minimised in the present study. The motivation for this is that highly efficient engines are known for their lower BSFC. Therefore, a minimization objective is pursued for this factor since we desire our engines to be increasingly efficient. The BSFC helps to compare the efficiency of engines of the internal combustion type with shaft outputs.

Brake Specific Energy Consumption (BSEC): In this work, the BSEC is a response to be optimized. Given the understanding that the product of the BSFC and the fuel calorific value gives the BSEC, a picture of how efficient the fuel energy received from the particular fuel is the BSEC. More particularly, the BSEC is mathematically represented as the ratio of the energy received through the burning of the formulated biodiesel in one hour to the real energy. It has a dimensionless outlook.

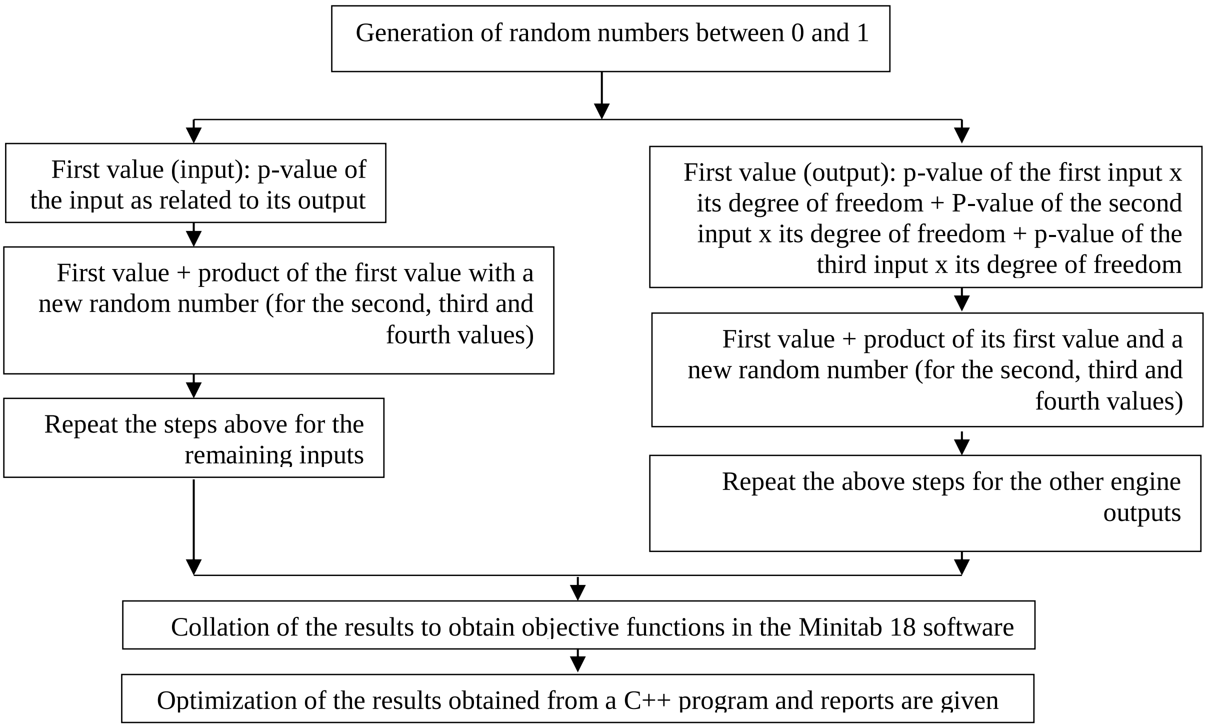

Fig. 1. Research scheme

Exhaust gas temperature (EGT): During the combustion of the biodiesel used in the present study, the internal combustion engine produces gases, known as exhaust gases, at unregulated or regulated temperatures. These gases, which include nitrogen, water and carbon dioxide are normally produced at high temperatures and their effects in heating the environment where the combustion activities are conducted may be intense. Therefore, minimization of these gases is desired. The EGT is shown to impact the health of the combustion engine, biodiesel-air mixture quality and the combustion efficiency.

Exhaust Oxygen: During the combustion of biodiesel in the internal combustion engine, oxygen is one of the gases produced. However, elevated amounts of exhaust oxygen are desired for the combustion to be efficient. Therefore, for the response named exhaust oxygen, incomplete combustion is often avoided which is an indication of a low threshold of exhaust oxygen.

Furthermore, the main purpose is to study the optimal process parameters of different biodiesel fuel blends combusted in an internal combustion diesel engine. The parameters used to form Table 1 were obtained from the analysis of variance in Table 9 of (Teoh et al., 2022). Table 1 shows the input parameters, responses and the optimization operations on them to yield optimal results.

Table 1: Input parameters and responses with objectives

S/No.	Inputs	Responses	Operation on responses
1	Blend Ratio (%)	Brake specific fuel consumption (g/kWhr)	Minimize
2	Speed (rpm)	Break specific energy consumption (MJ/kWhr)	Maximize
3	Load (%)	Exhaust gas temp. (dC)	Minimize
4		Exhaust O_2	Minimize
5		CO (%)	Minimize
6		Smoke (%)	Minimize
7		NOx (ppm)	Minimize
8		Start of Fuel Injection (SFI)	Maximize
9		Main Injection Duration (us) (MID)	Maximize
10		Rail Pressure (bar)	Maximize
11		Turbocharge Boost Air Pressure	Maximize
12		Load Demand (%)	Minimize

BSFC measures how efficiently fuel is used to produce braking power. However, the higher the value of the BSFC, the lower the measure of the efficiency of the engine becomes. This is why it was minimized. The ratio of the energy produced by burning gasoline per hour to the absolute energy or brake power produced at the wheels is known as brake-specific energy consumption. This serves as the opposite of brake-specific fuel consumption. Therefore, it is maximized. The exhaust gas temperature (EGT) is evaluated at the exhaust manifold. It is used to regulate the fuel/air combination entering the engine using the temperature of the exhaust gas. Therefore, the more fuel consumed, the greater the temperature obtained so it is minimized. Meanwhile, exhaust oxygen is the measure of the amount of oxygen obtained from the exhaust gas. When this is too much, leakages might occur and that is why it is being minimized. CO, smoke and

NOx are all injurious gases that may lead to the death of humans. As a result, they are all minimized.

The start of injection in the diesel engine is the point at which fuel is sprayed on the compressed air from the intake stroke which sets the piston working. This is why it was maximized. Moreover, the main injection duration is the timeline at which actuators force the injector to open or close as a result of little or no flow rate. This grants an optimal performance to the engine thereby why it was maximized. Rail pressures for diesel engines are expected to be high to effectively drive the valves in it. This is the reason for its optimization. Meanwhile, the turbo boosts air pressure is the pressure produced for efficiency in an engine where there is a greater push of air into the engine with an equal amount of fuel to burn. This was why it was maximized. Lastly, load demand hampers the speed of the engine and therefore has to be minimized. The results used for the first responses were obtained by multiplying the P-values with the degree of freedom in front of each input and then summing them together. The other results (second, third and fourth values) were obtained by adding the results obtained to the product of random numbers between 0 and 1 for the remaining three results each.

Furthermore explanations are given on how the responses and input parameters to the internal combustion engine at the right. In this work the data from (Teoh *et al*., 2022) which contains the result on the analysis of variance (ANOVA) for all the output variables of the combustion process was extracted. (Teoh *et al*., 2022) conducted experiment and stated the details of the responses to the combustion process and the input parameters in an experiment. The further details stated are the p-value and the Degree of Freedom. While some optimization studies have been conducted previous, using the optimal parametric settings from Taguchi method, on study has developed a statistical approach as an input to the objective function of any evolutionary algorithm for its optimization. By diverging from the literature the statistical information provided by (Teoh *et al*., 2022) is explored and used to formulate the objective function which was introduced into the optimization mechanism of the grey wolf optimizer. For each response four values are obtained, namely first, second, third and fourth values.

To obtain the first value of BSFC (brake specific fuel consumption), the p-value of the blend ratio is taken, which is 0.476. This is multiplied by the degree of freedom which is 4. The answer obtained is added to the product of the p-value of the speed (i.e. 0.001) and the degree of freedom of that speed parameter (i,e. 3) this cumulative product sum is added to the product of the p-value from the load parameter (i.e. 0.001) and its degree of freedom, which is 3. The cumulative of all these calculations is the BSFC (first value). For the second value of the BSFC, the first value of the BSFC taken and it is multiplied by a random number between 0 and 1. In this instance the random number used is 0.7141. Its product with the BSFC (first value) gives 1.363931. By adding the first value of 1.9100, the BSFC (second value) is 3.2939. For the third value of BSFC, the same approach is used as previously, where the first value is considered as 1.9100. This is added to the product of the same first value and a new random number (i.e. 0.8289), which where the first value (i.e 1.9100) is added to the product of 1.9100 and a new random number (i.e. 0.8289) is added to the product of 1.9100 and a new random number (i.e. 0.2983) to give 2.4798. In summary, the BSFC (first value) BSFC (second value), BSFC(third value) and BSFC (fourth value) are 1.9100, 3.2739, 3.4836 and 2.4798 respectively.

Mathematically, the expressions for responses are given as

BSFC(first value) = p-value on blend ratio x DF + p-value o speed x DF + p-value on load x DF (1)

BSFC (second value) = first value + first value x random number (2)

BSFC (third value) = first value + first value x random number (3)

BSFC (fourth value) = first value + first value x random number (4)

Furthermore, the values for the input for the input parameters are computely as follows: this includes the generation of four values each for the blend ratio, speed and load. For the blend ratio, the first p-value is already known, which is 0.4760. Notice that this is the blend ratio for BSFC. To obtain the Blend ratio (second value), the first P – value, which is 0.4760 is multiplied by the random number 0.9442 to yielded 0.44943, which in turn is added to the P – value of 0.4760 to obtain 0.5209. The same procedure is used for the Blend ratio (third value) and Blend ratio (fourth value) to obtain 0.4875 and 0.55125 where 0.9442 and 0.1581 are the random numbers for Blend ratio (third value) and Blend ratio (fourth value) respectively. In addition, it should be noted that the random numbers used for the speed (second value), speed (third value), and speed (fourth value) are 0.6502, 0.0062 and 0.9764 respectively. Also the random numbers for the load (second value), load (third value) and load (fourth value) are 0.9919, 0.6799 and 0.3715, respectively. Based on this information, the mathematical expression for the input parameters are as follows:

Blend ratio (first value) = P – value on blend ratio for BSFC = 0.4760

Blend ratio (second value) = P – value + P – value x random number (5)

Blend ratio (third value) = P – value + P – value x random number (6)

Blend ratio (fourth value) = P – value + P – value x random number (7)

Speed (first value) = P – value on speed for BSFC = 0.0010

Speed (second value) = P – value + P – value x random number (8)

Speed (third value) = P – value + P – value x random number (9)

Speed (fourth value) = P – value + P – value x random number (10)

Load (first value) P – value on load for BSFC = 0.0010

Load (second value) P – value + P – value x random number (11)

Load (third value) P – value + P – value x random number (12)

Load (fourth value) P – value + P – value x random number (13)

These sets of steps were taken for the remaining 12 responses before optimization took place and can be seen in Table 2.

Table 2: Shows the results for the parameters involved with BSFC.

Blend ratio (%)	Speed (rpm)	Load (%)	BSFC (g/kWhr)
0.4760	0.0010	0.0010	1.9100
0.5209	0.0065	0.0019	3.2739
0.4875	0.0010	0.0017	3.4836
0.4835	0.0019	0.0014	2.4798

Table 2 needs to be summarised to extract information on the blend ratio, speed, and load from it. Along the first column containing the blend ratio, the following numbers are observed: 0.4760, 0.5290, 0.4875 and 0.4835. If these numbers are arranged in increasing order it is found that 0.4760 comes first and the last number is 0.5209. These are the lower and upper boundaries for the blend ratio parameter. Likewise, considering the speed parameter, the rearranged values from the second column are 0.0010, 0.0010, 0.0019 and 0.065. Accordingly, 0.0010 and 0.0065 are chosen as the lower and upper boundaries, respectively. Moreover, on considering the load parameter, the four values shown in Table 2 can be rearranged in ascending order as 0.0010, 0.0014, 0.0017 and 0.0019. This reveals that the lower and upper boundaries are 0.0010 and 0.0019, respectively. Besides these values, the parameters Blend ratio, speed and load are represented as X1, X2 and X3 respectively for ease of analysis and coding of the procedure using the C_{++} programming software.

3. RESULTS AND DISCUSSION

At present, the information arising from the empirical models developed in the section on methodology is substituted as the objective functions in the GWO algorithm to be optimized. This objective function contains the variables that influence the generation of the BSFC. However, the computation procedure for solving the GWO algorithm is intensive. Therefore, the C++ programming language is used for the process. Here, the researchers established the optimal process parameters for the various outputs. Thus the explanation of the steps followed will be made during the first iteration while these steps are repeated for other iterations but are not shown here.

Objective 1: Minimize BSFC

Objective function for BSFC = -2.9 × BR – 45 × Speed + 2507 × Load (14)

The Upper and lower boundaries of the parameters shown in Table 3 were obtained from Table 2.

Table 3. Boundaries of process parameters and representation with symbols

Parameters	**Lower boundaries**	**Upper boundaries**	**Representations**
Blend Ratio	0.4760	0.5209	X1
Speed	0.0010	0.0065	X2
Load	0.0010	0.0019	X3

Population Size (number of wolves): 5

Number of iterations: 200

Step 1 – Initialization of the grey wolf's population

To achieve this goal of randomly initializing the grey wolf population, we have to consider each parameter. These parameters have boundaries (upper and lower) which are important in determining the contribution of each wolf to the park. In all, five rows are considered, which means five wolves, expressed in a matrix, determined by Equation (15):

$$x = L + r(U\text{-}L) \tag{15}$$

where

L represents the lower boundary of the equation
U is the upper boundary of the equation
r shows the values of random numbers between 0 and 1

The following random numbers are generated for the first wolf: 0.603595 0.380871 0.770318

Table 4. Upper and lower boundaries for the first wolf alongside the values of the factors

Inputs	L (Upper limits)	U (Upper limits)	r ε (0,1)	X
BR	0.4760	0.5209	0.603595	0.5031
Speed	0.0010	0.0065	0.380871	0.0031
Load	0.0010	0.0019	0.770318	0.0017

Blend ratio = 0.4760 + 0.603595 (0.5209 - 0.4760) = 0.5031
Speed = 0.0010 + 0.380871(0.0065 - 0.0010) = 0.0031
Load = 0.0010 + 0.770318 (0.0019 - 0.0010) = 0.0017

The matrix obtained is shown below. However, all the values obtained fall within the upper and lower boundaries of the process parameters that they represent

Blend Ratio	Speed	Load	BSFC
0.5031	0.0031	0.0017	2.6468
0.4889	0.0045	0.0015	2.1205
0.4997	0.0021	0.0014	2.0386
0.5097	0.0017	0.0014	2.0466
0.4852	0.0033	0.0018	2.9941

The values for BSFC (the last column) were obtained by inputting the values of x into the objective function previously obtained for BSFC.

BSFC = -2.9 BR - 45 Speed + 2507 Load

$$-2.9 \times 0.5031 - 45 \times 0.0031 + 2507 \times 0.0017 = 2.6468$$

Iteration 1

Step 2 – Searching for the best wolf, X_α, second best wolf, X_β and the third best wolf, X_γ, positions. However, an objective of this work is to minimize BSFC. Here, the best position will be the wolf having the least AF S/N ratio. But the second-best wolf will have the next least S/N value while the third-best wolf will be the one having the third least BSFC S/N ratio.

X_α	0.4996	0.0021	0.0014	2.0386
X_β	0.5097	0.0017	0.0014	2.0466
X_γ	0.4889	0.0045	0.0015	2.1205

Step 3 – Find X_1, X_2 and X_3

Some parameters such as “a” and “A” are obtained using the equations (2) and (3) as stated below.

$$a = 2(1- (\text{iteration}/\text{maximum iteration})) \tag{16}$$

Iteration = 1, Max Iter = 200 which gives a = 1.99

In the first wolf, the steps stated above were followed in obtaining X_1 are shown below with each equation vital to the next.

$$A_1 = 2a.r - a \tag{17}$$

a = 1.99, r = 0.604694 and A_1 = 2(1.99)(0.604694) – 1.99 = 0.4167

From Niu et al. (2019), the grey wolves are grouped into grades in a pyramidal form where the alpha wolves occupy the apex of the pyramid showing that they possess the best hunting power, attacking skills, chasing prowess and leadership acumen. These are followed chronologically by the beta wolves, delta wolves and any other set of wolves in the group.

Table 5. Formulae for obtaining X_1, X_2 and X_3

X_1	X_2	X_3
$A_1 = 2a.r - a$	$A_2 = 2a.r - a$	$A_3 = 2a.r - a$
$C_1 = 2.r$	$C_2 = 2.r$	$C_3 = 2.r$
$D_\alpha = \lvert C_1 X_\alpha - X(t)\rvert$	$D_\beta = \lvert C_2 X_\beta - X(t)\rvert$	$D_\gamma = \lvert C_3 X_\gamma - X(t)\rvert$
$X_1 = X_\alpha - A_1 D_\alpha$	$X_2 = X_\beta - A_2 D_\beta$	$X_3 = X_\gamma - A_3 D_\gamma$

Table 5 depicts

$$C_1 = 2.r \tag{18}$$

$$C_1 = 2(0.365154) = 0.7303$$

$$D_\alpha = \lvert C_1.X_\alpha - X(t)\rvert \tag{19}$$

X_α	0.4996	0.0021	0.0014
X(t)	0.5031	0.0031	0.0017

$D_\alpha = \lvert 0.7303\ (0.4996\ \ 0.0021\ 0.0014) - (0.5031\ \ 0.0031\ \ \ 0.0017)\rvert$

$D_\alpha = \lvert\ 0.13820.0016\ \ \ \ 0.0007\ \rvert$

$X_1 = X_\alpha - A_1 D_\alpha$(20)

$X_1 = (0.4996\ \ 0.0021\ 0.0014) - 0.4167\ (0.1382\ \ \ 0.0016\ \ \ \ 0.0007)$

$X_1 = 0.44180.00150.0012$

Follow the same steps to obtain the values for X_2 and X_3 by implementing the C++ programming language. The values of X_2 are -0.2833% for the blend ratio, -0.0037 rpm for the speed and -0.0013% for load while for X_3, the values for blend ratio, speed and load are 0.1230%, 0.0005rpm and 0.0005% respectively. Furthermore, the average of X_1, X_2 and X3 is being calculated and termed Xnew. The values for this are 0.09384%, -0.0009rpm and 0.00012% for blend ratio, speed and load respectively. In addition, the greedy selection is carried out which involves the values of X. The process parameters are placed in the objective function to calculate the output of the BSFC response. But our objective at this point is to minimize the BSFC response. Thus, with a smaller value to the previously obtained BSFC response for the wolf, the X_{new} replaces that wolf. Notwithstanding, retain the wolf if the reverse case exists. The previous value was 2.64681(g/kWhr) while the new value is 1.0816(g/kWhr). Since these are the values obtained during the minimization process, the new value replaces the old value. Therefore, the current wolves would now be

Blend Ratio	Speed	Load	BSFC
0.476	0.0010	0.0010	1.0816
0.4889	0.0045	0.0015	2.1205
0.4997	0.0021	0.0014	2.0386
0.5097	0.0017	0.0014	2.0466
0.4852	0.0033	0.0018	2.9941

The same operations are conducted using other wolves from the population. Following each iteration, assign the current X_α as the best value. This means the best wolf has the smallest S/N value, obtained for the iterations.

At the 200th iteration, the process parameters that makeup X_α are adopted as the optimal process parameters for BSFC.

Iteration 1: 1.0816
Iteration 2: 1.0816
Iteration 3: 1.0816
...
...
...
Iteration 198: 1.0816
Iteration 199: 1.0816
Iteration 200: 1.0816

By running 200 iterations, X_α is obtained to be:

Table 6. Optimal values of process parameters essential for obtaining minimum BSFC

Blend Ratio	Speed	Load	BSFC
0.4760	0.0010	0.0010	1.0816

Notice that the boundaries, population size and the number of iterations are unchanged in all objectives from that of the BSFC.
Objective2: Maximize BSEC
Objective function for BSEC = 1915 BR - 1989 Speed + 2.37 Load (21)

By running 200 iterations, X_α is obtained to be:

Table 7. Optimal values of process parameters essential for obtaining maximum BSEC

Blend Ratio	Speed	Load	BSEC
0.0018	0.0010	1.8719	5.8944

Objective3: Minimize EGT
Objective function for EGT = 20.3 BR - 0.238 Speed + 2.28 Load (22)
By running 200 iterations, X_α is obtained to be:

Table 8. Optimal values of process parameters essential for obtaining minimum EGT

Blend Ratio	Speed	Load	EGT
0.0010	0.0279	0.0060	0.0273

Objective4: Minimize Exhaust O_2 (Gas)
Objective function for Exhaust O_2 = -3.72 BR + 3582 Speed + 2638 Load (23)
By running 200 iterations, X_α is obtained to be:

Table 9. Optimal values of process parameters essential for obtaining minimum Exhaust O_2 (Gas)

Blend Ratio	Speed	Load	Exhaust
0.9406	0.0010	0.0010	2.7210

Objective5: Minimize CO (Gas)
The objective function for CO = -4.07 BR - 25 Speed - 63 Load (24)

By running 200 iterations, X_α is obtained to be:

Table 10. Optimal values of process parameters essential for obtaining minimum CO (Gas)

Blend Ratio	Speed	Load	CO
0.2520	0.0011	0.0012	0.9233

Objective 6: Minimize Smoke
Objective function for Smoke = 12.75 BR - 1.695 Speed + 8.08 Load (25)
By running 200 iterations, X_α is obtained to be:

Table 11. Optimal values of process parameters essential for obtaining minimum smoke

Blend Ratio	Speed	Load	Smoke
0.0010	0.0030	0.00120	0.0157

Objective 7: Minimize NOx
The objective function for Smoke = 4.039 BR + 1176 Speed - 846 Load (26)
By running 200 iterations, X_α is obtained to be:

Table 12. Optimal values of process parameters essential for obtaining minimum NOx

Blend Ratio	Speed	Load	NOx
0.857	0.0010	0.0010	3.7914

Objective 8: Maximize SFI
The objective function for SFI = 3.60 BR + 2954 Speed - 2340 Load (27)
By running 200 iterations, X_α is obtained as Table 13.

Table 13. Optimal values of process parameters essential for obtaining maximum SFI

Blend Ratio	Speed	Load	SFI
1.4911	0.0019	0.0013	7.9076

Objective 9: Maximize MID
The objective function for MIJ = 8.5 BR - 1347 Speed - 2117 Load (28)
By running 200 iterations, X_α is obtained as Table 14.

Table 14. Optimal values of process parameters essential for obtaining maximum MID

Blend Ratio	Speed	Load	MID
1.6399	0.0011	0.0013	9.7721

Objective10: Maximize Rail Pressure
Objective function for RP = -4.47 BR + 10271 Speed - 2719 Load(29)
By running 200 iterations, X_α is obtained as Table 15.

Table 15. Optimal values of process parameters essential for obtaining maximum rail pressure

Blend Ratio	Speed	Load	Rail pressure
1.0498	0.0017	0.0010	10.0491

Objective 11: Maximize Turbocharge Boost Air Pressure
Objective function for TBAP = 8.937 - 13.82 BR + 2514 Speed + 5643 Load (30)
By running 200 iterations, X_α is obtained as Table 16.

Table 16. Optimal values of process parameters essential for obtaining maximum turbocharge boost air pressure

Blend Ratio	Speed	Load	TBAP
0.9590	0.0014	0.0020	10. 5409

Objective 12: Minimize Load Demand
Objective function for LD = 2.49 BR + 2.13 Speed + 3.82 Load (31)
By running 200 iterations, X_α is obtained as Table 17.

Table 17. Optimal values of process parameters essential for obtaining minimum load demand

Blend Ratio	Speed	Load	Load demand
0.0017	0.0010	0.0010	0.0102

Each input was used in the optimization of the engine outputs using the Minitab 18 software. Fig. 1 to 3 show the plots pf blend ratios against engine outpits, speed against engine outputs and load against engine outputs, respectively.

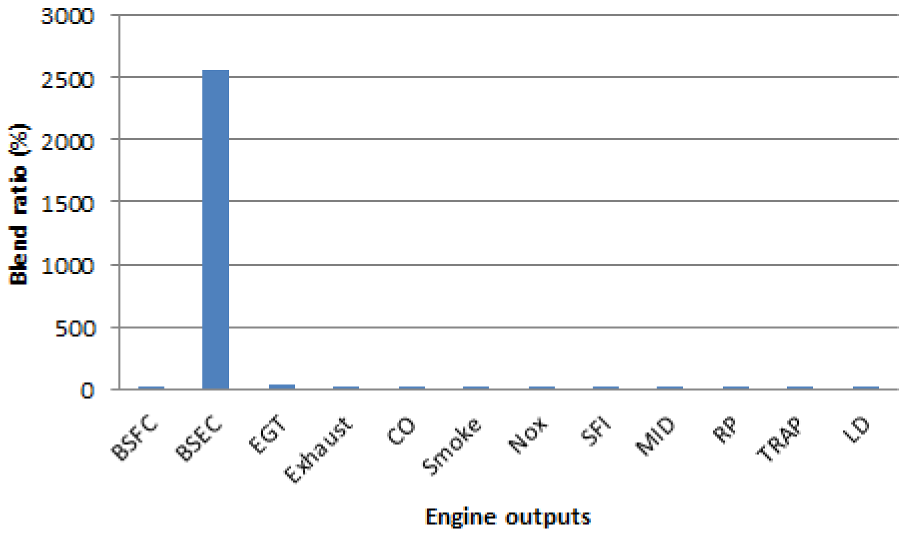

Fig. 1. Blend ratio against engine outputs

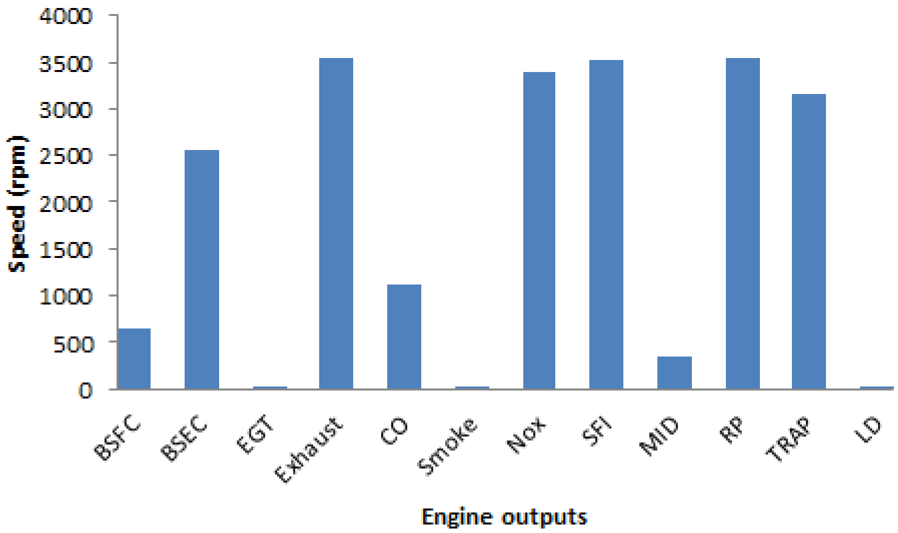

Fig. 2. Speed against engine outputs

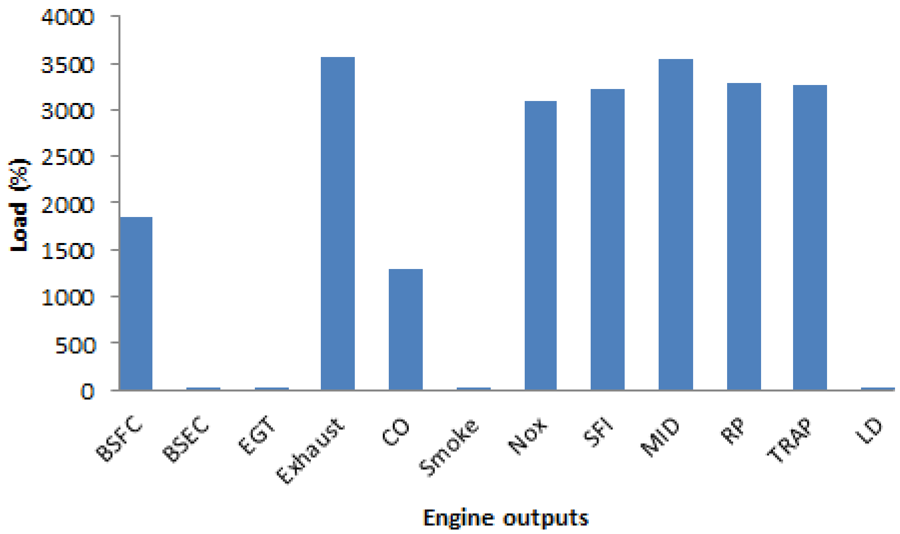

Fig. 3. Load against engine outputs

Moreover, in the first part of the research, three inputs namely blend ratio (%), speed (rpm) and load (%) were used in the optimization of the engine outputs (Figs. 1, 2, 3). The brake-specific fuel consumption was minimized to an optimal value of 1.0818 g/kWhr at blend ratio, speed and a load of 0.4760 %, 0.001 rpm and 0.001 % respectively. However, the optimal maximization of brake-specific energy consumption yielded 5.8944 MJ/kW-hr at a blend ratio of 0.0018 %, speed of 0.001rpm and load of 1.8719 %. Moreover, exhaust gas temperature yielded 0.0273 dC at its optimal reduction with blend ratio, speed and load at 0.001 %, 0.0279 rpm and 0.006 % respectively. Meanwhile, exhaust O_2 (gas) was optimally lowered to obtain 2.7210 at a blend ratio of 0.9406 %, speed of 0.001 rpm and load of 0.001 % respectively. In addition, CO was drastically reduced to an optimal value of 0.9233 % at a blend ratio of

0.9604%, speed of 0.001 rpm and load of 0.001%. In conjunction with CO, smoke was also greatly lowered to an optimal value of 0.0157 at which the blend ratio, speed and load were 0.001%, 0.003 and 0.0012% respectively. NOx was optimally minimized to obtain 3.7914 ppm at a blend ratio of 0.875%, speed of 0.001rpm and load of 0.001%.

Furthermore, the start of fuel injection was raised to 7.9076 at a blend ratio, speed and load of 1.4911%, 0.0019 rpm and 0.0013% respectively. Main injection duration was maximized and a value of 9.7721μs was obtained at a blend ratio, speed and load of 1.6399%, 0.0011rpm and 0.0013% respectively. Rail pressure was also increased to 10.0491 bar at a blend ratio of 1.0498%, a speed of 0.0017 rpm and a load of 0.001%. Turbocharge boost air pressure was maximized to a value of 10.5409 at a blend ratio, speed and load of 0.9590%, 0.0014 rpm and 0.002% respectively. However, load demand was reduced to an optimal value of 0.0102% where the blend ratio was 0.0017%, speed was 0.001rpm and load was 0.001%.

Moreover, the second part of the work dealt with the optimization of each input against all engine responses. The blend ratio was first taken against the responses. At the end of the process, the Break Specific Energy Consumption (BSEC) was seen to be the one with the highest value as compared with the rest while CO had the least value. Break Specific Energy Consumption (BSEF) is likely the most to be directly proportional to the blend ratio. CO might be the least in value as a result of a nice blend of the biodiesel used for the experiment. In addition, Speed was optimized for the engine outputs. The Exhaust (gas), Rail pressure and Start of Fuel Injection were seen to be the first, second and third respectively with the highest values while Exhaust Gas Temperature was the lowest. CO was seen to possess the maximum value as a result of it being proportional to the speed. Meanwhile, for the load concerning the engine responses, Exhaust (gas), Main Injection Duration and Rail pressure had maximum values as related to the first, second and third respectively while the Break Specific Energy Consumption (BSEC) had the least value. The exhaust (gas) is greatest as a result of it being directly proportional to the load. The Brake-Specific Energy Consumption (BSEC) has the least value as it is inversely proportional to the load.

Furthermore, it is essential to understand how much the model proposed in the present study deviates from values by other researchers in other studies. This research was done by comparing the results of the present work with Teoh et al. (2019) that uses Taguchi method and then compared the performance using correlation analysis Table 18. A correlation value of r as 0.7822 was obtained. This means that there is a strong positive correlation, which means that high current study variable scores go with high Teon et al. (2019) variable scores (and vice versa). This gives and encouragement that the proposed method can be used in other studies since the relationship between the results of the present study and Teoh et al (2019) is acceptable.

Table 18. Comparison of Current study and Teoh et al. (2019) using correlation analysis

S/No.	Response	Parameters	Current study	Teoh et al. (2019) (Taguchi method)	Statistical results
1	BSFC	Blend ratio	0.476	0.476	M_x: Mean of X Values M_y: Mean of Y Values $X - M_x$ & $Y - M_y$: Deviation scores $(X - M_x)^2$ & $(Y - M_y)^2$: Deviation Squared $(X - M_x)(Y - M_y)$: Product of Deviation Scores X Values (Current study) $\sum = 9.604$ Mean = 0.267 $\sum(X - M_x)^2 = SS_x = 9.787$ Y Values (Teoh et al., 2019) $\sum = 6.208$ Mean = 0.172 $\sum(Y - M_y)^2 = SS_y = 4.149$ X and Y Combined N = 36 $\sum(X - M_x)(Y - M_y) = 4.984$ R Calculation $r = \sum((X - M_y)(Y - M_x)) / \sqrt{((SS_x)(SS_y))}$ $r = 4.984 / \sqrt{((9.787)(4.149))} = 0.7822$ Decision: the value of r is 0.7822. This is a strong positive correlation, which means that high current study variable scores go with high Teon et al. (2019) variable scores (and vice versa).
		Speed (rpm)	0.001	0.001	
		Load (%)	0.001	0.001	
2	BSEC	Blend ratio	0.0018	0.001	
		Speed (rpm)	0.0010	0.001	
		Load (%)	1.8719	0.945	
3	Exhaust gas temperature	Blend ratio	0.0010	0.001	
		Speed (rpm)	0.0276	0.023	
		Load (%)	0.0060	0.006	
4	Exhaust	Blend ratio	0.9406	0.731	
		Speed (rpm)	0.0010	0.001	
		Load (%)	0.0010	0.001	
5	CO	Blend ratio	0.2520	0.252	
		Speed (rpm)	0.0011	0.001	
		Load (%)	0.0012	0.001	
6	Smoke	Blend ratio	0.0100	0.001	
		Speed (rpm)	0.0030	0.003	
		Load (%)	0.0012	0.001	
7	NOx	Blend ratio	0.8570	0.857	
		Speed (rpm)	0.0010	0.001	
		Load (%)	0.0010	0.001	
8	SOI	Blend ratio	1.4911	0.960	
		Speed (rpm)	0.0019	0.001	
		Load (%)	0.0013	0.001	
9	Main Injection duration	Blend ratio	1.6399	0.944	
		Speed (rpm)	0.0091	0.001	
		Load (%)	0.0013	0.001	
10	Rail pressure	Blend ratio	1.0498	0.959	
		Speed (rpm)	0.0017	0.001	
		Load (%)	0.0010	0.001	
11	Turbocharge boost air pressure	Blend ratio	0.9590	0.963	
		Speed (rpm)	0.0014	0.001	
		Load (%)	0.0020	0.001	
12	Load demand	Blend ratio	0.0017	0.017	
		Speed (rpm)	0.0010	0.001	
		Load (%)	0.0010	0.001	

4. CONCLUSIONS

This research was conducted to optimize the parameters of a combustion process where biodiesel is combined with other substances. Twelve objective functions were formulated and solved with the grey wolf optimization method. Seven of the objective functions were from the minimization perspective while five responses were formulated from the maximization viewpoint. The twelve responses used in this work include the BSFC, brake-specific energy consumption, exhaust gas temperature, exhaust O_2, CO, Smoke, NO_x, the start of fuel injection, main injection duration, rail pressure, turbocharge boost pressure and load demand. These responses are the feedback obtained when the following inputs are utilized in the process: blend ratio, speed and load. All 200 iterations were run using the C++ programming platform. Based on the results obtained from the work, the following conclusions are valid:

1. Load demand could be seen to have the least value of all the engine outputs. This shows that there is appropriate and optimal usage of the biodiesel mixture.
2. TBAP had the highest value of all engine outputs that were optimally maximized. This in turn shows adequate effects on the speed variations, efficiency and power flow of the engine. In addition, the biodiesel blend is maximally utilized at variable speed with little load applied.
3. In this article, engine responses that were found to be hazardous to human lives were drastically reduced during the process and those that were relevant were adequately and optimally maximized for efficiency and economic reasons.
4. The blend ratio had its highest value when optimized alongside MID. This probably shows proper periodical injection of the biodiesel blends supply for the effective rotation of the crankshaft.
5. Speed had its maximum value when optimized alongside EGT probably as a result of more oxygen being burnt to raise the exhaust temperature at high speed.
6. The blend ratio had its maximum value at BSEC when singlehandedly optimized with the engine outputs but was lowest at CO at the same condition. This might be a result of the biodiesel blend being better to generate less or insignificant amounts of poisonous outputs.
7. Speed had its maximum value at RP and lowest at EGT when singlehandedly optimized with the engine outputs.

Further research is essential to improve the solution quality of the problem by introducing the sensitivity analysis to establish which of the parameters is most sensitive to changes thereby focusing on such variables for significant performance improvement. Moreover, it is recommended that other input parameters should be considered during the revisit of this article to bring about a vast improvement and advancement in the automobile industry. Also, we recommend that other optimization tools like the Aquila method of analysis should be used in future articles to further improve the process and thereby lay a building block on the already laid foundation. Besides, we recommended that various biodiesel blends be studied and worked on to fit in for diesel consumption to make them affordable, effective and efficient.

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