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Optimization of biodiesel production of spirulina-platensis algae biomass using RSM integrated with whale optimization algorithm

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Sustainable sources for biodiesel production from non-edible feedstocks are gaining attention due to limited sources of crude petroleum and concern related to the harmful emission of fossil fuels. In this study, Spirulina-Platensis algae biomass has been used for biodiesel production. The effect of methanol to algae biomass ratio, temperature, time, catalyst concentration, and stirring speed for optimization of algae biomass biodiesel using the transesterification process has been studied. The proposed work has implemented the quadratic regression equation obtained by RSM with the whale optimization algorithm. The result shows maximum production of algae biomass biodiesel (89.87%) obtained at the algal biomass/methanol ratio of 5.56, temperature of 54.64 °C, time of 78 minutes, H_2SO_4 of 77.06% w/w, and stirring speed of 450 rpm. The RSM and WOA prediction models have been compared for more. The experimental result shows that WOA optimization can accurately predict the optimal point with a small error. The fundamental properties of algae biomass biodiesel have been checked and compared with fossil diesel.

Keywords: Whale optimization algorithm, RSM, Spirulina platensis, Transesterification

1 Introduction

Energy is currently the most crucial resource for humanity and its sustainable growth due to the energy crisis, which has become a critical global concern[1]. Fuels are an essential source of energy because of their high energy content. Our way of life primarily depends on fossil fuels like gasoline, coal, and natural gas since they provide more than 80% of the energy needed for transportation, home use, and industrial production worldwide. Population is growing faster than the volume of production of crude petroleum oil and its derivatives[2]. The crude petroleum oil price fluctuations, especially in underdeveloped countries, contribute to regional and global wars. Only 12.8 % of the world's energy demand has been fulfilled by renewable energy, regarded as one of the most essential resources[3]. Liquid biofuels have become a vital sustainablealternative fuel due to their high energy content, low carbon dioxide emission profile, and renewability[4].

Three generations of liquid biofuels can be separated based on the feedstocks and manufacturing method. Corn, sugarcane, and vegetable oils were among the food crops utilized to produce the first generation of liquid biofuels, such as bioethanol and biodiesel. Since food crops are consumed in the process of producing fuel, the effects of first-generation liquid biofuels were on the food supply, and there was an increase in the price of food crops. Therefore,itis necessary to use second-generation liquid biofuels from animal fats, vegetable oil, non-edible plant seed oil, and waste cooking oil [5].Second-generation liquid biofuels addressed the problems faced by their first-generation predecessors, leading to more fuel consumption and significant challenges in obtaining reliable feedstock. As a clean substitute for gasoline-diesel, biodiesel is the basis for developing third-generation liquid biofuels, such as algae biodiesel [6-7]. Biodiesel (fatty acid alkyl esters) is a sustainable liquid diesel fuel produced by combining vegetable oils or lipids with alcohol in the presence of a catalyst[8]. The biodiesel is non-toxic, biodegradable, and environmentally beneficial[9-10]. It may be produced from specific microalgae, animal fat, vegetable oils, etc.[11-12]. The ability of microalgae to reproduce quickly (every two to three weeks), produce oil ten times more abundant than most oilseed crops, reduce greenhouse gas emissions (one kilogram of algal biomass requires approximately 1.83 kilograms of CO_2), and grow in wastewater has led to their recent attention as a promising biomass feedstock with significant potential for the production

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of biodiesel [13]. Since microalgae are not an essential food source, their use as a fuel source has little impact on the food problem.

Biodiesel can be produced from microalgae oil via transesterification[14,15]. For this process, pre-extracted oil is usually utilized as the raw material. It is generally created by mechanical pressing, after which the leftover oil is extracted using a solvent to remove any remaining oil. Finally, the oil is converted to Fatty acid alkyl esters and glycerol. Enzymes, alkalis, or acidic can all catalyze the transesterification. The alkaline-catalyzed transesterification method would not be suitable for producing biodiesel from microalgae oil due to the high FFA level in microalgae lipids. This is because utilizing alkaline catalysts with high FFA oils would result in the Development of soap and complicate the subsequent separation and purification of biodiesel. The use of sulfuric acid as a reaction catalyst has been referred to as microalgal lipid transesterification because of its insensitivity to the FFA content of this oil feedstock and the fact that acidic catalysis facilitates the transesterification and esterification reactions of biodiesel production[16].

Additionally, as the alcohol-to-oil ratio is large (approximately 40:1), research is ongoing on using enzymes as catalysts for transesterification. Commercial biodiesel synthesis from microalgae still faces difficulties because of the high costs associated with the existing biomass production and fuel conversion methods [17].One method of producing biodiesel from microalgae lipids is “in-situ transesterification” or “reactive extraction.”The process combines pure methanol and acid catalysts simultaneously with dry powder microalgal biomass added to the solution. Methanol extracts the lipids from the microalgal biomass and trans-esterifies them to create fatty acid methyl esters using acid catalyzes[18].

The goal of metaheuristic algorithms is to combine local search and randomization equitably. Consequently, most of these techniques are used for worldwide optimization [19]. The Hybrid model techniques such as RSM-ANN, RSM-GWO, ANN-Ant colony optimization, and RSM-ANFIShave been utilized in the transesterification process for various feedstocks [20–23]. The whale optimization technique of updating their location gives the WOA a vast capability for exploration. The WOA accelerates convergence while avoiding local optima through repetitions[24].

The optimization of algal biomass transesterification process variables through nonlinear regression in conjunction with the WOA algorithm has not yet been documented in any research. This study aims to improve biodiesel yield by optimizing transesterification process parameters using the RSM-WOA. Additionally, time and money can be saved by reducing the number of experiments by establishing relationships between independent variables and modelling the system statistically. The conformity experiment has been carried out to check the quality of algae biomass biodiesel, which is suggested by the whale optimization algorithm at a given input parameter.

2 Materials and Methods

2.1 Materials

The powder (biomass)of spirulina-Platensis microalgae has been used,and sulphuric acid, which is 98% pure, has been used to catalyse the transesterification process. Methanol has been used in this research with a 99.9% purity level as the reactive alcohol. A magnetic stirrer attached to the temperature sensor and a 500 ml laboratory glass flask has been used forthe experiment’s reaction.

2.2 Method

The acid-methanol solution has been made by mixing fresh sulfuric acid in predetermined amounts with methanol. H_2SO_4 has been continually swirled on a magnetic stirrer for five minutes to dissolve it. The solution has been produced freshly to preserve the catalytic activity. The catalyst and alcohol mixture are gently mixed on low for several minutes after adding 50 grams of dried microalgae. The simultaneous extraction and transesterification reaction began when the catalyst and alcohol solution reacted with the triglyceride (oil) in the microalgae strain and broke a fatty acid chain. The appropriate temperatures have been then maintained in the reaction mixture’sflask for a predetermined period.

The range of consideration variables has been selected based on available research[25–27]. In a 500 ml lab flask, biodiesel from algal biomass has been produced. As the transesterification process is complete, the algal biomass biodiesel and glycerol have been allowed to separate into two discrete layers by gravitational force. The crude algal biomass biodiesel has been cleaned and dehydrated after decanting the glycerol layer[28]. The yield of biodiesel produced has been calculated according to equation 1.

$$Biodiesel\ yield(\%) = \frac{Biodiesel\ Production}{Oil\ used} X\ 100 \quad \dots (1)$$

2.3Development of RSM model

The RSM model has been used in this work to evaluate key process input parameters, including the algal biomass (g)/methanol (ml) ratio, temperature (°C), time (minute), catalyst amount (wt%), and stirring speed (rpm), which affect the amount of biodiesel yield. As shown in Table 1, a variety of the investigated factors, including the 2:1–6:1 methanol to algal biomass ratio, the temperature range of 30–70 °C, the period of 30–90 minutes, the amount of 25–100% of catalyst, and the stirring speed of 200–700 rpm have been used. RSM has been used to obtain 50 experimental designs to avoid needless run repeats.

Table 2 shows the experiment design for algae biomass biodiesel production suggested by RSM. Table 3 shows theimpact of the five parameters on the yield of biodiesel produced from algae biomass. The significance test and analysis of variance (ANOVA) have been used to evaluate the effectiveness of the quadratic equation response model. Equation 2 serves as a representation of the fitted model[29-30].

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{14} X_1 X_4 + \beta_{15} X_1 X_5 + \beta_{23} X_2 X_3 + \beta_{24} X_2 X_4 + \beta_{25} X_2 X_5 + \beta_{34} X_3 X_4 + \beta_{35} X_3 X_5 + \beta_{45} X_4 X_5 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_4 X_{44}^2 + \beta_{55} X_5^2 \quad \dots (2)$$

Where Y is the yield of algae biomass biodiesel, β_0 is the constant term; β_1, β_2, β_3, β_4, and β_5 are the various linear coefficients; β_{12}, β_{13}, β_{14}, β_{15}, β_{23}, β_{24}, β_{25}, β_{34}, β_{35}, and β_{45} are the various interaction coefficients; β_{11}, β_{22}, β_{33}, β_{44} and β_{55} are the various quadratic coefficients; and X_1, X_2, X_3, X_4 and X_5 are the non-actual independent parameters.

2.4 Development of model for the whale optimization algorithm

The WOA was presented as a optimization strategy based on population by Mirzalili and Lewis in 2016 [31].

Table 1 — Variable factor range.

Factor	Name	Units	Minimum Value	Maximum Value
A	Methanol to algal biomass ratio	ml/g	2	6
B	Temperature	°C	30	70
C	Time	minute	30	90
D	Catalyst	%	25	100
E	Stirrer speed	rpm	200	700

The locations of individual humpback whales are considered independent variables,and the objective isassociated with the distance of thewhale fromthe food.

The operational process of the whale is divided into three phases: shrinking and encircling of prey, exploitation phase (bubble-net attackingapproach), and exploration phase (prey exploration).

2.4.1Encircle of prey

Humpback whales possess the ability to detect and enclose their prey for food. The whale optimization algorithm indicates that the primary best solution is either to target prey or reachvery near to it because of the optimum design location in the search space. Once the best search agent has been determined, the other search agents nearby will update their locations. Equation (3) and equation(4) describe the behavior of the mechanism.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{best}}(t) - \vec{X}(t)\right| \quad \dots (3)$$

$$\vec{X}(t+1) = \overrightarrow{X_{best}}(t) - \vec{A}.\vec{D} \quad \dots (4)$$

Where X position vector,t is current iteration, and $\overrightarrow{X_{best}}$ best position vector, respectively, $\|$ is absolute value, and " · " is element-by-element multiplication. The Coefficient vectors$\vec{A}$ and $\vec{C}$, calculated using equation (5) and equation(6).

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \quad \dots (5)$$

$$\vec{C} = 2.\vec{r} \quad \dots (6)$$

Where $\vec{a}$decreases from 2 to 0 through iterations inexploration and exploitation phasesand $\vec{r}\in[0, 1]$ isa random vector.

2.4.2 Bubblenet attacking technique

This strategy is also known as the exploitation phase. The bubble-net technique is one that whales might utilize to attack their prey. This has led to the establishment of bubble-net techniques for humpback whales. The whale has used the shrinking encircling mechanism to modify their new location (X_{best}, Y_{best}), utilizing the agent's prior positionto obtain the best position in a two-dimensional space (shown in Fig. 1. This was accomplished by reducing the $\vec{a}$ value in equation (4). After that, the feeding mechanism (spiral bubble-net)is developed by measuring the distance between the whale's position and the prey. The spiral movement of the whale and its prey is then simulated using equation (7).

Table 2 — Experiment design for algae biomass biodiesel production suggested by RSM.

Run	Methanol to algae biomass ratio	Temperature	Time	Catalyst	Stirrer speed	Yield	RSM Predicted Yield	WO Predicted Yield
		°C	minute	%	Rpm	%	%	%
1	4	50	60	62.5	450	82	80.32	80.682
2	6	70	90	25	700	71	69.31	69.4944
3	6	30	30	100	700	67	65.11	65.4721
4	2	30	90	100	700	47	48.79	48.1486
5	2	70	90	25	200	45	45.82	46.0018
6	4	50	60	62.5	450	82	80.32	80.682
7	2	30	30	25	700	32	33.91	33.985
8	2	30	30	100	700	54	52.15	52.5089
9	4	70	60	62.5	450	71	72.15	72.6587
10	2	30	90	100	200	53	51.13	52.4942
11	2	70	30	25	200	37	35.8	35.9871
12	2	70	30	25	700	41	42.33	42.5165
13	4	30	60	62.5	450	62	62.97	63.1898
14	2	50	60	62.5	450	70	72.26	72.6301
15	2	30	90	25	700	36	34.92	34.9997
16	6	50	60	62.5	450	83	82.85	83.2184
17	4	50	60	62.5	200	75	76.79	76.1595
18	2	70	90	100	700	65	63.72	64.5551
19	2	70	90	100	200	61	63.19	64.0257
20	6	30	90	25	700	55	56.13	56.213
21	6	70	30	100	700	69	71.04	71.8786
22	6	70	90	100	200	73	72.02	72.8639
23	4	50	90	62.5	450	82	82.44	82.8066
24	6	30	90	100	700	69	70.63	70.9869
25	2	70	90	25	700	51	50.22	50.4062
26	2	70	30	100	200	59	57.55	58.386
27	2	30	30	100	200	50	52.37	51.7295
28	6	70	30	25	700	52	52.55	52.7297
29	4	50	60	62.5	450	83	80.32	80.682
30	2	70	30	100	700	61	60.2	61.0404
31	6	70	90	100	700	83	83.43	84.2683
32	2	30	30	25	200	32	30.25	30.3306
33	4	50	60	25	450	59	60.5	60.631
34	6	70	30	100	200	58	57.51	58.3492
35	6	30	90	25	200	43	43.73	43.8085
36	6	30	30	100	200	53	54.46	54.8177
37	4	50	60	62.5	450	81	80.32	80.682
38	4	50	30	62.5	450	73	74.68	75.0419
39	6	70	30	25	200	36	35.14	35.3253
40	4	50	60	100	450	78	78.62	79.2174
41	6	30	30	25	200	31	31.72	31.7938
42	6	70	90	25	200	53	54.03	54.215
43	4	50	60	62.5	450	84	80.32	80.682
44	4	50	60	62.5	450	82	80.32	80.682
45	4	50	60	62.5	700	84	84.32	84.689
46	2	30	90	25	200	34	33.39	33.4703
47	6	30	90	100	200	64	62.1	62.4574
48	4	50	60	62.5	450	82	80.32	80.682
49	6	30	30	25	700	48	46.24	46.3232
50	4	50	60	62.5	450	75	80.32	80.682

Table 3 — ANOVA for algae biomass biodiesel production.

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	13481.51	20	674.08	137.02	< 0.0001	significant
A-Moler ratio	952.94	1	952.94	193.7	< 0.0001	
B-Temperature	715.76	1	715.76	145.49	< 0.0001	
C-Time	512.47	1	512.47	104.17	< 0.0001	
D-Catalyst	2790.12	1	2790.12	567.15	< 0.0001	
E-Stirrer speed	481.88	1	481.88	97.95	< 0.0001	
AB	9.03	1	9.03	1.84	0.1859	
AC	157.53	1	157.53	32.02	< 0.0001	
AD	0.7813	1	0.7813	0.1588	0.6932	
AE	236.53	1	236.53	48.08	< 0.0001	
BC	94.53	1	94.53	19.22	0.0001	
BD	0.2813	1	0.2813	0.0572	0.8127	
BE	16.53	1	16.53	3.36	0.0771	
CD	38.28	1	38.28	7.78	0.0092	
CE	9.03	1	9.03	1.84	0.1859	
DE	30.03	1	30.03	6.1	0.0196	
A^2	18.81	1	18.81	3.82	0.0602	
B^2	402.56	1	402.56	81.83	< 0.0001	
C^2	7.64	1	7.64	1.55	0.2226	
D^2	286.24	1	286.24	58.18	< 0.0001	
E^2	0.1451	1	0.1451	0.0295	0.8648	
Residual	142.67	29	4.92			
Lack of Fit	90.79	22	4.13	0.5569	0.8612	not significant
Pure Error	51.88	7	7.41			
Cor Total	13624.18	49				

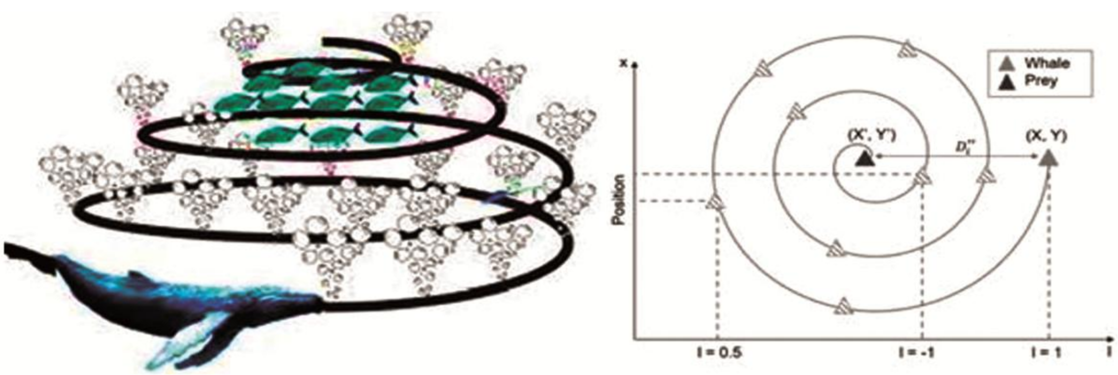

Fig. 1 — Hunting nature of humpback whales[32].

$$\vec{X}(t+1) = \left|\overrightarrow{X_{best}}(t) - \vec{X}\right| . e^{bl} . cos(2\pi l) + \vec{X}_{best}\,(t) \quad \ldots (7)$$

Where $\left|\overrightarrow{X_{best}}(t) - \vec{X}\right|$ is the distance between the whale's position and the prey, l is random number between 0 and 1, and b is the constant used in the logarithmic. In addition to swimming in a decreasing circle, humpback whales move in a spiral pattern with their prey. To show this concurrent behavior, we estimate a 50% possibility of using either the spiral model or the shrinking encircling mechanism to update whale positions during the optimization. The mathematical model is defined by equation (8).

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X_{best}}(t) - \vec{A} . \vec{D} \; if \; p < 0.5 \\ \left|\overrightarrow{X_{best}}(t) - \vec{X}\right| . e^{bl} . cos(2\pi l) + \vec{X}_{best}\,(t) \\ \quad if \; p \geq 0.5 \end{cases} \quad \ldots (8)$$

2.4.3 Prey exploration

In the exploration phase,the humpback whale updates its location using the $\vec{A}$vector through the bubble net striking. As shown by equation (9) and equation (10), the humpback whale $\vec{A}$ conduct a random prey hunt in the iteration to prevent falling into the ideal solution.

$$\vec{D} = \left|\vec{C}.\overrightarrow{X_{rand}}(t) - \vec{X}(t)\right| \quad \ldots (9)$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}}(t) - \vec{A}\,.\,\vec{D} \quad \ldots (10)$$

Where $\overrightarrow{X_{rand}}$ is position vector randomly is chosen from the population.

3 Results and Discussion

3.1 ANOVA analysis

ANOVA, suggested by response surface methodology, has been used to check the significance of the model in predicting the ideal condition forbiodiesel production from algal biomass. The quadratic model has been selected based on the P-values (0.0001) compared to the P-values of other models. However, the models' F-values can serve as a different criterion for choosing the best model.

The findings of the ANOVAare highlighted in Table 3. For the sake of this analysis, a significance level of 0.05 has been maintained. The predicted F value is 137.02 with a negligibly small probability value (0.0001), so the developed model is significant at a 95% confidence level. The confidence level shows how reliable the fitted model is in predicting the biodiesel yield from algal biomass. The regression coefficient (R^2), adjusted $R^{2,}$ and predicted R^2 valuesare0.9895, 0.9823, and 0.9720, respectively. The P values for the variables listed in Table 3 have been calculated.: A(algae biomass/methanol ratio), B(temperature), C(time), D(catalyst amount), E(stirring speed), AC(algae biomass/methanol ratio and time), AE(algae biomass/methanol ratio and stirring speed), BC(temperature and time), CD(time and stirring speed), DE(algae biomass/methanol ratio and stirring speed). Others (AB, AD, BE, CE, A^2, C^2, and E^2), on the other hand, are shown to be insignificant. Equation (11) shows the quadratic regression equation for algae biomass biodiesel production.

$$\begin{aligned}\text{Yield} =\ & -78.78 + 4.03 * \text{Algae biomass/methanol ratio} + 3.24 * \text{Temperature} + 0.17 * \text{Time} + 1.30 * \text{Catalyst} - 0.007 * \text{Stirring} - 0.013 * \\ & \text{Algae biomass/methanol ratio} * \text{Temperature} + 0.04 * \text{Algae biomass/methanol ratio} * \text{Time} + 0.002 * \\ & \text{Algae biomass/methanol ratio} * \text{Catalyst} + 0.005 * \text{Algae biomass/methanol ratio} * \text{Stirring} + 0.003 * \\ & \text{Temperature} * \text{Time} - 0.00012 * \text{Temperature} * \text{Catalyst} + 0.00014 * \text{Temperature} * \text{Stirring} - \\ & 0.00097 * \text{Time} * \text{Catalyst} - 0.00007 * \text{Time} * \text{Stirring} - 0.0001 * \text{Catalyst} * \text{Stirring} - 0.69 * \\ & (\text{Algae biomass/methanol ratio})^2 - 0.032 * \text{Temperature}^2 - 0.002 * \text{Time}^2 - 0.0076 * \text{Catalyst}^2 + \\ & 0.00004 * \text{Stirring}^2 \end{aligned} \quad \ldots (11)$$

Fig. 2 and Fig. 3 show the three-dimensional interaction of surface for the yield of algal biomass predicted by the RSM model. The effect of temperature and the ratio of methanol to algal biomass on the output of algae biomass-based biodiesel is shown in Fig. 2. The algae biomassbiodiesel production increased as the temperature and the ratio of methanol increased. With a 5.56 methanol/algae biomass ratio and 54 °C temperature, after that, it began to decrease because

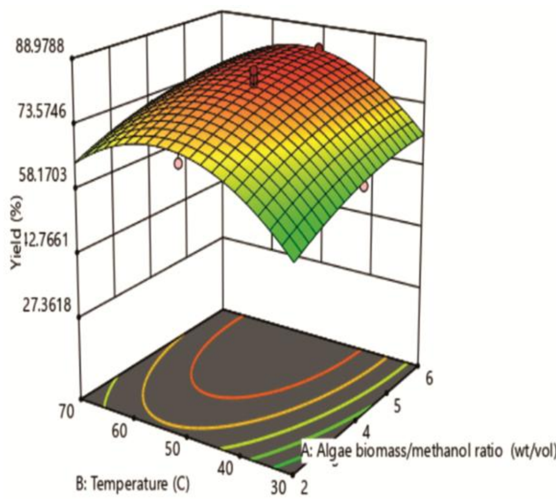

Fig. 2 — Interaction surface between methanol/algae biomass and temperature to yield of algae biomass biodiesel.

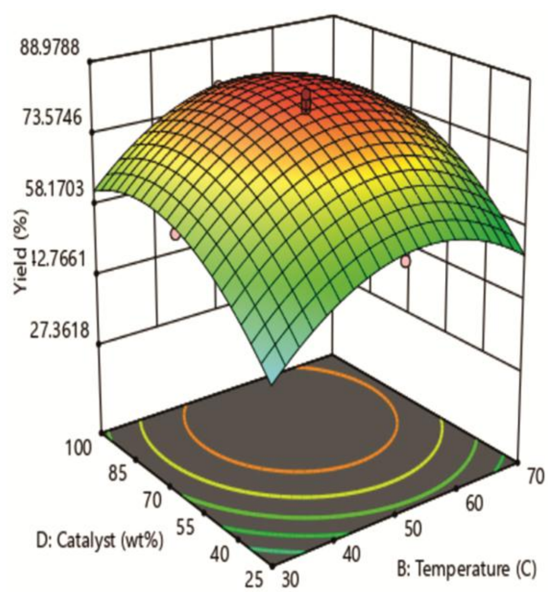

Fig. 3 —Interaction surface between temperature and catalyst to yield of algae biomass biodiesel.

when temperature increases, oil viscosity decreases, allowing for better oil-to-methanol interaction. Compared to the transesterification reaction, side reactions such as the hydrolysis of methyl esters of fatty acids into corresponding acids and alcohols occur more quickly at higher temperatures 32. Fig. 3 shows the surface interaction between temperature and catalyst to yield algae biomass biodiesel. From 25 to 66% of the catalyst concentration, it has been discovered that the biodiesel yield increases; however, beyond 66%, the yield begins to decline. Higher catalyst concentrations encourage triglyceride side reactions, making more triglycerides accessible for biodiesel production. Further, at greater catalyst concentrations, emulsion is formed, increasing viscosity and making biodiesel recovery very challenging[33,34].

3.2 Modelling using the WOA technique

A model for projecting the yield of algae biomass biodiesel has been created using WO algorithms. Five variables have been selected as the model's inputs, including the algal biomass. The output of algal biomass biodiesel has been established in response at the same time. The boundary conditions established for the response surface methodology have been applied for the outputs and inputs process parameters for WOA, and analyses have been carried out using MATLAB software to maximize the power equation's indexes. Table 4 shows the whale optimization algorithm parameters. Table 5 shows the optimal yield of algal biomass biodiesel suggested by WOA with their experimental validation. Trial and error methods have been used to determine an appropriate valueof parameters. The biodiesel yield model developed by WOA is more accurate for each run than the RSM predicted yield.

Experimental yield compared to RSM projected and WOA predicted yields are shown in Table 2. Fig. 4 and Fig. 5 show the linear equations (0.9896x + 0.6414) and (0.9968x 0.5244) suitable for the variations of yield obtained from experimental and response surface methodology and experimental and whale optimization algorithm yield, respectively. The R^2 value is 0.9895 for the RSM model and

0.9902 for the WOA model, respectively. As a result, the WOA model could accurately estimate the yield of algae biomass biodiesel compared to the RSM model.

Table 4 — Parameters setting Whale optimization algorithm.

Variables Name	No.
Search Agents no.	30
Number of iterations	200

3.3 Optimal condition of biodiesel from algae biomass biodiesel

The ideal situation for the production of algal biomass biodiesel is shown in Fig. 6. Table 5 shows the methanol/algal biomass ratio of 5.56 ml/g, temperature 54.64 °C, time 78 minutes, catalyst at 77.06 wt (%), and stirring speed 450 minutes resulted in the highest yield of algae biomass biodiesel (89.87%). The experimental yield from the justification

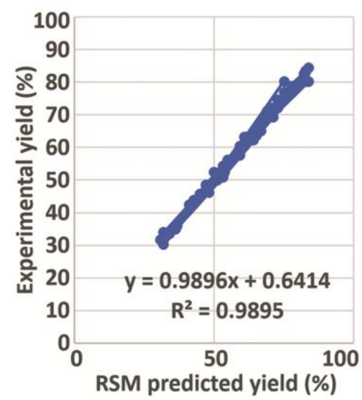

Fig. 4 — Comparision of experimental yield (%) and RSM predicted yield (%).

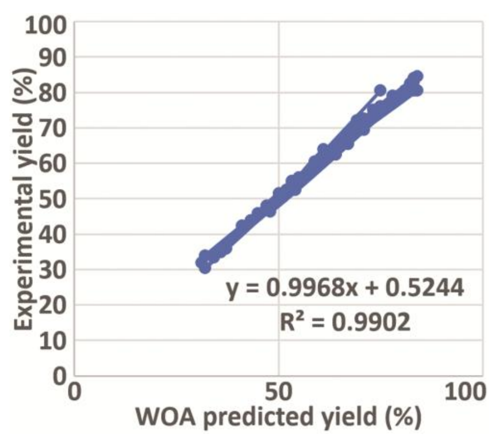

Fig. 5 — Comparision of experimental yield and WOA predicted yield.

Table 5 — Experimental validation of algae biomass biodiesel.

Algae biomass(g)/methanol(ml) ratio	Temp. ^{0}C	Time Mint.	Catalyst %	Stirring rpm	Predicted yield (%)	Experimental yield (%)	% Error
5.56	54.64	78	77.06	450	89.87	87.07	3.12

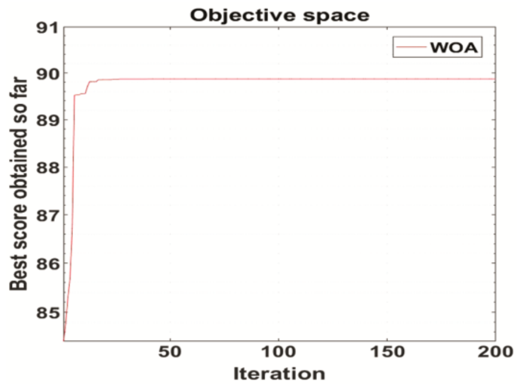

Fig. 6 — Best fitness score obtained by the whale optimisation algorithm.

Table 6 — Various fundamental characteristics of algae biomass biodiesel and diesel.

Properties	Algae Biomass Biodiesel	Diesel
Calorific value (MJ/Kg)	38.42	45.5
Density at 27 °C (g/L)	0.87	0.856
Flash point	176	69.5
Kinematic viscosity at 40°C (mm^2 /s)	11.2	3.073
Moisture (g/100g)	<0.1	0.05 max
Cetane number	67	48
Cloud point (°C)	-1	-7
Pour point (°C)	-6	-8
Acidic value (mg NaOH/g)	0.576	6.032

test utilising the optimized experimental parameters has been 87.07%. It is discovered that there is an average error of 0.0312% between the predicted and actual values. The validation results show the model's accuracy because of the lower percentages of prediction errors.

Table 6 shows the fundamental characteristics of the produced algal biomass biodiesel. The biodiesel properties of algal biomass met those of conventional diesel[35]. Biodiesel produced from algal biomass can reduce fuel usage and enhance the performance of diesel engines.

4 Conclusion

The study concludes that the RSM coupled with the Whale optimization algorithm (WOA) can optimize process parameters for biodiesel production from algal biomass on the lab scale. The 89.87% algae biomass biodiesel has been obtained at an algal biomass/methanol ratio of 5.56, temperature of 54.64 °C, time of 78 minutes, H_2SO_4 of 77.06% w/w, and stirring speed of 450 rpm. The predicted coefficient of determination (R^2) for the RSM model is 0.9895, while the R^2 for the WOA model is0.9902, indicating the WOA model's superiority to the RSM model. The WOA accurately predicted the yield as compared to RSM's predicted yields. The fuel's characteristics complied with the range of criteria for fossil diesel characteristics.

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