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Research Article

Optimization of Oil Yield from the Macro Algae Spirogyra by Solvent Extraction Process Using RSM and ANN

S. Aravind,[1] **Debabrata Barik**,[2] **and Nagaraj Ashok**[3]

[1]*Research Scholar, Department of Mechanical Engineering, Karpagam Academy of Higher Education, Coimbatore 641021, India*
[2]*Department of Mechanical Engineering, Karpagam Academy of Higher Education, Coimbatore 641021, India*
[3]*Faculty of Mechanical Engineering, Jimma Institute of Technology, Jimma University, Jimma, Ethiopia 378*

Correspondence should be addressed to Debabrata Barik; debabrata93@gmail.com and Nagaraj Ashok; nagaraj.ashok@ju.edu.et

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The present work was done to optimize the process parameters of the oil extraction from the algae species spirogyra by using n-hexane as the solvent using the Soxhlet apparatus. The response surface methodology (RSM) and artificial neural network (ANN) were employed to optimize the particle size of the algae powder, dryness level of the algae powder, solid to solvent ratio, reaction time, and extraction temperature of the oil extraction process. Also, the physiochemical properties of the extracted oil were investigated. The comparative evaluation was done between the RSM and ANN models to select the more precise and accurate model. The coefficient of determination, R^2 of 98.92%, and the mean absolute percentage deviation (MAPD) of 0.492% for ANN revealed that the current model created with a network topology of 3 : 11 : 1 with tansig (hyperbolic tangent sigmoid) transfer function in the input layer and purelin (pure linear) transfer function in the output layer trained with trainlm (Levenberg–Marquardt) algorithm found to provide the optimal solution with better accuracy in prediction of the output. The physicochemical properties investigated, such as heating value, flashpoint, density, viscosity, iodine number, acid value, saponification value, and cetane index, showed that the extracted oil from the algae spirogyra species can be used as an alternative fuel.

1. Introduction

The advancement of technology in the fields of different energy-dependent sectors resulted in heavy energy consumption. The world's demand for energy to be met has started increasing drastically. All these paved the path for finding an alternative and renewable energy source. The use of fossil fuels is a major reason for the emission of greenhouse gases, which leads to the global warming effect. To avoid such cases, biomass-based energy is welcomed internationally [1]. Various biomass-based energy sources are available in that biofuels play a major role in replacing mineral fuels. Biomass is a renewable source, and it utilizes CO_2 for its growth through the photosynthetic effect. Compared to various biomasses available, the algae seem to have a higher level of photosynthetic effect. They can be grown in large quantities effectively in a controlled environmental condition. Some of the algae species contain high lipid content, and around 15,000 gallons of oil for one acre of land for one complete year can be produced from such a source globally [2, 3]. Yuvarani et al. [4] extracted oil from the algae species *Cladophora glomerate* using various solvents like n-hexane, toluene, chloroform, methanol, isopropanol, and co-solvent mixtures of chloroform/methanol, hexane/isopropanol and they found that the oil yield for hexane was highest compared to other types of solvents. For hexane, the oil production was around 11.7 w/wt% for 100 g of the biomass at an extraction temperature of 65 °C and extraction time of 3.5 hours. Another group of researchers, Halim et al. [5], used n-hexane as a solvent to extract oil from the algae species *Chlorococcum*. They found that with four grams of *Chlorococcum* sp. and 300 ml of hexane in a Soxhlet apparatus for an extraction time of 7.5 hours; the oil yield was around 5.5 w/wt%. Abdullah et al. [6] studied the effect of operating parameters like extraction temperature, extraction time, and mixing rate of the solvent for extracting oil from the algae species *chlorella vulgaris* using heptane as solvent. Their study revealed that the optimum parameters were 65 °C of extraction temperature and 5 hours of extraction time, resulting in an oil yield of 61.27%. Hidalco et al. [7] carried out a solvent extraction process on the algae species *Botryococcus braunii* with polar and nonpolar solvents and mixtures of them. They found that the oil yield of 19.8 w/wt% by using chloroform/Methanol in the ratio of 1 : 3. When compared to other solvents, the mixture of polar and nonpolar solvents showed more oil yield. Attach et al. [8] performed the Soxhlet method to extract oil from pumpkin, melon, oil bean, and rubber seeds using solvents with different dielectric constants. They also exhibited that the dielectric constant of the solvent had a noticeable effect on the oil extraction rate. The dielectric constant was low for a nonpolar solvent, whereas for the polar solvents, it was high. Dasari et al. [9, 10] used the nonpolar solvent n-hexane to extract the oil from castor seeds using the Soxhlet method. The oil yield was around 52.8% for a solvent ratio of 1 : 3 for an extraction time of 13 hours. Lohani et al. [11] carried out the solvent extraction process using n-hexane and ethyl acetate as a solvent on various oil-bearing seeds like camelina, flax, mustard, and canola by considering three levels of process parameters such as extraction time and extraction temperature with constant solid to solvent ratio of 1 : 4. They documented that the oil yield was maximum for canola which was in the range of 21-36% for n-hexane solvent.

Apart from the production of oil from the algae and conversion of the same into biodiesel, the effect of various process parameters affecting the production rate of bio-oil from biomass sources was studied, and researchers optimized the parameters. The application of response surface methodology (RSM) and artificial neural network (ANN) techniques for optimizing the process seems to be commonly used in many areas of research work. The ability to optimize the process with a minimum number of experimental runs made RSM and ANN popular tools for optimization. The optimization of oil extraction parameters was carried out in several works with a combination of factorial designs.

Ajala et al. [12] optimized the process of extracting shea butter from their kernels by using the Box-Behnken response surface methodology. The significance of the process parameters was also studied with analysis of variation (ANOVA). The optimized oil extraction of 67% of shea butter from the kernel was obtained for 30 g of kernels, 346 ml of n-hexane, and an extraction time of 40 minutes as optimal process parameters. Selvan et al. [13] employed the central composite design (CCD) for RSM with a second-order polynomial equation and found the optimal conditions for extracting oil from Aegle marmelos. They also employed ANN for the prediction of optimal parameters. Their results showed that the coefficient of determination was higher for ANN (0.998) than for RSM (0.976). Bokhari et al. [14] found the optimal conditions for extracting the oil from crude rubber seed oils by solvent extraction method using CCD RSM. The optimal conditions were found to be the seed to solvent ratio of 1 : 40, extraction temperature of 60 °C, the reaction time of 4.5 hours, and ventilation time for the seeds of 3 hours. Okeleye et al. [15] conducted extensive work in optimizing the oil extraction from the Kariya seeds by solvent extraction method using D-optimal RSM and ANN. Their result showed that the prediction level was higher for ANN when compared to RSM. Osman et al. [16] used different optimization techniques to optimize the process parameters for extracting the oil from the sesame seeds using various solvents in the solvent extraction method. Their results showed that the ANN model showed very consistent performance compared to RSM and other modelling techniques. Ajala et al. [17] optimized the process parameters using D-optimal RSM and ANN for extracting oil from the yellow oleander seed by solvent extraction method. The optimized value obtained by both techniques was the same, but the level of fit and coefficient of determination was better for the ANN model.

Table 1: Levels of the input parameters.

			Coded level		
Input parameter		Unit	−1	0	+1
Particle size	θ_1	μm	0.366	0.462	0.641
Dryness level	θ_2	%	50	75	100
Solid to solvent ratio	θ_3	g/ml	1 : 5	1 : 10	1 : 15
Reaction time	θ_4	Hours	1	2	3
Reaction temperature	θ_5	°C	65	70	75

Abdissa [18] implemented the RSM technique to optimize the oil yield from the algae sludge using various solvents like methanol, ethanol, and hexane. The optimization result showed that the solvent hexane showed 61% of oil yield compared to other solvents. Aygün et al. [19] optimized Dyacrodes edulis seed oil extraction using polar and nonpolar solvents using RSM and ANN models. The optimization results showed better results using both techniques. Venkatesan et al. [20] used RSM and ANN models to optimize and predict the oil extraction from the C. innophyllum. The optimized biodiesel as 98.1% is derived with 0.94 volume to volume ratio of methanol to oil molar ratio, 0.98% by weight of potassium hydroxide catalyst loading, and 1 hour 20 minutes of reaction time with 70 °C constant reaction temperature as predicted by Kriging model. Kenechi et al. [21] used the RSM model to predict the oil extraction of the luffa seed oil. The RSM model showed significant results with an R^2 value of around 84.7% and with a mean square error in the range of 0.55. The RSM indicated the temperature as the major factor influencing oil extraction from the luffa seed. Gul et al. [22], in their investigation, used wet microalgae Chlorella pyrenoidosa to extract the biodiesel by using the RSM model as the optimization technique. They used factors such as time, temperature, solvent-to-wet biomass ratio, and hydrochloric acid concentration with varying ranges. They identified that the RSM model showed temperature as the significant factor with a low p value and highest f value.

In the present work, algae oil was produced from spirogyra species using the Soxhlet apparatus with n-hexane as solvent. The process parameters involved during the oil

Table 2: The CCD arrived with Design-Expert factorial design and the response values.

Exp. no	Particle size θ_1 μm	Dryness level θ_2 %	Solid to solvent ratio θ_3 g/ml	Reaction time θ_4 Hours	Extraction temperature θ_5 ˚C	Oil yield % Experimental value	Predicted value RSM	Predicted value ANN
1	− 1	-1	+1	− 1	− 1	22.13	22.42	22.15
2	− 1	+1	− 1	+1	− 1	20.97	21.44	20.98
3	− 1	-1	+1	+1	− 1	23.05	23.06	22.95
4	− 1	+1	+1	− 1	− 1	22.61	22.90	22.64
5	− 1	+1	− 1	− 1	1	21.56	21.71	21.59
6	− 1	+1	− 1	− 1	− 1	20.05	20.22	19.86
7	− 1	+1	− 1	+1	+1	23.19	22.98	23.46
8	− 1	− 1	+1	− 1	+1	23.58	23.30	23.60
9	− 1	+1	+1	− 1	+1	23.48	23.52	23.52
10	− 1	− 1	+1	+1	+1	23.53	24.00	23.54
11	− 1	− 1	− 1	+1	− 1	20.49	20.81	20.53
12	− 1	+1	+1	+1	− 1	23.53	23.56	23.55
13	− 1	− 1	− 1	− 1	+1	21.03	21.36	21.06
14	− 1	0	0	0	0	23.63	24.31	23.65
15	− 1	− 1	− 1	+1	+1	22.71	22.62	22.75
16	− 1	− 1	− 1	− 1	− 1	19.57	19.61	19.73
17	− 1	+1	+1	+1	+1	23.59	24.23	23.61
18	0	0	0	0	− 1	23.26	22.87	23.27
19	0	0	0	− 1	0	23.98	24.78	24.00
20	0	0	0	0	0	24.78	25.42	25.20
21	0	0	− 1	0	0	24.04	24.48	24.07
22	0	0	0	+1	0	26.10	25.80	26.12
23	0	0	+1	0	0	26.58	26.65	26.54
24	0	0	0	0	0	25.23	25.42	25.20
25	0	0	0	0	0	25.58	25.42	25.20
26	0	− 1	0	0	0	24.41	25.11	24.44
27	0	0	0	0	0	25.70	25.42	25.20
28	0	0	0	0	0	24.83	25.42	25.20
29	0	0	0	0	0	24.90	25.42	25.20
30	0	+1	0	0	0	25.72	25.52	25.75
31	0	0	0	0	0	25.35	25.42	25.20
32	0	0	0	0	+1	23.46	24.30	23.48
33	0	0	0	0	0	25.41	25.42	25.20
34	+1	+1	+1	− 1	+1	22.82	22.80	22.83
35	+1	− 1	+1	+1	+1	23.44	23.44	23.44
36	+1	+1	− 1	− 1	− 1	18.81	18.80	18.89
37	+1	− 1	− 1	+1	− 1	19.25	19.56	19.27
38	+1	+1	+1	+1	− 1	22.29	22.55	22.32
39	+1	+1	− 1	+1	+1	21.96	22.11	21.97
40	+1	− 1	+1	− 1	− 1	20.89	21.31	20.91
41	+1	− 1	+1	+1	− 1	21.81	22.08	21.83
42	+1	+1	− 1	+1	− 1	19.72	20.15	19.74
43	+1	− 1	− 1	− 1	− 1	18.34	18.22	18.38
44	+1	+1	+1	− 1	− 1	21.35	21.75	21.38
45	+1	+1	+1	+1	+1	23.34	23.64	23.35
46	+1	− 1	1	− 1	+1	22.34	22.61	22.44

Table 2: Continued.

Exp. no	Particle size θ_1 μm	Dryness level θ_2 %	Solid to solvent ratio θ_3 g/ml	Reaction time θ_4 Hours	Extraction temperature θ_5 ˚C	Oil yield % Experimental value	Predicted value RSM	Predicted value ANN
47	+1	− 1	− 1	+1	+1	21.47	21.77	21.48
48	+1	0	0	0	0	23.54	23.32	23.65
49	+1	+1	− 1	− 1	+1	20.26	20.71	20.28
50	+1	− 1	− 1	− 1	+1	20.37	20.38	19.88

production process were the solid to solvent ratio, reaction temperature, reaction time, the particle size of algae powder, and the dryness level of the algae powder which were considered and analyzed. The effect of these parameters on the yield of oil was computed using RSM and ANN. The combined analysis by RSM and ANN gives optimized process parameters for more oil yield. Also, a physiochemical analysis for the produced oil was undergone to find the suitable application of the produced algae oil.

2. Materials and Methodology

2.1. Materials. The algae *spirogyra* species algae were cultivated in a water tank at Karpagam Academy of Higher Education. Then, the collected algae were sun-dried and ground to a fine powder using a mechanical grinder. The algae were harvested with the help of a round metal mesh of a grid size of 1 mm. From 30 micron mesh, the powder obtained had an average size of 0.366 μm. Similarly, from a 40-micron mesh, the average powder size was 0.462 μm, and from a 60-micron mesh, the average powder size obtained was 0.641 μm. The n-hexane used for the experiments was purchased from the local dealer, and it specifies to the standard.

2.2. Methodology. The Soxhlet apparatus was loaded with the algae powder in the thimble fitted with the filter paper. The round bottom flask was filled with n-hexane in the quantity of 750 ml, and the process was carried out as per the experimental design [6–8]. At the completion of each experiment, the oil was extracted from the oil-solvent mixture through the distillation process by heating them to a temperature of 75 ˚C (boiling range of n-hexane). The oil yield is calculated using the following equation:

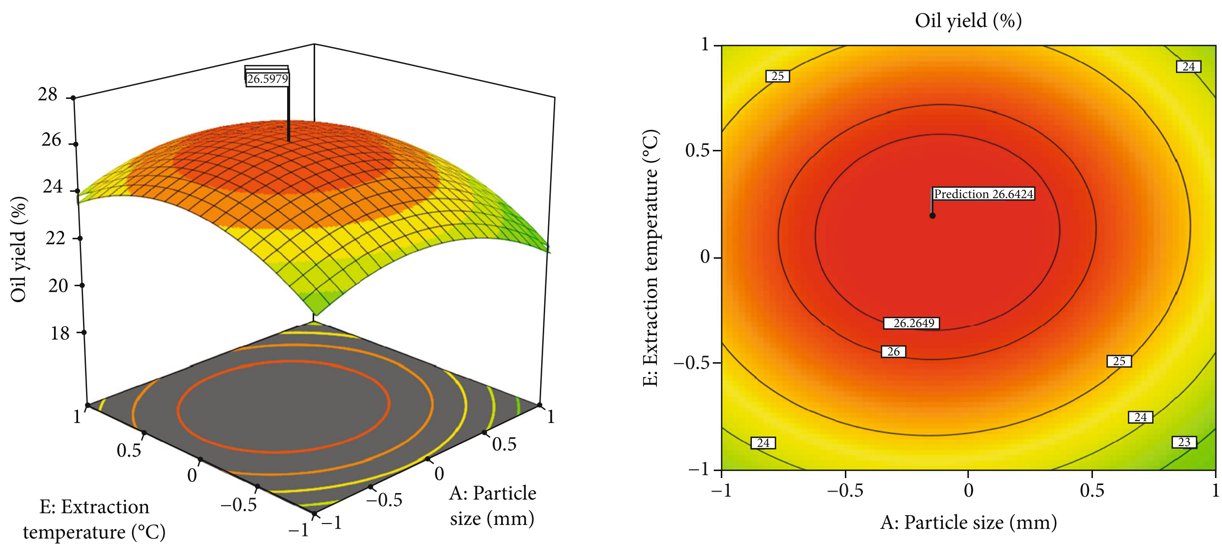
$$\text{Oil yield (\%)} = \frac{\text{Mass of extracted algae oil}}{\text{Mass of the total oil content present in 50g of algal powder used}} \times 100\%. \quad (1)$$

3. Experimental Design and RSM Modelling

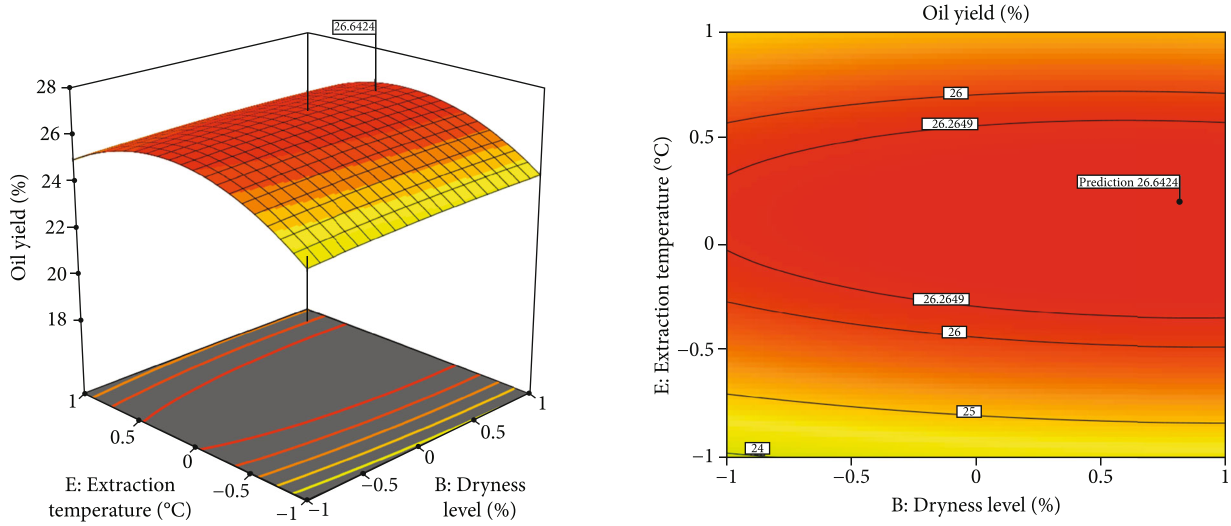
The response surface methodology (RSM) can be abridged as defining the collaboration between the independent variables, modelling the system under design mathematically, and it saves time and cost by reducing the number of trials. With these advantages of RSM, a central composite design (CCD) factorial design with five input parameters and a second-order polynomial equation was employed to represent the oil yield (output parameter) [23]. The solid to solvent ratio, reaction temperature, reaction time, the powder's particle size, and the algae powder's dryness level were considered the input parameters for the modelling. The reason for selecting the input parameter for the optimization process is purely based on the factors influencing the extraction of the oil content from the algae. The factors which majorly influencing the oil extraction was found to be solid to solvent ratio, reaction temperature, reaction time, particle size of the powder, and the dryness level of the algae powder. The levels for the input parameters are given in Table 1. The level codes are given as −1 low, 0 middle, and +1 upper. For RSM modelling, a second-order polynomial was chosen as given in the following equation:

$$\begin{aligned} Y = {} & \beta_0 + \beta_1\theta_1 + \beta_2\theta_2 + \beta_3\theta_3 + \beta_4\theta_4 + \beta_5\theta_5 + \beta_{12}\theta_1\theta_2 \\ & + \beta_{13}\theta_1\theta_3 + \beta_{14}\theta_1\theta_4 + \beta_{15}\theta_1\theta_5 + \beta_{23}\theta_2\theta_3 + \beta_{24}\theta_2\theta_4 \\ & + \beta_{25}\theta_2\theta_5 + \beta_{34}\theta_3\theta_4 + \beta_{35}\theta_3\theta_5 + \beta_{45}\theta_4\theta_5 + \beta_{11}{\theta_1}^2 \\ & + \beta_{22}{\theta_2}^2 + \beta_{33}{\theta_3}^2 + \beta_{44}{\theta_4}^2 + \beta_{55}{\theta_5}^2, \end{aligned} \quad (2)$$

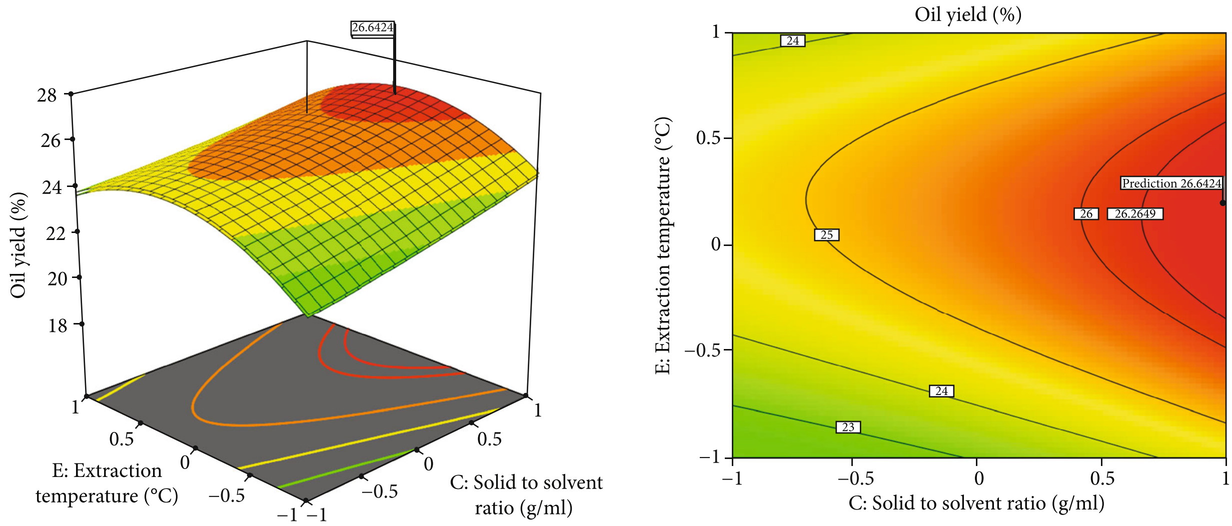
where Y represents the output variable (i.e., oil yield) and θ_1 to θ_5 represents the design factors. β_0 denotes the regression coefficient, and β_1 to β_{55} denotes the linear, interactive, and quadratic regression coefficients, respectively. According to the CCD factorial design, the number of experimental runs was found to be 50. All the experiments were carried out, and the coefficients of the second order polynomial equation were fitted through regression analysis. The significance of the statistical model was evaluated by using ANOVA. The Design-Expert (version 11.0) was used to



(a)

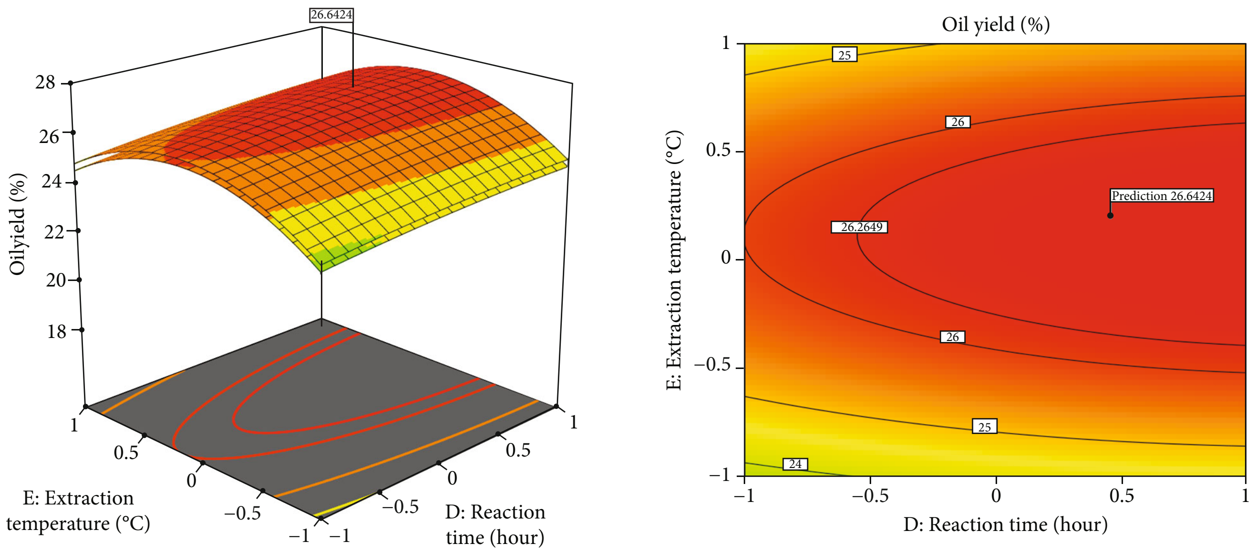


(b)



(c)

Figure 1: Continued.



(d)

Figure 1: (a), (b), (c), (d) 3D surface plot and contour plot of the effect of oil yield % with the design factors.

conduct the statistical analysis. The coded levels using CCD with the help of the Design-Expert factorial design and the corresponding response values are shown in Table 2.

4. ANN Modelling

The artificial neural network (ANN) model can learn by itself with a limited set of input data and has high accuracy in predicting the output data. Also, the input data are stored in their database and have not been considered a separate data set, which is another benefit. This nature of ANN helps avoid the loss of data that does not work effectively in the model. Hence, based on these advantages, an ANN model was created using MATLAB R2009a version with neural network toolbox. The experimental data were normalized to avoid surfeiting the data set due to low to high variations. This normalization enhances the training of the prediction model. The standardization is done using the following equation [23]:

$$\text{standardization} = \left[\frac{2(\alpha_{\text{actual}} - \alpha_{\text{min}})}{(\alpha_{\text{maxi}} - \alpha_{\text{min}})}\right] - 1, \quad (3)$$

where α_{actual}, α_{min}, and α_{max} are the experimental data's actual, minimum and maximum values. The standardization process produces data from − 1 to +1. The performance of the ANN model relies on the number of the input layer, the number of neurons in the hidden layer and the number of output layers with different transfer functions and training algorithms. The $x-y-z$ topology was followed, where x denotes the number of the input layers, y represents the number of neurons in the hidden layer, and z denotes the number of the output layer. A three-layer ($x = 3$) feed-forward network with transig as a transfer function in the hidden layer, with the number of neurons ranging from $y = 5$ to 20, was studied by taking different transfer functions in the output layer ($z = 1$). The ANN model was trained using different training algorithms, and the model with the best coefficient of determination (R^2) and mean square error (MSE) was selected as the best prediction model.

5. Model Validation

The RSM and ANN models were validated to check for their efficiency in predicting the optimal values of the process parameters. This validation can be done by comparing the experimental data set with the predicted data set by the two models. In order to help this validation process, statistical formulas can be employed. Equations (4), (5), (6), (7), (8), and (9) represent the coefficient of determination, adjusted R^2, mean absolute error, root mean square error, standard error prediction, and the mean absolute percentage deviation, respectively [15, 17, 23–25]:

$$\text{coefficient of determination, } \mathrm{R}^2 = 1 - \frac{\sum_{j=1}^{m}\left(z_{j,p} - z_{j,e}\right)^2}{\sum_{j=1}^{m}\left(z_{j,p} - z_{e,avg}\right)^2}, \quad (4)$$

$$\text{adjusted}\mathrm{R}^2 = 1 - \left[\left(1 - \mathrm{R}^2\right) \times \frac{m-1}{m-k-1}\right], \quad (5)$$

$$\text{Mean absolute error, MAE} = \sqrt{\frac{\sum_{j=1}^{m}\left|\left(z_{j,e} - z_{j,p}\right)\right|}{m}}, \quad (6)$$

$$\text{Root mean square error, RMSE} = \sqrt{\frac{\sum_{j=1}^{m}\left(z_{j,e} - z_{j,p}\right)^2}{m}}, \quad (7)$$

Table 3: ANOVA analysis.

Source	SS	Df	MS	F value	p value	
Model	199.75	20	9.99	62.85	< 0.0001	Significant
$\theta_1 - \theta_1$	8.19	1	8.19	51.53	< 0.0001	
$\theta_2 - \theta_2$	1.38	1	1.38	8.68	0.0063	
$\theta_3 - \theta_3$	39.30	1	39.30	247.30	< 0.0001	
$\theta_4 - \theta_4$	8.76	1	8.76	55.13	< 0.0001	
$\theta_5 - \theta_5$	16.92	1	16.92	106.47	< 0.0001	
$\theta_1\theta_2$	0.0018	1	0.0018	0.0111	0.9169	
$\theta_1\theta_3$	0.1504	1	0.1504	0.9462	0.3387	
$\theta_1\theta_4$	0.0358	1	0.0358	0.2255	0.6385	
$\theta_1\theta_5$	0.3365	1	0.3365	2.12	0.1563	
$\theta_2\theta_3$	0.0351	1	0.0351	0.2206	0.6421	
$\theta_2\theta_4$	0.0006	1	0.0006	0.0035	0.9533	
$\theta_2\theta_5$	0.1349	1	0.1349	0.8490	0.3644	
$\theta_3\theta_4$	0.6062	1	0.6062	3.81	0.0605	
$\theta_3\theta_5$	1.47	1	1.47	9.22	0.0050	
$\theta_4\theta_5$	0.0053	1	0.0053	0.0332	0.8567	
${\theta_1}^2$	6.27	1	6.27	39.44	< 0.0001	
${\theta_2}^2$	0.0300	1	0.0300	0.1888	0.6671	
${\theta_3}^2$	0.0411	1	0.0411	0.2585	0.6150	
${\theta_4}^2$	0.0459	1	0.0459	0.2887	0.5952	
${\theta_5}^2$	8.20	1	8.20	51.58	< 0.0001	
Residual	4.61	29	0.1589			
Lack of fit	3.75	22	0.1704	1.39	0.3440	Not significant
Pure error	0.8595	7	0.1228			
Cor total	204.36	49				
R^2	0.9854		Adj R^2	0.9752		
C. V %	1.76					

$$\text{Standard error prediction, SEP} = \frac{\text{RMSE}}{z_{avg,e}} \times 100, \quad (8)$$

$$\text{Mean absolute percentage deviation, MAPD} = \frac{100}{m}\sum_{j=1}^{m}\frac{\left|(z_{j,e} - z_{j,p})\right|}{\left|(z_{j,e})\right|}, \quad (9)$$

where $z_{j,p}$ denotes the predicted response, $z_{j,e}$ denotes the experimental value, $z_{e,avg}$ is the average of the total experimental data, m is the total number of experiments conducted, and k is the total number of design factors.

6. Results and Discussion

6.1. Results Obtained from the RSM. The experimental design based on CCD for full factorial was created, and the 50 sets of experiments were carried out. The results are shown in Table 2. The range of oil yield was found to be around 18.34 to 26.58%. The regression analysis was performed, and the regression of the second order polynomial equation was found to be

$$\begin{aligned} Y\,(\text{oil yield}) = {} & +25.2 - 0.4907\,\theta_1 + 0.2013\,\theta_2 + 1.0751\,\theta_3 \\ & + 0.5076\,\theta_4 + 0.7054\,\theta_5 - 0.0074\,\theta_1\theta_2 \\ & + 0.0685\,\theta_1\theta_3 + 0.0334\,\theta_1\theta_4 + 0.1025\,\theta_1\theta_5 \\ & - 0.0331\,\theta_2\theta_3 + 0.0042\,\theta_2\theta_4 - 0.0649\,\theta_2\theta_5 \\ & - 0.1376\,\theta_3\theta_4 - 0.2140\,\theta_3\theta_5 + 0.0128\,\theta_4\theta_5 \\ & - 1.5918\,{\theta_1}^2 - 0.1102\,{\theta_2}^2 + 0.1289\,{\theta_3}^2 \\ & - 0.1362\,{\theta_4}^2 - 1.8205\,{\theta_5}^2. \end{aligned} \quad (10)$$

The optimal process parameters were found using the regression equation (Equation (10)). On solving this equation, for an optimal oil yield of 26.62%, the optimal parameters were found to be 0.336 μm of particle size, 98.2% of dryness level, 1 : 14.9 solid to solvent ratio, 1.75 hours of reaction time, and 70.98 °C of extraction temperature. To confirm the above predicted optimal values

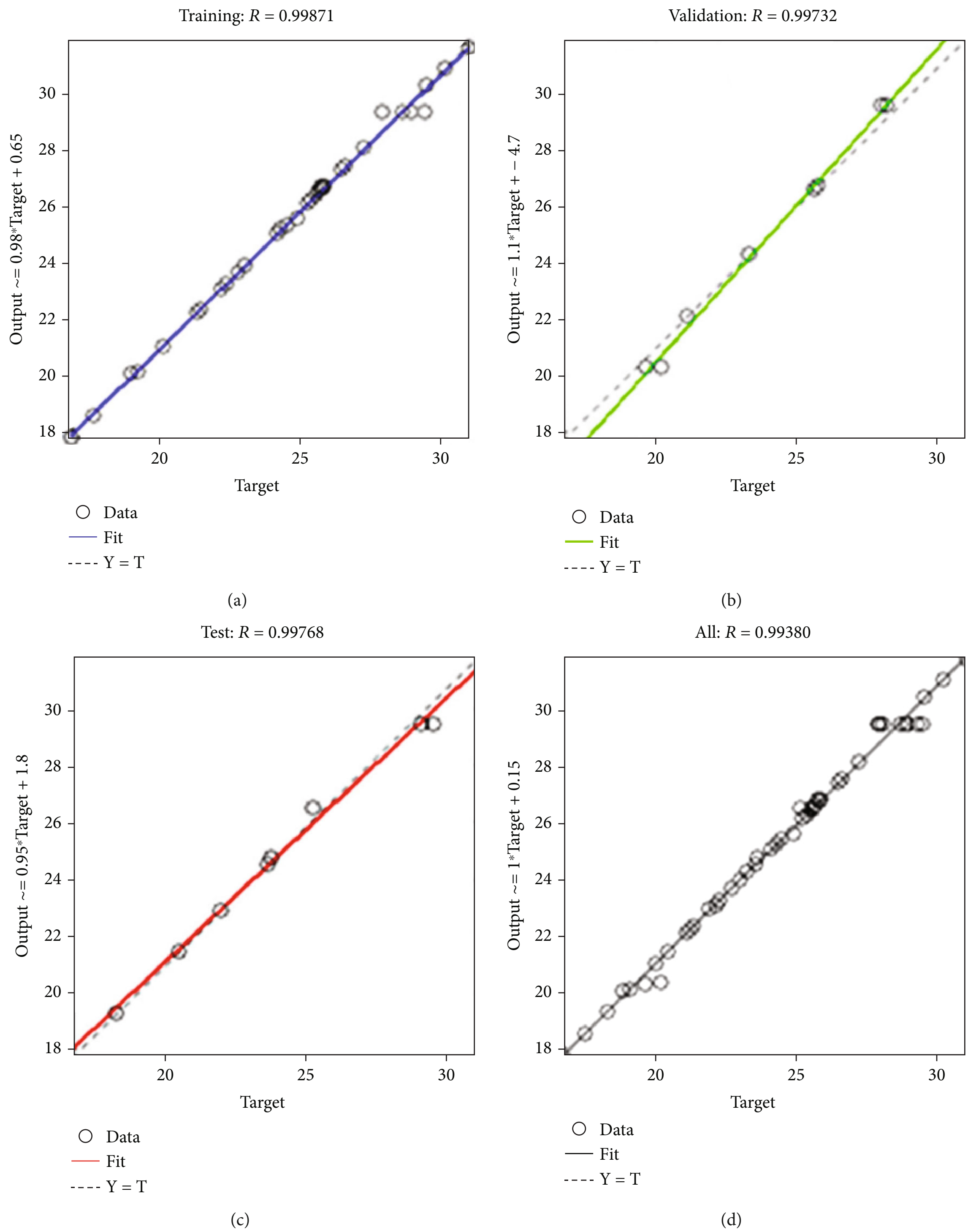


Figure 2: (a) Training data, (b) validation data, (c) test data, and (d) relation between predicted and experimental data set of the optimal ANN model.

using a regression equation, an experimental run was conducted, and the oil yield was found to be 26.34%. Figure 1 shows the interaction of different process parameters with the oil yield in the form of 3D surfaces and contour surfaces. All the contours showed that smaller particle size, maximum dryness level, maximum solid to solvent ratio, intermediate reaction time, and extraction temperature of

Table 4: Evaluated results of RSM and ANN model.

Performance parameters	R^2	Adj R^2	MAE	RMSE	SEP %	MAPD %
RSM	0.9854	0.9752	0.8524	0.4892	1.4251	1.3054
ANN	0.9892	0.9887	0.3057	0.1973	0.8365	0.4092

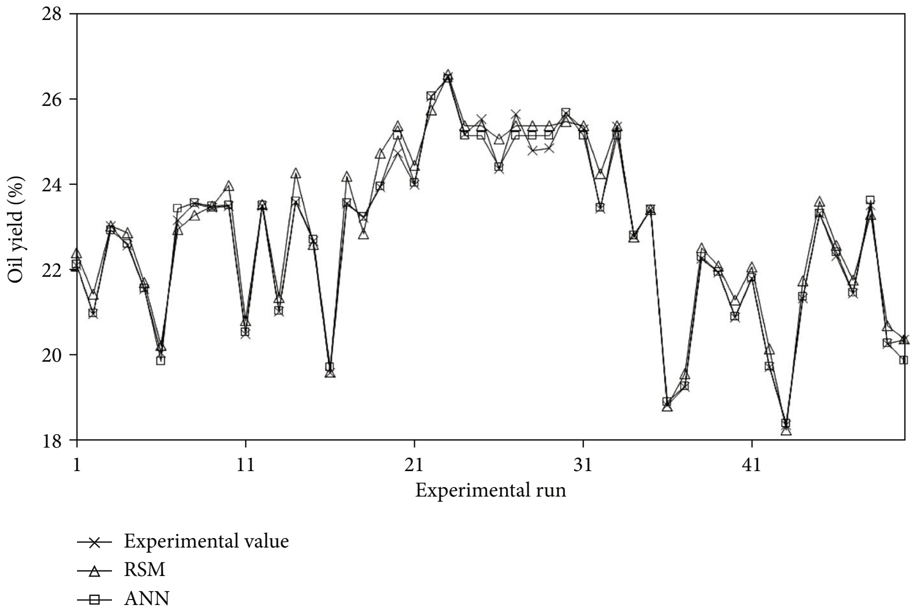


Figure 3: Comparison of experimental, predicted values of RSM and ANN.

the solvent resulted in the maximum oil yield from the algae spirogyra species. In order to know the significance of this model, an ANOVA analysis is given in Table 3. The p value less than 0.05 is considered to be significant; in this present RSM model, the interaction levels of the design factors θ_1 to θ_5, $\theta_3\theta_4$, θ_1^2, and θ_5^2 were less than 0.05. The R^2 of this present model is 0.9854, and the adj R^2 is 0.9752, which is in reasonable agreement and thus makes the model significantly. The lack of fit F value of 1.39 implies that the lack of fit is not significant relative to the pure error. There is a 34.40% chance of a lack of fit F value. This large F value could have occurred due to noise. Nonsignificant lack of fit is good [24, 26]. Also, the C.V of this model is 1.76, which is less than 5%, which shows that the model's reproducibility is good.

6.2. Results of ANN Model. The ANN model built for this present study was investigated by considering three layers ($x = 1$) of input factors of feed-forward type, the hidden layer withstanding transfer function with neurons ranging from $y = 5$ to 20 and the output layer of $z = 1$ for various training algorithms like Traingda, Traingdm, Traingdx, Trainlm, Trainrp, and Trainseg. The experimental data set was segregated into 70% of data for training remaining 30% of data for testing and validation [24]. The network model was run for various topologies, and the optimal topology was found with the model's best R^2 value and MSE. It was found that the optimal network topology was 3 : 11 : 1 with transig as transfer function in the input layer and purelin as transfer function in the output layer for Levenberg–Marquardt training algorithm [15, 17, 24]. The optimal network is showcased in Figures 2(a)–2(d) with R values for training, validation, testing, and overall, as 0.9987, 0.9973, 0.9976 and 0.9938, respectively. These R values confirm the degree of better correlation with the experimental and predicted data. The coefficient of determination for the optimal network topology was 0.9892 and MAE of 0.012; this shows that the prediction accuracy of the optimal model is very high. The oil yield values predicted by this model are equivalence to the experimental oil yield values [27, 28].

6.3. Evaluation of the RSM and ANN Model. The precision and accuracy of the developed RSM and ANN models were evaluated by calculating the performance parameters like R^2, adj R^2, MAE, RMSE, SEP, and MAPD using the Equations (4) to (9). The values calculated are shown in Table 4. The R^2 value for the RSM and ANN model seems to be nearby, making both the models better for optimizing the oil yield parameters. But the MAPD for RSM is higher than the ANN, which makes the ANN model reliable and consistent. Figure 3 compares the predicted values of RSM and ANN with the experimental values. It can be seen that the predicted values of the ANN model were very close to the experimental value when compared to the RSM predicted values. The capability of the ANN model for nonlinear data evaluation is more precise than the second-order polynomial model of RSM. Hence, the ANN model efficacy is better than the RSM model for optimization and modelling of this present study [24, 26].

6.4. Physiochemical Properties of the Extracted Oil. The various physicochemical properties of the extracted oil were compared with standard algae oil, diesel, biodiesel, algae oil from other species, and biomass using the solvent extraction method, shown in Table 5 [29]. The heating value of the extracted oil was found to be 32.57 MJ/kg, comparable to diesel biodiesel standard [28, 30]. The flash point of the extracted oil was around 79 °C, which is in range with the standard value. The density and the kinematic viscosity of the extracted oil were less than the standard values, which shows that the oil extracted can be used as an alternative fuel source in IC engines. The saponification value shows the

Table 5: Physio chemical properties of various biomass compared with standard values of diesel and biodiesel with the present study.

Type of biomass	Solvent used	Density kg/m^3	Specific gravity	Kinematic viscosity, mm^2/s	Acid value, mg KOH/g oil	Iodine value, g I_2/100 g oil	Saponification value, mg KOH/g oil	Calorific value, MJ/kg	Cetane number	Flash point, °C	Ref. no
ASTM standards		4052-91	D5355	D445	D1980-87	D96	D221	D240	D613	D664	
Diesel	—	837	0.835	3.96				44.8	45-50	72	
Standard biodiesel	—	860-900	0.903 -0.921	1.9-6.0	0.8	120	—	37.27	47	130	[30]
Spirogyra sp. (present study)	n-Hexane	858	0.852	3.72	2.142	67	174.56	32.57	32.7	79	
Cladophora glomerata	n-Hexane	892	0.892	3.8	0.935	76.24	244.1	33.6	55.82	110	[31]
Chlorella sp.	n-Hexane/ethanol	912	0.912	4.73	0.37	97.12	—	37.86	—	179	[30]
Chlorophyta sp	n-Hexane	887	0.887	—	1.24	81.27	256	—	—	108	[27]
Dunalliela sp.	n-Hexane/methanol	864	0.864	4.13	0.835	48	196	34.53	—	168	[28]
Acutodesmus obliquus	Ethanol/n-hexane	945	0.945	3.33	7.4	156.4	165.66	36.54	31.82	127	[32]
Castor oil	n-Hexane	958	0.958	4.5	3.2	84.6	378.6	35.45	38.1	112	[33]
Calophyllum seed oil	n-Hexane -methanol (1 : 1)	885	0.885	2.6	13	126.8	152	—	—	—	[32]
Sandbox seed oil	n-Hexane	941	0.941	4.18	1.878	186.28	242.63		26.25		[34]
Kariya seed oil	n-Hexane	903	0.903	7.149	2.12	55.78	249.76	41.36	—	140	[35]

amount of potassium hydroxide required to form soap from one gram of lipid content. For the present study, the value found was 174.56 mg KOH/g of oil, which is within the standard value [30]. The free fatty acids present in the oil have saturated and unsaturated parts. The amount of unsaturated fatty acids present in the oil can be identified with the iodine value of that particular oil. Higher the values of iodine number, the higher the presence of double bonds of C = C in the oil. The iodine value of the algae oil in this study is in the range, which shows that the oil can be a better alternative energy source. The acid value illustrates the damaging effect of the oil-used material. The higher the acid value, the higher the damaging effects. In this present study, the acid value for the extracted oil was found to be 67 g I_2/100 g of oil, which is in the permissible range [28]. The cetane index of the extracted oil was found to be 32.7, which is a better value and shows that it can be used as fuel in CI engines [30]. In comparison, it can be shown that the algae oil obtained from the *Spirogyra* can be used as an alternative fuel.

7. Conclusion

The present work represents the modelling of the solvent extraction process by the Soxhlet apparatus to extract oil from the algae species spirogyra. The optimization models were created using RSM and ANN to find the optimal process parameters for oil extraction from the algae. The optimal conditions were found to be 0.336 μm of particle size, 98.2% of dryness level, 1 : 14.9 solid to solvent ratio, 1.75 hours of reaction time, and 70.98 °C of extraction temperature for an optimum oil yield of 26.62%. The ANN model was found to be the best model when compared with the RSM model with improved performance parameters. The physiochemical properties were determined as per ASTM standards for the extracted oil, and the results showed that the extracted oil from the spirogyra species could be a better alternative energy source. Further, the extracted oil from the algae spirogyra species can be produced in large quantity by cultivating them in large tanks. And this extracted oil can be mixed with the mineral fuels in certain ratio and used as an alternative fuel in the diesel engine.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this article.

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