Application of Fuzzy Modelling and Particle Swarm Optimization to Enhance Lipid Extraction from Microalgae

Ahmed M. Nassef[1, 2], Hegazy Rezk[1,3, *], Mohammad Ali Abdelkareem[4,5,6**], Abed Al-Aswad[7], and A. Olabi[5,7]
[1]College of Engineering at Wadi Addawaser, Prince Sattam Bin Abdulaziz University, KSA
[2]Computers and Automatic Control Engineering Department, Faculty of Engineering, Tanta University, Egypt
[3]Electrical Engineering Department, Faculty of Engineering, Minia University, Egypt
[4]Chemical Engineering Department, Faculty of Engineering, Minia University, Egypt
[5]Dept. of Sustainable and Renewable Energy Engineering, University of Sharjah, P.O. Box 27272, Sharjah, UAE
[6]Center for Advanced Materials Research, University of Sharjah, PO Box 27272, Sharjah, United Arab Emirates
[7]Mechanical Engineering and Design, Aston University, School of Engineering and Applied Science, Aston Triangle, Birmingham, B4 7ET, UK

Corresponding authors:
*Hegazy Rezk; Tel.: 00966547416732, Fax:00966115882000, Email: hegazy.hussien@mu.edu.eg
**Mohammad Ali Abdelkareem; Tel 0097165053917, Email:mabdulkareem@sharjah.ac.ae

Abstract

Lipid extraction from microalgae is maximized by defining the optimal operating conditions of the microwave pretreatment method. Using the experimental data, a robust model that describes the lipid extraction is generated using fuzzy logic. Then, the optimal extraction conditions of the lipid are determined using Particle Swarm Optimization (PSO) algorithm. Three different operating parameters influence on the recovered lipid from Microalgae. These parameters are power (*W*), heating time (minutes), and extraction time (hours). Accordingly, during the optimization process, these parameters are used as a decision variables for PSO optimizer in order to maximize the recovered lipid that used as a cost function. The resulting plots demonstrated a well-fitting between the fuzzy model and the experimental data. Based on the built model, the optimization process achieved a significant increase in the lipid extraction by 22% compared to that obtained experimentally and using the ANOVA.

Key-words: Fuzzy-Modeling; Particle Swarm optimization; Biodiesel; Microalga; Lipid extraction

1. Introduction

Environmental impact and limited resources of fossil fuels, resulted in rapid growth usage of renewable energy [1-5]. Among the different renewable energy sources, biomass energy is not only a renewable and clean energy source, but also it can contribute to the waste management projects if it is planned correctly [6-9]. Transportation sector consumes huge amounts of diesel that is coming from fossil fuel [10, 11]. Biodiesel is an alternative diesel fuel that is renewable and offers better environmental impacts [12, 13] when compared with conventional diesel oil. It is currently produced, commercially, from plant and animal oils, such as soybeans, animal fat, palm oil, waste cooking oil [14]. However, these feedstocks are recognized limited which affected the further expansion of producing biodiesel [15]. Alternatively, it has been recognized that triacylglycerol, the fundamental component needed in biodiesel production, is contained as lipid within the microalgae cells [16-18]. Indeed, microalgae offers more advantages when compared with other feedstocks, including higher growth rates, significantly better CO_2 fixation rates (almost double their dry weight in some cases), and the fact that they don't compete with land or food crops. Moreover, coupling microalgae cultivation with wastewater treatment has been intensively studied aiming to use the nutrients in wastewater to cultivate microalgae for different applications [19]. Biodiesel production from microalgae consists four different stages, namely, the cultivation, harvesting, lipid extraction, and transesterification. On the other hand, due to the recalcitrant nature of microalga cell wall and composition, lipid extraction is a major limitation that needs substation research [20]. However, it is proven that the lipid extraction process is a key to increasing the whole process efficiency by increasing the amount of lipid exposed during transesterification, and thus enhancing the economic feasibility of the process [21, 22]. Cell disruption is a fundamental process in the lipid extraction, during which, lipids are released from cellular components and move to the adjacent medium [23]. Different techniques were used to assure that, including mechanical and non-mechanical methods. Mechanical methods were used to physically rupture the microalgae cell walls, using either high pressure homogenizers or bead beating, while other methods tend to weaken the cell membrane to increase the penetration of the solvent and help in extracting, either chemically, biologically, or thermally [24]. The use of microwaves as a cell rupture technique was explored since 2008, with the benefit of quick and economic heating compared with the conventional heating systems [25]. Moreover, it has been proven that microwave is more efficient in small scale extraction due to the non-corrosive and low maintenance cost [26]. Microwaves induce the vibration in the wet biomass medium which will result in water evaporation and in applying a high pressure on the cell walls leading to cell disruption, along with the thermal effect that is weakening the cell walls [27]. Several reports were carried out to study the operating parameters microwave extraction. It is found that lipid extraction is increased with increasing microwave power [28, 29]. For instance increasing microwave power from 400 to 1000 W resulted in increasing lipid extraction from 14% to 28% using n-heptane/2-propanol (2/1) [28]. Biller et al. demonstrated that increasing the microwave power from 25 to 61 Wh/g resulted in increasing lipid extraction from 1.6 to 10% using *Nannochloropsis* sp. [30]. In another study, Passos et al. reported that lipid extraction increased with increasing the microwave power depending on the temperature and duration of the irradiance [31]. Some researchers used optimization algorithms as effective tools for maximizing the yielding process and the biodiesel production using a minimum number of experiments [32, 33]. For instance, Anyanwu et al. [34] optimized the effect of air temperature and velocity on the dewatering of the microalgae using Response Surface Methodology (RSM). An optimized operating conditions of 4 m/s air velocity and an air temperature of 48 °C achieved 92.83% dewatering efficiency. In our previous study, we used the microwave to extract lipid from *Scenesdemus quadricauda* microalgae. We used ANOVA to optimize the extraction conditions that revealed a 49 % lipid extraction at optimum conditions of 600 W, 8 min heating time and an extraction time of 3.5 minutes [26]. Applying fuzzy logic modeling in conjunction with the optimization techniques enriches the industrial and control applications [35-37]. The main contribution of this work is to present a new methodology based on Fuzzy logic and the Particle Swarm Optimization (PSO) to determine the optimum parameters required to achieve the maximum lipid recovery. Based on the experimental data set of the lipid extraction process, an accurate Fuzzy logic based-model for the lipid extraction process is created. Then, the optimal operating parameters are identified using PSO algorithm. Three different operating parameters influence on the recovered lipid from Microalgae. These parameters are power, heating time, and extraction time. Accordingly, during the optimization process, these parameters are used as a decision variable for PSO optimizer in order to maximize the recovered lipid that used as a cost function. Finally, a comparison between both techniques is also presented.

2. Experimental Setup

A 50 ml of *Scenesdemus quadricauda* was cultured in the University of the West of Scotland, using the unicellular culture medium (K10) in 4 L flasks as described in [26]. During cultivation, cell concentration has changed from 1.815108 cell/ml at the beginning to 7.76371016 cell/ml by the end of the cultivation duration (20 days). Afterward, a sample of 500 ml of the wet algae was subjected to microwave pre-treatment using a round bottom open glass. The samples were pre-treated at a microwave power ranging between 180 W to 600 W for times ranging between 2 minutes to 8 minutes. Furthermore, different extraction times were tested between 3 and 4 hours. 15 experiments were recorded according to the design matrix used in [26] as shown in Table 1:

Table 1: Design matrix showing the effect of the parameters on the recovered lipid [26]

Power [W]	Heating time [min]	Extraction time [hours]	Recovered lipid [%]
180	5	3	14.01
180	2	3.5	14.14
180	8	3.5	10.38
180	5	4	18.86
390	2	3	18.87
390	8	3	18.87
390	5	3.5	32.43
390	5	3.5	11.68
390	5	3.5	25.46
390	2	4	14.44
390	8	4	37.84
600	5	3	32.43
600	2	3.5	18.69
600	8	3.5	48.65
600	5	4	25.45

3. Fuzzy Modelling of the Lipid Extraction from Microalgae

Fuzzy logic (FL) is still proving as an efficient modeling tools in many industrial and control applications despite it has been emerged in the mid of sixties. Its robustness comes from its ability to track the data trend even if it is superimposed with noise or it is uncertain. Therefore, the model can be built using fuzzy modeling technique with very few numbers of training epochs. Three modeling phases are the fuzzy modeling procedure. It starts by the fuzzification phase which maps the crisp value to its corresponding fuzzy value via membership functions

(MFs). Every MF represents the degree of belonging to a subset/class of data over the domain of discourse. The very popular fuzzifying MFs are the Gaussian and triangular shapes. The fuzzy variable is then fed to the rule-base, the core of the fuzzy inference system, in the second phase. The Mamdani and Takagi-Sugeno-Kang (TSK or Sugeno) types are the two forms of the fuzzy rule. They only differ in the output formulation. However, the Mamdani-type forms the output as a fuzzy MF while the TSK considers the output as a function of the inputs. The antecedent is produced by the logical AND or the Min operator of the fuzzy inputs. The fired fuzzy rules are then aggregated to produce the final fuzzy output. To obtain the final crisp output, a defuzzification method is applied which represents the third and last phase. There are many well-known defuzzification methods in the literatures, but Center of Gravity (COG) is very common in Mamdani-form, however the Weighted Average (Wtaver) is preferred in the case of TSK-form.

For the sake of enhancing the production of biodiesel from wet microalgae using microwave pre-treatment, some operating variables such as the microwave power (W), heating time (minutes) and extraction time (hours) are controlling parameters in the lipid extraction process. In our previous study [26], we have investigated the effect of these three operating parameters on the lipid extraction process. Implementing Design of Experiment methodologies, modeling and optimization were carried out using a set of 15 different experiments conducted at different operation conditions. As it has been mentioned previously, FL offers robust modeling for uncertain and noisy data. The model obtained in our previous study using ANOVA [26] is highly nonlinear with noisy data set as shown in Figure (1). In this work, we have built a fuzzy model using a 3-input and one-output set of the 15 runs conducted in our previous study [26]. The data set is divided into training and testing with 13 data points used for training the system and 2 data points used for testing. The features of the fuzzy model are shown in Table 2.

Table 2: Features of the Fuzzy Model

Fuzzy Process	**Attribute**
Rules form	Sugeno-type
Rule-base builder	SC
ANDing Operation	Product

ORing Operation	Probabilistic OR
Defuzzifying Method	Wtaver
Implication	Min
Aggregation	Max
Number of Rules	13
Number of Training Epochs	50
Output	Linear function

Before starting the training phase, the rule-base and the structure of the fuzzy have been constructed, and an ANFIS of ‘Sugeno-type’ is built based on 3-inputs and one ‘linear’ output. The rule-base is configured using the ‘Subtractive Clustering’ method. The proposed model has 13 fuzzy rules. The model’s training process has been done with 13 samples for 50 epochs. The accuracy of the modeling is confirmed through training the model till an adequate small testing error is met. Furthermore, the mean squared errors (MSE) were calculated for the models’ predictions in both the training and testing phases and compared to those of the experimental data. The MSEs were found to be $4.2275*10^{-07}$, 0.67325 and 0.089768 for training, testing, and whole data, respectively, which were found the lowest over all the training trials. Figure (1) shows a comparison between the obtained results using the fuzzy model obtained in this study in comparison with the measured data as well as the optimized results using ANOVA. As clear from the figure, the built model using fuzzy is well matching the experimental results to a large extent compared to those in case of the ANOVA one indicating the reliability of the fuzzy model. The Root Mean Squared Error (RMSE) and the coefficient of determination (R^2) as statistical test metrics between the proposed fuzzy model and the ANOVA model have been estimated. The RMSE values are 0.0898 and 114.09 for fuzzy model and ANOVA respectively. Whereas as the values of the coefficient of determination are 0.994 and 0.7854 respectively for fuzzy model and ANOVA. This prove the superiority of the fuzzy model, which gave minimum RMSE and maximum R^2 values.

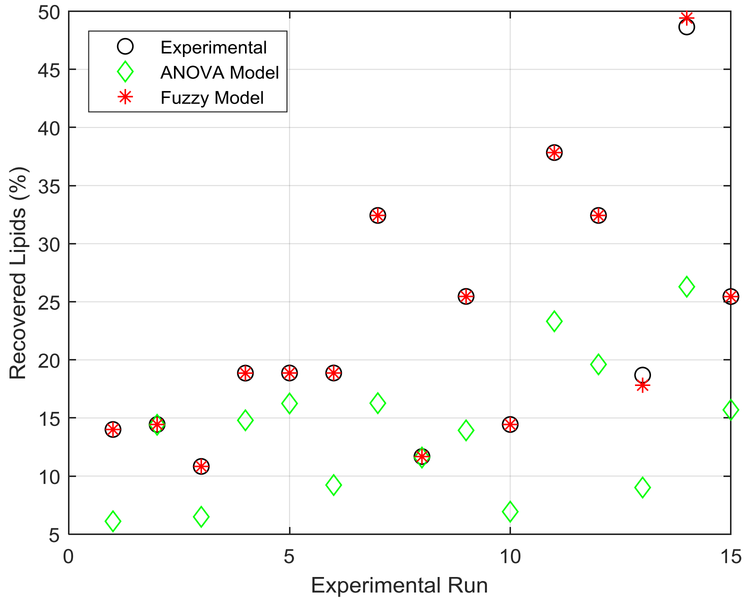
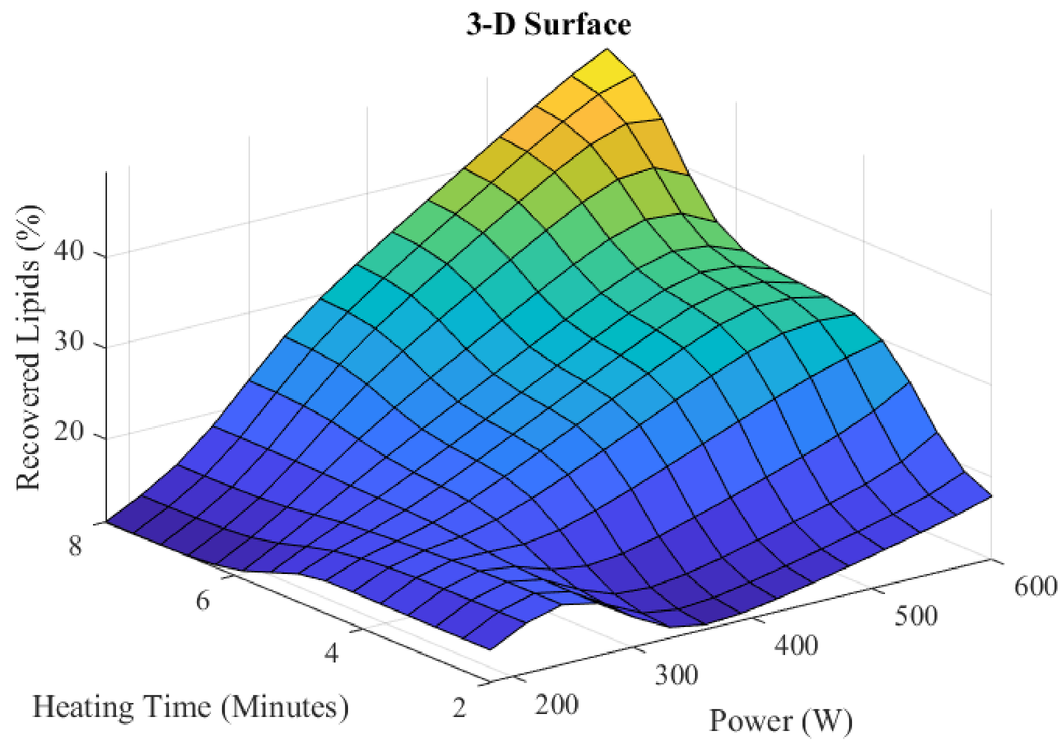
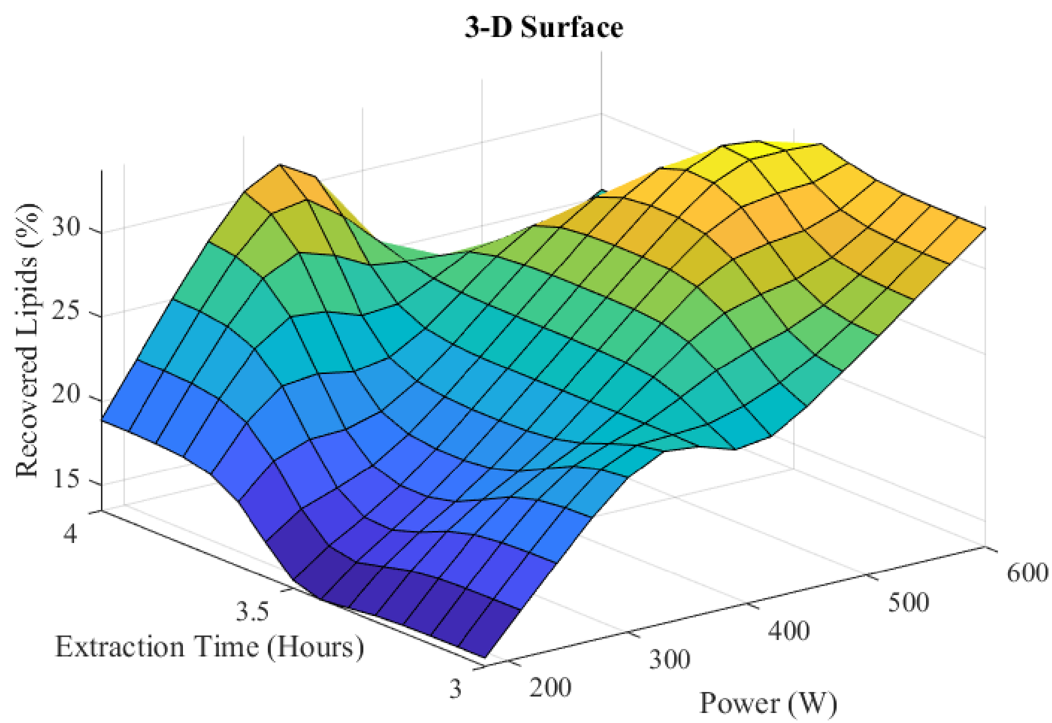


Fig. 1. The fuzzy and ANOVA models' performances against the experimental data

Figure (2) shows a 3-D spatial shape of the recovered lipids for each combination of the input data in the fuzzy model, while the fuzzy membership functions of the system inputs are shown in Figure (3).


3-D Surface
Recovered Lipids (%)
40
30
20
8
6
4
2
Heating Time (Minutes)
200
300
400
500
600
Power (W)


3-D Surface
Recovered Lipids (%)
30
25
20
15
4
3.5
3
Extraction Time (Hours)
200
300
400
500
600
Power (W)

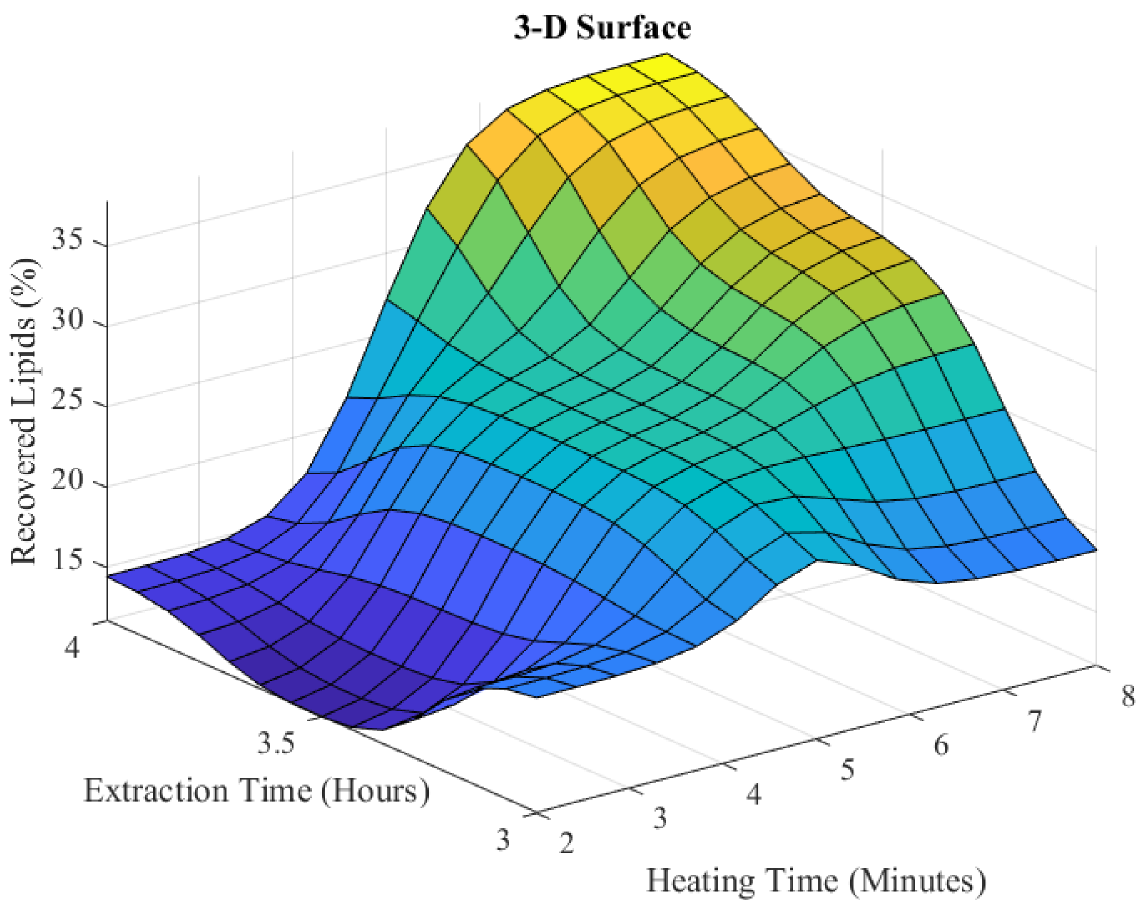


Fig. 2 The 3-D spatial shape of the recovered lipid using inputs data of a) power and heating time inputs, b) power and extraction time, and c) heating time and extraction time.

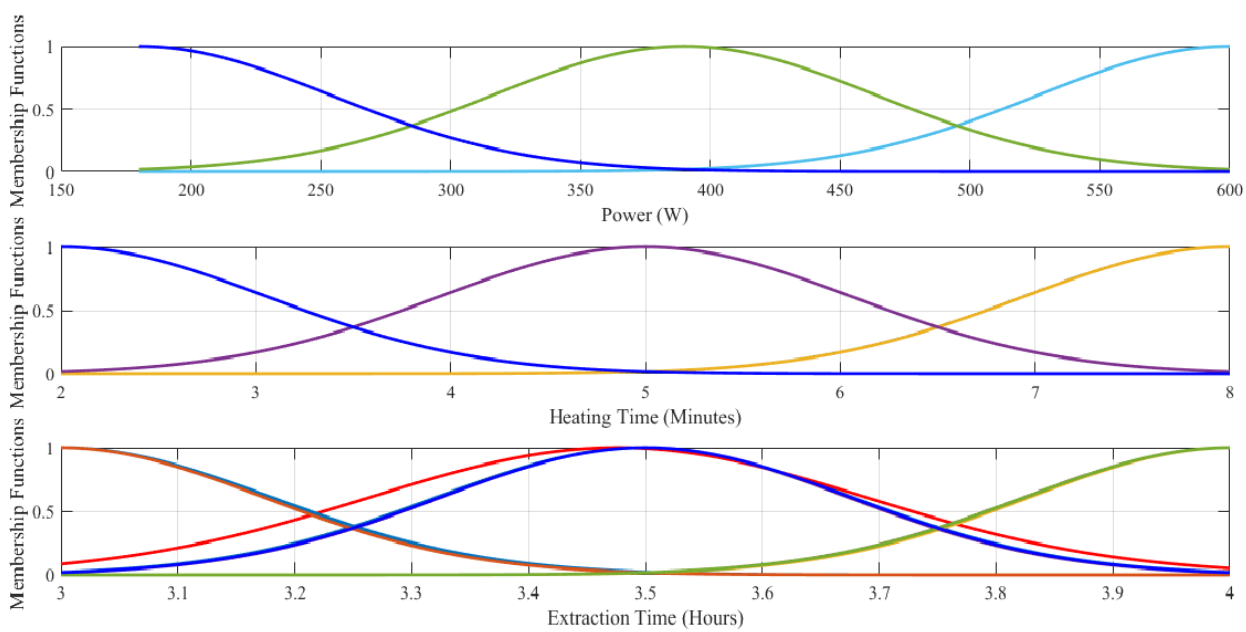


Fig. 3 The fuzzy model inputs' MFs

Testing the modeling accuracy to assure the resulting performance of the model for any unseen pattern of the input data is very crucial. For assessing the prediction accuracy, the model's performance (prediction) is plotted against the experimental output (target) in both training and testing phases as presented in Figure (4). The plot illustrates that the fuzzy model's predictions for both training and testing phases are spreaded closely around the diagonal line that represents the one hundred percent accuracy.

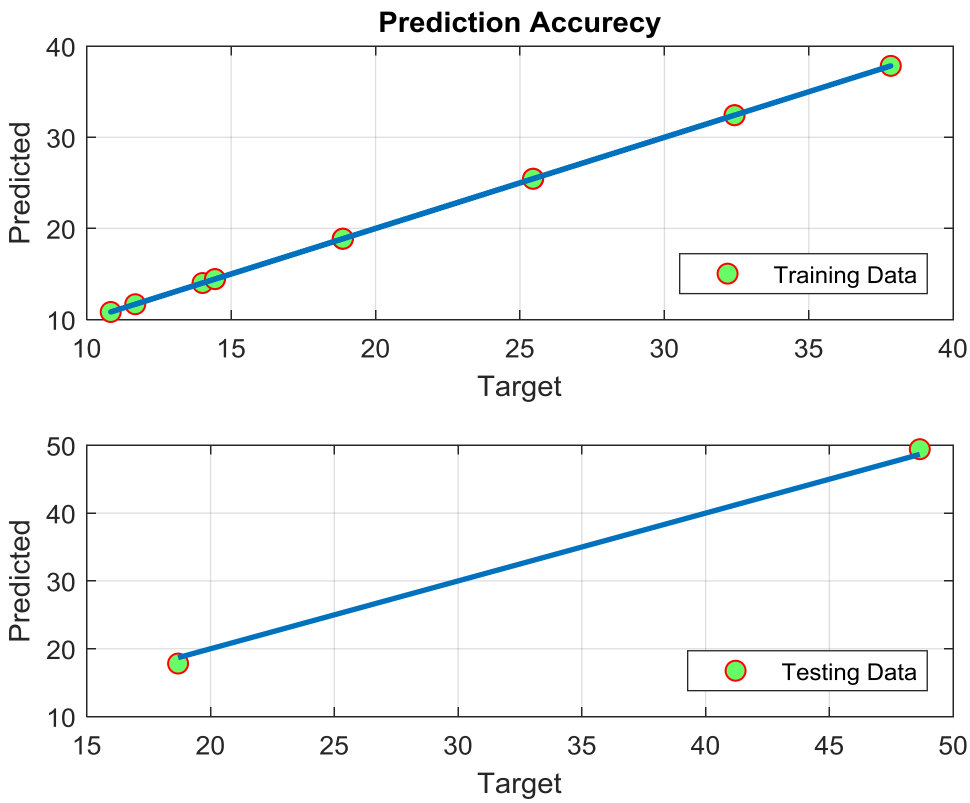


Fig.4 Prediction Accuracy

4. Parameter determination based on Particle Swarm Optimization

Particle Swarm Optimization (PSO) emulates the birds movements. Its main idea is based on the use of some suggested solutions typically named particles [38]. The proposed particles move inside the searching area to hopefully locate the optimal solution. Throughout the searching task, each particle is modifying its orientation and location iteratively according to the best location of itself in addition to the best location found so far of the whole swarm's particles [39]. In each iteration, every particle in the swarm updates its velocity $v(k+1)$ and position $p(k+1)$ based on the previous velocity $v(k)$ and position $p(k)$ using the following relations [40];

$$p\ (k+1)= p(k) + v\ (k+1) \tag{1}$$

$$v\ (k+1)= w*v\ (k)+ c_1 * r_1 * (pBest - p) + c_2 * r_2 * (gBest - p) \tag{2}$$

where, w is the weight of inertia; *pBest* denotes the local best; *gBest* is the global best; c_1 and c_2 represent the local experience weight and the global experience weight, respectively; r_1 and r_2 are two variables changes randomly from 0 to 1.

Three different operating parameters influence on the recovered lipid from Microalgae. These parameters are power (W), heating time (minutes), and extraction time (hours). Accordingly, during the optimization process, these parameters are used as a decision variable for PSO optimizer in order to maximize the recovered lipid that used as a cost function, as illustrated in Figure (5).

Therefore, the cost function will be represented by Eq 3.

$$f(x) = -(R_{Lipeds}) \tag{3}$$

Where, R_{Lipids} is the recovered lipids' percentage, the negative sign here used for the ease change from maximization to minimization.

Table 3 illustrates the parameters of the PSO used in this study and Figure 5 shows the optimization process configuration. The plot of the maximum cost-function found so far all over the 100 runs through optimization process is shown in Figure 6.

Table 3: The PSO parameters

Parameter	**Value**
Maximum Iterations	50
Population Size	10
Local experience	1.5
Global experience	2.0
Weight of Inertia	1

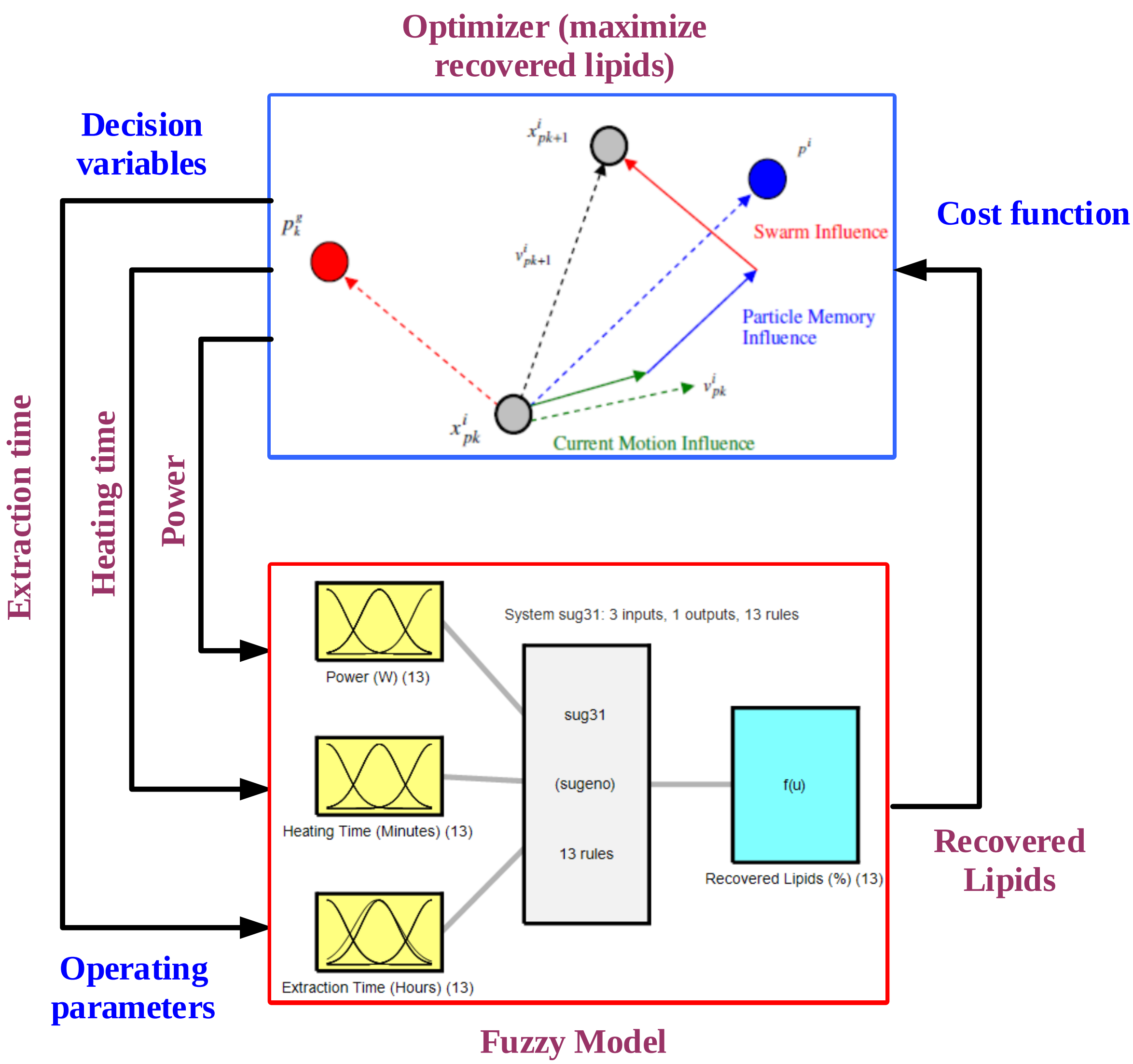


Fig. 5. Schematic diagram showing the optimization of lipid recover process

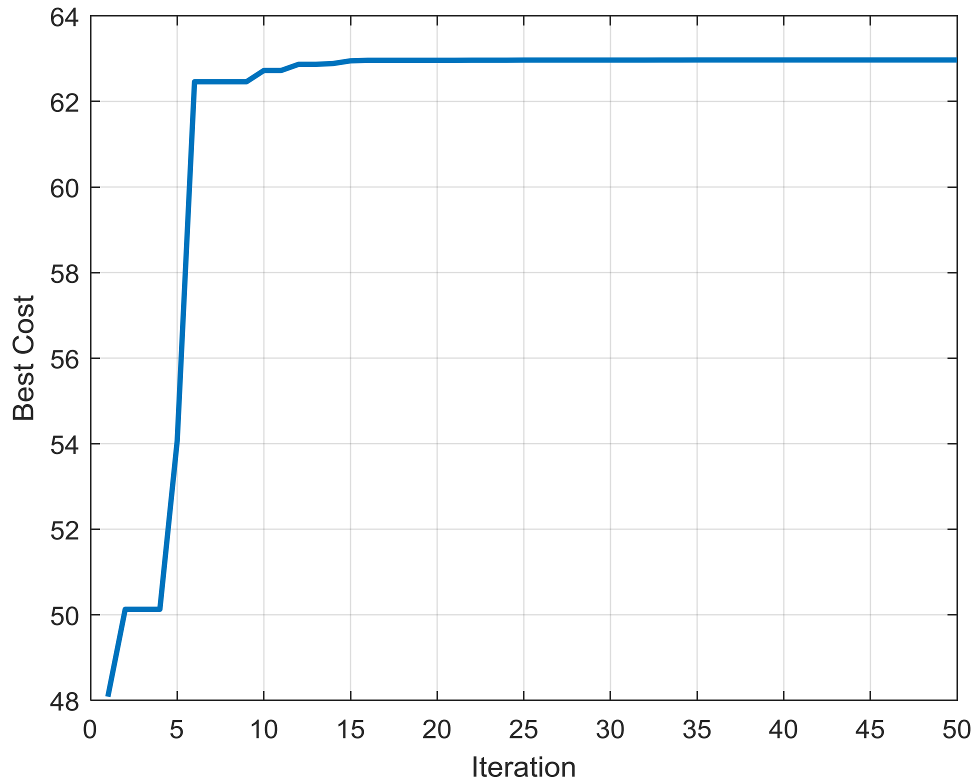


Fig. 6 The plot of the maximum cost-function all over the 100 runs optimization process

Table 4 shows a comparison between the optimal operating conditions and the corresponding outputs obtained in this study compared to those obtained in our previous work [26]. As clear from the table, applying the PSO optimizer based on the fuzzy model resulted in a significant increase in the lipid recovery by 22% over that in [26].

Table 4: Lipid recovery percentages and the optimal parameters obtained in this study compared to those obtained in ANOVA [26]

Method	**Power (W)**	**Heating Time (minutes)**	**Extraction Time (hours)**	**Lipids (%)**
Optimal as in [26]	600	8	3.5	48.65
Optimal using Fuzzy Model-PSO	672.51	10	4.18	62.97

Due to the stochastic behavior of the swarm optimizers, the optimizer results cannot trusted unless many trial have been done. Therefore, the optimization process was executed for 100 times. The values of the statistical metrics of the whole runs are presented in Table 5. The metrics included the minimum (Min) value, the maximum (Max) value, the average (Avg) value, the standard deviation (StD) and the RMSE. By a simple comparison, it can be noticed from Table 5 that the average value of the extracted lipids is found to be very near to the maximum value which reinforces the results obtained from the PSO optimizer and make it more reliable. The optimization results are also strengthened by the very small value of the standard deviation StD which ensures that the outputs of the 100 runs are distributed closely around the average value.

Table 5: The values of statistical metrics of the resulting output and their associated optimal variables of the 100 optimization runs

Statistical Metric	Lipids (%)	Associated Decision Variables		
		Power (W)	**Heating Time (minutes)**	**Extraction Time (hours)**
Min	61.6494	750.0	10.0	3.5195
Max	62.9700	672.5136	10.0	4.1795
Avg	62.9302	674.8366	10.0	4.1598
StD	0.2264	13.2870	0.0	0.1134
RMSE	0.2287	13.4230	0	0.1145

To illustrate the convergence, the movements of the solution particles are recorded during the optimization process. Figures (7a), (7b), and (7c) illustrate the convergence curves for the solutions with the optimizing variables of the power, heating time and extraction time, respectively.

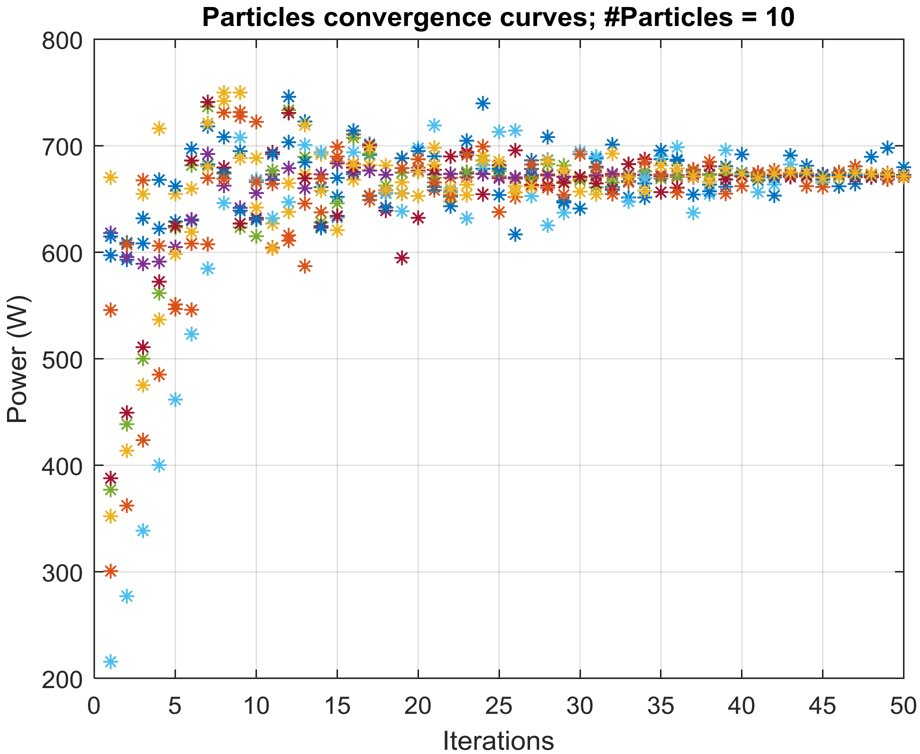


Fig. 7a. Particles' convergence plots for the power.

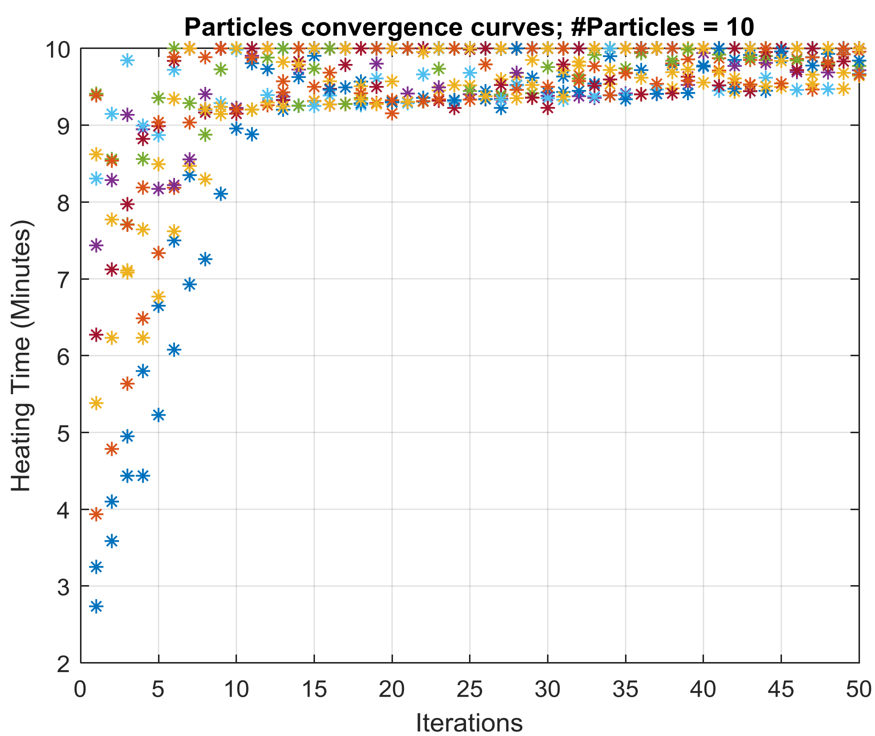


Fig. 7b. Particles' convergence plots for the heating time.

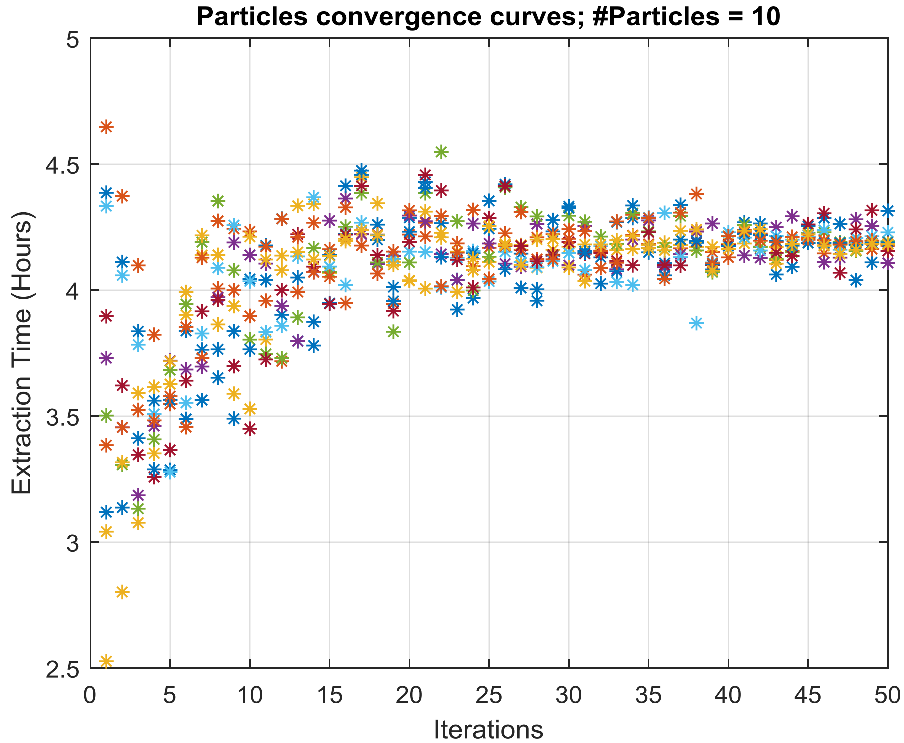


Fig. 7c. Particles' convergence plots for the extraction time.

4. Conclusions

A robust model of the lipid extraction from microalgae following a microwave cell rupture method was carried out using the fuzzy logic based on the experimental data provided in [26]. Furthermore, the optimized operating conditions of the lipid recovery process were determined using Particle Swarm Optimization (PSO) optimizer. The decision variables used in the optimization process were; microwave power, heating times and extraction time aiming to maximize the percentage of lipid recovery. The Fuzzy model built was trained with 13 samples for 50 epochs till an adequate small testing error is met. The model's predictions for both training and testing phases were found spread very near to the diagonal line which represented high accuracy. The RMSE values are 0.0898 and 11.0925 for fuzzy model and ANOVA respectively. Whereas as the values of the coefficient of determination are 0.994 and 0.7854 respectively for fuzzy model and ANOVA. This prove the superiority of the fuzzy model, which gave minimum RMSE and maximum coefficient of determination values. Moreover, The lipid recovery obtained under the optimized operating conditions was compared with those achieved under optimized experimental conditions. The obtained results confirmed that using the proposed

PSO based fuzzy model resulted in a higher lipid percentage. The recovered lipid achieved was 62 %, i.e., a 22% increase over the results reported by using Design of Experiments methodology. The optimum parameters can be used for achieving high lipid extraction rates on both lab and pilot scale.

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