Modeling of Carbon Dioxide Fixation Rate by Micro Algae Using Hybrid Artificial Intelligence and Fuzzy Logic Methods and Optimization by Genetic Algorithm

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Research Article

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Modeling of carbon dioxide fixation rate by micro algae using hybrid Artificial Intelligence and Fuzzy Logic methods and optimization by Genetic Algorithm

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Abstract

In this study we are reporting a prediction model for the estimation of carbon dioxide (CO_2) fixation based on the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Genetic Algorithm (GA) hybrid approach. The experimental parameters such as temperature and pH conditions of the micro-algae-based carbon dioxide uptake process were taken as the input variables and the CO_2 fixation rate was taken as the output variable. The optimization of ANFIS parameters and formation of the model structure were performed by genetic algorithm (GA) algorithm in order to achieve optimum prediction capability and industrial applicability. The best-fitting model was figured out using statistical analysis parameters such as RMSE, R^2 and AARD. According to the analysis, GA-ANFIS model depicted a superior prediction capability over ANFIS optimized model. The Root Mean Square Error (RMSE), coefficient of determination (R^2) and AARD for GA-ANFIS were determined as 0.000431, 0.97865 and 0.044354 in the training phase and 0.00056, 0.98457 and 0.032156 in the testing phase, respectively for the GA-ANFIS Model. As a result, it can be concluded that the proposed GA-ANFIS model is an efficient technique having very high potential to accurately calculate CO_2 fixation rate and the exploration of the industrial scale-up process for commercial activities.

Keywords: Adaptive Neuro-Fuzzy inference system, Genetic algorithm, CO_2 fixation rate and Root Mean Square Error, Industrial scale-up, Carbon capture

1. Introduction

It is evident that the rising in the level of gas emissions caused higher global temperatures which have led to the increase in frequency and the scale of the natural disasters (Xu et al. 2021; Appiah et al. 2021). These disasters and calamities are testing their extremes and have deeply impacted humans, animals and the plants. Human activities can be mostly attributable to the increase in greenhouse gases since the scaled industrial production leading to the industrial revolution (1880) (De Vries 1994). The greenhouse gas emissions which account to about 375 billion tonnes of carbon that have been emitted by humans into the atmosphere as carbon dioxide (CO_2), roughly estimated as 1374 gigatons, and the emission climbed to a recorded 37.1 gigatons in the year 2018 with very alarming future projections (Kahia and Jebli 2021; De Vries 1994). Significant reasons for such scaled emission involve the combustion of traditional fuels such as fossil fuels producing a large amount of CO_2, which is responsible for climate changes and global warming. Statistically, the combined land and ocean temperature have increased at an average of 0.07°C (0.13°F) per decade since 1880. Scientific progresses to reduce the impact of emissions of carbon dioxide are undergoing in the broad fields of biotechnology (Ghosh and Kiran 2017), nanotechnology (Moniz 2010; Aiyer et al. 2016; Kushwaha et al. 2015; Meena et al. 2019) and renewable energy (Panwar et al. 2011). The promising results are obtained from solar cell technology (Brabec et al. 2001; Singh and Kushwaha 2013), fuel cell technology (Barbir 2012; Kushwaha et al. 2013; Kushwaha et al. 2014) and the wind energy (Burton 2011). Accounting to this, Carbon Capture and Storage (CCS) becomes an area of significant global interest and concern for the researchers. CCS is the most common method for CO_2 management (Dods et al. 2021). CCS technology rose as the novel and effective carbon capture technology to achieve environmental benefits with harmful CO_2 emissions to the atmosphere in the limited land area and energy benefits from derived algal biomass (Boot-Handford et al. 2014; Gibbins and Hannah 2008).

The Microalgae growing system might be a potential environmentally friendly technique for efficiently converting inorganic CO_2 into biomass through photosynthesis, which can then be utilized to produce high-density biofuels and high-value medicinal components. Microalgae cultivation system offers several advantages such as high photosynthetic efficiency and growth rate, allowing it to be harvested in a short period of time; low-quality water, can be used for growth thus eliminating the need for extra nutrients; using non-fertile land not suited for agriculture; and

microalgae having high tolerance towards SO_x and NO_x in flue gases thus CO_2 demand might be met by using flue gas (Sayre and Richard 2010; Jonker et al 2013). The **Figure 1** depicts the CO_2 fixation using Micro-algal based process.

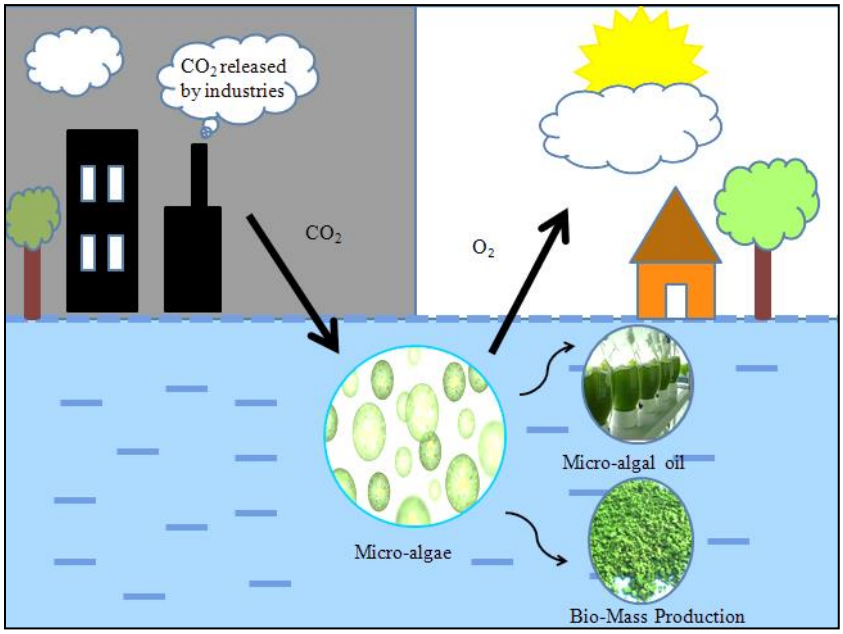


Fig. 1 A representative diagram showing carbon dioxide fixation using Micro-algae-based process

Artificial Neural Networks (ANNs) and Fuzzy Logic (FL) have been immensely used in many upcoming engineering and technological sectors (Jang 1993; Buragohain & Mahanta 2008). ANN which is the branch of Artificial Intelligence (AI), function in a similar way to the human brain using historical data (Jang 1993; Buragohain & Mahanta 2008). **Figure 2** depicts the overview of the application of AI to solve Industrial Problems. They have the potentiality of learning from the datasets using the parallel connected nodes called neurons, which process inputs with respect to their adaptable weights usually in an iterative manner for approximation. (Buragohain & Mahanta 2008)

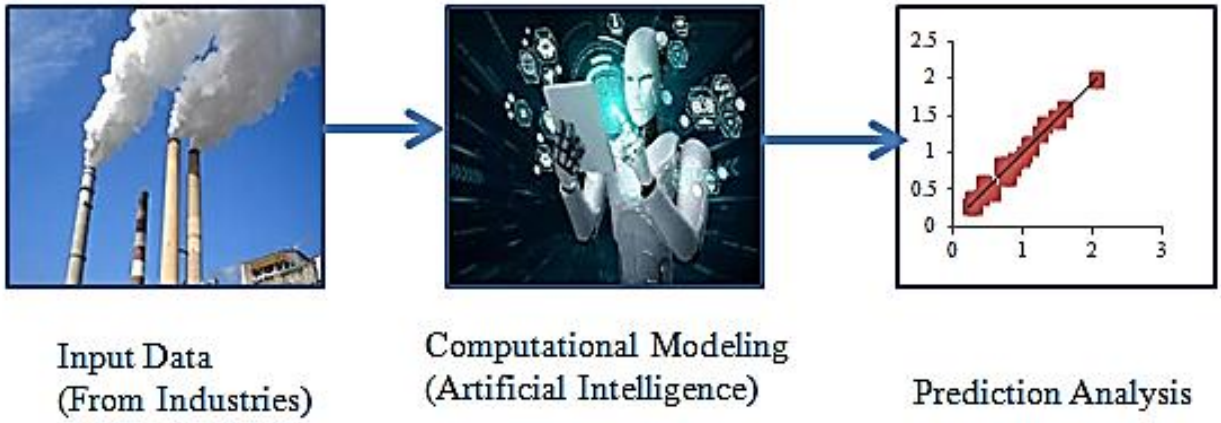


Fig. 2 An overview diagram of application of AI to solve Industrial Problems

Fuzzy logic is employed to manoeuvre the fundamental idea of partial truth, where the truth value may differ between completely true and completely false. Takagi and Sugeno improvised the Fuzzy Logic with a novel rule-based modeling technique (Rezakazemi et al. 2017; Singh et al. 2012). Acquiring the mathematical models was very intricate and sluggish in time consumption due to the complex process of designing the operating point and linearization. Fuzzy Logic permits one to generate a model for a system using human intelligence along with IF- THEN rules. On the other hand, ANN deals only with datasets rather than the linguistic expressions. Thus, the above inadequacy may be improved by combining both ANN and Fuzzy logic (Zhou et al. 2019; Singh et al. 2012).

This paper uses Adaptive Neuro Fuzzy Inference System (ANFIS) that eliminates the basic problems in ANN using the learning ability of fuzzy system design for automatic if-then rule generation and parameter optimization. The combination of ANN and Fuzzy system is called the Neuro fuzzy system (Zhou et al. 2019; Alarifi et al. 2019). ANFIS is one of the best hybrids of neural and fuzzy system, has better smoothness than ANN. Regardless of the fact that ANFIS can handle complicated engineering problems, it has a number of drawbacks, including a sluggish convergence rate, a low learning rate, and the possibility of being caught in a local extreme. An evolutionary algorithm combined with ANFIS was utilized to tackle these problems and improve network reliability by avoiding local minima and achieving global convergence quickly and

correctly. Many optimization algorithms (OA), such as the genetic algorithm (GA), may be used to change the weight and bias of ANNs to improve their performance and lower the total mean squared error (Alarifi et al. 2019).

The concept of natural selection and hereditary behavior based genetic algorithms (GAs) are nowadays predominantly employed for the optimization than the other optimization techniques. The potentiality of the binary digit control system also causes the genetic algorithms distinctive from the rest other methodologies (Vaefi et al. 2015). Ergo there is an extreme necessity to construct such a model that can establish perfect connection between the output and the input factors. The GA integrated hybrid approach such as GA-ANFIS is propounded in this analysis, to scrutinize the impact of process variables on the CO_2 fixation rate (Yang et al. 2020; Sarkheyli et al. 2015). The GA integrated hybrid approach is suitable to develop a better inter-connection between the process parameters and the response values by improvising the performance level of ANFIS model. In this work, the GA- ANFIS is used to optimize the micro-algae-based carbon capture process by varying the cultivating conditions (pH and temperature) to obtain the best-desired product and the most beneficial outcome (CO_2 fixation rate) (Vaefi et al. 2015; Yang et al. 2020).

2. Materials and Methods

2.1 Dataset

The principal focus of this study is to forecast Micro-algae selectivity based on the analysis results which can be acquired effortlessly, instantly and without needing exorbitant and sophisticated equipment. Thus, in this study, the components of analysis, temperature and pH are used as input parameters to obtain CO_2 fixation rate as an output. To ensure that the proposed model has a wide range of validity, a data set containing CO_2 with different characteristics was created by reviewing the literature (Jacob-Lopes et al. 2009; Murakami and Ikenouchi 1997; Yun et al. 1997; Scragg et al. 2002; Stephenson et al. 2010; Sakai et al. 1995; Chiu et al. 2011; Zhao et al. 2019; Huntley and Redalje 2007; de Morais and Costa 2007b; Gomez-Villa et al. 2005). Repeated samples were extracted from this data set and a simplified data set containing 27 samples was obtained. The

temperature of samples was ranged from approximately 19 °C to 40 °C by weight. Similarly, the pH was found between 5.5 to 9.4. The output CO_2 fixation rate was 0.280 to 2.04. In the present study only 27 datasets have been used so as to study the behavior of ANFIS and GA-ANFIS models on training, and testing a smaller number of datasets.

2.2 ANFIS (Adaptive Network based Fuzzy Inference System)

Adaptive neuro-fuzzy inference system is the combination of quick-witted techniques of neural network and fuzzy inference system. ANFIS is a unique methodology which is employed especially in the modelling of the non-linear functions. The modeling was performed to develop a relation between the independent and dependent variables. The advantage of using these soft computing methods is to develop a black box model without the need of mathematical models (Najafi et al. 2018a; Khashei-Siuki et al. 2015). The fuzzy system alone was unable to acquire the precise outcome because it couldn't alter the membership functions automatically. The amalgamation of both (ANN and Fuzzy) was capable of generating the precise value at any circumstances. ANFIS is used to formulate a heuristic pattern between the input-output based on the initial given fuzzy system and available input-output data pairs by employing learning methodologies (Yang et al. 2020; Najafi et al. 2018a). The most pre-dominantly employed fuzzy inference system (FIS) which are used in diverse applications are the Mamdani inference system and Sugeno inference system (Najafi et al. 2018a). Further, in the present study MATLAB R2020a software package was used to develop the models, and the modelling was performed in two stages: Training and Testing. In this work, 70 % of the dataset is employed to train models and the remains, 30 % is used for testing the models. The training stage is a vital step in the formation of networks. After developing the target network, the selected testing data is then applied to the network in order to obtain the results of the testing stage (Najafi et al. 2018a; Yilmaz et al. 2011). It is very important to go for the pertinent sample for training and testing towards the decrease of prediction error. **Figure 3** represents the basic ANFIS model structure using MATLAB R2020a.

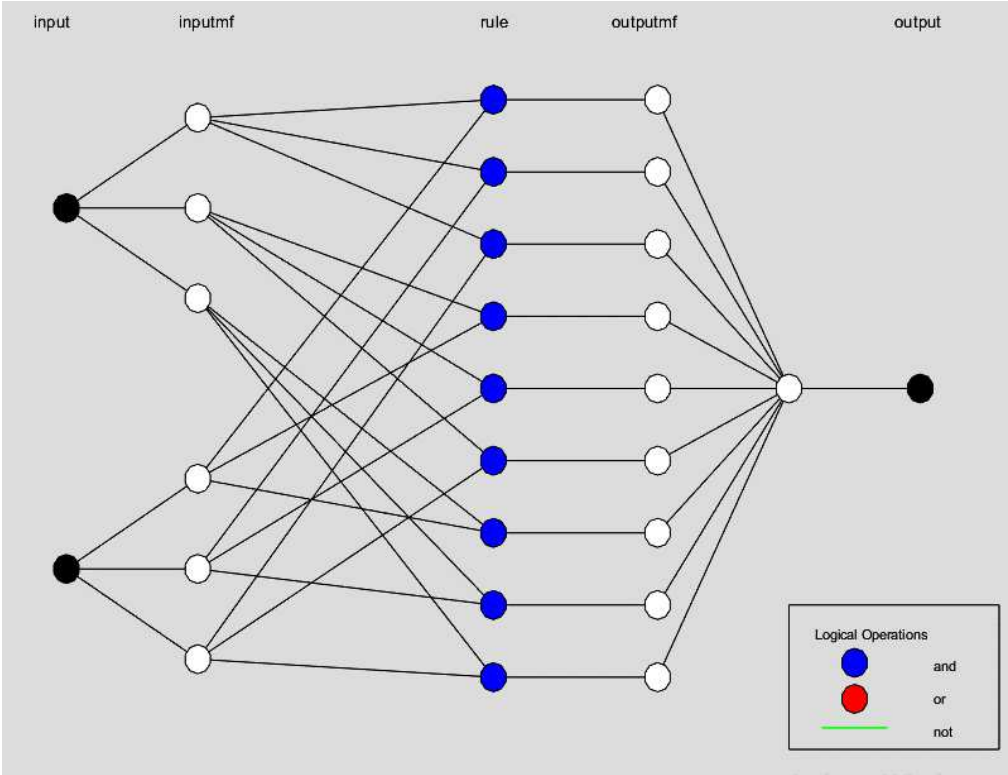


Fig. 3 A representative outlay of the basic ANFIS Architecture

2.3 Modeling using ANFIS

The two most commonly employed fuzzy inference systems (FI) which are used for various application are Mamdani inference system and Sugeno inference system (Rezaeianzadeh et al. 2014). In the present work ANFIS is constructed using Sugeno fuzzy model (Najafi et al. 2018b). The representation of rules for Sugeno fuzzy inference system is given below in the **Figure 4**.

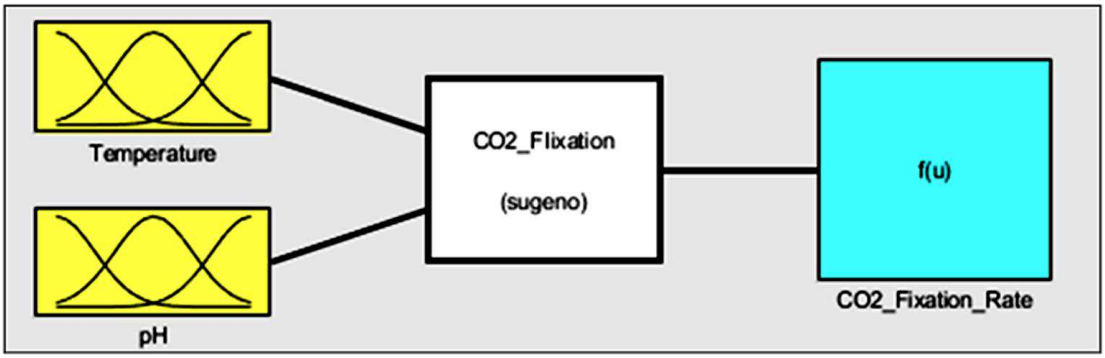


Fig. 4 A representative overview of the Sugeno fuzzy model.

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$ (1)

Rule 2**:** If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$ (2)

Where, x and y are the two inputs. A and B are the membership function. p, q, and r linear parameter. 1,2, represent the number of rules.

The architecture of ANFIS comprises of five different layers. Each layer of the network accommodates several nodes described by the node function (Yaseen et al. 2017). The overview and further details of the multilayered ANFIS architecture can be observed in **Figure 5**.

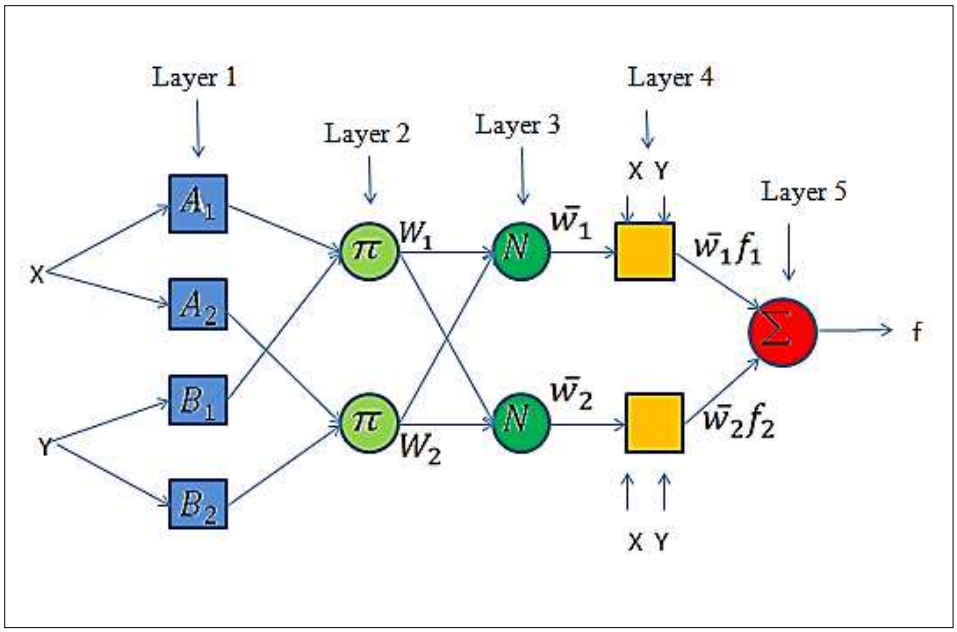
Layer 1

This layer also known as fuzzification layer. In this layer the nodes are squares with a Membership function associated with each one of them.

$$O_i^1 = \mu_{Ai}(x) \quad (3)$$

Where, x serves as an input to the particular node, A_i being the linguistic label, O_i^1 is the output of the first layer and $\mu_{A_i(x)}$ is the membership function. The membership used in this study is Triangular membership function (trimf) The further details regarding triangular membership function for the input variables are given in **Figure 6.**

$$f(x;a,b,c) = \left\{ \begin{array}{ll} 0, & x \leq a \\ \dfrac{x-a}{b-a}, & a \leq x \leq b \\ \dfrac{c-x}{c-b}, & b \leq x \leq c \\ 0, & c \leq x \end{array} \right\}$$



181

182 **Fig. 5** A representative overview of the ANFIS Architecture.

183

184 **Layer 2**

185 Nodes of this layer execute the function of multiplying the inputs and passing out the product.
186 The output of various nodes depicts the strong firing of the rule.

187 $$w_{i=}\mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1,2 \tag{5}$$

188 **Layer 3**

189 Nodes of this layer execute the purpose of calculating the ratio of the ith rule's firing strength to
190 the sum of all rule's firing strength:

191 $$W_i = \frac{w_i}{w_1+w_2}, \quad i = 1,2 \tag{6}$$

192 **Layer 4**

193 Nodes of this layer are adaptive in nature and execute the overall output:

194 $$O_i^4 = W_i f_i = W_i(p_i x + q_i y + r_i) \tag{7}$$

Layer 5

This single node is a circular node with the symbol Σ (sigma) that is employed to calculate the overall summation of all the incoming signals.

$$O_1^5 = \text{overall output} = \sum_i w_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

ANFIS employs the hybrid-learning algorithm, which comprises of the amalgamation of "gradient descent" and "least squares" methods to upgrade the model parameters (Yaseen et al. 2017; Kaveh et al. 2018)

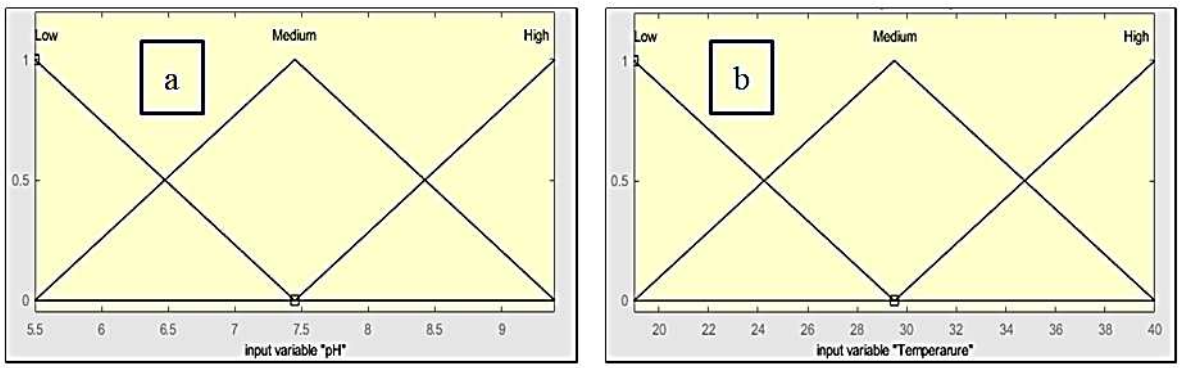


Fig. 6 Triangular membership function for the input variables **(a)** pH and **(b)** Temperature.

2.4. Genetic Algorithm (GA)

Genetic Algorithm (GA) is an evolutionary heuristic search algorithm which reckon on natural selection and genetic science based on Charles Darwin's theory of Natural evolution. This furnishes an arbitrary search that is employed to decipher optimization problems (Shahlaei et al. 2012, Maulik et al. 2000). In nature, rivalry between individuals for insufficient resources always leads to the emergence of the strongest individuals who dominate the weakest. The GA generally initializes by generating an initial population with an assemblage of possible solutions. Each population has a chromosome with the same length as the total number of process variables (Houck

et al. 1995; Maulik et al. 2000). The objective function fitness value is considered when assessing these chromosomes. Selection, Crossover, and Mutation processes are predominantly employed to create new chromosomes termed off-spring. The chromosome with the elevated fitness value has the best prospect of being chosen (Mathew 2012). In the present study the computation is accomplished when the fitness function and the chromosomes achieve the point of convergence, at which the optimum process parameter value for maximum CO_2 fixation rate is attained (Shahlaei et al. 2012; Kaveh et al. 2018).

2.5 GA-ANFIS hybrid approach

GA-ANFIS is a hybrid approach for handling non-linear datasets where adaptive neuro-fuzzy inference (ANFIS) executes the process of training the dataset and eventually performs optimization using GA. ANFIS is a hybrid approach that uses the advantages of both neural networks' best learning skills and fuzzy systems' inference capabilities to accomplish a desired execution (Houck et al. 1995; Moayedi et al. 2019). The main objective of the fuzzy controller is to accomplish proper execution in the presence of fluctuations (Vafaei et al. 2015). The ANFIS methodology is employed to delineate the MFs and regulate the fuzzy inference system (FIS) file using back propagation algorithm. The lesser the epoch error, the more exact the training model is executed. The FIS data created by the model after learning is then used with GA to obtain optimized results (Yadav et al. 2019; Karimi et al. 2012).

To improve the ANFIS results, GA is used in this study. To put it in other way, GA is used to find the optimum ANFIS parameters as shown in ANFIS-GA flow chart in **Figure 7** (Yadav et al. 2019). Here we can say that this evolutionary hybrid method has perfectly accounted for its significance in the outcomes to improve the CO_2 fixation rate so as to further the result optimization of the process of CO_2 capture (Vafaei et al. 2015, Moayedi et al. 2019; Yadav et al. 2019). The potentiality of this hybrid method to tune the member functions (MFs) of fuzzy inference systems and managing intricate decision-making or diagnosis systems through hybrid earning rules made this method to be triumphant.

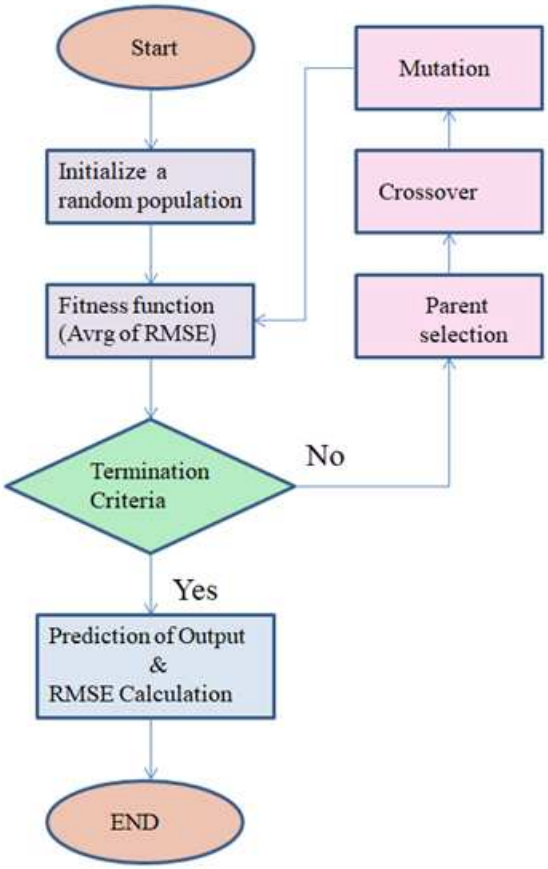


Fig. 7 ANFIS-GA Flow Chart

2.6 Evaluation of Model Performances

The performances of models were evaluated according to the statistical tools such as root mean square error (RMSE), and coefficient of regression (R^2), Average absolute relative deviation (AARD) (Wei et al. 2013). The related equations for calculation of, RMSE, AARD, R^2 are given in Eqs. 9,10 and 11 as follows:

$$RMSE = \sqrt{\left(\frac{1}{N}\right)\sum_{i=1}^{N}(X_i^{exp} - X_i^{predicted})^2} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i^{exp} - X_i^{predicted})^2}{\sum_{i=1}^{N}(X_i^{exp} - X^{exp})^2} \quad (10)$$

$$AARD = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{X_i^{exp} - X_i^{predicted}}{X_i^{exp}}\right| \quad (11)$$

The R^2 accepts values between 0 and 1, with values close to 1 depicting a better fit, helps assess the model's performance in modeling the data set. The RMSE is used to calculate the square root of variance of the prediction model's data and the actual data Which can be used to check the accuracy of the developed models (Wei et al. 2013; Fazlic et al. 2015). The deviation between the predicted and the experimental value was evaluated using absolute average relative deviation (AARD). The model resulting in the least value of the AARD will be the best model that can be used for forecasting the CO_2 fixation (Kaveh et al. 2018; Fazlic et al. 2015).

3. Results and Discussion

3.1 ANFIS Modeling

As the principal focus of this analysis is to forecast the Micro-algae selectivity for Carbon (CO_2) Capture under the operating conditions, the CO_2 fixation rate was taken as the output parameter, while the temperature and pH conditions were taken as the input parameters. It is mandatory to fix the number and type of MFs, as well as the number of iterations, in order to employ the ANFIS model (Lei et al. 2007; Wei et al. 2013). The input and output data ranges are critical and should not be omitted while determining various operating range parameters (Lei et al 2007; Rubio et al. 2019).

The ANFIS model may be effectively trained without degrading the results by normalizing or scaling (Najafi et al. 2018b). The boundary is [0 1], and variables are scaled in this boundary via mapping. MineMax equation (12) is generally employed to normalize the outputs and inputs:

$$X_n = \frac{X' - X_{min}}{X_{max} - X_{min}} \quad (12)$$

Where X_{max}, X_{min} and X_n are maximum, minimum and normalized data for every parameter.

The data for model development was obtained from the experimental results available in the literature. Determining the input parameters for learning is necessary for ANFIS, and it is among the substantial challenges in the nonlinear systems modeling. The total 27 datasets are shown in **Table S1** (see the supporting information) split into training (20) and testing (7) to avoid over-fitting. The Training data comparison with the ANFIS outputs is shown in **Figure 8**.

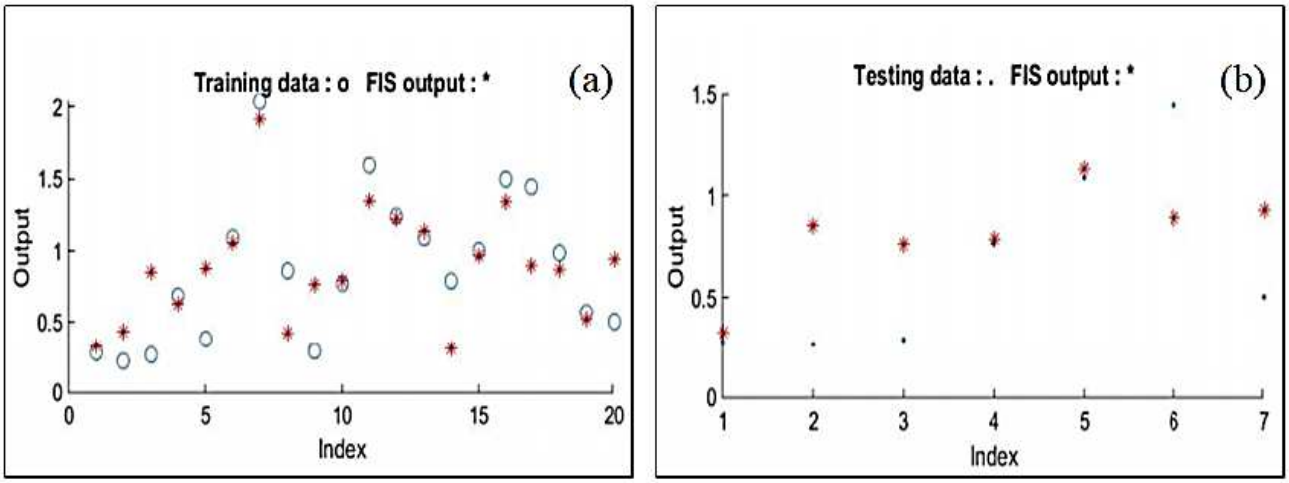


Fig. 8 (a) Training and **(b)** Testing Data Comparison-ANFIS

The training error (the difference between the training data and output value) calculated using root mean squared error (RMSE) at each epoch and found as 0.012962 as shown in **Figure 8a**. The testing data is used to check the generalization potentiality of the fuzzy inference system at each epoch and to validate the fuzzy inference model (Kurian et al. 2006). The testing error was found RMSE as 0.024753 as shown in the **Figure 8b**. The result obtained from the ANFIS models suggests that the best model is considered as the one which has got the lowest testing data error. At the initial part, a hybrid learning employed for predicting the parameters. The model training was set at 1000 epochs and the computational duration was less than 1 minute (Kurian et al. 2006; Ghiazi et al. 2016).

The ANFIS methodology was employed to forecast the CO_2 fixation rate and to find out the relation between the input variables and output variables. **Table 1** represents the ANFIS parameters. The most vital advantage of a Sugeno Fuzzy Inference System is that they capitulate

297 a more accurate relationship between a larger number of outputs and inputs. Therefore, the MFs
298 are determined via trial-and-error method.

299

300 **Table 1** Details of the ANFIS for predicting the CO_2 fixation rate

Type	Description/Value
Fuzzy Structure	Sugeno-type
MF type	Triangular (trimf)
Output MF	Constant
Number of fuzzy Rules	9
Number of Inputs	2
Number of Outputs	1
Training Maximum epoch number	1000
Computational Time	Less than one min

301

302 The structure of ANFIS model-developed in this study was based on Triangular membership
303 function for the input and Constant membership function for the Output (Husein et al. 2019). The
304 parameters of the triangular membership function for the input variables and their ranges are shown
305 in **Table S2** and **Table S3** (see the supporting information). The parameters of the constant
306 membership function and their ranges for the output variable (CO_2 fixation rate) is shown in **Table**
307 **S4** (see the supporting information). The Number of fuzzy rules was 9 which are shown in **Table**
308 **2.** The values of the output membership functions for the rules are given in **Table S4** (see the
309 supporting information). It is very clear that the maximum CO_2 fixation can be obtained for the
310 following rules (Alarifi et al. 2019; Dasari et al. 2019)**.**

- If (Temperature is Low) and (pH is High) then (CO_2_fixation_rate is 2.28708)
- If (Temperature is High) and (pH is Medium) then (CO_2_fixation_rate is 2.86869)

Table 2 Fuzzy Rule base of the optimum ANFIS structure for predicting the CO_2 fixation rate

S.No	Rules
1	If (Temperature is Low) and (pH is Low) then (CO_2_fixation_rate is out1mf1)
2	If (Temperature is Low) and (pH is Medium) then (CO_2_fixation_rate is out1mf2)
3	If (Temperature is Low) and (pH is High) then (CO2_fixation_rate is out1mf3)
4	If (Temperature is Medium) and (pH is Low) then (CO2_fixation_rate is out1mf4)
5	If (Temperature is Medium) and (pH is Medium) then (CO2_fixation_rate is out1mf5)
6	If (Temperature is Medium) and (pH is High) then (CO2_fixation_rate is out1mf6)
7	If (Temperature is High) and (pH is Low) then (CO2_fixation_rate is out1mf7)
8	If (Temperature is High) and (pH is Medium) then (CO2_fixation_rate is out1mf8)
9	If (Temperature is High) and (pH is High) then (CO2_fixation_rate is out1mf9)

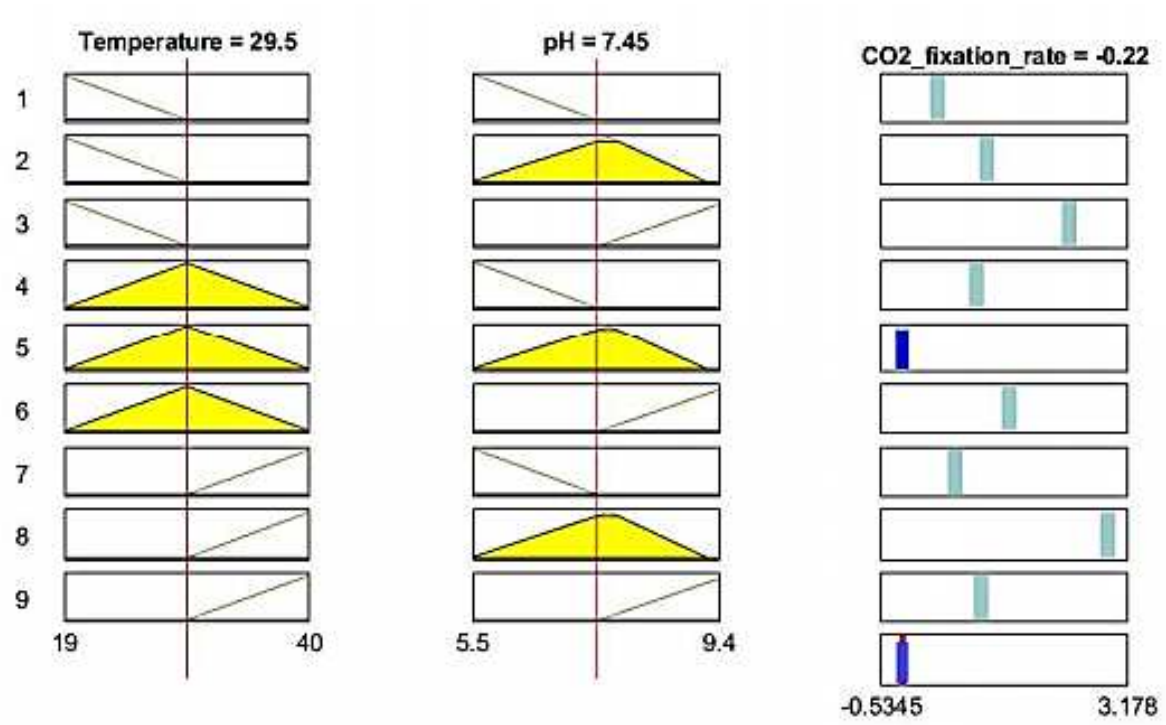
3.2 Interpolation by ANFIS model

One of the benefits of ANFIS is that it has the capability to forecast a certain parameter for different inputs within the training data range. Hence, in this research, the data from various resources were taken into account as ANFIS model's inputs to forecast the selectivity as shown in **Figure 9** (Lei et al. 2021; Jiang et al. 2021)**.**

Additionally, the **Figure 10** illustrates the CO_2 fixation rate versus temperature and pH. As observed, the temperature and pH have a significant effect on the CO_2 fixation rates. While increasing the temperature and pH, there is observed an increase in the CO_2 fixation rate which further decreases above 35 °C. This may be attributed to the fact that the CO_2 tolerance of green

325 algae decreases at elevated temperatures. It is very clear from the results that low or medium
326 temperature conditions and high pH conditions are highly suitable for maximum CO_2 fixation
327 rates. The above results can be used by the industries for scaling up the Carbon-capture process
328 using Micro-algal species (Eseye et al. 2017; Xu et al. 2011).

329



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331 **Fig. 9** Rules used in ANFIS for the input parameters temperature and pH, and the output
332 parameter CO_2 fixation rate.

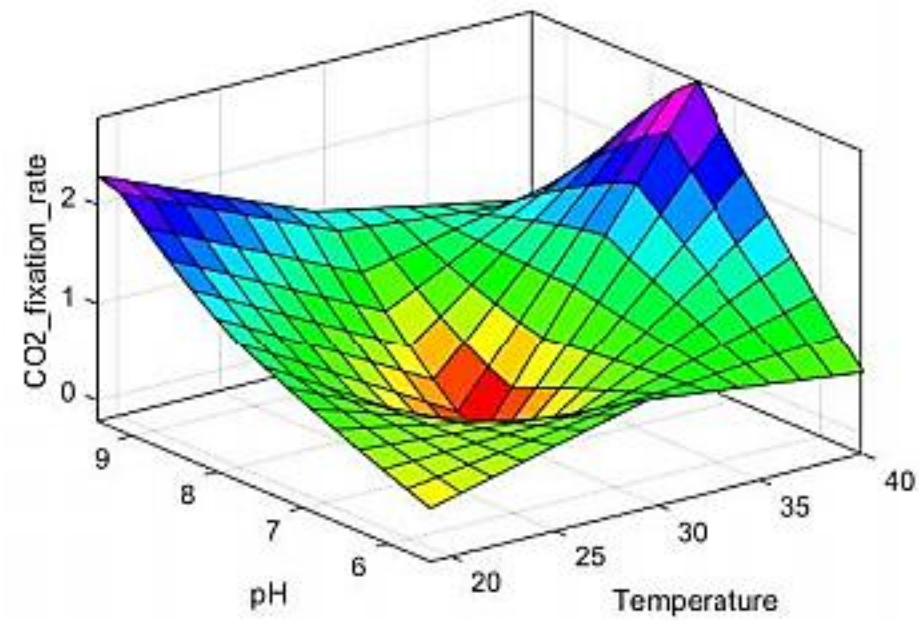

Fig. 10 Surface plot of the CO_2 fixation rate with respect to pH and temperature

3.3 Configuring GA-ANFIS model for CO_2 Fixation rate optimization

In this study, using the programming language of MATLAB R2020a, GA-ANFIS hybrid approach was propounded for CO_2 fixation rate prediction. As the first step, the parameters (Temperature and pH) were set as input factors, and CO_2 fixation rate was set as output factor for the ANFIS Models. The results from ANFIS shows that Training and Testing datasets have an R^2 value of 0.92345 and 0.91724 respectively as shown in **Table 3.**

In order to increase the prediction potentiality of the ANFIS model, hybrid models were formed by using GA algorithm to optimize the ANFIS parameters. In GA-ANFIS, GA and ANFIS are integrated to enlarge its prediction efficiency. GA-ANFIS method was also configured by coding in MATLAB 2020a to forecast the CO_2 fixation rate of various micro-algal species. The average of the Root mean square error (RMSE) of the training and testing datasets was considered as the fitness function for the Genetic Algorithm (Shahlaei et al. 2012). GA is accomplished to ameliorate ANFIS performance and lessen the error percentage by tuning and optimizing the membership functions of a Sugeno type fuzzy inference system (Yadav et al. 2019; Karimi et al. 2012)**.**

350 **Table 3** Stastical indexes for the prediction model of CO_2 fixation rate (ANFIS/GA-ANFIS)

	ANFIS		GA-ANFIS	
	Training dataset	Testing dataset	Training dataset	Testing dataset
RMSE	0.012962	0.024753	0.000431	0.00056
R^2	0..92345	0.91724	0.97865	0.98457
AARD	0.083262	0.064512	0.044354	0.032156

351

352 Global Optimization tool box in MATLAB R2020a were used for generating the evolution of the
353 best and average fitness over 150 generations using 'ga' function. The pertinent GA parameters
354 used in the optimization system are given in **Table 4.** The number of individuals in each iteration
355 or population is 100 and maximum number of generations is 150 (based on trial-and-error method)
356 (Shahlaei et al. 2012). In the present study, the Population Size is set to 100. By enlarging the
357 population size, the genetic algorithm is able to discover more points and produce a better outcome.
358 (Momeni et al. 2014; Armaghani et al. 2019).

359

360 **Table 4** GA Parameters

Parameter	**Value**
Maximum Iterations Number	300
Population size	100
No of generations	150
Parent selection	Stochastic uniform
Elite count	3
Crossover fraction	0.9
Mutation function	Adaptive feasible

361

362

Crossover Fraction is defined as the fraction of individuals in the upcoming generation, excluding the elite children, that are generated by crossover (rest of them are generated by mutation). A crossover fraction of '1' delineates that all children except the elite individuals are crossover children. (Saraswat et al. 2013). A crossover fraction of '0' delineates that all children are mutation children. (Shahlaei et al. 2012). A crossover rate of 90 % is used and the crossover operator is executed using scattered crossover function. Scattered crossover function generates an arbitrary binary vector that amalgamates the genes to produce new chromosome (Karimi et al. 2012). An adaptive mutation function has been employed that arbitrarily generates directions that are adaptive with respect to the last triumphant or unsuccessful generation. The mutation determines the direction and step length that assuage bounds and linear constraints (Shahlaei et al. 2012; Kaveh et al. 2018). In the present study the elite count is 3 which signifies the number of individuals with the best fitness values in the present generation that are guaranteed to survive to the next generation. These individuals are better known as the elite children (Badhwar et al. 2020; Kumar et al. 2019).

The performance of a GA is affected by the diversity of the initial population as shown in **Figure 11a** and **Figure 11b**. If the average distance between the individuals is large, it is indication of high diversity, if the average distance is small its represent low diversity in the population. If the diversity is too high or too low, the genetic algorithm might not perform well (Momeni et al. 2014; Armaghani et al. 2019). The best fitness plot for the GA maps the convergence of the best fitness values of successive generations towards the final optimum value as shown in **Figure 11c**. In the present study, the population size is set to 100 (Badhwar et al. 2020; Kumar et al. 2019). Increasing the population size permits the genetic algorithm to explore more points and as a way to obtain a better result (Momeni et al. 2014; Armaghani et al. 2019). Some of the eminent selection methods used includes uniform, roulette wheel and tournament. The selection method used in the present study is stochastic uniform an individual can be chosen as a parent several times; in which case it gives its genes to multiple children.

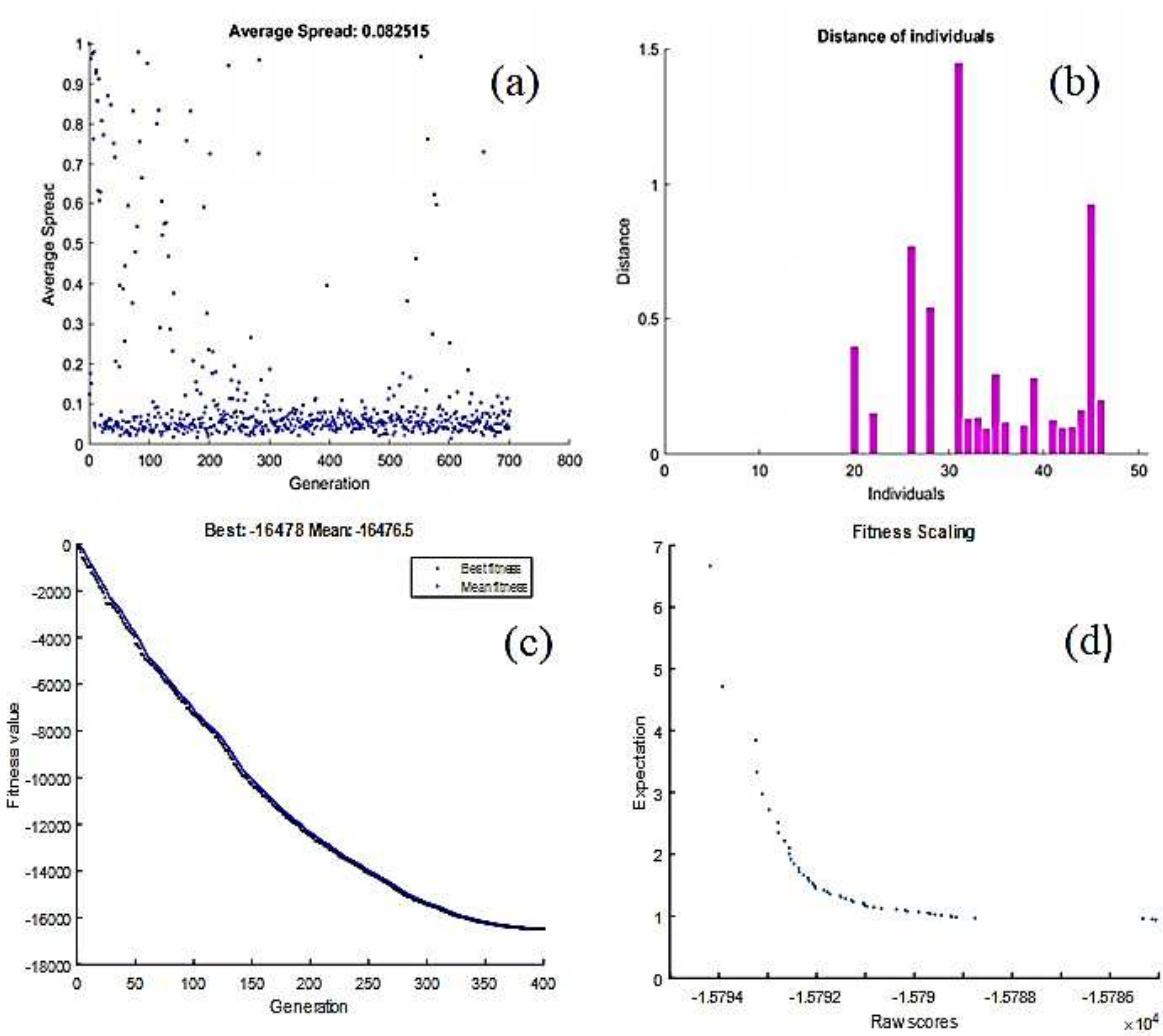

Fig. 11 (a) Average spread of the Individuals with respect to the Generations using Genetic Algorithm **(b)** verage distance between the Individuals using Genetic Algorithm **(c)** Representative plots generated from the optimization by GA using MATLAB R2020a: Best and average fitness values with successive generations showed good convergence to the optimum value **(d)** Fitness scaling of the raw scores

Eventually, another parameter that influences the diversity of the population is the fitness scaling as shown in **Figure 11d.** Before the GA's selection phase, the fitness scaling modulates the fitness values (scaled values). This is accomplished without altering the ranking order, thus the fittest individual based on raw fitness value is still the best in the scaled rank. The only thing that changes

are the values, and hence the likelihood of an individual being chosen for mating via the selection method (Saraswat et al. 2013). If the fitness values differ too extensively, the individuals with the least values replicate instantly, taking over the population gene pool too swiftly and preventing the GA from searching other areas of the solution space (Badhwar et al. 2020; Armaghani et al. 2019). Contrarily, if the values differ only a bit, all individuals have almost the same possibility of reproduction and this process will advance very deliberately. Table 3 indicates the R^2, RMSE and AARD values for the given ANFIS and GA-ANFIS models. The results clearly show that GA-ANFIS have better performance compared to ANFIS models as shown in **Table 3** and **Figure S1** and **Figure S2** (see the supporting information) (Kumar et al. 2019; Badhwar et al. 2020).

4. Conclusions

The higher CO_2 fixation rate of micro-algae is of great significance in determining the potential of biomass and its possible application areas for industrial purpose. In this study, the effect of two input-parameters on CO_2 fixation rate have been investigated with artificial intelligence tools such as, ANFIS, GA-ANFIS models. The prime findings have been summarized as-

A dataset consisting of 27 data pairs (CO_2 fixation rate) collected from various sources were employed to examine the authenticity of the ANFIS and GA-ANFIS models and to study their behavior for training a small number of datasets. Firstly, ANFIS models were developed for predicting the CO_2 fixation rate for the given micro-algae with Temperature and pH as the input parameters. The Gaussian membership function was used for the input and constant membership function was used for the output respectively. The hybrid GA-ANFIS models improved the prediction efficiency of the ANFIS model to avoid local minima and achieve global convergence rapidly with a great precision. The statistical parameters demonstrated that the GA-ANFIS model has the best predicting performance compared to ANFIS and have better prediction results for small datasets. The developed models in the present study may be of great importance to the researchers in order to increase the CO_2 fixation rate for industrial scale-up.

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Authorship contribution statement HP: data collection and validation, method validation, writing draft. KK: formal analysis, review OSK: conceptualization, methodology, project management, visualization, , investigation, supervision, writing.

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Data availability The data generated or analyzed during this study is included in this published article and its supplementary information files.

Compliance with ethical standards

Ethics approval and consent to participate Not applicable for this section.

Consent for publication Not applicable for this section.

Conflict of interest The authors declare that they have no competing interests.

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