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Application of Artificial Neural Network in Modeling separation of microalgae

Raziye Seyfi

Department of Biotechnology-Chemical Engineering, College of Science , Kermanshah Branch, Islamic Azad University, Kermanshah, Iran and Tehran Science and Research Branch, Islamic Azad University, Kermanshah, Iran.

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ABSTRACT

The economization and commercialization of the biofuels production from microalgae require solving some problems facing it. One of the most important and expensive stages is the separation of microalgae from the medium culture. The modeling of Separation biological processes can be used as a safe tool to save the economy and avoid repeated testing. Among the methods of modeling, artificial neural network is accurate and widely used in biotechnological processes. Results of the study showed that correlation coefficient reached 1 indicating that there is a good match between actual values and those predicted by modeling. From a total of ۱۸ data, two-thirds of data was used to train a network and the remaining third was used to assess the modeling accuracy. The middle transition function purelin , output transfer function tansig and the number of neurons (five) were determined as the best parameters to train the network. The error rate of network training was estimated to be 0.0511 and error evaluation of the network accuracy was found to be 0.992.

Keyword:
iofuel, separation, microalgae, *modeling, artificial neural networks, regression*

*** Corresponding author: Saifi4508@yahoo.com**

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1. INTRODUCTION

Energy security, renewability, and climate change have led to the world seek alternative energy sources. Replacing the fuels and petroleum products with renewable resources is needed to minimize environmental problems. [1] Biomass source has many advantages compared to other renewable sources due to the variety of the biomass source, different processes,and productive and application products. [2.3] Biofuel production is one of the most important methods for utilizing biomass resources. Biofuels are divided into three different groups based on the type of the resource. The first group such as corn and barley due to overlap with the food consumption and the second group such as lignocellulose due to the damage to the forest resources and its time-consuming replacement have been replaced the third group i.e. microalgae. Algae have the proper growth rate and high-fat production; they require less water to grow and their fuel amount is greater than the initial groups. [4-7]

The economization of the biofuel production from microalgae requires solving some of the current problems that separation of microalgae from the medium culture is one of the most important and expensive stages. [8] In this research, first, biomass separation methods from the culture medium were investigated and then their modeling was carried out. Retention time, pH, and electrical current density were investigated and removal rate, consumed electrical energy, and strategic cost were evaluated. [9] A cultivated alga requires appropriate methods for harvesting which include gravity deposition, centrifugation, filtration, micro-screening, ultrafiltration, and flotation. [10-12]

Thus, in order to resolve the problem effectively, the study and modeling of biological systems require methods that are very close to human's thinking. Artificial neural network is one the methods used in this context. Artificial neural networks can model complex systems with nonlinear characteristics that have become the most popular tool for modeling biological processes.

A limited number of studies have been conducted on the application of modeling genetic algorithm- neural network to model and control micro-biological processes. However, some studies have been reported by Fernandez et al. (2007) who used artificial neural networks to examine microbial growth and introduced the method as a convenient one for microbial prediction [13] . Garcia et al. (2009) modelledleuconostocmesenteroides growth using artificial neural network. Predictive models of the growth of the artificial neural network have been introduced as one of the proper tools to estimate growth parameters of leuconostocmesenteroides .. Sofo and Eckenjie (2007) studied estimation of the shelf life of yogurt with artificial intelligence model . Another example of application of artificial neural network in biotechnology concerns with the presentation of a computerized model to predict the shelf life of lactobacillus acidophilus in probiotic yogurt [14-16]

This paper modelled Separation of biological processes using artificial neural network and compared experimental results with data obtained from the modeling.

2. Theory

In neural network modeling that is derived from the human brain performance, knowledge or rules behind data is transferred to the network structure by processing experimental data. In other words, general laws are trained to the network by performing calculations on numerical data. The resulting network will be able to model and predict very complex processes with respect to the training provided with it. For instance, this method is used to detect hand-written notes and convert voice (speech) into handwriting (text). [17]

The human brain contains a large number of (about 1011) interconnected components (104)connections per component) that is called neurons. The neurons include three main components: Dendrites, Cell body, and Axon.

Dendrites are tree-like receptor networks, including nerve fibers that transmit electrical signals into Cell body. Cell body gathers these input signals effectively and places them on thethreshold. Axon is a long sequence that transmits signal from Cell body to other neuron. Point of contact between Axon, a Cell body and another Dendrite is called Synapse. Efficiency of neural network is determined by arranging neurons and strength of Synapses, which are determined by a complex chemical process.

Each artificial neuron consists of one or more inputs, weight (for multi-input neuron, multiple-weight), bias or offset, collector, activation or transfer function) and one output. Scalar input p is multiplied by scalar weight w to form wp that is one of the terms that will be sent to the collector. Another input, 1, is multiplied by bias, b and sent to the collector. Collector output n that is usually called input net is sent to transfer function f that produces neuron scalar output a. If we compare this model with biological neuron, the weight w will relate to the strength of Synapse, Cell body will be expressed by collector and transfer function and neuron output will express the signal on the Axon.

An artificial neural network consists of several layers of neurons. Input data enters input layer. Outputs of the layer form the input of the next layer, and output of the last layer is the network output. Each layer is comprised of a number of neurons. The layer whose outputs are the network output is called output layer. Other layers are called hidden layers .

3. Test description

The microalga used in this study (Fig. 1) is cultivated in four 10-liter photobioreactors. Ruddick culture medium is selected as a feed which is given in (Table 1). The synthesis methods of solutions of the culture medium are as follows: First, phosphate materials were mixed separately, then were autoclaved, and finally were aerated to air pump with 40 L/min intensity. [18]

Fig 1 - A picture of micro algae

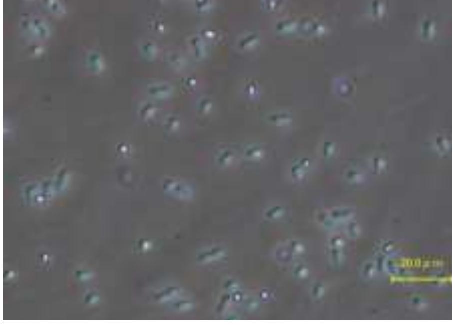


Table 1 - Materials used in Roddick culture medium per liter

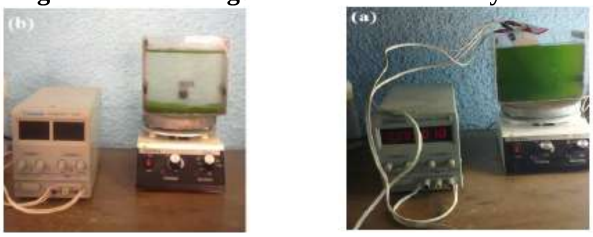
type of materials	Weight per liter of culture medium
$NaNo_3$	۳۰۰mg
KH_2PO_4	20mg
KH_2PO_4	80 mg
NaCl	20 mg
$CaCl_2$	47 mg
$MgSO_4.7H_2O$	10 mg
$ZnSO_4.7H_2O$	0.1 mg
$MnSO_4.7H_2O$	1.5 mg
$CuSO_4.7H_2O$	0.08 mg
H_3BO_3	0.3 mg
$(NH_4)_6Mo_2O_{24}.4H_2O$	0.3 mg
$FeCl_{3.}6H_2O$	17 mg
$Co(NO_3)_2.H_2O$	0.2 mg
EDTA	7.5 mg
Sea Salt	33 g

Fluorescent lamps were embedded within each of the photobioreactors for providing the light.Examples of the used bioreactors are shown in(Fig. 2)

Fig 2 - The bioreactor used to cultivate the microalgae

The GBC spectrometer model was used to measure the algae growth..The unit used for ECF consists of a DC power supply reactor and a magnetic stirrer. The reactor was placed on a magnetic stirrer for better mixing and four parallel electrodes were used in each test. 1280ML mixture of algae and water was poured into the reactor. (fig 3)

Fig 3 - Electric coagulation and flotation system



Each test was started by connecting the electrical current and turning on the magnetic stirrer and it ended after the reaction time by disconnecting the electricity current. After the end of the reaction, 30 min retention times are given to the reactor to alga come up to the surface and are seprated from the water.(Table 2)shows the measured tests and results.

Table2. Experimental conditions and characteristics

number	pH	CD (mA/cm$^{2)}$	t (min)	Removal efficiency (%)	Energy consumed (kWh/m$^{3)}$	Electrode Consumed (kg / m3)	Total wight (USD/M3)
1	8.4	20	11	85.23	0.63	0.134	0.36
2	6	20	12	86.57	0.62	0.028	0.26
3	7.2	1015	5	56.97	0.104	0.022	0.054
4	7.2	15	2.61	46.71	0.098	0.071	0.042
5	7.2	6.59	8.5	88.23	0.313	0.071	0.138
6	7.2	15	8.5	60.86	0.096	0.071	0.06
7	7.2	15	8.5	83.95	0.313	0.071	0.138
8	6	20	8.5	96.23	0.308	0.067	0.138
9	7.2	15	5	85.56	0.254	0.0121	0.138
10	5.18	15	8.5	80.78	0.308	0.056	0.138
11	8.4	10	8.5	87.39	0.292	0.071	0.137
12	7.2	10	12	87.58	0.232	0.111	0.129
13	8.4	15	14.39	81.47	0.486	0.0134	0.233
14	7.2	20	5	90.14	0251	0.071	0.108
15	7.2	15	8.5	89.2	0.319	0.111	0.217
16	6	23.4	8.5	92.19	0.647	0.134	0.259
17	7.2	20	12	84.39	0.6	0.071	0.138
18	6	15	8.5	95.02	0.308	0.067	0.129

4. Modeling

The modeling in the study included the following steps:

Step one: the input dataset (laboratory data) was included and recorded in Excel software and then was loaded and called for network training phase in the MATLAB environment (two-thirds of data). The data were chosen from the entire dataset of the main base so that it represented characteristics of the entire set

Step two: inputs and outputs were defined for this stage, and pH , Density، , time were introduced as inputs. Moreover, Removal efficiency , Energy consumed , ElectrodeConsumed ,Total wight were introduced as outputIn fact, the network had an input layer of neuron (node) as well as an output layer of neuron. Then, characteristics of the network were discussed.

Step three: transfer functions of hidden layers and output were determined in this step. We have two elements of weight w and transfer function f for a simple neuron. Input p is applied on neuron and is weighted by multiplying the weight w. The sum was added to the corresponding bias, applied as an input on the transfer function f and final output was obtained. Transfer function is a linear or non-linear function. There are 12 common transfer functions in neural networks. Different functions of each layer were tested in the study and the best results were observed for the transfer function of the hidden layer tansig and output layer purelin.

Step four: the number of nodes or hidden layer neurons were obtained in this step. The number of input layer neurons and the number of neurons in the output layer were equal to the number of output data. The number of hidden layer neurons was achieved by trial and error. In fact, the error rate was determined by trial and error through changes in the number of hidden layer neurons. five neuron had the lowest error in the study. Therefore, it was possible to reach the best answer with five neuron for hidden layer.

Levenberg-Marquardt (LM) is the best method of learning algorithm. Levenberg-Marquardt is a network training function that updates weight and bias values based on Levenberg-Marquardt optimization. Levenberg-Marquardt is often the fastest back propagation algorithm that is highly recommended as a first-choice supervised algorithm. Now, that the network has been trained, the
remaining one-third of the original dataset was used to evaluate and test the network. Error rate was measured and network error was drawn

5. Discussion and conclusion

Training in the neural network is based on the assumption that usually about two thirds of the available experimental data are randomly selected for training the network and the remaining one-third of the data is used to evaluate the model. Two important definitions that are used to evaluate network are mean square error (MSE) and regression coefficient (R^2), which are defined as follows:

$$MSE = \frac{\sum_{i=1}^{n}(b_i - b_i^{exp})}{n}, \quad R^2 = 1 - \frac{\sum_{i=1}^{n}(b_i - b_i^{exp})^2}{\sum_{i=1}^{n}(b_i^{exp} - b_m)^2} \qquad (1)$$

In the above equation, b_i,b_m and n respectively are the model output, laboratory output, experimental data mean and the number of data. If the network responses are drawn according to the expected outputs (laboratory values), a straight line of 45 degrees should be obtained. The linear regression coefficient close to 1 and MSE close to zero indicate accuracy of the model.

In order to determine the transfer functions of the middle and output layers as well as the number of neurons in the middle layers,the number of the neurons in the middle layer is assumed to be 5 and various transfer functions are tested for the output layer with constant transfer function of the middle layer as function purelin. Therefore, the function with the lowest error is selected as the transfer function of the output layer. Table 3 shows the results. According to the results, the function tansig has the least error rate in the output layer. These two functions are defined as follows:

$$purelin(x) = \frac{1}{(1+e^{-x})} \quad \tan sig(x) = x \qquad (2)$$

Table 3. Determination of the best transfer function for the output layer

No	The number of middle neurons	Transfer function of middle layer	Transfer function of output layer	Network training algorithm	Error of network training	Error of network testing
1	5	tribas	hardlim	trainlm	1.7647	3.1669
2	5	tribas	radbas	trainlm	0.8236	2.1551
3	5	tribas	satlin	trainlm	1.2344	0.72221
4	5	tribas	logsig	trainlm	0.8779	3.1001
5	5	tribas	tansig	trainlm	0.7769	0.0234
6	5	tribas	poslin	trainlm	1.0522	0.7788

In the second phase, 6 neurons of middle layer and the transfer function tansig of the output layer were selected and different transfer functions were examined. According to the results in Table 4, the lowest error rate related to the transfer function purelin. The function is defined as follows:

$$\tan sig(x) = \frac{2}{(1+e^{-x})} - 1 \qquad (3)$$

Table 4. Determination of the best transfer function for the middle layer

No	The number of middle neurons	Transfer function of middle layer	Transfer function of output layer	Network training algorithm	Error of network training	Error of network testing
1	5	hardlim	tansig	trainlm	3.2341	1.6527
2	5	radbas	tansig	trainlm	0.1133	3.4446
3	5	satlin	tansig	trainlm	0.4531	4.2288
4	5	logsig	tansig	trainlm	0.9811	1.7887
5	5	poslin	tansig	trainlm	1.1034	2.9972
6	5	purelin	tansig	trainlm	0.0011	0.0955

The number of neurons in the middle layer was determined by identifying transfer functions of the middle and output layers in the final step. According to Table 5, 5neuron has the lowest error rate.

Table 5. Determination of the number of appropriate neurons for the middle layer

No	The number of middle neurons	Transfer function of middle layer	Transfer function of output layer	Network training algorithm	Error of network training	Error of network testing
1	1	purelin	tansig	trainlm	1.2409	0.7792
2	2	purelin	tansig	trainlm	0.3432	2.344
3	3	purelin	tansig	trainlm	1.1156	2.0011
4	4	purelin	tansig	trainlm	1.7774	4.1390
5	5	purelin	tansig	trainlm	0.0023	0.0711
6	6	purelin	tansig	trainlm	0.2177	2.5567
7	7	purelin	tansig	trainlm	0.1026	1.7851
8	8	purelin	tansig	trainlm	2.7854	4.9899
9	9	purelin	tansig	trainlm	1.5579	1.1189
10	10	purelin	tansig	trainlm	2.8876	3.6768
11	11	purelin	tansig	trainlm	2.6118	3.1168
12	12	purelin	tansig	trainlm	1.0235	2.0022
13	13	purelin	tansig	trainlm	0.1190	4.2367
14	14	purelin	tansig	trainlm	0.2443	1.5560
15	15	purelin	tansig	trainlm	1.5327	4.7887
16	16	purelin	tansig	trainlm	1.5526	3.6768
17	17	purelin	tansig	trainlm	1.1044	2.0078
18	18	purelin	tansig	trainlm	1.7784	3.1168
19	19	purelin	tansig	trainlm	0.7738	2.9001
20	20	purelin	tansig	trainlm	0.2654	3.1112
21	21	purelin	tansig	trainlm	4.0485	3.٥٥88
22	22	purelin	tansig	trainlm	0.0079	2.2344
23	23	purelin	tansig	trainlm	0.8844	1.6668
24	24	purelin	tansig	trainlm	1.٠401	2.0023
25	25	purelin	tansig	trainlm	0.2287	1.٠٠99
26	26	purelin	tansig	trainlm	1.0067	1.٠٠57
27	27	purelin	tansig	trainlm	1.٠٠42	1.7877
28	28	purelin	tansig	trainlm	0.1183	1.0055
29	29	purelin	tansig	trainlm	1.1678	3.6661
30	30	purelin	tansig	trainlm	1.3118	2.8771

In order to show the match between data from modeling and experimental data, the data was plotted on a graph. The graph that is also called linear regression evaluates the match between data from modeling (predicted) and actual or target data (experimental) and shows the result in the form of a straight line passing through the line of 45 degrees. If the line drawn on the line of 45 degrees is more cinsistent, it will indicate a better match between modeling and real data. All modeling and real data in the graph is plotted as dots around the line of 45 degrees. Figure 4 shows changes in regression coefficient for the trained network.

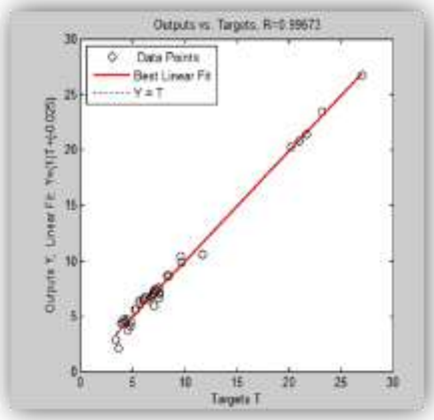


Figure 4. Changes in regression coefficients for the trained network

As seen in Figure 4, the network outputs for data used for training were compared with experimental data. The straight line passing through the graph is well coincided with the line of 45 degrees. Moreover, these data points are very close to the straight line. Therefore, the developed model has good accuracy.

In order to evaluate whether the network can well generalize trained rules to other data, evaluation data (the remaining one-third of the data) were used. Figure 5 shows a similar comparison for the evaluation of the model accuracy. As shown, the straight line passing through the graph also coincides with the line of 45 degrees. These data points are also very close to the straight line. Therefore, the trained network can generalize rules to new data.

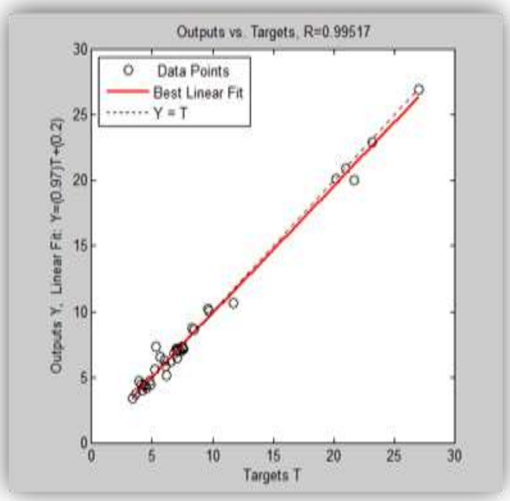


Figure 5. Changes in regression coefficient for the evaluation of the accuracy of modeling

6. Conclusion

- Results of linear regression showed that correlation coefficient obtained (R-Value) between the measured and predicted output variables is close to 1 indicating that the network response is satisfactory.
- The results also showed that training artificial neural network with the process data to separation of microalgae has been successful.
- With proper training, ANN can successfully predict the system output for new conditions.

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