E3 Journal of Biotechnology and Pharmaceutical Research Vol. 3(3), pp. 62-68, May 2012
Available online at http://www.e3journals.org/JBPR
ISSN 2141-7474 © 2012 E3 Journals

Full Length Research Paper

Prediction of bioelectricity production by neural network

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Accepted 19 May, 2012

Microbial fuel cell (MFC) is a new advance technology for production of green electricity from different resources. This technology is able to treat biodegradable organic matter and generate bio-electricity simultaneously. Electrons and protons produce with oxidation of organic matter and then electrons move from external resistance while protons transfer across membrane and reaction between electron, proton and oxygen produce water on the cathode surface. Different kinds of configurations are developed for microbial fuel cell such as the dual and single chamber with membrane and without membrane. In this recent study, artificial neural network was implemented for prediction of fabricated MFC performances. A multilayer perceptron was used which results of prediction were shown a good fit between actual and prediction data with negligible mean square error. Artificial neural network was utilized interconnected mathematical nodes or neurons to form a network that can model complex functional relationship.

Key words: Artificial neural network, Multilayer perceptron, Microbial Fuel cell.

INTRODUCTION

Microbial fuel cells (MFCs) are a new technology that converts the energy stored in bond of organic material to electrical energy (Song et al., 2009; Mohan et al., 2008; S Mathuriya and Sharma, 2009; Weifang et al., 2011; Rahimnejad et al., 2011). MFCs are regarded as promising power source for mobile and stationary application (Du et al., 2008; Wilkinson, 2000). Power generated by MFC can supply the needed amount of electricity for consumption of other devices (Rahimnejad et al., 2009). Traditional MFCs have an anodic chamber and cathodic compartment which connected by a proton exchange membrane (PEM) or salt bridge to allow protons to move from the anodic chamber to the cathodic chamber while prevent diffusion of oxygen into the anode chamber (Ghangrekar and Shinde, 2007; Min et al., 2005; Logan et al., 2005; Du et al., 2007; Rabaey and Verstraete, 2005; Rahimnejad et al., 2012). These designs are used commonly in laboratories, but these designs have many problems such as high cost and biofouling of membrane. In spite of being a promising technology, MFC has some bottlenecks such as low power density, high cost. The factors which affect the performance of a MFC are substrate conversion rate, over potential of the anode and cathode, the ion-exchange membrane performance, operational parameters, cell configuration and the electrode surface properties(Mohan and Das. 2009; Rabaey and Verstraete. 2005; Ringeisen et al., 2007; Rozendal et al., 2008). These parameters effect on MFCs performances. Prediction of produced power and current are important parameter to use of MFCs in small devices such as laptop computer and other devices (Rahimnejad et al. 2011; Logan, 2010).

There are several mathematical models for oxidizing and reducing agent based on mass balance for MFCs. Outputs of these models include time dependent production of current, current –power and current –voltage and also progression of chemical species concentration (Picioreanu et al., 2007). Used models for

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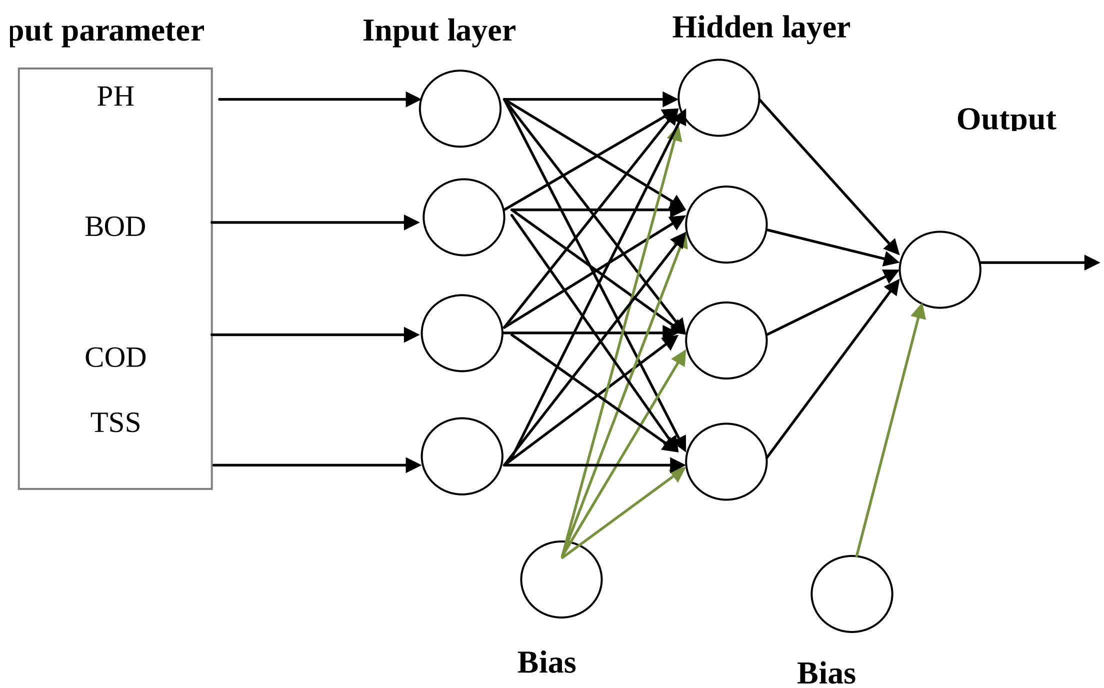

Figure 1. General topology of feedforward artificial neural network

prediction of MFC performance, which integrate macro – scale time dependent mass balances for solutes and biomass in the anodic solution with a micro scale individual – based two dimensional biofilm model is also developed (Picioreanu et al., 2010).

Although in the field of chemical fuel cells, mathematical models are highly developed and widely used (Kinoshita et al., 1988; Wang., 2004) but application of them for MFC is too low. For scientists working on MFC, mathematical models can help to detect rate – limiting steps and to allow the development of strategies to improve the MFCs design and power output. Furthermore, Biologist can use computational to test the hypothesis about microbial community composition, size activity and mode of electron transfer in MFC or to design new experiments to enhancement of MFCs performances. Moreover, the computational models help by pointing to the most important MFC parameter that should be experimentally measured and reported. Many kinds of neural network exist (Hagan et al., 1996) such as multi-layer perceptron (MLP), radial basis function (RBF) networks and recurrent neural network (RNN) ,but all of them consists of the same basic features; nodes, layers and connections. Some of the artificial neural networks are popular such as; MLP and RNN(Movagharnejad and Nikzad. 2007). In this study, MLP neural network was used for investigation of MFC behavior. The nodes are the smallest part of an artificial neural network. Each node receives a signal from connection, the signal is then summed together before being applied to transfer function to produce the output. The output signals are then propagated to other nodes until it reaches the output of the network. This class of networks consists of three layers. Input, hidden and output layer which data move to input layer, then hidden layer and at the end to output layer that is this direction is forward. Figure 1 shows a feed forward artificial neural network. Neurons of each layer connect together with a factors W_{ij} and W_{jk}. Each layer receives a sum of inputs which produce the output by applying the transfer function. There are different kinds of transfer function but easy derivation evaluating is reason for selection of this transfer function. Before using of artificial neural network must use training for network. Target of using training method is finding of optimum weight factor and biases. Neural network learns by training which generate new outputs with iterative method. Back propagation is a common method for training. First of training process, initial weights were given to connections randomly. Inputs are inserted into input layer and then move forward through the hidden layer of neurons to the output layer. At the end outputs would be compared with real outputs. Changing of weight coefficient can decrease need time and calculated errors. After that the neural network was prepared. Before using any method for training an artificial neural network have to normalize input and output, So input data and output by following equation was normalized between 0 and 1.

$$\text{Normalize value} = \frac{(\text{Actual})_{\text{value}} - (\text{minimum})_{\text{Actual value}}}{(\text{maximum})_{\text{Actual value}} - (\text{minimum})_{\text{actual value}}} \quad (1)$$

Training is an iterative process that optimizes weights and biases. Inputs have been divided into two parts which 70% of data is used for training and 30% data used for testing of data. Back propagation is a method for training of (ANN). As mention above; consider a MLP which is consists of L interlayers for each interlayer like$l$, N_l node and $N_l \times N_{l-1}$connections with weight$W \in R^{N_l \times N_{l-1}}$.$N_l$ And $N_{l-1}$are number nodes in interlayer l and l-1.W_{ji} explains connection between node j of layer l to node I of layer l-1. In each interlayer l and neuron j input value integrate and generate

$$\varphi = \sum_{i=1}^{N_{l-1}} W_{ji}^{l}.X_{i}^{1-l} \tag{2}$$

Base of these equations are on sigmoid function. In the next step, the transfer function would be used to generate X_j^l .

$$X_j^l = \theta(\varphi_j^l) = \theta \left\{\sum_{i=1}^{N_{l-1}} W_{ji}^l .X_i^{l-1}\right\} \tag{3}$$

One of the most common functions used in back propagation method is the sigmoid function:

$$\theta(\varphi) = \frac{1}{1+e^{-\varphi}} \tag{4}$$

In each interlayer a weight W_{ji}^lat iteration (t) will be changed from its previous value $(t-1)$ according to equations 5:

$$W_{ji}^l = W_{ji}^l(t-1) + \Delta W_{ji}^l(t) \tag{5}$$

$$\Delta W_{ji}^l = \eta \delta_j^l.X_j^{1-l} + \mu \Delta W_{ji}^{l(\text{previous})} \tag{6}$$

ΔW_{ji}^l Explain weight change which can be calculated by delta rule (equations 7).

$$\Delta b_{ji}^l = \eta.\delta_j^l + \mu.\Delta b_{ji}^{l(\text{previoue})} \tag{7}$$

η In these equations is learning rate and μ is momentum coefficient,X_i^{1-l} is input from 1-l the interlayer and b is bias.

$$\delta_j^l = (X_j^L - Y_j)X_j^L(1-X_j^L) \tag{8}$$

For the neuron in hidden layer δ_j^l was calculated by equation 9:

$$\delta_j^l = X_j^l(1-X_j^l)\sum_{k=1}^{r} \delta_k^{l-1}.W_{kj}^{l+1} \tag{9}$$

The above equations are based on sigmoid function.$X_j^l(1-X_j^l)$ and $(X_j^l - y_i)X_j^l$ would be different for other transfer function (Mohanty. 2005; Mehdizadeh and Movagharnejad, 2011).

MATERIALS AND METHODS

MLP feed forward model was selected prediction of MFC in the study. Key factor in ANN design is the type of transfer functions. ANNs owe their non linear capability to the use of non linear transfer function. Different transfer function can be used for neurons in the different layers. Several transfer function were examined in each layers separately and with respect to the mean squared error (MSE) of testing data. At the final, the proper transfer functions were chosen from the obtained results.

After training of artificial neural network, some data were used for testing of produced network. These works was done by MATLAB 7.7.0 software for programming, training, validation and testing of the network. Network structure has considerable effects on the predicted results. The number of input and output nodes are equivalent to the number of input and output data respectively (4 and 1 in this study). Nevertheless the number of hidden layers and the number of nodes in each layer are case dependent and there is no straightforward method for determining them.

RESULTS AND DISCUSSION

Prediction of current with ANN

After definition of net architecture for neural network and it's training, the network was tested, input data for testing of network was used and the results was shown for different wastewater and comparison between predicted and actual results was shown a good prediction for input data.

Fabricated ANN was used for prediction of bioelectricity from several wastewater such as Beer brewery, sugar industry, Dairy wastewater, municipal and paper industry in which data was obtained by Mathuriya and Sharma (S Mathuriya and Sharma., 2009). Each wastewater had many characteristics which were selected; pH, biological oxygen demand (BOD), chemical oxygen demand (COD), total suspended solid (TSS) and time (day) as input data and produced current was selected as an output data. All these characteristics were measured based on standard method (Eaton and Franson. 2005). Table 1. show characteristics of different kinds of wastewater. Results of predicted current were draw versus actual current for wastewater.

MSE is an important factor for investigation of accuracy

Table 1. Characteristics of different waste waters (S Mathuriya and Sharma., 2009).

Type of Wastewater	pH	BOD	COD	TSS
Beer brewery wastewater	6.4	429	1778	405
Sugar industry	6.1	539	1229	287
Dairy wastewater	5.5	654	1487	329
Municipal	7.6	234	1235	256
Paper wastewater	8.3	267	1581	395

Table 2. Mean square error (MSE) for different kinds of wastewater**.**

Type of Wastewater	Sugar industry	Beer brewery	Municipal	Dairy wastewater	Paper industry
Mean square error	1.5417	1.27738	0.642529	1.341535	0.3037746

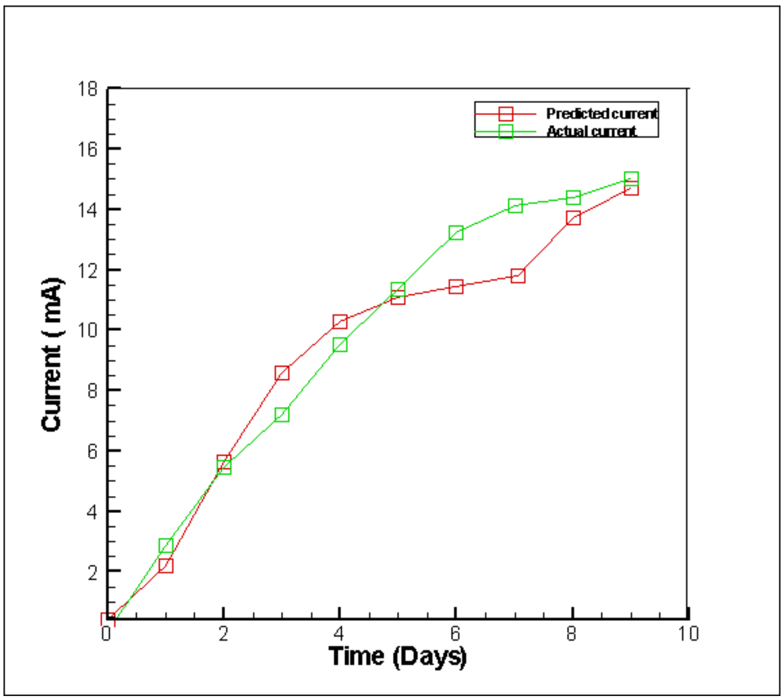

Figure 2. Current versus time (day) for sugar wastewater

predicted data. MSE is calculated by equation 10, that Y^{exp} shows experimental data and Y^{cal} shows predicted data.

$$MSE = \frac{\sum_{i=1}^{N}(Y^{exp} - Y^{cal})^2}{N} \quad (10)$$

Results obtained by neural network and experimental data have shown a consistency between them, because of low mean square error which is an important factor for accuracy of prediction (Table 2).

After prediction of data by neural network and obtaining mean square error, predicted current versus time is drawn and also experimental data is drawn versus times which are shown in Figures 2,3,4,5,6 for different wastewater.

Mean absolute error (MAE) is another factor for comparison between actual experimental results and predicted results, so MAE is calculated by equation 11 and presented in Table 3.

$$MAE = \frac{\sum_{i}^{N}|Y^{exp} - Y^{cal}|}{N} \quad (11)$$

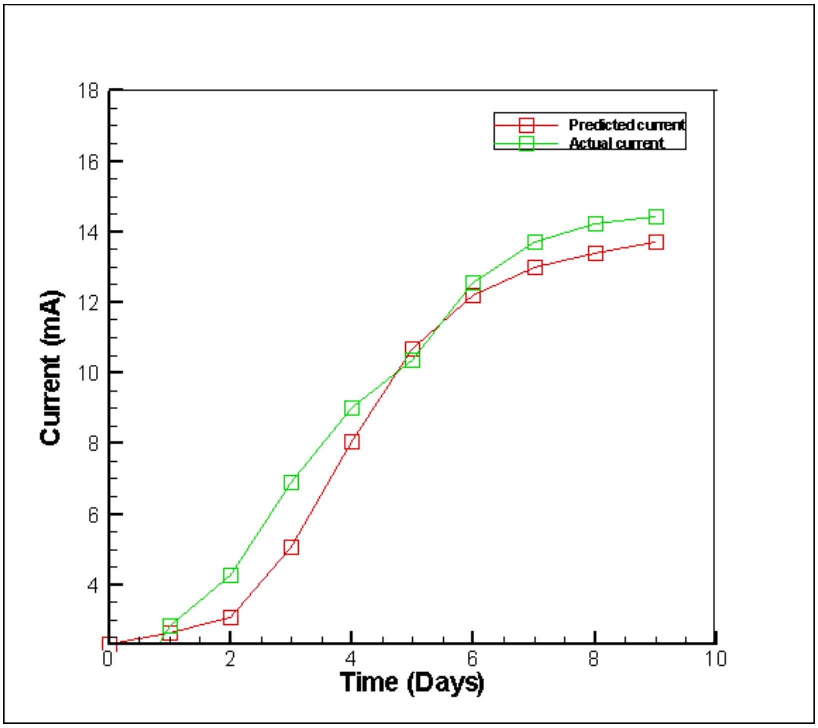

Figure 3. Current versus time (day) for beer brewery

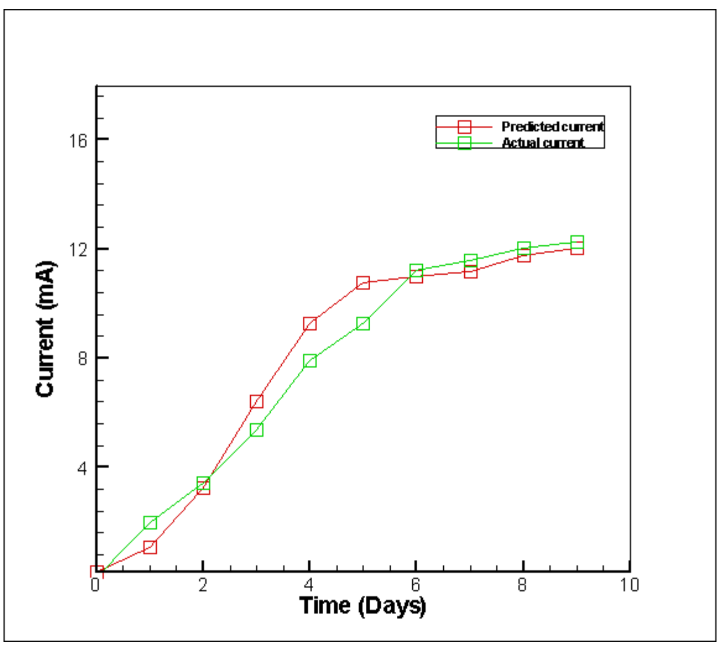

Figure 4. Current versus time (day) for municipal wastewater

Actual produced current and prediction produced current based on developed model for sugar wastewater is presented in Figure 2. The obtained results showed good relation between predict and exact data. The similar results for four different substrate were presented in Figures 3 to 6. These figures show that this model have

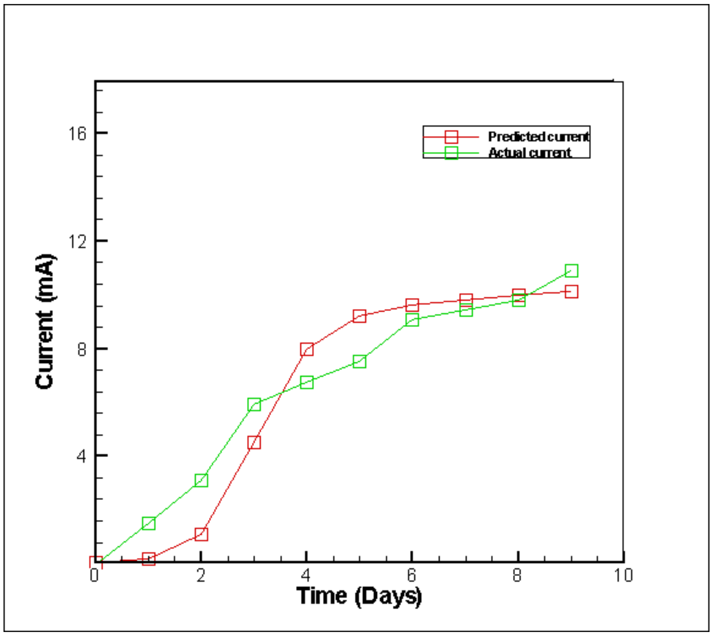

Figure 5. Current versus time (day) for Dairy wastewater

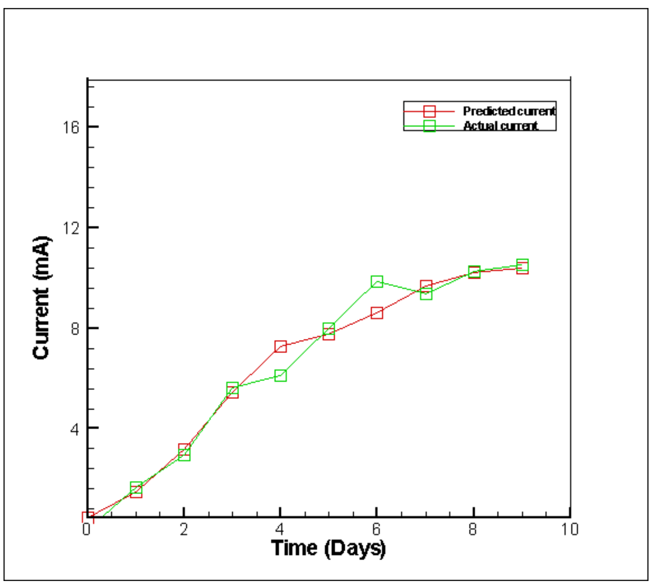

Figure 6. Current versus time (day) for Paper wastewater

good ability for bioelectricity production because the predicted data are very similar to actual data (Figure 3 to 6).

Conclusion

Investigation of MFC behavior by artificial neural network is a new method which could predict the amount of current of MFC by inputs pH, biological oxygen demand, chemical oxygen demand and total suspension solid which results was shown in above figures. MLP is a good neural network for prediction of characteristics of MFC. ANN modeling technique has many favorable features such as efficiency, generalization and simplicity, which make it an attractive choice for modeling of complex

Table 3. Mean absolute error (MAE) for different kinds of wastewater.

Type of Wastewater	Sugar industry	Beer brewery	Municipal	Dairy wastewater	Paper industry
Mean absolute error	0.936656	0.941124	0.6346	5.81086	0.41956

systems, such as MFC.

ACKNOWLEDGMENT

The authors wish to acknowledge Biotechnology Research Center, Noshirvani University of Technology, Babol, Iran for the facilities provided to accomplish the present research

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