Journal of Environmental Management 290 (2021) 112594

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Experimental and validation with neural network time series model of microbial fuel cell bio-sensor for phenol detection

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ARTICLE INFO

Keywords:
MFC-Based biosensor
Scaled conjugate gradient (SCG) algorithm
Time series Model
Phenol
Toxicant

ABSTRACT

Phenol is one of the most commonly known chemical compound found as a pollutant in the chemical industrial wastewater. This pollutant has potential threat for human health and environment, as it can be easily absorbed by the skin and the mucous. Here, we prepared dual chambered microbial fuel cell (MFC) sensor for the detection of phenol. Varying concentration of phenol (100 mg/l, 250 mg/l, 500 mg/l, and 1000 mg/l) was applied as a substrate to the MFC and their change in output voltage was also measured. After adding 100 mg/l, 250 mg/l, 500 mg/l, and 1000 mg/l of phenol as sole substrate to the MFC, the maximum voltage output was obtained as 360 ± 10 mV, 395 ± 8 mV, 320 ± 7 mV, 350 ± 5 mV respectively. This biosensor was operated using industrial wastewater isolated microbes as a sensing element and phenol was used as a sole substrate. The topologies of ANN were analyzed to get the best model to predict the power output of MFCs and the training algorithms were compared with their convergence rates in training and test results. Time series model was used for regression analysis to predict the future values based on previously observed values. Two types of mathematical modeling i.e. Scaled Conjugate Gradient (SCG) algorithm and Time-series model was used with 44 experimental data with varying phenol concentration and varying synthetic wastewater concentration to optimize the biosensor performance. Both SCG and time series showing the best results with R^2 value 0.98802 and 0.99115.

1. Introduction

Microbial fuel cell (MFC) has been seen to be a promising technology in recent years in terms of its potential application in water quality monitoring (Chouler and Di Lorenzo, 2015). MFC is a device in which chemical energy present in the organic matter is converted to electrical energy by microbial metabolic pathways (Allen and Bennetto, 1993). This device contains two types of electrodes, anode and cathode. A microbial biofilm develops on the surface of the anodic electrode which consists of electrogenic microbes. These electroactive microbes generate electrons during the oxidation of organic matter and transfer them to the electrode. Therefore, the output current generated from the MFC can be directly linked with the metabolic activity of electroactive microbes on the anode surface (Di Lorenzo et al., 2014). If the microbial metabolic process is disturbed due to any changes such as the presence of a toxic compound, organic load or any environmental changes, then this disturbance directly translates into a change in electrical output (Di Lorenzo et al., 2009) (Stein et al., 2010). This is the principle based on which the MFC device is used to detect toxic compounds in water (Jiang et al., 2015). MFC -based biosensor is known for its "simplicity" as compared to other devices. The biofilm grown over the anode surface acts as a recognition component in MFC-based biosensors (Chouler and Di Lorenzo, 2015). The response of the recognition component in the presence of a toxic substance reduces the electron transfer rate to the transducer (the anode), thus generating a change in current output. Detection of toxic compounds is one of the most important parameters for water quality analysis since these compounds are harmful to the environment as well as human health. Therefore, detection of toxic compounds is crucial in water quality monitoring, processing of drinking water and wastewater treatment (Kim et al., 2007; Dávila et al., 2011; Stein et al., 2012). There are various methods and traditional techniques available to detect the presence of toxic compounds in water but these methods cannot provide some key information like the bioavailability and biotoxicity of these compounds (D'Souza, 2001). If the microbial biofilm is exposed to any chemical toxicant then the cell viability and the metabolic activity of the microbes are inhibited. This inhibition can be monitored by using several techniques namely, fluorescent microscopy to test the cell viability and other respiration assays

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https://doi.org/10.1016/j.jenvman.2021.112594
Received 8 October 2020; Received in revised form 5 April 2021; Accepted 9 April 2021
Available online 24 April 2021

that monitor metabolic activity (Kim et al., 2007; Dávila et al., 2011).

The discharge of contaminated wastewater into water sources from commercial, agricultural and domestic activities is responsible for the presence of phenolic compounds in water bodies. They are often induced by natural phenomena. These compounds are considered to be toxic and affect both humans and animals with serious and long-term effects. They are carcinogenic and cause damage, even at low levels, to red blood cells and the liver.

Detection of phenol in wastewater is very much important as it has carcinogenic effects on human health (Anku et al., 2017). Most well-known methods and techniques that are used to detect phenol and its derivatives include electrophoresis, spectrophotometry and chromatography (Khoddami et al., 2013; XU et al., 2017). However, these traditional methods are impractical for environmental samples as these samples have to go through various pre-treatment processes like extraction, purification, and concentrations before detection. These pre-treatment processes require trained and skilled personnel. Also, it is a very time-consuming and costly process, making these detection methods unsuitable for in situ analyses (Kumar and Sharma, 2017). Therefore, electrochemical or MFC-based biosensors are an easier, user-friendly and cost-effective process for toxicant detection. Moreover, it is also suitable for online in situ monitoring. In the cathode chamber, Jaroo et al. used *Chlorella vulgaris* microalgae to produce oxygen as an electron accepter by photosynthesis to generate bioelectricity power and to treat wastewater from oil refineries by microorganisms in both anode and cathode (Jaroo et al., 2019). Various industrial treated wastewater from various industries contains toxic heavy metals, which is one of the major reason of water contamination. These pollutants are harmful to human helath as well as for animals. To consider its use for purification of metal finishing wastewater, the adsorption activity of pistachio hull powder (PHP) as a low-cost adsorbent of concerning nickel (II) ions has been studied (Beidokhti et al., 2019).

MFC)-based biosensing can be integrated with artificial neural networks (ANNs) to identify specific chemicals present in water samples. A very important and continuously emerging area within AI is artificial neural networks (ANNs). They are mathematical models and motivate biological neural networks. It consists of a collection of simple processing units called nodes or neurons organized in layers with high connectivity that allow for the transmission of inputs through the different layers until output values are generated. In any model based on a neural network approach, the following elements are present:

- Input signs of external or other neuronal data (x_1, x_2, … x_n).
- Output signals (y_1, y_2, y_m) representing the output value of the network.
- Weights (w_{1k}, w_{2k}, … w_{nk}), the association between two neurons. During network training, the weights are adjusted such that the desired performance values are obtained.
- Biases (θ_1, θ_2, θ_K, …) which relate to the values of each node, enabling the triggering function to switch to left or right to suit the data better.

Different criteria can be used to classify ANNs according to such topology (single or multilayer), type of learning (consult or unmonitored) or type of layer relation (feed-forward or feedback) (Mas and Flores, 2008).

As in other areas of study, ANNs are used to model the success of MFCs and the number of papers published during the last few years is growing (Sewsynker-Sukai et al., 2017). The feed substrata of 69 distinct microbial communities has recently been predicted by ANNs. In this work, the authors developed 6-mechanical algorithms to determine the feed substrate from genomic data based on 4-ingredient variables. The model showed 93 ± 6 percent maximum exactitude using an ANN educated in phylum-taxonomic-grade data sets (Cai et al., 2019). This technique was also used to predict the anodic biofilm communities and efficiency of MFCs induced by changes in the composition of feedstock with a total of 33 tests. In this case, when taxonomically categorized at the family level, the authors could estimate the power density production by the method with a minimum of 5.76 ± 3.16 percent error (Singh et al., 2019).

ANNs have also estimated the stabilization time of the power production of MFCs. This model suggested that these systems require a stable electricity generation of 12–16 weeks (Singh et al., 2019). The research carried out by Tsompanas et al. (Michail-Antistheniset al., 2019) is one of the most recent works which include the analysis of ceramic MFCs fed with real waste. ANNs are used in this work to model the polarisation curves in various MFC settings. The authors' model achieved 99.66% accuracy in the data prediction with a total of 264 experiments. Anode angle for the inlet flow direction of the electricity produced by the MFC has also been used to forecast the impact of particular design parameters such as the anode angle. Ali et al. (2018) recently carried out an experimental test to optimize the setup of MFCs to maximize energy output. The authors examined the impact of various factors such as salt bridging as separators, as well as various salt concentrations, temperatures, or the electrode surface. The authors employed a four-layer ANN feed-forward method to simulate systems voltage. The built model predicted the generation of voltage by correlating 99.9 percent of the experimental outcomes to simulated results.

Mirra et al.'s (Mirra et al., 2020) study shows that when there is no wastewater generation, the oxygen uptake rate (OUR) in the reactor is very low (0.0007–0.0015 mg/l.s) and thus, does not require a high oxygen supply. However, when wastewater flushes into the onsite wastewater treatment plant (WWTP) (i.e., the water level increases), the oxygen demand increases rapidly and (OUR) reaches the range of 0.0040–0.0063 mg/l.s depending on the type and the quantity of the incoming substrate. These results should be further verified with field experiments. Cordier et al. used ultrafiltrate seawater to cultivate microalgae (Cordier et al., 2020).

In this study, a dual-chambered microbial fuel cell sensor was prepared for the detection of phenol. Varying concentration of phenol was applied as a substrate to the MFC and the change in output voltage was measured. The concentration of phenol with respect to time was also measured to check the degradation of phenol. Two types of mathematical modeling, i.e., Scaled Conjugate Gradient (SCG) algorithm and Time-series model were used with 44 experimental data sets with varying phenol concentrations and varying synthetic wastewater concentrations to optimize the biosensor performance. ANN's topologies were analyzed to get the best model for predicting the MFC power output and the training algorithms were compared on the basis of training and test performance according to their convergence rates. Time series model was used for regression analysis to predict the future values based on previously observed values.

2. Material and methods

2.1. Microbial culture

The microbial culture used in this MFC sensor was isolated previously from industrial wastewater (Naik and Jujjavarappu, 2019). About 1% (V/V) of microbial seed culture concentration was used as initial inoculum. For microbial culture, synthetic wastewater was used as a microbial medium. Synthetic wastewater (Peptone 256.55 mg/l, Tryptone 354.24 mg/l, NaCl 407.4 mg/l, Na_2SO_4 44.6 mg/l, K_2HPO_4 44.6 mg/l, $MgCl_2.6H_2O$ 3.7 mg/l, $FeCI_2.2H_2O$ 3.7 mg/l, $CaCI_2.2H_2O$ 3.7 mg/l, $MnSO_4$ 0.057 mg/l, H_2MoO_4 0.031 mg/l, NaOH 0.008 mg/l, $ZnSO_4$ 0.046 mg/l, $CoSO_4$ 0.049 mg/l, $CuSO_4$ 0.076 mg/l) was prepared and inoculated with microbial seed culture. The microbial culture flasks were incubated at 37 °C for 24 h with a constant agitation of 150 rpm and then the culture was used for MFC setup.

2.2. MFC preparation

A dual chambered microbial fuel cell was constructed as a biosensor. The MFC-based biosensor was prepared using two polypropylene autoclavable bottles, separated from each other by a proton exchange membrane (Nafion117 membrane). As showed in Fig. 1, each chamber consistedof two distinct holes with 1 mm and 6 mm diameter in the cap. The 1 mm diameter hole was made to insert a copper wire for holding the electrodes and the 6 mm diameter hole was made to take out samples. The Nafion membrane was pre-treated before it was used in the MFC as per the protocol explained by (Biffinger et al., 2008). The working volume of each chamber was 300 ml. The cathode chamber consisted of one inlet for constant oxygen supply. A graphite sheet was used as anode and a carbon cloth was used as cathode in the setup. Both the electrodes were pre-treated before being used in the MFC as described by (Bond and Lovley, 2003). The copper wire was also sterilized with 70% ethanol before being used in the MFC. Before working the entire setup was autoclaved to avoid contamination. In the anodic chamber, synthetic wastewater inoculated with industrial microbial seed culture was used as an analyte and in the cathodic chamber, 100 Mm potassium ferricyanide prepared in 50 mM phosphate buffer solution (PBS) was used as catholyte. The anolyte was supplemented with the desired amount of phenol as a sole substrate. The setup was kept at room temperature and was made completely airtight to avoid contamination. The voltage output was measured using a digital multimeter.

2.3. Test of toxic events

To evaluate and optimize the operational parameters of MFC-based biosensor, the effect of different concentrations of phenol on output voltage was estimated (100 mg/l, 250 mg/l, 500 mg/l and 1000 mg/l). The MFC-based biosensor was operated under batch conditions. The desired amount of phenol was applied to the fuel cell and the change in voltage output was measured at different time intervals.

2.4. Analytical method to measure phenol degradation

As discussed in the previous section (introduction), electricity generation can be obtained directly from the degradation of organic matter with a simultaneous recovery of high amount of energy (Logan, 2004). In anaerobic conditions, phenol can be degraded by methanogens, denitrifying bacteria, iron bacteria and sulfate-reducing bacteria. Therefore, MFC possesses potential applications in detection as well as biodegradation of phenol. To evaluate the phenol degradation in MFC-based sensor device, phenol concentration was measured time at specific time periods by using UV spectrophotometer. Full wavelength scan was done in the range of 200–800 nm. Maximum absorption was observed at 314 nm under alkaline conditions. To determine the phenol concentration, 50 μl sample was taken from MFC and added into 3 ml of 0.1 M of NaOH solution and the absorbance was measured at 314 nm.

2.5. Optimization of various parameters of MFC-based sensor via mathematical modelling

2.5.1. Data preparation

The main goal of this study was to develop an advanced ANN model for predicting the biodegradation of phenol in synthetic wastewater by using various parameters such as varying concentrations of phenol as a feed and different concentrations of synthetic wastewater composition with respect to time. In ANN model, data preparation and data encoding are the most important functions to train the ANN model and to improve the neural network performance. After data preparation, performance of data pre processing is essential in order to give equal priority to all the variables.

2.5.2. Neural network methodology

Here, we used the Scaled Conjugate Gradient (SCG) algorithm to predict and optimize the performance of MFC-based sensors by varying the input parameters like phenol substrate concentration and the composition of synthetic wastewater composition. SCG algorithm is generally used to solve large-scale problems and it is a well-known network-based method that computes second-order information from the two first-order gradient parameters by using all training databases. To predict the performance of the MFC-based biosensor with respect to phenol degradation rate in synthetic wastewater and voltage output, 44 experimental data sets with varying phenol concentrations (10 mg/l to 440 mg/l) and varying synthetic wastewater compositions were used as variables to develop the ANN model.

2.5.3. Time Series Modelling

Time Series Modelling is a method which deals with time-based data to predict the reactor performance. 44 experimental data sets with

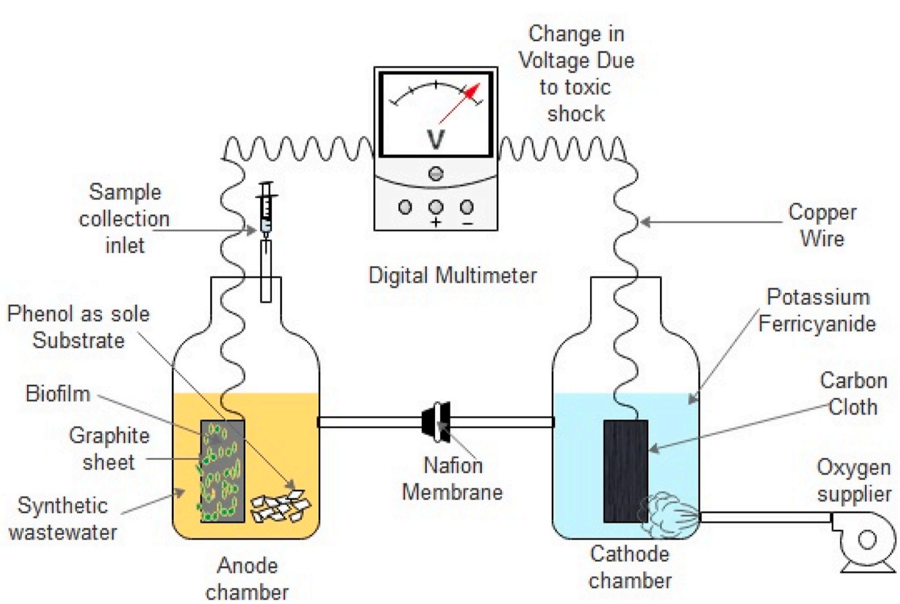

Fig. 1. Schematic representation of Microbial Fuel Cell-based Biosensor.

varying phenol concentrations and varying synthetic wastewater compositions were used as variables. It differs from SCG model; in time series we only use data at a particular time interval. The data was collected at 5 h in all 44 experimental setups for conducting a time series model.

3. Results

3.1. Voltage output and phenol degradation

As depicted in Fig. 2, the voltage output gradually increased to a maximum value of 360 ± 10 mV and the phenol concentration gradually decreased from 100 mg/l to 39 mg/l in 125 h. These results indicated that the increase in output voltage was due to the growth of the electroactive bacteria and also, due to phenol degradation. When the phenol concentration was below 39 mg/l the output voltage gradually began to decrease.

Fig. 3 represents the voltage output and phenol concentration againsttime interval after applying 250 mg/l phenol as a sole substrate to the MFC system. Here, too, the maximum voltage output was observed to be 395 ± 8 mV and the phenol concentration also decreased from 250 mg/l to 0 mg/l at 225 h. When all the phenol substrate was utilized by the system the voltage suddenly dropped.

Fig. 4 represents the voltage output and phenol concentration against the time interval after applying 500 mg/l phenol as a sole substrate to the MFC system. The voltage output gradually increased to 320 ± 7 mV and the phenol concentration decreased from 500 mg/l to 120 mg/l at 225 h. After phenol concentration decreased to 120 mg/l, the voltage output also slowly decreased.

Fig. 5 represents the voltage output and phenol concentration with respect to time interval after applying 1000 mg/l phenol as a sole substrate to the MFC system. The voltage output gradually increased to a maximum voltage of 350 ± 5 mV and the phenol concentration decreased from 1000 mg/l to 120 mg/l at 360 h. After the phenol concentration decreased below 120 mg/l, the voltage output also slowly decreased.

3.2. Neural network training results

As discussed earlier, varying phenol concentrations and varying synthetic wastewater compositions were used as variables for SCG model and were set in MATLAB for conducting neural network modeling. The training, testing and mean square error (MSE) were chosen for error criteria. 44 experimental data were used to predict the performance of the MFC-based sensor for detecting phenol degradation and voltage output in the system. Out of the 44 experimental data, 33

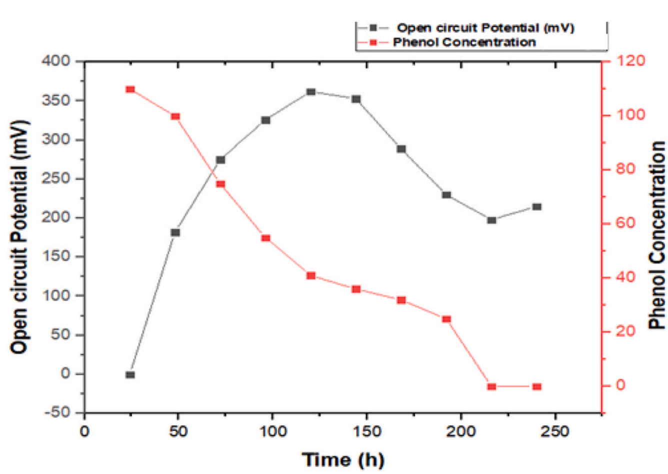

Fig. 2. Time Vs voltage and phenol concentration of Microbial fuel cell using 100 mg/l phenol as substrate.

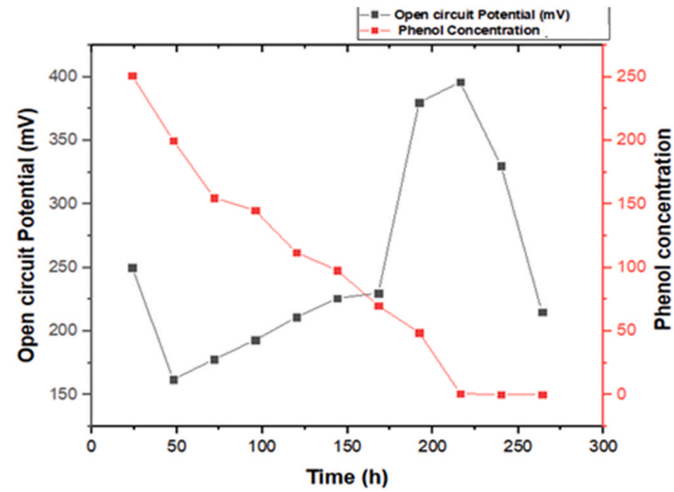

Fig. 3. Time Vs voltage and phenol concentration of Microbial fuel cell using 250 mg/l phenol as substrate.

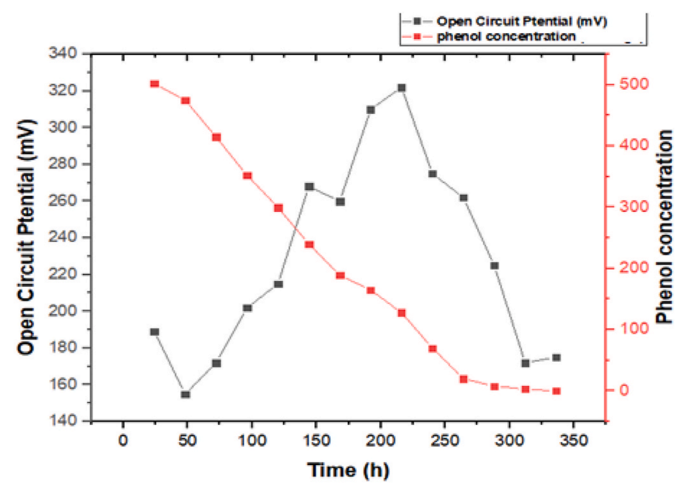

Fig. 4. Time Vs voltage and phenol concentration of Microbial fuel cell using 500 mg/l phenol as substrate.

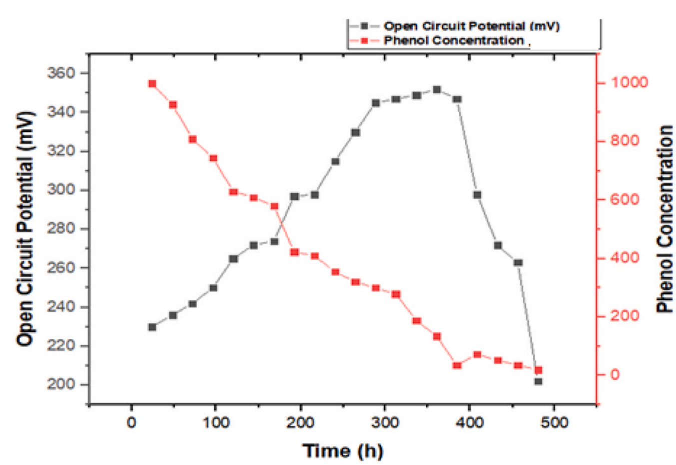

Fig. 5. Time Vs voltage and phenol concentration of Microbial fuel cell using 1000 mg/l phenol as substrate.

were used to train the network, 5 for validation and 5 for testing. The regression plot was used to validate the neural network performance. For training, testing and validation of respected targets, the regression plot showed the neural network output. The performance of the neural network with R^2 value is shown in Fig. 6. The correlation coefficients refering to all the parameters are shown, which signify a perfect fit as all data are found to lie near the line. The R^2 value with training was found to be 0.98802, R^2 value obtained with testing was 0.95896, R^2 value obtained after validation wass 0.97231 and the overall considering all the 44 sets was 0.97938. The R^2 value indicates the relationship between the target and the output values. From all 44 experimental data used for optimization, the performance observed was around 75%, 12.5% and 12.5% for training, validation, and testing, respectively. From the figure, we can predict that 10 hidden nodes with testing set 12.5% and validation set 12.5% were showed optimal performance. The results are very close to neural network results showing the best validation performance. From Fig. 7, we can see that in the training state graph, the error decreased with respect to iterations. "Mean Squared error" vs "14 epochs" graph was plotted to show best validation performance as depicted in Fig. 8. The best validation performance was 6.2171 at 8 epochs. The error between the predicted and targeted values were trained in neural network as shown in Fig. 9 in the form of an error histogram. The blue bar in the error histogram represents the training data, the green bar depicts alidation data and red bar indicates testing data. The negative values indicated how predicted values differed from targeted values. The line with dashes in each graph explains the perfect and good outcome which is outputs equal to targets and the solid line

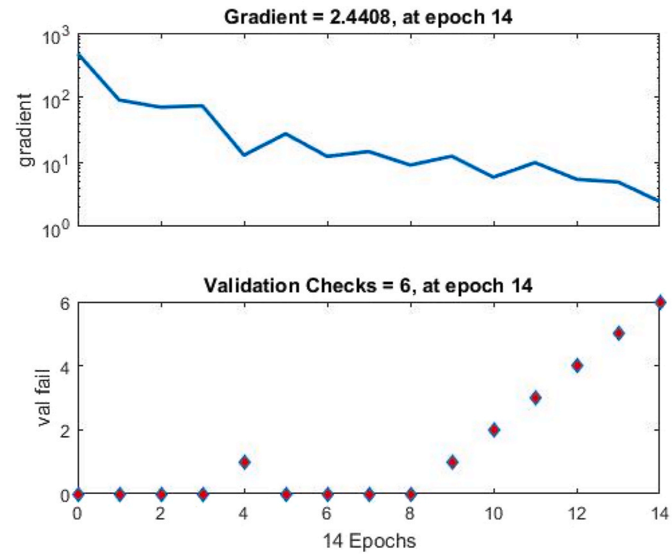

Fig. 7. Training state of Scaled Conjugate Gradient model.

explaining about the best finest match of the linear regression of outputs (predicted values) and targets (experimental values) (experimental values). The R^2 value showed the relationship between the outputs and goals. Greater the value of R^2 (close to 1), the more reliable is the linear

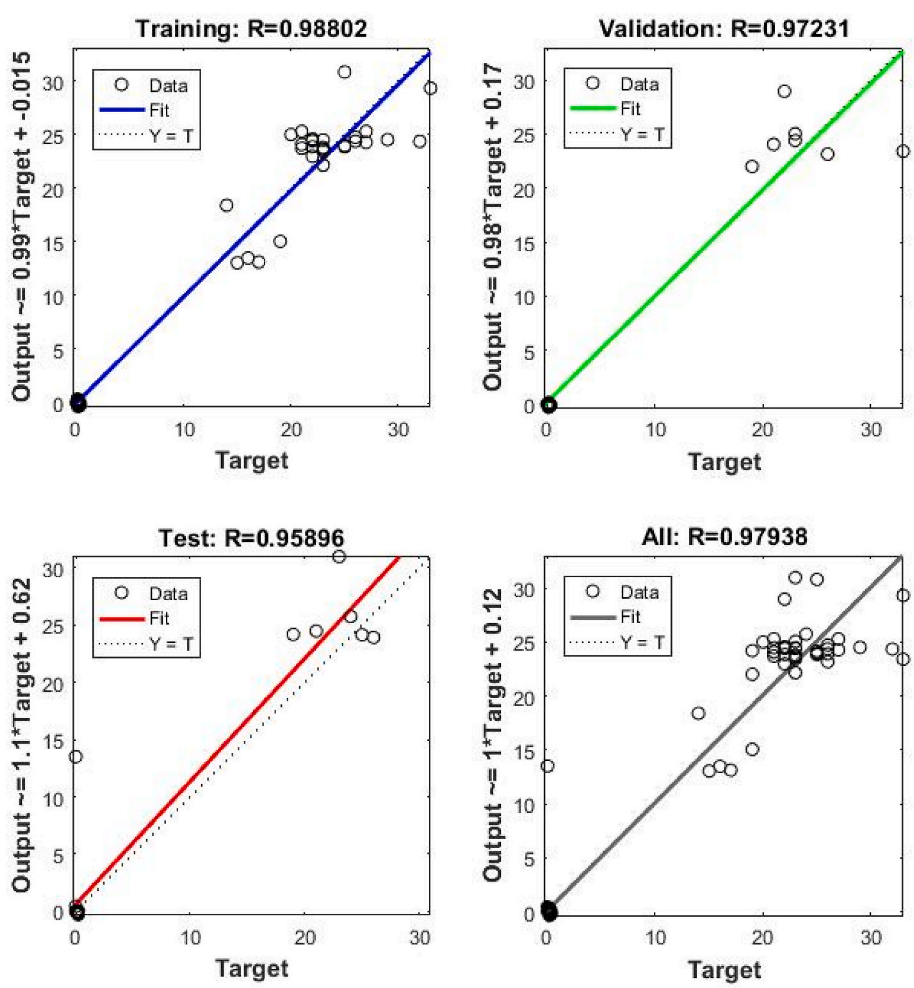

Fig. 6. Regression, training and Validation reports using Scaled Conjugate Gradient model of MFC biosensor Performance.

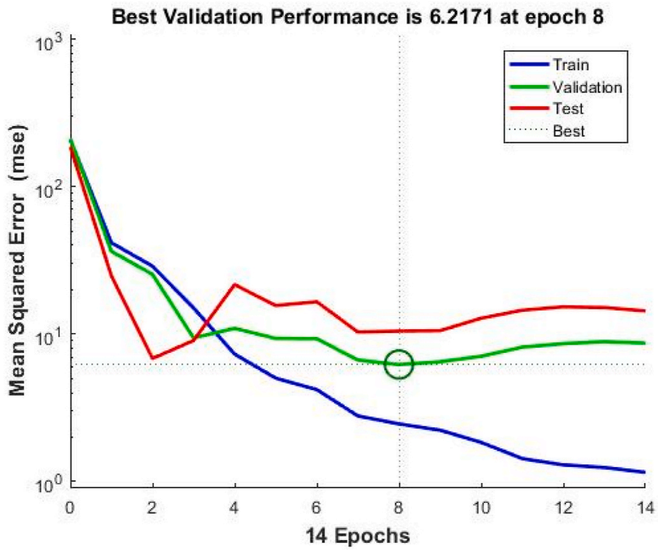

Fig. 8. Performance of Scaled Conjugate Gradient model.

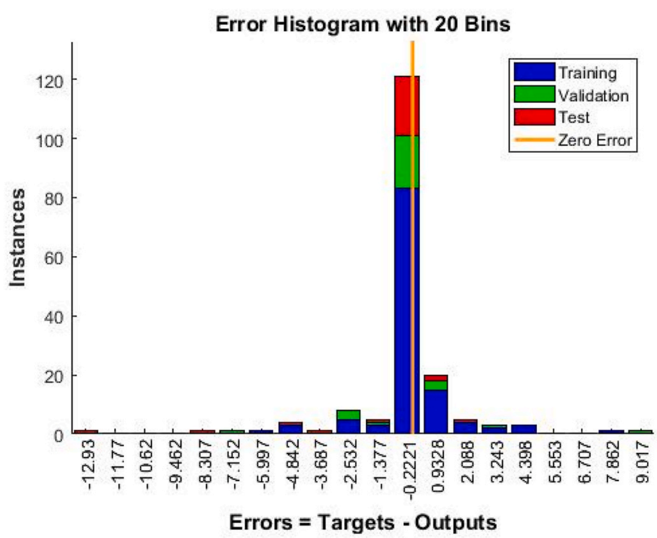

Fig. 9. Error histogram of Scaled Conjugate Gradient model.

relationship between the outputs and targets.

3.3. Time Series Modelling results

Out of the 44 experimental data, 30 were used to train the network, 7 for validation, and 7 for testing (Fig. 10). The R^2 value with training was 0.79444, R^2 value obtained with testing was 0.96118, R^2 value obtained after validation was 0.99115 and with the total number of sets the R^2 value was 0.8435. From Fig. 11, we can see that in the training state graph, the error gradually decreased with respect to iterations. Fig. 12 was prepared with "Mean Squared error" vs "7 epochs" showing best validation performance. The error between the predicted and targeted values trained in the neural network are shown in Fig. 13 as an error histogram. The negative value indicated how predicted values were different from targeted values. The basis of this method is the time series reversal of current time series values based on past values and past values of other variables. Since time series data points are obtained at neighboring time intervals, there is a probability that the observations will overlap. This is one of the characteristics that differentiate time-series data from transversal data. The greater R^2 value represents an accurate relationship between the previous values and future output values.

4. Discussion

ANNs are now a common way to predict MFC outputs.. As compared to control models, which can provide intermediate equations and phenomena in the system, ANNs can be very quickly and easily created, but since they are trained with unique output data, they cannot provide any additional output. The analysis of the weights of neurons in the network will, however, show the relationships between inputs and outputs. Such an examination will display the relative importance of inputs in the output creation. Results from the above study indicate that MFC-based sensor can increase the rate of phenol degradation as compared to others. During phenol degradation in the MFC-based sensor, the transfer of an electron to the terminal electron acceptor, oxygen in the cathode, instead of other electron acceptors such as metals and sulfate in the anaerobic anode chamber, suggest an indirect aerobic degradation (Morris and Jin, 2008). Thus, MFC based sensor has potential application in phenol treatment.

In our study, it was observed that the output voltage increasd initially due to the growth and metabolic activity of electroactive microbes. These results also indicate that the microbes used in this sensor possess phenol degradation capacity. Initially, the electroactive microbes used phenol as a substrate which lead to an increase in voltage. The phenol concentration slowly decreased due to the utilization of phenol inside the chamber, leading to a voltage drop. Up to a certain concentration, the microbes could use phenol as a substrate. Subsequently, the high concentration of phenol showed a toxic effect on the microbes. Now-a-days, the use of ANN model for the prediction of MFC output is very popular due to its accuracy and fast implementation. Both SCG and time series showed good results with R^2 values of 0.98802 and 0.99115, respectively. Both the models proved to be accurate in their prediction. The result of ANN and SCG showed a close correlation between the actual and predicted values, indicating that the ANN results can fit the actual experimental data completely. The correlation between actual and predicted values demonstrateed the good non-linear fitting effects of the model. R^2 and MSE values of the experiments were used to estimate the precision of the model. The R^2 value of 0.98802 indicated the excellent prediction of the model. These modeling results confirmed that the experimental values were very close to the predicted values. Therefore, this model was validated.

There are several reports on phenol being used as a substrate microbial fuel cell. Zhang et al. evaluated the performance of MFC based on anodic biofilm activity by analyzing the current output and phenol degradation rateThey used a graphite rod as both anode as well as a cathode. They found the phenol degradation rate was high with high columbic efficiency in graphite rod electrodes. It was reported that the electrogenic bacteria *Geobacter* sp. was involved in the phenol degradation (Zhang et al., 2017). Maallah et al. also analyzed the oxidation and detection of phenol using a novel electrochemical biosensor with a bacterial electrode. Here, they had modified the electrode to detect hazardous phenol. The electrode was prepared by using graphite carbon powder and natural phosphate powder and then the composite material was coated with polymer and bacteria inoculum. Polymer coating resulted in a loss of conductivity of the electrode and the microbial biofilm increased the rate of electrode activity and oxidation of phenol (Maallah and Chtaini, 2018). Hao et al. used microbial fuel cell technique to treat phenol in wastewater by using sulfonated polyether ketone as a proton exchange membrane. They used phenol as a substrate in the microbial fuel cell to treat the phenol and concluded that phenol at a particular concentration, i.e., below 50 gm/l can be removed completely using microbial fuel cell (Wu et al., 2018). Huzairy et al. also investigated phenol degradation using a microbial fuel cell. They used a microbial consortia isolated from industrial wastewater and domestic wastewater. The performance of MFC was successfully investigated for

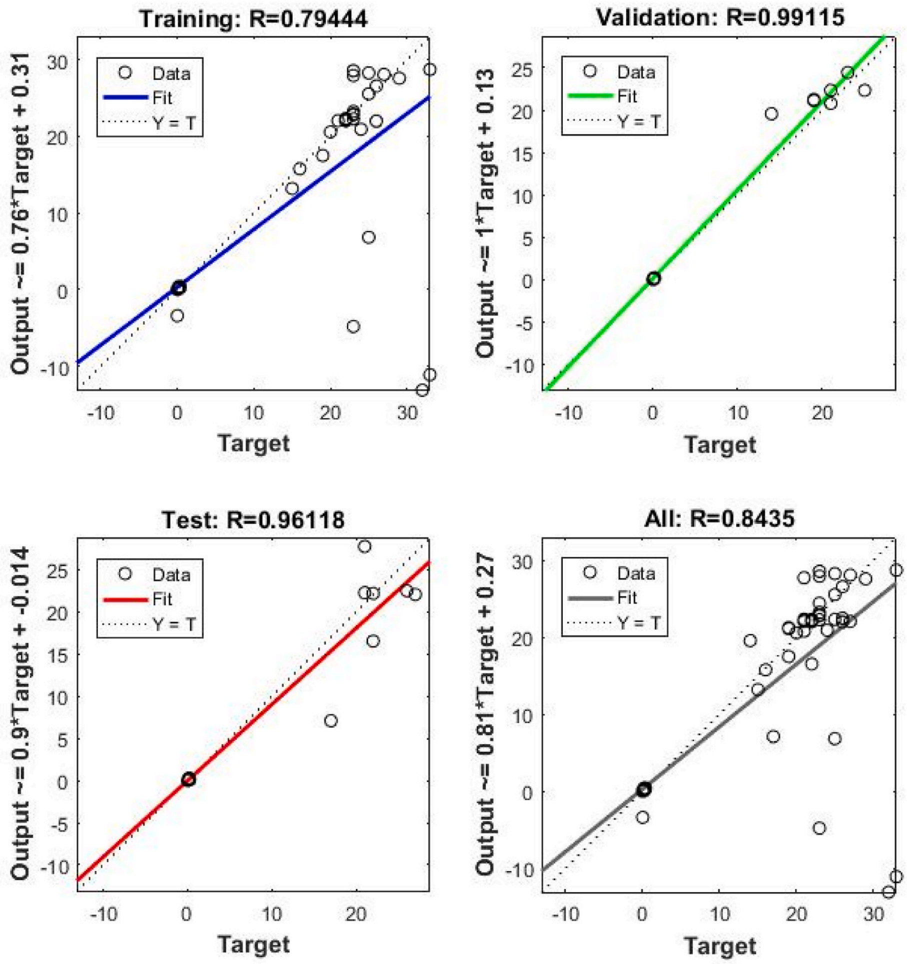

Fig. 10. Regression, training and Validation of Time Series model.

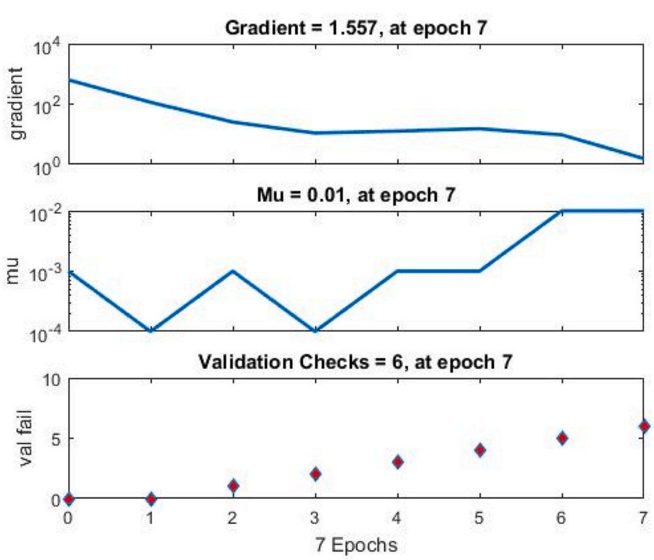

Fig. 11. Training state of Time Series model.

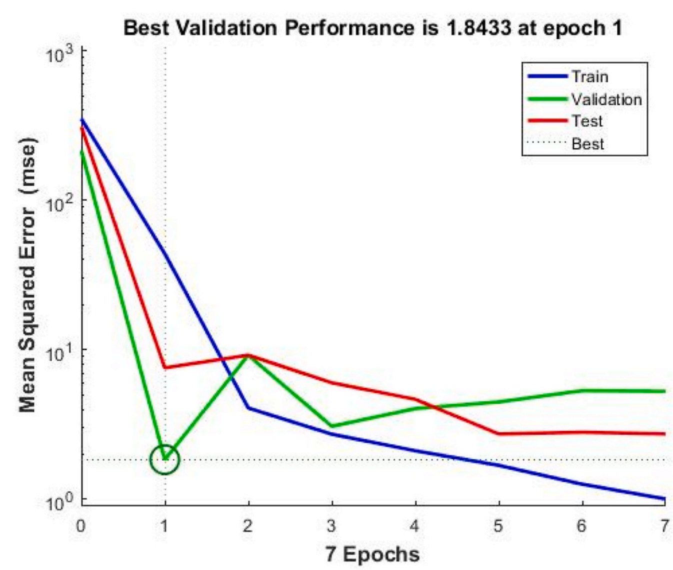

Fig. 12. Performance of time series model.

phenol degradation. Their research showed that domestic microbial consortia can effectively degrade the phenolic compounds. The domestic microbial consortia composed of microbes like *Shewanella, Arcobacter, Aeromonas, Acinetobacter, Cloacibacterium,* and *Pseudomonas* (Hassan et al., 2018). Maallah et al. prepared a bio-electrochemical biosensor for the detection of phenol degradation. They used a novel aluminum-based microbial electrode. They immobilized the bacteria upon the electrode surface, showing greater performance with effective degradation of

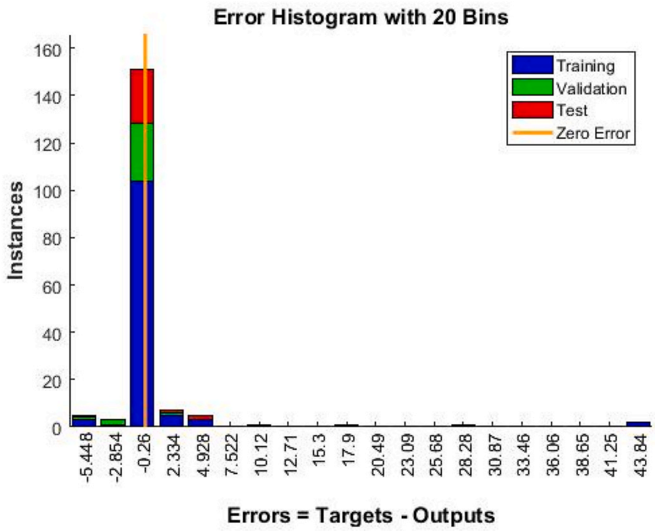

Fig. 13. Error histogram of Time Series model.

phenol (Maallah et al., 2019).

5. Conclusion

The experimental results indicated that the dual-chambered microbial fuel cell biosensor is appropriate for phenol detection. This biosensor was operated using microbes isolated from industrial waste water as a recognition element or sensing element and phenol was used as a sole substrate. This biosensor showed accuracy, good stability and high yielding capacity for phenol detection. The factor of time can be introduced as an aspect of future work in the ANN to estimate the MFC outputs as a time series. The development of this ANN form will be the first step in the development of an efficient MFC rapid reaction controller. As MFCs can change the voltage-current relation, traditional maximum power point tracking algorithms are inadequate, particularly if voltage overflow is observed. Mathematical modeling with SCG and time series model was done with 44 experimental data, where varying phenol concentrations and varying synthetic wastewater concentrations was used as variables to optimize the performance of MFC-based biosensor. Both models showed very good results with accuracy. It was concluded that varying the above variables in the hidden layer improved the prediction results performance with the same computational time even with an increase in the complexity of the algorithm. Time series modeling for MFC output results have not yet been reported. So this will be the first step towards designing an effective, fast responding controller for MFCs. The results demonstrated that this biosensor has the potential for toxicant detection; it is very cost-effective and appropriate for real-time monitoring.

Credit author statement

Sweta Naik:Conceptualization, Methodology, Data curation, Writing – original draft. Jujjavarapu Satya Eswari, Supervision, Writing-Reviewing and Editing, Visualization, Software, Investigation

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors are thankful to the National Institute of Technology Raipur, India, for providing the necessary facilities to prepare the manuscript and permission to publish it and DST-SERB for funding this research work under Project No. ECR/2016/001208.

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