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Performance evaluation of microbial fuel cell by artificial intelligence methods

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ABSTRACT

In the present study, performance of microbial fuel cell (MFC) has been modeled using three potential artificial intelligence (AI) methods such as multi-gene genetic programming (MGGP), artificial neural network and support vector regression. The effect of two input factors namely, temperature and ferrous sulfate concentrations on the output voltage were studied independently during two operating conditions (before and after start-up) using the three AI models. The data is randomly divided into training and testing samples containing 80% and 20% sets respectively and then trained and tested by three AI models. Based on the input factor, the proposed AI models predict output voltage of MFC at two operating conditions. Out of three methods, the MGGP method not only evolve model with better generalization ability but also represents an explicit relationship between the output voltage and input factors of MFC. The models generated by MGGP approach have shown an excellent potential to predict the performance of MFC and can be used to gain better insights into the performance of MFC.

1. Introduction

Microbial fuel cell (MFC) is an electrochemical device that converts the chemical energy in organic wastes into electricity by means of catalytic activities (reactions) of living microorganisms (Wei, Yuan, Cui, Han, & Shen, 2012). The phenomenon of generation of electricity from the contaminants in wastewater could provide environmental and economic benefits. Researchers have conducted several studies on power generation from the organic wastes in water. MFC technology has promising benefits but its practical implementation is limited due to low power generation, low energy efficiency as well as high material costs involved. According to recent developments in microorganisms, electrodes, operating conditions, matrix, ionic strength, different substrates and electrochemical characteristics, it was found that both microorganism as well as a biological factors has a significant impact on the power generation and thus responsible for the successful implementation of MFC (Logan et al., 2006).

Researchers pointed out that number of factors influence the power generation in MFC. One such factor is temperature which directly influences growth and reproduction of microorganism thus affecting intracellular and extracellular chemical process. Experimental studies are often conducted to determine the effect of various factors that influence the performance of MFC. The effect of temperature and anode media on the performance of MFC was studied by Min, Roman, and Angelidaki (2008). The maximum power density estimated at temperatures 30 °C and 22 °C was found to be 70 mW/m^2 and 43 mW/m^2 respectively. It was also noticed that at 15 °C, there was no power generation. The reason for this behavior of MFC can be that the catalytic activity of microorganism could have become inactive at 15 °C. Similar behavior of MFC was observed by Zhang and Shen (2006). It can be observed from this study that the microbial activity became inactive at 50 °C. Enhanced performance of the MFC is observed in the temperature range of 25–45 °C. Wei et al. (2012) studied the effect of temperature and hydraulic retention on the performance of a two-chambered MFC. Their studies showed that the MFC exhibited a rapid start-up for high substrate concentrations and was able to generate maximum power for long period of time.

It is also important to note that though experiments can satisfactorily determine the influence of various factors on the performance characteristics of fuel cell, limitations exists on the factors of cost and time required to perform the experiments. To overcome this limitation, several studies focused on developing mathematical models for estimating the performance of MFC (Choi, Jung, Kim, & Jung, 2003; Picioreanu, Katuri, van Loosdrecht, Head, & Scott, 2010; Pinto, Srinivasan, Manuel, & Tartakovsky, 2010; Pinto, Tartakovsky, & Srinivasan, 2012; Sousa & Gonzalez, 2005; Yao et al., 2004). These mathematical models (Vijayaraghavan & Wong, 2013a; Wong & Vijayaraghavan, 2012b) prove to be an effective tool for investigating the influence of various factors on MFC per-

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formance in addition to being cost effective and less time consuming (Oliveira, Simões, Melo, & Pinto, 2013). The mathematical models are generally formulated using differential and algebraic equations (Vijayaraghavan & Wong, 2013b; Wong & Vijayaraghavan, 2012a) and their derivation is based on the different phenomenon taking place inside the MFC. Although, these models provide accurate prediction, the formulation of these models requires a thorough knowledge on the functionality and the configuration of the MFC system.

Application of soft computing methods such as genetic programming (GP), artificial intelligence (AI), fuzzy logic and neural networks can be used as an alternative method for modeling complex physical non-linear systems such as a fuel cell system. These methods require input training data which can be obtained from the experimental data that is based on a specific design and operating condition of a fuel cell. Based on the input, the soft computing method can then be able to generate meaningful solutions for complicated problems (Castelli, Vanneschi, & Silva 2013; Garg, Rachmawati & Tai, 2013a; Garg, Tai, Lee, & Savalani, 2013b; Nazari, 2012; Peteiro-Barral, Guijarro-Berdiñas, Pérez-Sánchez, & Fontenla-Romero, 2013).

Additionally, among the various soft computing methods described above, GP offers the advantage of a fast and cost-effective explicit formulation of a mathematical model based on multiple variables without any pre-definition of non-linear structure of the model (Al-Sahaf, Song, Neshatian, & Zhang, 2012; Giot, & Rosenberger, 2012; Kala, 2012; Kovacic & Brezocnik, 2003; Mabu, Hirasawa, Obayashi, & Kuremoto 2013; Mabu, Tjahjadi, & Hirasawa, 2012; Milfelner, Kopac, Cus, & Zuperl, 2005; Tsakonas, 2013; Tsakonas & Gabrys, 2012). The analytical model hence obtained can then be used by fuel cell developers to optimize the performance of their fuel cell based on specific operating conditions. It is to the best of authors' knowledge that limited or no work exists on the application of soft computing methods on the performance prediction of an MFC system. Hence, in the present study, the performance characteristics of a MFC is modeled using three soft computing techniques viz., multi-gene genetic programming (MGGP), support vector regression (SVR) and artificial neural network (ANN). These methods are applied to model the operating voltage of MFC based on two input parameters (temperature and ferrous sulfate concentrations) at two operating conditions such as before start-up (BS) and after start-up (AS). An explicit formulation is derived for the output voltage as a function of time and each input parameter (temperature and ferrous sulfate concentrations) for BS and AS operation of MFC. Additionally, the performance of MGGP method to those of SVR and ANN has been compared. The remainder of this paper is organized as follows. In Section 2, the experimental details of the MFC are discussed in brief. In Section 3, three AI methods namely the MGGP, SVR and ANN are discussed and applied to data collected in Section 2. In Section 4, the performance of three AI methods is compared. Finally, Section 5 concludes with the recommendations for future work.

2. Experimental details

2.1. Data collection from microbial fuel cell (MFC)

The experimental data was collected from the literature and used to train and test different AI models (Wei et al., 2012). The data obtained from the experiment comprise of two input parameters namely, temperature and ferrous sulfate concentrations and output parameter voltage. The experimental description is provided as discussed in (Wei et al., 2012). Experiments were performed on two-chambered MFC comprising of two plexiglass bottles, which served as an anode and a cathode, each with an operating volume of 1 L. The carbon paper (5 × 5 cm each), proton exchange membrane (PEM), adjustable resistor and data acquisition system (DAS) were used in the system. In order to study the effects of different temperatures and ferrous sulfate concentrations on MFC performance, the experiments were divided into two series.

Table 1
Input parameter considered for each operating condition (Wei et al., 2012).

No.	Operating condition	Input parameter	Unit
1	BS	Temperature	°C
2	AS	Temperature	°C
3	BS	Ferrous sulfate concentration	mg/L
4	AS	Ferrous sulfate concentration	mg/L

To explore the effect of different temperatures on MFC performance, the MFC was operated at five different temperatures of 40, 35, 25, 20, or 15 °C identified as M_T1, M_T2, M_T3, M_T4 and M_T5, respectively. To study the effect of ferrous sulfate concentrations on MFC performance, experiments were divided into four groups identified as $M_{Fe}1$, $M_{Fe}2$, $M_{Fe}3$ and $M_{Fe}4$ with ferrous sulfate at concentrations increment of 50, 100, 200 and 400 mg/L in anolyte respectively. The MFC was operated in a batch mode. Each experiment was repeated at least three times with all data reported as the average of replicate experiments. The external resistance of the set was initially 99999.9 U and this was changed to 2000 U after 48 h of operation. After the internal resistance test (the time period between 50 and75 h), the external resistance was changed to 1000 U and all tests were operated under this condition for 525 h (Wei et al., 2012).

2.2. Data preparation for training of the three AI models

The voltage was measured as a function of time and each input parameter independently for before start-up (BS) as well as after start-up (AS) operating condition. Table 1 shows the input parameter considered for the two operating conditions. For measuring temperature effect on fuel cell performance, 95 and 60 data samples were obtained for BS and AS operating condition respectively. For measuring concentration effect on fuel cell performance, 76 and 60 data samples were obtained for BS and AS operating condition respectively. In this way we have four set of data samples. For better training of models, each data set is divided randomly into training and testing data of 80% and 20% respectively. In the following section, the AI methods are discussed and applied to this set of data.

3. Artificial Intelligence Methods

3.1. Multi-gene genetic programming

This section gives an overview of the theory and principle of the genetic programming (GP) method followed by discussion on the multi-gene genetic programming method (MGGP). GP based on principle of Darwinian natural selection generates computer programs or models for solving regression problems. The extension of genetic algorithms (GAs) is GP. The only difference between GP and GA is that the solutions are represented by tree structures in GP while the solutions are represented in string form in GAs. In brief, the GA is parameter optimization while GP is structural optimization method. For proper selection of subset for training and testing, various performance evaluation methods such as Kennard-stone algorithm, cross validation methods etc. can be applied. The initial population of models/trees is randomly created by combining elements of function and terminal sets. The elements of function and terminal set are chosen by user. A function set F con-