Journal of New Materials for Electrochemical Systems
Vol.25, No.1, January 2022, pp. 72-78
Journal homepage: http://iieta.org/journals/jnmes

Improve microbial fuel cell efficiency using receding horizon predictive control

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https://doi.org/10.14447/jnmes.v25i1.a10

Received: November 21, 2021
Accepted: January 05, 2022

Keywords: *microbial fuel cell; renewable energy; predictive control; receding horizon; stability; uncertainty; unknown parameters*

ABSTRACT

One of the promising technologies in the field of clean and renewable energy is the microbial fuel cells, which in addition to generating electrical energy from the metabolism of microorganisms, can also be used to improve the environment in wastewater treatment. In fact, this paper designs an integrated control model that in the presence of uncertainty and unknown parameters can consider the effect of input variables for two-population in a chamber. In addition to maintaining closed loop stability, it has acceptable behavior in terms of time to reach steady state and reduce system error and provide satisfactory performance in terms of output energy. Lyapunov analysis ensures system stability and system control functions are demonstrated by MATLAB / Simulink simulations.

1. INTRODUCTION

Most of the electricity needed by human societies is currently supplied by non-renewable sources such as fossil fuels and nuclear energy. Along with the rapidly increasing demand for electricity due to the industrialization of global life and population growth, the high pollution of these methods along with the depletion of existing resources, is one of the most important factors in encouraging scientists to study new technologies to make more use of renewable resources in electricity generation. In the last few decades, extensive research has been done in the field of technologies related to renewable energy such as biomass, solar energy, geothermal, wind energy, and etc., in addition to meeting the demand for energy at a reasonable price, the upward trend of global warming can be reduced by reducing the level of carbon emissions from fossil fuels such as natural gas and coal, etc. [1-4]. In fact, the best way to balance the reduction of energy production by fossil fuels is to develop the use of renewable energy sources. On the other hand, energy produced from renewable sources is pure, efficient and environmentally friendly [1]. One of the effective ways in this field that can be both productive is the extraction of energy from waste (organic or inorganic), which is also a solution to remove the limitations of energy generation and prevent environmental pollution. As a result, fuel cell (FC) and microbial fuel cell (MFC), which have the ability to convert chemical energy into electrical energy, have received more attention in recent years. Because compared to other mentioned sources, it has the highest efficiency and does not produce any polluting gas. Microbial fuel cells are complementary to fuel cells and are considered as suitable devices for converting biochemical energy into electrical energy [5].

We know that most wastewater treatment technologies are inefficient, costly and unsustainable. On the other hand, industrial growth in the modern world and increasing population density in industrial societies have increased water pollution and made the optimal wastewater treatment plan one of the most important problems in developed and developing countries in recent years. Therefore, more attention has been paid to the use of more advanced technologies and development in wastewater treatment [6]. Sewage is the meeting place of complex types of microorganisms such as Shewanella putrefaciens, Proteobacteria, microorganisms Pseudomonas, G. Sulferredunces, E. coli, Firmicutes and Proteus vulgaris, etc. [3] which are generally fermentative, metanogenic and anodophilic [7]. The conversion of biochemical energy into electricity can be done by microbial fuel cells i.e. electricity is produced from wastewater that is full of microorganisms and bacteria [8]. The main elements of MFCs are anode, cathode, substrate, membrane and bacterial species in two parts of anode chamber (including electrode, microorganisms, substrate anolite under anaerobic conditions) and cathode chamber (including electrode, electron acceptor and catalyst with aerobic conditions and anaerobic) [9-10]. Bacteria facilitate the transfer of electrons from the anode in two direct ways (by means of intracellular mediation or the use of nanowires) and indirectly (by means of external electrical connection) [11-12]. In this case, the force is extracted and fresh water is collected by combining electrons and protons. Platinum or microorganisms are used as catalysts in the cathode part and these two parts are separated by the interface membrane [10]. Figure 1 shows an anode-based single Chamber two-population MFC without the use of an intermediate membrane.

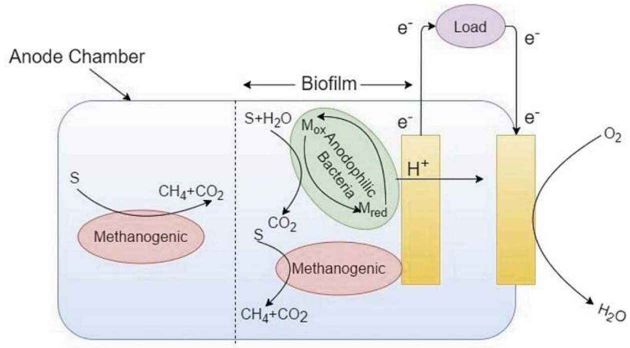

Figure 1. Single Chamber two-population MFC

Higher conversion rates, the ability to generate electricity and efficiency at ambient temperature are the three main reasons for replacing this method with conventional wastewater treatment methods [13-15]. For the oxidation of the substrate in the MFC anode chamber, due to the different bacterial species such as acetate, glutamate (glucose), surface water, propionate, ethanol, rebuttal, etc., which are responsible for the production of positive and negative ions, more than Glucose and acetate are used [16-17]. The performance of MFCs in this area depends on two categories of parameters: design parameters and operational parameters. The size, material and surface of the electrodes, the size of the biofilm, the types of electron donors, the internal losses and the types of membranes, etc. are in the first category. Bacterial growth rate, temperature, amount of acid (pH) in the anode chamber, effective substrate concentration, external resistance, etc. are in the second category [18-21]. The second category parameters affect the performance of MFC in terms of voltage and power density.

The best way to facilitate the analysis of the effect of different parameters on the performance of any complex dynamic system is mathematical modeling [22-23]. Cultures of microorganisms (pure or multiple bacterial cultures), reactions in chambers, and substrate supply modes are the basis for modeling MFCs [24]. The operation of MFCs must be performed under controlled conditions to provide stable output with optimal performance. Since this technology is still in the laboratory stage, more and more research should be done on it and different mathematical models for this system should be obtained to determine the relationships between parameters, inputs, outputs and system behavior and therefore apply different control strategies to MFCs. For example, in [25] two-chamber MFC mathematical modeling with one bacterial species and in [26-27] single- chamber MFC modeling with two bacterial species are described. So far, different modeling has been applied to these systems along with different control schemes. For example, in [28] with digital changes due to electric charge, ambient temperature and discharge in the substrate and the use of microcontrollers for MFC stack and controlled output voltage at a constant level, a sample discrete time controller is designed. [29] describes the PID-fuzzy controller design for MFC with two-chamber for constant output voltage; and [30-31] introduce adaptive compensator-based control in the presence of parametric uncertainty for better performance. In [32-33] predictive mode controller and adaptive fuzzy techniques under temperature disturbances are used. These controllers and other similar methods have been developed for different types of MFC models.

To find the overall function of MFCs, their dependence on microorganisms must be considered. In [25-26] single chamber MFC models are presented. [27] introduced thermophilic and methanogenic chambers with anode-based MFC model in four sets, so that two sets have been developed for parameter estimation and the other two sets for model validation. This validation is performed by connecting an external resistor between the anode and cathode terminals and the announced result indicates that the proposed model will be suitable for real-time process control. [34] accurately model methanogenic microorganisms, as they can reduce the overall columbic efficiency as well as the amount of electricity produced. In this paper, this challenging and important two-chamber sample is examined. This choice is negligible for reasons such as uniform distribution of bacterial species, without significant changes in temperature and pH in practice, assuming gas transfer values through cathode elements and the bed gradient in the biofilm. Precise mathematical modeling and chemical reaction and dynamics of the MFC system are described in [31] and [35].

In this paper, the receding horizon control (RHC) or predictive model control (MPC) method is used [36]. In this strategy, at any time, the first element of the input path is selected to optimize the performance of the index. [37-40] show that due to the lack of limitations about the model used in the prediction, many formulations can be created for linear and nonlinear systems. Using a linear model and a second-order objective function, the nominal MPC algorithm transforms itself into a structured second-order convex (QP) program and the algorithm provides a reliable solution with the best convergence mode. The online computational complexity of this method is a major concern in nonlinear systems, especially if we have to fast sampling or higher order systems. Because the numerical techniques used to solve the optimization problem may be longer than the time available for online computing. To solve this problem, we can use MPC extended semi-definite programs for nonlinear systems, linear dynamic approximation with approximation error bounds [41-42], etc. In recent years, the method of using the minimum-maximum formulation with quadratic criteria has been proposed as linear matrix inequality (LMI) optimization [43-44]. This method is very flexible in allowing many parts of the design do's and don'ts, such as the size and structure of the matrix, the degree of exponential stability, the time delay and etc. In this paper, we want to use LMI capabilities in accordance with MPC-based techniques for a two-chamber microbial fuel cell system with a bacterial species.

In this paper, to apply effective MFC control by collecting appropriate parametric ranges, an LMI-based predictive model control method is presented for single-chamber MFC with state space model. In the presence of unmodulated uncertainties, this design reduces the time to steady state and aggregation of the system error by maintaining the stability of the closed-loop system, which was investigated by Lyapunov analysis, and its performance on the MFC system is confirmed by simulation. They are used to ensure the performance, asymptotic stability and robustness of the nonlinear dynamic system in the presence of uncertainty parameters at certain reasoned limits. The proposed predictive control method improves the performance of MFC under parametric uncertainties and effectively estimates uncertain parameters online.

The paper is organized as follows: In the second part, a two-chamber MFC control model with a bacterial species is presented. In the third part, the control strategy and design of the LMI-based model predictive control are described and in the fourth part, the simulation results are studied. In the fifth section, the conclusion is stated.

2. THE PROPOSED LMI-BASED MODEL PREDICTIVE CONTROL

This section describes the proposed LMI-based predictive model control method. The control law $u(k)$ designed through the prediction model ensures the stability of the manifold pressure error of the power supply. For this purpose, Equation (4) defines the desired error vector, such that $i = 1, 2, 3$:

$$e_i(k) = x_i(k) - x_{id} \quad (4)$$

And according to the dynamic equation of the system (2), the dynamic equations of the error will be as follows:

$$e(k+1) = Ae(k) + Bu(k) + \delta(e(k)) \quad (5)$$

δ (x, k) is the Lipchitz nonlinear constant related to the model uncertainty. To satisfy the following constraint, we need state and control variables:

Where $\mathbb{X}$ and $\mathbb{U}$ are compact sets of R^n and R^m that contain both origins as an interior point. To design a state-feedback control rule $u(k+i|k) = L(k)x(k+i|k)$ $(i \geq 0)$ for (5), one way to minimize the problem with respect to u (.) is the infinite horizon cost function by using of Equation (7):

$$J(K) = \sum_{i=0}^{\infty} e(k+i|k)^T Q e(k+i|k) + u(k+i|k)^T \mathscr{R} u(k+i|k) \quad (7)$$

So that equation (5) is satisfied; Q and $\mathscr{R}$ are definite positive weight matrices. Here we introduce a quadratic function $V(x) = e^T P e$ with condition $P > 0$ corresponding to the state $e(k|k)$ of the system expressed in (5) with initial value$V(0) = 0$. If we assume the sampling time k, an inequality (8) will be obtained:

$$V(k+i+1|k) - V(k+i|k) \geq -e(k+i|k)^T Q e(k+i|k) + u(k+i|k)^T \mathscr{R} u(k+i|k) \quad (8)$$

By summing (8) from $i = 0$ to $i = \infty$ we will have:

$$e(\infty|k)^T P e(\infty|k) - e(k|k)^T P e(k|k) \geq -J \quad (9)$$

We know that if the closed-loop system of Equation (5) is stable, then $e(\infty|k)$ must be zero, and then we have:

$$J \leq e(k|k)^T P e(k|k) \leq -\gamma \quad (10)$$

Where γ is a positive number and is considered as the upper bound of Equation (7); Then:

$$\sum_{i=0}^{\infty} e(k+i|k)^T Q e(k+i|k) + u(k+i|k)^T \mathscr{R} u(k+i|k) \leq \gamma \quad (11)$$

Before entering into the continuation of the discussion, let us state the lemma (1) and lemma (2), the proofs of which are given in [47] and [48], respectively. lemma (1), which is related to the Schur supplement in relation to LMI, is expressed as (12):

$$\begin{bmatrix} Q(x) & S(x) \\ S(x)^T & R(x) \end{bmatrix} > 0 \quad (12)$$

Where $Q(x) = Q(x)^T$ and $R(x) = R(x)^T$ and $S(x)$ are functions of x and are equivalent to:

$$R(x) > 0,\ Q(x) - S(x)R(x)^{-1}S(x)^T > 0 \quad (13)$$

Of course, this equation can also be written in another way:

$$Q(x) > 0,\ R(x) - S(x)Q(x)^{-1}S(x)^T > 0 \quad (14)$$

If M and N are real constant matrices and P is positive matrix of compatible dimensions, Lemma (2) will be expressed as follows:

$$M^T P N + N^T P M \leq \varepsilon M^T P M + \varepsilon^{-1} N^T P N \quad (15)$$

Which is true with the condition $\varepsilon > 0$.

One of the problems with MPCs in minimization is the timely detection of duplicate inputs, which we propose a convex optimization method to solve. In such a way that instead of being minimum in (7), we minimize its upper bound. For the nonlinear discrete time system (5), the upper bound is minimized by a feedback-state control in the form $u(k+i|k) = L(k)e(k+i|k)$ $(i \geq 0)$ and then give a representation of MPC law in terms of feasible solutions to LMIs.

To form the L matrix, which is the state-feedback matrix, we use the following theorem:

Theorem (1)

For all times k, consider the discrete time system (5) and assume that $e(k|k)$ is the measured states of $e(k)$. Then the state-feedback matrix L in the control law is obtained by minimizing the upper bound of $V(e(k|k))$ in the objective function and is represented at all times k as $L = YX^{-1}$, where it is always $X > 0$. In this relation, Y is obtained by solving the following optimization problem in terms of the given variables

γ, ξ, X, Y and $Z = [X; Y]$. (16)

$$\min_{\gamma,\xi,X,Y} \gamma$$

Provided that (17) and (18) are always met.

$$\begin{bmatrix} -I & * \\ x(k) & -X \end{bmatrix} \quad (17)$$

z

Proof

To reach (18), we must first edit the quadratic function V to satisfy the desired conditions as follows:

$$\begin{bmatrix} -X & * & * & * & * \\ \sqrt{(1+\varepsilon)}(AX+BY) & -X & * & * & * \\ \sqrt{\left(1+\frac{1}{\varepsilon}\right)}WZ & 0 & -\varepsilon I & * & * \\ Q^{1/2}X & 0 & 0 & -\gamma I & * \\ R^{1/2}Y & 0 & 0 & 0 & -\gamma I \end{bmatrix} \quad (18)$$

$$V(k+i+1|k) - V(k+i|k) \le e(k+i|k)^T Q e(k+i|k) + u(k+i|k)^T \mathscr{R} u(k+i|k) \quad (19)$$

Then by substituting the state space (5) into an inequality (19) we have:

$$u(k+i|k)^T \mathscr{R} u(k+i|k) + e(k+i|k)^T Q e(k+i|k) - e(k+i|k)^T P e(k+i|k) + \{Ae(k+i|k) + Bu(k+i|k) + \delta(e(k+i|k))\}^T \times P\{Ae(k+i|k) + Bu(k+i|k) + \delta(e(k+i|k))\} < 0 \quad (20)$$

Now we define the function $h(e, u)$ as follows:

$$h(e, u) = \{Ae(k+i|k) + Bu(k+i|k) + \delta(e(k+i|k))\}^T P \times \{Ae(k+i|k) + Bu(k+i|k) + \delta(e(k+i|k))\} = \{Ae(k+i|k) + Bu(k+i|k)\}^T P\{Ae(k+i|k) + Bu(k+i|k)\} + \{Ae(k+i|k) + Bu(k+i|k)\}^T \times P\{\delta(e(k+i|k))\} + \{\delta(e(k+i|k))\}^T P\{Ae(k+i|k) + Bu(k+i|k)\} + \{\delta(e(k+i|k))\}^T \times P\{\delta(e(k+i|k))\} \quad (21)$$

And using lemma (2) and considering that $P \le \lambda_{max} I \le \mu I$, we can define the upper bound of $h(e, u)$ as follows:

$$h(e, u) \le (1+\varepsilon)\{Ae(k+i|k) + Bu(k+i|k)\}^T P \times \{Ae(k+i|k) + Bu(k+i|k)\} + (1+\varepsilon^{-1})\{\delta(e(k+i|k))\}^T P \times \{\delta(e(k+i|k))\} \quad (22)$$

In the proposed equation λ_{max} is the eigenvalue of the maximum P and μI of the upper bound, so we have:

$$h(e, u) \le (1+\varepsilon)\{Ae(k+i|k) + Bu(k+i|k)\}^T P \times \{Ae(k+i|k) + Bu(k+i|k)\} + (1+\varepsilon^{-1})\mu\{\delta(e(k+i|k))\}^T P \times \{\delta(e(k+i|k))\} \quad (23)$$

Since the relations related to $\delta(.)$ in the above equation are finite, i.e.

$$\{\delta(e(k+i|k))\}^T \delta(e(k+i|k)) \le [e(k+i|k)^T u(k+i|k)^T] W^T W [e(k+i|k), u(k+i|k)] \quad (24)$$

Then

$$h(e, u) \le (1+\varepsilon)\{Ae(k+i|k) + Bu(k+i|k)\}^T P \times \{Ae(k+i|k) + Bu(k+i|k)\} + (1+\varepsilon^{-1})\mu[e(k+i|k)^T u(k+i|k)^T] W^T W [e(k+i|k), u(k+i|k)] \quad (25)$$

To satisfy Equation (22) for all i≥0s, the following relation must be guaranteed to be negative:

$$u(k+i|k)^T R u(k+i|k) + e(k+i|k)^T Q e(k+i|k) - e(k+i|k)^T P e(k+i|k) + (1+\varepsilon)\{Ae(k+i|k) + Bu(k+i|k)\}^T P \times \{Ae(k+i|k) + Bu(k+i|k)\} + (1+\varepsilon^{-1})\mu[e(k+i|k)^T u(k+i|k)^T] W^T W [e(k+i|k), u(k+i|k)] < 0 \quad (26)$$

By placing $u(k+i|k)$ with $Le(k+i|k)$, and rewrite the relation (26):

$$(1+\varepsilon)e(k+i|k)^T (A+BL)^T P (A+BL) e(k+i|k) - e(k+i|k)^T P e(k+i|k) + e(k+i|k)^T Q e(k+i|k) + e(k+i|k)^T L^T R L e(k+i|k) + (1+\varepsilon^{-1})\mu e(k+i|k)^T [I L^T] W^T W [I, L] \times e(k+i|k) < 0 \quad (27)$$

Which is valid for all $i \ge 0$; If

$$(1+\varepsilon)(A+BL)^T P (A+BL) - P + QL^T RL + (1+\varepsilon^{-1})\mu[IL^T] W^T W [I, L] < 0 \quad (28)$$

If substitutions are made for $X = \gamma P^{-1}$, $X > 0$ and $Y = Lx$, as well as $\xi = \gamma\mu^{-1}$, before and after multiplying X by (28) and using the Schur supplement provided that $-X + \xi I \le 0$ is valid, we can rewrite (28) as follows:

$$\begin{bmatrix} -X & * & * & * & * \\ \sqrt{1+\varepsilon}(AX+BY) & -X & * & * & * \\ \sqrt{\left(1+\frac{1}{\varepsilon}\right)}WZ & 0 & -\xi I & * & * \\ Q^{\frac{1}{2}}X & 0 & 0 & -\gamma I & * \\ R^{\frac{1}{2}}Y & 0 & 0 & 0 & -\gamma I \end{bmatrix} \le 0 \quad (29)$$

Note that the * symbol in the above matrix represents the symmetric expressions in Equation (29). Using the Schur supplement we have:

$$\begin{bmatrix} -I & * \\ x(k) & -X \end{bmatrix} \le 0 \quad (30)$$

By solving the inequalities (24) and (25), the problem of convex programming (7) can be solved with the benefit of L feedback. The stability of the system defined according to Equation (5) is guaranteed by the obtained control law. In this algorithm, using the immutable elliptic set $S = \{e | e^T X^{-1} e \ e \le 1\}$, the stability range is obtained and is evaluated in a new iteration unit. Therefore, convergence to the local minimum at any sampling time is guaranteed for the proposed algorithm.

3. SIMULATION RESULTS

To analyze and evaluate the performance of microbial fuel cells, it is necessary to design advanced control techniques by considering parameters in the presence of uncertainty. The proposed control scheme of this paper is a LMI based model predictive controller. The performance of such a controller under parametric uncertainty and uncertainty has been compared in simulation with an adaptive control method under similar modeling conditions and more suitable results have been obtained through it. To confirm the effectiveness of the proposed design, the model is simulated by MATLAB/Simulink and the results are presented in the following figures. The control parameters related to LMI are recorded as follows:

$$Q = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (31)$$

$$R = 1$$

$$W = \begin{bmatrix} 0.001 & 0 & 0 \\ 0 & 0.001 & 0 \\ 0 & 0 & 0.001 \end{bmatrix}$$

$$\varepsilon = 0.01$$

The variablesθ_1 and θ_2 are also considered as uncertainty.

$$\theta_1 = \begin{cases} 0.5 & if\ t > 2 \\ 1.4 & otherwise \end{cases} \quad (32)$$

$$\theta_2 = \begin{cases} 0.3 & if\ t > 2 \\ 0.1 & otherwise \end{cases}$$

Now we can compare the behavior of the three main variables of our state space, namely $x_1(t)$, $x_2(t)$and $x_{13}(t)$with a nonlinear adaptive controller with similar conditions, as shown in Figures (2), (3) and (4). The goal is to adjust the state space variables and bring them to zero equilibrium points. As a law, a controller that can reach the state variable to zero in less time has a better function and is more suitable. This comparison is performed in Table (2).

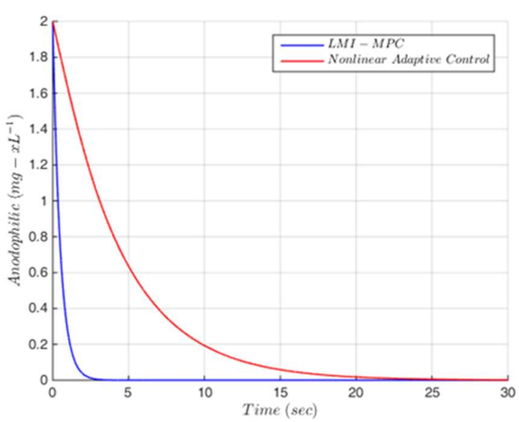

Figure 2. Trajectory of $x_1(t)$ under proposed LMI based MPC and nonlinear adaptive control

As shown in Figure 2, the first state variable has reached equilibrium in a much shorter time compared to the nonlinear adaptive controller, indicating the strength and efficiency of proposed design. Achieving steady state in less than three seconds versus more than twenty seconds to reach steady state in adaptive method announces the strength and efficiency of proposed LMI based controller. In the following, we will express this trend for other state variables as well.

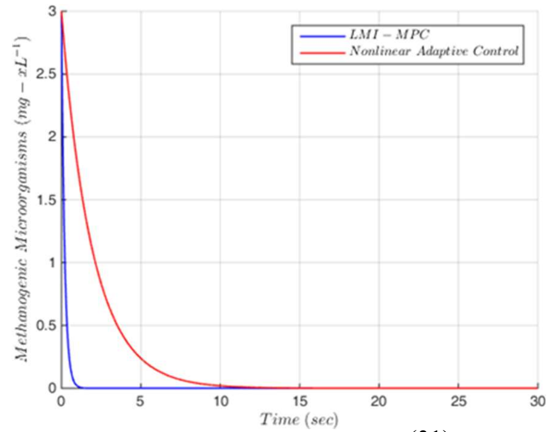

Figure 3. Trajectory of $x_2(t)$ under proposed LMI based MPC and nonlinear adaptive control

Figure (3) clearly shows that second state variable has reached a steady state of equilibrium in less than two seconds. Compare this time with a nonlinear adaptive controller that took about ten seconds to reach equilibrium. So in the case of the second variable, the proposed method has shown more power and efficiency.

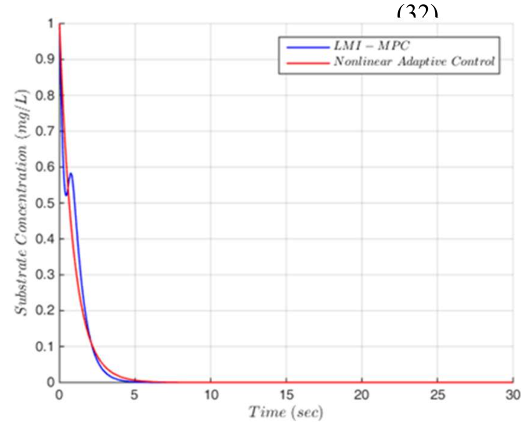

Figure 4. Trajectory of $x_3(t)$ under proposed LMI based MPC and nonlinear adaptive control

In Figure (4), we have examined the third variable of the state, namely the substrate concentration. In this case, although the time difference between the two control methods is small, but still the proposed LMI based MPC method reaches a stable equilibrium state about two seconds earlier. These results can be carefully observed and examined in Table (2).

Table 2: time comparison to reach the steady state in the proposed and the adaptive methods

	$x_3(t)$	$x_2(t)$	$x_1(t)$
Time to reach steady state in the proposed design	4s	2s	3s
Time to reach steady state in the adaptive method	5s	11s	23s

The figures and table above clearly show that reaching the steady state in the proposed method is much less than the adaptive controller, although the time to reach the steady state is close in the case of substrate concentration. The second point in the figures is that there is less error than the adaptive method used for comparison, which serves as another strength for the proposed layout. It is quite clear that the system behavior with the LMI predictive model controller has less error compared to the nonlinear adaptive controller and reaches a stable equilibrium state in a much shorter time.

Another issue to compare is the control signal. As shown in Figure (5), the control signal in the nonlinear adaptive controller has a very small value and is considered with a coefficient of 10^{-4}. This means that the controller is passive and inactive and it could not display the proper control behavior and have not the correct control behavior, but in the proposed control method, the value of the control signal is close to 1 and on the other hand controls the system in less than 5 seconds.

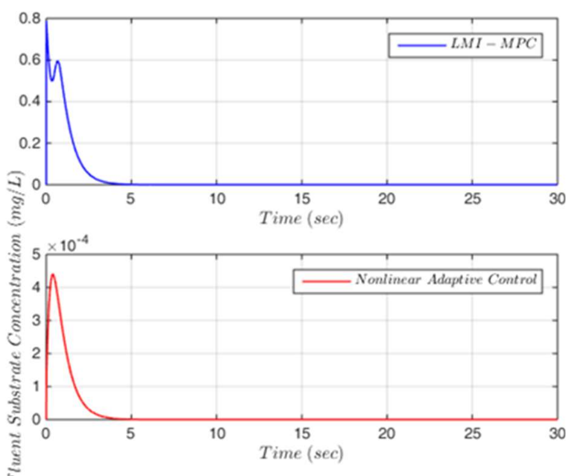

Figure 5. Control Signal obtained through proposed LMI based MPC and nonlinear adaptive methods

In general, what is achieved in simulation is that the proposed design behaves efficiently, robustly and reliably due to much less time to achieve stable equilibrium, less error value and proper control signal size compared to nonlinear adaptive controller.

4. CONCLUSION

The development of model-based control strategies and their optimization by considering different parameters has been very important to analyze the behavior and performance of complex MFC systems. In this paper, efforts to develop modeling in MFCs have been compared and discussed in terms of bacterial species, enclosure modeling and different modeling methods. To apply the effective control of MFC, by collecting the appropriate parametric ranges, a LMI based model predictive control is designed for MFC with nonlinear state space model. This design reduces the steady state reaching time and the error and confirms its performance on the MFC system through simulation in the presence of unmodulated uncertainties, in addition to maintaining the stability of the closed-loop system which is investigated by Lyapunov analysis.

ACKNOWLEDGEMENT

This work was financially supported by the Priority Discipline Construction Program of Jiangsu Province (Grant No. 2016-9), the Top-notch Academic Programs Project of Jiangsu Higher Education Institutions (Grant No.2020-9), the Key R & D Plan of Jiangsu Province (Grant No.BE2018010-4), and the Young and middle-aged scientific research backbone of NIT (Grant Nos. ZQNGG305, ZQNGG102).

REFERENCES

[1] P. Choudhury, U.S.P. Uday, N. Mahata, et al., Performance improvement of microbial fuel cells for waste water treatment along with value addition: a review on past achievements and recent perspectives, Renew. Sustain. Energy Rev. 79 (May) (2017) 372–389.

[2] Zhang, Xiaolong, Yongbing Tang, Fan Zhang, and Chun_Sing Lee. "A novel aluminum_graphite dual_ion battery." Advanced energy materials 6, no. 11 (2016): 1502588.

[3] Wang, M., Jiang, C., Zhang, S., Song, X., Tang, Y., & Cheng, H. M. (2018). Reversible calcium alloying enables a practical room-temperature rechargeable calcium-ion battery with a high discharge voltage. Nature chemistry, 10(6), 667-672.

[4] Li, Jin, Feng Wang, and Yu He. "Electric vehicle routing problem with battery swapping considering energy consumption and carbon emissions." Sustainability 12.24 (2020): 10537.

[5] S.J. Peighambardoust, S. Rowshanzamir, M. Amjadi, Review of the Proton Exchange Membranes for Fuel Cell Applications, Elsevier Ltd, 2010.

[6] P. Hu, Y. Ouyang, L. Wu, L. Shen, Y. Luo, P. Christie, Effects of water management on arsenic and cadmium speciation and accumulation in an upland rice cultivar, J. Environ. Sci. (China) 27 (C) (2015) 225–231.

[7] R.P. Pinto, B. Tartakovsky, M. Perrier, B. Srinivasan, Optimizing treatment performance of microbial fuel cells by reactor staging, Ind. Eng. Chem. Res. 49 (1) (2010) 9222–9229.

[8] R. Kumar, L. Singh, A.W. Zularisam, D. Mohd Fadhil, Exoelectrogens in microbial fuel cells toward bioelectricity generation: a review, Int. J. Energy Res. 39 (8) (2015) 1048–1067.

[9] T. Yoshizawa, M. Miyahara, A. Kouzuma, K. Watanabe, Conversion of activated-sludge reactors to microbial fuel cells for wastewater treatment coupled to electricity generation, J. Biosci. Bioeng. 118 (5) (2014) 533–539.

[10] R. Kumar, L. Singh, A.W. Zularisam, F.I. Hai, Potential of porous Co3O4 nanorods as cathode catalyst for oxygen reduction reaction in microbial fuel cells, Bioresour. Technol. 220 (2016) 537–542.

[11] D.R. Lovley, The microbe electric: conversion of organic matter to electricity, Curr. Opin. Biotechnol. 19 (6) (2008) 564–571.

[12] D.R. Lovley, Bug juice: harvesting electricity with microorganisms, Nat. Rev. Microbiol. 4 (7) (2006) 497–508.

[13] A.S. Mathuriya, V.N. Sharma, Bioelectricity production from paper industry waste using a microbial fuel cell by

Clostridium species, J. Biochem. Technol. 1 (2) (2009) 49-52.

[14] M. Qin, E.A. Hynes, I.M. Abu-Reesh, Z. He, Ammonium removal from synthetic wastewater promoted by current generation and water flux in an osmotic microbial fuel cell, J. Clean. Prod. 149 (2017) 856–862.

[15] E. Hao Yu, S. Cheng, K. Scott, B. Logan, Microbial fuel cell performance with non-Pt cathode catalysts, J. Power Sources 171 (2) (2007) 275–281.

[16] J. Tahere, G. Ali Asghar, N. Ghasem Darzi, F. Sakine, R. Mostafa, Investigation on performance of microbial fuel cells based on carbon sources and kinetic models, Int. J. Energy Res. 37 (12) (2012) 1539–1549.

[17] D. Pant, G. Van Bogaert, L. Diels, K. Vanbroekhoven, A review of the substrates used in microbial fuel cells (MFCs) for sustainable energy production, Bioresour. Technol. 101 (6) (2010) 1533–1543.

[18] G.S. Jadhav, M.M. Ghangrekar, Bioresource Technology Performance of microbial fuel cell subjected to variation in pH, temperature, external load and substrate concentration, Bioresour. Technol. 100 (2009) 717–723.

[19] J.R. a E. Kim, S. Cheng, Membranes in Microbial Fuel Cells 41 (2007), pp. 1004–1009.

[20] A. Janicek, Y. Fan, H. Liu, Design of microbial fuel cells for practical application: a review and analysis of scale-up studies, Biofuels 5 (2014) 79–92.

[21] B.E. Logan, B. Hamelers, R. Rozendal, U. SchrÃder, J. Keller, S. Freguia, P. Aelterman, W. Verstraete, K. Rabaey, Microbial fuel cells: methodology and technology, Environ. Sci. Technol. 40 (2006) 5181–5192.

[22] V.M. Ortiz-Martínez, M.J. Salar-García, A.P. de los Ríos, F.J. Hernandez-Fernandez, J.A. Egea, L.J. Lozano, Developments in microbial fuel cell modeling, Chem. Eng. J. 271 (2015) 50– 60.

[23] D. Recio-Garrido, M. Perrier, B. Tartakovsky, Modeling, optimization and control of bioelectrochemical systems, Chem. Eng. J. 289 (2016) 180–190.

[24] S. Luo, H. Sun, Q. Ping, R. Jin, Z. He, A review of modeling bioelectrochemical systems: engineering and statistical aspects, Energies 9 (2) (2016) 1–27.

[25] Y. Zeng, Y.F. Choo, B.-H. Kim, P. Wu, Modelling and simulation of two-chamber microbial fuel cell, J. Power Sources 195 (2010) 79–89.

[26] A. Abul, J. Zhang, R. Steidl, G. Reguera, X. Tan, Microbial fuel cells: control-oriented modeling and experimental validation, Am Control Conf (2016) 412–417.

[27] R.P. Pinto, B. Srinivasan, M.F. Manuel, B. Tartakovsky, A two-population bio- electrochemical model of a microbial fuel cell, Bioresour. Technol. 101 (14) (2010) 5256–5265.

[28] H.C. Boghani, R.M. Dinsdale, A.J. Guwy, G.C. Premier, Sampled-time control of a microbial fuel cell stack, J. Power Sources 356 (2017) 338–347.

[29] M. Yan, L. Fan, Constant voltage output in two-chamber microbial fuel cell under fuzzy PID control, Int. J. Electrochem. Sci. 8 (2013) 3321–3332

[30] R. Patel, D. Deb, Parametrized control-oriented mathematical model and adaptive backstepping control of a single chamber single population microbial fuel cell, J. Power Sources 396 (2018) 599–605.

[31] R. Patel, D. Deb, Control-oriented parametrized models for microbial fuel cells, in: 6th Int. Conf. On Computer Applications in Electrical Engineering-Recent Advances (CERA), 2017, pp. 152–157.

[32] L. Fan, J. Zhang, Xiaolin Shi, Performance improvement of a microbial fuel cell based on model predictive control, Int. J. Electrochem. Sci. 10 (2015) 737–748.

[33] L. Fan, C. Li, K. Boshnakov, Performance improvement of a Microbial fuel cell based on adaptive fuzzy control, Int. J. Electrochem. Sci. 10 (2015) 685–690.

[34] A. Capodaglio, D. Cecconet, D. Molognoni, An integrated mathematical model of microbial fuel cell processes: bioelectrochemical and microbiologic aspects, Processes 5 (4) (2017) 1–14.

[35] Patel R, Deb D, Dey R, Balas V. Adaptive and intelligent control of microbial fuel cells. Intelligent Systems Reference Library Book Series, Springer. https://doi.org/10.1007/978-3-030- 18068-3.

[36] Clarke D.W., Mohtadi C., Tuffs P.S.: 'Generalized predictive control – Part 1. The basic algorithm', Automatica, 1987, 23, (3), pp. 137–148.

[37] Garcia C.E., Prett D.M., Morari M.: _Model predictive control: theory and practice _ a survey_, Automatica, 1989, 25, pp. 335_347.

[38] Rawling J.B., Meadows E.S., Muske K.R.: _Nonlinear model predictive control: a tutorial and survey_. Proc. IFAC Int. Symp. Adv. Control of Chemical Processes, ADCHEM, Kyoto, Japan, 1994

[39] Mayne D.Q.: 'Optimization in model based control'. Proc. IFAC Symp. Dynamics and Control of Chemical Reactors, Distillation Columns and Batch Processes, Helsingor, 1995, pp. 229–242

[40] Van Den Boom T.J.J.: 'Model based predictive control: status and perspective'. Symp. on Control, Optimization and Supervision. CESA'96 IMACS Multi conference, Lille, 1996, pp. 1– 12

[41] Michalska H., Mayne D.Q.: 'Receding horizon control of nonlinear systems', IEEE Trans. Autom. Control, 1993, 38, (11), pp. 1623–1632

[42] Chen H., Allgower F.: 'A quasi-infinite horizon nonlinear model predictive control scheme with guaranteed stability', Automatica, 1998, 34, (10), pp. 1205–1217

[43] Kothare M.V., Balakrishnan V., Morari M.: 'Robust constrained model predictive control using linear matrix inequalities', Automatica, 1996, 32, (10), pp. 1361–1379

[44] Lu Y., Arkun Y.: 'Quasi-min–mar MPC algorithms for LPV systems', Automatica, 2000, 36, (4), pp. 527–540

[45] R. Maier, I. Pepper, Environ. Microbiol. 8 (2015) third ed.

[46] W. Zi-Qin, S. Sigurd, Ying Zhao, Exact linearization control of continuous bioreactors: a comparison of various structures, in: IEEE conf. on control applications, 1993, pp. 107–112.

[47] Boyd S., Ghaoui L.E., Feron E., Balakrishnan V.: 'Linear matrix inequalities in control theory' (SIAM, Philadelphia, 1994)

[48] N. Poursafar, H.D. Taghirad, M. Haeri, Model predictive control of non-linear discrete time systems: a linear matrix inequality approach, IET Control Theory Appl. 4 (10) (2010) 1922–1932.