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Adaptive Neuro-Fuzzy Inference System Modeling and Optimization of Microbial Fuel Cells for Wastewater Treatment

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Abstract: Due to their toxicity, Cr(VI) levels are subject to strict legislation and regulations in various industries and environmental contexts. Effective treatment technologies are also being developed to decrease the negative impacts on human health and the environment by removing Cr(VI) from water sources and wastewater. As a result, it would be interesting to model and optimize the Cr(VI) removal processes, especially those under neutral pH circumstances. Microbial fuel cells (MFCs) have the capacity to remove Cr(VI), but additional research is needed to enhance their usability, increase their efficacy, and address issues like scalability and maintaining stable operation. In this research work, ANFIS modeling and artificial ecosystem optimization (AEO) were used to maximize Cr(VI) removal efficiency and the power density of MFC. First, based on measured data, an ANFIS model is developed to simulate the MFC performance in terms of the Cu(II)/Cr(VI) ratio, substrate (sodium acetate) concentration (g/L), and external resistance Ω. Then, using artificial ecosystem optimization (AEO), the optimal values of these operating parameters, i.e., Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance, are identified, corresponding to maximum Cr(VI) removal efficiency and power density. In the ANFIS modeling stage of power density, the coefficient-of-determination is enhanced to 0.9981 compared with 0.992 (by ANOVA), and the RMSE is decreased to 0.4863 compared with 16.486 (by ANOVA). This shows that the modeling phase was effective. In sum, the integration between ANFIS and AEO increased the power density and Cr(VI) removal efficiency by 19.14% and 15.14%, respectively, compared to the measured data.

Keywords: microbial fuel cell; artificial ecosystem optimization; ANFIS modeling

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1. Introduction

A conceptual framework known as the water–energy–food (WEF) nexus acknowledges the interdependencies and connections between water, energy, and food systems [1,2]. It emphasizes the necessity for integrated and sustainable management techniques and draws attention to the complex relationships and trade-offs among various areas [3,4]. Water is necessary for many human activities, such as residential use, industry, and agriculture. It is necessary to produce energy, process food, and irrigate crops. Water resources are limited and must contend with issues like scarcity, pollution, and rivalry from other industries. Food must be produced, processed, transported, and distributed. It is essential for the distribution, treatment, and delivery of water. Fossil fuels, hydropower, biomass, and renewable energy sources have varying effects on water resources, and energy production can exacerbate water pollution and stress [5]. Agriculture depends on energy inputs for machinery, transportation, processing, and water for irrigation. Food production can significantly influence water resources, including water use, fertilizer and pesticide contamination, and land degradation. Agricultural production and food security can both be impacted by water availability and quality. The WEF nexus paradigm acknowledges the possibility of cascading impacts from changes or disruptions in one sector to others. For instance, the availability of food and agricultural productivity may need to be improved by securing water resources. Crop yields, energy output, and water availability are all impacted by climate change. The WEF nexus demands integrated planning, policy coordination, and decision-making that considers the synergies and trade-offs across these interconnected systems to be managed effectively and sustainably [6,7]. It entails locating opportunities for resource optimization, expanding food production's water and energy efficiency, supporting renewable energy sources, lowering food waste, and boosting climate change resilience. When addressing issues related to water, energy, and food, the WEF nexus method aids policymakers, academics, and practitioners in adopting a holistic perspective to achieve more resilient and sustainable development pathways.

Although traditional wastewater treatment requires massive energy [8,9] for proper treatment before safe discharge to the environment, wastewater contains biomass energy that can provide considerable energy if properly used [10,11]. Using microorganisms and the bio-electrochemical process of microbial metabolism, microbial fuel cells (MFCs) convert organic matter into electrical energy [12,13]. A microbial fuel cell primarily transforms organic substrates into electrical energy while treating organic waste or wastewater [14,15]. MFCs are vital for generating renewable energy. The fuel cell's anode can capture the released electrons when microbes degrade organic matter and transport them to the cathode, creating an electrical current. MFCs may be used as sustainable power sources in distant or off-grid places [16]. Microbial fuel cells may be essential in the treatment of wastewater. The anode chamber's microorganisms break down organic debris as they consume it, detoxifying the wastewater. The MFC procedure can assist in removing organic contaminants and lowering the wastewater's COD. MFCs may find use in bioremediation, which entails eliminating or degrading contaminants from the environment. Utilizing microorganisms' metabolic processes, MFCs can speed up the breakdown of some pollutants or change them into less dangerous forms [17,18]. MFCs can be a power source for low-power sensors or monitoring equipment. Thanks to their ability to produce power from organic matter, they can supply sensors used for environmental monitoring or remote sensing applications with sustainable and self-sufficient energy. In disciplines including microbiology, bioelectrochemistry, and renewable energy, MFCs are valuable tools in research. They serve as a platform for research into electrochemical and microbiological processes and improve energy conversion effectiveness. Even though microbial fuel cells have shown promise in several applications, more study and development are still required to increase their effectiveness, scalability, and viability for commercial use.

MFCs can perform better thanks to artificial intelligence (AI) approaches since they can help optimize, control, and make decisions [19–21]. AI has been used to improve MFC performance [22]. Particle swarm optimization and genetic algorithms are two examples of AI techniques that can improve MFC systems' design and configuration. AI can assist in identifying the best electrode materials, reactor layouts, and operating conditions to maximize power output and efficiency by considering various characteristics and restrictions. AI-based solutions are capable of enabling real-time monitoring and control of MFC functioning. To gain insights into the performance of MFCs, machine learning techniques can be used to analyze sensor data, microbial activity, and other pertinent characteristics. Using this data, operational parameters can be changed, power generation can be optimized, and system problems can be avoided. AI can help create performance-based predictive models for MFC [23]. Machine learning algorithms can analyze historical data to grasp the intricate correlations between operational parameters and power output. Then, these models may be applied to forecast MFC performance under various scenarios, facilitate decision-making, and enhance system performance. By automating some jobs and decision-making procedures, AI can assist in streamlining the overall MFC process. Continuous data analysis, adaptive operational condition adjustment, and resource allocation optimization are all capabilities of AI algorithms. This can increase power generation, maximize energy efficiency, and simplify MFC operation. It is crucial to remember that AI approaches in MFCs are still a developing topic, and work is being undertaken to fully realize their potential. The particular MFC system, the data that are accessible, and the optimization or control goals will determine the individual AI methodologies and approaches used. The performance, effectiveness, and sustainability of microbial fuel cells could be improved by using AI technology in research and development.

Both fuzzy sets and fuzzy logic are used in the computational methods of ANFIS (adaptive neuro-fuzzy inference system) and fuzzy logic. ANFIS and fuzzy logic, however, differ significantly in a few crucial ways [24,25]. Fuzzy logic is a mathematical framework for representing and manipulating imprecise or uncertain information using linguistic variables and fuzzy rules [26]. It is based on the fuzzy sets theory, in which membership functions define the degree of membership of an element in a set. A hybrid computational model that blends fuzzy logic and neural networks is called ANFIS. ANFIS uses a neural network topology to represent a fuzzy inference system, and a learning algorithm is used to update the membership function and fuzzy rule parameters. Human experts often define fuzzy rules and membership functions based on their domain expertise and intuition. To modify the fuzzy inference system's parameters, ANFIS uses a learning technique often based on gradient descent or backpropagation. Thanks to this learning process, ANFIS may automatically modify the fuzzy rules and membership functions based on training data.

The removal of Cr(VI) depends on an MFC systems working circumstances, including substrate type and concentration [27,28], external resistance [29], and others. According to Koók et al. [29], external resistance impacts how extracellular electrons are transferred from the bacteria that produce them to the electrode surface. The substrate concentration influences the number of electrons created at the anode during the oxidation process, which correlates to the number of electron moves from the anode to the cathode, and thus significantly impacts electricity production [28]. Therefore, this research aims to improve the MFC's power density and Cr(VI) removal efficiency by utilizing artificial ecosystem optimization (AEO) and ANFIS modeling. To simulate the MFC in terms of the Cu(II)/Cr(VI) ratio, substrate (sodium acetate) concentration (g/L), and external resistance, an ANFIS model is first created based on observed data. In order to achieve the highest Cr(VI) removal efficiency and power density, the ideal values of the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance are then determined using AEO.

2. Microbial Fuel Cells

Microbial fuel cells (MFCs) have a generally established working mechanism. The microbial metabolism of organic matter, which entails several crucial phases and activities, is the basis upon which MFCs operate [26]. A biofilm or anode electrode coated with microorganisms, usually bacteria, is found in the anode chamber of an MFC. These bacteria can oxidize organic material found in substrates or effluents. Microbes break down organic matter as they metabolize it through various biochemical processes, such as oxidation or fermentation [30]. Electrons and protons are liberated from the organic molecules during this process. The anode electrode, which serves as the electron acceptor, receives the emitted electrons from the microbial metabolism.

The microorganisms on the anode surface create direct or mediated electron transfer channels to aid in this electron transfer process. The anode chamber becomes more acidic due to the simultaneous release of protons (H+) created during the oxidation of organic materials into the solution. These protons move towards the cathode chamber through the electrolyte. A membrane or ion exchange separator separates the anode and cathode chambers, which also permits proton migration. As a result, the anode and cathode solutions cannot be mixed directly. A second electrode serves as the electron acceptor in the cathode chamber, typically for oxygen reduction. Water is created when oxygen from the cathode and protons and electrons from the anode chamber come together. Electrons produced at the anode travel via an external circuit to produce an electric current that can be used to power electronics or recharge batteries, among other valuable applications. A continuous flow of electrons from the anode to the cathode is made possible by the external circuit's flow of electrons, which completes the electrochemical circuit. The microbial metabolism and the voltage differential between the anode and cathode electrodes propel this electron flow. Figure 1 shows schematic diagram of the main components of the MFC. The microbial oxidation of organic materials at the anode, which produces electrons and protons, is the main component of the microbial fuel cell mechanism [31]. It is important to note that different MFCs may use different microbial species, substrate compositions, electrode materials, and system configurations, which might affect performance and efficiency. Microbial fuel cells' processes and operating parameters are now being further understood and optimized for better performance and broader applications.

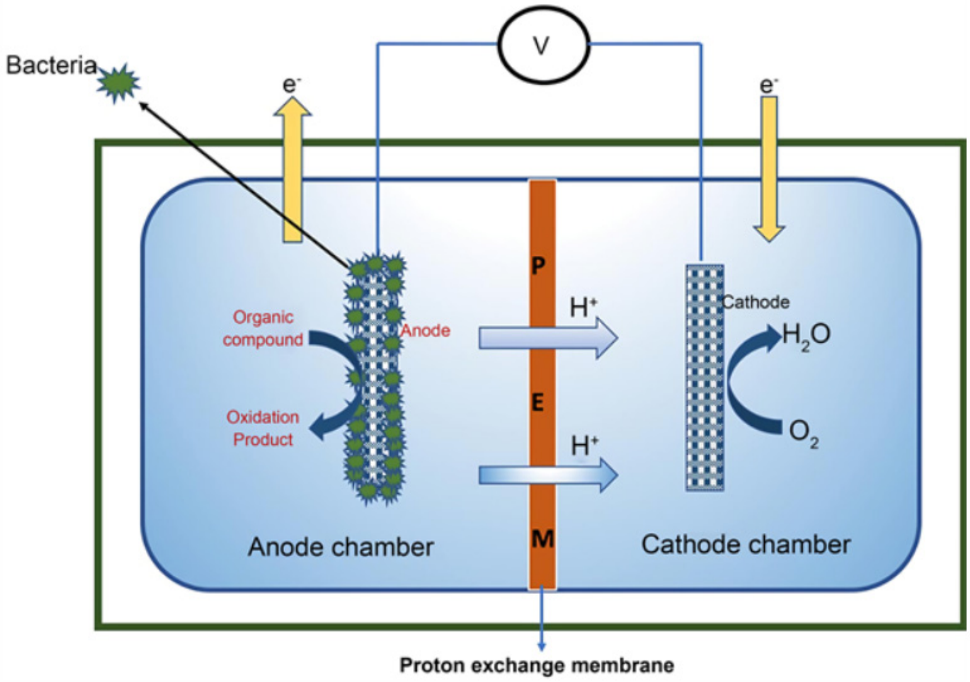

Figure 1. Operation of MFC.

Given the potential risks to both human health and the environment, treating wastewater containing Cr(VI) is garnering more attention. Because Cr(VI) is highly hazardous, carcinogenic, and mutagenic, it must be removed correctly to keep it from entering the environment. Cr(VI) concentrations in wastewater produced by industrial processes such as electroplating, leather tanning, welding, and dyeing can range from 5.7 to 87 mg/L (wastewater from electroplating) [32]. If these concentrations are not appropriately handled, they can present serious dangers. On the other hand, Cr(III) is less harmful to organisms and tends to precipitate as $Cr(OH)_3$. Wastewater containing Cr(VI) must be treated to lessen its adverse effects on ecosystems and human health. Chemical precipitation, adsorption, ion exchange, membrane filtration, and biological therapy are some of the treatment techniques that can be used. Each approach has pros and cons, and the choice is made based on the baseline Cr(VI) concentration, the required level of treatment efficacy, cost, and infrastructure accessibility. Cr(VI) concentrations can be effectively brought down to safe levels by effective treatment techniques, allowing for regulatory compliance and reducing environmental contamination. To ensure the preservation of the environment and human health, applying effective treatment technologies and adopting sound management practices for Cr(VI) is essential. Additionally, continuous monitoring and adherence to environmental standards are crucial to stopping the discharge of Cr(VI) into ecosystems and water bodies.

An MFC system's ability to remove Cr(VI) is influenced by its operational circumstances, including substrate type and concentration, external resistance, and others [33]. The external resistance impacts the extracellular electron transfer from the bacteria that produce extracellular electrons to the electrode surface. The number of electron suppliers, or the substrate concentration, determines how many electrons are produced at the anode during the oxidation process, which significantly impacts how much power is produced. The kind and concentration of the substrate used in the MFC are essential for removing Cr(VI) and producing electricity. The substrate supplies the microorganisms in the anode chamber with the carbon they need for their metabolic activity. The bacterial oxidation of organic material causes the release of electrons that help produce power. Up to a certain optimum point, the substrate concentration influences electron donor availability, and a higher concentration may result in increased electricity production and improved Cr(VI) elimination. However, extremely high substrate concentrations may result in unwanted microbial metabolic byproducts or substrate inhibition. The MFC's exterior resistance impacts how extracellular electrons are transported from the bacteria that produce them to the electrode surface. The resistance, which is frequently managed by an external load or resistor, affects the circuit's electron flow and regulates the amount of current produced. The external resistance can be adjusted to achieve the best balance between power production and Cr(VI) removal efficiency. Depending on the specific goals of the MFC operation, adjusting the external resistance might help maximize power output or prioritize the removal of Cr(VI).

Therefore, to effectively remove Cr(VI) and generate energy, an MFC system's working parameters must be optimized, considering substrate concentration, external resistance, and the Cu(II)/Cr(VI) ratio. The MFC's performance can be optimized by adjusting these parameters, making it more suitable for specific applications and ensuring efficient Cr(VI) remediation while producing sustainable energy.

In the current research, the considered data were obtained from [32]. These measurements were obtained using a two-tank microbial fuel cell (MFC). Each tank had a 700 mL functional capacity. The anode was made of carbon cloth, measuring 12 cm^2. Meanwhile, the cylindrical cathode was made of conductive carbon black combined with 10.24% wt polyvinyl alcohol (PVA). External resistors of 12 mm in length were used to link the anode and cathode. More details can be found in [32]. The number of data points is 19. Three input parameters are used as follows. The lower and upper limits for Cu(II)/Cr(VI) ratio are 0.33 and 1.672, respectively. The lower and upper percentages of the substrate concentration are 0.244 and 1.756. The minimum and maximum external resistance values are 244 Ω and 1000 Ω, respectively. Under these conditions, the power density (PD) of the MFC system ranged from 0.45 mW/m^2 to 36.76 mW/m^2, and the Cr(VI) removal (RE) ranged from 30% to 75%, suggesting that the PD and Cr(VI) RE of the MFC system were affected by the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance. A modeling approach may successfully handle small amounts of nonlinear data. ANFIS combines the advantages of fuzzy logic and neural networks to create a hybrid model capable of capturing nonlinear relationships; therefore, it is used in the current study.

3. ANFIS Model of MFCs

Fuzzy offers a versatile and user-friendly framework for processing imprecise or uncertain information. A rich representation of information and reasoning is possible thanks to its ability to handle complicated fuzzy rules and membership functions [34]. ANFIS introduces neural networks' processing power and learning capacity, enabling them to learn and optimize the fuzzy inference system's parameters automatically. When the fuzzy rule base or membership functions need to be modified based on data, or when they are not well defined, ANFIS can be especially helpful. Fuzzy is widely employed in many areas, including expert systems, decision-making, pattern recognition, and control systems.

ANFIS has found use in tasks including system identification, modeling, prediction, and control, where both fuzzy logic and neural networks are advantageous. In conclusion, ANFIS and fuzzy logic use fuzzy sets and fuzzy logic concepts. Still, ANFIS blends fuzzy logic with neural networks and includes learning algorithms to change the fuzzy inference system's settings. Unlike classical fuzzy logic, which depends on predefined rules and membership functions, this hybrid method enables ANFIS to learn from data and optimize its performance [35].

Numerous steps are usually involved in the modeling process for the ANFIS. Preparing and prepping the input and output data for ANFIS modeling is the initial stage of the procedure. Data normalization, cleansing, and set division into training and testing sets are all included in this. ANFIS begins by creating a set of fuzzy rules based on the input-output information. The intricacy of the problem and the quantity of input variables determine the number of rules and the structure of those rules. Typically, clustering methods or grid partitioning techniques are used to construct the fuzzy rules. The membership function parameters connected to each input variable in the created fuzzy rules are determined in the following step. The least squares approach and gradient descent algorithms are frequently used parameter estimation techniques. The fuzzy inference system is built at this stage using the generated fuzzy rules and the estimated membership function parameters. The fuzzy inference system integrates the input variables and their corresponding fuzzy sets to make fuzzy inferences using fuzzy rules. To modify the fuzzy inference system's parameters, ANFIS employs a hybrid learning technique. The fuzzy rules' associated weights and membership function parameters are updated in this phase. The learning algorithm, such as the backpropagation method, often uses the training data to reduce the error between the expected and actual output values. Following the learning phase, the ANFIS model is assessed and validated using the testing data. Metrics like mean squared error (MSE), root mean squared error (RMSE), or correlation coefficients are used to evaluate the model's performance to gauge its accuracy and generalizability. The ANFIS model can make predictions or carry out system control operations based on new input data once it has been trained, validated, and optimized. It is crucial to remember that the specific implementation and variations in ANFIS modeling can change depending on the issue domain, the data that is accessible, and the particular application needs. Although the stages above offer a broad framework for ANFIS modeling, specifics may change based on the model architecture and learning methods.

The output of the ANFIS model is mapped to crisp form during the defuzzification phase. The map of input–output is formulated by IF–THEN rules. An example of the fuzzy rule is presented below.

$$\text{IF } x \text{ is } A_1 \text{ and } y \text{ is } B_1 \text{ then } f_1 = g_1(x, y)$$

$$\text{IF } x \text{ is } A_2 \text{ and } y \text{ is } B_2 \text{ then } f_2 = g_2(x, y)$$

where, the A_1 and B_1 are the MFs of the two inputs x and y.

The final output f is estimated as following.

$$f = \widetilde{\omega}_1 f_1 + \widetilde{\omega}_2 f_2 \quad \text{(Output Layer)}$$

where $\widetilde{\omega}_1$ and $\widetilde{\omega}_2$ are the firing strength of rules.

Evaluating

$$\widetilde{\omega}_1 g_1(x, y) \text{ and } \widetilde{\omega}_2 g_2(x, y) \quad \text{(Defuzzification Layer)}$$

$$\widetilde{\omega}_1 = \frac{\omega_1}{\omega_1 + \omega_2} \text{ and } \widetilde{\omega}_2 = \frac{\omega_2}{\omega_1 + \omega_2} \quad \text{(N Layer)}$$

where ω_1 and ω_2 are the weights.

$$\omega_1 = \mu_{A_1} * \mu_{B_1} \text{and } \omega_2 = \mu_{A_2} * \mu_{B_2} \quad (\pi \text{ Layer})$$

$$\mu_{A_1}, \mu_{A_2}, \mu_{B_1} \text{ and } \mu_{B_2} \text{ are the MF values of the two inputs (Fuzzification Layer)}$$

4. Parameter Identification by an Artificial Ecosystem Optimizer

An innovative method for resolving optimization issues is called artificial ecosystem-based optimization (AEO). It uses the principles of adaptability, cooperation, and rivalry seen in biological systems to tackle challenging optimization issues. It takes inspiration from natural ecosystems. AEO assembles a population of individual solution candidates, or "organisms," that represent potential answers to the optimization issue to form an artificial ecosystem. These organisms interact and change over time due to numerous factors, including competition, mutation, reproduction, and selection. The following steps are commonly included in the optimization process in AEO: A population of initial solution candidates is randomly generated within the search space. The fitness or objective function value is computed to evaluate each potential solution. Reproduction, crossover, and mutation are just a few of the mechanisms the solution candidates use to interact with one another and imitate the principles found in natural ecosystems. This enables the sharing of genetic data and the research of various search space locations [36]. Candidates for the solution are chosen depending on how likely they are to survive and reproduce in the following generation. Positive traits or qualities are transmitted to succeeding generations. A termination criterion, such as reaching a present number of generations or arriving at a good solution, must be satisfied before the optimization process can be completed. Similar to other methods like genetic algorithms, particle swarm optimization, or ant colony optimization, AEO is regarded as a metaheuristic or nature-inspired optimization methodology. Simulating the dynamics and interconnections of natural ecosystems provides a new way to approach the solution of optimization problems. It is crucial to remember that the precise application and variants of AEO can change based on the issue at hand, the goal of the optimization, and the particular algorithms or methods employed inside the framework. To find a solution, AEO typically uses the following guidelines. The production operator can be modeled as follows [36].

$$\begin{array}{l} x_1^{t+1} = (1-a)x_n^t + a x_{rand}^t \\ a = (1 - \frac{t}{t_{Max}})r_1;\ x_{rand} = r(ub - lb) + lb \end{array}$$

where n presents the population size, r_1 and r are random factors, and x_{rand} is a random position produced in the search space. The consumption operator can be modeled as

$$\begin{array}{l}
x_i^{t+1} = x_i^t + C(x_i^t - x_1^t),\ \ i \in [2, ..\text{n}];\ \ if\ rand < 1/3 \\
\left\{ \begin{array}{l} x_i^{t+1} = x_i^t + C(x_i^t - x_j^t),\ \ i \in [3, ..\text{n}] \\ j = randi([\ 2 \quad i-1\ ]) \end{array} \right. ;\ \ if\ 1/3 < rand < 2/3 \\
\left\{ \begin{array}{l} x_i^{t+1} = x_i^t + C(r_2(x_i^t - x_j^t) \\ \qquad +(1-r_2)(x_i^t - x_j^t)), \\ j = randi([\ 2 \quad i-1\ ]) \end{array} \right. \ \ i \in [3, ..\text{n}];\ \ if\ rand > 2/3
\end{array}$$

The decomposition operator can be modeled as

$$\begin{array}{c} x_i^{t+1} = x_n^t + D(e x_n^t - h x_i^t),\quad i \in [1, ..\text{n}] \\ D = 3u,\quad u \sim N(0,1) \\ e = r_3.randi([1 \quad 2]) - 1 \\ h = 2r_3 - 1 \end{array}$$

The AEO flowchart is presented in Figure 2. As explained in Figure 2, in the consumption stage, the consumer feeds on another consumer with a lower energy level or on a producer. For the consumer classes, carnivores, herbivores, and omnivores.

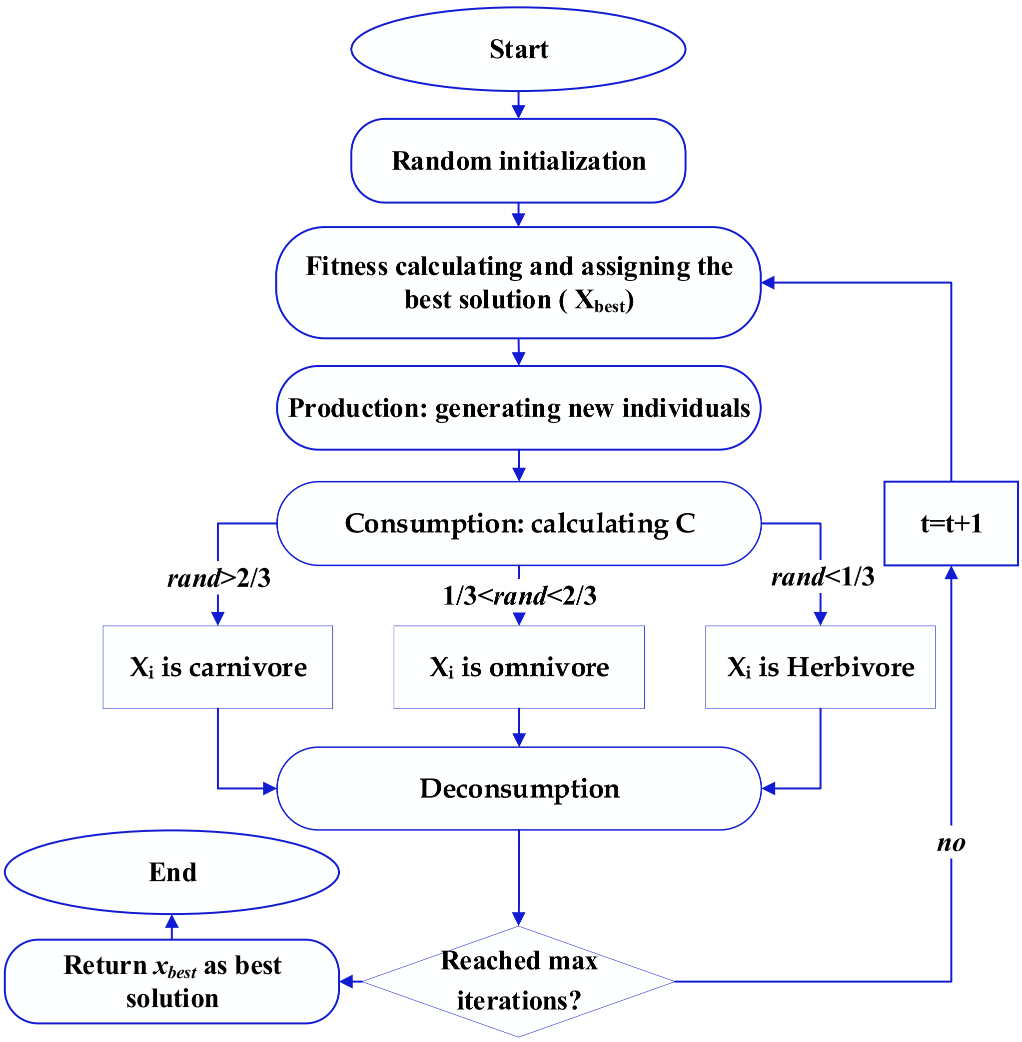

Figure 2. AEO flowchart.

The primary purpose of the optimization phase is to acquire the optimal values of Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance that generate the maximum Cr(VI) removal efficiency and power density. Therefore, during the optimization process, the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance are assigned as decision variables, whereas the Cr(VI) removal efficiency and power density are the objective function that had to be most significant. The problem statement of the current optimization procedure may be written as

$$x = \underset{x \in R}{\text{argmax}}(y)$$

where x is the set of input variables, and y is the output variable.

5. Results and Discussion

5.1. Modeling Phase

The ANFIS model was developed using 19 experiments. The data are divided into two groups: training and testing. Fifteen points comprise the first component, which is used to train the model; the remaining points are used to test the model. The hybrid training method employs LSE for the forward path and backpropagation for the backward direction. The system's rules, which number 15, were constructed using the SC. These models were subsequently trained until a reduced RMSE was attained. Table 1 displays the statistical metrics that the ANFIS model produced.

Table 1. Statistical metrics of ANFIS models.

RMSE			Coefficient of Determination (R^2)		
Train	**Test**	**All**	**Train**	**Test**	**All**
Model of power density					
9.64×10^{-6}	1.0598	0.4863	1.0	0.9864	0.9981
Model of Cr(VI) removal efficiency					
2.63×10^{-5}	2.1275	0.9761	1.0	0.9991	0.9963

Note: All means the total data containing both training and testing data sets.

Regarding Table 1, the RMSE values for the training and testing data sets for the ANFIS model of the power density are 9.64×10^{-6} and 1.0598, respectively. For training and testing, the coefficients of determination are 1.0 and 0.9864, respectively. The coefficient of determination is enhanced from 0.992 (by ANOVA) to 0.9981 (by ANFIS), and the RMSE is decreased from 16.486 (by ANOVA) to 0.4863 (by ANFIS). For the training and testing data sets, the RMSE values for the ANFIS model of Cr(VI) removal efficiency are 2.63×10^{-5} and 2.1275, respectively. For training and testing, the coefficients of determination are 1.0 and 0.9991, respectively. The coefficient of determination is enhanced from 0.951 (by ANOVA) to 0.9963 (by ANFIS), and the RMSE is decreased from 22.60 (by ANOVA) to 0.9761 (by ANFIS). This shows that the fuzzy modeling phase was effective. Figure 3 depicts the 3-input, single-output fuzzy model architecture, and Figure 4 depicts the general contours of the Gaussian form of MFs.

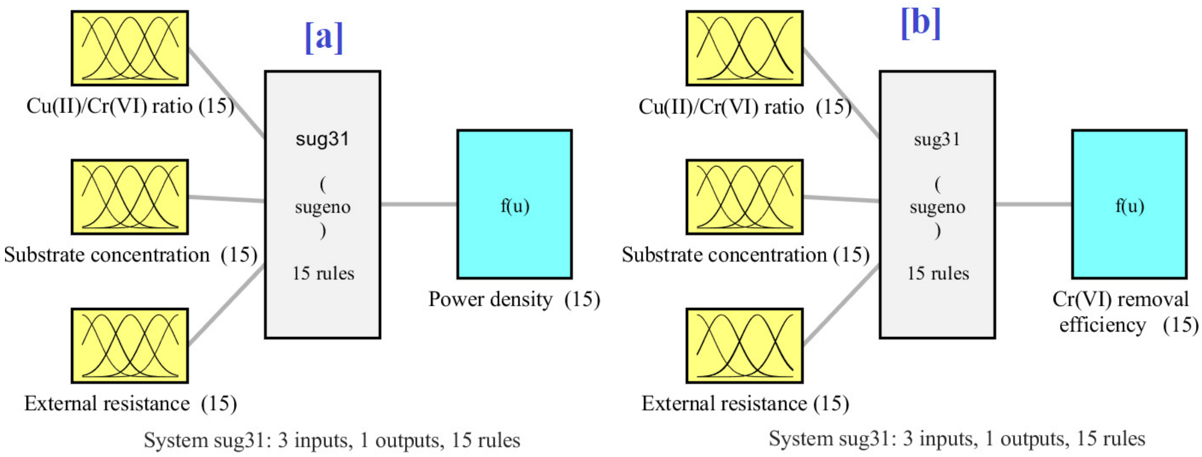

Figure 3. Configuration of ANFIS models [**a**] power density and [**b**] Cr(VI) removal efficiency.

Figure 5 provides a three-dimensional spatial representation, including the contour plots of the input-output functions for every combination of inputs. The color scale ranges from dark red, representing the maximum output value, to dark blue, which indicates the minimum output value. There is an enhancement in PD and Cr(VI) RE with an increase in substrate concentration. However, a decrease in PD and Cr(VI) RE is observed when external resistance deviates from an optimal range, either by increasing too much or decreasing substantially. This can be attributed to the fact that excessively high external resistance raises the obstacle to electron transfer from anode to cathode, lowering the current and making electricity generation and Cr(VI) removal less favorable. On the other hand, if the external resistance is too low, it results in an inadequate potential difference between the anode and cathode, impairing electron transfer and destabilizing the MFC system. Hence, an optimal level of external resistance is conducive to power generation in the MFC system and the removal of Cr(VI). Among the factors, substrate concentration exerts the most significant influence on PD; therefore, an adequate amount of substrate is preferable. On the other hand, a shortage of substrate greatly diminishes the PD. Consequently, addressing both external resistance and substrate concentration in evaluating the PD is imperative.

Figure 5 also elucidates that augmenting the substrate concentration and the ratio of Cu(II) to Cr(VI) is beneficial for the PD. This is associated with the rise in electron production owing to the availability of organic material in the anode compartment for microbial degradation.

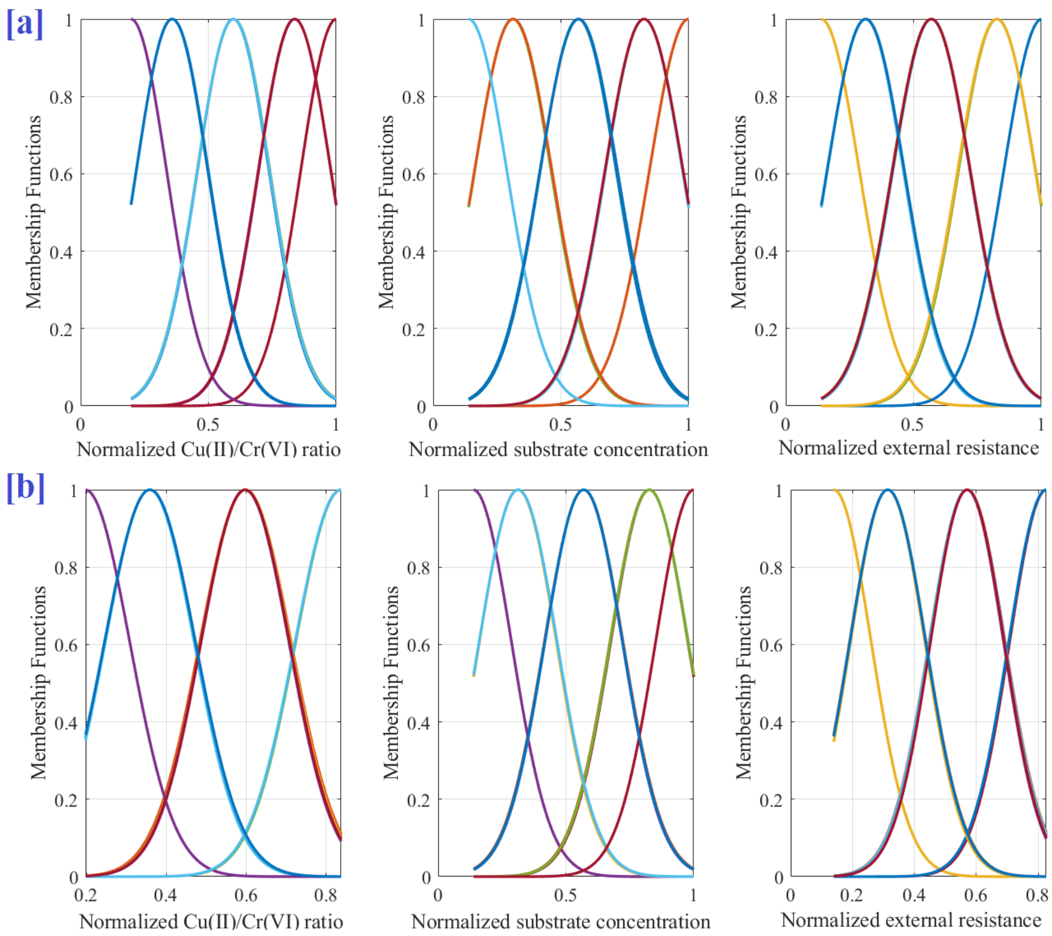

Figure 4. Inputs' MFs of ANFIS models: [**a**] power density and [**b**] Cr(VI) removal efficiency.

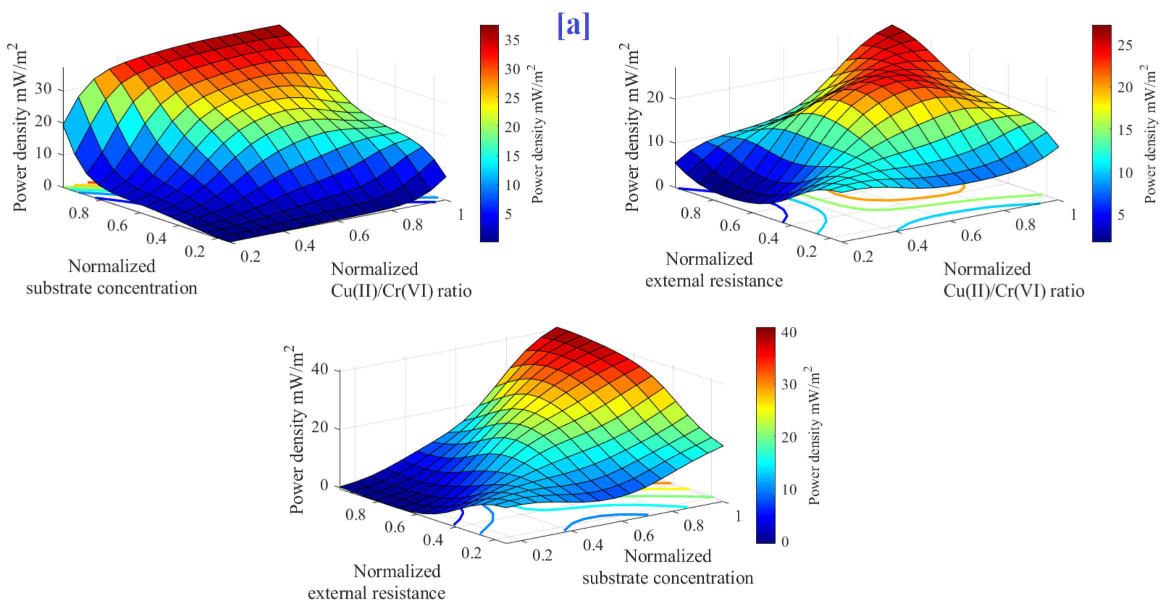

Figure 5. *Cont.*

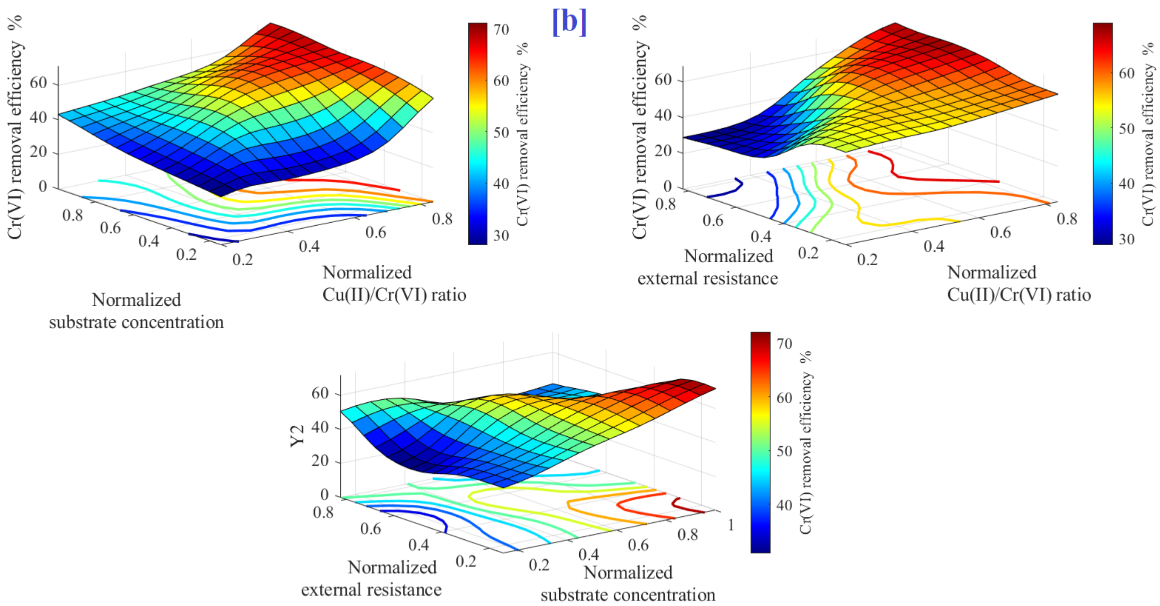

Figure 5. Three-dimensional plot of controlling parameters: [**a**] power density and [**b**] Cr(VI) removal efficiency.

Figure 6 shows the predicted versus measured data of the ANFIS model of power density and Cr(VI) removal efficiency. It is clear that the estimated and measured values fit each other well. The image presented in Figure 7 also shows the predictions' plots around the line of 100% accuracy for both the training and testing phases.

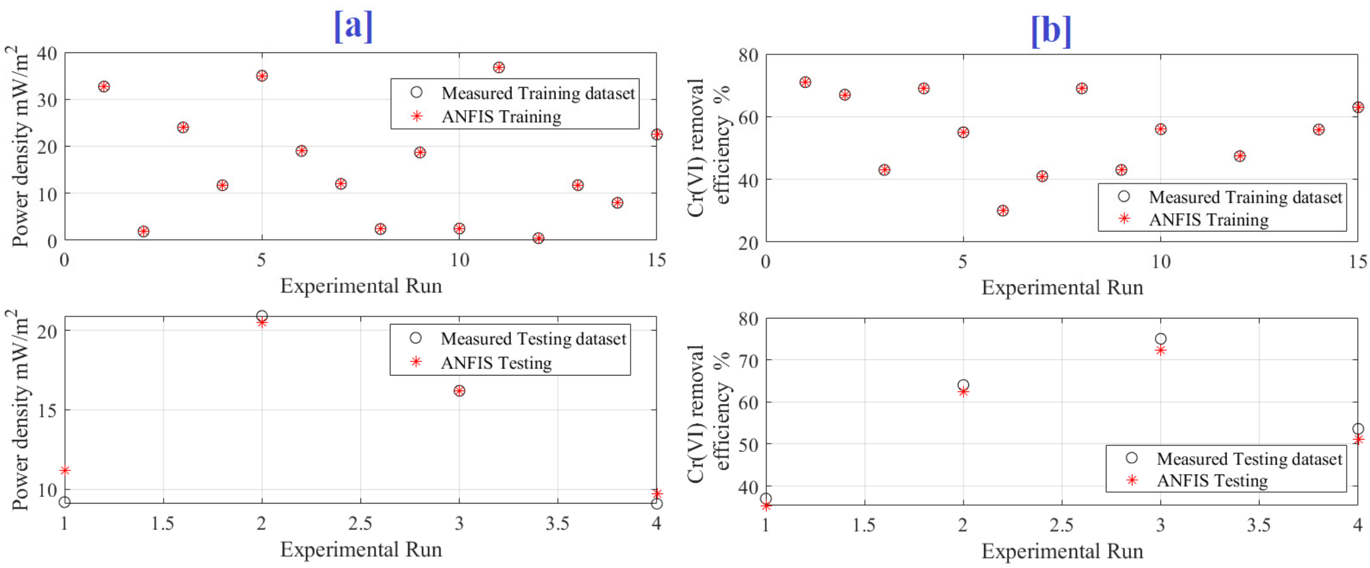

Figure 6. Predicted versus measured data of the ANFIS model: [**a**] power density and [**b**] Cr(VI) removal efficiency.

5.2. Optimization Phase

This section aims to identify the optimal levels of Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance corresponding to maximum Cr(VI) removal efficiency and power density. As a result, AEO has been used to predict the best values for three regulating parameters after building trustworthy ANFIS models. The top experimental input and output parameters and the AEO are shown in Table 2. The integration between ANFIS and AEO increased the power density from 32.7 mW/m^2 to 38.96 mW/m^2 (by 19.14%) compared to measured data. In addition, boosting the Cr(VI) removal efficiency from 71% to 81.75% (by 15.14%) compared to measured data. Under this condition, the optimal values are 1.672, 1.756 (g/L), and 1404.8 Ω, respectively, for the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance. Figure 8 shows the particle convergence of objective function, normalized Cu(II)/Cr(VI) ratio, normalized substrate concentration, and normalized external resistance. The figure demonstrated that all particles converged to the optimal value after 35 iterations.

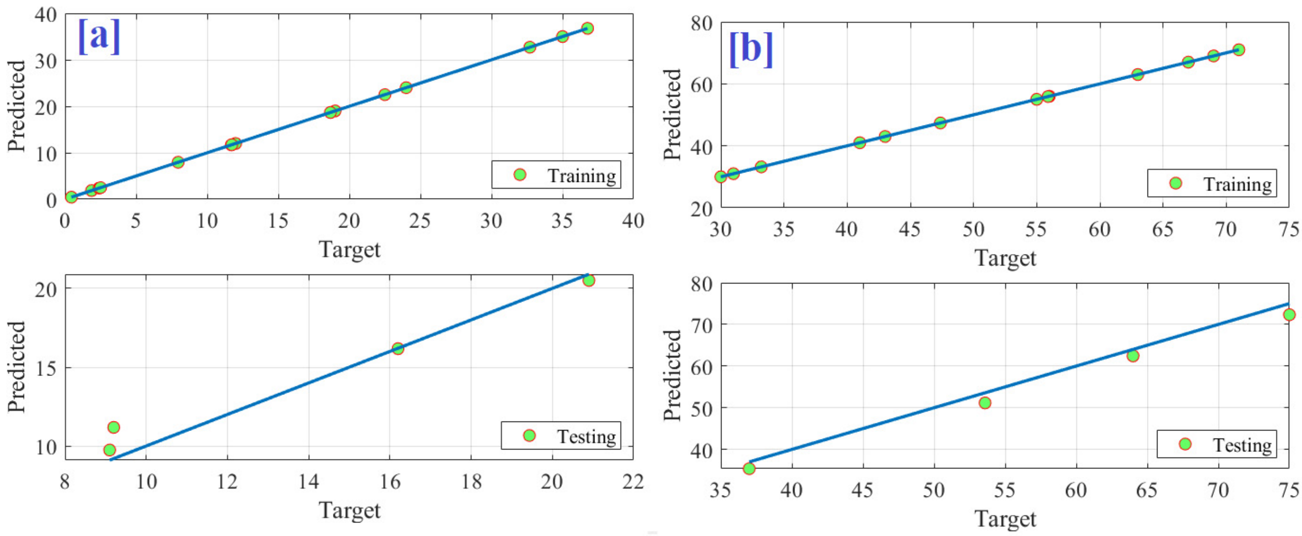

Figure 7. Prediction accuracy of the ANFIS model: [**a**] power density and [**b**] Cr(VI) removal efficiency.

Table 2. Best parameters by measured, ANOVA, and proposed methods.

	Cu(II)/Cr(VI) Ratio	Substrate Concentration	External Resistance	Power Density, mW/m^2	Cr(VI) Removal Efficiency	Change in Power Density	Change in Cr(VI) Removal Efficiency
Measured [32]	1.4	1.45 (g/L)	1000 Ω	32.7	71%	0.0	0.0
ANOVA [32]	1.65	1.36	1360	33.84	71%	3.48%	0.0
ANFIS and AEO	1.672	1.756 (g/L)	1404.8 Ω	38.96	81.75%	19.14%	15.14%

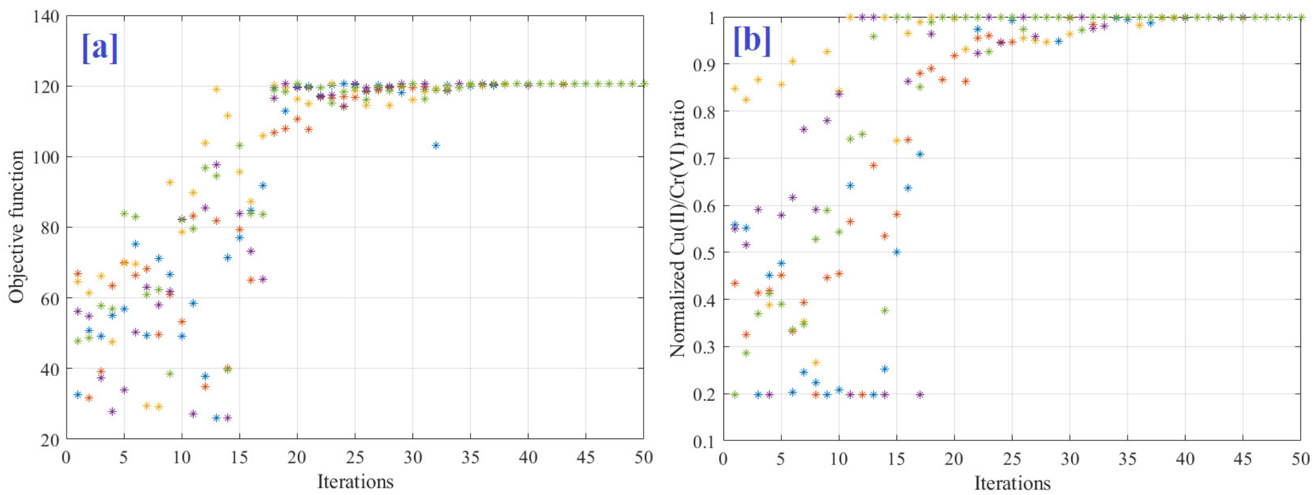

Figure 8. *Cont.*

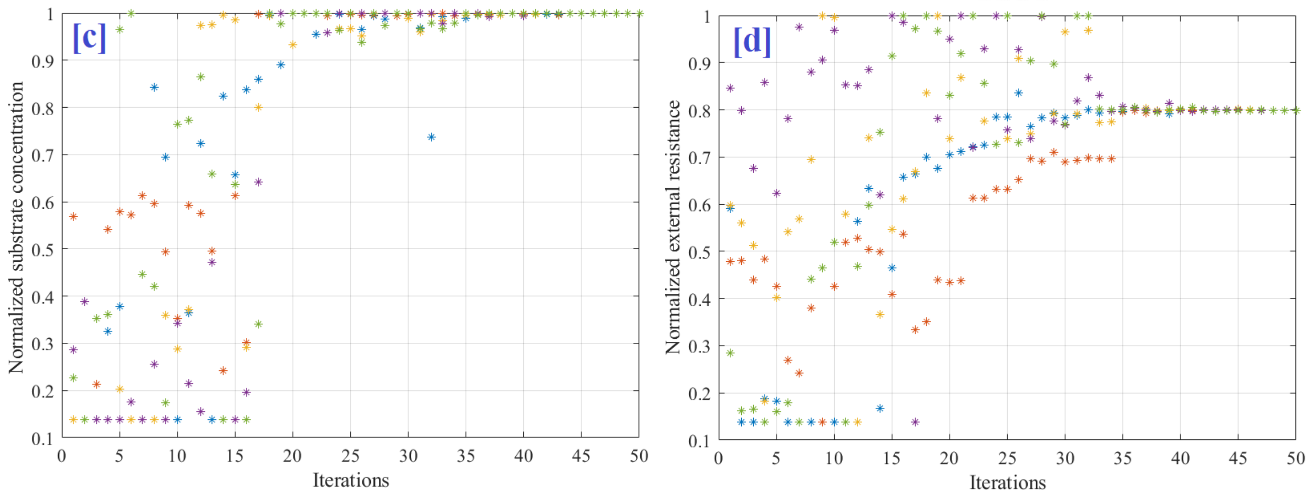

Figure 8. Particles convergence during parameter identification: [**a**] cost function, [**b**] normalized Cu(II)/Cr(VI) ratio, [**c**] normalized substrate concentration, and [**d**] normalized external resistance.

6. Conclusions

Boosting Cr(VI) removal efficiency and power density of microbial fuel cells using ANFIS and artificial ecosystem optimization (AEO) is the main target of this research. The proposed methodology contains two phases: modeling and parameter identification by artificial ecosystem optimization (AEO). First, based on measured data, an ANFIS model is developed to simulate the MFC in terms of the Cu(II)/Cr(VI) ratio, substrate (sodium acetate) concentration (g/L), and external resistance Ω. Then, using AEO, the optimal values of the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance are identified, corresponding to maximum Cr(VI) removal efficiency and highest power density. For the training and testing data sets, the RMSE values for the ANFIS model of Cr(VI) removal efficiency are 2.63×10^{-5} and 2.1275, respectively. For training and testing, the coefficients of determination are 1.0 and 0.9991, respectively. The coefficient of determination is enhanced from 0.951 (by ANOVA) to 0.9963 (by ANFIS), and the RMSE is decreased from 22.60 (by ANOVA) to 0.9761 (by ANFIS). This shows that the fuzzy modeling phase was effective. Finally, the integration between ANFIS and AEO increased the power density from 32.7 mW/m^2 to 38.96 mW/m^2, by 19.14%, compared to measured data. In addition, it boosted the Cr(VI) removal efficiency from 71% to 81.75%, by 15.14%, compared to measured data. Under this condition, the optimal values are 1.672, 1.756 (g/L), and 1404.8 Ω, respectively, for the Cu(II)/Cr(VI) ratio, substrate concentration, and external resistance. The obtained results are not verified experimentally; therefore, they could be used as a basis for further investigations using more parameters than those investigated in the current research.

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