

Analyzing the Effects of Electrode Conductivity and Effective Bacterial Surface Area on Predicted Current Density in Microbial Fuel Cells

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ABSTRACT

Microbial fuel cells (MFCs) have gained attention as a sustainable technology because they can simultaneously generate electricity and treat organic waste through the metabolic activity of electroactive bacteria. This study developed a modified Nernst-Monod computational model to investigate how electrode conductivity and effective bacterial surface area influence the normalized current-density response in *Geobacter sulfurreducens* MFCs under saturation conditions. Peer-reviewed literature and published experimental studies were used to develop and evaluate the computational framework. The effects of electrode properties on predicted MFC performance were analyzed through heatmaps, three-dimensional response surfaces, sensitivity analyses, Monte Carlo uncertainty analysis, and qualitative comparison with a published experimental dataset. The model predicted that increasing electrode conductivity and effective bacterial surface area increased the normalized current-density response, although the rate of improvement diminished at higher parameter values due to saturation behavior incorporated into the modified computational framework. The Monte Carlo simulations showed that the model produced consistent trends despite random variation of conductivity and surface area, suggesting that the computational framework was relatively stable under simulated uncertainty. A qualitative comparison with a published experimental dataset matched similar trends predicted by the model. These findings demonstrate that extending the Nernst-Monod framework with electrode conductivity and effective bacterial surface area provides a useful computational approach for studying the individual and combined influences on normalized current-density response. This framework can help scientists generate hypotheses and guide future experimental investigations.

INTRODUCTION

An increase in demand for sustainable energy technologies has fueled greater interest in systems capable of producing renewable energy while simultaneously reducing environmental waste (Handoyo, 2026). Traditional energy production methods rely heavily on fossil fuels, which contribute to greenhouse gas emissions and climate change (United Nations, 2022). Because of this, researchers have looked into

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alternative technologies that can recover energy from waste materials to lower the environmental impact. One of these alternative technologies is microbial fuel cells (MFCs). MFCs are bioelectrochemical systems that convert organic matter into electrical energy through the metabolic activity of microorganisms. MFCs have attracted much attention because of their ability to generate both electricity and treat wastewater simultaneously. During microbial metabolism, electrons released from the breakdown of organic compounds are transferred to an electrode, producing an electrical current. Although MFC technology offers a way for energy production, power output remains relatively low compared to conventional energy technologies (Chakma et al., 2025). This makes improvements in electron-transfer efficiency an important research challenge.

One of the most extensively studied microorganisms in MFC systems is *Geobacter sulfurreducens* (Torres et al., 2007). This bacterium is studied extensively because of its ability to perform extracellular electron transfer, which allows electrons to be released during metabolism and transferred to conductive surfaces. *Geobacter sulfurreducens* forms electrically conductive biofilms and uses conductive pili to facilitate extracellular electron transport. These properties allow *Geobacter sulfurreducens* to be an important model organism for studying factors that influence MFC performance (Bond & Lovley, 2003).

Electrode properties are among the key factors that affect MFC operation because electron transfer occurs between bacterial biofilms and electrode surfaces. Although previous studies have shown that a larger effective surface area enhances bacterial attachment and biofilm growth (Li et al., 2014), increasing conductivity or surface area does not always produce proportional improvements in MFCs because of biological and transport limitations.

Literature Review

Previous studies have shown that electrode conductivity plays a crucial role in MFC performance. Conductivity has correlated with improved electron-transfer efficiency because electrons generated during metabolism must be transferred to the electrode surface (Renslow et al., 2013). Different carbon-based electrode materials such as carbon cloth, carbon fiber, and graphite have been studied extensively because the materials possess conductive properties and compatibility with microbial growth (Yang et al., 2017). Studies have shown that materials with greater conductivity often produce higher current densities compared to less conductive materials (Gadkari & Sadhukhan, 2020). This information emphasizes the importance of conductivity as a major factor that influences MFC output.

Effective bacterial surface area is another impactful factor that contributes to MFC performance (Choudhury et al., 2017). A larger surface area provides more sites for bacterial attachment and biofilm formation, allowing greater bacterial colonization (Du & Shao, 2025). Materials such as porous graphite and activated carbon cloth have been found to increase bacterial colonization and electrical performance (Hung et al., 2019).

Although various studies have found a positive effect on the performance of MFCs due to conductivity and surface area, some studies have identified biological limitations that restrict the performance (Rismani-Yazdi et al., 2008). One limitation is excessive biofilm thickness. When the biofilm becomes thicker, nutrient transport and diffusion become more difficult, resulting in reduced activity of bacteria located in the biofilm (Mirghani et al., 2022). Other factors include electron-transfer bottlenecks and biofilm saturation, which limit MFC performance at higher surface-area values (Mahmoud et al., 2022).

Carbon cloth, graphite-based electrodes, porous graphite, and stainless steel mesh are commonly studied in MFC studies because they have different combinations of conductivity, surface morphology, and bacterial attachment characteristics (Zhang et al., 2012). Beyond experimental studies, computational modeling has become an important approach for studying MFCs because it allows researchers to test the system's performance under a wide range of operating conditions without requiring a physical laboratory. In MFCs, the Nernst-Monod model is one of the most widely used frameworks for describing current generation in *Geobacter sulfurreducens* MFCs (Torres et al., 2007).

Research Gap

Although numerous studies have investigated electrode conductivity and effective bacterial surface area independently, few computational studies have examined how these variables jointly influence microbial fuel cell performance within a simplified extension of the Nernst-Monod framework that incorporates saturation behavior (Xia et al., 2017).

Research Question

This study aims to answer the following question: How do electrode conductivity and effective bacterial surface area influence the predicted normalized current density response in a simplified extension of the Nernst-Monod framework?

Hypothesis

It was hypothesized that the predicted normalized current-density response would increase as electrode conductivity and effective bacterial surface area increase. However, because the modified computational framework incorporated saturation behavior representing biological and electrochemical limitations, there would be diminishing increases at higher parameter values.

METHODOLOGY:

Data Collection:

Data collection describing the performance of *Geobacter sulfurreducens* MFCs was obtained from previously published peer-reviewed studies. Peer-reviewed studies were chosen if they reported electrode material, current density, or electrode characteristics relevant to extracellular electron transfer. The primary electrode materials that were analyzed were carbon cloth, graphite rod, stainless steel mesh, porous graphite, and other commonly studied conductive electrode architectures.

For each electrode material, data describing electrical conductivity, effective bacterial surface area, electrode potential, and reported current density were derived from peer-reviewed literature. When exact material-property values were unavailable, dimensionless relative indices were assigned using published material characteristics reported within the corresponding studies. Relative indices were assigned by ranking materials according to the reported qualitative or comparative material characteristics described in the literature and then normalizing those rankings for use in the computational model. These values were the inputs in the computational model.

Because the values were derived from multiple different peer-reviewed studies, all continuous variables were normalized before analysis to allow direct comparison between electrode materials.

Parameter Normalization

Electrical conductivity and effective bacterial surface area were transformed to dimensionless indices for the parameter sweeps. Only conductivity and effective bacterial surface area were systematically varied during the simulation, while the remaining parameters were held constant at representative literature values.

$$x_{scaled} = 0.01 + 0.99\left(\frac{x - x_{min}}{x_{max} - x_{min}}\right)$$

“x” represents the original parameter value, x_{min} represents the minimum value within the selected parameter range, and the x_{max} represents the maximum value. This transformation converted conductivity and effective bacterial surface area into a common dimensionless scale ranging from 0.01 to 1. This allowed their relative influence to be evaluated despite their different units and numerical ranges. A lower bound of 0.01 was used to prevent either multiplicative modifier from becoming exactly zero because both conductivity and surface-area modifiers were incorporated multiplicatively into the modified Nernst-Monod equation.

Computational Model Development

Using Google Colab, a computational model to test the effects of electrode conductivity and effective bacterial surface area on predicted MFC performance was built.

The computational model was based on the Nernst-Monod framework, which combines microbial substrate utilization kinetics with electrochemical potential limitations.

Nernst-Monod Relationship...(1)

$$j = j_{\max} \left(\frac{S}{K_s + S} \right) \left[\frac{1}{1 + \exp\left(-\frac{F}{RT}(E_{\text{anode}} - E_{K_A})\right)} \right]$$

- j = Current Density
- $j_{\max}$ = Maximum Current Density
- S = Substrate Concentration
- K_s = Half-Saturation Constant
- E_{anode} = Electrode Potential
- E_{K_A} = Half-Saturation Potential

Using the Nernst-Monod relationship, the model was extended using two multiplicative modifier functions representing electrode conductivity and effective bacterial surface area. For this study, the conductivity and surface-area saturation constants (K_σ and K_A) were both set at a value of 0.3. The values were the same because it allowed the independent effects of conductivity and effective bacterial surface area to be compared under the same mathematical framework instead of introducing differences caused by different parameter values.

Monod-Type Conductivity Saturation Function...(2)

$$f_\sigma = \frac{\sigma}{K_\sigma + \sigma}$$

- f_σ = Conductivity Modifier
- σ = Normalized Electrode Conductivity
- K_σ = Conductivity Half-Saturation Constant

The Monod-type saturation function represents diminishing returns, where increasing conductivity continues to improve electron transfer but produces progressively smaller increases once conductivity becomes sufficiently high (Gadkari & Sadhukhan, 2020).

Monod-Type Effective Bacterial Surface Area Saturation Function...(3)

$$f_A = \frac{A}{K_A + A}$$

- f_A = Effective Bacterial Surface Area Modifier
- A = Normalized Effective Bacterial Surface Area
- K_A = Surface-Area Half-Saturation Constant.

The function represents diminishing biological benefit at larger surface areas because increasing biofilm thickness and mass-transfer limitations reduce the effectiveness of additional attachment sites (Krieg et al., 2018).

The individual model components were combined to produce the overall current-density prediction equation:

$$j = j_{max} \left(\frac{S}{K_S + S} \right) \left[\frac{1}{1 + \exp\left(-\frac{F}{RT}(E_{anode} - E_{KA})\right)} \right] f_{\sigma} f_A \dots (4)$$

This equation accounts for the established electrochemical foundation of the Nernst-Monod model while allowing electrode conductivity and effective bacterial surface area to be evaluated simultaneously. These modifiers are phenomenological rather than mechanistic.

The conductivity and effective bacterial surface-area terms were multiplied into the modified Nernst-Monod framework because each term represents a specific process that impacts current generation in an MFC. The Nernst-Monod component accounts for the effects of substrate availability and electrode potential, while the conductivity and surface area account for the influence of electron transport and bacterial attachment. By multiplying these terms together, each term acts as a limiting factor on the normalized current-density response. This means that favorable conductivity cannot fully compensate for extremely limited bacterial surface area, and favorable surface area cannot fully compensate for poor conductivity. This approach was used to investigate relative trends rather than reproduce the complete electrochemical complexity of experimental systems.

The model parameters used in Equation (4) are summarized in Table 1

Table 1. Model Parameters Used in the Modified Nernst-Monod Computational Framework

Parameter	Symbol	Value	Unit	Source / justification
Maximum current density	$j_{\max}$	1.0	Dimensionless	Normalization constant; this study
Substrate concentration	S	20.0	mM	Pocaznoi et al. (2012)
Half-saturation constant	K_s	0.5	mM	Baseline model input; this study
Faraday constant	F	96,485	C mol ⁻¹	NIST/CODATA
Universal gas constant	R	8.3145	J mol ⁻¹ K ⁻¹	NIST/CODATA
Temperature	T	313.15	K	Baseline operating condition; this study
Anode potential	E_{anode}	-0.20	V vs. SCE	Pocaznoi et al. (2012)
Half-maximum rate potential	E_{KA}	-0.375	V	Baseline electrochemical input; this study
Conductivity saturation constant	K_{σ}	0.30	Dimensionless	Phenomenological parameter; this study
Surface-area saturation constant	K_A	0.30	Dimensionless	Phenomenological parameter; this study

Table 1. Model parameters used in the modified Nernst-Monod Computational framework. Physical constants such as F and R were taken from standard reference values. The substrate concentration (S) and anode potential (E_{anode}) were selected based on representative values reported in the literature, while T , E_{ka} , and K_s were selected based on commonly reported values in MFC literature, and the conductivity and surface-area saturation constants such as K_{σ} and K_A were used in the study as phenomenological parameters to account for the diminishing-return behavior. The choice of Monod-type saturation functions is consistent with previous MFC modeling studies that report conductivity- and substrate-dependent saturation behavior. A value of 0.30 was used as a moderate phenomenological baseline that produced gradual saturation across the normalized parameter range while keeping sensitivity to changes in conductivity and effective bacterial surface area. Since this study focused on understanding how different parts of the system interact rather than matching a specific lab experiment, the saturation constants were not adjusted to fit exact experimental data. The value of 0.30 produced gradual, leveling-off behavior while still allowing the model to convey clear trends as the parameters changed. Accordingly, the absolute magnitude and curvature of the predicted response depend on the selected phenomenological constants, whereas the study mainly interprets the broader directional relationships observed across the parameter space.

Table 2. Literature-Informed Normalized Electrode-Property Indices

Electrode Material	Conductivity Classification	Conductivity Index	Effective Surface-Area Classification	Surface-Area Index	Literature Source(s)
Carbon cloth	High	0.67	High	0.67	Choudhury et al. (2017); Li et al. (2014)
Graphite rod	High	0.67	Low	0.01	Bond & Lovley (2003); Choudhury et al. (2017)
Stainless-steel mesh	Very high	1.00	Moderate	0.34	Yang et al. (2017); Zhang et al. (2012)
Porous graphite	High	0.67	Very high	1.00	Choudhury et al. (2017); Zhang et al. (2012)

Note. Indices are dimensionless literature-informed modeling values, not directly measured conductivity or surface-area values. Electrode materials were classified ordinally based on qualitative and comparative characteristics reported in the cited literature. Ranks were transformed to the model's 0.01–1.00 normalized scale.

Table 2. Literature-informed normalized electrode-property indices were used to represent relative conductivity and effective bacterial surface area. The indices are dimensionless modeling values taken from ordinal classifications based on qualitative and comparative characteristics reported in the different cited literature. They do not represent directly measured conductivity or surface-area values.

Table 2 shows the material-specific reference values used to characterize electrode properties within the normalized modeling framework. The values were converted into dimensionless indices using the normalized procedure that is described below because the conductivity and surface-area measurements reported across studies were derived from multiple studies.

Simulation Procedure

The modified Nernst-Monod computational model simulated different combinations of conductivity and effective bacterial surface area over the parameter range of 0.01 to 1.00. To calculate current density under different electrode conditions, parameter sweeps were performed. The calculated numerical values were stored in a computational matrix and used to generate heatmaps and three-dimensional surface plots. The heatmaps were used to illustrate the regions of high and low predicted current density. Sensitivity analyses were performed with varying conductivity and surface area while holding the rest of the variables constant. This was needed to evaluate the effect of each parameter on the predicted current density.

Monte Carlo Simulation

To evaluate the model's uncertainty and prediction stability, the Monte Carlo simulation was used. The simulation consisted of 10,000 simulations. Electrical conductivity, effective bacterial surface area, and saturation constants were randomly perturbed using normal distributions centered around their baseline values with a standard deviation of 10%. The distributions were used to evaluate the strength of the predicted trends.

For each trial, the conductivity effect was calculated as the difference in predicted normalized current-density response when normalized conductivity increased from 0.25 to 0.75 with the normalized surface area held constant at 0.5. The surface-area effect was calculated similarly to the conductivity effect by calculating the difference in predicted normalized current-density response when normalized surface area increased from 0.25 to 0.75 with the normalized conductivity held constant at 0.5. The values of 0.25, 0.5, and 0.75 were used to represent low, intermediate, and high values within the normalized 0.01 - 1.00 parameter range. This was used to calculate the difference between the high and low values and compare them to show the relative effects of the two model parameters.

Parameter-Sweep

Conductivity and effective bacterial surface area were varied across their normalized parameter ranges (0.01 - 1.00). This generated a two-dimensional parameter space. The model was tested at each parameter combination while all remaining variables were held constant at their literature-informed values. The results from the response surface were visualized using heatmaps and three-dimensional surface plots.

Data Visualization and Analysis

All simulations, parameter sweeps, and visualizations were generated using Python libraries such as NumPy and Matplotlib within Google Colab. To visualize the data, heatmaps, normalized current-density curves, sensitivity plots, and material comparisons were generated to evaluate the nonlinear relationships between conductivity, effective surface area, and predicted normalized current-density response.

Model Evaluation

The computational model was evaluated to provide evidence that the model's prediction was consistent with what happened in actual MFC experiments. To evaluate the model, the predicted normalized current-density responses were compared with published experimental data that was found in the literature related to MFC electrode materials. The model was not designed to reproduce exact experimental current densities; instead, it used normalized conductivity and effective bacterial surface-area indices.

The model's evaluation compared relative trends and material rankings with experimental values. If the relative trends aligned with experimental values, it was an indication of qualitative support for the model's ability to represent expected relationships between electrode properties and MFC performance. This comparison should not be interpreted as quantitative validation of the model, which would require calibration against a standardized experimental dataset.

RESULTS

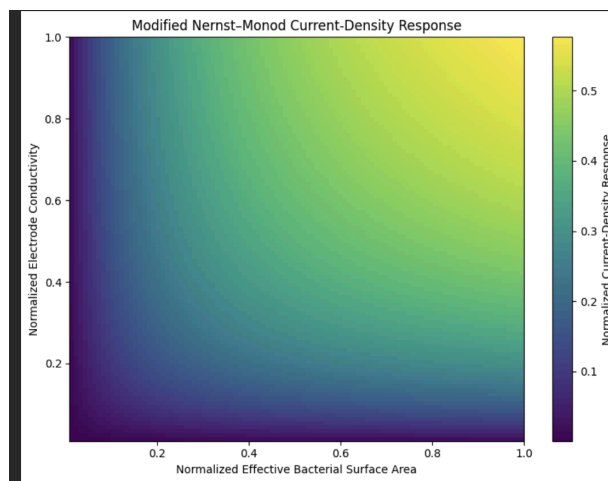


Figure 1. Heatmap of the normalized current-density response generated using the modified Nernst-Monod computational model. The color intensity represents the predicted normalized current-density response as a function of normalized electrode conductivity and normalized effective bacterial surface area. The warmer the color, the higher the predicted response.

The nonlinear change across the parameter space shows diminishing gains in predicted response at higher conductivity and effective bacterial surface area values. The pattern is consistent with the saturation behavior incorporated into the modified computational framework.

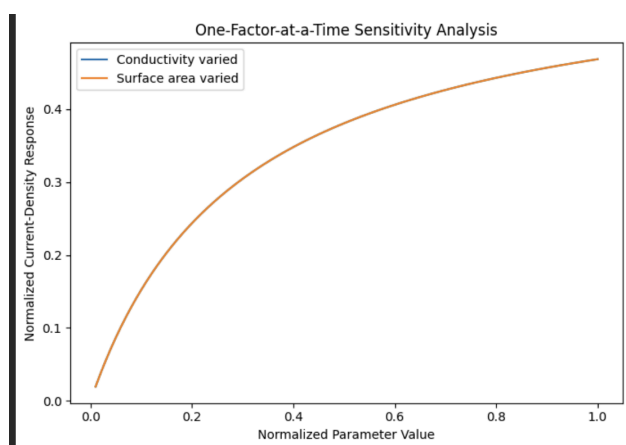


Figure 2. One-factor-at-a-time sensitivity analysis of the modified Nernst-Monod model. Both conductivity and effective bacterial surface area were varied independently while all other parameters were held constant.

As the parameter value increased, the curve gradually started to plateau, indicating progressively smaller gains in predicted response at higher conductivity and surface-area values. The conductivity and effective bacterial surface-area curves overlap because both modifier functions use the same Monod-type saturation equation and the same saturation constant of 0.3. Because of this, changing either parameter independently produces the same mathematical response.

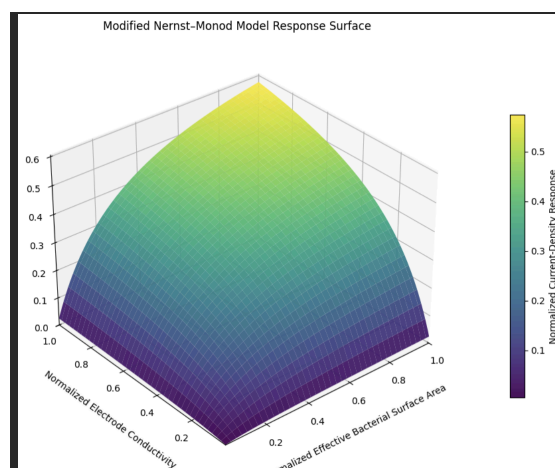


Figure 3. Three-dimensional response surface generated by the modified Nernst-Monod computational model to show the combined effects of normalized electrode conductivity (σ) and normalized effective bacterial surface area (A) on the predicted normalized current-density response. When both parameters increased, higher responses were reported.

The three-dimensional response surface (Figure 3) shows the multiplicative structure of the model. A low value of either conductivity or effective bacterial surface area constrains the overall predicted response even if the other parameter is high. This indicates that improvements in one modeled electrode property cannot fully compensate for limitations in the other.

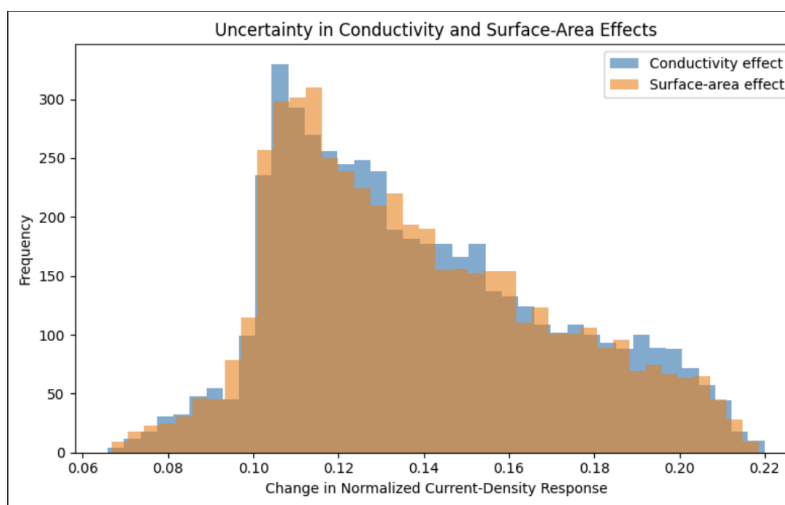


Figure 4. Monte Carlo uncertainty analysis of the modified Nernst-Monod computational model. The conductivity effects represent the change in predicted normalized current-density response when normalized conductivity is increased from 0.25 to 0.75 while normalized surface area was held constant. The surface area represents the change in predicted normalized current-density response when normalized surface area is increased from 0.25 to 0.75 while normalized conductivity was held constant at 0.5. To evaluate the model stability, randomized perturbations were used in conductivity and effective bacterial surface-area parameters. The overlaps represent similar uncertainty ranges for both parameters under the simulated conditions.

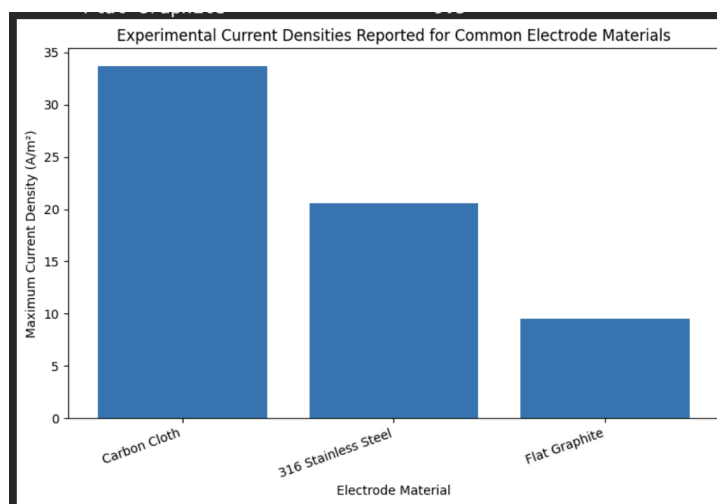


Figure 5. Experimentally measured maximum current densities of carbon cloth, 316 stainless-steel mesh, and flat graphite electrodes under identical operating conditions. Values were derived from Pocaznoi et al. (2012). The experimental comparison showed that carbon cloth exhibited the highest reported maximum

current density, followed by stainless-steel mesh and flat graphite under identical operating conditions. Even though the computational model was not designed to reproduce exact experimental values, the model produced material rankings that were consistent with the experimentally observed relationships between improved electrode properties and increased normalized current density.

DISCUSSION

As shown in Figures 1-3, the modified Nernst-Monod computational model demonstrated that increasing electrode conductivity and effective bacterial surface area increased the normalized current-density response. Figure 1 shows that the highest normalized response occurred when both conductivity and surface area were simultaneously high. Likewise, based on Figures 2 and 3, the improvements in both conductivity and surface area increased the predicted response until higher parameter values were reached. Within the structure of the modified model, conductivity and bacterial surface area work together to increase the predicted current-density response. High conductivity may facilitate electron transport from bacterial biofilms to the electrode, while greater effective bacterial surface area may increase the number of electrochemically active microorganisms participating in electron transfer.

The diminishing response at higher parameter values accounts for the saturation behavior incorporated into the modified computational model. This suggests that improvements in electrode properties alone could provide progressively smaller gains in predicted current-density response once biological and electrochemical limitations become dominant.

Figure 4 represents the Monte Carlo uncertainty analysis of the computational model. There were similar distributions of the normalized current-density response when there were randomized variations in conductivity and effective bacterial surface area. These findings demonstrate that the qualitative relationships predicted by the computational framework remained relatively stable even with small changes in the input parameters. This supports the stability of the model under the simulated uncertainty conditions.

Connection to Literature:

The positive correlation between conductivity and predicted current density is consistent with previous MFC research (Gadkari & Sadhukhan, 2020). The model's results indicated that increasing conductivity resulted in higher predicted current densities across the tested ranges, which aligns with past research that conductive electrode materials improve electron-transfer efficiency by reducing resistance between bacterial biofilms and the electrode surface (Dadsena et al., 2026; Gadkari & Sadhukhan, 2020). This finding supports the hypothesis that improving the electrical properties of electrode material could increase current generation by reducing resistance to extracellular electron transfer.

Along with conductivity, the results regarding bacterial surface area are also consistent with previous studies. Based on past research, a greater surface area helps with bacterial attachment and biofilm

formation to produce a greater number of electrochemically active microorganisms to participate in electron transfer (Yalcinkaya et al., 2024). In the computational model, as surface area increased, predicted current density increased as well. However, the model also shows that increasing surface area alone is unlikely to produce unlimited gains because of biological limitations that become increasingly important as the biofilm develops (Roy et al., 2023).

While there has been much research on how surface area and conductivity affect performance independently, this study tested both under biological limitations. The heatmap and three-dimensional surface analysis showed that the highest predicted current densities occurred when both conductivity and effective bacterial surface area were high. Even though both were high, the model predicted that, at a certain point, incorporating saturation effects led to diminishing returns at larger surface areas.

Overall, these findings suggest that electrode optimization strategies should consider conductivity and effective bacterial surface area simultaneously when studying MFC electrode design. The model predicts that increasing both parameters produced the highest normalized current-density response, while the incorporated saturation behavior resulted in diminishing gains at higher parameter values. These trends can help future experimental studies and hypotheses in studying electrode optimization.

LIMITATIONS & STRENGTHS:

Several limitations should be considered in this computational study. The model represents a simplified extension of the Nernst-Monod framework and does not explicitly simulate complex biofilm dynamics, diffusion-reaction processes, or Butler-Volmer electrode kinetics (Picioreanu et al., 2007). Additionally, normalized material-property values were used to investigate trends in MFC performance rather than reproducing specific experimental systems.

Even with these limitations, there are many strengths in this study. A major strength of this study is that it uses a literature-informed computational framework that integrates established MFC kinetics with electrode-property modifiers. By taking a computational approach, it allows rapid evaluation of parameter interactions without the cost and time required in a laboratory. The model therefore incorporates a flexible framework to incorporate additional biological, electrochemical, or transport-related variables in future experimental studies.

Additionally, the experimental comparison was based on three electrode materials from a single study (Pocaznoi et al., 2012) for an initial qualitative evaluation. This comparison should be interpreted as a qualitative ranking check rather than comprehensive experimental validation. Future work should compare the materials against additional experimental datasets to test if the trends remain consistent across different conditions.

Furthermore, the conductivity and surface-area saturation constants were not experimentally fitted and should not be interpreted as universal physical constants. The model is best used as a tool for exploring relative parameter interactions and generating hypotheses rather than exactly predicting experimental current densities.

FUTURE WORK

Future work will focus on strengthening the modified computational framework by utilizing larger experimental datasets and incorporating extra variables such as biofilm thickness, internal resistance, and pH. By doing this, the model can broaden its applicability to a wider range of MFC systems.

CONCLUSION

This study demonstrates that a modified Nernst-Monod computational framework can be used to investigate the influence of individual and combined effects of electrode conductivity and effective bacterial surface area on MFC performance. The results demonstrate that computational modeling can show how these electrode properties influence the normalized current-density response and identify trends such as diminishing returns at higher conductivity and surface area values. Although the computational framework is simplified, it demonstrates how computational modeling offers a valuable counterpart to laboratory studies by pinpointing relationships among electrode properties, generating testable hypotheses, and informing future laboratory studies aimed at optimizing microbial fuel cell performance.

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