Enhancing Microbial Fuel Cell Performance Prediction and IoT Integration Using Machine Learning and Renewable Energy

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This study aims to enhance Microbial Fuel Cells (MFCs) reliability for remote environmental monitoring, emphasizing unexplored facets of accurate energy prediction and the integration of renewable energy-powered Internet of Things (IoT) devices. Following comprehensive research, design, and component procurement, an innovative and cost-effective IoT system was developed, leveraging renewable energy from MFCs. Using an Arduino UNO-WiFi, data was collected and showcased on a web page while logged in a Google Firebase database, with an Android app created for intuitive smartphone visualization. Over four months, sensor data was accumulated. An Artificial Intelligence (AI) model, employing Autoregressive Integrated Moving Average (ARIMA), precisely forecasted MFC energy production (RMSE: 0.0119 and 0.0113 for trials 1 and 2). Despite the initial energy production surge, a subsequent decline occurred due to organic matter depletion. This prototype represents an affordable and sustainable solution for cloud-based IoT environmental monitoring with AI-driven energy forecasts, embodying innovation in renewable energy applications and sustainable practices.

Keywords: machine learning, microbial fuel cells, renewable energy, autoregressive integrated moving average

INTRODUCTION

The urgency of transitioning to renewable energy sources is no longer optional but imperative to mitigate climate change consequences. The International Energy Agency asserts that renewable energy must triple its global power supply contribution by 2050 for climate neutrality(Gielen et al., 2019). Market forecasts predict the global microbial fuel cell (MFC) market will exceed $15 million by 2025(Sanusi et al., 2023). MFCs convert chemical energy into electricity through microorganism activity, requiring optimization(Mathuriya, 2018). Although promising, the use of Artificial Intelligence (AI) for sustainable MFC electricity generation remains underexplored(Garg & Lam, 2017). Microbial Fuel Cells offer the potential for sustainable energy generation(Atique et al., 2019; Ieropoulos et al., 2005).

PROBLEM STATEMENT

The primary challenge centers on the precise prediction of Microbial Fuel Cell (MFC) performance(Lesnik & Liu, 2017). MFCs represent a breakthrough in converting microbial metabolic activity into electricity, yet realizing their optimal functionality requires accurate performance forecasting(Dwivedi et al., 2022). This includes predicting energy production, influenced by microbial growth and availability of organic matter (Mathuriya, 2018). Current methods are inadequate due to the complex dynamics inherent in MFCs(Jung & Pandit, 2019).

The critical need for Integrating MFCs into Renewable Energy-Powered IoT Devices is evident(Khan et al., 2020). While the Internet of Things (IoT) enhances environmental monitoring, traditional power sources, such as batteries, pose reliability issues linked to depletion concerns.

The engineering objective is to develop a cost-effective IoT system utilizing renewable energy from MFCs for monitoring purposes. Artificial Intelligence enhances the accuracy of renewable energy forecasts(Khan et al., 2020). The prototype integrates environmental monitoring, renewable energy utilization, and precise energy prediction to address these challenges.

HYPOTHESES

1. The proposed IoT System with AI will demonstrate accurate energy production forecasting.
2. Voltage generation is expected to exhibit a gradual increase over time.
3. The system will effectively capture and display temperature, voltage, and water level data on an internet-connected webpage.

METHODOLOGY AND APPROACH

This study employs a comprehensive strategy involving precise energy production forecasts for MFCs and their integration into renewable energy-powered IoT devices. The methodology includes:

Performance Prediction through Machine Learning

Utilizing the Autoregressive Integrated Moving Average (ARIMA) algorithm to forecast energy production accurately. ARIMA is chosen for energy production forecasting, given its prowess in time series modeling, flexibility, statistical rigor, easy parameter tuning, and interpretability as a baseline model(Alberg & Last, 2018; Atique et al., 2019). This method captures intricate patterns in MFCs' performance. The ARIMA model, trained with historical data, predicts variations in energy production.

IoT Device Design and Development

Creating a cost-effective IoT device that integrates MFCs and solar energy. This device captures environmental data and forecasts energy supply. The design prioritizes renewable energy sources, cost-effectiveness, and real-time data tracking for enhanced sustainability and efficiency.

Design Constraints

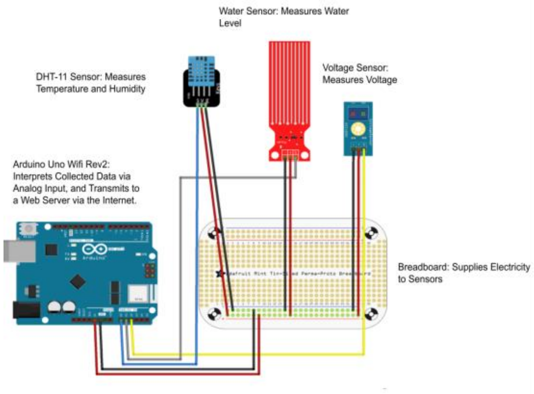
A commitment to cost-effectiveness guides the development of the IoT system.

Product Design

The final iteration of the prototype exhibits an advanced array of functionalities, intricately managing essential environmental variables like temperature, water levels, and voltage. This refined processing system contributes to a nuanced comprehension of the ambient conditions. The collected data is effortlessly transmitted to a remote server through cloud technology, establishing a streamlined infrastructure for efficient energy management and enabling seamless remote monitoring.

Furthermore, the IoT device is intricately designed to seamlessly interface with diverse sensors. This augments the precision of data collection and ensures a user-friendly interface, providing convenient access to processed environmental data directly on smartphones. Integrating these sophisticated features embodies a holistic approach, optimizing functionality for operational efficiency and user accessibility.

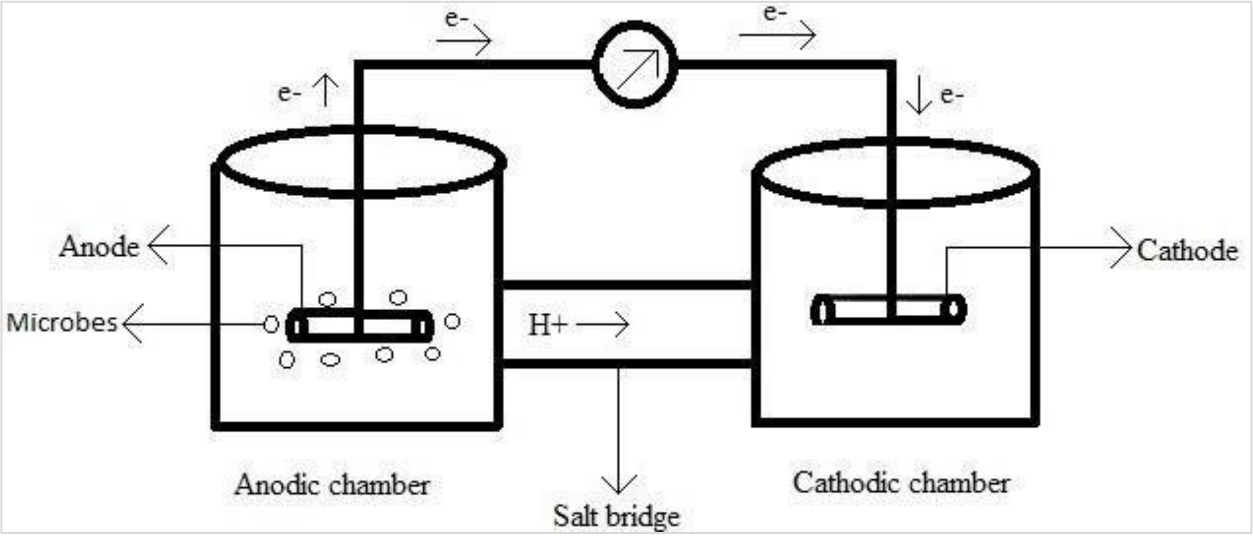
FIGURE 1
PROTOTYPE DESIGN AFTER EXPLORATION OF ALTERNATIVES



An essential realization during testing was that a single MFC's electrical generation couldn't sustain IoT demands. A design shift incorporated a solar power bank, addressing energy deficiencies and enhancing system performance and reliability. This adaptation aligns with the design objectives.

Microbial Fuel Cell (MFC) Setup and Phenomena

FIGURE 2
SCHEMATIC REPRESENTATION OF MFC SETUP



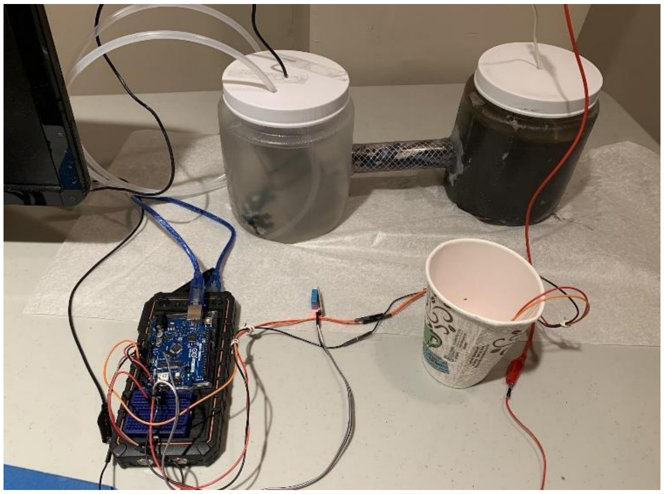
Aswin et al., 2017

The Microbial Fuel Cell (MFC) is a sophisticated device characterized by two fundamental chambers, the anode and cathode, which serve as the cornerstone of its operational framework. Within these chambers, an intricate interplay of essential components, including electrodes, wiring, a pump, water, sludge, and a salt bridge, collaborate to orchestrate the complex energy generation process. Figure 2 provides a schematic representation of this MFC setup, offering a visual insight into its structural elements.

At the heart of the MFC's functionality lies the involvement of microorganisms, predominantly bacteria, pivotal in the oxidation process(Jiang et al., 2016). This process involves the breakdown of organic matter within the sludge, releasing electrons as a byproduct. The journey of these liberated electrons is of paramount significance as they undergo transfer to oxygen molecules, a process known as reduction. This electron transfer, occurring from microorganisms to oxygen molecules, represents a crucial step in the metabolic processes of these microorganisms. The orchestrated movement of electrons along a pathway involving electrodes and an external circuit connecting the anode and cathode generates a measurable electric current, signifying the flow of electrical energy. As electrons reach the cathode, their interaction with oxygen molecules in a reduction process produces water molecules as a byproduct. This facilitates the transfer of metabolic energy within microorganisms and results in a tangible flow of electrical energy ready for practical applications. In summary, the Microbial Fuel Cell adeptly harnesses surplus electrons from the metabolic activities of microorganisms, guiding them through a controlled pathway to convert biochemical reactions into a measurable electrical current, thus offering a promising avenue for sustainable energy generation.

Prototype Developed

FIGURE 3
IOT AND MFC SETUP



In a Microbial Fuel Cell (MFC) setup(Nave, 2022), energy is obtained through the metabolic activities of microorganisms.

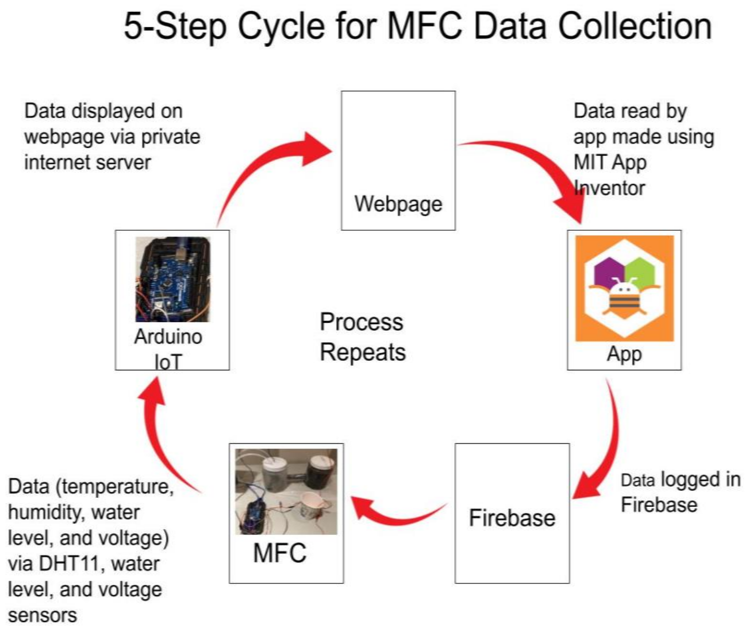
1. This system typically consists of two distinct chambers: the sludge chamber, containing microorganisms, and the water chamber. These chambers are separated by a salt bridge, allowing ion transport without mixing contents.
2. Within this setup, crucial components include electrodes, copper wires, and an air pump. The microorganisms within the sludge chamber engage in oxidation processes, breaking down organic matter. This generates surplus electrons as byproducts. The electrodes, typically made of materials like carbon, serve as conduits for the movement of these electrons.
3. The copper wires create a closed circuit between the anode (where oxidation occurs) and the cathode (where reduction occurs). This allows the flow of electrons, creating an electric current.
4. The air pump provides oxygen to the cathode chamber, where oxygen reduction occurs. As the surplus electrons reach the cathode, they combine with oxygen and protons from the electrolyte to produce water as a byproduct.

5. To monitor the environmental conditions, a DHT-11 sensor is employed. This sensor measures temperature and humidity in the surroundings, providing valuable data for analysis.
6. The UNO WiFi Rev2 board is utilized for Internet of Things (IoT) integration. It connects the MFC system to the online platform, enabling remote data transmission and control.
7. Analog pins are used to measure input signals from various sensors. These pins convert physical parameters like voltage or resistance into digital values that the microcontroller can process.
8. A water sensor measures the water level in a water body, adding another layer of environmental monitoring to the system.
9. To enhance energy availability, a solar bank is incorporated. This component collects solar energy and converts it into electrical energy that can be used to power the system.
10. The collected data from sensors and energy generation is stored and analyzed within the IoT framework. This involves the use of cloud-based platforms, databases, and analytics tools to manage and interpret the information gathered from the MFC setup. Data analysis helps optimize system performance and predict trends.

In summary, the MFC setup harnesses microbial metabolic processes to generate energy. It utilizes various components, sensors, and technologies to monitor environmental conditions, facilitate IoT integration, and optimize energy utilization, contributing to sustainable energy generation and environmental monitoring.

DATA COLLECTION, STORAGE, AND ANALYSIS

FIGURE 4
IOT CLOUD FRAMEWORK FOR POWER MANAGEMENT THAT ALLOWS INDEPENDENT OPERATION OF MFC



Google Firebase for Data Collection and Real-Time Data Storage

Communication is imperative in fast-paced environments, and keeping this communication in real-time is essential. Therefore, a real-time database was needed for this system to function properly, so data could be tracked in real-time. Firebase was used to provide such real-time database servers as well as various other services, which allowed for easy app development.

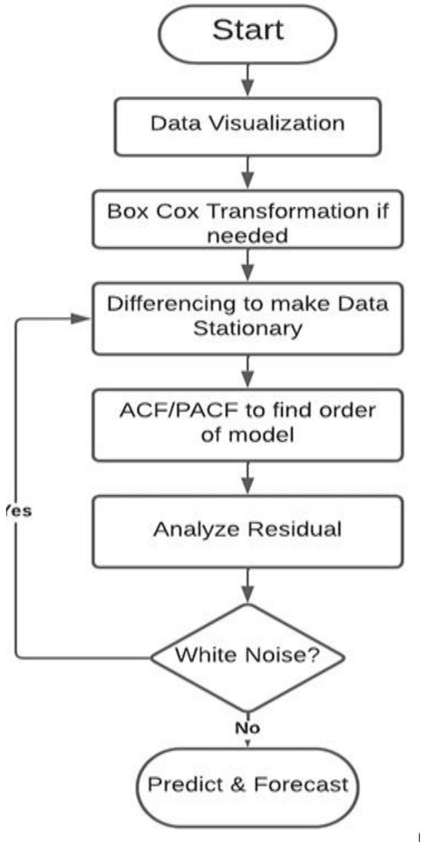
MIT App Inventor for Remote Monitoring Using a Phone

MIT App Inventor is a visual programming environment for creating apps for Android-based smartphones and tablets. Block programming was used to develop a mobile app. When you click on the Android app, it reads values from the webserver. it displays the same values from the web server on the phone for remote monitoring. A Firebase database is used, where the environment and voltage-produced data are logged on a remote server. Data can be transferred from Firebase to Google Sheets or Excel, for forecasting and analysis.

Artificial Intelligence Using Autoregressive Integrated Moving Average (ARIMA)

Many real-world processes are represented using time series by: X(t-p), ...x(t-2), ...x(t-1), ...x(t). In the past, linear techniques such as auto-regressive integrated moving average models (ARIMA) developed by Box and Jenkins were used to forecast time series, as ARIMA may be implemented only if the mean difference and standard deviation remain constant over time intervals. Arima-based machine learning model was developed that uses the training data from the firebase to forecast energy values in the future and locate any unusual data read by the sensors.

FIGURE 5
ALGORITHM FOR ANALYZING THE DATA AND PREDICTING



Steps in the process of time series analysis and forecasting using Box-Jenkins methodology and differencing.

1. *Data Visualization*
    - ○ Begin by visually inspecting the time series data. Plot the raw data over time to identify any noticeable patterns, trends, or seasonality.
2. *Box-Cox Transformation*

- Apply the Box-Cox transformation to stabilize the variance of the time series if necessary. This is particularly useful when the variance of the series is not constant over time.

3. *Differencing*
   - Implement differencing to make the time series stationary, where the mean and variance are relatively constant over time. This involves subtracting the value at the previous time point from the current value.
4. *Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)*
   - Examine the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. These plots help identify the order of autoregressive (AR) and moving average (MA) terms in an ARIMA model. Peaks in the ACF and PACF plots indicate potential orders for AR and MA components.
5. *Model Fitting and Residual Analysis*
   - Fit an ARIMA model to the different time series. Analyze the residuals to ensure they resemble white noise. If patterns exist in the residuals, further adjustments to the model may be needed.
6. *White Noise Check*
   - Examine the residuals to confirm if they exhibit characteristics of white noise. A white noise residual implies that the model captures all the information in the time series.
7. *Prediction and Forecasting*
   - Use the fitted ARIMA model to make predictions on the training set. Validate the model's performance using unseen data. Forecast future values based on the identified patterns and trends.

This process involves transforming, differencing, and modeling the time series data to create a predictive model. The ACF and PACF plots guide the determination of model parameters, and the white noise analysis ensures the model captures all relevant information. The ultimate goal is to create a robust model for predicting and forecasting future values in the time series.

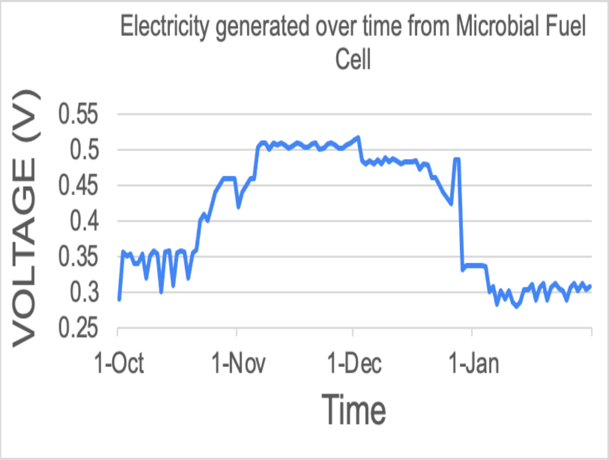
RESULTS AND FINDINGS

Our research yields significant insights into the accurate prediction of MFC energy production and the integration of MFCs into renewable energy-powered IoT devices. Key findings include:
The product was tested for four months, and data was logged for two trials.

TABLE 1
RESULTS

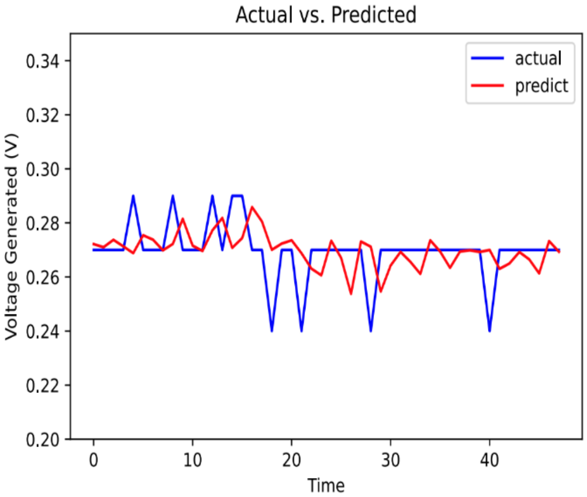
Aggregate Data	**Trial 1 (Oct-Nov)**	**Trial 2 (Dec-Jan)**
Avg Voltage Generated	**0.43 V**	**0.38 V**
Avg Temperature	**12.8°C**	**-3.5°C**
Avg Water Level	**645**	**644**
RSME (Accuracy)	**0.0119**	**0.0113**

FIGURE 5
ELECTRICITY GENERATION OVER TIME FROM MFC



Our first hypothesis was supported, indicating the system's accuracy in predicting electricity production with low RMSE values (Table 1) The second hypothesis was partially supported, showing a gradual increase in electricity production, followed by a decline due to organic matter depletion (Fig 5), suggesting the need for additional waste matter for sustained generation. The third hypothesis was supported, affirming the system's ability to read and display sensor data on a webpage.

FIGURE 6
PERFORMANCE PREDICTION RESULTS W/ ARIMA ALGORITHM



The blue line graphically presents the actual dataset, while the ARIMA model demonstrates impressive precision, evident from notably low RMSE values—around 0.012 for trial one and approximately 0.011 for trial 2 (Fig 6). This precision underscores the ARIMA model's practical efficacy. The alignment between the model's predictions and actual data, represented by the blue line, reinforces its accuracy and robustness. These results validate our approach and highlight the model's adaptability. This success encourages further exploration of its applications and integration, underpinned by rigorous testing and validation. This accomplishment underscores our commitment to leveraging machine learning for enhanced energy production prediction and advancing sustainable energy technologies.

DISCUSSION AND IMPLICATIONS

Applying the ARIMA algorithm to predict energy production in Microbial Fuel Cells (MFCs) underscores its potential as a valuable predictive tool. Contrary to initial expectations, individual MFCs prove inadequate in generating sufficient power to independently sustain IoT devices. Consequently, integrating a solar power bank becomes imperative, resulting in establishing a self-sufficient system. Introducing an air pump into the MFC setup significantly improves electric charge efficiency, emphasizing the pivotal role of operational conditions in energy generation. This research contributes to sustainable energy utilization and environmental enhancement by providing valuable insights for optimizing Microbial Fuel Cell (MFC) performance and integration with IoT, facilitating broader adoption.

However, it is essential to recognize the study’s limitations. The use of a singular sludge sample, the lack of diversity in its sources, and the reliance on a relatively small sample size may impact the generalizability of the findings. Future research endeavors should prioritize broadening the range of sludge sources and increasing the sample size to enhance the study’s overall robustness and applicability.

FUTURE RESEARCH DIRECTIONS

In this study, we acquired valuable insights into auto-regressive models like ARIMA, MFC setup dynamics, data collection techniques, and IoT device development. The study emphasizes the critical role of renewable energy in achieving sustainability. The ability to independently troubleshoot technical challenges is a valuable skill that emerged during this research.

For future research, we propose exploring the utilization of supercapacitors charged by multiple MFCs, managed through efficient power systems, to power IoT devices. Additionally, transitioning from laboratory-based setups to small-scale field deployments presents a promising avenue for long-term usability assessment. Moreover, investigating alternative AI and machine learning algorithms such as neural networks (LSTM), ensemble methods (Random Forest), and non-parametric methods (k-Nearest Neighbors) to enhance energy demand forecasts remains an area of exploration with MFC.

In conclusion, our research represents a significant step forward in accurately predicting MFC energy production using the ARIMA algorithm and the integration of MFCs into renewable energy-powered IoT devices. The potential to revolutionize environmental monitoring while promoting sustainable energy sources holds promise for a greener and more resilient future.

CONCLUSION

Our proposed approach with Machine learning offers a sustainable and cost-effective solution to address the challenges of accurate energy prediction and renewable energy integration. The seamless coupling of MFCs and solar energy within IoT devices allows continuous, real-time environmental monitoring. The findings underscore the potential of renewable-powered IoT systems to enhance environmental data acquisition and contribute to the global transition towards sustainable energy sources.

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