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# A STATISTICAL ANALYSIS TO IDENTIFY THE KEY PARAMETERS AFFECTING WASTEWATER TREATMENT USING MICROBIAL FUEL CELL

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***Abstract***

*In the present effort to manage water resources more sustainably, wastewater is now viewed as a resource that may be used for electricity, plant nutrients, and water. The primary focus is the exploitation of organic materials and microorganisms from wastewater to produce electricity. The organic stuff is used by the organisms in the wastewater for metabolic processes. The prospect of direct biological conversion of wastewater's organic components into energy exists, even if major breakthroughs are needed for this process to compete with anaerobic biological conversion of wastewater organics into electricity generation. With the development of more advanced membrane techniques and full anaerobic wastewater treatment, wastewater treatment could cease to be a significant energy consumer and instead become a net energy producer. The treatment of home wastewater and the use of graphite electrodes by microorganisms to generate energy are the main topics of this research. Because graphite has a large surface area and is noncorrosive, it is an excellent material for use in waste water applications.*

***Keywords:*** *Wastewater, Descriptive Statistics, Correlation, One Way ANOVA, Regression, Electricity.*

## 1. INTRODUCTION

Domestic wastewater (DWW) treatment consumes a substantial quantity of electrical energy worldwide each year. Energy expenses are expected to rise in the future due to the growing demand for energy resources and the depletion of fossil fuel supplies. But the chemical energy found in organic materials in DWWs may be able to help wastewater treatment plants balance their energy and financial resources if the proper technology is applied.

Since it covers both organic and mineral materials transported through liquid media, the word "wastewater" is now frequently used in place of "sewage." Mineral content in wastewater can dissolve in water, create deposits, and contribute to the effluent's water hardness, whereas the organic portion of the wastewater decomposes biologically.

One promising technology that has been created to address the problems of wastewater treatment and energy generation is the bioreactor. This gadget cleans the wastewater while converting organic molecules present in sewage water into bioelectricity through the interaction of bacteria and electrodes. In the anode compartment, the bioreactor serves as a biocatalyst.

Despite recent advancements in the technology, extensive field applications are still in the early stages of development. Its wider application is now restricted by scaling issues such cathode difficulties, size restrictions, and resistance from both the inside and outside.

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## 2. METHODS AND METHODOLOGY

### 2.1 Collection of Waste Water

The wastewater was collected from a residential building's sewage treatment system, which served 500 residents in an apartment. The primary factor in selecting a residential building was the organic load found in wastewater, which is made up of water from home sources including the kitchen, shower, sink, and toilet that is produced by human activity.

### 2.2 Material used in the Bioreactor

The better conductivity, chemical stability, and biocompatibility of graphite electrodes with microbial populations are the reasons behind their selection. Excellent electrical conductivity of graphite electrodes allows for effective electron transmission and maximizes the efficiency of energy generation. Even after extended exposure to wastewater conditions, graphite electrodes exhibit consistent performance due to their resistance to fouling and deterioration.

The reactor system is run without recirculating household wastewater, and the first sample was taken from the residential flat. The experiment's initial conditions are reflected in this sample. Wastewater could only travel through the reactor once due to the bioreactor's lack of wastewater recirculation. The last sample was taken, signifying the end of the experiment conducted in a non-recirculated environment.

### 2.3 Bioreactor Set up & Process

A rectangular tank with the following measurements is placed in the experimental setup length, width, and height are all fixed. The reactor's input and outflow apertures are situated at 1.5 cm from the bottom and 1 cm from the top, respectively. The reactor's intake is linked to a storage of 20-liter tank connected to a 0.5-inch flexible hose. A pinch valve is used to control the continuous flow that the reactor is intended to run at. The pinch valve can be manually adjusted to change the flow rate. The modules and electrode pairs are kept submerged by the reactor's 40 liter capacity. Six more liters of free board are included to stop the wiring from corroding. To guarantee appropriate flow, the 40-liter capacity is kept below the input chamber's height. To stop sludge from dispersing through the exit, the reactor's outlet is positioned 1.5 cm above the reactor's base. Once the outflow valve is opened and calibrated by measuring the volume of waste water flow with respect to time, the outflow rate can be fixed. The intake valve is manually operated to regulate the flow of water entering once the flow rate is fixed.

### 2.4 Working of Bioreactor

The reactor is configured with the necessary combinations of modules and electrode pairs based on the day's experimental needs. Twenty liters are filled in the storage tank and forty liters overall are filled in the reactor. Using a pinch valve, the wastewater flow rate is manually changed to control the flow through the system. For the purpose of measuring and recording the voltage and current measurements during the experiment, the electrode wirings are linked to an Arduino board.

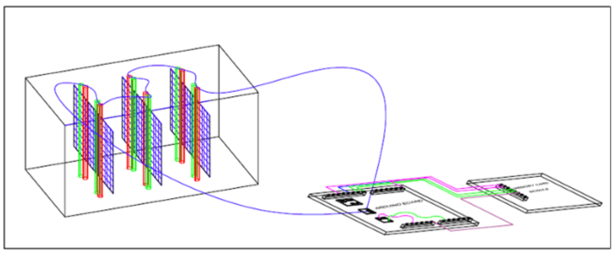

**Figure 1: Auto CADD drawing showing 3 Module 2 Electrode Pairs model set up**

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### 2.5 Sampling and Analysis

To ascertain several parameters, including TDS, TSS, BOD, COD, DO, Ammonical Nitrogen, Nitrate, and Nitrite, the obtained water samples are evaluated. The system's efficiency in producing power and treating wastewater is evaluated using the recorded readings from the Arduino board. Data collected after sampling & the readings from the Arduino is analyzed in SPSS and done statistical analysis like Descriptive statistics, correlation, One Way ANOVA & Regression and predict the average voltage from the regression equation obtained.

## 3. RESULTS AND DISCUSSION

From Table1, the elimination efficiency of ammonical nitrogen, chemical oxygen demand (COD), biological oxygen demand (BOD), total suspended solids (TSS), and total dissolved solids (TDS) is determined by descriptive statistics. For all of these pollutants, the average removal efficiency was 20.48%. All things considered, the data points to a somewhat successful water treatment system in terms of eliminating impurities from the water. The system performed best at eliminating ammonical nitrogen and least well at eliminating TDS.

**Table 1: Descriptive Statistics Results from the Data Collected**

| Descriptive Statistics | | | |
|---|---|---|---|
| | Mean | Std. Deviation | N |
| Modules | 3.5 | 0.506 | 42 |
| Run Time | 292.86 | 77.971 | 42 |
| Electrode Pairs | 3 | 0.826 | 42 |
| Distance between Modules | 13.5 | 1.518 | 42 |
| Distance between EP | 5.133 | 2.31 | 42 |
| Flowrate | 60 | 20.242 | 42 |
| Removal Efficiency TDS | 8.34 | 5.2 | 42 |
| Removal Efficiency TSS | 21.0345 | 8.46 | 42 |
| Removal Efficiency BOD | 24.0074 | 6.6 | 42 |
| Removal Efficiency COD | 20.9817 | 8.18 | 42 |
| Removal Efficiency Ammonical Nitrogen | 28.0429 | 8.75 | 42 |
| Average Removal Efficiency | 20.48 | 5.56 | 42 |
| Voltage Max | 1.626 | 0.9622 | 42 |
| Voltage Max Time | 95.24 | 63.42 | 42 |
| Power Density Max | 0.00050876 | 0.00057086 | 42 |
| Voltage Min | 0.0667 | 0.07999 | 42 |
| Voltage Min Time | 124.64 | 52.048 | 42 |
| Power Density Min | 4.9263E-06 | 6.5503E-06 | 42 |
| Voltage Avg | 0.6769 | 0.32956 | 42 |
| Power Density Avg | 3.4641E-05 | 4.0657E-05 | 42 |
| Influent TDS | 795.04 | 0 | 42 |
| Influent TSS | 38.37 | 0 | 42 |
| Influent BOD | 18.38 | 0 | 42 |
| Influent COD | 86.95 | 0 | 42 |
| Influent Ammonical Nitrogen | 4.33 | 0 | 42 |
| Effluent TDS | 728.69 | 41.101 | 42 |
| Effluent TSS | 30.176 | 3.6775 | 42 |
| Effluent BOD | 13.957 | 1.2264 | 42 |
| Effluent COD | 68.686 | 7.1006 | 42 |
| Effluent Ammonical Nitrogen | 3.095 | 0.3844 | 42 |

From Table 2, 3 & 4, A Pearson correlation coefficient is a measure of the linear relationship between two variables. It can range from -1 to 1. A value of -1 indicates a strong negative correlation, meaning that as the value of one variable increases, the value of the other variable decreases. A value of 1 indicates a strong positive correlation, meaning that as the value of one variable increases, the value of the other variable also increases. A value of 0 indicates no correlation between the two variables.

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**Table 2: Pearson Correlation Result from the Data Collected**

| | | Modules | Run Time | Electrode Pairs | Distance between Modules | Distance between EP | Flowrate |
|---|---|---|---|---|---|---|---|
| Modules | Pearson Correlation | 1 | 0 | 0 | -1.000** | 0 | 0 |
| | Sig. (2-tailed) | | 1 | 1 | 0 | 1 | 1 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |
| RUN TIME | Pearson Correlation | 0 | 1 | 0 | 0 | 0 | -.992** |
| | Sig. (2-tailed) | 1 | | 1 | 1 | 1 | 0 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |
| Electrode Pairs | Pearson Correlation | 0 | 0 | 1 | 0 | -.999** | 0 |
| | Sig. (2-tailed) | 1 | 1 | | 1 | 0 | 1 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |
| Distance between Modules | Pearson Correlation | -1.000** | 0 | 0 | 1 | 0 | 0 |
| | Sig. (2-tailed) | 0 | 1 | 1 | | 1 | 1 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |
| Distance between EP | Pearson Correlation | 0 | 0 | -.999** | 0 | 1 | 0 |
| | Sig. (2-tailed) | 1 | 1 | 0 | 1 | | 1 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |
| Flowrate | Pearson Correlation | 0 | -.992** | 0 | 0 | 0 | 1 |
| | Sig. (2-tailed) | 1 | 0 | 1 | 1 | 1 | |
| | N | 42 | 42 | 42 | 42 | 42 | 42 |

**. Correlation is significant at the 0.01 level (2-tailed).

**Table 3: Pearson Correlation Result from the Data Collected**

| CORRELATION | | | | | | |
|---|---|---|---|---|---|---|
| | | REMOVAL EFFICIENCY TDS | REMOVAL EFFICIENCY TSS | REMOVAL EFFICIENCY BOD | REMOVAL EFFICIENCY COD | REMOVAL EFFICIENCY AMMONICAL NITROGEN |
| REMOVAL EFFICIENCY TDS | Pearson Correlation | 1 | 0.089 | .494** | .542** | 0.087 |
| | Sig. (2-tailed) | | 0.574 | 0.001 | 0 | 0.585 |
| | N | 42 | 42 | 42 | 42 | 42 |
| REMOVAL EFFICIENCY TSS | Pearson Correlation | 0.089 | 1 | .323* | 0.275 | .636** |
| | Sig. (2-tailed) | 0.574 | | 0.037 | 0.077 | 0 |
| | N | 42 | 42 | 42 | 42 | 42 |
| REMOVAL EFFICIENCY BOD | Pearson Correlation | .494** | .323* | 1 | .893** | .537** |
| | Sig. (2-tailed) | 0.001 | 0.037 | | 0 | 0 |
| | N | 42 | 42 | 42 | 42 | 42 |
| REMOVAL EFFICIENCY COD | Pearson Correlation | .542** | 0.275 | .893** | 1 | .454** |
| | Sig. (2-tailed) | 0 | 0.077 | 0 | | 0.003 |
| | N | 42 | 42 | 42 | 42 | 42 |
| REMOVAL EFFICIENCY AMMONICAL NITROGEN | Pearson Correlation | 0.087 | .636** | .537** | .454** | 1 |
| | Sig. (2-tailed) | 0.585 | 0 | 0 | 0.003 | |
| | N | 42 | 42 | 42 | 42 | 42 |

In this case, the table shows that there is a strong negative correlation (coefficient of -1.000) between the distance between the modules and flow rate. This means that as the distance between the modules increases, the flow rate decreases. There is a strong positive correlation between removal efficiency of BOD and COD (coefficient of 0.893). This means that these two removal efficiencies tend to increase together.

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**Table 4: Pearson Correlation Result from the Data Collected**

| CORRELATION | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Voltage MAX | Voltage MAX Time | Power Density MAX | Voltage MIN | Voltage MIN Time | Power Density MIN | Voltage AVG | Power Density AVG |
| Voltage MAX | Pearson Correlation | 1 | .413** | .416** | -0.133 | .335* | -0.293 | .719** | .330* |
| | Sig. (2-tailed) | | 0.007 | 0.006 | 0.401 | 0.03 | 0.06 | 0 | 0.033 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Voltage MAX Time | Pearson Correlation | .413** | 1 | 0.301 | 0.022 | 0.19 | 0.024 | 0.194 | 0.143 |
| | Sig. (2-tailed) | 0.007 | | 0.053 | 0.891 | 0.228 | 0.878 | 0.219 | 0.367 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Power Density MAX | Pearson Correlation | .416** | 0.301 | 1 | -0.109 | -0.031 | -0.25 | 0.029 | .394** |
| | Sig. (2-tailed) | 0.006 | 0.053 | | 0.493 | 0.846 | 0.111 | 0.858 | 0.01 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Voltage MIN | Pearson Correlation | -0.133 | 0.022 | -0.109 | 1 | -0.007 | .702** | 0.01 | 0.26 |
| | Sig. (2-tailed) | 0.401 | 0.891 | 0.493 | | 0.966 | 0 | 0.949 | 0.096 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Voltage MIN Time | Pearson Correlation | .335* | 0.19 | -0.031 | -0.007 | 1 | 0.015 | .392* | 0.031 |
| | Sig. (2-tailed) | 0.03 | 0.228 | 0.846 | 0.966 | | 0.924 | 0.01 | 0.848 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Power Density MIN | Pearson Correlation | -0.293 | 0.024 | -0.25 | .702** | 0.015 | 1 | -0.117 | -0.06 |
| | Sig. (2-tailed) | 0.06 | 0.878 | 0.111 | 0 | 0.924 | | 0.459 | 0.708 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Voltage AVG | Pearson Correlation | .719** | 0.194 | 0.029 | 0.01 | .392* | -0.117 | 1 | .399** |
| | Sig. (2-tailed) | 0 | 0.219 | 0.858 | 0.949 | 0.01 | 0.459 | | 0.009 |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| Power Density AVG | Pearson Correlation | .330* | 0.143 | .394** | 0.26 | 0.031 | -0.06 | .399** | 1 |
| | Sig. (2-tailed) | 0.033 | 0.367 | 0.01 | 0.096 | 0.848 | 0.708 | 0.009 | |
| | N | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |

Each value represents the Pearson Correlation Coefficient between two variables. For instance, there's a significant positive correlation (0.719**) between Voltage AVG and RE AVG (Removal Efficiency Average). This means on average, higher voltage leads to higher removal efficiency.

**Table 5: Model Summary of Regression Analysis for COD**

| Model Summary[a] | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Change Statistics | | | | | |
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change | Durbin-Watson |
| 1 | .506a | 0.256 | 0.152 | 7.53699 | 0.256 | 2.471 | 5 | 36 | 0.05 | 1.868 |

a. Predictors: (Constant), Flowrate, Modules, Distance between EP, RUN TIME, Electrode Pairs

b. Dependent Variable: REMOVAL EFFICIENCY COD

**Table 6: One Way ANOVA for COD**

| ANOVA[a] | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | df | Mean Square | F | Sig. |
| 1 | Regression | 701.962 | 5 | 140.392 | 2.471 | .050b |
| | Residual | 2045.021 | 36 | 56.806 | | |
| | Total | 2746.983 | 41 | | | |

a. Dependent Variable: REMOVAL EFFICIENCY COD

b. Predictors: (Constant), Flowrate, Modules, Distance between EP, RUN TIME, Electrode Pairs

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From Table 5, the correlation coefficient is 0.506, suggesting a good positive relationship between the predictors and the dependent variable, Removal Efficiency COD. The R2 value is 0.256, indicating that approximately 25.6% of the variance in Removal Efficiency COD can be explained by the model. And from Table 6, the F statistic is 2.471, which assesses the overall statistical significance of the model. The fact that the Sig. F Change is 0.050 (less than 0.05) indicates that the model is statistically significant. The Durbin-Watson statistic is 1.868, which is close to 2, suggesting that there is no substantial autocorrelation in the residuals.

**Table 7: Predicting Regression Analysis for COD**

| Coefficients[a] | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 266.45 | 178.649 | | 1.491 | 0.145 |
| | Electrode Pairs | -54.231 | 34.568 | -5.475 | -1.569 | 0.125 |
| | Distance between EP | -18.373 | 12.335 | -5.198 | -1.489 | 0.145 |
| | Distance between Modules | 1.129 | 0.775 | 0.209 | 1.456 | 0.154 |
| | Modules | -3.386 | 2.326 | -0.209 | -1.456 | 0.154 |
| | RUN TIME | 0.031 | 0.12 | 0.297 | 0.259 | 0.797 |
| | Flowrate | 0.237 | 0.464 | 0.587 | 0.512 | 0.612 |

a. Dependent Variable: REMOVAL EFFICIENCY COD

From Table 7, the constant term (266.450) represents the predicted value of the dependent variable (removal efficiency COD) when all of the independent variables are zero. The coefficient for electrode pairs is statistically significant (Sig. = 0.125), with a negative beta (-5.475). This means that for every one-unit increase in electrode pairs, there is a decrease of 5.475 in removal efficiency COD, holding all other independent variables constant. The coefficient for distance between EP is statistically significant (Sig. = 0.145), with a negative beta (-5.198). This means that for every one-unit increase in distance between EP, there is a decrease of 5.198 in removal efficiency COD, holding all other independent variables constant. And the estimated equation for COD is

Y=3.386X154.231X2+1.129X318.373X4+0.237X5+266.450. (1)

With this equation we can predict the voltage average values from the MFC performance.

**Table 8: Model Summary of Regression Analysis for BOD**

| Model Summary[b] | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | | Durbin-Watson |
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change | |
| 1 | .449a | 0.201 | 0.09 | 6.29536 | 0.201 | 1.814 | 5 | 36 | 0.0135 | 1.836 |

a. Predictors: (Constant), Flowrate, Modules, Distance between EP, RUN TIME, Electrode Pairs

b. Dependent Variable: REMOVAL EFFICIENCY BOD

From Table 8, the correlation coefficient is 0.449, suggesting a good positive relationship between the predictors and the dependent variable, Removal Efficiency BOD. The R2 value is 0.201, indicating that approximately 25.6% of the variance in Removal Efficiency BOD can be explained by the model. And From Table 10, the F statistic is 1.814, which assesses the overall statistical significance of the model. The fact that the Sig. F Change is 0.0135 (less than 0.05) indicates that the model is statistically significant. The Durbin-Watson statistic is 1.836, which is close to 2, suggesting that there is no substantial autocorrelation in the residuals.

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**Table 9: Predicting Regression Analysis for BOD**

| Coefficients$^b$ | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | 260.485 | 149.219 | | 1.746 | 0.089 |
| | Electrode Pairs | -50.029 | 28.873 | -6.264 | -1.733 | 0.092 |
| | Distance between EP | -17.65 | 10.303 | -6.193 | -1.713 | 0.095 |
| | Distance between Modules | 1.25 | 0.648 | 0.288 | 1.931 | 0.061 |
| | Modules | -3.751 | 1.943 | -0.288 | -1.931 | 0.061 |
| | RUN TIME | 0.025 | 0.101 | 0.297 | 0.25 | 0.804 |
| | Flowrate | 0.166 | 0.387 | 0.51 | 0.429 | 0.67 |

a. Dependent Variable: REMOVAL EFFICIENCY BOD

**Table 10: One Way ANOVA for BOD**

| ANOVA$^b$ | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | df | Mean Square | F | Sig. |
| 1 | Regression | 359.512 | 5 | 71.902 | 1.814 | .135b |
| | Residual | 1426.736 | 36 | 39.632 | | |
| | Total | 1786.248 | 41 | | | |

a. Dependent Variable: REMOVAL EFFICIENCY BOD
b. Predictors: (Constant), Flowrate, Modules, Distance between EP, RUN TIME, Electrode Pairs

From Table 9, the constant term (260.450) represents the predicted value of the dependent variable (removal efficiency BOD) when all of the independent variables are zero. The coefficient for electrode pairs is statistically significant (Sig. = 0.092), with a negative beta (-6.264). This means that for every one-unit increase in electrode pairs, there is a decrease of 6.264 in removal efficiency BOD, holding all other independent variables constant.The coefficient for distance between modules is statistically significant (Sig. = 0.061), with a positive beta (0.288). This means that for every one-unit increase in distance between modules, there is an increase of 0.288 in removal efficiency BOD, holding all other independent variables constant. The coefficient for distance between EP is statistically significant (Sig. = 0.095), with a negative beta (-6.193). This means that for every one-unit increase in distance between EP, there is a decrease of 6.193 in removal efficiency BOD, holding all other independent variables constant. And the estimated equation for BOD is

Y=3.751X150.029X2+1.250X317.650X4+0.166X5+260.485. (2)

With this equation we can predict the voltage average values from the MFC performance.

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**Table 11: Prediction for Power Density, Voltage Avg & Removal Efficiency**

| MODULES (X1) | EP (X2) | DISTANCE B/W MODULES (X3) | DISTANCE B/W EP (X4) | FR (X5) | Predicted Values for Power Density | Predicted Values for Voltage Avg | Predicted Values for Removal Efficiency |
|---|---|---|---|---|---|---|---|
| 5 | 2 | 10 | 8 | 30 | -3.655 | 1.882 | 50.517 |
| 6 | 2 | 8.5 | 8 | 30 | -2.5205 | 2.212 | 42.057 |
| 7 | 2 | 7.5 | 8 | 30 | -1.6855 | 2.509 | 37.528 |
| 8 | 2 | 6.6 | 8 | 30 | -0.9104 | 2.7994 | 33.7852 |
| 9 | 2 | 5.6 | 8 | 30 | -0.0754 | 3.0964 | 29.2562 |
| 5 | 3 | 10 | 5 | 30 | -0.647 | 2.119 | 50.886 |
| 6 | 3 | 8.5 | 5 | 30 | 0.4875 | 2.449 | 42.426 |
| 7 | 3 | 7.5 | 5 | 30 | 1.3225 | 2.746 | 37.897 |
| 8 | 3 | 6.6 | 5 | 30 | 2.0976 | 3.0364 | 34.1542 |
| 9 | 3 | 5.6 | 5 | 30 | 2.9326 | 3.3334 | 29.6252 |
| 5 | 2 | 10 | 8 | 50 | -0.915 | 1.902 | -1.163 |
| 6 | 2 | 8.5 | 8 | 50 | 0.2195 | 2.232 | -9.623 |
| 7 | 2 | 7.5 | 8 | 50 | 1.0545 | 2.529 | -14.152 |
| 8 | 2 | 6.6 | 8 | 50 | 1.8296 | 2.8194 | -17.8948 |
| 9 | 2 | 5.6 | 8 | 50 | 2.6646 | 3.1164 | -22.4238 |
| 5 | 3 | 10 | 5 | 50 | 2.093 | 2.139 | -0.794 |
| 6 | 3 | 8.5 | 5 | 50 | 3.2275 | 2.469 | -9.254 |
| 7 | 3 | 7.5 | 5 | 50 | 4.0625 | 2.766 | -13.783 |
| 8 | 3 | 6.6 | 5 | 50 | 4.8376 | 3.0564 | -17.5258 |
| 9 | 3 | 5.6 | 5 | 50 | 5.6726 | 3.3534 | -22.0548 |
| 5 | 2 | 10 | 8 | 70 | 1.825 | 1.922 | -52.843 |
| 6 | 2 | 8.5 | 8 | 70 | 2.9595 | 2.252 | -61.303 |
| 7 | 2 | 7.5 | 8 | 70 | 3.7945 | 2.549 | -65.832 |
| 8 | 2 | 6.6 | 8 | 70 | 4.5696 | 2.8394 | -69.5748 |
| 9 | 2 | 5.6 | 8 | 70 | 5.4046 | 3.1364 | -74.1038 |
| 5 | 3 | 10 | 5 | 70 | 4.833 | 2.159 | -52.474 |
| 6 | 3 | 8.5 | 5 | 70 | 5.9675 | 2.489 | -60.934 |
| 7 | 3 | 7.5 | 5 | 70 | 6.8025 | 2.786 | -65.463 |
| 8 | 3 | 6.6 | 5 | 70 | 7.5776 | 3.0764 | -69.2058 |
| 9 | 3 | 5.6 | 5 | 70 | 8.4126 | 3.3734 | -73.7348 |

From Table 11, we predict the regression equation for the voltage average in order to find out the best values while comparing with voltage average and removal efficiency which has a higher capacity from the values obtained. The predicted average voltage achieved was 2.5V, However for the different combination and flow rates, the Max average voltage was higher at 3.3V for 9 Module, 3 Electrode Pairs & Flow Rate 50, 70, 90. The best predicted model from the equation is 9 Module, 3 Electrode Pairs & Flow Rate 30, while considering both Average voltage and removal efficiency and neglecting the negative values from the table.

## 4. CONCLUSION AND FUTURE WORK

The design of electrochemical treatment systems should take the recirculation of wastewater into account, since this can have a big impact on the efficiency of treatment and voltage generation. The best arrangements could change depending on the particulars of the wastewater, like its composition, flow rate and its connection in the bio reactor. To find the best configuration for a particular type of wastewater, it is essential to experiment with several setups. The results obtained from SPSS after running through various analysis like descriptive statistics, correlation, regression and one way ANOVA through different parameters considered. Out of 5 parameters, BOD & COD are having significant values and the regression equation estimated from the analysis for voltage generation prediction. The maximum average voltage for 9 modules, 3 electrode pairs, and flow rates of 50, 70, and 90 was 3.3

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volts, notwithstanding the variations in voltage generation. The expected average voltage, however, was 2.5 volts. When average voltage, removal efficiency, and the negative numbers from the table are ignored, the optimal anticipated model from the equation is 9 Module, 3 Electrode Pairs, & Flow Rate 30. Subsequent research endeavours may go more profoundly into comprehending the mechanics underlying the noted variations in voltage generation and removal efficiency circumstances. Examining elements including mass transport dynamics, electrolyte composition, surface area, and electrode material may help improve the effectiveness and efficiency of electrochemical wastewater treatment systems.

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