

Quantification of Renewable Energy Extraction from Domestic Wastewater Using Microbial Fuel Cells: A Statistical Evaluation of Performance Metrics

Sushma R¹, Lakshmi C², N Balasubramanya³, Nikhil T R⁴

¹ Assistant Professor, Department of Civil Engineering, M S Ramaiah university of Applied Sciences, 560054, Bangalore, Karnataka, India *

² Professor, Department of Civil Engineering, SJB Institute of Technology, Bangalore- 560060 Karnataka, India

³ Professor and Dean-Administration, Department of Civil Engineering, Acharya Institute of Technology, Bangalore- 5600107Karnataka, India

⁴ Assistant Professor, Department of Civil Engineering, Faculty of Engineering and technology, M S Ramaiah university of Applied Sciences, 560054, Bangalore, Karnataka, India

*Corresponding Author E-mail : sushma4116@gmail.com

Abstract

The goals of this research were to compute the wastewater quality index and investigate statistical correlations between various variables. The study employed a quantitative approach to assess the physicochemical characteristics of water quality in wastewater samples, following the guidelines and recommendations provided by the regulatory authority. The wastewater quality index is recognized as a valuable tool for informing stakeholders about the quality aspects of wastewater. The Weighted Arithmetic Index technique was utilized to calculate the wastewater quality index for wastewater samples. Additionally, a statistical analysis was conducted to identify the primary factors influencing wastewater quality index. It was observed that statistical regression analysis is a highly effective tool within SPSS.

Keywords: Wastewater Quality Index (WWQI), Descriptive Statistics, Correlation, One Way ANOVA, Regression

1. Introduction

The caliber of waste produced increases together with the growth of cities and industry [16]. The suitability of surface waterways, such as lakes, rivers, and oceans, for human consumption is determined by the discharge of untreated sewage [10]. A numerical expression that is computed cumulatively is used by the Water Quality Index (WQI) to determine a certain level of water quality. The purpose of water quality indices is to convey the water quality of a source as a single number, simplifying a difficult statement and facilitating the analysis of monitoring data [5]. The Water Quality Index (WQI) simplifies complex data regarding water quality for managers and the public to grasp by using terms like excellent, good, poor, etc. Several academic improvements have been made to this strategy to alter the procedure.

To communicate with management and the public, the Water Quality Index (WQI) effectively condenses large amounts of data on water quality into terms that are simple to comprehend (such

as excellent, good, poor, etc.). Numerous academic adjustments have been made to this method to modify the approach according to certain applications and the qualities under analysis. One study[17], for example, considered thirteen distinct parameters and gave each equal weight inside their model. Moreover, managers and decision-makers can benefit greatly from being able to compare various wastewater treatment methods using WQI. An indicator like this can quickly determine if treated wastewater is suitable for applications like recreation or agriculture[20]. Moreover, a single, all-encompassing metric that measures a treatment plant's total effectiveness in removing pollutants using physical, biochemical, and microbiological processes must be established[13].

A groundbreaking fuzzy approach has been implemented, as introduced by Gabrieli et al. [10]. The Wastewater Quality Index (WWQI), represented on a numerical scale from 0 to 1, serves as an indicator of wastewater quality. Developing the WWQI in a manner like the Water Quality Index (WQI) is anticipated to enhance its applicability and support decision-making processes for authorities. The Weighted Arithmetic Index method was used to calculate the maximum, minimum, and average values required for determining the WWQI. Once WWQI was established, the correlation between each parameter and the WWQI was analyzed. Additionally, factor analysis (FA) was employed to interpret the elemental data [8].

To assess the quality of treated wastewater, One-Way ANOVA, correlation analysis, and descriptive statistics were applied to six key parameters. The study aimed to address this issue by developing the WWQI and calculating correlation and regression equations using the SPSS tool. The analysis identified TSD, COD, DO, BOD, TSS, and ammoniacal nitrogen as the parameters significantly influencing WWQI.

Furthermore, descriptive statistics, correlation, regression, and One-Way ANOVA were conducted in SPSS, focusing on these significant parameters. The results were then used alongside WWQI values to establish correlations and identify the model that best fit the analysis.

2. METHODS AND METHODOLOGY

Experimental methodology

2.1 Site Selection

The domestic wastewater used in this study was collected from a residential complex comprising over 130 units, housing approximately 400 residents. The complex generated 3,000 liters of wastewater daily. The influent characteristics of the wastewater were carefully monitored throughout the reactor's operational period.

2.2 Experimental Setup

The Microbial Fuel Cell (MFC) model serves as the central point for designing and operating a continuous flow reactor in the experimental setup, where influent and effluent samples are collected, analyzed and obtained data was used for statistical analysis. Throughout the procedure, the operational volume of the reactor was maintained consistently. The reactor models were systematically evaluated at three different flow rates: 0.2 liters per minute, 0.5 liters per minute, and 0.7 liters per minute. These were thoroughly assessed to determine their impact on the reactor's performance with varied electrode configurations.

3.0 WASTE WATER QUALITY INDEX

The Water Quality Index (WQI) is a dimensionless metric that normalizes values according to subjective grading curves, consolidating multiple water quality parameters into a single score. The criteria for including parameters in the WQI model may vary depending on the intended water uses and regional preferences. These parameters include temperature, nutrients (nitrogen

and phosphorus), total coliform bacteria, dissolved oxygen (DO), pH, BOD, and COD, among others. Each of these parameters is expressed in different units and occurs within various ranges. The WQI combines the complex scientific data of these variables into a single numerical value. The WQI was calculated using the Weighted Arithmetic Index method. For each water quality parameter, a quality rating (Q_i) was determined using the formula:

$$Q_i = 100 \frac{(V_s - V_i)}{(V_n - V_i)}$$

where V_n represents the actual measurement of the parameter, V_i is the ideal value for the parameter (set to 0 for all except pH and DO, with pH having an ideal value of 7.0 and DO an ideal value of 14.6 mg/L), and V_s is the recommended standard for the parameter according to World Health Organization (WHO) guidelines. The relative weight (W_i) for each parameter was assigned based on a value inversely proportional to its WHO recommended standard (S_i), where K is a constant derived from the application of the formula.

$$K = \frac{1}{\sum(\frac{1}{S_i})}$$

$$W_i = K S_i$$

Water Quality Index (WQI) is typically evaluated based on the specific intended use of the water. In this study, the WQI is assessed for human consumption, with the acceptable threshold for drinking water set at 100. The overall WQI was determined using the following equation:

$$WWQI = \frac{\sum W_i Q_i}{\sum W_i}$$

The WQI Value range 90 to 100: Excellent, 70 to 90: Good, 50 to 70: Medium, 25 to 50: Bad, 0 to 25: Very Bad

3.1 STATISTICAL ANALYSIS

Evaluating wastewater quality from multiple samples with varying criteria through statistical analysis is a complex task. Various techniques have been developed for water quality analysis, including multi-stressor water quality indices and the statistical analysis of individual parameters [1]. Statistical methods are typically employed to assess the accuracy of the estimated WWQI. In this study, descriptive statistics, correlation analysis, linear regression, and one-way ANOVA were used to accomplish this.

Table 1: Descriptive Statistics for WWQI

Descriptive Statistics			
	Mean	Std. Deviation	N
WWQI	6.66	5.66	42
TDS	8.34	5.21	42
TSS	21.03	8.46	42
BOD	24.01	6.60	42
COD	20.98	8.18	42
Ammonical Nitrogen	28.04	8.75	42

It appears to be a composite metric for wastewater quality, the average WWQI in the data set is 6.66 with a standard deviation of 5.66. Table 1 shows that the wastewater treatment process is most effective in removing ammonia nitrogen followed by BOD, TSS, COD and TDS.

Table 2: Pearson Correlation for WWQI

Correlations							
		WWQI	Removal Efficiency TDS	Removal Efficiency TSS	Removal Efficiency BOD	Removal Efficiency COD	Removal Efficiency of Ammonical Nitrogen
Pearson Correlation	WWQI	1.000	-.377	-.610	-.818	-.771	-.874
	TDS	-.377	1.000	.089	.494	.542	.087
	TSS	-.610	.089	1.000	.323	.275	.636
	BOD	-.818	.494	.323	1.000	.893	.537
	COD	-.771	.542	.275	.893	1.000	.454
	Ammonical Nitrogen	-.874	.087	.636	.537	.454	1.000
Sig. (1-tailed)	WWQI	.	.007	.000	.000	.000	.000
	TDS	.007	.	.287	.000	.000	.293
	TSS	.000	.287	.	.019	.039	.000
	BOD	.000	.000	.019	.	.000	.000
	COD	.000	.000	.039	.000	.	.001
	Ammonical Nitrogen	.000	.293	.000	.000	.001	.
N	WWQI	42	42	42	42	42	42
	TDS	42	42	42	42	42	42
	TSS	42	42	42	42	42	42
	BOD	42	42	42	42	42	42
	COD	42	42	42	42	42	42
	Ammonical Nitrogen	42	42	42	42	42	42

From Table 2, a strong negative correlation (values close to -1) is observed between the removal efficiency of ammonia nitrogen and all other pollutants listed (TDS, TSS, BOD, COD). This indicates that as the concentration of these substances in the water increases, the removal efficiency of ammonia nitrogen decreases. Additionally, there is a strong positive correlation between TSS and COD, with a correlation coefficient of 0.879, which is close to 1. This suggests that as TSS increases, COD also tends to increase. A similar strong positive correlation is observed between BOD and COD, with a correlation coefficient of 0.809, indicating that as BOD increases, COD also tends to rise. There is a moderate positive correlation between TSS and BOD, with a correlation coefficient of 0.661. This suggests that higher values of TSS tend to correspond with higher values of BOD, though the correlation is weaker than that between TSS and COD or BOD and COD. The correlation coefficient represents the strength of the linear relationship between two variables, showing the extent to which they vary together, whether in the same or opposite directions. Its value ranges from -1 to 1, with values nearer to -1 or 1 indicating a stronger correlation.

Table 3: Model Summary for BOD

Model Summary^a										
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	0.818 ^a	0.669	0.660	0.330	0.669	80.761	1	40	0.00	2.126

* Dependent Variable: WWQI Predictors: (Constant), Removal Efficiency BOD

Table 4: One Way ANOVA for BOD

ANOVA^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8.798	1	8.798	80.761	0.000 ^b
	Residual	4.357	40	.109		
	Total	13.155	41			

*Dependent Variable: WWQI Predictors: (Constant), Removal Efficiency BOD

Table 5: Regression Analysis for BOD

Coefficients^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.348	.194		42.971	0.000
	BOD	-.070	.008	-.818	-8.987	0.000

*Dependent Variable: WWQI

The constant term (8.348) represents the projected value of the WWQI when all independent variables are zero. Table 4 demonstrates that the model fits significantly with an F-value of 80.761 (Sig F: 0.000) and an RMSE of 0.000. The Durbin-Watson test statistic for this model is 2.126, which is greater than 2, indicating no issue with autocorrelation (Table 3). Since BOD was found to have a strong correlation with largest of the other factors, TDS was excluded, and regression analysis was performed again to obtain a new equation. After removing TSS, COD, TDS, Ammoniacal Nitrogen, and adding WWQI as the dependent variable, the regression model was re-fitted, yielding the following regression equation with an accuracy of 82% (Table 3):

$$Y = -0.070X_1 + 8.348$$

This equation indicates a statistically significant relationship between BOD and WWQI.

Table 6: Model Summary for Ammonical Nitrogen

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	0.874 ^a	0.764	0.758	0.278	0.764	129.18	1	40	0.000	1.585

*Dependent Variable: WWQI Predictors: (Constant), Removal Efficiency of Ammonical Nitrogen

Table 7: One Way ANOVA for Ammonical Nitrogen

ANOVA ^b						
Model		Sum Squares	df	Mean Square	F	Sig.
1	Regression	10.045	1	10.045	129.183	0.000 ^b
	Residual	3.110	40	0.078		
	Total	13.155	41			

* Dependent Variable: WWQIPredictors: (Constant), Removal Efficiency of Ammonical Nitrogen

Table 8: Regression Analysis for Ammonical Nitrogen

Coefficients ^b						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.250	.146		56.486	0.000
	Removal Efficiency of Ammonical Nitrogen	-0.057	0.005	-0.874	-11.366	0.000

*Dependent Variable: WWQI

The constant term (7.006) from Table 6 represents the predicted value of the WWQI when all independent variables are zero. According to Table 7, the model fits significantly with an F-value of 129.183 (Sig F: 0.000) and an RMSE of 0.000. The Durbin-Watson test statistic for this model is 1.585, which is close to 2, indicating no autocorrelation issue (Table 6). Ammoniacal nitrogen was found to have a strong correlation with most of the other metrics. After excluding TDS, TSS, COD, and BOD, and adding WWQI as the dependent variable, the regression model was re-fitted, yielding the following regression equation with 88% accuracy (Table 6):

$$Y = -0.057X_1 + 8.250$$

For removal efficiency of Ammoniacal Nitrogen, the significance level is 0.000. Since this value is less than 0.05, we can reject the null hypothesis for removal efficiency of Ammoniacal Nitrogen. This indicates a statistically significant relationship between ammonia nitrogen and the WWQI.

Table 9: Model Summary for WWQI

Model Summary ^c										
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	0.980 ^a	0.961	0.955	0.1198	.961	176.327	5	36	0.000	1.753

* Dependent Variable: WWQIPredictors: (Constant), Removal Efficiency Ammonical Nitrogen, Removal Efficiency TDS, Removal Efficiency TSS, Removal Efficiency COD, Removal Efficiency BOD

Table 10: One Way ANOVA for WWQI

ANOVA ^c						
Model		Sum Squares	df	Mean Square	F	Sig.
1	Regression	12.639	5	2.528	176.327	0.000 ^b
	Residual	0.516	36	0.014		
	Total	13.155	41			

*Dependent Variable: WWQI

Predictors: (Constant), Removal Efficiency of Ammonical Nitrogen, Removal Efficiency TDS, Removal Efficiency TSS, Removal Efficiency COD, Removal Efficiency BOD

Table 11: Regression Analysis for WWQI

Coefficients ^c						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8.728	.082		106.852	0.000
	Removal Efficiency TDS	-0.008	0.004	-0.077	-1.893	0.066
	Removal Efficiency TSS	-0.007	0.003	-0.100	-2.325	0.026
	Removal Efficiency BOD	-0.019	0.007	-0.225	-2.882	0.007
	Removal Efficiency COD	-0.017	0.005	-0.241	-3.184	0.003
	Removal Efficiency of Ammonical Nitrogen	-0.037	0.003	-0.574	-11.607	0.000

*. Dependent Variable: WWQI

The constant term (8.728) in Table 11 represents the expected value of the WWQI when all independent variables are zero. According to Table 10, this model fits significantly with an F-value of 176.327 (Sig F: 0.000) and an RMSE of 0.000. The Durbin-Watson test statistic for this model is 1.753, which is close to 2, indicating no autocorrelation issue (Table 9). With WWQI as the dependent variable and TDS, TSS, COD, BOD, and Ammoniacal Nitrogen found to be strongly correlated with all other parameters, the regression model was re-fitted, resulting in the following regression equation with 96% accuracy (Table 9):

$$Y = -0.008X_1 - 0.007X_2 - 0.019X_3 - 0.017X_4 - 0.037X_5 + 8.728$$

This suggests a statistically significant association between the factors analyzed and the WWQI

4.CONCLUSION

The WWQI was initially calculated, and the correlation between various factors and their relationship with the WWQI was analysed using SPSS. The analysis revealed a significant correlation between WWQI and six factors: TDS, TSS, BOD, COD, Cl, and DO, indicating that these six parameters account for most of the variation in WWQI values. Additionally, BOD and Ammoniacal Nitrogen were found to have a significant correlation with WWQI at the 0.01 level. A regression equation developed using five key parameters was determined to have an accuracy of approximately 96%. Furthermore, after excluding DO, Nitrate, and Nitrite, the constructed regression equation was found to match the original WWQI with 96% accuracy.

REFERENCES

- [1] A N Kobundu, Quality assessment of Aba River using heavy metal pollution index, *Am. J. Environ. Engin.*, 2012, 2(1), 45-49.
- [2] American public health association, (APHA). *Standard methods for the examination of water and wastewaters*, 2003. (21thedn). Washington, DC, USA.
- [3] L Balteiro and C Romero, In search of a natural systems sustainability index, 2004, *Ecological Economics*, 49 (3), 401-405.
- [4] N Bhartiand Katyal D., Water quality indices used for surface water vulnerability assessment, *International Journal of Environmental Science*, 2011, 2(1), 154-173.
- [5] A A Bordalo, R Teixeira and W J Wiebe, A water quality index applied to an international shared river basin: The case of the Douro River, *Environ. Manag.*, 38(1), 2006, 910–920.
- [6] Y C Chen, H P Lien, G H Tzengand L S Yang, Fuzzy MCDM approach for selecting the best environment-watershed plan, *Applied Soft Computing Journal*, 2011,11(1), 265-275.
- [7] I Chenini and S Khemiri, Evaluation of ground water quality using multiple linear regression and structural equation modelling, *Int.J. Environ. Sci. Tech.*, 2009, 6 (3), 509-519.
- [8] Evangelos., *P mastering visual basic 6*, BPP Publications, New Delhi, (2000).
- [9] P L Florence, A Paulraj, T Ramachandramoorthy water Quality Index and correlation study for the assessment of water quality and its parameters of Yercaud Taluk, Salem District, Tamil Nadu, India, *Chem. Sci.Trans.*, 2010,1(1), 139-14.
- [10] R Gabrieli, M Divizia,D Donia,Ruscio, L Bonadonna, C Diotallevi, Villa, L, G Manzone, A Panà, Evaluation of the wastewater treatment plant of Rome airport. *Water Science and Technology*, 1997, vol. 35, issue 11-12. p. 193-196
- [11] C Hwang and K Yoon Multiple attribute decision making – methods and applications, A state of the art survey, Springer-Verlag, Berlin. ,1981.
- [12] A I Jamrah, Assessment of characteristics and biological treatment technologies of Jordanian wastewater, 1999, *Bioprocess Engineering*, 21: 331 340.
- [13] P Jamwal, A K Mittal and J M Mouchel, Efficiency evaluation of sewage treatment plants with different technologies in Delhi, (India). 2009, *Environmental Monitoring assessment*,153, 293-305.
- [14] A Kaufman and M M Gupta, Fuzzy mathematical modelling in engineering and management sciences, *Fuzzy Set and Systems*, 1991, 43, 17–32.
- [15] G J Klirand B Yuan, Operation of fuzzy sets in: Ruspini, E. H., Bonissone, P. P. and Pedryez W., *Handbook of Fuzzy Computation*, Institute of Physics Publishing, Dirac House, temple Bath, Bristol , 1998.
- [16] B Mohammed, Design and Performance Evaluation of a Wastewater Treatment Unit.” *Australian Journal of Technology*. , 2006, 9(3): 193-198 .
- [17] L Prati, R Pavanello and F Pesarin, Assessment of surface water quality by a single index of pollution, *J. Wat. Res.*,1971, 5(1), 74.
- [18] G K Rastogi and D K Sinha, A novel approach to water quality management through correlation study, *Journal of Environmental Research and Development* , 2011, 5 ,(4), 1029-1035.
- [19] P Ravikumar, B Liza, Pinto. and R K Somashekar, Assessment of the Efficiency of Sewage Treatment plants: A Comparative Study between NagasandraandMailasandra Sewage Treatment Plants. 2010, Kathmandu University, *Journal of Science Engineering and Technology*, 6(2), 115-125.

- [20] E Rene and M B Saidutta, Prediction of Water Quality indices by regression analysis and artificial neural networks, *Int. Environ. Res.*, 2008,2(2), 183-188.
- [21] D Singh and L K Robert and Tiong, A fuzzy decision framework for contractor selection, 2005, *Journal of Construction Engineering and Management (ASCE)*, 131(1), 62-70.
- [22] M Thirupathaiah, C Samatha and C Sammaiah, Analysis of water quality using physico-chemical parameters in lower manair reservoir of Karimnagar district, Andhra Pradesh, *Int. J. Environ. Sci.*, 2012,3(1), 172-180.
- [23] K Venkatesharaju, R K Somashekar and K L Prakash, Study of seasonal and spatial variation in surface water quality of Cauvery River Stretch in Karnataka, *J. Ecol. Nat. Environ.*, 2010, 2(1), 1-9.
- [24] P Verlicchi, L Masotti and A Gallett, Wastewater polishing index: a tool for a rapid quality assessment of reclaimed wastewater. *Environmental Monitoring and Assessment*; 2011, 173(1-4):267-77. 10.1007/s10661-010-1386-7. Epub 2010 Mar 9.