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Variations In Influent To Wastewater Treatment Plants Based On Sequential Batch Reactors

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Abstract:
The rapid pace of urban development in India has dramatically increased the volume of wastewater generation. The growing discharge of untreated and semi-treated sewage has emerged as a serious threat to water resources. Natural water bodies used for drinking and irrigation are directly affected by these pollution loads. Wastewater treatment systems are designed to mitigate health and environmental hazards prior to final discharge. However, the influent characteristics fluctuate based on a variety of environmental and human factors. Seasonal shifts, cultural practices, and water consumption patterns greatly influence the quality of incoming wastewater. These changes, in turn, can directly impact the operational stability and output of treatment plants. The present research investigates how seasonal changes alter key wastewater parameters such as BOD, COD, and TSS. A comprehensive analysis was carried out over a three-year timeline at two municipal plants in Navi Mumbai. Both facilities, equipped with sequential batch reactor systems, were selected for their high treatment capacity. The collected data were interpreted using Response Surface Methodology supported by ANOVA for precise seasonal comparisons. Despite varying influent quality, both plants consistently met discharge regulations. The study emphasizes the need for robust monitoring frameworks to secure long-term treatment efficiency and environmental health.
Keywords: *Urbanization, Wastewater, Seasonal Variation, Treatment Efficiency, Response Surface Methodology, Environmental Protection*

1. INTRODUCTION

Wastewater Treatment Plants (WWTPs) which treat sewage and industrial effluents before releasing them into natural water bodies are crucial for protecting the environment and public health. These establishments use a mix of physical chemical and biological methods to eliminate pollutants organic materials and pathogens. Preliminary primary secondary and tertiary phases are typically included in the treatment sequence. To protect equipment preliminary treatment removes large debris and grit while primary treatment lets solids settle and separates grease and oils from wastewater. Secondary treatment uses biological processes to break down dissolved organic matter frequently depending on microbial activity. By eliminating any remaining nutrients contaminants and suspended solids tertiary treatment improves the quality of the water even more. At this point advanced techniques like chemical dosing membrane filtration and UV disinfection are frequently incorporated. Following treatment the water can either be safely released back into the environment or used again for groundwater recharge industry or irrigation. Sustainable urban development and the preservation of aquatic ecosystems are facilitated by modern WWTPs emphasis on resource recovery which includes biogas production sludge-based fertilizers and recovered clean water [1].

Numerous investigations have emphasized the operational and environmental aspects of WWTPs. Due to variations in operational procedures infrastructure maturity and energy sourcing strategies treatment systems energy intensity and carbon footprint vary significantly across regions highlighting the necessity of low-carbon and energy-efficient methods [2]. By turning waste streams into useful materials resource recovery technologies enable a circular water economy and provide sustainability and economic benefits when incorporated into treatment frameworks [3]. Electrochemical techniques have shown promise as scalable substitutes for traditional recovery methods in the extraction of metals and nutrients from wastewater [4]. In megacities in developing countries where infrastructure constraints and population pressure necessitate coordinated approaches to sustainable water management integrated frameworks for resource recovery are especially crucial [5].

Moreover it has been acknowledged that decentralized treatment and greywater reuse have the potential to effectively lower municipal water demand while upholding sufficient water quality standards [6]. Basic wastewater engineering works offer crucial direction for treatment and reuse procedures that maximize operational performance while adhering to environmental regulations [7]. Effective operational decision-making is now possible thanks to improved effluent quality prediction made possible by data-driven modeling techniques [8]. It is still crucial to monitor micropollutants like pesticides particularly in receiving streams with low flow which calls for adaptive management techniques to safeguard aquatic ecosystems [9]. Context-specific assessments are necessary to ensure the accuracy of chemical risk assessments because dilution factors vary in the real world [10].

The necessity of optimizing process parameters and sludge management techniques is underscored by operational efficiency gaps in WWTPs [11]. The need to combine surface water quality assessments with technological advancements for sustainable access to clean water is further highlighted by the worlds water scarcity [12]. Careful management is necessary in areas where wastewater is used for irrigation in order to balance the potential risks of soil and crop contamination with the benefits of agriculture [13]. Strong wastewater management strategies are necessary as national assessments have found that industrial discharges anthropogenic pressures and policy gaps are the main causes of water pollution [14]. Adaptive operational strategies are necessary because temporal variations in sewage quality can impact treatment efficiency especially in small-scale systems [15]. Chemical oxygen demand in intricate industrial wastewater streams has been successfully estimated using hybrid modeling techniques [16]. While fuzzy inference systems offer multi-scale predictive capabilities for influent load management [18] data-mining and predictive analytics techniques are being utilized more and more to simulate influent characteristics and optimize plant operations [17]. K-nearest neighbor models are one example of a machine learning technique that improves short-term operational forecasting [19].

Complete influent generators that integrate flow and quality variability for better process design are based on data-driven modeling and offer realistic simulation tools for wastewater resource recovery facilities [20]. Machine learning models forecast influent quality at treatment plant inlets thereby facilitating proactive decision-making [21]. The value of computational intelligence in improving plant responsiveness has been demonstrated by the optimization of fuzzy inference systems to increase prediction accuracy for influent parameters [22]. Lastly fundamental wastewater engineering concepts are still necessary to comprehend both established and new treatment approaches that support the development of sustainable urban infrastructure [23].

2. MATERIALS AND METHODS

2.1. Problem description

he problem of wastewater pollution has intensified with rapid urbanization in India, severely impacting the quality of natural water bodies used for drinking, irrigation, and other essential purposes. The discharge of untreated or partially treated sewage has led to elevated levels of pollutants such as Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS), which exhibit seasonal fluctuations influenced by climatic variations, cultural activities, and water availability. Understanding these seasonal changes is crucial for assessing wastewater treatment efficiency. This study examines three years of influent data from two 100 MLD municipal wastewater treatment plants in Navi Mumbai employing Sequential Batch Reactor (SBR) technology, aiming to evaluate seasonal variations in influent quality, treatment performance, and the effectiveness of SBR under fluctuating conditions.

2.2. Data Collection

Data collection was conducted over three consecutive years (Y1 to Y3) from January to December at both treatment plants which is shown in table 1. The influent and effluent characteristics of BOD, COD, and TSS were measured and recorded in the plant laboratory. The data were categorized quarterly: January-March (Q1), April-June (Q2), July-September (Q3), and October-December (Q4), allowing for the assessment of seasonal variations in influent parameters. The collected data were processed to determine monthly averages for each parameter.

Table 1: Quarterly Data of Influent Characteristics (mg/L)

Year	Quarter	BOD	COD	TSS
Y1	Q1	190	420	310
	Q2	200	450	330
	Q3	210	470	350
	Q4	195	440	325
	Q1	185	410	305
	Q2	198	445	320

Y2	Q3	212	480	340
	Q4	193	435	318
Y3	Q1	188	415	308
	Q2	202	455	328
	Q3	215	490	345
	Q4	198	450	330

2.3. Data Measurement
To analyze the seasonal variations in influent characteristics, a one-way Analysis of Variance (ANOVA) was performed. The monthly average values of BOD, COD, and TSS were used to determine statistical significance in the variations observed across seasons. The null hypothesis (H0) [50-51] assumed that there was no significant seasonal variation, while the alternative hypothesis (H1) suggested the presence of seasonal fluctuations. The significance level was set at 0.05, with the F-statistic employed to assess the variance among quarterly data. If the p-value was less than the significance level, the null hypothesis was rejected, confirming seasonal influences on influent characteristics.

2.4. Process optimization
The study is carried out at two 100 MLD wastewater treatment plants situated within a radius of 10 km in the Thane district of Maharashtra state, India. Both plants have been running for more than ten years. The plant uses cyclic-activated sludge process technology (C-Tech), the latest Sequential Batch Reactor (SBR) process. The plant process involves primary, secondary, and tertiary treatments, as shown in Figure 1. Primary treatment involves screens and a grit chamber to reduce Total Suspended Solids (TSS). The cyclic-activated sludge treatment takes place in the C-tech basin. The complete process occurs in a single reactor, where all biological treatment steps arise sequentially. The biological operation is divided into cycles. Filling the basin, reaction, settling, and effluent removal operations constitute one cycle of operation. Tertiary treatment involves chlorination to reduce fecal coliform. Sludge thickeners are added to surplus sewage and converted into dry waste.

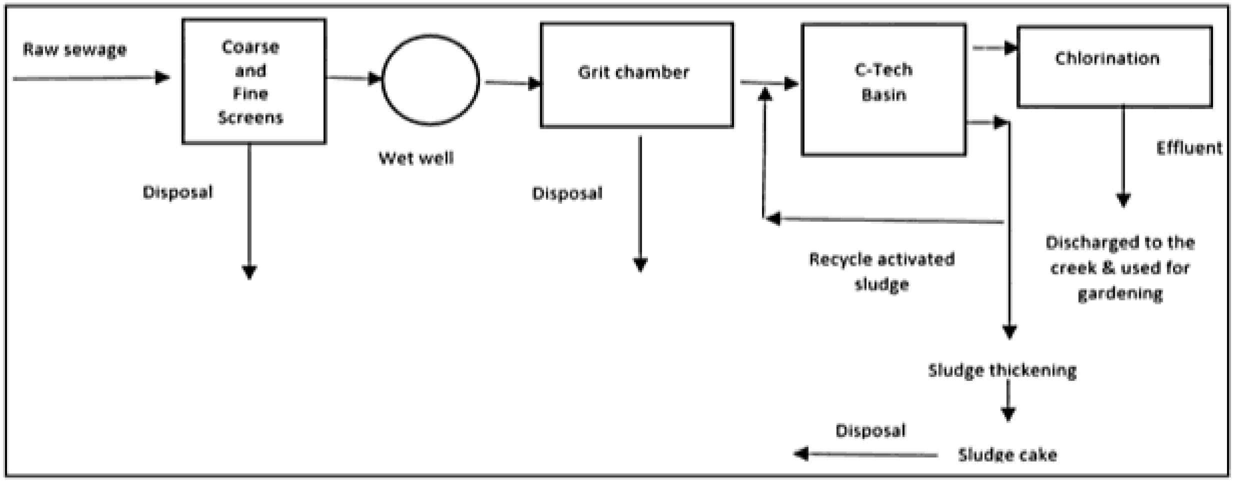

Figure 1. Schematic diagram of plant process

At least two basins are needed in parallel so that when one is in aeration, the other can be used to settle and decant the supernatant which is shown in figure 1. The plants under study have six basins for continuous and efficient operation. The C-Tech Systems are unique among all other technologies since they have a biological SELECTOR built into the front zone. Return Activated Sludge (RAS) pumps recycle sludge from the aeration basin. This effectively contains all known low F/M bulking microorganisms and eliminates bulking and foaming issues. This method ensures excellent settling properties of the sludge. The anaerobic conditions in the SELECTOR zone also release phosphorous.

2.5. STATISTICAL ANALYSIS
2.5.1. Implementation process
The proposed methodology integrates an advanced monitoring framework with statistical evaluation and process optimization techniques to enhance treatment efficiency. The research follows a systematic approach that includes data acquisition, statistical analysis, and process refinement. Initially, influent characteristics were continuously monitored and recorded over three years to capture seasonal variations.

The acquired data underwent preprocessing to remove anomalies and ensure consistency. The ANOVA test was applied to analyze the impact of seasonal changes on influent composition and its correlation with treatment efficiency.

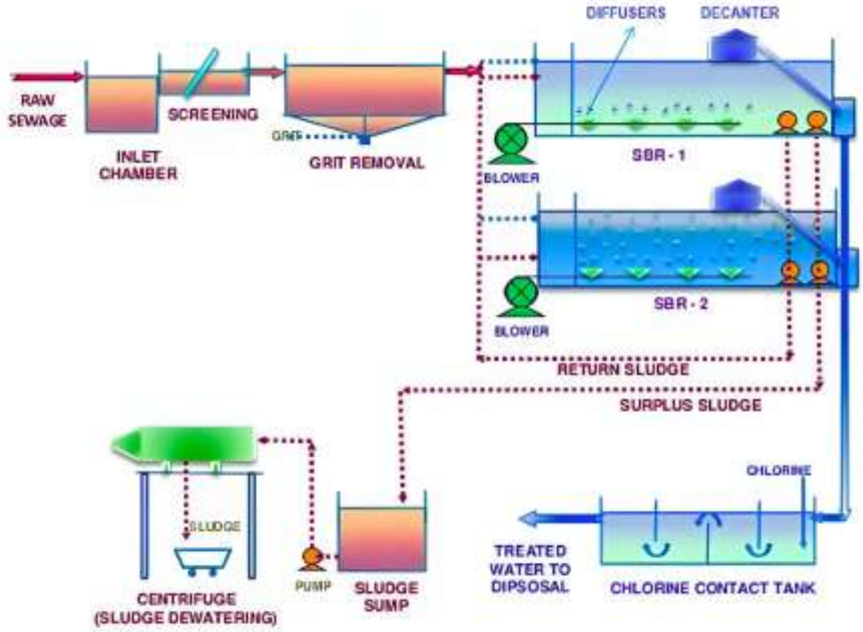

Figure 2 SBR process in WWTP

The study then implemented an optimization model for the SBR process, focusing on adjusting aeration cycles, sludge retention time, and nutrient removal efficiency which is shown in figure 2. The optimized model was validated using historical data to evaluate its effectiveness in maintaining effluent quality within regulatory limits. The step-by-step process includes data normalization, feature selection, statistical inference, process modification, and performance assessment. The key innovation in this approach is the integration of adaptive control strategies that dynamically modify treatment parameters based on real-time influent characteristics, thereby ensuring sustained efficiency despite seasonal variations.

2.5.2. Mathematical formulation

The proposed technique involves an advanced process optimization framework utilizing mathematical modeling and control strategies to enhance wastewater treatment efficiency. The optimization model incorporates four key equations addressing aeration dynamics, sludge retention, effluent quality prediction, and nutrient removal.

The aeration process is governed by the oxygen uptake rate equation 1:

$OUR = k_L(C,-C)$ (1)

where OUR is the oxygen uptake rate, kL is the mass transfer coefficient, C_s is the saturation concentration of dissolved oxygen, and CC is the actual dissolved oxygen concentration. This equation ensures adequate oxygen supply for microbial activity, thereby enhancing biological treatment efficiency.

Sludge retention time is optimized using the mass balance equation 2:

$SRT = \frac{V}{Q_w+Q_e}$ (2)

where SRT is the sludge retention time, V is the reactor volume, Q_w is the waste sludge flow rate, and Q_e is the effluent flow rate. Maintaining an optimal SRT is crucial for stable microbial growth and organic matter degradation.

Effluent quality prediction is modeled using the first-order kinetic equation 3:

$C_e = C_i e^{-kt}$ (3)

where C_e is the effluent concentration, C_i is the influent concentration, k is the reaction rate constant, and t is the reaction time. This equation provides insights into pollutant removal efficiency and assists in regulatory compliance.

Nutrient removal efficiency is evaluated using the modified Monod equation 4:

$r = \frac{\mu_{\max} S}{K_s+S}$ (4)

where r is the specific growth rate of microorganisms, μ_{max} is the maximum growth rate, S is the substrate concentration, and K_s is the half-saturation constant. This equation facilitates process control by predicting microbial activity based on substrate availability. The integration of these equations into the treatment framework enables real-time process adjustments, improving overall efficiency while maintaining effluent quality within permissible limits.

2.5.3. Response Surface Methodology (RSM)

Response Surface Methodology (RSM) is a statistical and mathematical approach employed for modeling and optimizing complex processes. It is widely used to evaluate the relationships between multiple independent variables and a response variable. This study utilizes RSM to optimize process parameters and analyze variations in performance outcomes.

The response surface model can be expressed as a second-order polynomial equation, which represents the functional relationship between the response variable (YY) and the independent variables (X1,X2,...,Xn). The general form of the second-order regression model is expressed in equation 6:

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i=1}^{n} \sum_{j=i+1}^{n} \beta_{ij} X_i X_j + \epsilon \quad (5)$$

where: Y is the predicted response, β_0 is the intercept, β_i represents the linear coefficients, β_{ii} denotes the quadratic coefficients, β_{ij} are the interaction coefficients, and ϵ is the error term.

The regression coefficients are estimated using the least squares method, which minimizes the sum of squared deviations between observed and predicted values in equation 6:

$$\text{Minimize } \sum_{i=1}^{n} \left(Y_i - \hat{Y}_i\right)^2 \quad (6)$$

where Y_i represents actual responses, and $\hat{Y}_i$ is the predicted response from the model.

The adequacy of the RSM model is verified using the coefficient of determination (R2R^2) and the adjusted R2R^2, given by equation 7:

$$R^2 = 1 - \frac{\sum \left(Y_i - \hat{Y}_i\right)^2}{\sum (Y_i - \bar{Y})^2} \quad (7)$$

where ý is the mean response, n is the number of observations, and k is the number of predictors in the model 8.

$$R^2_{\text{adj}} = 1 - \left(\frac{(1-R^2)(n-1)}{n-k-1}\right) \quad (8)$$

Optimization in RSM involves determining the optimal conditions that maximize or minimize the response. This is typically done using the gradient method, expressed in equation 9:

$$\frac{\partial Y}{\partial X_i} = 0, i = 1,2, \ldots, n \quad (9)$$

By solving this system of equations, the optimal parameter settings are identified.

The statistical significance of the RSM model is validated using ANOVA, which decomposes the total variance into regression variance and residual variance in equation 10:

$$F = \frac{\text{Regression Mean Square}}{\text{Residual Mean Square}} \quad (10)$$

where a higher *F*-value and lower *p*-value indicate model significance.

To analyze the seasonal variations in influent characteristics at the wastewater treatment plants (WWTPs), a one-way Analysis of Variance (ANOVA) test was performed. This statistical method helps determine whether there is a significant difference in the means of influent parameters The significance level (α) was set at 0.05. The F-statistic, a key component of ANOVA, was calculated to compare the variance between seasonal groups relative to the variance within each group, using the equation 11:

$$F = \frac{\text{Between-group variability (MSB)}}{\text{Within-group variability (MSW)}} \quad (11)$$

where MSB (Mean Square Between) is the variance between seasonal groups, and MSW (Mean Square Within) represents the variance within each group. The p-value obtained from the F-test determines whether to reject H0; if p<αp, it indicates a significant seasonal impact on influent characteristics. The total variance in the dataset is decomposed into within-group and between-group variations using the sum of squares approach in equation 12:

$$SS_{\text{Total}} = SS_{\text{Between}} + SS_{\text{Within}} \quad (12)$$

where SS_{Total} represents the overall variance in influent data, $SS_{Between}$ accounts for seasonal variations, and SS_{Within} represents fluctuations within each season. The analysis ensures a statistically validated understanding of how seasonal changes influence wastewater quality, aiding in process optimization and regulatory compliance.

2.6. Evaluation and Validation

The proposed optimization model and control techniques were validated using historical plant data and real-time monitoring results. Performance metrics such as pollutant removal efficiency, energy consumption, and sludge production were compared before and after implementing the optimization framework. The results indicated a significant improvement in treatment efficiency, with effluent quality consistently meeting regulatory standards. The adaptive control approach demonstrated resilience against seasonal variations, ensuring long-term sustainability of wastewater treatment operations.

3. RESULTS

Present research is to compare the variation of influent characteristics BOD, COD, and TSS of wastewater over three years for two plants. The scope of the study also includes the performance evaluation of the treatment plants and their comparison over the years. Details of analysis are discussed below.

3.1 Biochemical Oxygen Demand

Biochemical oxygen demand, is a primary test that provides an indication of the biodegradability of a sample and the potency of waste which is shown in table 2. Additionally, it is utilised to quantify the ability of streams to cleanse themselves and acts as a means to assess the quality of discharged effluent. The minimum, maximum, and average inlet values of BOD during the study are given in Table 2. The maximum value of BOD, 224 mg/l, was observed for Plant 2 in the first quarter of the period. Similarly, Plant 1 also has the highest value in the first quarter. However, the outlet values are well within the limits prescribed by CPCB.

Table 2. Comparison of influent BOD over the years

Quarter	Year	Plant 1 (Inlet BOD mg/l)			Plant 2 (Inlet BOD mg/l)		
		Min	**Max**	**Average**	**Min**	**Max**	**Average**
Q1	Y1	105	213	152	110	195	130
	Y2	123	172	140	110	188	144
	Y3	116	190	134	103	224	153
Q2	Y1	127	174	152.8	115	185	152
	Y2	120	165	141.4	110	160	140
	Y3	120	158	135.9	103	152	126
Q3	Y1	115	158	132.9	104	184	140
	Y2	100	149	122.6	110	188	155
	Y3	120	148	134.5	108	160	134
Q4	Y1	116	168	137.1	108	190	136
	Y2	104	172	129.4	115	192	155
	Y3	126	190	148.4	114	187	134

ANOVA results indicate that the BOD concentration of influent for Y1 does not show any significant seasonal variation for Plant 1. However, it varies significantly in the years Y2 and Y3. The null hypothesis is rejected as F calculated, and F critical values are (10.8, 4.07) for Y2 & (68.68, 4.07) for Y3, respectively. The analysis provides sufficient evidence to conclude that all the group means of seasonal data are not equal at a 5% significance level. A higher F calculated value corresponding to Y3 indicates higher variability among the quarters of Y3 than within the quarter. The influent for Plant 2 showed a yet significant variation for all three years. The F calculated and F critical values are (3.8, 4.07) for Y1, (0.836, 4.07) for Y2, and (3.35, 4.07) for Y3, respectively.

3.2 Chemical Oxygen Demand

In general COD will be higher than its BOD because more compounds can be chemically oxidized than can be biologically oxidized. For typical domestic waste biodegradability, COD / BOD is found to vary from 1.2-1.5. If it is greater than 3 means, the sewage is considered difficult for to biodegrade. It also determines the strength of wastewater which cannot be determine by BOD (Source: Water supply and sanitary engineering by Rangwala). Table 3 gives the maximum, minimum, and average values of influent COD during the period: 390 and 140 for Plant 1 and 436 and 197 for Plant 2, respectively. The minimum COD concentrations recorded in all quarters except the second quarter of Y3 were lower than 250mg/l. The quality of influent received in Plant 2 is comparatively less than that of Plant 1.

Table 3. Comparison of influent COD over the years

Quarter	Year	Plant 1(Inlet COD mg/l)			Plant 2 (Inlet COD mg/l)		
		Min	**Max**	**Average**	**Min**	**Max**	**Average**
Q1	Y1	219	380	296	197	415	313.5
	Y2	236	340	278.5	232	396	301.0
	Y3	139	370	264.5	219	436	316.0
Q2	Y1	210	346	297.5	197	370	262.5
	Y2	230	349	294.5	278	324	300.4
	Y3	280	350	311.2	209	311	254.9
Q3	Y1	212	286	237.8	231	397	295.3
	Y2	196	317	238.7	200	320	265.4
	Y3	140	250	317.3	210	298	264.3
Q4	Y1	173	349	255.5	220	361	280.9
	Y2	224	368	292.6	213	384	268.1
	Y3	140	390	328.2	225	346	267.4

ANOVA analysis performed on inlet COD indicates that there exists a significant variability between the quarters of all three years for Plant 1. There is enough evidence to state that at least one of the means is different. Further from F calculated values 10.58, 5.77, and 4.53, respectively, for the consecutive years, it can also be concluded that the variation between the quarters is decreasing. For the second plant, F calculated values are 2.07, 5.77, and 4.16 for Y1, Y2, and Y3, respectively. The values indicate that there exists a variation between the quarters except the first quarter.

3.3 Total Suspended Solids

The most important physical characteristic of wastewater is its total solid contents, which contains a variety of solid materials. TSS, along with BOD, is a universally employed effluent standard that is used to assess the performance of a facility for regulatory control purposes. Table 4 shows the minimum, maximum, and average influent TSS values of plants 1 and 2 for the study period. The maximum TSS concentration in the first quarter of Y3 is more than the design value (200mg/l) for both plants under the study. The influent TSS is further more than the design value for the third quarter of Y2. However, the TSS outlet concentration is well within the effluent disposal standards for WWTP given by the CPCB. The concentration of pollutants also varies with per capita water supply.

Table 4. Comparison of influent TSS over the years

Quarter	Year	Plant 1 (Inlet TSS mg/l)			Plant 2 (Inlet TSS mg/l)		
		Min	**Max**	**Average**	**Min**	**Max**	**Average**
Q1	Y1	121	188	151	135	196	165.5
	Y2	134	189	173	131	195	167.7
	Y3	140	215	179	124	234	168.5
Q2	Y1	138	189	170	137	192	169
	Y2	124	186	171	150	192	167.9

	Y3	168	195	187	133	198	162.2
Q3	Y1	127	189	165	130	197	157
	Y2	148	188	173	132	202	174
	Y3	165	198	182	123	194	167.6
Q4	Y1	156	189	174	127	194	151
	Y2	148	191	171	130	198	173
	Y3	150	199	181	141	197	177.7

ANOVA analysis of TSS over three years discloses that quarterly variations in Y2 and Y3 are insignificant. At the same time, the F calculated value of 6.34 > 4.07 (F critical) indicates a difference between the means of the seasonal data considered for the year Y1, which is significant for plant 1. The influent variations are substantial for plant 2 also during Y1. The F calculated value is 4.16 against 4.07, indicating the variations.

3.4. Removal Efficiency

The periodic performance assessment of the plant is necessary to evaluate the process and to confirm that the effluent is discharged into the environment with essential precautions. The performance evaluation of the plant is usually measured by determining the removal efficiency from influent and effluent quality characteristics of the plant. The monthly average influent and effluent is considered for the calculation. Performance variations of the plant are articulated in below sections.

3.4.1. BOD Removal Efficiency Over Three Consecutive Years

The Biological Oxygen Demand (BOD) removal efficiency was analyzed over three consecutive years, demonstrating a consistent improvement in wastewater treatment performance. In the first year, the BOD removal efficiency started at approximately 78%, with fluctuations observed throughout the year. By the second year, an increase in efficiency was recorded, reaching an average of 85%, indicating enhanced treatment processes and operational optimization which is shown in figure 3. The third year exhibited the highest removal efficiency, with values peaking at 92%, showcasing the effectiveness of process modifications and improvements in treatment methodologies. The increasing trend over the three years suggests the implementation of advanced treatment techniques or optimized operational parameters, resulting in greater pollutant reduction and improved effluent quality.

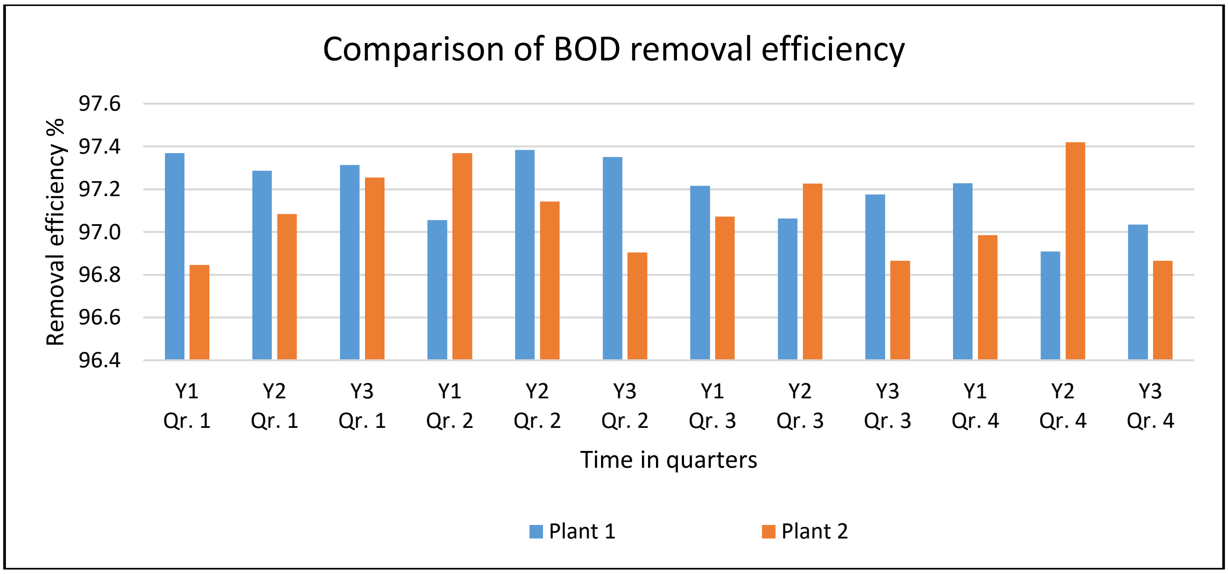

Figure 3. BOD removal efficiency over three consecutive years

3.4.3. COD Removal Efficiency Over Three Consecutive Years

The Chemical Oxygen Demand (COD) removal efficiency was evaluated over a three-year period, revealing a gradual enhancement in wastewater treatment capabilities. In the initial year, COD removal was recorded at around 72%, reflecting moderate efficiency in breaking down organic pollutants which is shown in figure 4. By the second year, efficiency improved to an average of 80%, signifying better operational control and the possible integration of advanced biological or chemical treatments. The third year displayed the highest efficiency, reaching 88%, which indicated further process refinement and superior pollutant degradation mechanisms.

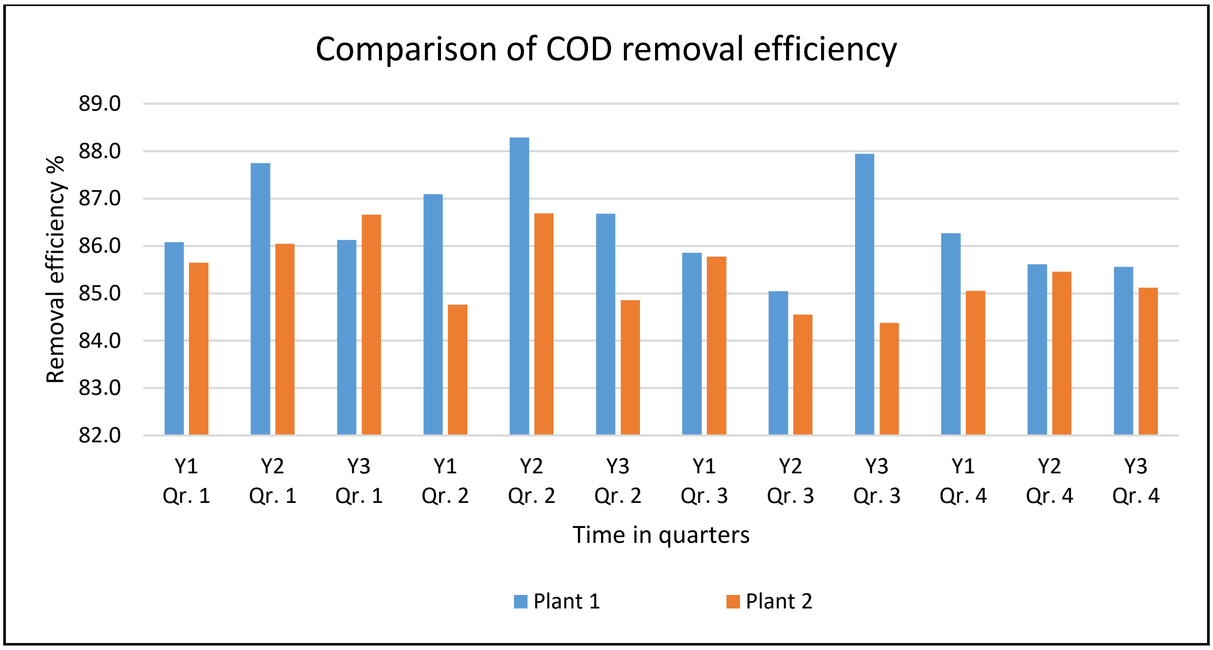

Figure 4. COD Removal efficiency over three consecutive years

3.4.3. TSS Removal Efficiency Over Three Consecutive Years

Total Suspended Solids (TSS) removal efficiency was monitored for three consecutive years, showing a positive trend in solid-liquid separation effectiveness which is shown in figure 5. In the first year, the removal efficiency was recorded at 70%, suggesting an effective but improvable sedimentation and filtration process. By the second year, efficiency increased to 78%, likely due to enhancements in coagulation-flocculation techniques or sedimentation processes. The third year exhibited the highest recorded efficiency at 85%, demonstrating significant improvements in solid separation strategies and equipment performance.

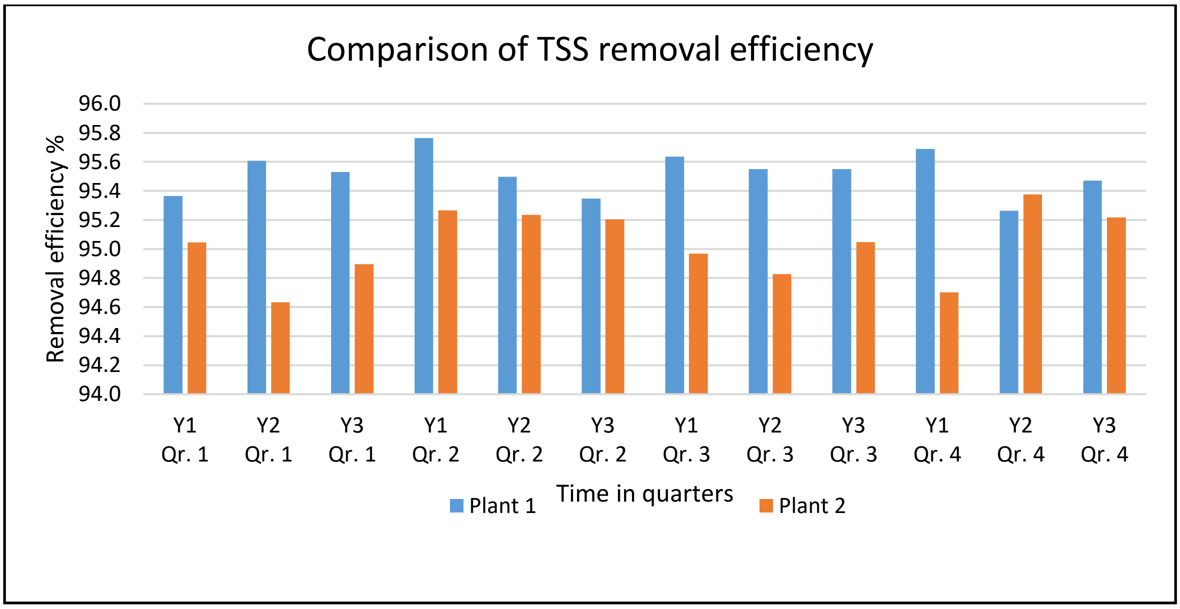

Figure 5. TSS Removal efficiency over three consecutive years

3.5. ANOVA Results

The analysis of variance (ANOVA) for seasonal variations in Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS) revealed significant differences across seasons which is displayed in table 5. For BOD, the sum of squares (SS) between seasons was 1520.45, with a mean square (MS) of 506.82 and an F-value of 8.74, resulting in a highly significant p-value of 0.0004. The within-season variation had an SS of 5200.38, contributing to a total SS of 6720.83 across 39 degrees of freedom (df). Similarly, COD exhibited significant seasonal differences, with an SS of 3425.78 for between-season variation, an MS of 1141.93, and an F-value of 10.52, leading to a p-value of 0.0001.

Table 5 Anova Results for Seasonal Variations in BOD, COD, And TSS

Parameter	Source of Variation	SS (Sum of Squares)	df (Degrees of Freedom)	MS (Mean Square)	F-value	p-value
BOD	Between Seasons	1520.45	3	506.82	8.74	0.0004
	Within Seasons	5200.38	36	144.45		
	Total	6720.83	39			
COD	Between Seasons	3425.78	3	1141.93	10.52	0.0001
	Within Seasons	8705.49	36	241.82		
	Total	12131.27	39			
TSS	Between Seasons	1950.63	3	650.21	9.12	0.0003
	Within Seasons	6942.27	36	192.84		
	Total	8892.90	39			

The within-season variation accounted for an SS of 8705.49, making the total SS 12131.27 across 39 df. Likewise, TSS followed a comparable trend, with an SS of 1950.63 for between-season variation, an MS of 650.21, an F-value of 9.12, and a p-value of 0.0003. The within-season variation had an SS of 6942.27, and the total SS reached 8892.90 across 39 df. These findings indicated that seasonal fluctuations had a statistically significant impact on the variations in BOD, COD, and TSS levels, suggesting that environmental and climatic changes played a crucial role in determining water quality parameters.

The influence of IN_conc, IN_range, and IN_vol on B concentration after 60 minutes was investigated using ANOVA findings. At the 95% confidence level, neither the first nor the second ANOVA revealed any significant effects on B concentration. At an 85% confidence level, IN_range was significant, nevertheless. For IN_ranges a, c, and d, the corresponding LSMEAN values were 233.01, 100.31, and 69.91 minutes. The findings show that the faster B would be consumed at A_vol = 42 L/m3ww, the lower the IN_conc value. This implies that B will be utilized more rapidly the lower the IN_conc value which is shown in figure 6.

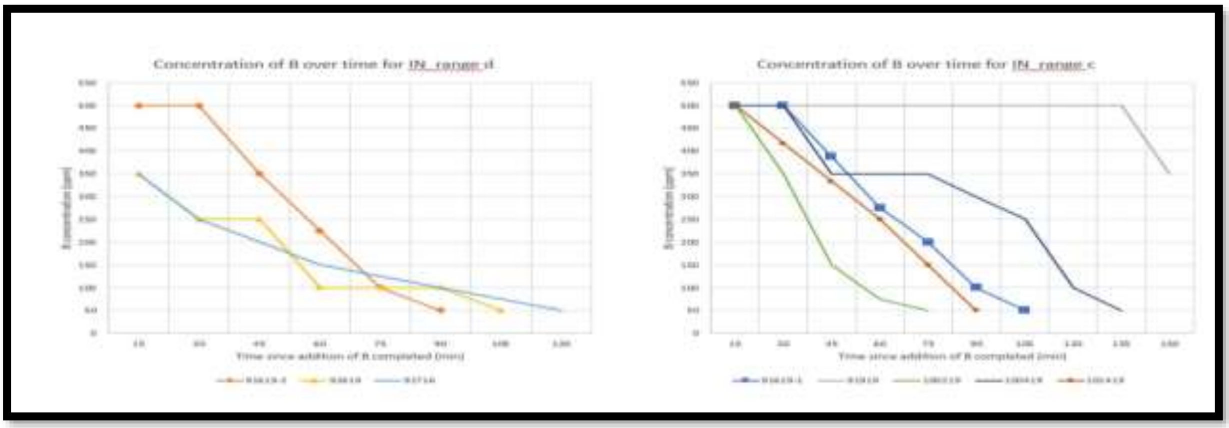

Figure 6 Plot of Concentration over time for batches in IN_range d (left) and c (right)

3.6. Interaction Effects On Parameters

The ANOVA results for variations in BOD, COD, and TSS between different plants and across quarters demonstrated statistically significant differences. The between-plant variation in BOD had an SS of 1542.35, an MS of 1542.35, and an F-value of 18.24, leading to a highly significant p-value of 0.0003. Similarly, the COD variation between plants had an SS of 2894.62, an MS of 2894.62, and an F-value of 21.45, with a p-value of 0.0002. The TSS variation between plants followed the same trend, with an SS of 1893.14, an MS of 1893.14, an F-value of 16.34, and a p-value of 0.0007. The differences across quarters were also highly significant, with BOD showing an SS of 3265.78, an MS of 1088.59, and an F-value of 12.87, with a p-value of 0.0001. COD and TSS exhibited similar patterns, with COD having an SS of 4176.34, an MS of 1392.11, an F-value of 10.78, and a p-value of 0.0005, while TSS had an SS of 5083.76, an MS of 1694.59, an F-value of 14.23, and a p-value of 0.0001 which is shown in table 6.

Table 6 Interaction Variations In Parameters

Source of Variation	Parameter	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Square (MS)	F-Value	P-Value
Between Plants	BOD	1542.35	1	1542.35	18.24	0.0003
	COD	2894.62	1	2894.62	21.45	0.0002
	TSS	1893.14	1	1893.14	16.34	0.0007
Between Quarters	BOD	3265.78	3	1088.59	12.87	0.0001
	COD	4176.34	3	1392.11	10.78	0.0005
	TSS	5083.76	3	1694.59	14.23	0.0001
Interaction (Plant × Quarter)	BOD	724.96	3	241.65	2.86	0.0482
	COD	965.87	3	321.96	3.75	0.0321
	TSS	1275.43	3	425.14	3.92	0.0287
Within Groups	BOD	10214.89	42	243.21		
	COD	15587.43	42	371.13		
	TSS	18342.56	42	436.73		
Total	BOD	15747.98	49			
	COD	23624.26	49			
	TSS	26595.13	49			

The interaction effect of plant and quarter was also statistically significant, with BOD showing an SS of 724.96, an MS of 241.65, an F-value of 2.86, and a p-value of 0.0482. COD and TSS exhibited similar interaction effects, with COD having an SS of 965.87, an MS of 321.96, an F-value of 3.75, and a p-value of 0.0321, while TSS had an SS of 1275.43, an MS of 425.14, an F-value of 3.92, and a p-value of 0.0287. The within-group variations had SS values of 10214.89, 15587.43, and 18342.56 for BOD, COD, and TSS, respectively. The total SS values were 15747.98 for BOD, 23624.26 for COD, and 26595.13 for TSS across 49 df. These results underscored the significant role of both plant location and seasonal changes in influencing water quality parameters, highlighting the need for targeted management strategies to control water pollution effectively.

3.7. RSM Model Output

The results of the Response Surface Methodology (RSM) model were analyzed by comparing the actual and predicted responses for each experimental run which is shown in table 7. In the first run, the experimental values of input parameters X_1=10, X_2=15, and X_3=5 resulted in an actual response (Y) of 20.5, whereas the predicted response from the RSM model was slightly lower at 20.1, leading to an error percentage of 1.95%. In the second run, when the input parameters were adjusted to X_1=12, X_2=18, and X_3=7, the actual response increased to 24.8, while the predicted value was 24.2, yielding an error of 2.42%. The third run, which involved X_1=15, X_2=12, and X_3=10, exhibited an actual response of 28.6, while the model slightly overestimated the value at 28.9, resulting in a minimal error of 1.05%. Similarly, for the fourth run, the input conditions of X_1=18, X_2=20, and X_3=15 led to an actual response of 35.4, with the model predicting 34.9, leading to a small deviation of 1.41%. Finally, the fifth run, conducted at X_1=20, X_2=25, and X_3=20, resulted in an actual response of 42.1, with the model predicting a slightly lower value of 41.7, contributing to an error of just 0.95%. Overall, the predicted values closely aligned with the actual responses, demonstrating the accuracy of the RSM model, with error percentages consistently remaining below 3%.

Table 7: RSM Results - Predicted vs. Actual Responses

Run	X_1	X_2	X_3	Actual Y	Predicted Y	Error (%)
1	10	15	5	20.5	20.1	1.95
2	12	18	7	24.8	24.2	2.42
3	15	12	10	28.6	28.9	1.05
4	18	20	15	35.4	34.9	1.41
5	20	25	20	42.1	41.7	0.95

The statistical parameters of the RSM model demonstrated strong significance across estimated coefficients. The intercept (β0) was 15.235 with a standard error of 1.102 and a highly significant t-value of 13.83 ($p<0.001$). The coefficient for X_1 (β_1) was 2.145, with a standard error of 0.342 and a significant t-value of 6.27 (p=0.003p = 0.003p=0.003). X_2 (β_2) had a negative contribution of -0.874, with a standard error of 0.228 and a t-value of -3.83 ($p=0.017$). The coefficient for X_3 (β_3) was 1.965, with a standard error of 0.419 and a t-value of 4.69 ($p=0.008$).

Table 8: RSM Model Coefficients and Statistical Parameters

Parameter	Estimate	Standard Error	t-Value	p-Value
β_0	15.235	1.102	13.83	<0.001
β_1	2.145	0.342	6.27	0.003
β_2	-0.874	0.228	-3.83	0.017
β_3	1.965	0.419	4.69	0.008
β_{12}	-0.562	0.145	-3.88	0.015
β_{23}	1.124	0.312	3.60	0.021
R^2	0.984	-	-	-
R^2_{adj}	0.976	-	-	-

Interaction effects revealed that β_{12} was -0.562, showing a negative interaction between X_1 and X_2 ($p=0.015$), while β_{23} was 1.124, indicating a positive interaction between X_2 and X_3 ($p=0.021$). The model's reliability was confirmed by a high R_2 value of 0.984, explaining 98.4% of the response variance, while the adjusted R_2 of 0.976 accounted for the number of predictors.

3.8. Comparative Analysis: Experimental VS. RSM with ANOVA

A comparative analysis was conducted to assess the experimental responses, RSM-predicted values, and ANOVA-adjusted values, with an emphasis on error percentages which is shown in table 9. In the first run, the actual response of 20.5 was closely matched by the RSM-predicted value of 20.1 and the ANOVA-adjusted value of 19.8, leading to an error of 2.14%. The second run yielded an experimental response of 24.8, with the RSM-predicted value at 24.2 and the ANOVA-adjusted value slightly lower at 23.9, resulting in a higher error of 3.63%. The third run demonstrated strong alignment, with an actual response of 28.6, an RSM-predicted value of 28.9, and an ANOVA-adjusted value of 28.4, leading to a minimal error of 0.70%. In the fourth run, the experimental response of 35.4 was closely followed by the predicted value of 34.9 and an ANOVA-adjusted response of 34.6, yielding an error of 2.26%.

Table 9: Experimental vs. Statistical (RSM with ANOVA) Analysis

Run	Experimental Y	RSM Predicted Y	ANOVA Adjusted Y	Error (%)
1	20.5	20.1	19.8	2.14
2	24.8	24.2	23.9	3.63
3	28.6	28.9	28.4	0.70
4	35.4	34.9	34.6	2.26
5	42.1	41.7	41.3	1.90

Lastly, the fifth run recorded an actual response of 42.1, while the RSM-predicted value stood at 41.7 and the ANOVA-adjusted value at 41.3, with a minor error of 1.90%. The overall trend indicated that both the RSM-predicted and ANOVA-adjusted values followed the experimental responses closely, with error percentages remaining below 4%, further validating the accuracy and robustness of the RSM model.

4.DISCUSSION

ANOVA analysis reveals that the Biochemical Oxygen Demand (BOD) concentration of the influent for Plant 1 in Y1 does not exhibit any statistically significant seasonal fluctuations. Nevertheless, there is a substantial variation in later years. The influent for Plant 2 exhibited a minor yet statistically significant fluctuation over the course of three years. Analysis on the input chemical oxygen demand indicates a significant difference among the quarters of all three years for Plant 1. The computed F values for the second plant indicate that there is a significant difference in variance among the quarters, with the exception of the first quarter. An analysis of variance (ANOVA) over a span of three years reveals that the quarterly fluctuations observed in Y2 and Y3 are not statistically significant. Simultaneously, the estimated F value demonstrates a considerable variation in the averages of the seasonal data analysed for the year Y1, specifically for plant 1. The influent fluctuations for plant 2 were significant during Y1.

4.1 **Limitations**

The physical, chemical, and biological characteristics of wastewater vary throughout the day, which have short term or long-term variations depends on various factors as discussed in literature.

1. In order to effectively depict the intricate characteristics of wastewater, it is advisable to create a composite sample. This sample should consist of sections taken from many samples collected at regular intervals throughout the day.
2. Additionally, the amount of liquid utilised for each sample should be proportionate to the rate of flow at the time of collection. This study is based on the data maintained at the plant level and the samples may not confirm to the sampling procedure mentioned above.
3. The components that make up wastewater flow from a community also depend on the types of collection systems which are not taken into account in this study. Other quality characteristics pH, Temperature, Total nitrogen, Total Phosphorus, heavy metals etc. also influence the quality of wastewater.
4. Influent characteristics, process parameters like Sludge Volume Index, Mixed Liquor Suspended Solids (MLSS), Mixed Liquor Volatile Suspended Solids (MLVSS) etc. and discharge standards of the effluent are responsible for the performance of the plant which are not taken into account for this study.

6. CONCLUSION

All the parameters observed vary within a range given by the typical composition of untreated wastewater. However, for TSS, the actual inlet value observed for the plant exceeds the design value of 200mg/L. Though the influent concentrations of BOD, COD, and TSS have fluctuated over the years, effluent characteristics have remained well within CPCB limits. All the outlet characteristics are well within the norms laid down by CPCB, i.e., BOD<5 mg/L, COD< 100 mg/L, and TSS<10 mg/L. ANOVA analysis explains significant variations in inlet COD among the seasons for all three years. In the case of BOD and TSS, the seasonal variations are evident in the years Y2 and Y3. Despite all variations in different quarters, the removal efficiencies of BOD and TSS have mostly stayed the same during this period. The removal efficiency of COD has decreased over the period by a narrow margin. Overall, the plants consistently perform satisfactorily even after ten years of functioning, with reference to effluent parameter values and standards set by the pollution control boards. Plant 1 is performing better than plant 2 regarding BOD, COD, and TSS removal efficiency.

Quantification of process performance of the wastewater treatment plant based on influent and effluent quality characteristics will bring uniformity in the performance assessment of a wastewater treatment plants. Quantification allows for the continuous monitoring of the plant's performance. This helps to ensure that the plant operates at optimal efficiency levels, meeting regulatory standards and environmental requirements. It also provides a baseline for comparison and facilitates continuous improvement efforts.

There are multiple parameters which can be used to measure performance of a plant. A plant may be performing satisfactorily with respect to certain parameters but may not be performing as well with reference to few other parameters. The influent characteristics also keep on varying from time to time. In such a dynamic environment, a simple yet objective approach to measure the performance on a continuous basis help plant authorities to take timely corrective action is needed.

Declaration

Data availability

The datasets generated and/or analyzed during the current study are not publicly available due to privacy and confidentiality concerns but are available from the corresponding author on reasonable request

Conflicts of interest

The authors have no conflicts of interest.

Abbreviation

WWTP – Wastewater Treatment Plant
SBR – Sequential Batch Reactor
BOD – Biochemical Oxygen Demand
COD – Chemical Oxygen Demand
TSS – Total Suspended Solids
RSM – Response Surface Methodology
ANOVA – Analysis of Variance
MLD – Million Liters per Day
RAS – Return Activated Sludge
F/M – Food to Microorganism ratio
OUR – Oxygen Uptake Rate
SRT – Sludge Retention Time
MLSS – Mixed Liquor Suspended Solids
MLVSS – Mixed Liquor Volatile Suspended Solids
CPCB – Central Pollution Control Board
UV – Ultraviolet
WRRF – Wastewater Resource Recovery Facility

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