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ENVIRONMENTAL AND ECONOMIC PERFORMANCE ASSESSMENT OF MUNICIPAL WASTEWATER TREATMENT PLANTS IN KANPUR FOR SUSTAINABLE URBAN WATER MANAGEMENT

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ABSTRACT
Water treatment (WT) is the procedure that takes place in order to remove contaminants from water to make it suitable for consumption, in industry, or for release to the environment. Wastewater treatment (WWT) is specifically concerned with removing contaminants from combined sewage and industrial effluents in an effort to protect human health and the environment. In all cases, the early detection of contaminants is important in order to maximize efficacy of treatment, while also preventing adverse impacts to the environment and overall water use.However, a significant challenge lies in the limited adaptability of existing treatment technologies to varying wastewater compositions, dependence on consistent energy supply, and difficulty in managing sludge by-products, which delays widespread implementation in diverse municipal contexts.In this manuscript, environmental and economic performance assessment of municipal wastewater treatment plants in Kanpur for sustainable urban water management (MWTPK-HSO) is proposed. Initially, input data is collected from the Kanpur-Municipal-Wastewater-Treatment-Plants-Dataset The major objective is to enhance particulate organic carbon (POC) removal using physical advanced primary treatment (APT) with micro screening for sustainable wastewater treatment. The micro screen-based treatment improves solids and carbon removal, enhancing treatment efficiency and reducing chemical dependency in wastewater management. The House Swallow Optimizer (HSO) is used to optimize the wastewater cleaning. The proposed MWTPK-HSOapproach is implemented in MATLAB.The proposed MWTPK-HSO approach achieves the highestpermeates flux of 1.0 $m^3/m^2/h$, compared to 0.35 for physical cleaning and 0.1 in the fouled state. Optimal flux is also observed under 30s run–30 backwashes at 20 Hz, reaching over 1.0 $m^3/m^2/h$, while 50s run–10 backwashes shows the lowest performance across all frequencies. This result demonstrates that the MWTPK-HSO technique outperforms existing methods, proving to be a highly effective solution for municipal wastewater treatment.

KEYWORDS: Municipal Wastewater Treatment, Wastewater, Micro Screening, Water, Primary Treatment, Wastewater Treatment Plants, House Swallow Optimizer.

1. INTRODUCTION
Water scarcity is an important global issue in many countries, including India, due to industrialisation, population growth and climate change [1]. Wastewater reclamation provides a practical way to address water availability and environmental protection through reusing treated wastewater [2]. The relatively low toxicity and biodegradability of municipal wastewater (urban water) represents an appealing resource [3]. However, a significant amount of wastewater is released untreated, resulting in environmental pollution and human health concerns [4]. Effective wastewater treatment processes are necessary to address the possible proliferation of viruses in the water supply [5]. There are many technologies and processes available, often resulting in varying costs and capabilities [6]. Local conditions will inform the choice of technology that is appropriate for contiguous, sustainable water management practices [7]. Technologies must reflect user demands while attempting to consider social, economic and environmental ramifications [8].
A significant issue is the absence of a systematic and reliable means to choose the optimal wastewater treatment technology for certain local environments [9]. The current choices often result from experience instead of careful consideration, resulting in less-than-effective treatment and increased costs [10]. Wastewater treatment plants can underperform when the appropriate technology is not matched with local resources [11]. Furthermore, the challenge of weighing technical efficiency against cost, operational requirements, and environmental sustainability is complex [12]. Decision-makers can struggle to develop a framework that incorporates many

variables of land use, energy use, maintenance costs, etc. into an overall evaluation [13]. This complexity leads to an inefficient water investments and undermines the promise of water reuse and sustainability [14].
It is important to create a decision-making tool that factors in the availability of local resources and user priorities in evaluating wastewater treatment options to overcome these issues [15]. In practice, properly weighting factors related to performance and costs, along with energy use, leads to a more realistic and customized evaluation of technologies [16]. By converting the factors into a common metric, decision-makers can compare alternatives objectively and determine which alternative meets their criteria [17]. This simplified comparison facilitates reduced subjectivity and increases consistency in selecting appropriate technologies [18]. This supports improved matching between the capabilities of the technology and local requirements to promote sustainable and cost-effective irrigation systems [19]. In the end, this also supports better-informed investments that maximize water reuse while minimizing environmental and social economic issues [20].

1.1. Literature Survey

There are various research works based on Municipal Wastewater Treatment Plants in Kanpur. Some of them are reviewed here.
R. Vingerhoets et al. [21] have presented an integrated system that combines anaerobic digestion (AD) and direct membrane filtration (DMF) to enhance the management of organic waste and wastewater in tropical urban areas. The method overcomes the drawbacks of traditional activated sludge processes, increases biogas production, decreases pollutant discharge, and concentrates organics for codigestion with food waste.A disadvantage of the DMF+AD system was the potential for membrane fouling, which can increase maintenance costs and reduce operational efficiency.
S. Sippi and D. Parmar [22] have presented a multicriteria decision-making framework using a modified TOPSIS method to rank sewage treatment plants by combining effluent quality with regulatory standards to understand their impact on receiving water bodies without relying on complex models.A disadvantage of the approach was that it may oversimplify complex water quality interactions by not incorporating detailed environmental and hydrological factors.
S. Cavazzoli et al. [23] have presented quantification and characterization of microplastics in effluent and influent of municipal wastewater treatment plants (WWTP) using various technologies, assessing removal efficiencies through standardized sampling and advanced analysis methods like TD-GC/MS, highlighting the persistent release of microplastics despite treatment efforts.A disadvantage of the approach was the high cost and complexity of advanced analytical techniques, which may limit widespread monitoring of micro plastics in wastewater.
S. Cavazzoli et al. [24] have presented analysis of micro plastics across stages of a municipal WWTPutilizing multiple methods, including LDIR, FPA micro-FTIR, and TD-GC/MS, combining particle characterization and polymer quantification to evaluate micro plastic composition, size, and removal efficiency throughout the treatment process. A disadvantage of the approach was the reliance on multiple complex and costly analytical methods, which may limit its practical application for routine monitoring.
Y. Ma et al. [25] have presented an exceedance early warning mechanism for municipal WWTPaccording to fluctuation coefficients of water pollutants, developed using one year of continuous monitoring data, analyzing pollutant variations and seasonal patterns to establish critical thresholds for maintaining stable and compliant effluent discharge. A disadvantage of the mechanism was that it may not accurately predict sudden or unexpected pollutant spikes outside established fluctuation patterns.
K. Wang et al. [26] have presented the effects of microplastics (aged PVC), antibiotics (ciprofloxacin), and their interactions on anaerobic membrane bioreactor (AnMBR) processes in municipal WWT, focusing on treatment performance and membrane fouling. A disadvantage was that the presence of microplastics and antibiotics may accelerate membrane fouling, increasing maintenance requirements and operational costs.
Y. Li et al. [27] have presented an developed Bayesian neural network method, DGPAEP, for predicting carbon emissions from a full-scale WWTP, using advanced approximation algorithms to enhance computational efficiency and accuracy, with its generalization performance validated against advanced models on public datasets. A disadvantage of the DGPAEP model was its high computational complexity, which may limit application in resource-constrained environments.Table 1 displays the summary of literature survey

Table 1: Summary of Literature Survey

Author(s)	Objective	Advantages	Disadvantages
R. Vingerhoets et al. [21]	Improve wastewater, waste management	Boosts biogas, reduces pollutants	Membrane fouling, costly maintenance
S. Sippi and D. Parmar [22]	Rank sewage plants by standards	Simple, combines quality, standards	Oversimplifies water quality factors
S. Cavazzoli et al. [23]	Quantify microplastics in wastewater	Assesses removal, standardized sampling	High cost, complex techniques
S. Cavazzoli et al. [24]	Analyze microplastics stages	Detailed composition, size data	Multiple costly methods required

Y. Ma et al. [25]	Early warning for pollutant spikes	Uses continuous monitoring data	Fails in sudden pollutant spikes
K. Wang et al. [26]	Study microplastics, antibiotics effects	Focus on performance, fouling	Fouling accelerated, higher costs
Y. Li et al. [27]	Predict carbon emissions	Accurate, efficient prediction	High computational complexity

The generic review of recent research on integrated wastewater treatment and monitoring systems has shown that the effectiveness of existing methods is limited by factors such as membrane fouling, oversimplification of complex water quality interactions, high costs and technical complexity of advanced micro plastic detection, and limited predictive accuracy for sudden pollutant spikes. Many researchers have addressed these challenges using various approaches such as combining direct membrane filtration with anaerobic digestion, multicriteria decision-making frameworks, advanced analytical techniques, and Bayesian neural network models. DMF and AD systems improve biogas production and pollutant reduction but suffer from increased membrane fouling and maintenance costs. Decision-making frameworks effectively rank treatment plants but may overlook detailed environmental factors, reducing their accuracy. Advanced micro plastic detection methods provide thorough characterization but are often prohibitively expensive and complex for routine use. Predictive models enhance emission forecasting but generally require high computational resources, limiting their practicality. In the literature, only a few approaches have focused on integrating treatment efficiency, cost-effective monitoring, and robust predictive capabilities into a single adaptable system. These limitations have motivated the need for this research to develop a scalable, efficient, and practical framework that can enhance wastewater treatment performance and support reliable environmental management.

The objective of this work is to assess municipal wastewater treatment plants in Kanpur to increase treatment efficiency and optimize resource use. It focuses on improving operational performance while reducing environmental pollution and resource waste for sustainable urban water management.

In this research, the proposed MWTPK-HSO framework effectively addresses key challenges in municipal wastewater treatment. The approach improves POC removal and treatment efficiency by integrating physical micro screening with advanced optimization. The Kanpur-Municipal-Wastewater-Treatment-Plants-Dataset supports accurate analysis of treatment parameters. Micro screening enhances solids and carbon removal, reducing chemical dependency and operational costs. The HSO algorithm optimizes critical operational parameters, further boosting treatment performance and sustainability. As a result, MWTPK-HSO provides a scalable and eco-friendly solution for sustainable urban water management in Kanpur.

Main contribution of this research work is abridged as follows,

- The MWTPK-HSO technique is proposed to enhance environmental and economic performance assessment of municipal WWTP in Kanpur for sustainable urban water management
- Utilizes wastewater plant dataset to evaluate system performance, focusing on contaminant removal and overall treatment efficiency enhancement.
- Combines physical treatment with micro screening to improve solids and carbon removal, reducing chemical dependency in wastewater processes.
- Applies HSO to optimize wastewater cleaning, increasing operational stability and lowering maintenance costs.

The balance paper is ordered as follows: Part 2 displays Materials and methods, Part 3 displays result and discussion and Part 4 concludes the paper.

2. MATERIALS AND METHODS

In this part, the environmental and economic performance of municipal wastewater treatment plants in Kanpur for sustainable urban water management (MWTPK-HSO) is proposed. It begins with the collection of Municipal Wastewater Treatment Plants Dataset, which feeds into the wastewater treatment process . This process leads to municipal wastewater treatment, which is further enhanced by an efficient cleaning process involving primary and micro-screen treatment. Following this, sampling procedures and analytical methods are applied to estimate the treatment efficacy. Finally, the optimization of the entire process is achieved using the HSO, ensuring improved performance and efficiency of the WWTP. Figure 1 shows the municipal wastewater treatment and Figure 2 displays the block diagram of the proposed MWTPK-HSO.

Figure 1: Municipal Wastewater Treatment

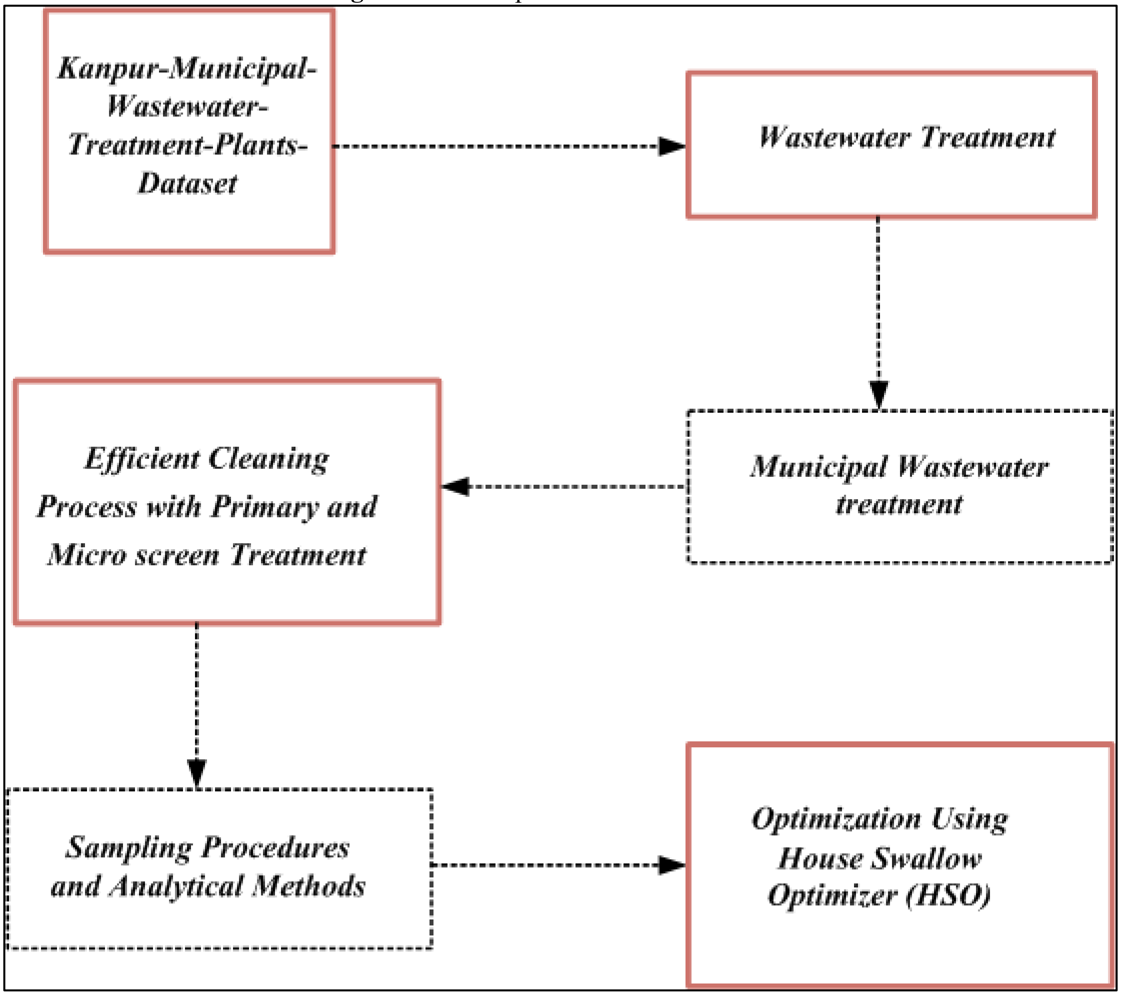

Figure 2: The Block Diagram of the proposed MWTPK-HSO

2.1. Data Collection

Kanpur Municipal Wastewater Treatment Plants Dataset [28] provides detailed operational data from multiple sewage treatment plants (STPs) in Kanpur, India, including the 130 MLD and 43 MLD plants in Jajmau and the 210 MLD plant in Bingawan, featuring performance metrics, influent and effluent quality, flow rates, and estimated parameters, making it a valuable resource for research, environmental analysis, and infrastructure planning related to wastewater treatment.

2.2. Wastewater Treatment

In order to create an effluent that can be safely reintroduced into the water cycle with the least amount of negative environmental impact, wastewater treatment involves removing and eliminating contaminants from wastewater. Water reclamation is the process of reusing this treated water. A facility called a WWT plant is where the entire treatment process takes place. Different types of wastewater are handled by the right kind of WWT facility.

- Sewage Treatment Plants
- Industrial Wastewater Treatment Plants

- Agricultural Wastewater Treatment Plants
- Leachate Treatment Plants

2.2.1. Sewage Treatment Plants

Sewage treatment is a form of wastewater treatment that removes contaminants from sewage, making it safe for environmental discharge or reuse. It involves primary, secondary, and sometimes tertiary or quaternary stages. Systems range from decentralized to centralized networks, treating household, commercial, and industrial wastewater, often including storm water in combined sewers.

2.2.2. Industrial Wastewater Treatment Plants

Processes for treating wastewater produced as a byproduct of industrial operations are referred to as industrial wastewater treatment. Treated effluent may be reused or discharged into sewers or natural water bodies. Industries with high pollutant loads often use specialized or pre-treatment systems to meet regulatory standards before discharging to municipal or environmental systems.

2.2.3. Agricultural Wastewater Treatment Plants

Agricultural WWT manages pollution from animal operations and runoff contaminated by fertilizers, pesticides, or waste. It’s essential for continuous activities like milk and egg production. Treatment methods include mechanized units, anaerobic lagoons, settling basins, or constructed wetlands, depending on land availability and seasonal needs during breeding or harvest cycles.

2.2.4. Leachate Treatment Plants

Leachate treatment facilities use biological treatment, ultrafiltration, activated carbon filters, and electrochemical processes to treat wastewater from landfills like electrocoagulation and reverse osmosis with disc tube module technology. These treatments remove harmful substances to ensure the leachate is safe for discharge or further processing.

2.3. Municipal Wastewater treatment

Wastewater treatment processes specific to municipalities are well accustomed to and effectively treat sewage from the urban environment. However, there are still challenges with these systems as loads increase with population, equipment failures create off-spec water requiring re-treatment, and large storms create system overloads. Often these challenges can burden the infrastructure and/or treatment efficiency. To climb these challenges, many systems incorporate advancements in monitoring, upgrades to system components, and strategies to manage storm-water. Even with these challenges, treated municipal wastewaters are routinely used in non-potable applications to irrigate landscapes because it saves freshwater resources and supports sustainable water management practices in the urban environment that typically does not have enough fresh water for growth. However, conventional treatment systems often come up against some operational limitation on consistently producing treated water that meets water quality standards. To expand on the challenges facing conventional wastewater treatment, advanced cleaning processes that include primary sedimentation and micro-screen filtration will be discussed in the following section.

Figure 3: Wastewater Treatment plant in Kanpur city map

2.4. Efficient Cleaning Process with Primary and Micro screen Treatment

Municipal wastewater is collected and pre-treated to initiate a wastewater treatment phase before passing through primary sedimentation to separate solid material from the water. Next, the wastewater passes through a micro screen filtration unit, which will effectively separate more finely suspended particles from the water. An innovative, automated backwashing system utilizes programmable elements to backwash the filter mesh to sustain the micro screen's performance and match anticipated filter load. The overall system layout, with its key components including the primary sedimentation tank, micro screening unit, backwashing controller, and downstream treatment, is presented in a schematic diagram (Figure 4). This summary outlines key components that you will be better able to understand from the details in the following subsections.

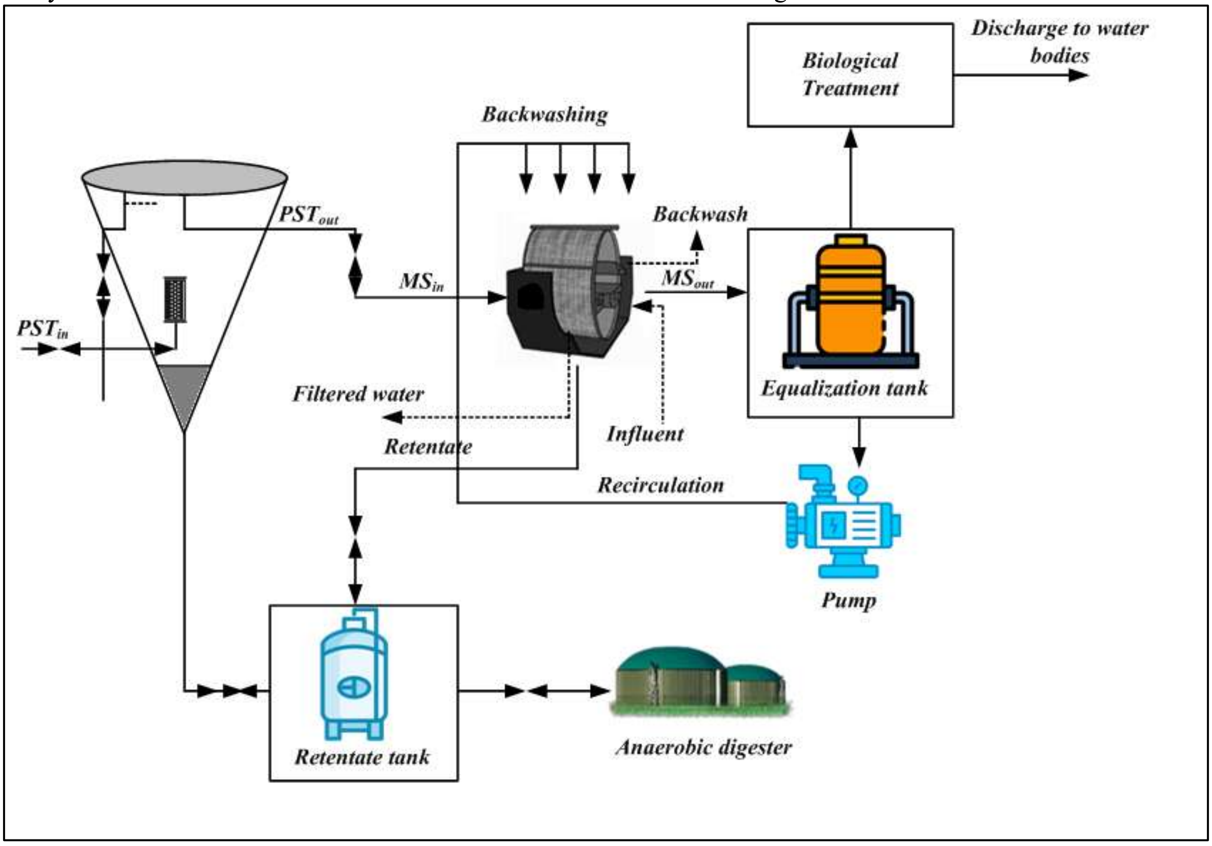

Figure 4: Schematic Diagram of Integrated Wastewater Treatment Process System

2.4.1.Wastewater Collection and Pre-Treatment

Municipal wastewater was collected and underwent initial pre-treatment by being passed through grit and grease chambers to remove large solids and fats. The partially treated wastewater was then conveyed to an equalization tank that was in continuous motion to ensure uniform flow and mixing. Once at the equalization tank, a screw pump pumped the wastewater to the primary settling tank, where solids began to settle out. The pre-treatment process acted to stabilize the wastewater before additional treatment, providing flow consistency and reducing organic loading for the subsequent treatment units. Continuous flow and turbidity measurements during the collection and pre-treatment processes facilitated optimal operation.

2.4.2.Primary Sedimentation Tank (PST)

The PST receives wastewater that has been preliminarily treated, where sedimentation of suspended solids occurs through gravitational forces. This greatly reduces the total suspended solid (TSS) and organic load to later treatment stages. The PST is operated under controlled flow conditions to maximize sedimentation effectiveness, allowing heavier particles to settle at the bottom of the tank while clearer water moves on to the next treatment unit. The PST is designed to continuously monitor inflow and outflow to manage performance and stabilize system conditions. The PST effectively removes settleable solids, providing important protections for downstream processes and improving overall treatment efficiency.

2.4.3.Micro screen (MS) Filtration

The modified Micro Screen (MS) filtration system has a stainless-steel drum that is designed to employ fine mesh media to efficiently filter wastewater. The unit features a recycling capability of the filtered water to clean the mesh surface via backwashing, utilizing an air-pressure pump to hold the appropriate cleaning pressure. In contrast to typical backwashing setups being pressure-driven, this filtration system uses controllers to modify the drum's rotation speed and the timing of the backwash cycle. This time-based cleaning process improved efficiency in the filtration process by reducing fouling and providing consistency in municipal wastewater treatment.

2.4.4. Backwashing and Cleaning

In the Micro Screen system, backwashing and cleaning is done using permeate water that is recycled through an air-pressure pump that removes the solids that have accumulated on the surface of the mesh. The process is conducted at controlled water pressure to appropriately clean the media without damaging it (or producing an excessive collapse). Whereas typical systems rely on changing the pressure to initiate cleaning, this system has automatic controllers that determine the operational speed of the drum and timing of backwash frequency. This time-based method results in optimal backwash frequencies and durations, which reduces fouling and maintains the efficiency of filtration and increases the reliability and performance of the wastewater treatment system.

2.5. Sampling Procedures and Analytical Methods

2.5.1. Sampling and Monitoring

Sampling and monitoring at the pilot plant involved automatic composite samplers installed at key points to collect wastewater samples throughout the day, ensuring representative data on inflow and outflow conditions. Turbidity meters recorded water clarity continuously, capturing fluctuations every minute over an extended period, while electromagnetic flow meters monitored flow rates to maintain system control. Additionally, grab samples were taken on different days to complement composite data and assess short-term variations, particularly focusing on suspended solids load. This comprehensive monitoring approach allowed detailed evaluation of treatment performance and system dynamics in response to varying wastewater characteristics.

2.5.2. Analytical Measurements:

Analytical measurements were performed using standard ISO methods to evaluate treatment efficiency. Turbidity, chemical oxygen demand (COD) and total suspended solids (TSS), were measured following established protocols. These analyses allowed accurate determination of pollutant removal efficiencies and overall performance of the wastewater treatment process.

2.5.2.1. Interpretation of the data

For example, TSS and COD, the mean removal rate (R, %) of each term was calculated using equation (1).

$$R(\%) = \left[\frac{(C_{in} - C_{out})}{C_{in}}\right] * 100 \tag{1}$$

Here, $C_{in}\ (mgL^{-1})$ indicated as the inflow concentration and $C_{out}\ (mgL^{-1})$ indicated as the outflow concentration. For computingload, eqn (2) was applied

$$Surfaceload(g\,m^{-2}h^{-1}) = \frac{Q_{in} * C_t}{A_{MS}} \tag{2}$$

Where, $C_t\ and\ A_{MS}$ give the concentration (mgL^{-1}) for the time interval of t, and filtration area of MS, correspondingly.Equation (3) was used to calculate the average whole removal efficiency (RT) of the APT system.

$$R_T(\%) - R_{PST} + R_{MS} \tag{3}$$

Here, R_{PST} (%) and R_{MS} (%) represent the removal rate of PST and MS. Equation (4) was defined in order to ascertain the impact of implementing various flux $q\,(m^3h^{-1}m^{-2})$ on the MS system's efficiency.

$$q\,(m^3h^{-1}m^{-2}) = \frac{Q_{in}}{A_{eff}} \tag{4}$$

Where, $Q_{in}\,(m^3h^{-1})$ represent the inflow rate to the MS and $A_{eff}\,(m^2)$ reflects the effective filtration area. Since the drum sieve is constantly rotating the whole drum are is considered as the effective area of filtration.

$$PCOD(mg\,L^{-1}) = TCOD - SCOD \tag{5}$$

Here, $TCOD$ and $SCOD$ represent the total and soluble chemical oxygen demand (mgL^{-1}) correspondingly.

2.6. Optimization Using House Swallow Optimizer (HSO)

In this section, Optimization using House Swallow Optimizer (HSO) is discussed [28-29]. CPOA method is utilized to optimizewastewater cleaning. HSO enhances Municipal Wastewater Treatment Plants by optimizing process parameters for improved efficiency and cost-effectiveness. Its chaotic dynamics help avoid local optima, ensuring better solutions in complex systems like wastewater treatment. Advantages include faster convergence, improved pollutant removal, energy savings, and adaptive control in varying conditions, leading to more sustainable and reliable plant operations with reduced environmental impact. Table 2displays the pseudo-code of the HSO

Table 2: Pseudo code for HSO

Pseudo code for HSO
After initialization the input fitness function for wastewater treatment plant performance

Set parameters: the maximum evaluation number $\max FEs$, the problem dimension $\dim$, and the population size N
for $t = 1$: Max_iter
Updating of the optimal operational factors of wastewater treatment plants according to the objective function value criterion;
for $i = 1 : N$
if $r < 0.5$
Phase 1
Update the parameters of wastewater treatment plant
else
Phase 2
Update the parameters of wastewater treatment plant
end
Phase 3
Update the parameters of wastewater treatment plant
Retain the most optimal candidate solutions up to this point.
end
end
Output: the optimal treatment performance value and corresponding optimal plant parameters.

Step 1: Initialization
The input variable is created randomly in matrix form based on the initialization.

$$Q = \begin{bmatrix} Q_1 \\ \vdots \\ Q_i \\ \vdots \\ Q_N \end{bmatrix}_{N\times\dim} = \begin{bmatrix} q_{1,1} & \cdots & q_{1,j} & \cdots & q_{1,\dim} \\ \vdots & \ddots & \vdots & \iddots & \vdots \\ q_{i,1} & \cdots & q_{i,j} & \cdots & q_{i,\dim} \\ \vdots & \iddots & \vdots & \ddots & \vdots \\ q_{N,1} & \cdots & q_{N,j} & \cdots & q_{N,\dim} \end{bmatrix}_{N\times\dim} \quad (6)$$

Where, Q stands for the house swallow population, Qi for the i^{th} individual's position (candidate solution), and $q_{i,j}$ for the i^{th} individual's choice variable value, j^{th} Is the person in the dimension. The variable dim is the count of decision variables, while N represents the total number of possible solutions.

Step 2: Random Generation
Through HSO, the input fitness function acquired randomness after initialisation.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(Q_1) \\ \vdots \\ F(Q_i) \\ \vdots \\ F(Q_N) \end{bmatrix}_{N\times 1} \quad (7)$$

Where F indicated as the vector of objective functions, and F_i is denoted as the objective function value for the i^{th} house swallows. This vector stores the output of the objective function for each candidate, which in this study evaluates mechanical performance.

Step 3: Fitness Function
The objective function establishes the fitness of the system. In order to ascertain the fitness function,

$$Fitness\ Function = (optimize\ [\text{wastewater cleaning}]) \quad (8)$$

Step 4: Roosting and hovering
Roosting and hovering behaviors in the HSO metaphorically represent the exploration and exploitation phases in optimizing municipal wastewater treatment processes. Roosting simulates the stable solution refinement, while hovering mimics the dynamic search for better treatment parameters to enhance efficiency and pollutant removal.

$$q_{i,j}^{p1} = \begin{cases} q_{i,j} + (1+\cos r_2)\times(best_j - q_{i,j}) & F_{K_1} < F_i \\ q_{i,j} + \alpha \times x \times (q_{k_1,j} - q_{i,j}) & else \end{cases} \quad (9)$$

Where $q_{i,j}^{p_1}$ indicated as the position of the i^{th} house swallow dimension, while $q_{i,j}$ denotes the decision variable value of the i^{th} individual (candidate solution) in the j^{th} dimension. The term r_2 is a randomly generated value within the range [0, 1]. $best_j$ Signifies the optimal location of the house swallows in the j^{th} dimension with respect to the objective function. The parameter x is calculated based on the inhabiting behavior of domestic house swallows. Additionally, F_{k_1} represents the objective function value corresponding to q_{k_1}, and F_i indicates the objective function value of the i^{th} house swallow.

$$Q_i = \begin{cases} Q_i^{p_1} & F_i^{p_1} < F_i \\ ub + lb - q_{i,j}^{p_1} & F_{OBL} < F_i < F_i^{p_1} \\ Q_i & F_i < F_{OBL} \end{cases} \tag{10}$$

Where Q_i indicated as the position of the i^{th} house swallow, $q_{i,j}^{p_1}$ indicated as the location of the i^{th} house swallow in the j^{th} dimension, $Q_i^{p_1}$ indicates the new position generated by the i^{th} house swallow , while $F_i^{p_1}$ is indicated as the objective function value corresponding to $Q_i^{p_1}$, F_i denotes the objective function value for the present position Q_i . The variables ub and lb refer to the upper and lower bounds of the search space, correspondingly. Finally, F_{OBL} indicated as the objective function value according to the adversarial learning strategy.

Step 5: Preying

In the HSO, preying represents the targeted search for optimal solutions by actively exploring promising areas, similar to how precise adjustments are made in municipal wastewater treatment to maximize contaminant removal. This behavior helps fine-tune treatment parameters, ensuring efficient performance and improved water quality.

$$q_{i,j}^{p2} = best_j - L_1 * V_{levy} \times \left(q_{i,j} - best_j\right), \tag{11}$$

$$Q_i = \begin{cases} Q_i^{p_2} & F_i^{p_2} < F_i \\ Q_i & else \end{cases} \tag{12}$$

Where $q_{i,j}^{p_2}$ represents the i^{th} house swallow in the j^{th}, $Q_i^{p_2}$ indicated as the new location generated by the i^{th}, with $F_i^{p_2}$ serving as its objective function value, L_1 is a value that adapts with the number of iterations.

Step 6: Nesting

In the HSO, nesting symbolizes the process of consolidating and preserving the best-found solutions, analogous to stabilizing effective treatment strategies in municipal wastewater treatment. This phase ensures that optimized parameters are maintained for consistent and reliable pollutant removal performance.

$$q_{i,j}^{p3} = q_{i,j} + L_2 * \xi \times \left(q_{i,j} - best_j\right), \tag{13}$$

Where $q_{i,j}^{p_3}$ Represents the new position of the i^{th} house swallow in the j^{th} dimension, $q_{i,j}$ indicated as the presentlocation of the i^{th} house swallow in the j^{th} dimension, ξ indicated as the flight ability of the house swallow during its nesting period, $best_j$ Represents the optimal position found so far for the objective function value of the house swallows in the j^{th} dimension.

$$Q_i = \begin{cases} Q_i^{p_3} & F_i^{p_3} < F_i \\ Q_i & else \end{cases} \tag{14}$$

Where Q_i Represents the updated location of the i^{th} house swallow, $Q_i^{p_3}$ Represents the new location generated by the i^{th} house swallow, $F_i^{p_3}$ Is the objective function value for the new location $Q_i^{p_3}$ generated by the i^{th} house swallow, F_i Is the present objective function value for the i^{th} house swallow.

Step 7: Termination

Verify by checking and repeating the process until the best option is found if the termination criteria are not met. HSO finishes in this step, and the output is the best solution found during each process iteration. Finally HSO optimized the wastewater cleaning. Figure 5 displays the flowchart of HSO method. Table 3 shows the hyper parameters of HSO.

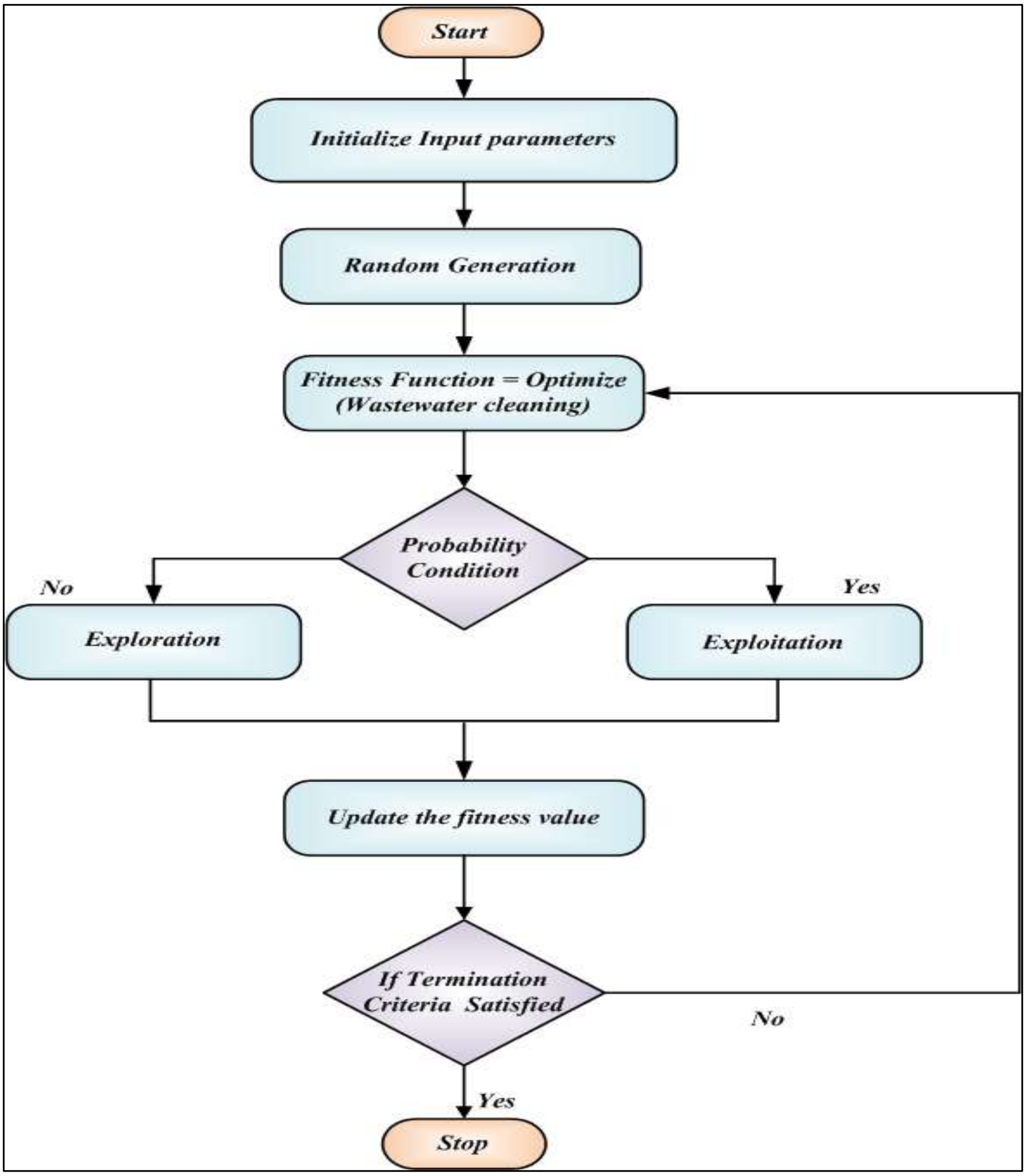

Figure 5: The flowchart of HSOmethod

Table 3: Hyper Parameters of HSO

Parameter	**Value**
Population size	10
Maximum iterations	30

Table 3 outlines the key hyper parameters used for the HSO algorithm, where the population size is set to 10, meaning that 10 candidate solutions are considered in each iteration. The maximum count of iterations is limited to 30, indicating that the algorithm will run through 30 cycles of solution updates to find the optimum parameters for the problem, balancing computational effort and optimization performance.

3. RESULT AND DISCUSSION

This part demonstrates the performance of the proposed technique using simulation results. This research introduces the MWTPK-HSO technique to increase the efficiency.The proposed method is simulated in MATLAB. The device runs MATLAB version 24.2.0.2712019 (R2024b). The operating system is Microsoft Windows 11 Pro, Version 10.0 (Build 22621). The Java version installed is 1.8.0_202-b08, running with Oracle Corporation Java Hotspot (TM) 64-Bit Server VM in mixed mode. The analysis results of the proposed MWTPK-HSO approach is presented below;

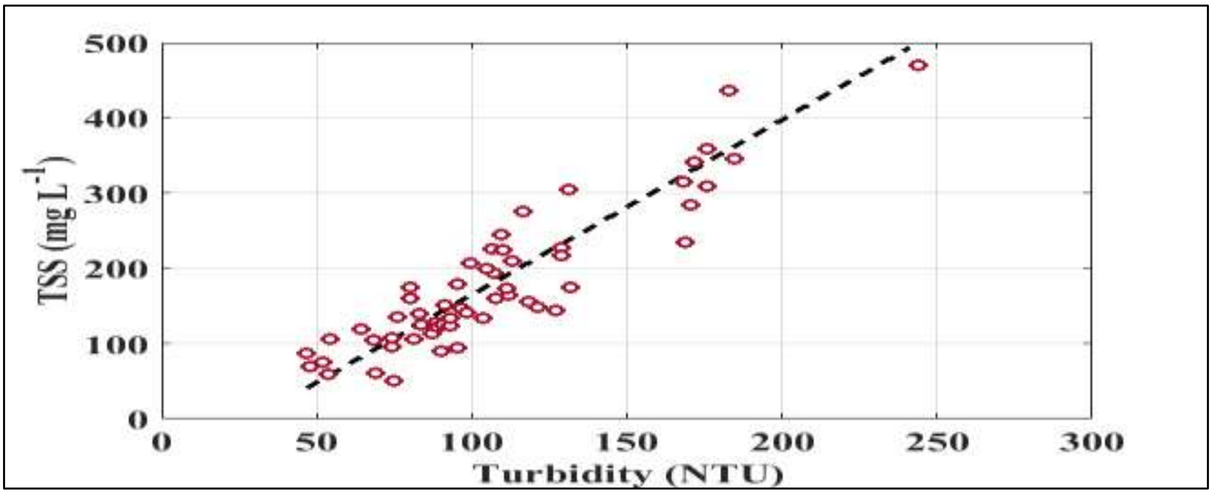

Figure 6: Analysis of relationship between Turbidity and Total Suspended Solids (TSS) in Water Samples

Figure 6 analysis of the scatter plot reveals a strong positive correlation between Turbidity (NTU) and Total Suspended Solids (TSS, mg L^{-1}), with turbidity values ranging from approximately 40 to 250 NTU and TSS values ranging from about 50 to 500 mg L^{-1}. The data points show a clear upward trend, representing that as turbidity increases, the concentration of suspended solids also rises. The dashed black line represents a fitted trend line, closely following the distribution of the red data points, which demonstrates the consistency of this linear relationship across the entire dataset. This suggests that turbidity can be a reliable predictor of TSS within the measured range.

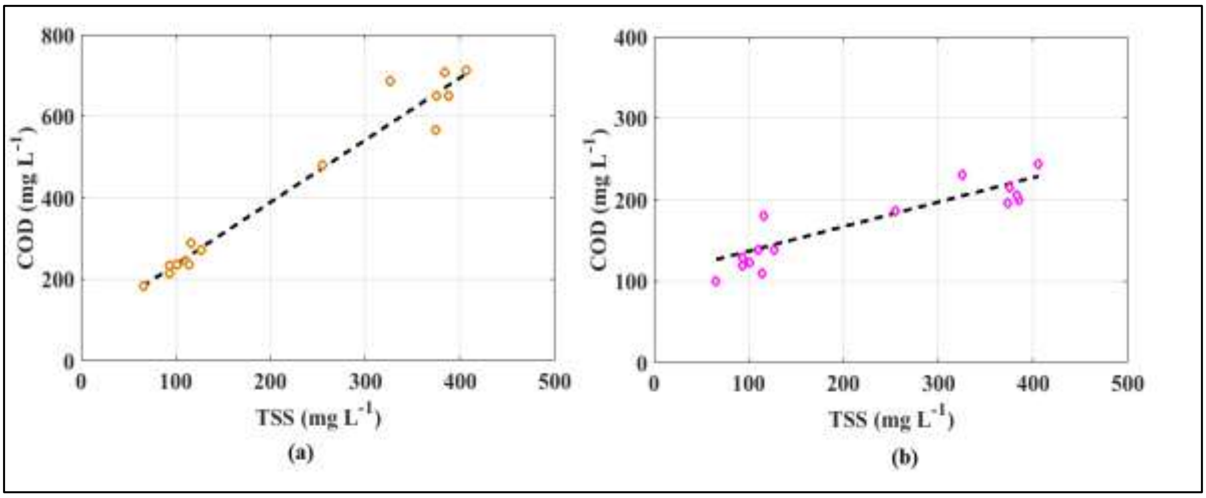

Figure 7: Analysis of relationship between (a) Total Suspended Solids (TSS) and (b) Chemical Oxygen Demand (COD) fewer than Two Different Conditions

Figure 7 analysis of the scatter plots shows the relationship between (a) Total Suspended Solids (TSS, mg L^{-1}) and (b) Chemical Oxygen Demand (COD, mg L^{-1}) under two different conditions. In 7(a), a strong positive correlation is evident, with COD values increasing sharply from around 180 to 720 mg L^{-1} as TSS rises from approximately 50 to 400 mg L^{-1}, indicated by the tight clustering of orange data points around the dashed trend line. In contrast, 7(b) shows a weaker positive correlation, with COD values ranging from about 90 to 250 mg L^{-1} for a similar range of TSS values, and the magenta data points are more widely scattered around the trend line. This comparison highlights differing degrees of association between TSS and COD in the two scenarios presented.

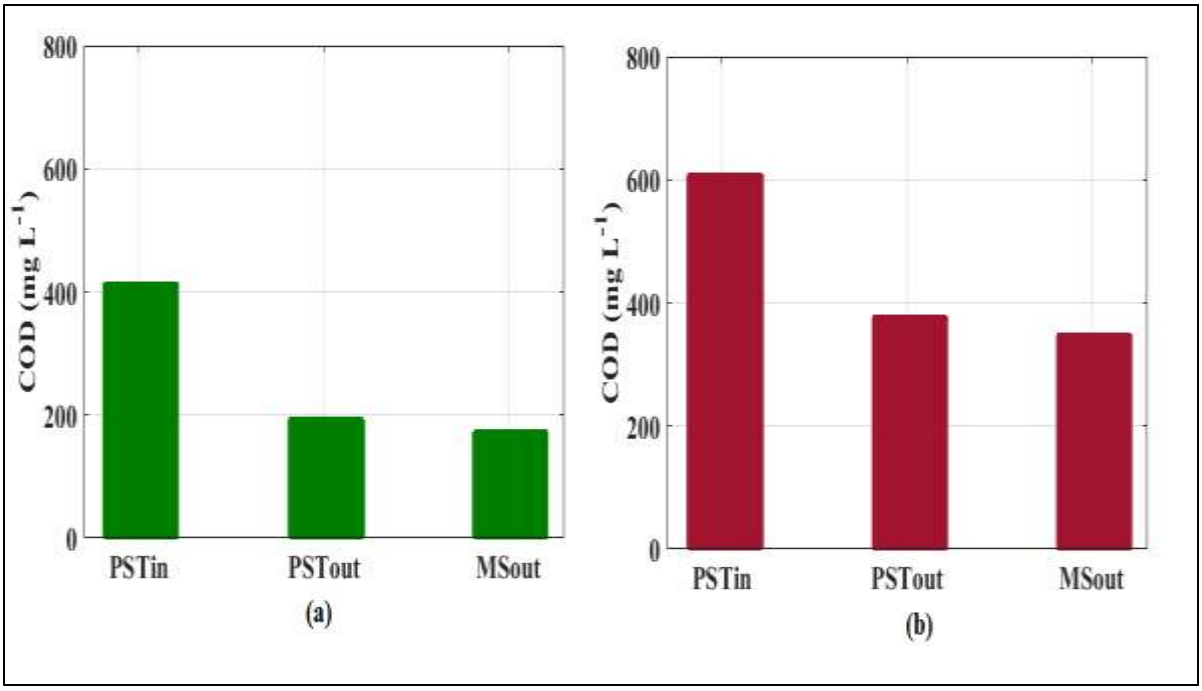

Figure 8: Analysis of Chemical Oxygen Demand (COD) Levels at Different Sampling Points in Two Conditions in (a) and (b)

Figure 8 analysis of the bar charts illustrates the Chemical Oxygen Demand (COD, mg L^{-1}) levels at three different sampling points: PSTin, PSTout, and MSout. In 8(a), represented in green, the COD concentration is highest at PSTin 420 mg L^{-1}, followed by a significant decrease at PSTout around 200 mg L^{-1} and a slight further reduction at MSout about 180 mg L^{-1}. 8(b), shown in maroon, displays a similar trend with higher overall COD values, peaking at PSTinaround 610 mg L^{-1}, then dropping at PSTout 390 mg L^{-1} and MSout close to 350 mg L^{-1}. These results indicate a consistent reduction in COD levels from the inlet to the outlet points in both conditions.

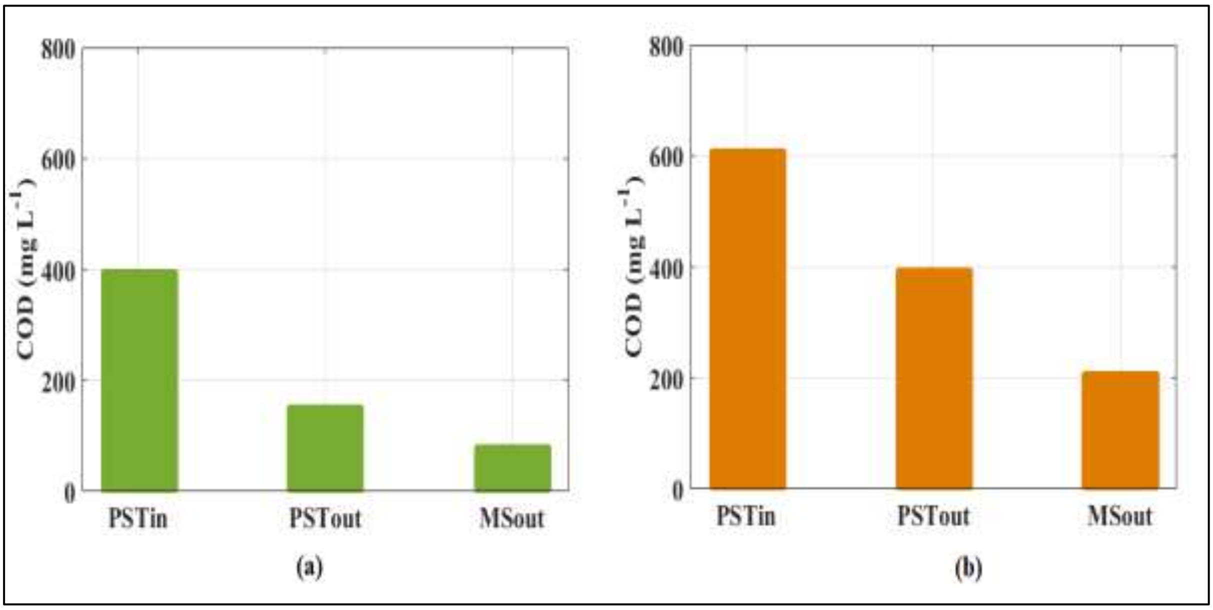

Figure 9: Analysis of COD concentrations at different treatment stages for two systems: (a) and (b)

Figure 9 analyses of the provided bar charts reveal the variation in Chemical Oxygen Demand (COD) concentrations at three different treatment stages: PSTin, PSTout, and MSout, for two different scenarios or systems. In 9(a), COD levels show a significant decrease from approximately 400 mg L^{-1} at PSTin to around 150 mg L^{-1} at PSTout, and further drop to below 100 mg L^{-1} at MSout, indicating effective COD removal through the treatment process. Similarly, 9(b) starts with a higher COD concentration of around 620 mg L^{-1} at PSTin, which reduces to approximately 450 mg L^{-1} at PSTout, and further to about 250 mg L^{-1} at MSout. While both systems demonstrate a consistent reduction in COD across treatment stages, the system in 9(a) shows a higher overall removal efficiency compared to the one in 9(b).

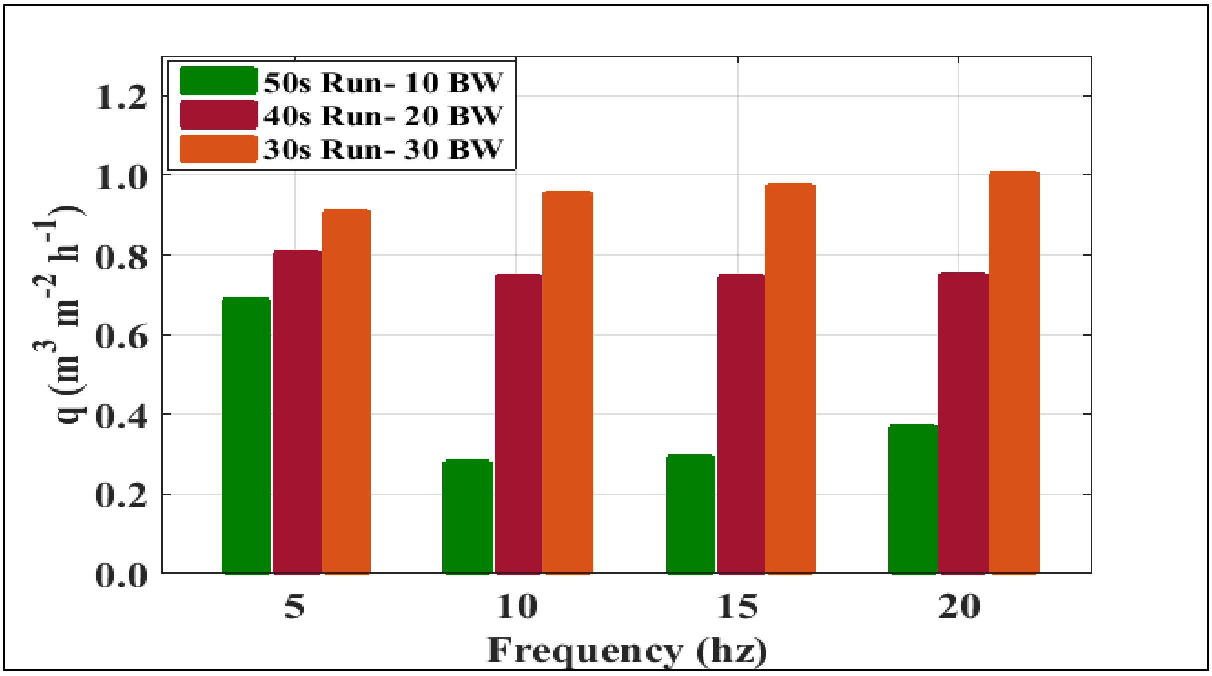

Figure 10: Analysis of Effect of frequency on permeate flux (q) for different operation conditions

Figure 10 analysis of the impact of varying frequencies (5, 10, 15, and 20 Hz) on the permeate flux (q) under three different operational conditions: 50s Run–10 BW, 40s Run–20 BW, and 30s Run–30 BW. Across all frequencies, the permeate flux increases as the run time decreases and the number of backwashes (BW) increases. The 30s Run–30 BW condition consistently exhibits the highest flux values, reaching above 1.0 $m^3\ m^{-2}\ h^{-1}$ at 20 Hz, indicating superior performance. Conversely, the 50s Run–10 BW setup shows the lowest flux across all frequencies, with minimal improvements as frequency increases. This trend suggests that shorter run durations combined with more frequent backwashing significantly enhance membrane performance, likely due to reduced fouling and improved cleaning efficiency.

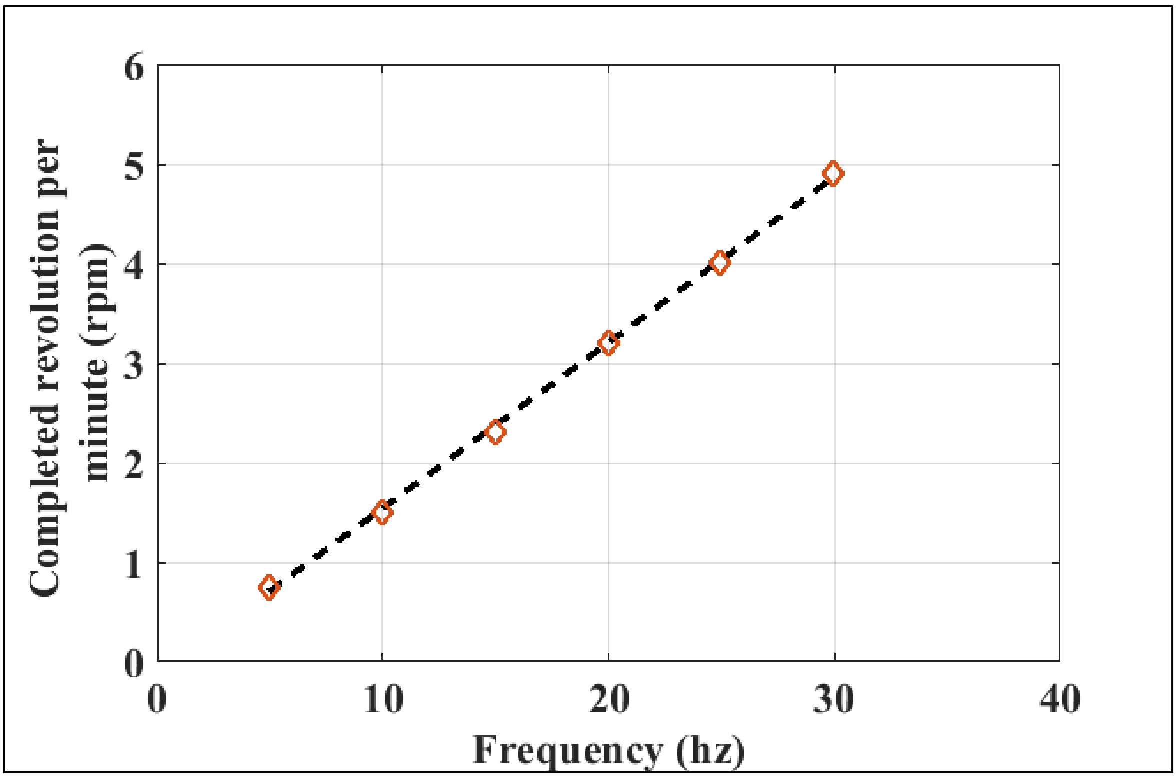

Figure 11: Analysis ofcorrelation between frequency and completed revolutions per minute

Figure 11 illustrates the relationship between frequency (Hz) and completed revolutions per minute (rpm). As frequency increases from 5 Hz to 30 Hz, there is a linear rise in rpm from approximately 0.75 to 5.0. This strong linear correlation, indicated by the dotted trend line, suggests that the system's rotational speed scales directly with input frequency. Such a relationship confirms consistent mechanical performance, where higher actuation frequencies result in proportionally greater completed revolutions, which is crucial for systems relying on frequency-dependent motion or mixing.

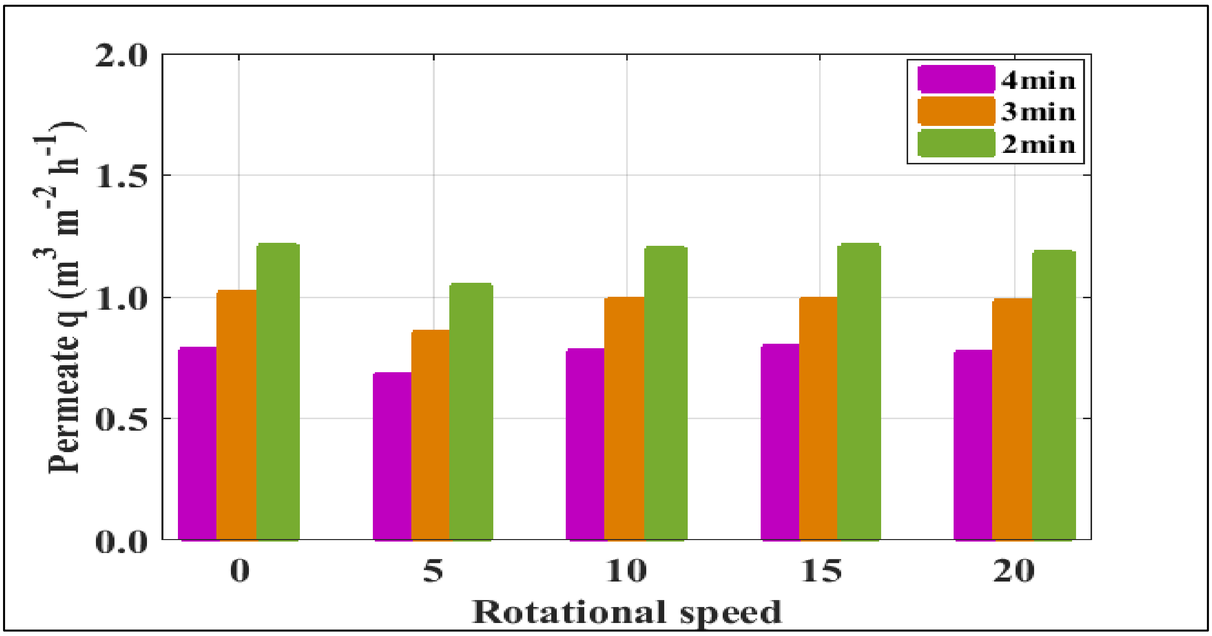

Figure 12: Analysis ofEffect of Rotational Speed and Processing Time on Permeate Flux

Figure 12 analysis of the graph reveals the relationship between rotational speeds and permeate flux (q) for different time durations 2 min, 3 min, and 4 min. It is evident that the permeate flux increases with rotational speed for all time intervals, with the highest permeate flux observed at 2 minutes and the lowest at 4 minutes. The permeate flux values range from about 0.7 to 1.2 $m^3/m^2/h$, showing a consistent trend where shorter processing times correspond to higher permeate flux at each rotational speed level. This indicates that shorter durations potentially enhance permeate flow under varying rotational speeds.

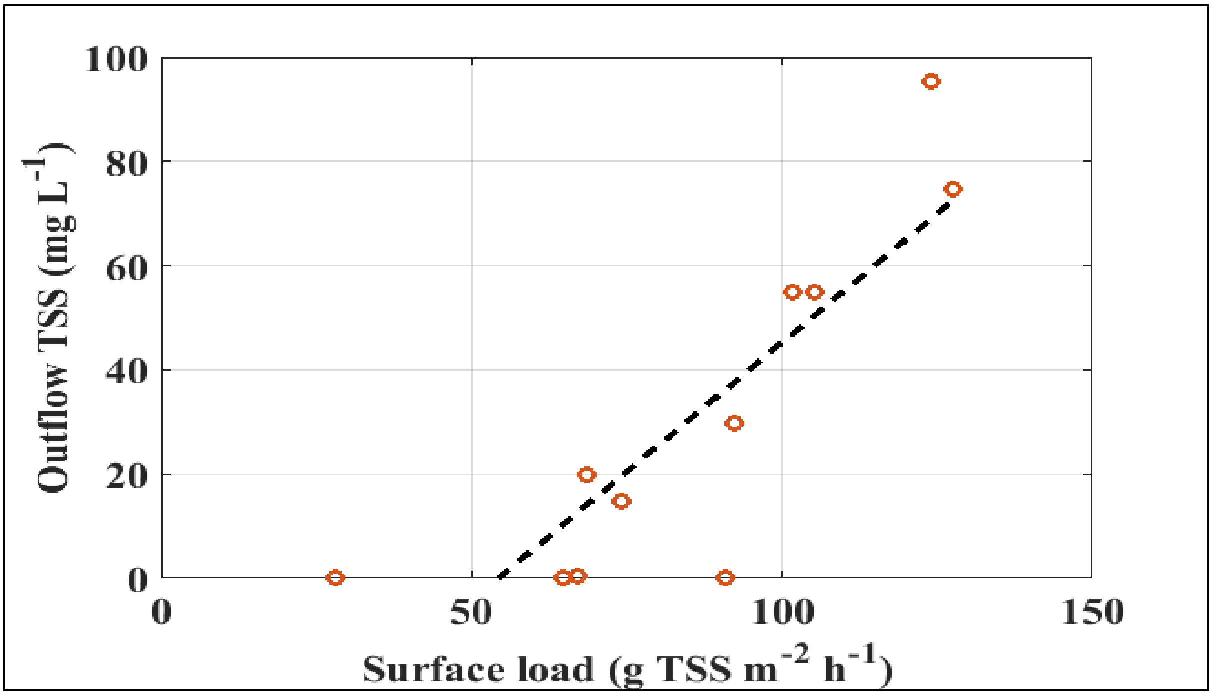

Figure 13: Analysis ofCorrelation between Surface Load and Outflow Total Suspended Solids (TSS)

Figure 13 analysis of the scatter plot shows the relationship between surface load ranging from 10 to 130 g TSS m^{-2} h^{-1} and outflow TSS concentration ranging from 0 to about 95 mg L^{-1}. The data points indicate a strong positive correlation, where an increase in surface load corresponds to a significant increase in outflow TSS levels.

The dashed regression line emphasizes this trend, suggesting that as the surface load increases beyond 60 g TSS m^{-2} h^{-1}, the outflow TSS concentration rises sharply, reaching values close to 95 mg L^{-1} at the highest surface loads. This relationship highlights potential difficulties in controlling TSS concentrations in the outflow under high surface loading conditions.

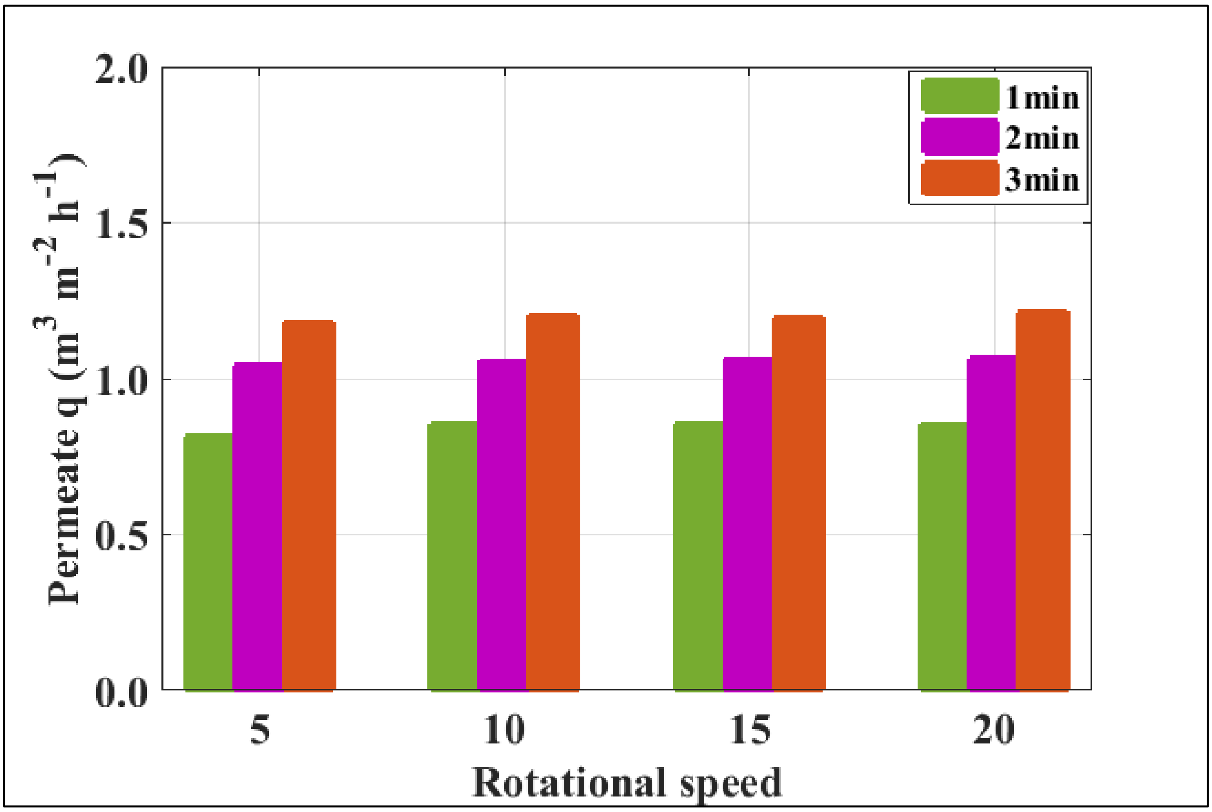

Figure 14: Analysis ofInfluence of Rotational Speed and Processing Time on Permeate Flux

Figure 14 analysis of the graph illustrates the effect of rotational speed on permeate flux (q) at different processing times (1 min, 2 min, and 3 min). The permeate flux increases consistently with rotational speed across all time intervals, with values ranging from approximately 0.8 to 1.2 $m^3/m^2/h$. Among the durations, the highest permeate flux is observed at 3 minutes, followed by 2 minutes, and the lowest at 1 minute, indicating that longer processing times enhance permeate flux. The steady increase in permeate flux with rotational speed suggests improved membrane performance or fluid dynamics at higher speeds for each given time.

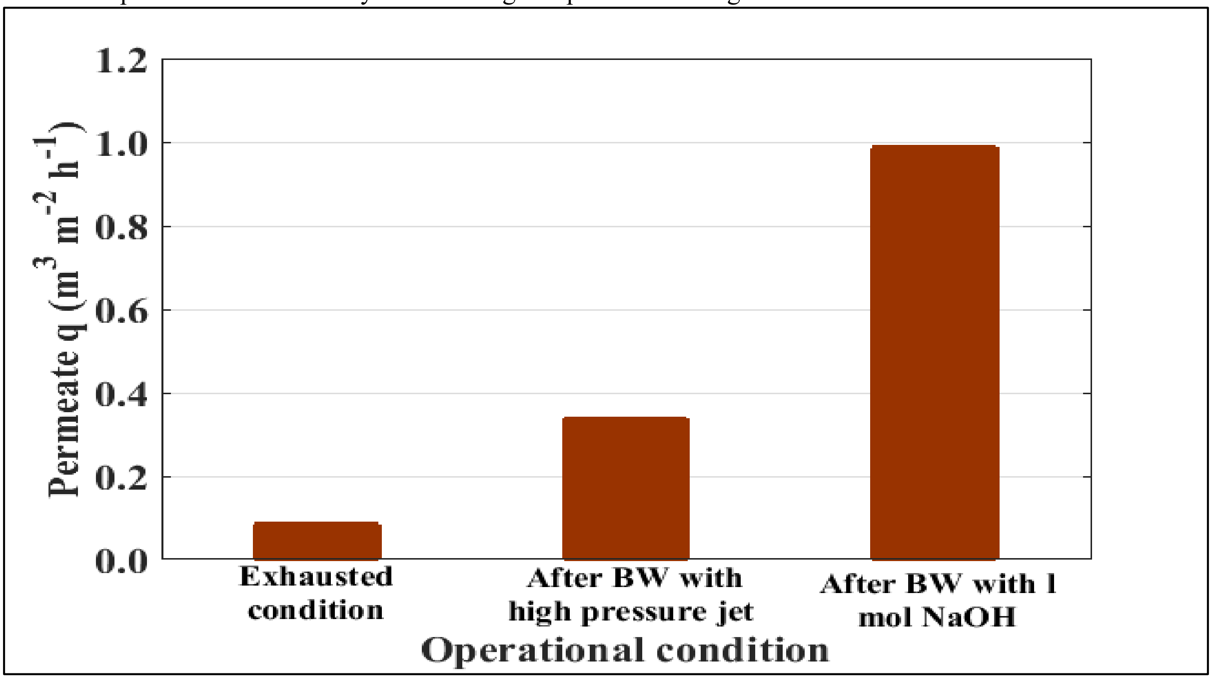

Figure 15: Analysis ofpermeate Flux under Different Membrane Cleaning Conditions

Figure 15 illustrates the impact of different cleaning or backwash (BW) procedures on the permeate flux (q) of a membrane system, measured in units of $m^3 m^{-2} h^{-1}$. Initially, the system is shown in an "Exhausted condition," which represents the state where the membrane has become significantly fouled, leading to a dramatically reduced performance. Under this fouled state, the permeate flux is at its lowest recorded value, approximately 0.1 $m^3 m^{-2} h^{-1}$. This physical cleaning technique effectively removes some of the foulants accumulated on the membrane surface, leading to a substantial increase in the permeate flux to roughly 0.35 $m^3 m^{-2} h^{-1}$. This chemical treatment is superior in removing a wider range of foulants, such as organic materials, proteins, and biological matter, resulting in a dramatic recovery of the membrane's permeability, with the permeate flux reaching a near-maximal value of 1.0 $m^3 m^{-2} h^{-1}$. The comparison highlights that while physical cleaning with a high-pressure jet is beneficial, chemical cleaning using a strong alkaline solution is the most effective method for restoring the membrane's permeability and achieving the highest operational flux.

Table 4: Technical Parameters of Micro Screen

Parameter	Unit	Value
Water intake for backwashing	Lh^{-1}	200
Mesh size	μm	15-20
Residence time	h	0.6
Surface area	m^2	0.71
Effective filtration area	m^2	0.354
Volume of MS	m^3	0.06
Constant flow to the system	Lh^{-1}	20
Permeate used for backwashing	1000	20

Table 5: Standard used for conducting analytical analysis

Parameter	TSS	COD	Turbidity
Corresponding international standard	ISO 11923:1997 (Water Quality –TSS)	ISO 15705:2002 (WQ-COD)	ISO 7027:1-2016
Applied for	Methods for measuring suspended solids using membrane filter filtration	Chemical oxygen demand index (ST-COD) determination using the small-scale scaled tube method	Measurement of water turbidity that encompasses a broad spectrum of turbidity levels

3.2. Discussion

The proposed MWTPK-HSO model advances municipal wastewater treatment by integrating physical APT with micro screening to enhance pollutant removal and reduce chemical dependency. Turbidity shows a strong positive correlation with total suspended solids, ranging from 40 to 250 NTU and 50 to 500 mg/L respectively, establishing turbidity as an effective predictor of solids concentration. The model achieves significant reductions in chemical oxygen demand from 420 to 610 mg/L at the inlet to 180 to 350 mg/L at the outlet, demonstrating effective treatment across stages. Operational optimization with shorter run times of 30 s, increased backwash cycles up to 30, and frequencies up to 20 Hz improves permeate flux beyond 1.0 $m^3/m^2/h$ by minimizing membrane fouling. Surface load from 10 to 130 $g/m^2/h$ strongly correlates with outflow suspended solids reaching up to 95 mg/L. Chemical cleaning restores membrane flux from 0.1 to nearly 1.0 $m^3/m^2/h$, outperforming physical cleaning. These results highlight MWTPK-HSO as a sustainable and efficient solution for urban wastewater management.

4. CONCLUSION

It effectively addresses water quality monitoring challenges by demonstrating turbidity values from 40 to 250 NTU reliably predict TSS levels between 50 and 500 mg/L, while TSS ranging from 50 to 400 mg/L corresponds with COD increases from 180 to 720 mg/L under different conditions. Additionally, the treatment systems achieve substantial COD reductions from over 600 mg/L at the inlet to below 250 mg/L at the outlet, with one system showing higher removal efficiency. Operational optimizations such as 30-second run times, backwash frequencies up to 30 cycles, and increased rotational speeds improve permeate flux beyond 1.0 $m^3/m^2/h$ at 20 Hz. Membrane cleaning restores flux from 0.1 to near 1.0 $m^3/m^2/h$, highlighting chemical cleaning as the most effective method. Overall, this approach offers a robust and efficient solution for optimizing water treatment performance. Municipal wastewater treatment faces high costs and energy use. It struggles with aging infrastructure and sludge disposal. Removing all contaminants is difficult, especially new pollutants like pharmaceuticals.Future work in municipal wastewater treatment involves developing energy-efficient technologies, enhancing removal of emerging contaminants, upgrading infrastructure, advancing resource recovery, implementing smart monitoring systems, and promoting sustainable, cost-effective treatment methods.

Data Availability: https://kanpurhamstp.in/reports/

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