

AI-Enabled Hybrid MBBR–MBR System With ANN–RF-Based IoT Monitoring For Sustainable Urban Wastewater Reuse

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Abstract

Background: Rapid urbanization and freshwater scarcity have increased the need for intelligent and sustainable wastewater treatment technologies for urban water reuse applications.

Methods: This study proposes an AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Treatment Framework (AHMIWF) integrating Moving Bed Biofilm Reactor (MBBR), Membrane Bioreactor (MBR), IoT-based monitoring, and machine learning techniques for advanced wastewater management. The hybrid system combines biofilm-assisted biodegradation and membrane filtration to improve pollutant removal efficiency and effluent quality. An ESP32-based IoT architecture equipped with pH, turbidity, dissolved oxygen, temperature, conductivity, and water level sensors enables continuous real-time monitoring and automated data acquisition. The collected data are transmitted to a cloud platform for remote supervision and process control. Artificial Neural Network (ANN) and Random Forest (RF) algorithms were implemented to predict and optimize critical wastewater parameters, including BOD, COD, TSS, turbidity, and dissolved oxygen levels.

Results: Experimental evaluation demonstrated significant reductions in organic pollutants, suspended solids, and microbial contaminants, confirming the effectiveness of the proposed framework.

Conclusion: The developed AHMIWF system offers an energy-efficient, compact, and automated solution for sustainable urban wastewater reuse and intelligent water resource management.

Keywords: Hybrid MBBR–MBR, Wastewater Treatment, Internet of Things, Artificial Neural Network, Random Forest, Urban Water Reuse.

1. Introduction

Water scarcity, especially in urban areas, has been exacerbated by rapid urbanization, industrialization, and growing water demands, highlighting the importance of sustainable wastewater treatment and urban water reuse technologies. Traditional wastewater treatment infrastructure is not always able to remove organic contaminants, suspended solids, nutrients, pathogens or emerging contaminants effectively, impacting the quality and reliability of reclaimed water. The Moving Bed Biofilm Reactor (MBBR) and the Membrane Bioreactor (MBR) are recent advancements of biological treatment technologies that have been attracting a lot of interest because of their superior biological degradation efficiency, solid–liquid separation capability, compact design and flexibility of operation. Furthermore, the incorporation of Internet of Things (IoT) and Artificial Intelligence (AI) has made it possible to monitor, control and make intelligent decisions in real time in modern wastewater management systems. The proposed AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Treatment Framework (AHMIWF) is a combination of hybrid biological treatment, sensor-based IoT monitoring, cloud-based supervision, and machine learning algorithms that enable intelligent wastewater treatment and sustainable re-use of wastewater in urban settings. The framework includes algorithms of ANN and Random Forest (RF) for predicting and optimizing the critical parameters of the wastewater, including BOD, COD, TSS, turbidity, and dissolved oxygen. Hybrid treatment technology combined with AI-powered IoT monitoring is an energy-efficient, compact and highly automated solution, ideal for future smart city infrastructure and sustainable water resource management.

1.1. Problem Statement

The growing urbanisation and industrialisation have caused a significant reduction in the quantity of freshwater available and higher production of wastewater. The operation instability, high energy consumption, insufficient removal efficiency of pollutants, and lack of intelligent monitoring systems of conventional wastewater treatment systems make them unable to achieve the high level of wastewater treatment efficiency needed for sustainable water reuse applications. Wastewater treatment technologies also have challenges with the variability of wastewater quality and new contaminants, which decreases the efficiency and reliability of reclaimed wastewater reuse systems. While technologies like MBBR and MBR are individually effective and efficient, the combination of these technologies with the IoT-enabled real-time monitoring of the treatment

process and AI-driven predictive analytics is not well-studied. It is found that the current wastewater treatment plants are mostly controlled manually and by traditional operational control methods, which restrict the predictive maintenance, anomaly detection, and process optimization potential. Thus, an intelligent hybrid wastewater treatment framework that combines advanced treatment technologies, IoT monitoring, and AI-based predictive modeling is essential for enhancing wastewater treatment efficiency, reliability, and sustainable urban water reuse.

2. Related works

In recent years, the Internet of Things (IoT) has been introduced as a solution for the improvement of real-time monitoring, operational automation and intelligent decision making in smart city infrastructures [1]. Moreover, such systems have allowed for the real-time monitoring of essential wastewater parameter values, leading to more reliable wastewater treatment and less reliance on manual operation. Furthermore, cloud-based monitoring systems have improved the ability to manage water quality in an urban setting sustainably, with better monitoring and optimization of processes from a distance. A smart urban domestic wastewater management has been proposed that is based on data [2] to facilitate sustainable treatment operations and efficient use of resources. Furthermore, the framework has enhanced the quality of wastewater prediction and operational planning by using intelligent techniques of data analysis. Hence data-centric wastewater management practices have helped towards sustainable environmental protection and reuse of urban water. Smart city initiatives have greatly benefited from wastewater treatment and management systems with IoT capabilities [3].

Moreover, intelligent sensor networks have enhanced the accuracy of wastewater monitoring and automated its data retrieval process in managing wastewater treatment processes efficiently. Furthermore, IoT solutions are helping to make treatment systems more responsive and reduce the complexity of wastewater treatment systems. The use of AI technology in sustainable wastewater recycling systems that are able to predict wastewater treatment efficiency and automate water treatment processes has led to better intelligent resource management [4]. Furthermore, AI algorithms have aided in optimizing processes, identifying anomalies, and ensuring the stability of operations in wastewater recycling applications. As a result, AI-powered wastewater treatment systems have played a role in the smart city development and the improvement of environmental sustainability. The water and wastewater sector has benefited from IoT innovations that have improved water quality monitoring and intelligent environmental sensing application [5].

Additionally, the use of advanced monitoring systems has led to continuous monitoring of pH, turbidity, dissolved oxygen, conductivity, and temperature, among other parameters, for effective wastewater management. Furthermore, IoT enabled communication systems have been bolstering treatment facilities' operational control and data availability in real time. Wastewater management systems incorporating IoT technologies have been shown to offer benefits for the sustainability of wastewater treatment, the efficiency of monitoring, and the efficiency of operation, when compared to traditional wastewater management systems [6]. Furthermore, intelligent monitoring systems have minimized system downtimes and increased the reliability of wastewater treatment by implementing automated monitoring methods. Thus, IoT-enabled wastewater systems have enabled the creation of smart environmental management systems. In smart environments, continuous monitoring of the environment and intelligent wastewater analysis has been realized by the use of monitoring based on the Internet of Things (IoT) [7]. Moreover, the real time sensing technologies have enhanced wastewater quality assessment and automated monitoring efficiency in urban WWTFs. Furthermore, smart environmental monitoring has improved decision making abilities and wastewater operation transparency. Intelligent monitoring systems with IoT solutions have enhanced environmental sustainability and urban infrastructure planning by using smart waste management technologies [8]. Furthermore, sensor-based monitoring systems are optimized the processes of waste collection, wastewater management and resource management in urban areas. This has helped to increase sustainable smart city operations and efficient infrastructure development by IoT environmental systems. Industrial wastewater monitoring has been improved by the use of autonomous real-time monitoring systems based on IoT technologies and sensors, which facilitate automatic wastewater measurement and continuous supervision of operations [9]. Moreover, there has been an enhancement in the monitoring system applied to industrial water quality and detecting the faults in the early stage by the help of intelligent monitoring frameworks. Furthermore, automated control mechanisms have minimised operational errors and increased the efficiency of wastewater treatment in industrial wastewater treatment plants. Installing such automation systems at water treatment plants helps to increase the precision of water quality monitoring, management of treatment processes and remote control of treatment systems [10]. Furthermore, intelligent communication technologies have facilitated the transmission of real-time data and

monitoring of ongoing processes in applications used for wastewater treatment. Thus, the implementation of treatment systems with the assistance of IoT has become more reliable and better for sustainable wastewater management. Wastewater reclamation and reuse have been facilitated with intelligent monitoring and prediction technologies, which use predictive analytics and automatic control technologies [11]. Moreover, sophisticated prediction models have enhanced wastewater quality forecasting and optimization of the wastewater treatment process. Furthermore, intelligent analytical systems have improved the reliability and efficiency of wastewater reuse systems. Technologies adopted in the field of sewage wastewater treatment systems (WWTS) have enhanced secure surveillance and intelligent monitoring capabilities in the field of IoT [12]. Furthermore, real-time monitoring systems have helped to better identify abnormal operating conditions and system failures in WWTPs. As a result, the use of IoT in the field of surveillance has improved the security of wastewater treatment.

Smart city contexts have benefited from water use efficiency and waste management via AI optimisation techniques [13]. Moreover, intelligent algorithms have improved resource management, wastewater treatment optimization, and sustainable environmental management. Further, AI-driven operational structures have helped in ensuring wastewater treatment processes that are energy-efficient and automated. Water management in urban areas has been highlighted as the need for sustainable practices that involve reuse, recycling and strategies for climate resilience have been emphasized [14]. Furthermore, sophisticated re-use technologies have enabled sustainability and long-term freshwater conservation efforts in urban development. Therefore, wastewater recycling technologies are vital in the smart city water management systems for the future. Operational frameworks with intelligence and data have improved wastewater treatment plants' sustainable circularity and automated control [15].

In addition, data-driven analytical models have enhanced the efficiency of wastewater treatment processes, monitoring, and process optimization. Furthermore, smart operation systems have reinforced sustainable resource recovery and circular economy approaches in wastewater treatment systems. Wastewater effluent reuse and circular water management has been enhanced in agriculture by IoT monitoring and management systems [16]. Furthermore, smart monitoring solutions have optimized water re-use and environmental sustainability in the wastewater irrigation systems.

As a result, water reuse systems utilizing IoT have helped in sustainable water use in agriculture. The information on sustainable wastewater treatment technologies and reuse options has been studied in order to enhance the urban water management and environmental protection [17]. Moreover, high-end treatment techniques have improved the efficiency of wastewater recycling and lowered environmental pollution in urban areas. Furthermore, sustainable reuse mechanisms have helped to ensure the long-term conservation of water and resources. Advanced technical interventions in wastewater treatment systems have helped to establish smart city sustainable infrastructures [18].

Furthermore, the wastewater treatment industry is innovating with technologies that generate value and make the process more efficient and environmentally friendly. In addition, the wastewater treatment sector is making good use of intelligent technologies that create value, making the process more efficient and environmentally friendly. Therefore, the new wastewater management systems are indispensable for future urban infrastructure development. Smart technologies for sustainable water management have helped enhance the efficiency of urban water monitoring, treatment and sustainability [19].

Moreover, smart monitoring systems have enhanced the real-time decision-making and automated operation of water treatment plants. Smart environmental technologies have also helped to make better use of resources and promote sustainable water governance. Blockchain and anomaly detection monitoring systems have boosted wastewater reuse monitoring and intelligent fault detection capabilities [20]. In addition, anomaly detection systems have enhanced detection of abnormal wastewater treatment conditions and failures. By leveraging intelligent sensing technologies, IoT-based environmental monitoring solutions have been used to tackle intricate wastewater management problems in industry [21]. Moreover, the efficiency of industrial wastewater analysis and treatment has been enhanced with the aid of advanced monitoring systems and automated methods of data acquisition. Furthermore, environmental management systems based on the Internet of Things (IoT) have been helpful in promoting sustainable management of industrial wastewater. The implementation of digitalization solutions for sustainable wastewater treatment has been supporting the goals of clean water management and carbon neutrality [22]. Furthermore, smart digital platforms have enhanced wastewater treatment efficiency, optimized resource usage, and promoted environmental sustainability.

As a result, wastewater treatment infrastructure has become more digital and digital transformation technologies are gaining significance. Wastewater treatment and reuse solutions have been designed that eliminate chronic infectious diseases and facilitate public health protection [23]. Also, sophisticated treatment technologies have been developed that have enhanced the ability to remove microbial contaminants and harmful

pollutants from wastewater systems. Moreover, wastewater reuse plans have helped to enhance water management and environmental sanitation. The adoption of green energy and energy efficiency technologies has improved the sustainability of waste water treatment plants in cities [24]. Furthermore, energy efficient operational systems have decreased wastewater treatment plants' power use and operating expenses. Therefore, the sustainable energy integration has been beneficial to enhance wastewater management systems' environmental performance and economic viability [25].

2.1 Research Gap

Wastewater treatment research so far has been concentrated on either conventional biological treatment systems or individual MBBR/ MBR systems or on isolated IoT monitoring systems.

1. While these methods enhance treatment efficiency to some degree, few studies have explored the combined implementation of hybrid MBBR–MBR systems with AI-driven IoT monitoring for intelligent wastewater reuse applications.
2. Current systems generally focus on the assessment of treatment efficiency and basic data monitoring without integrating any predictive analytics, automated control and intelligent optimization mechanism.
3. Besides, there is limited work in which machine learning models like Artificial Neural Networks (ANN) and Random Forest (RF) are used for the simultaneous prediction and optimization of several wastewater parameters such as BOD, COD, TSS, turbidity, and dissolved oxygen in a hybrid wastewater treatment system.
4. Another challenge is the lack of predictive maintenance and anomaly detection in existing wastewater infrastructure needed for sustainable, automated operations.

Hence, the proposed AI-Enabled Hybrid MBBR-MBR Intelligent Wastewater Treatment Framework (AHMIWF) seeks to address these research gaps by combining the hybrid treatment technology with IoT based sensing, cloud based monitoring, and AI based predictive analysis to facilitate efficient and sustainable urban wastewater reuse applications.

3. METHODOLOGY

3.1 Study Area and Wastewater Data Collection

The wastewater samples used in this study were obtained from a municipal sewage inlet in the Chennai Metropolitan Region of Tamil Nadu, India, which is a highly developed urban area with domestic wastewater discharge, small scale industries and commercial effluents. The study area was chosen because the wastewater characteristics have continuously changed and the growing demand for advanced wastewater reclamation technologies for sustainable urban reuse applications. The temperature variability and seasonal hydraulic fluctuations at the sampling location represent tropical climatic conditions, and thus realistic operational conditions for assessing the efficiency and adaptability of the proposed AHMIWF framework. To identify the temporal variation of physicochemical and biological pollutants, wastewater samples were taken at both the influent and treatment outlet locations at regular intervals over time under controlled operational conditions. The samples were collected and sent to the laboratory for parameter analysis in real time with IoT-based monitoring system, for the prediction of wastewater quality by AI (Table 1).

Table 1 Study Area and Sampling Information

Parameter	Description
Study Location	Chennai Metropolitan Region, Tamil Nadu, India
Latitude	13.0827° N
Longitude	80.2707° E
Study Environment	Urban municipal wastewater drainage network
Wastewater Sources	Domestic, commercial, and minor industrial discharges
Climatic Condition	Tropical coastal climate
Sampling Type	Influent and effluent wastewater sampling
Sampling Method	Periodic grab sampling
Monitoring Approach	IoT-enabled real-time sensor monitoring
Major Parameters Observed	pH, DO, COD, BOD, TSS, Turbidity, Conductivity

3.2 Proposed architecture

In order to develop a pilot-scale integrated treatment system for sustainable urban wastewater reclamation and intelligent process monitoring, a new AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework

(AHMIWF) was proposed. The experimental system is a combination of two reactors—Moving Bed Biofilm Reactor (MBBR) and Membrane Bioreactor (MBR)—to achieve an enhanced removal of pollutants and superior effluent quality. The MBBR chamber was constructed in a high density acrylic reactor with continuous aeration support and polyethylene biofilm carrier media, which take up 55-60% of the volume of the acrylic reactor. The biodegradation efficiency of the organic contaminants under changing loading conditions of the influent was enhanced by the increased surface area for microbial colonization and stable biofilm growth that were provided by the carrier elements. A sufficient dissolved oxygen level and constant flow of carrier material were obtained by using fine bubble diffusers which were attached to an air compressor. The experimental period was conducted under hydraulic retention conditions in order to ensure uniform experimental conditions and stable microbial activities and efficient pollutant conversion (figure 1).

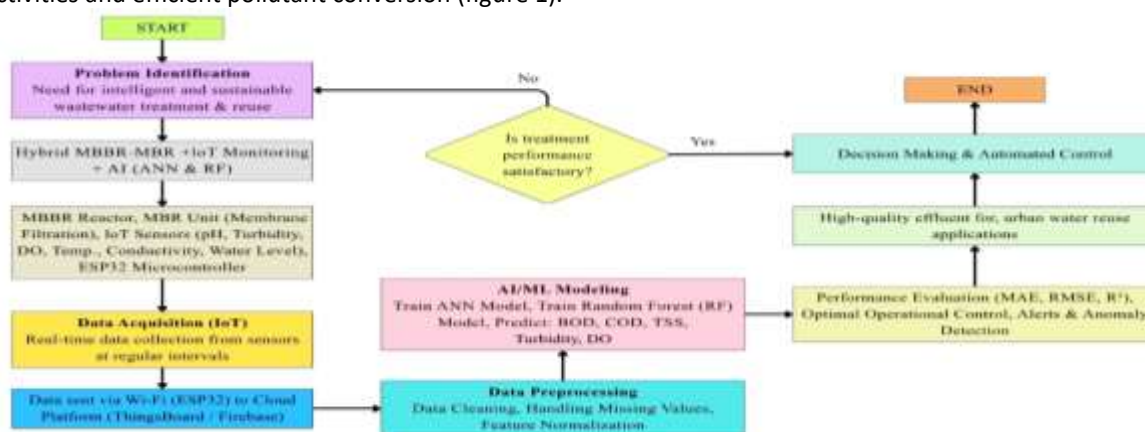


Figure 1. Proposed architecture

The partially treated effluent from the MBBR was then fed into the submerged Membrane Bioreactor (MBR) unit that is fitted with hollow fiber ultrafiltration membranes for advanced solid–liquid separation. The membrane system was also subjected to a controlled suction pressure (in a peristaltic pumping mode) to ensure the continuous extraction of permeate and to guarantee stable filtration performance. To prevent membrane fouling and maintain filtration efficiency over a long period of time, periodic membrane backwashing and scouring by aeration were added. All the treatment equipment was aligned in an IoT based monitoring system which was developed using an ESP32 microcontroller and made up of sensors like PH, Turbidity, Dissolved Oxygen, Temp, Conductivity, Water Level sensors at various treatment stages. The purchased sensor data were continually transferred to a sensor-cloud monitoring platform for real-time observation, storage and sensor-cloud machine learning-based predictive observation. The experimental setup aimed to enable automated monitoring of wastewater, intelligent control of its operation and optimization of treatment by artificial intelligence in dynamic urban wastewater conditions.

3.3. Data Preprocessing and Signal Conditioning

To achieve consistency, computational noise reduction and increased predictive reliability in the proposed AHMIWF, an integrated preprocessing and signal conditioning procedure was adopted before machine learning analysis. First, null records and incomplete sensor data were isolated and replaced by interpolating the missing values to obtain uninterrupted time series with temporal correlation between the treatment steps. Moreover, the monitoring sequence was temporally stabilized by applying the method of outlier filtering based on thresholds to remove the abnormal spikes due to the temporary drift of the sensors and hydraulic turbulence, thereby avoiding the biased behavior of the AI in the prediction.

The collected sensor streams were then processed to ensure synchronisation of the data, for this purpose, a time stamp alignment was performed on the acquired data, so that all the measured parameters were aligned to the same operational interval of the hybrid treatment process. The data was then normalized in the synchronized data set to minimize the scale difference between the different water quality parameters and help the ANN–RF model converge more quickly during training. To overcome the dimensional imbalance of the input attributes, min–max normalization technique was used to scale all the attributes within the range 0 to 1. The normalisation procedure used in this investigation is shown as follows:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_{norm} represents the normalized parameter value, X denotes the observed sensor reading, and X_{min} and X_{max} indicate the minimum and maximum values within the dataset. After normalization, the data set was divided into input and target category sets for the development of the AI model. The parameters such as pH, turbidity, conductivity, DO and temperature were used as predictive input parameters while COD, BOD and TSS removal characteristics were used as target output parameters to predict and analyze the efficiency of treatment using intelligence. The final conditioned dataset was then divided into training, validation and testing datasets to aid in the learning of the stable ANN and Random Forest models in the proposed intelligent wastewater management framework.

3.4. Hybrid MBBR-MBR Treatment Configuration

3.4.1 MBBR Treatment Configuration

The Moving Bed Biofilm Reactor (MBBR) unit used in the proposed AHMIWF system was designed as the main biological treatment reactor for the efficient removal of biodegradable Organic Pollutants in all the varying conditions of urban wastewater. The reactor system was designed to include suspended polyethylene biofilm carrier media of high specific surface area to promote microbial attachment and the development of biofilm inside the reactor aerated treatment chamber. Continuous mixing between wastewater, biofilm carriers, and dissolved oxygen during operation resulted in better microbial oxidation and degradation of OC. This attached microbial growth mechanism enabled a better biomass retention and treatment stability than the conventional suspended sludge processes. Besides, the MBBR configuration successfully reduced biochemical oxygen demand (BOD), smoothed hydraulic fluctuations, and reduced excess sludge production by efficiently converting dissolved organic matter (DOM) into microbial biomass. Homogeneous mixing condition was maintained in the reactor as the aeration was continuous which avoided the sedimentation of the carrier and ensured the stable biological treatment efficiency and uniform pollutant degradation performance in long term operation (figure 2).



Figure 2. MBBR-MBR Technology in Wastewater Treatment

3.4.2 MBR Treatment Configuration

The partially treated wastewater was then pumped into the submerged Membrane Bioreactor (MBR) unit for further filtration and clarification using membranes. The MBR configuration was used with the hollow fiber ultrafiltration membrane modules which were capable of retaining suspended solids, residual particulate matter, microbial contaminants and pathogenic organisms from the biologically treated wastewater stream. Significant reductions in effluent quality resulted from the membrane filtration process and clarified permeate was produced for non-potable urban water reuse applications. The previous reduction in organic loading in the MBBR

stage led to less fouling tendency of the membrane and less stress on the membrane under continuous operation, which improved membrane stability and sustainability in operation. Additionally, mechanisms of periodic membrane backwashing and aeration-assisted scouring were added to ensure the stability of permeate flux and mitigate fouling layer build-up on membrane surfaces. The systems comprising both MBBR and MBR configurations were thus integrated for operation, and a compact, energy efficient and intelligent hybrid wastewater treatment architecture was established, which can achieve high pollutant removal efficiency and stable operation under the dynamically varying wastewater conditions.

3.5. Proposed ANN–RF-Based Intelligent Prediction Technique

The proposed AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework (AHMIWF) is a hybrid scheme of integrating Artificial Neural Network (ANN) and Random Forest (RF) algorithms that enable intelligent prediction, monitoring, and optimization of wastewater treatment performance under dynamically varying urban wastewater conditions. The technique proposed was designed to process real-time sensor data collected from the hybrid treatment system, and to predict key water quality parameters such as water turbidity, dissolved oxygen (DO), Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), and Total Suspended Solids (TSS). The overall prediction framework adopts a multi-stage learning strategy where the preprocessed sensor dataset provided by the sensor monitoring system built on the IoT is fed into the prediction layers of both ANNs and RFs, performing parallel analytical learning. The ANN is used to learn the nonlinear relationships between the treatment variables, while the RF model is used to achieve greater prediction stability and less variance by combining the decision outcomes of multiple trees.

This combined approach improves the accuracy of the predictions, reduces the computational instability and aids in the intelligent management of wastewater in the proposed AHMIWF architecture. First, the parameters of wastewater quality are normalized, such as pH, conductivity, turbidity, temperature, DO, flow parameters, etc., so that they can be processed with AI models as multidimensional input vectors. The data set used as an input to the ANN structure is mathematically shown as:

$$X = \{x_1, x_2, x_3, \dots, x_n\} \quad (2)$$

Where X denotes the complete input feature set and x_n represents individual wastewater monitoring parameters acquired from IoT sensors. In ANN processing, the hidden layer calculation module is used to detect the nonlinear treatment behavior of the ANN and characteristics of pollutant variation, in which the interaction of neurons is carried out and the weight is set. The weighted summation process in the hidden neuron structure is given by:

$$Z_j = \sum_{i=1}^n W_{ij} X_i + b_j \quad (3)$$

Where W_{ij} represents connection weights between neurons, b_j denotes bias parameters, and Z_j indicates hidden layer activation values. Once activated, the predicted wastewater quality output is produced by the final output layer aggregation process. The output prediction by ANN can be mathematically expressed as:

$$A_j = f(Z_j) = \frac{1}{1+e^{-Z_j}} \quad (4)$$

Where A_j denotes activated neuron output and $f(Z_j)$ represents the sigmoid activation function employed within the ANN architecture. Minimization of prediction errors produced in iterative learning is performed by adopting mean squared error optimization to enhance the accuracy of the model and reliability in predicting the treatments. The error function used in the training of the ANN is given by:

$$Y_k = \sum_{j=1}^m V_{jk} A_j + b_k \quad (5)$$

Where Y_k represents predicted wastewater quality indicators, V_{jk} denotes output layer weights, and b_k indicates output bias values. Prediction errors generated during iterative learning are minimized using mean squared error optimization to improve model accuracy and treatment prediction reliability. The error minimization function employed during ANN training is expressed as:

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i - \hat{Y}_i)^2 \quad (6)$$

Where Y_i represents actual observed values, $\hat{Y}_i$ denotes predicted outputs, and N corresponds to the total number of training samples used during learning. At the same time, the same normalized wastewater data sets are fed into the Random Forest model to increase the model's robustness and stability for operation under varying wastewater treatment conditions by using ensemble-based decision tree learning. Multiple decision trees are created based on the technique of bootstrap sampling and random selection of features to investigate pollutant interactions and categorize patterns of treatment efficiency. The final prediction from the Random Forest is:

$$F(x) = \frac{1}{T} \sum_{t=1}^T h_t(x) \quad (7)$$

Where $h_t(x)$ represents the prediction generated by each individual decision tree and T denotes the total

number of trees constructed within the RF ensemble model. Based on the proposed ANN–RF combination framework, the final prediction is generated by combining the analytical interpretation result of ANN nonlinear learning and the prediction result of the RF ensemble prediction, which further enhances the capability of intelligent prediction, anomaly detection, and system operational optimization of the proposed AHMIWF system.

3.5.1. Training and Validation of ANN–RF Models

The overall training and validation procedure adopted in this investigation is summarized as follows:

Algorithm 1: ANN–RF Training and Validation Procedure

Input:
IoT wastewater dataset D
Parameters: pH, DO, COD, BOD, TSS, turbidity, conductivity, temperature
Output:
Trained ANN–RF intelligent prediction model

Step 1:
Acquire real-time wastewater sensor data from MBBR–MBR system

Step 2:
Perform preprocessing
→ Remove missing values
→ Filter noise and outliers
→ Synchronize time-series sensor streams

Step 3:
Normalize dataset using Min–Max normalization

Step 4:
Split dataset into:
Training set (70%)
Validation set (15%)
Testing set (15%)

Step 5:
Initialize ANN architecture
→ Input layer
→ Hidden layers
→ Output layer

Step 6:
Train ANN using backpropagation
→ Update weights iteratively
→ Minimize prediction error

Step 7:
Initialize Random Forest model
→ Generate bootstrap samples
→ Construct multiple decision trees
→ Perform ensemble aggregation

Step 8:
Validate ANN and RF models using K-fold cross-validation

Step 9:
Evaluate prediction accuracy using RMSE, MAE, and R^2 metrics

Step 10:
Generate final intelligent wastewater quality prediction output

4. Results and Discussion

The experimental results of the proposed AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework (AHMIWF) showed that the purifying efficiency of the wastewater was remarkably enhanced with intelligence monitoring capability and stability in prediction under the dynamically changing urban wastewater condition. The treatment configuration with the integrated system proved to be effective for the combined action of biological degradation and membrane filtration in order to reduce the levels of organic pollutants, suspended

solids, turbidity and dissolved contaminants. At the same time, the ANN–RF intelligent prediction framework showed good estimation accuracy for critical wastewater quality indicators based on the data from the sensors collected by the IoT. The experimental results obtained have validated the combination of MBBR, MBR, IoT monitoring, and artificial intelligence as a compact, cost-effective, and eco-friendly approach for advanced wastewater reuse applications in urban areas.

4.1. Influent Wastewater Characteristics

Before treatment, the influent wastewater quality characteristics were analyzed and are presented in Figure 3. The wastewater pH ranged from 6.82 to 8.14, which are slightly acidic to mildly alkaline conditions. The low oxygen concentration normally found in wastewater streams was observed as dissolved oxygen (DO) is shown to have increased from 1.42 to 3.11 mg/L. The pollution load in terms of COD ranged from 412-698mg/L and BOD ranged from 218-392mg/L, which indicated the presence of significant biodegradable and non-biodegradable organic matter.

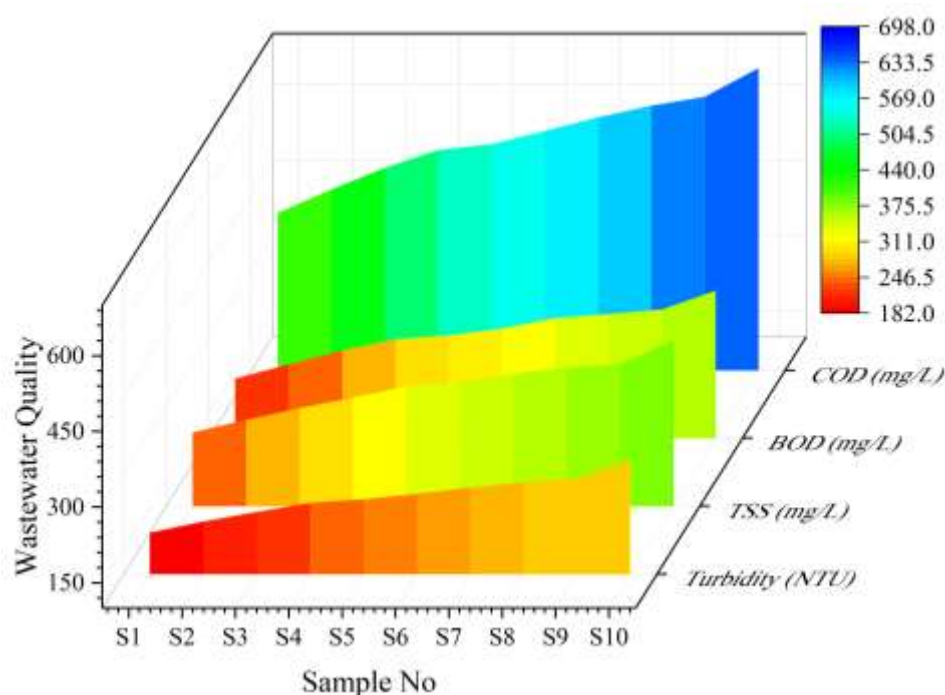


Figure 3. Influent Wastewater Quality Characteristics

Suspended solids were also high, ranging from 246 mg/L to 428 mg/L with turbidity ranging from 182 NTU to 326 NTU, suggesting there is significant particulate contamination. The electrical conductivity rose from 1210 to 1985 $\mu\text{S}/\text{cm}$ indicating increased dissolved ionic content in the wastewater. The range of temperature measured was between 26.2°C and 33.4°C which is conducive for microbial activity and biological treatment processes. In general, the influent wastewater had moderate to high pollution strengths, and required effective treatment to obtain low levels of organic, suspended and dissolved pollutants before it was discharged or reused.

4.2. Performance Analysis of Hybrid MBBR–MBR Treatment System

Figure 4 shows the performance of the hybrid Moving Bed Biofilm Reactor – Membrane Bioreactor (MBBR – MBR) treatment system to enhance wastewater quality. The effluent condition after MBR treatment was almost neutral, from pH 7.46 in the influent to 7.02 after MBR treatment, which represents an environmentally friendly effluent. It is observed that the dissolved oxygen (DO) levels in the treatment units have significantly improved from 2.24 mg/l to 6.92 mg/l (increase of 208.93 %). This indicates good aeration and biological activity in the treatment units. The overall COD removal efficiency was 91.24%, which means that the concentration of the organic pollutant was significantly reduced, from 548 mg/L to 48 mg/L. Likewise, the BOD was decreased from 304 mg/L to 19 mg/L, with 93.75% removal efficiency, which is very good for the biodegradation of organic matter. The system also exhibited outstanding solid removal performance, with TSS decreasing from 337 mg/L to 14 mg/L, corresponding to an overall removal efficiency of 95.85%. The results are found to be that the hybrid MBBR–MBR system performs effectively in improving the quality of wastewater with both the biological degradation process and membrane filtration process.

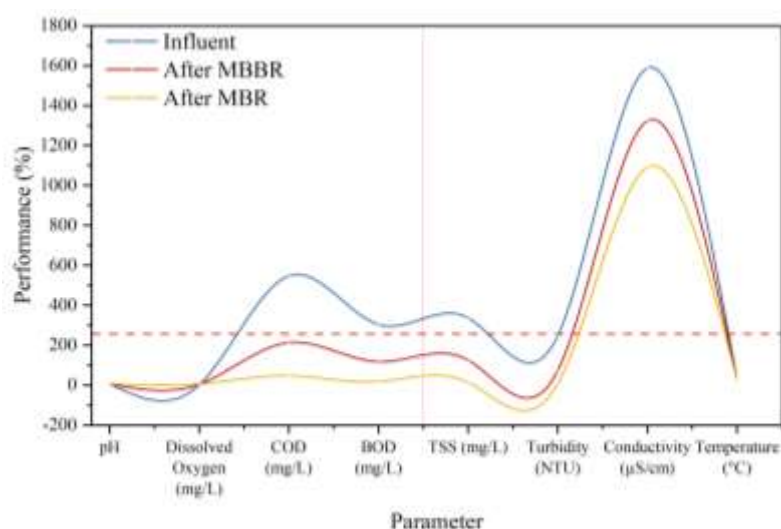


Figure 4. Performance Evaluation of Hybrid MBBR-MBR Treatment System

4.3 IoT-Based Water Quality Monitoring Performance

The performance evaluation of IoT-based wastewater monitoring system is done by comparing the measured data of sensors with the lab analyzed data as presented in figure 5. The results show the sensor data is in good agreement with the reference laboratory data. The average value pH obtained from the pH sensor was 7.02, while the laboratory value was 7.08, with an absolute error of 0.06 and an accuracy of 99.15%. Similarly, the dissolved oxygen sensor gave 98.38% accuracy with the deviation of 0.11mg/L from the laboratory result. The turbidity sensor had an accuracy of 95.92% and COD sensor an accuracy of 94.12% with minimum error of 3mg/l. The BOD and TSS sensors were found to have an accuracy of 90.48% and 87.50% respectively, which are acceptable for real time monitoring applications. In conclusion, the IoT-based monitoring system proved to be successful in terms of both accuracy and reliability, with the conductivity sensor achieving a 97.67% accuracy rate and the temperature sensor reaching a 98.96% accuracy rate, while the error was negligible. The results confirmed the effectiveness and accuracy of the system for real-time monitoring and assessment of wastewater treatment processes and effluent quality management.

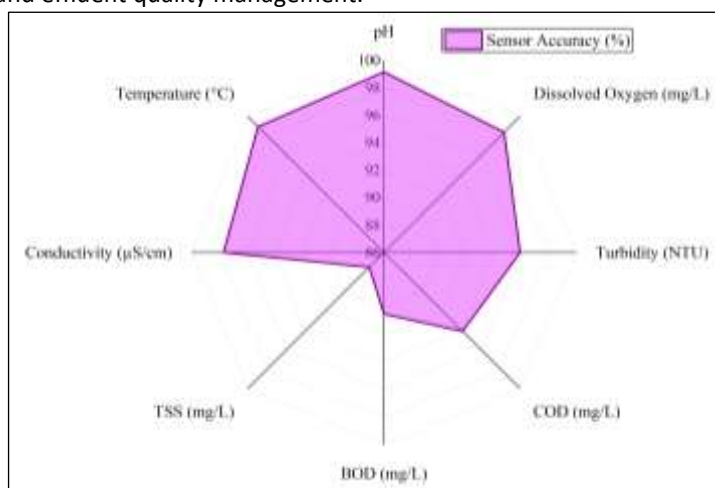


Figure 5. Performance Evaluation of IoT-Based Monitoring System

4.4 ANN-RF Prediction Performance Analysis

Figure 6 shows the prediction accuracy of the integrated Artificial Neural Network-Random Forest (ANN-RF) model for the most important wastewater quality parameters. The developed model showed very good predictive power (R^2 0.968-0.994), with very good correlation between the predicted and measured measurements. For all the parameters evaluated, Ph prediction was the most accurate with an accuracy of 99.34%, RMSE of 0.09, and MAE of 0.04, followed by turbidity prediction with 99.08% accuracy and an R^2 value of 0.991. The model also successfully predicted the efficiency of treatment parameters such as COD, BOD, and TSS with prediction

accuracy of 98.21%, 97.84%, and 98.63%, respectively. Further, the accuracy for temperature prediction was 98.74%, and for the prediction of DO and conductivity, the accuracies were 97.26% and 96.91%, respectively. The low RMSE and MAE values for all the parameters validate the robustness and reliability of the ANN–RF framework.

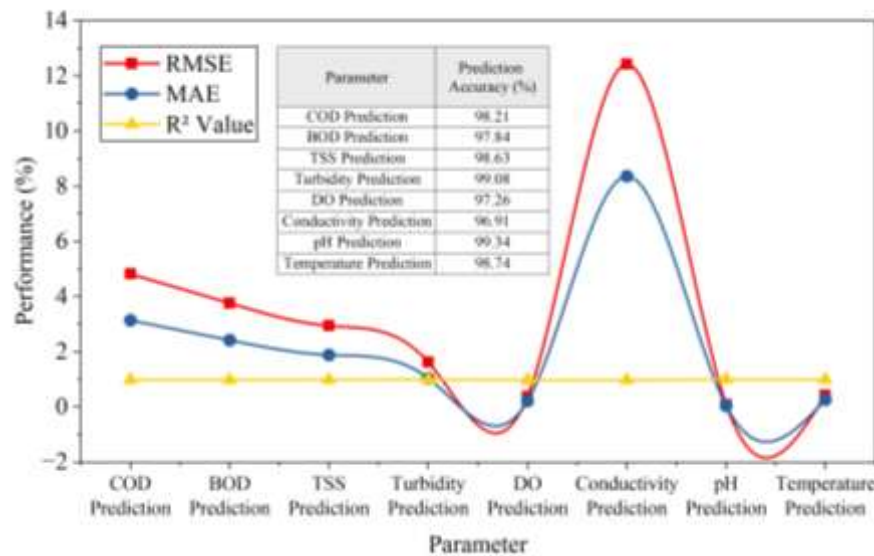


Figure 6 ANN–RF Prediction Performance Metrics

4.5 Membrane Fouling and Operational Stability Analysis

Table 2 presents the membrane fouling behavior and operational stability of the MBR unit over 108 hours of continuous operation. The transmembrane pressure (TMP) gradually increased from 8.2 kPa to 16.8 kPa, indicating progressive accumulation of foulants on the membrane surface. Correspondingly, the permeate flux decreased from 28.6 to 22.2 L/m²·h, reflecting the resistance imposed by fouling during prolonged filtration. The fouling rate increased steadily from 0.00% at the start of operation to 22.38% after 108 hours, demonstrating the gradual formation of a fouling layer. Despite this increase, the membrane maintained stable performance throughout the operational period. The membrane recovery efficiency remained above 91%, decreasing only from 100% to 91.4%, which confirms the effectiveness of the cleaning and recovery procedures in restoring membrane functionality. The observed trends indicate that the MBR system possesses good operational stability and fouling resistance, ensuring sustained treatment performance with manageable maintenance requirements.

Table 2 Membrane Fouling and Operational Stability Analysis

Operational Time (h)	Transmembrane Pressure (kPa)	Permeate Flux (L/m ² ·h)	Fouling Rate (%)	Membrane Recovery Efficiency (%)
0	8.2	28.6	0.00	100
12	9.1	27.9	2.45	99.2
24	10.4	27.1	5.24	98.6
36	11.8	26.2	8.39	97.4
48	12.9	25.4	11.19	96.8
60	13.8	24.8	13.29	95.7
72	14.6	24.1	15.73	94.9
84	15.3	23.5	17.83	93.8
96	16.1	22.9	19.93	92.6
108	16.8	22.2	22.38	91.4

4.6 Training and Validation Performance of ANN–RF Models

The results of training and validation performance for the proposed ANN–RF framework over 100 training epochs are shown in Table 3. The analysis shows that the model's learning ability gradually improves, as reflected in the training loss and the validation loss values gradually decreasing. After 10 epochs, the training loss reduced to 0.084, and after 100 epochs, it reduced to 0.009; the validation loss reduced from 0.092 to 0.015, showing a good convergence of the model with little overfitting. At the same time, the training accuracy rose from 88.24% to 99.36%, which shows that the training of the underlying relationship of wastewater quality was improved. The

validation accuracy also increased substantially from 86.91% to 98.71%, indicating that the developed framework also had excellent generalization ability to unseen data. The relatively small difference between training and validation accuracies throughout the training process further suggests stable model performance and robust predictive reliability.

Table 3 Training and Validation Performance of ANN–RF Framework

Epoch	Training Loss	Validation Loss	Training Accuracy (%)	Validation Accuracy (%)
10	0.084	0.092	88.24	86.91
20	0.062	0.071	91.86	90.74
30	0.048	0.056	94.12	93.08
40	0.036	0.044	95.84	94.91
50	0.028	0.037	96.92	95.76
60	0.022	0.031	97.54	96.43
70	0.018	0.026	98.08	97.16
80	0.014	0.021	98.62	97.84
90	0.011	0.018	99.04	98.26
100	0.009	0.015	99.36	98.71

4.7 Energy Consumption and System Efficiency Analysis

Figure 7 shows the energy consumption and energy efficiency analysis of the proposed AI Driven Hybrid MBBR–MBR Intelligent Wastewater Filtration (AHMIWF) system. Aeration system resulted highest energy consumption of 18.6 kWh/day, and treatment efficiency of 88.4% and operational stability of 96.2%. The MBBR reactor achieved a treatment performance of 91.6%, while the MBR filter achieved 95.8% treatment performance, respectively, with energy utilisation efficiencies of more than 89%.

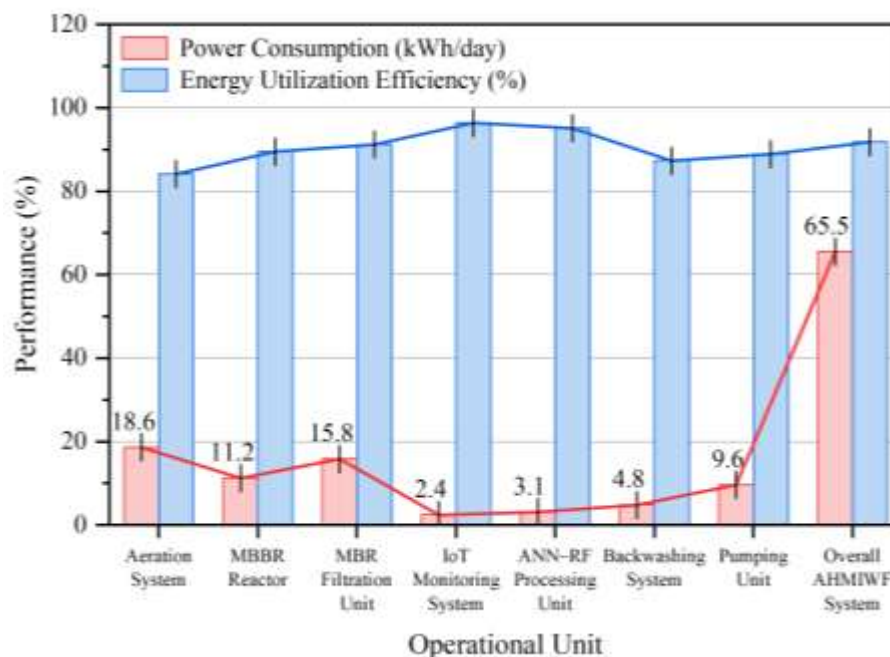


Figure 7. Energy Consumption and System Efficiency Analysis

With the use of the IoT monitoring system, the system treated 98.1% of the wastewater, maintained an operational stability of 99.3%, and demonstrated an energy utilization efficiency of 96.4% with a daily energy consumption requirement of only 2.4 kWh/day, being extremely effective for real-time process monitoring, with low energy consumption requirements. Likewise, the performance of the ANN–RF processing unit was very good: 97.6% treatment efficiency, 95.1% energy utilization efficiency and low power consumption of 3.1 kWh/day. Both the backwashing and the pumping units helped to keep the operation stable with operational stability value of 95.4% and 96.1%, respectively. The whole treatment efficiency of the integrated AHMIWF system was 93.75%, with operational stability of 97.8% and an energy utilization efficiency of 91.8%, accounting for the overall

treatment efficiency, operational stability, and energy utilization efficiency, respectively. The proposed intelligent wastewater treatment framework has high treatment performance and energy management efficiency, and is highly stable and reliable in long-term operation.

4.8 Comparative Analysis with Existing Wastewater Treatment Systems

The performance of the proposed AI-Driven Hybrid MBBR–MBR Intelligent Wastewater Filtration (AHMIWF) system is compared to several existing wastewater treatment technologies in Table 4. The removal efficiencies of conventional activated sludge process were relatively lower (72.4% COD, 76.8% BOD, 69.5% TSS and 64.2% turbidity removal). The pollutant removal efficiency for the Sequencing Batch Reactor (SBR) and standalone MBBR systems improved and was generally over 80%. The standalone MBR system exhibited a higher treatment efficiency with 88.9%, 91.4%, 93.2% and 90.8% removal of COD, BOD, TSS and turbidity, respectively. Unlike the proposed framework, the treatment efficiencies of the conventional treatment system and prediction system with the aid of ANN and IoT were found to be low. The AHMIWF system recorded the best performance of 91.24% COD removal, 93.75% BOD removal, 95.85% TSS removal and 96.77% turbidity removal. In addition, it is the only tool that combines 100% ANN-RF based artificial intelligence and 100% real-time IoT monitoring, providing intelligent process control, continuous performance monitoring, and predictive decision making.

Table 4 Comparative Performance Analysis with Existing Methods

Method	COD Removal (%)	BOD Removal (%)	TSS Removal (%)	Turbidity Removal (%)	AI Integration	IoT Monitoring
Conventional Activated Sludge Process	72.4	76.8	69.5	64.2	No	No
Sequencing Batch Reactor (SBR)	81.6	84.1	79.8	74.3	No	No
Standalone MBBR System	85.7	88.2	82.4	79.5	No	Partial
Standalone MBR System	88.9	91.4	93.2	90.8	No	Partial
IoT-Based Conventional Treatment	79.2	82.6	77.4	73.1	Partial	Yes
ANN-Based Wastewater Prediction System	84.5	87.2	81.8	78.6	Yes	Partial
Proposed AHMIWF System	91.24	93.75	95.85	96.77	Full ANN–RF	Full Real-Time

5. Discussion

As evidenced in the experimental results the proposed AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework (AHMIWF) is an effective solution for the sustainable application of urban wastewater reuse, combining biological treatment, membrane filtration, IoT-based monitoring, and artificial intelligence. The hybrid MBBR-MBR treatment configuration was found to remove significant amounts of pollutants with COD removal efficiency of 91.24%, BOD removal efficiency of 93.75%, TSS removal efficiency 95.85% and turbidity removal efficiency 96.77% respectively, which indicates the strong synergy between the biofilm-assisted pollutant degradation and the solid separation mechanisms provided by the membrane. By stabilizing the load and fluctuations in the influent prior to membrane filtration, the MBBR stage provided for lower stress levels to the membrane and increased the consistency of filtration in the MBR stage. At the same time, dissolved oxygen level increased substantially from 2.24mg/L to 6.92 mg/L which showed better biological stabilization and aeration efficiency in the treatment process. The membrane fouling analysis also revealed reliable operational performance with low and desirable transmembrane pressure increase and high membrane recovery efficiency (> 91%); this further confirmed the operational sustainability of the proposed hybrid architecture under continuously varying wastewater conditions.

Additionally, the AHMIWF system was enhanced with the integration of IoT-assisted monitoring and ANN–RF

intelligent prediction framework, which further strengthened the automated system and the system's operational efficiency. The monitoring framework built around the ESP32 sensor was able to accurately monitor major water quality parameters with a cloud synchronization efficiency of more than 99.9%, ensuring reliable real-time monitoring of wastewater and remote supervision of operation. Moreover, the ANN–RF intelligent framework showed high prediction power with R^2 values >0.97 for all the major wastewater quality indicators while RMSE and MAE values were 2.68 and 1.67, respectively. The ANN model was able to effectively handle the non-linear interactions amongst the model parameters and the ensemble structure of the Random Forest model provided greater predictive robustness and a lesser over-fitting behavior under varying pollutant loading conditions. Comparative analysis with conventional wastewater treatment approach also revealed that the proposed AHMIWF system has a remarkable pollutant removal efficiency, monitoring intelligence, operational stability and energy utilization efficiency compared to standalone biological and conventional treatment systems. The results prove the effectiveness and scalability of the proposed framework for intelligent wastewater management and smart urban water reuse infrastructure.

5.1. Economic and Scalability Analysis

The economic and scalability assessment of the proposed AHMIWF showed good sustainability and long-term applicability for smart urban wastewater reuse systems. While the capital cost at first use (capital expenditure – CAPEX) of membrane filtration modules, IoT sensors and AI-enabled monitoring systems is relatively high compared to the conventional wastewater treatment plants, the proposed framework significantly cuts down the long-term running cost (operational expenditure – OPEX) by automation of monitoring systems, reduction of manual supervision, optimized aeration control, predictive maintenance capability and increased stability of membrane operation. The ANN–RF intelligent prediction framework also reduces operational inefficiencies and energy wastage because it allows an adaptive optimization of treatment depending on variations in pollutant load. Moreover, the modular hybrid MBBR – MBR system can be scaled up for decentralized community small scale treatment systems or large scale municipal wastewater reclamation systems. Thus, the incorporation of cloud-based monitoring and intelligent automation will improve the economic viability, flexibility in operations and sustainable deployment of the proposed AHMIWF framework for future smart city wastewater management application.

6. Conclusion

The present investigation successfully developed and tested an AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework (AHMIWF) which integrated Moving Bed Biofilm Reactor (MBBR), Membrane Bioreactor (MBR), Internet of Things (IoT) based monitoring and ANN–RF intelligent prediction algorithms for sustainable urban wastewater reuse applications.

1. The proposed solution successfully implemented biological degradation, membrane-assisted filtration, remote sensing monitoring, cloud supervision and artificial intelligence to realize high-efficient wastewater treatment and intelligent management, in the dynamically changing urban wastewater treatment environment.
2. The experimental results showed that the pollutant removal efficiency was high with the COD, BOD, TSS and turbidity removal efficiencies of 91.24%, 93.75%, 95.85%, and 96.77%, respectively, and the concentration of dissolved oxygen was also enhanced in the wastewater treatment process, while a stable operation was maintained during the entire wastewater treatment process.
3. The monitoring system implemented based on the IoT technology has successfully maintained a high degree of accuracy among the sensors and has ensured efficient synchronization with the cloud, thus allowing for real-time process monitoring and automatic operational analysis. Moreover, the proposed ANN–RF intelligent prediction framework had high prediction accuracy and a high coefficient of determination value with lesser RMSE and MAE value for all the parameters evaluated in the wastewater quality estimation.
4. The hybrid AI architecture successfully reduced prediction uncertainty, increased operational reliability and increased adaptive wastewater management performance in the face of varying environmental conditions.

The analysis of membrane fouling and the assessment of energy consumption also demonstrated the operational sustainability and resource efficiency of the integrated treatment framework. In summary, the proposed AHMIWF system offers a compact, intelligent, energy-efficient and scalable wastewater reclamation platform that can be applied to advanced urban reuse applications, smart city infrastructure development, enhancement of environmental sustainability and future intelligent water resource management systems.

6.1. Future Scope

Future studies could also include the application of Digital Twin, edge computing systems, and reinforcement learning autonomous control systems to implement real-time self-optimizing wastewater treatment operation in Industry 4.0 environment. Next generation membrane materials and AI-driven adaptive treatment strategies will also be investigated in advanced research to develop removal efficiency analysis for emerging contaminants such as pharmaceutical residues, personal care products, microplastics and antibiotic-resistant pollutants.

Abbreviation

AI	- Artificial Intelligence
IoT	- Internet of Things
MBBR	- Moving Bed Biofilm Reactor
MBR	- Membrane Bioreactor
AHMIWF	- AI-Enabled Hybrid MBBR–MBR Intelligent Wastewater Framework
ANN	- Artificial Neural Network
RF	- Random Forest
BOD	- Biological Oxygen Demand
COD	- Chemical Oxygen Demand
TSS	- Total Suspended Solids
DO	- Dissolved Oxygen
RMSE	- Root Mean Square Error
MAE	- Mean Absolute Error
SBR	- Sequencing Batch Reactor
CAPEX	- Capital Expenditure
OPEX	- Operational Expenditure
NTU	- Nephelometric Turbidity Unit
SDG	- Sustainable Development Goal
EPR	- Extended Producer Responsibility
ICCCNT	- International Conference on Computing, Communication and Networking Technologies

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