Enhanced Performance of Membrane Bioreactor in Sewage Treatment through Integrated Control Strategy

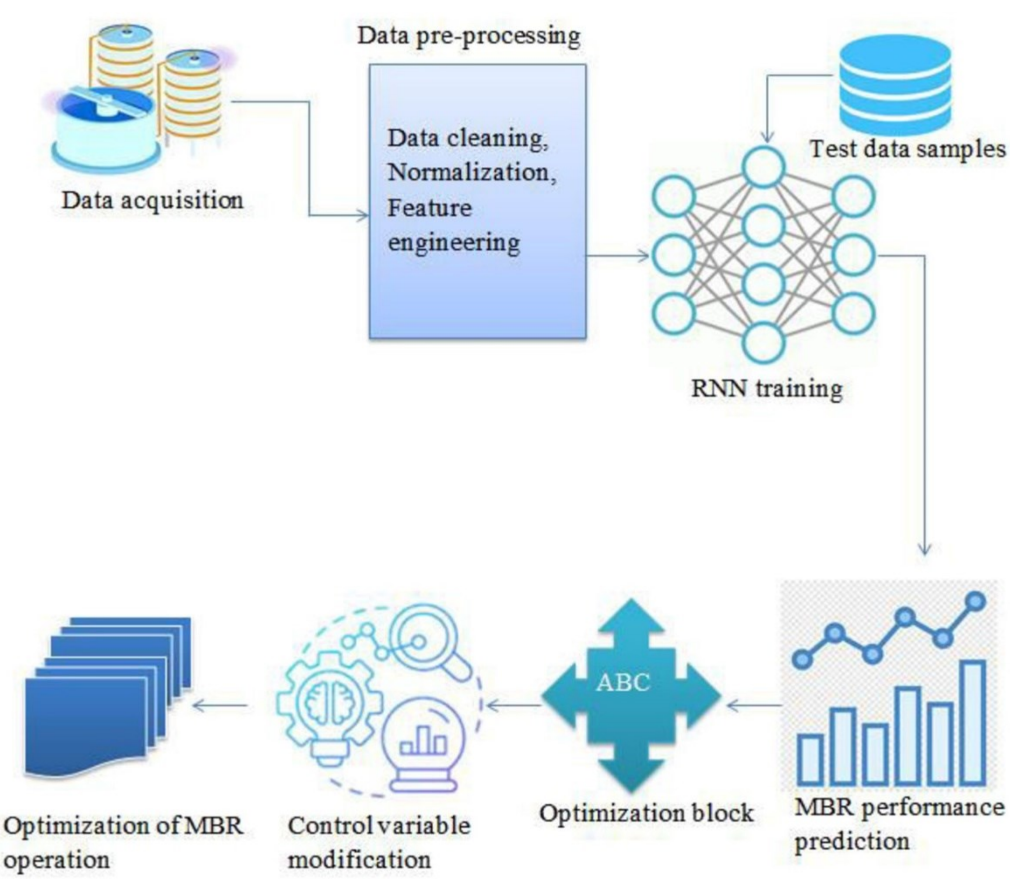
Dr. M. Yuvaraju[1*], D. Deena[2]

[1*]Department of Electrical and Electronic Engineering, Anna University Regional Campus, Coimbatore, India

[2]Department of Electrical and Electronic Engineering, United Institute of Technology, Coimbatore, India

[1*]Corresponding Author Mail id: myuvaraju254@gmail.com

GRAPHICAL ABSTRACT



ABSTRACT

Wastewater includes sewage water, which presents serious environmental problems that necessitate effective treatment techniques. Membrane Bioreactors (MBRs) have emerged as promising solutions, albeit plagued by membrane fouling and computational loading issues. To resolve these issues, this research article presents an innovative control strategy combining both artificial bee colony optimization (ABC) and recurrent neural network (RNN) to regulate the performance of MBR in sewage treatment. Initially, the influent wastewater data was collected and pre-processed using the regression imputation approach. RNN architecture was designed and trained using the pre-processed data to forecast the performance of the MBN system. Further, the ABC algorithm was applied to optimize the function of MBR by adjusting the control variables. The developed model was validated with the publically available wastewater treatment plan dataset and the effectiveness of the developed model was validated by performing intensive performance and comparative assessment. The performance evaluation demonstrates that the proposed methodology attained greater results of 98.59% effluent quality, 98.70% of nutrient removal efficiency, less computational time of 2.87s, and a low membrane fouling index of 1.23%. The comparative analysis illustrates that the presented approach achieved improved performances than the existing methodologies.

Keywords: Artificial intelligence, sewage treatment, Recurrent neural network, Artificial bee optimization, Membrane bioreactor.

Nomenclature

MBR	Membrane Bioreactors
ABC	artificial bee colony optimization
RNN	recurrent neural network
AOX	absorbable organic elements
MBSP	membrane-based separation
ANN	artificial neural network
MLP	multilayer perceptron
RBF	radial basis function
FFNN	feed-forward neural network
ML	machine learning
OMER	osmotic MBR
AGS	aerobic granular sludge
LSTM	long short-term memory

COD	chemical oxygen demand
BOD	biochemical oxygen demand
TMP	transmembrane pressure
WWTP	Wastewater Treatment Plant
NMPC	Model Predictive Control Design
FLC	Fuzzy logic control
PSO	Particle Swarm Optimization

1. INTRODUCTION

Owing to the increased industrial revolution, the existence of persistent and emergent pollutants including absorbable organic elements (AOXs) in wastewater is emerging as a global issue [1]. Recently, various innovative treatment approaches are designed to remove the pollutants present in the wastewater [2]. But the selection of an appropriate approach is significant for the proper treatment of wastewater. Therefore, membrane-based separation techniques (MBSPs) are utilized widely to treat the variety of polluted water and wastewater instigated from different municipal and industrial sources [3]. However, this membrane-based approach was selected based on the wastewater pollution load and the chosen technique must be sustainable, eco-friendly, and feasible [4]. In addition, achieving sustainable development is important for designing eco-friendly, and economically feasible MBSPs for wastewater treatment [5]. Recent studies reported that treatment proficiency is one of the parameters, which defines the selection of an appropriate approach among the conventional techniques [6]. Currently, the MBSPs are assumed as the most effective method to handle the largely polluted water [7]. Moreover, the researches illustrate that the conventional techniques along with the integration of filtration of the biological treatment method provide highly effective isolation of the pollutants [8].

This method integrates the benefits of physical isolation of the pollutant and their deprivation through micrograms [9]. This makes the researchers concentrate on the development of MBRs. Therefore, to support industrial applications different kinds of aerobic and anaerobic MBRs are designed [10]. However, they face some challenges in providing highly effective wastewater treatment [11]. The membrane fouling is one of the significant issues of the MBSPs, but managing the quality of the treated sewage is interconnected with the composition and performance of the microbial groups [12]. This shows that the design of integrated approaches like MBRs enables effective sewage treatment [13]. But the existing parameter controller tools including the negative feedback control models are not accurate in confirming the high-quality water treatment [14]. Hence, artificial intelligence (AI) approaches are deployed to control the entire wastewater treatment process. This approach enables the system to predict the control parameters, which the existing technique faces difficulty [15, 16].

The utilization of the AI approach integrates the computer-controlled machine pertaining such as generalization, and learning, which makes the system learn from experiences (data) for predicting the control parameters [17]. In this approach, the data related to sewage treatment are collected and utilized to predict the outcomes and control parameters in the future [18]. Numerous researches described that the utilization of AI techniques increased the performance of various applications associated with agriculture, health, disaster management, etc., [19]. In addition, it is deployed to predict environmental factors and control pollution. Moreover, the researchers demonstrated that the application of AI techniques such as artificial neural network (ANN), multilayer perceptron (MLP), radial basis function (RBF), feed-forward neural network (FFNN), etc., enables the system to manage the water quality and provide highly cleaned water in the polluted regions [20]. However, the performance of these systems depends on the quality of the training data and it faces high computational complexity. To resolve these issues, meta-heuristic algorithms such as genetic algorithms, particle swarm optimization, etc., are utilized. Moreover, the recent conventional approaches such as the machine learning (ML) based approach [21], AI-based prediction model [22], integrated ANN, and the adaptive network-based fuzzy system [23], etc., are prone to overfitting, interoperability, computational complexity, and its performance depends on the quality of the training set. Therefore, an artificial intelligence-based control strategy was designed for bioreactors in sewage treatment.

When every aspect is considered, the RNN is good at managing different input lengths, remembering information, and processing sequential data. By efficiently recording temporal dependencies, it can analyze time-series data and forecast future events. By simulating the exploitation and recruitment of food sources, ABC optimizes solutions repeatedly, taking inspiration from the foraging behavior of honeybee swarms. Across a wide range of optimization issues, this population-based approach finds applications and performs exceptionally well while exploring search areas. Wastewater treatment efficiency is increased by the MBR, which combines biological treatment and membrane filtration. MBR systems, which are essential in municipal and industrial wastewater treatment facilities, efficiently eliminate pollutants by using semi-permeable membranes. This results in effluent of a higher caliber than using traditional methods.

The work combines the RNN control strategy with the ABC optimization technique to regulate MBR systems in sewage treatment shows its novelty. With the help of influent wastewater data, this novel method accurately forecasts MBR performance and adjusts operating parameters in real time. The suggested approach outperforms traditional control systems by integrating AI-based prediction with optimization to provide improved effluent quality, decreased membrane fouling, and increased nutrient removal efficiency, therefore solving important environmental concerns in wastewater treatment.

The major contributions of the presented research work are described below,

- Collect the MBR-sewage treatment database and pre-process the raw dataset to ensure the quality and reliability of the dataset.
- Design the RNN architecture and train it using the pre-processed dataset to predict the performance of the MBR.
- Applying the ABC approach optimizes the operation of the MBR by adjusting the control variables continuously.
- Finally, the results of the developed model were examined and evaluated with traditional control strategies in terms of nutrient removal efficiency, computational time, effluent quality, and membrane fouling index.

The organization of the research paper is described as the 2nd section analyzes the recent research articles related to the proposed work, the 3rd section describes the system model and its problems, the 4th section details the working of the proposed methodology, the 5th section analyzes the outcomes of the proposed work, and the 6th section demonstrates the research conclusion.

2. RELATED WORKS

Some of the research works associated with the proposed work are reviewed as follows, Muhammad Yaqub and Wontae Lee [21] designed a machine learning (ML) based approach for predicting nutrient removal efficiency. This method deploys the anaerobic MBR and extreme gradient boosting design to identify the elimination of nutrients like nitrogen, ammonium, etc., from the water. The simulation results describe that the developed model enhances the functional efficiency of the anaerobic MBR. However, this technique is prone to overfitting challenges.

In recent times, the osmotic MBR is being widely utilized for sewage treatment in various industrial and municipal corporations. Nguyen Duc Viet and Am Jang [22] designed an AI-based prediction model for forecasting the osmotic MBR outcomes. This method improves the system's performance by minimizing the environmental impacts of wastewater. The extensive evaluation shows that the designed framework is highly effective in predicting and optimizing the osmotic MBR. But this method cannot handle the variations in the input data.

Ahmad Hosseinzadeh *et al* [23] proposed an integrated framework to predict water flux in osmotic MBR (OMBR). This method hybrid the ANN and the adaptive network-based fuzzy system for effective and accurate forecasting of OMBR performance. The intensive simulation analysis demonstrated that this method earned a very low RMSE of 0.252. Furthermore, a sensitivity assessment was made to evaluate the efficiency of the developed model under data variations. However, the training and optimization of this hybrid approach are computationally intensive and time-consuming.

Jiahao Liang *et al* [24] presented an aerobic granular sludge (AGS) approach for the management of flow back water from shale gas extraction. This method controls the environmental factors of the natural gas industry. The evaluation results effectively remove the effluents like COD, NH4+-N, and TN. In addition, the 3-layered ANN is responsible for eliminating the dynamics of pollutants present in the water. However, this approach is prone to membrane fouling.

Typically, the MBR faces issues like fouling, which increases the cleaning and maintenance costs. To resolve these issues, Yasser Algoufily *et al* [25] developed a prediction and monitoring framework to detect the fouling in MBR. In this approach, the total resistance of the membrane was determined using the stochastic design based on the information interconnected to membrane fouling. Moreover, an ANN-based control system was designed to manage the temperature in their setpoints. But this method produces false positives and negatives in the fouling prediction.

For wastewater treatment, the anaerobic MBR is considered one of the most eco-friendly solutions. However, these MBRs are prone to fouling, thus it increases energy consumption and cost. Therefore, José M. Cámara *et al* [26] presented an accurate fouling prediction framework using the neural network. The integration of both numerical and neural networks enhances prediction efficiency. However, this method demands large computational memory and power.

Muhammad Yaqub *et al* [27] designed a framework to predict the effluent removal efficiency of an anaerobic MBR using long short-term memory (LSTM). This method considers the influent wastewater features such as total nitrogen, ammonium, dissolved oxygen, etc., as inputs and the removal efficiency as output. Furthermore, data normalization and analysis were utilized in the system to increase its learning speed. The prediction outcomes describe that the designed model attained high accuracy. However, tuning the hyperparameters are complex in this approach.

Yifeng Chen *et al* [28] introduced an innovative algorithm using the backpropagation ANN and generalized regression neural system to measure the interfacial power interconnected with the MBR fouling. This method was trained and validated using the five apparent databases and a case study was made to evaluate the feasibility and robustness of the approach. The results validate that the designed framework achieved huge quantification efficiency. But the integration of these different techniques is complex and requires more resources.

The incorporation of a hybrid ABC-RNN control technique specifically designed for MBR regulation in sewage treatment makes the suggested system unique. It combines artificial bee colony optimization and recurrent neural networks for effective prediction and optimization of MBR performance, in contrast to previous approaches that were prone to overfitting or computing intensity. By addressing issues like fouling and energy usage, this integration improves the quality of effluent and the effectiveness of nutrient removal. By utilizing the hybrid technique, it exceeds the constraints of traditional strategies and provides greater precision and adaptability to dynamic wastewater treatment processes. In the end, it results in notable enhancements to MBR performance and treatment efficacy as a whole.it leads to significant improvements in MBR operation and overall treatment effectiveness.

3. SYSTEM MODEL AND ITS PROBLEM

An MBR is an emerging wastewater treatment approach, which integrates traditional biological treatment and membrane filtration into a single unit. Thus, it overcomes the typical sewage treatment model and provides greater effluent quality, a small footprint, etc. However, to confirm effective functioning and maintain optimal treatment performance, it is important to design a control mechanism for MBRs in sewage treatment [29]. The control approach regulates and monitors the various parameters such as effluent flow rate, membrane fouling rate, etc., thereby ensuring optimal system performance. In recent times, various control strategies such as predictive control, adaptive control, model-based control, etc., are employed to optimize the process performance. However, they face difficulty in parameter tuning, reliability, interoperability, and model complexity. Hence, the artificial intelligence-based control mechanism was employed for MBR in sewage treatment. The AI-based models utilize the real-time data collected using the sensors and actuators and learn the interconnection between the input features and desired outcomes. Then, it adjusts the operational parameters based on the prediction to optimize the MBR performance. However, the efficiency of the model depends on the quality of collected data and requires a large-scale historical database for training. In addition, the AI-based models face difficulty in generalizing to unseen data (incoming input data). Hence, an optimized intelligent control mechanism was designed in this article to control the MBR in sewage treatment.

4. PROPOSED METHODOLOGY

A novel hybrid ABC-RNN control strategy was designed to regulate the MBR in sewage treatment. This method integrates the benefits of recurrent neural systems [30] and artificial bee colony optimization [31]. Initially, the influent wastewater database was collected and pre-processed. The pre-processing involves data cleaning, data normalization, and feature engineering. After pre-processing, the filtered dataset was utilized to train the RNN model [32]. The RNN model was trained to predict the performance of the MBR system. The predicted MBR performances are passed to the optimization block, which modifies the control variables to optimize the MBR operation. The proposed framework is explained in Fig 1.

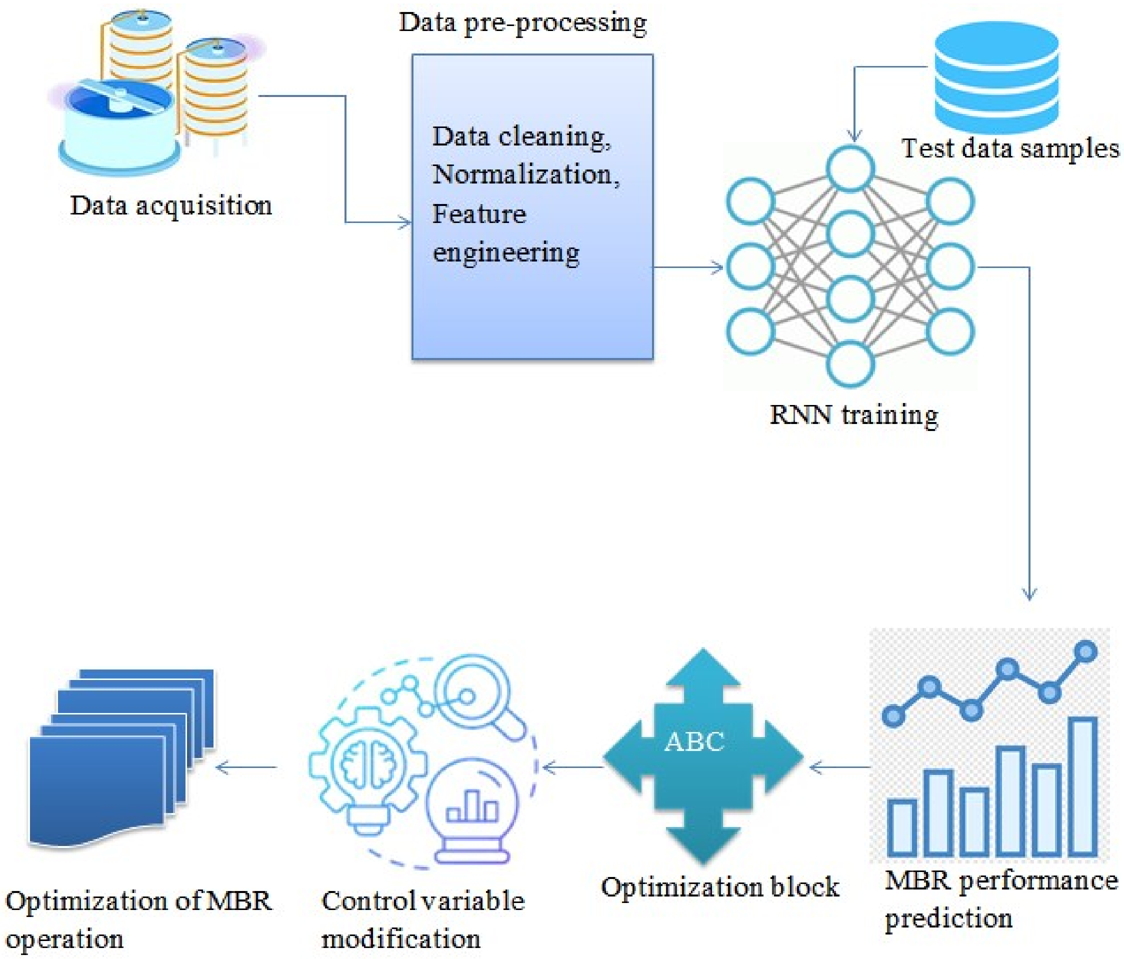


Fig. 1 ABC-RNN framework

4.1 Data accumulation

Data accumulation involves the collection of influent wastewater data from the MBR-assisted sewage treatment process. The influent wastewater data includes the collection of information regarding the flow rate, pH, temperature, nutrient concentrations, chemical oxygen demand (COD), biochemical oxygen demand (BOD), etc. Flow rate determines the volume of wastewater arriving through the MBR system per unit of time. This enables us to understand the hydraulic loading on the MBR. The temperature data defines the thermal criteria of the influent wastewater. It determines the rate of biological processes occurring in the MBR. The pH data defines the alkalinity and acidity of the influent wastewater and ranges from 0 to 14. COD information indicates the volume of oxygen required to oxidize organic elements chemically in the wastewater. This measures the organic pollutant load in the wastewater. BOD data denotes the quantity of oxygen necessary for the biological degradation of organic elements in wastewater. It measures the biodegradable organic content of the influent. Nutrient concentrations data involves the collection of nutrients present in the influent including nitrogen (ammonia, nitrite, and nitrate), phosphorus, and other components. This data helps to understand the wastewater composition and characteristics of the wastewater arriving in the MBR system. However, this collected data contains errors, outliers, missing values, etc., therefore, before the training process the collected data must be pre-processed.

4.2 Data Preprocessing

The process of eliminating the errors, missing values, outliers, etc., from the collected database, is termed as data pre-processing. The data pre-processing involves three major steps namely, cleaning, normalization, and feature extraction. Data cleaning is the process of managing the missing values, outliers, and any inconsistencies present in the database. Here, the regression imputation approach was utilized to detect and resolve these issues in the dataset. This helps to confirm data quality and reliability. The regression imputation is an algorithm, which is mainly utilized to fill the missing values by detecting their values based on other attributes present in the database. This technique is based on the assumption that the missing values are interrelated to the values available in the dataset. Initially, this method detects the feature with missing values. Then the dataset is split into two parts: one part contains complete data (variables without missing values) and the other part with missing values (target attributes). A linear regression model was designed to detect the target attribute using the other variables available in the database. Further, the developed regression unit was applied to the part containing the missing values and the regression model considers the values present in the other part as inputs to predict the missing values for the target variable. Finally, replace the missing values with the predicted values in the dataset. Thus, the technique to replace missing values in the dataset by estimating their values based on other variables existing in the database is called regression imputation, and it is applied in the suggested study.

The first step is to locate the missing values in the dataset. Next, using the portion of the dataset that contains all of the data, a linear regression model is built. Using predictor variables found in the dataset, the regression model attempts to forecast the missing values.The mathematical formulation of the regression model is expressed in Eqn. (1).

$$M_v = R_0 + R_1 P_{v1} + R_2 P_{v2} + R_3 P_{v3} + ... + R_n P_{vn} + E_t \quad (2)$$

Where M_v defines the missing values, $R_0, R_1, R_2, R_3, ...R_n$ refers to the regression coefficients, $P_{v1}, P_{v2}, P_{v3}, ..., P_{vn}$ represents the predictor variables, and E_t denotes the error term. The regression coefficients are determined using the part with complete data. After replacing the missing values, the database was normalized using the min-max scaling approach. This enables to avoid the biases due to differences in scales among the input attributes. Finally, feature extraction was performed, which involves capturing and extracting the most relevant features from the normalized database. In this process, the system extracts meaningful information and eliminates the meaningless data present in the dataset, thereby enhancing the learning process. This data standardization process converts the raw dataset into a suitable format for effective model training [33].

4.3 RNN model training

In the developed control strategy, the RNN was utilized to predict the performance of the MBR based on the historical influent wastewater data. The RNN is a kind of artificial neural network, which has the unique feature to maintain an internal state commonly known as a hidden state. The proposed work is utilized to learn and predict the interconnections and relationships between the input features and the outcomes. Here, pre-processed data was fed into the model training block to train the RNN design. The RNN learns the interconnection between the influent data, MBR performance, and operational parameters. The typical RNN model contains three main layers namely, the input layer, the recurrent layers, and the output layer. It is important to note that the RNN model contains one or more recurrent layers and each layer comprises a sequence of recurrent units, which maintains a hidden state indicating the memory of the network. The input layer accepts the pre-processed database as inputs, the recurrent layers process the input sequences and learns the interconnections between the input sets and the desired results and the output layer detects the target values based on the processed input sequence. Before the training process, the pre-processed dataset must be split into input sets and corresponding target sets. Each input set comprises a sequence of time steps, while the target set consists of the desired outcomes for each time step [34]. In the initial phase of training, the weights and biases of the RNN design were initialized with small random values. An accurate initialization of weights and biases enables the system to achieve better convergence during the training process. After initialization, the forward propagation step was performed. In this step, the input sets are fed into the RNN model to determine the predicted result. At each time step, the recurrent layer progresses the input sets and updates the hidden state. After updating, the recurrent layer passes the hidden state to the next time step and this process continues until updating the final hidden state. The final hidden state is utilized to predict the output. The hidden state updation and output calculation are expressed in Eqn. (2), and (3).

$$H_T = A_f\left(W_{hm} * H_{T-1} + W_{im} * I_T + B_v\right) \quad (2)$$

$$O_T = A_o\left(W_{om} * H_T + B_o\right) \quad (3)$$

Here H_T defines the hidden state at a time step T, A_f refers to the activation function of the recurrent layer, W_{hm} denotes the weight matrix of the hidden state, W_{im} indicates the weight matrix for the input set, I_T denotes the input sequence at a time step T, B_v defines the bias vector of the recurrent layer, O_T represents the predicted output at a time step T, A_o indicates the output layer activation function, W_{om} refers to the weight matrix of the output layer, and B_o defines the bias vectors of the output layer. Further, during the training process, the weight and biases of the RNN model are updated to reduce the errors in the prediction process. Typically, the gradient descent optimization approach has utilized the gradients of the loss function. The mathematical derivation for the updation of weight and bias is expressed in Eqn. (4) and (5).

$$W_{Tn} = W_{To} - \nu * G_a \quad (4)$$

$$B_{sn} = B_{so} - \nu * G_a \quad (5)$$

Where W_{Tn} defines the updated weight, W_{To} represents the old weight, ν indicates the learning rate, G_a refers to the gradient, which indicates the loss function relative to the weight and bias,

B_{sn} defines the updated bias vector, and B_{so} refers to the old bias vector. Finally, the backpropagation was utilized to measure the loss function of the gradient. The backpropagation technique propagates the error back through the recurrent layers, thus it minimizes the overall loss. The loss function measures the deviation between the actual and predicted outcomes at each time step. The loss function is formulated in Eqn. (6).

$$L_{fn} = \left(\frac{1}{S_m}\right)\sum\left(P_o - A_v\right)^2 \tag{6}$$

Where L_{fn} defines the loss function, S_m represents the training samples, P_o denotes the predicted output, and A_v refers to the actual value. The process is repeated iteratively until the prediction error achieves its minimum level. The predicted performances of the MBR such as effluent quality, membrane fouling, energy consumption, etc., are fed as inputs to the optimization block.

4.4 Optimization

The Artificial Bee Colony (ABC) algorithm rapidly searches for ideal solutions to control parameters, minimizing membrane fouling, and improving nutrient removal efficiency, all of which maximize the performance of MBR systems. By investigating and taking advantage of possible solutions, it imitates the foraging activity of bees to enhance effluent quality and reduce energy usage. In the optimization block, the ABC approach uses the predicted MBR performance data to optimize the MBR operation. The ABC algorithm adjusts the control variables such as aeration rate, sludge wasting rate, membrane flux, etc., to optimize the MBR operation. This approach is developed to solve the optimization problems especially the issues in the control mechanism. As a result the wastewater treatment process is extremely effective and efficient. [35]. In the ABC approach, initially, the population of employed bees is initialized with random control variable values indicating different sequences of control parameters for the MBR system. Further, evaluate the fitness of each employed bee's solution by passing the control variables into the MBR system and estimate the performance of the MBR corresponding to its control variables. The objective of the fitness function is to maximize the MBR operation by minimizing the energy consumption and membrane-fouling index and maximizing the effluent quality. The fitness solution of the ABC optimization is expressed in Eqn. (7).

$$Fv_{(C_v)} = f_1(E_c) + f_2(M_{fi}) + f_3(E_q) \tag{7}$$

Where $Fv_{(cv)}$ defines the fitness value relative to the control parameters, f_1 f_2 and f_3 indicates the fitness parameters, which optimizes the MBR performances, E_c M_{fi} E_q and denotes the MBR performance metrics indicating energy consumption, membrane-fouling index, and effluent quality. After defining the fitness function, the employee bee phase begins. In the employee bee phase, each employed bee performs a local search operation by adjusting the control variables around its current solution. Further, generate a new solution by perturbing the current solution using a random displacement vector. It is expressed mathematically in Eqn. (8).

$$C_v(x+1) = C_v(x) + R_v(x) * E_f \tag{8}$$

Here $C_v(x+1)$ defines the new solution defining the adjusted control variables, $C_v(x)$ denotes the current position representing the control variables, $R_v(x)$ refers to the random displacement vector for the employee bee x, and E_f denotes the exploration factor. After adjusting the control variables, evaluate the fitness function for the new solution in the MBR system. If the fitness value for the new solution is greater than the current solution, update the employed bee solution. It is expressed in Eqn. (9).

$$E_{up}(x) = \begin{cases} if\left(Fv_{(C_v(x+1))} > Fv_{(C_v(x))}\right); & C_v(x) = C_v(x+1) \\ else & ; C_v(x) = C_v(x) \end{cases} \tag{9}$$

Where E_{up} defines the function for updating the employee bee solution, $Fv_{(C_v(x+1))}$ refers to the fitness value for the new solution, and $Fv_{(C_v(x))}$ defines the fitness value for the current solution. This process is iteratively repeated until the desired level of optimization is achieved. Thus, the proposed model continuously adjusts the control variables and optimizes the MBR performances.

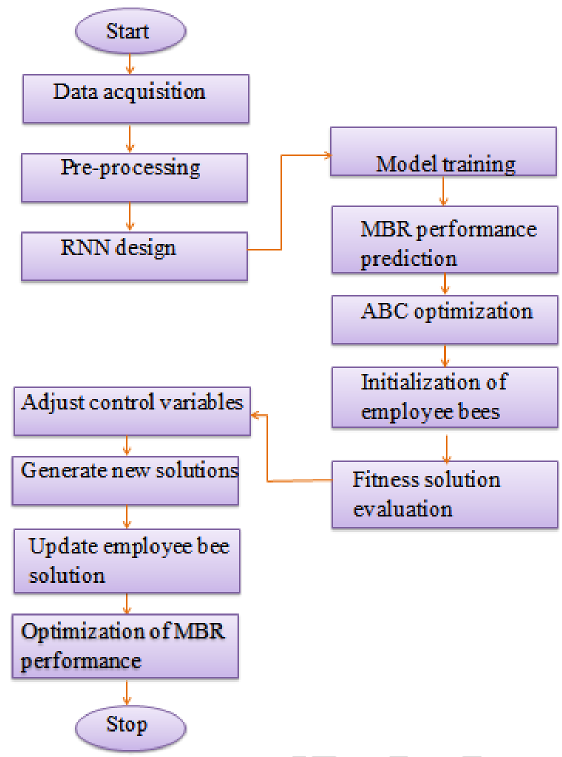


Fig. 2 ABC-RNN workflow

The workflow of the designed model is illustrated in Fig 2. The optimization of MBR operation increases its performances such as effluent quality, and nutrient removal efficiency, and minimizes the energy consumption, and membrane-fouling index. This is achieved by continuously adjusting the control variables of the MBR such as aeration rate, hydraulic retention time, mixed liquor concentration, sludge waster flux, etc., to its optimal range.

5. RESULTS AND DISCUSSION

An optimized intelligent framework was developed to optimize the performance of the MBR system in sewage treatment. This method integrates the benefits of the ABC and RNN algorithms to regulate the operation of the MBR system. The RNN model was trained to forecast the performance of the MBR system and the predicted performances are fed into the optimization block. In the optimization block, the ABC approach was applied to optimize the performance by adjusting the control variables effectively. The designed framework was modeled and implemented in the MATLAB tool, version R2020a. Finally, the performances of the developed scheme were estimated and validated with some existing controller models.

5.1 Dataset description

The presented work was trained and tested with the publically available MBR plant dataset named "Wuhan MBR Dataset." The data was gathered since 2006 from a large-scale (industriak, municipal) MBR plant with a minimum design capacity of 10,000 m^3/day in Wuhan,China. This database includes information related to the operational parameters such as influent flow rate, transmembrane pressure (TMP), mixer liquor suspended solids concentration, and water quality factors like nutrient concentrations including nitrogen, ammonia, phosphorus, COD, BOD, etc. In this dataset, the information is collected on an hourly basis.

5.1.1. Origin of data

Important participants in this development include the Wuhan Sanjintan WWTP and the Fuzhou Yangli Wastewater Treatment Plant (WWTP) Phase IV, among others. In 2014, accomplished projects such as the Macau WWTP and the Chengdu Qingbaijiang WWTP (Upgrade) are notable for their significant capacity for the treatment and repurposing of industrial and municipal wastewater. The data includes significant contributions from companies such as Beijing Origin Water Technology Co., Ltd., which has emerged as a key player in the development of wastewater treatment infrastructure in China. This database was widely utilized by researchers and educational institutions for MBR performance prediction analysis.

5.2 Training and testing performance

Initially, the input database was split into two parts, 80% for training and the remaining 20% for testing purposes. During the training and testing phase, the model's performances are evaluated in terms of accuracy and loss. In the training phase, the accuracy defines the rate at which the proposed model predicts the MBR system performance. In addition, it indicates how well the developed approach is performing on the training database and it represents how fast the developed model learns the interconnections between the input data and the desired outcomes. The training accuracy is estimated by increasing the number of iterations from (0 to 500). The increasing curve of training accuracy demonstrates that the proposed model is more accurate in predicting the performance of the training data. During the initial training phase, the developed model attained 0.8, and it increases on increasing the number of epochs. In model training, the developed model achieved an appropriate accuracy of 0.99.

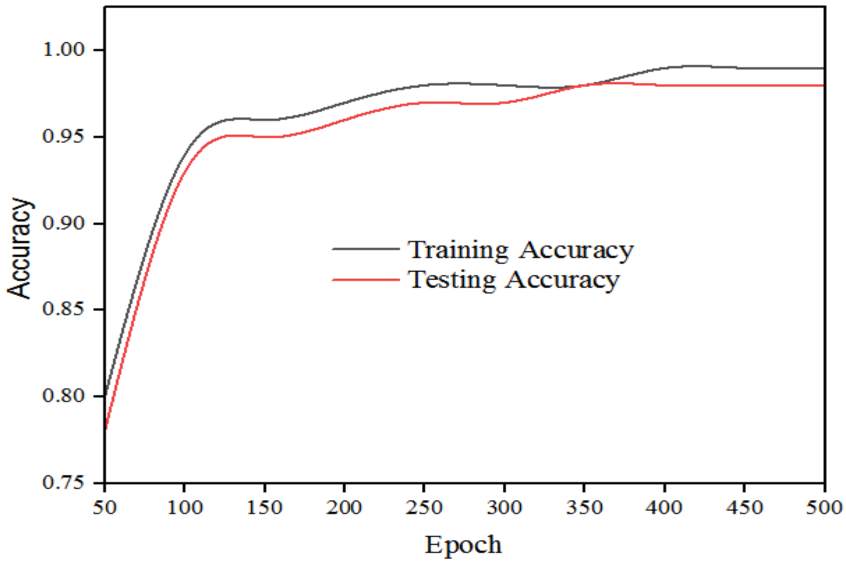


Fig. 3 Training and testing accuracy evaluation

Similarly, the testing accuracy determines the rate at which the proposed model performs over the unseen test data. Typically, the RNN model learns the patterns and relationship between the input data and the desired outcomes in the training phase. In the testing phase, based on the trained information it predicts the performance of the MBR system for the incoming new dataset. The testing accuracy also offers an evaluation of how well the developed model generalizes and accurately predicts the performance of new data. The testing accuracy increases over the epochs, representing that the designed model generalizes well to the new data. The presented framework attains an appropriate testing accuracy of 0.98, which illustrates that it performs well on the test data. The training and testing accuracy of the developed model is evaluated in Fig 3.

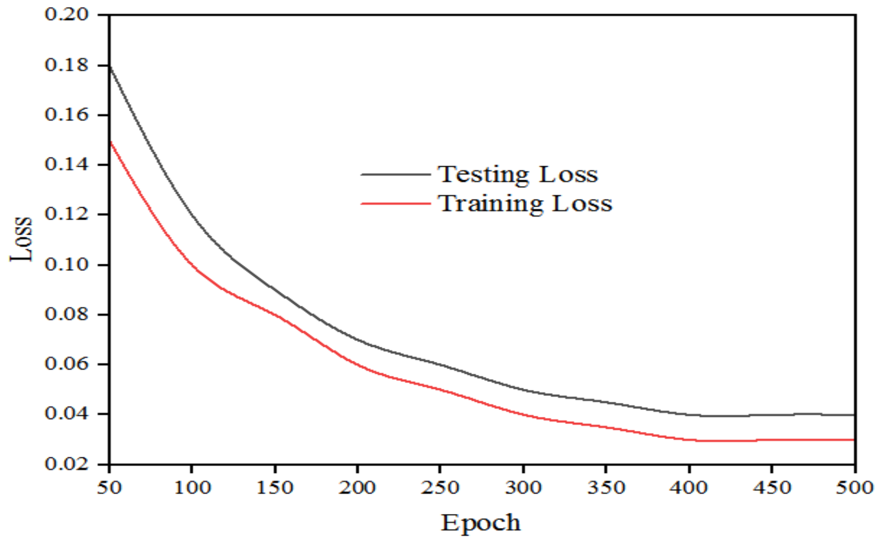


Fig. 4 Training and testing loss evaluation

Similarly, the training and testing losses were evaluated in Fig 4. The training loss indicates the error occurred during the model training. It measures the variation between the actual and predicted performance of the MBR system in the training set. The loss function present in the RNN model evaluates the training loss and it estimates how efficiently the developed model is learning from the training samples. From the performance evaluation, it is observed that the training loss decreases over several iterations. This demonstrates that the developed model accurately predicts the performance of the MBR system with a minimum loss percentage of 0.03. On the other hand, the testing loss determines the deviation between the predicted and actual outcomes for the testing set. It is also known as evaluation loss or validation loss. It measures how well the system generalizes to unseen data. Similar to the training loss, it is evaluated using the loss function in the RNN model. The presented approach attained a very low loss rate of 0.04 for the testing samples, and it decreases with increasing the number of epochs.

5.3 Comparative analysis

In this section, the performances such as effluent quality, energy consumption, computational time, membrane fouling index, nutrient removal efficiency, and sludge production rate are examined and validated with the conventional control strategies. The existing control methods utilized for performance validation include Nonlinear Model Predictive Control Design (NMPC)

[36], Fuzzy logic control (FLC) [37], Particle Swarm Optimization (PSO) [38], ANN [25], and MLP [21].

5.3.1 Effluent Quality

Effluent quality represents the number of removed pollutants or the amount of treated water discharged from the MBR system. It defines the effluent pollutant concentration which is the concentration of contaminants present in the treated water. In addition, it indicates the pollutant removal efficiency, which is determined by comparing the influent and effluent pollutant concentration and it is formulated in Eqn. (10).

$$Ef_q = \left(\frac{C_{ip} - C_{ep}}{C_{ip}} \right) \times 100 \tag{10}$$

Where Ef_q indicates the effluent quality rate, C_{ip} refers to the concentration of influent pollutant, and C_{ep} represents the concentration of effluent pollutant. The greater rate of effluent quality defines that the concentration of pollutants in the treated water is very low.

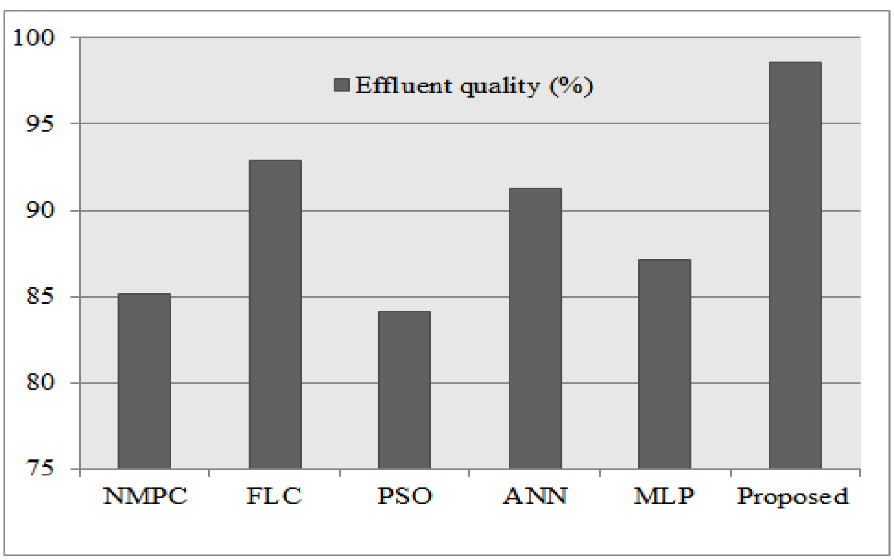


Fig. 5 Validation of effluent quality

The objective of the proposed work is to optimize the MBR system performances such as effluent quality, membrane fouling index, etc. The integration of the proposed control strategy in the MBR system enables it to achieve a greater effluent quality rate of 98.56%. Further, to validate that the attained effluent quality rate is higher than existing models, it is compared with conventional methods like NMPC, FLC, PSO, ANN, and MLP. The incorporation of these control methodologies in the MBR system earned effluent quality of 85.17%, 92.86%, 84.10%, 91.28%, and 87.12%, respectively. This comparative performance evaluation determines that the optimization of MBR operation using the proposed model enhances the effluent quality. The comparative performance of effluent quality is shown in Fig 5.

5.3.2 Membrane fouling index

The membrane-fouling index is an important performance metric, which illustrates the working efficiency of the MBR system. It measures the fouling of the membranes in an MBR system during wastewater treatment. Moreover, it estimates the extent of fouling on the membrane surface, which affects the functional efficiency of the MBR system. The mathematical formula for the calculation of it is expressed in Eqn. (11).

$$T_{mdi} = \left(\frac{Tmd_t - Tmd_{t-1}}{\Delta T \times A_r} \right) \times 100 \tag{11}$$

Where T_{mdi} denotes the transmembrane index (TMP), Tmd_t defines the transmembrane pressure at the current time step t, Tmd_{t-1} represents the transmembrane pressure at the previous time step $t-1$, ΔT refers to the time interval between the measurements, and A_r denotes the area of the membrane surface. The greater TMP index represents a rapid increase in pressure and a higher rate of fouling.

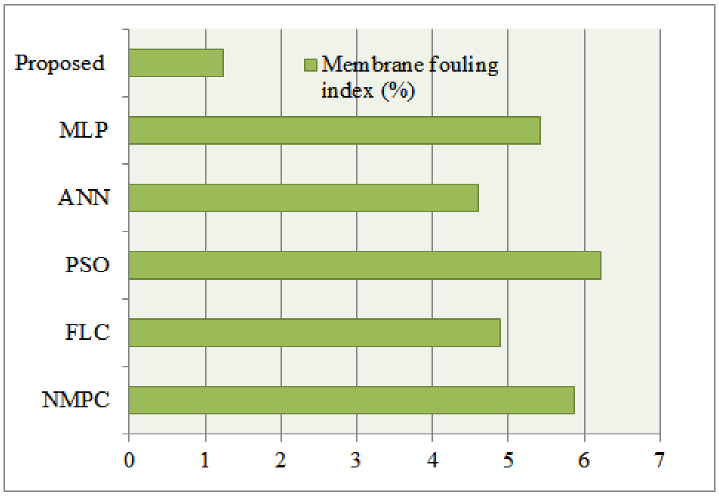


Fig. 6 Comparative performance of membrane fouling index

The membrane fouling index performance of the MBR was examined to evaluate the effectiveness of the developed control mechanism in optimizing the TMP index. The comparative performance of the membrane fouling index is displayed in Fig 6. The integration of the proposed control design in the MBR system enables it to attain a lower fouling index of 1.24%. On the other hand, the existing techniques such as NMPC, FLC, PSO, ANN, and MLP obtained 5.87%, 4.90%, 6.23%, 4.61%, and 5.43%, of the TMP index, respectively. From the comparative analysis, it is clear that the developed control design effectiveness minimizes the fouling index.

5.3.3 Nutrient Removal Efficiency

The nutrient removal efficiency quantifies how effectively the MBR system removes the nutrient components such as ammonia, nitrogen, phosphorus, etc., from the wastewater during the treatment process. It measures the rate at which the MBR system reduces the nutrient content from the wastewater. The formula for the estimation of nutrient removal efficiency is expressed in Eqn. (12).

$$N_{Rf} = \left(\frac{I_{nc} - E_{nc}}{I_{nc}} \right) \times 100 \tag{12}$$

Where N_{Rf} is the nutrient removal efficiency, I_{nc} refers to the concentration of nutrients in the wastewater, and E_{nc} defines the effluent nutrient concentration.

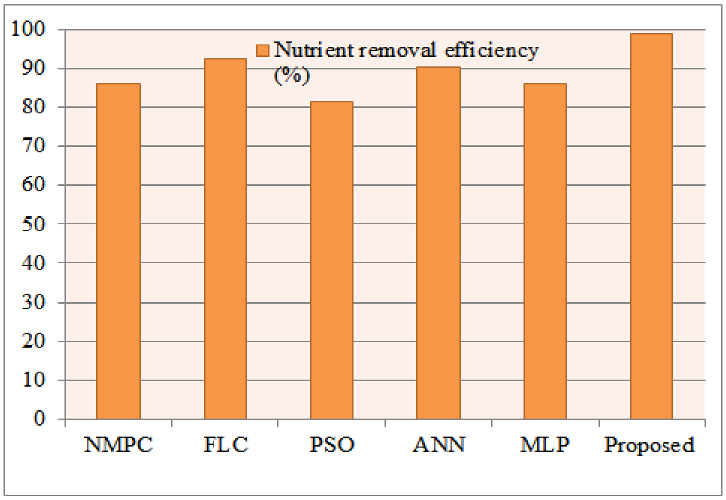


Fig. 7 Evaluation of nutrient removal efficiency

The nutrient removal efficiency is one of the important performance metrics of the MBR system, which defines the quality of treated water. Achieving greater nutrient removal efficiency is significant for regulatory compliance and environmental protection. The nutrient removal efficiency of the developed model is compared with existing methods like NMPC, FLC, PSO, ANN, and MLP. These traditional control designs attained 85.98%, 92.46%, 81.23%, 90.37%, and 85.89%, of nutrient removal efficiency, respectively. The nutrient removal efficiency attained by the proposed model is 98.70%, which is high compared to the nutrient removal efficiency achieved by the conventional models. This comparative assessment validates that the optimization of the MBR function and control variables using the developed control model increases nutrient removal efficiency. The evaluation of nutrient removal efficiency is visualized in Fig 7.

5.3.4 Computational time

The computation complexity defines the time consumed by the proposed model for performing data pre-processing, model training, optimization process, and other computational tasks. The computational time attained by the developed model is tabulated in Table 1. The total computational time achieved by the presented model is 2.87s, in which the system consumed 0.42s for pre-processing the dataset, 1.20s for RNN model training, 0.65s for the optimization process, and 0.60s for other computational tasks.

Table 1 Computational Time Analysis

Tasks	Time (s)
Data-processing	0.42
RNN model training	1.20
Optimization process	0.65
Other computational tasks	0.60
Total computational time	2.87

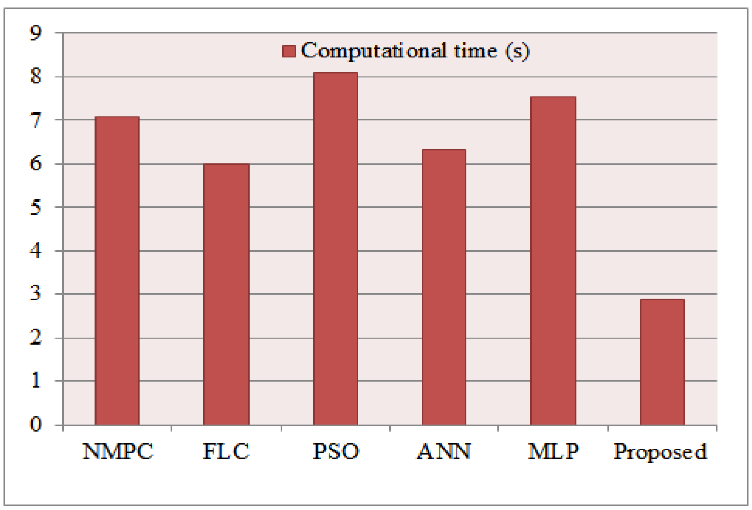


Fig. 8 Computational time validation

The computational time validation is important to manifest the effectiveness of the designed framework. The comparative analysis of computational time is displayed in Fig 8. The designed framework consumed very less time 2.87s, whereas, the traditional control designs like NMPC, FLC, PSO, ANN, and MLP consumed 7.09s, 5.98s, 8.11s, 6.32s, and 7.52s, respectively. The comparison of computational time manifests that the designed model quickly learns the interconnection between the input features and desired performances and effectively optimizes it with minimum time consumption.

5.3.5 Energy Consumption

Energy consumption (W) refers to the quantity of electrical power used when the Membrane Bioreactor (MBR) operates in sewage treatment. Sustainable wastewater treatment depends on the efficient use of energy resources, which is indicated by a lower value in this parameter. The suggested approach shows its efficacy in optimizing energy usage and encouraging energy-efficient MBR operations by attaining a noticeably lower energy consumption of 27.9 watts in comparison to alternative control strategies.

Table 2 Numerical analysis of comparative performance validation

Approach	Effluent quality (%)	Energy consumption (W)	Nutrient removal efficiency (%)	Computational time (s)	Membrane fouling index (%)
NMPC	85.17		85.98	7.09	5.87
FLC	92.86		92.46	5.98	4.90
PSO	84.10		81.23	8.11	6.23
ANN	91.28		90.37	6.32	4.61
MLP	87.12		85.89	7.52	5.43
Proposed	98.56	27.9	98.70	2.87	1.24

The overall numerical analysis of the comparative performance is tabulated in Table 2. It lists the performances such as effluent quality, membrane-fouling index, nutrient removal efficiency, energy consumption, and computational time attained by the traditional approaches and the developed framework. This comprehensive performance comparison demonstrates that the integration of the proposed method in the MBR system optimizes its operations and improves performance. Furthermore, it is observed that the utilization of neural network-based control strategies in the MBR system provides better performances than the typical controller designs such as PSO and NMPC.

6. CONCLUSION

The presented research work develops an innovative approach ABC-RNN approach to optimize the performance of the MBR in sewage treatment. This hybrid approach provides a comprehensive solution to improve MBR performance by leveraging the benefits of optimization and intelligent models. In the proposed framework, the RNN design examines and learns the patterns and relationships between the input and output parameters to predict the dynamic performance of the MBR system. The ABC block utilizes these predicted outcomes and intelligently searches for the best control variables to optimize the MBR performances. Thus, the developed hybrid model controls the varying influent parameters and system dynamics effectively. The developed model was modeled in MATLAB and evaluated with the publically available Wuhan MBR database. Finally, a comprehensive comparative assessment was carried out with the existing NMPC, ANN, FLC, PSO, and MLP models to validate the performances of the proposed model. The comparative analysis illustrates that the performances such as effluent quality and nutrient removal efficiency are improved by 14.46% and 17.47%, and the membrane-fouling index and computational time are 3.37%, and 3.11s, respectively. Hence, it is proved that the optimization of MBR in sewage treatment using the proposed ABC-RNN model enhanced the effluent quality, minimized the membrane fouling index, improved the nutrient removal efficiency, and decreased the time consumption.

Compliance with Ethical Standards

Conflict of interest

The authors declare that they have no conflict of interest.

Human and Animal Rights

This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent

Informed consent does not apply as this was a retrospective review with no identifying patient information.

Funding: Not applicable

Conflicts of interest Statement: Not applicable

Consent to participate: Not applicable

Consent for publication: Not applicable

Availability of data and material:

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

REFERENCES

1. Kamali, Mohammadreza, et al. "Artificial intelligence as a sustainable tool in wastewater treatment using membrane bioreactors." Chemical Engineering Journal 417 (2021): 128070.
2. Crini, Grégorio, et al. "Innovative technologies to remove alkylphenols from wastewater: a review." Environmental Chemistry Letters 20.4 (2022): 2597-2628.
3. Maqsood, Quratulain, et al. "Novel strategies and advancement in reducing heavy metals from the contaminated environment." Archives of Microbiology 204.8 (2022): 478.
4. Behera, Meerambika, et al. "A review on the treatment of textile industry waste effluents towards the development of efficient mitigation strategy: An integrated system design approach." Journal of Environmental Chemical Engineering 9.4 (2021): 105277.
5. Fu, Rongzhan, et al. "The application and progress of techno-economic analysis and life cycle assessment in biomanufacturing of fuels and chemicals." Green Chemical Engineering (2022).
6. Fernandes, Steven Lawrence, et al. "A reliable framework for accurate brain image examination and treatment planning based on early diagnosis support for clinicians." Neural Computing and Applications 32 (2020): 15897-15908.
7. Lalle, Yandja, et al. "Communication technologies for smart water grid applications: Overview, opportunities, and research directions." Computer Networks 190 (2021): 107940.
8. Ahmed, S. F., et al. "Recent developments in physical, biological, chemical, and hybrid treatment techniques for removing emerging contaminants from wastewater." Journal of hazardous materials 416 (2021): 125912.

9. Lu, Zhe, et al. "Phosphorus deficiency stimulates dominance of Cylindrospermopsis through facilitating cylindrospermopsin-induced alkaline phosphatase secretion: Integrating field and laboratory-based evidences." Environmental Pollution 290 (2021): 117946.
10. Saidulu, Duduku, Abhradeep Majumder, and Ashok Kumar Gupta. "A systematic review of moving bed biofilm reactor, membrane bioreactor, and moving bed membrane bioreactor for wastewater treatment: Comparison of research trends, removal mechanisms, and performance." Journal of Environmental Chemical Engineering 9.5 (2021): 106112.
11. Pandey, A. K., et al. "Utilization of solar energy for wastewater treatment: Challenges and progressive research trends." Journal of Environmental Management 297 (2021): 113300.
12. Li, Zhong, et al. "Bacterial biofilms as platforms engineered for diverse applications." Biotechnology advances (2022): 107932.
13. O'Dwyer, Edward, et al. "Optimisation of wastewater treatment strategies in eco-industrial parks: Technology, location and transport." Chemical Engineering Journal 381 (2020): 122643.
14. Xu, Yanran, et al. "Data-driven prediction of neutralizer pH and valve position towards precise control of chemical dosage in a wastewater treatment plant." Journal of Cleaner Production 348 (2022): 131360.
15. Merabet, Ghezlane Halhoul, et al. "Intelligent building control systems for thermal comfort and energy-efficiency: A systematic review of artificial intelligence-assisted techniques." Renewable and Sustainable Energy Reviews 144 (2021): 110969.
16. He, Zhaoyu, Weimin Guo, and Peng Zhang. "Performance prediction, optimal design and operational control of thermal energy storage using artificial intelligence methods." Renewable and Sustainable Energy Reviews 156 (2022): 111977.
17. Pan, Yue, and Limao Zhang. "Roles of artificial intelligence in construction engineering and management: A critical review and future trends." Automation in Construction 122 (2021): 103517.

18. Zhu, Junren, Zhenzhen Jiang, and Li Feng. "Improved neural network with least square support vector machine for wastewater treatment process." Chemosphere 308 (2022): 136116.
19. Sharifi, Abbas, Mohsen Ahmadi, and Ali Ala. "The impact of artificial intelligence and digital style on industry and energy post-COVID-19 pandemic." Environmental Science and Pollution Research 28 (2021): 46964-46984.
20. Rehamnia, Issam, et al. "Simulation of seepage flow through embankment dam by using a novel extended Kalman filter based neural network paradigm: Case study of Fontaine Gazelles Dam, Algeria." Measurement 176 (2021): 109219.
21. Yaqub, Muhammad, and Wontae Lee. "Modeling nutrient removal by membrane bioreactor at a sewage treatment plant using machine learning models." Journal of Water Process Engineering 46 (2022): 102521.
22. Viet, Nguyen Duc, and Am Jang. "Development of artificial intelligence-based models for the prediction of filtration performance and membrane fouling in an osmotic membrane bioreactor." Journal of Environmental Chemical Engineering 9.4 (2021): 105337.
23. Hosseinzadeh, Ahmad, et al. "Modeling water flux in osmotic membrane bioreactor by adaptive network-based fuzzy inference system and artificial neural network." Bioresource technology 310 (2020): 123391.
24. Liang, Jiahao, et al. "Aerobic sludge granulation in shale gas flowback water treatment: Assessment of the bacterial community dynamics and modeling of bioreactor performance using artificial neural network." Bioresource Technology 313 (2020): 123687.
25. Algoufily, Yasser, Peiying Hong, and Taous-Meriem Laleg Kirati. "Membrane Bioreactor control and Fouling Monitoring using Artificial Neural Network-Based Approach." IFAC-PapersOnLine 55.33 (2022): 66-71.
26. Cámara, José M., Victorino Diez, and Cipriano Ramos. "Neural network modelling and prediction of an Anaerobic Filter Membrane Bioreactor." Engineering Applications of Artificial Intelligence 118 (2023): 105643.

27. Yaqub, Muhammad, et al. "Modeling of a full-scale sewage treatment plant to predict the nutrient removal efficiency using a long short-term memory (LSTM) neural network." Journal of Water Process Engineering 37 (2020): 101388.
28. Chen, Yifeng, et al. "Quantification of interfacial energies associated with membrane fouling in a membrane bioreactor by using BP and GRNN artificial neural networks." Journal of colloid and interface science 565 (2020): 1-10.
29. Jadhav, Anuja R., Pranav D. Pathak, and Roshani Y. Raut. "Water and wastewater quality prediction: current trends and challenges in the implementation of artificial neural network." Environmental Monitoring and Assessment 195.2 (2023): 321.
30. Xiao, Jianqiong, and Zhiyong Zhou. "Research progress of RNN language model." 2020 IEEE International Conference on Artificial Intelligence and Computer Applications (ICAICA). IEEE, 2020.
31. Wang, Hui, et al. "Improving artificial bee colony algorithm using a new neighborhood selection mechanism." Information Sciences 527 (2020): 227-240.
32. Rajagopal, R., MohdAsif Gandh, N. Selvam, Sandip S. Kanase, V. Bhoopathy, Nitin Mishra, and A. Rajaram. "Optimising Waste Collection and Recycling in Urban Areas with Vanet." (2024).
33. Indira, D. N. V. S. L. S., Rajendra Kumar Ganiya, P. Ashok Babu, A. Jasmine Xavier, L. Kavisankar, S. Hemalatha, V. Senthilkumar et al. "Improved artificial neural network with state order dataset estimation for brain cancer cell diagnosis." *BioMed Research International* 2022 (2022).
34. Rajaram, A., K. Padmavathi, Srivardhan Kumar Ch, A. Karthik, and K. Sivasankari. "Enhancing Energy Forecasting in Combined Cycle Power Plants using a Hybrid ConvLSTM and FC Neural Network Model." *International Journal of Renewable Energy Research (IJRER)* 14, no. 1 (2024): 111-126.
35. Pushpavalli, M., D. Dhanya, Megha Kulkarni, R. Rajitha Jasmine, B. Umarani, M. RamprasadReddy, Durga Prasad Garapati, Ajay Singh Yadav, and A. Rajaram. "Enhancing Electrical Power Demand Prediction Using LSTM-Based Deep Learning Models for Local Energy Communities." *Electric Power Components and Systems* (2024): 1-18.

36. Guo, Xingang, Peiying Hong, and Taous-Meriem Laleg-Kirati. "Nonlinear Model Predictive Control Design for BSM-MBR: Benchmark of Membrane Bioreactor." IFAC-PapersOnLine 53.2 (2020): 16524-16530.
37. Singh, Nitin Kumar, et al. "Artificial intelligence and machine learning-based monitoring and design of biological wastewater treatment systems." Bioresource technology (2022): 128486.
38. Ye, Xudong, et al. "System Control and Optimization in Wastewater Treatment: A Particle Swarm Optimization (PSO) Approach." Soft Computing Techniques in Solid Waste and Wastewater Management. Elsevier, 2021. 393-407.