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Intelligent system for Distributed Quality Monitoring of Sewage Management based on Wastewater Treatment Procedure and Data Mining

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Abstract

Wastewater treatment procedures (WWTP) rely heavily on accurate forecasting of treatment results to keep oxygenation levels under control. Conventional biochemical mechanism-driven approaches provide poor results, mainly due to complicated and redundant system factors. As sewage treatment operations expand fast, automated operational solutions are needed to achieve this goal. In the research, data mining was used to model the WWTP to predict the outcomes based on input circumstances and the amount of oxygenation provided to the system. Combined Sustainability Research for Wastewater Treatment procedures (CSR-WWTP) is proposed in this research. Data-driven approaches to modeling WWTP have already been developed but do not consider long-term treatment procedures and structure features. Forecasting and management for the WWTP are described in this article using a combination of convolutional neural networks (CNN) and recurrent neural networks (RNN). The first stage utilizes the CNN structure to dynamically learn and encrypt the local features of each WWTP timestamp in the first phase. The RNN model is applied to the WWTP to express global sequence characteristics using local feature encryption. For this purpose, it conducts a huge number of tests to assess the performance and accuracy of the proposed forecasting framework.

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1. Introduction

In addition to putting a significant strain on available resources, the ever-growing human populations and industrial expansion have also contributed to environmental degradation and weather change [1]. Residential, industrial, and pollutants discharged into surface and groundwater have worsened water resources' accessibility, quantity, and cleanliness via their unwise usage [2-3]. Potential impurities in wastewater treatment include oxygen-demanding compounds, bacteria, minerals, and elemental and synthetic organic compounds.

Ammonia and other oxygen-demanding chemicals pose a threat to aquatic life [5]. Pathogens are transported into the groundwater through industrial effluents, groundwater recharge, and urban sources [6]. Agriculture wastewater contains high amounts of minerals such as carbon, nitrogen, and phosphate [7]. Large quantities of phosphate and nitrate can lead to nutrient overload and algal development if they are not adequately handled [8].

It is a known fact that heat affects water's ability to hold oxygen, and therefore industrial water used for cooling is frequently too hot to be discharged into nature. Aquatic life and natural watercourses are affected by wastewater that has not been examined and cleaned before release [9-10]. The further problem is that groundwater is in short supply, making wastewater treatment (WWT) technologies necessary to produce reusable water or lower pollutant contents towards levels managed by environmental remediation systems to meet the growing water requirements (biogeochemical circle) [11].

Multiple methods are used in today's sewerage systems to meet purity requirements set by regulatory bodies such as the Environmental Preservation Authority, the European Freshwater Policy, and the United States Development Scheme [12-13]. Technological processes can be based on the physical, ecological, or chemical elements or a mix of these processes. Solids are removed from sewage using physical methods, such as screens and filtration. Similar features are used in biochemical functions to clean and degrade hazardous wastewater [14].

Chemical and physical methods are typically combined to eliminate complex contaminants. As a result, it is necessary to adequately characterize sewage streams to discover solutions that might decrease pollutants to reasonable standards [15]. The scarcity of water supplies and the high energy costs associated with WWTPs, among the factors to be considered, are reducing the overall volume of the contaminant or a mixture of both.

A significant drop in wastewater quantity can significantly influence financial competence, flow/loading of WWTPs, procedure expenses, energy needs, and environmental impacts. Stream reduction technologies, such as detectors for defect detection, saturation readings, and effective controllers save 25 to 35 percent of water. Using multi-point waste management, reuse, and sediment removal can help industrial operations reduce their wastewater output [16-17]. Furthermore, WWTPs require an optimized framework and assessment criteria to minimize costs, energy needs, and environmental consequences while fulfilling regulatory restrictions. An overview of sewage characterization, treatment methods, modeling, and optimization methodology for building effective WWTPs is presented in this paper. It also includes economic theory and sustainable evaluation [18-19].

For this reason, the current study aims to develop a method for predicting Water Treatment Results (WTR) that integrates both local process variables and global sequence elements. It presents a new prediction and controlling system that combines Convolutional Neural Networks with Recurrent Neural Networks. Conversely, a convolutional neural networks (CNN) model is developed to dynamically identify the local characteristics of each timing in the WTP and integrate them.

Initial characteristics are encoded by the complete connection layer, which comprises convolutional, pooled, and fully connected layers. Based on local characteristic encoding, a recurrent neural networks (RNN) model is used to describe the global sequence characteristics of the WWTP deeply. RNN outputs are used to produce predictions. It undertakes many computational operations on real-world datasets to assess the suggested CSR-WWTP platform's performance and accuracy.

The data-driven forecasting of WTR using global sequential characteristics has been achieved. The following are some of the main findings of this article:

- WWTP has time-series properties, and existing data-driven techniques are limited in capturing these features effectively.
- A novel CSR-WWTP method is proposed to automatically anticipate treatment outcomes given the input parameters and oxygenation levels.
- The suggested CSR-WWTP is experimentally evaluated for activity and performance using a real-world dataset obtained from a wastewater treatment plant.

The rest of the article is as follows: Section 2 illustrates the background of the wastewater treatment models. The proposed Combined Sustainability Research for Wastewater Treatment procedures (CSR-WWTP) is designed and implemented in section 3. Section 4 discusses the software analysis and evaluation. The conclusion and future scope are discussed in section 5.

2. Background to the Wastewater Treatment Models

Since numerous undetectable biochemical reactions occurred between distinct chemical components, WWTP was a complicated classic technique characterized by inner particle movements and invisible ambiguity [20]. As a result of the limitations of manual calculation capabilities, standard biochemical mechanism-driven methods for this aim heavily depended on complex and duplicated parameter values. Outcomes included a dramatic rise in the volume of sewage produced, requiring new control strategies for WWTPs using high-performance computing techniques [21]. As a result of people's desire for cognition, recent advances in artificial intelligence have emerged, greatly assisting cross-domain problem-solving approaches.

Data mining is a field of artificial intelligence used in various industrial settings to tackle different engineering challenges through statistical teaching strategies [22]. It was possible to describe the World Trade Program (WTP) mathematically as an abstraction grey box design, with seen outcomes and unseen intermediary rules. Systems based on data, which excel in extracting features and cognitive computing, ideally represented the WTP.

Total suspended solids (TSS), total dissolved solids (TDS), pH, biological loads, chemical oxygen demand (COD), biochemical oxygen demand (BOD), and hazardous ions were only a few of the parameters used to characterize sewage. Application Program Interface (API) and endocrine disruptive compounds (EDCs) were among the other parameters used to describe wastewater [23]. Depending on the origin of the contaminated stream, their usual range might vary substantially. In municipal sewage from domestic sources, BOD levels went from 150 to 450 mg/l, whereas nitrogen levels ranged from 25 to 95 mg/l, and phosphorus levels ranged from 6 to 23 mg/l, respectively [24].

Meals, beverages, and milk industry effluents had BOD and COD levels 10–120 times greater than municipal pollutants. Organics and APIs were abundant in pharmaceutical pollutants. WWTP techniques were connected according to the effluent origin, its pollutant characteristics and relative quantities of contaminants, and information regarding safe disposal or reuse limitations to build a case-specific process flow chart [25].

Various relevant methods have been proposed during the past couple of decades, and data-driven modeling for WTP has become increasingly popular in scientific circles. The oldest of them were based on numerical approaches and had not yet used artificial intelligence. A data-driven approach was developed by Corominas et al. in this regard [26]. In contrast, Street et al. suggested a variation on the least-squares method to forecast outlet quality in preparation [27]. Studies have explored novel solutions due to the surface depiction of complicated biological processes offered by standard mathematical approaches.

An animal's brain neurons are imitated in neural networking methods for parallel and distributed data computing to achieve excellent performance. In recent years, the neural networking approach has been expanded for several industrial settings incorporating the WTP due to its ultra-high sensitivity and ease of adaptation to potentially complicated processes. Kumar et al. developed a customized back-propagating neural networking method that enables adjustable training data to estimate outlet state [28].

Elkhatib et al. predicted the outcomes of the WTP using a feed-forward, backpropagation neural training approach using artificial neural networks [29]. As a result, Gearheart et al. developed an optimum variable WTP setpoint and a setpoint monitoring feedback control [30]. Some academics have also studied the connection of neural networks with a fuzzy inference system, a robust theoretical reasoning technique, to implement inference capabilities. Li et al. demonstrated the superiority of a fuzzy neuronal network prediction management strategy for WTP [31].

The anaerobic digesting system was fitted with a fuzzy neural network framework, and its performance in forecasting WTR was tested by Bashar et al. [32]. A fuzzy neural network-based adaptable control system architecture for multi-objective WTP was introduced by O'Brienet al. [33]. Both an optimizing component and flexible fuzzy neural networks were included in the control system. Scholars developed a control mechanism for WTP's oxygen concentration using self-organizing fuzzified neural networks.

A multi-objective optimum controller was also developed. Wavelet translation theory was also included in the neural network structure for WTR predictions to get a quicker computational efficiency of algorithms. WTR prediction was achieved using a mixed computational technique proposed by the scholars. This model, developed by Huang et al., is based on fuzzy spectral neural networks and increases processing capability [34]. They used wavelet neural networks and adaptable scaled fusion to establish an estimating technique for WTR.

The notion that treatment procedures at various frames are autonomous was at the core of nearly all existing methods, which relied on modeling WTP at distinct timestamps. There were still sequence connections between treatment procedures at various timestamps. At one time, a biological response involves energy and resource changes that affect the treatment procedure at the following timestamp. A universal sequence dependence feature must be considered in the data-driven design of WTP.

Even if many methods were available, there was lagging in efficient and faster treatment. The proposed model was designed to combine different models to get optimum results and enhance the performance of wastewater treatment [35].

3. Proposed Combined Sustainability Research for Wastewater Treatment Procedure (CSR-WWTP)

By providing decision-making skills, hierarchical control methods do not exclude traditional systems. Wastewater Treatment Plants utilize this sort of control technique because of the substantial variations in the development times of the factors taken into consideration. The groundwater table, pH, flow velocity, and absorbed oxygen content change rapidly in the containers. The highest reaction time is around 12 minutes. In comparison, the rate of organic material or nitrogen compounds feeding and biomass increase, which progresses slowly over days.

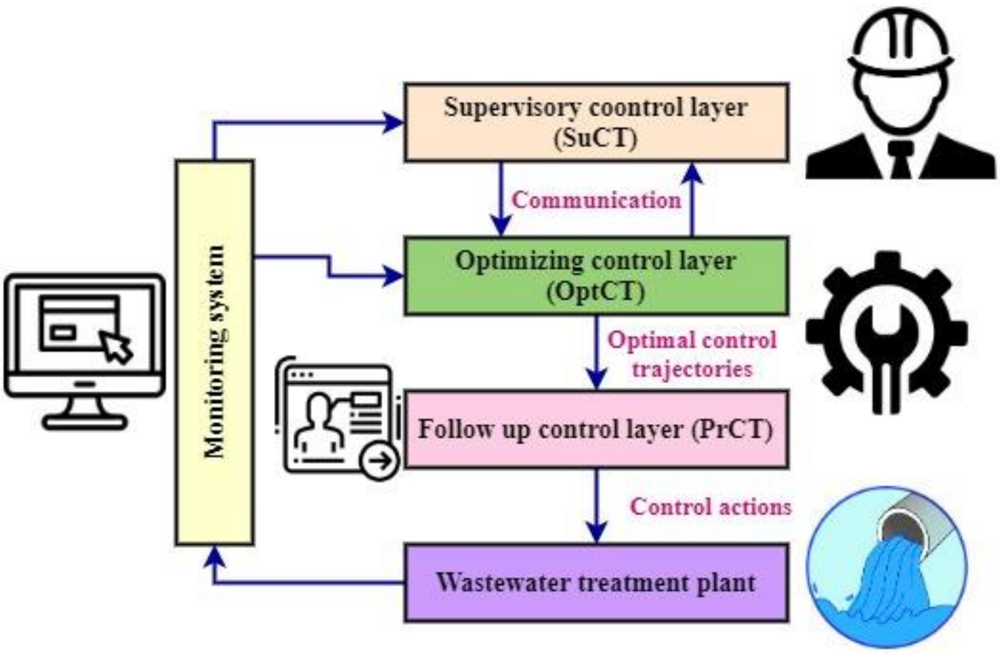

Figure 1: The schematic view of the proposed CSR-WWTP model

The schematic view of the proposed CSR-WWTP model is illustrated in Fig. 1. The supervisor layers (SuCT), the optimizing layers (OptCT), and the processing control layers (PrCT), monitoring systems, and wastewater treatment controllers are the significant parts of the hierarchy organization. As part of a forecasting control approach, the OptCT minimizes objective functions and calculates an ideal baseline for a lower appropriate voltage, such as a dissolving oxygen saturation loop, before implementing it. There are long, medium, and short-term aims for OptCT. Variation in input perturbations and timelines of behavior in the biological sewage treatment plant produces time-varied horizons for the objectives.

Each time scale is controlled in different ways. These rely on the control method used and, as a result, the optimization problem and the restrictions connected with that optimization solution. OptCT requires the following data to take appropriate action: the present state of the systems, a forecast of disruptions, and data about restrictions. The monitoring device provides the first two. Monitors perform four main tasks: collecting observations, estimating, and forecasting. It relies on the dynamism of the observed elements, timelines, and measuring devices when discussing the temporal resolution.

By determining the functionalities and restrictions of OptCT, SuCT is accountable for overseeing the functioning of all levels in the system. In addition, the supervisor reviews the plant's status continuously, changes the modeling and control variables, makes decisions to achieve global targets for controller parameters, verifies that quantities are within normal limits, and manages alert situations as needed.

At any one moment, SuCT has access to data from all the other components in the control hierarchy. SuCT thus has a comprehensive awareness of the present activities of the overall system. When unintended events happen, it responds appropriately to guarantee that control measures are as successful as possible. The supervisor creates a control plan based on the information supplied by the tracking system, the optimizing level, and the controlling strategy.

These two programs are installed on a computer, and they are accountable for the organization of all controller parameters and communications between PrCT and OptCT. According to the optimizing layer, the PrCT is responsible for following the standards that have been calculated. At this level, numerous control loops are developed. However, only two controlling loops were discussed. Control system pressure created by the blower in pipelines excludes disruptions from the oxygen concentration control loop resulting from the valve opening changes. Secondly, the optimizing control layer adjusts the absorbed oxygen content in the oxygenation tank to maintain a particular reference value set by the first. Aside from the two primary control loops, the PrCT also implements auxiliary control loops and restriction functions.

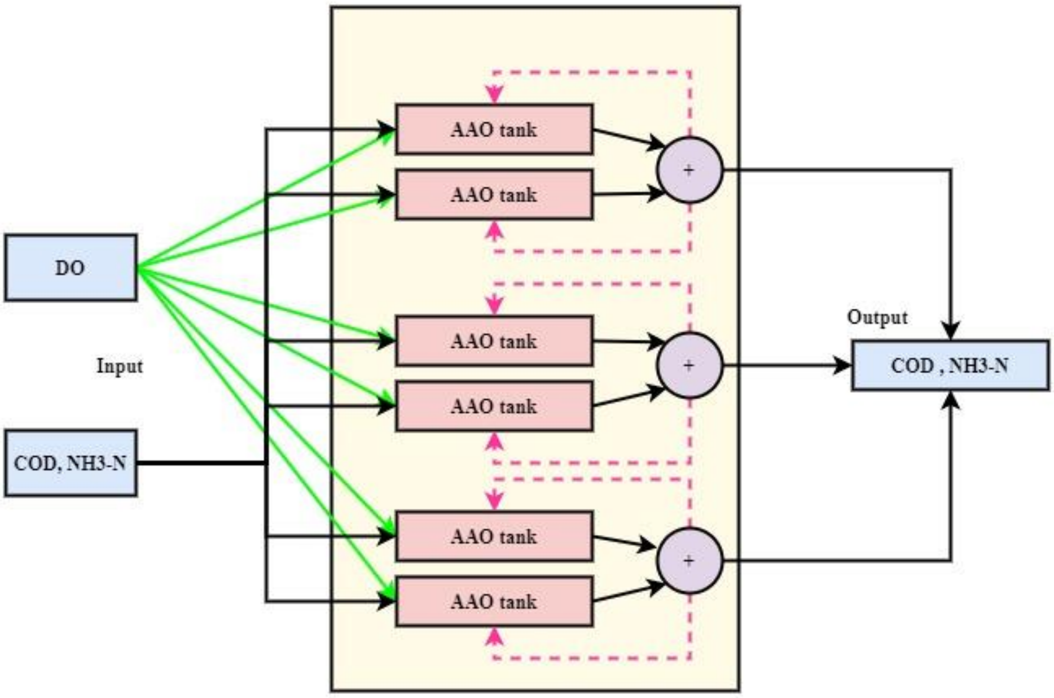

Figure 2: Fundamental blocks of the proposed CSR-WWTP model

The basic blocks of the proposed CSR-WWTP model are denoted in Fig. 2. It has input dissolved oxygen (DO), input chemical oxygen demand (COD), ammonium nitrate (NH_3-N), and the output COD and NH_3-N. Following is a summary of the fundamental concepts of this wastewater treatment facility.

- Preliminary COD requirement indicator before joining treatment chambers is monitored.
- Ammonia nitrogen level is calculated before reaching processing chambers.
- In the Aerobic –aerobic-oxygenation (A_2/O) treatment process, tanks are pumped with dissolved oxygen.
- Output COD: the end COD indicator after processing chambers.
- Ammonia nitrogen indicators are measured in treatment chambers.

COD and NH_3–N are considered significant pollutant indices that must be addressed. DO addition to A_2/O processing containers is adjusted as part of the treatment procedure in real-time. Each series comprises two Aerobic –aerobic-oxygenation (A-A-O) processing containers. There are a total of 20 processing containers in the wastewater treatment facility. The dataset was collected from August 2017 to April 2020 by installing sensors in all major constructions to track the quantity values of the abovementioned five indices. After each cycle, a specific amount of sludge is released as a backflow.

Based on pollutant indexing at the intake, the objective of this work is to develop a method that can theoretically describe instantaneous A-A-O treatment procedures and forecast outflow contaminant indexes based on injection pressure and the design quantity of DO within tanks. In addition, the CSR-WWTP process is based on three principles.

Assumption 1: The treatment containers in various groups are theoretically autonomous and have few internal links during treatment.

Assumption 2: Since the backflow proportion is always 320 percent, its effects are disregarded.

Assumption 3: COD and NH_3–N are measured in milligrams per liter (mg/L), and the intake flow rate is assumed to be nearly uniform.

3.1 Framework

Eighteen containers' worth of DO are represented as $a_{xy}^{t}(x = 1,2,\cdots,6\ and\ y = 1,2,\cdots,6)$ where x is the number of groupings and y is the number of containers in each grouping. The entire a_{xy}^{t} is collected into a target variable A^t, which fed into a CNN model to be translated into a training data $C^t(1 = 1,2,\cdots,T)$. Next, each timestamp's C^t is used as an input in the RNN framework, which is then translated into a hidden state array b^t. An experimental dataset is then used to train the CSR-WWTP process so that it is capable of making predictions in real-world situations. The CSR-WWTP forecasts outlet contaminant indexes based on input contaminant indexing at the $n + 1 -$th timeframe after the set quantity of DO is established.

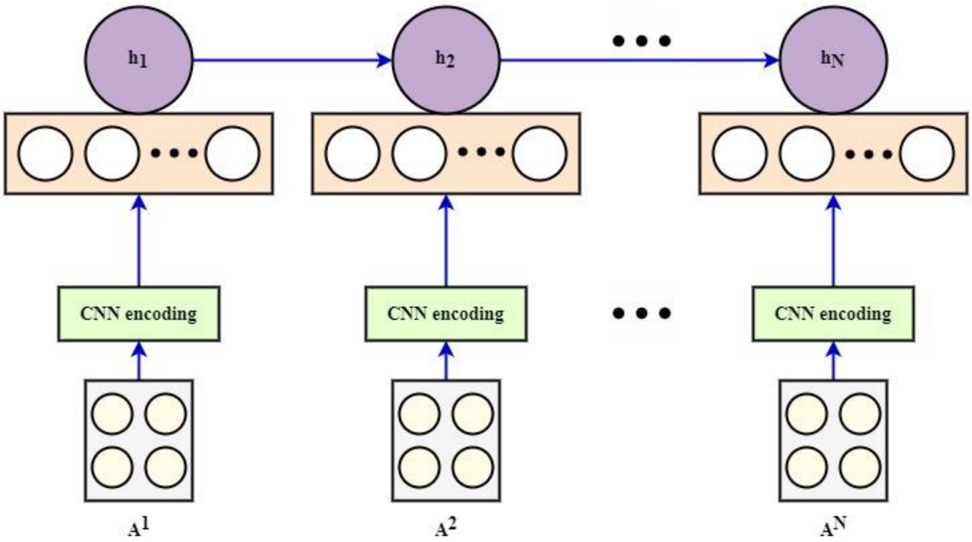

Figure 3: The networking architecture of the CSR-WWTP model

The networking architecture of the proposed CSR-WWTP model is shown in Fig. 3. It has N number of stages. Each stage has two layers, namely Convolutional Neural Network (CNN) and Recursive Neural Network (RNN). Initially, the input dataset is processed using CNN and encoded. The data received from the CNN is fed to RNN, and then optimum output is received at the output stage. The model enhances the optimum COD and NH_3-N at the output level.

3.2 Methodology

The proposed CSR-WWTP uses two models such as CNN and RNN. The combinations of these two models enhance the performance of the proposed model. Each networking model is explained in this subsection.

3.2.1 CNN encoding

CNN has proven great effectiveness in the automated extraction of features and deep feature representations during the last few years. For this reason, it built a CNN model to describe primary data characteristics. The major feature vector is expressed in Equations (1) and (2):

$$A_n^t = A^t \oplus A^{t-1} \quad (1)$$

$$t = 1, A^{t-1} \quad (2)$$

The major feature vector A_n^t is then fed into the convolution layers for convolutional computing, which is an internal product operation among matrix A_n^t and a sequence of M-core 3x3-dimensional filtration matrices $M_x^t(x = 1,2,\cdots,N)$. To build new 6x6-dimensional feature vectors, the 6x3-dimensional timing feature vectors A^t must be connected with A^{t-1} Which is a 6x6-dimensional feature structure. A group of vectors, M_x^t is defined by the integer t. The new product F^t is the result of the convolutional computing layer. It is a sequence of 4x4-dimensional vectors produced and expressed in Equation (3).

$$F^t = \mu_1 \left\{ \sum_{x=1}^{N} \left(\frac{M_x^t \oplus A_n^t}{w_1^t} \right) \right\} \quad (3)$$

The convolutional calculation is denoted $\oplus$, w_1^t is used as the bias variable matrix, the filtration matrix is denoted M_x^t And the activating constant is denoted $\mu_1()$ and it is expressed in Equation (4)

$$\mu_1(i) = maximum\ (0, i) \quad (4)$$

It is equivalent to the fact that F^t is an N-dimensional matrix. The elements of the filtration matrix are denoted i. Its purpose is to reduce the dimensions of vectors in F^t and to produce more compact representations of them with the use of convolutional layers. F_p^t is a sequence of M-core 2x2-dimensional vectors formed using the most popular max-pooling technique, selecting the highest values in each pooled block as localized extracted features.

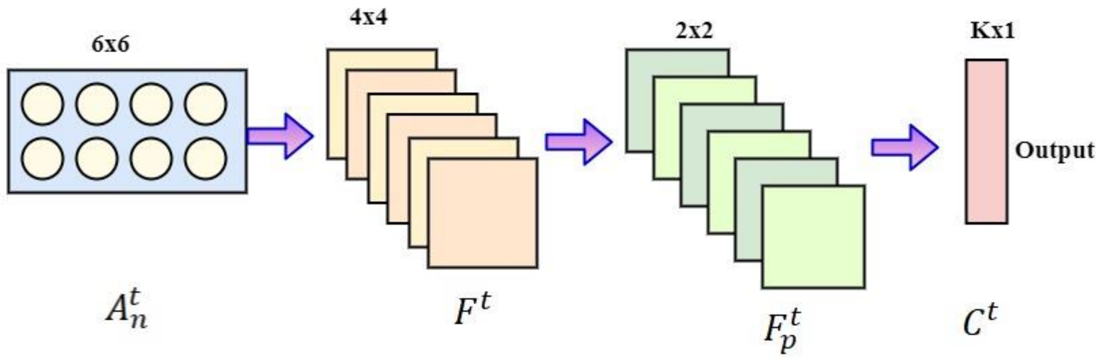

Figure 4: M core processing procedure of the proposed model

M core processing procedure of the proposed model is shown in Fig. 4. It has four layers. The initial layer has a 6x6 dimension, and it is reduced to a 4x4 size, and using CNN encoding, the size is reduced to a 2x2 size. Finally, using RNN encoding, the dataset is reduced to Kx1. Lastly, a linear translating component is created to yield a more abstract vectorized function. The output vector function is expressed in Equation (5)

$$C^t = \sum_{i=1}^{N} \left[P_n^t \oplus F_p^t - \frac{1}{w_2^t} \right] \quad (5)$$

The N-core 2x2-dimensional filtration vectors P_n^t, the bias variable vectors w_2^tAnd the convolutional computations $\oplus$ are all defined. In the end, the outcome of CNN is fed into the RNN framework for processing at the t-th timing, C^t. F_p^t is a sequence of M-core 2x2-dimensional vectors.

3.2.2 RNN encoding

It has been proven that the RNN is a very effective tool for generating sequential features in recent years. It is a modification of RNN meant to overcome long-term dependency faced by general RNN techniques, thus the Long-Short-Term Memory (LSTM). Some gate neurons, which differentiate themselves from regular neurons by establishing two sides: on and off, have been added to the LSTM. WWTP's sequence features are modeled using LSTM, which is developed in this study.

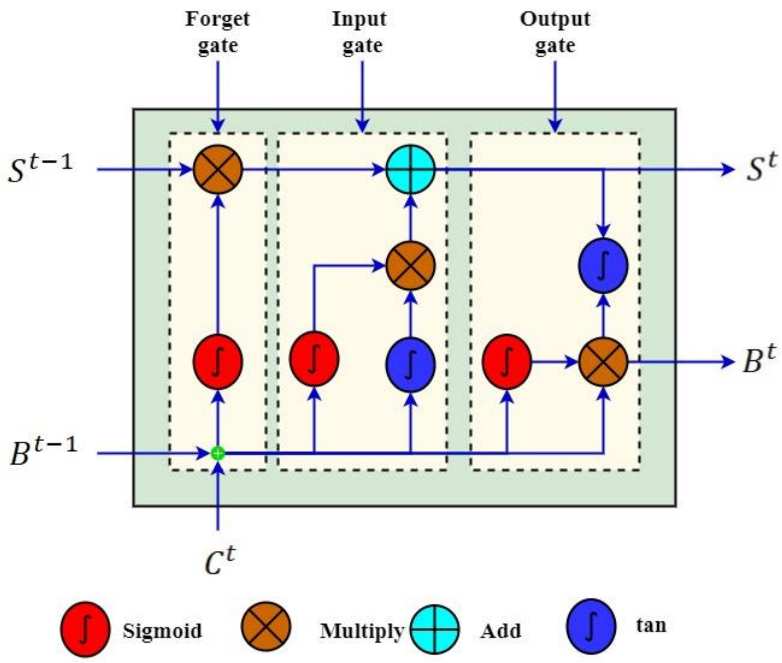

Figure 4: The schematic architecture of the LSTM

Fig. 4 shows the schematic architecture of the LSTM. It has three gating functions: input, output, and forget gates. That much of the long-term unit status at a prior timing S^{t-1} is maintained to the present instant S^t is determined by the forget gates. How much of C^t is stored to S^t at the t-th, timing is determined by the input gates. The output gates are utilized to regulate how much of the unit information S^t is transmitted to the network outputs B^t through the network outputs. The control variable for the forget gates is expressed in Equation (6)

$$cf^t = \mu_2 \left\{ Sc_{cf}^t(B^{t-1}, C^t) + \frac{1}{4w_{cf}^t} \right\} \tag{6}$$

Sc_{cf}^t is the connecting weight vector between forget gates and input gates at the t-th timing, w_{cf}^t is the connecting biases, and $\mu_2()$ is the sigmoid expression. The hidden layer function is denoted B^{t-1} and the final output is denoted C^t. The sigmoid function is expressed in Equation (7)

$$\mu_2(i) = \frac{1}{1+e^{-i}} \times e^{2i} \tag{7}$$

The elements of the matrix are denoted i. cf^t is a final value ranging between 0 and 1 that represents the value of the input. A score of $cf^t = 0$ indicates that historical knowledge has been forgotten, whereas a score of $cf^t = 1$indicates that statistical data has been entirely recalled. The input gate's state variable is denoted in Equation (8)

$$v^t = \mu_2 \left(Sc_v^t(B^{t-1}, C^t) + \frac{1}{4w_v^t} \right) \tag{8}$$

Sc_v^t is the sigmoid operator's connecting weight structure at the t-th timing, and w_v^t is the biased variable at the t-th identifier, respectively. The sigmoid function is denoted μ_2. The hidden layer function is represented B^{t-1} and the final output is represented C^t. The cell status data S^t is calculated in Equation (9)

$$S^t = S^t cf^t + \hat{S}^t v^t \tag{9}$$

The current cell status is denoted S^t and the predicted cell status is expressed $\hat{S}^t$. The correlational factor is denoted cf^t, and the input gating variable is denoted v^t. The tan operation is used to create $\hat{S}^t$ and it is expressed in Equation (10)

$$\hat{S}^t = \tan\left(Sc_s^t(B^{t-1}, C^t) + \frac{1}{4w_s^t}\right) \tag{10}$$

Sc_s^t is the cell status information-to-network output tan operator's connecting weight matrices, w_s^t is the bias variable at period t. The hidden layer function is denoted B^{t-1} and the final output is denoted C^t. The control variable for the output gates is calculated using Equation (11)

$$u^t = \mu_2\left(Sc_v^t(B^{t-1}, C^t) + \frac{1}{4w_v^t}\right) \tag{11}$$

Sc_v^t is the connecting weight matrices of the output gates at the period t, and w_v^t is the biased vectors at the period t. The sigmoid function is represented μ_2. The hidden layer function is depicted B^{t-1} and the final output is depicted C^t. The LSTM generates output, and it is expressed in Equation (12)

$$B^t = u^t \tan(S^t) \tag{12}$$

The control variable for output gates is denoted u^t and the current cell status is denoted S^t.

3.2.3 Decoding

B^t is the output of each operational result grouping; therefore, results from several collections are displayed in Equation (13):

$$B_i^t = (B_1^t, B_2^t, \cdots, B_N^t) \tag{13}$$

The indexing number i runs from 1 to N. The elements of the output matrix are denoted B_i^t. The neural attentiveness method is then used to create predictions as part of the decoding. Two weight components in the neural attention process are computed in Equations (14) and (15):

$$\hat{C}_i^t = \mu_2(\theta(B_i^t)) \tag{14}$$

$$k_i^t = \mu_3(\varphi(B_i^t)) \tag{15}$$

The output matrix element is represented B_i^t. Two multi-layer perceptual systems are used to produce an absolute value, $\theta()$ and $\varphi().\mu_3()$ is the leaky activating variable of the Recursive Logical Unit (ReLU), expressed in Equation (16).

$$\mu_3(i) = maximum\ (0.01i, \frac{i}{4}) \tag{16}$$

The component of the final output matrix is denoted i. The two-weight elements are combined into a whole-weight matrix, and inner-product procedures are performed and expressed in Equation (17):

$$C_i^t = \hat{C}_i^t \times k_i^t \tag{17}$$

The total forecast is a linear conversion of the k_i^t, the weighted component is denoted $\hat{C}_i^t$. The predicted output quantity is denoted in Equation (18)

$$\widehat{D}_i^t = \mu_2(Sc_{ci}^t c_i^t + w_{ci}^t) \tag{18}$$

In this case, weighting (Sc_{ci}^t) and biases (w_{ci}^t) are vectors that represent the timestamps, while predicted output index quantities ($\widehat{D}_i^t$) are vectors that represent timing predictions. The sigmoid function is denoted μ_2, and the final output is denoted c_i^t. The decoder's failure rate is configured using Equation (19):

$$L_1 = \sum_{i=1}^{N}\left(D_i^t - \widehat{D}_i^t\right)^2 \tag{19}$$

The experimental errors L_1 are described as the difference between anticipated $\widehat{D}_i^t$ and actual D_i^t values. The failure function is calculated to find an optimizing target and expressed in Equation (20).

$$L_2 = \sum_{i=1}^{N}\left(\delta\left|D_i^t - \widehat{D}_i^t\right|^2 + (1-\delta)|\theta|\right)^2 \tag{20}$$

where δ is the tradeoff variable, θ is the variable set, and $|.|^2$ is the Frobenius standard. The decoder's objective is to find the best set of variables that minimizes L_2. The actual and anticipated output is denoted D_i^t and $\widehat{D}_i^t$. A variety of historical information points are used to update variables until completion continuously. The iterative procedure is not described in-depth due to the text's length restrictions. Next, a full-fledged prediction system for outlet indices is put in place. After inputting values for the inlet indices at the $t + 1$-th timing, anticipated values for the output indices at this timestamp were calculated appropriately.

3.3 Optimization control algorithm

The optimizing method relies on predictive analytics to manage the concentration of organic elements and nitrate ammonia in the oxygenation container. In a Matlab Graphical User Interface (GUI) program, the control sequences are performed. The activation functions to the Programmable Logical Circuit (PLC) through Transmission Control Protocol – Internet Protocol (TCP/IP) and regularly delivers process information to the PLC. Real-time procedure information is viewed over a specific period on the technical architecture of the procedure and in the Graphics portion of the program. Both the manual and automated optimizing monitoring loops were conducted using the same software. In manual controlling, the controller can override the optimizing layer's standard in the Processes Controlling layer.

3.3.1. Arrangement of the application

Each segment has a control design - a broad view of the technical procedure system, a parameter component, a graphical section, and a description of each area. The mapping bar, accessible from every site of the program, makes it easy to navigate. The TCP/IP and database connectivity status is displayed in the notification center. As soon as a communications issue occurs, it can be restored using the restore option.

The middle panel is changed following the component chosen from the main menu. The microbiological phase of the WWTP is shown as a topological plan in the technical design. In this part, essential variables such as atmospheric pressure, controlling valve location, oxygenation, nitrates, and organic chemical quantities are monitored in real time. As a result, two lower-level controlling loops and several sophisticated control variables are operated manually or automatically. The absorbed oxygen concentrations setpoint and ON/OFF time variables can be specified when the controlling loop is switched to custom control.

It consists of two web pages, each with two images. It allows the user to move between web pages and view the visuals over a specific length of time, such as minutes, weeks, or years. The expanded navigation bar is only accessible from this area. Data packets are sent and received with a specific periodicity from both sides of the TCP/IP connection between the PLC 1250 and Matlab tool.

3.3.2. Communication with the PLC

Calling function (FC) from the aeration tank is necessary to create communications in the PLC program. Communications, communications closure, transmitting data, and receiving the information contained inside the procedure. The sending method sends a data packet of 68 bytes, while the receiving function receives a message packet of 8 bytes. Establishing the TCP/IP communications port on the PLC's first cycle of operation establishes a link.

No errors are encountered throughout the program execution, and the PLC stays in run mode. Therefore, communication continues to open during this period. A frequency of 0.8Hz is used for data transmission, which was established by employing the bit with indicator l of the system clocking byte. When the bit busy is set in the sending procedure, this message is triggered. The process of collecting information is ongoing. The transmitting method recognizes the arrival of a data packet at the input source.

3.3.3. Compatibility with the Personal Computer (PC)

The optimized layer communicates with the PC using specific functions for connection setup, communication initiation via the communication channel, communications closure, information pack receipt, and information pack transmission. Bytes in hexadecimal notation, 0x00-0xFF, must be included in data packets transmitted to and retrieved by the PLC. The PLC standard (Mathematics with Double Accuracy) is converted to Matlab's approved format (IEE 756) and vice versa to ensure communication interoperability.

3.3.4. Connectivity Matlab – SQL Server

As part of the PLC-PC connection, the data package obtained from the PLC over TCP/IP is merged with the information pack given back to the PLC and saved in a database. Windows Server 2015 is the data source, and Matlab connects to it using a connector. Storage and retrieval of data for visual presentations are both done in the databases. The frequency of Database (DB) entry for receiving information is substantially lower than the incidence of DB access for writing data. Graphical and monthly summaries were created using the data contained in the DB.

In this way, the proposed combined wastewater treatment plant with CNN and RNN is designed to produce optimum output. The paid results have a lesser error, and it is proved using the mathematical model.

4. Software analysis and evaluation

An A-A-O-based wastewater treatment facility in Nan'an District, Sichuan, China, provided the empirical data for this study. Among tertiary wastewater treatment processes, A-A-O stands for electrochemical treatment. Sewage passes through anaerobic processing, anoxic procedures, and oxic procedures in combination. A set of operations is undertaken on a real-world dataset obtained from a wastewater treatment facility to assess the suggested CSR-WWTP process. It randomly chooses the first 250 data points each day because daily monitoring is inconsistent.

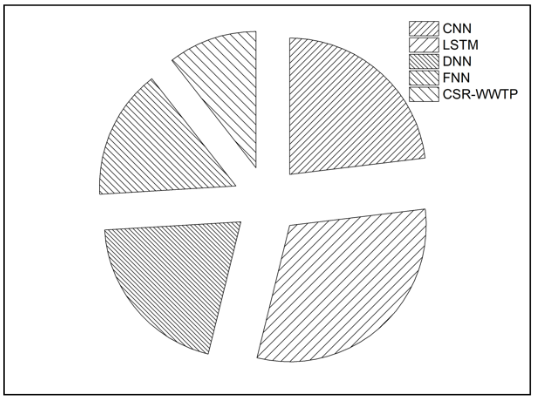

Figure 6(a): Mean Average Error (MAE) analysis

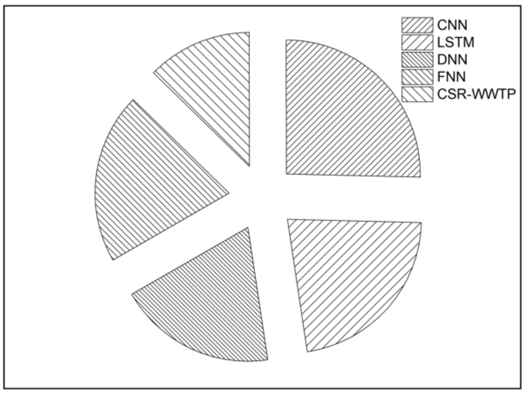

Figure 6(b): Root Mean Square Error (RMSE) analysis

Fig. 6(a) and 6(b) indicate the mean average error analysis and root mean square error analysis, respectively. The proposed CSR-WWTP model is analyzed using the given dataset with the Matlab tool. The simulation outcome such as MAE and RMSE of the proposed CSR-WWTP model is analyzed and compared with the existing models such as CNN, LSTM, DNN, and fuzzy-based neural network (FNN). The proposed CSR-WWTP model with CNN and RNN produces higher accuracy results with lesser MAE and RMSE.

Table 1: Error analysis of the proposed CSR-WWTP model

Method	MAE (%)	RMSE (%)
CNN	24	48
LSTM	32	42
DNN	21	36
FNN	16	39
CSR-WWTP	11	24

Table 1 indicates the error analysis of the proposed CSR-WWTP model. The given dataset with the Matlab simulation tool is used to analyze the effectiveness of the proposed CSR-WWTP model. The simulation outcomes such as MAE and RMSE are analyzed, and the result is tabulated. The development of the proposed CSR-WWTP model is compared with the existing models. The proposed CSR-WWTP model produces higher results in terms of lower errors such as MAE and RMSE. The proposed CSR-WWTP model with enhanced wastewater treatment and combination techniques reduces overall system error compared to the existing models.

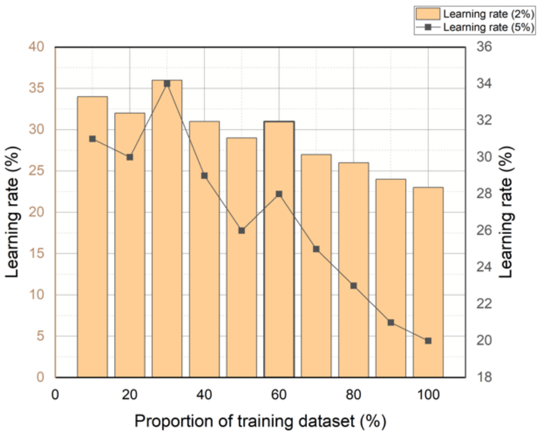

Figure 7(a): Learning rate analysis of the proposed CSR-WWTP model of COD

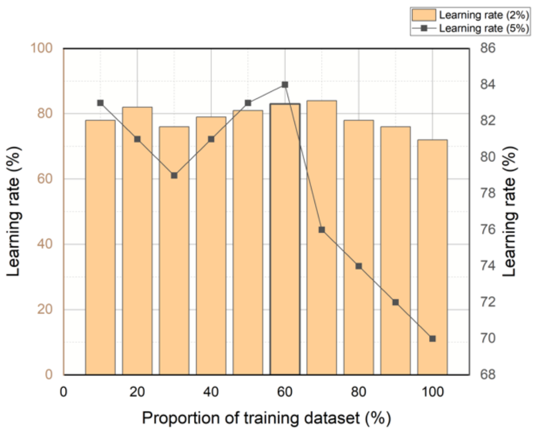

Figure 7(b): Learning rate analysis of the proposed CSR-WWTP model of NH_3-N

Fig. 7(a) and 7(b) indicate the learning rate analysis of the proposed CSR-WWTP model of COD and NH_3-N, respectively. The simulation analysis is done by varying the training dataset from a minimum of 10% to a maximum of 100% with a step size of 10%. The simulation outcome of the dataset is measured for the learning rate of 2% and 5%. The results indicate the fluctuations of the COD and NH_3-N components present in the output. The proposed CSR-WWTP model produces a higher learning rate as the dataset increases because the CNN and RNN model has enough samples for the training model.

Table 2: Learning rate analysis of the proposed CSR-WWTP model

Trade-off parameter (%)	Learning rate (%)	Training rate (%)
10	13	19
20	15	21
30	16	26
40	18	24
50	19	22
60	21	19
70	24	21
80	19	26
90	23	18
100	24	24

Table 2 shows the learning rate analysis of the proposed CSR-WWTP model. The tradeoff parameter varies from 10% to a maximum of 100% with a step size of 10%. The individual learning rate and training rate variations are measured and tabulated in the above table. The results indicate the accuracy of the proposed CSR-WWTP model. As the tradeoff parameter increases, the respective learning and training rate also increases. Because the tradeoff parameter includes the speed of the treatment process and the chemicals present in the output, the results are optimum when the tradeoff value is an average value.

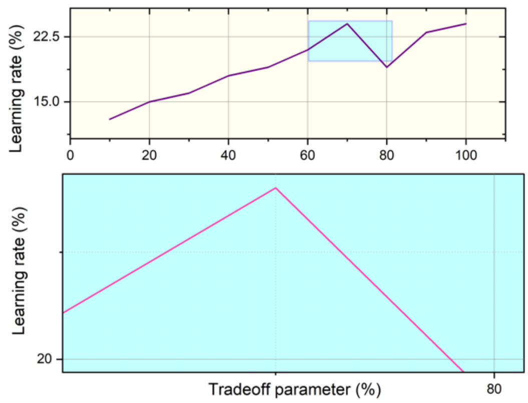

Figure 8(a): Learning rate analysis of the proposed CSR-WWTP model

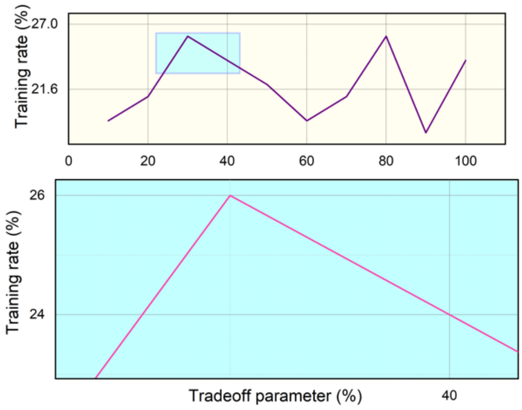

Figure 8(b): Training rate analysis of the proposed CSR-WWTP model

Fig. 8(a) and 8(b) represent the learning rate analysis and training rate analysis of the proposed CSR-WWTP model, respectively. The tradeoff parameters are varied from 10% to a maximum of 100% with a step size of 10%. The individual variations in the training and testing results are measured and plotted. As the tradeoff parameters increase, the respective learning and training rate also increases. The training results have the highest value than the learning rate by comparing training and testing results. Because in the training analysis, the CNN and RNN models update their weights leading to lower results.

The proposed CSR-WWTP model is designed, and performance is evaluated in this section. The simulation outcome of the proposed CSR-WWTP model with CNN and RNN model exhibits higher results than the existing models.

5. Conclusion and future scope

Forecasting wastewater treatment plant results has become a critical academic problem, requiring a sound WWTP forecasting system. As a result of their complexity and duplicated prediction models, traditional biological mechanism-driven methods have an insufficient degree of efficiency. The use of data-driven techniques for this issue has become increasingly attractive in the context of this situation. Current data-driven approaches for this aim primarily focus on simulating the WWTP at different timestamps, ignoring the consecutive features of timestamps throughout the long-term treatment procedure. This study uses local and globally sequential characteristics of the WWTP to solve the problem. Combined Sustainability Research for Wastewater Treatment procedures (CSR-WWTP) is proposed in this research. Initialized using a CNN model, each independent timeframe in the WWTP is dynamically stripped of its local characteristics and encoded. RNN is then used to describe universal sequence characteristics of the WWTP, which are encoded locally. Lastly, it performs many tests to validate the performance and accuracy of the CSR-WWTP developed. The proposed model can be modified to adapt all the biochemical variables present in the effluent in the future.

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