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Multi-Objective Optimization of Wastewater Treatment Strategies under Hydrological Uncertainty

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Abstract
Efficient wastewater treatment under variable hydrological conditions is critical for environmental sustainability and operational cost management. Increasing inflow variability, pollutant spikes, and high-dimensional operational data present significant challenges for conventional optimization methods. To develop an integrated framework capable of optimizing multiple conflicting objectives in wastewater treatment while effectively handling uncertainty induced by variable inflow and pollutant loads. This research introduces a Convolutional Neural Network (CNN)-assisted Multi-objective Decomposition Differential Evolution–driven Ant Colony Optimization (MO-DDE-ACO+CNN) algorithm, which integrates decomposition-based differential evolution with ant colony optimization to efficiently identify Pareto-optimal solutions under hydrological uncertainty. The treatment of wastewater data in different hydrological environment conditions are used in this research and are preprocessed with the missing value imputation, outlier detection based on Z-score and normalization techniques. A CNN is used to acquire nonlinear and spatial patterns on the high-dimensional data, which offer structured features to optimize the information. The ant colony optimization algorithm decomposed differential evolution algorithm is utilized to simultaneously optimize cost, energy consumption and effluent quality and ensures that it is diverse as well. MO-DDE decomposes complex multi-objective wastewater optimization problems into simpler sub problems to efficiently identify well-distributed Pareto-optimal solutions. The proposed achieves higher R^2 = 0.99 and lower MAE = 0.002, RMSE = 0.208, MAPE = 1.08%, indicating superior performance. MO-DDE-ACO+CNN has better convergence, uniformly distributed Pareto fronts and is also robust to large variations in inflow and pollutants than the base optimization methods.
Keywords: *Wastewater treatment, Ant Colony Optimization, Differential Evolution, Hydrological uncertainty, Effluent quality.*

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1. Introduction

Wastewater Treatment Processes (WWTP) can be regarded as essential to the issues of aquatic pollution and fresh water shortage. The process of a typical municipal WWTP consists of four steps, namely, sludge action, lesser management, tertiary action, and primary treatment. The primary objective of the secondary stage is the removal of nitrogen and phosphate due to the complex reactions of these substances with the chemical reactions and requires advanced treatment management methods [1]. The administration of the WWTP management system was urgent in the production of quality reused water that was able to address both ground water as well as the surface resource deficits [2]. The wastewater produced by the human activity in the up-stream regions especially the high-populated regions defines the water status of the streams, lakes, and ultimately waterways in all the populated regions in the universe [3]. The ecological status of rivers is determined by the utilization of resources and Wastewater Treatment Control (WWTC) methods. Since tiny rivers affect the water regulation and have hydrochemical markers for bigger rivers, effective sewage treatment is essential [4]. For hydraulic simulation in urban streams, wastewater collection, processing, and reuse are crucial and occasionally taken into account in small-scale models. Septic tanks are used as a treatment option in the Soil and Water Assessment Tool (SWAT), which simulates nutrient uptake structure, dirt-soil connections, and wastewater penetration into soils [5, 6].

Sewage flow, intrusion water, and commercial wastewater released into urban sewers are collectively referred to as Dry Weather Flow (DWF). When the flow surpasses the network's maximum transportation capacity, the excess is released into the surroundings via Combined Sewer Overflows (CSOs) [7]. Wastewater quality degradation and increased uncontrolled emissions have negative effects on society and ecology in addition to raising operating expenses [8]. WWTP systems can be divided into two primary treatment strategies: Household or city water is treated by biological processes, whereas wastewater from factories is usually treated by physicochemical methods [9].WWTP effluents can contain toxins that could have an impact on recipient communities' biotic environments. Local WWTP influent/effluent usually shows periodic fluctuations, with two daily peak values and least value occurring early in the day [10, 11]. WWTPs have the potential to induce riverine hydro-morphological deterioration, including hydraulic stress from high flows, particularly during periods of intense rainfall [12]. However, because of their focus on social activity and fixed system variables, typical WWTP operation and regulator approaches find it difficult to adjust to constantly fluctuating influent countryside and unpredictable external variables [13, 14]. Water pollution remains one of the global issues. One of the manifestations of the wastewater treatment progress is urban wastewater treatment that is characterized by irregular control properties, latency, and variability of properties [15]. The WWTP is facing the severe challenges connected to the poor treatment effectiveness, excessive energy consumption, significant eco-environmental impact, and crucial management issues. This is mainly due to the inherent complexity of optimization of WWTP [16, 17]. The construction of sewer lines and wastewater treatment plants is one of the most significant measures that can be taken to reduce toxic waste, as well as improve the excellence of water [18].

Research objectives and scope: The objectives of the research are to develop an effective multi-objective optimization model capable of addressing hydrological uncertainty in WWTP. Using high-frequency wastewater and hydrological data, the scope covers improving energy use, operational costs, and effluent quality. Under varying inflow and pollution conditions, the proposed CNN-assisted Multi-Objective Decomposition Differential Evolution-driven Ant Colony Optimization (MO-DDE-ACO+CNN) method, CNN yields stable and well-distributed Pareto-optimal solutions.

Section organization: The research is organized as follows: Section 1 describes the background of WWTP, Section 2 reviews existing studies, Section 3 details data processing and the proposed MO-DDE-ACO+CNN framework in methodology, Section 4 depicts the results and discussion, and Section 5 presents the conclusion, summarizes findings and outlines future research directions.

2. Literature review

Effluent quantity, energy conservation, uncertainty modeling, site feasibility, and immediate forecasting are the main topics of related studies that use machine learning, optimization, digital twins, and GIS-based frameworks to manage wastewater.

2.1 Intelligent Optimization Frameworks for Effluent and WWTC

For effluent management in WWTP employing an influent estimate, a Reinforcement Learning-Assisted Particle Swarm Optimization (RLA-PSO) approach was created [19]. The method enhances effluent quality and processes efficiently. To enable optimizing WWTP under dynamic real-world settings, the research [20] suggests hybrid digital-twin architecture. The result demonstrates significant organic matter removal. Using the Water Evaluation and Planning (WEAP) hydrology, the research [21] identifies important limits, and promotes resilient scheduling and handling decisions. AquaFlowNet was a Machine Learning (ML)-based system that forecasts fluctuations and optimizes treatment procedures to manage wastewater flows in real-time [22]. Wastewater discharge consequences are assessed using Geographic Information System (GIS)-based mapping and Random Forest (RF) to pinpoint pollution areas and significant industrial contributors [23].

Using a hybrid Fuzzy- Analytic Hierarchy Process (AHP) and RF, land capacity for biological WWTP in Mangalore Taluk was assessed [24]. The framework achieves 91.3% accuracy in identifying highly and moderately suitable zones. Employing an integrated Remote Sensing (RS), and ML, viable sites for Sewage Treatment Plants (STPs) in an urban area are determined [25]. The framework forecasts energy usage and wastewater quality (ammonia, Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD)) in dealing facilities using transformer ensemble models and multitask Bidirectional Gated Recurrent Unit (Bi-GRU) learning [26]. By improving accuracy, hybrid pretreatment offers a scalable, intelligent instrument for effective, sustainable control of wastewater.

2.2 GIS and ML-Based Approaches for Wastewater Planning and Siting

Urban wastewater treatment is represented with less data dimension and improved predictability by means of an Extreme Learning Machine (ELM) was discussed in this research [27]. PCA-ELM outperforms conventional methods, increasing projections for BOD, COD, and Total Nitrogen (TN) [28]. The River Chess water standard is modeled using ML with high-frequency electrical conductivity and temperature data, and important human-induced drivers are identified by Shapley Additive explanations (SHAP) [29]. The method precisely measures the effects of WWTP outflow, detecting changes in conductivity throughout the day and a 1°C increase in temperature downstairs.

In a Jiangsu WWTP, a TN and a wastewater COD are predicted in real-time by Improved FFNN (IFFNN) and a Genetic Algorithm (GA) [30]. The GA-IFFNN improves accuracy, and minimizes overfitting and depicts the complex nonlinear correlations in sewage data. Forecasts of the effects of groundwater and associated wastewater in the Ardabil

Plain in Iran were made with the help of Long Short-Memory network with Lower and Upper Bound Estimation (LUBE) using uncertainty analysis [31]. In the case of very sensitive devices, the LSTM performs superior to the FFNN, with a smaller detection width, smaller forecast interval and higher accuracy.

2.3 The WWTP Multi-Objective Optimization and Data-Driven Modeling.

RF, Extreme Gradient Boosting (XGBoost) and LSTM are ML models used to predict wastewater intake during rainstorms at a coastal WWTP [32]. XGBoost will give the most optimal results and it assists in proactive operations in case of floods and therefore it provides precise short term predictions based on sparse information. A Feature Stream Network (FSN) Deep Learning (DL) model predicted the daily Harmful Algal Blooms (HABs) in most river surveillance sites; capturing time and spatial connectivity fluctuation [33] and identifying significant upstream effects, and estimating the abundance of algae with accuracy. The structural layout of a horizontal drainage wetland is optimized for WWTP using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [34], reducing size and expenses while maximizing elimination of contaminants and velocity. Research [35] uses simulation-based multi-objective optimization to reduce glasshouse gas releases and effluent impacts within a WWTP. A Multi-Task Interpolated Echo State Network (MTIESN) was created to predict energy use in wastewater [36]. The approach generates a compact network and enhances simulation accuracy by combining data computation. The research [37] uses long-term industry data to forecast effluent BOD through the application of ML-based soft sensors to wastewater treatment and achieving high accuracy in the real-time wastewater process.

2.4 Research gap

Numerous study gaps nevertheless exist in WWTP utilizing machine learning, optimization, GIS, and digital-twin frameworks, notwithstanding notable advancements in this field. Existing research frequently addresses cost, energy, or effluent quality separately and mostly concentrates on single-objective optimization, forecast accuracy, or geographical appropriateness analysis [19-28]. Simultaneously maximizing several divergent goals under hydrological uncertainty receives less attention, despite the fact that hybrid AI models and reinforcement learning enhance forecasting and decision-making under dynamic situations [19, 20, and 32]. Furthermore, the majority of optimization-based methods are not resistant against severe inflow and pollutant variability, as they rely on static or hypothetical assumptions [34, 35]. By combining the hybrid differential evolution, and ant colony optimization and CNN, the proposed MO-DDE-ACO+CNN approach overcomes these drawbacks and allows the simultaneous multi-objective optimization of cost, power, and effluent quality.

3. Methodology

The methodology combines a hybrid MO-DDE-ACO+CNN optimization framework, and data preprocessing. Data quality is ensured by probabilistic imputation, normalization, and outlier elimination, and resilient Pareto-optimal wastewater treatment techniques under hydrological uncertainty are jointly derived by DDE and ACO; these were illustrated in Figure 1.

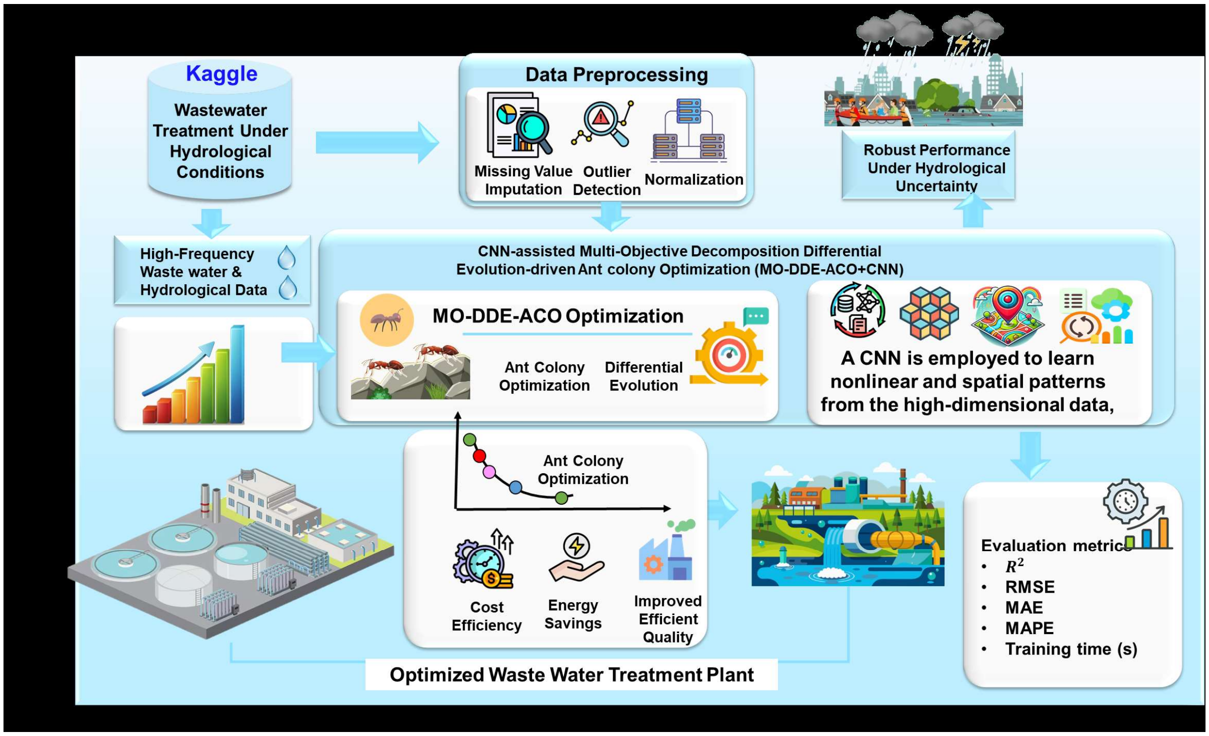

Figure 1: Methodology design.

3.1 Wastewater Treatment under Hydrological Conditions Dataset

The Wastewater Treatment Under Hydrological Conditions utilized in the research is obtained from Kaggle (https://www.kaggle.com/datasets/programmer3/wastewater-treatment-under-hydrological-conditions/data).As a result of shifting hydrological regimes, such as dry weather, wet spells, and exceptional influx events, the dataset records temporal variability in influent flow and pollutant concentrations. Operational control parameters, including aeration rates, sludge recirculation ratios, chemical dosing levels, and retention durations, are integrated with influent water quality variables like suspended particles, nutrients, and BOD and COD. The dataset includes clear indications of energy consumption, operational cost, and effluent quality performance in addition to process and water quality data, allowing for the simultaneous assessment of sustainability, environmental, and economic goals. A single structured CSV file with 2,400 high-frequency observations includes all of the variables, contains 2400 rows and 20 columns. The dataset is split into 80% for training and 20% for testing.

3.2 Data Cleaning and Standardization Methods

The dataset is preprocessed with probabilistic imputation, Z-score outlier removal, and Z-score normalization to recover missing values, reduce anomalies, and standardize wastewater variables for accurate CNN learning and MO-DDE-ACO optimization.

A probabilistic imputation technique that maintains the original data distribution is used to impute missing values in high-frequency wastewater and hydrologic data to provide dependable multi-objective optimization under hydrological uncertainty. Assume that the original multivariate input feature vector is $N \in \{0,1\}^o$, represents the observed and missing entries are indicated via a binary mask vector. A model of imputation, completed samples are produced by $IMP(\cdot)$ denoted in Equation (1).

$$\bar{Y} = IMP(\hat{Y}, N),\ \ \hat{Y} \sim P(Y|\hat{Y},\ N) \tag{1}$$

The finalized dataset is acquired in Equation (2).

$$\bar{Y} = Y \odot N + (1 - N) \odot \bar{Y} \tag{2}$$

Where $Y = (Y_1, Y_2, \dots Y_o)$is the original multidimensional feature vector (e.g., influent flow, pollutant levels, and operational parameters), $\hat{Y}$is the pre-imputed information with substitutes for the missing values, and $N = (N_1, N_2, \dots N_o)$ is a binary filter indicating. The imputation model is represented by $IMP(\cdot)$, the projected amount for the entries lacking derived from the conditional range is represented by $\bar{Y}$, the final entire dataset is represented by $\bar{Y}$, and element-wise doubling is shown by $\odot$.

The wastewater and hydrological datasets are subjected to Z-score-based outlier detection to improve water quality and guarantee dependable optimization under hydrological volatility. Outliers were identified using a typical z-score approach represented in Equation (3).

$$Y = \frac{w-\mu}{\sigma} \quad (3)$$

Where w is the actual value of a specific variable such as influent flow, BOD or COD, μ is the related feature's mean, σ is its standard deviation, and Y is the observation's relative deviation from the mean. Because they indicate excessive inflow data points with $Z > 3$ are detected as outliers and eliminated. Figure 2 (a-b) shows how probabilistic imputation and statistical outlier identification are used to improve data quality and modeling robustness in wastewater data.

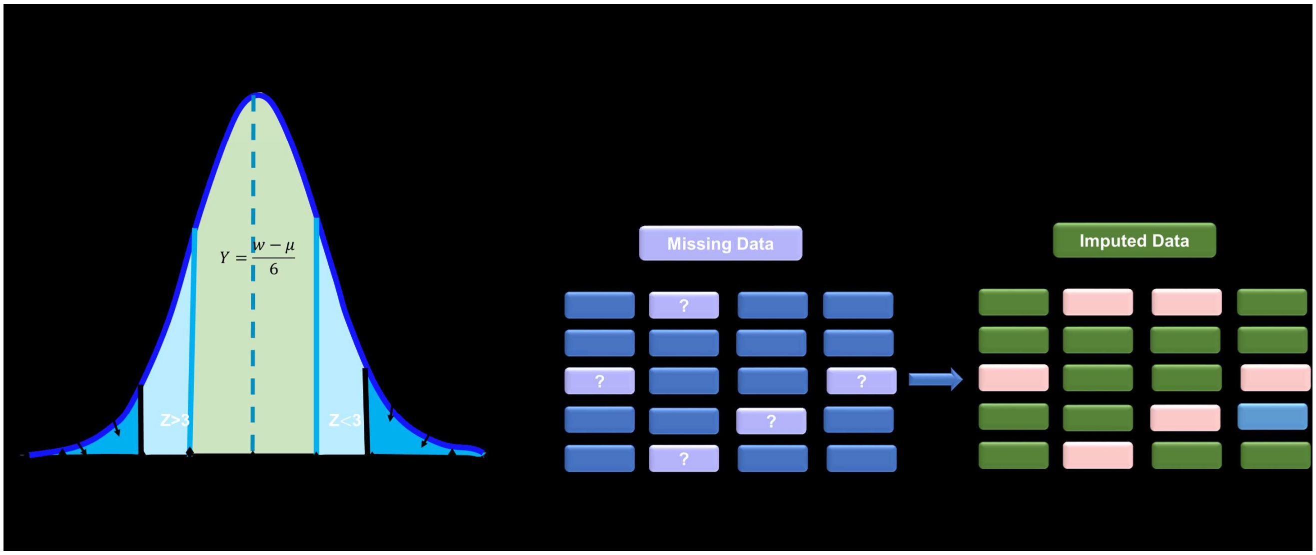

Figure 2: Illustration of (a) Z-score–based outlier detection and (b) Probabilistic missing value imputation process.

Z-score normalization or standardization is a popular method for normalizing data in statistical analysis and ML. Z-score normalization is used to standardize rainfall intensity using BOD, COD indicators that facilitate robust multi-objective optimization under hydrological uncertainty. The Z-score normalization formulation is represented in Equation (4).

$$y' = \frac{y-mean\,(y)}{std\,(y)} \quad (4)$$

Where y signifies the original assessment of a wastewater parameter, y' is the normalized rate following Z-score transformation, $mean(y)$ is the feature y's mean value, and $std(y)$ is the attribute's average deviation.

3.3 Multi-objective Decomposition Differential Evolution driven Ant Colony Optimization (MO-DDE-ACO+CNN) for effectively handling uncertainty induced by variable inflow and pollutant loads

To produce reliable wastewater treatment methods, the proposed MO-DDE-ACO+CNN framework combines adaptive Gaussian mutation, decomposition-based differential evolution, Pareto dominance, multi-objective optimization, and ant colony optimization.

3.3.1 Multi-objective Decomposition Differential Evolution

MO formulation of Conflicting Objectives in WWTP: Real-world optimization tasks frequently require the simultaneous optimization under dynamic hydrological conditions. MO minimization framework is adopted to optimize influent flow, pollutant removal and operational cost. The MO problem is generally stated in Equations (5), (6), and (7).

$$\min G(Y) = (g_1(Y), g_2(Y), \dots, g_N(Y)) \quad (5)$$

Subject to:

$$h_j(Y) \le 0, \quad j = 1,2,\dots,n \quad (6)$$

$$i_k(Y) = 0, \quad k = 1,2,\dots,o \quad (7)$$

Where $Y = (y_{1,}y_2, \dots, y_E)'^{U}$ is a decision vector representing a candidate solution. $G(Y)$ represents the objective vector that maps a decision vector Y to multiple values, $g_l(Y)$, $l = 1,2,\dots,O$ is an individual objective function to be minimized, $h_j(Y)$ denotes an inequality constraint function, n and o are the total number of inequality constraints, and $i_k(Y)$ denotes the equality constraint function in WWTP operations.

- **Pareto Dominance (Comparing Solutions) -** There is typically no single optimal solution because multiple goals are optimized concurrently. Rather, Pareto dominance is used for contrasting alternatives. A workable solution Y_1 is considered to be Pareto dominated by a different solution Y_2 represented in Equations (8).

$$g_j(Y_1) \leq g_j(Y_2), \ \forall_j = 1,2, \dots, O \quad (8)$$

In other words, Y_1 is absolutely better in just one category and no worse in any of the others. Where, Y_1 and Y_2 are two feasible decision vectors representing different wastewater treatment operational strategies (e.g., influent flow handling, pollutant removal and energy usage), g_j is the j-th objective function, O is the entire amount of plans considered in the proposed multi-objective optimization model, $\forall_j$ indicates that solution Y_1 performs no worse than Y_2 across all wastewater treatment objectives.

DE for Continuous Parameter Optimization technique: The proposed multi-objective function, which seeks to enhance the model's accuracy while preserving stability and expansion, is optimized using the DE technique.

- **Population initialization-** Within predetermined parameters of the wastewater treatment decision variables, a starting population of potential solutions is produced. Each person represents a workable WWTP operational arrangement, represented in Equation (9).

$$y_{j,k}^0 = y_{k,min} + rand(0,1) * \left(y_{k,max} - y_{k,max}\right), \quad k = 1,2, \dots, E \quad (9)$$

$y_{j,k}$ is the decision variable of the j-th candidate solution, $y_{k,max} and y_{k,max}$ are the lower and upper bounds of the j-th variable, $rand(0,1)$ is the uniformly distributed random number in $[0,1]$, i is the population index, and j is the dimension of the decision vector.

- **Mutation operation -** Mutation is carried out as follows to improve exploration and direct the search toward the best answers in WTTP strategy, as shown in Equation (10).

$$W_j^u = Y_{q1}^u + G(Y_{q2}^u - Y_{q3}^u) \quad (10)$$

By mixing pre-existing parameter vectors, this technique creates new candidate WWTP operational cost solutions, allowing for effective search space exploration and avoiding premature convergence. $W_j^u is$ the j-th individual's mutant vector at iteration u, Y_{q1}^u, Y_{q2}^u, and Y_{q3}^u are three different strategies chosen at random from the BOD, COD indicators, G is the scaling (mutation) factor that determines the step size, and u is the iteration number.

MO-DDE an Enhanced Evolutionary Optimization Strategy: By including DE, a neighbor intimacy process, and a Gaussian mutation method with variable step size, this algorithm improves the traditional MO-DDE framework to ensure stable optimization in WWTP operations.

Neighbor Intimacy Operation: There has to be a balance between consistency and the variety of responses in the multi-objective differential evolution framework that is proposed to optimize the WWTP operations in the face of hydrological uncertainty. When optimizing competing objectives derived from dataset variables such as influent flow, BOD, COD, nutrient concentrations, usage of energy, and operating cost, this method prevents premature convergence.

Gaussian Mutation Method with Adjustable Step Size: Mutation is essential for investigating viable operational regions in the WWTP multi-objective optimization problem while guaranteeing steady convergence toward the best trade-offs between effluent quality compliance, energy efficiency, and environmental impact. Slow convergent or unstable operational results might result from fixed mutation step sizes. A Gaussian mutation approach with an adjustable step size is used to get around this restriction. The definition of the mutation mechanism is represented in Equations (11 and 12).

$$y_{j,k}^u = y_{j,k}^u + O(0,\sigma) \quad (11)$$

$$\sigma = \begin{cases} --\dfrac{y_{j,k}^u - y_k, min}{2+d*\left(\frac{u}{U}\right)^c}, s = 0 \\ \dfrac{y_{k,max}, y_{j,k}^u}{2+d*\left(\frac{u}{U}\right)^c}, \ s = 1 \end{cases} \quad (12)$$

Where $y_{j,k}^u$ denotes the k-th dimension of the j-th particle within the. The current iteration number and the maximum number of iterations are represented by the u-th iteration U, which is a one-dimensional average random number with a mean value of 0. σ is the variance, and d and c are the two control parameters, which are chosen at random from $(0,1)$. By determining the path of mutation with respect to the feasible boundaries, the binary variable $s \in \{0,1\}$ permits balanced exploration around the present solution and avoids boundary paralysis. To improve convergence speed, solution diversity, and stability across iterations by integrating probabilistic Gaussian mutation, adaptive neighborhood interaction, differential evolution-based approach generation, and external archiving of non-dominated solutions within the MO framework. Initialization, neighborhood-guided mutation, Gaussian perturbation, reference updating, and Pareto archive management are all included in the flowchart that depicts the iterative MO-DDE process in Figure 3.

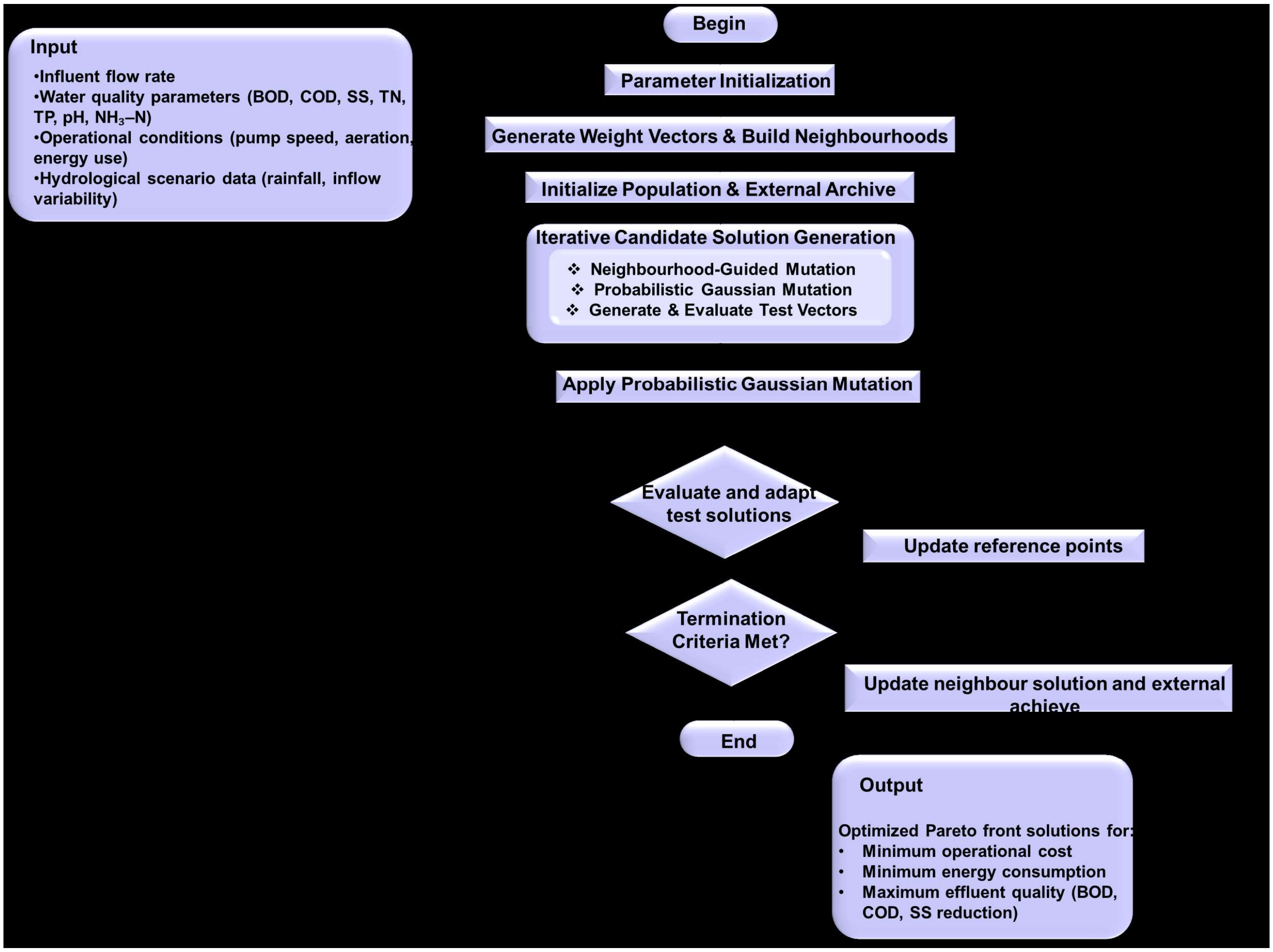

Figure 3: Flowchart of the MO-DDE Optimization Procedure with Neighborhood Interaction and External Archiving.

3.3.2 ACO for Constraint-Aware Solution Refinement

ACO has been developed to optimize wastewater treatment operational methods under hydrological uncertainty, with the goal of minimizing operational costs and energy consumption while improving effluent quality compliance under fluctuating inflow and pollutant load circumstances. As a bio-inspired system, ACO simulates how ants forage by using pheromone trails to communicate indirectly and find the best routes.

Step 1: Set up the parameters initially

First, it is necessary to initialize the ACO's parameters for WWTP operations. The highest number of iterations L, the total count of ants N, cognitive factor α, projected heuristic factor β, fragrance absorption factor ρ, and pheromone level R are some of these factors of control variables aeration rate, sludge recirculation and hydraulic retention time constrained within dataset-derived bounds.

Step-2: Path search iteratively

Ants build potential WWTP in each iteration by choosing operational choices one after the other. In conventional ACO, Equation (13) defines the probability choice rule for the ant going after the j-th argument to the k-th position for the l-th ant.

$$q_{jk}^{n} = \begin{cases} \frac{[\tau\ (j,k)]^{\alpha} * [\eta(j,k)^{\beta}]}{\sum_{t\in K_n(j)}[\tau\ (j,t)]^{\alpha} * [\eta(j,t)^{\beta}]}, & (j,k) \in K_n \\ 0, & otherwise \end{cases} \tag{13}$$

Where $\tau\ (j,k)$ denotes the value of the substance, $\propto$ is the importance of the WWTP feature, β is the weighting coefficient of the experiential purpose, K_n denotes the set of available grids for ant n in the following iteration, and q_{jk}^{n} represents the chance of transition for each alternative path from the j-th theme to the k-th point and $\eta(j,t)$ is the heuristic desirability derived from WWTP variables (lower BOD/COD at reduced energy cost).

Step-3: Updates on pheromones

The pheromone concentration on the chosen operational choices is updated based on the overall multi-objective efficiency once each ant completes a program, including effluent quality in WWTP. Higher pheromone reinforcement is given to strategies that result in lower operating costs, lower energy consumption, and has better effluent quality. Equations (14 and 15) display the pheromone intensity updating rule:

$$\tau_{u+1}^{n}(j,k) = (1-\rho) * \tau_{u}^{n}(j,k) + \sum_{n=1}^{N} \triangle \tau_{u}^{n}(j,k) \quad (14)$$

$$\triangle \tau_{u}^{n}(j,k) \begin{cases} = R/_{M_n}, & if ant n travels on node j to node k \\ = 0 & otherwise \end{cases} \quad (15)$$

Where R is a relentless that shows WWTP quality, $\triangle \tau_{u}^{n}(j,k)$ designates the entire distance of the n-th ant in the present repetition, $\tau_{u}^{n}(j,k)$ signifies the pheromone quantity difference of the n-th ant on the track from the j-th position to the k-th point in the existing repetition, and ρ indicates the global pheromone elimination factor with an amount between 0 and 1and M_n denotes the aggregated multi-objective cost of the WWTP constructed by ant n and N is the total number of ants, each representing a candidate wastewater treatment operational strategy, represented in Figure 4. The hybrid MO-DDE-ACO+CNN model integrates ACO for guided decision-making, adaptive Gaussian mutation for local refinement, and DDE for global search, depicted in Algorithm 1.

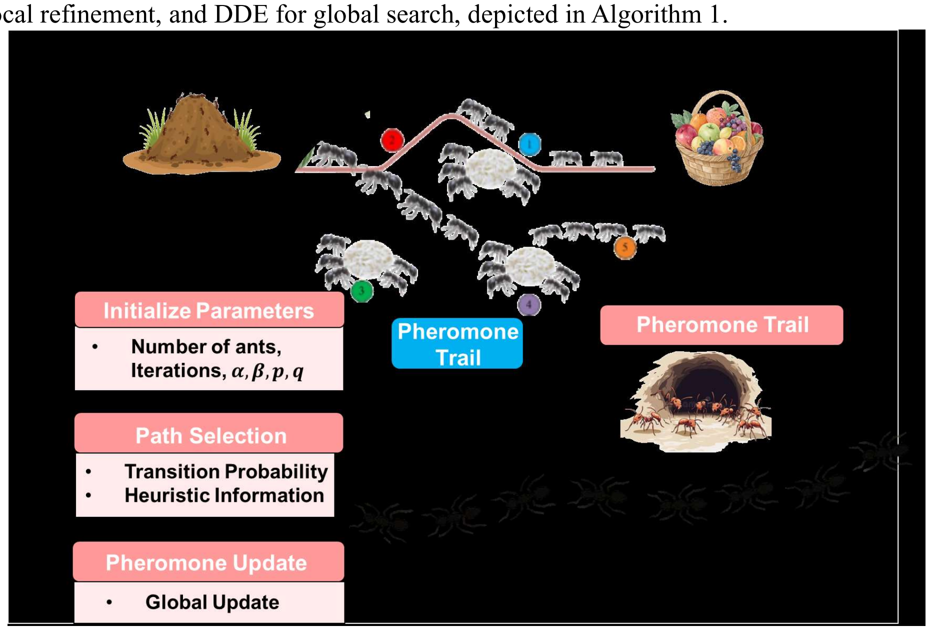

Figure 4: ACO Mechanism for Pheromone-Guided Path Selection.

Algorithm-1: MO-DDE-ACO+CNN

Input:
I : Population size
U : Maximum number of iterations
G : DE mutation factor
α, β : ACO pheromone and heuristic control parameters
ρ : Pheromone evaporation rate
R : Pheromone reinforcement constant
CNN : Trained CNN model
Bounds : Lower and upper bounds of WWTP decision variables

Output:
Archive : Pareto-optimal WWTP operational strategies

Begin

1. Data Preparation
- Preprocess wastewater-hydrological dataset
- Handle missing values and remove outliers
- Normalize influent flow, BOD, COD, nutrients, and energy variables

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2. Initialization
   - Initialize population Y using decision variable bounds
   - Initialize neighborhood sets for MO-DDE
   - Initialize pheromone matrix τ uniformly
   - Initialize empty Pareto Archive

3. Hybrid MO-DDE-ACO+CNN Optimization Loop
  for u = 1 to U do:

      for each solution Y[j] in population:
          CNN_state[j] = CNN.predict(Y[j])
          Adjust objective weights and constraints using CNN_state[j]

      for j = 1 to I do:

          # Neighbor intimacy-based DE mutation
          Select q1, q2, q3 from neighborhood(j)
          W_j = Y[q1] + G * (Y[q2] - Y[q3])

          # Adaptive Gaussian mutation
          s = random choice {0, 1}
          if s == 0:
              σ = (Y[j] - lower_bound) / (2 + d * (u / U)^c)
          else:
              σ = (upper_bound - Y[j]) / (2 + d * (u / U)^c)

          Y_mut = Y[j] + Gaussian(0, σ)


          Enforce operational constraints on Y_mut
          Y_mut = CNN_guided_adjustment(Y_mut)

          Compute objectives g(Y_mut)
          if Y_mut dominates Y[j]:
              Y[j] = Y_mut
              Archive.append(Y_mut)
              Archive = remove_dominated(Archive)

      for each ant n = 1 to I do:
          Initialize solution path
          current_state = start_state

          while not terminal_state(current_state):
              Compute transition probabilities using:
                  τ, η, and CNN_state
              next_state = roulette_wheel_selection()
              Append transition to solution path
              current_state = next_state

          M_n = CNN_evaluated_multiobjective_cost(solution path)

          τ = (1 - ρ) * τ + (R / M_n)

      Maintain diversity and update external Archive
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4. Termination Check
if stopping criteria satisfied:
break

5. Output
Return Archive as CNN-guided Pareto-optimal WWTP strategies

End

3.4 Convolutional neural network (CNN) -Driven Pattern Learning for Wastewater Analytics
Discriminative characteristics are automatically extracted from the input data using a CNN. Convolution layers are followed by fully connected layers in a CNN model. Influent flow rate, nutrient levels, suspended particles, chemical and physiological oxygen demands (BOD and COD), energy usage, and operational control variables like aeration rate and sludge circulation make up the CNN's input.

Convolution operation: A learnable filter is slid across the input data in the convolution operation to identify local patterns. The convolution operation is represented mathematically as follows for an input image J, which describes the multivariate wastewater-hydrological feature map of dimension $(n \times n)(o \times o)$ and a convolution kernel (filter) G, as represented in Equation (16).

$$D = J \otimes G \tag{16}$$

Where D stands for the final feature (convolution) map and $\otimes$ represents the convolution operator. The balanced total of the zone of overlap among the input image and the filter is used to calculate each element of D.

Activation function: The CNN can predict intricate and nonlinear interactions between wastewater and hydrological indicators (BOD and COD) through its activation functions. To add linearity to the feature extraction procedure, a nonlinear activation function is applied to the convolution map D, demonstrated in Equation (17).

$$D_\alpha = g(D) \tag{17}$$

Where D_α is the convolution map following the application of the nonlinear activation function g, and $g(D)$ indicates the nonlinear activation function.

Pooling operation: The pooling operation is represented by mathematical Equation (18), where *pool* is the pooling operation, and Q is the pooling map. Average-pooling, max-pooling, and min-pooling are the three most popular pooling operations in wastewater patterns.

$$Q = Pool\ (D_\alpha) \tag{18}$$

Concatenation operation: The mathematical expression for this Concatenation operation is represented in Equation (19).

$$Z = \begin{bmatrix} Q_1^d \\ Q_2^d \\ Q_3^d \end{bmatrix} \tag{19}$$

Where Z represents the concatenation vector, d shows the dimensions of each feature map, $and\ Q_i^d$ illustrates the output feature map derived from the ith convolution layer following activation and pooling. The entire number of convolution filters employed on the wastewater and hydrological input data is represented by the index $i = 1, 2, \ldots, n$.

Fully connected layer: The concatenation vector Z, which is used to identify discriminative patterns associated with wastewater treatment actions, is processed by the fully connected layer. Through hidden layers with weighted neuron connections X, the CNN produces the output z, which represents the classified hydrological operational state used for further optimization and decision-making, represented in Equation (20), and G^j is denoted in Equation (21).

$$Z^j = g(G^j) \tag{20}$$

$$G^j = X^j Z^{(j-1)} + C^j \tag{21}$$

j denotes the index of the completely linked coating, Z^j is the matrix of weights, C^j is the vector of bias, G^j represents the weighted total of the inputs, $g(G^j)$ is the activation function, and represents the mass atmosphere linking the $(j-1)^{th}$ layer to the j^{th} layer, $Z^{(j-1)}$ is the input feature vector from the previous layer, depicted in Figure 5.

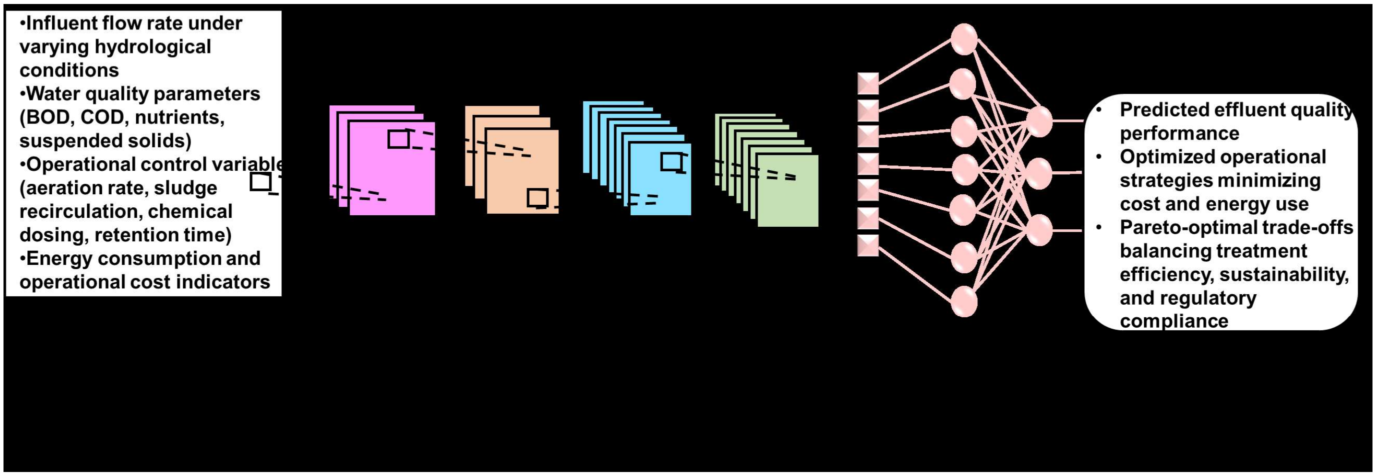

Figure 5: CNN-Assisted MO-DDE-ACO Framework for WTTP Optimization under Hydrological Uncertainty.

4. Findings

The proposed MO-DDE-ACO+CNN framework's prediction accuracy, optimization efficacy, computational efficiency, and resilience in wastewater treatment applications are examined using the experimental setup, learning dynamics, and evaluation criteria.

4.1 Experimental setup

Tables 1 summarize the hardware specifications and software tools used to implement, train, and evaluate the proposed framework.

Table 1: Hardware and Software Setting

Constituent	Specification	
Processor (CPU)	Intel® Core™ i9-12900K	
Clock Speed	3.2 GHz (up to 5.2 GHz Turbo)	
RAM	32 GB DDR5	
Storage	1 TB NVMe SSD	
GPU	NVIDIA RTX 3080 (10 GB VRAM)	
Operating System	Windows 11 Pro (64-bit)	
Software		
Software / Tool	**Version**	**Purpose**
Python	3.10	Core programming language
NumPy	1.24	Numerical computation
SciPy	1.11	Optimization and scientific utilities
DEAP	1.4	Evolutionary algorithm components
PyACO (custom)	—	Ant Colony Optimization module
Pandas	2.0	Data handling and preprocessing
Matplotlib	3.7	Visualization of Pareto fronts
Scikit-learn	1.3	Performance metrics and normalization

The learning dynamics of the suggested model over training epochs are shown in Figure 6. Strong generalization is demonstrated in Figure 6(a), where training accuracy rises quickly from roughly 0.76 to over 1.00 in the first 20 epochs, while validation accuracy stabilizes between 0.95 and 0.97. Training loss lowers significantly from roughly 0.52 to nearly 0.01 in Figure 6(b), while validation loss first drops to about 0.17 and then progressively rises to about 0.30, indicating effective optimization with controlled overfitting.

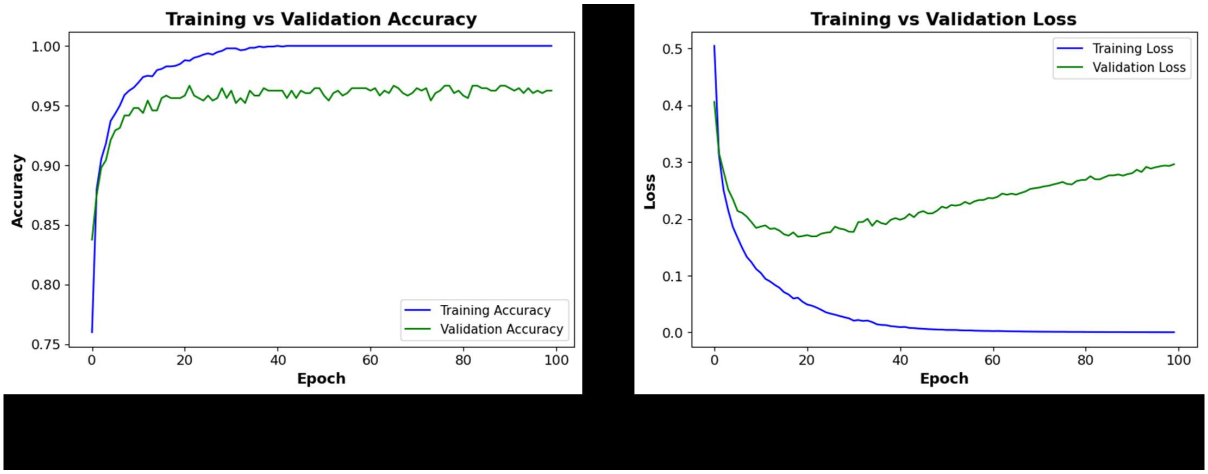

Figure 6: Performance evolution during model training of (a) Training and validation accuracy across epochs and (b) Training and validation loss convergence behavior.

A thorough valuation of the suggested model's prediction accuracy and optimization effectiveness is shown in Figure 7. The Precision–Recall curve in Figure 7(a) demonstrates strong performance under class imbalance, with precision continuously exceeding 0.95 for the majority of recall levels and just slightly declining close to complete recall. Strong discriminative ability is demonstrated in Figure 7(b), where an AUC of 0.984 indicates good separation between operational modes. The ECDF of operational cost is shown in Figure 7(c), where about 80% of solutions converge below a cost of about 70 units, indicating successful optimization toward less expensive, energy-efficient wastewater treatment techniques.

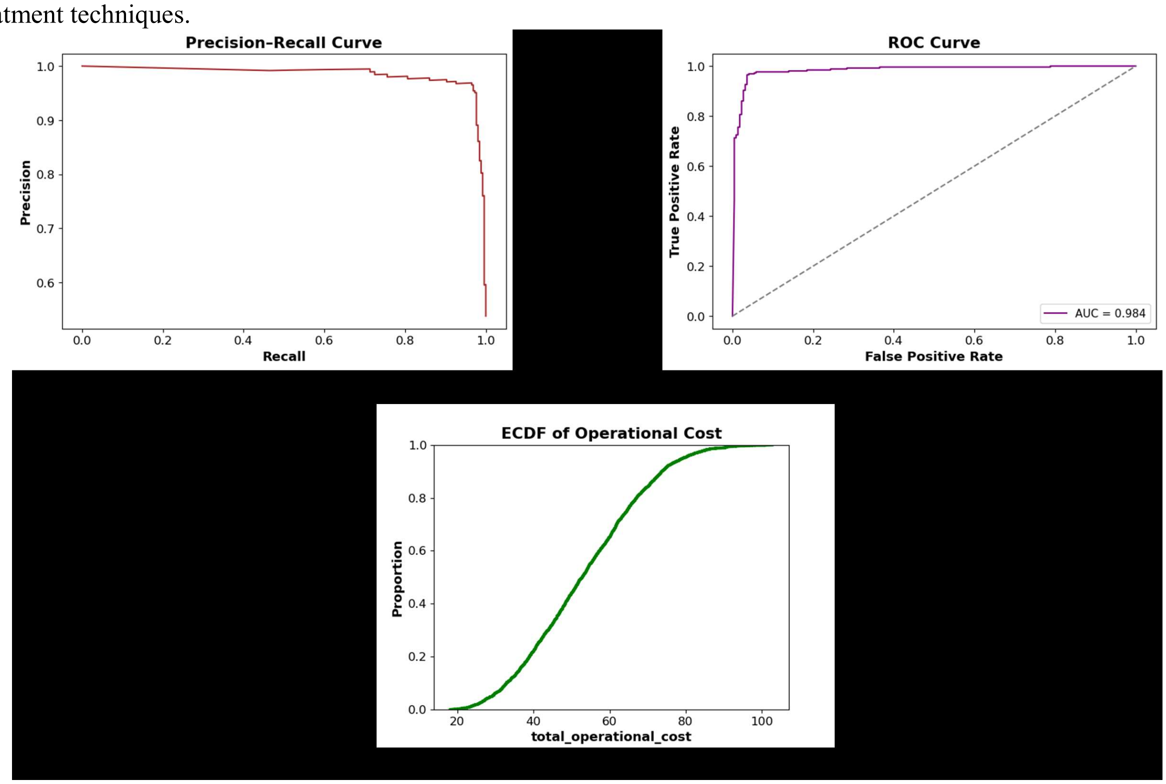

Figure 7: Performance evaluation and optimization outcomes in (a) Precision–Recall characteristics, (b) ROC analysis, and (c) ECDF of operational cost.

With 214 true negatives and 248 true positives, the confusion matrix shows good classification ability, accurately identifying both normal and critical wastewater conditions. Low misinterpretation rates, balanced range and specificity, and accurate identification of operational states under various hydrological conditions are demonstrated in the observation of just 8 false positives and 10 false negatives (Figure 8).

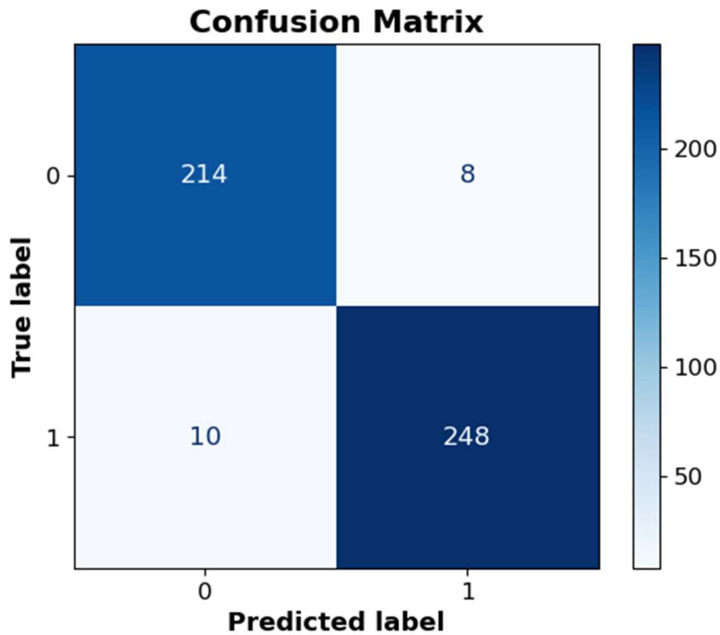

Figure 8: Confusion matrix illustrating the organization performance of the proposed model.

Figure 9 displays the output graphs in Energy–hydrology and load interaction analysis. Different patterns of energy use under wet and dry regimes are depicted in Figure 9(a). Increasing energy demand at increasing BOD levels is depicted in Figure 9(b). As input rates rise, Figure 9(c) illustrates rising energy use. Dense operational regions are shown in Figure 9(d), which denotes the predominant energy-inflow operating zones in sewage treatment systems.

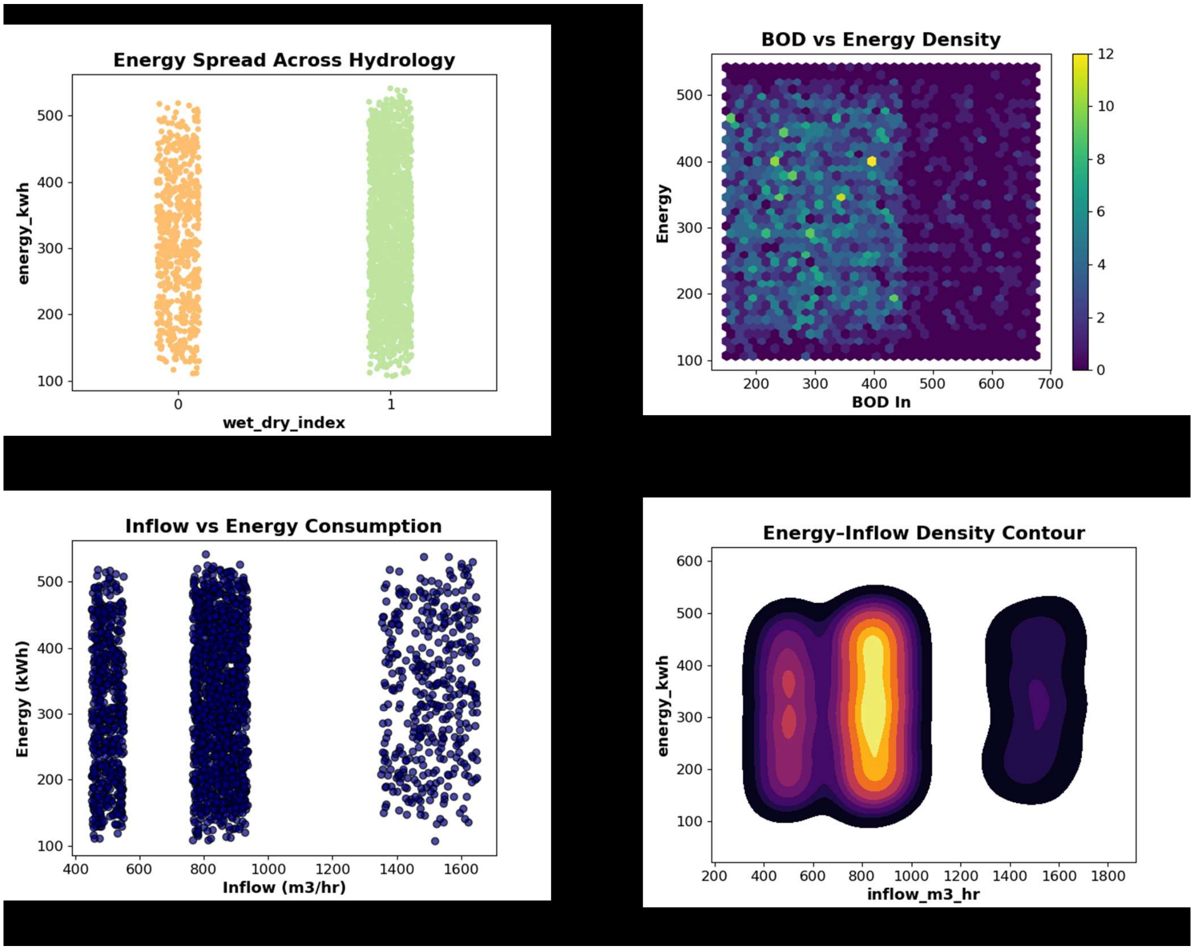

Figure 9: Demonstration of (a) Energy variation under wet and dry hydrological conditions, (b) Density relationship between influent BOD and energy consumption, (c) Inflow rate versus energy consumption distribution, and (d) Energy–inflow density contour representation.

4.2 Model Performance Metrics and Evaluation Criteria

R^2: **R^2** quantifies how well the alteration in the actual data is clarified by the expected values. Better classical performance is indicated by a higher **R^2** value; values nearer 1 indicate great prediction accuracy and an accurate depiction of wastewater system dynamics.

Mean Absolute Error (MAE): The mean error among the anticipated and real values is measured using MAE. The fact that the model predicts the parameters of wastewater points that reliably are estimated without a marked deviation is reflected in the lower MAE values indicating a better prediction and a reduced error value.

Mean Absolute Percentage Error (MAPE): MAPE is the median value of expected and actual variance. Lower MAPE values can also be specifically useful in the wastewater treatment applications when comparing the model performance with different scale because they demonstrate greater predictive reliability.

Root Mean Square Error (RMSE): The emphasis made by RMSE is higher errors; RMSE is calculated as the square root of the mean squared errors of prediction. Lower RMSE is a more indicative measure of better forecast stability and resilience particularly in the capture of high input or pollutant changes in wastewater systems.

Time Spent Training (s): The overall computing time needed to train a model is referred to as training time. Higher computing power, quicker adoption, and applicability for huge-scale or real-time wastewater treatment optimization systems are all indicated by shorter training times.

4.3 Comparative Performance Evaluation of the Proposed Multi-Objective Optimization Frameworks

All compared methods (MO, MO-DDE, MO-DDE-ACO, and the proposed MO-DDE-ACO+CNN) in Table 2 were trained and evaluated using the same Wastewater Treatment under Hydrological Conditions dataset comprising influent flow, BOD, COD, energy consumption, operational cost, and effluent quality variables under varying hydrological conditions.

Table 2: Performance comparison of proposed optimization frameworks across key wastewater variables and evaluation metrics

Research constructs	Metric	MO	MO-DDE	MO-DDE-ACO	MO-DDE-ACO+CNN (Proposed)
Influent Flow Rate	RMSE	0.412	0.336	0.265	0.208
	MAE	0.351	0.284	0.219	0.162
	R^2	0.91	0.94	0.97	0.99
BOD Concentration	RMSE	0.386	0.312	0.248	0.198
	MAE	0.322	0.267	0.203	0.154
	R^2	0.92	0.95	0.97	0.99
COD Concentration	RMSE	0.401	0.329	0.259	0.205
	MAE	0.336	0.274	0.214	0.161
	R^2	0.91	0.94	0.97	0.99
Energy Consumption	RMSE	0.448	0.351	0.276	0.208
	MAE	0.381	0.297	0.228	0.172
	R^2	0.90	0.93	0.96	0.99
Operational Cost	RMSE	0.462	0.364	0.289	0.214
	MAE	0.392	0.306	0.236	0.179
	R^2	0.89	0.93	0.96	0.98
Effluent Quality Index (EQI)	RMSE	0.371	0.298	0.231	0.187
	MAE	0.309	0.246	0.191	0.146
	R^2	0.92	0.95	0.97	0.99

4.4 Evaluation of MO-DDE-ACO+CNN under Competing Modeling Approaches

The proposed MO-DDE-ACO+CNN is compared to existing DL, hybrid optimization, and ensemble learning algorithms, such as Long Short-Term Memory with Attention (LSTM + Attention) [38], Gated Recurrent Unit with Optimization (GRU +Optimization) [38], Residual Network + Self-Attention + Grey Wolf Optimization (ResNet + Self-Attention + GWO) [38], LSTM [39], GRU [39], Transformer [39], Random Forest Regressor [40], Extreme Gradient Boosting (XGBoost) [40], and Categorical Boosting (CatBoost) [40]. A thorough examination of forecast accuracy, robustness, and computing efficiency under varied inflow and pollutant load conditions in wastewater treatment systems is ensured by this comparative study.

The R^2 values of various wastewater prediction models are compared in Table 3 and Figure 10. MO-DDE-ACO+CNN has the highest $R^2$of 0.99 and therefore, the explanatory power of the model is superior to the current methods and is resilient to the changing input and pollution conditions.

Table 3: R^2 performance comparison with currently existing and the proposed MO-DDE-ACO+CNN

Methods	R^2
LSTM + Attention [38]	0.924
GRU +Optimization [38]	0.911
ResNet + Self-Attention + GWO [38]	0.957
LSTM [39]	0.95
GRU [39]	0.94
Transformer [39]	0.98
Random Forest Regressor [40]	0.13
XGBoost [40]	0.79
CatBoost [40]	0.75
MO-DDE-ACO+CNN [Proposed]	**0.99**

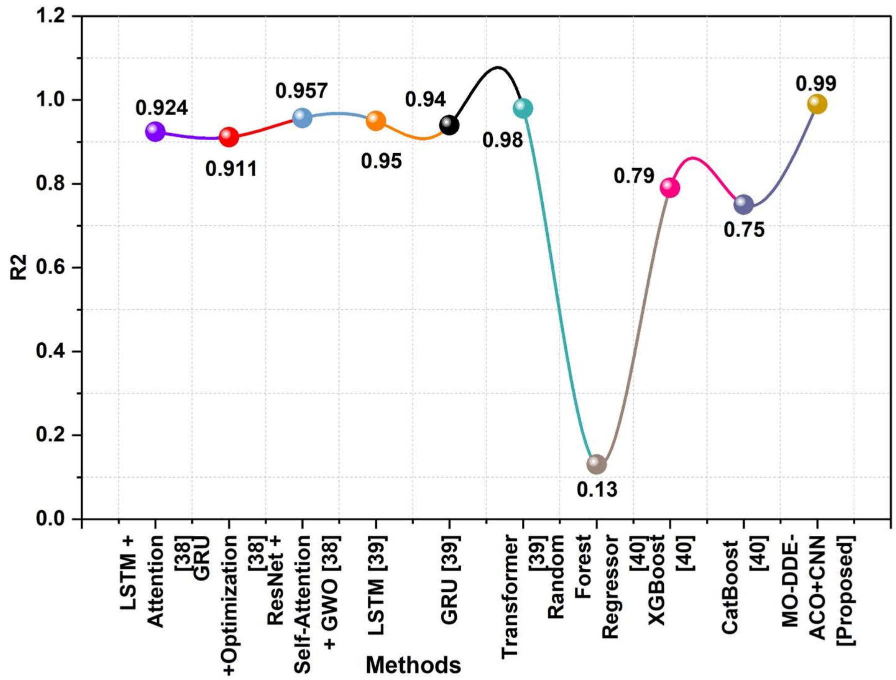

Figure 10: R^2metric performance.

Table 4 and Figure 11 indicate the RMSE of various models. Hybrid DL methods achieve values in the range of 0.285 to 0.325 as RMSE. The MO-DDE-ACO+CNN has the lowest RMSE of 0.208 in wastewater system modeling, and it provides the best prediction stability and reduces the size of errors.

Table 4: RMSE comparison of the proposed and existing

Methods	RMSE
LSTM + Attention [38]	0.298
GRU +Optimization [38]	0.325
ResNet + Self-Attention + GWO [38]	0.285
MO-DDE-ACO+CNN [Proposed]	**0.208**

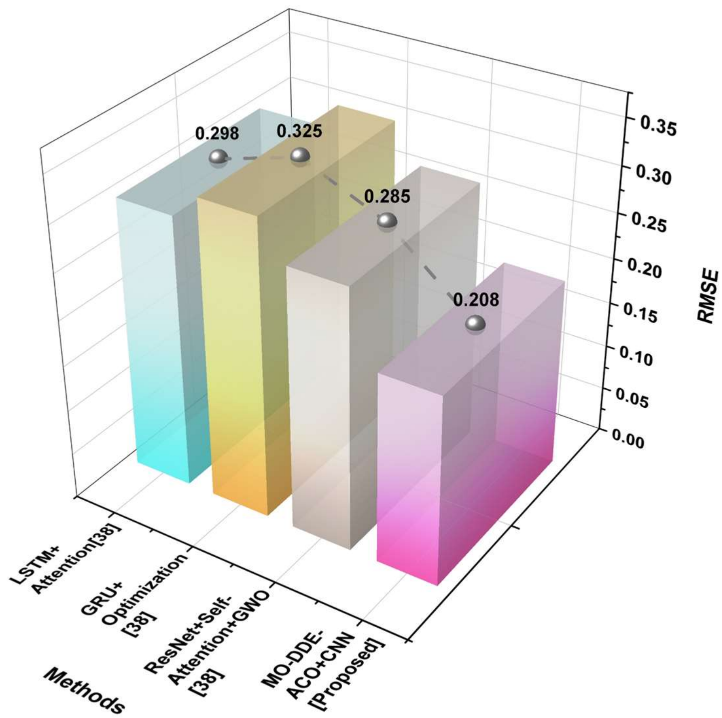

Figure 11: Evaluation of Model Prediction Errors

Having very low MAE of 0.002, and MAPE of 1.08, the proposed MO-DDE-ACO+CNN has high accuracy in prediction and minimal percentage error. These findings testify to the great ability of the model to model unpredictable dynamics of wastewater and provide reliable predictions in a range of inflow and pollutant loads conditions, as shown in Table 5 and Figure 12.

Table 5: Comparative analysis of MAE and MAPE for different models

Methods	MAE	MAPE (%)
LSTM [39]	0.41	3.57%
GRU [39]	0.46	3.99%
Transformer [39]	0.006	2.34%
MO-DDE-ACO+CNN [Proposed]	**0.002**	**1.08%**

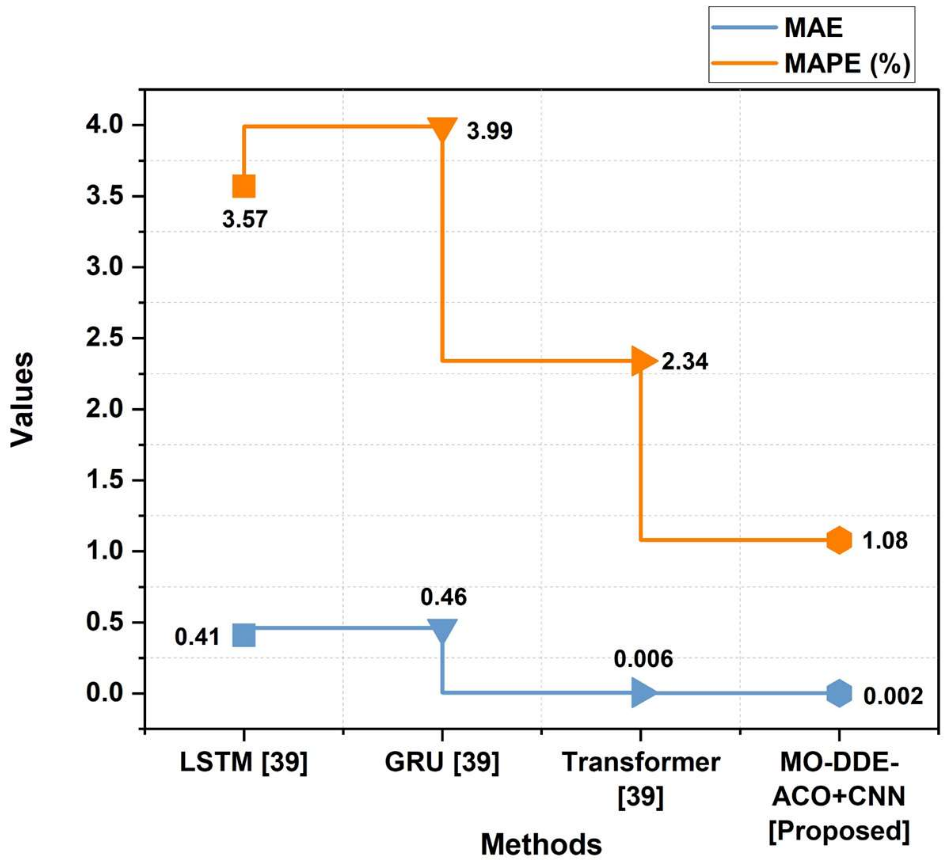

Figure 12: Error Metric Comparison for Wastewater Prediction Models.

The models' computational training times are contrasted in Table 6 and Figure 13. Higher training times (226.97–450 s) are needed for DL and hybrid techniques. With the minimum training period of 198s, the proposed MO-DDE-ACO+CNN exhibits greater predictive performance along with quicker convergence.

Table 6: Training time comparison of learning and optimization models

Methods	Training Time (s)
LSTM + Attention [38]	450
GRU +Optimization [38]	380
ResNet + Self-Attention + GWO [38]	360
LSTM [39]	226.97
GRU [39]	293.47
Transformer [39]	293.29
MO-DDE-ACO+CNN [Proposed]	**198**

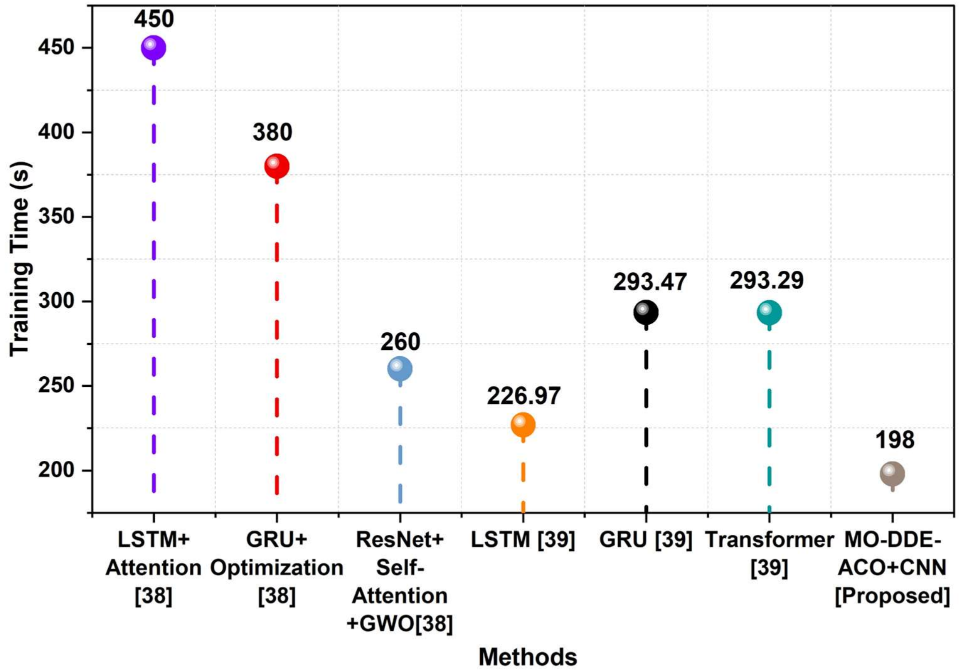

Figure 13: Training Time Performance of Baseline and Proposed Method.

4.5 Discussion

Existing creates a sophisticated framework that ensures stable operation under operational risk while precisely modeling and minimizing energy usage in sewage pumping systems. But, for large-scale, multipurpose wastewater energy optimization under dynamic operating conditions, LSTM + attention has limited effectiveness, required careful hyperparameter tuning, and had a high computational cost and lengthy training period. GRU + optimization reduces complexity but has a small interpretive capacity, can prematurely converge and shows uneven performance in conditions of highly nonlinear wastewater processes as well as under changing inflow, energy demand conditions. ResNet + self-attention + GWO [38] is computationally expensive, inapplicable in real time, variable-dependent and liable to create bias under a number of wastewater working conditions. LSTM models have a disadvantage in that they decline performance due to delayed temporal adjustability, high computation cost, and dependence on sequence length. GRU also has limitations on its ability to model long-term dependencies since it can learn faster than LSTM. Transformer [39] models require large training data sets and substantial processing power. Random Forest Regressor cannot extrapolate because of its group structure based on averaging, making it slow to make inferences with large data sets, consuming large amounts of memory and unable to handle extreme influx events. XGBoost requires much computing power and careful fine-tuning of hyperparameters. CatBoost [40] is an effective algorithm that handles categorical data, but it has more computational costs and demanding procedures in training.

Practical implication: Wastewater treatment plants can save energy and operating expenses and maintain effluent standards through the suggested MO-DDE-ACO+C CNN framework to accomplish information-driven operations decisions within variable inflow conditions.

4.5.1 MO-DDE-ACO+CNN uses: Removing the limitations of the current approaches.

Using MO, DDE and pheromone-guided search together the proposed MO-DDE-ACO+CNN can achieve improved performance without facing the shortcomings of the DL and ensemble models. It copes with nonlinear variability of varying load of inflow and pollutant, prevents premature convergence, preserves Pareto diversity and offers sustainable, understandable and rapid solutions of optimization of sewage treatment and concomitantly optimization of accuracy, robustness and computational expense.

5. Conclusion

The suggested MO-DDE-ACO+CNN is an efficient Pareto-based optimization application that strongly manages changing inflows and pollutant loads by optimizing WWTP with a balance point cost, energy and effluent quality under hydrological uncertainty. High-frequency WWTP under Hydrological Conditions data are used in the investigation. Features are standardized, outliers are eliminated, and MVIs are probabilistically imputed. A CNN extracts nonlinear and spatial patterns, resulting in robust feature representations for multi-objective optimization under hydrological uncertainty. With MAE = 0.002, RMSE = 0.208, MAPE = 1.08%, and R^2 = 0.99, the proposed

MO-DDE-ACO+CNN outperforms the competition while cutting training time to 198 s. Improved convergence, balanced Pareto fronts, and robust optimization under varying input and pollution conditions are shown by the results.
Limitations and Future Scope: The proposed paradigm is predicated on fixed operational limitations and validated using small plant-specific datasets. Multi-plant generalization, real-time deployment, digital twin integration, adaptive online learning, and the incorporation of regulatory, carbon-emission, and uncertainty-aware decision objectives for large-scale sewage systems will be the main areas of future research.

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