

Applied Mathematics and Nonlinear Sciences

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Design and optimization of multidimensional control strategy based on optimization algorithm and modeling of wastewater treatment process

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Submission Info

Communicated by Z. Sabir
Received October 27, 2024
Accepted February 10, 2025
Available online March 24, 2025

Abstract

Aiming at the problems of excessive energy consumption and serious exceeding of effluent water quality in the control of wastewater treatment process, after analyzing the wastewater treatment process, we propose an intelligent optimization control strategy by integrating a multi-strategy multi-objective sparrow algorithm. First, the relationship between the objective function and the controllable variables is found by analyzing the mechanism of the sewage treatment process, and energy consumption and effluent water quality models are constructed. Then the SSA is improved from five aspects, including population initialization, position update of discoverer and alert, optimal position perturbation strategy and external archive update mechanism, and a multi-objective sparrow algorithm incorporating multi-strategies is proposed to solve the model. The experimental results show that the convergence and diversity of the proposed algorithm have been significantly improved, and it can effectively reduce the energy consumption of the sewage treatment process and achieve the expected optimization purpose while meeting the effluent water quality standards.

Keywords: Wastewater treatment process; Multi-objective sparrow algorithm; Multi-strategy; Good point set; Dynamic inertia weights.

AMS 2010 codes: 03C65

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ISSN 2444-8656



<https://doi.org/10.2478/amns-2025-0732>



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1 Introduction

Wastewater treatment is one of the important contents of modern urban environmental protection, and its process requires the comprehensive use of physical, chemical and biological and other technical means to treat the water quality in accordance with the relevant national standards [1-2].

Primary treatment is the first step of wastewater treatment, and its purpose is to remove most of the precipitable and suspended matter. Firstly, the sewage will be passed through the grating to remove the large solid impurities, and then the sewage will flow into the sand sedimentation tank or precipitation tank, in the process of resting, the heavier suspended matter will be settled to the bottom and form sludge [3-6]. Biological treatment is a step of further purification of sewage after primary treatment. This process mainly utilizes the action of microorganisms to decompose and transform organic matter and nutrient salts such as nitrogen and phosphorus. Common biological treatment methods include activated sludge method, fixed membrane method and so on. After the primary and biological treatment, the organic matter and nutrient salts in the wastewater have been greatly reduced, but a certain amount still exists [7-10]. Secondary treatment aims to further reduce these organic matter and nutrient salts to prevent eutrophication and biological processes in the water body. Common secondary treatment methods include sedimentation, oxidation ditch, and artificial wetland [11-13]. Advanced treatment is used to purify wastewater that has undergone primary, biological and secondary treatment to achieve higher purification standards. Common advanced treatment technologies include adsorption, membrane separation, and activated carbon filtration [14-16]. Disinfection is the last line of defense to kill residual bacteria and viruses. Common disinfection methods include chlorination, ultraviolet irradiation, and ozone oxidation [17-18].

Literature [19] discusses the characteristics of wastewater and the technologies used in wastewater treatment. Innovative technologies are revealed to be constantly evolving, as well as conventional practices in wastewater treatment plants. The importance of introducing sustainable and friendly procedures is emphasized. Literature [20] is based on a literature review in order to provide results about the advantages, disadvantages and applications of wastewater treatment processes. Information related to technologies still under development is also provided. The results describe a discussion of the impact of applying the proposed process in a sludge production line to a very large capacity wastewater treatment plant. Literature [21] proposes the application of machine learning methods such as ELM and SVM for modeling wastewater treatment plants. And these machine learning methods are compared with the conventional ARIMA. The simulation results point out that ELM model performs better in comparison to other models. Literature [22] takes particle swarm optimization algorithm and activated sludge wastewater treatment method as the research object, and based on the experiment, it verifies that the particle swarm optimization algorithm can play an important role in wastewater treatment system, and it can also be applied to other wastewater plants using activated sludge oxidation ditch process, which is of great value for promotion. Literature [23] modeled, calibrated and validated the activated sludge process in a wastewater treatment plant. The process parameters of the validated model were optimized using a multi-objective optimization approach and the study was carried out using ANSGA-III, NSGA-II and PSO optimization algorithms. The results show that the ANSGA-III algorithm and the multi-objective optimization method have good capability in energy conservation and retrofitting of wastewater treatment plants. Literature [24] proposed RLPSO to optimize the control settings in wastewater treatment process and tested RLPSO. The simulation results verified that the RLPSO has good performance and its ability to effectively reduce energy consumption while ensuring qualified water quality. Literature [25] proposes the algorithm DMOPSO-CD consisting of an optimization module and a self-organizing fuzzy neural network aiming at obtaining an optimal solution for the balance between EC and EQ in the wastewater treatment process. By using the algorithm in a benchmark simulation model, the results show that the proposed algorithm performs better compared to other algorithms, which is important for decision

making in wastewater treatment optimization. Literature [26] proposed an intelligent control method for wastewater treatment by combining the MOPSO algorithm. And based on practice, it is shown that the intelligent control system combined with the MOPSO algorithm can make the COD in wastewater treatment quickly reach the expected requirements and effectively improve the performance of wastewater treatment.

In order to better solve the multi-objective optimization problem of wastewater treatment process with effluent water quality meeting the standard and low total energy consumption, a multi-objective sparrow algorithm incorporating multiple strategies is proposed after the multi-objective optimal control modeling of wastewater treatment process. Firstly, the good point set is used to initialize the sparrow population to make the population distribution more uniform and improve the search space, and the optimal bootstrap strategy and dynamic inertia weights are introduced in the finder position updating formula to improve the origin convergence problem of the finder, and balance the algorithm's global exploration and local exploitation ability. Secondly, to improve the algorithm's local escape ability, the vigilante position update strategy is improved and the optimal position of the sparrow individual is perturbed. Finally, the population updating method is introduced in the external archive updating process to accelerate the convergence speed of the algorithm and increase the diversity of the population. On this basis, in order to prove the effectiveness of the multi-objective optimization control method proposed in this paper, the algorithm is validated using the international benchmark simulation platform for activated sludge wastewater treatment.

2 Process analysis of sewage treatment processes

2.1 Activated sludge series model

Activated sludge series models fall under the category of mathematical models that are primarily used to describe the behavior of sewage in the biological treatment process. These models are all based on basic principles of conservation of mass, momentum, and energy, etc. By describing the processes of material transfer, biological reaction and air transfer in the activated sludge system, and considering the influence of environmental factors on the effect of sewage treatment, these models can predict the operation status and metabolites of the sewage treatment system, etc., and provide a basis for the actual engineering operation [27]. Common activated sludge series models are ASM1, ASM2, ASM2d, ASM³, ASM³d, etc. Different models consider different factors and complexity in describing the wastewater treatment process, so the selection of a suitable model needs to consider the specific engineering situation and needs.

The activated sludge model utilizes the concurrent consumption of oxygen or nitrate as a receptor, and is able to reflect the removal of organic carbon compounds and ammonium nitrogen in activated sludge. The activated sludge model was then developed as ASM1 to address biological nitrogen and phosphorus removal from effluents in wastewater treatment plants. Since then, more sophisticated ASM2 and ASM³ models have also emerged to model the biological removal of nitrogen by biopolymers under transient conditions.

2.2 Modeling of wastewater treatment processes based on international benchmarks

The most popular current method for treating biological wastewater is known as the activated sludge process, which is characterized by stable performance and low operating costs. The activated sludge process is a biological method widely used in municipal and industrial wastewater treatment. This process is used to purify water quality by introducing sewage containing organic substances and nutrients into a reaction tank, and utilizing microbial groups (i.e., activated sludge) with anaerobic

and aerobic effects to decompose and degrade the organic substances therein. The activated sludge process can be divided into preliminary treatment, primary treatment, secondary treatment (biological treatment), sludge treatment, and finally sludge recycling and utilization. Preliminary treatment involves removing floating materials and settling inorganic solids. The sludge treatment process mainly includes thickening, digestion and dewatering, and the activated sludge treatment process is shown in Figure 1:

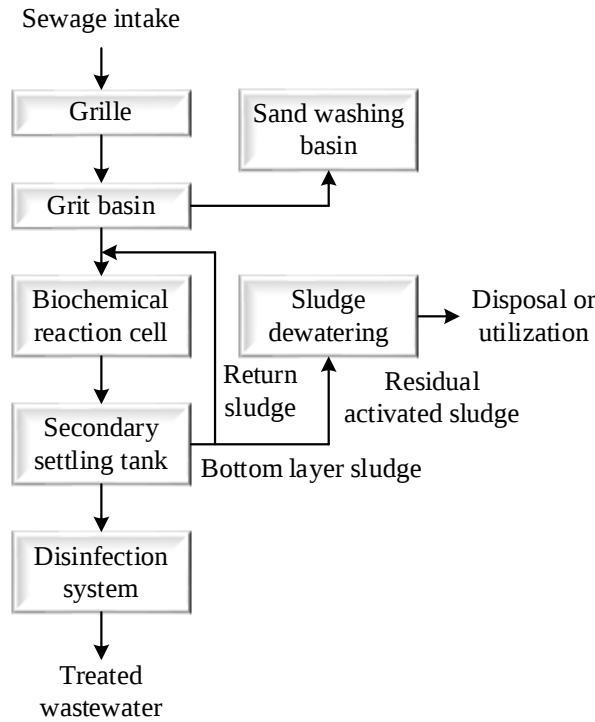


Figure 1. The Schematic of wastewater treatment process

The main facilities of the BSM1 wastewater simulation platform are five activated sludge reaction tanks and one secondary sedimentation tank. The five activated sewage reaction tanks are composed of two anoxic tanks and three aerobic tanks respectively. The average daily sewage volume of the platform is 20000m³, and the biodegradable chemical oxygen demand is 300mg/L; in order to realize biological nitrogen removal, the sewage treatment process includes nitrification and pre-denitrification process.

The BSM1 model integrates eight reaction processes, including oxidation and nitrification reaction processes, as well as five stoichiometric constants, fourteen kinetic coefficients, and thirteen components. Of the thirteen components, the soluble component is denoted by the symbol S , where the seven soluble components are $S_I, S_O, S_S, S_{NO}, S_{NH}, S_{ND}$ and S_{ALK} , respectively, and the insoluble component is denoted by the symbol X , where the six insoluble components are $X_I, X_S, X_{BH}, X_{BA}, X_P$ and X_{ND} , respectively.

2.3 Wastewater treatment performance evaluation indicators

Four error assessment metrics are proposed in this paper to measure the ability to predict the results during the soft measurement process of wastewater treatment. The four error assessments are root mean square error, mean absolute error, mean absolute percentage error and correlation coefficient.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (ob_i - pr_i)^2} \quad (1)$$

$$MAPE = \sum_{i=1}^n \left| \frac{pr_i - ob_i}{pr_i} \right| \times \frac{100}{N} \quad (2)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |ob_i - pr_i| \quad (3)$$

$$R = \frac{\sum_{i=1}^n (pr_i - \overline{pr_i})(ob_i - \overline{ob_i})}{\sqrt{\sum_{i=1}^n (pr_i - \overline{pr_i})^2} \times \sqrt{\sum_{i=1}^n (ob_i - \overline{ob_i})^2}} \quad (4)$$

where ob_i and pr_i denote the mean values of the reference and soft measurement samples, respectively; n denotes the length of the time series, and ob_i and pr_i denote the reference and soft measurement values, respectively.

According to the objective function set by dissolved oxygen, the performance of the established optimization control model is evaluated by the value of energy consumption (EC) and the value of effluent water quality (EQ) given by BSM1. Among them, EQ is the evaluation index of effluent water quality, the smaller the EQ value is, the better the water quality is, and vice versa, the worse, the formula is as follows:

$$EQ = \left(\frac{1}{1000T} \int_{t_0}^{t_f} [2SS_e(t) + COD(t) + 30S_{nkj,e}(t) + 20S_{No,e}(t) + 2BOD_5(t)] Q_e(t) dt \right) \quad (5)$$

$$COD = S_S + S_I + X_S + X_I + X_{B,H} + X_{B,A} + X_P \quad (6)$$

$$BOD_{5,e} = 0.25[S_{S,e} + X_{S,e} + (1 - f_p)(X_{P,e} + X_{I,e})] \quad (7)$$

$$SS_e = 0.75(X_{S,e} + X_{I,e} + X_{B,H,e} + X_{B,A,e} + X_{P,e}) \quad (8)$$

$$S_{NKj,e} = S_{NH,e} + S_{ND,e} + X_{NH,e} + i_{XB}(X_{B,H,e} + X_{B,A,e}) + i_{XP}(X_P + X_I) \quad (9)$$

$$AE = \frac{S_{o,sat}}{1800T} \int_{t_0}^{t_f} \sum_{k=1}^5 V_k K_L a_k(t) dt \quad (10)$$

$$PE = \frac{1}{T} \int_{t_0}^{t_f} (Q_a(t) + Q_r(t) + Q_w(t)) d(t) \quad (11)$$

$$EC = PE + AE \quad (12)$$

where AE is the aeration energy consumption and PE is the pumping energy consumption e is the number of partitions of the biochemical reactor, Q_e is the flow rate of partition e , Z_e is the concentration of substrate components in partition e , V_e is the volume of partition e , Q_0 is the influent flow rate of the system, Q_a is the internal return flow rate of the system, Q_r is the external return flow rate of the system K_{Lae} is the coefficient of oxygen transfer of partition e , $S_{o,e}$ is the content of dissolved oxygen in partition k , and $S_{o,sat}$ is the effluent content in the aftermath.

3 Multi-objective optimal control of wastewater treatment processes

3.1 Optimization objective of multidimensional control of wastewater treatment process

3.1.1 Optimization problem description

Based on the BSM1 platform using multi-objective optimal control, the essence is to optimize two key and contradictory indicators to achieve relative balance: water quality (I_{EQ}) and total energy consumption (I_{OC}). I_{EQ} is expressed as:

$$I_{EQ} = \frac{1}{T \times 1000} \int_{t_0}^{t_f} (2S_{TSS}(t) + S_{COD}(t) + 3S_{NKJ}(t) + 10S_{NO}(t) + 2S_{BOD_5}(t)) Q_e(t) dt \quad (13)$$

Where $S_{TSS}, S_{COD}, S_{NKJ}, S_{NO}, S_{BOD_5}$ and Q_e represent the concentration of suspended solids, chemical oxygen demand, Kjeldahl nitrogen concentration, nitrate nitrogen concentration, 5-day biochemical oxygen demand and clear water discharge, respectively.

The expression for I_{oc} is:

$$I_{OC} = E_A + E_P + 3E_C \quad (14)$$

where E_A denotes aeration energy consumption, E_P denotes pumping energy consumption, and E_C denotes carbon source cost, which is expressed as:

$$E_A = \frac{8}{T \times 1.8 \times 1000} \int_{t_0}^{t_f} \sum_{i=1}^5 V_i K_{Lai}(t) dt \quad (15)$$

$$E_P = \frac{1}{T \times 1000} \int_{t_0}^{t_f} (4Q_a(t) + 8Q_r(t) + 50Q_w(t)) dt \quad (16)$$

$$E_C = \frac{400}{T} \int_{t_0}^{t_f} \sum_{k=1}^5 q_{EC,j} dt \quad (17)$$

Where T is the sampling period, t_0 and t_f denote the start time and end time respectively, V_i and K_{Lai} denote the volume and aeration of the i th biochemical reactor respectively, Q_a, Q_r and

Q_w denote the internal return flow, the external return flow and the residual sludge flow respectively, and q_{EC}, j denote the flow of carbon source added to the j th reaction zone.

The optimization problem of wastewater treatment process can be described as:

$$\begin{aligned} \min F(X) &= \{f_{OCI}(X), f_{EQI}(X)\} \\ \text{s.t. } S_{Nh,e,avg} &< 4 \text{ mg/L} \\ S_{Ntot,e,avg} &< 18 \text{ mg/L} \\ S_{BOD_5,e,avg} &< 10 \text{ mg/L} \\ S_{COD,e,avg} &< 100 \text{ mg/L} \\ S_{TSS,e,avg} &< 30 \text{ mg/L} \end{aligned} \quad (18)$$

Where $f_{OCI}(X)$ and $f_{EQI}(X)$ denote the optimization functions of I_{OC} and I_{EQ} , respectively; $S_{Nh,e,avg}$ denotes the average concentration of ammonia nitrogen in the effluent; $S_{Ntot,e,avg}$ denotes the average concentration of total nitrogen in the effluent; X is the decision vector, $X = (x_1, x_2)$, x_1 , and x_2 are $S_{0.5}$ and $S_{NO,2}$, respectively; and $l_i \leq x_i \leq u_i$, u_i , and l_i denote the upper and lower bounds of each decision variable, $i = 1, 2$ respectively. The limitations are based on five water quality parameters given in the nationally established effluent discharge standards, the average concentration of which meets the standards before being allowed to discharge.

3.1.2 Multi-objective optimization and optimal setting value selection

The setting values of $S_{0.5}$ and $S_{NO,2}$ directly affect $S_{Nh,e}$ and $S_{Ntot,e}$, and K_{Lai} and Q_a affect the concentration setting, so choosing the correct setting values can effectively reduce energy consumption and improve the water quality. In this paper, the setpoints of $S_{0.5}$ and $S_{NO,2}$ are optimized by using the multi-objective evolutionary algorithm based on decomposition (DPMNMOEA/D) algorithm based on dynamic population multi-neighborhood MOEA/D (DPMNMOEA/D), and the PID controller achieves real-time tracking control of the setpoints by adjusting K_{Lai} and Q_a , so as to achieve the goal of improving water quality and reducing energy consumption.

After the multi-objective evolutionary algorithm for $S_{0.5}$ and $S_{NO,2}$ set values for an optimization, the optimization process will produce a series of Pareto solutions, although the entire optimization and control process of water quality to meet the emission standards, but part of the optimization cycle there is an average of the phenomenon of water quality exceeding the standard, so for the cycle of exceeding the standard for the selection of the most suitable for the set values of $S_{0.5}$ and $S_{NO,2}$, to ensure that in order to improve the quality of water on the basis of reducing energy consumption, the specific The process is as follows:

Step1: Take the Pareto solutions obtained from the preference search as $S_{0.5}$ and $S_{NO,2}$ set values in turn, substitute them into the prediction model, and keep the solutions that satisfy the constraints on the average effluent quality in the cycle and deposit them into the solution set P_A .

Step2: If P_A is not equal to the empty set, it means that the solutions in the set satisfy the condition of meeting the water quality standard, at this time, the reduction of energy consumption becomes the primary goal, so the preferred solution (X_{select}) selected from P_A should obtain the lowest energy consumption (f_{OCmin}).

Step3: If P_A is equal to the empty set, it indicates that all the solutions can not guarantee that the water quality can meet the standard, at this time to improve the water quality has become the main goal, so the selected preference solution should obtain the optimal water quality (f_{EQmin}).

The method of selecting setting values can prejudge whether the water quality is up to standard or not, and selecting the preferred solutions as $S_{0.5}$ and $S_{N0.2}$ setting values according to the water quality up to standard can minimize the energy consumption under the premise of ensuring that the water quality is up to standard. Although this method can improve the effluent water quality, but can not completely avoid the phenomenon of $S_{Nh,e}$ and $S_{Ntot,e}$ peaks exceeding the standard, so it is necessary to design a suppression strategy to deal with the problem of exceeding the standard. In order to verify the advantages and disadvantages of the suppression strategy, on the basis of the evaluation indexes of energy consumption and water quality, the percentage of water quality exceeding time P is selected as the evaluation index, i.e., the ratio of the total water quality exceeding time T_c to the total operation time T_z , and its expression is:

$$P = T_c / T_z \quad (19)$$

3.2 Multi-objective sparrow algorithm incorporating multiple strategies

3.2.1 Canonical point set based population initialization

The set of good points was proposed by Hua Luogeng et al. Its basic definition is: Let G_s be the unit cube of a s -dimensional Euclidean space, i.e., $x \in G_s$, $X = (x_1, x_2, x_3, \dots, x_s)$, where the point $r = (r_1, r_2, \dots, r_s)$ in $0 \leq x_i \leq 1, i = 1, 2, \dots, S$, G_s , such that $r \in G_s$, and the deviation $\varphi(n)$ of the form $P_n(k) = \{(r_1(k), \dots, r_s(k)), k = 1, 2, \dots, n\}$ satisfy $\varphi(n) = C(r, \varepsilon)n^{-1+\varepsilon}$, where $C(r, \varepsilon)$ is a constant related only to r , $\varepsilon (\varepsilon > 0)$, then $P_n(k)$ is said to be the set of good points, and r is the point of goodness [28].

The optimization performance of the algorithm has a certain relationship with the diversity of the initial population, the better the diversity, the faster the algorithm converges and the higher the accuracy. In the basic sparrow algorithm, the initialization of the population adopts the random number initialization method, which is easy to fall into the local optimum due to the uneven distribution of the population and the poor diversity, while the initialization of the population based on the set of good points has an even distribution history and the initial population diversity is better, which can effectively improve the performance of the algorithm. The specific steps of initializing the population based on the good point set: (1) Generate the good point set $X = \{x_1, x_2, \dots, x_i, \dots, x_k\} (i = 1, 2, \dots, k)$, k for the population size; (2) The arbitrary dimensional component in $x_i = \{x_{i1}, x_{i2}, \dots, x_{ij}, \dots, x_{id}\}$ is $x_{ij} = i \times 2 \cos(\frac{2\pi j}{p})$, d for the spatial dimensions; (3)

Map the good point set to the search space: $x_{ij} = Lb_j + \text{mod}(x_{ij}, 1) \times (Ub_j - Lb_j)$, where x_{ij} is the position of the sparrow, and Ub_j , Lb_j represents the upper and lower bounds of the j th dimension.

To verify the superiority of the good point set initialized population, it is used as a comparison with random number initialized population and tent mapping initialized population. The random number initialized population method generates an initial population by randomly generating individuals in the solution space. tent mapping initialized population method first generates a chaotic sequence by using tent mapping, and then generates an initial population by mapping the sequence into the solution space.

3.2.2 Discoverer Position Update under Optimal Bootstrapping Strategy

In the original discoverer position update strategy, when $R_2 < ST$, the discoverer is prone to converge to the origin in the late iteration, and the discoverer in turn guides the population in its search, which can easily cause the algorithm to fall into a local optimum. When the individual sparrows do not detect the danger, the original position update formula, which does not utilize the globally optimal position, lacks sufficient and effective communication between the discoverers. The improved formula, which incorporates an optimal bootstrapping strategy, allows optimal position information to be quickly passed between discoverers. Meanwhile, a decreasing inertia weight w is introduced, which makes the algorithm have strong global search capability in the early iteration and strong local exploitation capability in the late iteration. The improved finder position update formula is:

$$X_i^{t+1} = \begin{cases} X_i^t \cdot w + \text{randn}(0,1) \cdot |X_i^t - X_{best}^t| & \text{if } R_2 < ST \\ X_i^t + Q \cdot L & \text{if } R_2 > ST \end{cases} \quad (20)$$

$$w = r_1 - r_2 \cdot (t / \text{MaxIt})^2 \quad (21)$$

where r_1 and r_2 are the two weight coefficients, t is the number of iterations, and MaxIt is the maximum number of iterations of the algorithm.

3.2.3 Improvement of the formula for updating the position of the vigilantes

For the vigilant at the edge of the population, i.e., the individual of $f_i \neq f_g$, decreasing inertia weight w_2 is used to bring it closer to the optimal position step by step to speed up the convergence of the algorithm; for the vigilant at the center of the population, increasing inertia weight w_1 is used to increase the ability of the algorithm to jump out of the local optimum at the later stage of the iteration. Meanwhile, the fitness values f_i and f_w in the multi-objective optimization problem are multi-dimensional vectors, which are unable to calculate the position of the vigilantes, so their updating formulas are improved, and the updating formulas are:

$$X_z^{t+1} = \begin{cases} X_{best}^t + w_2 \cdot |X_z^t - X_{best}^t| & \text{if } f_i \neq f_g \\ X_z^t + w_1 \cdot |X_z^t - X_{worst}^t| & \text{if } f_i = f_g \end{cases} \quad (22)$$

$$w_1 = r_3 + r_4 \cdot (t / \text{MaxIt})^2 \quad (23)$$

$$w_2 = r_5 - r_6 \cdot (t / \text{MaxIt})^2 \quad (24)$$

where r_3, r_4, r_5, r_6 are all weighting coefficients.

3.2.4 Optimal positional perturbation strategy

The improved position update formulas for both the discoverer and the vigilant introduce a globally optimal position, which will cause the algorithm to fall into a local optimum if that optimal individual is a locally optimal individual due to the gradual convergence to the optimal individual in the later iterations of the algorithm [29]. To address this problem, this paper adopts a perturbation strategy to improve the ability of the algorithm to jump out of the local optimum by transforming the probability P_m and perturbing the optimal position.

$$P_m = 1 - \frac{t}{\text{MaxIt}} \quad (25)$$

From Eq. (25), the transition probability decreases with the number of iterations. When P_m is larger than the generated random number r between $[0, 1]$, then the optimal position is not perturbed, and in the algorithm in the pre iteration P_m is larger, the probability of perturbation is smaller, so that the algorithm in the early stage of the rapid search for the global optimal solution; conversely, the optimal position is perturbed, and in the late stage of the iteration P_m of the algorithm is smaller, the probability of perturbation is larger. The perturbation formula is:

$$ct = \frac{X_{\text{rand}(i_1)} + X_{\text{rand}(i_2)}}{2} - X_{\text{best}} \quad (26)$$

$$X' = r_c \cdot ct + X_{\text{best}}, r_c \in (0, 1) \quad (27)$$

where $X_{\text{rand}(i_1)}$ and $X_{\text{rand}(i_2)}$ are two random sparrow individual positions, ct is the perturbation term, r_c is a random number between $[0, 1]$, and X' is the global optimal position after the perturbation.

3.2.5 Renewal of stocks and updating and maintenance of external archives

Population renewal is performed by comparing the relationship between individuals in the previous generation population and individuals in the new population:

- 1) If the individuals of the previous generation population dominate the individuals of the new population, replace the positions and fitness values of the corresponding individuals of the previous generation population with the positions and fitness values of the new population.
- 2) If the new population individuals dominate the previous generation of population individuals, the replacement is made with a small probability, preserving the diversity of the population to some extent.
- 3) If they do not dominate each other, then replacement is done with 50% probability.

By this method of updating the population, the individuals with high adaptation can be updated in the next iteration, which not only improves the subgeneration utilization rate and algorithm convergence speed, but also improves the diversity of the population to a certain extent.

The updated population is used as the next-generation population and is non-dominated sorted with the optimal solution set archive to produce a new elite external archive that replaces the previous generation optimal solution set archive in the next generation update. The cycle continues until the termination condition is satisfied and the final elite archive is output.

3.3 Multi-objective optimization control process for wastewater treatment

The multi-objective optimization control structure for wastewater treatment mainly includes the following: firstly, there is no clear mathematical relationship between OCI, EQI and $S_{O,5}, S_{NO,2}$, and it is necessary to collect the process data of $S_{O,5}, S_{NO,2}$, OCI and EQI offline, and use LSSVM to establish the soft measurement model of EQI and OCI and use it as the optimization objective function; then use MSIMOSSA to optimize the optimization objective function, and get the optimized set values of $S_{O,5}$ and $S_{NO,2}$ the optimized set values; finally, PID tracking control was used to control the dissolved oxygen concentration and nitrate nitrogen concentration by adjusting the dissolved oxygen conversion factor (K_{La5}) and the internal return flow rate (Q_a) in the fifth partition, respectively. The control structure is shown in Figure 2.

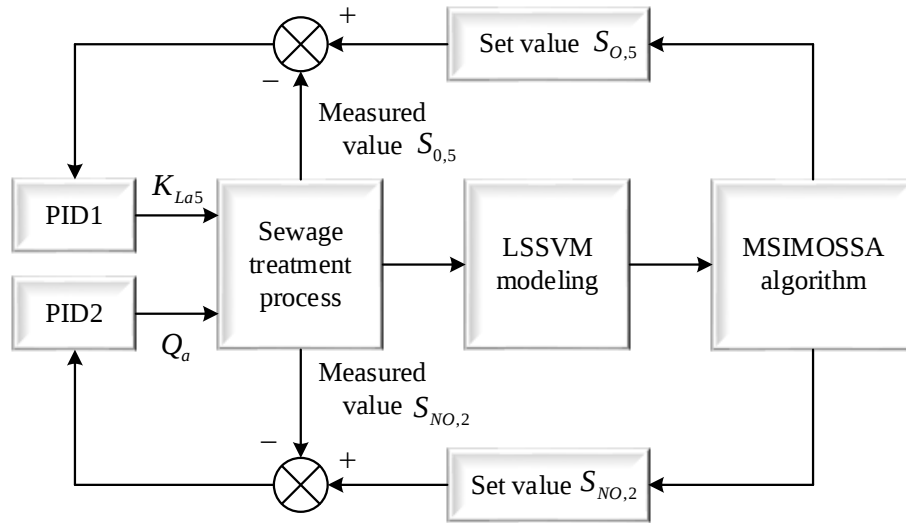


Figure 2. Multi-objective optimization control structure of wastewater treatment

4 Experimental simulation studies

4.1 Experimental design

The objective of this chapter is to evaluate the level of control of dissolved oxygen and nitrate nitrogen using the MSIMOSSA-based optimization control method proposed in this paper. All the experiments were carried out on the BSM1 simulation platform and were realized in the Microsoft Windows 8 environment using MATLAB 2014b programming. In order to objectively understand the performance of the control strategies under different conditions, 7 d of data from the BSM1 database were used to simulate the weather conditions, in which the sampling interval was 15 min and the

optimization period was 2 h. The simulated binary crossover and polynomial variation methods were used in this experiment, with the crossover parameter ηc and the variation parameter ηm set to 20, and the crossover and variation probabilities of 0.9 and $1/n$, respectively, with n being the number of decision variables; The shape parameter q is set to 11.

Figures 3 and 4 show the modeling results of MSIMOSSA for EC and EQ, respectively. From Fig. 3, it can be seen that MSIMOSSA's prediction for EC can better approximate the actual output value, while the original sparrow algorithm cannot accurately and efficiently track the EC value when it has a steeper inflection point. Similarly, it can be seen from Fig. 4 that for the prediction of EQ, MSIMOSSA can track the actual EQ values better except for a smaller deviation in the range of 1-5 at the inflection point. In contrast, the original Sparrow algorithm showed large deviations and could not accurately track the actual EQ values. Therefore, for the establishment of the objective function, MSIMOSSA shows better prediction and tracking results compared to the original sparrow algorithm.

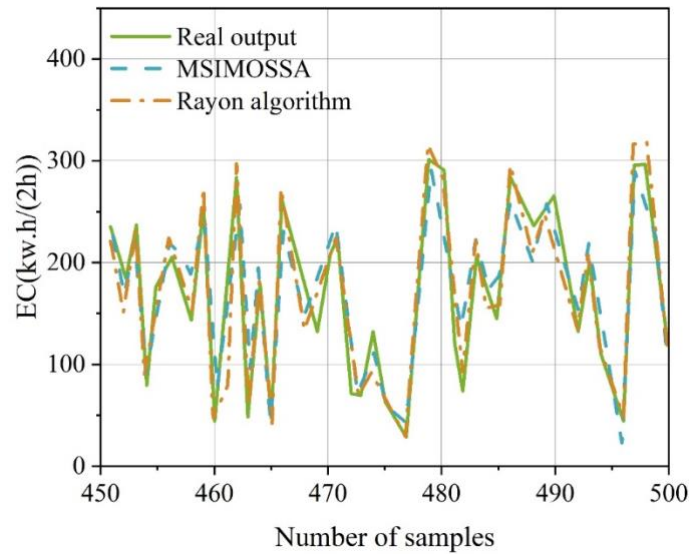


Figure 3. Model results of EC

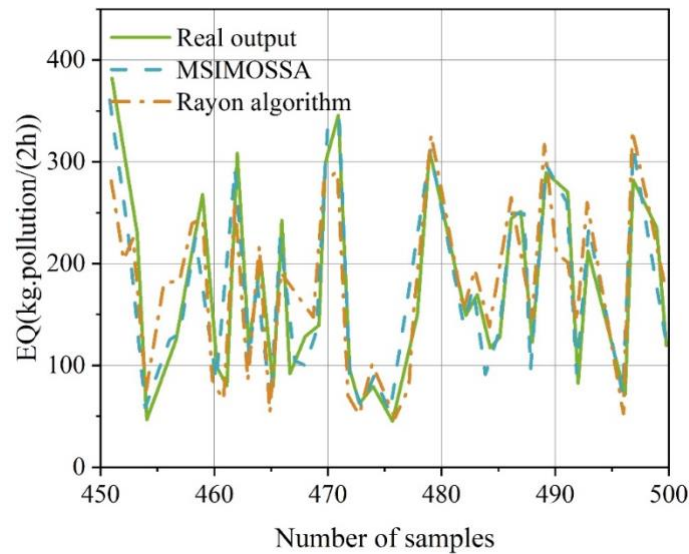


Figure 4. Model results of EQ

As the wastewater treatment should get different set values in different situations, in order to verify the performance of the multi-objective optimization algorithms in this control strategy, the optimization results of different multi-objective optimization algorithms for EC and EQ set values are shown in Fig. 5 for one optimization cycle, and the optimized results are kept unchanged in each cycle, meanwhile, this experiment selects every two hours as an optimization cycle, and the experiment is The results are compared with the three optimization algorithms NSGAI, dMOPSO and BBMOPSO respectively. The Pareto optimal solution sets of the above algorithms in the first optimization cycle of the second day, and the preferred solutions decided by the decision system are given in Fig. From the figure, it can be seen that MSIMOSSA has better convergence and distribution than other optimization algorithms. And it has the lowest energy consumption set value of up to 384, with the same quality of effluent water.

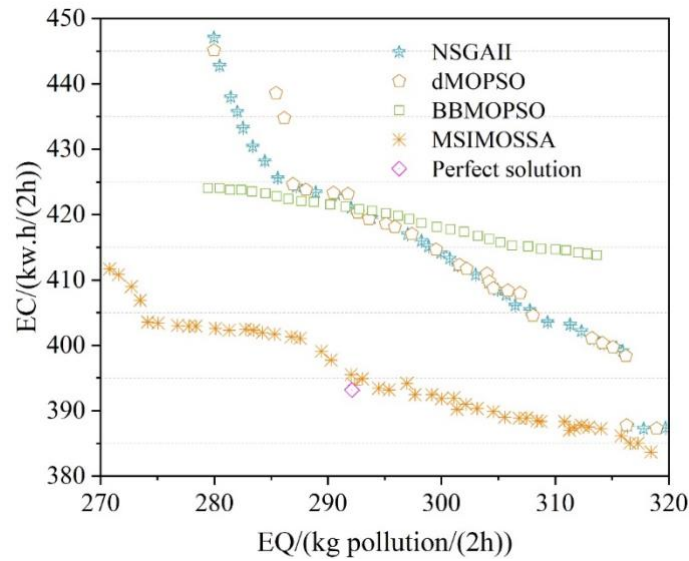


Figure 5. Pareto optimal solutions and identify of preferred solution

The nonlinear changes of working conditions in the wastewater treatment process, and the biochemical and nitrification reactions occurring, etc., according to the dynamic changes of the influent flow, in order to reduce the EQ while the EC meets the standard, it is necessary to track and control the real-time changes of the variables $S_{o,5}$ and $S_{No,2}$. Fig. 6 and Fig. 7 show the control effect and error of the PID controller tracking and optimizing the setpoints $S_{o,5}$, respectively. From Fig. 6, it can be seen that the PID controller can track the real-time changing $S_{o,5}$ setpoints better. Where the tracking error is shown in Fig. 7, it can be seen that $S_{o,5}$ the error between the actual output value and the optimized set value always stays within ± 0.37 mg/L. The experimental results show that the PID controller can achieve $S_{o,5}$ optimal control with a small tracking error.

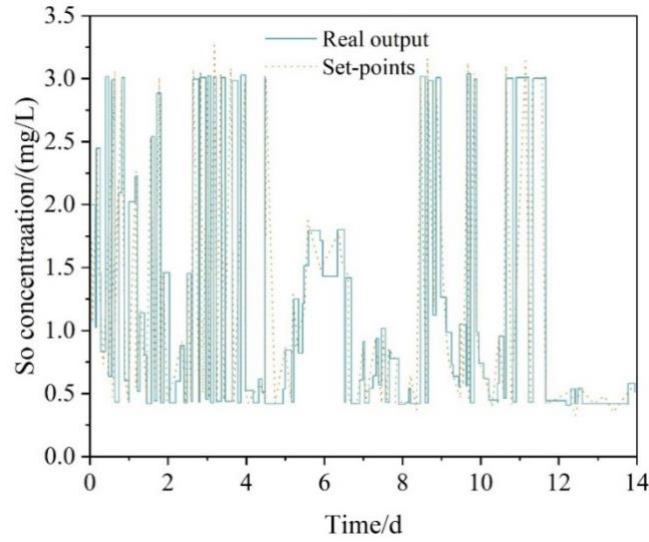


Figure 6. Solution of solution and control

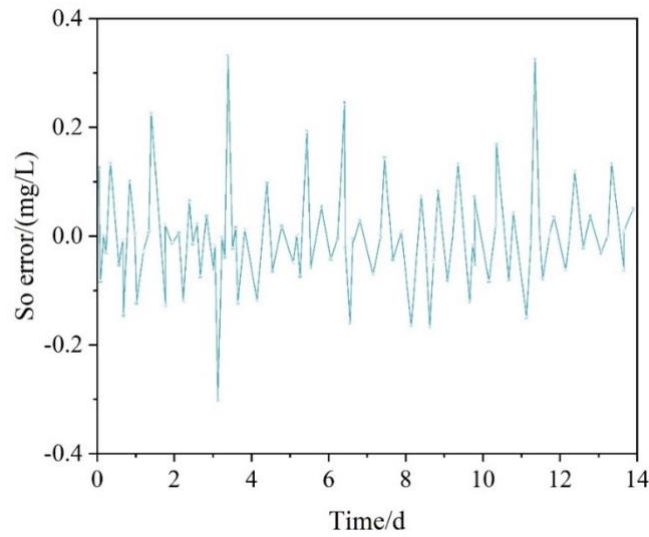


Figure 7. Solution of solution

The control effect and error of the PID controller tracking the optimized setpoint $S_{No,2}$ are given in Fig. 8 and Fig. 9, respectively. From Fig. 8, it can be seen that the tracking effect of the PID controller is better with the real-time change of the $S_{No,2}$ set value. The tracking error is given in Fig. 9, from which it can be seen that the error between $S_{No,2}$ the actual output value and the optimized set value is always within the range of ± 0.87 mg/L. The results show that the PID controller can achieve $S_{No,2}$ optimized control with a small tracking error.

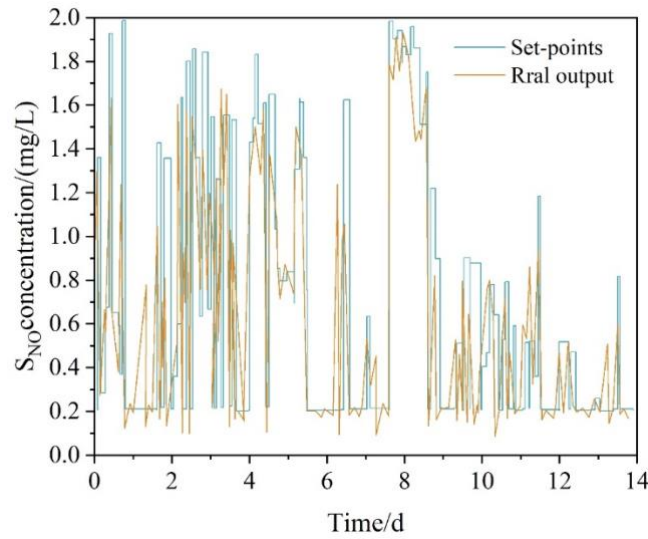


Figure 8. The determination of nitrate and the tracking control

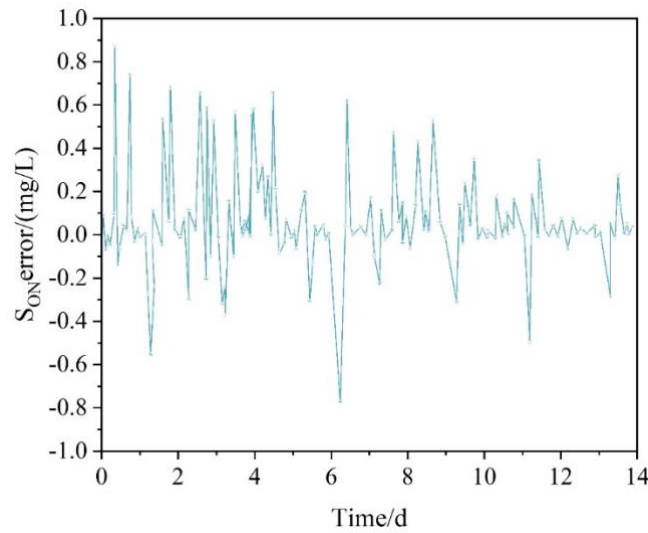


Figure 9. Nitrous nitrogen tracking control error

In the wastewater treatment process, the concentrations of $S_{o,5}$ and $S_{No,2}$ are mainly controlled by $K_L a$ and Q_a respectively, so the tracking control effect of $S_{o,5}$ and $S_{No,2}$ is closely related to the changes of $K_L a$ and Q_a , which are shown in Figures 10 and 11.

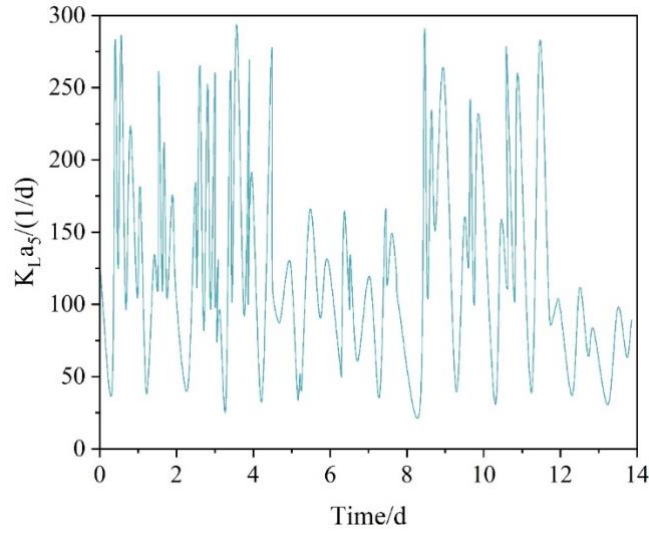


Figure 10. Variations of $K_L a_s$ with different time

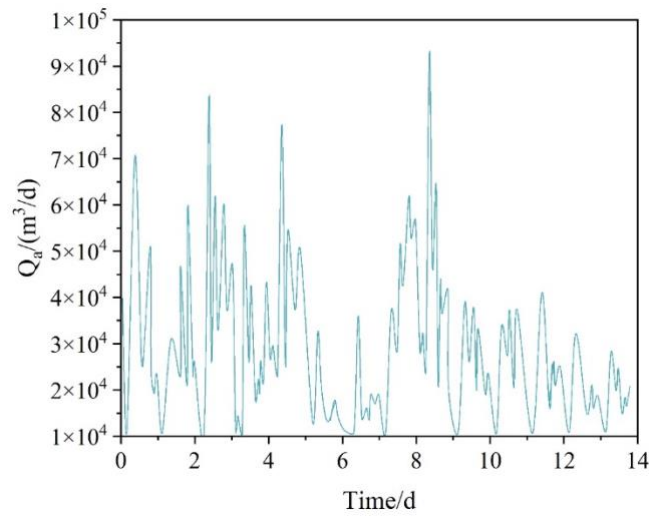


Figure 11. Variations of Q_a with different time

4.2 Experimental results and analysis

4.2.1 MSIMOSSA Algorithm Test Experiments

The parameter information of six test functions selected from the CEC2019 series is shown in Table 1.

Table 1. 6 cecc2022 test function parameter information

Function name	Target number	Functional relation	The solution exists
MMF1	2	Nonlinearity	No
MMF2	2	Nonlinearity	Yes
MMF3	2	Nonlinearity	Yes
MMF8	2	Nonlinearity	No
MMF12	2	Linearity	Yes
MMF15	3	Linearity	Yes

The modified sparrow algorithm (MSIMOSSA) is compared with several other optimization algorithms with specific parameter settings as shown in Table 2.

Table 2. Parameter setting of different multi-objective optimization algorithm

Algorithm	Parameter setting
MSIMOSSA	$Q=230, q=450, FAD_s=0.1, P=0.4$
MOEA/D	$Q=230, q=450, w=0.4$
MODA	$Q=230, q=450, w=0.4 \sim 0.8$
MOALO	$Q=230, q=450$
MOMVO	$Q=230, q=450$
MSSA	$Q=230, q=450$

The IGD and rPSP values of MSIMOSSA with MOPSO, MODA, MOALO, MOMVO and MSSA algorithms in the test functions are shown in Table 3 and Table 4. From the test results, it can be seen that the overall IGD mean and variance of the MSIMOSSA algorithm proposed in this paper is better than that of MOEA/D, MODA, MOALO, MOMVO, and MSSA in MMF1, MMF2, MMF3, MMF8, and MMF12, and although there is a slight shortfall in MMF15 the difference is very small, with a difference of only 0.0284~0.0073 Range. Among the rPSP values, MSIMOSSA and MOEA/D show better solution coverage. However, the rPSP metrics of MOMPA are smaller and satisfy most of the test functions when compared to the two. The above analysis shows that the MOMPA algorithm is superior in convergence and diversity.

Table 3. IGD values of different optimization algorithms

Function name	Index	MSIMOSSA	MOPSO	MODA	MOALO	MOMVO	MSSA
MMF1	Mean	0.0077	0.0098	0.008	0.0108	0.0081	0.0221
	Variance	0.0044	0.0054	0.0036	0.0044	0.0036	0.0083
MMF2	Mean	0.0062	0.0137	0.0502	0.0166	0.0137	0.0204
	Variance	0.0036	0.0073	0.0214	0.0067	0.0086	0.0075
MMF3	Mean	0.0059	0.0125	0.0325	0.0138	0.0068	0.0188
	Variance	0.0035	0.0067	0.0116	0.0062	0.0031	0.0071
MMF8	Mean	0.008	0.0117	0.0102	0.0151	0.009	0.0192
	Variance	0.0045	0.0063	0.0056	0.007	0.0038	0.0071
MMF12	Mean	0.0758	0.086	0.0927	0.0876	0.0792	0.0874
	Variance	0.0378	0.0427	0.046	0.0305	0.0284	0.0311
MMF15	Mean	0.2148	0.1978	0.1939	0.2175	0.2262	0.2517
	Variance	0.1013	0.093	0.094	0.0729	0.0757	0.0846

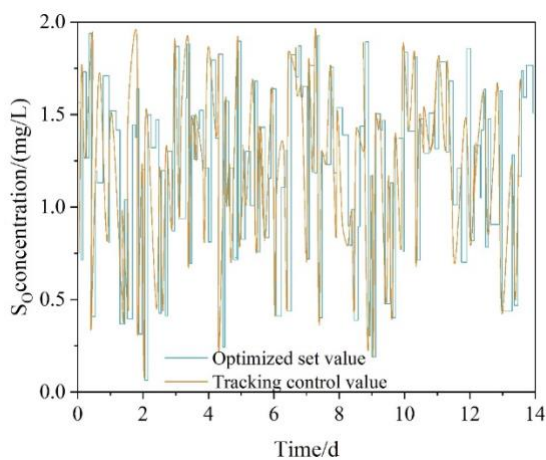
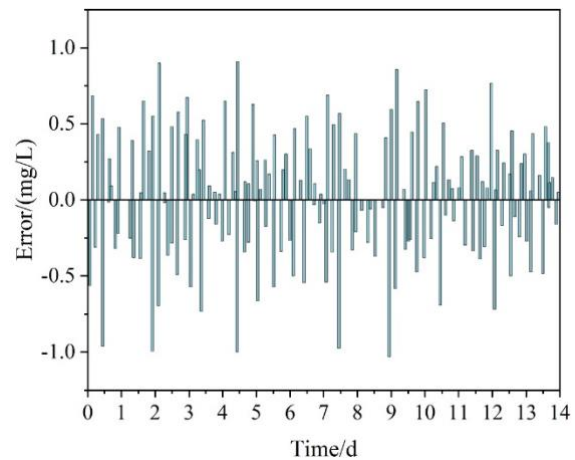
Table 4. RPS pvalues for different optimization algorithms

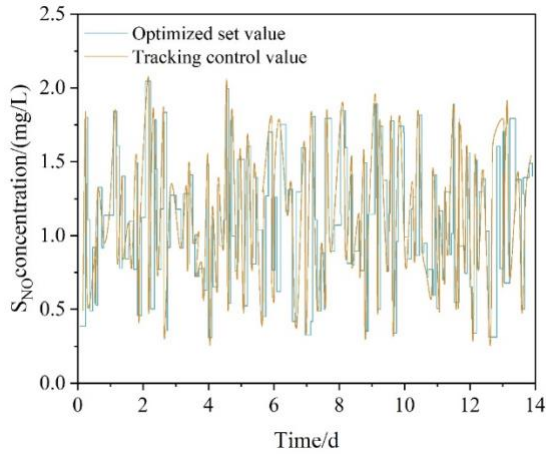
Function name	Index	MSIMOSSA	MOPSO	MODA	MOALO	MOMVO	MSSA
MMF1	Mean	0.0876	0.0816	0.0836	0.1286	0.0969	0.2215
	Variance	0.049	0.0463	0.0285	0.0434	0.0328	0.0742
MMF2	Mean	0.0686	0.0359	0.0931	0.1304	0.0726	0.0778
	Variance	0.0362	0.0198	0.0338	0.0874	0.0373	0.027
MMF3	Mean	0.0471	0.0689	0.0865	0.0675	0.0512	0.0986
	Variance	0.0241	0.0395	0.0365	0.0277	0.045	0.0396
MMF8	Mean	0.1424	1.0264	0.1843	1.4026	1.453	1.8445
	Variance	0.0808	0.6093	0.1064	0.7393	0.6186	0.7991
MMF12	Mean	1.0448	1.4048	1.0592	2.0869	2.3115	2.7801
	Variance	0.5952	0.8052	0.5926	0.9307	0.7662	1.1146
MMF15	Mean	0.1962	0.4926	0.4136	0.4438	0.6363	0.5434
	Variance	0.0927	0.2252	0.185	0.2199	0.2108	0.2218

4.2.2 Wastewater Treatment BSM1 Simulation

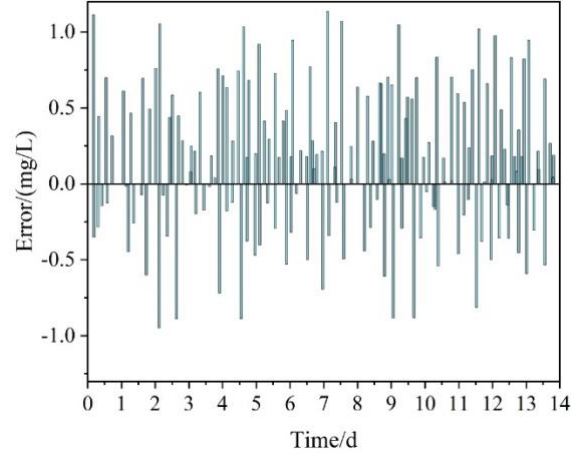
In order to verify the effectiveness of MOMPA, the algorithm was applied to the BSM1 simulation platform, and the total optimization period was set to be 14d, the performance index optimization period was set to be 2h, and each sampling interval was set to be 15 min. The simulation data were selected as the wastewater data under the sunny, rainy, and stormy days, respectively. The optimization ranges of S_o and S_{NO} are 0~2.7 mg/L and 0~2 mg/L, respectively. Fig. 12 shows the optimization control curves and error plots of MSIMOSSA algorithm for S_o and S_{NO} in sewage treatment under sunny day data.

From the figure, it can be seen that under sunny weather, the change process of effluent water quality indexes is relatively smooth. MSIMOSSA algorithm presents good tracking control effect according to the actual operation status of the system, the tracking trajectory and the set value change process basically coincide, and the average value of the overall discharge concentration of the effluent water quality parameter is in the range of effluent discharge indexes of 0~2.7 mg/L, which meets the effluent treatment process. The constraints of the wastewater treatment process are met, which verifies the superiority of MSIMOSSA in the optimization of wastewater treatment, and is a prerequisite to further ensure that the energy consumption achieves the best treatment results.

(a) The S_o -optimized control curve(b) The S_o error plot



(c) The S_{NO} -optimized control curve



(d) The S_{no} error plot

Figure 12. Optimized control curves and error plots of S_O and S_{NO} in sunny days

5 Conclusion

The study proposes performance evaluation indexes for the soft measurement and optimization control part of the wastewater treatment process. For modeling prediction of $S_{Nh,e}$ and $S_{Ntot,e}$, LSTM is used to model and predict the two parameters, and the concentrations of $S_{O,5}$ and $S_{NO,2}$ are added to the input variables of the prediction model to improve the accuracy of the prediction model. Then a multi-objective sparrow algorithm incorporating multiple strategies is proposed to achieve simultaneous optimization of effluent quality and total energy consumption in wastewater treatment processes. And the conclusions have been drawn through mechanism analysis and simulation experiments:

- 1) The MSIMOSSA algorithm is used to determine the optimal setpoints and the substructure is a PID controller for tracking the optimal setpoints of $S_{O,5}$ and $S_{NO,2}$. The results show that the system has a significant reduction in energy consumption compared to the original PID control.
- 2) On the BSM1 simulation platform, the MSIMOSSA algorithm is used to find the optimal setting values of S_O and S_{NO} in the sewage treatment process, and the results show that the MSIMOSSA algorithm is very competitive compared with other algorithms, which not only makes the effluent quality of sewage treatment meet the requirements for discharge but also reduces the energy consumption significantly.

Funding:

This 2023 is one of the achievements of the project “Construction and research of reclaimed water reuse system in green intelligent buildings” (project number: 2023KY1116), which aims to improve the basic scientific research ability of young and middle-aged teachers in Guangxi universities.

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