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Retraction

Retracted: Intelligent Optimal Control of Sewage Treatment Based on Multiobjective Evolutionary Algorithm

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] X. Jia, C. Xiang, J. Wang, X. Gao, and Y. Ye, "Intelligent Optimal Control of Sewage Treatment Based on Multiobjective Evolutionary Algorithm," *Journal of Control Science and Engineering*, vol. 2022, Article ID 6218545, 8 pages, 2022.

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Research Article

Intelligent Optimal Control of Sewage Treatment Based on Multiobjective Evolutionary Algorithm

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In order to solve the problem of optimal control of the sewage treatment process based on a multiobjective evolutionary algorithm, an intelligent optimal control of sewage treatment based on a multiobjective evolutionary algorithm is proposed in this paper. In this paper, the decomposition based multiobjective evolutionary algorithm (MOEA/D) is improved, and it is expected that the uniformly distributed approximate Pareto frontier can be obtained with fewer evolution times. For each new solution generated by the MOEA/D algorithm, the improved algorithm in this paper finds the most suitable subproblem for the new solution from all subproblems and replaces the population in its neighborhood. On the basis of the original subproblem, it carries out secondary optimization to improve the utilization rate of the children and then finds the approximate Pareto frontier in the optimization problem with fewer iterations. The experimental results show that AE, PE, and EC Based on SS–MOEA/D optimal control method are reduced by 6.91%, 1.54%, and 5.58%, respectively. *Conclusion*. The algorithm significantly reduces the number of steps to find the Pareto frontier, significantly improves the performance of the MOEA/D algorithm, and achieves the optimization goal in the optimization of the sewage treatment process.

1. Introduction

The municipal waste water treatment process (MWWTP) consists of a primary sedimentation tank, aeration tank, secondary sedimentation tank, and other processes. It is a typical industrial system composed of multiple processes [1]. Each process is closely linked and interacts with each other. Urban sewage treatment is a complex dynamic operation process, which includes physical, chemical, and biological reaction processes. At the same time, the operation process of urban sewage treatment is constrained by a variety of dynamic performance indicators. Therefore, how to realize the optimal operation of the urban sewage treatment process is still a difficult problem to be solved [2].

The optimization control method realizes the optimization of performance indicators by designing appropriate optimization strategies and control strategies and has been widely used in the process of urban sewage treatment [3]. However, there are two problems in the process of implementing the optimal control of urban sewage treatment: how to design the performance indicators of the urban sewage treatment operation process and how to realize the optimization of performance indicators [4].

In the whole sewage treatment process, the ultimate goal is to make the effluent quality such as chemical oxygen demand, biochemical oxygen demand, and ammonia nitrogen meet the standards [5]. In recent years, the sewage treatment capacity of sewage treatment plants in some cities in China has increased year by year. At the same time, the strict national requirements for effluent quality and energy-saving policies have increased the operating cost of sewage treatment. It can be seen that in order to ensure that the effluent quality in the sewage treatment process meets the discharge standard, reduce the cost in the sewage treatment process, and realize the optimal control of the sewage treatment process is an urgent problem for the sewage treatment plant [6].

The purpose of optimal control of sewage treatment is to achieve energy conservation and consumption reduction under effluent constraints [7]. The total cost of control operation mainly includes two aspects: system energy consumption and fines caused by effluent quality exceeding the standard. These two evaluation indexes contradict each other in the process of sewage treatment control, and many variables are limited by the indexes. Therefore, it is of great significance to study a method that can deal with multi-objective optimization problems for the process of sewage treatment control.

2. Literature Review

In order to describe the effluent quality index of the urban sewage treatment process, Chu and others proposed a prediction model of effluent chemical oxygen demand based on the standard mechanism model of urban sewage treatment. The model can describe the relationship between effluent chemical oxygen demand and process variables such as dissolved oxygen concentration, temperature, and redox potential. The experimental results show that the proposed effluent COD prediction model has high accuracy [8]. In addition, Enami and others designed an effluent quality prediction model based on an activated sludge mathematical model to obtain the correlation between effluent organic matter concentration, solid residence time, and internal circulation [9]. The results show that the proposed effluent quality model can accurately obtain the effluent quality characteristics of the urban sewage treatment process. In order to describe the energy consumption index and effluent quality index of the urban sewage treatment process at the same time, Wan and others proposed a comprehensive evaluation model of sewage treatment process performance based on the mechanism reaction model to describe the relationship between performance indexes such as energy consumption and effluent quality and process variables such as dissolved oxygen concentration and suspended solids concentration [10]. The experimental results show that the performance evaluation model based on multi-index can accurately obtain the dynamic characteristics of the sewage treatment process, so as to improve the operation efficiency of the sewage treatment process. Aleshkin and others established a prediction model for evaluating the operation performance of the sewage treatment process through an in-depth analysis of the computational fluid dynamics model of the sewage treatment process. The performance evaluation prediction model can express the relationship between energy consumption, outlet water quality, and process variables such as inlet water flow and dissolved oxygen concentration. The results show that the proposed performance evaluation prediction model can accurately express the dynamic characteristics of energy consumption and effluent quality [11]. However, the performance index model based on the mechanism model has many parameters, which is difficult to ensure the accuracy of the model.

At present, the performance improvement of multi-objective genetic algorithm is still an important research. Therefore, for the multiobjective optimization problem in the sewage treatment process, this paper improves the MOEA/D algorithm and carries out the secondary search (SS–MOEA/D) based on it. The experimental results show that the performance of the MOEA/D algorithm can be improved [12]. Using the improved algorithm, the solutions found in the multi-objective problem of balancing energy consumption and effluent quality can be distributed as evenly as possible, and the optimal set values of dissolved oxygen and nitrate nitrogen concentration can be obtained, which solves the problem that the process variables of optimization control are complex and it is difficult to realize real-time optimization.

3. Method

3.1. Analysis of Sewage Treatment Process

3.1.1. Simulation Model. The sewage treatment process is a complex nonlinear dynamic system. The reaction process includes a series of physical and biochemical reactions [13]. The flow and load will cause a great disturbance to the whole system. The sewage treatment plant must ensure the safe and continuous operation of the system. Therefore, it is obviously infeasible to compare the advantages and disadvantages of the control scheme in the actual sewage system. In order to prove the feasibility and advantages and disadvantages of the control scheme, it is necessary to simulate the environment of the sewage treatment plant [14]. The "benchmark simulation model 1 (BSM1)" for sewage treatment, jointly developed by the International Water Association and the European Union Organization for science and technology cooperation, is currently internationally recognized as a test platform for sewage treatment processes.

The equipment structure selected for the benchmark model is a relatively simple but widely used layout, which is composed of a bioreactor unit and a secondary sedimentation tank unit [15]. The bioreactor unit includes 2 anaerobic tanks and 3 aerobic tanks. The activated sludge ASM1 model is used in the biochemical reaction tank to simulate the whole biochemical reaction process, and the secondary exponential sedimentation rate model is used in the secondary sedimentation tank to simulate the sewage sedimentation process.

The effect of biological treatment on sewage is also a key factor to control the energy consumption of aeration and pumping [16]. Therefore, optimizing the set values of dissolved oxygen concentration in the fifth zone and nitrate nitrogen concentration in the second zone is an important means to improve the optimization performance of energy saving and consumption reduction in the sewage treatment process under the effluent constraint.

3.1.2. Optimization Model. In the sewage treatment process of the sewage treatment plant, the system energy consumption reflects the total energy consumption of a series of control equipment in the control process. According to the traditional control method, the control equipment needs long-term high load control to achieve the goal of meeting the effluent quality standard; if the system energy consumption is reduced, it means that the control equipment control is not fully controlled, which may lead to excessive effluent quality and cause fines. It can be seen that system energy consumption and fines caused by excessive effluent quality are a pair of contradictory indicators, which need to be modeled and analyzed. The main energy consumption costs include aeration energy consumption and pumping energy consumption, which account for more than 70% of the total energy consumption. Therefore, the optimization problem of the energy consumption model is defined as follows:

$$\mathrm{EC} = \mathrm{AE} + \mathrm{PE}, \tag{1}$$

where EC represents energy consumption, AE represents aeration energy consumption, and PE represents pumping energy consumption. According to the reaction variables and model parameters in the sewage treatment process, AE and PE are expressed as formulas (2) and (3), respectively:

$$\mathrm{AE} = \frac{S_O}{T \cdot 1.8 \cdot 1000} \int_{kT}^{(k+1)T} \left(\sum_{i=1}^{5} V_i \cdot K_{La_i}(t) \right) \mathrm{d}t, \tag{2}$$

$$\mathrm{PE} = \frac{1}{T} \int_{kT}^{(k+1)T} \left(0.004 Q_a(t) + 0.008 Q_r(t) + 0.05 Q_w(t)\right) \mathrm{d}t, \tag{3}$$

where SO is the concentration of dissolved oxygen; T is the optimization cycle; V is the unit volume of the reaction pool; K_{La_i} is the oxygen conversion coefficient; Q_a is the internal flow, Q_r is the sludge return flow, and Q_w is the sludge flow.

EQ refers to the cost to be paid for discharging pollutants to the receiving water body. According to the benchmark definition, the following formula is used. The smaller the value, the less the corresponding treatment cost. At the same time, EQ is also a comprehensive indicator to measure the effluent quality after sewage treatment. The smaller the value, the better the effluent quality. On the contrary, the larger the value, the worse the effluent quality.

$$\mathrm{EQ} = \frac{1}{T \cdot 1000} \int_{kT}^{(k+1)T} \sum_{i=1}^{5} X_i(t) Q_e(t) dt, \tag{4}$$

$$\begin{cases} X_1(t) = B_{SS} \cdot SS_e(t) \\ X_2(t) = B_{CO\,D} \cdot COD_e(t) \\ X_3(t) = B_{NO} \cdot S_{NO,e}(t) \\ X_4(t) = B_{Nkj} \cdot S_{Nkj,e}(t) \\ X_5(t) = B_{\mathrm{BOD}} \cdot \mathrm{BOD}_e(t) \end{cases}. \tag{5}$$

Here, BSS, BCOD, BNO, BNkj, and BBOD are the weight factors of the influence of effluent suspended solids concentration, chemical oxygen demand, nitrate nitrogen concentration, Kjeldahl nitrogen concentration, and biochemical oxygen demand on EQ. Where: BSS = 2, BCOD = 1, BNO = 30, BNkj = 20, BBOD = 2.

In this paper, EQ and EC are optimized by the improved MOEA/D method according to the optimization performance index of the sewage treatment process. Various chemical and biochemical reactions are required in the sewage treatment process of the activated sludge process. The predenitrification treatment process makes the dissolved oxygen concentration in the aerobic zone strongly affect the nitrate nitrogen concentration in the anoxic zone. At the same time, the nitrate nitrogen in the anoxic zone flows through the aerobic zone. Therefore, the control variables in the sewage treatment process are seriously coupled, and there are contradictory multi-objective optimization characteristics among aeration energy consumption, pumping energy consumption, and effluent indicators. EC and EQ indicators are performance indicators with typical conflict characteristics, that is, to improve effluent quality (EQ becomes smaller), energy consumption must be increased (EC becomes larger); on the contrary, lower energy consumption (smaller EC) will also lead to worse effluent quality (larger EQ). Therefore, the optimization of energy consumption and water quality performance indicators for sewage treatment is essentially a multi-objective optimization problem.

For the whole sewage treatment process, the optimization relationship between the performance index and the optimization setting value should be determined first [17]. According to the limit value of the effluent index and the limit of dissolved oxygen concentration in the fifth unit and nitrate nitrogen concentration in the second unit in the actual setting process, let x_1 be the set value of dissolved oxygen concentration, x_2 be the set value of nitrate nitrogen concentration, $x = [x_1, x_2]$ be the optimization setting direction quantity composed of two set values, fEQ and fEC are the functional expression between EQ and EC and optimization vector respectively and establish the following multi-objective optimization model (6):

$$\min F(x) = \left\{ f_{EQ}(x), f_{EC}(x) \right\}. \tag{6}$$

The inequality constraint is

$$\text{s.t.} \begin{cases} N_{tot}(x) \le 18 mg \cdot L^{-1} \\ \mathrm{COD}(x) \le 100 mg \cdot L^{-1} \\ S_{NH}(x) \le 4 mg \cdot L^{-1} \\ SS(x) \le 30 mg \cdot L^{-1} \\ \mathrm{BOD}(x) \le 10 mg \cdot L^{-1} \\ x_1^{\mathrm{low}} \le x_1 \le x_1^{\mathrm{high}} \\ x_2^{\mathrm{low}} \le x_2 \le x_2^{\mathrm{high}} \end{cases}, \tag{7}$$

where Ntot is the total nitrogen concentration, SNH is the ammonia nitrogen concentration, and x_1^{low}, x_1^{high} and x_2^{low}, x_2^{high} are the lower and upper limits of the optimal set values of dissolved oxygen concentration and nitrate nitrogen concentration, respectively. The multiobjective minimization problem is composed of inequality constraints and the relationship between EQ and EC and the set value.

3.2. Optimization Control Method for Sewage Treatment

3.2.1. MOEA/D Algorithm. The multiobjective optimization algorithm based on decomposition decomposes the multiobjective problem into n scalar subproblems. It solves all subproblems at the same time by evolving a population of one generation solutions. The degree of association between adjacent subproblems is defined by the distance between their aggregation coefficient vectors. The newest population is the optimal set of each subproblem selected from all generations.

When MOEA/D converts the problem of solving the approximate solution of the Pareto frontier into a set of scalar optimization problems, the Chebyshev aggregation method is adopted, and its calculation is

$$\arg\min g^{te}(x|\lambda, z^*) = \max\{\lambda_i|f_i(x) - z^*\} \quad 1 \le i \le m. \tag{8}$$

Here, m represents the number of solutions, λ_i is the i-th weight vector, and z^* represents the reference vector. It means that in each subproblem, under its assigned reference vector, the point with the greatest decline relative to the reference point is found, which ensures that each iteration enables the population to evolve towards the Pareto front.

Although the decomposition based multiobjective evolutionary algorithm can find the Pareto front, its optimization speed and the distribution of the final Pareto solution need to be improved [18]. For the sewage treatment process, the solution set of the multiobjective optimization problem can be found with the shortest evolution times, and ensuring the good distribution of the solution set can further improve the sewage treatment optimization scheme.

3.2.2. SS-MOEA/D Algorithm. For a multiobjective optimization algorithm, its performance is judged by its convergence and distribution. In the MOEA/D algorithm, the core of finding the optimal solution is to generate subindividuals through cross mutation, compare the quality of subindividuals with all current individuals, and replace them among populations [19]. Thus, in the process of population evolution based on a decomposition multiobjective evolutionary algorithm, the process of comparing the offspring with the current population neighbors is particularly important.

For the i-th subproblem, two individuals are randomly selected as parents in its neighborhood to cross mutate to produce a child, and then the solution is updated by comparing the Chebyshev value of the solution and the new solution in the neighborhood of the i-th subproblem. However, there are the following problems: the offspring individuals generated by cross mutation may not be suitable for the current subproblem I, and may be more suitable for subproblem J. In the process of replacing the old solution with the new solution each time, if the replacement of the old solution is only carried out in the i-th subproblem, the replacement ability of the new solution will be weakened to a certain extent, so that the evolution of each solution is not complete, thus reducing the optimization speed of the algorithm.

In order to solve this problem, this paper defines a relationship between a new individual and a subproblem and finds the subproblem most closely related to the new individual from n subproblems. The definition of formula (9) is as follows:

$$i^* = \arg\min\left\{g_k^{te}(x) - g^{te}(x_{\text{new}})\right\} \quad 1 \le k \le N. \tag{9}$$

In formula (9), $g_k^{te}(x)$ is the Chebyshev value of the k-th subproblem, $g^{te}(x_{\text{new}})$ is the Chebyshev value of the new solution, N is the number of subproblems decomposed, and i^* is the sequence number of the most appropriate subproblem for the new solution. After finding this subproblem, the new solution and the old solution are replaced by comparing the Chebyshev values of all solutions and new solutions in the neighborhood; at the same time, for the subproblem that generates the new solution, the solutions in its neighborhood are not necessarily better than the new solution, so the optimal solution and the inferior solution are also replaced in the neighborhood of the original subproblem, so as to increase the utilization of the new solution and make the population converge more quickly. Because the new solution is not generated by cross mutation in the neighborhood of subproblem i^*, but is replaced in the neighborhood of subproblem i^*, the diversity of the population is also increased to a certain extent, and the diversity of individual genes generated by a cross mutation in the next generation is increased.

The new solution is replaced by the new solution in the neighborhood of the subproblem and the subproblem that generates the new solution. Compared with the replacement of the new solution only in the subproblem that generates the new solution, the advantage lies in that firstly, the utilization efficiency of the new solution is improved, and the optimization speed of the algorithm is further improved; secondly, the diversity of the population is increased to prevent the algorithm from falling into local optimization.

Figure 1 shows the quadratic optimization diagram of finding the appropriate subproblem with the new solution of the improved MOEA/D algorithm. For two objective functions, the objective space is established by two objective function values, where z^* represents the reference point, B represents the weight vector, xnew represents the new solution obtained through genetic variation, and fit represents the objective function value corresponding to each individual in the objective space [20]. After calculating the Chebyshev relationship between the individual and the subproblem to get the most suitable subproblem, the range of the new solution will become larger, which will significantly improve the overall evolution speed of the population. At the same time, when the new solution is used as a parent in different subproblems to generate a child, it increases the diversity of solutions in the subproblems to a certain extent, so as to avoid falling into local optimization, so as to better complete the optimization process of the optimization algorithm [21]. The inputs of the improved SS–MOEA/D algorithm are multi-objective optimization problems and algorithm termination conditions; The output of the

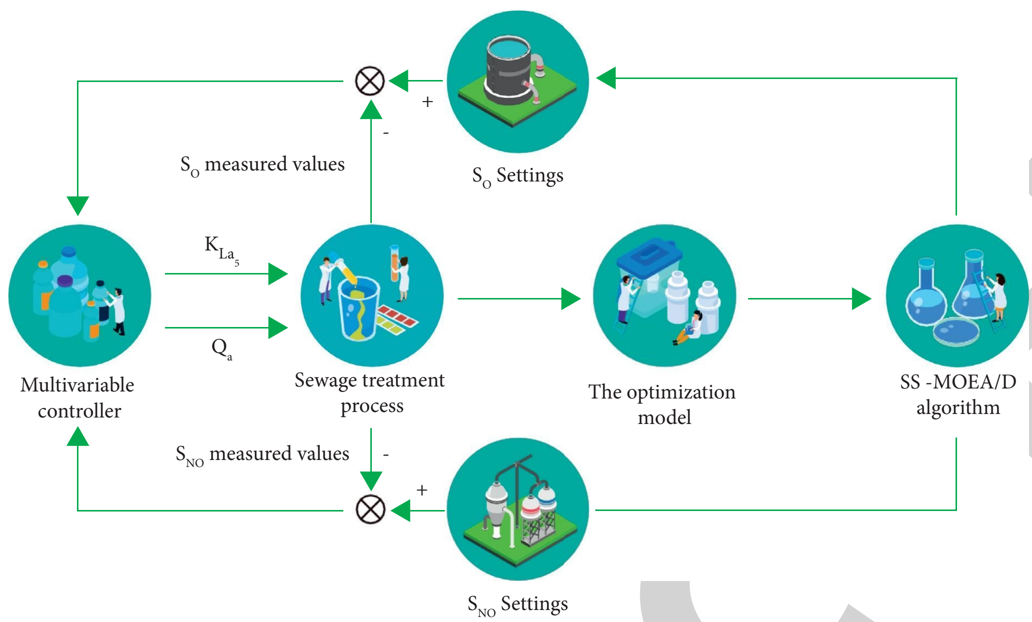

Figure 1: Optimization control framework.

algorithm is the optimal solution $\{x_1, \ldots, x_N\}$ and the function value $\{f(x_1), \ldots, f(x_N)\}$ of the corresponding objective problem.

3.2.3. Optimization Control Process of Sewage Treatment. In the multiobjective optimization problem, the multiobjective optimization algorithm solves the problem that multiple objectives reach the optimum at the same time, and the obtained solution is considered to be of equal status in the multiobjective optimization problem [22]. However, in the sewage treatment process, all solutions in the solution set obtained by the SS-MOEA/D algorithm meet the constraint conditions, that is, all solutions meet the effluent quality index [23]. When any solution in the Pareto optimal solution set calculated by the SS-MOEA/D algorithm is selected as the tracking set value of dissolved oxygen and nitrate nitrogen controller, the final water quality obtained from sewage treatment meets the discharge standard. Therefore, considering that all solution sets meet the constraints when finding the current most satisfactory set value from the Pareto solution set, this paper compares the energy consumption of each solution to the system at the current time and selects the solution with the lowest energy consumption as the current most satisfactory optimization set value. The optimization set value found according to this method not only meets the requirements of effluent quality but also minimizes the energy consumption of the system [24].

After adding the SS-MOEA/D optimization algorithm to the established sewage treatment optimization model, a set of Pareto optimal solutions for EC and EQ optimization problems in the sewage treatment process are obtained. Among these solutions, it is necessary to find a group of satisfactory optimization solutions in the current state as the tracking set points of the controller. The optimization control framework of the whole sewage treatment process is shown in Figure 1.

In this framework, the optimization control system of the whole sewage treatment process is shown: firstly, the multiobjective optimization model of the sewage treatment process is constructed by establishing the functional relationship between the energy consumption and effluent quality in the sewage treatment process and the set values of dissolved oxygen and nitrate nitrogen concentration through the optimization model; then, aiming at the established multiobjective optimization problem, the Pareto optimal solution is obtained by the SS-MOEA/D algorithm, and the most satisfactory solution at the current time is selected as the optimal set value of dissolved oxygen concentration and nitrate nitrogen concentration; finally, the multivariable controller tracks and controls the dissolved oxygen and nitrate nitrogen in the sewage treatment process by the difference between the real value and the optimal setting value. The controller used in this paper is a PID controller, which controls the concentration of dissolved oxygen in sewage by adjusting the dissolved oxygen conversion coefficient (kla5) in the fifth zone and controls the concentration of nitrate nitrogen by adjusting the internal return flow (QA).

3.3. Simulation Experiment

3.3.1. ZDT Optimization Problem. ZDT (1, 2, 3, 4, 6) series of problems are a series of multiobjective optimization problems proposed to test the advantages and disadvantages of multiobjective optimization algorithms, including the continuous and discontinuous Pareto frontiers. It is recognized as an optimization problem to test the performance of optimization algorithms. The inverted generational distance (IGD) index is an important index to evaluate the multiobjective optimization algorithm. Its calculation formula (10) is as follows:

$$\mathrm{IGD} = \left(P^{*}, P\right) = \frac{\sum_{v \in P^{*}} d\left(v, P\right)}{\left|P^{*}\right|}. \tag{10}$$

In equation (10), $P*$ is the real Pareto frontier, and P is the frontier obtained by the optimization algorithm. The index can simultaneously reflect the diversity and convergence of the optimization algorithm. The more obvious the value is, the closer the Pareto front is to the real Pareto front, and the better the distribution is; on the contrary, the larger the value, the more the Pareto front deviates from the real front, and the worse the distribution.

In order to compare the SS-MOEA/D algorithm proposed in this paper to improve the number of optimization steps, the following experiments are designed: Aiming at the 1 and 2 problems of the ZDT series, the optimization algorithm is iteratively optimized. The stop condition is to reach a fixed IGD value ($\mathrm{IGD} < 0.6...10^{-3}$). Compare the number of iteration steps of the algorithm, and the program runs 20 times. The comparison results of the MOEA/D algorithm and improved SS-MOEA/D algorithm are shown in Table 1. It can be seen from the Table that in the problems of zdt1 and zdt2, the maximum, minimum, and average iterative steps required by the improved SS-MOEA/D algorithm to reach the same IGD value in 20 experiments are less than those of the MOEA/D algorithm, which proves that the improved SS-MOEA/D can find the Pareto frontier with fewer optimization steps.

In order to compare the performance of the SS-MOEA/D algorithm proposed in this paper, the designed experiments are as follows: for problems 1, 2, 3, 4, and 6 of the ZDT series, make the algorithm iterate 300 times, calculate the IGD index, run the program 20 times, take the average value and sort. The comparison results are shown in Table 2.

As shown in Table 2, SS-MOEA/D can perform prominently in most multi-objective problems when solving ZDT problems, especially in ZDT (2, 6), the results are significantly better than other algorithms; For zdt3, although the performance of the optimization method in this paper is not optimal, it has little difference with the results of the optimal algorithm. By synthesizing the results of all ZDT problems, it is proved that the algorithm is effective in solving the continuous and discontinuous Pareto frontier optimization problems, and the convergence and diversity are improved.

3.3.2. Sewage Treatment Optimization Simulation Experiment. Aiming at the optimization between energy consumption and effluent quality in the sewage treatment process, the optimization method proposed in this paper is tested. The research of this experiment is based on the BSM1 model of the international benchmarking platform. The actual operating conditions of the real sewage treatment plant are simulated by using the sewage flow and component changes in sunny weather. The sampling interval is 15 min, the simulation time is 7 d, and the optimization cycle is 2 h.

Table 1: Comparison of iteration steps.

Problem	Iteration steps	MOEA/D	SS-MOEA/D
ZDT1	Maximum	275	228
	Minimum value	153	137
	Average value	235	183
ZDT2	Maximum	360	233
	Minimum value	148	117
	Average value	220	164

Table 2: Comparison of IGD indicators.

Problem	Index	NSGA-II	MOEA/D	SS-MOEA/D
ZDT1	IGD	1.47E − 04	7.10E − 03	3.52E − 04
	Sort	1	3	2
ZDT2	IGD	1.10E − 01	3.79E − 03	3.75E − 04
	Sort	3	2	1
ZDT3	IGD	1.04E − 02	1.32E − 03	3.65E − 03

The parameter settings of the SS-MOEA/D algorithm and PID controller are shown in Table 3.

4. Results and Discussion

The multiobjective optimization method is optimized in the BSM1 quasibenchmark model. The set values of dissolved oxygen concentration in the fifth zone and nitrate nitrogen concentration in the second zone will change with the sewage environment. Figures 2 and 3 are the tracking control curves of the optimization process of dissolved oxygen and nitrate nitrogen.

It can be seen from Figure 2 that the so optimization setting value can be continuously adjusted according to the real-time operation of the system during the sewage treatment process, and the PID controller can track the so optimization setting value with high control accuracy. It shows that the optimization algorithm can optimize the set value of dissolved oxygen in the process of sewage treatment in real time.

Figure 3 shows the change process of SNO optimization setting value. It can be seen from the figure that the system can change the concentration setting value of nitrate nitrogen in real time according to the optimization problem.

In order to reflect the optimization effect of EC and E in the sewage treatment process of the optimization strategy, PIDx closed-loop control is carried out under the same conditions, and SNO is set at 2 mg/L and 1 mg/L, respectively. Table 4 shows the comparison of average effluent values of PID closed-loop control and SS-MOEA/D optimization control methods within 7 days. It can be seen from the Table that the average water quality obtained by the SS-MOEA/D optimization algorithm meets the discharge standard.

The data in Table 5 show the comparison of the energy consumption of the sewage treatment process system by

Table 3: Parameter settings.

Optimization algorithm		PID controller	
Neighborhood size	$H = 5$	Dissolved oxygen	Nitrate nitrogen
Problem dimension	$D = 2$	$K_{P\cdot O} = 200$	$K_{P\cdot NO} = 20000$
Population size	$N = 20$	$K_{I\cdot O} = 15$	$K_{I\cdot NO} = 5000$
Evolution times	$M = 30$	$K_{D\cdot O} = 2$	$K_{D\cdot NO} = 400$

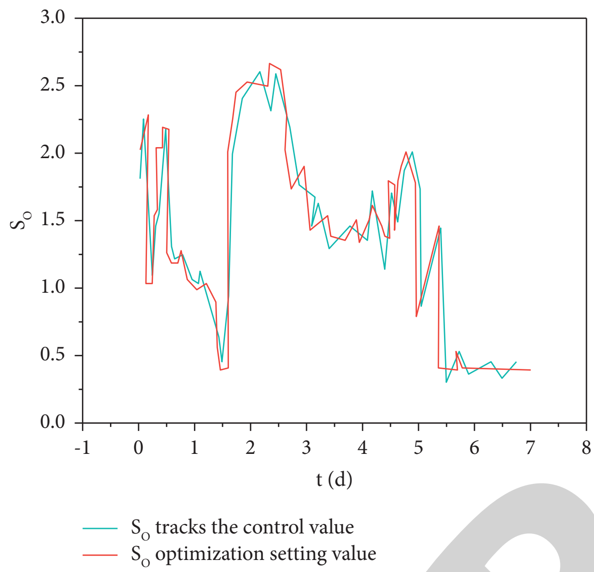

Figure 2: SO tracking control diagram.

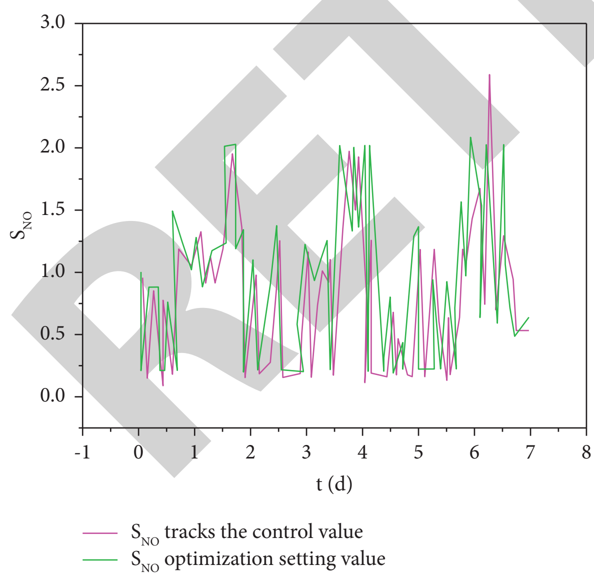

Figure 3: SNO tracking control diagram.

adding an optimization algorithm and direct control. Compared with PID closed-loop control, AE based on the SS-MOEA/D optimization control method decreased by 6.91%, PE increased by 1.54% and EC decreased by 5.58%.

Table 4: Comparison of average effluent quality.

	BOD^5	COD	TSS	N_{tot}	S_{NO}
Index limit	10	100	30	18	4
PID	2.68	47.51	12.62	16.88	2.30
SS-MOEA/D	2.69	47.38	12.54	17.17	2.23

Table 5: Comparison of energy consumption.

	AE/ $(kWh \cdot d^{-1})$	PE/ $(kWh \cdot d^{-1})$	EC/ $(kWh \cdot d^{-1})$
PID	3677	232.5	3909.5
SS-MOEA/D	3422.88	268.27	3691.15

The experimental results show that the proposed SS-MOEA/D based optimal control method is effective in the sewage treatment process.

5. Conclusion

This paper presents the research on intelligent optimal control of sewage treatment based on a multiobjective evolutionary algorithm. The following conclusions are obtained through theoretical analysis and simulation experiments: for each new solution generated by the MOEA/D algorithm, this paper finds the most suitable subproblem from all subproblems and replaces the population in its neighborhood. Based on the original subproblem, this paper carries out secondary optimization to improve the utilization rate of offspring. Under the same iteration times, for ZDT series optimization problems, it can quickly converge to the Pareto frontier and improve the diversity of solutions. Aiming at the optimization of the sewage treatment process, this method optimizes the set values of so and SnO on the BSM1 imitation benchmark platform, achieves the goal of simultaneously optimizing the effluent quality and energy consumption, meets the requirements of sewage discharge with less energy consumption, and effectively reduces the cost of the sewage treatment process.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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