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Mathematical modeling and simulation of biodegradation process in a reaction tank during wastewater treatment in high alpine and high altitude areas

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Abstract The increasing water consumption in cities and towns makes the municipal sewage treatment in alpine and high altitude areas more and more difficult, and the optimization of the biochemical reaction effect of the reaction tanks in the sewage treatment process has become an important way to solve this problem. In this paper, starting from the structure of sewage treatment system in alpine and high altitude areas, based on the mathematical model of activated sludge method, its biological reaction process and multi-layer sedimentation model are analyzed. Then combined with MATLAB software, based on the model assumptions and the material balance equation of the concentration of each component in the reaction tank, the simulation model of the biodegradation process in the wastewater treatment reaction tank was constructed and the biochemical reaction under the change of the dosing ratio and temperature was analyzed through simulation. Then the outlet water quality and the total energy consumption of wastewater treatment were taken as the objective functions, and a multi-objective optimization model of wastewater treatment process was constructed, and the improved cuckoo search algorithm was introduced for optimization and solution. The results showed that when the value of input ratio was 0.008, the ammonia nitrogen concentration in the wastewater treatment reactor was stabilized in about 17 days and the concentration was less than 0.99 mg/L. By increasing the temperature to 36°C, the highest value of μH could be reached to 2.45 d-1, and the COD concentration of effluent could be controlled to about 49.96 mg/L. The results showed that the maximum value of μH could be reached to 2.45 d-1 by increasing the temperature to 36°C, and the COD concentration in the effluent could be controlled to about 49.96 mg/L. And the ICS algorithm can realize the optimal result solution of the multi-objective optimization model of wastewater treatment, which helps to improve the efficiency of wastewater treatment and reduce the energy consumption of wastewater treatment in alpine and high altitude areas.

Index Terms activated sludge, biological reaction process, MATLAB software, material balance equation, multi-objective optimization model, ICS algorithm

I. Introduction

Most of the alpine and high altitude regions have a cold winter climate with a large temperature difference between day and night, and these regions are sparsely populated with a low population density, a predominantly ethnic minority population, and a low water consumption [1], [2]. Many of the wastewater treatment plants in this region have an impact on the microbial reaction process in wastewater treatment due to the difficulty of operation in winter due to very low influent temperatures and the difficulty of meeting effluent standards [3], [4]. Among the many factors affecting microbial activity in wastewater treatment, the role of temperature is very important, the temperature is suitable to promote the strengthening of microbial physiological activities, the temperature is not suitable, it will lead to microbial physiological activities to reduce the weakening, and may even die [5]-[8]. In the ultra-low temperature environment, the traditional activated sludge process and biofilm process have no “use” [9]. In addition, due to the blind pursuit of strict emission standards, not fully considering the actual situation in the region, keen to use integrated wastewater treatment facilities, and a variety of process types, to the later sewage treatment of biological degradation brings greater pressure [10]-[12]. Therefore, it is necessary to establish the biodegradation process model of the reaction tank in the sewage treatment process, and provide technical support for engineering applications by optimizing the research process design and operating conditions [13], [14].

Numerical simulation methods are used to optimize wastewater treatment plant processes, to solve the shortcomings of on-site optimization experiments, and to provide support for the design of faster and more economical wastewater treatment optimization schemes. Based on the ASM1 mathematical model of activated sludge method, the article constructed a simulation model of the biodegradation process of wastewater treatment reactors through model assumptions and limitations, combined with the material balance equations of each component concentration and MATLAB software. Using the simulation model, the changes of biochemical reactions in the wastewater treatment reactor were analyzed under different input ratios and temperatures. Then based on the wastewater treatment outlet water quality and total energy consumption as the objective function, the ICS algorithm introducing the dynamic discovered strategy of the optimization progress and the dynamic change strategy of the step length is solved, aiming to further improve the wastewater treatment outlet water quality and reduce the economic cost of wastewater treatment in high alpine and high altitude areas.

II. Wastewater treatment based on the activated sludge method

With the development of the economy and people's living standards continue to improve, wastewater emissions continue to increase, the corresponding pollution of the water environment is also becoming increasingly serious, mainly in the diversification of the type of pollution and the deepening of the degree of organic pollution, but also makes the difficulty of water treatment continues to increase. For some of the toxic substances that are difficult to biodegradation can use strong oxidizing agent to oxidize and decompose them to reduce the degree of pollution.

II. A. Wastewater activated sludge treatment system

II. A. 1) Basic structure of the system

Wastewater treatment system can be divided into pretreatment, primary treatment, secondary treatment, deep treatment and sludge treatment and disposal according to the treatment unit [15].

(1) Pre-treatment includes grating and sand sedimentation tank. Its main role is to retain large debris in the sewage, sand and gravel to ensure the normal operation of subsequent equipment.

(2) Primary treatment is mainly the initial sedimentation tank. Its main role is to remove the suspended solids in the sewage by sedimentation, generally about the removal of suspended solids and about.

(3) The secondary treatment consists of aeration tank and secondary sedimentation tank. The main role is through the metabolism of microorganisms in the sewage pollutants into CO2, H2O and N2, P and focus on the remaining sludge in order to deal with.

(4) Deep treatment mainly includes coagulation, sedimentation and filtration, and its main purpose is to meet the high standard requirements of the receiving water body or as the need for water reuse. It will be an important direction for the future development of urban wastewater treatment as people's requirements for the environment are increasing and water resource problems are becoming more and more strained.

(5) Sludge treatment and disposal. Sludge treatment mainly includes thickening, digestion, dehydration, etc., and sludge disposal mainly includes composting, incineration sanitary landfill, etc..

After the pollutants in the sewage and the reflux sludge in the secondary sedimentation tank are fully contacted and oxidized, it enters the secondary sedimentation tank for mud-water separation, and is discharged into the receiving water body through disinfection or arranged for appropriate tertiary treatment according to the requirements of the effluent. The residual sludge generated during the treatment process is generally thickened, digested and dewatered before final disposal.

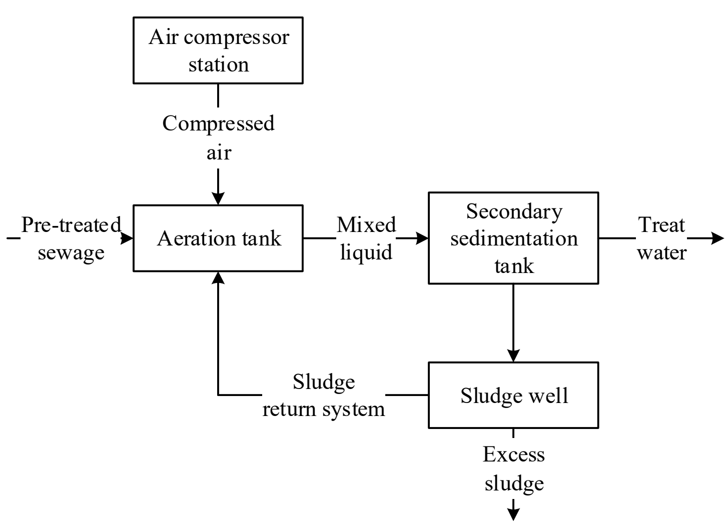


Figure 1: Traditional activated sludge process flow

II. A. 2) Activated sludge process

Activated sludge method is a wastewater biological treatment technology with activated sludge as the main body, and its basic process flow is shown in Figure 1. The system takes the activated sludge reactor-aeration tank as the core treatment equipment, in addition to the secondary sedimentation tank, sludge return system, and aeration and air diffusion system, etc. [16].

The sewage treated by the primary sedimentation tank or hydrolysis acidification device, the continuous reflux of activated sludge from the secondary sedimentation tank and the compressed air sent from the air compressor station are mixed with each other and fully contacted in the aeration tank, so that the reaction of activated sludge is carried out normally, and the organic pollutants in the sewage are degraded and removed, the sewage can be purified, and the activated sludge itself is grown.

After the activated sludge purification effect of the mixture from the aeration tank outflow into the secondary sedimentation tank, activated sludge through precipitation and sewage separation, clarified sewage as treated water discharge system. After precipitation, the concentrated sludge is discharged from the bottom of the sedimentation tank, part of which is returned to the aeration tank as inoculated sludge, and the excess part is discharged from the system as residual sludge.

II. B. Mathematical modeling of the activated sludge process

II. B. 1) Biological reaction processes

The activated sludge mathematical model (ASM1) describes 13 water quality components and classifies them into two main categories of dissolved and particulate components according to their morphology. Among the above water quality components, alkalinity (SALK) was measured using molar HCO3- (mmol/L), organic carbon (SI, SS, XI, XS), microorganisms (XB,H, XB,A), microbial attenuation products (XP), and dissolved oxygen (SO) were used as COD (mg/L), and all nitrogen components (SNO, SNH, SND, and XND) were used as N (mg/L) Measurement [17].

The mathematical model of activated sludge has eight biological reaction sub-processes, each of which contains several components, each of which participates in several biological reaction sub-processes. For example, in the sub-process of hydrolysis of particulate organic matter (ρ7), the components involved in the reaction are slow biodegradable organic carbon (XS), heterotrophic bacteria (XB,H), dissolved oxygen (SO) and nitrate nitrogen (SNO). Also, dissolved oxygen (SO) is involved in biological reaction sub-processes such as aerobic growth of heterotrophic bacteria (ρ1), anoxic growth of heterotrophic bacteria (ρ2), aerobic growth of autotrophic bacteria (ρ3), hydrolysis of particulate organic matter (ρ7), and hydrolysis of particulate organic nitrogen (ρ8).

In an activated sludge system, the biological reaction rate is expressed as the sum of the rates of each component in each biological reaction process, which can be expressed by the mathematical equation:

$$r_i = \sum V_{ij} \rho_j \tag{1}$$

where r_i is the biological reaction rate of the i th component in the activated sludge system, V_{ij} is the stoichiometric coefficient of the i th component in the j th process, and ρ_j is the mathematical expression for the basic rate of the j th biological reaction process.

In each sub-biological reaction process, ρ_j is expressed as:

(1) Aerobic growth of heterotrophic bacteria ρ_1 as:

$$\rho_1 = \mu_H \left[\frac{S_S}{K_S + S_S}\right]\left[\frac{S_o}{K_{OH} + S_O}\right] X_{BH} \tag{2}$$

(2) Heterotrophic bacteria grow anoxically ρ_2 for:

$$\rho_2 = \mu_H \left[\frac{S_S}{K_S + S_S}\right]\left[\frac{K_{OH}}{K_{OH} + S_O}\right]\left[\frac{S_{NO}}{K_{NO} + S_{NO}}\right] \eta_g X_{BH} \tag{3}$$

(3) Aerobic growth of autotrophic bacteria ρ_3 for:

$$\rho_3 = \mu_A \left[\frac{S_{NH}}{K_{NH} + S_{NH}}\right]\left[\frac{S_O}{K_{OA} + S_O}\right] X_{BA} \tag{4}$$

(4) The attenuation of heterotrophic bacteria ρ_4 is:

$$\rho_4 = b_H X_{BH} \tag{5}$$

(5) The decay of autotrophic bacteria ρ_5 is:

$$\rho_5 = b_A X_{BA} \tag{6}$$

(6) The nitrogenation of dissolved organic nitrogen ρ_6 is:

$$\rho_6 = k_a S_{ND} X_{BH} \tag{7}$$

(7) The hydrolysis of particulate organic matter ρ_7 is:

$$\rho_7 = k_h \frac{X_s / X_{BH}}{K_X + (X_S / X_{BH})} \left\{ \left[\frac{S_O}{K_{OH} + S_O} \right] + \eta_h \left[\frac{K_{OH}}{K_{OH} + S_O} \right] \left[\frac{S_{NO}}{K_{NO} + S_{NO}} \right] \right\} X_{BH} \tag{8}$$

(8) Hydrolysis of particulate organic nitrogen ρ_8 for:

$$\rho_S = k_h \frac{X_S / X_{BH}}{K_X + (X_S + X_{BH})} \left\{ \left[\frac{S_O}{K_{OH} + S_O} \right] + \eta_h \left[\frac{K_{OH}}{K_{OH} + S_O} \right] \left[\frac{S_{NO}}{K_{NO} + S_{NO}} \right] \right\} \left(\frac{X_{ND}}{X_S} \right) X_{BH} \tag{9}$$

II. B. 2) One-dimensional multilayer sedimentation models

The assumptions of the one-dimensional multilayer sedimentation model are as follows:

(1) Sludge is uniformly distributed within the pool body with the same concentration at each level.

(2) Sewage in the pool body flows only in the direction of gravity, and turbulence is not considered.

(3) There is no biochemical reaction in the tank body.

The one-dimensional model of the secondary sedimentation tank is based on the law of conservation of mass to simulate the settling state of the particles in the tank. The expression combining the Takacs settling velocity model is:

$$v_s(X) = \max[0, \min\{v_0', v_0(e^{-r_h(x - x_{\min})} - e^{-r_f(x - x_{\min})})\}] \tag{10}$$

where $X_{\min} = f_{ns} X_f$.

The one-dimensional multilayer sedimentation model divides the secondary sedimentation tank into ten layers of fixed thickness, and material balance calculations for solids are done for each layer to predict the distribution of solids concentration in the secondary sedimentation tank. The model is based on a conventional solids flux study except for a critical concentration that limits the downward solids flux, which can be handled by the following layers.

The terminology used in the one-dimensional multilayer sedimentation model and its meaning are as follows:

A_C is the cross-sectional area of the pool, J_{dn} is the solids flux due to the underflow, J_j is the downward solids flux in the jth layer, J_s is the solids flux due to gravitational settling, J_{Up} is the solids flux due to outflows, and Q_i is the flow rate, Q_r is the sludge return flow rate.

III. Model simulation and control performance evaluation

With the increasing water consumption in cities and towns, the treatment of municipal wastewater has become more and more difficult, and the construction of more wastewater treatment plants has become an important way to solve this problem. The sewage treatment plant in the alpine and high altitude area is facing the situation of unstable and substandard effluent quality, and it is time-consuming and laborious to optimize the process through the way of “small trial - pilot - application”, and the use of sewage treatment plant simulation technology can realize the accurate and rapid optimization of the process.

III. A. Biochemical reactor model

III. A. 1) Model assumptions and limitations

The process of system modeling is also a process of simulation and emulation of the system, and therefore some degree of simplifications and assumptions must be made about the physical system in order to make the model immune to the effects of certain uncertainties. Some of these simplifications and assumptions are related to the physical structure of the system itself and some are related to the mathematical model. Often these simplifications and assumptions define the scope of the application of the system model, and if the assumptions are not met, the validity of the model's approximation of the physical system may be seriously compromised. In order to prevent this, the main assumptions and qualifications related to the model as well as the physical system are listed below.

(1) The temperature is considered constant during operation of the wastewater treatment system. However, in the system analysis that examined the effect of temperature on the system, the role of temperature variations in influencing the process design was explored as a function of temperature.

(2) pH is constant and near neutral. Because pH will have an effect on many model parameters, but there are few relevant functional expressions to express the extent of this effect, the system model needs to assume constant pH to avoid fluctuations in parameters.

(3) Changes in the nature of the characteristic components of the pollutant are not considered in the system model, i.e., the mass concentration of the pollutant can change, but the composition and constituents do not change, and such changes do not affect the default values of the kinetic parameters of the rate expressions in the model.

(4) The limiting effects of N, P, and other inorganic nutrients on organic matter removal and microbial growth were not considered in the model. Although inorganic nutrient deficiencies will likely result in altered sludge settling performance, sufficient inorganic nutrients are assumed to be available in the model to ensure microbial growth requirements.

(5) Various correction factor parameter values that are constant for a given effluent composition. These correction factors may be affected by the composition of the system, but are not considered in the model.

(6) Microorganisms do not undergo strain type changes over time, indicating that the effects of substrate concentration gradients, reactor configuration factors, etc., on sludge settling performance are not considered in the system model.

(7) In the process of system modeling, none of the models established through the material balance relationship considered the accumulation of pollutant components, i.e., the system was regarded as a steady state, and only the system input and output terms and the reaction term were considered, and the accumulation term was zero.

III. A. 2) Material balance equations for component concentrations

The ASM1 model uses a matrix form to represent the components and biochemical processes in the activated sludge system and the interrelationships between them. In a certain biochemical reaction process, if a certain component is not involved in its process change, its measurement coefficient is zero, which is indicated by a space in the matrix expression. The sign of the coefficient of measurement indicates the change in the size of the component during the reaction process, with a large change being positive and a small change being negative.

The total conversion rate of a component is:

$$r_i = \sum_j v_{ij} \rho_j \tag{11}$$

where v_{ij} denotes the coefficient of measurement in i rows and j columns.

As an example, the calculation of the total reaction rate of the slow biodegradable organic matter X_s, i.e., $i=4$, gives:

$$r_4 = \sum_j v_{4j} \rho_j = v_{44}\rho_4 + v_{45}\rho_5 + v_{47}\rho_7 \tag{12}$$

The corresponding stoichiometric coefficients and reaction process rates are then substituted into the above equation:

$$\begin{aligned} r_4 &= (1-f_p)(b_H X_{BH} + b_A X_{BA}) \\ &-K_h\left(\frac{X_S / X_{BH}}{K_X + X_S / X_{BH}}\right)\left[\left(\frac{S_O}{K_{OH}+S_O}\right) + \eta_h\left(\frac{K_{OH}}{K_{OH}+S_O}\right)\left(\frac{S_{NO}}{K_{OH}+S_{NO}}\right)\right] X_{BH} \end{aligned} \tag{13}$$

In an aeration tank, the material balance equation is:

$$\begin{aligned} &\text{Input quantity - output quantity} \\ &+ \text{reaction product quantity} = \text{cumulative quantity} \end{aligned} \tag{14}$$

It can be expressed by the following equation:

$$\frac{dZ}{dt} = \frac{Q}{V}(Z_{in} - Z) + r(Z) \tag{15}$$

where $Z = [S_I, S_S, X_I, X_S, X_{BH}, X_{BA}, X_P, S_O, S_{NO}, S_{NH}, S_{ND}, X_{ND}, S_{ALK}]^T$, denotes the vector of concentrations of all components in the aeration tank, Z_{in} denotes the vector of input concentrations of all components, and $r(Z)$ is the vector of total reaction rates of the components, $r(Z) = [r_1, r_2, r_3, r_4, r_5, r_6, r_7, r_8, r_9, r_{10}, r_{11}, r_{12}, r_{13}]^T$, Q is the inlet rate, and V is the volume of aeration tank.

Taking the concentration of slow biodegradable organic matter X_s as an example, from Eqs. (12)~(15) we get its material balance equation as:

$$\frac{dX_s}{dt} = \frac{Q}{V}(X_{S,m} - X_S) + r_4 \tag{16}$$

In the ASM1 model, the aeration tank contains five reaction tanks, combined with the process flow of activated sludge method of wastewater treatment, the material balance equation in each reaction tank can be obtained:

$$\begin{cases} \frac{dZ_1}{dt} = r(Z_1) + \frac{1}{V_1}(Q_0 Z_q - Q_1 Z_1 + Q_a Z_a + Q_r Z_r) \\ \frac{dZ_2}{dt} = r(Z_2) + \frac{1}{V_2}(Q_1 Z_1 - Q_2 Z_2) \\ \frac{dZ_3}{dt} = r(Z_3) + \frac{1}{V_3}(Q_2 Z_2 - Q_3 Z_3) \\ \frac{dZ_4}{dt} = r(Z_4) + \frac{1}{V_4}(Q_3 Z_3 - Q_4 Z_4) \\ \frac{dZ_5}{dt} = r(Z_5) + \frac{1}{V_3}(Q_4 Z_4 - Q_5 Z_5) \end{cases} \tag{17}$$

where $Z_k (k = 1, \ldots, 5)$ denotes the concentration vector of all components in the k th reactor, $r(Z_k)$ denotes the vector of total reaction rates of all components in the k th reactor, V_k is the volume of the k th reactor, Q_a denotes the inner cycle, Q_r denotes the sludge return flow in the outer cycle, Z_a, Z_r denote the concentration vectors of all the components in the inner and outer cycles, respectively, Q_0 denotes the influent flow rate, and Q_{k-1} denotes the influent flow rate of the k th reactor pool, which is also the $k-1$ outlet water flow of the first reaction pool.

In this paper, the dissolved oxygen concentration as the controlled quantity, the design of the controller to regulate the aeration, in the process, will be through the blower to the aerobic tank oxygen, that is to say, dissolved oxygen has an additional input, the expression will be different, from the material balance equation can be obtained dissolved oxygen concentration expression is:

$$\frac{dS_{O_k}}{dt} = r_{s,k} + \frac{1}{V_k}(Q_{k-1} S_{O_{k-1}} - Q_k S_{O_k}) + K_L a_k (S_O^* - S_{O_k}) \tag{18}$$

where $r_{s,k} (k = 1, \ldots, 5)$ denotes the total dissolved oxygen reaction rate in the k th reaction cell, and S_O^* is the saturation value of dissolved oxygen, in the design of this paper, we will select $K_L a_k$ as the control quantity, and $K_L a_k$ is the total gas transfer coefficient, which responds to the aeration disk in the aeration system.

III. B. MATLAB simulation modeling and control

III. B. 1) Simulation Modeling

The MATLAB language is an engineering mathematical computing software, MATLAB is based on matrix operations and integrates computation, visualization, programming, and computer simulation into an interactive working environment. Engineering computation, algorithm research, modeling and simulation, data analysis and visualization, scientific and engineering graphics, and application software development (including graphical interface design) can be achieved here [18].

In this study, the M file of MATLAB is used to edit the initial inlet data, system parameters and controller parameters. Then use the "sim" command in the M-file to call the object model of Simulink simulation, obtain the output data of the simulation, and then feedback to the M-file for controller parameter adjustment, until a satisfactory output is obtained. In the whole process, MATLAB Workspace stores all the data in the control process and acts as the "middleman" of the whole process.

Relying on MATLAB software for system model simulation, combined with the ASM1 mathematical model given in the previous section and the relevant assumptions, the simulation model is constructed as shown in Fig. 2, and the relevant variables are named, in which Q represents the flow rate, and Z represents the concentration of the 13 components.

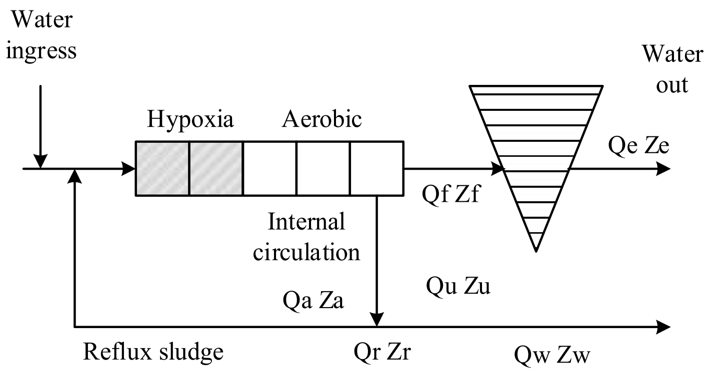


Figure 2: Simulation model of system

In order to solve the differential equations it is necessary to prepare and call the subroutine of the Lungkuta method, and when simulating the object model using Simulink, the ODE Solder provided by MATLAB can be used directly, so that the problem can be greatly simplified.The ODE adopts the fourth-order/fifth-order Lungkuta method, that is, the Taylor expansion of the product function is accurate to the fourth/fifth order, and the truncation error is the fifth/fourth order. The ODE function in MATALB is an adaptive variable step-size integral solution method, which is chosen here because of its high computational accuracy.

III. B. 2) Evaluation of wastewater treatment performance

In order to compare the simulation process of biodegradation in the sewage treatment process, this paper carries out the performance evaluation for the effectiveness of the model, in which the process evaluation mainly includes the effluent quality indicators and economic indicators, as follows:

(1) Effluent quality indicators

Effluent quality index (EQ) refers to the average effluent quality within 7 days, i.e.:

$$EQ = \frac{1}{1000T}\int_0^{*} \begin{matrix} b_{TSS}TSS_e(t) + b_{COD}COD_e(t) \\ + b_{BOD}BOD_e(t) + b_{TKN}TKN_e(t) + b_{NO}NO_e(t) \end{matrix} \tag{19}$$

where TSS_e is the total solids concentration in the effluent, then:

$$TSS_e = 0.75(X_{S,e} + X_{BH,e} + X_{BA,e} + X_{P,e} + X_{I,e}) \tag{20}$$

COD_e is the chemical oxygen demand of the effluent, then:

$$COD_e = S_{Se} + S_{Le} + X_{Se} + X_{BH,e} + X_{BA,e} + X_{P,e} + X_{L,e} \tag{21}$$

BOD_e is the Biochemical Oxygen Demand of the effluent, then:

$$BOD_e = 0.25(S_{S,e} + X_{S,e} + (I - f_p)(X_{BH,e} + X_{BA,e})) \tag{22}$$

TKN_e is the total Kjeldahl nitrogen concentration in the effluent, then:

$$TKN_e = S_{NH,e} + S_{ND,e} + X_{ND,e} + i_{XB}(X_{BH,e} + X_{BL,e}) + i_{XP}(X_{L,e} + X_{P,e}) \tag{23}$$

NO_e is the effluent nitrate and nitrite concentration, then:

$$NO_e = S_{NO,e} \tag{24}$$

$\beta_{TSS}\beta_{COD}\beta_{BOD}\beta_{TKN}\beta_{MO}$ is the relevant scale factor.

(2) Economic indicators

The economic indicators are divided into sludge production and treatment number use, total energy consumption of aeration splitter and total energy consumption of sewage transfer pump.

Sludge production includes the following indicators:

Sludge discharge, i.e:

$$P_{sludgr} = [\Delta M(TSS_{system}) + M(TSS_w)] / T \tag{25}$$

Here $\Delta M(TSS_{system})$ is the change in sludge concentration, including sludge from biochemical reactors and secondary settling tanks, i.e:

$$M(TSS_W) = 0.75\int_*^* [X_{s,w}(t) + X_{BH,w}(t) + X_{BA,w}(t) + X_{P,w}(t) + X_{L,w}(t) f^{Q_w(t)dt} \tag{26}$$

Total sludge discharge, i.e:

$$P_{scad\_sladge} = P_{sbadge} + M(TSS_e) / T \tag{27}$$

Here:

$$M(TSS_s) = 0.75\int_0^t [X_{ss}(t) + X_{BH,s}(t) + X_{BA,s}(t) + X_{P,s}(t) + X_{I,s}(t)] Q_s(t)dt \tag{28}$$

The total energy consumption for aeration can be expressed as:

$$AE = \frac{24}{T}\int_0^{24m}\sum_{i=1}^{i-5}[0.4032K_La_i(t)^2 + 7.8408K_La_i(t)]dt \tag{29}$$

The total energy consumption of the sewage transfer pump is expressed as:

$$PE = \frac{0.04}{T}\int_s^{t_{sss}}[Q_o(t) + Q_r(t) + Q_w(t)]dt \tag{30}$$

From the point of view of protecting the environment, the higher the quality of water, the better, but from the point of view of the operating costs of the enterprise, the high quality of water means that the economic indicators are not cost-effective, if you can design a control method to make the economic indicators and the quality of water are improved, this is the optimal method. If this is not possible, a trade-off can only be made between water quality and economic indicators.

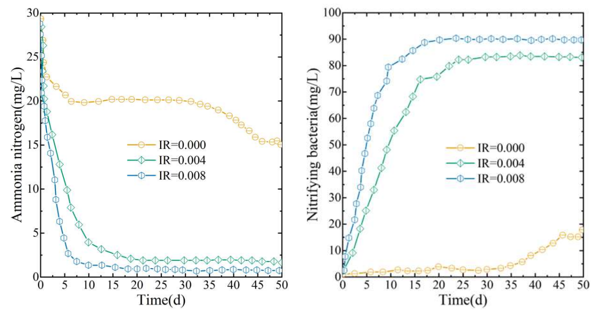
III. C. Simulation and analysis of biochemical reactions

III. C. 1) Dosing ratio change curve

Under the wastewater treatment system established in this paper, the enriched nitrifying bacteria should have basically the same mechanism of action as the primary nitrifying bacteria after they are put into the main reactor, and the modeling only increases the quantity share of the nitrifying bacteria individually each time the sludge is returned to the anaerobic tank, and no longer splits the components in the matrix. Moreover, the added nitrifying bacteria only flow back to the anaerobic tank with the sludge, the lateral flow reactor does not discharge mud, and all of its sludge discharge is returned to the anaerobic tank as the added sludge, and the sludge discharge is controlled by the age of the sludge.

Using MATLAB to write the program, and simulate the results of 50 days of arithmetic, from the injection ratio (IR) to analyze, IR refers to the sidestream reactor to the main reactor to the main influent flow rate of the ratio of the flow and the main influent flow rate, the simulation data for the aerobic section of the end of the water quality data. Figure 3 shows the simulation results of biodegradation in the wastewater treatment process, in which Figures 3(a)~(b) represent the change curves of ammonia nitrogen and nitrifying bacteria with the input ratio, respectively.

As can be seen from the figure, with the increase of the input ratio, the greater the rate of ammonia nitrogenation in the wastewater treatment process, when the value of the input ratio is 0.008, the ammonia nitrogen concentration stabilizes in about 17 days, and the concentration is less than 0.99 mg/L. When the value of the input ratio is 0.004, the ammonia nitrogen concentration stabilizes in about 21 days, but it is slightly higher than the situation when the input ratio is 0.008. Similarly, the higher the value of the input ratio, the faster the growth rate of nitrifying bacteria, and when the input ratio was 0.008, the nitrifying bacteria reached stability in less than 18 days, and the concentration was relatively maximum. The same is true for the no-input case (i.e., the input ratio is 0), because there is no external nitrifying bacteria and the mud age is not high, the nitrifying bacteria started to grow slowly only after about 35 days and the ammonia-nitrogen concentration was maintained at a relatively high level. In the case of no addition, and the mud age is very short, the overall nitrification capacity are very weak, due to the mud age is too short, nitrifying bacteria almost can not grow up. In the case of addition, the ammonia and oxygen degradation is very fast, only the concentration of nitrifying bacteria is different when stabilized, and the ammonia and nitrogen concentration of the effluent is almost the same. This shows that, for biological addition, under a certain dosing ratio, the influence of mud age on nitrifying bacteria is weakened, which can strengthen the nitrogen removal at the same time, but also alleviate the contradiction of mud age with phosphorus removal.

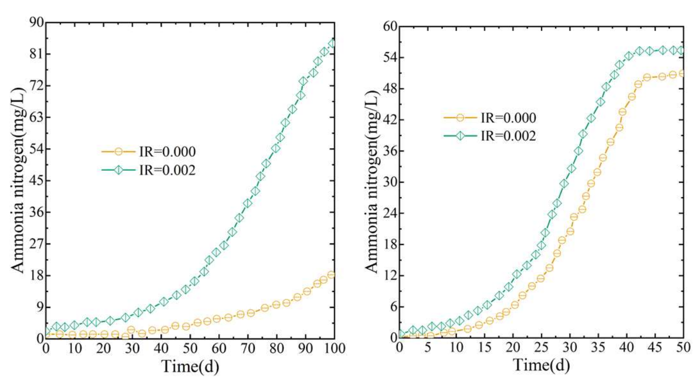


(a) Ammonia nitrogen (b) Nitrifying bacteria

Figure 3: Simulation results of biodegradation

In addition, this paper further analyzed the growth of nitrifying bacteria in the aerobic tank as well as the growth of polyphosphorus bacteria in the anaerobic tank under different biological feeding ratios, and the specific results were shown in Figure 4, in which Figure 4(a)~(b) shows the growth distribution of nitrifying bacteria and polyphosphorus bacteria, respectively.

From Fig. 4(a), it can be seen that the number of nitrifying bacteria obviously increased rapidly with the increase of injection ratio, and the nitrification capacity of the whole reactor was significantly improved. In addition, in Fig. 4(b), with the increase of the input ratio, the time for the polyphosphorus bacteria to reach the steady state was shortened, and the number of bacteria at the steady state was relatively reduced, and the relative steady state was reached when the concentration of polyphosphorus bacteria at the input ratio of 0 was 50 mg.COD/L, and the concentration of the polyphosphorus bacteria at the input ratio of 0.002 was 55.39 mg.COD/L. This indicates that with the increase of the input ratio, the phosphorus removal ability of the whole wastewater treatment system was Weakened, but compared with the increase in the number of nitrifying bacteria, the decrease in the number of polyphosphorus bacteria is very small, and the overall phosphorus removal capacity is not much weakened. That is to say, when doing biological addition, as long as you choose the appropriate dosage ratio, you can alleviate the contradiction between the age of nitrifying bacteria and polyphosphorus bacteria.



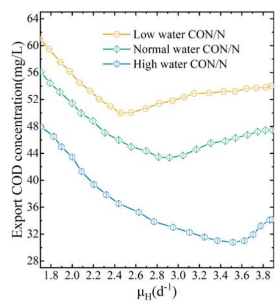
(a) Nitrifying bacteria (b) Polyphosphor

Figure 4: The growth of different bacteria

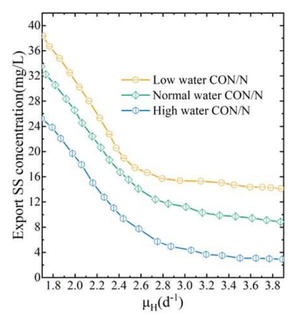
III. C. 2) Biochemical reaction kinetics

In the existing studies, it is known that temperature will have a linear effect on the biodegradation reaction in the wastewater treatment system, which suggests that the purpose of improving the function of wastewater treatment essence can be achieved by controlling the temperature. Combined with the existing related studies, this paper will use the simulation model constructed in the previous section to simulate the relationship between aerobic bacteria (μ_H) and autotrophic bacteria (μ_A) and effluent water quality, in order to further improve the effect of biodegradation reaction in the wastewater treatment process, and then to enhance the efficacy of wastewater treatment. Table 1 shows the effect of temperature on the biochemical reaction process under different influent COD/N. Figure 5 shows the relationship between the simulated effluent water quality and the specific growth rate of microorganisms at different temperatures, in which Figures 5(a)~(c) show the relationship between μ_H and effluent chemical oxygen demand (COD), microbial metabolism of influent organic matter (SS), and dissolved microbial products (SMP), respectively, and Fig. 5(d) shows the relationship between μ_A and ammonia-nitrogen dissolved matter (SNH).

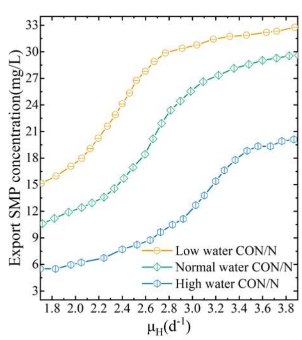
From the point of view of biochemical reaction kinetics, nitrifying bacteria belong to thermophilic bacteria, so when the temperature is less than 16°C, their activity (μ_H and μ_A) is inhibited by temperature, and the effect of temperature on their growth process is more obvious (the coefficients of variation of the temperature of nitrifying bacteria under low and high influent COD/N are 0.025 and 0.098, respectively), which then affects the rate of pollutant degradation. The microbial activity was less affected by temperature at high temperatures, i.e., temperatures greater than 36°C, with coefficients of 0.006 and 0.012 at low and high influent COD/N, respectively.In addition, for the same temperature, μ_H and μ_A increased with increasing influent COD/N. The temperature coefficients of μ_H and μ_A were 0.025 and 0.098 for low and high influent COD/N, respectively. And for the same influent COD/N, the temperature coefficients of variation of μ_A were all larger than those of μ_H, i.e., the effect of temperature on μ_A was more pronounced than on μ_H.



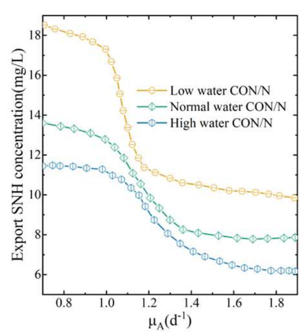
(a) μH and COD



(b) μH and SS



(c) μH and SMP



(d) μA and SNH

Figure 5: The effluent quality and the specific growth rate of microorganisms

From Figures 5(a) to (d), it can be seen that for the same influent COD/N, the general trend is that the effluent pollutant concentration decreases with the increase of μ_H or μ_A, and then maintains at a lower level. This is a guideline for the optimal control of biodegradation during wastewater treatment as follows:

Under low influent COD/N, when the temperature was in the range of 9 to 36°C, by increasing the temperature take-off to 36°C, the μ_H and μ_A could be maximized to 2.45 d^{-1} and 1.17 d^{-1}, respectively, which in turn controlled the effluent COD, SMP, and SNH concentrations to about 49.96 mg/L, 25.34 mg/L, and 11.32 mg/L, respectively. At high influent COD/N, when T is in the range of 9-16°C, by increasing the temperature fetch to 16°C, the μ_H and μ_A

fetches can be maximized to 3.51 d^{-1} and 1.59 d^{-1}, respectively, and thus the effluent COD, SMP and SNH concentrations can be controlled to be around 30.78 mg/L, 19.34 mg/L and 6.48 mg/L, respectively, so as to achieve the improvement of the biodegradation purification function in the wastewater treatment process.

Table 1: The influence of temperature on biochemical reaction kinetics

Influent COD/N	Specific growth rate	Temperature range	Coefficient of change	Temperature range	Coefficient of change
Low	μ_H	9~36℃	0.031	36~40℃	0.009
	μ_A		0.025		0.006
Normal	μ_H	9~26℃	0.025	26~40℃	0.005
	μ_A		0.042		0.008
High	μ_H	9~16℃	0.019	16~40℃	0.004
	μ_A		0.098		0.012

IV. Research on optimization strategies for wastewater treatment processes

Wastewater treatment belongs to the research field of chemical biology, because the treatment process is directly related to the growth and multiplication of microorganisms, the reaction and degradation of pollutants. It contains chemical reactions between various pollutants, biochemical reactions of microorganisms, and settling and accumulation processes of non-degradable substances. These processes require the joint action of complex biological reaction tanks and sedimentation tanks to be well controlled. In order to achieve further optimization of the wastewater treatment process, this paper introduces an improved cuckoo search algorithm for multi-objective optimization, with a view to achieving process optimization of wastewater treatment in alpine and high altitude areas.

IV. A. Wastewater treatment process optimization model

Based on the previous related analysis, the optimization problem with effluent quality constraints in the wastewater treatment process is described as:

$$\min F(X)=\left\{f_{EC}(X),f_{EQ}(X)\right\}$$
$$s.t\begin{cases}g_1(X)=f_1(X)-4\le 0\\ g_2(X)=f_2(X)-18\le 0\\ g_3(X)=f_3(X)-10\le 0\\ g_4(X)=f_4(X)-100\le 0\\ g_3(X)=f_3(X)-30\le 0\\ x_1^l\le x_1(k)\le x_1^u\\ x_2^l\le x_2(k)\le x_2^u\end{cases} \tag{31}$$

where $X=[x_1,x_2]=[S_{O,p},S_{NO,p}]$ is the control vector, $f_j(X)$ is the mathematical relationship between the optimization variables and the effluent water quality parameters, $j=1,\cdots,5$, x_i^j and x_i^u are the upper and lower limits of the i th optimization variable, $i=1,2$. Where EQ is the effluent quality and EC is the total cost of wastewater treatment.

The cost of sewage treatment and effluent quality is a pair of conflicting objective functions, in order to ensure that the effluent water quality to meet the standard at the same time to reduce energy consumption, then only when the pollutant concentration in the effluent water quality is closer to the upper limit of the specified value, the lower the cost of sewage treatment. In addition, since only ammonia nitrogen and total nitrogen concentrations in the effluent water quality of wastewater treatment are easy to exceed the standard, and several other parameters are less affected by the control strategy, the constraints are simplified in the description of the wastewater treatment optimization problem in this paper to consider only the effluent ammonia nitrogen and total nitrogen.

The wastewater treatment model with constraints is not convenient for subsequent multi-objective algorithm optimization, so the constraints are added to EQ and EC as additional terms by the following equation with the help of penalty function method. The constraint penalty term defined is:

$$f_{perai\gamma}(X)=\max\{g_1(X)-4,0\}+\max\{g_2(X)-18,0\} \tag{32}$$

The aeration energy consumption and pumping energy consumption targets for adding the penalty term are:

$$\begin{cases} f_{EC}^{'}(X) = f_{EC}(X) + \mathrm{C} \cdot f_{penaly}(X) \\ f_{EQ}^{'}(X) = f_{EQ}(X) + \mathrm{C} \cdot f_{penaly}(X) \end{cases} \tag{33}$$

That is, the established constrained optimization problem of wastewater treatment process is transformed into an unconstrained multi-objective optimization problem. Where C is the penalty factor, which is often taken as 100.

In summary, the wastewater treatment process constrained multi-objective optimization problem is described as follows:

$$\min F(X) = \{f'_{EC}(X), f'_{EQ}(X)\}$$
$$s.t \begin{cases} g_1(X) = f_1(X) - 4 \le 0 \\ g_2(X) = f_2(X) - 18 \le 0 \\ x_1^l \le x_1(k) \le x_1^u \\ x_2^l \le x_2(k) \le x_2^u \end{cases} \tag{34}$$

where $X = [x_1, x_2] = [S_{O,SP}, S_{NO,SP}]$ is the control vector, $f_j(X)$ is the mathematical relationship between the optimization variables and the effluent water quality parameters, $j = 1, 2$, and x_i^l and x_i^u are the i th upper and lower limits of the optimization variables, $i = 1, 2$.

IV. B. Improved Cuckoo Search Algorithm

IV. B. 1) Improving the cuckoo algorithm

(1) Basic principle of cuckoo algorithm

In nature, cuckoos find nests by some randomized way, in order to the simplicity of the algorithm and increase operability, the cuckoo (CS) algorithm first needs to set the following three ideal conditions on its constraints:

a. Each individual lays one egg at a time and a nest is randomly selected for nurturing.

b. Among the selected nests, the best adapted nest is taken as the best location and saved to the next generation ready for update replacement [19].

c. The number of nests n in the population is fixed, and the probability of finding an alien egg is set to be P_a, and the host sheds nests with this probability during population evolution, where $P_a \in [0,1]$.

The CS algorithm follows the Levy flight mechanism, i.e., the positional transformation at the i th nest follows the following pattern:

$$x_i^{t+1} = x_i^t + \alpha \otimes Levy(\lambda) \tag{35}$$

where x_i^t denotes the position of the i th bird's nest updated to the t th generation, α denotes the step control factor, and $\otimes$ denotes the point-to-point multiplication. $Levy(\lambda)$ denotes the Levy random search path, which is a random wandering and obeys the Levy distribution with parameter λ. This path is the flight path of the cuckoo bird searching for the host nest, which is computed as:

$$Levy(\lambda) \sim \mu = t^{-\lambda}, 1 < \lambda < 3 \tag{36}$$

where t is the wandering step size and λ is the step size parameter. In the process of dealing with practical problems, in order to improve the efficiency of operation, the following formula is generally used for calculation, i.e.:

$$Levy \sim \frac{\varphi\mu}{|v|^{\frac{1}{\beta}}} \tag{37}$$

$$\varphi = \frac{\Gamma(1+\beta)\sin\frac{\pi\beta}{2}}{\Gamma\left(\left(\frac{1+\beta}{2}\right)\beta 2^{(\beta-1)/2}\right)} \tag{38}$$

The expression for α is:

$$\alpha = \alpha_0 (x_i^t - x_{best}^t) \tag{39}$$

where x_{best} denotes the location information of the best nest at the t th generation iteration, and α_0 is generally set to 0.01, which is used to control the step control factor in the search process.

Summarizing the above can be obtained:

$$X_i^{t+1} = X_i^t + \alpha_0 \frac{\varphi\mu}{|v|^{\frac{1}{\beta}}}(X_i^t - X_{best}^t) \tag{40}$$

A random number $k \in (0,1)$ is generated by a random function in the optimization search process, k is compared with P_a, and if $k < P_a$, the previous nest is kept. If $k > P_a$, the previous nest is not kept and the new nest is updated using the following equation:

$$X_i^{t+1} = X_i^t + R(X_g^t + X_k^t) \tag{41}$$

where R is the deviation coefficient, and X_g^t and X_k^t are the positions of the g and k nests at the t th iteration, respectively.

(2) Improvement of cuckoo search algorithm

a. Dynamic discovered strategy adjustment combined with the progress of the search for excellence

At the time of CS algorithm, there is an important assumption that the generation of new solutions in the step of CS algorithm execution is determined by two parts. One is the generation of new solutions by finding new nests using a global random search strategy, and the other is the passive generation of new solutions due to the discovery of parasitic eggs by their hosts.

In order to reduce the probability of discarding the high-quality solution (location) and increase the probability of discarding the poor-quality solution (location), the search speed and accuracy are accelerated. In this paper, we combine the change of fitness in the process of searching for superiority and introduce it to the process of generating and adjusting random numbers, and use the adjusted random numbers to judge the generation of new solutions and improve the performance of the algorithm.

Define the fitness bias μ of a solution (location) xi in the t th generation as:

$$\mu_{x_i}^t = f_{x_i}^t - f_{aierage}^t \tag{42}$$

where f denotes the fitness of the solution and the subscript average denotes the average fitness.

At this point, the random number ε generated by $rand(0,1)$ is then adjusted to:

$$\xi_{x_i}^t = \varepsilon_{x_i}^t + \frac{\mu_{x_i}^t}{f_{worst}^t - f_{best}^t} \tag{43}$$

where the subscripts WORST and BEST correspond to the worst and optimal fitness of the t th generation solution, respectively.

For the inferior solution, μ_x^t is greater than 0, so $\xi_{x_i}^t > \varepsilon_{x_i}^t$, which is more likely to be greater than p_a, and thus discarded, and a new solution is generated by the formula given in the previous section. The opposite is true for the better solution, μ_x^t is less than 0, so $\xi_{x_i}^t < \varepsilon_{x_i}^t$, which is more likely to be less than p_a, and thus be retained well into the next generation. This has the advantage of reducing the probability of better quality solutions being randomly discarded to some extent, ensuring the quality of the population.

b. Dynamic change strategy of step size

The step size of the CS algorithm has a great influence on the global optimal solution and search accuracy of the algorithm, large step size search is beneficial for the algorithm to avoid local optimization, but large step size search will inevitably reduce the convergence accuracy and speed of the algorithm, and small step size search can obviously improve the convergence speed and convergence accuracy of the algorithm, however, the small step size search will easily make the algorithm fall into the local optimization. Therefore, the search step size is a key factor that affects the convergence speed and convergence accuracy and avoids falling into local optimization. In this paper, we design an adaptive search step size improvement strategy for CS algorithm, so that the search step size can be adaptively adjusted by the optimal solution of the previous generation and the current number of iterations.

Considering the current degree of optimization search, i.e., there is a certain relationship between the current iteration number and the maximum iteration number, the cuckoo search step size S is defined as follows:

$$S = \frac{m}{bestX_{i-1}} \times \exp\left(-k \times \left(\frac{t}{t_{\max}}\right)^{p}\right) + S_{\min} \tag{44}$$

where $m \in [0,1]$ is the moderating factor, $bestX_{i-1}$ is the optimal bird's nest location in the previous generation population, and k is the limiting factor, which takes values between 0 and 1. t and $t_{\max}$ are the current iteration number and the maximum iteration number, respectively, $S_{\min}$ is the minimum value of the search step, and p is an integer between 1 and 30.

IV. B. 2) Wastewater treatment optimization process

Based on the CS algorithm under the improvement of the two strategies in the above paper, combined with the multi-objective optimization model in the wastewater treatment process given in the previous paper, this paper utilizes the Improved Cuckoo Search (ICS) algorithm to solve the model, so as to achieve the balance between the economic cost and the effluent quality in the wastewater treatment process.

The steps of ICS algorithm to solve the multi-objective optimization model of wastewater treatment are as follows:

Step1 Set the objective function $f(X)$ and initialize the relevant parameters of ICS algorithm. Including the population size, the dimension of the independent variables, the maximum number of iterations or accuracy, and the maximum and minimum values of the discovered probability p_a. And generate the initialization values of n solutions, denoted as $X_0 = (x_1^0, x_2^0, \cdots, x_n^0)$.

Step2 Substitute the initialized solution into the objective function and compute the current optimal objective function value, denoted as $best_{f(X)}$.

Step3 Record the optimal solution set of the previous generation, calculate the current step S, and update the value and state of the solution set. I.e:

$$x_i^{t+1} = x_i^t + \alpha \oplus S, i = 1, 2, \cdots, n \tag{45}$$

Step4 Generate random numbers $\varepsilon \in [0,1]$, compare the discovery probability p_a calculated by the formula, if $\varepsilon > p_a$, change the value of x_i^{t+1}, otherwise, keep the same. Finally, keep the optimal solution.

Step5 Compare the current objective function value with the last generation optimal value, if it is better than the last generation function value, replace the last generation function value with the current function value: otherwise, keep the last generation function value.

Step6 Judge whether the termination condition is reached, if not, return to Step2 to continue; otherwise, execute the next step.

Step7 Output the optimal solution set and optimal function value.

IV. C. Improving the effectiveness of the optimization algorithm

IV. C. 1) Michalewicz function optimization simulation

In order to better solve the multi-objective optimization model for wastewater treatment, this paper designs the ICS algorithm for solving. In order to intuitively reflect the superiority of the ICS algorithm, this paper selects the Michalewicz function as the test function, and selects the SGA and CIA algorithms as a comparison, and uses the three optimization algorithms to run continuously for six times, once to obtain the extreme value of the function. The threshold of this function is set to 35.71, that is, in the given maximum number of iterations, the fitness of the population optimal antibody is considered to be globally convergent if it reaches the threshold, otherwise it is considered that the algorithm falls into a local extreme value. The results of the optimization search are shown in Table 2, and Fig. 6 shows the curve of the evolutionary process of each algorithm.

From the chart, it can be intuitively known that the SGA algorithm is very unstable when the maximum number of evolutionary generations is 500, and it still can not be stabilized when it is close to the maximum number of generations, and it is difficult to converge into the threshold even if the maximum number of evolutionary generations is increased to 1,000 generations. It can be seen that for Michalewicz's complex function optimization, it is difficult to get the optimal solution by using SGA.CIA algorithm can converge faster than SGA algorithm, but due to the fact that it does not have the dynamic discovery strategy of the optimization progress and the dynamic change of the step size in the late search like ICS algorithm, only 1 out of 6 optimization searches can reach the threshold value. It can be seen that for the optimization of Michalewicz's function, which has many local extremes near the optimal value, the algorithm is also more difficult to search for the optimal solution. From the optimization results obtained by the ICS algorithm, its optimization stability and success rate are very good, each time the optimal solution can be searched, and the maximum number of iterations required is not more than 150 generations, the convergence speed is fast, and it is suitable for solving the optimization problem of complex functions.

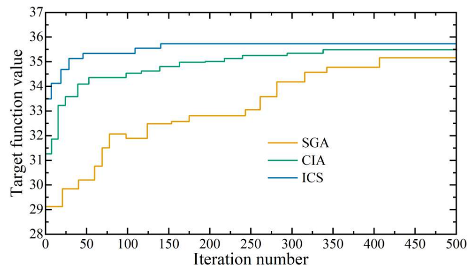


Figure 6: Evolution process curves of each algorithm

Table 2: The optimization results of the Michalewicz function

Algorithm	The result of the i-th optimization					
	1	2	3	4	5	6
SGA	35.2162	35.1149	35.0814	35.1647	35.6251	35.2831
CIA	35.3478	35.6127	35.6982	35.7163	35.6849	35.6328
ICS	35.7217	35.7535	35.7103	35.7159	35.7152	35.7137

IV. C. 2) Simulation results for solving the ICS algorithm

In order to verify the control effect of the proposed optimization method for wastewater treatment, simulation experiments were conducted on a simulation platform, where the BSM contains influent data under three weather conditions (sunny, rainy, and stormy). The sampling time of each set of data is 20 min, in which, the influent data of the weekend has a big change compared with the week, and the influent and component mass concentrations are reduced. In this experiment, the data under sunny weather conditions were selected for simulation, and the data patterns from Monday to Friday were similar, and the influent flow on Saturday and Sunday had a more obvious decreasing trend. In the multi-objective optimization simulation model for wastewater treatment, the oxygen transfer coefficient of the aerobic tank was set to 250, the outgoing return flow was 18,446 m3/d, and the sludge discharge was 385 m3/d. In the ICS algorithm, the initial population size was 50, and the maximum number of iterations was 400.

SGA algorithm and CIA algorithm are selected as the comparison algorithm of this paper, and three different algorithms are used to solve the multi-objective optimization model of wastewater treatment under the above conditions, and the optimization results under different algorithms are obtained as shown in Table 3.

Table 3: Optimization results under different algorithms

Algorithms	The quality and concentration of the effluent (mg/L)					
	COD	TSS	SMP	SNH	STN	BOD5
SGA	48.51	13.06	14.64	3.57	12.13	2.79
CIA	47.42	13.18	15.06	3.49	13.57	2.65
ICS	47.38	12.73	14.28	2.91	10.68	2.58
Algorithms	Energy consumption comparison (kW·h/d)					
	Aeration		Pumping		Total energy consumption	
SGA	3654.32		396.31		4050.63	
CIA	3631.48		272.54		3904.02	
ICS	3428.15		281.82		3709.97	

Under different optimization algorithms, the chemical oxygen demand concentration (COD), suspended solids concentration (TSS), 5-day biochemical oxygen demand concentration (BOD5) did not change much, and the multi-objective optimization results of wastewater treatment obtained by the ICS algorithm proposed in this paper were better than the other two optimization algorithms. The total nitrogen concentration (STN) and ammonia nitrogen concentration (SNH) changed more obviously, and reflected the conflicting characteristics of these two indicators, i.e., when the total nitrogen concentration increases, the ammonia nitrogen concentration decreases, and vice versa. However, in general, all five indicators can meet the constraints. Combined with the changes in energy consumption in the table, it can be seen that the aeration energy consumption is significantly reduced, the pumping energy consumption is slightly increased, but the total energy consumption has a significant reduction in energy saving effect, and the aeration energy consumption and pumping energy consumption also have more obvious conflict characteristics.

V. Conclusion

This paper combines MATLAB software and ASM1 model to construct a simulation model of biodegradation process in wastewater treatment reaction tank in alpine and high altitude area, and analyze the change of its biochemical reaction, and introduce the improved cuckoo search algorithm for multi-objective optimization of wastewater treatment process to solve the problem. Based on the simulation results, it can be seen that when the input ratio in the reactor tank is 0.008 in the wastewater treatment process, its ammonia nitrogen concentration tends to be stabilized in about 17 days, and when the temperature is increased to 36℃, the effluent COD, SMP, and SNH concentrations can be controlled at about 49.96 mg/L, 25.34 mg/L, and 11.32 mg/L. Using the improved cuckoo search optimization algorithm can obtain the optimal wastewater treatment strategy and achieve the reduction of wastewater treatment capacity on the basis of ensuring the quality of wastewater treatment effluent.

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