An Effective Dynamic Immune Optimization Control for the Wastewater Treatment Process

Fei Li (✉ lifei@bistu.edu.cn)

Beijing Information Science and Technology University - Qinghe Xiaoying Campus: Beijing Information Science and Technology University <https://orcid.org/0000-0003-3199-9489>

Zhong Su

Beijing Information Science and Technology University - Qinghe Xiaoying Campus: Beijing Information Science and Technology University

Gongming Wang

Beijing University of Technology

Research Article

Keywords: Wastewater treatment , Dynamic immune optimization , Optimization control

Posted Date: July 13th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-605575/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Version of Record: A version of this preprint was published at Environmental Science and Pollution Research on November 27th, 2021. See the published version at <https://doi.org/10.1007/s11356-021-17505-3>.

An effective dynamic immune optimization control for the wastewater treatment process

Fei Li^{1,2} · Zhong Su¹ · Gongming Wang²

Abstract

Aiming at the conflict of multiple performance indicators in the complex wastewater treatment process (WWTPs), an effective optimization control based on dynamic multi-objective immune (DMOIA-OC) is designed. This method first designs a dynamic optimization control scheme. It also divides the control process into a dynamic optimization layer and a tracking control layer. Secondly, based on analyzing the performance of WWTPs, the optimization layer establishes energy consumption and effluent quality models that adapt to the environment. Thirdly, an adaptive dynamic immune optimization algorithm is proposed to optimize complex and conflicting performance indicators. Besides, a suitable preference solution is selected from many Pareto solutions. It is to obtain the best set values of dissolved oxygen and nitrate nitrogen. Finally, the solution will be tested on the benchmark simulation platform (BSM1). The results show that the DMOIA-OC method can solve the complex optimization problem of multiple performance indicators in WWTPs. And it has a competitive advantage in the control effect.

Keywords Wastewater treatment · Dynamic immune optimization · Optimization control

1 Introduction

With the ongoing improvement of the economy and living standards, water consumption and wastewater discharge increase dramatically. To improve the wastewater status of the environment, a large number of wastewater treatment plants are built (Luna et al. 2016; Löwenberg et al. 2014). However, due to the typical nonlinear, multi-variable, unstable, and time-varying characteristics of the wastewater treatment process (WWTPs), higher requirements are put forward for the operation and management. Under the premise of more strict water quality standards, energy-saving and emission reduction are major challenges (Büyükoçkan et al. 2021; Li et al. 2021; Shiek et al. 2021; Busch et al. 2013; Liu et al. 2018).

To design an effective control strategy, many scholars do much research on the process control of WWTPs (Liu et al. 2014; Cheng 2014). Over the past decades, how to achieve water quality standards has been focused on. For example, Guerrero et al. proposed a model-based set-point optimization method to improve the performance of control systems (Guerrero et al. 2011). A single cost function is used to evaluate the optimal performance of fixed and time-varying settings. The experimental results show that it can effectively reduce the cost while improving the water quality. Document uses a generalized simplified gradient method to design optimal control strategy for WWTPs (Shorbaghy et al. 2011). It can effectively save the annual total cost and operation cost. Also, Xie et al. designed an optimal control strategy based on an adaptive genetic algorithm to optimize the solid residence time and internal circulation ratio to obtain the optimal operation variable (Xie et al. 2011), thereby improving the quality of the output water. Overall, these strategies can achieve stable operation of WWTPs, thus reaching the water quality standards. However, the coupling relationship between energy consumption (EC) and effluent quality (EQ) are rarely studied (Santin et al. 2015).

At present, to solve the trade-off between multiple conflicting objectives (such as EQ, EC, and operation stability) in WWTPs, the research value of multi-objective optimization control is very high (Han et al. 2014; Li et al. 2013). Vega et al. proposed a hierarchical optimal control strategy for WWTPs, which evaluates the improvement in terms of EC and EQ (Vega et al. 2014). The results show that this strategy can ensure EQ to satisfy the standards and reduce costs. Also, the ant colony algorithm is used to optimize EC and control system stability, and this optimal control method can achieve a better control effect (Schlüter et al. 2009). Although the results of the above methods are improved effectively, the essence of them is to convert the multi-objective problem into a single-objective problem, in which the weight factor of the multi-objective function is difficult to obtain (Cai et al. 2016).

To fundamentally resolve the conflict between EC and EQ, Guerrero et al. developed a multi-criteria optimal control strategy that selected the appropriately controlled variable as the setpoint and generated a set of solutions with Pareto optimal distribution to meet energy-saving and emission reduction (Guerrero et al. 2012). The results show that the control

✉ Fei Li
lifei@bistu.edu.cn
Zhong Su
sz@bistu.edu.cn
Gongming Wang
wanggm@tsinghua.edu.cn

¹ School of Automation, Beijing Information Science & Technology University, Beijing 100192, PR China

² Faculty of Information Technology, Beijing University of Technology, Beijing 100124, PR China

effect can be improved by optimizing water quality, cost, and microbial action. In addition, an interactive multi-objective optimization strategy is designed to simultaneously optimize multiple objective functions (Hakanen et al. 2013). This method combines control systems with interactive multi-objective optimization software to enable decision-makers to understand the interdependence between conflicting objective functions. Other multi-objective optimization control strategies are introduced in (Dominic et al. 2015) and (Yetilmezsoy et al. 2012). However, most of them are difficult to obtain reliable optimal solutions.

In recent decades, the intelligent optimization algorithm is applied (Chakraborty et al. 2011; Hu et al. 2016) with its good global searchability. The multi-objective genetic algorithm (MOGA) and sensitivity analysis are designed to the control strategies of WWTPs (Beraud et al. 2008). The results show that EC and EQ are improved. To further improve the convergence of MOGA, a non-dominant sequencing MOGA based on elite strategy is designed to handle conflicting MOPs in WWTPs (Iqbal et al. 2009). Thus it improves the control performance under the condition that the effluent quality meets the standards. At the same time, some other MOEAs-based optimization control strategies are successfully applied to WWTPs (Wang et al. 2014; Tabatabaei et al. 2015). However, they can obtain reliable multi-objective optimization solutions, which can improve performance. However, different wastewater treatment plants do not have a common cost function, the above optimal control strategies are inevitably unable to match the actual WWTPs. For this, a data-driven control strategy is proposed to solve the dynamic optimization of WWTPs. Exemplified by the optimal operation system of a WWTPs (Qiao et al. 2018), an adaptive multi-objective differential evolution algorithm and an adaptive fuzzy neural network control system are presented. The results show that the control system has better stability and lower EC than traditional control methods. Sweetapple et al. designed an optimal control strategy using NSGAI to obtain the optimal settings for the activated sludge WWTPs (Sweetapple et al. 2014). This strategy can reduce greenhouse gas emissions and operating costs. Besides, a dynamic multi-objective optimization strategy is presented (Hreiz et al. 2015), which uses precise bottom-level modeling and NSGAI algorithm to optimize the relationship between EC and EQ. However, the above methods still have the following problems: 1) The WWTPs are highly non-linear, have a fast fluctuation of water inflow, limited storage space, and so on. Therefore, it is difficult to obtain an accurate EC and EQ model in real-time (Liu et al. 2019). 2) WWTPs is a complex dynamic system, with multiple goals changing with time. Whether the optimal settings of dissolved oxygen (S_O) and nitrate nitrogen (S_{NO}) are real-time or not directly related to EC and EQ, this presents a new challenge to the multi-objective optimization algorithm that changes dynamically over time. 3) In WWTPs, the traditional proportional-integral differentiation (PID) controller is no longer sufficient to compensate for various disturbances caused by the interaction of large circuits. Therefore, how to select the appropriate controller and track the optimal settings with stable and high accuracy which change with the environment is significant.

For the first problem, the mechanism models of EC and EQ are studied. However, the parameters of the model are fixed, so it can not adapt to the operating conditions of WWTPs. Qiao et al. use radial basis network to predict EC and EQ, and obtain the objective function of multi-objective optimization (Han et al. 2018). Hang et al. established a model between energy consumption, water quality, and variables in the procedure by using the adaptive regression kernel function method, and obtained a good prediction accuracy. However, due to the time-varying input water composition and flow rate in WWTPs, the fixed structure prediction model obviously cannot meet the requirements of high accuracy prediction of energy consumption and water quality standard. In this paper, a fast online self-organizing fuzzy neural network (ILM-SVDFNN) based on SVD is constructed by analyzing the operation characteristics and data of wastewater treatment combined with the improved LM algorithm. The single-sided Jacobi transformation is used to achieve singular value decomposition (Qiao et al. 2017), the rule layer neurons are grown and trimmed according to the size of the output matrix singular values of the rule layer. And it is used to build EC and EQ models.

Secondly, in order to obtain the optimal settings for S_O and S_{NO} , Sina et al. proposed a scheme-based optimization method and defined two types of performance evaluation criteria to assess WWTP energy consumption in various situations. However, the optimization results depend on the quality of the scheme, so there are some limitations. Therefore, Han et al. used the multi-objective particle swarm optimization algorithm to optimize the objective function to obtain the optimal settings of the control variables. The hybrid multi-objective backbone particle swarm optimization algorithm is designed to optimize two conflicting objectives, EC and EQ, so as to obtain an optimal result with good convergence (Zhou et al. 2017). However, due to the time-varying biochemical reactions, input water components and flow rates in WWTPs, the above methods can not better solve the dynamic EC and EQ problems. For this, Han et al. proposed a dynamic multi-objective particle swarm optimization controller (DMOPSO-OC) (Han et al. 2019). The results show that it can improve the optimal control performance and meet the requirements of multiple conflicting targets. However, there is still the shortcoming of uneven distribution of individuals in the target spatial, and how to more accurately predict the location of Pareto front remains challenging when the environment changes. This poses a new challenge for setting more precise and dynamic values of S_O and S_{NO} . To solve this problem, an adaptive dynamic immune optimization method is designed. When the environment changes, the method adaptively selects representative individuals with good distribution and convergence to improve the distribution of individuals in the population during the iteration process, thus increasing the diversity of Pareto solutions. The multi-direction prediction strategy is used to more accurately predict the moving location of the Pareto set, so as to improve the performance of the evolutionary algorithm in solving dynamic multiple target optimization problems. The optimal settings for real-time optimal S_O and S_{NO} are obtained.

Fig. 1 The optimized control based on NSGAII a) AE value, b) PE value, c) EQ value

In addition, in order to improve the control accuracy, stationarity, and adaptive ability of the bottom control method in WWTPs, (Qiao et al. 2018) an adaptive fuzzy neural network control system suitable for multi-objective operation of WWTP is studied. A fuzzy neural network controller (FNNC) based on second-order Begg-Marquart (L-M) is used to track the settings of S_O and S_{NO} (Han et al. 2018). However, WWTPs is a time-varying system, and the flow and composition of the input water are constantly changing. Therefore, a recursive fuzzy neural network with a time-varying structure is needed to adapt to the changes in operating conditions. For this reason, Zhou et al. combine HBBMOPSO with the self-organizing controller to realize intelligent control of WWTPs (Zhou et al. 2017). However, to approximate the non-linear dynamic relationship in wastewater treatment process control effectively, a better control effect can be achieved in WWTPs. At the same time, because the recursive fuzzy neural network combines the advantages of the fuzzy system and the neural network, it has the ability of fuzzy inference and non-linear mapping. Therefore, a self-organizing recursive fuzzy neural network controller is used to track the optimal settings of S_O and S_{NO} concentrations.

In summary, this paper puts forward a sewage treatment control strategy based on adaptive dynamic immune optimization to optimize the control of WWTPs. Unlike the existing optimal control, the innovations and advantages of DMOIA-OC are as follows: 1) Designing an adaptive dynamic optimal control system for WWTPs that can reduce EC while meeting the EQ standards. A fast online self-organizing fuzzy neural network (ILM-SVDFNN) based on SVD is constructed to model the EC and EQ of WWTPs under a complex dynamic environment (Qiao et al. 2017). 2) An adaptive dynamic immune optimization algorithm is proposed to obtain the optimal settings of S_O and S_{NO} in real-time. 3) Self-organizing recursive fuzzy neural network controller is used to track the optimal settings of S_O and S_{NO} . To verify the effectiveness of the proposed dynamic optimization control method, all the algorithms are validated by applying the international benchmark simulation platform for WWTPs. The results show that when the flow and concentration change, the proposed dynamic immune optimization control method can significantly reduce EC while improving the outflow water quality, thereby effectively improving the control performance of WWTPs.

The outline of the paper is as follows: Section 2 describes the characteristics of the dynamic process of WWTPs. In Section 2, the dynamic optimization control system composed of objective function design, dynamic immune optimization algorithm, and tracking controller are discussed in detail. The simulation results and experiments are given to verify the effectiveness of the proposed DMOIA-OC in Section 4. Section 5 gives a summary.

2 Problem formulation

2.1 Dynamic Characteristics of WWTPs

WWTPs is a dynamic system that is affected by different physical and biological phenomena. The features are: the

biochemical reaction cycle of WWTPs is long and the state changes with time; the microbial population with indeterminate living conditions and reaction rules; the composition and flow in the process vary with time, and it is difficult to get the content and quantity of pollutants; the biochemical reaction process is complex and susceptible to external factors (such as temperature, pH, etc) (Han et al. 2019).

In recent years, with the increasingly stringent requirements of environmental laws and regulations, the operation of WWTPs has been greatly improved. At the same time, from the economic point of view, it is extremely important to reduce the operation costs. However, due to the potential interactions and complex biochemical reactions, a large number of design parameters, and a variety of complex objectives (EQ, operating costs, etc.), how to ensure stable operation and effectively reduce operating costs under the premise of ensuring the quality of effluent water, formulating efficient optimal control strategies for wastewater treatment is still an urgent problem to be solved. Therefore, the design of a dynamic optimization algorithm to optimize multiple conflicting objectives and the use of an optimal controller for stable tracking control become the basic requirements to improve the control performance of WWTPs.

2.2 Optimal control Problem

Because the inflow flow and composition of sewage treatment change with time, the traditional mechanism models of water quality, pumping and aeration energy consumption cannot accurately reflect the dynamic process of WWTPs. For this reason, this chapter uses a self-organizing fuzzy neural network (Qiao et al. 2017) with structure and parameters that can be dynamically adjusted online to determine conflicting objective functions. Based on the operation data and dynamic characteristics of the wastewater treatment process, the main input variables and process variables related to EC, EQ, and PE are analyzed and a soft measurement model is set up. The relevant variables are solid suspension concentration (SS), chemical oxygen demand (COD), nitrate-nitrogen concentration (S_{NO}), Kelvin nitrogen concentration (S_{Nkj}), biochemical oxygen demand (BOD_5) on day 5, oxygen conversion coefficient (K_{La5}) in unit 5, and internal return flow (Q_a). The optimal objective function for time t is:

$$\min \mathbf{F}(\mathbf{X}, t) = (f_1(\mathbf{X}, t), f_2(\mathbf{X}, t), f_3(\mathbf{X}, t))^T \quad (1)$$

$$\mathbf{X} = (x_1, x_2) \quad (2)$$

where $t = 0, 1, 2, \dots \in T$ represents the current moment; $\mathbf{F}(\mathbf{X}, t)$ is a target vector composed of three time-varying objective functions. $f_1(\mathbf{X}, t)$ is the AE model at time t , $f_2(\mathbf{X}, t)$ is the PE model at time t , $f_3(\mathbf{X}, t)$ is the EQ model at time t , $\mathbf{X}$ is the decision vector, and there are two decision variables in the wastewater treatment process, x_1 is dissolved oxygen and x_2 is nitrate nitrogen (Han et al. 2019).

Fig.1 shows the curves of the three conflicting performance indicators of AE, PE, and EQ. They are in the control of the WWTPs based on NSAGII. It can be seen that AE, PE, and EQ have obvious nonlinear and time-varying characteristics. And there are many local optimal solutions in the target space. AE and PE fluctuate greatly. Therefore, the Pareto front is complex and changeable. So, higher requirements are put forward. They're about to choose the appropriate optimization control method and obtain the precise optimized setting values. For this reason, the optimization problem of WWTPs is studied at a deeper level: 1) Time-varying objective function: it is on how to accurately and quickly establish an objective function model to provide a basis for the optimization process. 2) Optimization of complex problems: the problem is to select appropriate optimization methods to effectively coordinate complex optimization problems dynamically. This is the key to optimal control. 3) Dissolved oxygen and nitrate nitrogen setpoints: that is on how to choose the best Pareto solution from a set of optimization results, and get the optimal setpoint at that moment. This becomes an effective guarantee for optimal control. 4) Computing resources: how to quickly and effectively obtain optimized solutions, reduce the occupation of computing resources, and ensure the simplification and efficiency of the control process.

3 Framework of Proposed DMOIA-OC

In WWTPs, AE, PE, and EQ are coupling performance indices. They are the primary role of performance evaluation. Due to the fact that different process variables can influence these indices, a two-layer structure is used as a platform system for establishing different control objective according to the dynamic response time. Fig. 2. shows the diagram of the DMOIA-OC scheme that includes the upper-optimized layer, and lower-controlled layer. The system realizes energy-saving and efficient operation of WWTPs through optimization layer and tracking control layer respectively.

The optimization layer is mainly composed of two parts: B, the optimization objective function, and C, the dynamic-optimized module. The module shown in Fig. 2.B determines a sequence of online-optimized-objective function models [AE, PE, and EQ] in Fig. 2.B. The dynamic-optimized algorithm shown in Fig. 2.C provides the best optimal solution [the sets of S_O and S_{NO} settings]. These sets ensure the WWTPs minimize energy consumption while meeting water quality standards. The lower layer as shown in Fig. 2D is mainly used to track the set values of S_O and S_{NO} . Self-organization recursive fuzzy neural network (SORFNN) controller can address these requirements that are of stable operation (Qiao et al. 2017). The detailed design of each control layer is presented in the following sections.

Fig. 2 Multi-objective optimal control chart of wastewater treatment

4 DMOIA-Based Optimization layer Design

Due to the complexity of biochemical reaction in WWTPs, to accurately obtain the mechanism model of a dynamic process, the self-organizing FNN with adaptive parameters is used to calculate the time-varying objective function model of energy consumption and water quality. In addition, An adaptive immune optimization algorithm with better convergence and distribution is designed to obtain the best set value of dissolved oxygen and nitrate nitrogen in real-time, so as to provide the best control target for the underlying tracking control.

4.1 Optimization Objectives

Due to the strong nonlinearity and time-varying characteristics of WWTPs, the traditional fixed-parameter mechanism model cannot meet the dynamic process of WWTPs. For this reason, this paper first analyses the process variables related to energy consumption and water quality according to the operation characteristics and operation data of sewage treatment. From formula (4), and formula (5), it can be seen that EC is affected by S_O , S_{NO} , MLSS and other variables, while EQ is mainly related to S_O , S_{NO} , SS , S_{NH} and other variables (Li et al. 2021). Therefore, S_O , S_{NO} , MLSS, S_{NH} are selected as model input variables, EC and EQ as output variables, since online measurement of mixed liquor solid suspended concentration (MLSS) is easier than SS. Secondly, the relationship between input variables, and EC and EQ is modeled. It is done by using a self-organizing fuzzy neural network (SOFNN) (Qiao et al. 2017). The self-organizing fuzzy neural network is as follows:

$$y = \sum_{j=1}^m h_j w_j \quad (3)$$

$$h_j = v_j / \sum_{j=1}^m v_j = e^{-\frac{\sum_{i=1}^n (x_i - c_{ij})^2}{\sigma_{ij}^2}} / \sum_{j=1}^m e^{-\frac{\sum_{i=1}^n (x_i - c_{ij})^2}{\sigma_{ij}^2}} \quad (4)$$

$$v_j = \prod_{i=1}^n \varphi_{ij} = e^{-\frac{\sum_{i=1}^n (x_i - c_{ij})^2}{\sigma_{ij}^2}}$$

$$\varphi_{ij} = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}, \quad j = 1, 2, L, m \quad (5)$$

where y is the output of the neuron, ω_j is the connection weight between the regular layer and the output layer, v_j and h_j are the j th neuron output and normalized output, c_{ij} and σ_{ij} are the center and width of the Gauss function of the j th neuron in the 2nd layer corresponding to the 1st layer the j th neuron, and φ_{ij} is the output of the neuron in the corresponding membership function layer.

The main parameters FNN needs to learn are the connection weight ω_j between layers 3 and 4 and the central c_{ij} and the width σ_{ij} of the membership function of layer 2. An improved LM algorithm is used here to realize online learning of parameters. Singular value decomposition (SVD) is used in the output matrix of the FNN rule layer. The size of the singular value is compared and the root mean square error of the training set is combined with the network learning process to realize the growth and pruning of the rule layer neurons, thus realizing the online optimization of the network structure. The evaluation indexes of growth and pruning, and root mean square error are defined as follows:

$$I_g = \max(\xi) / \sum_{s=1}^{n_s} \xi_s$$

$$I_d = \sum_{s=1}^d \xi_s / \sum_{s=1}^{n_s} \xi_s \quad (6)$$

$$E(\Theta(t)) = \sqrt{\frac{1}{S_a} \sum_{s_a=1}^{S_a} (y_d^{S_a}(t) - y^{S_a}(t))^2} \quad (7)$$

where I_g is the growth indicator, I_d is the pruning indicator, singular value vector ξ is arranged from small to large, I_d is the ratio of the sum of the current d smaller singular values to all singular values, n_s is the number of current singular values, S_a is the size of sample, $y_d^{S_a}$ is the expected output and y^{S_a} is the actual network output. When $E(\Theta(t)) > E(\Theta(t-1))$, and $I_g > I_{gth}$ (I_{gth} is the preset threshold for growth), the neuron g with the largest current singular value is split to adjust the network structure to improve performance. When $E(\Theta(t)) < E(\Theta(t-1))$ and $I_d < I_{dth}$ (I_{dth} is the preset pruning threshold), the neurons s ($s=1, 2, \dots, d$) corresponding to the current d smaller singular values will be deleted.

The EC and EQ model of WWTPs based on an online self-organizing fuzzy neural network (Qiao et al. 2017) can not only adjust parameters adaptively according to the error between actual output and expected output, but also adjust network structure self-organizing according to a root mean square error, growth and pruning evaluation index. A higher improvement of the speed of network modeling, prediction accuracy, and generalization ability to a large extent is of great importance to the real-time establishment of energy consumption and water quality models in sewage treatment processes.

4.2 Dynamic Optimization Algorithm Design

As the real-time change of the incoming water flow and concentration happens frequently, an adaptive dynamic immune optimization algorithm (DMOIA) is designed. So, the adaptive-dynamic-changed SO and SNO setting values are obtained. To implement DMOIA, we first solve the optimization problem at the representative individuals with good diversity and distribution, once a change in the environment is detected. Therefore, an efficient elite selection strategy based on uniform distribution is proposed. This strategy first judges the number g of representative individuals, $g = \lceil g_1 + \Phi(t) * (g_2 - g_1) \rceil$, $g_1=4$, $g_2=9$, g_1 and g_2 are the upper and lower limits of g . it is according to the severity of environmental changes, $\phi(t)$.

$$\Phi(t) = \frac{1}{M_o} \frac{1}{N_o} \sum_{j=1}^{M_o} \sum_{i=1}^{N_o} |f'_j(A_i) - \varphi_j(q)| \quad (8)$$

$$f'_j(A_i) = \frac{f_j(A_i, q) - f_j(A_i, q-1)}{u_j(q) - l_j(q)} \quad (9)$$

among them, $M_o=3$ is the number of objectives, N_o is the population size, and $f_j(A_i, q)$ is the j th objective function value of the i th individual in the q th iteration. $l_j(q)$ and $u_j(q)$ are the minimum and maximum values of $f_j(A_i, q)$, respectively. $\varphi_j(q)$ is the average value of f'_j .

$$\varphi_j(q) = \frac{1}{N_o} \sum_{j=1}^{N_o} \left| \frac{f_j(A_i, q) - f_j(A_i, q-1)}{u_j(q) - l_j(q)} \right| \quad (10)$$

After the number of representative solutions is calculated, we propose a uniform distribution mechanism for selecting the representative solutions. Firstly, the population are mapped to the target space and evenly divided into g intervals. Based on the nondominated sort, the more representative individuals are chosen from each interval. The mechanism is described as follows:

$$\mathbf{D} = (D_1, L, D_i, L, D_g) \quad (11)$$

$\mathbf{D}$ is the set of intervals, D_i is the i th interval, $i \in [1, g]$. In the interval D_i , when the number of individuals $N_{D_i} \geq 1$, the

populations in the interval are sorted according to the crowding distance. And the individual with the largest crowding distance is selected. In addition, if $N_{D_i} = 0$, the individual which is closest to the interval is selected for mutation. Then the sets of representative individuals at time t and $t-1$ are:

$$R^t = \{r_1^t, L, r_i^t, L, r_g^t\} \text{ and } R^{t-1} = \{r_1^{t-1}, L, r_i^{t-1}, L, r_g^{t-1}\} \quad (12)$$

r_i^t is the representative individual in the i th interval. Then the evolution direction Δr_i^t of the individual r_i^t is:

$$\Delta r_i^t = r_i^t - r_i^{t-1} \quad (13)$$

Second, to quickly respond to environmental change and save computing resources, the new individuals x_i^{t+1} are generated as:

$$x_i^{t+1} = x_i^t + \Delta r_i^t + \varepsilon^t \quad (14)$$

among them, $\varepsilon^t \sim N(0, \theta^t)$, ε^t is a random value with a normal distribution of variance θ^t and 0. In the following, to increase the diversity of the population and improve the convergence speed, the remaining $N_o - g$ individuals are generated by the limit optimization mutation strategy (Li et al. 2018).

4.3 The proposed DMOIA Framework

The proposed DMOIA algorithm is presented as Algorithm 1. First, we randomly initialize the N_o individuals in the search space (Lines 2 to 4). The environmental change is respected to be detected by R_g and $f(R_g)$ (Lines 6 to 11). When a change occurs, the severity of environmental changes, $\phi(t)$ is calculated (Line 12), and the number of representative individuals, g can be got (Line 13). Then, the individuals are mapped and clustered to the hyperplane (Line 14), and we evenly divide the target space into g intervals, (Line 15). Next, the crowding distance is calculated and select for all the individuals. The individual with the largest crowding distance is chosen from every interval, then the representative individuals R_t are acquired (Line, 16). If there is no individual in the interval, the one which is nearest to this interval is chosen to generate new representative individuals by the limit optimization mutation strategy (Qiao et al. 2020). The evolutionary trajectories are built up by the g representative individuals (Line, 17), then a part of the initial population is generated for the new environment. And the other ($N_o - N_d$) individuals are randomly generated (Line, 18). We combine the two parts as the initial population (Line, 19). If a change does not occur, the crossover and variation operations on all the individuals are used to generate the initial population (Lines 20 to 24). When meet the stopping criterion, complete the program and output the PS, go to Line 7.

Due to the proposed DMOIA algorithm, representative individuals with good distribution and diversity are selected. So, it can improve the convergence, accelerate convergence speed, and avoid falling into the local optimum. At the same time, the limit optimization mutation strategy is applied to increase the local search and exploration ability of the population. It provides the best solution for the dynamic acquisition of the set values of S_O and S_{NO} .

4.4 Choose the Best Pareto Solution

In order to select a suitable preference solution from many excellent Pareto solutions, a fuzzy membership function (Zhou et al. 2017) is used to make an intelligent decision. This system determines the optimal set-points of S_O and S_{NO} as follows:

$$PR_i^k = \begin{cases} 1 & f_i(x_k) \leq f_i^{\min} \\ \frac{f_i^{\max} - f_i(x_k)}{f_i^{\max} - f_i^{\min}} & f_i^{\min} < f_i(x_k) < f_i^{\max} \\ 0 & f_i(x_k) \geq f_i^{\max} \end{cases} \quad (15)$$

among them, PR_i^k is the satisfaction degree of the non-dominant solution x_k . $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum value of the i th objective function f_i , respectively. $f_i(x_k)$ is the i th objective function value of x_k .

$$PR^k = \frac{\sum_{i=1}^3 PR_i^k}{\sum_{k=1}^{|\varepsilon|} \sum_{i=1}^3 PR_i^k} \quad (16)$$

among them, 3 is the target number, $|\varepsilon|$ is the number of elements in external reserve set. The selected preference solution is the solution corresponding to the maximum value of PR^k .

5 SORFNN Control

Due to frequent change in the flow and components of WWTPs, it is difficult to ensure that the fixed structure recursive fuzzy neural network (RFNN) controller can adapt to all working conditions. For this, a SORFNN controller (Liu et al. 2018) is adopted to track the set-points of S_O and S_{NO} . Seen from Fig.1D, it consists of the input layer, RBF layer, recursive layer, TSK fuzzy layer, and output layer. The network structure and parameters of the RFNN are adaptively adjusted over time. To adapt the changes in set points, the structure and parameters are adjusted as follows:

1) Growth method:

For performance evaluation of SORFNN, the error $e(t)$ between the actual value and the predicted value of the control variable is defined as:

$$e(t) \geq E_{th} \quad (22)$$

where E_{th} is a fixed constant that needs to be determined by the system requirements. In most cases, input variables do not have perfect matching rules. Therefore, the rules for structure self-organizing is:

$$J_{sum} < 1, J_{sum} = \sum_{j=1}^{N_\sigma} o_j^{(3)} \quad (23)$$

Among them, $J_{sum}(t)$ is the evaluation criterion of global- approximation ability (Liu et al. 2018), $o_j^{(3)}$ is the output of the rule layer, and N_σ is the number of centers.

In SORFNN, each rule corresponds to a set of membership functions. Euclidean distance between two membership function centers is as follows:

$$\begin{aligned} dis(i, j) &= \|c_i - c_j\|, i \neq j, i, j = 1, 2, L, N_R \\ N_R &= (\gamma - 1)!; disc(i) = \|\mathbf{X} - c_i\|, i = 1, 2, L, \gamma \end{aligned} \quad (24)$$

where $dis(i, j)$ is the Euclidean distance between two membership function centers. c_i is the center of the i th membership function, N_R is the centers number of membership function layer, γ is the number of rules, $disn(i)$ is the Euclidean distance to the central of all membership functions. $\mathbf{X}(t)$ is a new set of input data, $\mathbf{X}(t) = (x_1(t), x_2(t), \dots, x_m(t))$. dis_{max} and dis_{min} are the maximum and minimum value of $dis(i, j)$, respectively. If (25) is satisfied:

$$dis_{min} > dis_{max} \quad (25)$$

or formula (22) and (23) are satisfied, a rule needs to be added, and the new parameters are as follows:

$$\begin{aligned} \sigma'(t+1) &= \min_{1 \leq j \leq \gamma(t)} v \times |x_i(t) - c_{ij}(t)| \\ c'(t+1) &= x_i(t), \omega'(t+1) = \psi, i = 1, 2, L, N_x(t) \\ \psi &= \frac{(a + eb) \cdot (b + 1) - a \cdot b}{(N_x(t) + 1)x_i(t)b} \\ a &= \sum_{j=1}^{\gamma} o_j^{(5)}(t), b = \sum_{j=1}^{\gamma} o_j^{(4)}(t) \end{aligned} \quad (26)$$

where $c'(t+1)$, $\sigma'(t+1)$ and $\omega'(t+1)$ are the centers, widths and weights of the new rules at the next moment. $v \in (0, 1)$ is a random value, $x_i(t)$ is the i th dimension input variable, $\mu_{ij}(t)$ is the j th center corresponding to $x_i(t)$. $N_i(t)$ is the size of the i th dimension-input samples. $o_j^{(4)}$ and $o_j^{(5)}$ are the output of the j th TSK fuzzy layer and recursive layer, respectively.

2) Pruning method:

When some rules are redundant, redundancy and bad generalization may be existing. For this, the overall redundancy criteria $Jr(t)$ is defined (Liu et al. 2018) as:

$$Jr(t) = J_{sum}(t) - J_{lmin}(t) > 1 \quad (27)$$

Among them, $J_{lmin}(t)$ is the rule of the least contribute in the activation region S . The width of S is

$\sigma_{j^*}(t) = \|\sigma_{j^*1}(t), \sigma_{j^*2}(t), L, \sigma_{j^*m}(t)\|$ the center is $\mathbf{c}_{j^*} = (\mu_{j^*1}(t), \mu_{j^*2}(t), L, \mu_{j^*n}(t))$, j^* represents the maximum activation-intensity rule.

$$\begin{aligned} dis(i, j^*) &= \|c_i - c_{j^*}\|, j^* \neq i, i = 1, 2, L, N_\sigma \\ dis(j) &< \sigma_{j^*} \end{aligned} \quad (28)$$

where $dis(i, j^*)$ is the Euclidean distance between j^* th and the other rule centers. If (28) is satisfied, the j th rule belongs to S , then $J_{lmin} = \argmin(S)$, $\argmin$ is the minimum value of S . If (22) and (28) are satisfied, the v th rule which has the least contributing in S needs to be pruned. the weight $\omega_{v'}$ of the v 'th rule which is closest to the v th is adjusted as follows:

$$\omega_{v'}(t+1) = \omega_{v'}(t) + \varepsilon \quad (29)$$

$$\varepsilon = - \frac{\alpha - o_{j^*}^{(5)} - \alpha(b - o_{j^*}^{(4)})/b}{(\rho + 1)o_{v'}^{(4)}x_i} \quad (30)$$

where, ρ is the dimension of the input variable.

6 Experimental results and analysis

All experiments are carried out on the BSM1 simulation platform, and under Microsoft Windows 8 environment, they are implemented by MATLAB 2014b. The computer processor is 3.6GHz and 8GB RAM. To objectively understand the performance of control strategies under different conditions, 14-day data from the BSM1 database are used to simulate weather cases, where the sampling interval is 15 minutes. IAE is used to evaluate the control performance of the system, and the proposed DMOIA-OC system is compared with others.

6.1 Experimental Setup

In order to compare dynamic multi-objective optimization algorithms, the population size is 150, the number of iterations

Table 1 Performance IGD Comparison of results on the test problems

Problem	Algorithm	DNSGAI*	PPS*	MOEA/D*	DCOE*	DMOIA*
FDA1	(5,10)	6.4053E-1	2.0885E-1	3.5649E-1	6.3686E-2	2.0126E-1
		(9.8895E-2)	(8.4104E-2)	(4.9023E-2)	(1.1610E-2)	(2.3652E-2)
		5.8213E-2	4.2736E-2	1.2112E-1	4.1342E-2	4.0569E-2
	(10,10)	(3.8909E-3)	(1.9486E-2)	(1.1879E-2)	(6.5605E-3)	(3.4259E-3)
		4.1464E-2	1.6218E-2	4.0424E-2	2.3984E-2	1.4983E-2
	(20,10)	(4.2405E-3)	(7.9450E-3)	(2.2617E-3)	(2.2878E-3)	(2.0698E-3)
FDA2	(5,10)	2.8517E-2	8.1301E-2	8.4088E-2	7.2853E-2	2.5326E-2
		(2.4351E-3)	(3.0399E-2)	(1.3585E-2)	(3.8658E-2)	(2.2698E-3)
		1.0805E-2	6.3561E-2	3.3894E-2	4.7325E-2	1.0126E-2
	(10,10)	(9.0279E-4)	(1.0647E-2)	(8.8878E-3)	(3.3605E-2)	(8.1259E-4)
		6.5124E-3	6.2768E-2	1.6459E-2	3.2472E-2	6.3395E-3
	(20,10)	(5.2611E-4)	(9.0724E-3)	(4.9937E-3)	(4.6061E-2)	(5.1611E-4)
FDA3	(5,10)	2.6346E-1	4.4378E-1	2.4764E-1	2.6371E-1	2.2654E-1
		(6.0463E-2)	(1.1102E-1)	(2.3050E-2)	(3.5505E-2)	(3.3426E-2)
		1.0821E-1	2.1946E-1	1.3090E-1	1.9526E-1	1.0162E-1
	(10,10)	(3.3153E-2)	(1.8132E-2)	(2.5891E-2)	(3.2807E-2)	(1.9596E-2)
		9.0365E-2	1.9259E-1	5.4535E-2	1.2625E-1	5.1569E-2
	(20,10)	(2.8703E-3)	(2.4153E-2)	(8.3567E-3)	(3.1398E-2)	(2.0695E-3)
FDA4	(5,10)	1.4906E+0	3.0719E-1	1.3602E-0	1.6224E-1	1.4732E-0
		(1.2669E-1)	(1.9145E-2)	(1.6118E-1)	(6.1969E-3)	(1.1596E-1)
		7.6342E-1	2.1151E-1	5.7713E-1	1.2450E-1	2.5986E-1
	(10,10)	(4.4885E-2)	(2.0215E-2)	(5.4877E-2)	(4.5799E-3)	(4.6598E-2)
		2.6255E-1	1.7909E-1	2.2277E-1	1.0303E-1	1.3615E-1
	(20,10)	(1.6817E-2)	(3.0438E-3)	(1.3352E-2)	(1.7584E-3)	(1.2631E-2)
FDA5	(5,10)	1.7611E+0	6.5562E-1	1.5704E+0	4.3378E-1	4.2631E-1
		(1.0707E-1)	(3.1705E-2)	(1.3189E-1)	(4.6953E-2)	(2.9654E-2)
		1.0239E+0	4.8031E-1	8.1980E-1	3.6283E-1	3.3269E-1
	(10,10)	(5.4901E-2)	(3.5207E-2)	(6.0501E-2)	(4.0631E-2)	(3.0156E-2)
		4.8890E-1	3.7195E-1	4.0732E-1	3.1016E-1	2.9523E-1
	(20,10)	(1.2544E-2)	(1.2431E-2)	(1.4768E-2)	(2.7499E-2)	(1.1561E-2)
dMOP1	(5,10)	1.3135E-1	4.1528E-1	1.3604E-2	6.9595E-2	1.18965E-1
		(1.1037E-2)	(7.4997E-1)	(9.0549E-3)	(1.4007E-2)	(4.3259E-3)
		8.8338E-3	5.0918E-2	9.3916E-3	3.9362E-2	8.1256E-3
	(10,10)	(5.0638E-3)	(9.3741E-2)	(1.1914E-3)	(6.2467E-3)	(1.9856E-3)
		7.3907E-3	4.3965E-2	7.1797E-3	1.8848E-2	6.5623E-3
	(20,10)	(3.2736E-3)	(8.4779E-2)	(2.7117E-3)	(2.3214E-3)	(1.3569E-3)
dMOP2	(5,10)	6.8741E-1	1.5635E-1	4.9102E-1	1.2043E-1	2.0238E-1
		(7.5422E-2)	(1.8877E-2)	(4.1828E-2)	(2.0546E-2)	(3.0159E-2)
		1.1864E-1	4.2819E-1	1.8898E-1	7.3299E-2	8.5231E-2
	(10,10)	(9.4674E-3)	(1.7367E-2)	(4.3151E-2)	(8.9931E-3)	(1.0126E-2)
		1.5741E-1	2.0207E-2	5.6301E-2	3.4622E-2	2.2569E-1
	(20,10)	(6.7003E-4)	(2.4955E-3)	(3.9135E-3)	(4.3234E-3)	(3.0259E-3)
dMOP3	(5,10)	5.6244E-1	1.7617E-1	3.4211E-1	4.9556E-2	4.1596E-2
		(3.9864E-2)	(8.0705E-2)	(1.9264E-2)	(4.8079E-3)	(2.0156E-3)
		2.0009E-1	1.1367E-1	1.6853E-1	2.9589E-2	4.3262E-2
	(10,10)	(1.5091E-2)	(1.2092E-2)	(1.0496E-2)	(2.4806E-3)	(1.8962E-3)
		1.0780E-1	8.9901E-2	6.2795E-2	1.6366E-2	1.2695E-2
	(20,10)	(8.5053E-3)	(6.7418E-3)	(4.3764E-3)	(1.7152E-3)	(1.0326E-3)

* The data are from the reference (Jiang et al. 2016).

Fig. 5 a) The control results of S_O in the dry weather, b) The control results of S_{NO} in the dry weather, c) The control errors of S_O and S_{NO}

is 100. The crossover parameter $\eta_c = 20$, the mutation parameter $\eta_m = 20$, the crossover and mutation probabilities are 0.9 and $1/N_d$, respectively. $N_d=10$, which is the number of decision variables; the shape parameter $N_q=11$; also, the algorithm runs 20 times independently on each test instance. In order to test the convergence, distribution, and diversity of the algorithm, the inverse distance IGD (Lin et al. 2018) is used as the test index.

6.2 Simulation results

(1) DMOIA algorithm validation

To evaluate the performance of DMOIA, four algorithms: dynamic population prediction strategy (PPS), dynamic non-dominant sorting genetic algorithm II (DNSGAI), decomposition-based dynamic multi-objective evolution algorithm (MOEA/D), and dynamic competitive co-evolution algorithm (DCOEA) are used to validate the performance. At the same time, to study the effect of changing frequency on the performance of the algorithm, different combinations of changing severity and frequency are used to experiment, namely $(n_t, \tau_t)=(5, 10)$, $(10, 10)$ and $(20, 10)$ (Li et al. 2018). Because IGD is mainly used to reflect the convergence and distribution of POF, so it is used to test the performance of the algorithm.

Table 1 gives the IGD and its standard deviation values obtained by five algorithms on FDA (Goh et al. 2008) and dMOP (Farina et al. 2004) problems to show the best results of the five algorithms in bold. From Table 1, the PPS and DCOEA algorithms show good performance for FDA4, dMOP2, and dMOP3 problems. DNSGAI performs the worst on FDA1, FDA4, FDA5, dMOP1, and dMOP3. In addition, for FDA2, FDA3, and dMOP1 problems, PPS has the worst effect. However, DMOIA performs best in most test functions of FDA and dMOP, i.e. DMOIA performs better in dynamic optimization than other comparison algorithms. The results show that DMOIA can approximate PF stably and effectively in a dynamic environment for three-dimensional problems. Because DMOIA has better population diversity and distribution, it shows better optimization performance significantly.

(2) DMOIA-OC experimental results

WWTPs have a non-linear change due to biochemical and nitrification reactions. When water flow changes dynamically, DMOIA-OC achieves the goal of lowering EQ before EC meets the standards. In order to assess the control performance of the DMOIA-OC method, three different weather conditions (dry, rainy, and storm) are experimented with. It is compared with five algorithms, which are two optimization controllers: virtual reference feedback adjustment control strategy (VRFT-CS) (Roman et al. 2016), scale integral optimization controller based on non-dominant sorting genetic algorithm (NSGA+PI-OC) (Vitor et al. 2021); adaptive multi-objective particle swarm optimization algorithm based on the parallel unit coordinate system (pccsAMOPSO-OC) (Hu et al. 2015), cluster MOPSO (Zhang et al. 2012) and dynamic multi-objective particle swarm optimization control method (clusterMOPSO-OC) (Chakraborty et al. 2011). The simulation results in three kinds of weather are shown in Fig. 5- Fig. 7.

1) dry weather

396 In dry weather, the control results of S_O and S_{NO} are shown in Fig. 5a) and Fig. 5 b). It can be seen that DMOIA-OC can
 397 generate time-varying settings based on actual input and has good tracking performance. In addition, Fig. 5 c) shows the
 398 control error between the actual output values of S_O and S_{NO} and the set values. The control errors are small when they are
 399 all kept within (+) 0.4mg/L.

400 To further validate the performance of DMOIA-OC, Table 2 shows the results compared with the other five methods. It
 401 can be seen that IAE has the best control effect than other comparison methods. The AE, PE and EQ values of DMOIA-
 402 OC are the lowest, that is, the EC and EQ of the outlet are the lowest. In addition, the concentration of SS in NSGA+PI-
 403 OC is slightly lower than that of in DMOIA-OC. However, its EC and EQ are significantly lower than that of NSGA+PI-
 404 OC. In conclusion, under dry conditions, DMOIA can output the best water quality with the least energy consumption and
 405 the best control effect.

406 2) Rainy weather

407 In rainy weather, the S_O and S_{NO} control results are given in Fig. 6 a) and Fig. 6 b). Seen from that, S_O settings fluctuate
 408 more than sunny days, and S_{NO} settings change relatively smoothly. Similarly, DMOIA-OC has good tracking performance.
 409 In addition, in order to observe the control effect of DMOIA-OC more intuitively, the control error is given in Fig. 6 c). It
 410 can be seen from that the error is also within ± 0.4 mg/L, the control error is small, and the prediction error of S_{NH} is
 411 greater than that of S_O .

412 Table 2 shows the results of DMOIA-OC compared with the other five methods. It shows that the concentration of SS
 413 is the lowest. Compared with other comparison algorithms, DMOIA-OC has the lowest AE, PE, and EQ values, NSGA+
 414 PI-OC (Jiang et al. 2004) has the lowest EQ, and cluster MOPSO-OC has the lowest AE and PE values. The control effect
 415 of DMOPSO-OC is only inferior to DMOIA-OC. Also, DMOIA-OC has the smallest IAE value. To sum up, DMOIA can
 416 output the best water quality with the least energy consumption and the best control effect under cloudy and rainy weather
 417 conditions.

418 3) Storm weather

419 Fig. 7 a) and Fig. 7 b) show the control results of S_O and S_{NO} in rainstorm conditions. The settings for rainstorm weather
 420 fluctuate more frequently than those for sunny and rainy days, and the fluctuations in the back section are more frequent
 421 than those in the front section. In addition, in order to verify the control effect of DMOIA-OC more intuitively, control
 422 errors are given in Fig. 7 c). From that, the error of the latter segment remains within ± 0.4 mg/L, and the error of the latter
 423 segment fluctuates considerably relative to the former. The prediction error of S_O is greater than that of S_{NO} , but the overall
 424 control error is smaller. In addition, Table 2 show the results of DMOIA-OC compared with the other five methods. As
 425 seen that, the concentration of SS is slightly higher than that of DMOPSO-OC. The AE, PE and EQ values of DMOIA-OC
 426 are the smallest compared with other comparison algorithms. The result of pccsAMOPSO-OC is the worst, DMOPSO-
 427 OC is second only to DMOIA-OC. VRFT-CS (Peng et al. 2007), NSGA+PI-OC (Jiang et al. 2004), cluster MOPSO-OC

431 Fig. 6 a) The control results of S_O in the rain weather, b) The control results of S_{NO} in the rain weather,
 432 c) The control errors of S_O and S_{NO}

Fig. 7 a) The control results of S_O in the storm weather, b) The control results of S_{NO} in the storm weather, c) The control errors of S_O and S_{NO}

Table 2 Comparison of different control strategies for the mean energy consumption and effluent quality with effluent parameters in three different weather

Weather	Optimal control strategy	SS/mg·L ⁻¹	AE/kW·h	PE/kW·h	EQ/kg poll.units	IAE/mg·L ⁻¹
Dry	DMOIA- OC	12.31	3620	231	6430	0.091
	DMOPSO-OC*	12.52	3630	235	6558	0.099
	clusterMOPSO-OC*	12.45	3691	254	7291	0.122
	pccsAMOPSO-OC*	13.25	3674	239	7103	0.120
	NSGA+PI-OC*	12.15	3694	243	7214	0.100
	VRFT-CS*	12.32	3655	239	7151	0.102
Rainy	DMOIA- OC	13.20	3695	248	7860	0.087
	DMOPSO-OC*	13.48	3701	251	7873	0.091
	clusterMOPSO-OC*	13.25	3768	280	8148	0.121
	pccsAMOPSO-OC*	13.51	3728	261	8214	0.102
	NSGA+PI-OC*	13.71	3706	271	8341	0.099
	VRFT-CS*	13.41	3746	263	8251	0.076
Storm	DMOIA- OC	13.24	3859	220	7498	0.101
	DMOPSO-OC*	13.06	3869	224	7509	0.105
	clusterMOPSO-OC*	13.84	3884	251	7578	0.124
	pccsAMOPSO-OC*	13.54	3915	261	7621	0.109
	NSGA+PI-OC*	13.78	3919	250	7551	0.125
	VRFT-CS*	13.91	3990	232	7598	0.098

* The data are from the reference

(Zhang et al. 2012) ranked third to fifth, respectively, and DMOIA-OC (Lu et al. 2019) has the smallest IAE value. In summary, DMOIA can also obtain the best EQ with the least EC and the best control effect under heavy rain conditions.

6.3 Discussion on Experimental Results

Based on the experimental results, we do find some regularities that can explain what factors affect the overall performance of DMOIA-OC. They are summarized as follows:

- 1) Excellent optimization performance: The proposed DMOIA selects representative individuals with better distribution and convergence. Thus, it has better global search capabilities. The state of the first two moments is used to estimate its motion trajectory, and new individuals are uniformly generated in the new Parato front. This way avoids the problem of no or few solutions in part of the Pareto front. Meanwhile, the limit optimization mutation method (Li et al. 2018) is used to increase the diversity of the population and improve its convergence speed. The above methods provide an

excellent dynamic optimization scheme for solving complex optimization problems. Besides, the IGD results in Table 1 verify the excellent optimization performance of DMOIA.

- 2) Accurate tracking control: There is a consideration for the nonlinear time-varying of the optimized setting values of S_O and S_{NO} in WWTPs. So, it is difficult for a fixed structure controller to achieve a good effect of tracking control. Therefore, this paper adopts a self-organizing recursive fuzzy neural network controller (Qiao et al. 2017) with adaptive adjustment of structure and parameters to effectively improve the control accuracy. It can be seen from Fig. 4 to Fig. 6 that the DMOIA-OC has a stable and high-precision control effect.

Conclusion

In order to solve the multi-index coupling problem in the complex WWTPs, an advanced DMOIA-OC control method is proposed. The IGD results of different optimization problems are compared, and the control results are demonstrated on BSM1. It shows that DMOIA-OC can effectively optimize multiple performance indicators, and track and control them steadily and accurately. The conclusions are as follows:

1) Establish dynamic self-adaptive performance indicators: There is a need to adapt to the strong nonlinear and time-varying characteristics of WWTPs. There is a need to study the operation characteristics and operating data of sewage treatment. And there is also a need to analyze the process variables related to energy consumption and effluent water quality. Therefore, the SOFNN algorithm with dynamic adjustment of structure and parameters is adopted. And the relationship model between input variables, and EC and EQ is established. A good foundation is laid for the optimization of WWTPs.

2) Real-time dynamic acquisition of the best S_O and S_{NO} setting values: The DMOIA method is designed in this paper. It attributes to the dynamic and time-varying performance indicators such as EC and EQ in WWTPs. When the environment changes, new populations with better diversity and distribution are adaptively generated. Thus, it can obtain the S_O and S_{NO} set values with the lowest energy consumption under the standard water quality conditions. In terms of solving complex dynamic optimization, the results show that DMOIA has the best performance. This result comes from comparing with other proposed dynamic optimization methods.

3) High-quality tracking control effect: On the basis of obtaining the best S_O and S_{NO} setting values, a recursive fuzzy neural network controller with high adaptive capability is used for tracking control. The experimental results show that in sunny and rainy days and under heavy rain, the proposed DMOIA-OC method has the best optimized control performance.

Acknowledgements The authors thank all the consort and groups who were involved in the compilation of data from patients for public use. Our sincere thanks to all the patients who have indirectly contributed to the scientific community by providing consent for sharing their data for research use.

Author's contributions Fei Li: Conceptualization, Software, Methodology, Writing-Original Draft, Validation, Formal analysis; Zhong Su: Supervision, Conceptualization, Resources, Data Curation, Validation, Project administration, Funding acquisition; Gongming Wang: Investigation, Data Curation.

Funding This work was supported by the National Key Research and Development Program of China under Grants [2020YFC1511702], the National Natural Science Foundation of China under Grants [61771059], [61971048] and [62003185], Beijing Science and Technology Project under Grants [Z191100001419012], Beijing Scholars Program, Open Project of Beijing Key Laboratory of High Dynamic Navigation Technology, Key Laboratory of Modern Measurement & Control Technology (Beijing Information Science & Technology University), Ministry of Education.

Data availability All the data related to the study has been mentioned in the article.

Compliance with ethical standards

Ethical approval Not applicable

Consent for participate Not applicable

Consent to publish The authors provide consent to publish the data presented in the article.

Competing interest The authors declare that they have no conflict of interest.

References

- Beraud B, Steyer J, Lemoine C et al (2008) Optimization of WWTP control by means of multi-objective genetic algorithms and sensitivity analysis. *Comput Aid Chem Eng* 25: 539-544
- Busch J, Elixmann D, Kühl P et al (2013) State estimation for large-scale wastewater treatment plants. *Water Res* 47: 4774-4787

- Büyüközkan G, Tüfekçi G (2021) A multi-stage fuzzy decision-making framework to evaluate the appropriate wastewater treatment system: a case study. *Environ sci pollut R* 25: 1-13.
- Cai X, Yang Z, Fan Z et al (2016) Decomposition-based-sorting and angle-based-selection for evolutionary multiobjective and many-objective optimization. *IEEE T Cybernetics* 47(9): 2824-2837
- Chakraborty P, Das S, Roy GG et al (2011) On convergence of the multi-objective particle swarm optimizers. *Inform Sciences* 181(8): 1411-1425
- Cheng R, Jin Y (2014) A competitive swarm optimizer for large scale optimization. *IEEE T Cybernetics* 45(2): 191-204
- Dominic S, Shardt YA, Ding SX et al (2015) An adaptive, advanced control strategy for KPI-based optimization of industrial processes. *IEEE T Ind Electron* 63(5): 3252-3260
- Farina M, Deb K, Amato P (2004) Dynamic multiobjective optimization problems: test cases, approximations, and applications. *IEEE T Evolut Comput* 8(5): 425-442
- Goh CK, Tan KC (2008) A competitive-cooperative coevolutionary paradigm for dynamic multiobjective optimization. *IEEE T Evolut Comput* 13(1): 103-127
- Guerrero J, Guisasola A, Vilanova R et al (2011) Improving the performance of a WWTP control system by model-based setpoint optimization. *Environ Modell Softw* 26(4): 492-497
- Guerrero J, Guisasola A, Comas J et al (2012) Multi-criteria selection of optimum WWTP control setpoints based on microbiology-related failures, effluent quality and operating costs. *Chem Eng J* 188(1): 23-29
- Hakanen J, Sahlstedt K, Miettinen K (2013) Wastewater treatment plant design and operation under multiple conflicting objective functions. *Environ Modell Softw* 46: 240-249
- Han HG, Qian HH, Qiao JF (2014) Nonlinear multiobjective model-predictive control scheme for wastewater treatment process. *J Process Contr* 24(3): 47-59
- Han HG, Zhang L, Liu HX et al (2018) Multiobjective design of fuzzy neural network controller for wastewater treatment process. *Appl Soft Comput* 67: 467-478
- Han HG, Liu Z, Lu W et al (2019) Dynamic MOPSO-Based Optimal Control for Wastewater Treatment Process. *IEEE T Cybernetics* 1-11.
- Hreiz R, Roche N, Benyahia B et al (2015) Multi-objective optimal control of small-size wastewater treatment plants. *Chem Eng Res Des* 102: 345-353
- Hu W, Yen GG (2015) Adaptive multiobjective particle swarm optimization based on parallel cell coordinate system. *IEEE T Evolut Comput* 19(1): 1-18
- Hu WW, Tan Y (2016) Prototype generation using multiobjective particle swarm optimization for nearest neighbor classification. *IEEE T Cybernetics* 46(12): 2719-2731
- Iqbal J, Guria C (2009) Optimization of an operating domestic wastewater treatment plant using elitist non-dominated sorting genetic algorithm. *Chem Eng Res Des* 87(11): 1481-1496
- Jiang J, Zhang YM (2004) A novel variable-length sliding window blockwise least-squares algorithm for on-line estimation of time-varying parameters. *Int J Adapt Control* 18(6): 505-521
- Jiang S, Yang S (2016) A steady-state and generational evolutionary algorithm for dynamic multiobjective optimization. *IEEE T Evolut Comput* 21(1): 65-82.
- Li M, Yang S, Li K et al (2013) Evolutionary algorithms with segment-based search for multiobjective optimization problems. *IEEE T Cybernetics* 44(8): 1295-1313
- Li SY, Qiao JF, Li WJ et al (2018) Advanced Decision and Optimization Control for Wastewater Treatment Plants. *Acta Auto Sinica* 44(12): 2198-2209
- Li D, Huang D, Liu Y (2021) A novel two-step adaptive multioutput semisupervised soft sensor with applications in wastewater treatment. *Environ sci pollut R* 7: 1-15.
- Lin QZ, Ma YP, Chen JY et al (2018) An adaptive immune-inspired multi-objective algorithm with multiple differential evolution strategies. *Inform Sciences* 430: 46-64.
- Liu D, Wang D, Wang FY et al (2014) Neural-network-based online HJB solution for optimal robust guaranteed cost control of continuous-time uncertain nonlinear systems. *IEEE T Cybernetics* 44(12): 2834-2847
- Liu YQ, Liu B, Zhao X J et al (2018) A mixture of variational canonical correlation analysis for nonlinear and quality-relevant process monitoring. *IEEE T Ind Electron* 65(8): 6478-6486
- Liu ZJ, Wan JQ, Ma YW et al (2019) Online prediction of effluent COD in the anaerobic wastewater treatment system based on PCA-LSSVM algorithm. *Environ sci pollut R* 26(13): 12828-12841.
- Löwenberg J, Zenker A, Baggenstos M, et al (2014) Comparison of two PAC/UF processes for the removal of micropollutants from wastewater treatment plant effluent: process performance and removal efficiency. *Water Res* 56: 26-36
- Lu W (2019) Design and Application of Dynamic Multiobjective Particle Swarm Optimization Algorithm. Beijing University of Technology
- Luna FDVB, Aguilar EDLR, Naranjo JS et al (2016) Robotic sstem for automation of water quality monitoring and feeding in aquaculture shade house. *IEEE Trans Syst Man Cybern Syst* 47(7): 1575-1589
- Peng JX, Li K, George WI (2007) A novel continuous forward algorithm for RBF neural modelling. *IEEE T Automat Contr* 52(1): 117-122

- Qiao JF, Han GT, Han HG et al (2017) Wastewater treatment control method based on a rule adaptive recurrent fuzzy neural network. *Inter J Intel Comput Cyber* 10 (2): 94-110
- Qiao JF, Zhou HB (2017) Prediction of effluent total phosphorus based on self-organizing fuzzy neural network. *Contr Theory A* 34(2): 224:232
- Qiao JF, Hou Y, Zhang L et al (2018) Adaptive fuzzy neural network control of wastewater treatment process with multiobjective operation. *Neurocomputing* 275 (31) 383-393
- Qiao JF, Li F, Yang SX et al (2020) An adaptive hybrid evolutionary immune multi-objective algorithm based on uniform distribution selection. *Inform Sciences* 512: 446-470.
- Roman RC, Radac MB, Precup R E et al (2016) Virtual reference feedback tuning of MIMO data-driven model-free adaptive control algorithms. *Doctoral Conference on Computing, Electrical and Industrial Systems*. Springer, Cham 253-260.
- Rong M, Gong D, Zhang Y et al (2018) Multidirectional prediction approach for dynamic multiobjective optimization problems. *IEEE T Cybernetics* 49(9): 3362-3374
- Santin I, Pedret C, Vilanova R (2015) Applying variable dissolved oxygen set point in a two level hierarchical control structure to a wastewater treatment process. *J Process Contr* 28: 40-55
- Schlüter MJ, Egea A, Antelo LT et al (2009) An extended ant colony optimization algorithm for integrated process and control system design. *Ind Eng Chem Res* 48(14): 6723-6738
- Shiek AG, Machavolu VRK, Seepana MM et al (2021) Design of control strategies for nutrient removal in a biological wastewater treatment process. *Environ sci pollut R* 28:12092-12106.
- Shorbaghy WE, Nabil N, Droste RL (2011) Optimization of A2O BNR processes using ASM and EAWAG Bio-P models: Model formulation. *Water Qual Res J Can* 46(1): 13-27
- Sweetapple C, Fu G, Butler D (2014) Multi-objective optimisation of wastewater treatment plant control to reduce greenhouse gas emissions. *Water Res* 55: 52-62
- Tabatabaei M, Hakanen J, Hartikainen M et al (2015) A survey on handling computationally expensive multiobjective optimization problems using surrogates: non-nature inspired methods. *Struct Multidiscip O* 52(1): 1-25
- Vega P, Revollar S, Francisco M et al (2014) Integration of set point optimization techniques into nonlinear MPC for improving the operation of WWTPs. *Comput Chem Eng* 68: 78-95
- Vitor TS, Vieira JCM (2021) Operation planning and decision-making approaches for Volt/Var multi-objective optimization in power distribution systems. *Electr Pow Syst Res* 191: 106874.
- Wang Q, Poh KL (2014) A survey of integrated decision analysis in energy and environmental modeling. *Energy* 77: 691-702.
- Xie WM, Zhang R, Li WW et al (2011) Simulation and optimization of a full-scale Carrousel oxidation ditch plant for municipal wastewater treatment. *Biochem Eng J* 56(1-2): 9-16
- Yetilmezsoy K (2012) Integration of kinetic modeling and desirability function approach for multi-objective optimization of UASB reactor treating poultry manure wastewater. *Bioresour Technol* 118: 89-101
- Zhang R, Xu ZB, Huang GB et al (2012) Global convergence of online BP training with dynamic learning rate. *IEEE T Neur Net Lear* 23(2):330-341.
- Zhou HB (2017) Dissolved oxygen control of wastewater treatment process using self-organizing fuzzy neural network. *CIESC J* 68(4): 1516-1524
- Zhou HB, Qiao JF (2017) Optimal control of wastewater treatment process using hybrid multi-objective barebones particle swarm optimization algorithm. *CIESC J* 68(9): 3511-3521