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ORIGINAL ARTICLE

Dynamic multi-objective optimization control for wastewater treatment process

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Abstract A dynamic multi-objective optimization control (DMOOC) scheme is proposed in this paper for the wastewater treatment process (WWTP), which can dynamically optimize the set-points of dissolved oxygen concentration and nitrate level with multiple performance indexes simultaneously. To overcome the difficulty of establishing multi-objective optimization (MOO) model for the WWTP, a neural network online modeling method is proposed, requiring only the process data of the plant. Then, the constructed MOO model with constraints is solved based on the NSGA-II (non-dominated sorting genetic algorithm-II), and the optimal set-point vector is selected from the Pareto set using the defined utility function. Simulation results, based on the benchmark simulation model 1 (BSM1), demonstrate that the energy consumption can be significantly reduced applying the DMOOC than the default PID control with the fixed set-points. Moreover, a tradeoff between energy consumption and effluent quality index can be considered.

Keywords Dynamic multi-objective optimization control · Neural network modeling · NSGA-II · Wastewater treatment process

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1 Introduction

Wastewater treatment processes (WWTPs) are complex and energy-intensive systems, whereas they have to be operated continuously with effluent requirements. Moreover, stringent standards and regulations have been introduced worldwide to protect the environment from the harmful effluent discharged to receiving waters [1, 2]. From the points of energy saving and environment protection, the optimal control of the WWTP is an appealing strategy, and has attracted considerable attention recently [3–5].

Single-variable optimizations are paid more attention and have been widely studied, especially for the dissolved oxygen (DO) concentration [6–10]. In order to improve the optimal performance, multi-variable optimization strategies are proposed for the WWTP [11–15]. However, these control methods view the optimization of the WWTP as a single-objective problem. Actually, the physical and chemical phenomenon happened in a sludge treatment is complicated and interaction, and some performances, such as aeration energy (AE), pumping energy (PE) and effluent quality index (EQ), are conflicting in the WWTP. Therefore, it would be reasonable to consider the optimization of the WWTP as a multi-objective problem [2, 16, 17]. Han et al. proposed a nonlinear multi-objective model-predictive control (NMMPC) scheme with multi-objective gradient optimization for the WWTP [2]. Simulations reveal that the NMMPC can lead to satisfactory tracking and disturbance rejection performance. Nevertheless, this work pays more attention to the system control performance. An improved multi-objective optimization model was studied and employed for optimizing the treatment cost and effluent quality indexes of a municipal wastewater treatment plant [18]. However, this work mainly focuses on the discussion of decision factors. Based on the BSM1, Chen et al. studied the optimal design of activated sludge process (ASP) using multi-objective optimization, which includes four performance indexes: percentage of overall cost index (OCI), effluent violation (PEV), total suspended solids and total volume [19]. The results indicate that multi-objective optimization is a useful approach for the optimal design of ASP. However, this strategy mainly optimizes the design parameters of the WWTP and the optimization is an off-line mode.

In this paper, a dynamic multi-objective optimization control (DMOOC) scheme is proposed for the WWTP, where the set-points of DO concentration and nitrate level are dynamically optimized with multiple performance indexes simultaneously. The difficulties in formulating the DMOOC problem lie in three aspects. First, there is no existing multi-objective optimization (MOO) model for the WWTP. Due to the complex relationship among the energy consumption (EC, mainly including AE and PE), EQ and optimal set-points, the optimization model is not easy to obtain from the mechanism knowledge of the WWTP. Second, the optimization under study is a dynamic MOO with constraints. The WWTP is a nonlinear dynamic system with large disturbance and uncertainties, such as the influent flow, pollutant concentration and weather variations. Therefore, the optimization of the WWTP should be a dynamic optimization process. Moreover, effluent constraints must be met while applying the optimization strategy. Third, a satisfactory solution (optimal set-points) needs to be selected from the Pareto set to realize the close-loop control of the WWTP. However, MOO algorithm provides a group of equally excellent Pareto optimal solutions generally.

The main contributions of this paper are as follows. First, the MOO model of the WWTP is constructed by the neural network (NN) online modeling method only using the process data, which establish the underlying relationships between the set-points and concerned performances. Second, the set-points of DO concentration and nitrate level are dynamically optimized based on the NSGA-II (non-dominated sorting genetic algorithm-II) with effluent constraints treatment, and the defined utility function. Third, the proposed strategy is tested and evaluated on the benchmark simulation model 1 (BSM1), where energy saving is achieved and a tradeoff between EC and EQ can be considered as well.

The reminder of this paper is organized as follows. Section 2 describes the optimization problem of the WWTP. The design process of the DMOOC scheme is demonstrated in Sect. 3. In Sect. 4, the case studies are provided based on the BSM1. Finally, conclusions are drawn in Sect. 5.

2 Problem description

2.1 BSM1

To objectively evaluate different control strategies applied to the WWTP, BSM1 [20] has been developed by the IWA (International Water Association) and COST (European Cooperation in the Field of Science and Technology). The layout of BSM1 is described in Fig. 1, which is a typical pre-denitrifying activated sludge treatment process.

BSM1 mainly includes a five-compartment activated biological reactor, and a secondary clarifier described by the double-exponential settling velocity function [21]. Activated Sludge Model 1 (ASM1) is selected to describe the biological phenomena taking place in the biological

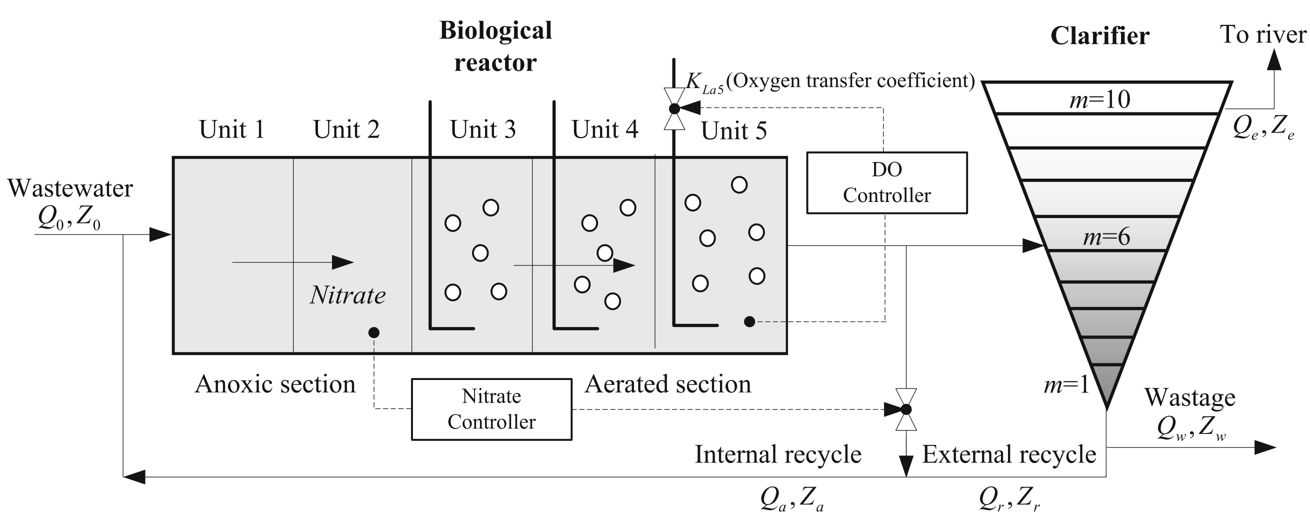

Fig. 1 Layout of the BSM1

reactor. Three kinds of weather disturbance data files, which are collected from the real WWTP, are provided in the BSM1: dry weather, rain weather (a combination of dry weather and a long rain period) and storm weather (a combination of dry weather with two storm events).

DO concentration in unit 5 and nitrate level in unit 2 are two crucial controlled parameters, which strongly influence the biological reaction process, effluent quality as well as energy consumption [20]. Therefore, the optimization of their set-points has been regarded as an effective way to save energy and improve effluent quality [13, 22].

2.2 Evaluation criteria

Two types of performance indexes are considered in this work: One is the EC (energy consumption), which is the sum of AE (aeration energy) and PE (pumping energy); the other is EQ (effluent quality index). AE, PE and EQ can be calculated by the following equations.

$$AE = \frac{S_{\mathrm{O,sat}}}{T \times 1.8 \times 1000} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \sum_{i=1}^{i=5} V_i \cdot K_{Lai}(t)\mathrm{d}t \tag{1}$$

$$PE = \frac{1}{T} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} (0.004 \cdot Q_a(t) + 0.05 \cdot Q_w(t) + 0.008 \cdot Q_r(t))\mathrm{d}t \tag{2}$$

$$EQ = \frac{1}{T \cdot 1000} \int_{t=7\,\mathrm{days}}^{t=14\,\mathrm{days}} \begin{pmatrix} B_{\mathrm{SS}} \cdot \mathrm{SS}_e(t) + B_{\mathrm{COD}} \cdot \mathrm{COD}_e(t) \\ +B_{\mathrm{NO}} \cdot S_{\mathrm{NO}}, e(t) + B_{\mathrm{NK}j} \cdot S_{\mathrm{NK}j}, e(t) \\ +B_{\mathrm{BOD5}} \cdot \mathrm{BOD}_e(t) \end{pmatrix} \cdot Q_e(t)\mathrm{d}t \tag{3}$$

where K_{Lai} and V_i are the mass transfer coefficient and volume of the ith biological reactor, respectively; $S_{O,sat}$ is the saturation concentration for oxygen; T (7 days) is the evaluation cycle; According to the benchmark BSM1 platform, the lower limit and upper limit of the integrals takes 7 days and 14 days, respectively. Q_{a}, Q_{w} and Q_{r} are the internal recycle flow rate, waste sludge flow rate and return sludge recycle flow rate, respectively. DO concentration (S_O) and nitrate concentration (S_{NO}) are manipulated by the K_{La5} and Q_{a}, respectively. B_i represent weighting factors for the different kinds of pollution to convert them into pollution units, and according to the BSM1, the weighting factor parameter is chosen as follows: $B_{\mathrm{SS}} = 2$, $B_{\mathrm{COD}} = 1$, $B_{\mathrm{NO}} = 10$, $B_{\mathrm{NK}j} = 30$ and $B_{\mathrm{BOD5}} = 2$; SS, COD, S_{NO}, S_{NKj} and BOD are the concentration of suspended solids, chemical oxygen demand, nitrite, Kjeldahl nitrogen and biological oxygen demand, respectively. The subscript e corresponds to the effluent. And these effluent parameters have a major influence on the quality of the receiving water. The units of flow rates are in m^3/day, the units of effluent loads concentration are in mg/l, the units of weighting factors are in g pollution unit.g^{-1}, the units of AE and PE are in kWh d^{-1}, and the unit of EQ is in kg pollution units d^{-1}. EQ value reflects the level of the treated wastewater (smaller EQ value means better effluent quality), and the EQ value will impact the operation cost of WWTP if the effluent discharge fee is executed strictly.

Aside from the EQ, five effluent parameters are required to reach the followling specified standard.

$$\begin{aligned} &N_{\mathrm{tot}} < 18\,\mathrm{mg/l}, S_{\mathrm{NH}} < 4\,\mathrm{mg/l}, \\ &\quad \mathrm{SS} < 30\,\mathrm{mg/l}, \mathrm{COD} < 100\,\mathrm{mg/l}, \mathrm{BOD}_5 < 10\,\mathrm{mg/l} \end{aligned} \tag{4}$$

Therefore, the optimization of the WWTP is the one with effluent constraints. Detailed definitions and explanations of the parameters in Eqs. (1)–(4) can be found in BSM1 [20].

2.3 Analysis of MOO model

To realize the DMOOC, the first thing is to provide an appropriate MOO model for the WWTP. Figure 2 demonstrates the relationships among the optimized variables, manipulated variables and performance indexes from the perspective of control flow in the WWTP.

It can be observed that there exist a close relationship between the performance indexes discussed and the optimized variables. However, we cannot deduce their relationship easily using the mechanism knowledge of the sludge treatment process. Therefore, a neural network online modeling method, requiring only the process data of the plant, is proposed in this paper to establish the mapping between the performance indexes and optimized variables.

It should be noted that ammonia nitrogen (S_{NH}) and total nitrogen (N_{tot}) are two special effluent parameters, which reflect the level of nitrification and denitrification process, and are prone to exceed effluent standards as well. Therefore, only these two effluent parameters are considered as constraints in the current study.

3 DMOOC design

3.1 MOO modeling

Construct the following MOO model for the WWTP

$$\begin{cases} \min F(\mathbf{x}) = \{f_{AE}(\mathbf{x}), f_{PE}(\mathbf{x}), f_{EQ}(\mathbf{x})\} \\ s.t. \, \mathbf{x} \in S \end{cases} \tag{5}$$

where $\mathbf{x} = [x_1, x_2] = [S_{o,sp}, S_{No,sp}]$ is the optimal vector; denote $f_1(\mathbf{x}) = f_{AE}$, $f_2(\mathbf{x}) = f_{PE}$, $f_3(\mathbf{x}) = f_{EQ}$; $S = \{\mathbf{x} \in$

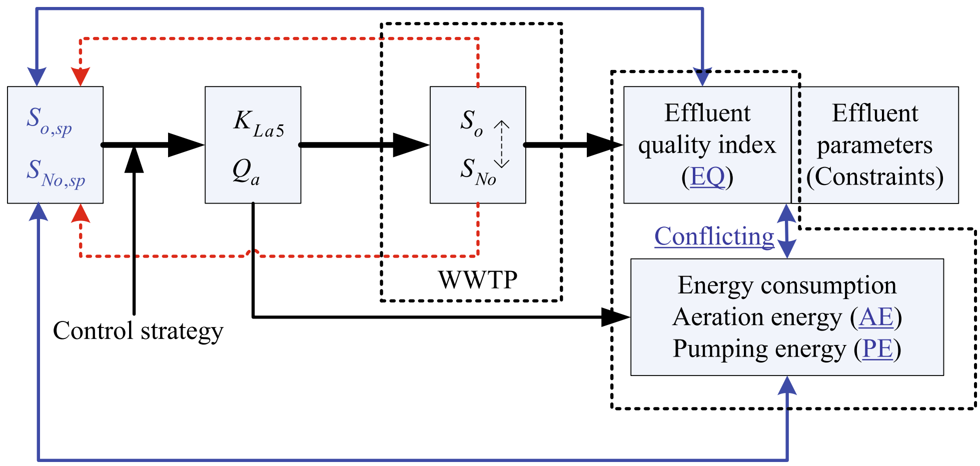

Fig. 2 Relationships among the optimized variables, manipulated variables and performance indexes in the WWTP

$R^2|g_j(\mathbf{x}) - C_j \leq 0, j = 1, 2, x_i^l \leq x_i \leq x_i^u, i = 1, 2\}$ represents the constraint set of the optimal variables; x_i^l and x_i^u are the lower limit and upper limit for each optimal variable, respectively; $g_j(\mathbf{x})$ denotes the effluent parameter, and the inequality constraints in set S can be rewritten as

$$\begin{cases} g_{S_{\mathrm{NH}}}(\mathbf{x}) - 4 \leq 0 \\ g_{S_{\mathrm{Ntot}}}(\mathbf{x}) - 18 \leq 0 \end{cases} \tag{6}$$

TS-fuzzy neural networks (TS-FNNs) are employed in this study to establish these underlying function relationships involved in the MOO model, including performance indexes, effluent constraints and effluent state variables discussed. Each of them can be expressed by (7)–(9).

$$\hat{y}(z) = \sum_{j=1}^{n} \varphi_j(z) h_j(z, \theta_j) \tag{7}$$

$$h_j(z, \theta_j) = [1, z^T]\theta_j \tag{8}$$

$$\varphi_j(z) = \frac{\prod_{k=1}^{r} A_k(x_k)}{\sum_{j=1}^{n} \prod_{k=1}^{r} A_{jk}(x_k)} \tag{9}$$

where $z = [z_1, z_2, \ldots, z_r]$ is the input vector of the TS-FNN, r is the number of input variables; θ_j is the consequent parameter of the FNN; $\hat{y}(z)$ is the output of the FNN; $A(\cdot)$ denotes the fuzzy set and Gaussian function is chosen (center c_j and width σ_j); $j = 1, 2, \ldots, n$, n is the number of fuzzy rules.

Define the objective function of FNN as

$$J = \frac{1}{2} e(k)^2 = \frac{1}{2} (\hat{y}(k) - y(k))^2 \tag{10}$$

Let $\alpha = \left[\theta^T, c^T, \sigma^T\right]^T$ be the parameter vector of the network and the gradient descent algorithm is adopted for the parameter learning. Then, the update law can be expressed by

$$\alpha(k+1) = \alpha(k) - \eta \frac{\partial J(k)}{\partial \alpha(k)} \tag{11}$$

where $\eta \in (0, 1)$ is the learning rate of the FNN; $\hat{y}(k)$ represents the output of the FNN; $y(k)$ is the real value generated by the BSM1.

It should be noted that the process model of WWTP is complex from the aspect of the mechanism analysis. Furthermore, it is much more difficult to deduce an optimal model from the mechanism perspective. Actually, the model description problem has been a bottleneck for the optimization control of WWTP. In this paper, NN technology is employed such that the optimal relationships between the performance indexes and optimized variables can be established by some simple models, which are much easier to optimize.

3.2 MOO algorithm with constraint treatment

In this work, NSGA-II [23], one of the most excellent evolution multi-objective optimization algorithms, is employed to solve the MOO problem of the WWTP. However, extra issues need to be considered. First, the MOO problem of the WWTP is a dynamic optimization process with effluent constraints. Therefore, the effluent constraints need to be integrated into the NSGA-II. Second, a unique optimal solution must be presented to realize the closed-loop control. NSGA-II can provide a group of equally excellent Pareto solutions. Therefore, an effective evaluation criterion is required to select a satisfactory optimal solution from the Pareto set.

To handle the effluent constraints, the penalty function method is used in this paper. Let the penalty function defined as

$$f_{\mathrm{penalty}}(\mathbf{x}) = \max\{g_{S_{\mathrm{NH}}}(\mathbf{x}) - 4, 0\} + \max\{g_{S_{\mathrm{Ntot}}}(\mathbf{x}) - 18, 0\} \tag{12}$$

Then, the performance functions with penalty item can be formulated as

$$f_{i,\text{constraint}}(\mathbf{x}) = f_i(\mathbf{x}) + C \cdot f_{\text{penalty}}(\mathbf{x}), \quad i = 1, 2 \tag{13}$$

where C is the penalty factor with larger positive value. When constraints are violated, the value of performance function will become larger. As a result, those solutions with violation records will be dispelled away from the Pareto set.

A summary of NSGA-II algorithm applied in our experiment can be described as follows:

1. Initialize the population $P(0)$, population size N, maximum generation M, optimal variable dimension D;
2. Calculate the values of performance indexes for each individual in $P(0)$ (utilize the mathematical mappings established by the neural networks and the constraint treatment method); calculate the crowding distance index;
3. Proceed fast non-dominated sorting for the initial population $P(0)$, and let the generation t=1;
4. Repeat the following steps until the evolutionary generation t reaches the maximum generation M;
   (a) Select the parent population $P_p(t)$ from the population $P(t)$ using the binary roulette method;
   (b) Proceed the crossover and mutation for the parent population $P_p(t)$, generate the child population $P_c(t)$;
   (c) Combine the parent population $P_p(t)$ and child population $P_c(t)$ into a new temporary population $P_i(t)$;
   (d) Calculate the performance function values and crowding distance values for each individual in population $P_i(t)$;
   (e) Proceed the fast non-dominated sorting for the population $P_i(t)$;
   (f) Select the most excellent N individuals from the population $P_i(t)$) as the next generation population $P(t+1)$;
   (g) $t = t + 1$;
5. Obtain Pareto solutions (the most excellent N individuals) for the current optimal cycle.

3.3 Satisfactory optimal solution

Obtaining a satisfactory optimal solution from the Pareto set is a process of the second optimization. Define the utility function of each optimal solution in Pareto set

$$d_{\text{utility}}(\mathbf{x}^p) = \sum_{i=1}^{l} \omega_i f_i(\mathbf{x}^p), \ \sum_{i=1}^{l} \omega_i = 1, p = 1, 2, \ldots, k \tag{14}$$

where k is the number of the Pareto solutions; l is the number of the performance indexes. The value of utility function reflects the satisfactory level of each optimal solution in Pareto set, which is related to the current demands from the treatment plant.

Find the solution with the minimum of the utility function

$$K = \arg \min_{p=1,2,\ldots,k} \{d_{\text{utility}}(\mathbf{x}^p)\} \tag{15}$$

The final satisfactory optimal solution needs to be determined based on the decision information and the values of all the performance functions, and the minimum value of the utility function is found out. Then, $\mathbf{x}^K$ is selected as the satisfactory optimal solution (the optimal set-point vector).

The differences of the MOO method used in our studies with a "classical" multi-objective optimization mainly lie in two aspects: Firstly, the search scope of Pareto solutions is broadened since a group of equally excellent solutions can be provided not just a single Pareto solution (when the optimization views as a "classical" multi-objective optimization problem). Therefore, we can obtain much more feasible solutions for choosing a satisfactory optimal solution. Secondly, the adopted optimal style is convenient to the weights adjustment, which provides a possible way to realize an intelligent decision management based on the system operation information.

The control structure of DMOOC is demonstrated in Fig. 3.

The optimization process can be described as follows. First, the MOO model of the WWTP is established by the FNN using the process data of the plant. Then, the MOO model with constraints is solved by the NSGA-II algorithm, and Pareto optimal solutions are provided to the decision module. Finally, the optimal satisfactory solution (the optimal set-points $S_{O,sp}$ and $S_{NO,sp}$) is chosen from the Pareto set based on the defined utility function. The MOO model is continuously modified during the process such that the modeling networks can reflect the dynamic characteristics of the WWTP and the optimal set-points are provided at every optimized time. For the control layer, the task is to track the optimal set-points closely. PID is adopted as the lower-level controller for convenience of comparison with the default control in BSM1.

The proposed strategy is also a hierarchical control structure, which includes decision-maker layer, optimization layer and control loop layer. However, it is different from the common hierarchical control applied in the WWTP. Firstly, the optimization layer is a multi-objective optimization process and the optimal model is established dynamically using the neural network, which provides an easy and effective multi-objective optimization model for the WWTP. Secondly, the decision-maker layer is designed for the satisfactory solution determination. Compared our strategy with the published works [7, 11] considering

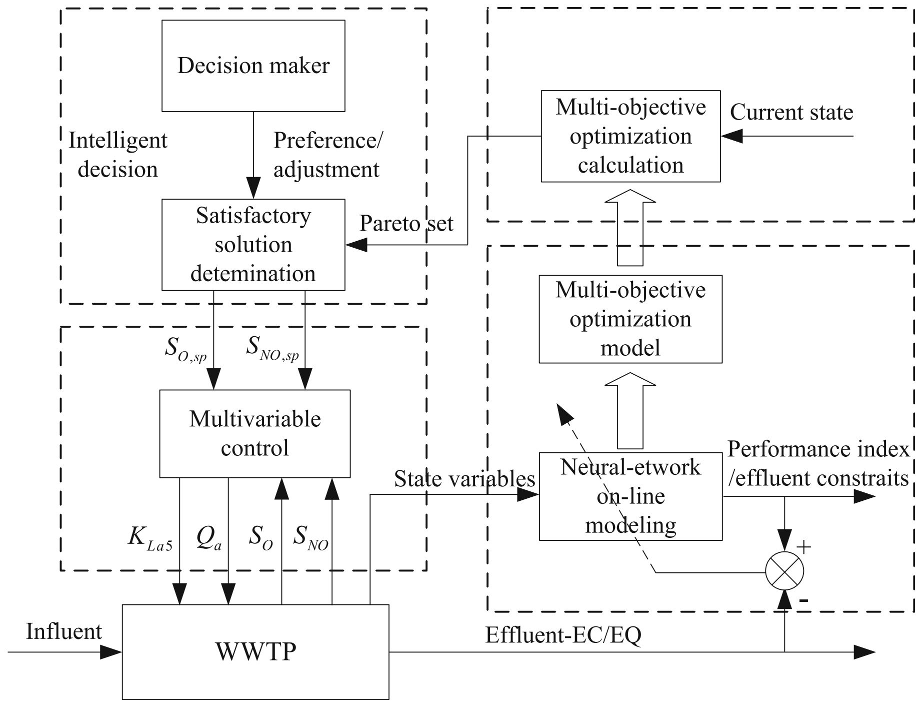

Fig. 3 Structure of the control system

multi-objective optimization (OCI and EQ simultaneously), the main contribution of our proposed method lies in that a multi-objective optimization model of WWTP is established using the neural network based on the analysis of the mechanism knowledge. The constructed optimal model solves the problem that no existing optimal model is provided between the optimized variables and performance indexes.

4 Experiment studies

4.1 Experimental environment and parameter setting

All experiments are operated in a MATLAB environment and tested on the BSM1 platform. The sampling interval is 15 min. The optimal cycle is chosen as 2 h according to our previous studies [13, 14]. For comparisons, the open-loop control and default PID control with fixed set-points (DO concentration and nitrate concentration are set to 2 and 1 mg/l, respectively) have been introduced and operated in the same simulation environment. According to the experience and experiment results, the parameters of PID controllers are set as follows: for S_O, the proportional, integral and differential coefficients are 200, 15 and 2, respectively; for S_{NO}, these coefficients are 20,000, 5,000 and 400, respectively. The structures of NNs are chosen as 2-10-1 for the modeling of AE and PE (input is $[S_{\mathrm{O}}, S_{\mathrm{NO}}]^T$), and 3-10-1 for the modeling of effluent parameters and constraints (input is $[S_{\mathrm{O}}, S_{\mathrm{NO}}, Q_{\mathrm{in}}]^T$, and Q_{in} is the influent flow rate that has large impact on the effluent parameters). It should be noted that the input numbers of NNs are decided by the analysis of process variables, and the hidden numbers of the NNs are determined based on the experience and experiment results. The optimal ranges of set-points are chosen as 0.4–3/mg/l for S_{O} and 0.2–2 mg/l for S_{NO} [12]. The penalty factor C is set for 10,000. The sizes of populations and evolution generations in NSGA-II are chosen as 40 and 20, respectively, which are suitable for the current study through experimental verification. For the neural network modeling, the updating period is same to the sample time (15 min). The Pareto set can be obtained at every sample time and the optimized set-points can be obtained every 2 h. The simulation time is 14 days, and the data of the last 7 days are used for evaluation.

4.2 Results and analysis

Case 1 In this case, the emphasis is to evaluate the performance of energy saving under the DMOOC. Performance functions are chosen as $f_1 = f_{\mathrm{AE}}$ and $f_2 = f_{\mathrm{PE}}$ with the same weight factor. Aside from the open-loop control and default PID control, the single-objective optimization control (SOOC) is also introduced, where the optimization objective is to minimize the sum of AE and PE instead of optimizing AE and PE simultaneously. Compared with the DMOOC method, the SOOC method can only obtain one of the Pareto solutions and decrease the search scope of the feasible solutions. For the PID, the optimal set-points are not updated, i.e., a single couple of optimal set-points is determined. The data of rain weather are used in this case.

Figure 4 demonstrates the optimal results of the set-points and tracking performance under the DMOOC. Figure 5 shows the variation of several key effluent parameters under the DMOOC compared with the default PID control.

From the figures, we can see that the set-points of the DO concentration and nitrate level are dynamically adjusted with the treatment process and the lower-layer controller can well track the optimal set-points under the DMOOC. For the effluent, the concentrations of COD and BOD_5 are below the specified standards all the time and have little change between the control strategies. Compared with the default PID control, N_{tot} has an obvious decrease and over-limit phenomenon at the peak time has also been improved under the DMOOC. Nevertheless, S_{NH}

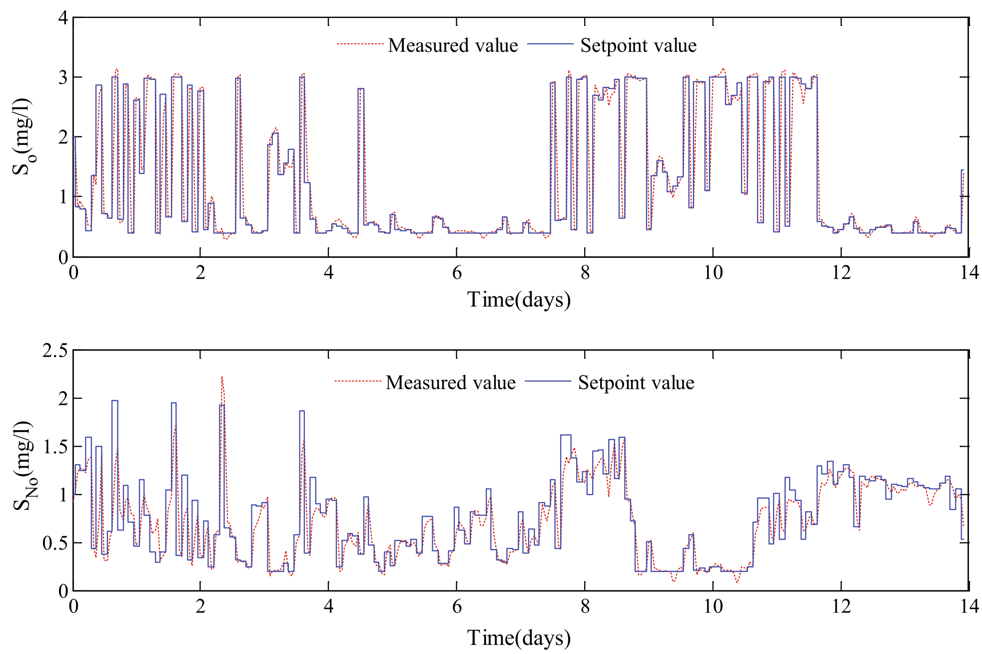

Fig. 4 Optimized set-points and online tracking control performance under the DMOOC in the rain weather

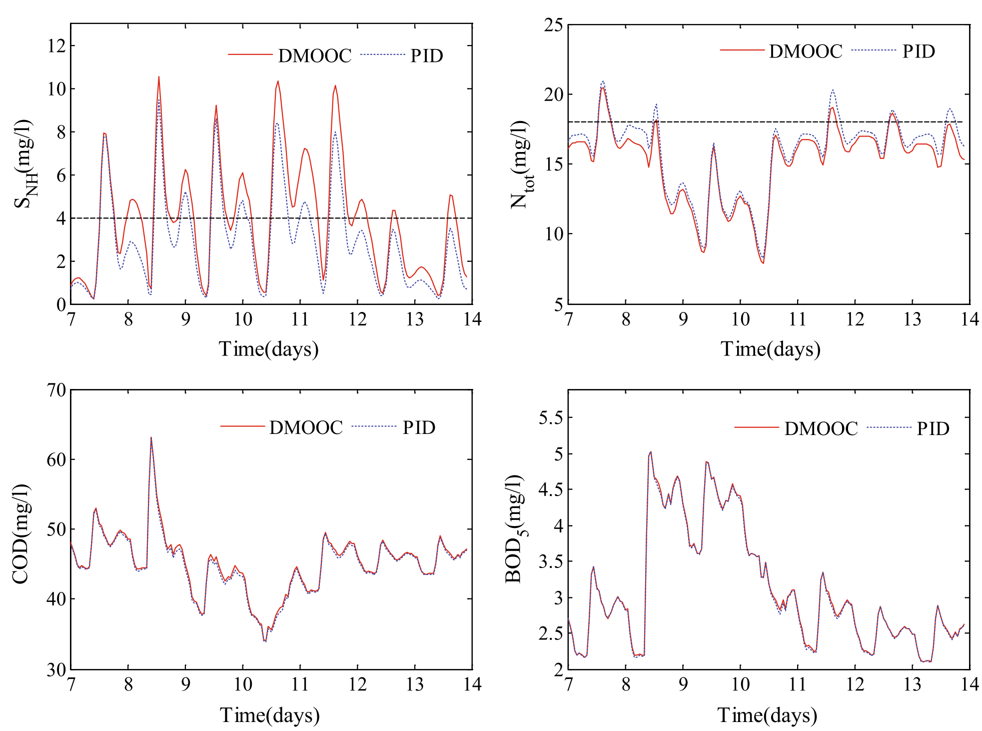

Fig. 5 Comparisons of the effluent parameters between the DMOOC and PID control in the rain weather

Table 1 A comparison of the energy consumption with different control strategies

Weather	Control method	AE	PE	EC	Up/down
Rain	Open-loop	3341.26	388.16	3729.42	–
	PID	3663.01	253.72	3916.72	–
	SOOC	3572.91	257.98	3830.89	2.20%
	DMOOC	3459.12	264.66	3723.78	4.94%

Table 2 A comparison of the average effluent parameters and EQ with different strategies

		BOD5	COD	N_{tot}	S_{NH}	SS	EQ
Rain	Limit	10	100	18	4	30	–
	Open-loop	2.91	46.45	15.36	4.81	13.47	8147.34
	PID	2.88	46.34	16.49	2.69	13.47	7592.88
	SOOC	2.89	46.36	16.31	3.05	13.48	7702.70
	DMOOC	2.89	46.39	16.18	3.46	13.48	7867.17

appears to increase under the DMOOC compared with the default PID control. It is a reasonable conclusion because N_{tot} and S_{NH} are a pair of conflicting effluent parameters from the mechanism knowledge of the WWTP. Actually, there still exist other conflicting parameters (performances) in the WWTP. Fortunately, the multi-objective optimization can provide an effective balance tactics.

Detailed comparisons of the AE, PE, EC, EQ and some key effluent parameters under different control strategies are represented in Tables 1 and 2. And the effluent parameters are average values between the 7th and the 14th day.

The results show that the optimal strategies (SOOC and DMOOC) achieve better performance of energy saving compared with the default PID control, and moreover, the DMOOC is superior to the SOOC obviously. For the DMOOC, the EC is decreased by 4.94% compared with the default control, and the value is 2.20% for the SOOC. This indicates that the DMOOC can obtain much better optimal result than the SOOC, and it is consistent with the analysis that the optimization of the WWTP should be viewed MOO problem. From the values of AE and PE, we can also see that the AE and PE indexes are conflicting, i.e., the AE value increases while the PE value decreases and vice versa. Therefore, it is much more reasonable that the PE and AE are treated as two-objective functions. Combining PE and AE in a single-objective function can only obtain a single optimal solution (one of the Pareto solution). However, treating PE and AE as two-objective functions is a method of multi-objective optimization essentially, which can obtain a group of equally optimal solutions (Pareto solutions). These solutions broaden the optimal search scope, and this treatment style can also provide a convenient decision adjustment. Although the open-loop control has the lowest EC value, the average concentration of S_{NH} exceeds the effluent standard and EQ value is the highest among the control methods. The EQ value under the DMOOC has a slight increase. This is in agreement with the fact that the EC and EQ are conflicting performances as well. For the current treatment plant, lower EC value is the most expected and thus this case is paid more attention to the EC index.

The modeling performance of the AE, PE and effluent parameters (S_{NH} and N_{tot}) are shown in Fig. 6 and Table 3. Simulation results show that the outputs of modeling

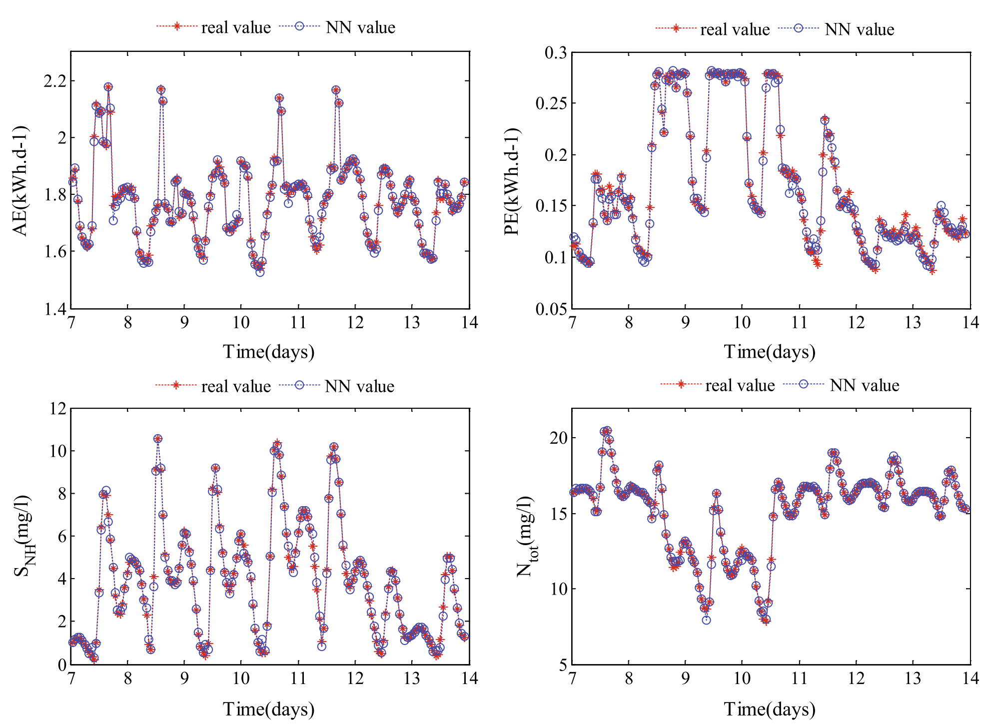

Fig. 6 Modeling performance of the energy consumption (AE and PE) and effluent parameters (S_{NH} and N_{tot}) in case 1

Table 3 Performance of the modeling network

	AE	PE	S_{NH}	N_{tot}
RMSE	0.0106	0.0052	0.0611	0.0436
DEVmax	0.0272	0.0133	0.2762	0.1993

networks can well approximate the real values of the WWTP. RMSE (root-mean-squared error between the evaluation values and the real values) and DEV^{max} (maximum value of the modeling errors) of the modeling NNs are within 0.07 and 0.3, respectively.

Case 2 In this case, performance functions are chosen as $f_1 = f_{AE} + f_{PE}$ and $f_2 = f_{EQ}$, that is, EC and EQ are optimized simultaneously. It should be noted that EC and EQ are a pair of conflicting indexes, and the fee of effluent discharge should be included into the treatment cost of the WWTP. For the plants, lower energy or cost is expected. The environmental protection departments pay more attention to the water protection, and the smaller EQ value is also expected. In this experiment, three different demands for the optimization are provided and described in Table 4, which means different utility functions can be obtained.

First, the data of the rain weather are used. Performance comparisons of the AE, PE, EC, EQ, S_{NH} and N_{tot} under three optimal cases, open-loop control and default PID control are reported in Table 5.

We can see that the lowest EC value is obtained in Case A (decrease by 5.25% compared with the default PID control), but the EQ value increases by 4.73% compared with the default PID control. For Case B, the EC and EQ have the median values among three optimal strategies. When EQ index is emphasized just as Case C, the EQ value increases by 1.06% compared with the default control and the energy saving is still achieved (decrease by 2.36% compared with the default control).

Figure 7 demonstrates the optimal set-points of DO concentration and nitrate level, and tracking control performance under DMOOC for Case C.

The simulation results show that the set-points of DO concentration and nitrate level are dynamically optimized during the treatment process and the lower-layer controller can well track the optimal set-points, just as the case 1. Further, the dry weather and storm weather scenarios are also evaluated in this case, and performance comparisons of the AE, PE, EC, EQ, S_{NH} and N_{tot} are listed in Table 6.

From the results of dry and storm weather, it also can be seen that the EC under the DMOOC is significantly reduced compared with the default PID control, while the effluent parameters meet the specified standards. Under the dry weather, the EC is reduced by 5.14%, 3.17% and 2.42% for Case A, Case B and Case C, respectively. For the storm weather, these values are 5.99%, 3.88% and 2.64%, respectively. Similarly, a tradeoff between EC and EQ can be achieved using the DMOOC. It should be noted that the lower EC is paid more attention for the current treatment plant.

From the theoretical point, the approach adopted in this paper can be applied to the real-time optimization of WWTPs. Firstly, a WWTP system belongs to a slow time-varying control system; the modeling and optimization algorithm employed in this paper can meet the time requirement. Secondly, measuring instruments used in WWTPs are becoming more and more precise and popular, which is convenient to employ the NN modeling technology and will improve the control performance further.

5 Conclusions

Optimization control strategies provide significant benefit for energy saving of the WWTP. However, it is a challenging task that the performance indexes of EC and EQ

Table 4 Description of three different demands for the optimal control of the WWTP in case 2

	EC weight	EQ weight	Description
Case A	1	0	Energy saving preferred
Case B	0.5	0.5	Equal importance of energy saving and effluent quality
Case C	0.2	0.8	Effluent quality preferred

Table 5 Performance comparisons with different control strategies in case 2

Weather	Method	AE	PE	EC	Up/down	EQ
Rain	Open-loop	3341.26	388.16	3729.42	–	8147.34
	PID	3663.01	253.72	3916.72	–	7592.88
	Case A	3421.96	289.13	3711.10	5.25%	8013.19
	Case B	3534.32	259.90	3794.22	3.13%	7780.04
	Case C	3565.78	258.504	3824.28	2.36%	7674.03

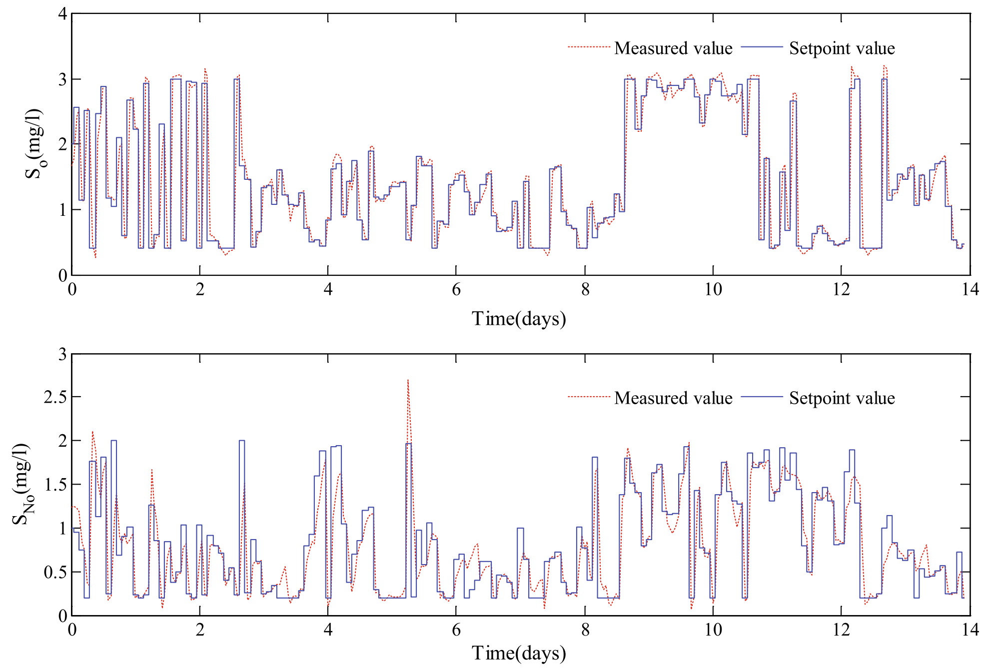

Fig. 7 Optimal set-points and tracking performance of Case C under the DMOOC in the rain weather

Table 6 Performance comparisons of different control strategies in the dry weather and storm weather scenarios for case 2

Weather	Method	AE	PE	EC	Up/down	EQ	N_{tot}	S_{NH}
Dry	Open-loop	3341.26	388.15	3729.28	–	7027.83	15.74	4.69
	PID	3675.07	231.47	3906.54	–	6567.31	17.30	2.42
	Case A	3461.61	244.02	3705.63	5.14%	6965.84	17.07	3.70
	Case B	3515.32	246.05	3761.37	3.71%	6898.17	17.15	3.44
	Case C	3577.80	233.84	3811.64	2.42%	6834.45	17.33	3.19
Storm	Open-loop	3341.26	388.16	3729.38	–	7687.46	15.62	5.01
	PID	3685.87	243.99	3929.87	–	7111.87	16.88	2.69
	Case A	3425.43	268.88	3694.32	5.99%	7561.50	16.35	4.13
	Case B	3528.17	249.08	3777.25	3.88%	7507.52	16.88	3.75
	Case C	3623.06	239.13	3862.19	2.64%	7443.85	17.22	3.40

are considered simultaneously during the complex treatment process. In this paper, a DMOOC scheme is proposed for the WWTP. The set-point values of DO concentration and nitrate level can be dynamically optimized with multiple performance indexes simultaneously. The difficulty of establishing MOO model for the WWTP is solved by the neural network online modeling method. The results show that DMOOC can significantly reduce the energy consumption while meeting effluent requirements, and a tradeoff between EC and EQ can be considered as well. The proposed strategy is more flexible and reasonable than the single-objective optimization for the WWTP and indicates dynamic multi-objective optimization control is a promising strategy that can further improve the optimal performance of the WWTP.

Nevertheless, some issues still remain to be addressed for the multi-objective optimization of the WWTP. Following work of our team includes two aspects. One is to construct the interpretable MOO model. In this paper, the MOO model is constructed by the neural network online modeling method. However, it is favorable that the understandable mechanism knowledge can be added to the modeling such that the optimization problem described is more practical and transparent. The other is to improve the MOO algorithm. NSGA-II has been verified to be an excellent MOO algorithm, especially under two objectives. However, there will be more than two objectives to be optimized for further improving the optimal performance.

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