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Intelligent Control of Wastewater Treatment Processes Based on Adaptive Immune Optimization

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Keywords

wastewater treatment process, self-organization fuzzy neural network, immune multi-objective optimization, intelligent control system, energy consumption

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Keywords: wastewater treatment process; self-organization fuzzy neural network; immune multi-objective optimization; intelligent control system; energy consumption

基于自适应免疫优化的污水处理过程控制

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摘要：为解决污水处理过程控制中能耗过高、出水水质差的问题，提出一种基于自适应免疫优化(AIOIC)的智能控制系统。设计*分层控制策略*，采用基于奇异值分解的快速在线自组织模糊神经网络(SVDFNN)构建污水处理能耗和出水水质模型。采用自适应*混合免疫优化算法*，获得最佳的溶解氧和硝态氮设定值。利用底层的*自组织递归模糊神经网络控制器*跟踪该优化设定值。结果表明：所提出的免疫优化智能控制策略不仅能满足出水水质标准，而且能显著降低污水处理能耗。

关键词：污水处理；自组织模糊神经网络；免疫多目标优化；智能控制系统；能耗

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Introduction

In order to study how to reduce costs based on ensuring the effluents quality to meet standards for the wastewater treatment processes (WWTPs), some

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scholars have built loss function by weight factor, which transforms the problem of multi-objective optimization, including energy consumption (EC) and quality effluent DOS (EQ) into a single objective optimization problem[1]. However, it is difficult to determine the weight factor of the method and achieve the ideal balance between EQ and effluent EC. Zeng et al. applied the economic model for model forecasting control (EMPC) to optimize the EC and EQ[2]. However, due to the complexity of the WWTPs process, it is difficult for the single objective optimization method to reflect the balance between related objectives (EC and EQ), and the determination of the weight coefficient is random and subjective[3]. Therefore, these methods are not the best way to solve the multi-objective problem of WWTPs[4-5]. To better control the WWTPs process, multi-objective optimization control method has received a lot of attention[6]. For example, Dai et al. proposed a multi-objective optimization algorithm to solve the contradiction between EQ, EC and operational stability[7]. The results show that the multi-objective optimization method has more effective control function than the traditional method. Han et al. has presented a nonlinear model-predictive control (NMPC) with a gradient multi-objective optimization method[8]. However, the gradient method is easy to fall into place ideal, so it is just difficult to get more quality dissolved oxygen point sets (S_{O}) and nitrate nitrogen (S_{NO}). To this end, the non-dominated sorting genetic algorithm (NSGAII) to optimize the control parameters of WWTPs is used in Ref. [9], so that the operation cost, greenhouse gas and pollution emissions can be minimized without redesigning or modifying the control strategy. However, this algorithm is a kind of random search algorithm, which has the problem of high operation frequency, slow convergence rate and poor resolution distribution[10]. An intelligent multi-objective optimization control (IMOOC), based on an adaptive multi-objective differential evolution algorithm (AMODE)[11], is proposed to seek out suitable set-points to balance treatment performance and operational costs. However, the above multi-objective optimization control methods still have the following problems: ① The WWTPs is highly nonlinear, and has the characteristics of fast fluctuation of inflow and limited storage space. Therefore, it is difficult to obtain accurate EC and EQ model in real time. ② The optimal adjustment values of dissolved oxygen and nitrate nitrogen in WWTPs are directly related to whether the EQ can meet the standard energy consumption[12]. Therefore, how to select the multi-objective optimization algorithm with better convergence and distribution is particularly important[12]. ③ It is very important to choose a suitable controller to track the optimal setting value with stable and high accuracy.

An optimized control strategy of WWTPs based on adaptive immune optimization is proposed. Based on the analysis of control parameter variables and operation parameter variables, the objective and operation performance of the sewage treatment plant are optimized, and the hierarchical control system of the sewage treatment plant is designed. The EC and EQ models of sewage treatment plant are optimized by multi-objective algorithm, based on the principle of adaptive combined immune complex (AUDHEIA), the selection is made on the basis of uniform distribution. The optimum value of oxygen and nitrogen dissolution was obtained. At the same time, the fuzzy neural network self-tuning controller is

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used to track the optimal parameters of S_O and S_{NO}[13]. In order to verify the effectiveness of the proposed multi-objective optimal control method, reference simulation model 1 (BSM1) is used to verify all the algorithms[14]. The results show that EC can be effectively reduced on the premise of improving EQ. Therefore, the optimal immune control strategy proposed in this paper can greatly improve the control efficiency of sewage treatment plant.

1 Wastewater treatment process analysis

In order to solve the problems of excessive EC and excessive EQ in the production of WWTPs, an adaptive immune optimization intelligent control system for WWTPs is proposed for its dynamic characteristics , which is a hierarchical control system. To optimize the layer, the upper layer adopts self-organizing fuzzy neural network, and establishes EC and EQ models. The EC and EQ are optimized using the previously developed AUDHEIA to obtain the optimal initial values of S_O and S_{NO}. The lower layer is the tracking control layer. For effectively tracking and controlling the real-time changing set values of S_O and S_{NO}, the self-organizing recursive fuzzy neural network is used as the controller.

WWTPs are affected by three kinds of weather, including dry weather, rainfall and stormy weather. To objectively evaluate the performance of control strategies, EC and EQ are used as evaluation criteria[12]. Among them, EC is mainly produced by aeration energy (AE) and pumping energy (PE), and EQ represents the tax or penalty paid to the acceptance of pollutants discharged from the water body[12].

2 Intelligent control based on immune optimization

An intelligent control system for WWTPs based on immune optimization is proposed in this paper, aiming at precise set point of S_O and S_{NO} and tracking control with high accuracy. As shown in Fig. 1, the structure of the control system has two layers[15]. Because of the coupling relationship between energy consumption (EC) and water quality (EQ), an artificial immune hybrid algorithm based on adaptive uniform distribution (AUDHEIA) is designed to obtain the best S_O value and S_{NO}, aiming at the problem of how to meet the discharge standards of effluent water quality while reducing operation costs. Fig. 1 shows that the layer is composed of a self-organizing fuzzy neural network (SOFNN) prediction model (Fig. 1B) and AUDHEIA (Fig. 1C). The next goal is to track and control S_O and S_{NO} set-points to obtain the minimum tracking error. In this paper, the SOFNN is used as the controller (Fig. 1D)[16].

In addition, in order to solve the multi-objective optimization problem of WWTPs, the optimization objectives need to be analyzed. It can be seen from formula (1)~(2) that EC is mainly related to the operating variables K_La_k and Q_a, while EQ is mainly related to the five effluent quality parameters. However, there is no clear mathematical relationship between EC, EQ and S_O, and S_{NO}[12]. At the same time, key EQ parameters that constitute the constraint conditions cannot be measured online. Therefore, firstly, on-line modeling of EC and EQ is needed. To establish an accurate soft sensor model, the optimized objective function is obtained by SOFNN prediction model[16].

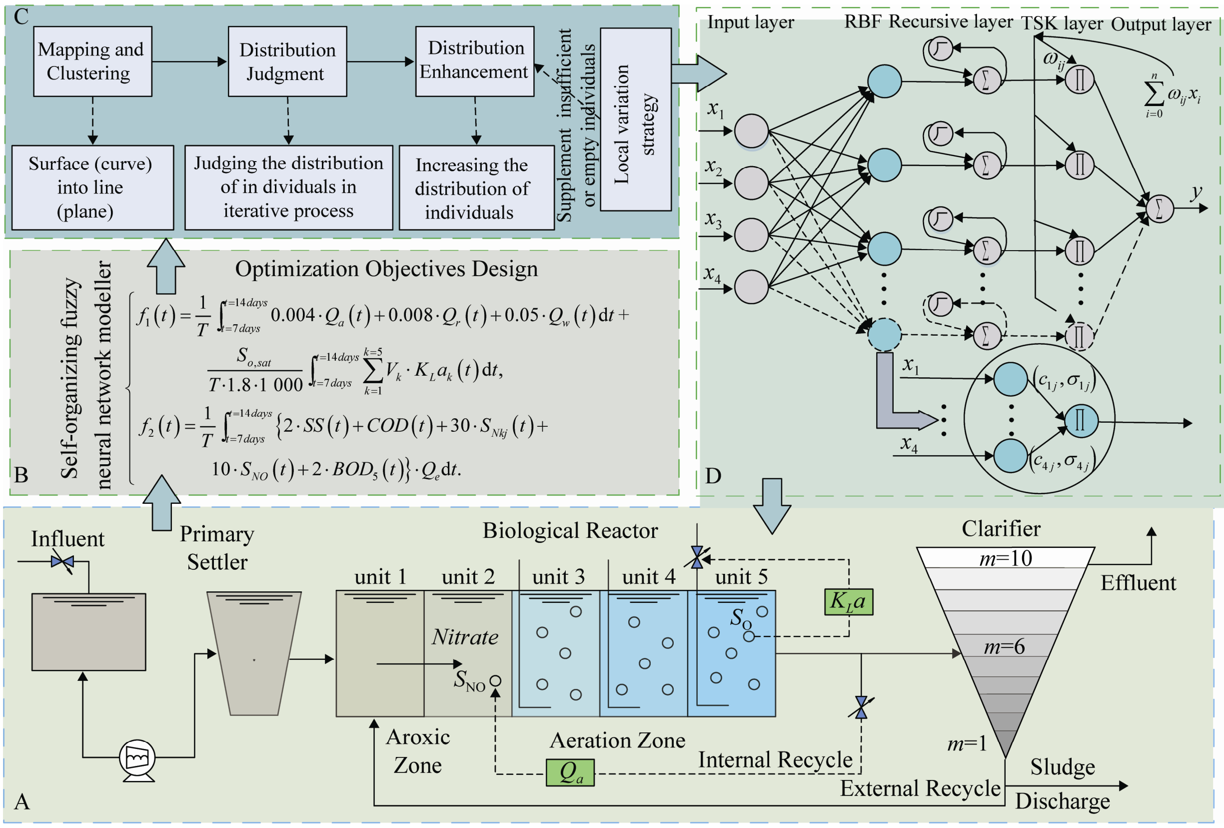

Fig. 1　Multi-objective optimization control architecture

2.1 Design of AUDHEIA

How to balance EQ and EC has become one of the key problems of WWTPs. Therefore, a set of higher quality candidate solutions for WWTPs' immune optimization intelligent control system is provided to achieve the minimum energy consumption under the premise of water quality standard. This paper recommends using AUDHEIA to optimize EC and EQ. The structure is shown in Fig. 1C. It consists of clustering and mapping module, distribution judgment module and distribution enhancement module. Among them, the local mutation strategy is used to supplement insufficient individuals.The purpose of optimizing EC and EQ[17] is:

$$\begin{aligned}&\min\left[f_1\left(\boldsymbol{S}_{\mathrm{op}}(t)\right), f_2\left(\boldsymbol{S}_{\mathrm{op}}(t)\right)\right]\\&f_1\left(\boldsymbol{S}_{\mathrm{op}}(t)\right)=\mathrm{EC}\left(\boldsymbol{S}_{\mathrm{op}}(t)\right),\\&f_2\left(\boldsymbol{S}_{\mathrm{op}}(t)\right)=\mathrm{EQ}\left(\boldsymbol{S}_{\mathrm{op}}(t)\right)\end{aligned}\tag{1}$$

The corresponding decision space is $\boldsymbol{S}_{\mathrm{op}}(t)=[\boldsymbol{S}_{\mathrm{op1}}(t), \boldsymbol{S}_{\mathrm{op2}}(t)]^{\mathrm{T}}$, $\boldsymbol{S}_{\mathrm{op1}}(t)=[S_{\mathrm{op11}}(t), S_{\mathrm{op12}}(t), \cdots, S_{\mathrm{op1Np}}(t)]$ and $\boldsymbol{S}_{\mathrm{op2}}(t)=[S_{\mathrm{op21}}(t), S_{\mathrm{op22}}(t), \cdots, S_{\mathrm{op2}N\mathrm{p}}(t)]$ respectively, which are S_{O} and S_{NO} concentrations at time t; N_{p} is the population size, and the initial value of $\boldsymbol{S}_{\mathrm{op}}(t)$ is generated randomly. In addition, the optimal solution $\boldsymbol{S}^*_{\mathrm{op}}(t)$ chosen from the decision space is $\boldsymbol{S}^*_{\mathrm{op}}(t)=\left[S^*_{\mathrm{op1}}(t), S^*_{\mathrm{op2}}(t)\right]$ and $S^*_{\mathrm{op1}}(t), S^*_{\mathrm{op2}}(t)$ are a set of S_{O} and S_{NO} set-points, respectively, $0 < S^*_{\mathrm{op1}}(t) < 2.5\mathrm{g{\cdot}COD/m^3}$, $0 < S^*_{\mathrm{op2}}(t) < 2.5\mathrm{g{\cdot}N/m^3}$.

Because individuals are unevenly distributed during the iterative process, the types of clustering are unevenly distributed[17]. Therefore, how to distinguish and improve the distribution of individuals during the whole iterative process is very critical. The distributed enhancement module is designed to determine the distribution of individuals.

The module equally divides the target space and selects the same number of individuals from each section. The distribution is judged according to the number of clustering subgroups in each uniform segment interval. The specific descriptions are as follows:

$$\begin{cases} c_i(t) < \delta(t), \ Case\, 1 \\ c_i(t) = \delta(t), \ Case\, 2 \end{cases} \tag{2}$$

Case 1: Activate the distributed enhancement module.

Case 2: Select the first $\delta(t)$ individuals according to the crowding distance which are sorted from large to small[17].

The cluster number $c_i(t)$ is within the ith interval of the tth iteration. $\delta(t)$ is the threshold for the tth iteration. For the distribution of individuals constantly change, the value of $\delta(t)$ is adaptively set according to the distribution information (PS) as:

$$P_s(t+1) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\bar{M}_D(t+1) - M_{Di}(t+1)\right)^2} \tag{3}$$

Among them, $P_s(t+1)$ is information on population distribution in the $(t+1)$ iteration, N is the population size, $M_{Di}(t+1)$ is the minimum distance between the ith antibody and other individuals in Manhattan. $\bar{M}_D(t+1)$ is the average minimum distance from all Manhattan antibodies. The strategy for adjusting thresholds is as follows:

$$\delta(t+1) = \begin{cases} \delta(t)+1, & P_s(t+1) < P_s(t) \\ \delta(t)-1, & P_s(t+1) > P_s(t) \\ \delta(t), & P_s(t+1) = P_s(t) \end{cases} \tag{4}$$

$$\delta(1) = ceil\left(\frac{N}{K}\right), \min \delta(t) = \max(t) \tag{5}$$

Among them, $\delta(1)$ and min $\delta(t)$ are the initial and minimum threshold, respectively[17]. The threshold of the $(t+1)$th iteration is $\delta(t+1)$. To improve the convergence rate, the ratio between population size and clustering number is rounded as the initial threshold due to the weak distribution of individuals in the initial development phase. To ensure that individuals are selected in each group, the maximum number of groups for the entire time period is used as the lower limit. However, some intervals are smaller than others, and even some intervals are empty. Choosing individuals is a problem that needs to be solved. Therefore, the distribution enhancement module[17] is designed, which can keep the expanding individuals in a good distribution, the same number of individuals belonging to different polymer classes are selected in each interval.

Extreme optimization mutation strategy is adopted in order to solve individual shortage and empty problem at the above interval[18]. It is necessary to find an individual with the maximum crowding distance at intervals when the number of individuals in the interval is insufficient. At the same time, when the individual of the interval is empty, it need to find the two nearest which are far away. This paper adopts two local optimization strategies. Among them, the first mutation strategy only mutates one decision variable, because it can only search in a small range, so it has a strong ability of local adjustment. Another mutation strategy avoids falling into local optimum and improves search speed by mutating each decision variable.

2.2 SORFNN controller

Due to the large variation range of inflow flow and components in WWTPs, it is difficult to ensure that the fixed structure recursive fuzzy neural network controller (RFNN) can adapt to all working conditions. Because of the characteristics of WWTPs, a self-organizing RFNN (SORFNN) controller[16] is adopted to track S_O and S_{NO} sets. It ensures that the neural network can obtain the most compact structure

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with all the information. Its structure is shown in Fig. 1D. The SORFNN is composed of input layer, RBF layer, regression layer, fuzzy TSK layer and output layer. As seen in Fig. 1D, RBF layer includes obedience layer and regulation layer. The input layer is composed of four input variables[13]. They are the error and error change between the set value and the actual value of S_O and S_{NO}, respectively[13]. The network structure and parameters of the RBF layer are adaptively adjusted over time.

3 Simulation experiment

3.1 Experimental design

The aim of this section is to evaluate the S_O and S_{NO} control level through the intelligent multi-objective optimization algorithm proposed by WWTPs. All the experiments are carried out on BSM1 simulation platform, under Microsoft Windows 8 environment, and by Matlab 2014b programming. Computer processors are 3.6 GHz and 8 GB RAM. To understand objectively the results of the control strategy under different conditions, the data of fourteen days of the BSM1 database are used to simulate the weather conditions, in which the sampling interval is 15 minutes and the optimization period is two hours.

3.2 Control Results

The experiment adopts the method of simulating binary hybridization and polynomial variation. The crossover parameter η_c=20, and mutation parameter η_m=20, the probabilities of crossover and mutation are 0.9 and 1/N_d, respectively. The decision variables number is N_d, and the shape parameter N_{sp} is set to 11. In addition, the effectiveness of the proposed control strategy is proved by quadratic error integral (ISE) and absolute error integral (IAE)[19].

$$\begin{aligned} ISE &= \int_{t=7\mathrm{d}}^{t=14\mathrm{d}} e^2 \mathrm{d}t \Big/ (14-7), \\ IAE &= \int_{t=7\mathrm{d}}^{t=14\mathrm{d}} |e| \mathrm{d}t \Big/ (14-7) \end{aligned} \tag{6}$$

where e is the control error.

The algorithm is compared with five algorithms, they are MOOC[19], AMODE-PI[11], DMOOC[18], RTO-NMPC[20], AMODE-AFNN[21]. Fig. 2 shows the control effect of SORFNN controller tracking S_O, and Fig. 3 shows the control error.

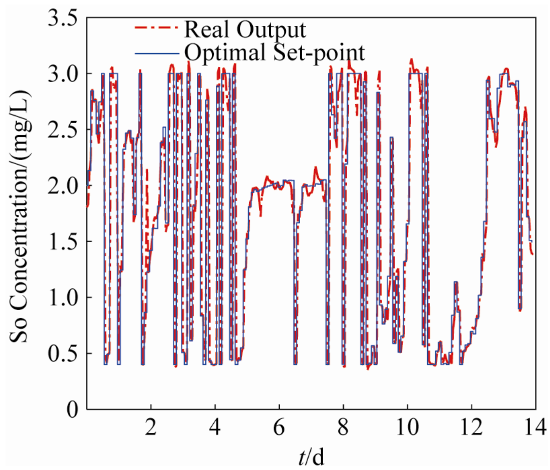

Fig. 2 Tracking results of SO in sunny weather

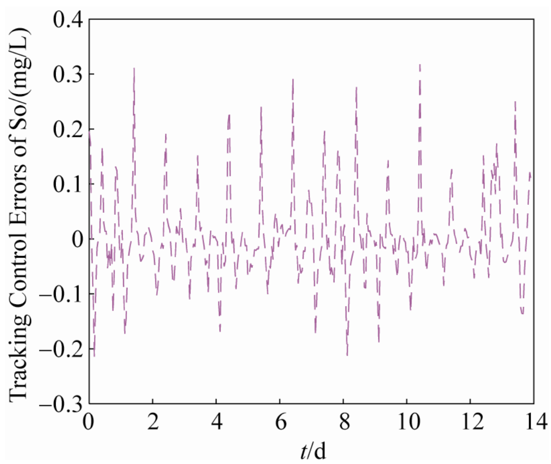

Fig. 3 Tracking errors of SO in sunny weather

Fig. 2 shows with RTO-NMPC, although EQ increases slightly (all in the case of water quality standards), control strategies can significantly reduce EC. Performance comparison of multi-objective optimization control strategies, MOOC[19], DMOOC[18], AMODE-PI[11], AMODE-AFNN[21] are used for comparison. The results in Tab. 1 show that compared with MOOC and DMOOC, while energy consumption increases, SORFNN controller can track realtime changes of S_O settings. The tracking error is shown in Fig. 4. Therefore, the error between the actual S_O output and the device optimization is always in the range of –0.3 ~ +0.35 mg/L. It shows that SORFNN controller can achieve small tracking error. Fig. 4 and Fig. 5 show the control effect and error. As shown in the figure, the error between the actual S_{NO} output and the installation optimization is always in the range of –0.4 ~ +0.6 mg/L, and the tracking error is small.

The results are shown in Tab. 1, showing the average power consumption and EQ, which are characterized by different optimal regulation strategies under sunny conditions. RTO-NMPC[20] is a nonlinear model predictive control based on real time optimization. The EQ and EC decrease significantly compared with RTO-NMPC in Tab. 1. Compared with AMODE-PI and AMODE-AFNN, the energy consumption controlled by AIOIC is obviously lower and the water quality is relatively higher, but all of them are within the standard range.

Tab. 1 Optimal control performance of different controllers in dry weather

Control Method	Computation time/s	EC(€/d)	EQ(kg/d)	ISE/(mg/L)		IAE/(mg/L)	
				S_O	S_{NO}	S_O	S_{NO}
AIOIC	185.36	730.20	7 256.50	**0.004 2**	**0.031 2**	**0.041 5**	**0.093 5**
MOOC	**180.26**	728.80	7 539.80	0.005 0	0.034 4	0.044 5	0.101 2
AMODE-PI	-	740.40	6 048.25	-	-	0.158 0	0.158 0
DMOOC	197.71	**722.41**	7 867.17	0.007 9	0.067 1	0.051 9	0.119 7
RTO-NMPC	200.11	740.00	7 102.90	0.008 6	0.078 0	-	-
AMODE-AFNN	-	736.10	**6 045.62**	-	-	0.092 0	0.092 0

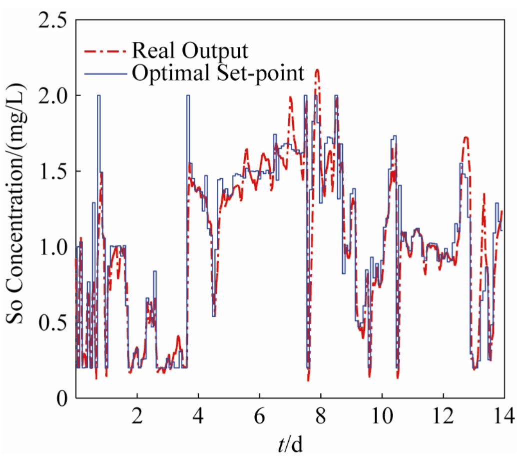

Fig. 4 Tracking results of SNO in sunny weather

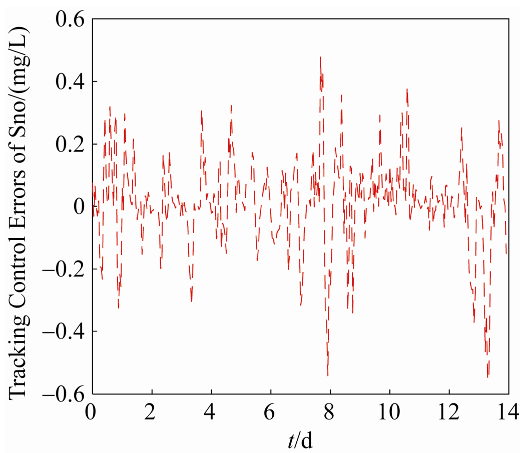

Fig. 5 Tracking errors of SNO in sunny weather

At the same time, the control performance of AIOIC is evaluated by ISE and IAE. As shown in Tab. 1, the results of ISE and IAE, S_O and S_{NO} are the least. In summary, AIOIC is superior to most control strategies in energy consumption except MOOC[19] and DMOOC[18]. Moreover, besides AMODE-PI[11], RTO-NMPC[20] and AMODE-AFNN[21], AIOIC is superior to most control strategies in water quality. It has the minimum ISE and IAE values. Compared to the WWTPs control proposed above, the proposed multi-objective optimization control strategy can achieve more balance, thus having a better performance of optimization and control of high precision tracking[15]. The value of AIOIC is smaller than that of control strategy except AMODE-AFNN[21] and AMODE-PI[11]. But the EC of AIOIC is better than AMODE-AFNN and AMODE-PI. However, ISE and IAE values of S_O and S_{NO} are smaller than those of the other five control strategies. The IAE value of S_{NO} is slightly larger than that of AMODE-AFNN, and smaller than the other four control strategies. Therefore, under the condition of rainstorm, the management strategy can well balance the relationship between EC and EQ, and has a stable tracking control effect.

4 Conclusion

An immune optimization control strategy of WWTPs is proposed. Performance evaluation is based on environmental, economic and technical standards. The results show that AIOIC system can effectively improve the productivity of WWTPs. The conclusions are as follows:

(1) In order to meet the standards of water quality and minimum EC, an AUDHEIA algorithm is proposed, which can determine the optimal parameters of S_O and S_{NO}. The algorithm improves the decision allocation in the search process through distributed judgment module and distributed module. Therefore, the AUDHEIA algorithm proposed in this paper has better convergence, so as to provide a set of higher quality candidate solutions for intelligent optimal control system of WWTPs.

(2) The SORFNN controller is studied. The RFNN and nonlinear mapping ability are used to effectively approximate the nonlinear dynamic relationship in the management of WWTPs. At the same time, RFNN is used to adapt to the change of real-time operation mode.

(3) The proposed AIOIC system consists of two layers. The upper structure is based on the autonomous model of fuzzy neural network, and the EC and EQ models are based on the optimization of objective function. The optimal set-points are obtained by AUDHEIA optimization algorithm. The substructure is a self-adjusting FNN controller for tracking the most suitable fixed points of S_O and S_{NO}, purchased by senior personnel. The EC is then significantly reduced while meeting the EQ standard.

It also provides a reference for researchers in the optimization design of WWTPs. In future research, dynamic multi-objective control optimization strategy will be developed to realize real-time optimization of S_O and S_{NO} parameters, so as to better deal with the changing process of WWTPs with the inflow flow and the inflow components, and thus improve the optimal control performance of WWTPs.

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