Fuzzy inference-based control and decision system for precise aeration of sewage treatment process

Wenru Zeng,1 Zhwei Guo,1 Huiyan Zhang,1 Jianhui Wang,1 Xu Gao,1 Yu Shen,1,2,* and Samir Ibrahim Gadow3

1National Research Base of Intelligent Manufacturing Service, Chongqing Technology and Business University, Chongqing, China
2Chongqing South-to-Thais Environmental Protection Technology Research Institute Co., Ltd., Chongqing, China
3National Research Centre, Cairo, Egypt

*Email: shenyu@ctbu.edu.cn

The sewage treatment systems manage to reduce pollutants of wastewater to make it reach some requirement. The core of it is to effectively control and determine intermediate aeration amount, which is always challenging. Therefore, a multi-objective planning mechanism (multi-objective optimization design combining GRA and fuzzy logic inference) that combines grey relational analysis and fuzzy logic inference, to find the optimal dissolved oxygen solubility for achieving better outlet water quality, is proposed. First of all, grey correlation coefficient between each optimization target and the reference target is calculated, and are converted into fuzzy inference values through the four steps. After that, it is expected to analyse the average values of process variables to obtain the optimal parameters combinations. A real-world dataset collected from a realistic sewage treatment plant is utilized as the simulation environment to evaluate the proposed multi-objective optimization design combining GRA and fuzzy logic inference. Experimental results show that the multi-objective optimization design combining GRA and fuzzy logic inference makes promotion of 47.34% for fitted outlet water quality compared with the original average annual water quality.

Introduction: The sewage treatment system (STS) is an imperative part of urban planning and construction management. The core of STS is to control the density of dissolved oxygen (DO/ml) in intermediate processes so that the index values of pollutants can be meet the standard [1]. Also, too high or too low DO density is detrimental to STS. Too low DO density will inhibit the metabolic rate of microorganisms, and make sludge bulking possible. As a result, the outlet water quality is not up to standard, especially the density of outlet NH3-N. Conversely, if DO density is too high, the endogenous respiration of microorganisms will affect the sedimentation performance and activity of activated sludge. This will result in wasted aeration volume and energy consumption, reducing aeration efficiency and oxygen transfer rate. Therefore, it is imperative to design a system that can determine the optimal aeration.

In addition, the processing results of STS usually need to meet multiple goals at the same time. However, the traditional fuzzy inference systems are used to solve single-objective optimization problems [2]. Therefore, this research introduces grey relational analysis (GRA), proposes a multi-objective optimization design combining GRA and fuzzy logic inference (MO-GF), and applies it to STS. First, perform a series of operations to obtain the grey fuzzy inference value of the DO process parameters of the A2/O process. Then, obtain the optimal parameter combination of the six oxic tanks through the analysis of means (ANOM), in order to solve the problem of difficult control of multiple sewage indicators in STS [3].

The workflow of MO-GF: (1) Determine multiple goals, process parameters and their levels, set up an orthogonal experiment matrix and test, and obtain a comparison sequence matrix \( X(k) \); (2) Normalize the test results, establish the grey correlation relationship, and obtain the matrix \( X_0^*(k) \); (3) Calculate the grey relational coefficient (GRA) \( \xi(k) \); (4) Use the membership function of \( \xi(k) \) to formulate fuzzy inference rules [4], use the maximum–minimum synthesis method for fuzzy inference, and select the Centroid method as the defuzzification operator; (5) Calculate the grey fuzzy inference value \( \eta \); (6) Perform ANOM on \( \eta \), construct a factor level effect diagram, optimize process parameters, and conduct experimental verification.

Grey relational analysis: GRA is a systematic analysis method to analyze and determine the influence degree of between factors, or the contribution degree of factors to the main behaviours [5]. The GRC describes the correlation degree of between a comparison sequence (a collection of measurement or experimental results) and a reference sequence (target value).

The specific calculation steps are as follows:

1. Establish the reference sequence \( X_0(k) \) and the sequence to be compared \( X(k) \).
2. Data normalization processing. Since the dimensions of each column in the comparison sequence are different, it needs to be normalized. Convert the value to a dimensionless decimal between (0, 1) to ensure the quality and reliability of the system analysis. The normalized comparison sequence is \( X_0^*(k) \).

Data normalization processing can be expressed as

\[
X_0^*(k) = \frac{\text{max}_i X_0^*(k) - X(k)}{\text{max}_i X_0^*(k) - \text{min}_i X(k)}, \quad (1)
\]

\[
X_0^*(k) = \frac{X(k) - \text{min}_i X(k)}{\text{max}_i X(k) - \text{min}_i X(k)}, \quad (2)
\]

where \( \text{max}_i X(k), \text{min}_i X(k) \) are the maximum and minimum values of \( X(k) \), respectively. Formulas (1) and (2) respectively represent that the smaller and larger the index, the better.

3. Calculate GRA, which is calculated as follows:

\[
\xi_i(k) = \frac{\Delta_{\text{min}} + \rho \cdot \Delta_{\text{max}}}{\Delta_{\text{max}}(k) + \rho \cdot \Delta_{\text{max}}}, \quad (3)
\]

where \( \Delta_{\text{max}}(k) = |X_0^*(k) - X^*_0(k)|, \text{min} \) and \( \text{max} \) are the maximum and minimum of \( \Delta_{\text{max}}(k) \), respectively; \( \rho \in [0, 1] \), it is the resolution coefficient, usually takes 0.5.

Calculate GRA \( r_i \), which is calculated as follows:

\[
r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k). \quad (4)
\]

Fuzzy logic inference: Fuzzy logic inference is to imitate the uncertainty concept judgment and reasoning thinking mode of the human brain [6]. As shown in Figure 1, fuzzy logic inference is composed of fuzzification module, fuzzy inference module and defuzzification module.

The fuzzification module maps the input to the proper membership function \( \mu(u) \). \( \mu(u) \) represents the membership relationship of the element \( u \) in the field \( U \) to the common set \( A, \mu_A(u) \in [0, 1] \) Among, the membership function is adopted to distinguish whether the elements in a set belong to a specific sub-set.

The fuzzy inference module formulates fuzzy rules and combines the results of all the rules. Fuzzy inference adopts the following “if-then” rules according to the form of generation rules:

- \( \text{if } \xi_1 = A_{11} \text{ and } \xi_2 = A_{12} \ldots \text{ and } \xi_3 = A_{13} \text{ then } \eta = D_1 \) else

Finally, the defuzzification module converts the combined result into a specific output value \( \eta \). \( \eta \) is the output result of defuzzification through the maximum–minimum composite fuzzy inference (Mamdani) and
Fig. 2 The technological process of A2/O sewage treatment plant

Table 1. Orthogonal factor level table

| Level | 1   | 2   | 3   | 4   | 5   |
|-------|-----|-----|-----|-----|-----|
| DO (ml) | 1-2 | 2-4 | 4-6 | 6-8 | 8-10 |

Fig. 3 Membership function of input and output

Centroid method. The calculation formula of Centroid method is as follows:

\[ \eta_0 = \frac{\sum \eta \mu_{D_0}(\eta)}{\sum \mu_{D_0}(\eta)} \]  

(5)

Data description: The data for this study comes from an A2/O sewage treatment plant in Chongqing, China. As shown in Figure 2, the plant consists of three series of A2/O tanks, and each series is divided into two groups. And set the DO density in Tank1-A, Tank1-B, Tank2-A, Tank2-B, Tank3-A and Tank3-B as A, B, C, D, E and F.

Orthogonal experimental design: In order to reduce the pollutant indicators of STS, this article takes output chemical oxygen demand (COD/ml) and output ammonia nitrogen (NH3-N/ml) as the experimental targets. And DO parameters in six oxic tanks are used as experimental factors. The experimental factors are the same chemical substance in different scenarios, so the setting level is consistent [7].

The test factor level table is shown in Tables 1 and 2, and Table 2 exhibits the orthogonal experimental design matrix.

Calculate GRC and grey fuzzy inference value: When performing GRA, it is necessary to perform normalization data processing on the comparison sequence. Reference sequence \( X_0 (k) = [1, 1, 1] \). According to STS requirements for outlet pollutants, the lower the outlet COD and NH3-N concentration, the better. Therefore, adopt formula (1) for normalization. GRC \( \xi (k) \) can be calculated by formula (5), and \( \rho \) is 0.5. The normalized comparison sequences \( X^*_k (\eta) \) and \( \xi (k) \) are displayed in Table 3.

In this fuzzy inference system, the grey correlation coefficients \( \xi (1) \) and \( \xi (2) \) of the outlet COD and outlet NH3-N are used as input, and the grey fuzzy inference value \( \eta \) is output. The input membership function curve and output membership function are demonstrated in Figure 3.

According to the “if-then” form, formulate nine fuzzy logic rules as follows in Figure 4. The regular surface description of outlet COD \( \xi (1) \), outlet NH3-N \( \xi (2) \) and grey fuzzy inference value \( \eta \) is shown in Figure 5.

Table 2. Orthogonal array of experiment and results

| NO. | A  | B  | C  | D  | E  | F  | Output COD | Output NH3-N |
|-----|----|----|----|----|----|----|------------|---------------|
| 1   | 1  | 1  | 1  | 1  | 2  | 2  | 20.26      | 1.99          |
| 2   | 1  | 1  | 1  | 2  | 1  | 4  | 23.43      | 1.39          |
| 3   | 1  | 2  | 4  | 1  | 4  | 2  | 22.74      | 2.86          |
| 4   | 1  | 3  | 1  | 1  | 4  | 3  | 26.67      | 2.47          |
| 5   | 1  | 4  | 2  | 2  | 4  | 5  | 23.69      | 2.24          |
| 6   | 1  | 2  | 3  | 2  | 3  | 5  | 17.49      | 2.11          |
| 7   | 2  | 1  | 3  | 2  | 1  | 2  | 16.85      | 0.83          |
| 8   | 2  | 2  | 4  | 2  | 3  | 3  | 29.24      | 2.52          |
| 9   | 2  | 3  | 2  | 2  | 4  | 4  | 20.05      | 1.09          |
| 10  | 2  | 2  | 2  | 3  | 2  | 5  | 27.08      | 3.08          |
| 11  | 2  | 4  | 1  | 1  | 5  | 5  | 26.51      | 2.96          |
| 12  | 3  | 1  | 2  | 2  | 3  | 2  | 36.61      | 3.76          |
| 13  | 3  | 2  | 2  | 2  | 2  | 5  | 34.33      | 4.67          |
| 14  | 3  | 3  | 3  | 3  | 5  | 2  | 32.16      | 2.50          |
| 15  | 3  | 4  | 1  | 1  | 4  | 4  | 35.63      | 2.40          |
| 16  | 4  | 1  | 1  | 2  | 1  | 2  | 35.84      | 3.94          |
| 17  | 4  | 1  | 3  | 3  | 4  | 2  | 32.16      | 2.50          |
| 18  | 4  | 1  | 2  | 1  | 3  | 3  | 30.21      | 3.28          |
| 19  | 4  | 2  | 2  | 2  | 5  | 2  | 31.00      | 1.67          |
| 20  | 4  | 2  | 3  | 3  | 4  | 4  | 35.26      | 2.74          |
Table 3. GRC and grey fuzzy inference grade

| NO. | ξ_i(1) | ξ_i(2) | η | Rank |
|-----|--------|--------|---|------|
| 1   | 0.83   | 0.70   | 0.74 | 0.62 | 0.67 |
| 2   | 0.67   | 0.85   | 0.60 | 0.78 | 0.63 |
| 3   | 0.70   | 0.47   | 0.63 | 0.49 | 0.58 |
| 4   | 0.50   | 0.57   | 0.50 | 0.54 | 0.50 |
| 5   | 0.65   | 0.63   | 0.59 | 0.58 | 0.56 |
| 6   | 0.97   | 0.67   | 0.94 | 0.60 | 0.80 |
| 7   | 1.00   | 1.00   | 1.00 | 1.00 | 0.94 |
| 8   | 0.98   | 0.99   | 0.97 | 0.98 | 0.94 |
| 9   | 0.84   | 0.93   | 0.76 | 0.88 | 0.74 |
| 10  | 0.48   | 0.41   | 0.49 | 0.46 | 0.49 |
| 11  | 0.54   | 0.44   | 0.52 | 0.47 | 0.50 |
| 12  | 0.00   | 0.24   | 0.33 | 0.40 | 0.40 |
| 13  | 0.12   | 0.00   | 0.36 | 0.33 | 0.36 |
| 14  | 0.37   | 0.56   | 0.44 | 0.53 | 0.49 |
| 15  | 0.05   | 0.59   | 0.34 | 0.55 | 0.46 |
| 16  | 0.04   | 0.19   | 0.34 | 0.38 | 0.39 |
| 17  | 0.23   | 0.56   | 0.39 | 0.53 | 0.47 |
| 18  | 0.32   | 0.36   | 0.43 | 0.44 | 0.48 |
| 19  | 0.28   | 0.78   | 0.41 | 0.70 | 0.56 |
| 20  | 0.07   | 0.50   | 0.35 | 0.50 | 0.46 |

Figure 5, where X-axis denotes ξ_i(2), and Y-axis denotes ξ_i(1) and Z-axis denotes η. It can clearly display η under different combinations of ξ_i(2) and ξ_i(1).

Use the maximum–minimum synthesis method for fuzzy inference, and select the Centroid method as the defuzzification operator. And solved on Matlab fuzzy toolbox, the grey fuzzy inference value η is shown in Table 3.

Results and discussion: First, the experimental results in Table 3 are corresponding to the orthogonal matrix in Table 2. That is to calculate the average value of η under different levels of each process parameter. Then, compare the difference between the maximum mean value and the minimum mean value of each process parameter to analyse the influence of each process parameter on η. Among the average values corresponding to the process parameters, the maximum level is the optimization level of the process parameters. Finally, the optimal process combination is thus obtained.

Table 4. ANOM of grey fuzzy inference value

| Model | Outlet COD (ml) | Outlet NH3-N (ml) | Average rate of reduction (%) |
|-------|-----------------|-------------------|-----------------------------|
| MO-GF | 17.15           | 0.86              | 47.34                       |
| AHP   | 20.73           | 1.51              | 25.80                       |

Table 5. Comparison of MO-GF and AHP

Subsequently, calculate the mean value of η under different DO densities of each oxic tank by ANOM. The specific calculation can be expressed as:

\[
\eta_i = \frac{\sum^n_{j=1} \eta_j}{n},
\]

where \(r\) denotes the serial number of the oxic tank, and \(i\) is the level of DO density. The average analysis result of η is exhibited in Table 4. It should be noted that “–” represents that the ANOM of η does not obtain a suitable value in the corresponding level. It can be seen from above table that when the DO content in Tank1-A, Tank1-B, Tank2-A, Tank2-B, Tank3-A and Tank3-B are at levels 2, 2, 4, 2, 3, and 3, η through the MO-GF proposed in this paper is the largest. According to the principle that the bigger the better, the optimal combination of process parameters can be obtained as A2-B2-C4-D2-E3-F3. And from the range of Table 4, it can be judged that the priorities of oxic tanks influencing the grey fuzzy inference value is: Tank3-B > Tank1-B > Tank3-A > Tank2-B > Tank2-a > Tank1-A.

Substituting the optimal parameter combination obtained by MO-GF into the original data fitting, the outlet COD content is 17.15 ml, and the outlet NH3-N content is 0.86 ml. Then, compare the outlet water quality fitted by the new optimal parameter combination with the annual average water quality of the original data. It is known that the outlet COD and outlet NH3-N content of the sewage treatment plant are 25.69 and 0.47 ml, respectively.

And compared with the optimization results of the common multi-objective planning method analytic hierarchy process (AHP), the comparison results are shown in Table 5. It is remarkable to observe from the table that the average reduction rate corresponding to MO-GF proposed in this study is higher than that of AHP. Therefore, the MO-GF has a good contribution to determining the aeration range in the oxic tank in STS.

Conclusion: In this letter, we propose an architecture for multi-objective optimization of STSs. Through the orthogonal experiment matrix and GRA, enumerate 20 possibilities in STS and covert the target value to GRC. Then, obtain the grey fuzzy inference value corresponding to each row in the orthogonal matrix through select a membership function, formulate fuzzy rules and defuzzification of a series of operations. In this way, the problem of this research is transformed into a single-objective
optimization system. The outlet water quality obtained by the proposed MO-GF fitting is 47.34% better than the original annual average water quality of STS.

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Ethical statement: This manuscript is original and has not been published elsewhere. And the study is not split up into several parts to increase the quantity of submissions and submitted to journals over time. Besides, this article does not contain any studies with human participants or animals performed by any of the authors. All the experiments were conducted on computers via programming design.

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