

Optimal design activated sludge process by means of multi-objective optimization: case study in Benchmark Simulation Model 1 (BSM1)

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ABSTRACT

Optimal design of activated sludge process (ASP) using multi-objective optimization was studied, and a benchmark process in Benchmark Simulation Model 1 (BSM1) was taken as a target process. The objectives of the study were to achieve four indexes of percentage of effluent violation (PEV), overall cost index (OCI), total volume and total suspended solids, making up four cases for comparative analysis. Models were solved by the non-dominated sorting genetic algorithm in MATLAB. Results show that: ineffective solutions can be rejected by adding constraints, and newly added objectives can affect the relationship between the existing objectives; taking Pareto solutions as process parameters, the performance indexes of PEV and OCI can be improved more than with the default process parameters of BSM1, especially for N removal and resistance against dynamic $\text{NH}_4^+\text{-N}$ in influent. The results indicate that multi-objective optimization is a useful method for optimal design ASP.

Key words | activated sludge process, BSM1, multi-objective optimization, non-dominated sorting genetic algorithm-II, optimal design, trade-offs

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INTRODUCTION

Operators of wastewater treatment plants are often reluctant to test new or different design or control strategies on a real plant because of the potential for unexpected behavior in the process (Benedetti *et al.* 2010). However, mathematical models can be useful tools for solving this problem and for identifying the different sources of uncertainty. Therefore, some earlier studies have used the mathematical model to analyze and design the activated sludge process (ASP) (Ossenbruggen *et al.* 1996; Flores-Alsina *et al.* 2012). To date, several mathematical models for ASP have been widely used, especially the activated sludge model (ASM) series (Henze *et al.* 2000).

Evaluating strategies for ASP does not just relate to one single objective, rather, it involves several objectives, such as effluent quality (Gernaey *et al.* 2004), operation cost (Vanrolleghem & Gillot 2002), as well as the stability of the strategies (Flores-Alsina *et al.* 2008). Obviously, these objectives must be taken into account simultaneously in the design and control process for ASP. However, the traditional method usually converts multiple objectives into a single objective function by weighting factors (Vanrolleghem *et al.* 1996; Guerrero *et al.* 2011). Although this method simplifies the optimization process, the weighting factors are sometimes

hard to determine and could lead to the wrong set of operation conditions. Usually, only one optimal solution can be obtained with the traditional method, and the decision makers (DM) have no other choice. Fortunately, the multi-objective optimization method can optimize different objectives simultaneously without weighting factors, and a set of equally good solutions named Pareto solutions can be obtained, which offer the trade-offs between different objectives (Cohon 2004). This provides a big benefit to DM because they are able to make their own decision after evaluating the trade-offs.

Problems involving multiple objectives are called multi-objective optimization problems (MOOP); to date, increasing numbers of researchers have concentrated their interests on these problems (Coello Coello 2006; Rangaiah 2009). However, very few published works (Flores-Alsina *et al.* 2008; Beraud *et al.* 2008; Hakanen *et al.* 2011) have considered multi-objective methods in ASP. Instead, they have mainly used this method in control strategies to obtain optimized setpoints for some important parameters (Beraud *et al.* 2008; Hakanen *et al.* 2011), and for evaluating the influence of input uncertainty in the decision making process (Flores-Alsina *et al.* 2008). Methods for solving MOOP are

mainly based on genetic algorithms, for example, the non-dominated sorting genetic algorithm (NSGA) (Deb et al. 2002).

The main objective of this paper was to optimally design ASP using a multi-objective optimization method, and the results showed that the optimized strategy exhibited better effluent quality and energy consumption.

MATERIAL AND METHODS

Benchmark process

With the aim of comparing process performance using different parameters, this research used the benchmark process in the COST/IWA Benchmark Simulation Model 1 (BSM1) (Copp 2002) as a case study. The benchmark process enables the comparison of different control strategies fairly, and many control methodologies have been tested (Shen et al. 2008; Belchior et al. 2012).

The layout of BSM1 is shown in Figure 1. There were three weather influents (dry, rain and storm) for BSM1, and each influent contained 14 days' worth of dynamic data with a sample time of 15 minutes. The biological tanks were simulated by the ASM1 model (Henze et al. 1987) and the clarifier was separated into ten layers and simulated with the solid flux model using the double-exponential setting velocity function of Takács (Takács et al. 1991).

Formula for the multi-objective optimization problem

Four objectives, 11 decision variables and their constraints are introduced in this section.

Objectives

This research employed four objectives to evaluate strategies for BSM1, which were percentage of effluent violation

(PEV, %), overall cost index (OCI), total volume (TV, m³) and total suspended solid (TSSa5, mg/L). The first objective, PEV, was to calculate the total '% of time in violations' for effluent chemical oxygen demand (COD) (≤ 100 mg/L), biochemical oxygen demand (BOD₅) (≤ 10 mg/L), NH₄⁺-N (≤ 4 mg/L), TN (≤ 18 mg/L) and TSSe (≤ 30 mg/L). The second objective, OCI, was calculated according to Equation (1), where AE (kWh/d) is aeration energy, PE (kWh/d) is pumping energy and SP (kgSS/d) is the sludge production to be disposed of. AE and SP are calculated based on Equation (2) and Equation (3), respectively, where $K_L a$ represents the oxygen transfer coefficient (d⁻¹), Q_a (m³/d) is mixed liquor return rate, Q_r (m³/d) is sludge return rate, and Q_w (m³/d) is excess sludge wasting rate. The third objective, TV, comprises the volume of five tanks, which is calculated as Equation (4), where V_i refers to the volume of the i th biological tank. The last objective, TSSa5, represents average TSS in tank 5. The first two objectives were the principal, while TV was mainly used for optimizing the volume distribution between anoxic and aerobic tanks and the last could limit the sludge concentration in tanks, thereby avoiding excessive loading for the clarifier. All necessary calculation formulas can be found in Copp (2002). It must be pointed out that the usable data cover the last 7 days

$$\text{OCI} = \text{AE} + \text{PE} + 5 \cdot \text{SP} \quad (1)$$

$$\text{AE} = \frac{24}{T} \int_{t=7 \text{ days}}^{t=14 \text{ days}} \sum_{i=1}^{i=5} [0.4032 \cdot K_L a_i(t)^2 + 7.8408 \cdot K_L a_i(t)] \cdot dt \quad (2)$$

$$\text{PE} = \frac{0.04}{T} \int_{t=7 \text{ days}}^{t=14 \text{ days}} [Q_a(t) + Q_r(t) + Q_w(t)] \cdot dt \quad (3)$$

$$\text{TV} = V_1 + V_2 + V_3 + V_4 + V_5 \quad (4)$$

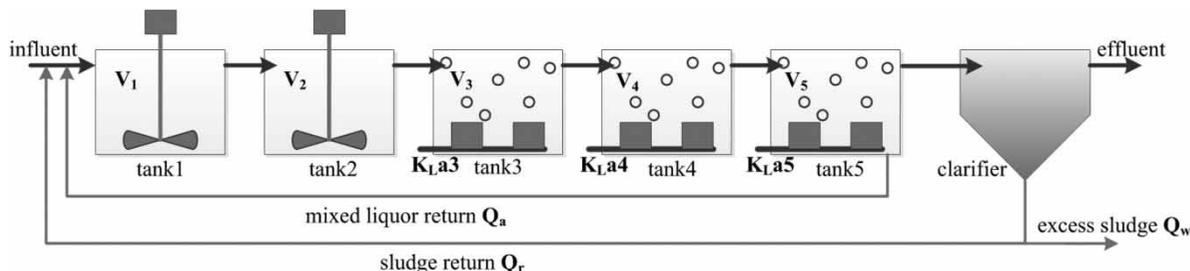


Figure 1 | BSM1 benchmark layout.

Decision variables and constraints

There were 11 decision variables ($V_1, V_2, V_3, V_4, V_5, Q_a, Q_r, Q_w, K_{La3}, K_{La4}$ and K_{La5}) for the multi-objective optimization models and the limits of these decision variables mainly made up the constraints. The lower limits of V_i were set to 300 m^3 instead of 0, which ensured that there were five tanks. Others were set to 0. The upper limits of the 11 decision variables estimated according to default values are: $1,500 \text{ m}^3, 1,500 \text{ m}^3, 2,000 \text{ m}^3, 2,000 \text{ m}^3, 2,000 \text{ m}^3, 70,000 \text{ m}^3/\text{d}, 25,000 \text{ m}^3/\text{d}, 700 \text{ m}^3/\text{d}, 300 \text{ d}^{-1}, 300 \text{ d}^{-1}, 300 \text{ d}^{-1}$. In fact, the goal was not to overly constrain the research space so that the algorithm would not miss any potential solution (Beraud *et al.* 2008).

Cases

This study built four cases to analyze the roles of the objectives and constraints.

Case 1:

Minimize $f = (\text{PEV}, \text{OCI})^T$
Subject to $X \in S$

Case 2:

Minimize $f = (\text{PEV}, \text{OCI})^T$
Subject to $X \in S$
 $\text{PEV} < 14.88\%$

Case 3:

Minimize $f = (\text{PEV}, \text{OCI}, \text{TV})^T$
Subject to $X \in S$
 $\text{PEV} < 14.88\%$

Case 4:

Minimize $f = (\text{PEV}, \text{OCI}, \text{TV}, \text{TSSa5})^T$
Subject to $X \in S$
 $\text{PEV} < 14.88\%$

where $X = (V_1, V_2, V_3, V_4, V_5, Q_a, Q_r, Q_w, K_{La3}, K_{La4}, K_{La5})^T$, and S is the feasible zone made up by the constraints (lower and upper limits) of decision variables.

The programs of multi-objective optimization models were carried out in MATLAB and solved using the non-dominated sorting genetic algorithm II (NSGA-II) (Deb *et al.* 2002), which was provided by the optimization toolbox in MATLAB. Settings for NSGA-II parameters were determined using the default, except that the population size was 100 and the number of generation was 100.

RESULTS AND DISCUSSION

Constraints and objectives analysis

Tradeoffs between PEV and OCI in Case 1 and Case 2 under dry influent are shown in Figure 2(a) and 2(b). The difference between the two cases is the constraint $\text{PEV} < 14.88\%$. It can be seen that the Pareto solutions for Case 2 are more focused and all PEV values are no greater than 14.88% , (between 2.47 and 7.23%), while the maximum PEV of Case 1 is approximately 100%. High PEV values indicate poor effluent quality, which is not a desirable result for operators of wastewater treatment plants. Therefore, the availability of solutions is improved owing to the constraint.

In order to compare Case 2, Case 3 and Case 4, all objectives: PEV, OCI, TV and TSSa5, were calculated as shown in Figure 2(c)–2(e). In Figure 2(c), Case 2 shows that if the DM wants to achieve a solution that has better PEV performance, then the DM will have to pay more OCI and vice versa. Case 3 and Case 4 have no such obvious variation tendency because these two cases consider other objectives in their models; apparently the additional objectives affect the relation between PEV and OCI. At the same value of PEV, the OCI of Case 2 are lower than for Case 3 and Case 4, which means Case 2 consumes less energy without degrading the treatment performance, compared to Case 3 and Case 4. By analyzing the reasons, this study found that objective TV, which was not included in Case 2, was the main factor that caused big differences between cases.

As can be seen from Figure 2(d), all solutions for Case 2 have almost the same TV values, being about $6,650 \text{ m}^3$ while the TV values for Case 3 and Case 4 are widespread, from 5,784 to $6,610 \text{ m}^3$ and 5,699– $6,602 \text{ m}^3$, respectively separately. So Case 2 compromises TV to get better OCI performance. Larger TV values also explain the result that the PEV of Case 2 is distribution-concentrated and the maximum value equals 7.23%; nevertheless, it is about 14.88% for Case 3 and Case 4.

Figure 2(e) is the trade-offs between TSSa5 and PEV; TSSa5 values in Case 2 and Case 3 mostly remain at 5,000–5,150 mg/L. Case 4 has the requirement of minimizing TSSa5, therefore, the TSSa5 of Case 4 are mostly lower than Case 2 and Case 3.

Solutions analysis in Case 4

Based on the comparison of four cases, one optimized solution was selected from Case 4 to present the usefulness of the multi-objective optimization method in the optimal

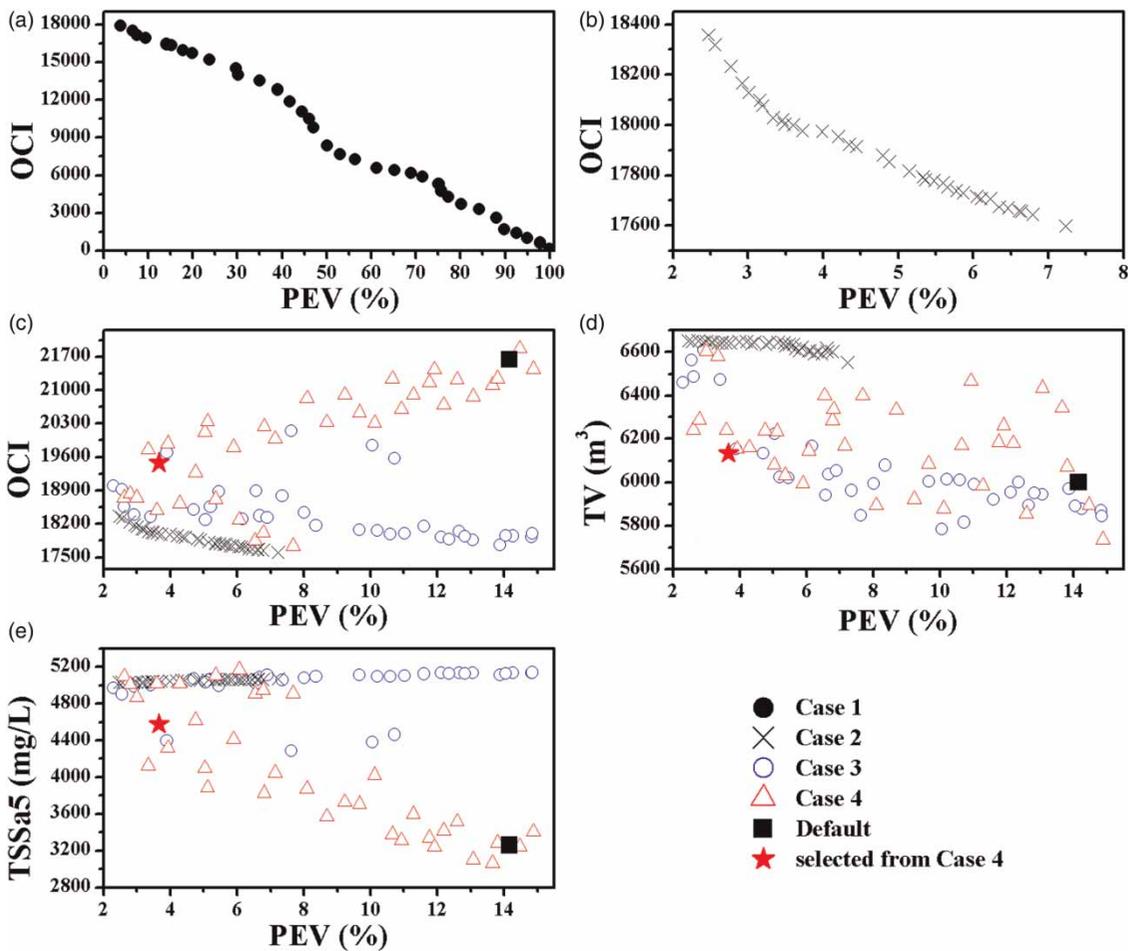


Figure 2 | Constraints and objectives analysis for four cases and the default strategy with dry influent.

design of ASP. The selecting criterion mainly referred to the minimization of PEV, OCI, TV and TSSa5. In fact, no solution could meet this criterion perfectly even though there were numerous solutions, which made the problem seemingly more complicated. However, the DM could exercise the power of decision-making based on his/her preference after evaluating the pros and cons between different solutions. The authors of this paper have selected one solution for further study, which is represented by the solid red star in Figure 2. Even though there are solutions with a smaller PEV and OCI (bottom left of Figure 2(c)), their TV and TSSa5 are overly compromised. The objectives' values for the selected solution and the default strategy are listed in Table 1, while the decision variables' values under dry influent are shown in Table 2. It can be observed that the optimized strategy performs better on effluent quality (PEV) and energy consumption (OCI), change (−74.16, −67.83, and −58.49%) and (−9.97, −9.92, and −9.71%) compared with the default strategy (represented by the

solid black square in Figure 2) under three weather influents, respectively; however, its TV and TSSa5 are compromised. The AE, PE and SP of the optimized strategy are all lower than the default. The effluent COD, BOD₅, NH₄⁺-N, TN and TSS_e of the default and the optimized strategy under dry influent are compared and shown in Figure 3.

It can be seen from Figure 3, under dry influent, that the effluent COD (Figure 3(a)), BOD₅ (Figure 3(b)) and TSS_e (Figure 3(e)) of the default and optimized solutions all meet the effluent standard: 100, 10 and 30 mg/L respectively. In addition, the relations are almost the same: optimized > default. The authors consider the reason behind this is that decision variable Q_w (Table 2) controlling the sludge retention time (SRT) is smaller in the optimized strategy than in the default, so the SRT is extended and the concentration of TSS in tanks is increased. As a result, the clarifier load will increase and the effluent may contain more particulate matter. Effluent NH₄⁺-N (Figure 3(c)) of the default and optimized strategies are sometimes below

Table 1 | Comparison performance of the default and optimized strategies under three influents (COD, BOD₅, TN, NH₄⁺-N, TSSe represent PEV (%); units of AE, PE, SP and TV are kWh/d, kWh/d, kgSS/d and m³, respectively)

	Dry		Rain		Storm	
	Default	Optimized	Default	Optimized	Default	Optimized
COD	0	0	0	0	0	0
BOD ₅	0	0	0	0	0	0
TN	1.64	0	0.86	0	1.64	0
NH ₄ ⁺ -N	12.53	3.66	12.74	4.38	12.89	5.24
TSSe	0	0	0	0	0.03	0.80
PEV ^a	14.17	3.66	13.60	4.38	14.56	6.04
AE	6,476	6,297	6,476	6,297	6,476	6,297
PE	2,967	2,634	2,967	2,634	2,967	2,634
SP	2,438	2,109	2,354	2,036	2,602	2,268
OCI ^a	21,631	19,475	21,214	19,110	22,453	20,272
TV ^a	5,999	6,134	5,999	6,134	5,999	6,134
TSSa5 ^a	3,256	4,578	2,978	4,170	3,229	4,438

^aFour objectives.**Table 2** | Values of decision variables in the default and optimized strategies under dry influent

Decision variables	V ₁ (m ³)	V ₂ (m ³)	V ₃ (m ³)	V ₄ (m ³)	V ₅ (m ³)	Q _a (m ³ /d)	Q _r (m ³ /d)	Q _w (m ³ /d)	K _{La3} (d ⁻¹)	K _{La4} (d ⁻¹)	K _{La5} (d ⁻¹)
Default	1,000	1,000	1,333	1,333	1,333	55,338	18,446	385	240	240	84
Optimized	1,093	879	1,314	1,478	1,370	47,637	17,982	230	227	238	87

required limits, but the values of the optimized strategy are always lower than for the default strategy. The effluent TN (Figure 3(d)) of the optimized strategy meet the effluent standard of 18 mg/L, indicating that the optimized strategy has better N removal efficiency. Moreover, it can be seen from Figure 3(c), that the optimized solutions have smaller variation scope than the default, which demonstrates that the optimized strategy has better resistance against the dynamics of NH₄⁺-N.

The benefits of this approach include the following:

- (i) Different objectives can be considered simultaneously instead of converting them into a single cost function, thus saving the effort of determining the effects of weighting factors in the cost function on the solutions obtained (Guerrero *et al.* 2011).
- (ii) Constraints can be used for limiting the range of some important variables, for example PEV in this paper, to make solutions more practical.
- (iii) The process parameters of BSM1 can be set as decision variables, indicating that this approach can be used for designing the ASP.

- (iv) There are other objectives that are important in optimizing an ASP, except effluent quality and energy consumption, such as TV and TSSa5. The motivations have been clearly shown in Figure 2.
- (v) There are lots of solutions for a multi-objective optimization problem, and more objectives make the optimization problem more complicated. However, the DM could exercise the power of decision-making based on his/her opinion or preference after evaluating the pros and cons between different solutions.
- (vi) Performance of the optimized process can be improved more than with the default process parameters of BSM1, especially for N removal and the resistance against dynamic of NH₄⁺-N.

CONCLUSIONS

This study optimally designs the benchmark process (BSM1) using the multi-objective optimization method, considering four objectives: PEV, OCI, TV and TSSa5, and 11 decision

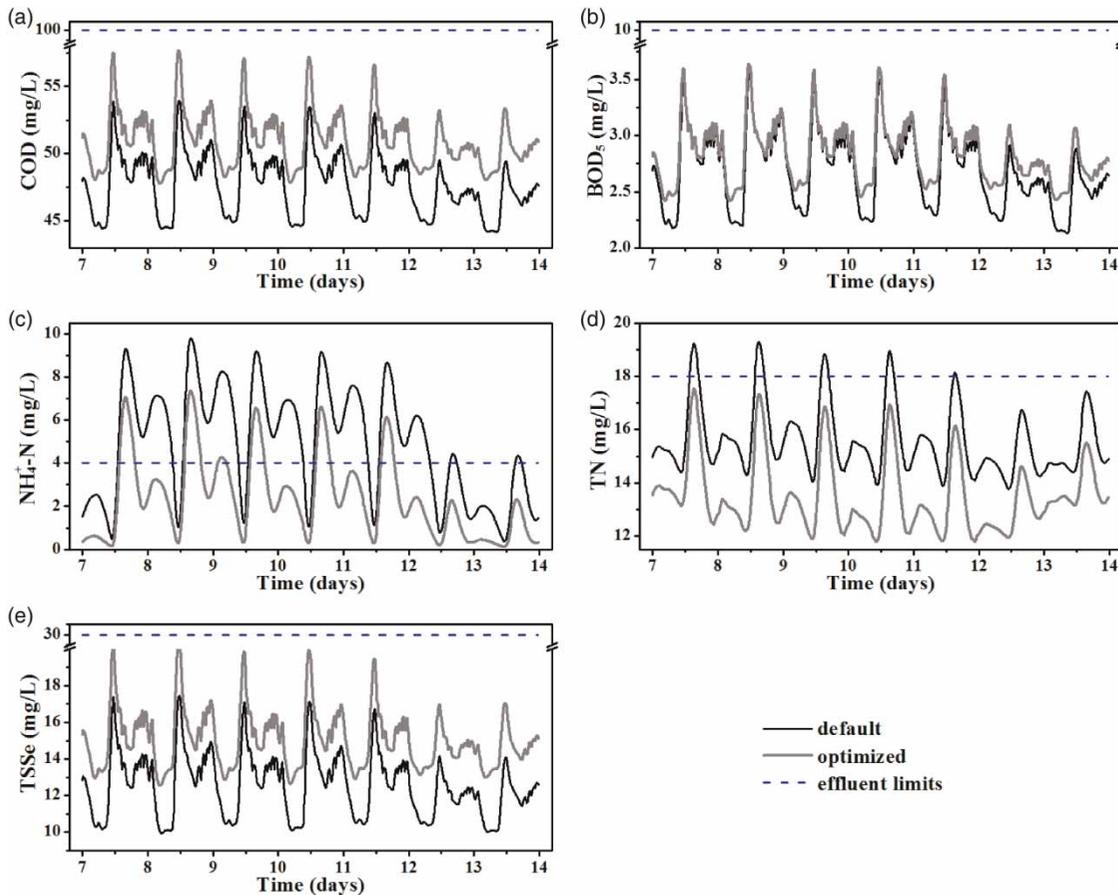


Figure 3 | Variations of effluent COD (a), BOD₅ (b), NH₄⁺-N (c), TN (d) and TSSe (e) of the last 7 days under dry weather influent.

variables. The authors analyze the effects of constraints and objectives on results of multi-objective optimization models through four cases. The results obtained from the case studies are very promising and the multi-objective optimization method can find tradeoffs among different objectives, rather than minimizing all of them. Therefore, the multi-objective optimization method is a useful tool for optimally designing ASP and it will improve effluent quality and save energy consumption.

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