The application of multi-objective optimization method for activated sludge process: a review

Hongliang Dai, Wenliang Chen and Xiwu Lu

ABSTRACT

The activated sludge process (ASP) is the most generally applied biological wastewater treatment approach. Depending on the design and specific application, activated sludge wastewater treatment plants (WWTPs) can achieve biological nitrogen (N) and phosphorus (P) removal, besides the removal of organic carbon substances. However, the effluent N and P limits are getting tighter because of increased emphasis on environmental protection, and the needs for energy conservation as well as the operational reliability. Therefore, the balance between treatment performance and cost becomes a critical issue for the operations of WWTPs, which necessitates a multi-objective optimization (MOO). Recent studies in this field have shown promise in utilizing MOO to address the multiple conflicting criteria (i.e. effluent quality, operation cost, operation stability), including studying the ASP models that are primarily responsible for the process, and developing the method of MOO in the wastewater treatment process, which facilitates better optimization of process performance. Based on a better understanding of the application of MOO for ASP, a comprehensive review is conducted to offer a clear vision of the advances, and potential areas for future research are also proposed in the field.

Key words | activated sludge models, activated sludge process, emission reduction, energy conservation, multi-objective optimization

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INTRODUCTION

With the rapid economic development and improvement of living standards, water resources consumption and wastewater emission volumes are sharply increased, thus aggravating the water shortages and eutrophication (Qu & Fan 2010). The fundamental way to protect water resources and improve the water environment is by controlling the source of sewage discharge, strictly limiting the emissions of nitrogen (N), phosphorus (P) and other nutrients to the natural water (Vymazal 2007). The activated sludge process (ASP) is the most commonly used biological wastewater treatment process due to the features of favorable effect, stable performance and lower cost (Hauduc *et al.* 2013). After 100 years of development, its focused research has evolved from achieving stable operation at the beginning, followed by meeting effluent standards, and now to the stage of energy conservation and emission reduction (Wett *et al.* 2007). Wastewater treatment is a high-energy consumption industry, and must be upgraded to prevent excessive growth of energy consumption in the circumstances of global energy shortage (Abma *et al.* 2010). In order to overcome the problems, a large number of wastewater treatment plants (WWTPs) through using new technologies, adding equipment and upgrading processes, have aimed to make the effluent meet the standard of wastewater discharge under energy conservation in different countries/regions (Jetten *et al.* 1997).

Currently, most literature has mainly focused on the technical aspects of the wastewater treatment process, such as using the variable frequency motor (Kalker *et al.* 1999; Springman & Marsch 2013), exploiting a novel wastewater treatment process (Khin & Annachhatre 2004; Shi *et al.* 2012; Lu *et al.* 2013) and employing intelligent systems to monitor the whole process (Dewettinck *et al.* 2001; Petrov *et al.* 2002). Few studies reported the trade-offs relationship between energy conservation and emission reduction in the wastewater treatment process, due to the fact that the ASP-based process is a complex system and requires dozens of experimental days to achieve the

doi: 10.2166/wst.2015.489

steady-state after each change of operating strategy (Flores-Alsina *et al.* 2008). Meanwhile, the conventional optimization method for ASP is a single objective by using linear programming (Vanrolleghem *et al.* 1996; Vanrolleghem & Gillot 2002; Iqbal & Guria 2009; Guerrero *et al.* 2011); it is difficult to deal with the trade-offs relationship between energy conservation and emission reduction. Furthermore, the uncertainty of weight coefficients among multiple objectives hampered the applications of converting multi-objective optimization (MOO) to single-objective optimization (SOO) (Guerrero *et al.* 2011, 2012; Hakanen *et al.* 2013). Therefore, assessing the performance and energy consumption of optimized processes was limited by estimating all related parameters, and a decision support tool which can take simultaneously these different objectives into account and help the designer to analyze their interdependencies is required. The above-mentioned approach enables a more realistic idea on how the WWTPs should be designed to balance the conflicting objectives.

The first Benchmark Simulation Model (BSM1) of ASP was released in 2002 by the International Water Association (IWA) (Copp 2002). Subsequently, an improved version of the Benchmark Simulation Model (BSM2) was presented in 2006 (Jeppsson *et al.* 2006, 2007). Both of them included the calculation methods for standard-exceeding indices of water quality and the amount of energy consumption. The water quality indices involved excessive effluent concentration of carbon, nitrogen and phosphorus. Energy consumption indices involved energy consumption of aeration, pump and agitation, etc. The calculation methods for the above-mentioned indices in BSMs provided significant scientific progress for the wastewater treatment process with regard to the trade-offs relationship between energy conservation and emission reduction (Abusam *et al.* 2004; Jeppsson & Pons 2004; Nopens *et al.* 2010; Guerrero *et al.* 2011, 2012; Belchior *et al.* 2012; Ostace *et al.* 2013).

ACTIVATED SLUDGE PROCESS AND ACTIVATED SLUDGE MODELS

ASP is an effective biological wastewater treatment method for organic wastewater treatment, especially for the urban sewage treatment (Seyssiecq *et al.* 2003; Bitton 2005; Ni & Yu 2012). The principle of ASP is that the formation of flocculent sludge is dependent on the aerobic microbial growth under continuous aeration in wastewater, and the flocculent sludge can adsorb and oxidize organic compounds due to the zooglea (Li *et al.* 2008). The process possesses the characteristics of outside interference, nonlinear, time-varying and tight coupling, because the survival principles and conditions of microorganisms in wastewater have not been fully investigated, and the field trials required a long period and high cost (Wu *et al.* 2007; Ratkovich *et al.* 2013).

A computer simulation model based on the principle of ASP seemed to be an important technique of researching related issues in the wastewater treatment process (Hauduc *et al.* 2013). On the basis of the simulation results, obtaining the automatic control rule has scientific significance for ensuring a stable operation system, optimizing system operation and lowering operating costs and nutrient emissions in wastewater treatment. There are two main reasons in favor of ASP modeling as follows: (i) the mathematical models contribute to realizing and describing the complexity of the activated sludge reaction, and then providing underlying theory for the actual process design in theoretical research; (ii) the mathematical model can simulate the dynamic process of the treatment operation and predict the effluent quality, so that accurately and timely measures could be taken according to the changing environment (water quantity, water quality and other parameters) (Ratkovich *et al.* 2013). Mathematical models show advantages in the diagnosis of operational problems, adjusting the sensitive variables (aeration, return flow, inflow, etc.) for the effectiveness of the process, providing theory for the operation optimization and facilitating the designer to select the most economically viable parameters from a variety of processes (Keskitalo & Leiviskä 2012).

The activated sludge models (ASMs) family was established as a standard for ASP modeling, and developed by a task group of the International Association on Water Quality (IAWQ) (Henze 2000). These are mechanistic models, in which the various phenomena occurring in the bioculture were described by first to third order differential equations. The reaction rates of different substances, e.g., fractions of organic carbon and nitrogen, are obtained by integrating the differential equations over time and factoring them with substance-specific stoichiometric coefficients. These coefficients are based on continuity of key parameters (total chemical oxygen demand, total nitrogen, total phosphorus and charge), which ensured model integrity. ASMs, as an important simulation and control system, have been widely used in environmental engineering for the biological wastewater treatment process (Henze 2000; Hauduc *et al.* 2013). Table 1 summarizes essential features of various ASMs.

The Activated Sludge Model No. 1 (ASM1) is considered as the reference model (Henze *et al.* 1987), since

Table 1 | Comparison of various ASMs

Models	Functions	Constituents	Reactions	Stoichiometric coefficients	Kinetic constants	References
ASM1	C and N removal	13	8	5	14	Henze *et al.* (1987)
ASM2	C, N and P removal	19	19	22	42	Henze *et al.* (1995)
ASM2D	C, N and P removal	19	21	22	45	Henze *et al.* (1999)
ASM3	C and N removal	13	12	15	21	Gujer *et al.* (1999)

this model triggered the general acceptance of WWTP modeling, first in the research community and later on also in industry. The basic concept of ASM1 was adapted from the activated sludge defined by (Dold *et al.* 1980), and the specific process is shown in Figure 1. The model focuses on describing the basic principles and related reactions of the activated sludge treatment method, and not only includes the removal of carbon-containing organic compounds, but also contains the nitrification and denitrification reactions. The concept of 'switching function' was also applied in the model to describe specific components that inhibited the reaction process. The ASM2 extends the capabilities of ASM1 to the description of bio-P removal. It contained P uptake and release, anaerobic hydrolysis, glycolysis and P-accumulating organisms (PAOs) of the four related reaction processes (Henze *et al.* 1995). Chemical P removal via precipitation was also included. The ASM2D model builds on the basis of ASM2, adding the denitrifying activity of PAOs because the dynamics of P and N removal were then better understood (Henze *et al.* 1999). In the ASM2D model, PAOs can utilize the organic compounds in the cell under the limited electron acceptor condition. Compared with the ASM2 model, the mechanism of P and N removal in the ASM2D is more accurate and close to the actual sewage treatment reaction process. The ASM3 model was also developed for biological N removal, with basically the same goals as ASM1 (Gujer *et al.* 1999). The ASM3 model is intended to become the new standard model, correcting a number of defects that have appeared during the usage of the ASM1 model (Krishna & Van Loosdrecht 1999). The substrate flows of ASM1 and ASM3 are shown in Figure 2.

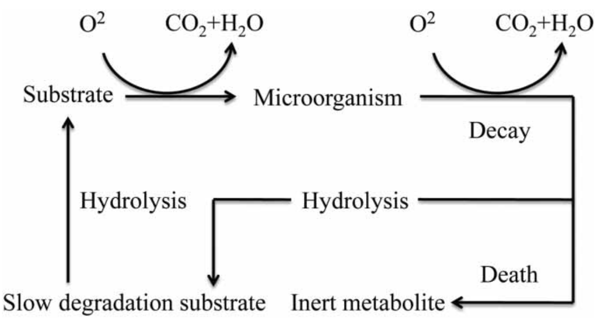

Figure 1 | Schematic diagram of death and regeneration theory. *Source:* redrawn from Dold *et al.* (1980), Copyright IWA Publishing.

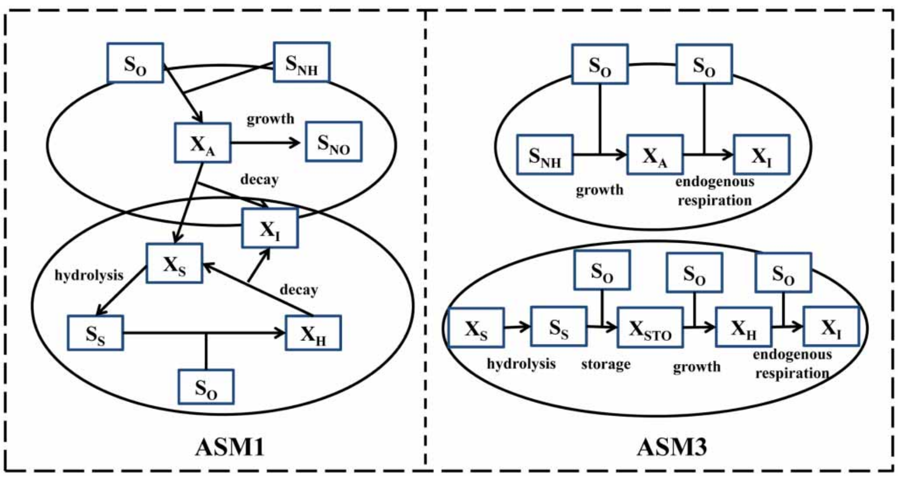

Figure 2 | Substrate flows in ASM1 and ASM3. *Source:* redrawn from Gujer *et al.* (1999), Copyright IWA Publishing.

THE OPTIMIZATION OF BIOLOGICAL WASTEWATER TREATMENT PROCESS

The theory of multi-objective optimization

The idea of MOO originated from the utility theory of economics and had first been proposed in the study of economic balance, and then the concept of Pareto optimal solution sets was introduced into the MOO (Carlos & Peter 1995; Marler & Arora 2004). MOO, as a new discipline in applied mathematics, is developing rapidly, and was applied in studying the optimization problems of the vector objective function that satisfied certain constraints. The study of MOO has aroused great concerns and attention due to the fact that it can provide an appropriate solution for the optimization process in many fields. Especially in the last 20 years, with the theoretical exploration deepening and application range extending, the rapid growth of the research community reflects a progressive enthusiasm. In general, many optimization problems in scientific research and engineering practice belong to MOO, and every optimization objective in the system must be restricted by decision variables. One of the optimization objectives must depend on other goals, but the unit of each objective is often inconsistent. So, it is difficult to assess the pros and cons of the solution (Li 2009). The mathematical form of MOO problems is shown in Equation (1):

$$\begin{aligned} &\text{Minimize} \quad f(x) = [f_1(x),\ f_2(x),\ \ldots\ldots,\ f_n(x)]^{\mathrm{T}} \\ &\text{s.t.} \quad x \in X \end{aligned} \tag{1}$$

In the formula, $f(x)$ is the optimization objectives; x, the decision variables; and X, the constraint condition.

The differences between single-objective and multi-objective optimization

MOO, a kind of operations research method, is suitable for complex multi-objective optimal decisions, and is developed on the basis of linear and nonlinear optimization. In contrast to SOO, the solution to a multi-objective problem is more of a concept than some absolute definition. Typically, there is no single global solution, and it is necessary to determine a set of points that all fit a predetermined definition for an optimum (Marler & Arora 2004). Solving MOO problems is regarded as finding the Pareto optimal solution which best satisfies the needs of a decision maker (DM). Thus, the final solution of a MOO method is often considered as the most preferred solution. Compared with SOO, the advantages of MOO are as follows: (i) MOO plays the role of analyst and DM for the optimization and decision-making process. Analysts optimize the actual problems and give feedback to DM, then DM can make a final decision based on the feedback information and personal preferences; (ii) MOO contains a wider range of solution sets, from which the preferred solution can be selected by DM; (iii) the participants may have a more accurate understanding on the practical issues that considered multiple objectives. Obviously, seeking the optimization points does not belong to the SOO of mathematical programming, but the MOO can solve this problem appropriately. MOO has become an effective tool for solving multi-objective decisions in modern management because it has the ability to handle multiple conflicting objectives.

Pareto solutions and non-dominated sorting genetic algorithms

The solution of MOO is called Pareto solutions or non-dominated solutions. As shown in Figure 3, considering the minimal optimization problem of two targets (Y1, Y2), the closed area represents all feasible solutions of the optimization process. The MOO solution is the boundary line composed of A, B, C, D, E and F. Compared to other feasible solutions, a better solution can always be found from the boundary line. For example, the two objective values in solution D are smaller than that in solution of H, I, J, K and L. All solutions on the boundary line exhibited good performance in the mathematical sense. For example, comparing solution B and C, the Y1 value in solution B is better than that in solution C, but the Y2 value in solution C is better

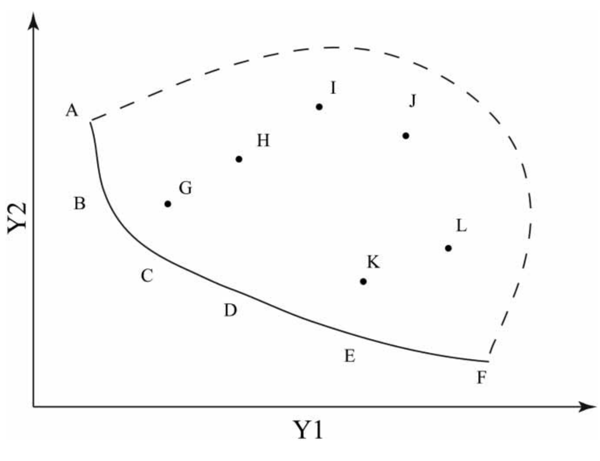

Figure 3 | Schematic diagram for Pareto solutions.

than that in solution B, so it is difficult to determine the better solution. The DM is required to choose the suitable solution under the practical issues.

With the improvement of the genetic-algorithms-based global search algorithm, the application of MOO had a rapid development in the engineering field. A genetic algorithm has the characteristics of ensuring the potential optimal solution, and can pass down from generation to generation, which is suitable to the search for Pareto solutions in MOO. The non-dominated sorting genetic algorithm (NSGA) was developed in 1994 (Srinivas & Deb 1994), and the second version of NSGA-II was proposed in 2000 (Deb *et al.* 2000). NSGA-II was integrated in the optimization toolbox of Matrix Laboratory (MATLAB) software for obtaining the Pareto solutions of MOO. In the NSGA-II, the fast non-dominated sorting method can reduce the complexity of calculation, and use the degree of congestion and comparison operators in the replacement of the fitness sharing strategy of the specify shared parameter (σshare). The calculation process of NSGA-II is shown in Figure 4 (Deb *et al.* 2000; Gao 2006).

The approaches used in optimization of ASP

Experimental method and computer simulation are recognized as vital approaches to weigh the relationship between energy conservation and emission reduction in ASP. In the experimental method, effluent quality and energy consumption are measured under different operation strategies, and the relationship between energy conservation and emission reduction is also studied. However, this is

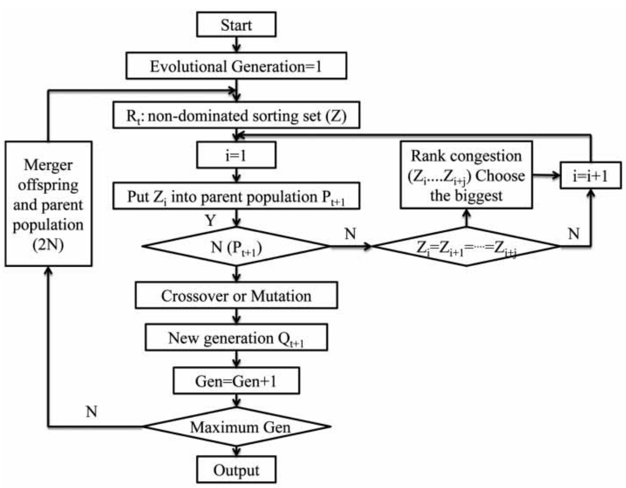

Figure 4 | Calculation process of NSGA-II. *Source:* adapted from Deb *et al.* (2000) and Gao (2006).

difficult to be applied in actual work because ASP contains multiple reactors, a recycle of mixed liquor and activated sludge. In addition, a lot of material and financial resources are consumed in the experimental process (Gernaey *et al.* 2004). In the computer simulation method, the mathematical optimization model is used to achieve the optimization of energy conservation and emission reduction. A mathematical model needs to be established and calibrated before studying the process (Sin *et al.* 2005). Then, the integrated model is investigated by using computer simulation which consists of process model and optimization system. It is the appropriate choice for using computer simulation to study the trade-offs relationship between energy conservation and emission reduction in ASP due to the fact that computer simulation possesses the characteristics of high-speed operation performance and large storage capacity, and various commercial software programs are available (Copp 2002; Gernaey *et al.* 2004; Jeppsson & Pons 2004).

The composition of multi-objective model and BSM1

In the MOO model, effluent quality (EQ), operation energy consumption (OC), the volume of reaction tank and sludge concentration, etc., were chosen as the objective function. The decision variables included the oxygen mass transfer coefficient, return flow of mixture and sludge, emission amount of sludge and the running time of different stages. The constraint condition was the range of objective function and decision variables (Jeppsson & Pons 2004). On the premise of effluent meeting the discharge standard, the goal of energy conservation and emission reduction in ASP is to reduce the management and operation costs, including chemical cost, sludge disposal cost, equipment power consumption and staff wages. In order to achieve these objectives, the intelligent control strategy of ASP is indispensable. At present, some researchers have developed a variety of control strategies for the ASP, e.g., adjusting the amount of aeration to control the concentration of dissolved oxygen in the aerobic tank (Ma *et al.* 2005) and monitoring the changes of water quantity and quality to conduct a feed-forward control in the processes (Holenda *et al.* 2008; Shen *et al.* 2008). Although these strategies could meet the requirements of energy conservation and emission reduction to some extent, it is difficult to compare and popularize these strategies due to the different evaluation criteria. These evaluation criteria included: (i) the structure of ASP; (ii) the interference of the external environment, including the deviation of on-line sensors; (iii) the calculation method for the evaluation index; and

(iv) the different wastewater drainage standards in various countries or regions. For a fair comparison of the pros and cons of various control strategies, it is particularly necessary to develop a complete set of benchmark processes.

The standardized simulation benchmark of a wastewater treatment process was originally developed by the first IAWQ Task Group on Respirometry-Based Control of the ASP. Subsequently, it was modified by the European Cooperation in the field of Scientific and Technical Research (COST) 682/624 Actions in cooperation with the second IWA Respirometry Task Group (Copp 2002). The simulation benchmark was developed to provide an unbiased benchmarking system for comparing various control strategies without reference to a particular facility. The layout of BSM1 is shown in Figure 5.

Four objectives are used to evaluate the strategies for BSM1; they are percentage of effluent violation (PEV, %), total volume (TV, m^3), OC and total suspended solids (TSS_a, mg/L). The first objective, PEV, was to calculate the total '%' of time in violations for effluent. The objective OC was calculated according to Equation (2), 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 PE are calculated based on Equation (3) and Equation (4), respectively, where K_La represents the oxygen transfer coefficient (d^{-1}), Q_a (m^3/d) is mixed liquor return rate, Q_r (m^3/d) is sludge return rate, and Q_w (m^3/d) is excess sludge wasting rate (Chen *et al.* 2014).

$$\mathrm{OC} = \mathrm{AE} + \mathrm{PE} + 5 \cdot \mathrm{SP} \tag{2}$$

$$\mathrm{AE} = \frac{24}{T}\int_{t_7}^{t_{14}} \sum_{i=1}^{5} [0.4032 K_L a_i(t)^2 + 7.8408 K_L a_i(t)]dt \tag{3}$$

$$\mathrm{PE} = \frac{0.04}{T}\int_{t_7}^{t_{14}} [Q_a(t) + Q_r(t) + Q_w(t)]dt \tag{4}$$

The objective TSS_a, representative of average TSS in tank 5, was calculated according to Equations (5), (6), (7) and (8). All necessary calculation formulas can be found in the literature reported by Copp (Copp 2002). It must be pointed out that the usable data cover the last 7 days.

$$\mathrm{TSS}(t) = \mathrm{TSS_a}(t) + \mathrm{TSS}_S(t) \tag{5}$$

$$\mathrm{TSS_a}(t) = 0.75 \sum_{i=1}^{5} (X_{S,i} + X_{I,i} + X_{BH,i} + X_{BA,i} + X_{P,i})V_i \tag{6}$$

$$\mathrm{TSS}_S(t) = 0.75 \sum_{j=1}^{10} (X_{S,j} + X_{I,j} + X_{BH,j} + X_{BA,j} + X_{P,j})z_j A \tag{7}$$

$$\mathrm{SP} = \frac{1}{T}\left(\mathrm{TSS}(14) - \mathrm{TSS}(7) + 0.75 \cdot \int_{t_7}^{t_{14}} (X_{S,w} + X_{I,w} + X_{BH,w} + X_{BA,w} + X_{P,w})Q_w(t)dt\right) \tag{8}$$

where TSS_S is total suspended sludge in settling tank; X_S is slowly biodegradable substrate; X_I is particulate inert organic matter; X_{BH} is active heterotrophic biomass; X_{BA} is active autotrophic biomass; X_P is particulate products arising from biomass decay; V is volume of settling tank; z is depth of settling tank; A is cross-sectional area of settling tank.

THE APPLICATION OF MOO IN WASTEWATER BIOLOGICAL TREATMENT PROCESSES

The application of MOO required a mathematical model which can simulate the relevant processes. Therefore, it has been widely applied in the field of chemical engineering because of the well-established mathematical models (Rangaiah 2009). Along with the development of MOO,

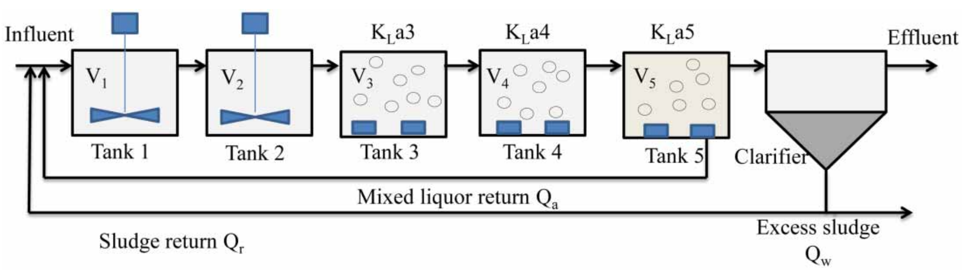

Figure 5 | Schematic representation of the BSM1.

calculation methods and related mathematical models' usability, MOO was used in the field of environmental engineering (Monarchi et al. 1973; Sasikumar & Mujumdar 1998; Anderson et al. 2005; Liu et al. 2013). But in the sewage treatment process, MOO only has a few applications, such as optimizing and designing the ASPs (Flores-Alsina et al. 2007; Beraud et al. 2009; Iqbal & Guria 2009); determining the optimal set-point value of internal control parameters in the sewage treatment system (Beraud et al. 2008; Hakanen et al. 2011; Guerrero et al. 2012; Chen et al. 2015); assessing the impact of the model parameters, water quality, water quantity and other uncertainties for the decision-making process (Flores-Alsina et al. 2008); and obtaining the trade-offs relationship between the optimization goals under different process parameters (Chen et al. 2014; Zhang et al. 2014). A summary of the applications of MOO in ASPs is given in Table 2.

The design of ASPs with MOO

During the past decade, the increased energy consumption in wastewater treatment processes led to the consideration of different types of objectives, i.e. economical, technical and environmental, etc., into the process design efforts. Thus, the traditional design approaches should turn into more complex assessment methods including different types of objectives in order to conduct integrated assessments. Flores-Alsina et al. (2007) presented and discussed the usefulness of three evaluation tools, based on multi-criteria decision analysis (MCDA), and supported the conceptual design of activated sludge systems. Those tools contained mathematical modeling, sensitivity analysis, and knowledge extraction and reuse to support the designer during the selection of the best alternative according to the considered objectives and process performance. The results contributed to solving the problem of design with a systematic procedure that supports the DM when dealing with the existing close interplay and ambiguity of the competing options evaluated in a multi-criteria approach.

WWTP control and monitoring can achieve good effluent quality in a complex and highly nonlinear process. Benedetti et al. (2010) presented a method to conduct scenario analysis of process designs, which combined Monte Carlo (MC) simulations and multi-criteria evaluation. It was applied to the open-loop version of BSM2 and two closed-loop versions, one with a simple oxygen controller and the other one with an ammonium controller to regulate the set-point of the oxygen controller (cascade controller). The results showed much greater benefits of the cascade controller compared to the simple controller, both in environmental and economic terms. The uncertainty analysis of the optimal designs, also performed with MC simulations, highlighted the improved and more stable effluent under closed-loop control.

Optimizing the weighted sum of the objective functions is named the weighting method and is one of the earliest methods in MOO. One of its widely known drawbacks is that the solution obtained does not follow the weights selected; in other words, it does not necessarily emphasize the objective functions that are given the biggest weights.

Table 2 | The application of MOO in ASPs

Purposes	ASPs	Methods	Results	References
Process design	All ASPs	MCDA tools	Conceptual design of ASPs	Flores-Alsina et al. (2007)
	BSM2	Monte Carlo simulations	Cascade controller better than simple controller	Benedetti et al. (2010)
	All ASPs	IND-NIMBUS and GPS-X	A useful tool for decision support	Hakanen et al. (2011, 2013)
	BSM1	NSGA-II	PEV and OCI be improved	Our study (Chen et al. 2014)
Process optimization	BSM2	Multi-criteria decision analysis, Monte Carlo simulations	Reduce the output uncertainty	Flores-Alsina et al. (2008)
	BSM1	Control laws and sensitivity analysis	The best trade-offs for energy conservation and emission reduction	Beraud et al. (2008)
	BSM1	NSGA-II	The optimization objectives were improved	Fu et al. (2008)
	A/O	NSGA and sensitivity analysis	Operation flexibility was improved	Iqbal & Guria (2009)
	A^2/O	BP algorithm	A more flexible and precise optimization	Zhang et al. (2014)
	SA^2/OCM	Different control strategies	EQ and OC were reduced	Our study (Chen et al. 2015)

Hakanen et al. (2011, 2013) developed a new interactive tool that was able to handle multiple objective functions simultaneously for WWTP design, which combined the commercial GPS-X wastewater treatment process simulator and the interactive non-differentiable interactive multi-objective bundle-based optimization system (IND-NIMBUS) software. The tool was aimed at supporting the designer for designing new WWTPs as well as optimizing the performance of already available plants. Effluent water quality, the usage amount of sodium carbonate and energy consumption were employed as the optimization objectives. Decision variables included the sludge concentration, the accelerating rate of sodium carbonate and dissolved oxygen concentration, and the solver by a controlled random search algorithm. The optimization results showed that the ammonia concentration in the effluent can be reduced under the lower amount of sodium carbonate and energy consumption. Furthermore, in the interactive MOO process, the optimization results can reflect the idea of the DM, and help the DM to control optimization results in a timely fashion. A flowchart describing the connection between GPS-X, IND-NIMBUS and their interaction with the DM is shown in Figure 6.

Our research team (Chen et al. 2014) studied the optimal design of ASP using MOO, with a benchmark process in BSM1 as a target process. The objectives of the study were to achieve four indices of PEV, overall cost index (OCI), TV and TSSs, making up four cases for comparative analysis. Models were solved by the NDSGA in MATLAB. Results showed 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 indices of PEV and OCI can be improved more than with the default process parameters of BSM1, especially for N removal and resistance against dynamic NH_4^+-N in influent. The results indicated that MOO is a useful method for optimal ASP design.

The optimization of ASPs with MOO

The optimization of the activated sludge wastewater treatment process via mathematical modeling is a complex activity because several objectives (economic, environmental, technical and legal) must be taken into account simultaneously, i.e. the optimization of the alternatives is a multi-criteria problem. Flores-Alsina et al. (2008), using a simplified version of BSM2 as a case study, studied the variations in the decision making when the uncertainty in ASM parameters was either included or not during the evaluation of WWTP control strategies. Optimization objectives included effluent quality, energy consumption and the stability of separating mud. Firstly, six control strategies were evaluated by using multi-criteria decision analysis, setting the ASM parameters at their default value. In the following section, the uncertainty was introduced, i.e. input uncertainty was characterized by probability distribution functions based on the available process knowledge. Subsequently, MC simulations were run to propagate input through the model and affect the different outcomes. Results showed that the control strategies with an external carbon source reduced the output uncertainty in the criteria used to quantify the degree of satisfaction of environmental, technical and legal objectives, but increased the economic costs and their variability as a trade-offs.

Beraud et al. (2008) presented the application of the multi-objective genetic algorithms NSGA-II to the optimization of a control law for a WWTP. A sensitivity analysis was then performed to check the long-term performances of the optimized controller settings. The combination of these two techniques obtained the best trade-offs for minimizing the effluent quality together with the energy consumption while providing information on the robustness of the controller settings.

Fu et al. (2008) investigated the optimization of multi-objective control of urban wastewater system using NSGA-II. The water quality indicators of the receiving

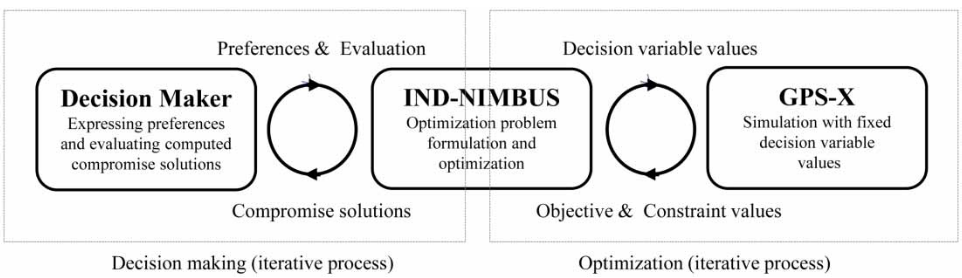

Figure 6 | A flowchart describing the connection between GPS-X and IND-NIMBUS and interaction with the DM. *Source:* redrawn from Hakanen et al. (2013), Copyright Elsevier.

water were considered as control objectives directly, rather than by reference to surrogate criteria in the sewer system or treatment plant. The Pareto optimal solutions illustrated the whole trade-off relationships between objectives. A case study was used to demonstrate the benefits of multiple objective control, and a significant improvement in each of the objectives could be observed in comparison with a conventional base case scenario. The simulation results showed the effectiveness of NSGA-II for the integrated urban wastewater system despite its complexity.

Iqbal & Guria (2009) optimized an ASM with extended aeration using a binary-coded elitist NSGA. The optimization objectives contained the maximum water quantity for treating, minimizing the concentration of pollutants and the energy consumption in the process. Decision variables included sludge age, sludge concentration of the reaction tank, and return sludge concentration. The author established the steady-state model of ASP, used for performance monitoring of the plant. For a given a set of operating plant data, the kinetic parameters in the ASM were firstly determined by minimizing the weighted sum of the square of the errors. These kinetic parameters were then used to solve several optimization problems involving single-, two- and three-objective functions for an existing WWTP. The results showed that the unique solution was obtained for the single-objective function optimization problem, and Pareto optimal sets of equally good non-dominated solutions were obtained for each multi-objective function optimization. Considering operating cost as an objective function, operation flexibility of the wastewater treatment unit was improved and further improved for the three-objective function optimization problems.

Guerrero *et al.* (2011) used a model-based set-point optimization to improve a WWTP control system. Several control strategies for an efficient biological C/N/P removal were evaluated in the anaerobic/anoxic/aerobic (A^2/O) pilot WWTPs. Optimization objectives included effluent quality, energy consumption and the settle ability of sludge in the settling tank. Model-based set-point optimization was shown as a good tool to improve the performance of the system. The optimized control system resulted in around a 45% decrease of operational costs with respect to the open-loop scenario, a significant improvement of the effluent quality and a drastic decrease of the time above discharge limits.

Compared with previous models that were mainly focused on the use of fixed decision factors and did not take into account the treatment cost, Zhang *et al.* (2014) developed a further improvement model by incorporating the back propagation (BP) algorithm, to identify the relationships between decision factors and optimization objectives. The model can continuously adjust and optimize the deciding factor depending on DM desire, so that the optimization model is more flexible and precise in the wastewater treatment process. In the optimization of the A^2/O process, optimization strategies could achieve energy conservation and emission reduction compared with the original operating strategy. The method in this literature is shown in Figure 7.

Our research team used the MOO method to improve performances of EQ and OC for a novel cycle operating ASP (Step A^2/O activated sludge process with Commutative Multi-influent (SA^2/OCM)) (Chen *et al.* 2015). One open-loop and three closed-loop strategies were conducted to evaluate the performance of the SA^2/OCM. The strategies were as follows: (i) open-loop optimization (OLO); (ii) time controller based on SNO_3 or $dSNO_3$ ($TCNO_3$); (iii) time controller based on SNH_4 or $dSNH_4$ ($TCNH_4$); and (iv) time controller based on SPO_4 or $dSPO_4$ ($TCPO_4$). Results showed that trade-offs between EQ and OC of each strategy could be presented, and the OLO and $TCNO_3$ strategies could be respectively used to achieve better performances under open-loop and closed-loop conditions.

CONCLUSIONS AND FUTURE DIRECTIONS

To date, MOO in the wastewater treatment process has steadily improved largely due to the high number of valuable studies from various disciplines. To our best knowledge, many unanswered questions in this field still remain in relation to numerous issues. Discussed below are a list of the primary conclusions from this review and some of the main issues that still remain to be resolved.

Conclusions

1. Mathematical models exhibit superiority in the diagnosis of operational problems, and can adjust the sensitive variables for the effect of processing. Thus, they can quantitatively reflect the randomness in the simulation process, make a direct instruction for operation optimization and facilitate the designer to select the most economically viable parameters from a variety of processes. The development of the ASM family and its related deformation has been established as a standard

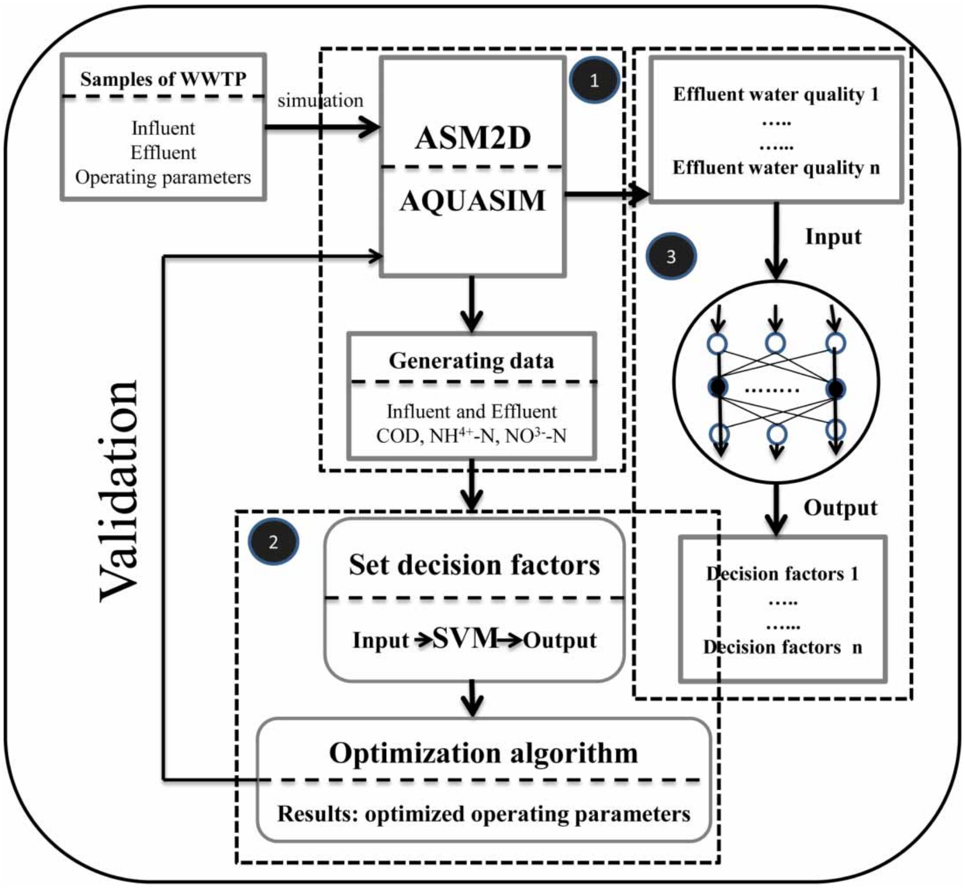

Figure 7 | Framework of the series of methods (SVM: support vector machine). *Source:* redrawn from Zhang *et al.* (2014), Copyright Elsevier.

for ASP modeling, laying a foundation for optimizing and controlling the wastewater treatment process.

2. The benchmark simulation models (BSM1 and BSM2) were released by IWA; both of them include the calculation methods for the standard-exceeding indices of water quality and energy consumption. The standard-exceeding indices of water quality involved excessive effluent concentration of carbon, nitrogen and phosphorus. Calculating energy consumption indices contained energy consumption of aeration, pump and agitation. The two indices' calculation method of BSMs has an important impact on the wastewater treatment process, especially providing instruction on the trade-offs between energy conservation and emission reduction.
3. MOO, as a kind of operations research method, was developed on the basis of linear and nonlinear optimization, and fitted the complex multi-objective optimal decisions. Solving MOO problems is recognized as finding the Pareto optimal solution which best satisfies the options of the DM. Consequently, the final solution of a MOO method is referred to as the most preferred alternative.
4. MOO can be used in handling problems involving multiple conflicting criteria (or objectives) in the wastewater treatment process, e.g. optimizing and designing the ASPs; determining the optimal set-point value of internal control parameters in sewage treatment systems; assessing the impact of the model parameters, water quality, water quantity and other uncertainties for the decision-making process; and weighing the trade-offs relationship between the optimization goals.

Future directions

Although MOO has been successfully applied in optimizing and controlling the process of wastewater treatment, several aspects involving challenges in this area still should be improved over the next few years. Some of them are the following.

1. The applications of MOO required a mathematical model which can simulate the relevant course of processes precisely. The development of mathematical models laid a foundation for MOO, but it also restricted the progress of MOO. ASP is a complex and highly nonlinear process, and most ASMs ignored the fluid flow state in the reaction tank and the biological reactions in the sedimentation tanks. Most mathematical models were developed on the basis of laboratory studies, and had a larger difference when applied at actual WWTP scale. Hence, further in-depth research on the appropriate mathematical model of ASP is required, and should be properly combined with the MOO results in the practice of sewage treatment plants in the future.
2. Currently, MOO in ASP has been investigated by computing and optimizing effluent quality and energy consumption based on the benchmark simulation models (BSM1 and BSM2). Although this method has been widely used in Europe, the water quality standards, constituent weight of wastewater, and energy prices, among others, all showed important differences between different countries and regions of the world. Therefore, it is required to develop a new and comprehensive method for calculating the indices of exceeding water quality and energy consumption based on the actual situation in the wastewater treatment process of different countries. Finally, a set of optimization strategies of energy conservation and emission reduction should be proposed for the domestic sewage treatment plant.
3. Screening the particular Pareto solutions of MOO by a DM is a subjective process, so the solution corresponding to the operating strategy is also subjective. In future research, an evaluation system for Pareto solutions should be developed for MOO, providing the instruction for the selection of a suitable solution in a series of Pareto solutions, and obtaining the reasonable parameters in the process.

ACKNOWLEDGEMENTS

This research has been supported by the National Twelfth Five-year Major Projects (2012ZX07101-005), the National Natural Science Foundation of China (51078074). The authors wish to thank the anonymous reviewers for their constructive comments that improved the manuscript and the copyright holders (Elsevier and IWA Publishing) for permission to use the figures of cited sources.

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First received 25 June 2015; accepted in revised form 8 September 2015. Available online 22 September 2015