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Optimizing municipal wastewater treatment plants using an improved multi-objective optimization method

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HIGHLIGHTS

- An improved multi-objective optimization model for WWTP optimization.
- Simultaneous optimization of treatment cost and effluent quality.
- BP algorithm was applied to determine decision factors according to requirement.
- More flexible and precise optimization of a full-scale WWTP was achieved.

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ABSTRACT

An improved multi-objective optimization (MOO) model was established and used for simultaneously optimizing the treatment cost and multiple effluent quality indexes (including effluent COD, NH_4^+–N, NO_3^-–N) of a municipal wastewater treatment plant (WWTP). Compared with previous models that were mainly based on the use of fixed decision factors and did not taken into account the treatment cost, this model introduces a relationship model based on back propagation algorithm to determine the set of decision factors according to the expected optimization targets. Thus, a more flexible and precise optimization of the treatment process was allowed. Moreover, a MOO of conflicting objectives (i.e., treatment cost and effluent quality) was achieved. Applying this method, an optimal balance between operating cost and effluent quality of a WWTP can be found. This model may offer a useful tool for optimized design and control of practical WWTPs.

1. Introduction

Water pollution remains a severe problem worldwide, especially in many developing countries like China (Qu and Fan, 2010; Wu et al., 1999). To reduce the pollutant release and lower the pollution burden of natural water bodies, increasingly stringent discharge standards have been adopted in China in the past decade (Li et al., 2012). However, this has also significantly increased the treatment costs. Therefore, how to balance the treatment performance and cost becomes a critical issue for operation of wastewater treatment plants (WWTPs), which necessitates a multi-objective optimization (MOO).

MOO is a common problem encountered in many practical processes. Although the basic theory of MOO has been well established, its practical implementation still faces many challenges (Marler and Arora, 2004; Tan et al., 2002). So far, most of the optimization works are based on process simulation (Sidiras et al., 2011; Yang et al., 2013) and single objective optimization (Fang et al., 2011; Zafar et al., 2012), which has many limitations. Taking wastewater treatment process as an example, when certain water quality index (e.g., effluent chemical oxygen demand (COD) concentration) is optimized, others indexes such as nitrogen removal might become even worse. Therefore, the optimal solution of MOO problems is not one single solution but a solution set, referred to as Pareto set. Most of the modern multi-objective algorithms to date, such as multiple objectives genetic algorithm, non-dominated sorting genetic algorithm, Niched Pareto genetic algorithm and multiple objective particle swarm optimization, are evolved from Pareto multi-objective evolutionary algorithms (Maneeratana et al., 2004; Tripathi et al., 2007). The Pareto sets are significantly affected by the decision factors in the algorithm. However, the problem is that an accurate determination of the decision factors is difficult, due to the fuzzy relationships between the decision factors and optimal objects in practical systems. This

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is especially true when the optimization objectives are in conflict with each other (Lamas, 2013; Xie et al., 2011; Yetilmezsoy, 2012).

In a previous study (Xie et al., 2011), a MOO model was established, based on an integrated use of the activated sludge model (ASM) and support vector regression, to simultaneously optimize several effluent quality indexes of a WWTP. This model took into account multiple operating parameters without need for complicated calculation, and successfully estimated a set of optimal operating parameters for improving effluent quality. However, this is not a dynamic model. If the optimization requirements are changed, all the calculations would have to be repeated. In addition, it is not suitable for MOO problems with conflicting optimization objectives. In this study, a further improvement of the model was made by incorporating back propagation (BP) algorithm to identify the relationships between decision factors and optimization objectives. In this way, appropriate operating parameters can be obtained precisely according to the expected optimization targets. Furthermore, a simultaneous optimization of effluent quality and treatment cost of a WWTP was achieved for the first time.

2. Methods

2.1. Sketch of the municipal wastewater treatment plant

The model was developed based on the data from a full-scale WWTP in Hefei, China, with a typical A^2/O process. After a primary clarifier, there are two parallel lines of treatment units, each consisting of an anaerobic tank, an anoxic tank and an aerobic tank. The solids retention time (SRT) of the system is 12 d, while the hydraulic retention times (HRTs) of the tanks are 2, 5, and 8 h, respectively. The internal recirculation ratio is 300%. The average concentrations of mixed liquor volatile suspended solids (MLVSS) and mixed liquor suspended solids (MLSS) are 2300 and 5230 mg/L, respectively. The average sludge volume index (SVI) is 105 mL/g. The average influent quality is: COD 210 mg/L, NH_4^+–N 20 mg/L and suspended solids 206 mg/L. The COD, NH_4^+–N, total nitrogen (TN), NO_3^-–N, total phosphorus (TP), MLSS, MLVSS and SVI were measured following the Standard Methods (APHA, 1995).

2.2. Multi-objective optimization methods

The MOO model in this study inherits a previous model by retaining the series of Mathematical model–Surrogate model–Optimization algorithm (Xie et al., 2011), but adds a relationship model to correlate the optimal objectives with the decision factors. Framework of the methods employed in this MOO model is shown in Fig. 1. In brief, an ASM2D model was firstly used to generate the influent and effluent data sets based on a wide range of operating conditions (243). These data sets formed a database for MOO in the next steps (Fig. 1, step 1). Second, before running the optimization algorithm, a surrogate model (support vector machine (SVM) in this case) of the ASM2D was created (Fig. 1, step 2). Third, decision factors are the key to balance the different objectives in a MOO problem, but are always fuzzy in traditional algorithms. Hence, to allow a better optimization of the multiple (even conflicting) indexes, a relationship model was developed to correlate the effluent data with the decision factors.

The optimization targets include the effluent COD, NH_4^+–N, NO_3^-–N concentrations and the treatment cost. The parameters to be optimized include HRTs and SRTs of the anaerobic, anoxic and aerobic tanks, as well as the internal recirculation ratio.

2.2.1. Mathematical model and dataset

ASMs have been widely used to simulate various activated sludge-based wastewater treatment processes (El Shorbagy et al., 2013; Fenu et al., 2010; Henze, 2000). In this study, ASM2D was used for the simulation using the AQUASIM software (Reichert, 1994). The simulation was performed under different operating parameters, and the effluent quality and treatment costs were calculated. The operating parameters, each has three possible values, were used with different combinations. Thus, in total $3^5 = 243$ columns of data sets were obtained. Dynamic data were generated from simulation based on each of the 243 set of operating parameters. Here, the average concentration data (calculated from the many dynamic data) was used, so that simple calculation can be allowed and more effective and reliable process control can be applied later based on the optimization. Thus, 243 sets of effluent quality data including average effluent concentrations of COD, NH_4^+–N and NO_3^-–N were predicted by ASM2D. These data sets were used for optimization in the next step.

The wastewater treatment cost on a per day basis can be estimated as:

$$c = p_{anaerobic} * h_{anaerobic} * e + p_{anoxic} * h_{anoxic} * e + p_{aerobic} * h_{aerobic} * e + p_{refluent} * h_{refluent} * e + F/SRT \quad (1)$$

where c is the treatment cost per day ($), $p_{anaerobic}$, p_{anoxic}, $p_{aerobic}$ and $p_{refluent}$ are the power consumption (kW) of the anaerobic tank, anoxic tank, aerobic tank and back flow, respectively, while $h_{anaerobic}$, h_{anoxic}, $h_{aerobic}$ and $h_{refluent}$ are the corresponding HRTs (hour); e is the electricity price ($); F is the total disposal cost for all the sludge in the WWTP ($), and F/SRT is the cost for the disposal of excess activated sludge ($) per day.

The following procedure were adopted to obtain the MOO solution set for the WWTP. First, the effluent quality indexes were normalized before the optimization:

$$c_i(j) = \frac{C_i(j) - \min C_i}{\max C_i - \min C_i} \quad (2)$$

where, C_i is the concentration of the effluent quality index i, $C_i(j)$ is the jth data set of C_i.

Decision factor is the key to balance the different optimization objectives in a MOO problem. For determination of decision factor, it is essential to compare the importance of each index and weigh them. With the set of decision factor, the comprehensive index can be calculated as:

$$df_i = \sum_{j=1}^{m} df_{i,j} * a_{i,j} \quad (3)$$

where df_i is the comprehensive index of the ith set, m is the number of the effluent quality indexes, i is the ith set of decision factor, $a_{i,j}$ is the normalized value of jth index and $df_{i,j}$ is its decision factor in the ith set.

2.2.2. Surrogate model and optimization algorithm

Surrogate models, especially machine learning methods, have been widely used for optimization of industrial design with reduced calculation time (Koziel and Bandler, 2007; Qian et al., 2006). One common machine learning method is SVM (Cortes and Vapnik, 1995), which can be used to correlate the input and output variables (Matic et al., 2012). In this study, SVM is used to simplify the calculation.

The operating parameter data sets were used as the input data of SVM, and the corresponding comprehensive indexes calculated from Eq. (3) were used as the output data. In total, 243 groups of input data set were employed. With this model, the optimal sets of operating parameters were then calculated. Genetic algorithm, which is based on the concepts of biologic inheritance and evolution for optimization, was used here as the optimization algorithm.