Parameter sensitivity analysis for activated sludge models No. 1 and 3 combined with one-dimensional settling model

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Abstract The aim of this study was to suggest a sensitivity analysis technique that can reliably predict effluent quality and minimize calibration efforts without being seriously affected by influent composition and parameter uncertainty in the activated sludge models No. 1 (ASM1) and No. 3 (ASM3) with a settling model. The parameter sensitivities for ASM1 and ASM3 were analyzed by three techniques such as SVM-Slope, RVM-SlopeMA, and RVM-AreaCRF. The settling model parameters were also considered. The selected highly sensitive parameters were estimated with a genetic algorithm, and the simulation results were compared as $D_{EQ}$. For ASM1, the SVM-Slope technique proved to be an acceptable approach because it identified consistent sensitive parameter sets and presented smaller $D_{EQ}$ under every tested condition. For ASM3, no technique identified consistently sensitive parameters under different conditions. This phenomenon was regarded as the reflection of the high sensitivity of the ASM3 parameters. But it should be noted that the SVM-Slope technique presented reliable $D_{EQ}$ under every influent condition. Moreover, it was the simplest and easiest methodology for coding and quantification among those tested. Therefore, it was concluded that the SVM-Slope technique could be a reasonable approach for both ASM1 and ASM3.

Keywords Activated sludge model; sensitivity analysis; genetic algorithm; parameter estimation; simulation benchmark

Introduction
It has been reported that the success or failure of a model application is strongly related to the cost of stoichiometric and kinetic parameter estimation (Sollfrank and Gujer, 1991; Ko et al., 2001). A sensitivity analysis is a decisive procedure to identify significant parameters that can have serious effects on process behavior, prior to numerical parameter optimization. The sensitivity of parameters can be affected by operating conditions, influent composition, and type of sensitivity index (Saltelli et al., 2000). For example, the maximum specific growth rate of autotrophs ($\mu_{\text{max,A}}$) would be very sensitive at a plant under high ammonia load, and vice versa (Lee et al., 2005; Ko et al., 2005).

Generally, the sensitivity analysis technique was used to evaluate the effect of single parameter variation on model output. The change of multiple parameters at a time was avoided, because of the interference effect of parameters. Recently, techniques with multiple parameter variation have spread, thanks to the development of statistical techniques. Spear and Homberger (1980) suggested the generalized sensitivity analysis (GSA) technique based on cumulative distribution function curves. The extended GSA technique, the generalized likelihood uncertainty estimation (GLUE), was applied to evaluate a hydrological model (Freer and Beven, 1996). The Fisher matrix approach (Weijers and Vanrolleghem, 1997) and the stochastic approach (Brun et al., 2002) were also used to...
select sensitive parameters. These techniques resulted in good performance but were limited in application to real plants due to complex calculation and program coding.

The aim of this study was to understand the sensitivity of the parameters for ASM1 and ASM3 and to suggest a proper technique for selecting sensitive parameters that can reliably predict effluent quality, and minimize calibration efforts without being seriously affected by influent composition or parameter uncertainty. Even though the secondary clarifier might have an impact on biological processes, the settling model was separated from the biological model in the case of sensitivity analysis. In this paper, the sensitivity of the settling model (Takacs et al., 1991) parameters was also examined.

Materials and methods

Overall procedure

The overall approach of this research is shown in Figure 1. The models considered were ASM1 and ASM3 with the settling model (Step 1 in Figure 1). As the first step, the reference simulation was performed to obtain the base effluent quality (EQ) index that would be used to calculate ΔEQ (Step 2). Next, the parameter sets were generated by two methods: the step variation of single parameter method (SVM) and the random variation of multiple parameters method (RVM) (Step 3). These methods are explained in detail later. Simulations were performed to calculate an objective function, ΔEQ, using these sets of parameters (Step 4), and the sensitive parameters were identified by three different sensitivity analysis techniques (Step 5). The identified sensitive parameters were estimated by a genetic algorithm (GA) (Step 6). Finally the reliability of these techniques was evaluated by examining the results (Step 7).

Biological wastewater treatment process and its models

The process used in this work was the denitrifying layout of the IWA simulation benchmark (Copp et al., 2002). The simulation benchmark adopted ASM1 and the one-dimensional settling model (Takacs et al., 1991) for biological reactors and the secondary clarifier, respectively. In this study, ASM3 was also included and a sensitivity analysis of the parameters was performed. Both model plants were coded with the C++ language.

Evaluation procedure for sensitive parameters

Reference simulations. The reference simulations for the IWA simulation benchmark with ASM1 and AMS3 were performed to obtain the base EQ that would be used to calculate ΔEQ. These simulations were executed with the default values of the parameters in the references, as shown in Table 1.

Figure 1 Overall procedure for selecting more reliable sensitivity analysis techniques
Parameter generation. The parameter sets were generated by the SVM and the RVM. In the SVM, each parameter was changed stepwise by 10% of the reference value within 50–200%, whereas others were fixed. In the RVM, all parameters were changed randomly within the same range by the subtractive random number generation method (Knuth, 1981). The number of tested parameter sets was 400 and 640 for ASM1 and ASM3, respectively, in the SVM, and 2,000 for both models in the RVM.

ΔEQ as sensitivity indexes. The objective function for sensitivity indexes was based on the effluent quality (EQ) index reported by the IWA Task Group (Copp et al., 2002). To apply it to both ASM1 and ASM3, the definition of EQ was slightly modified as below. The subscript \( e \) represents effluent.

\[
EQ = \beta_{TSS} \cdot TSS_e + \beta_{COD} \cdot COD_e + \beta_{NH_4} \cdot NH_4_e + \beta_{NOX} \cdot NOX_e
\]  

\[
COD_e = S_{i, e} + S_{i, e} + X_{S,b} + X_{i, e} + X_{BH,e} + X_{BA,e} + X_{P,e} \quad (\text{for ASM1})
\]

\[
= S_{i, e} + S_{i, e} + X_{S,b} + X_{i, e} + X_{BH,e} + X_{BA,e} + X_{STO,e} \quad (\text{for ASM3})
\]

\[
TSS_e = 0.75 \cdot (S_{i, e} + X_{i, e} + X_{BH,e} + X_{BA,e} + X_{P,e}) \quad (\text{for ASM1})
\]

\[
= iSS_XS \cdot X_{S,b} + iSS_XB \cdot (X_{BH,e} + X_{BA,e}) + iSS_XSTO \cdot X_{STO,e} \quad (\text{for ASM3})
\]

\[
\beta_{TSS}, \beta_{COD}, \beta_{NH_4}, \beta_{NOX} = \text{weighting factors; 2, 1, 20, and 20, respectively}
\]

\[
\Delta EQ = \beta_{TSS} |TSS_{Ref,e} - TSS_{Var,e}| + \beta_{COD} |COD_{Ref,e} - COD_{Var,e}| + \beta_{NH_4} |NH_4_{Ref,e} - NH_4_{Var,e}| - \beta_{NOX} |NOX_{Ref,e} - NOX_{Var,e}|
\]  

where the subscripts Ref and Var equal the reference simulation and the simulation with varied parameter values, respectively.

Identification of sensitive parameters. Three sensitivity analysis techniques were based on the plot of ΔEQ, depending on the parameter value expressed as a percentage (%) of the reference value. The first technique was named the SVM-Slope, which is shown in Figure 2. The slope of ΔEQ according to the concerned parameter values served as the sensitivity index. Other techniques were based on the RVM. The scatter plot of the ΔEQ according to varied parameter values was drawn and all of the ΔEQ values were divided into 15 vertical sections at every 10% interval of parameter variation. The moving average of the ΔEQ and its slope were calculated in each vertical section. If a parameter was insensitive, the dots distribution of each vertical section was relatively similar, and vice versa. The more sensitive the parameter was, the higher the slope was. This technique was named the
RVM-SlopeMA, which is shown in Figure 3. In the last technique, named the RVM-AreaCRF, every dot in the scatter plot was divided into four horizontal sections with the same number, and then each section was divided into 15 vertical sections in the same way as with the RVM-SlopeMA. The cumulative relative frequency (CRF) of each parameter was calculated for each horizontal section, as shown in Figure 4. This technique is similar to the GSA (Spear and Hornberger, 1980), and the difference in our study was the fact that the area between CRF plots was used as a sensitivity index.

Parameter estimation using GA. The five most sensitive parameters were optimized with the GA that was suggested by Kim et al. (2002). The Carroll GA (Yang et al., 1998) was also applied. The genetic operators used were two-member tournament selection, uniform crossover, flip and creep mutation, elitism, and niching (Goldberg, 1989). The setting of the GA parameters was as follows: a maximum generation of 50, a population size of 20, a cross-over probability of 0.5, a creep mutation probability of 0.04, and a flip mutation probability of 0.02. The objective function was to find a parameter matrix that could minimize $\Delta EQ$ as follows:

$$P_{\text{mat}}^\text{min} J(P_{\text{mat}}) = \Delta EQ$$

Tested conditions for simulation benchmark

Influent composition. In order to derive a general sensitivity analysis, three compositions were considered as follows:

1. Simulation Benchmark default ($S_d/S_{NH} = 2.2$). The constant steady-state influent at dry-weather was used.

2. High organic loading ($S_d/S_{NH} = 4.4$). The influent readily biodegradable substrate ($S_d$) was doubled and the others were the same as the Simulation Benchmark default.
High nitrogen loading ($S_S/S_{NH} = 1.1$). The influent ammonium ($S_{NH}$) was doubled and the others were the same as the Simulation Benchmark default.

Parameter uncertainties. Two cases of parameter uncertainties were considered. They were distinct in setting the values of insensitive parameters. In the first case, the same values as those in the reference simulation were used. This was termed an “ideal case.” In the second case, the values found in a different reference were applied as shown in Table 1 and termed a “practical case.” The “ideal case” was introduced to exclude the effect of insensitive parameters on the results of the parameter estimation. The “practical case” was introduced to consider the effect of insensitive parameters in applying the sensitivity analysis technique to a real plant. For the “ideal case”, only the simulation benchmark default influent was used. But for the “practical case”, three influent compositions as shown above were applied. The parameters that had different values from each other for the reference simulation and the estimation step were the following:

**ASM1**: $i_{XB}$, $\mu_{\text{max},A}$, $K_S$, $b_H$, $\eta_{H}$, $K_X$, $\mu_{\text{max},A}$, $b_A$, $k_3$

**ASM3**: $Y_{STO,OH}$, $Y_{STO,NO}$, $Y_{H,OH}$, $Y_{H,NO}$, $i_{N,XI}$, $i_{N,XS}$, $k_H$, $k_{STO}$, $\eta_{NO,H}$, $K_{S,H}$, $K_{STO}$, $\mu_{\text{max},H}$, $b_H$, $b_{STO}$, $\eta_{NO,\text{end,H}}$, $\mu_{\text{max},A}$, $b_A$, $\eta_{NO,\text{end,A}}$

Results and discussion

Identification of sensitive parameters

The results of the sensitivity analysis by the three techniques are shown in Figures 2, 3, and 4. All of them are results for ASM1, the Simulation Benchmark default influent, and the “ideal case.” The results from the SVM-Slope technique could be quantified easily, as shown in Figure 2. Simulations were performed using varied parameter values and then the slopes of $\Delta$EQs were calculated. Parameters with higher slopes such as $Y_{H}$ and $b_A$ were considered to be more sensitive.

The RVM-based techniques required a relatively complicated quantification procedure. In the RVM-SlopeMA technique, the scatter plot was drawn with 2,000 dots representing the $\Delta$EQ values, divided into 15 vertical sections, and then the slope of the averaged points of the $\Delta$EQ values in each vertical section was calculated as shown in Figure 3. Higher slope parameters such as $\mu_{\text{max,A}}$ in Figure 3(b) were more sensitive.

To apply the RVM-AreaCRF technique, the scatter plot was divided into four horizontal and 15 vertical sections. The CRF curves were obtained from the number of points in each section. The more sensitive parameters had the larger areas, as shown in Figure 4(b).
The RVM-AreaCRF technique might be affected by the number of horizontal sections. In order to evaluate this effect, the scatter plot was divided into 2–8 horizontal sections and the results were compared. The selected sensitive parameters were somewhat different among the seven cases, but no significant difference was found in $\Delta EQ$. The number of horizontal sections was set at four in this research, for two reasons. The first reason was that the identified sensitive parameters were similar to the results by other techniques and with different horizontal sections. The second reason was that relatively small $\Delta EQ$ were exhibited.

Parameters identified as sensitive in ASM1 and ASM3

The five most sensitive parameters were identified by the three techniques under four influent conditions. The values of those sensitive parameters were then estimated using the GA. A list of sensitive parameters and their simulation results is shown in Table 2 for ASM1 and in Table 3 for ASM3. The absolute error in the tables indicates the error of effluent COD, NH$^+_4$ - N, NO$_3^-$ - N, and TSS between the reference simulation and the simulation with the estimated parameter values.

ASM1. In the sensitivity analysis results for ASM1, the most outstanding aspect was that the SVM-Slope technique always identified the same sensitive parameters under every tested condition. This meant that this technique was not seriously affected by influent composition and parameter uncertainty. The number of generally identified parameters was three and four with the RVM-SlopeMA and the RVM-AreaCRF, respectively. The variance of sensitive parameter selection can result from invalid identification, so the RVM-based techniques might not be preferred for the ASM1. The RVM-based techniques identified one or two settling model parameters as sensitive, whereas the SVM-Slope did not. The reason was thought to be the fact that $\Delta EQ$ was not seriously affected by the settling model parameters because the weighting factor of TSS was much less than that of NH$^+_4$ - N and NO$_3^-$ - N only 10%. But there was a potential synergy effect if the settling model parameters were changed simultaneously with the activated sludge model parameters. $Y_H$ and $\mu_{max,A}$ were chosen as sensitive parameters by every technique. Practically, $Y_H$ was not regarded as a site-specific parameter. It was not changed much according to the operating condition and the value was usually from 0.64 to 0.70. The high sensitivity of $\mu_{max,A}$ resulted from a relatively high ammonia load and a lack of complete nitrification in the Simulation Benchmark. It was also interesting that $K_{Q,A}$ and $b_A$ were regarded as sensitive parameters by the SVM-Slope and the RVM-SlopeMA techniques even though those were considered to be insensitive parameters by Ho and Greenfield (1991).

ASM3. No technique identified consistently sensitive parameters under different conditions for the ASM3, as shown in Table 3. Some yield coefficients showed a high sensitivity, but each technique chose different values. This phenomenon was regarded as the representation of the high sensitivity of ASM3 parameters to which Lee et al. (2005) referred. However, $\mu_{max,A}$ was selected as a sensitive parameter by every technique under every condition, as with ASM1. The nitrogen content of $X_S$ ($n_{X_S}$) was frequently identified as a sensitive parameter by the RVM-based techniques. It was reasoned that it had a large impact on the nitrogen concentration to be nitrified. The ASM3 did not include ammonification but included the release of ammonia in $X_S$ due to hydrolysis. Besides, the sole source of $X_S$ was the influent for ASM3. The SVM-SlopeMA showed a relatively low $\Delta EQ$. The highest $\Delta EQ$ of the SVM-SlopeMA occurred in an ideal case but was not serious. It was only 2.66, which resulted from the effluent NH$^+_4$ - N error of
Table 2 Selected sensitive parameters and simulation results for ASM1

<table>
<thead>
<tr>
<th>Analysis technique</th>
<th>Influent composition</th>
<th>Selected sensitive parameters</th>
<th>ΔEQ</th>
<th>Absolute error (mg/L)</th>
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<tr>
<td></td>
<td></td>
<td>PU*</td>
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<td>COD</td>
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<td>Kinetic</td>
<td>Settling</td>
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<td>S. B. default**</td>
<td>I</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
</tr>
<tr>
<td></td>
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<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
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<tr>
<td></td>
<td>High org. load</td>
<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
</tr>
<tr>
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<td>High N load</td>
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<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
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<tr>
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<td>I</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
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<tr>
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<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
</tr>
<tr>
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<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₜₜ, aₙₚ</td>
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<tr>
<td>RVM-AreaCRF</td>
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<td>I</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₚₜₜ, aₙₚ</td>
</tr>
<tr>
<td></td>
<td>S. B. default</td>
<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₜₜ, aₙₚ</td>
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<tr>
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<td>High org. load</td>
<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₜₜ, aₙₚ</td>
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<tr>
<td></td>
<td>High N load</td>
<td>P</td>
<td>Yₜᵤ, bₜᵤ</td>
<td>μₚₜₜ, aₙₚ</td>
</tr>
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</table>

*Parameter uncertainty; I = ideal, P = practical  
**Simulation Benchmark default
<table>
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<tr>
<th>Analysis technique</th>
<th>Influent composition</th>
<th>PU</th>
<th>Selected sensitive parameters</th>
<th>ΔEQ</th>
<th>Absolute error (mg/L)</th>
</tr>
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<td>COD</td>
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</tr>
<tr>
<td></td>
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<td>P</td>
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<td>2.83</td>
<td>0.03</td>
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<tr>
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<td>in X&lt;sub&gt;5i&lt;/sub&gt; ,</td>
<td>1.58</td>
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<tr>
<td></td>
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<td>0.04</td>
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</table>
0.12 mg/L. Other techniques sometimes showed significantly high ΔEQ. The prediction errors of COD and TSS were relatively higher than those of NH$_4$$^+$ and NO$_3$$^-$, because of the smaller weighting factors for COD and TSS in the EQ calculation.

**Suggestions for sensitivity analysis technique**

The following questions should be considered to suggest a reliable sensitivity analysis technique that can be used generally:

- Which one is able to produce common sensitive parameter sets despite the changes in influent composition?
- Which one is able to most reliably predict the effluent quality?
- Which one is the easiest to apply for quantification of sensitivity and coding of the program?

It was revealed that the SVM-Slope technique was the answer to all of the above questions. Especially for the ASM1, the SVM-Slope technique undoubtedly showed the best performance among the tested techniques. It produced unique sensitive parameter sets regardless of the influent composition and parameter uncertainties. A generally applicable technique for ASM3 could not be defined. No technique identified consistent sensitive parameters under different conditions. Still, the SVM-Slope can be recommended. It identified relatively constant parameters as sensitive and showed smaller ΔEQ than the others. Moreover, it was simpler and easier for coding and quantification.

**Conclusions**

Three different sensitivity analysis techniques were compared for the ASM1 and ASM3 with the IWA simulation benchmark. The settling model parameters were also examined. For the ASM1, the SVM-Slope technique was proved to be an acceptable approach because it identified consistent sensitive parameter sets regardless of simulation condition and presented smaller ΔEQ. For the ASM3, no technique showed consistent results and no conclusion could be reached about which parameters were most sensitive. This phenomenon was thought to reflect the high sensitivity of ASM3 parameters. But, it should be noted that the SVM-Slope technique presented reliable ΔEQ under every influent condition. Moreover, it was the simplest methodology. Therefore, it was concluded that the SVM-Slope technique is a reasonable approach for both ASM1 and ASM3.

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