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A Review on Environmental Process Engineering

Ataei, A. , Lee, K. S. , Lim, J. J. , Kim, M. J., Liu, H. B., Kang, O. Y. , Oh, T. S. and Yoo, C. K.*

Department of Environmental Science and Engineering, Center for Environmental Studies, College of Engineering, Kyung Hee University, Seocheon-dong 1, Giheung-gu, Yongin-Si, Gyeonggi-Do, 446-701, Korea

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ABSTRACT: In this paper, we introduce environmental systems engineering (ESE) and describe some of its applications combined with process systems engineering (PSE) to problems related to environmental systems. These systems—the water cycle and ecosystem cycles—are complex and highly dynamic, with an uncertainty level comparable to that of chemical systems. To illustrate the challenges of applying PSE to ESE, some novel approaches and examples of the latter are shown for water and wastewater systems. The challenges associated with the modeling, control and optimization of environmental systems provide fascinating opportunities. These opportunities for PSE researchers, as well as the challenges, are the goals of this paper.

Key words: Ecosystem cycles, environmental informatics, environmental systems engineering (ESE), process systems engineering (PSE), water cycle

INTRODUCTION

Since the 1950s, process systems engineering (PSE) has been concerned with understanding and developing systematic procedures for the design, control and operation of chemical process systems. PSE has been successfully adapted and refined to address the needs of designing, controlling and operating chemical process systems in a holistic manner (Charpentier, 2007).

In the PSE literature, there are many reports of new trends and challenges. For example, Gani and Grossmann (2000) reported on a multi-scale model, mixture models, energy and sustainability, climate change issues, CO_2 storage and environmental-related matters. Charpentier (2007) suggested that the market needs products with specific nano- and micro-scale end-use properties that, through an integrated system approach, take into account the social and environmental constraints of industrial meso- and macro-scale processes. Other examples include Grossmann and Westerberg (2000) discussing the future trends of PSE as they relate to chemical-based products, energy, bio-systems engineering and enterprise-wide optimization; and Klatt and Marquardt (2007) examining PSE from academic and industrial perspectives with a focus on environmental issues, such as the effective use of resources to minimize water, energy and air pollution. Fig. 1 shows an environmental system, in this case an urban water cycle, as it interacts with urban catchment, natural runoff, sewers, storm-water treatment, wastewater treatment, groundwater and rivers (Olsson and Newell, 1999). In this system, computer-aided system engineering techniques, such as systems analysis, modelling, control and optimization tools, can be used to minimize pollution or eco-toxicological effects, thereby resulting in a healthier environment.

ESE is here an interdisciplinary field of engineering that focuses on how complex models represent mathematical, data-driven and biotic structures combined with physical, biological and ecological processes in waterways (e.g., rivers, etc.), air and ecosystems. While the history of ESE is relatively short, it has already been applied to various environmental systems concerned with devising, implementing and managing solutions to protect and restore the environment, all within the framework of sustainable development. In pursuit of this goal of sustainable development, ESE brings together two engineering disciplines—environmental engineering and systems engineering—to devise and implement solutions that manage the interrelated elements of the environment, industry and society.

Fig.2 shows the concept of ESE based on environmental modeling and process optimization in order to solve problems with environmental systems. The ultimate aim of ESE is to solve the problem of environmental pollution by optimizing existing

*Corresponding author E-mail: ckyoo@khu.ac.kr

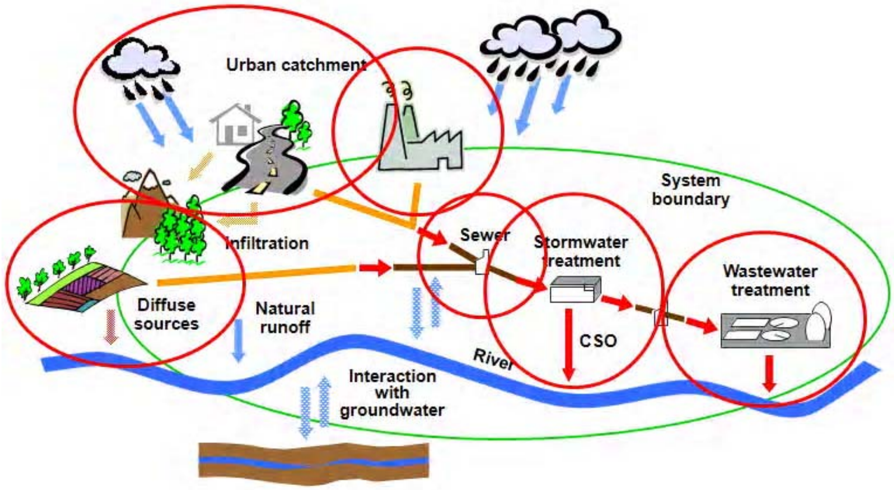


Fig. 1. System components of urban water cycle

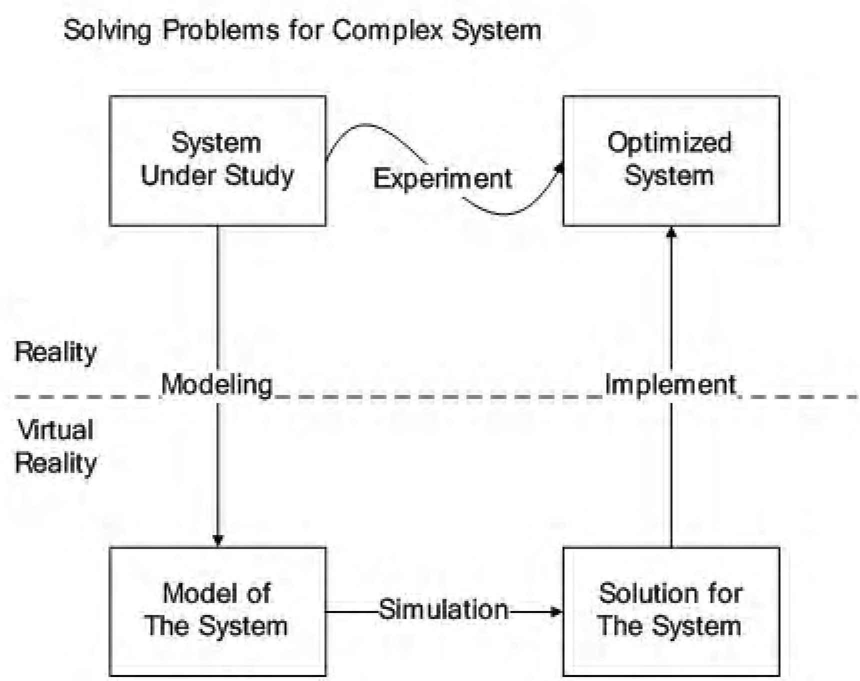


Fig. 2. Concept of environmental system engineering based on environmental modeling and process optimization

processes with minimal investments. Nielsen (2001) reported on a series of diverse case studies that showed an average 6% saving in operating costs and remarkably short payback times. Nielsen (2001) and Yoo et al. (2010) noted that instrumentation, control and automation technologies (ICA) can increase treatment capacities by 10% to 30% at wastewater treatment plants.

This paper focuses on environmental challenges and opportunities for PSE along with ESE to meet the needs for the effective usage of water, energy and for the minimization of the negative impacts on environment quality. This paper presents new approaches and the authors' experiences of modeling, monitoring, control and optimization of wastewater treatment systems followed by a conclusion of the issues addressed.

Wastewater Treatment System

Due to increasing environmental constraints and the necessity for reliable wastewater treatment, efficient modeling and monitoring methods are becoming more important. Better methods for biological wastewater treatment plants (WWTP) are necessary to maintain these systems' performance at or near optimal conditions. Improving performance means ensuring accurate knowledge of the process, which is why mathematical modeling and simulation are excellent tools to link microscopic and macroscopic scales, short- and long-time frames and fundamental and practical knowledge. Models and simulations are the knowledge management tools needed to effectively incorporate novel findings into the practical processes of designing and operating advanced reactor systems for biological wastewater treatment (Wilderer *et al.*, 2002). In this section, we introduce three novel approaches and examples of mathematical modeling, monitoring, sensor validation and control for wastewater treatment systems. These examples provide an opportunity to apply PSE to environmental systems. Modeling of activated sludge processes has become a common part of the design and operation of WWTPs. In 1987, the International Association on Water Quality (IAWQ) task group on mathematical modeling for the design and operation of biological wastewater treatment processes presented ASM1, which is a single-stage activated sludge system that performs simultaneous chemical oxygen demand (COD) oxidation, nitrification and denitrification processes. Subsequently, the task group developed ASM2, which incorporated a biological phosphorus removal process model, and then ASM2d, which included denitrifying PAOs' effects. These first two models were followed by ASM3, a model in which some of defects of ASM1 were fixed (Olsson and Newell, 1999; Henze *et al.*, 2000).

Even with several ASM models (i.e., ASM2, ASM2d and ASM3) and the modifications to the ASM family, ASM1 is still widely used in biological removal processes since it is well known and easily applicable to the modeling of full-scale treatment plants. ASM1 is presented in a matrix format and shows that the system reaction term, Υ_i, is obtained by summing the products of the stoichiometric coefficients υ_{ij} and the process rate expression ρ_j for the component *i* in the mass balance by the following equation (1):

$$\Upsilon_i = \sum_i \upsilon_{ij} \rho_j \qquad (1)$$

Also, different eight main processes are defined in ASM1, such as aerobic growth of heterotrophic biomass, anoxic growth of heterotrophic biomass, aerobic growth of autotrophic biomass, decay of biomass, ammonification of soluble organic nitrogen and hydrolysis of particulate organic matter. The stoichiometric and kinetic parameters of ASM1 are given in Table 1 (Henze et al., 2000). In the ASM1 model, the 13 main components are classified as either COD components or nitrogen components. Total COD and total nitrogen balance for the components in ASM1 is defined by equations (2) and (3), respectively as

$$COD_{tot} = S_I + S_S + X_I + X_S + X_{BH} + X_{BA} + X_P \qquad (2)$$

$$N_{tot} = S_{NH} + S_{ND} + S_{NO} + X_{ND} + X_{NI} + i_{XB} \cdot (X_{BH} + X_{BA}) + i_{XP} \cdot X_P \qquad (3)$$

where COD_{tot} is the total COD of the influent, S_I is the soluble inert organic matter, S_S is the readily biodegradable substrate, X_I is the particulate inert organic substrate, X_S is the slowly biodegradable substrate, X_{BH} is the active heterotrophic biomass, X_{BA} is the active autotrophic biomass, X_P is the particulate products arising from biomass decay, N_{tot} is the total nitrogen of the influent, S_{NH} is the $NH_4^+ + NH_3$ nitrogen, S_{ND} is the soluble biodegradable organic nitrogen, X_{ND} is the particulate biodegradable organic nitrogen, X_{NI} is the particulate inert organic nitrogen, $X_{B,H}$ is the active heterotrophic biomass, $X_{B,A}$ is the active autotrophic biomass, X_{NI} is the particulate inert organic substrate, $i_{XB,}$ is the mass N/mass COD in biomass, i_{XP} is the mass N/mass COD in products in biomass.

ASM1 can be applied to a full-scale plant's Doosan Nutrient Removal (DNR) process, an advanced biological nutrient removal process that consists of two anoxic reactors and clarifiers. The influent conditions used are as follows: flow 8,767m^3/d; TSS 114g/m^3; BOD_5 108 g/m^3; COD 206 g/m^3; and TKN 26 g/m^3. The selected process is designed using a general purpose simulator of wastewater treatment plant. In this study, the world-wide Engine for Simulation, Training and automation program (WEST®) program is used to model the process in Fig. 3.

General information to be used in the process modeling are collected and compiled from the activated sludge plant database, designed documents and/or personal communication with plant operators. The data for the process design are influent and effluent characteristics, physical characteristics such as volumes, compartments, pumping capacities, aerators and pipelines, and various kinetic parameters about microorganisms in the activated sludge process.

The optimization of the ASM is problematic due to model complexity because of many components, kinetic and stoichiometric parameters. To improve the prediction efficiency of the model, sensitivity analysis is performed to select the key parameters influencing the removal efficiency, because it is difficult to simultaneously consider all of the parameters when predicting the results at the same time. The phased change method of single parameter is applied between

Table 1. The typical stoichiometric and kinetic parameters of ASM1[10]

Parameters	Symbol	Unit	value
__Stoichiometric parameters__			
Heterotrophic yield	Y_H	g cell COD formed (g COD oxidized)$^{-1}$	0.67
Autotrophic yield	Y_A	g cell COD formed(g N oxidized)$^{-1}$	0.24
Fraction of biomass yielding part.products	f_p	dimensionless	0.08
Mass N/mass COD in biomass	i_{XB}	gN(gCOD)$^{-1}$ in biomass	0.086
Mass N/mass COD in products in biomass	i_{XP}	gN(gCOD)$^{-1}$ in endogenous mass	0.06
__Kinetic parameters__			
Heterotrophic max. specific growth rate	μ_H	day^{-1}	6.0
Heterotrophic decay rate	b_H	day^{-1}	0.62
Half-saturation coefficient(hsc) for hetero.	K_S	g COD m^{-3}	20
Oxygen hsc for heterotrophs	K_{OH}	g O_2 m^{-3}	0.20
Nitrate hsc for denitrifying heterotrophs	K_{NO}	g NO_3-N m^{-3}	0.50
Autotrophic max. specific growth rate	μ_A	day^{-1}	0.80
Autotrophic decay rate	b_A	day^{-1}	0.20
Oxygen hsc for autotrophs	K_{OA}	g O_2 m^{-3}	0.4
Ammonia hsc for autotrophs	K_{NH}	g NH_3-N m^{-3}	1.0
Correction factor for anoxic growth of hetero.	η_g	Dimensionless	0.8
Ammonification rate	k_a	m^3 (g COD day)$^{-1}$	0.08
Max. specific hydrolysis rate	K_h	g slowly biodeg. COD(g cell COD day)$^{-1}$	3.0
Hsc for hydrolysis of slowly biodeg. Substrate	K_X	g slowly biodeg. COD(g cell COD)$^{-1}$	0.03
Correction factor for anoxic hydrolysis	η_h	dimensionless	0.4

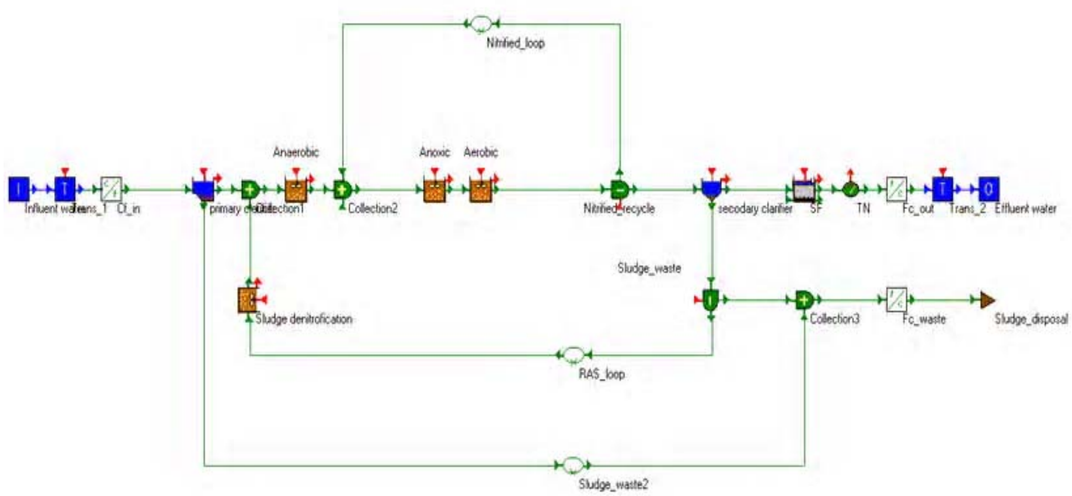


Fig. 3. Layouts of a full-scale DNR plant (WEST)

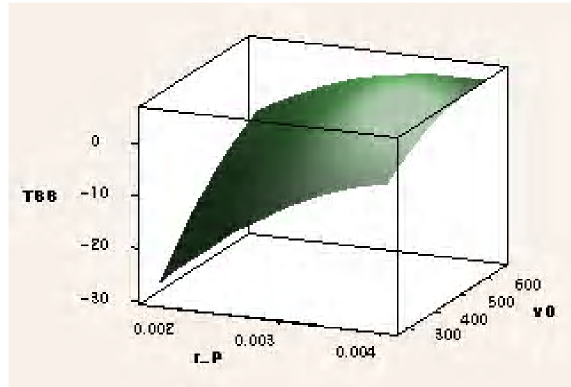
60 - 160% scopes of ASM1 parameters. Then, most sensitive parameters are determined by sensitivity analysis functions of the measured variables to the model parameters. Also, these selected parameters are estimated by using the optimal parameter estimation. The selected sensitive kinetic parameters of ASM1 at each reactor are given in Table 2. Finally, five parameters of b_H, K_S, μ_H, v_0 and r_p are selected for the parameter estimation.

Table 2. The selected sensitive parameters of ASM1 model by the sensitivity analysis

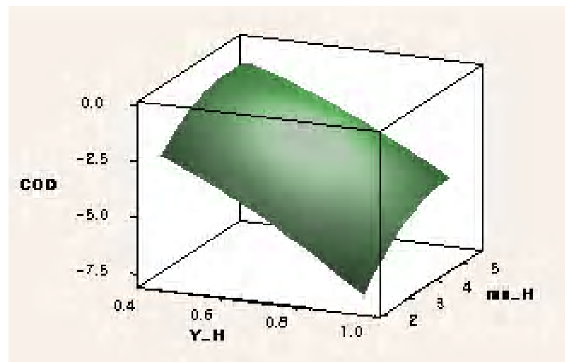
	Sensitive variables
Denitrification reactor	Y_H, b_H, f_P
Anaerobic reactor	Y_H, b_H, f_P
Anoxic reactor	Y_H, b_H, f_P
Oxic reactor	K_S, μ_H, Y_H
Secondary clarifier	v_0, r_P

By using mathematical optimization or genetic algorithm, one can find the optimal values of the ASM model parameters. In this study, polynomial models of linear, interaction, and quadratic terms are used to describe the relationship between the model parameters and the modeling errors. For the experimental model, an analysis of variance (ANOVA) method is used to analyze the aspects of the relationship for different parameter combinations. ANOVA is used to estimate whether the results of the model parameters are significant or not. If the results are not significant, the new model parameters are analyzed. Fig. 4 shows the response surface plots of total suspended solids (TSS), chemical oxygen demand (COD) and total keldhal nitrogen (TKN) with six kinetic parameters of ASM1. By using multiple response optimization, optimal parameters are found as b_H 0.56; K_S 28.0; μ_H 3.30; v_0 664.0; and r_P 0.004.

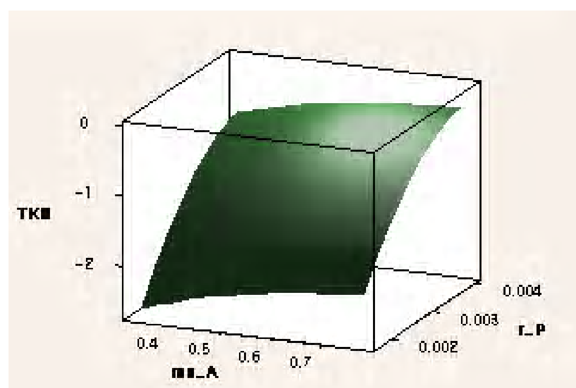
To compare the prediction results of the ASM1 model with the defaults and calibrated parameters for test data for comparison with the measured data of TSS, COD and TKN, the root mean squares error (RMSE) is used. RMSE values of ASM1 in Table 3 are 0.47 for TSS, 0.65 for COD and 0.12 for TKN, respectively. The data used for test period is not used for model building step. RMSE values of ASM1 for test data are 1.45, 1.96, and 0.34 for TSS, COD and TKN, respectively. Because the calibration results of ASM1 are closer to the measured data than that obtained by using the default parameters, ASM1 can model the dynamics of wastewater treatment plant. The calibrated model can be used to upgrade and optimize the plant.



(a) TSS for v_0 and r_P



(b) COD for μ_H and Y_H



(c) TKN for K_s and μ_H

Fig. 4. Response surface plots of (a) TSS, (b) COD, and (c) TKN with six kinetic parameters of ASM1

Table 3. Comparison of real data and ASM model results in DNR plant with the default parameters and the calibrated parameter

	Real data	Default	Calibration
TSS(mg/L)	1.83	15.23	8.79
COD(mg/L)	11.91	35.87	30.66
TKN(mg/L)	6.25	3.37	4.01

An industrial experience of process identification, multivariate monitoring, and control in a full-scale wastewater treatment plant is introduced here to show the power of PSE technology when applied in water industry (Yoo, *et al.,* 2005; Yoo and Kim, 2009). The objectives of this case study were (1) to monitor the process status using multivariate statistics, (2) to apply and compare the different process identification methods of proportional-integral-derivative (PID) auto-tuning for stable dissolved oxygen (DO) control, (3) to implement a process monitoring method that estimates the respiration rate simultaneously during the process identification step and (4) to propose a simple set-point decision algorithm for determining the appropriate set-point of the DO controller for optimal operation of the aeration basin.

Experiments were performed in the industrial coke wastewater treatment facility at a Korean iron- and steel-making plant that exhibits highly dynamic variations in its characteristics. The quantity and quality of the influent wastewater exhibited large and frequent variations, making it difficult to control the DO concentration in the aeration basin with conventional methods. Fig. 5 shows a scheme for the industrial plant used in this study. The plant has two parts: a biological activated sludge process and a chemical treatment process. As shown in Fig. 5, the biological activated sludge process has five aeration basins (#A, #B, #C, #D and #E) and one settling tank. Each aeration basin is equipped with sensors for pH, DO, oxidation reduction potential and mixed liquor suspended solids (MLSS), as well as a 37-kWh speed-controllable surface aerator that supplies oxygen.

First, having a process monitoring system for the biological treatment process is very important because recovery from failures is time-consuming and expensive. Moreover, some changes are difficult to detect and may grow gradually until they produce a serious operational problem. Therefore, early fault detection and isolation in the biological process are efficient as they enable the execution of corrective action well before a dangerous situation happens. A monitoring system for abnormalities is of primary concern for supervisory control and optimization.

Multivariate statistical process control (MSPC) is a possible solution to the dimensionality and collinearity problems. Contrary to univariate techniques, multivariate techniques are more successful solutions for monitoring the process data with severe collinearity and noise. These techniques involve such methods as principal components analysis (PCA) or partial least squares (PLS) combined with standard control charts. These methods are the basis of the field of chemometrics, which has traditionally been concerned with multivariate analyses in chemistry, particularly spectroscopy. PCA and PLS aim to present a multivariate set of measurements with

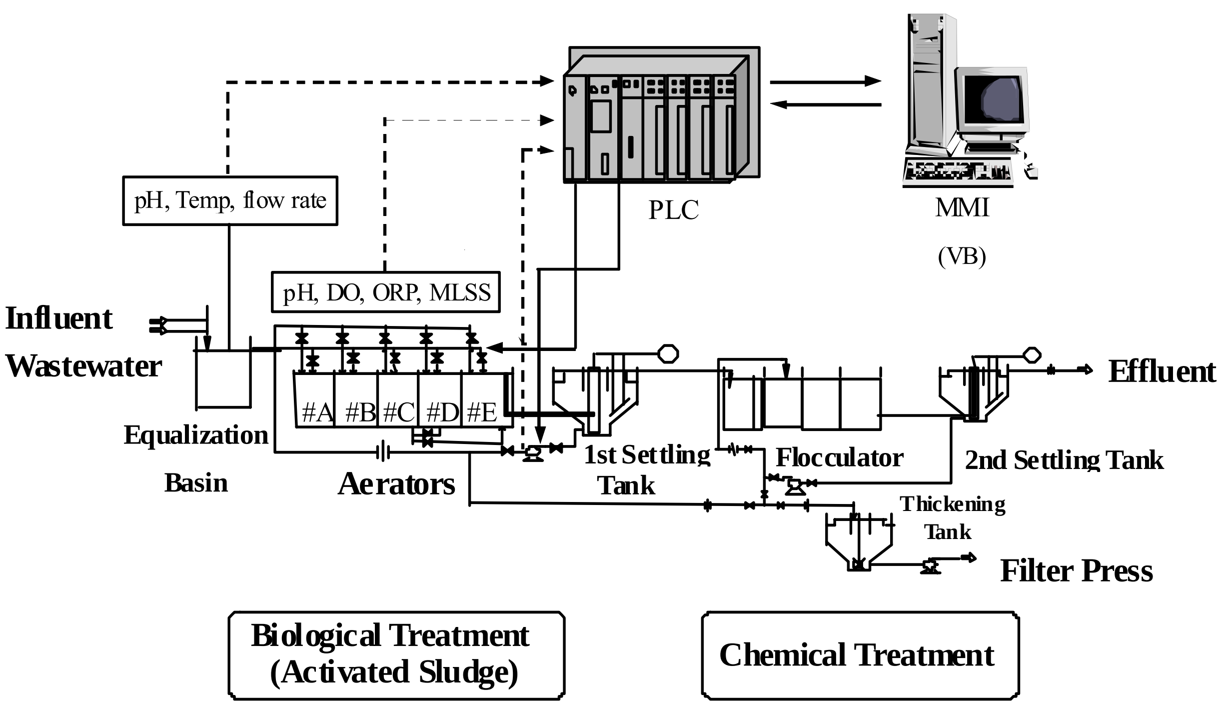


Fig. 5. Plant layout of a full-scale wastewater treatment plant

a smaller number of the transformed variables. To accomplish the task of statistically monitoring a wastewater treatment system, a multivariate statistical monitoring technique is used (Yoo, *et al.,* 2005).

For the interpretation of the plant, the PLS loading weights are considered to see how the **X** and **Y** variables are interrelated. The loading plot in Fig. 6 confirms the underlying physical and biological phenomena as the PLS model distinguishes the chemical and biological variables. As shown in the left middle side of Figure 6, the specific **X** and **Y** variables load strongly in the first two LVs, whereas the COD_3, COD_2 and $T_{aerator}$ for COD reduction are closely correlated. The first **Y** variable, the COD removal rate of the plant, is strongly influenced by the COD load from the second biological effluent treatment (BET2) and the third biological effluent treatment (BET3) and the temperature in the aerators. This result corresponds to the fact that heterotrophic biomass activity for the carbonaceous nutrients is influenced by the temperature in the biological treatment. These variables are uncontrolled or partially controlled throughout the process and therefore exhibit large variations. The second group for CN reduction is related to the CN_2, CN_3, $T_{influent}$, Q_2 and Q_3 and DO of aerator, which are rate-related components of the reaction rate, such as the monod equation. This indicates that the DO concentration in the aeration tank should be controlled. On the other hand, cyanides are known to be toxic to heterotrophic bacteria and inhibitory to their reaction rate. In Figure 6, the cyanide load is counter-connected with the heterotrophic organism concentration (MLSS_%E), which is shown in opposite directions in the loading plots. Hence, shock loading of cyanides in the wastewater influent causes a deterioration of the biological treatment process. The third group is made up of $MLSS_r$ and MLSS_%E with an SVI of the secondary settler in the right upper-side region. This proves that the settle-ability of biomass is related to the microorganism amount in the aerator ($MLSS_r$) and the settler (MLSS_%E).

An appealing feature of the PLS model is its modeling ability, in other words, its predictive capability. Fig. 7 shows the real and predicted value from the PLS model and displays the residual of ***Y*** blocks. The prediction values of the reduction of COD and the reduction of CN are explained well in the test periods and manifest the prediction power of the PLS model for the response **Y** variables. However, the prediction of the SVI of the secondary settler is not satisfied, unlike for the other two quality variables. This may be a result of measurement inaccuracy and the operator's carelessness; the operator needs precise measurement skills. The residual values of the **Y** blocks show that the sum of differences between the real and predicted values for three response variables are mainly caused by the residual error of the SVI prediction.

An integrated management system of process identification and simple set-point decision law in a full-scale industrial biological plant was verified at a full-scale plant. The efficiency of three input signals—set-point change of the PID controller, relay feedback and relay-plus-proportional-control signal—in auto-tuning and respiration-rate monitoring were tested in the dissolved oxygen control at the real plant. The tested aeration basin was the last basin. Fig. 8 shows the experimental results of the three process

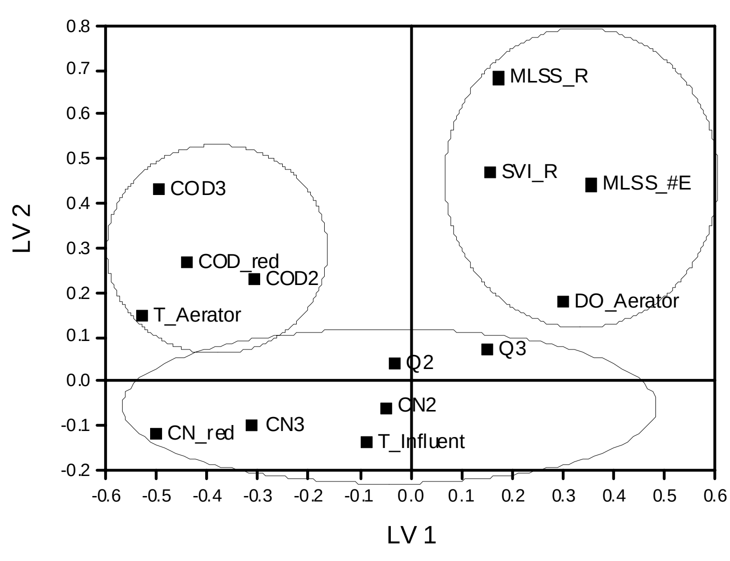


Fig. 6. Loading plot of the PLS model

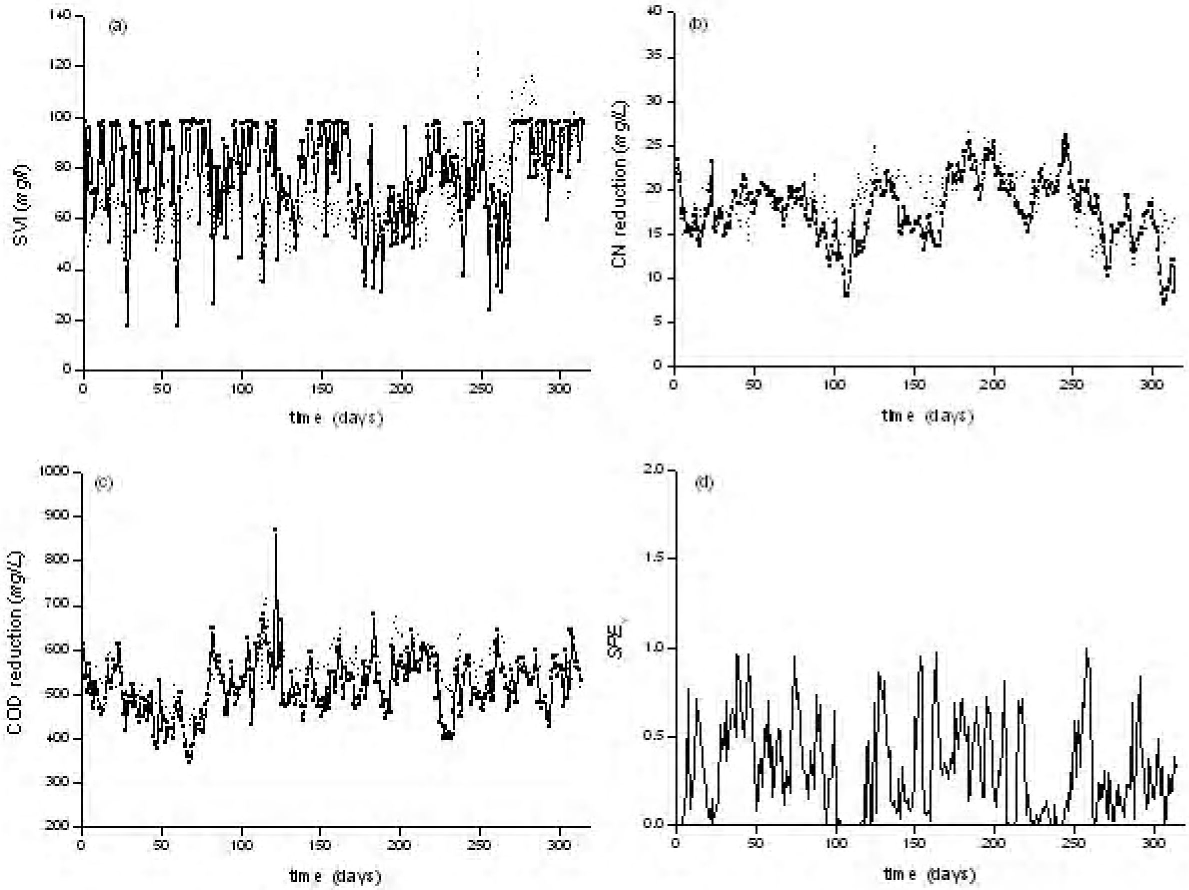


Fig. 7. Prediction results of the PLS model with real *Y* value (solid line with squares) and predicted value (dotted line), (a) SVI, (b) reduction of CN, (c) reduction of COD, (d) squared residual error of *Y* variables (SPE_Y)

identification methods in a full-scale WWTP (set-point change, relay feedback and relay-plus proportional control) for each of the three activating signals. These results clearly demonstrate the nonlinear dynamics of the DO process when testing the three process identification methods; asymmetry is clear where the upward and downward changes are not symmetrical.

In the plant, the following simple set-point decision rule was used during the normal influent load to suggest the set-point of the DO controller:

$$DO_s = -0.025\hat{R}(t) + 2.75 \qquad (4)$$

Where $\hat{R}(t)$ is the estimated respiration rate. Since the WWTP inevitably receives time-varying influent loads, the set-point decision rule based on the simple set-point decision rule should be updated, depending on the influent loading conditions and operators' experience.

Fig. 9 shows the hourly average values of the DO concentration when using the auto-tuned PID controller and the set-point decision algorithm in the full-scale WWTP during a relatively long time (50 days) when the initial set point of the DO controller was 2.0 mg/L. There were five big load changes during these 50 days (Fig. 9), and the DO set points at each load change were altered by the suggested set-point decision law and were executed on some discrete events. As shown in Fig. 9, the set point of the DO controller was changed several times during these 50 days. These are reasonable control results despite several set-point changes. The occasional spikes evident in the DO concentration are due to the automatic sensor cleaning system and two stoppages of electric power. Despite frequent load changes in the coke WWTP, the experimental results obtained for the full-scale WWTP indicate that the proposed method provides good control performance, even though this method is concise and does not rely on any complicated numerical techniques.

Fig s 10(a) and (b) show the effluent COD and electricity consumption of the full-scale WWTP over a four-year period. The effluent COD in Figure 10(a) remained relatively stable after implementing the proposed method,

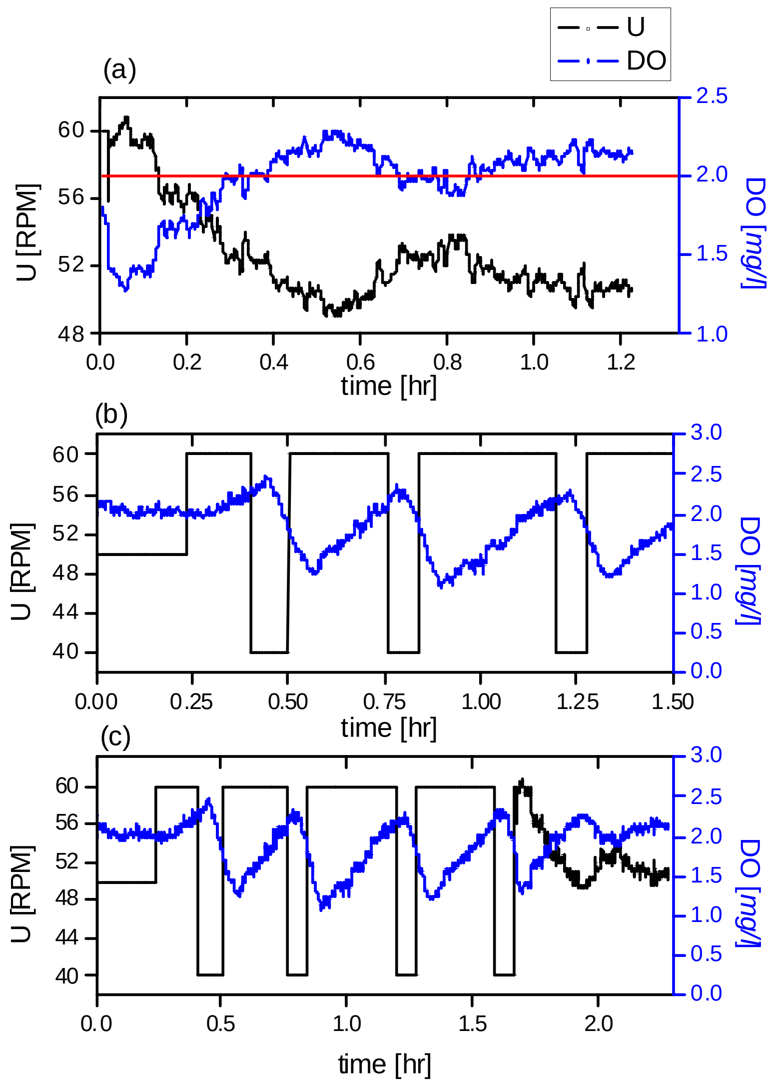


Fig. 8. Experimental results of different process identification methods of DO concentration and speed of the surface aerator in a full-scale WWTP. (a) Set-point change of PID controller, (b) relay feedback, and (c) relay-plus proportional controller

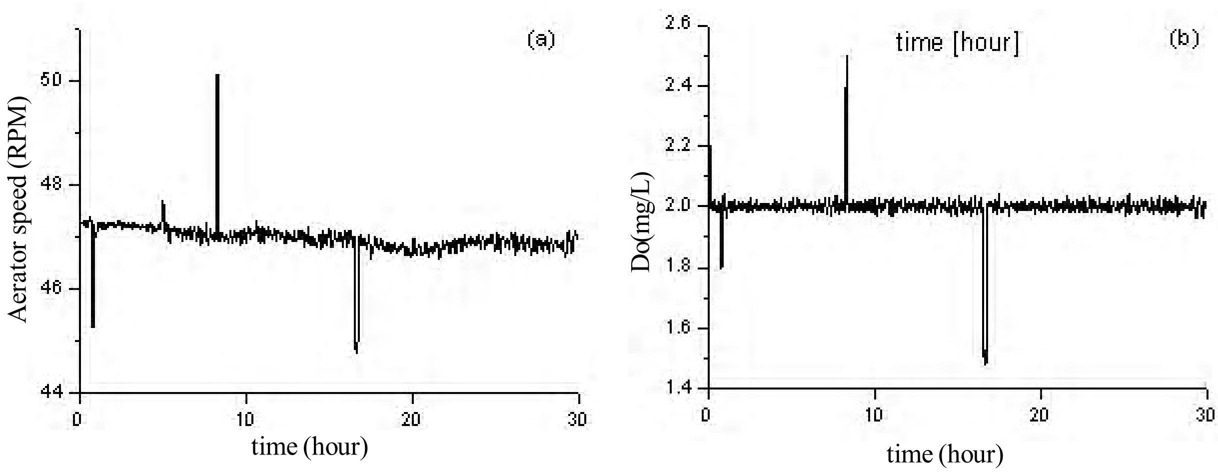


Fig. 9. Control results obtained using the autotuned PID controller. (a) Speed of the surface aerator, (b) DO concentration

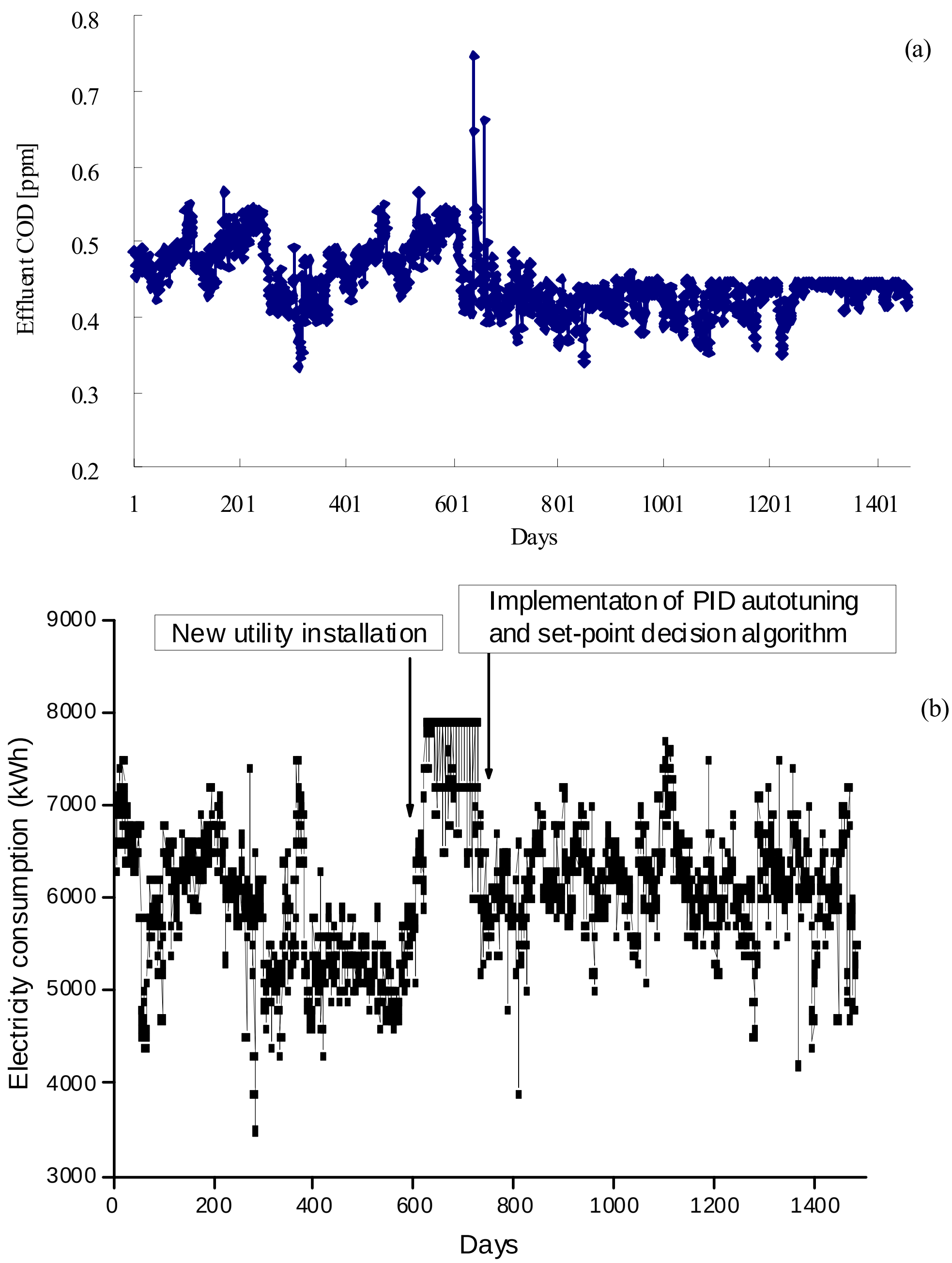


Fig. 10. (a) Effluent COD concentration and (b) electricity consumption in a full-scale WWTP over four years

indicating good control performance despite the frequent load variations, abrupt upstream transition and influent toxicity. Compared with prior results, Fig. 10(a) shows less standard deviation and asymmetric distribution of COD after the implementation. The reason for these results comes mainly from the stable treatment performance of the plant and to some extent from the operator's data treatment. The data shows that the introduction of both the PID auto-tuning and set-point decision law at approximately 700 days led to an overall improvement in effluent quality. In an industrial coke WWTP, the concentration of influent ammonia is generally higher than that of the readily biodegradable chemical oxygen. This mix represents favorable environmental conditions for the growth of nitrifying bacteria. Before the application of the proposed method to the WWTP, it was difficult to control the DO concentration in order to inhibit the growth of nitrifying bacteria. Under limited aeration conditions, i.e., the DO set-point was under 0.5 mg/L, the nitrification process with high concentrations of ammonia occurred with nitrite build-up, indicating that the activity of the nitrite oxidizers was slower than that of the ammonia oxidizers.

As a result of the developed method, the total electricity consumption in Fig. 10 (b) was reduced by 5% and the electricity cost by 15%, compared with the fixed gain PID controller (when considering only the surface aerators). The proposed method enabled the operation of larger equipment with the same electricity consumption, demonstrating that this method facilitates a much more efficient operation. This experience showed that PSE techniques of multivariate statistical monitoring, process identification and control resulted in better effluent quality and a reduction in the electricity cost.

The sensors and data in wastewater treatment and water transport systems have increased almost exponentially over the past decades.[6,8,9,10] This does not necessarily mean that the information has increased as much. Sensors typically represent one of the weakest elements when implementing online process control and monitoring at WWTPs. However, the performance and reliability of many online sensors and offline measurements (e.g., cheap sensors, nutrient sensors, respirometers and so on) have improved remarkably during the past decade and can now be used directly in many different control strategies (Vanrolleghem and Lee, 2003; Rieger *et al.,* 2003). However, WWTPs remain notorious for poor data quality and sensor reliability problems due to the hostile environment, missing data and other problems. In a WWTP, sensors may exhibit partial failures such as bias, drift or precision degradation. These failures cause the accuracy and reliability of the measurement to decrease, which may result in an erroneous control action and false perception of the performance of the monitored system (Qin and Li, 1999). Therefore, prompt detection of the occurrence and correct identification of the location of sensor faults and reliable reconstruction (or recovery) of faulty sensors are of primary importance for efficient operation.

To fill the missing data, the simplest approach is the list wise deletion method. This method has two main disadvantages: one is it may lose some useful information of system process, and the other disadvantage is it is time consuming and hard to implement if the data set is huge. Substitution method can be seen as a more advanced method compared with the list wise deletion method. It replaces missing data points with reasonable approximations. Fig. 11 shows the five substitution methods including mean substitution, median substitution, linear regression substitution, linear interpolation and nonlinear regression substitution.

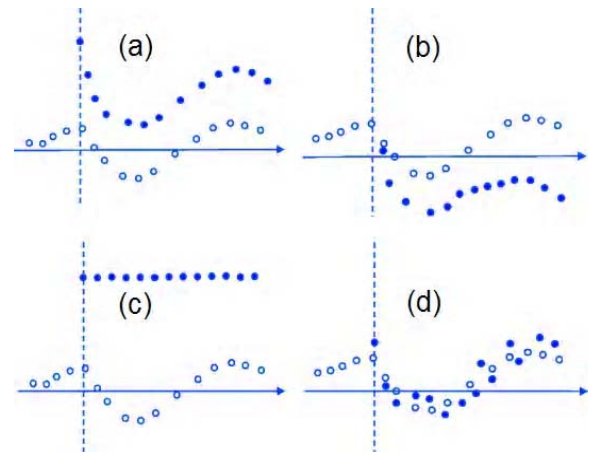


Fig. 11. Four common types of sensor faults: (a) bias, (b) drifting, (c) complete failure and (d) precision degradation

Sensors may exhibit partial failures such as bias, drift or precision degradation as displayed in Fig. 12. It decreases the accuracy and reliability of the measurement, which may result in an erroneous control action and false perception on the performance of the monitoring system. Faulty sensors that are either completely or partially failing (hard fault or soft fault) provide incorrect information for monitoring and control. This can be detrimental to various data-driven decision schemes. Moreover, data may not be available due to sensor malfunction or communication problems within the data collection system. These data problems make it difficult to extract and interpret information from data. Monitoring or control using the unhealthy measurements may become problematic.

Experiments with a sensor validation system for water system data was reported by Yoo et al. (2006). In this case, a sensor reconciliation method using maximum sensitivity based on the redundancy of the measurements was used to detect, identify and reconstruct faulty sensors in an environmental process. The researchers applied a sensor validation method to a lab-scale wastewater treatment reactor (Sharon reactor). The reactor is a 2-liter continuously stirred tank reactor (CSTR) without biomass retention. The pump flow rate of the synthetic influent determines both the hydraulic residence time and the sludge residence time (SRT), since both residence times are equal and defined as the ratio of the volume to the flow rate.

Table 4 summarizes the four types of abnormal conditions detected and lists fault and detection times. In order to reduce false alarms due to dynamic transients, an exponential weighted moving average (EWMA) filter with a coefficient r=0.90 was applied to generate the filtered signal for all four faulty cases.

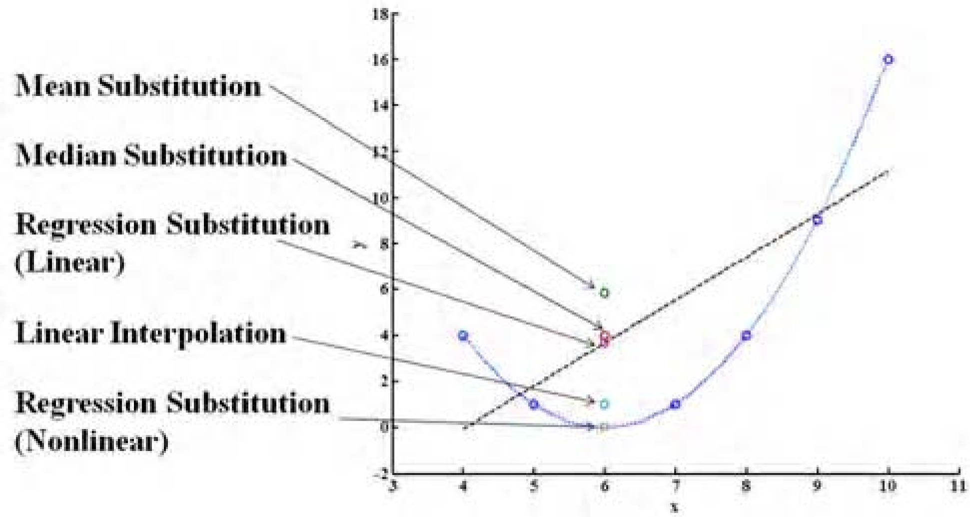


Fig. 12. Five substitution methods to deal with missing data

Table 4. Summary of four fault scenarios and the detection results

	Bias	Drift	CompleteFailure	PrecisionDegradation
Faulty sensor	DO	DO	pH	DO
Fault expression	$f_1(t)=b$	$f_2(t)=a(t-t_f)$	$f_3(t)=c$	$f_4(t)=n(0,\sigma^2)$
Fault size	DO(t)+2.0	DO(t)+0.3*(t-t_f)	pH(t_f)+1.0	DO(t)+ $n(0, 2^2)$
Fault time(t_f)	50	50	50	50
Detection time ($\hat{t}_f$)	53	52	52	54

The cumulative variance index (CVI) is used based on the unfiltered structured residuals with a moving window of five samples considering the hydraulic retention time.

A bias $f(t)$=2.0 that causes a shift in the measurements with a retained trend is artificially introduced to the measurement of the dissolved oxygen (DO) sensor at t_f=50. Fig. 13 shows the sensor fault identification and reconstruction results. The sensor bias fault is detected in the SPE plot with quite a long delay, but it is effectively detected in the filtered signal residuals (FSRs) within a relatively short time. To make a detailed identification, two indices of I_{FSR} and CVI are shown as sub-plots (c) and (d) in the left pane, where a value above one indicates a faulty situation. The FSR can correctly identify the faulty sensor, namely sensor 4 (DO), as the corresponding FSR is below the confidence limit. The CVI shows false identification results of normal sensors since the CVI-method is not designed for bias fault identification. In the right pane of Fig. 13, the reconstructed sensor signal indicates that the difference between normal and reconstructed sensor data is relatively small and can be replaced in the faulty data. These reconstructed data allows the quality of the real data to be checked by looking at the difference. The estimated fault size shows that this is a bias and how large the fault is.

On the other hand, in spite of sensor failures, the monitoring system for a WWTP should be fully operational, which requires a robust and reliable monitoring scheme. A sustainable process monitoring method combined with a sensor reconstruction scheme to tackle the sensor failure problems is proposed for biological wastewater treatment systems (Yoo *et al.*, 2001). Fig. 14 show the sustainable monitoring scheme which is able to detect and compensate for faulty measurements, enhances its monitoring usefulness further. First, sensor fault identification and reconstruction are executed by the sensor validation system in the second step. If any index of a sensor signal exceeds the confidence limit, sensor reconstruction should be executed. The sensor fault magnitude and fault type can be estimated by means of the reconstructed sensor value. When a faulty sensor has been identified, the reconstructed value for the corresponding measurement is used to replace the faulty measurement in the monitoring system. Finally the statistical monitoring system can discern abnormal events and disturbances from normal operational conditions.

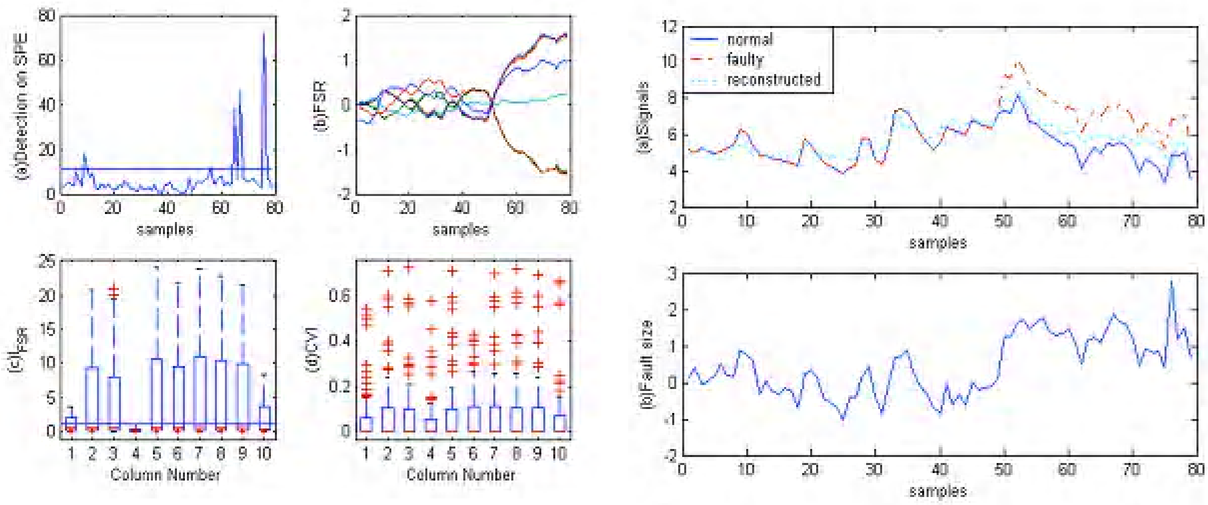


Fig. 13. (Left) Sensor fault detection and identification of DO sensor bias (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) CVI, (Right) Sensor reconstruction of DO sensor bias (a) normal, faulty and reconstructed signals, (b) fault size

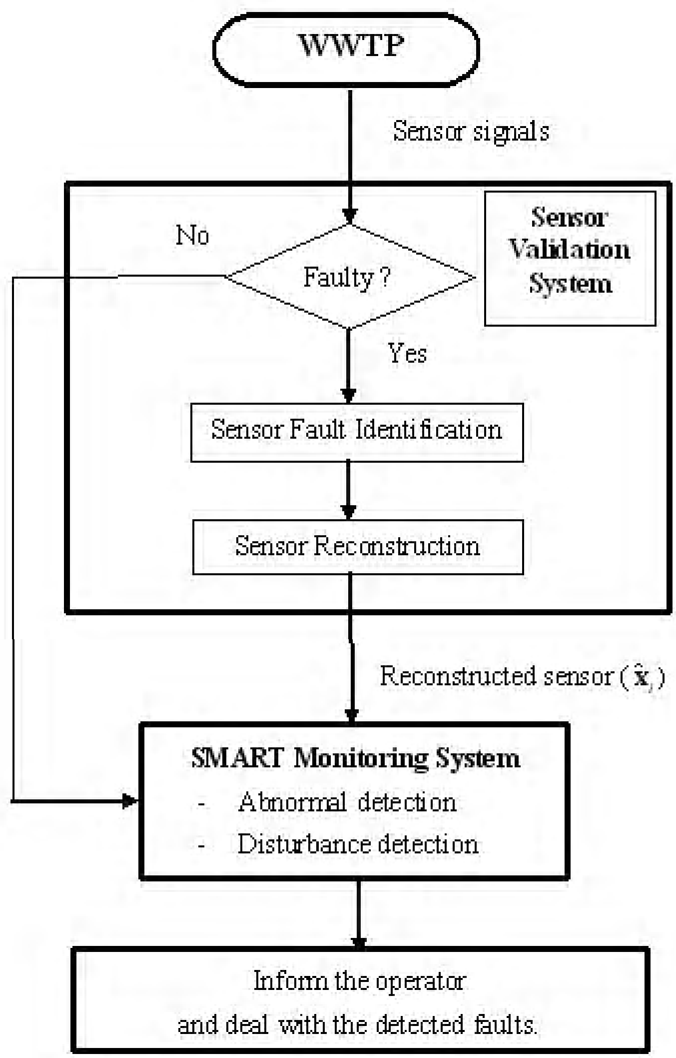


Fig. 14. The sustainable monitoring scheme with a sensor reconstruction module

For the sustainable monitoring system in wastewater system a complete failure of the DO sensor is tested. The failure is introduced at time 50, where the DO value is assumed to be constant at 9 *mg/L* and lasts until the end of the data set. As shown in Fig. 15, this sensor fault was detected, identified and reconstructed. The complete failure (sensor 4) is detected in the *SPE* plot at sample 52 and is effectively detected in the identification indices within a relatively short time. To illustrate the fault identification in detail, four fault indices are shown in Fig. 15. Values below one indicate faulty situations. FSR can exactly identify two sensors, number 4 (DO) and $NO_{3,e}$ which are below the confidence limit, as $NO_{3,e}$ is strongly correlated with DO. Since this fault is the result of a complete failure, all fault indices have a smallest value for the fourth sensor (DO) which makes the correct identification of the faulty sensor possible. The estimated fault size in Fig. 16 shows the result from a complete failure and how large the fault is. The monitoring performances affected by this fault are compared in Fig. 17. With the faulty sensor, the *SPE* charts in Fig.17 (a) remain above the control limits from sample 65 to the end although the operation status of SHARON process is normal and the faulty sensor had no effect on the wastewater treatment. Obviously, the reliability of the multivariate monitoring system is deteriorated and makes it subject to unfavorable criticism. When the sensor are reconstructed, the T^2 and *SPE* values in Fig. 17 (b) remain within the control limits except for the three abnormal events of extreme acid and base addition, hereby improving the robustness of the monitoring system.

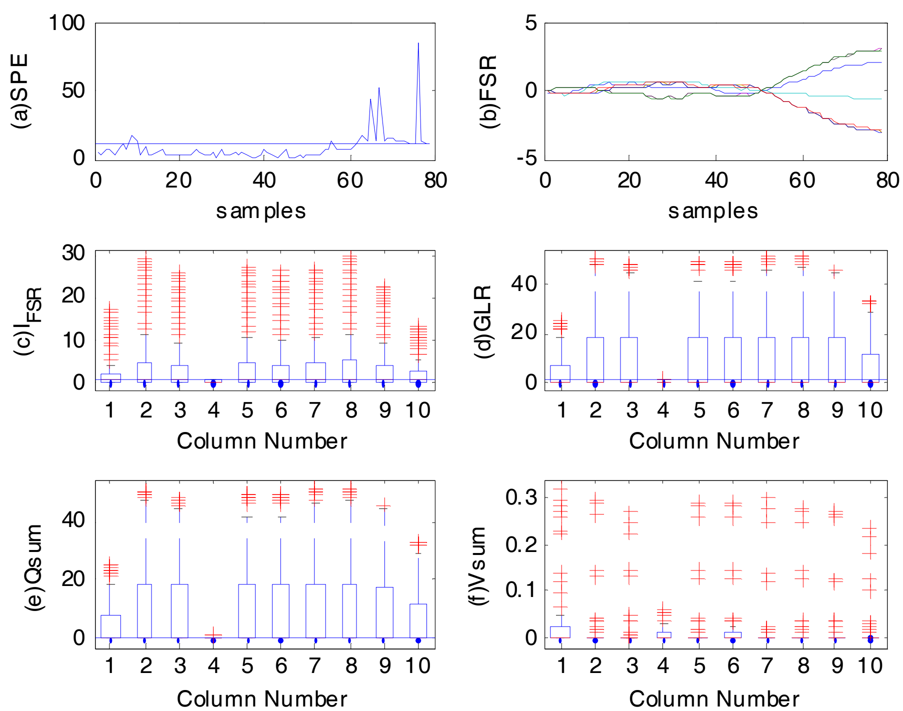


Fig. 15. Sensor fault identification of a complete failure in DO sensor, (a) SPE plot, (b) FSR, (c) I_{FSR}, (d) GLR, (e)Q_{SUM} , (f) V_{SUM}.

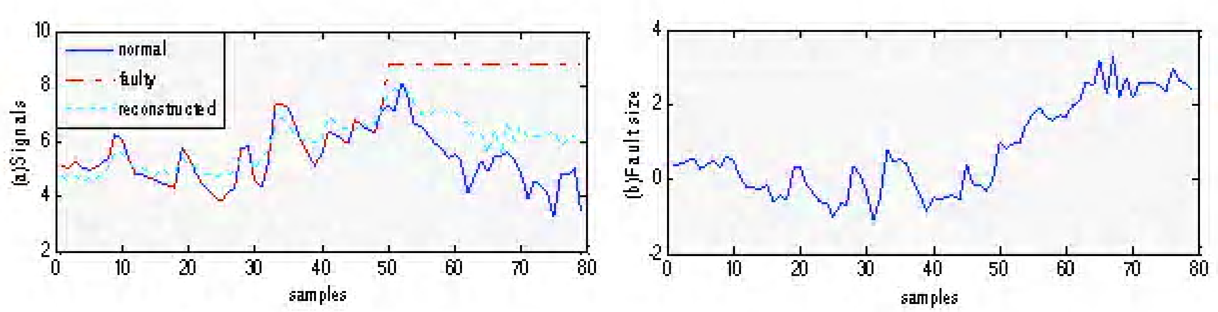


Fig. 16. Sensor reconstruction of a complete failure in DO sensor (a) normal, faulty and reconstructed signals, (b) fault size

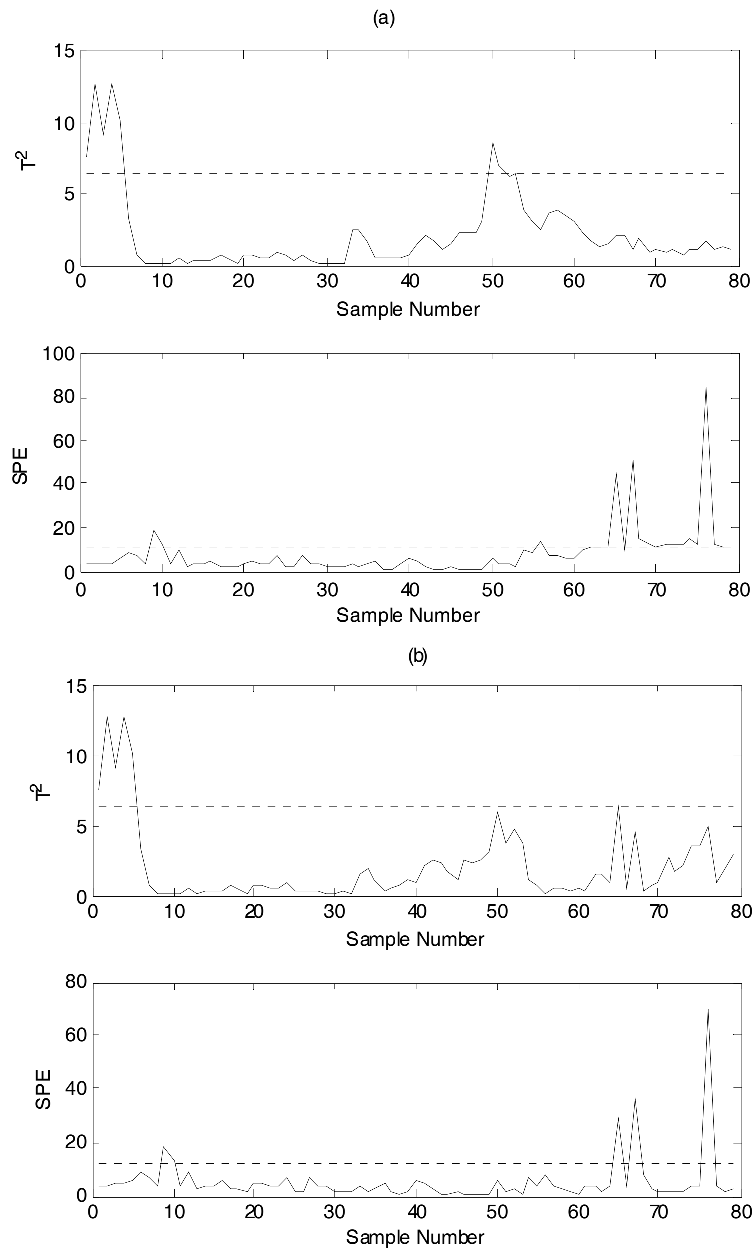


Fig. 17. T^2 and *SPE* plots of the PCA monitoring for a complete failure in DO sensor using (a) faulty sensor (b) reconstructed sensor

A sustainable monitoring method based on the sensor validation is used to detect and identify several sensor faults and to reconcile the failed sensor values in the process. The estimated fault magnitude allows generating a reconstructed sensor value, which can be used to develop more reliable prediction models. The sustainable monitoring approach used here therefore gives us the capability to keep the monitoring system running in the presence of faulty measurements.

CONCLUSION

This paper reflects on the authors' experience with ESE for researchers related to environmental systems. We introduced several examples of wastewater treatment systems and implementation issues in order to show new opportunities for PSE research topics. Based on what we learned from our experience, we conclude that ESE is an emerging research area and that PSE can be extended to environmental systems and used to develop sustainable management with new systematic technologies and tools to solve problems.

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